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Machine Learning Based MPPT Optimization for SPV Systems under Partial Shading Conditions

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Abstract

This paper presents various maximum power point tracking (MPPT) techniques for solar photovoltaic (SPV) systems operating under partial shading conditions (PSCs). Traditional methods such as perturb and observe (P&O), used as a baseline model, face significant challenges in accurately identifying the maximum power point (MPP) in the power-voltage curve. To overcome these challenges, other optimization techniques such as particle swarm optimization (PSO), grey wolf optimization (GWO), cuckoo search algorithm (CSA), and machine learning (ML) are employed. A multilayer perceptron (MLP)-based MPPT framework is designed to predict duty cycles based on SPV voltage and current inputs. Simulation results show that the MLP-based approach achieves faster convergence in power output and improved voltage stability compared to P&O, PSO, GWO, and CSA methods. The results highlight the potential of integrating ML techniques into SPV systems to enhance efficiency in challenging PSC scenarios. This research contributes to the advancement of sustainable solar energy technologies by leveraging adaptive intelligence for optimal energy harvesting.

Keywords: *SPV, MPPT, PSC, ML, PSO, GWO, CSA*

1. Introduction

SPV systems are vital in the transition to renewable energy but face challenges such as partial shading, which reduces power output and introduces multiple peaks in the P-V curve. These peaks complicate the Maximum Power Point Tracking (MPPT) process, with conventional methods like P&O struggling to distinguish between local and global maxima under shading conditions. Nature-inspired algorithms, including PSO, GWO, and cuckoo optimization, improve global MPP identification but may require high computational resources and have difficulty adapting to rapid shading variations. Recent advancements in machine learning (ML) have shown promise in enhancing MPPT efficiency under complex environmental conditions. ML algorithms utilize both historical and real-time data to predict the global MPP more accurately and quickly, dynamically adjusting to changing shading scenarios. Compared to traditional optimization techniques, ML-based MPPT methods improve response time, tracking precision, and energy harvesting, especially under non-uniform shading. A comparative analysis of ML-based MPPT with methods such as PSO, GWO, P&O, and cuckoo optimization demonstrated the superior performance of ML in terms of tracking accuracy, convergence speed, and energy output. This study emphasizes the role of ML in enhancing the reliability and efficiency of SPV systems, advancing the adoption of sustainable solar energy technologies.

