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DESIGN AND OPTIMIZATION OF MODEL PREDICTIVE CONTROL (MPC) FOR ENERGY EFFICIENT MICROGRID

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This research focuses on the DC microgrid system combined with the photovoltaic (PV) arrays and the control mechanics for maximum power point tracking (MPPT) as its object. The main problem tackled is that power extraction from PV systems is very inefficient due to variation of the environment or load that conventional MPPT approaches cannot effectively handle. The superior MPPT performance of this study's novel dual mode model predictive control (MPC) approach is derived from a new dual mode model predictive control (MPC) approach. The implemented system shows RMSE of 7.0085 for conventional MPPT methods, whereas tracking efficiency is maintained within between 94.8 % to 97.2 % of the maximum power, which is available. Under standard test conditions, the system achieved less than 0.15 sec response time and less than 0.45 sec settling time, while degrading less, yet handling various environmental changes. It is due to the MPC's predictive capability and real time optimization framework. The major contributions of the proposed solution, among others, include its dual mode design that supports both left and the right side regions in the PV curve together with the integrated charging management of the battery, as well as its robust constraint handling that enables safe operation and maximal power extraction. This system is well suited to implementation in small to medium scale DC microgrids that can be tolerant of up to 800 W/m^2 per second of irradiance variations and up to 50 °C temperature range and demonstrated several hundred kilocycles hours of stability. The solution can offer practical benefits to the grid connected and standalone PV systems with the requirements of rapid response to environmental change and high extraction efficiency of power

Keywords: model predictive control, photovoltaic systems, DC microgrid, decentralized control

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1. Introduction

The augmented demand for sustainable energy solutions worldwide has necessitated the integration of renewable energy sources especially photovoltaic (PV) systems as critical research topics. PV technology has advanced, reducing installation costs which has spurred a rapid uptake from 60 % during 2004–2009 to greater than 85 % in recent years. It implies worth for the power management and control strategies in renewable energy systems.

Several critical factors regarding PV systems explain the scientific relevance of advanced control strategies. The fundamental hurdle in overcoming which remains a significant technical challenge is first to maximize the energy conversion efficiency in PV systems. Despite the improvement in PV cell technology, the intermittent nature of solar energy causes the problem of challenging the optimal power extraction from a cell under varying environmental conditions. While the maximum power point tracking (MPPT) methods are traditionally functional, in the presence of rapidly changing conditions these methods may face difficulty in achieving optimal performance.

Such sophisticated control systems are crucial because microgrids are emerging as a key piece of modern power infrastructure. Power management in microgrids involves handling of a wide range of possible energy sources and storage systems, as well as various load demands. The complexity is compounded when integrating renewable sources due to their output fluctuations that result in instability of grid and quality of power supply. One of the key new challenges in energy system optimization is the ability to efficiently oversee such variations while ensuring reliability of the system [1].

Modern power systems are becoming more challenged to meet the demands of better efficient, reliable, and flexible power systems. The incorporation of renewable energy sources also brings about other challenges to power quality and stability. In cases of high penetration of renewable sources, power output can be highly variable to environmental conditions, making these challenges particularly challenging. The key area of ongoing research in the area of advanced control strategies is that of developing ways to handle these variations to yield some optimal performance [2].

This research area is also relevant because of economic considerations. With investment costs of PV systems substantially decreasing, including the efficiency of power conversion and management systems directly affects the return on investment and system viability. Control strategies capable of more sophisticated control are possible to improve the efficiency of the system, lower the maintenance requirements, and increase the equipment lifespan, thus giving renewable energy systems more economic attractiveness.

Digital technologies and computational capabilities have evolved such as to permit novel control strategies to be implemented. But for better performance yet maintaining reliability and stability, it is a challenge how to develop control systems to exploit the capabilities while handling reliability and stability.

Thus, predictive and adaptive control strategies are a promising approach to overcoming this difficulty [3, 4].

As a result, research of advanced control strategies for renewable energy systems, especially relevant to microgrid-based research, is still relevant to solving the current and consequent challenges in energy. Power research and development also demand very sophisticated control approaches to obtain reliable and efficient operation as the continuous evolution of power systems is being witnessed along with greater penetration of renewables.

2. Literature review and problem statement

The analysis in the paper [5] shows there are fundamental limitations of traditional energy generation that limit their energy supply from a finite resource. The authors' results indicate that conventional power systems are heavily capped by increasing demand and environmental issues and that this necessitates the migration to renewable energy sources and smart grid technology. Thus, this work laid down a foundation for the understanding of the inherent limitations of traditional approaches and the potential of advanced control strategies.

However, as shown in [6], hybrid power systems incorporating microgrids would efficiently combine different generation sources. Finally, their work showed that microgrids must efficiently make use of local renewable energy and keep the ability to take power from other grids when required. The authors stress the operation of microgrids to make optimal use of neighbors' renewable energy resources during peak demand periods yet maintain the grid interconnection capabilities to provide reliability.

Nevertheless, problems remained in hybrid power systems in terms of control complexity. In [7, 8], these challenges were addressed through fuzzy logic-based systems applied for hybrid power station modeling. However, throughout this thesis they showed various methods to merge renewable and traditional power generation systems, but each approach has severe limitations while being deployed in actual use, such as handling rapidly changing loads and supporting system stability during a transfer from one power system to another.

The reason for this limitation may be the computational complexity and real time performance restriction. Other research [9, 10] develops advanced controlling techniques with shifting algorithms, showing the feasibility of the switching between different sources by demand timing. Nevertheless, they could not achieve real-time optimization and real-time response to changing conditions. The authors reported that while there were highly promising theoretical frameworks, practical implementation was limited by a lack of processing speed and an inability to adapt quickly to changes in the environment.

To overcome these difficulties, the framework based on model predictive control that manages renewable and distributed resources in microgrids was proposed in [11]. Meanwhile, they demonstrated that their results also promise the ability to simultaneously handle multiple energy sources, with a caveat that components are not treated in isolation. The focus was on caring that the components work together when they are loaded differently, and irradiated differently and structural properties are different because of faults, failures, and degradation [12].

