Voltage and Power Control of PV Energy based AC Microgrids using Model Predictive Control Approach

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Abstract: *The development of microgrids is an advantageous option for integrating rapidly growing renewable energies. However, the stochastic nature of renewable energies and variable power demand has created many challenges like unstable voltage/frequency and complicated power management and interaction with the utility grid. In existing control techniques, the droop control is commonly adopted as a decentralized power sharing method at the cost of voltage deviations. Besides, conventional cascaded control featuring relatively slow dynamic response shows difficulties in handling the fluctuation of renewable energy outputs, leading to further voltage quality deterioration. Recently, predictive control with its fast transient response and flexibility to accommodate different constraints has presented huge potentials in microgrid applications with better performance. In this work, a parallel-inverter based ac microgrid with solar Photovoltaics (PVs) and Battery Energy Storage Systems (BESSs) is presented. Based on this configuration, a universal model predictive control method is proposed. The BESS system is integrated through a Model Predictive Current Control (MPPC) based bidirectional buck- boost converter, aiming to stabilize the dc-bus voltage for PV output smoothing. Furthermore, the parallel inverters are controlled by incorporating a Model Predictive Voltage Control (MPVC) scheme with Artificial Bee Colony (ABC) algorithm to ensure stable ac voltage output and proper load sharing. The proposed control strategy is validated by MATLAB/Simulink simulation.*

Keywords: *Solar photovoltaics, Battery Energy Storage Systems(BESS), Model Predictive Control(MPC), ABC algorithm, MATLAB/Simulink*

1. Introduction

To meet the escalating energy demand sustainably, dynamic energy distribution networks are needed. These networks should allow bidirectional power flows and the control of a mix of distributed energy resources (DERs), including distributed generators (DGs) and systems. A microgrid integrates interconnected loads and Distributed Energy Resources (DERs), capable of operating either in parallel with the grid or intentionally in island mode [1] [2]. Micrograms can be AC, DC or hybrid. Notably, AC microgrids are gaining prominence due to their synergy with the main grid, simplicity and cost-effectiveness.

Components within a typical microgrid include storage units, controllable Distributed Generators (DGs), Renewable Energy Resources (RESs) as non-controllable devices and controllable loads. Effective control of energy from the Distributed Generators (DGs) is required to align with load requirements. So a control scheme is necessary to govern power flow which helps in maintaining the reliability and quality of the power supply. Various control schemes are employed to keep the voltage and frequency of the microgrid constant, representing a primary objective in the implementation of microgrid control techniques. The traditional microgrid control system operates on hierarchical control which contains three distinct levels [3]. At the primary level, local control maintains frequency, voltage and power levels within regulatory bounds. It swiftly addresses transient disturbances, adjusting converter frequency and output voltage to facilitate inner current and voltage control loops while ensuring proper power sharing among Distributed Generators (DGs). The secondary level steps in to compensate for deviations in voltage and frequency from nominal values, overseeing real and reactive power regulation, optimal DG operation and synchronization with the grid during transitions. Monitoring the global operation of the microgrid, the tertiary level regulates power flows between the microgrid, main grid, and other microgrids at the Point of Common Coupling (PCC). It addresses load-generation power balancing through an optimal power flow solver.

Despite the widespread acceptance of this control structure, it has limitations such as slow dynamic response in multi-loop cascaded structures, impacting accurate transient power sharing. Additionally, practical concerns include vulnerability to communication network uncertainties and cyber-attacks. It also requires complex tuning model for changes in the system. Hence, a better control scheme is required with good dynamic response, easy inclusion of constraints with nonlinearities, resiliency in case of system parameter changes and stability.

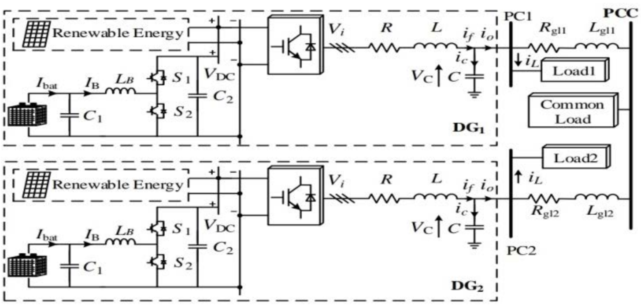

Figure 1. PV-battery based AC microgrid

Recently, the researchers focus on Model Predictive Control (MPC) schemes, where optimal switching states of power converters are determined based on a specified cost function which has shown improved performance[4]. While MPC has been applied for individual converters, its usage in the coordinated control of multiple converters in microgrids has not been considered. Existing system-level algorithms focus on overall goals without considering microgrid structures and converter control.

