

Genetic Algorithm-based Model Predictive Control for Partial Shading Mitigation on PV Array

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Abstract—Photovoltaic (PV) energy harvesting systems experience performance deterioration and efficiency drops mostly due to mismatching and partial shading conditions (PSCs). Although different algorithms have been established to mitigate the negative impact due to PSCs, there are still some challenges concerning the algorithms' robustness, accuracy, and reliability. To alleviate the effects of partial shading and enhance output power, PV array reconfiguration techniques emerged as solutions to this challenge. The purpose of this paper is to introduce the genetic algorithm (GA) based model predictive control (MPC) in order to mitigate the impact of PSCs on the PV array. This algorithm is considered due to its capability of taking multiple inputs and generating multiple output predictive signals. The proposed algorithm is implemented and simulated on MATLAB/Simulink for PV array performance optimization under PSCs. The results show that the GA-based MPC does not only mitigate the effects of PSCs but optimizes the PV array's performance as well. From the simulation results, the GA-based MPC significantly increased the overall power output from 562.0 W (under PSCs) to 852.6 W which is almost the maximum power (under normal conditions), making an improvement of 290.6 W which is technically 51.17 % of the overall power generated by the system.

Keywords: Photovoltaic, partial shading condition, model predictive control, genetic algorithm.

1 INTRODUCTION

There is a great deal of interest in using nonconventional energy sources, such as solar energy, due to the rising demand for affordable energy and environmental concerns (Aghaeipoor et al., 2023). Photovoltaic (PV) cells are an easy way to turn freely accessible and abundant solar energy into electrical energy (Mahapatra et al., 2021). PV energy sources play a pivotal role in the world's transition toward sustainable energy future (Hassan et al., 2024). The sources possess the benefit of low maintenance costs, no rotating or moving parts, and an energy conversion process devoid of pollution (Siwal et al., 2021). However, the PV energy sources competence is frequently constrained by the predominantly occurring partial shading conditions (PSCs) (Belhachat and Larbes, 2024).

The reliability and efficiency of PV modules in the array is not mainly affected by faults occurring in the systems such as ground faults but also by PSCs (Sharifi Miavaghi and Esmaeili, 2023). PSC is a common defect that results in high power mismatch and low power output in a PV array (Ghosh et al., 2023). The nonlinearity between the output voltage and output current, especially when operating under PSCs, is a significant shortcoming of PV systems (Rafique et al., 2022). The system power voltage (P-V) characteristic curve develops multiple peaks when partially shaded (Zhang et al., 2024). Figure 1 illustrates the characteristics of the P-V and current-voltage (I-V) curves for the uniform and partial irradiation levels for parameter performance assessment. Power loss due to multiple local maximum power points resulting from PSC could be noticed from figure. 1 (Akram et al., 2022). PV array operating under PSCs manifests multiple maximum power point (MPP) peaks resulting in challenges when establishing the actual MPP (Ahmed et al., 2023). Under full uniform irradiance conditions, the P-V characteristic curve has one maximum power peak while in the case of PSCs, the P-V curve includes multiple local peaks in addition to one global peak (Singh et al., 2023). Subsequently, the nonlinear I-V characteristic of solar PV cells is the first challenge to be dealt with in analysing power generation through the PV array system operating under PSCs (Saxena et al., 2023).

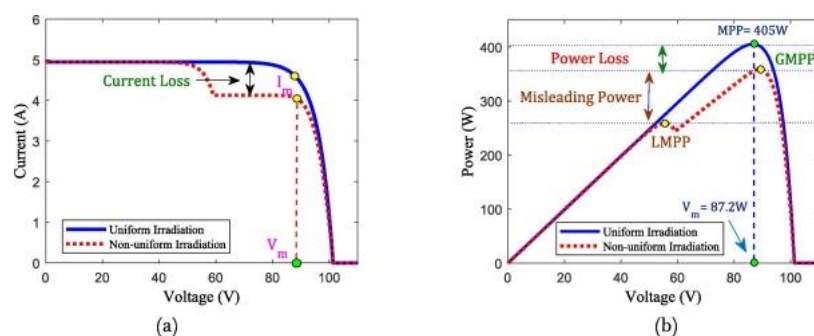


Figure 1: Comparison between (a) P-V (b) I-V curves during uniform and nonuniform irradiance (Akram et al., 2022).

There is a meaningful increase in demand for PSCs solution resulting in establishment of different algorithms to mitigate the negative impact due to PSCs (Diaz Martinez et al., 2021). However, there are still some challenges concerning the algorithms' robustness, accuracy and reliability (Nzoundja Fapiet al., 2023). To reduce hardware or boost performance, some modified algorithms have also been put forth (Triki et al., 2020), (Mathew et al., 2023), (Yap et al., 2020). Research on partial shading conditions suggests that using a standard MPPT during partial shadowing could result in significant losses in PV output power (Jariri and Aroudam, 2022). As a result, several researchers have looked into the restriction to raise tracking effectiveness (Sharma and Singh, 2023).

Owusu-Nyarko (2021) suggested a rapid scan on the power voltage curve for a short-circuit pulse-based MPPT to get the proportional parameter that is often employed in a current-based MPPT. The global maximum power point (GMPP) is discovered; however, to calculate the short-circuit current every few minutes, a second shunt switch must be installed with the PV source (Alwar et al., 2022). As a result, this approach costs extra and results in brief power outages (Brinkel et al., 2020). According to the Kurniawan and Shintaku (2020), the local maxima continuously diminish on either side of the GMPP based on observation and analysis of the P-V characteristic curve. Based on this fact, an MPPT strategy for a PV system operating under PCS is therefore proposed. All these efforts are meant to improve the performance of the PV system by ensuring that it operates at the maximum power available due to PSCs. The control algorithm behind the MPPT is essentially the proportional integral and derivative (PID) - a control feedback loop system that tracks the reference signal of a linear time-invariant (LTI) system.