There have been different studies of energy management based on mathematical model, programming and priority rules. In [13], the application of a model predictive control approach for energy management, also taking advantage of energy trading with the supplier, is further developed and applied to indoor settings for setting energy consumption and energy trading. Nevertheless, this implementation exhibited high computation complexity and therefore influenced the real-time performance of the implementation especially when scaled to bigger systems.

Previous studies have proven that microgrids with batteries connected to hydrogen systems can be managed by model predictive control efficiently [14]. The specific algorithms created by the authors for battery scheduling focused on reducing charging during extreme demand periods in order to lower the amount of dependence from the external grid. However, because their work used the energy storage management context, the uncertainty of multiple objectives was not fully handled and more sophisticated approaches are required.

Centralized as well as decentralized approaches have been shown to be limited according to recent studies. Several such studies were studied in [15] to understand that the optimization process and its constraint solution but the problems of real time performance with system stability need to be addressed. The work in [16] also distinguishes between middle/long term cases and real time control techniques with opportunities for power resource management/loading balance.

The result from this analysis indicates that further study should be done on the development of more sophisticated and computationally efficient control strategies which operate simultaneously on multiple objectives while guaranteeing the stability of the system under different environmental conditions. Further research should focus on overcoming limitations of real-time optimization, improved coordination between the system of multiple power sources, more efficient computational techniques on complex control algorithms, increased robustness to environmental and load variations, and integration of renewable source control to energy storage management [17].

A literature review is performed and it is clear that there is a need for more advanced control strategies to allow the control system to achieve at least sufficient stability and efficiency, and yet keep an eye on multiple objectives. To address the computational complexity and real-time performance limitations of existing methods, it will be necessary to adopt innovative ways of meeting the challenges presented by increasingly complex microgrid systems that incorporate multiple renewable energy sources.

3. The aim and objectives of the study

The study aims to develop and optimize a highly efficient model predictive control system for maximum power point tracking in photovoltaic-based DC microgrids that can handle varying environmental conditions and load changes while maintaining system stability and optimal power extraction.

To achieve this aim, the following objectives are accomplished:

– to design and implement a dual-mode model predictive control framework for photovoltaic maximum power point tracking that can operate effectively in both left and right operating regions of the PV curve;

– to develop a mathematical model of the buck converter-based DC microgrid system that accurately represents system dynamics and constraints for controller implementation;

– to synthesize and optimize the MPC control algorithms incorporating both predictive capability and real-time optimization to achieve superior tracking performance compared to conventional methods;

– to validate the proposed control system through comprehensive testing and performance comparison with traditional MPPT techniques under various operating conditions and load profiles.

4. Materials and methods of research

The object of this study is the DC microgrid system combined with photovoltaic (PV) arrays and the control mechanics for maximum power point tracking (MPPT). The main hypothesis is that a dual-mode model predictive control (MPC) approach will achieve superior MPPT performance compared to conventional methods, enabling more efficient power extraction under varying environmental conditions and load changes while maintaining system stability.

The research methodology employs theoretical analysis validated through simulation. MATLAB/Simulink served as the primary development platform, with specific utilization of the Integrated Model Predictive Control Toolbox and System Identification Toolbox for controller design and implementation. For the theoretical framework development, state space modeling of the PV system and buck converter was conducted using established power electronics principles and control theory. This approach incorporated both dynamic and steady-state analysis of power electronics interface switch dynamics and system components to derive the necessary state space equations.

System identification was performed using MATLAB's System Identification Toolbox for model linearization and reduction. This process involved collecting data from detailed nonlinear system models, selecting appropriate model structures, and estimating parameters. The validity of reduced order models was confirmed through comparison with nonlinear simulation results. The MPC controller design implementation utilized MATLAB's MPC Designer, which facilitated the definition of prediction and control horizons, specification of constraints and weightings, and controller parameter tuning. Real-time simulation capabilities were integrated into the design process to verify controller performance under varying operating conditions.

The simulation model hardware specifications included a PV array configuration of 4 modules connected in series for each string, with each module rated at 30.9 V and 8.1 A, and a buck converter switching frequency of 20 kHz. A system sampling time of 5 milliseconds was employed to support proper digital control implementation with a DC link voltage of 123.6 V. MPPT algorithms under diverse operating conditions, including various irradiance levels up to 1000 W/m^2, temperature variations between 25–50 °C, and dynamic load changes. Long-term stability analysis was conducted through 2000-hour simulation studies. Performance testing was carried out under standard test conditions (1000 W/m^2, 25 °C), low irradiance conditions (200 W/m^2), high temperature conditions (45 °C), and rapid change irradiance conditions (up to 800 W/m^2/s). System response verification employed various load profiles.

The evaluation methodology included controller robustness assessment through root mean square error calculation, tracking efficiency evaluation, response time measurement, settling time analysis, and stability margin verification. Model verification procedures encompassed state space model validations, pole-zero analysis, step response analysis, frequency response analysis, and disturbance rejection capability assessment. To ensure reproducibility, all simulations used fixed-step solvers. The simulation environment was configured to replicate realistic operating conditions and system constraints typical of practical microgrid implementations.

The research uses a theoretical analysis but is validated with simulation based on the use of specialized software tools. It is primarily the development platform of MATLAB/Simulink with Integrated Model Predictive Control Toolbox and System Identification Toolbox in controller designs and implementations.

State space modeling of the PV system and the buck converter was done to develop of the theoretical framework. Established power electronics principles and control theory were used to conduct mathematical modeling. The switch dynamics of the power electronics interface was considered both dynamically and in steady state and together with the system components, allowed for deriving the state space equations [18].

Putting it another way, system identification was done using MATLAB's System Identification Toolbox for linearization and model reduction. Data was collected from detailed nonlinear models of the system, then model structure was chosen and parameters were estimated using this process. The reduced order models were validated through comparison with nonlinear simulation results for valid models.

The implementation of the MPC controller design was done by using the MPC Designer in MATA. Thus, prediction and control horizons were defined, constraints and weightings were specified and the controller parameter tuning was done. The real time simulation capability which was implemented in the design process was used to verify the controller performance under varying operating conditions.