In the context of renewable energy-based AC microgrids with multiple power converters, this paper explores the possibility of replacing traditional cascade voltage or current feedback loops with MPC approaches. The key question addressed is the extent to which overall system performance can be enhanced. The developed control strategy utilizes MPC for AC microgrids, as depicted in Figure 1. The microgrid includes renewable energy sources like wind or solar, with a specific focus on a solar PV system in this example. The system comprises PV-battery energy sources and parallel inverters connected to AC loads. The proposed approach integrates Model Predictive Voltage Control (MPVC) incorporating Artificial Bee Colony (ABC) algorithm for parallel inverter load sharing. Additionally, Model Predictive Power Control (MPPC) is introduced to maintain DC-bus voltages and smooth PV outputs.

2. Model Predictive Control (MPC)

MPC is a sophisticated approach that iteratively predicts and optimizes a system's future states based on a dynamic model, offering enhanced performance in diverse industrial applications. MPC is like a smart planner. It keeps figuring out the best moves for the system in the near future by using a dynamic model, which is like a blueprint for the system's behavior. Even though this blueprint can get a bit complicated, MPC simplifies it using tricks like linearization. Now, since things might not always go exactly as planned, MPC doesn't stick to its first plan. It takes action based on the initial instructions, sees how well it worked, and then adjusts its plan accordingly. So, in simple terms, MPC is a smart, step-by-step decision-maker using predictions and feedback to make sure the system behaves optimally.

MPC relies on three fundamental requirements: a cost function (J), a predictive model and an optimization algorithm solving the specified cost function. Importantly, MPC allows for the incorporation of constraints in the optimization process, such as defining minimum and maximum values for robot states and inputs. This flexibility enhances MPC's applicability in diverse industrial scenarios.

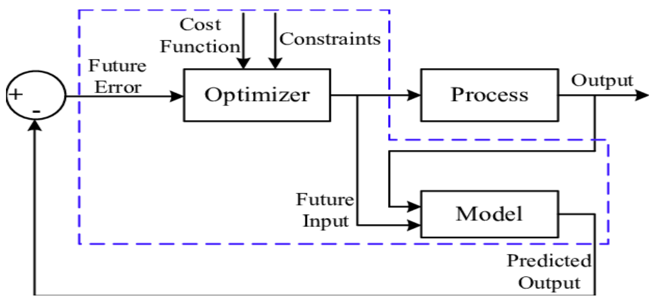

Figure 2. Structure of Model Predictive Controller

The cost function in Model Predictive Control (MPC) is like a guide for the system. The cost function, often denoted as J, is a way of quantifying how well the system is performing based on certain criteria or objectives. The cost function is a mathematical expression which involves terms that measure the system's performance relative to desired outcomes. These terms can include factors like minimizing the deviation from a reference trajectory, reducing errors in the system's behavior, optimizing control inputs, avoiding obstacles, or achieving specific objectives. MPC strives to find the control inputs that minimize this cost function over a specified prediction horizon, ensuring the system behaves optimally based on the defined criteria.

The predictive model refers to the dynamic model used to forecast the future behavior of the system. This dynamic model is a mathematical representation of how the system responds to different control inputs over time. The predictive model is essential for MPC because it enables the controller to simulate the future states of the system based on various possible inputs. This simulation is performed over a defined prediction horizon. While these models can be nonlinear, MPC might use methods like linearization to simplify them, especially for short-term predictions.

An optimization algorithm is employed to determine the optimal control inputs that minimize a specified cost function over a predefined prediction horizon. This optimization process involves searching for the control inputs that lead to the best performance of the system while adhering to any specified constraints. Several optimization algorithms can be utilized within the MPC framework, and the choice depends on factors such as computational efficiency and the complexity of the optimization problem. In this paper, MPC is applied for two parts of the system: Model Predictive Voltage control(MPVC) for parallel inverters and Model predictive Power Control(MPPC) for PV-battery energy sources.

2.1 Model Predictive Voltage Control (MPVC)

Model Predictive Voltage Control (MPVC) of parallel inverters is a control strategy used in power systems to regulate the voltage output of multiple inverters operating in parallel. MPVC focuses on capacitor voltage as control objective. The LC filter's mathematical model comprises two components: the dynamic vector equation governing the filter inductor current and the dynamic vector equation describing the filter capacitor voltage which is obtained from Fig 1.