The major drawback in the PID current injection algorithm is that the buck converter requires a versatile algorithm to inject the required amount of current (Ghamari et al., 2024). The PID algorithm employed for the MPPT algorithm struggles to track the reference signal under erratic weather conditions (Mazumdar et al., 2024). Therefore, an advanced or novel control algorithm must be utilized. This can be accomplished with standard industrial control techniques such as genetic algorithm (GA)-based model predictive control (MPC), neural network control (NNC), data-driven control (DDC), and adaptive control (Aruta et al., 2023), (Song et al., 2023), (Velarde et al., 2023). However, there is still a significant research void in the field of PV applications.

This paper is organized as follows; section 1 is the introduction. Then section 2 covers the literature review and section 3 delves deep into the methodology where the proposed GA-based MPC algorithm for DC injection control for PV partial shading mitigation for PV array optimization is discussed. Section 4 discusses the experiment and results. Finally, section 5 concludes the paper.

The main contributions of this paper are:

1. Development of an GA-based MPC in MATLAB/Simulink as a strategy in order to mitigate PSCs;
2. The developed GA-based MPC has a preternatural capability of taking multiple inputs and generating multiple output predictive signals and
3. The algorithm does not only mitigate the PSCs but also optimizes the PV array's performance.

2 LITERATURE REVIEW

In reaching peak energy efficiency and financial savings by refining PV modules, AI can serve as a revolutionary element that alters traditional practices entirely (Mohammad and Mahjabeen, 2023). AI-based algorithms guarantee that PV systems

perform at their highest capacity to generate sustainable and eco-friendly power (Haleem et al., 2023). Recently, AI models are extensively employed to enhance the accuracy of predictions and stabilize the performance of PV modules (Mohammad and Mahjabeen, 2023). AI generally encompasses computer systems capable of executing functions typically necessitating human cognitive abilities (Rayhan et al., 2023). The rise in the use of AI across sectors has been primarily propelled by the creation of sophisticated machine learning (ML) models (Bharadiya et al., 2023). In contrast to old-school software that is manually coded, AI algorithms use enormous collections of data to automatically adjust and improve (optimize) based on input regarding their predictions (Branka, 2023). Driven by the power of ML, AI is set to transform the swiftly expanding solar energy industry (Yao et al., 2023). Through examining extensive datasets from solar installations and using sophisticated algorithms, AI systems can configure the arrangement of solar panel parts for particular settings (Rojek et al., 2023).

Giurgi et al., 2022 proposed a relatively advanced control algorithm called fuzzy logic control (FLC). This control strategy ensures that the MPPT is not limited by local maxima and quickly recovers the new GMP in the event of changing weather (Giurgi et al., 2022). In contrast to traditional scanning MPPT, the algorithm scans the P-V curve while perturbation and observation are being made, therefore, a long-time delay is not necessary (Celikel et al., 2022). In this regard, the FLC algorithm transcends the conventional or contemporary control techniques such as PID which is generally utilized in the implementation of MPPT (Marar and Marar, 2022).

Much attention has recently been devoted to the use of machine learning and statistical methods to predict solar irradiance by means of satellite-driven models (Chen et al., 2024). It is imperative to emphasize that although satellite-driven methodologies have gained widespread acceptance for monitoring solar irradiance, they are subject to spatial and temporal limitations that hinder their ability to deliver real-time assessments of solar irradiance at the level of photovoltaic modules or arrays. Such real-time estimations are indispensable for enhancing the operational efficiency of solar-powered facilities (Wu et al., 2023), (Yang et al., 2024). Furthermore, the precision of these methods is entirely dependent on the global availability of satellite stations. This availability varies both quantitatively and qualitatively. Subsequently resulting with significant demand for alternative solutions Wen et al. (2023).

To achieve the highest possible power output from the bifacial PV module, an AI-driven fuzzy logic (FL) MPPT algorithm along with a boost converter configuration can be engaged (Siddiqui et al., 2023). FL is the key to boosting solar panel tracking efficiency. It allows real-time analysis of environmental factors, enabling PV systems to optimize their orientation for maximum power generation. This smart technology ensures solar panels are always positioned to capture the most sunlight (Yahiaoui et al., 2023). FL is a type of logic that deals with approximations and not fixed and precise logic (Zadeh, 2023). FL involves a simple, rule-based approach for solving a control problem rather than trying to represent the system numerically (Aghaeipoor et al., 2023). FL is a type of algorithm that deals with approximations and not fixed and precise logic (Zadeh, 2023). However, with slight changes on the system's behaviour, the algorithm lags adaptability and learning capability (Gu et al., 2023)

Utilizing harmony search (HS) algorithm can improve the efficiency of PV arrays during non-uniform irradiance scenarios (Mallick et al., 2024). HS algorithm is a recently developed swarm intelligent (SI) algorithm that takes inspiration from the process of music improvisation (Nakra and Duhan, 2024). It is rooted in the natural processes of musical performance, resembling the way musicians seek out improved states of harmony, particularly in the context of jazz improvisation (Karmakar et al., 2024). Jazz improvisation aims to discover a harmonious sound that is aesthetically pleasing, in a similar way to how the optimization process aims to find the best solution based on an objective function. The algorithm sets up the problem and algorithm parameters, initializes the harmony memory, and then creates a new harmony through improvisation (Qaiyum and Mohammad, 2024).

HS algorithm modelling and validation were conducted in MATLAB/Simulink using 5×5, 9×9, 9×5, and 3×3 arrays for different shading scenarios. The results were then compared with 22 conventional, static, and dynamic techniques and it was established that HS algorithm enhanced the PV array's performance by 24.64 % (Satpathy et al., 2023). HS is simple to adopt, rapidly reaches the best solution and achieves a sufficiently good solution within a reasonable amount of computational time (Zhou et al., 2023). Nevertheless, certain complicated practical problems still pose some unresolved issues, including premature convergence, insufficient optimization accuracy, and slow convergence speed (Thirunavukkarasu et al., 2023).

