



HAL
open science

A Model Predictive Control Approach for Energy Management in Micro-Grid Systems

Abdellatif Elmouatamid, R. Ouladsine, M. Bakhouya, N. El Kamoun, K. Zine-Dine, M. Khaidar

► **To cite this version:**

Abdellatif Elmouatamid, R. Ouladsine, M. Bakhouya, N. El Kamoun, K. Zine-Dine, et al.. A Model Predictive Control Approach for Energy Management in Micro-Grid Systems. 2019 International Conference on Smart Energy Systems and Technologies (SEST), Sep 2019, Porto, Portugal. pp.1-6, 10.1109/SEST.2019.8848995 . hal-04589508

HAL Id: hal-04589508

<https://hal.science/hal-04589508v1>

Submitted on 27 May 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Copyright

A Model Predictive Control Approach for Energy Management in Micro-Grid Systems

A. Elmouatamid^{1,2}, R. Ouladsine¹, M. Bakhouya¹, N. El kamoun², K. Zine-Dine², M. Khaidar²

¹ International University of Rabat

LERMA Lab, ECINE, Faculty of Computing and Logistics, Sala El Jadida, Morocco
{abdellatif.elmouatamid, radouane.ouladsine, mohamed.bakhouya}@uir.ac.ma

² Chouaib Doukkali University

STIC Lab, LAROSERI Lab, CUR''EnR&SIE'', Faculty of Sciences, El-jadida, Morocco
{elkamoun.n, zinedine, khaidar.m}@ucd.ac.ma

Abstract—MG systems integrate renewable energy sources (RES) together with storage devices for being connected to the traditional electrical grid in order to supply the power to the building's loads. However, management and control approaches are required for seamless integration of these systems in energy efficient buildings. In this paper, a model predictive control approach is introduced for efficient MG operation. The proposed approach allows minimizing the usage of the traditional electric grid for supplying the power to the building's loads by using as much as possible the power generated by RES while optimizing the storage devices operations. A model predictive control (MPC) strategy is proposed in order to balance the power flow in MG system. The deployed strategy controls the charge/discharge current of the battery depending on RES production, and load consumption variability. Simulations have been conducted using real dataset generated from our deployed MG system, and preliminary results show the usefulness of predictive control principles for the efficient operation of MG systems.

Keywords—renewable energy sources, micro-grid systems, model predictive control, state of charge, photovoltaic system, IoT/Big-data.

I. INTRODUCTION

Renewable energy technologies have been developed in the past decades as main sources for producing green energy while limiting CO₂ emissions. In fact, the high integration of these energy sources with different storage systems in buildings is being widely promoted to reduce the electric energy consumption [1]. Moreover, the aggregation of different sources and loads together with the traditional electrical grid stimulate the deployment of micro-grid (MG) systems into energy efficient buildings [2]. However, their integration into buildings introduced several challenges because of intermittency and uncertainty of RES-power generation. Optimal control and energy management approaches of MG systems are, therefore, one of the most challenging issues that have to be further tackled in order to ensure the Demand/Response balance while ensuring the safety and reliability of the electricity with a minimum total cost.

For that, a model predictive control (MPC) strategy is introduced for energy management in MG systems. As depicted in Fig. 1, the MPC is an advanced control technique, which has been proposed for predicting and forecasting the suitable actions by solving a finite-horizon open-loop control problem [3, 4]. For instance, a model predictive control approach is presented in [3] for ventilations' control using contextual building's data. This approach showed its efficiency in terms of occupants' comfort and energy reduction compared to other real-time

controllers (PID, state feedback). The MPC principles have been also used for MG systems control management (e.g. [6, 7]). However, most of research work focused on the control aspects without considering the whole system management chain (e.g., sense, analyze, forecast, predict, and act over knowledge base), which requires advanced metering and computing platforms using recent IoT and Big Data technologies together with real-time machine learning algorithms [8].

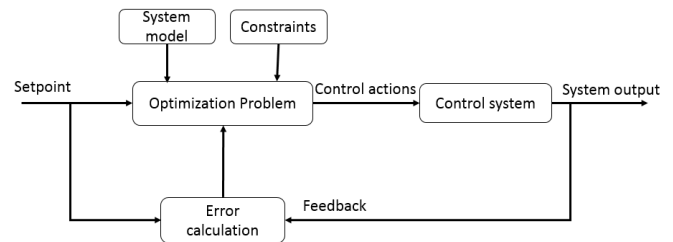


Fig.1. MPC operation scheme

In this work, the system to be controlled is an MG composed of a set of photovoltaic (PV) panels and storage devices connected together with the traditional electrical grid in order to satisfy the building's demand (e.g., lighting, ventilation system). The control strategy is based on the integration of an optimal scheduling technique, which could deal with the variability and the stochastic nature of the RES-power generation. In fact, the control strategy uses the following forecasted parameters as inputs, the power production (e.g., photovoltaic power), the batteries state-of-charge (SoC), and the electricity consumption with its daily costs in order to predict the suitable control decisions. More precisely, real measurements are used as forecasted inputs to the MPC strategy, mainly power production, load demand, and SoC, which are collected from different sensors (e.g., voltage sensors, current sensors). An IoT/Big-data platform was also deployed for data gathering, processing, and predictive analytics using recent machine learning algorithms. These algorithms are used to forecast the MPC input parameters (e.g., SoC) [9] in order to figure out the right decision according to actual situations. In fact, the MPC allows solving an optimization problem by determining the optimal control actions. Moreover, a Demand/Response control strategy is also developed and integrated into the platform for testing and performance evaluation. The control strategy uses the forecasted values of the input parameters not the real data in order to prediction the future actions.