The filter voltage expression is expressed as:

$$\frac{dV_C}{dt} = \frac{1}{C}\left(I_f - I_o\right) \tag{1}$$

The filter current expression is expressed as:

$$L\,\frac{dI_f}{dt} + I_f R = V_i - V_c \tag{2}$$

The two equations (1) and (2) can be re-written in state-space form as:

$$\frac{dx}{dt} = Ax + By \tag{3}$$

where

$$x = \begin{bmatrix} V_c \\ I_f \end{bmatrix} \quad y = \begin{bmatrix} V_i \\ I_o \end{bmatrix} \quad A = \begin{bmatrix} 0 & \frac{1}{C} \\ -\frac{1}{L} & -\frac{R}{L} \end{bmatrix} \quad B = \begin{bmatrix} 0 & -\frac{1}{C} \\ \frac{1}{L} & 0 \end{bmatrix}$$

For a sampling time T_s, Zero-Order Hold (ZOH) discretization was used to obtain the prediction of the system's behavior as follows:

$$x(k+1) = e^{T_s A} x(k) + A^{-1}\left(e^{T_s A} - I_{2X2}\right) B\, y(k) \tag{4}$$

Equation (4) is used to predict the capacitor voltage at (k+1)th instant. The goal of cost function is to minimize the deviation between the predicted output voltage and the reference voltage at the next sampling period (k+1). Therefore, the cost function J_V is defined as:

$$J_V = (V_{c\alpha}^{ref} - V_{c\alpha}^{k+1})^2 + (V_{c\beta}^{ref} - V_{c\beta}^{k+1})^2 \tag{5}$$

Where $V_{c\alpha}^{ref}$ and $V_{c\beta}^{ref}$ are reference voltages at α-axis and β-axis in the stationary rotating coordinate system respectively and $V_{c\alpha}^{k+1}$ and $V_{c\beta}^{k+1}$ are the predicted voltage for the α and β axes respectively. The voltage vector yielding the minimum cost in the cost function will be employed in the upcoming sampling period. By precisely controlling the α and β components, the V_c can effectively track its reference, ensuring the establishment of stable and sinusoidal voltage.

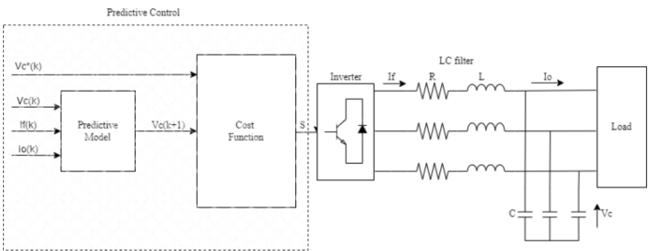

Figure 3. Block Diagram of MPVC

Building upon the successful voltage control of MPVC and the load-sharing capabilities of the droop method, a novel parallel inverter control strategy has been formulated, outlined in Figure 3. The conventional voltage and current feedback loops have been substituted with the MPVC scheme.

2.2 Model Predictive Power Control (MPPC)

The primary objective of the Battery Energy Storage System (BESS) is to address the power fluctuations resulting from the disparity between Photovoltaic (PV) output and the electrical load demand. This is achieved by consistently regulating the direct current (dc) bus voltage. In order to uphold a stable power equilibrium within the microgrid, it is imperative for the BESS to efficiently discharge and charge as necessary.

Given that the power supplied or absorbed by the Battery Energy Storage System (BESS) is effectively regulated by manipulating the buck-boost converter, it becomes crucial to analyze the impact of switching states on the absorbed or supplied power. Illustrated in Figure 4 is the BESS circuit, comprising the battery and the converter. When switch S2 is in a switching state (either 1 or 0) and S1 is kept OFF, the system operates in boost mode. This configuration allows the battery to discharge and supply power. Conversely, if switch S1 is in a switching state (either 1 or 0) while S2 is maintained OFF, the system operates in buck mode. In this mode, the battery is charged, thereby absorbing power.