To meet the simplicity requirement of the PV system, an innovative MPPT algorithm was implemented. This algorithm is based on the fractional open circuit voltage method, which has been enhanced through optimization using the GA (Chen et al., 2024). A GA can be applied to solve the problem of determining the MPP in case of partially shaded PV module/s on the array (Olabi et al., 2023). GA is a technique used to solve constrained and unconstrained optimization problems by imitating the

biological evolution process through natural selection (Fofanah et al., 2023). The algorithm adjusts a set of individual solutions multiple times. Then picks individuals from the current population randomly at each step to serve as parents to produce children for the subsequent generation. Over time, the population moves towards the best solution through evolution (Alhijawi and Awajan, 2024). GA creates a set of points in each iteration. The population's best point implies an optimal solution (Sohail, 2023). Pan et al. (2024) stated that the execution times achieved using the genetic algorithm approach confirm its strong performance.

The performance of a partially shaded PV array can be enhanced through backstepping control with genetic algorithm-optimized gains (Naoussi et al., 2024). A genetic algorithm (GA) is a technique used to address both limited and unlimited optimization issues, drawing inspiration from the natural selection process that resembles the evolution of living organisms (Mishra et al.). The method continuously alters a group of solutions. In every phase, the genetic algorithm randomly chooses members from the existing group to serve as parents, creating offspring for the upcoming generation (Gad, 2023).

One of the most effective methods used in industry to maximize the control of multivariable systems while imposing limitations on input and output variables is MPC (Taheri et al., 2022), (Taheri et al., 2022). In MPC, a mathematical programming problem—most commonly a quadratic program (QP)—is solved in real-time to compute the altered inputs (Hedjar, 2022). The QP is dependent upon a system dynamics model, which is frequently developed from experimental data (Thorbeck et al., 2023). The mathematical model of the plant, the restricted (nonlinear or linear) cost function, and the prediction horizon are the three fundamental foundations of MPC (Ławryńczuk, 2022).

The aforementioned essential elements of MPC are briefly discussed in the subsequent subsections. Figure 2 depicts the MPC control loop where the plant model and optimizer are used to implement an AI-based MPC algorithm.

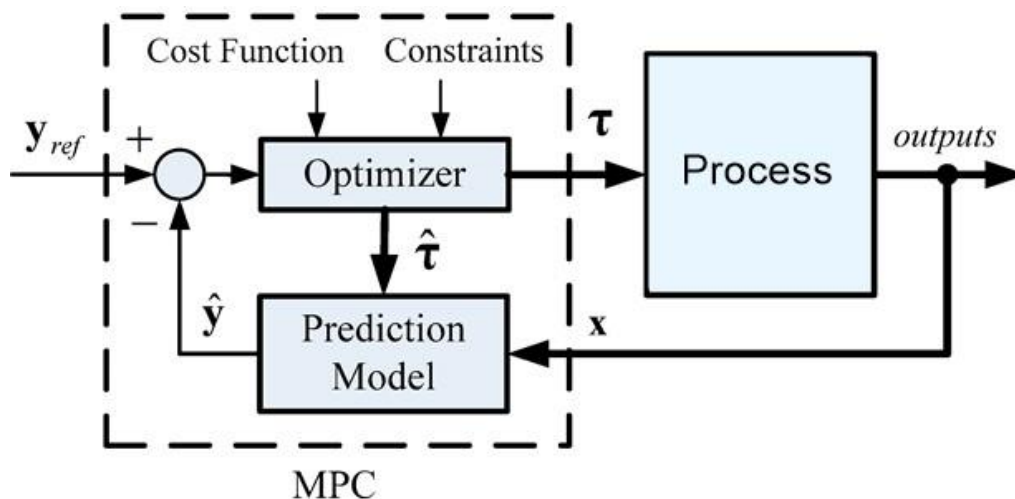


Figure 2. An MPC control loop.

3 MODELLING OF PV GA-BASED MPC

3.1 Mathematical Modelling

MPC is a model-based control method, as the name suggests (Rizk et al., 2023). An accurate plant model is indispensable in the formulation of an MPC algorithm (Karizaki et al., 2023). This model is used to compute projections using a set of various actuation signals for a certain period into the future and then utilize the optimum first-time step variable to make changes in the system dynamics (Wu et al., 2022). For instance, the continuous-time state space plant model of any dynamic linear or nonlinear system can be generally described using equation 1 where $\dot{x}$ is the first derivative of systems state vector x (Zhang et al., 2016), (Miranda et al., 2009). The control variables of the plant are normally circuit parameters such as capacitor voltage or inductor current in power electronics applications (Karamanakos and Geyer, 2018). The n_y plant output variables $y \in R^{n_y}$ are determined from equation 2.

$$\dot{x} = f_c(x(t), u(t)) \quad (1)$$

$$y(t) = g_c(\mathbf{x}(t), \mathbf{u}(t)) \quad (2)$$

where $u(t)$ is the time-dependent algorithm manipulated variable. Due to MPC flexibility, it can be utilized as a MIMO algorithm, a set of n_u manipulated variables can be defined using equation 3. The manipulated variables vector comprises integer values in case of indirect MPC control or switch states for direct MPC control (Geyer, 2016). In practical conditions, the function $f_c(\mathbf{x}(t), \mathbf{u}(t))$ can be augmented with an auxiliary disturbances vector $\mathbf{d} \in R^{n_d}$ to account for all external plant disturbances.

