Control of Microgrids using an Enhanced Model Predictive Controller

Muhammed Cavus*[*], Adib Allahham, Kabita Adhikari, Mansoureh Zangiabadi, Damian Giaouris

School of Engineering, Newcastle University, UK
[*]*m.cavus2@newcastle.ac.uk*

Keywords: RENEWABLE ENERGY SOURCE (RES), MICROGRID (MG), MODEL PREDICTIVE CONTROL (MPC), EPSILON VARIABLE METHOD (EVM).

Abstract

Renewable energy sources have been widely adopted to stop global warming. This growing adaptation has led to a significant change in topologies of traditional power networks, and now we have the concept of a microgrid. Model Predictive Control is an advanced method that is used to control power systems while satisfying several constraints to achieve an optimal solution based on various criteria. Although, Model Predictive Control is robust and has several advantages, its implementation is often very complex and requires high computational power. On the other hand, ε-variables based control strategies, which are practical methods to model control strategies in microgrids, are able to simplify the control structure allowing more scalability and even resilience. This paper presents, a hybrid method to simplify the implementation of Model Predictive Control using ε-variables and make it more effective on complicated energy systems. Our results demonstrate that combining Model Predictive Control with ε-variables can significantly simplify the control structure and hence allow for more complicated control strategies to be employed in order to provide extra benefits to the energy system like scalability and robustness.

1 Introduction

The development of renewable energy sources (RESs) and the increased usage of energy storage have led to the conversion of the traditional power network to novel topologies such as microgrids (MGs). MG that integrates different types of energy sources such as RESs (photovoltaic (PV) panel, wind), energy storage systems (battery, hydrogen, pumped hydro (water)), diesel generator, and load and control devices have been presented in [1], [2]. Also, a MG can decrease the network congestion in energy sources and reduce power losses and running costs by operating in a more decentralized way [3]–[5]. However, a MG has extra difficulties in terms of controllability because of unexpected power changes in real-time operation, intermittent energy generation, and random energy consumption [6], [7]. Therefore, advanced control technologies are required to ensure a satisfactory energy management system [8], [9].

In existing literatures, authors have reported several methods such as Fuzzy Logic Controller, Rule-Based Control, Linear Quadratic Integrator, Hysteresis Controller, Power Pinch Analysis and so on to control MG systems [9]–[12]. Moreover, a complex energy management strategy (EMS) algorithm was exploited using mixed-integer programming by Niu et al. [13] and Terlouw et al. [14]. Furthermore, Wu et al. [15] used stochastic dynamic programming. In contrast, a stochastic optimization algorithm was utilized by Acquah and Han [16] and Conte et al. [17]. Nevertheless, Model Predictive Control (MPC) is an advanced and more effective control scheme than traditional control strategies which cannot forecast uncertainties or disturbances. Also, MPC has a fast transient response [7] because the leading role of MPC is to integrate between new updated data and forecasts. By doing so, the MPC can make better decisions for the future demeanour of the system using various constraints [18].

A MPC has three main components (i) predictive model, (ii) objective (cost) function, and (iii) solving algorithm [19]. MPC can be effectively utilized in various ways to better control MG system compared to the other control strategies. For instance, the understanding of MPC is straightforward and intuitive. Also, it is flexible to implement in many power converter topologies. It works by taking into consideration several constraints and uncertainties [20]. On the other hand, it utilises complex algorithms and it imposes a high number of control parameters, so it requires longer time to solve than the other methods. In other words, it needs high processing power and computational time [21]. Hence, it needs to be improved in terms of complexity and scalability.

On the other hand, in [18] it was first proposed a new method to systematically model EMSs using a concept based on evolution operators and the state of the directed graph that represents the system. This method is based on the so called ε-variables describing the evolution and hence the control approach of a multi-vector energy system [22]. Key to this approach is that every asset in the system is being represented by a node and every flow of energy and/or matter is represented by an edge between the nodes (see Fig. 1).