In summary, the main contributions of this paper are as follows: A platform for data monitoring and real-time processing that integrates IoT/Big-data technologies is deployed together with a predictive control strategy in order

to balance the power flows between PV, batteries, and the traditional electrical grid. Using the data collected from a real MG, simulations have been conducted to study the usefulness of the platform and the effectiveness of the proposed control strategy.

The remainder of this paper is organized as follows. Section 2 presents briefly the existing work from literature by focusing on those using predictive control principles. Section 3 presents the deployed MG system. The MG equivalent model together with the predictive control strategy is introduced in Section 4. Simulation results are presented in Section 5. Finally, conclusions and perspectives are given in Section 6.

II. RELATED WORK

MG systems are a collocation of decentralized electrical energy sources, storage devices and loads, which are connected to the traditional electric grid. These distributed sources are connected together using an advanced control platform including recent communication and sensing technologies [10]. In literature, different control strategies have been proposed to manage the power sources as a hybrid system by using real-time data as input parameters. Recently, MPC-based approaches have been proposed for predicting future actions based on real-time forecasting of system's inputs (e.g., power production forecasting). In fact, significant research efforts have been dedicated to the integration of MPC strategies in MG systems for management and control.

For instance, authors in [11] presented a MPC control scheme for wind power generation with a battery energy storage system in order to compensate the intermittency and the stochastic nature of power production. The proposed control strategy allows to sell more electrical energy at peak demand/price times and to store it during normal periods. A MPC approach for MG control is presented in [12] and deployed by [13, 14] for PV power generation in a MG system with mixed storage devices, battery and hydrogen-based. The predictive controller optimizes the operational costs by considering the value of the generated energy, the cost of locally stored energy, and the operational constraints. The developed MPC approach presented in [13, 14] is validated in [15]. A MG testbed is implemented with a MPC-based approach to manage the power in a real sitting scenario for efficient and reliable operation of the MG, including a fuel cell and electrolyzer as main equipment.

In [6], authors presented the implementation of an MPC approach to balance the power in a hybrid system, which includes solar plant, fuel cell, and hydrogen storage. A mixed integer linear framework for MG modelling and optimization is illustrated in [7]. The proposed approach was investigated using experimental MG, which includes energy storage, grid interaction, and an MPC framework. Another interesting work is presented in [4]. Authors in [4] proposed a MPC approach for a PV system with storage devices with the aim to minimize the bill cost for customers by predicting information concerning the PV power generation, the load consumption, and the electricity price. In fact, the predicted values are used to optimize the operation of the PV system and the charge/discharge of the batteries. A strategy for energy management, based on MPC principles, is studied and developed in [16] for multi-MG systems. It was used mainly to achieve the balance between the power production and demand while minimizing the cost of the power supplied

by efficient coordination of the extra energy production between the MG systems.

In [17], authors introduced a MPC approach for real-time management of power generated by the PV panels with energy storage. The deployed approach allowed modifying the PV and energy storage's power according to the actual consumption. Authors in [18] proposed an electric energy system optimization approach by solving the economic and environmental dispatch problems. A MPC approach was introduced based on a dispatch algorithm, which actively relies on direct control of intermittent resources for compensating fast load fluctuations. The work presented in [19] focuses on the development of a control system using MPC for wind and solar power generation system. The control system computes the power references for the PV and wind at each sampling time and the obtained values are used by two local controllers in order to drive the sources to the request power references. The control strategy was designed to optimize the suitable cost function for a standalone MG system. According to the work presented in [19], authors in [20] replaced the two centralized MPC controllers by two distributed ones in order to manage the operation of PV and wind power generation while providing the required energy to the loads.

The work presented in this paper is a part of the work we are undertaking under an MIGRID project aiming at developing and deploying predictive control approaches for MG systems using recent IoT and Big data technologies together with predictive analytics. A platform is developed and deployed for gathering and processing data together with real-time control approaches. For instance, in [21], a control strategy is presented for balancing the power flow in the MG. This later is composed of PVs, batteries, and buildings equipment (e.g., ventilation system, lighting, HVAC). In this paper, the same control strategy is enhanced by using a MPC approach in order to balance the power production with the power consumption while considering the storage devices limits. Unlike the work presented in the literature, a centralized control is deployed and the maximum power generated by the PV is managed without limiting the sources to request power references. In fact, the battery storage operation is efficiently managed in order to optimize the use of energy by covering a maximum production from PV while minimizing the consumption from traditional electrical grid.