$$\mathbf{u} = [u_a u_b u_c]^T \quad (3)$$

Typical linear power electronic systems are categorized as linear and bilinear systems (Winston et al., 2020). Therefore, the general form of continuous-time state space equations for linear is given by equations 4 and 5 respectively. The transformation matrices $\mathbf{A}_c \in R^{n_x \times n_x}$, $\mathbf{B}_c \in R^{n_x \times n_u}$, and $\mathbf{C}_c$ are derived from the systems dynamics and can be constant or time-variant in nonlinear systems.

$$\dot{\mathbf{x}}(t) = \mathbf{A}_c \mathbf{x}(t) + \mathbf{B}_c \mathbf{u}(t) \quad (4)$$

$$y(t) = \mathbf{C}_c(\mathbf{x}(t)) \quad (5)$$

In contrast, the state-predictive function for a bilinear system is defined by equations 6 (Karamanakos et al., 2013), (Lopez et al., 2017).

$$f_c(\mathbf{x}(t), \mathbf{u}(t)) = [\mathbf{A}_{c1} + \mathbf{A}_{c2} \mathbf{u}(t) \mathbf{x}(t) + \mathbf{B}_c \mathbf{u}(t)] \quad (6)$$

The MPC algorithm is a digital algorithm, therefore, to implement it, it is necessary to discretize the continuous-time plant model described by equation 1. The predictive control variable vector $\mathbf{x}(k+1)$ is derived from the discrete state predictive function as given by equation 7.

$$\mathbf{x}(k+1) = f_c(\mathbf{x}(k), \mathbf{u}(k)) \quad (7)$$

Where $k \in R^+$ denotes the discrete time step and $\mathbf{x}(k)$, and $\mathbf{u}(k)$ are discrete state-space vector and discrete manipulated variables respectively. The exact, backward, and forward discretization techniques are generally utilized for this purpose (Karamanakos et al., 2020). The latter discretization techniques require less computation and therefore, they reduce the already professed computational complexities of MPC (Vazquez et al., 2021). Contrary to that, the exact discretization approach offers the benefit of precisely representing the dynamics of a continuous-time plant model at the expense of a relatively high computational load and thus, more appropriate for nonlinear systems (Zuo et al., 2023).

3.2 MPC Cost functions

The primary objective of MPC is to identify the set of algorithm output variables that, within a specified time frame, produce the optimum system behaviour, as determined by a predictive function (Yap et al., 2022), (Eddine et al., 2024), (Schwedersky and Flesch, 2022). To achieve this, several sampled optimum manipulated variables given by equation 8, are defined over a finite period of $N_p \in N^+$ called the prediction horizon (Schwenzer et al., 2021). Only the first optimum sample $\mathbf{u}(k+1)$ is used to track the reference signal and the rest of the predictive discrete values are discarded (Yao and Shekhar, 2021). The same procedure is repeated in the subsequent time steps until the steady state error of the system is zero (Zuo et al., 2020). Since only optimum predictions are considered, this implies that optimization is at the heart of MPC (Rajbhoj and Hamde, 2023).

$$\mathbf{u}(k) = [\mathbf{u}^T(k) \mathbf{u}^T(k+1) \dots \mathbf{u}^T(k+N_p-1)] \quad (8)$$

The anticipated response of the system can be predicted over the prediction horizon (Li and Wei, 2022). Subsequently, the selected cost functions are used to define the optimal control problem that forms the basis of MPC (Zhukov and Diachenko, 2019). The general expression for the cost function is given by equation 9 (Camacho et al., 2007). Some typical cost functions are given in table 1

$$\mathbf{J}(\mathbf{x}(k), \mathbf{u}(k)) = \sum_{l=k}^{k+N_p-1} \mathbf{J}(\mathbf{x}(l+1), \mathbf{u}(l)) \quad (9)$$

Table 1. Some typical MPC cost functions

No	Cost function expression	Source
1	$J_1 = \ u(k) - u(k-1)\ _1$	[65]
2	$J_2 = \ y_{err}(k+1)\ _1$	[66]
3	$J_3 = \ y_{err}(k+1)\ _2^2$	[67]
4	$J_4 = \ \Delta y_{err}(k+1)\ _1$	[68]
5	$J_5 = \ y_{err}(k+1)\ _Q^2$	[69]
6	$J_6 = \ y_{err}(k+1)\ _1 + \lambda_u \ \Delta u(k)\ _1$	[70]
7	$J_7 = \ y_{err}(k+1)\ _2^2 + \lambda_u \ \Delta u(k)\ _2^2$	[71]
8	$J_8 = \sum_{l=k}^{k+1} \ \Delta u(k)\ _1$	[72]

3.3 Prediction Horizon

It is common practice to formulate the cost function so that, for a given horizon N , the system output $y(k)$ tracks a specified reference $r(k)$ (Fiedler et al., 2023). Figure 3 shows the predictive horizon and control horizon. The optimization problem defined by equation 9 can be either an integer program (IP) (Scoltock et al., 2014) or a generally easy-to-solve convex QP (Kumar et al., 2021), depending on the type of optimization variable $u(k)$ and the system described by equation 7.

If computationally possible, IPs can be resolved by listing every possible solution in detail Dollar and Vahidi (2021). As an alternative, certain optimization techniques or heuristics that reduce average computational complexity are needed to enable real-time implementation of these algorithms without compromising optimality (Geyer and Quevedo, 2014). Conversely, off-the-shelf embedded solvers may effectively tackle convex optimization problems (Karamanakos et al., 2015).