More specifically, according to [18], a hybrid energy system can be easily described using graph theory. In other words, complex energy systems can be illustrated in such a way to simplify their analysis, operation and management with the help of graph theory enhanced by using the aforementioned evolution operators. This methodology says that any energy system comprises of three main elements: flows, accumulators, and converters. The flows represent the flow of energy and/or matter, the accumulators accumulate energy or matter, and the converters convert energy/matter to energy/matter. Finally, the control statements that operate the converters are the evolution operators that describe the EMS employed by the multi-vector system [23]. In this paper, we follow a similar approach with the goal of producing a more systematic approach to design MPC for hybrid energy systems. As a proof of concept, we use a simple energy system, Fig. 2, where flow is power, an accumulator is the battery (BAT), and converters are the photovoltaic (PV) array, utility grid (GR), and load (LD). The graph of that system us shown in in Fig. 1 and the assets of the microgrid system can be divided into two sets such as $\mathrm{Rs}^{\mathrm{Accumulator}} = \{\mathrm{BAT}\}$ and $\mathrm{Rs}^{\mathrm{Converters}} = \{\mathrm{PV}, \mathrm{GR}, \mathrm{LD}\}$, [18]. As can be understood clearly from Fig. 1, the flow can be defined as the connection between two nodes: for instance, PV to BAT and BAT to LOAD. Hence the set of flow in this paper can be considered as: $\mathrm{Flow} = \{(\mathrm{Electrical})\ \mathrm{Power}\}$.

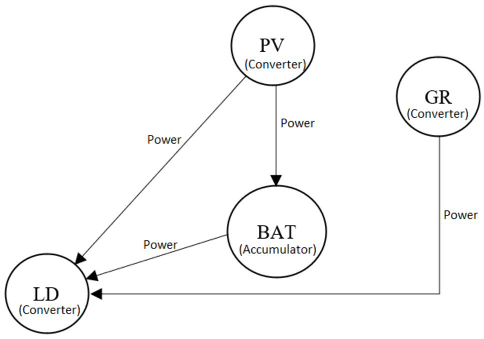

Fig. 1. The illustration of directed graph

This paper proposes a novel hybrid method to implement the MPC while keeping the same advantages of MPC but making it more scalable and straightforward using the EVM. This method can be called as hybrid MPC-ε-Variable Method (MPC-EVM).

2 Methodology

2.1 Structure of the PV-Battery-Grid System (PBG)

As shown in Fig. 2, the MG system is composed of a PV, a battery used as an energy storage system, and a utility grid system. The PV is utilized to meet the daily load demand for the MG system. Red and orange line might be be-directional; however, they were considered as one-directional in the paper.

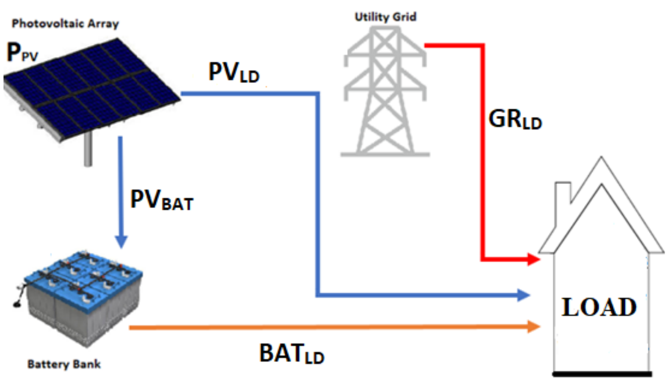

Fig. 2. Structure of the PBG system

2.2 The Implementation of MPC

As illustrated in Fig. 3, the MPC mechanism forecasts system's behaviour and optimizes its performance using the dynamic model (10), cost function, and constraints (1-9) in order to generate the best decision [24].