III. MG SYSTEM ARCHITECTURE

A MG system is deployed for conducting experimental evaluation of proposed approaches. It is connected to the grid in order to supply the power to the equipment when RES and storage are unavailable. The MG is mainly composed of PV, storage devices and active equipment (e.g., HVAC, stand alone ventilation system, lighting). Excess power can be shunted to the battery device to be stored for later usage. In fact, if the power is unavailable from RES, the storage devices continue delivering the electricity to the dedicated loads. It's worth noting that the system is modeled, simulated and experimented validating then all deployed equipment [21, 22]. Furthermore, a battery characterization approach is developed for SoC estimation and forecasting using machine learning methods [9, 23].

In the work presented in this paper, we have used the models already validated in our previous work and developed a predicted control strategy using real data gathered from the deployed MG system. In fact, to

investigate the behavior of this approach using both simulations and the experimentations, the same conditions (e.g., temperature, irradiance) are used to simulate the MG model by using also real stored data (e.g., power production and consumption). For that, a data collection platform is implemented and deployed for real testing and validation of proposed approaches. It is an IoT/Big-data platform, which is composed of four main layers, sensors and actuators layer, data acquisition, data processing, and data visualization/storage layer [24]. Furthermore, current and voltage sensors are installed to measure the PV production for real testing scenarios. The data collected from these sensors need to be processed in real-time in order to figure out the right control decision according to actual situations (e.g., energy consumption-production patterns, and weather conditions data). Furthermore, these data have to be stored for further analysis, especially for evaluating predictive control strategies based on the historical data. As illustrated in Fig.2, the platform's architecture contains a physical

programmable circuit board, which is connected to different sensors for data collection. In the same time, the board is connected to a mini-computer (e.g., Raspberry) used to send the data to the platform for pre-processing and storage. Moreover, weather conditions are stored in order to study the behavior of the PV system for a seamless integration in the MG system. In fact, several scenarios need to gather internal and external context data. For that, a weather station is deployed near to the wind turbine to have as precisely as possible the data concerning wind's speed and direction. The weather station was deployed and used to collect the data for real-time visualization and processing for further usage by other services and applications (e.g., PV power forecasting, Wind). Also, the power production is measured in order to compare experimental and simulation results and validate the deployed system and scenarios as well. All these data are gathered and processed in real-time using our IoT and Big data platform [22].