In boost operation, the discrete-time model for sampling time T_s is expressed as

$$\begin{cases} S_2 = 1,\ S_1 = 0:\ I_B(k+1) = \frac{T_S}{L_B} V_B(k) + I_B(k) \\ S_2 = 0,\ S_1 = 0:\ I_B(k+1) = \frac{T_S}{L_B}(-V_{DC}(k) + V_B(k)) + I_B(k) \end{cases} \tag{6}$$

Similarly the discrete-time model for sampling time T_s in buck operation is expressed as

$$\begin{cases} S_2 = 0,\ S_1 = 0:\ I_B(k+1) = -\frac{T_S}{L_B} V_B(k) + I_B(k) \\ S_2 = 0,\ S_1 = 1:\ I_B(k+1) = \frac{T_S}{L_B}(V_{DC}(k) - V_B(k)) + I_B(k) \end{cases} \tag{7}$$

The battery output power can be estimated as

$$P_{bat}(k+1) = \left| I_B(k+1) \cdot V_B(k) \right| \tag{8}$$

Similarly the required power by BESS at next control instant can be written as

$$P^*_{BESS}(k+1) = \left| I_{DC}(k+1) \cdot V^*_{DC}(k) \right| \tag{9}$$

To maintain power balance within the microgrid, BESS needs to supply the necessary power through the buck-boost converter. The objective is to minimize the following cost function:

$$J_P = \left| P^*_{BESS}(k+1) - P_{bat}(k+1) \right| \tag{10}$$

The MPPC strategy involves several key parameters: the Photovoltaic (PV) system output current (IPV), inverter input current (I_{AC}), actual DC-bus voltage (V_{DC}), and reference voltage (V_{DC}*). These parameters are initially utilized to compute the required power for the Battery Energy Storage System (BESS). Simultaneously, the battery voltage and current, along with the actual DC-bus voltage, are employed to predict the battery current $I_B(k+1)$. This prediction results in four potential values of $P_{bat}(k+1)$ as determined by (6) and (7). Subsequently, the switching behaviour minimizing (10) is selected to control the buck-boost converter.

3. Proposed Method

Here MPVC is incorporated with Artificial Bee Colony (ABC) algorithm. Combining the Artificial Bee Colony (ABC) algorithm with Model Predictive Voltage Control (MPVC) is like using a smart, adaptive approach to efficiently manage and optimize the voltage levels in an electrical power system. In essence, it's like having a group of bees (ABC) explore and suggest ways to adjust voltage, while a smart brain (MPC) predicts and evaluates the impact of these adjustments, leading to an optimized and efficient voltage control strategy for the electrical power system.

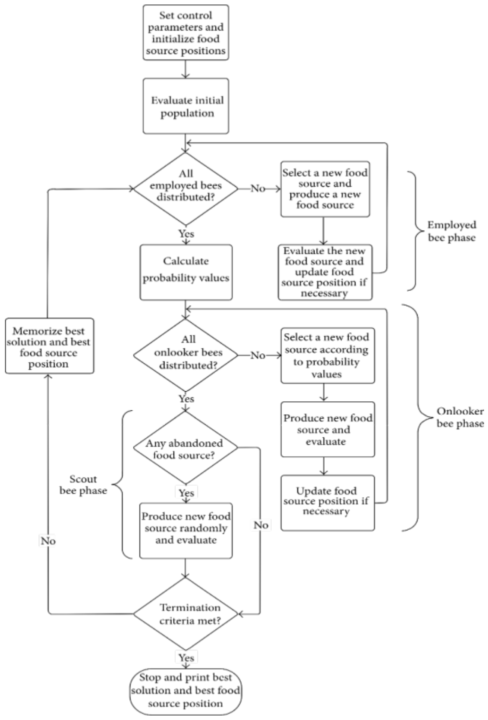

Figure 4. Flowchart of ABC Algorithm.

The ABC algorithm is a swarm intelligence optimization algorithm inspired by the foraging behaviour of honeybee colonies. It is characterized by its simplicity and ability to efficiently explore and exploit the search space. It has been successfully applied to various optimization problems, including function optimization, parameter tuning and machine learning. The key components of the ABC algorithm include the employed bee phase for exploration, the onlooker bee phase for exploitation and the scout bee phase for diversification. The algorithm's performance depends on parameter settings such as colony size, the number of cycles, and the abandonment limit for solutions. Researchers often fine-tune these parameters based on the characteristics of the optimization problem at hand.

4. Simulation And Results

To examine the performance of ABC algorithm along with MPVC and MPPC, the AC microgrid shown in Figure 1 is simulated using MATLAB/Simulink software. The parameters of PV system, BESS systems and paralleled inverters are tabulated in Table I. The ABC algorithm is written in command window of MATLAB. To verify the proposed method, PV system is subjected to varying irradiance at a constant temperature of 27^{o}C as shown in Figure 5.

