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► **To cite this version:**

Abdellatif Elmouatamid, R. Ouladsine, M. Bakhouya, N. El Kamoun, K. Zine-Dine, et al.. A Control Strategy Based on Power Forecasting for Micro-Grid Systems. 2019 IEEE International Smart Cities Conference (ISC2), Oct 2019, Casablanca, France. pp.735-740, 10.1109/ISC246665.2019.9071722 . hal-04591521

HAL Id: hal-04591521

<https://hal.science/hal-04591521v1>

Submitted on 31 May 2024

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A Control Strategy Based on Power Forecasting for Micro-Grid Systems

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Abstract— Balancing production and demand of energy is the main challenge to integrate the renewable energy sources (RES) in the micro-grid (MG) systems. However, the variability and the uncertainty nature of the production and the consumption make the system more difficult to control. In fact, weather conditions influences the production of the renewable energy sources and the occupancy influences the consumption of the power in the MG. Therefore, the development of accurate short term forecasts are needed for a seamless integration of RES (e.g. photovoltaic system, wind turbine) together with the traditional electrical grid in the MG systems. This paper presents a forecasting model implemented to predict the photovoltaic (PV) production as well as the consumption in the MG, and the state of the charge of the battery (SoC). Also, a control strategy is implemented to balance the Demand/Response by taking into account the forecasted values like input parameters combining with the obtained values in real time. Based on the data collected from a real MG system, simulation results are presented to show the effectiveness on power forecasting for MG control.

Keywords— micro-grid, power forecasting, control strategy, Demand/Response balance, state of charge, machine learning, IoT/Big-data platform, ARIMA model.

INTRODUCTION

In order to deal the variability and the stochastic nature of the RES and to ensure the safe and reliability of the electricity, the development of forecasting models together with control strategies represents an essential requirement to support high sharing of RES with storage devices in MG. In the MG, the power generated from RES is uncertain and stochastic. Therefore, a control strategy must be implemented to ensure a Demand/Response balance [1]. The control strategy uses the power production of different sources like input parameters to make decision, also, the state of charge (SoC) of the battery and the consumption are used. These different input control parameters are collected in real time. However, the time required to collect and transmit the data and to execute the control algorithm can be a limit for real time control. In fact, during a real scenario, the control algorithms take time to make decision and the command is generated after the moment of the blackouts of electricity. The idea is the development and the implementation of a forecasting method to predict the input parameters in order to avoid the electricity blackouts and to make decision before the switching moment (Fig.1).

The main objective of this work is to implement a control strategy based on the forecast tool for PV power, load, and SoC

using the historical behaviors of data collected from a real MG system. The deployed MG contains different RES (e.g. PV, Wind) and storage devices connected together to the traditional electric grid which can be used to ensure the power when the RES cannot satisfies the demand due to bad weather conditions or during the night [2]. The PV power production, load consumption, and SoC data in the MG are collected and stored in order to be used for testing the forecast algorithm together with the developed control strategy. The power generated by the PV system has priority in satisfying power demand over that delivered by the wind turbine or by the batteries, because in the site of testing there is more radiation during the day than wind. For that, the PV panels are used to ensure the power needed by ventilation and lighting systems installed in the deployed MG.

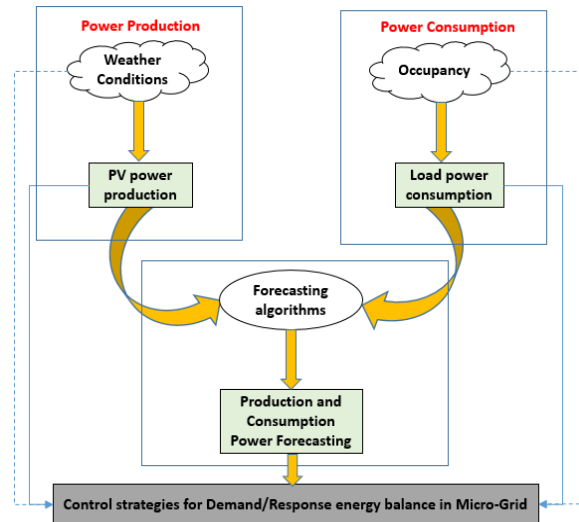


Figure 1. Adapted process of power forecasting and control

The MG contains an internet of things (IoT)/Big-data platform allows to store and analyze data. Different sensors (e.g. Current sensors, Voltage Sensors) are installed to collect the data which will be used to train the forecasting algorithms and to compare the obtained forecasting with the observed values [3, 4].