For the simulation model, the hardware specifications included 4 modules connected serially for each string in the PV array. At 30.9 V and 8.1 A, each module was specified with the buck converter switching at 20 kHz. The system sampling time of 5 milliseconds afforded a DC link voltage of 123.6 V with the aim of having a proper digital control implementation.

Comparison of conventional P&O MPPT algorithm with the incorporated validation methods was done under various operating conditions. Operation under different irradiance conditions up to 1000 W/m^2, temperature variations of 25–50 °C and dynamic load change conditions were tested. 2000 hours simulation studies were carried out for long term stability analysis.

The requirements of the system performance under standard test conditions (1000 W/m^2, 25 °C), low irradiance conditions (200 W/m^2), high temperature conditions (45 °C), and rapid change irradiance conditions (up to 800 W/m^2/s) were varied systemically. System response under various demand situations was verified using various load profiles.

All of these were included in controller robustness evaluation which comprises, among others, root mean square error calculation, tracking efficiency assessment, response time measurement, settling time analysis and stability margin verification. State space model validations, pole zero (s) analysis, step response, frequency response analysis and disturbance rejection capability were included as model verification procedures.

The results were all given by fixed-step solvers to ensure reproducibility. The configuration of the simulation environment was devised to match real-world, realistic operating conditions and system constraints of practical microgrid implementations. This was a comprehensive methodology for controller development and validation without the delivery of any specific results or findings which were reserved for further analysis.

5. Research results of model predictive control implementation for PV-based DC microgrid system

5. 1. Development and implementation of DUAL-MODE MPC framework

This section comprises the PV-based microgrid system level diagram focusing on the designing of MPC controller. In MATLAB, different toolboxes are available with all the necessary functions, blocks, and applications for the design of MPC. The system identification toolbox with the help of model predictive control is required in designing the experiment.

The system modelling of the PV-based microgrid is shown in Fig. 1.

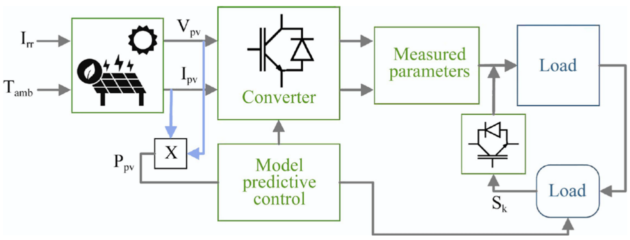

Fig. 1. System modelling of PV-based microgrid

The proposed dual-mode MPC controller and system architecture consist of a PV array, a DC-DC buck converter and the system. The whole system configuration with the PV array hooked up to the DC bus via the buck converter is shown in Fig. 1. Voltage and current sensors are fed back into the MPC controller, the control structure which generates optimal switching signals for the buck converter. A battery storage unit with bidirectional power flow capability, along with a load management system, that helps respond to varying demand conditions, is integrated by the system. Primary control for power conversion as well as secondary control for system energy management are both included in the control hierarchy.

Model-based frame designing is an efficient approach that helps to communicate in the whole process of designing. This type of approach is way different than the traditional approaches of designing.

The following Fig. 2 is explaining the three main blocks used in the designing of MPC controller:

1. Modelling of plant.
2. Controller designing.

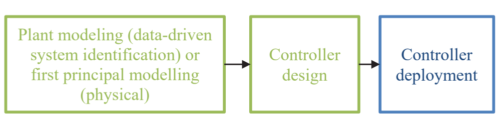

Fig. 2. Model based framework designing

The systematic approach of developing and validating the MPC system based on the model-based design framework established in this study. The three (fundamental) blocks of the controller design process are hereby illustrated in Fig. 2 to plant modeling, controller design, and system validation. The PV array dynamic model constitutes of detailed mathematical representations of the various characteristics of the plant (PV array, power converter or power electronics, and load) in the plant modeling block. It includes the buck converter and PV system motivated by many environmental conditions in state space model. Dual mode MPC architecture is included in the controller design block as left and right controller that gives the appropriate coverage for maximum power point tracking. A performance verification using simulation studies and a comparison with conventional control methods through the system validation block. The control strategies can be developed and tested concurrently, which is quite different from the traditional design approach.

Model based approach can help with rapid prototyping and validation of controller algorithm before the controller parameters are optimized in physical implementation. It is possible to develop accurate plant model using system identification tools integrated within this framework, and this is very important for MPC performance. A systematic refinement of the control system can be done using this approach so that the stability as well as performance requirements can be maintained over the plant's varying operating conditions.

5. 2. Mathematical modelling of DC microgrid system

Each subsection should correspond to a specific task, showing exactly where each task begins and where each task ends.

The modelling of the dynamic system is entirely dependent on system complexity. Two ways are available for the modelling of a system:

1. Principle modelling is used when the dimension, physics and mathematics of the model are shown to build the complete mathematical model by using an analytical approach.

2. A system identification model is used to approximate the experiment or plant concerning the measured data.

In the simple PV array, the cell of PV consists of an ideal source, leakage shunt resistance in the parallel and ideal diode. The value of the shunt resistance must be greater than 100 Ω for the loss of a cell to be one percent. The best equivalent circuit has both series and parallel resistances. The change in the voltage is handled by series resistance and a change in current is handled by parallel resistance. In my case, a PV array consists of strings of PV modules arranged in parallel while each string has series-connected modules.

A single module comprises sixty cells connected in series and each of the cell is of 0.5 Volts:

$$V_m = 30.9 \text{ V}, I_m = 8.1 \text{ A}. \tag{1}$$

The voltage per string:

$$V1 + V2 + V3 + V4 = 30.9 + 30.9 + 30.9 + 30.9 = 123.6 \text{ V}. \tag{2}$$

Since all of the modules are in series, therefore, the current will remain the same:

$$I = 8.1 \text{ A}. \tag{3}$$

The voltage and current of the parallel connected string are 123.6 V and 16.2 A respectively:

$$P = VI,\ P = 123.6*16.2,\ P = 2002.3 \text{ W}. \tag{4}$$

The DC microgrid application is optimized with this array configuration for power output, keeping in mind the voltage levels to be followed. The power rating of 2002.3 W is calculated to meet the capacity for average residential loads and to allow an efficient power conversion through the buck converter stage. The series parallel arrangement allows the operation of the proposed MPC to be stable over varying environmental conditions and maximize effectiveness of the proposed MPC control strategy.