Table 1 . System Parameters

Parameters	Values
PV System	
Module maximum power(W)	549
Array parallel module strings	66
Array series-connected modules	10
BESS	
Nominal Voltage(V)	500
Rated capacity(Ah)	1600
DC-Bus voltage(V)	1k
Paralleled Inverters	
Rated frequency(Hz)	50
Nominal phase-to-phase voltage V_{rms} (V)	380
Filter Inductance(mH)	2
Filter Capacitance(μF)	250
Line Resistance R_{DG1} and R_{DG2} (Ohms)	0.05,0.04
Line Reactance L_{DG1} and L_{DG2} (Ohms)	0.6,0.48
ABC Algorithm	
Number of decision variables	5
Maximum number of iterations	200
Population size	100
Number of onlooker bees	100

Figure 6 represents the output voltage at the load due to both DG1 and DG2. It represents a voltage waveform for the load which is stable and sinusoidal due to MPC approach.

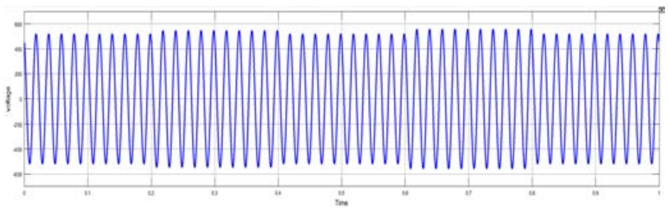

Figure 6. Output Voltage for the load

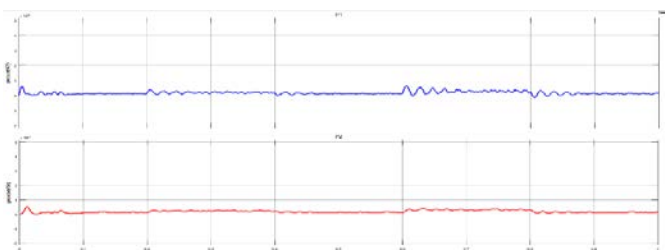

Figure 7(a). Power generated by DG1 And DG2 without ABC algorithm

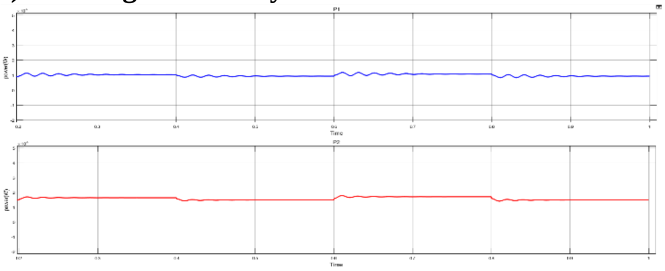

Figure 7(b). Power generated by DG1 and DG2 with ABC algorithm

Figures 7(a) and 7(b) shows the comparison of power generated by DG1 and DG2 for systems without ABC algorithm and with ABC algorithm. The comparison reveals that, in both methods, the parallel inverters possess the capability to automatically adjust their output to accommodate the fluctuating power demand, facilitated by the droop method. However, employing the proposed method results in a better performance. Specifically, the active power generated using the proposed method exhibits smoother transitions and faster responses compared to the traditional method. This improved performance is attributed to the exploring capabilities of ABC algorithm embedded in the proposed method.

5. Conclusion

The integration of Model Predictive Control (MPC) with the Artificial Bee Colony (ABC) algorithm for Photovoltaic (PV)-based AC microgrids offers a promising and effective approach for optimizing the system's performance. Through the use of MPC, the control system can predict and adapt to dynamic changes in the microgrid, ensuring efficient operation and adherence to specified objectives. The ABC algorithm enhances this optimization process by intelligently exploring and selecting control parameters, contributing to the overall effectiveness of the system. The MPVC, coupled with the ABC algorithm, provides superior voltage control capabilities, ensuring stable and reliable operation of the AC microgrid. The proposed method demonstrates smoother and faster transient performance in terms of active power compared to traditional methods. The adaptive and intelligent features of this integrated approach contribute to enhanced stability, efficiency, and responsiveness in managing the complexities of modern power systems. Further research and real-world implementations will likely unveil additional benefits and opportunities for refinement.

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