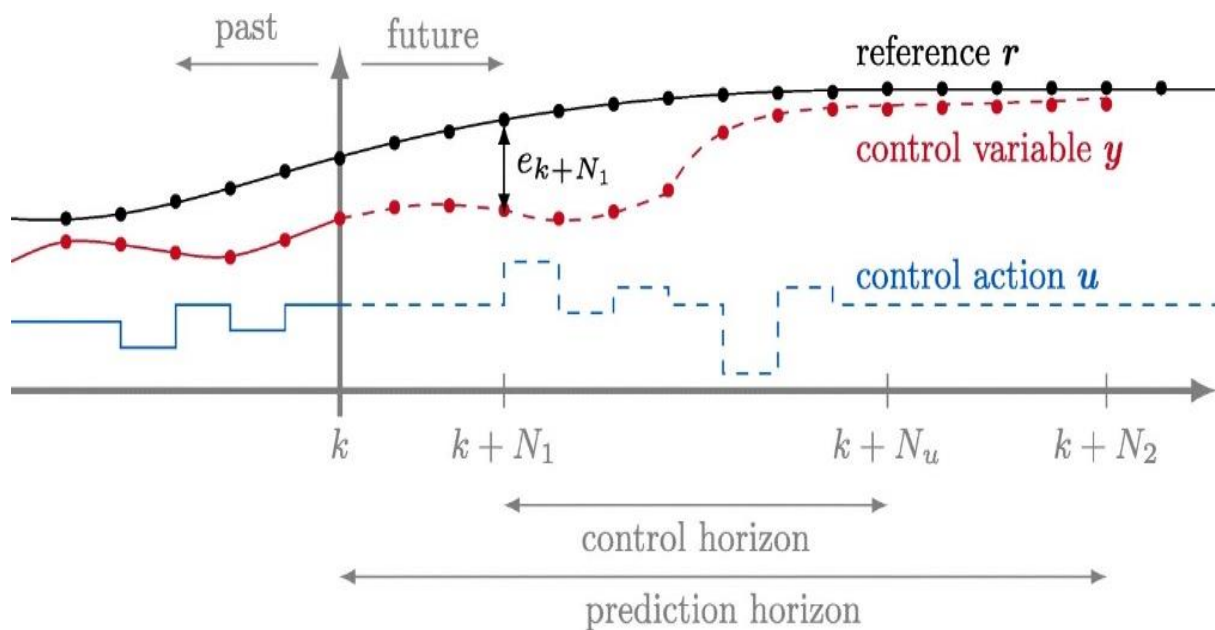


Figure 3. Prediction horizon (Yao and Shekhar, 2021).

3.4 Experimental set-up

Figure 4 shows an experimental setup for the proposed current injection method. The buck converter is supplied by the battery bank to supply the deficit PV module's current at the optimum terminal voltage (14 V) to supply 7 A at 28 V to the load. The buck converter is connected across a partially shaded PV module to inject surplus current to match the optimum power

output at a specified ambient temperature and irradiance of the PV array. From this arrangement, the total load power is 196 W (at an ambient temperature of 25 °C and irradiance of 980 W/m²) while the DC-DC converter supplies 35 W. When PV module P₂₂ is partially shaded, it generates a current of 1 A and voltage drastically decreases since the power has decreased due to less irradiance. Under these operating conditions, the total power output drops to 116 W, with an 80 W power loss. In essence, the power output of the PV array is greatly improved by employing the current injection topology. Since the only major power losses in buck converters are switching losses and can generally be neglected, the energy drawn from the battery bank is way less than the energy supplied to the battery bank during the charging phase. In this regard, the current injection topology not only mitigates the effects of PCS but also optimizes the entire PV array system.

As mentioned in previous sections, in a PV array, PSC influences not only the partially shaded PV module's power output but also the panels that are not partially shaded (Daus et al., 2022). A typical 2×2 series-parallel connected PV array MATLAB/simulation configuration is shown in figure 5. This configuration assumes the maximum operating point, that is, the irradiance and ambient temperature are 1000 W/m² and 25 °C. The electrical characteristics of the PV panels are given in table 2. The voltage-controlled source as seen in figure 4 emulates the MPPT algorithm used in practical applications.

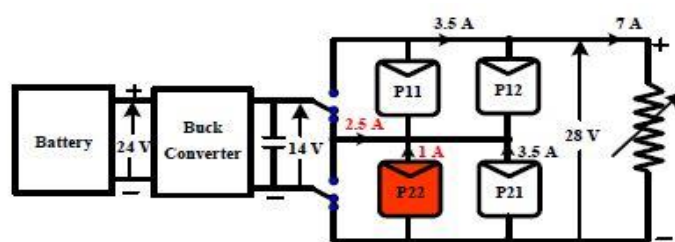


Figure 4. An experimental setup for the proposed current injection method to optimize PV array output power (Winston et al., 2020).

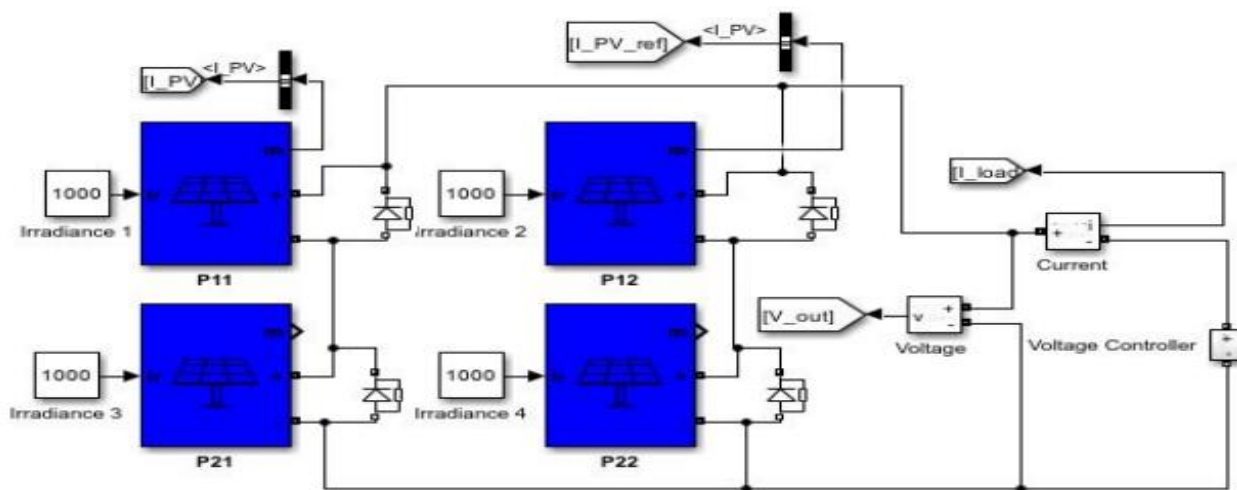


Figure 5. A typical 2 × 2 PV array.