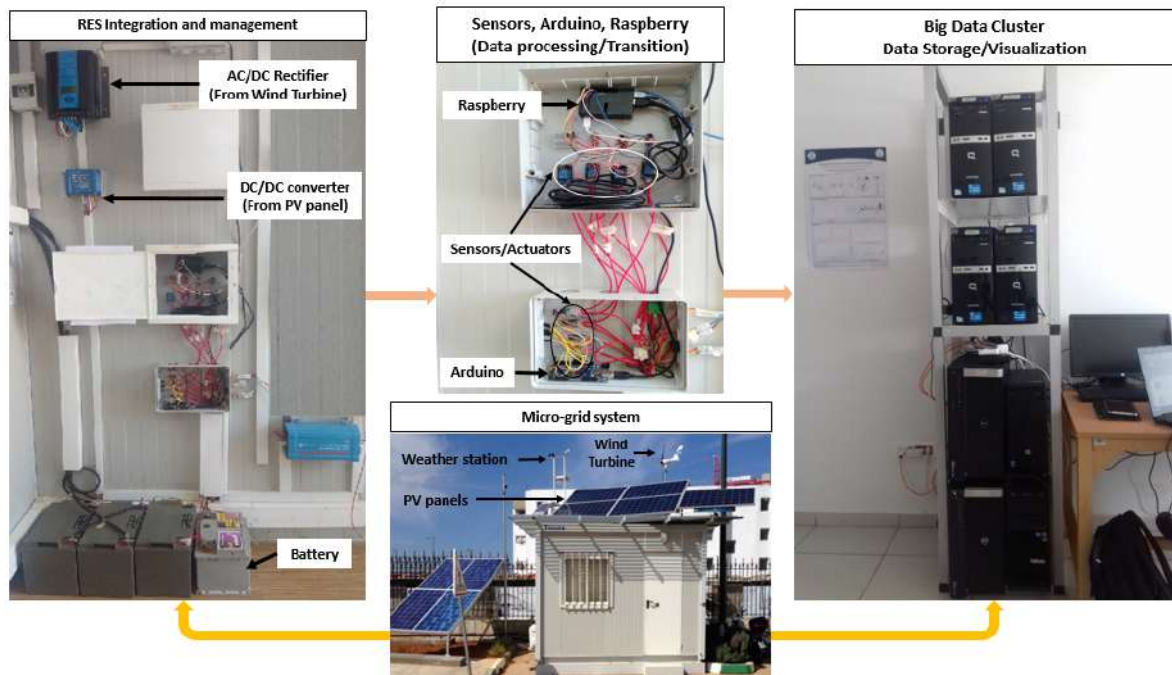


Figure 2. The deployed MG system

IV. SYSTEM MODELING AND CONTROL

The MG system includes RES (e.g., PV), which produce the power for supplying the loads (e.g., Lighting, ventilation system). The power excess is potentially stored in the batteries. However, the large variability of RES power generation, mainly due to the stochastic behavior of the weather condition (e.g., temperature, radiance, wind speed), increases the complexity in managing and controlling the whole system. Furthermore, the storage devices are important components of the system that should satisfy certain specifications by absorbing the variability of the RES power generation. Therefore, the control strategy should consider the SoC evolution in order to ensure the power requirements while maintaining the operating costs at a reasonable level. In this direction, an open circuit voltage (OCV) with resistance is chosen to simulate the battery model. The OCV can be established as a function of battery SoC using equation (1). In fact, the battery voltage is defined as the summation of the OCV and the dynamic voltage of the *ohmic* resistance R .

$$V_{bat}(t) = OCV(SoC(t)) + R \cdot I_{bat}(t) \quad (1)$$

This equation can be presented as follows, where a is an unknown parameter, which is calculated by the least-squares method using the experimental data extracted for the battery characterization [4, 5], I is the charge/discharge battery current, and R is the *ohmic* resistance:

$$Y(t) = a \cdot SoC(t) + R \cdot I \quad (2)$$

In fact, when the SoC reaches its maximal value, the charge current is null and the SoC can be extracted directly by the measurement of the battery's voltage. For that, the equation (3) can be expressed as follows:

$$Y(t) = SoC(t) \quad (3)$$

Moreover, the Coulomb counting method is often used to estimate the battery SoC, which is expressed as the available and nominal capacity C ratio. The quantity C of charge/discharge, which is accumulated during an operation period τ , can be computed by measuring the current flow rate

(charging/discharging) and integrating it over the time interval (equation (4)).

$$C(t + \tau) = C(t) + \Delta C \quad (4)$$

We can use the common equation (5) to calculate the future values of $SoC(t + 1)$ by accumulating the actual $SoC(t)$ and the forecasted I_{bat} . This is because the MPC approach is based on the forecasting input in order to return the feedforward.

$$SoC(t + 1) = SoC(t) + I_{bat}(t) \cdot \Delta t / C \quad (5)$$

The idea behind that is to control the battery charging/discharging power using a MPC model. In fact, the control strategy regulates the battery current in order to reach the operating goals and to make the right decision: charge, discharge, or battery-at-rest. These decisions are made depending on the following condition (equation (6)):

$$P_{load} = \begin{cases} P_{pv} + P_{bat} & \text{if } P_{pv} \geq 0 \text{ and } SoC > SoC_{min} \\ P_{grid} & \text{if } P_{pv} < P_{load} \text{ and } SoC < SoC_{min} \end{cases} \quad (6)$$

where P_{load} is the load demand, P_{pv} is the power generated by the PV panels, P_{bat} is the power generated or extracted from the battery, and P_{grid} is the power generated by the traditional electrical grid when the RES power is insignificant and the SoC is less than the threshold value, which is defined in the control strategy in order to avoid a deep discharge of the battery. In fact, the battery is forced to discharge when the load demand exceeds the PV generation ($P_{load} > P_{pv}$), it is forced to charge when the PV production is higher than the demand ($P_{load} < P_{pv}$), and finally the battery is at rest when the SoC is less than the threshold value and the PV production is null ($SoC < SoC_{min}$). Moreover, the surplus of the PV production is captured by the battery. The optimization function can be formulated in order to keep the battery SoC at its maximum state. The main idea is to minimize the given objective function E_N (equation (7)) within a future horizon n , while the problem constraints to be satisfied are presented in equation (8).

$$E_N = SoC_{max} \begin{pmatrix} 1 \\ \vdots \\ 1^n \end{pmatrix} - SoC(t) \begin{pmatrix} SoC(t) \\ \vdots \\ SoC(t+n) \end{pmatrix} \quad (7)$$

$$\begin{cases} SoC_{min} < SoC_k < SoC_{max} \\ P_{pv} + P_{bat} = P_{load} \end{cases} \quad (8)$$

The MPC strategy is then designed based on the abovementioned equations in order to obtain the equilibrium of power balance in MG systems. In fact, by considering the $SoC(t)$ as the system state, equation (3) can be represented by the equation state representation with the following form:

$$x(k + 1) = Ax(k) + BU(k) \quad (9)$$

where $x(k)$ is the state, $A=I$, and the $I_{bat}(t)$ is the input. By interpolation, this equation to n step-ahead could be rewritten as follows (equation 10):

$$\begin{cases} x(k+2) = A^2x(k) + ABU(k) + BU(k) \\ x(k+3) = A^3x(k) + A^2BU(k) + ABU(k+1) + BU(k+2) \\ \vdots \\ x(k+n) = A^nx(k) + A^{n-1}BU(k) + \dots + BU(k+n-1) \end{cases} \quad (10)$$