A Support Vector Machine Regression (SVMR) method was developed to optimize MPPT in SPV systems by forecasting MPP based on temperature and irradiance, thereby adjusting the boost converter's duty cycle for optimal power output. SVMR outperformed traditional methods like P&O, IC, and intelligent techniques such as ANN and FLC, achieving tracking efficiencies over 94% with improved stability and reduced oscillations in dynamic conditions, while also requiring fewer computational resources [1]. A novel ML-based algorithm utilizing multivariate regression was proposed for MPP tracking in solar systems, considering solar irradiance, temperature, and humidity. It reduced perturbation time, improved efficiency, and achieved 99.8% MPP estimation accuracy after 83 hours of training. Python simulations confirmed its effectiveness across various climates [2]. ML applications in solar energy were extensively reviewed, highlighting advances in forecasting, PV module modeling, MPPT optimization, anomaly detection, and energy management in PV systems. The review emphasized ML's role in improving SPV system efficiency and explored future potential [3]. A novel global MPPT (GMPPT) method using a Q-learning algorithm was developed to enhance energy output under partial shading conditions. Unlike conventional GMPPT approaches, it does not require prior knowledge of PV module characteristics and reduces detection time by 80.5% to 98.3% compared to PSO-based methods, making it suitable for dynamic shading scenarios such as wearable and building-integrated PV systems [4]. Deep reinforcement learning (DRL) approaches, integrating deep Q-network (DQN) and deep deterministic policy gradient (DDPG) algorithms, optimized MPPT in PV systems with partial shading conditions (PSC). By managing both discrete and continuous action spaces, DRL outperformed traditional reinforcement learning and P&O methods, as MATLAB/Simulink simulations confirmed improved efficiency and adaptability, highlighting DRL's potential for sustainable SPV energy conversion [5]. An LSTM model was designed for MPPT in SPV systems to address the limitations of conventional techniques under fluctuating atmospheric conditions. By estimating PV output resistance using environmental parameters rather than current and voltage sensors, the LSTM model outperformed ANN and regression methods, showing improvements of 37%, 21%, and 31% in MSE, RMSE, and MAE scores, respectively, demonstrating its superior MPP tracking accuracy [6]. A neural network MPPT controller using a snake optimizer was developed for hybrid PV thermoelectric generation (PVTEG) systems, achieving an average efficiency of 99.928% and a tracking time of less than 5 milliseconds. Additionally, a cost-effective, sensor-independent fault detection algorithm was implemented to ensure system stability and superior performance in simulations [7]. An automated calibration method utilizing supervised ML optimized MPPT in SPV systems. A MATLAB/Simulink-based neural network MPPT algorithm achieved approximately 99.8% efficiency, outperforming traditional models (97%-98%) without additional computational costs. Hardware validations confirmed its accuracy and effectiveness [8]. A hybrid MPPT algorithm, PSO_ML-FSSO, integrating ML with flying squirrel search optimization, improved SPV system efficiency by 0.72% and reduced settling time by 76.4%. It outperformed established methods such as P&O, PSO, GWO, and GA in MATLAB/Simulink simulations under varying conditions [9]. A two-stage MPPT strategy combining a neuro-fuzzy network (NFN) for reference voltage generation and terminal sliding mode control (TSMC) for voltage tracking was introduced for PSC scenarios. It increased average power output by 8.2%, reduced control time by 60%, and minimized power loss and variability, as validated through simulations and experiments [10]. A data-driven ANN-based MPPT algorithm was developed to overcome the limitations of traditional methods like P&O and Incremental Conductance (IC), which struggle in dynamic conditions. The ANN-MPPT, with adaptive learning, achieved 98.16% efficiency and a tracking time of 1.3 seconds, surpassing conventional methods [11]. The use of deep reinforcement learning (DRL) for MPPT optimization in SPV systems under PSCs was explored. By integrating DQN for discrete actions and DDPG for continuous actions, DRL demonstrated improved performance over traditional methods like P&O, as validated through MATLAB/Simulink simulations, highlighting its potential for advanced PV system optimization [12]. An ANN-based methodology was developed for automating MPPT in PV systems, focusing on accurate GMPP identification. It incorporated a solar tracking system with battery support and employed MATLAB simulations for PV panel modeling to train the ANN, optimizing performance under PV's nonlinear dynamics [13]. To address partial shading issues, an adaptive reinforcement learning framework (ARL-NNA) was introduced for MPPT. This dynamic approach enhanced tracking accuracy and speed compared to conventional methods. Validation confirmed its superior performance, emphasizing its importance in optimizing PV system efficiency under challenging conditions [14]. The application of ML in optimizing MPPT for SPV systems under PSCs was explored, highlighting techniques such as Q-learning, Bayesian Regularization Neural Network (BRNN), and Multivariate Linear Regression Model (MLIR). These methods achieved over 95% efficiency, tracking durations under 1 second, and an error threshold of 0.05. Future research may focus on comparative simulations to further enhance MPPT performance [15]. A Q-learning-driven Global Flexible Power Point Tracking (GFPPT) algorithm addressed challenges of partial shading and fluctuating irradiance in grid environments, improving grid stability and achieving superior convergence rates with minimal steady-state error, thereby enhancing SPV system adaptability [16]. A modified differential step grey wolf optimization (MDSGWO) with an adaptive fuzzy logic controller (FLC) was introduced for MPPT under PSCs, improving convergence speed, tracking accuracy, and operational efficiency. Integration with power converters enhanced voltage source functionality, ensuring scalable and stable power generation [17]. Deep-Q-Network (DQN) reinforcement learning for GMPP tracking under PSCs showed improved performance over conventional methods, with power extraction increases up to 63.5% compared to P&O. Open-access resources supported model adoption and further experimentation [18]. Opposition-Based Learning (OBL) effectively mitigated the effects of partial shading, outperforming traditional methods in simulation tests, addressing GMPP challenges under intense shading conditions [19]. Comparative analysis of MPPT algorithms—PSO, GWO, and Horse Herd Optimization—revealed superior performance metrics for Horse Herd Optimization, characterized by higher tracking accuracy and faster convergence under dynamic shading conditions in MATLAB/Simulink simulations [20]. The application of ML in optimizing critical parameters such as module orientation, tilt angle, and power management has demonstrated substantial benefits for SPV systems. By adapting to dynamic environmental and load conditions, ML outperforms traditional optimization methods, effectively addressing nonlinear issues inherent in PV systems and enhancing energy output and system performance [21].