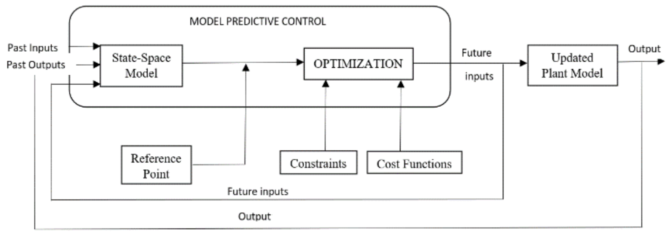

Fig. 3. The schematic of MPC

The MPC is implemented and calculated by employing the set point values, past inputs, outputs, and predictions of the future output values. It computes a set of Nc values of the input which can be represented as $\mathrm{u}(\mathrm{k} + \mathrm{Nc} - 1)$ at k^{th} sample. In other words, the set consists of the present input and future inputs are $\mathrm{u}(\mathrm{k})$ and $\mathrm{Nc} - 1$, respectively. On the one hand, calculating a set of Np predicted outputs $\mathrm{y}(\mathrm{k} + \mathrm{Np})$ continues until the system reaches the optimum values. Another prominent characteristic of MPC is 'receding horizon control' to gain the dispatching strategy. It the worthy of note that only the first move is applied, then a new sequence is estimated at the $\mathrm{k} + 1$. This step is re-applied for each sampling k time as represented in Fig. 3 [24].

2.2.1 The constraints of the components of PBG

The PV system is used to supply the load demand and charge the battery. It runs depending on several constraints at sampling time k, as follows:

$$0 \leq P_{PV}(k) \leq {P_{PV}}^{max} \tag{1}$$

$$0 \leq PV_{LD}(k) \leq {PV_{LD}}^{max} \tag{2}$$

$$0 \leq PV_{BAT}(k) \leq {PV_{BAT}}^{max} \tag{3}$$

where ${P_{PV}}^{max}$, ${PV_{LD}}^{max}$, and ${PV_{BAT}}^{max}$ represent the maximum energy from the PV to the load, to the battery and the grid, respectively. Also, the sum energy for meeting the load demand and charging the battery can be symbolized as P_{PV} as below:

$$P_{PV}\ (k) = PV_{LD}\ (k) + PV_{BAT}\ (k) \tag{4}$$

The battery is exploited both in charging and discharging mode relying upon whether the sunlight is sufficient or not. Hence, the charging and discharging of the battery can be defined by an equation as follows:

$$SOC\ (k{+}1) = SOC\ (k) + \frac{\eta_{ch} PV_{BAT}(k)}{C} - \frac{BAT_{LD}(k)}{C(\eta_{dis})} \tag{5}$$

In addition, constraints related to the battery can be represented as below:

$$SOC^{min} \leq SOC(k) \leq SOC^{max} \quad (6)$$

$$0 \leq BAT_{LD}(k) \leq BAT_{LD}{}^{max} \quad (7)$$

where SOC is the state of charge of the battery, SOC^{min} and SOC^{max} represent the minimum and maximum of SOC of the battery, respectively. $BAT_{LD}{}^{max}$ and C are consecutively hourly allowable maximum discharging power and battery capacity. Lastly, η_{ch} and η_{dis} are the charging and discharging efficiency of the battery, respectively.

The utility grid is exploited to meet the load demand when the PV panel and the battery are insufficient. This is the last option because this scenario is more expensive and not environmentally friendly. The only advantage of its exploitation is to be available at any time except for blackout.

Moreover, the constraints related to the grid system and load can be written as:

$$0 \leq GR_{LD}\ (k) \leq GR_{LD}{}^{max} \quad (8)$$

$$PV_{LD}\ (k) + BAT_{LD}\ (k) + GR_{LD}\ (k) = P_{LD}(k) \quad (9)$$

where $GR_{LD}{}^{max}$ is represents the maximum quantity of power from the utility grid.

2.2.2 Objective Functions of PBG

The cost functions of the PBG system are:

- To minimize the energy consumption from non-RES: $\sum_{k}^{k+Np} w_1^2 GR_{LD}(k)^2$
- To increase the life cycle of battery: $\sum_{k}^{k+Np} w_2^2 (PV_{BAT}(k)^2 + BAT_{LD}(k)^2)$
- To maximize the practicality of the renewable energy usage: $\sum_{k}^{k+Np} w_3^2 (PV_{LD}(k)^2 + PV_{BAT}(k)^2)$

where Np is the prediction horizon w_1, w_2, and w_3 are represent the cost weight factors.