Table 2. PV panel specification

S/No	Parameters	Rating
1	Maximum power (P_{max})	213.15 W
2	Open circuit voltage (V_{oc})	36.3 V
3	Short circuit current (I_{sc})	7.84 A
4	Voltage at maximum power (V_{max})	29 V

5	Current at maximum power (I_{max})	7.35 A
6	Cells per module	60
7	Diode saturation current I_o	2.927×10^{-10} A
8	Temperature coefficient of I_{sc} (K_I)	0.102 % /°C
9	Temperature coefficient of V_{OC} (K_V)	-0.36099 % /°C
10	Diode ideality factor	0.98119
11	Series resistance (R_S)	313.0553Ω
12	Shunt resistance (R_{SH})	0.39381Ω

When the irradiance of one of the PV panels, for instance, P_{11} , decreases due to partial shading, the power generated by the PV array decreases drastically. In such cases, the P-V characteristic curve of the array will have both local and GMPP. However, the MPPT algorithm can track the GMPP with relative ease. On the other hand, the PV array's net power output is decreased, so the system is not operating under optimum conditions. To curb this effect, the GA instructs the buck converter to connect a constant voltage current-dependent current source connected across P_{11} to supply the deficit current to match the current delivered by P_{12} and P_{22} . This does not only mitigate the power mismatch but optimizes the PV system as well.

The current injection topology based on GA-based MPC can be realized by connecting a buck converter across each PV panel to inject the necessary amount of current in cases of power mismatch. The system runs offline making it cheaper due to simple computation. The proposed GA-based MPC DC injection topology is shown in figure 5. The buck converter is powered by the battery bank and the GA-based MPC controls the inductor current so that the required current is injected. The inductor current of the buck converter comprises output DC and ripple capacitor current. In this regard, controlling the inductor current effectively controls the injected current. The digital GA-based MPC adopted for the current injection topology is depicted in figure 6. In contrast to conventional PID algorithms, the GA-based MPC has a preternatural capability of taking multiple inputs and generating multiple output predictive signals. In this context, the inductor current I_L - a control variable or state vector, reference signal I_{ref} , input voltage V_{in} and output voltage V_{out} serve as inputs to the GA-based MPC. The GA-based MPC algorithm has flexibility in controlling LTI systems under specified MIMO constraints. This means that a single adaptive GA-based MPC can control multiple PV panels by incorporating a compatible neural network algorithm.

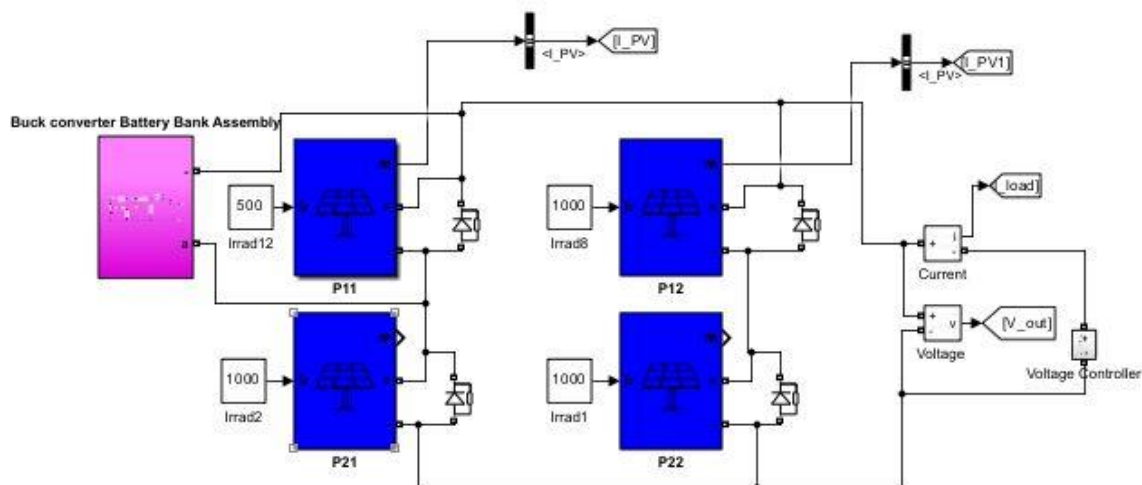


Figure 6. MPC controlled 2×2 PV array.