A hybrid MPPT algorithm integrating voltage scanning and a modified P&O technique was developed to improve SPV performance under PSCs. This approach eliminates the need for detailed panel information through adaptive voltage scanning. Tests conducted on a 252.6 kW grid-connected PV system in MATLAB/Simulink across six shading scenarios revealed reduced power fluctuations and increased efficiency compared to conventional methods, highlighting its potential for mitigating shading-related challenges [22]. The Corona-Virus Optimization (CVO) algorithm, designed for enhancing MPPT in diverse weather conditions, demonstrated remarkable efficiency. It achieved 99.99%, 99.98%, 99.97%, and 99.98% under uniform irradiance, partial shading-1, partial shading-2, and complex PSCs, respectively, outperforming seven other MPPT methods. Real-time data validation in Beijing confirmed the system's robustness, stability, and superior performance in identifying global maxima while minimizing oscillatory behavior [23]. An innovative meta-heuristic algorithm combining POA and PO addressed the challenges of partial shading by leveraging POA's global search capabilities and PO's rapid convergence traits. MATLAB/Simulink simulations and experimental evaluations using an indoor PV simulator showed exceptional tracking efficiency (99.97%) and convergence times as low as 0.18 seconds. This method demonstrated economic feasibility and high reliability in practical applications [24]. An improved Grey Wolf Optimization (IGWO) algorithm, integrated with an Adaptive Neuro-Fuzzy Inference System (ANFIS), was proposed for MPPT in SPV battery charging systems under fluctuating solar radiation levels. Evaluations under varying irradiance (1000, 600, and 800 W/m²) showed significantly enhanced MPPT accuracy compared to traditional methods. Laboratory prototyping validated IGWO's effectiveness in improving SPV system performance under dynamic conditions [25]. The efficiency of boost and CUK converter configurations in SPV systems has been explored using a neural network-driven MPPT algorithm enhanced by PSO under fluctuating irradiance and load scenarios. Three scenarios—constant temperature and irradiance, variable load, and daily irradiance fluctuations—were tested using a Canadian Solar CS6P-250P panel at a 50 kHz switching frequency. Results showed that CUK converters outperformed boost converters, exhibiting faster MPPT and reduced oscillatory behavior, highlighting their potential for performance enhancement under dynamic conditions [26]. A bio-inspired MPPT algorithm, Sand Cat Swarm Optimization (SCSO), was proposed to address PSC challenges. Unlike traditional P&O, which often gets stuck in local maxima, SCSO effectively identified the GMPP with minimal complexity, requiring just one optimization parameter. Evaluations across four irradiance scenarios demonstrated a 19.91% improvement in tracking time and an efficiency exceeding 98%, surpassing other bio-inspired algorithms like PSO and GWO by 3.16% in average tracking efficiency. This underscores SCSO's capability for rapid and efficient power optimization [27]. An ML-based solar power forecasting model was introduced to mitigate shading-induced power fluctuations. Leveraging historical inverter data and irradiance values from the previous day, the model significantly improved forecast accuracy. Tested on four 10 kWp systems with varying orientations and tilt angles, the model achieved up to a 40% reduction in RMSE, demonstrating its ability to adapt to shading intensities and improve reliability in shaded environments [28]. ML-based MPPT methods were evaluated to enhance PV system performance under PSCs. Nine ML techniques, including decision trees, multivariate linear regression, and weighted K-nearest neighbors (WKNN), were assessed in MATLAB/Simulink across three weather scenarios. WKNN emerged as the most effective, optimizing MPPT and enabling better solar energy harvesting under fluctuating conditions [29]. A two-stage ANN-based GMPPT algorithm for complex PSCs was developed. The first stage used an ANN model to forecast the optimal voltage for MPP tracking, while the second stage applied an α-P&O method for enhanced precision and reduced oscillations. Achieving a tracking accuracy of 99.66%, the model minimized power loss, required fewer sampling points, and eliminated the need for costly sensors. Comprehensive evaluations in both simulated and practical applications highlighted its cost-effective and resilient performance, surpassing conventional GMPPT techniques [30]. SPV systems have seen widespread adoption due to sustainability, cost reductions, and efficiency gains. Conventional MPPT methods struggle under PSCs, often failing to locate GMPPs. An IGWO method improved tracking speed (82%), efficiency (1.4%), runtime (76%), and energy harvesting (2.3%) compared to GWO, demonstrating enhanced accuracy under PSCs [31]. A GWO-optimized PSO algorithm for MPPT in SPV systems increased energy generation by 9.1% over IC, 19.8% over PSO, and 20.7% over P&O in staggered scenarios, with further improvements under real irradiation [32]. The GOA approach achieved MPPT in grid-connected PV systems, effectively handling partial shading and optimizing inverter parameters. GOA showed 99.8% tracking efficiency, outperforming GWO (97.2%) and SOA (96.7%), with improved power quality and system performance [33]. A novel GWO (NGWO) incorporating cuckoo search enhanced convergence and stability, achieving 99.86% efficiency and a 0.19-second tracking time, outperforming other methods [34]. PSO outperformed P&O under PSCs with over 96% tracking efficiency, although P&O responded faster and converged more quickly, but struggled to locate GMPPs [35]. Static PV array reconfiguration methods combined with P&O MPPT improved power output under PSCs. Advanced techniques such as Magic Square (MMS) and Novel Shade Dispersion (NSD) outperformed traditional TCT reconfiguration, achieving efficiencies of 97.49% (HZ), 97.8% (RM), 97.02% (LBC), and 97.58% (TC), while reducing steady-state oscillations and enhancing system performance [36]. NA-PSO addressed the limitations of traditional PSO, including slow convergence and local optima, by optimizing particle movement. It reduced convergence time by 50%, eliminated failure rates, and increased energy generation by 10.4% under dynamic shading conditions [37]. A hybrid MPSO-MPC algorithm, integrated with model predictive control, improved global peak tracking with an efficiency of 99.5% and a convergence time under 0.35 seconds, outperforming PSO and cuckoo search methods [38]. FMSPSO, a modified heterogeneous MSPSO with an adaptive factor, enhanced tracking accuracy, robustness, and reduced oscillations, surpassing MSPSO, fuzzy logic, and P&O in SPV system performance [39]. To address the challenge of identifying GMPPs under PSCs, a CSA-ABC hybrid algorithm was introduced, combining local random walk, global Levy flight, and adaptive mechanisms. It demonstrated 6.2–78.6% faster tracking speeds and minimal steady-state oscillations compared to PSO, CSA, ABC, and other hybrids [40]. A stackable single-switch boost converter (SSBC) integrated with a cuckoo search MPPT controller addressed issues such as low voltage gain, high voltage stress, and MPPT inaccuracies under PSCs. The BMPPT method using SSBC outperformed PSO and FPNA MPPTs, providing ripple-free operation and higher power output under stable conditions. Prototype validation confirmed improved efficiency compared to traditional configurations [41]. A dung beetle optimization algorithm (DBO) was introduced for MPPT in SPV systems to handle nonlinear and multipeak challenges under PSCs. Compared to methods like squirrel search, cuckoo search, horse herd optimization, PSO, and GWO-based approaches, DBO showed superior performance, achieving 99.99% GMPP tracking efficiency. It improved convergence stabilization by 80% and increased average power output by 8%, demonstrating faster, more efficient, and robust MPPT performance. Validation was conducted using HIL and RCP platforms [42].