The remainder of this paper is organized as follows. Section 2 describes existing work from literature. Section 3 introduces different forecasting methods classification used in the literature and the deployed method used in this work is

detailed. In section 4, simulation results are presented and discussed to validate the implemented forecasting method and a simple control strategy is proposed to balance the Demand/Response power in MG by considering the forecasted input parameters. Finally, conclusions and perspectives are given in Section 5.

RELATED WORK

The performance of a MG depends on the climate in which it is located because the weather variables have a significant impact on the RES production and electricity consumption. In fact, the RES production and load consumption forecasting are a current research topic and several approaches have been investigated in the literature. For instance, authors in [5] present a simple approach for short term forecasting of the power produced by a photovoltaic system connected to the grid. In their paper, one year database of solar irradiance, cell temperature and power produced by one megawatts of photovoltaic panels is used to develop three distinct artificial neural network (ANN) models, to be applied to three typical types of day (sunny, partly cloudy and totally cloudy).

In [6], tools for short term load and wind power forecasting were implemented and two loads predictors based on an autoregressive with exogenous variables model (ARX) and an ANN were designed. The authors conclude that the ARX model describes the future load for short prediction horizons better than the ANN, but for larger prediction the ANN outperforms the ARX model, as it is able to recognize more complex relations than the ARX-model. Authors in [7] developed an intelligent model with an autoregressive input sequence based on Bayesian Regularization Artificial Neural Networks (ABRANNs) to predict the global solar radiation, the results obtained are used to calculate the PV power generation for a half hour scale. Authors conclude that the optimal ANN architecture used to predict the global solar radiation is the architecture presented in [30, 31], in which authors propose an implementation of ANN to estimate accurate values of global solar radiation on tilted planes. A review on forecasting of wind speed and generated power considering different time scales is presented in [10]. In this work, authors propose a time scales classification and a comparison of present mechanisms to determine the best existing forecasting methods. Concerning load forecasting, in [11] authors present a prototype platform for real-time machine learning integration with recent IoT and Big data technologies. The platform is used for occupants' presence detection. The work presented in [12] investigates a regression based on the daily peak load forecasting method for a whole year including holidays. To forecast load precisely throughout a year, authors consider different seasonal factors that affect the load consumption. For example, in the winter season, average wind chill factor is added as an explanatory variable in addition to the explanatory variables used in the summer model. In transitional seasons, such as spring and autumn, the transformation technique is used to validate the proposed model. Authors in [13, 14] develop a load prediction model composed of three components: nominal load, type load and residual load. The nominal load is modelled such that the Kalman filter can be used and the parameters of the model are adapted by the exponentially weighted recursive least-squares method. Another interesting work, presented in [15], introduced an adaptive online load forecasting approach, and

the forecasting approach automatically adjusts the model parameters according to changing conditions based on time series analysis. The regression of this work is integrated in [16]; the model is adaptable to changing operational conditions. In [17], authors applied a wavelet transform Kalman filter method for load power forecasting. In this way, authors form two models, weather sensitive and insensitive. The wavelet coefficients are modelled and solved by the recursive Kalman filter algorithm. Others methods are used to predict the load power like the time series models, the load is assumed to be a linear combination of previous loads. For that, the work presented in [18, 19] propose an autoregressive (AR) model to present the load power profile compared to an ANN model. Another work presented in [21], in which authors developed ultra-short, short, medium and long-term prediction models of wind speed, based on computational intelligence techniques, using Autoregressive Integrated Moving Average (ARIMA), ANN, and hybrid models including forecasting using wavelets.

The work presented in this paper develops an energy management platform that allows managing micro-grid systems using a machine learning method to forecast the control inputs parameters. Unlike the work presented in [3] which is based on the real collected data to control the MG system, this present work is based on the same MG platform in order to develop an intelligent and predictive control strategy for MG systems.