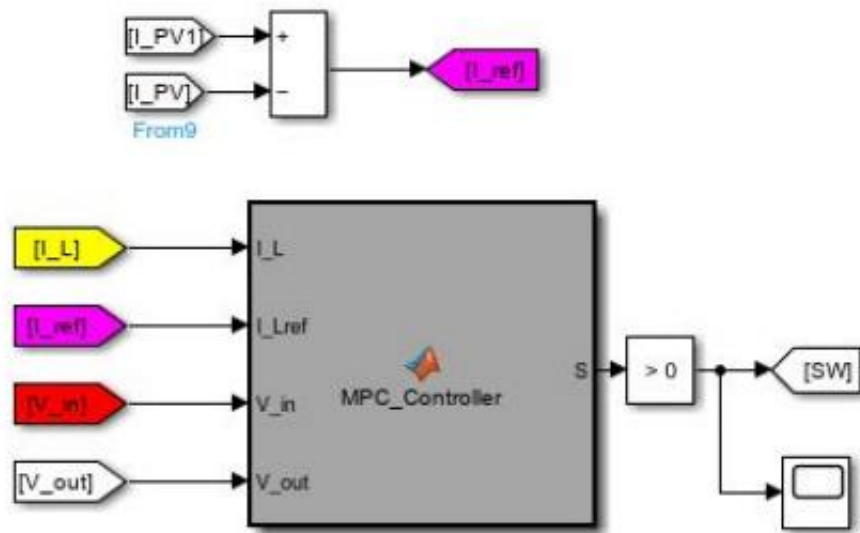


Figure 7. A digital MPC algorithm controlled 2×2 PV array.

From the literature, GA-based MPC can be classified into direct and indirect control. Since the GA-based MPC controls the inductor current $I_L(k)$ by controlling the switch states of the converter, the proposed algorithm can be regarded as direct GA-based MPC control. The discrete state predictive function of the GA-based MPC is given by equation 10 and it is derived from the combination of the continuous-time mathematical models of the buck converter for all possible switching states in conjunction with the forward-difference estimation method (Bergvall and Lundman, 2023) as given by equation 11. $k \in R^+$ is a discrete-time step as mentioned in the previous section.

$$I_L(k+1) = I_L(k) + \frac{T_s}{L} [V_{in}(S) - (R_L I_L(k) + V_{out})(S) - (R_L I_L(k) + V_{out})(1-S)] \quad (10)$$

$$\frac{dI_L}{dt} \approx \frac{I_L(k+1) - I_L(k)}{T_s} \quad (11)$$

Where S represents the switch state and T_s , V_{in} , R_L , V_{out} , and L are buck converter parameters and are provided in Table 3. The converter switch can only assume two states, that is, $S = 1$ when the switch closes and $S = 0$ when the switch is in the open position. The application's cost function is provided by equation 12. The reference signal is denoted by $I_L^*(k)$ and is the optimal PV panel's measurement current. It is essential to mention that the selected cost function corresponds to J_2 as defined in Table 1. The prediction horizon N_p as given in equation 9 is $N_p = 1$ to consider only the first optimal switch state. The choice of the optimization problem function is solely based on the fact that it is computationally cheap, and the results are quite accurate.

Table 3. Parameters of the buck converter adopted for MPC control

S/No	Parameters	Rating
1	Sampling period (T_s)	10 μs
2	Inductor series resistance (R_L)	20 m Ω
3	Inductor (L)	1 mH
4	Capacitor (C)	55 μF
5	Input voltage (V_{in})	120 V
6	Output voltage (V_{out})	29 V

$$J = |I_L^*(k) - I_L(k+1)| \quad (12)$$

4 EXPERIMENT AND RESULTS

The experimental setup for the proposed GA-based MPC-controlled 2×2 PV array is depicted in figure 6, while figure 7 depicts the proposed GA-based MPC. Assume that the irradiances of P_{12} , P_{21} , and P_{22} are held fixed at 1000 W/m^2 . PV panel P_{11} is bombarded with irradiances 800 W/m^2 , 500 W/m^2 , and 300 W/m^2 , at different instances. The terminal voltage of the PV array is varied from a short circuit condition ($IPV = ISC = 7.84 \text{ A}$ and $VPV = 0 \text{ V}$) to an open circuit condition ($IPV = 0$ and $VPV = VOC = 36.3 \text{ V}$). Figure 8 depicts the I–V characteristic curve with two peaks due to the PV array operating under PSCs (300 W per square metre). It is assumed that under this PSCs the PV array is divided into two subassemblies with different isolations resulting with difference in GMPP and local maximum power point (LMPP) voltages.

The P-V characteristics curves for the optimal operation of the PV array in conjunction with the operation under three PCSs are shown in figure 9. It is essential to note that the optimal power output of the entire PV array is $213.15 \text{ W} \times 4 = 852.6 \text{ W}$ at the terminal voltage of 58 V . Since the PV panels P_{12} and P_{22} generate a current of 7.35 A under specified operating conditions, the GA-based MPC utilizes the difference between P_{12} and P_{11} to generate a reference signal. The GA-based MPC then injects the right amount of current by manipulating the switch position S . It is important to note that the P-V characteristic curve is always optimum when the GA-based MPC-controlled buck converter is connected across PV panel P_{11} .

Table 4 compares the performance of a 2×2 array under optimized and normal operating conditions. P_{11} is subjected to different PSCs and the maximum power delivered to the load is measured when the PV array is controlled using the GA-based MPC and when the algorithm is not employed. Note that when the GA-based MPC is used to mitigate the effects of PSC, the entire PV array output power has a net power gain. For instance, when P_{11} has an irradiance of 300 W/m^2 , the buck converter supplies the maximum power of 156.6 W , and the output power of the array increases from 562.0 W to the optimal operating point of 852.6 W . This implies that the adoption of the GA-based MPC boosted the output power by 51.17% while the power drawn from the battery bank is just 156.6 W if converter losses are neglected. This is a good assumption because buck converter losses are essentially switching losses and can be neglected for practical purposes.