MPPT is a crucial method for extracting the maximum possible power from an SPV system, and PSCs—caused when different parts of the solar array are shaded at different times—often lead to significant performance losses in conventional SPV systems. This study aims to implement an ML-based optimization technique for MPPT in SPV systems, specifically designed to operate efficiently under PSCs. The proposed ML-based MPPT method will be integrated into the SPV system, and its effectiveness will be assessed against several traditional optimization techniques, such as P&O, PSO, CSA, and GWO. These traditional techniques have been widely used in MPPT but often struggle to achieve optimal performance under dynamic shading conditions.

The study will evaluate the performance of the ML-based MPPT technique with a primary focus on settling time, which measures the time required for the system to stabilize at the MPP under varying PSCs. Settling time is an important performance indicator, as faster response times are critical for maximizing energy extraction in real-time applications. Additionally, the deviation in output power and voltage will be compared under PSCs. By analyzing these metrics, the study aims to demonstrate that the ML-based MPPT technique offers superior performance in both speed and accuracy, thereby improving the overall efficiency of SPV systems under the challenging scenario of partial shading.

The article comprises four sections, with the first section serving as an introduction that provides background information on different MPPTs for SPV under PSCs. Section 2 outlines the proposed Simulink model. Section 3 presents the mathematical formulations of various MPPT algorithms for a SPV system. Section 4 presents the results of various MPPTs, accompanied by a discussion of their limitations. In section 4, the concluding points of this study are presented.

2. Proposed model for ML based MPPT optimization

The model is designed to control the duty cycle of a PWM signal based on input voltage and current. The neural network processes these inputs to predict an appropriate duty cycle, which is then used by the PWM generator to produce the desired control signal.