POWER FORECASTING TECHNIQUES

A. Classification of power forecasting techniques

Different machine learning methods can be used to forecast the power production and consumption using the historical behavior of data. The forecasting can be able to minimize the consumption from traditional electrical grid by maximizing the RES generation, in consequence reducing the electricity cost. An accurate forecast is used to reduce the uncertainties of the RES integrated in MG by implementing control strategies based on the forecast values. Different techniques that can be implemented for load and PV power forecasting: exponential smoothing, multiple regression, stochastic time series, statistical models, and artificial intelligence.

A lot of methods have been proposed in literature [20, 22, 23, 24, 25], selecting the best suitable ones to be used for MG control is required. In fact, power forecasting is an integral process in the planning and the control of electric utilities in the MG system, the power forecasting is frequently identified as an important tool to address the uncertainty and the variability of the power production and load consumption in the MG with a large RES integration. Some forecast algorithms need a high quantity of data to be trained and to have a low error (e.g. ANN, LSTM) [8, 9, 27, 29]. Generally, these algorithms need a long training time to be stabilized and to be executed; it can be used for medium and long term forecasting cases. Also, based on the time series analyze, a classification can appear (Fig.2). On another way, other algorithms can be trained by a low quantity of data to forecast a very short or short term in the future (e.g. ARIMA, ARX). During a period, the algorithms calculate the error between the observed and forecasted values in order to ensure that the error does not increase more than the threshold limits.

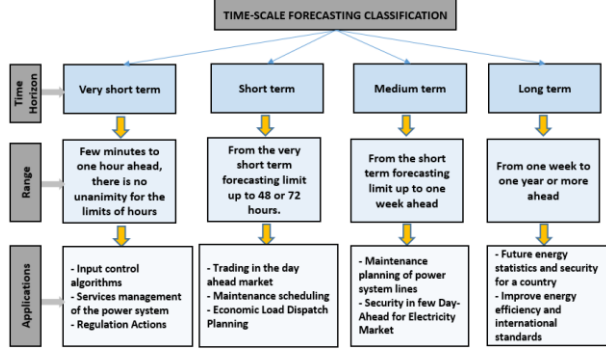


Figure 2. Time scale forecasting classification

While the applications area is an interesting point to define the categories and the algorithms of the forecast to implement. For the control, the time horizon can be very short, from a few minutes to one hour or more ahead to make decision. For that an algorithm, which demands a few time to be trained can be selected. For example, the control strategy can switch from PV panels and batteries to the traditional electric grid if the forecasted values show that in few moments the RES cannot satisfy the demand. This decision can be implemented based on the forecasted values obtained during a few minutes. Therefore, the integration of the price like input parameter to the control strategy needs a few hours ahead of the forecast values to stabilize the system. The electricity price varies during the time by considering the peak of the consumption and production. Another classification can be used by considering the stability of the data used to train the algorithm and the variability of the values to forecast. Fig.3 shows a basic classification of the methods that can be implemented to forecast the RES generation and the load consumption based on the data type used to train the algorithms (e.i., stationary or non-stationary).

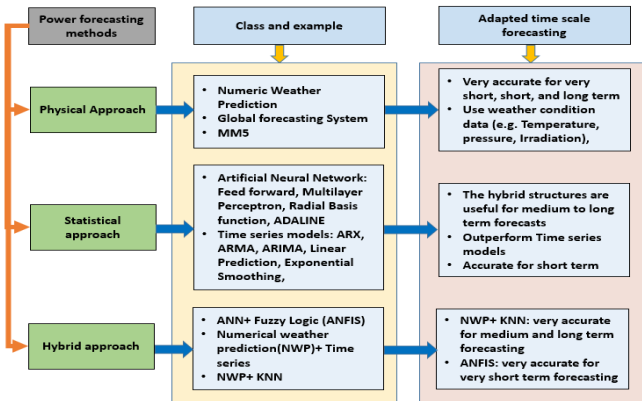


Figure 3. Power forecasting methods

B. Deployed forecasting technique

Statistical models approaches do not need internal functionality information from the system, which generate the value to forecast. It is a data driven approach able to extract relations on previous data to forecast the future behavior of the values. However, the quality of historical data is essential for an accurate forecast, a large historical of data is typically required. This approach benefits from the capability of correcting systematic errors associated to the measurement of

inputs [28]. These approaches include the regressive methods, which estimate a relationship between dependent (e.g. temperature, irradiation) and independent parameters (e.g. model temperature, wind speed).