This representation can be written in a matrix form as follows:

$$\begin{pmatrix} x(k+1) \\ \vdots \\ x(k+n) \end{pmatrix} = \begin{pmatrix} A \\ \vdots \\ A^n \end{pmatrix} x(k) + \begin{pmatrix} B & 0 & \dots & 0 \\ AB & \ddots & \ddots & \vdots \\ \vdots & \ddots & B & 0 \\ A^{n-1}B & \dots & AB & B \end{pmatrix} \begin{pmatrix} U(k) \\ \vdots \\ U(k+n+1) \end{pmatrix} \quad (11)$$

$$\bar{X} = \bar{A}x(k) + \bar{B}U(k) \quad (12)$$

Similarly and by interpolation, the observation equation to n steps ahead is represented as follows:

$$\begin{pmatrix} y(k+1) \\ \vdots \\ y(k+n) \end{pmatrix} = \begin{pmatrix} CA \\ \vdots \\ CA^n \end{pmatrix} x(k) + \begin{pmatrix} CB & 0 & \dots & 0 \\ CAB & \ddots & \ddots & \vdots \\ \vdots & \ddots & CB & 0 \\ CA^{n-1}B & \dots & CAB & CB \end{pmatrix} \begin{pmatrix} U(k) \\ \vdots \\ U(k+n+1) \end{pmatrix} \quad (13)$$

$$\bar{Y} = \bar{C}x(k) + \bar{D}U \quad (14)$$

For the input vectors, we consider the following change:

$$\begin{cases} U(k) = U(k-1) + \Delta U(k) \\ U(k+1) = U(k) + \Delta U(k+1) = U(k-1) + \Delta U(k) + \Delta U(k+1) \\ \vdots \\ U(k+n-1) = U(k-1) + \Delta U(k) + \Delta U(k-1) + \dots + \Delta U(k+n-1) \end{cases} \quad (15)$$

This equation can be rewritten in the following matrix form:

$$\begin{pmatrix} U(k) \\ U(k+1) \\ \vdots \\ U(k+n) \end{pmatrix} = \begin{pmatrix} 1 \\ \vdots \\ 1^n \end{pmatrix} U(k-1) + \begin{pmatrix} 1 & 0 & \dots & 0 \\ 1 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 1 & \dots & 1 & 1 \end{pmatrix} \begin{pmatrix} \Delta U(k) \\ \Delta U(k+1) \\ \vdots \\ \Delta U(k+n+1) \end{pmatrix} \quad (16)$$

$$\bar{U} = I_1 U(k-1) + I_2 \Delta \bar{U}(k) \quad (17)$$

Replacing (17) in (12), we obtain the following predictive model (equation 18):

$$\bar{X} = \bar{A}x(k) + \bar{B}I_1 U(k-1) + \bar{B}I_2 \Delta \bar{U}(k) \quad (18)$$

Replacing (12) in (11), we get the predictive observation model as follows:

$$\bar{Y} = \bar{C}x(k) + \bar{D}I_1 U(k-1) + \bar{D}I_2 \Delta \bar{U}(k) \quad (19)$$

The criterion cost to optimize and to obtain the adequate command $\Delta \bar{U}(k)$ for reducing the error is defined by equation (20). In fact, the battery is used to satisfy the demands and it is preferable to keep a maximum SoC as it is possible.

$$Y_{ref} = [SoC_{max}(k+1), SoC_{max}(k+2), \dots, SoC_{max}(k+n)] \quad (20)$$

According to the set points, which the control is willing to reach, the error is described by: $E = Y - Y_{ref}$. Then, the criterion will be optimized in order to get the control sequence ΔU as the following:

$$J = \frac{1}{2} (EQE^T + \Delta \bar{U} R \Delta \bar{U}^T) \quad (21)$$

The MPC strategy is designed by respecting the constraints. It forces the battery to be charged or discharged in order to absorb the production surplus or to supply the needed power to the loads. At the same time, by respecting the constraints, the battery cannot be discharged below a defined threshold value in order to avoid a deep discharge of the battery. Also, the battery should be kept as much as possible to its maximum SoC. It's worth noting that the SoC, which is used like an input parameter to the MPC, is obtained by forecasting the battery charge/discharge current, which is also conditioned by forecasting the PV production and the load consumption using machine learning methods.

V. SIMULATION RESULTS

In this section, a MPC design model is used to optimize the battery charge/discharge current by considering the PV production and the consumption variability. It is mainly deployed into the MG simulation model for testing and validation. Real data obtained from the deployed MG system, presented in Fig. 2, are used to simulate the behavior of the SoC using the MPC control. In fact, the system contains PV panels for charging a battery storage system and to supply the power to the loads demand as well (e.g.,

lighting, ventilation system). For instance, when the battery is fully charged, another load is used like a resistor to absorb the surplus. An IoT/Big-data platform is used to collect the data (e.g., PV production, consumption, charge/discharge battery current), which are used to train a machine learning algorithm to forecast the input parameters for the control [9]. Moreover, by forecasting the PV power production and the consumption, we can estimate the SoC of the battery by using the equation (6) and the forecasted values are used like input to the MPC strategy.