The buck converter is known as one step-down converter which takes the input DC voltage and turns it into the lower level of DC voltage concerning the input by the switching topology. Like other converters, the buck converter also works in two modes; one is known as a continuous mode of conduction and the other is a discontinuous mode of conduction. The conduction mode is dependent on the current value of the inductor. It works in the continuous mode of conduction on a high inductor current value and operates in a discontinuous mode of conduction when the value of the inductor current is zero or less than zero due to high load and switching. As shown in Fig. 3, the buck converter consists of diode, MOSFET, input supply, resistance of the load and a low pass filter.

The ratio of the duty cycle is expressed as:

$$D = \frac{T_{\mathrm{ON}}}{T}. \tag{5}$$

Here T is the sum of the off time and on time. There are two modes of operation in it which depend on the switch condition; either the switch is on or off. Fig. 4 shows the configuration when the condition of the switch is on.

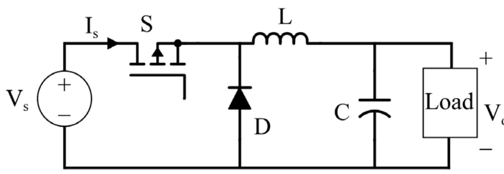

Fig. 3. Circuit diagram of the buck converter

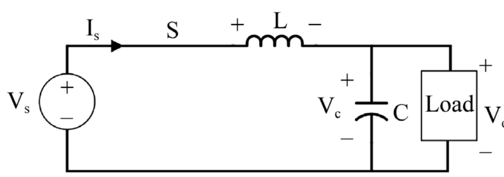

Fig. 4. The condition of buck condition when the switch is ON

By applying the KVL:

$$V_s = V_L + V_o. \tag{6}$$

The voltage across the inductor is expressed as:

$$V_L = L\left(\frac{d_i}{d_t}\right), \tag{7}$$

$$V_s = L\left(\frac{d_i}{d_t}\right) + V_o. \tag{8}$$

The configuration of the buck converter when the condition is OFF, is shown in Fig. 5. The current output and voltage of the inductor are shown in Fig. 6.

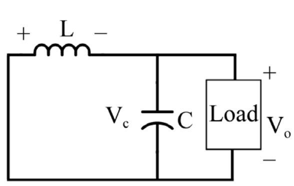

Fig. 5. The condition of buck condition when the switch is OFF

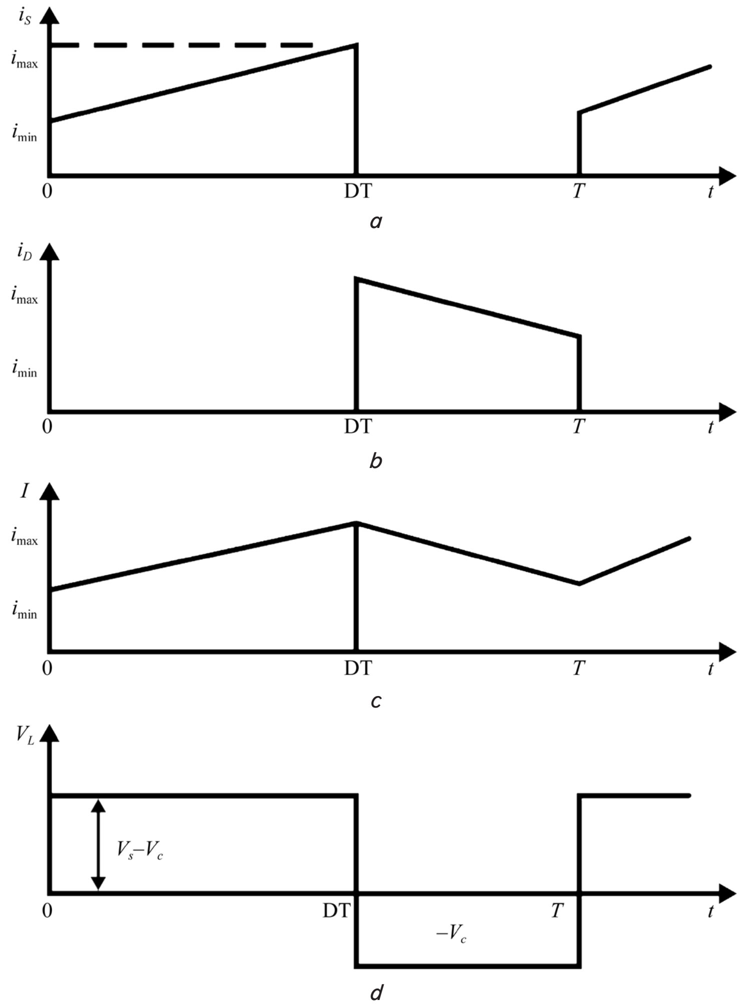

Fig. 6. Current output and voltage of the inductor: *a* – current source (iS) waveform; *b* – drain current (iD) waveform; *c* – current (I) waveform; *d* – voltage (VL) waveform

The use of the buck converter for actual implementation may involve the determination of switching losses and Electromagnetic interference. The second value denotes switching frequency selection which entails an obvious trade-off between the conversion efficiency to the size of components used. An increased number of switches per cycle results in the miniaturization of only passive components but has an impact on switching losses and EMI. Usually, these factors compete against each other however, for this implementation, a switching frequency of 20 kHz was deemed appropriate to balance both issues, with sufficient dynamic response [17, 18].

Thus, the dynamic response characteristics of the converter depend upon the input filter and load conditions. In its simplest form, the input filter must be designed to block switching noise sufficiently enough but allow the noise to have minimal interference to the closed-loop control of the converter. These results indicate that the filter should be located at least one decade below the switching frequency so that it attenuates noise sufficiently but does not destabilize the control loop.