ARIMA is one of the popular linear models in time series forecasting due to its statistical properties as well as Box Jenkins methodology in the model building process [26]. It is one of the most useful approaches used to analyze the non-stationary time series, by integrating two approaches for stationary time series, autoregressive (*AR*), moving average (*MA*), and combined *AR* and *MA* (*ARMA*) series.

The application of the ARIMA method has a fundamental impact on the study of the non-stationary time series analysis due to Box and Jenkins approach which includes five iterative steps [24] (Fig.4).

Differentiation step, in this phase general ARIMA models is presented to model the data. The general formulation is presented by equation (1) [25]:

$$\varphi_p(B)\Phi_{sp}(B^l)\Delta^d\Delta_l^{sd}X_t = \theta_{sq}(B^l)\theta_q(B)\epsilon_t \quad (1)$$

where B present the back-shift operator ($B: B^{-1}(X_t)=X_{t-1}$ and $B^{-l}(X_t)=X_{t-l}$), this functions can contain factors of polynomial functions on the following forms: $\varphi_p(B) = 1 - \sum_{l=1}^p \varphi_l B$, $\theta_q(B) = 1 - \sum_{l=1}^q \theta_l B$, $\Phi_{sp}(B^l) = 1 - \sum_{m=1}^{sp} \Phi_{ml} B^l$, $\Theta_{sq}(B^l) = 1 - \sum_{n=1}^{sq} \Theta_{nl} B^l$, the non-seasonal operators are $\varphi_p(B)$ and $\theta_q(B)$ and the seasonal operators are $\Phi_{sp}(B^l)$ and $\Theta_{sq}(B^l)$. The terms $\Delta^d = (1-B)^d$ and $\Delta_l^{sd} = (1-B^l)^{sd}$ are respectively the non-seasonal and seasonal differencing operator. X_t is the power at the actual time t , and ϵ_t present the error at the time period t .

Identification step is the estimated procedures applied to a data to find the best ARIMA model by determining appropriate parameters p , q , and d , in order to obtain the stationary time series. It is a critical step to build an *ARIMA* (p,d,q)(sp,sd,sq) model, where *AR*: p is the auto-regression order of the model which indicates the number of parameter φ , and I : d is the degree of differencing to make a stationary data X of the model, and *MA*: q is the order of the moving average aspect which indicates the number of the model parameter θ , sp is the seasonal *AR* order which indicates the number of parameter Φ , sq is the seasonal *MA* order which indicates the number of parameter Θ , and sd is the number of times the data series needs to be seasonally differenced to indicate a seasonally stationary series.

Estimation step, once the model is specified to obtain the stationary time series, the model parameters are estimated in such a way that the error is minimized. Its parameters are estimated from the conditional least squares methods, based on the values estimated during the identification step.

The last step of ARIMA model building is the diagnostic checking, after the identification and the estimation of the model parameters this step checks if the model is a good fit to the data, the assumptions about the errors (also known as the residuals) are satisfied, then determines if the autocorrelation is zero or insignificant. If the model is inadequate, a new model should be identified by the different steps of parameter estimation and model verification.

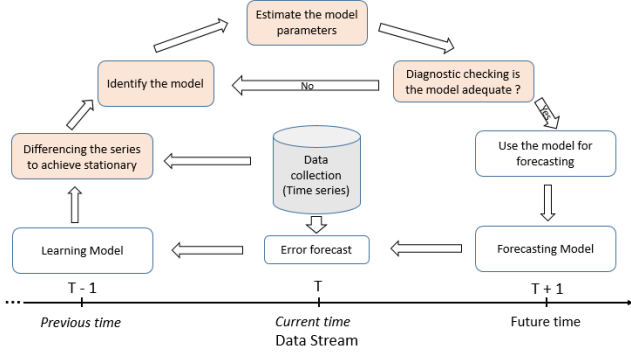


Figure 4. Different iterative steps of ARIMA model

The idea with *ARIMA* model is that the finale residual should look like white noise and verify if there is information available in the data to extract. In each step of *ARIMA* modeling (*AR*, *I*, *MA*), time series data is passed through these 3 parts to produce less residual. The sequence of three steps for *ARIMA* analysis is started by the integrated steep, in this steep the model subtracts time series with its lagged series to extract trends from the original series data. The differencing order is used to subtract the data, equation (2) presents the differencing order one and two.