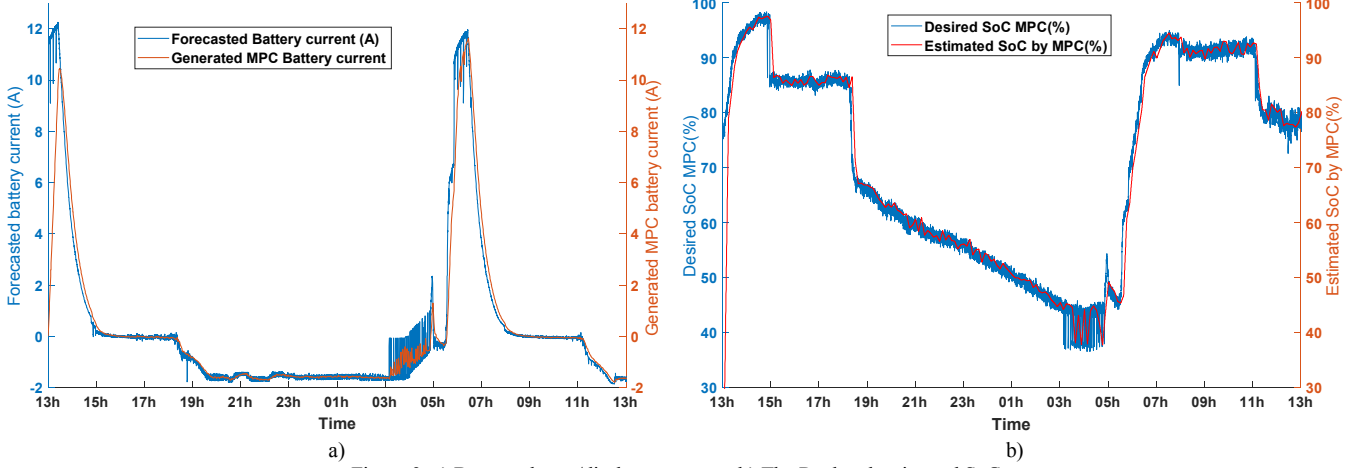


Figure 3. a) Battery charge/discharge current, b) The Real and estimated SoC

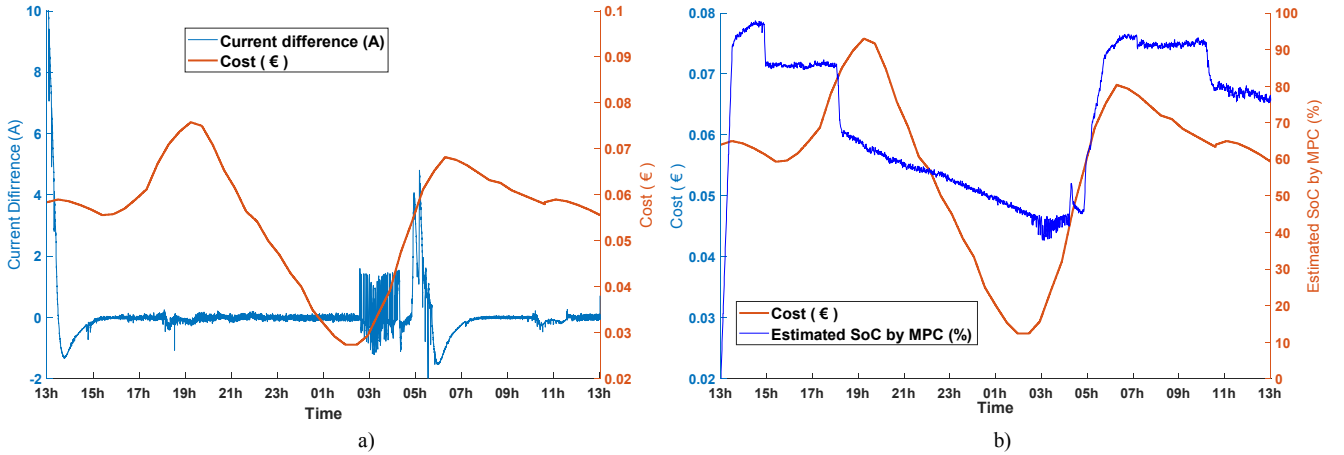


Figure 4. a) The electricity cost and current difference, b) MPC SoC and electricity cost

As mentioned above a small micro-grid was built to test the preliminary control strategy using the real data. It contains energy sources (PV, grid) storage devise (battery) and a load (two ventilators). The PV is used to charge the battery and the battery in turn provides power to the ventilation system. However, in bad weather conditions or during the night the battery discharges, in order to ensure the proper operation of the ventilation, the power must switch automatically to the grid following the proposed control strategy. The control strategy needs the SoC as an input together with other parameters to select the most suitable action for either switch to the battery or to the electric grid.