The linear state-space equation can be defined according to the battery equation. In general, the linear state-space equation can be represented as follows:

$$x(k+1) = Ax(k) + Bu(k) \quad (10)$$
$$y(k) = Cx(k) + Du(k)$$

where x is the state vector and SOC of the battery in this system, u is the input vector known as control vector as well and PV_{LD}, PV_{BAT}, and BAT_{LD}. Lastly, y is the output vector and GR_{LD} in the system. A, B, C, and D can be defined depending on Eq. (5). x, u, and y illustrate as follows:

$$x(k) = [SOC(k)] \quad (11)$$

$$u(k) = [PV_{LD}(k); PV_{BAT}(k); BAT_{LD}(k)] \quad (12)$$

$$y(k) = [GR_{LD}(k)] \quad (13)$$

2.2 The Implementation of hybrid MPC-EVM technique

As illustrated in Fig. 4, the 'data' that are exploited by the hybrid MPC-EVM technique as input data are initially obtained using the MPC method. The 'data' are GR_{LD}, PV_{LD}, PV_{BAT}, and BAT_{LD} in Fig. 4. Then, the evolution operators are calculated based on the state of the accumulators and the converters. More specifically:

- The evolution operator for the converters can be defined by three factors and symbolized by binary variables: ϵ_i^{Av}, ϵ_i^{Req}, and ϵ_i^{Gen} represent the availability of power, requirement for load, and potentially desired condition, respectively as shown in Fig. 4. The availability of energy relies upon the condition of the accumulators. In other words, the binary variable, ρ is 0 or 1 depending on the accumulators, as can be seen below:

$$\epsilon_i^{Av} = L_{Accumulator}^{Av}(\rho_i^{SOAcc^{BAT}}) \quad (14)$$

$$\epsilon_i^{Req} = L_{Accumulator}^{Req}(\rho_i^{SOAcc^{BAT}}) \quad (15)$$

$$\epsilon_i^{Gen} = L_{Accumulator}^{Gen}(\rho_i^{SOAcc^{BAT}}) \quad (14)$$

$$\varepsilon_i(k) = \epsilon_i^{Av}(k) \wedge \epsilon_i^{Req}(k) \wedge \epsilon_i^{Gen}(k) \quad (15)$$

where $L^{Availability}$ and $L^{Required}$ are the logical operators 'and' or 'or', while the general condition relies upon the condition of converters in general. Also, $\varepsilon_i(k)$ is state of converter i, $\epsilon_i^{Av}(k)$ and $\epsilon_i^{Req}(k)$ are boolean variables that determine the availability and requirement of converter i.

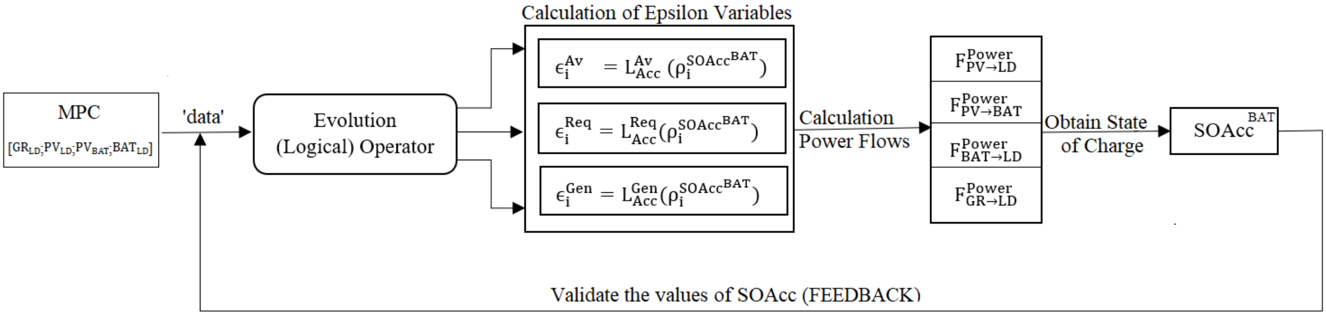

Fig. 4. The illustration of the proposed method (MPC-EVM)

- The power flows are calculated by multiplying equation (12) and (17), and equation (13) and (17).
  - $F^{Power}_{GR\to LD}(k)=y*\varepsilon_i(k)$
  - $F^{Power}_{PV\to LD}(k)=u(1)*\varepsilon_i(k)$
  - $F^{Power}_{PV\to BAT}(k)=u(2)*\varepsilon_i(k)$
  - $F^{Power}_{BAT\to LD}(k)=u(3)*\varepsilon_i(k)$
- The last step is to calculate the evolution operator for accumulator:

$$SOAcc^{BAT}(k+1)=SOAcc^{BAT}(k)+\frac{F^{Power}_{PV\to BAT}(k)-F^{Power}_{BAT\to LD}}{\text{Battery Capacity}} \quad (16)$$

- $SOAcc^{BAT}(k)\in[0,1]$

Depending on their working situation (activated or not), the converters are illustrated as: $\varepsilon_i(k) \in \{0,1\}$ where $i \in Rs^{Converters}$.