$$\left. \begin{aligned} (d = 1): X'_t &= X_t - X_{t-1} \\ (d = 2): X'_t &= X_t - X_{t-1} - (X_{t-1} - X_{t-2}) \end{aligned} \right\} \quad (2)$$

The formula is used to remove the trend in order to make data stationary on average but it is not stationary on variance. In order to produce reliable forecasts through ARIMA models, we need to make the series stationary on variance. For this reason, the original time series data is transformed by a logarithmic function. The following equation represents the process of log transformation mathematically (equation 3).

$$X''_t = \log_{10}(X_t) - \log_{10}(X_{t-1}) \quad (3)$$

After the time series data is transformed stationary in the integrated steep, the influence of the previous observed values on the current values is extracted in autoregressive steep. This is done through developing a regression model with the time-lagged period values as predictor variables. Equation (4) presents the general form for the regression model.

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \dots + \varphi_p X_{t-p} + \epsilon_t \quad (4)$$

Concerning MA steep, the influence of the previous period's error terms on the current period's error is extracted. MA part of ARIMA is developed with the simple multiple linear regression values with the lagged error values as predictor variables (equation 5).

$$X_t = \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_q \epsilon_{t-q} \quad (5)$$

ARIMA model is defined by coupling the three models (*AR*, *I*, *MA*). The values of ARIMA should firstly defined that optimize a metric of interest such as partial correlation and auto correlation of the series, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. The idea is to choose a model with minimum AIC and values. AIC is a measure of the quality of fitting an estimated model. It is based on the concept of entropy which is a measure of the information lost when a mathematical model is used to describe the actual data. The AIC can be defined by the equation (6).

$$AIC = \log Z + \frac{2n}{N} \quad (6)$$

where N is the number of values in the estimation data set, n is the number of the estimated parameters, and Z is the loss function.

It's worth noting that another key factor should be taken into consideration is the precision of the model. To measure the accuracy of the predictions, the errors between the forecasted values and actual data are analyzed. Tow indicators are used, mean absolute error (MAE) and the mean square error (MSE). These two indicators have been used to evaluate the accuracy of obtained model to be used for forecasting.

$$MAE = \frac{1}{N} \sum_{t=1}^N |X_t - F_t| \quad (7)$$

$$MSE = \frac{1}{N} \sqrt{\sum_{t=1}^N (X_t - F_t)^2} \quad (8)$$

CONTROL STRATEGY AND SIMULATION RESULTS

The proposed strategy could control the deployed MG system, which contains a PV panel connected to battery storage in order to ensure the power to a ventilation and lighting systems. In this case study, the control strategy is based on the forecasted values to make control decision according to the following cases: i) the power generated by the PV system has priority in satisfying power demand by loads over that delivered by the traditional electrical grid or by the batteries, ii) if the power generated by the PV system is higher than loads demand, the PV system is connected directly to the loads, iii) if the electric power generated by the PV system is less than demand, power will be supplied from the PV and the main storage, v) if the power generated by PV is less than the demand and the SoC of the battery is less than 40 % (to avoid a deep discharging), the power will be supplied by the traditional grid, during this time PV power is used to charge the main storage.

In fact, during the day the PV production is used to ensure the power to the loads and to charge the battery. As shown in Fig.5.a, from 01:00 pm to thereabouts 08:00 pm the irradiation decreases, during this time the battery starts to discharge in order to ensure the power to the loads together with the PV panel. Moreover, during the night only the battery is used to supply the power to loads, but when the SoC reaches the threshold value the control strategy presented in the next section switch from RES to the traditional electrical grid. Also, the power consumption data are collected and the ARIMA model is deployed to forecast the consumption during the same period for the test. In fact, the consumption depends on the occupants activities in the building. As shown in the Fig.5.c, the consumption variety is due to the ventilation system speed variety which depends to the indoor CO₂ concentration. The previous data are used to train ARIMA which starts to forecast the consumption around 01:00 am and the obtained results are compared to the real data.

The input parameters used for this control strategy are the PV power production, load consumption, and SoC of the battery. For that, a dataset of the PV power production, load consumption, and SoC is used to train the implemented ARIMA forecasting algorithm. The obtained algorithm is used to forecast the control strategy input parameters.