Fig. 3 (a) illustrates the battery charge-discharge current during 24 hours. Forecasting current values are used to estimate the SoC, which is used in this scenario as a setpoint for the MPC. In fact, the MPC generates a command to control the battery charge-discharge current depending on the variability of the PV production and the load consumption, which are presented indirectly by the variability of the battery current. The charge/discharge current varies in order

to accumulate the power depending on the equation (6). Moreover, the MPC controls the SoC by optimizing the battery current variability depending on the defined constraints. Fig.3 (b) presents the variability of the SoC obtained by the MPC model compared to the desired SoC. At each time, the MPC generates one hundred points in the future separated by three seconds. The obtained current is used to calculate the SoC presented in Fig. 3 (b). The red curve presents the SoC estimated by the MPC model depending on the variability of the current generated from MPC strategy and the blue curve presents the setpoint (desired SoC). In fact, the MPC uses the forecasted current to predict the battery charge/discharge actions depending on the variability of the demands and the production. The smooth curve of the SoC obtained by the MPC strategy is due to the prediction principle. For a set of values, the MPC estimates the equivalent value of the power to extract or to supply to the battery in order to avoid a sudden change of the current.

The blue curve presented in Fig. 4 a) shows the difference between the real battery current and the current

obtained by MPC control. The positive part means that the real current is higher than the estimated MPC current. In fact, the variability of the electricity cost is presented by the orange curve in order to show that the MPC discharges the battery when the electricity price is expensive. This cost function will be integrated in the future work in order to further optimize the price function. Moreover, as shown in Fig. 4 b), around 07:00 pm the battery starts discharging during the peak consumption period. In this work, the battery started to discharge because the PV production cannot satisfy the loads demands in this period of day without considering the price and the battery is discharging until the threshold (40%) value of the SoC is obtained (to avoid a deep discharging of the battery). For that, a cost function should be integrated in order to stop discharging the battery when the electricity price is inexpensive. Also, the traditional electrical grid can be even used to charge the battery at night when the cost is inexpensive in order to use it during the morning peak consumption. On another way, the charge/discharge cycle of the battery will be investigated in order to keep a good battery's state-of-health. The cost function variability used in this part is presented depending on European foundation [25].

VI. CONCLUSIONS AND PERSPECTIVES

In this paper, a model predictive control approach is designed for efficient MG operation. The aim is to minimize the usage of the traditional electric grid in order to supply the power to the building's loads. We mainly focused on optimizing the SoC variability by controlling the battery's current behavior. In fact, the MPC strategy was designed to balance the PV power production with the load demand by considering the battery storage devices constraints and charge/discharge optimization function. Also, an IoT/Big-data platform was deployed for data monitoring and processing. Preliminary results showed the usefulness of the proposed predictive control approach for efficient operation of MG systems. Our ongoing work is focusing on the integration of this strategy in our deployed MG system for conducting experiments in real sitting scenarios. In future work, the cost function will be optimized by considering the possibility to inject the electricity from RES into the traditional electrical grid by considering the price profile, the battery can be eventually charged from traditional electrical grid.