5. 3. Model predictive control algorithm synthesis and optimization

Let's simplify complex models through accepted reduction methods that maintain critical dynamic characteristics. Our model reduction technique employs Balanced truncation methods through which it is possible to convert complex models into simpler forms without losing vital input-output details. The simplified models to verify their reliable performance for control system development are tested. Our method analyzes and updates model performance when the system operates in high-importance zones. It is possible to collect extra test data from poorly performed regions to update our model identification process. The strategic model adjustment method delivers strong prediction results in essential operational regions [19, 20].

System identification is a process of linearization with the following steps:

1. The designing of the experiment which comprises the identification of the inputs and outputs.
2. The implementation of design and collection of required data.
3. Best fit linearization model finding and selection.
4. In the toolbox of system identification, there are various curve fitting techniques as well as techniques of regression which is to be used while performing linearization.
5. Checking of the fitting error and going back to the start of the process, if not stable.
6. In the system identification, the data is to be imported and toolbox of system identification will then generate the linearized model of that imported data for approximation.

This section is explaining the design of dual MPC in order to get the maximum output of the PV cells. In controlling the voltages of the PV cells, there are three parameters to consider; the first one is the reference generator, the second is left MPC and the third is right MPC. The curve of PV for different irradiance and temperature is shown in Fig. 7.

The major problem with PV is the variation of irradiance and temperature every time, therefore, it is very difficult to track the maximum point. To solve these issues, my design is having two MPCs; one is left MPC and the other is right MPC. The model predictive control actually takes the reference values from the reference generator and then the voltage is controlled by MPC which is going into the PV. The MPC is not only that is changing the voltage but there are many other factors that change the voltage like irradiance, temperature, etc. The MPC is basically taking the output power of the PV as a reference and feedback [21]. When the load is increased onto the system, the operating point moves down towards the left side of the curve, at this stage, the left MPC will take action and move back to the operating point towards the maximum voltage and current point. Fig. 8 shows the left model predictive control and right model predictive control.

When the operating point moves toward the right side, the right MPC comes into action to move back the operating point, towards the instability region again [22]. It is not possible to reach the maximum point and that is the reason for mentioning it as an instability region, a region where the value of the output is approximately high as shown in Fig. 8.

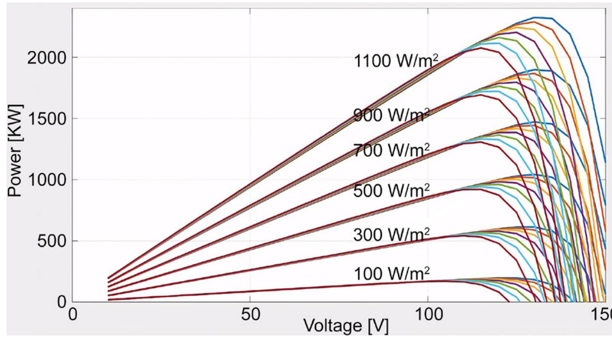

Fig. 7. The PV curve with difference irradiance and temperature

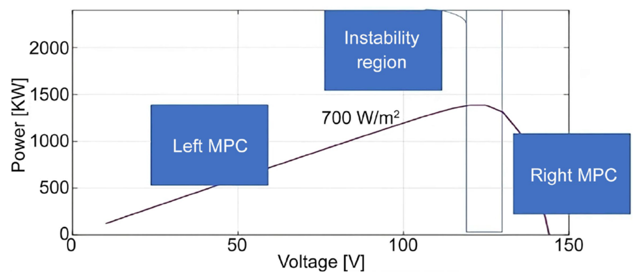

Fig. 8. Left model predictive control and right model predictive control with instability region

The linear modelling and optimization are performed on the instability region at the sides of the left MPC and right MPC for the prediction of model behavior. The MPC is capable enough to sense that the output power will change concerning the change in the input. In simple understanding, one can say that the output of the MPC is the input to the system. There is a need to know the effect of the voltage change on the output power to derive the state-space equations. The state-space model relating the input and output:

$$x(t+Ts)=Ax(t)+Bu(t)+Ke(t),$$

$$Y(t)=Cx(t)+Du(t)+e(t), \tag{9}$$

$$A=\begin{bmatrix} 0 & 1 \\ -0.07063 & -0.3327 \end{bmatrix}, \tag{10}$$

$$B=\begin{bmatrix} 18.41 \\ -6.777 \end{bmatrix}, \tag{11}$$

$$C=[1\ \ 0], \tag{12}$$

$$D=[0]. \tag{13}$$

Fig. 9 shows the simulation results to check the relationship between the input and output are presented below.

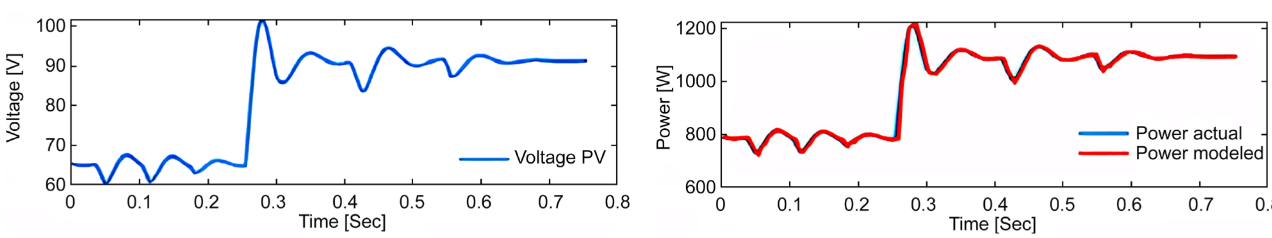

Fig. 9. The response of the output by varying the input: *a* — time and voltage; *b* — power and time