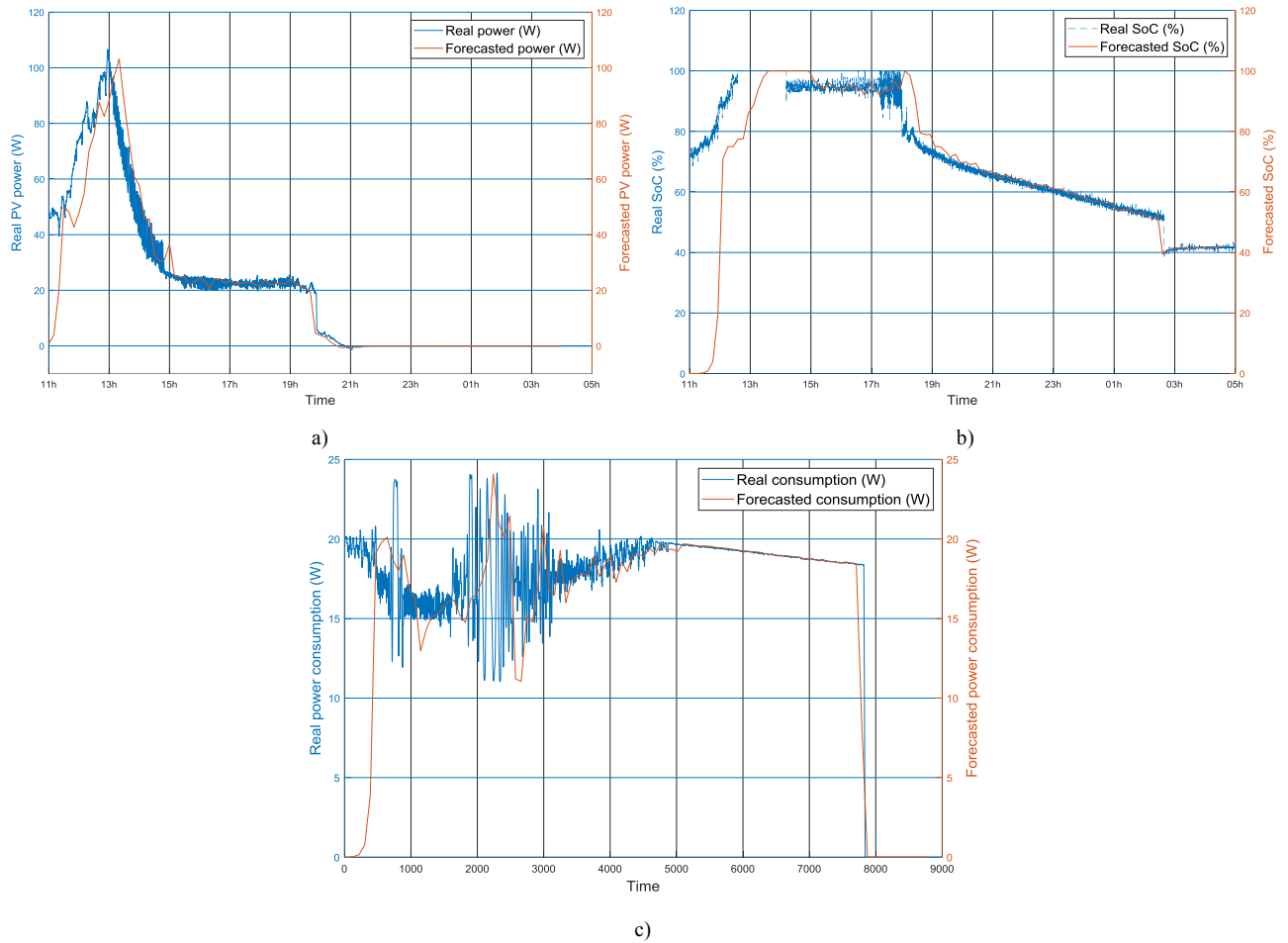


Figure 5. a) Forecasting and real PV power, b) Forecasting and real SoC, c) The real and the forecasted power consumption