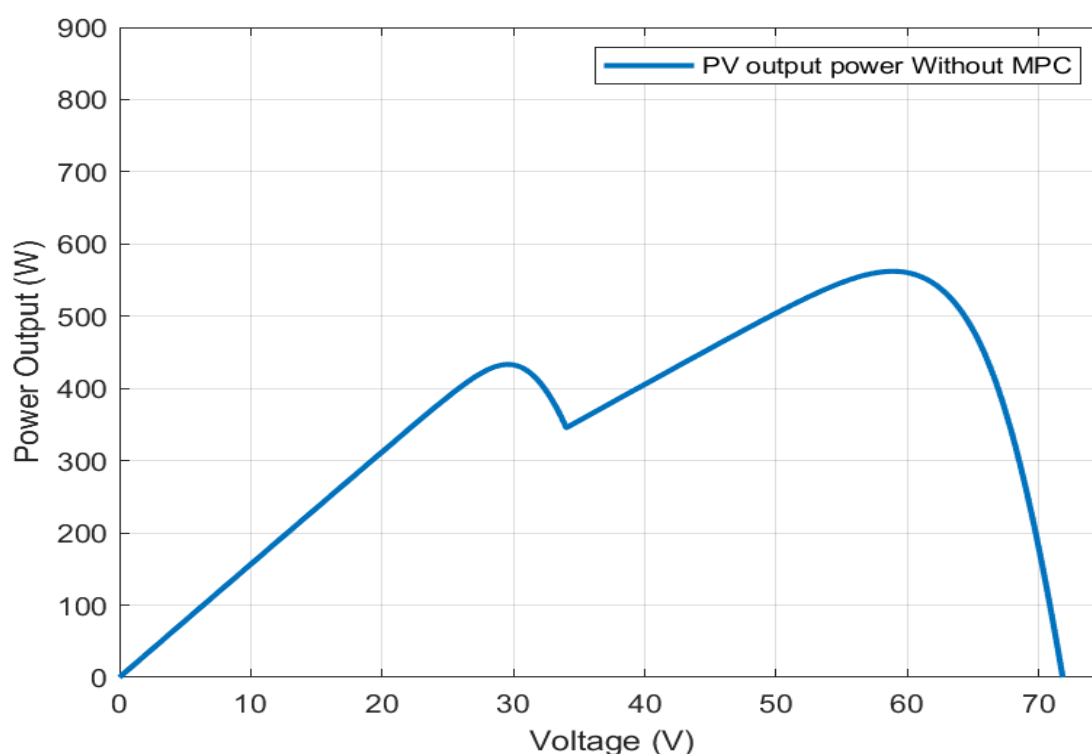


Figure 8. A P-V characteristic curve of a 2×2 PV array under PSCs.

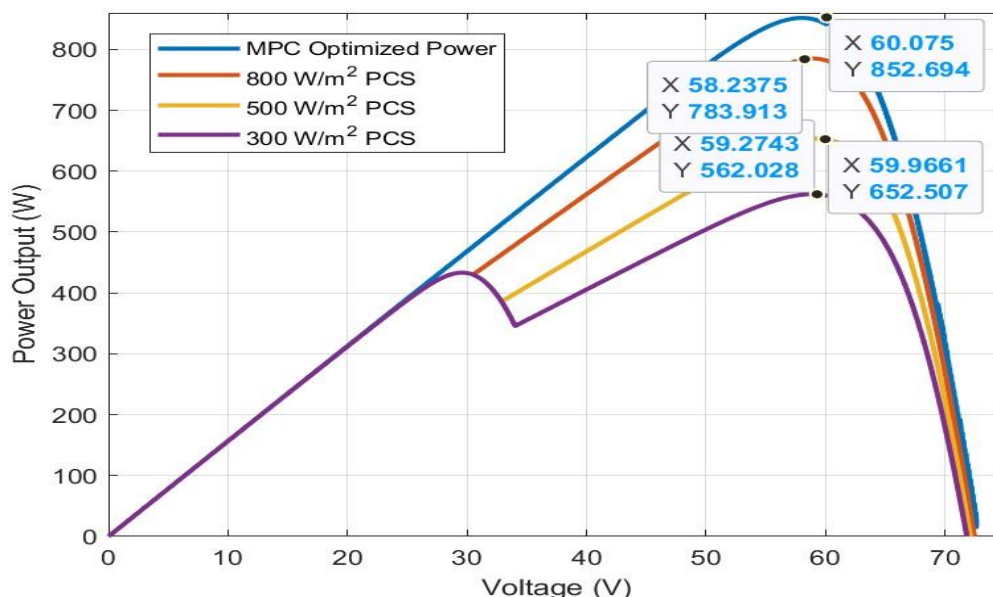


Figure 9. A P-V characteristic curve of a 2×2 PV array under various operating conditions.

Table 4. Performance comparison for MPC algorithm-based PV control and PV array output power under various PSCs

Irradiance (W/m ²)	MPC algorithm (W)	PV array (W)	Buck converter (W)	Gain (%)
1000	852.6	852.6	0.0	0.0
800	852.6	784.0	52.0	8.75
500	852.6	652.0	110.2	30.8
300	852.6	652.0	156.6	51.17

5 CONCLUSION

This paper discussed the existing MPPT algorithm for PSC mitigation. Other relatively advanced control algorithms such as GA-based MPC were discussed. The discussion of the GA-based MPC was restricted to the fundamental building blocks like the mathematical modelling of the system, cost function, or optimization problem as well as the prediction horizon which is sometimes referred to as the receding horizon in some literature. The GA-based MPC was developed and realized in MATLAB/Simulink to optimize a 2 × 2 PV array and mitigate the effects of PSCs. From the simulation results, the proposed GA-based MPC significantly increased the overall output power by up to 290.6 W of 852.6 W available power under matched operation conditions. Although the discussion was focused more on a 2×2 PV array, the application can be extended to large PV arrays. The GA-based MPC can be incorporated with neural network algorithms to control large arrays and match them to the predetermined optimal power. This is the subsequent stage of this research. Since the GA-based MPC employs a converter switch control, there might be undesirable high-frequency harmonics generated and therefore, this will be investigated in future research papers to ensure safety and compliance. The GA-based MPC will, in the foreseeable future, be implemented on a microcontroller to validate the proposed method and simulation results.

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CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

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