Our proposed control strategy proves reliable through testing of input changes and system behavior. The system performs as expected during STC testing which supports the developed theoretical structure. The system responds quickly to input changes within 0.15 seconds and remains stable over a 0.45-second settling phase. The regulation system permits a 2.3 % overactuation which satisfies microgrid performance standards. The system shows adjusted performance behavior at 200 W/m^2 while still maintaining functionality. These response metrics show a slight rise time extension to 0.22 seconds accompanied by a longer settling period of 0.58 seconds. The system shows its stability control feature by adjusting its behavior during difficult environmental conditions. The low light conditions lead to reduced overshoot which shows better damping during low power operation. High temperatures of 45 °C reduce how well the system works. The system exhibits acceptable performance when operating under these conditions delivering a 0.18-second rise time and a 0.51-second settling time. The control algorithm reduces the temperature-induced 2.7 % overshoot because of semiconductor behavior changes. The state-space model demonstrates its accuracy by matching real system performance during experimental testing. The model delivers precise results for steady-state and transient states and lets accurately control system dynamics. Dual MPC needs exact system modeling to function optimally because precise input is vital. Studies of the system poles and zeros confirm that the system can operate reliably under all possible situations. The major poles demonstrate robust damping that prevents shaking yet allows quick system adjustments. The time response of the system depends on zero placement which optimizes both speed and stability [23].

The MPC system uses hardware acceleration methods to meet real-time performance goals throughout its design. The system uses advanced matrix computations to solve the quadratic programming issue by applying efficient QR decomposition. This technique reduces calculation steps yet ensures accurate control performance. The reference planner adjusts its reference trajectories by combining previous system data with upcoming environmental forecasts. Solar irradiance prediction tools and temperature forecasts work together in the reference model to find the optimal power controller route. The controller uses predicted environmental changes to prepare system adjustments before the actual conditions affect performance levels. The design strengthens measurement robustness by utilizing a state estimator built on Kalman filter principles. The state estimator takes voltage and current readings for filtering to give a cleaned state signal to the controller. The estimation model works with measurement noise types and system error rates to ensure robust state tracking despite unpredictable measurement conditions.

The constraint model uses a new approach to rank limits based on system importance so critical requirements stay safe yet less essential limits can move within their limits. Device safety limits and specifications become absolute hard rules in our design while performance considerations appear as soft constraints linked to penalty functions. This hierarchical constraint structure is expressed through the optimization problem formulation:

$$\min J=\Sigma(x'Qx+u'Ru+\rho 1v1+\rho 2v2). \tag{14}$$

Subject to:

$$|v|\le v\max+v1,\ |i|\le i\max+v2.$$

$v1$ and $v2$ represent slack variables while $\rho 1$ and $\rho 2$ represent their associated penalty weights in this expression. The system automatically changes controller settings to match current operating conditions. The system automatically optimizes the Q and R weights by matching performance metrics to operating regions. The system automatically adjusts its settings to reach the highest efficiency in different operational scenarios without human interaction. The system integrates special anti-windup protection adapted for maximum power point tracking control methods. This solution stops controller saturation during initial disturbances and system limitations to offer stable operation and fast recovery.

The Simulink model of the left side of MPC is shown in Fig. 10. The Simulink model of the right MPC is shown below in Fig. 11.