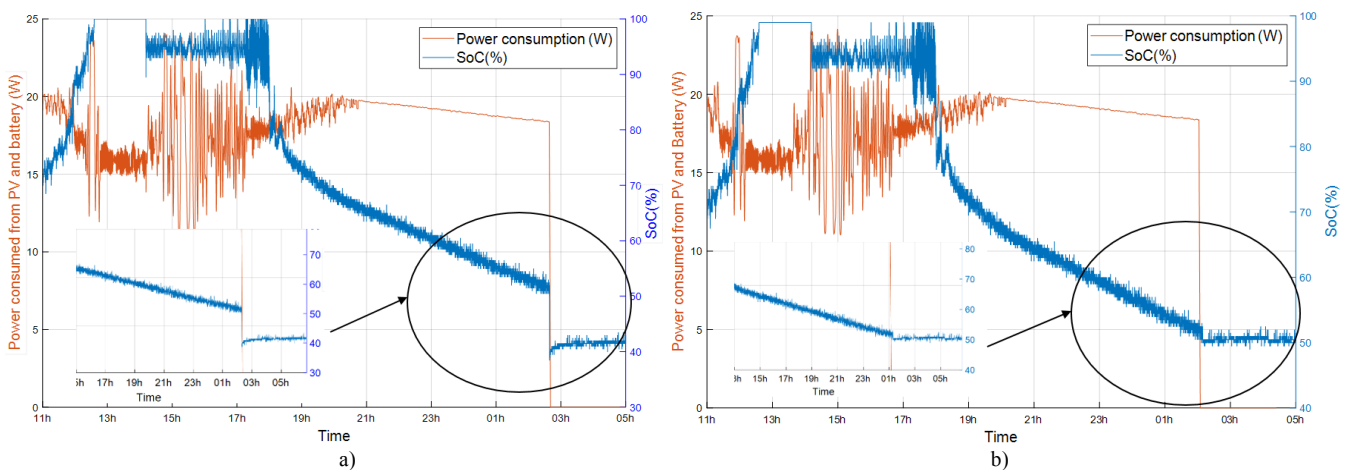


Figure 6: Control decision: a) The switching moment based on real time values, b) The switching moment based on forecast values

For the control, the time horizon is very short to short, from a few minutes to one hour or more ahead to make decision. For that an algorithms that demands a few time to be trained can be chosen for this case. ARIMA model is implemented for the simulation. Fig.5.a presents the forecasting power together with the real power of the PV, the values are obtained a few minutes before the real time values. The same for the SoC of the battery, Fig.5.b shows that around 2:30 AM the control strategy switch from RES to the traditional grid because the forecasting value obtained shows that the threshold value of the

SoC will be attended (Fig.6.b). For that, the SoC remains constant at 50% from 2:30 AM to the end of the simulation. Therefore, the battery is discharged to 40% around 3:00 AM (Fig.6.a) when the control strategy is based on the real time values of the SoC. Fig.6.a shows the switching moment of the control strategy based on the real data obtained. Around 3:00 AM the battery is discharged and the system switches in this moment, when the threshold value of the SoC is obtained, from the RES to the traditional electrical grid. The same model is simulated using the forecast values like input parameters to the

control strategy. Fig.6.b shows that the control strategy switches from PV and battery to the traditional grid when the threshold value of the SoC is obtained by the forecasting algorithm. In this case, the switching moment is obtained before the switching moment obtained in the case when the real values are used like input parameters. A predictive control strategy allows avoiding possible blackouts in the MG. In fact, the system is able, via the forecasting process, to process future values, which allow deciding on the best suitable source before getting in these blackouts situations. Moreover, a price function will be integrated in the future work in order to further optimize the price function and the control will be based on the price function to make decision.

CONCLUSIONS AND FUTURE WORK

In this paper, we have introduced a predictive control approach to balance the power generated from a PV panel using battery storage to ensure the power to a ventilation system. The input parameters used in the control strategy is the PV power production, SoC of the battery and the load power consumption. This input parameters are forecasted and the values obtained for a very short term are used like input parameters to the control strategy. Preliminary simulation results show the usefulness of the predictive control strategy to make decision in order to switch from a source to another in the MG. Our ongoing work focus on the integration of this predictive control strategy in a real MG deployed in our test site and a price function will be integrated together with the other control input parameters to balance the power flow and to minimize the electricity cost. Experimental results will be compared with those obtained from simulations.

ACKNOWLEDGMENT

This work is supported by MIGRID project (grant 5-398, 2017-2019), which is funded by USAID under the PEER program.

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