3 Results

3.1 Simulation results of hybrid MPC-EVM technique

Load and PV array data for 24-hours were obtained from the building in the UK for the simulation. Initially, we used the ε-variables to implement the MPC with the ε-variables, and we got identical results with the normal MPC, implying that the proposed method does not alter the basic goals and behaviour of the MPC. Having said that, using the ε-variables, we can easily expand to more complicated systems and more complicated control constraints by modifying the logical operators of the ε-variables. As an example, initially when the SOC is below 30%, the MPC will import energy from the grid, as illustrated in Fig. 5. However, there are cases where this may happen close to a point where the PV will produce enough power to compensate for the slight drop of SOC below 30% and hence increase the system's autonomy from the main grid. So, in this case, and without changing the MPC structure the evolution operator of the converter "Grid" will contain another term that will be logical 0 when it is anticipated that the PV will produce sufficient power in 1 or 2 samples. Since, in this work, this evolution operator uses the AND logical gate, when this new binary variable is 0, the evolution operator will also be 0 and hence the system will not import energy from the main grid, Fig. 6. However, the hybrid MPC-EVM will import energy from the utility grid between at 12 AM and 8 AM to meet the critical load demand.

4 Conclusion

To conclude, there are many reasons to utilize the MPC technique to manage the MG power system. The MPC can predict power generation and consumption and cope with uncertainties and disturbances by employing cost functions and constraints. However, the implementation of MPC is not straightforward especially in complex microgrid systems. Also, it requires high processing power and computational time. To overcome these problems, the EVM has been employed with the MPC technique in this paper. Using this hybrid method, the complexity of the MPC implementation is mitigated, and the scalability and controllability of the PBG system are improved at any given time. In other words, the system's control is made more straightforward using the MPC-EVM technique. In this paper we first demonstrated that the MPC and the MPC-EVM produce the same results, and then as a case study we gave an example of how the EMS can easily be altered without having to do any changes within the MPC. In future work, the scalability of the proposed method will be fully demonstrated on a real system that was built in Xanthi, Greece and that employs a fuel cell and an electrolyser in order to have complete autonomy from the main grid.

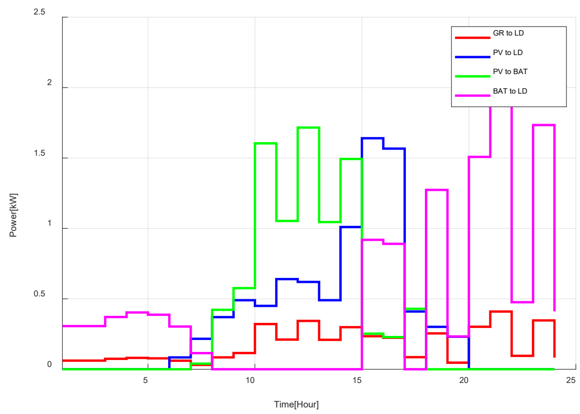

Fig. 5. Power flows using standard MPC

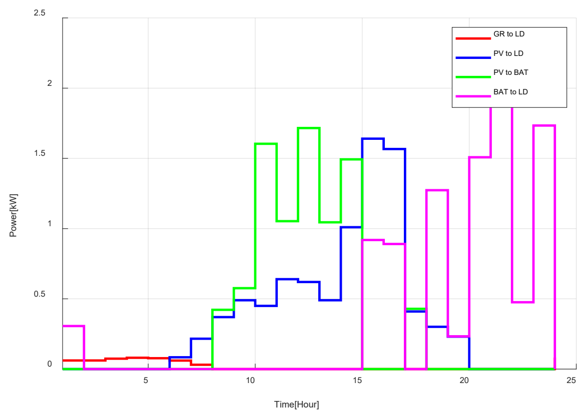

Fig. 6. Power flows using hybrid MPC-EVM

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