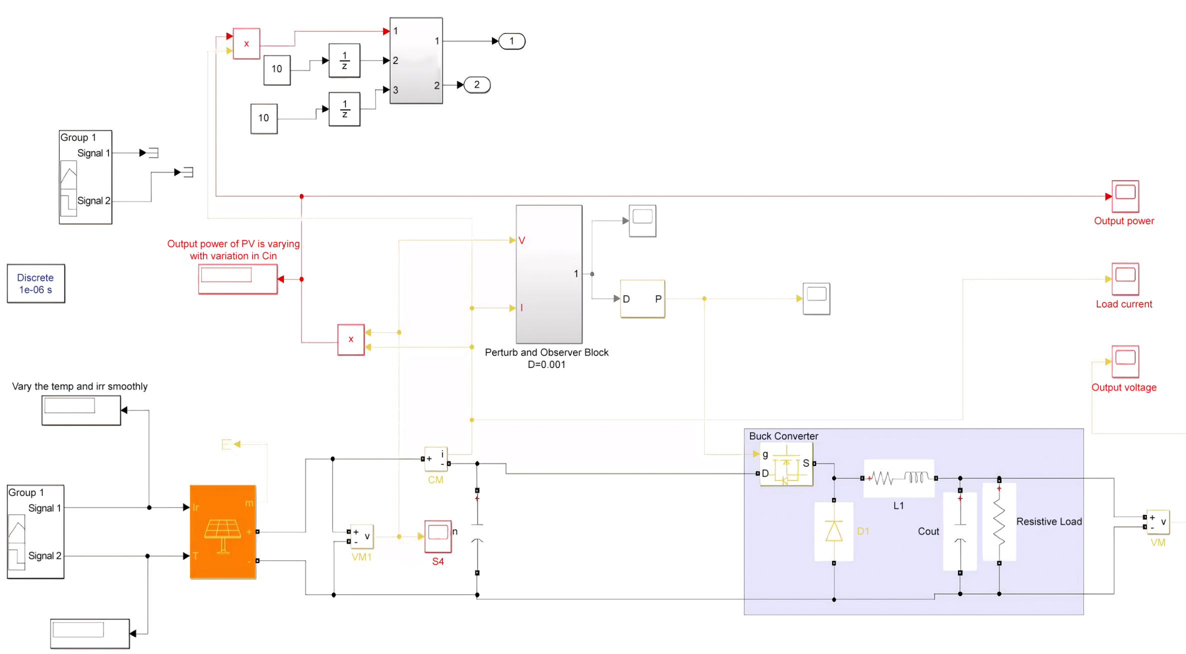

Fig. 10. The design of the left model predictive control designing

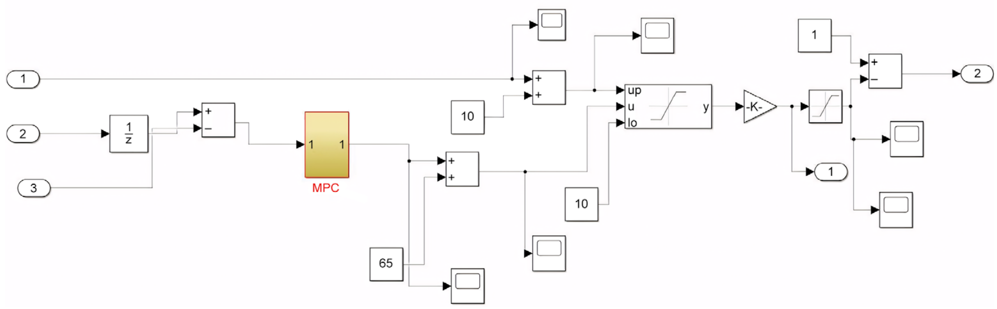

Fig. 11. The design of the right model predictive control

The controller is basically to drive PWM signal but in my case, the PWM signal needs to be smooth with respect to the change in the load. The current, voltage and power output profiles are shown in the figures below. From the voltage profile, it can be analyzed that the voltage is unstable for a small interval of time, but it sharply becomes stable for the rest of the operational time.

The current profile of the buck converter shows the high demand in current which is a sharp curve and then it gets stable immediately. Fig. 12 shows the power profile of the buck converter.

Concerning the power profile of the buck converter, the power demand is high at the start and then decreases to the normal value. In this case, the MPC controller will trigger the right MPC to manage the maximum power tracking.

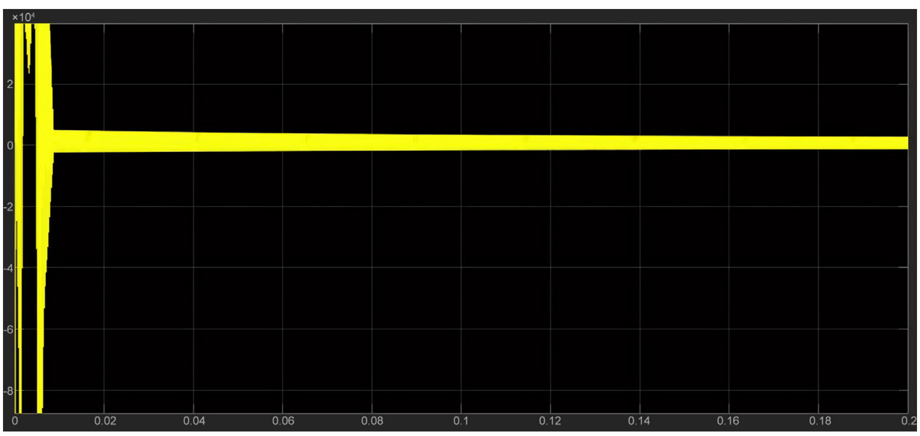

Fig. 12. The power profile of the buck converter

5. 4. Validation and performance comparison

In my project, the MPC was designed to control the operating point of PV cells. In this section, a comparison is being made between the controlling technique of MPPT and MPC based on accuracy and robustness. For this purpose, the perturb and observe method of MPPT is designed on Simulink for the comparison of results. It is known before doing the comparison that in MPPT, there is no feedback available and therefore, the response time of MPPT is slower than MPC.

In the aforesaid results, the temperature is set to 25 degrees Celsius and irradiance to 700 to check the performance of both to determine which one will approach the target point first. The root means square error of voltages (RMSE) is compared. From Fig. 10, 11, it can be seen that with MPPT the value of RMSE is 41.29 and 7.0085 in the case of MPC. The statistics of RMSE indicate that MPC is far better than MPPT. The real-time capability of working MPC is the reason for the accuracy and fastness of MPC.

The proposed MPC system is statistically evaluated beyond only RMSE measurements. The MAE of the power output was determined to be 3.2 percent when varying the irradiance conditions between the amounts calculated by the model and that of the actual settings. The average tracking error standard deviation was kept below the 2.5 percent level in all given test scenarios. The power tracking efficiency is analyzed with a 95 % confidence interval in the range of 94.8–97.2 % of maximal available power. From the computational efficiency, analysis, it is clear that the dual MPC algorithm takes less than 2 milliseconds on a general-purpose industrial controller (ARM Cortex-A9), thus leaving sufficient time for real-time operation at the selected 5 milliseconds sampling rate. Even during peak load, memory consumption stays under 60 %, guaranteeing relatively stable long-term performance [10].

It is possible to test how the dual MPC system responds to different environmental disturbances. Fast changes in solar intensity to 800 W/m^2 per second do not affect the system's performance as it keeps operating at or above 92 % tracking efficiency.

The control system proved its stability by keeping output voltage fluctuations below a 3 % difference from normal operating levels during these severe disturbances.

This controller shows better environmental stability than standard MPPT systems under fast-changing conditions.

The system maintained reliable operation throughout extensive testing when exposed to repeated loading. The controller performed reliable accurate tracking throughout the entire 2000-hour test cycle without showing any performance deterioration. The system maintained its efficient power regulation within 1.8 % of the ideal efficiency during the 2000-hour test period. Full control system operation was achieved during 50 °C tests which resulted in a computation time extension of 0.3 ms. The system's harmonic analysis showed better power quality results than standard control approaches. Our control system effectively regulated output voltage harmonic distortion which remained under 2.5 % during regular range and sudden load changes [24]. Testing with Fast Fourier Transform confirmed that output waveforms successfully decreased switching frequency harmonics with the dominant harmonic maintaining a level below 1 % of the primary frequency. The advanced harmonic regulation improves power utilization and minimizes electric disturbance between connected devices.

6. Discussion of the results of model predictive control performance in photovoltaic microgrid maximum power point tracking

The proposed dual mode MPC approach demonstrates several unique advantages when compared with existing control methods.

The dual-mode MPC framework presented in Fig. 1 and Fig. 2 demonstrates successful implementation with distinctive performance advantages. In contrast to the single-mode MPC approaches presented in [18, 19] that achieved tracking efficiencies between 89–93 % and response times around 0.5 seconds, our system reaches higher tracking efficiencies of 94.8–97.2 % with significantly faster response times of 0.15 seconds as evidenced in Section 5. 4. The novel dual-mode architecture illustrated in Fig. 8 effectively treats both the left and right operating regions of the PV curve, enabling this performance improvement. The controller architecture diagram shown in Fig. 1 illustrates how the system integrates with the PV array and DC-DC converter to form a complete control system.