ACKNOWLEDGMENT

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

REFERENCES

- [1] European Commission. Information Society. 2010, available at: http://ec.europa.eu/information_society/activities/sustainable_growth/buildings/index_en.htm
- [2] M. Bakhouya, Y. NaitMalek, A. Elmouatamid, F. Lachhab, A. Berouine, S. Boulmrharj, R. Ouladsine, V. Felix, K. Zinedine, M. Khaidar, N. Elkamoune, Towards a Data-Driven Platform using IoT and Big Data Technologies for Energy Efficient Buildings, invited paper at CloudTech,2017, Rabat, Morocco.
- [3] A. Berouine, R. Ouladsine, M. Bakhouya, F. Lachhab, M. Essaïdi, "A Model Predictive Strategy for Ventilation System Control in Energy Efficient Buildings," Submitted to 4th Edition of World conference on Complex Systems, WCCS 2019, Ouarzazate, Morocco.
- [4] Liu, B., Lu, Z., Yao, K., & Gao, F. (2015). A MPC Operation Method for A Photovoltaic System with Batteries. IFAC-PapersOnLine, 48(8), 807-812.
- [5] Li, J., & Danzer, M. A. (2014). Optimal charge control strategies for stationary photovoltaic battery systems. *Journal of Power Sources*, 258, 365-373.
- [6] A. del Real, A. Arce y C. Bordons, "Hybrid model predictive control of a two-generator power plant integrating photovoltaic panels and Fuel Cell," in Proc. IEEE Conf. on Decision and Control, New Orleans, 2007.
- [7] A. Parisio, E. Rikos, G. Tzamalís and L. Glielmo, "Use of model predictive control for experimental microgrid optimization," *Appl. Energy*, 2014, 115, 0, vol. 115, no. 0, pp. 37-46, 2014.
- [8] H. Elkhoukhi, Y. NaitMalek, A. Berouine, M. Bakhouya, D. Elouadghiri, M. Essaïdi, Towards a Real-time Occupancy Detection Approach for Smart Buildings, in The 15th International Conference on Mobile Systems and Pervasive Computing, Gran Canaria, Spain, *Procedia Computer Science*, V. 134, pp. 114-120, Elsevier, 2018.
- [9] Y. Naitmalek, M. Najib, M. Bakhouya, M. Essaïdi, Forecasting the State-of-Charge of Batteries in Micro-Grid Systems, WCCS 2019, IEEE, Morocco.
- [10] Nehrir, M. H., Wang, C., Strunz, K., Aki, H., Ramakumar, R., Bing, J. & Salameh, Z. (2011). A review of hybrid renewable/alternative energy systems for electric power generation: Configurations, control, and applications. *IEEE Transactions on Sustainable Energy*, 392-403.
- [11] Khatamianfar, A., Khalid, M., Savkin, A. V., & Agelidis, V. G. (2012, October). Wind power dispatch control with battery energy storage using model predictive control. In 2012 IEEE International Conference on Control Applications (pp. 733-738). IEEE.
- [12] Valverde L, Bordons C, Rosa F. Power management using model predictive control in a hydrogen-based microgrid. In: 38th annual conference on IEEE industrial electronics society, IECON 2012. Montreal, QC; Canada; 2012.
- [13] Salazar J, Valverde L, Tadeo F. Predictive control of a renewable energy microgrid with operational cost optimization. In: 39th annual conference of the IEEE industrial electronics society, IECON 2013. Vienna; Austria; 2013.
- [14] Pereira M, Limon D, Alamo T, Valverde L, Bordons C. Economic model predictive control of a smartgrid with hydrogen storage and PEM fuel cell. In: Industrial electronics society, IECON 2013 – 39th annual conference of the IEEE. Vienna; 2013.
- [15] Valverde L, Bordons C, Rosa F. Integration of fuel cell technologies in renewable-energy-based microgrids optimizing operational costs and durability. *IEEE Trans Industr Electron* 2015(99). vol.PP, pp.1-1.
- [16] Hu, K. Y., Li, W. J., Wang, L. D., Cao, S. H., Zhu, F. M., & Shou, Z. X. (2018). Energy management for multi-microgrid system based on model predictive control. *Frontiers of Information Technology & Electronic Engineering*, 19(11), 1340-1351.
- [17] E. Perez, H. Beltran, N. Aparicio, et al., "Predictive power control for pv plants with energy storage," *IEEE Trans.Sustain. Energy*, vol. 4, no.2, pp.482-490, 2013.
- [18] Xie, L., & Ilic, M. D. (2009, July). Model predictive economic/environmental dispatch of power systems with intermittent resources. In 2009 IEEE Power & Energy Society General Meeting (pp. 1-6). IEEE.
- [19] W. Qi, J. Liu, X. Chen, and P. Christofides, "Supervisory predictive control of standalone wind/solar energy generation systems," *IEEE Trans. Control Syst. Technol.*, vol. 19, no. 1, pp. 199-207, Jan. 2011.
- [20] W. Qi, J. Liu, X. Chen, and P. Christofides, "Supervisory predictive control for long-term scheduling of an integrated wind/solar energy generation and water desalination system," *IEEE Trans. Control Syst. Technol.*, vol. 20, no. 2, pp. 504-512, Mar. 2012.
- [21] Elmouatamid, A., NaitMalek, Y., Ouladsine, R., Bakhouya, M., Elkamoun, N., Zine-Dine, K., ... & Abid, R. (2018, April). Towards a Demand/Response Control Approach for Micro-grid Systems. In 2018 5th International Conference on Control, Decision and Information Technologies (CoDIT) (pp. 984-988). IEEE.
- [22] Elmouatamid, A., Bakhouya, M., Ouladsine, R., Zine-Dine, K., Khaidar, M., & Abid, R. (2019, May). Deployment and Experimental Evaluation of Micro-Grid Systems. In 2018 6th International Renewable and Sustainable Energy Conference (IRSEC) (pp. 1-6). IEEE.S.
- [23] Boulmrharj, Y., NaitMalek, A., El Mouatamid, M. Bakhouya, R. Ouladsine, M. Ouldoussa, K. Zine-dine, M. Khaidar, R. Abid, Towards a Battery Characterization Methodology for Performance Evaluation of Micro-Grid Systems, SEST'2018, IEEE, Seville, Spain, 2018.
- [24] El Mouatamid, A., Ouladsine, R., Bakhouya, M., Felix, V., Elkamoun, N., Zine-Dine, K., ... & Abid, R. (2017, December). Modeling and Performance Evaluation of Photovoltaic Systems. In 2017 International Renewable and Sustainable Energy Conference (IRSEC) (pp. 1-7). IEEE.
- [25] Prodan, I., & Zio, E. (2014). A model predictive control framework for reliable microgrid energy management. *International Journal of Electrical Power & Energy Systems*, 61, 399-409.