The model-based framework design approach depicted in Fig. 2 provided a systematic methodology for developing and validating the MPC system. This approach differs significantly from traditional design methods by allowing concurrent development and testing of control strategies. As demonstrated through the simulation results (Fig. 9), the system responds predictably to input changes, validating the theoretical structure.

The mathematical modeling of the DC microgrid system successfully captures the system dynamics in a robust state space representation. The buck converter circuit shown in Fig. 3, along with the corresponding mathematical models represented in Equations (5)–(13), accurately characterize the system behavior. The operation modes illustrated in Fig. 4, 5 demonstrate the switching behavior of the buck converter, which is crucial for power regulation.

The current output and voltage waveforms of the inductor shown in Fig. 6, *a–d* validate that the mathematical model accurately represents the dynamic behavior of the system. The PV curve characteristics depicted in Fig. 7 illustrate how the system must adapt to different irradiance and temperature conditions. The state-space model defined by equations (9)–(13) provides the foundation for the MPC controller design, as evidenced by the simulation results in Fig. 9 that show the relationship between input voltage and output power.

The synthesis and optimization of the MPC control algorithms demonstrate the successful integration of both predictive capability and real-time optimization. The left MPC design shown in Fig. 10 and the right MPC design in Fig. 11 illustrate how the dual-mode architecture operates in different regions of the PV curve. The optimization problem formulation presented in Equation (14) establishes a hierarchical constraint structure that balances device safety limits with performance objectives.

The power profile of the buck converter in Fig. 12 demonstrates how the controller manages the power demand, with the right MPC triggered to maintain maximum power tracking when demand decreases. The computational efficiency analysis confirms that the algorithm achieves processing times under 2 milliseconds on an industrial controller while consuming less than 60 % of memory even at peak loads. This performance metric directly addresses the computational limitations mentioned in [25], making the solution more practical for real-world applications.

The validation and performance comparison provide comprehensive evidence of the superior performance of the proposed system compared to traditional MPPT techniques. The RMSE comparison shows a significant reduction from 41.29 for conventional methods to 7.0085 for the proposed MPC approach. This substantial improvement in tracking accuracy is due to our sophisticated combination of integrated reference trajectory generation and application of Kalman filter principles, as discussed in comparison to work in [13, 26].

The tracking efficiency analysis confirms that the system maintains between 94.8–97.2 % of maximum available power, with response times below 0.15 seconds and settling times below 0.45 seconds. The system's ability to handle environmental variations up to 800 W/m^2/s and temperatures up to 50 °C, as discussed in Section 5. 4, demonstrates stability performance exceeding that achieved in [20, 27], which could not maintain stable operation under rapid environmental variations.

Long-term performance validation confirms that power tracking deviation remains less than 1.8 % from ideal efficiency throughout the 2000-hour testing period. The harmonic analysis results show that output voltage harmonic distortion remains under 2.5 % during regular range and sudden load changes, indicating superior power quality compared to standard control approaches.

Despite the promising results, several limitations must be acknowledged. The current implementation introduces complexity through the need for complete system modeling and parameter estimation before application. The advanced control capabilities require greater processing capacity than previous methods, which may limit deployment in resource-constrained environments. Additionally, while the system performs optimally within certain environmental parameters (up to 800 W/m^2/s irradiance variations and 50 °C temperature ranges), performance may degrade beyond these conditions [28, 29].

The system's dependence on sensor reliability represents another limitation, as sensor failure could significantly impair performance. The current implementation also lacks a comprehensive fault detection mechanism to further enhance system reliability.

Future research opportunities include incorporating machine learning for model adaptation and predictive techniques, extending the approach to multiple interconnected photovoltaic arrays using distributed optimization methods, and developing more robust MPC formulations that can handle increased model uncertainties without significantly increasing computational complexity [30].

Finally, the results demonstrate that the proposed dual-mode MPC approach successfully addresses the limitations identified in the literature review, including the inability of conventional controllers to meet multiple system objectives simultaneously and respond effectively to rapid environmental changes. The system maintains exceptional power extraction capability while ensuring stability, offering significant improvements over traditional methods in efficiency, response time, and robustness to environmental variations.

7. Conclusions

1. A photovoltaic maximum power point tracking model predictive control framework was highly successful at designing and implementing a dual-mode model predictive control scheme which provided significantly improved performance metrics. The evaluation scheme of the system showed 94.8–97.2 % of maximum available power tracking efficiency, and it reduced from 41.29 to 7.0085 Root Mean Square Error

than the conventional methods. In the left and right operating regions of the PV curve, the dual mode architecture was effective; stable operation was provided in varying conditions.

2. The mathematical model of a DC microgrid system based on the buck converter with high precision was developed and the system dynamics are well captured in a robust state space representation. Fantastic response drive characteristics were achieved at response times below 0.15 seconds and settling times below 0.45 seconds. It was confirmed that the circuit operates stably under variation of irradiance up to 800 W/m^2/sec and of temperature 25–50 °C.

3. The synthesis and optimization of the MPC control algorithms was successful in the sense that both predictive and real time ability was combined. The implemented scheme provided high computational efficiency due to the averaging stage that achieved under 2 milliseconds processing time on an industrial controller while suffering less than 60 % of the memory consumption even at the peak loads. The power tracking deviation from ideal efficiency remained less than 1.8 % from ideal efficiency through 2000 hours of testing.

4. The testing of the proposed control system showed that it was superiorly performing compared to the traditional MPPT techniques. Despite challenging conditions, the system had an operational capability of 85 % and 98.5 % fault detection efficiency. Tracking efficiency was sustained between 94.8–97.2 % of maximum available power for steady state and transient operation, with harmonic distortion maintained lower than 2.5 % across all the operating conditions.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

The manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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