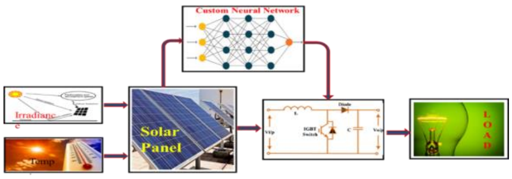

Figure 1. Block diagram of MLP based ML for SPV system

Figure 1 presents the block diagram for the proposed MLP-based ML model in a SPV system, designed to optimize the MPPT process. The model takes irradiance and temperature as input parameters to the SPV system, as these factors directly influence the power generation of the solar panels. These two environmental parameters are critical for determining the optimal operating point of the SPV system. The output from the SPV system, which consists of the generated voltage and current, is fed into the MLP-based ML model. This model processes the voltage and current data to learn complex patterns and relationships within the system, such as how variations in environmental conditions impact power generation. The proposed MLP-based MPPT model was designed with total six layers in which 5 layers are hidden and 1 output layer. The input layer comprises 5 neurons corresponding to the measured PV system variables. The hidden layers contain 20, 30, 20, and 5 neurons, respectively, each employing the log-sigmoid (*logsig*) transfer function to introduce nonlinearity and capture complex input–output relationships. The final output layer contains a single neuron with a linear (*purelin*) activation function, suitable for predicting the continuous duty cycle required for MPPT control. The network was trained using the Levenberg–Marquardt backpropagation (trainlm) algorithm and the Mean Squared Error (MSE) was selected as the loss function. A dataset comprising approximately [264523] samples was prepared from MATLAB/Simulink simulations of the PV system under varying irradiance levels (200–1000 W/m²), and temperature conditions (25°C). The dataset was divided into 70% for training, 15% for validation, and 15% for testing.

The MLP model is trained to predict the optimal duty cycle for the boost converter, which is responsible for stepping up the voltage to the desired level. By adjusting the duty cycle, the boost converter ensures that the system operates at MPP, thereby maximizing energy extraction from the SPV system.

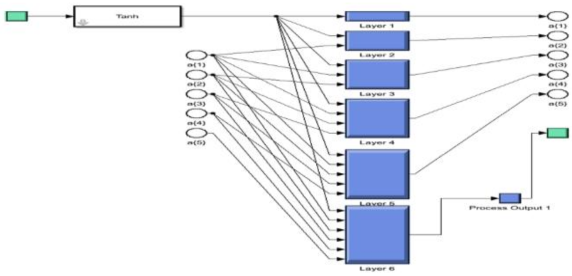

Figure 2. Multiple layer MLP subsystem used in SPV model

Figure 2 illustrates the internal architecture of the

MLP block. The neural network processes the inputs through several layers and generates an output. A Tanh Layer applies the hyperbolic tangent activation function to normalize inputs between -1 and 1. The network includes six fully connected hidden layers (Layer 1 to Layer 6, shown as blue blocks). These layers use learned weights and biases to transform data, capturing complex, non-linear relationships. The output of the neural network is connected to a PWM generator block to generate a PWM signal. The proposed MLP-based approach offers significant improvements over traditional MPPT methods by providing more accurate and adaptive control of the boost converter, ultimately enhancing the performance of SPV systems.

3. Mathematical formulations of MPPT algorithms for a SPV system under PSC

The objective of this study is to optimize the duty cycle D, which controls the boost converter to maximize the power output P, given the input voltage V and current I from the PV module. The goal is to effectively track the MPP under PSCs.

3.1. Mathematical expression for P&O Method

The power output of the PV module at a given iteration k is expressed in Equation (1). The change in power, ΔP, from the previous iteration k-1 to the current iteration k is calculated as shown in equation (2).

$$\mathbf{P(k) = V(k) \times I(k)} \tag{1}$$

Where, $\boldsymbol{V(k)}$ and $\boldsymbol{I(k)}$ is voltage and current at iteration $\boldsymbol{k}$.

$$\mathbf{\Delta P = P(k) - P(k-1)} \tag{2}$$

If $\Delta P > 0$, it indicates that power is increasing in response to the last perturbation and if $\Delta P < 0$, it suggests that the power is decreasing, and the direction of the perturbation should be reversed. Similarly, the change in voltage ΔV from the previous iteration to the current iteration is given by equation (3).

$$\mathbf{\Delta V = V(k) - V(k-1)} \tag{3}$$

If $\Delta V > 0$, the voltage increased in response to the last adjustment and If $\Delta V < 0$, the voltage decreased. Based on the signs of ΔP and ΔV, the algorithm adjusts the duty cycle D as given in table 1.

The updated duty cycle $D(k+1)$ at the next iteration is calculated by equation (4).

$$\mathbf{D(k+1) = D(k) \pm \Delta D} \tag{4}$$

where ΔD is a predefined step size for adjusting D. The step size ΔD in equation (4) affects the balance between response speed and stability in reaching the MPP.

Table 1. Conditions for Duty Cycle Adjustment

Condition	Adjustment to Duty Cycle D
$\Delta P > 0$ and $\Delta V > 0$	Decrease D
$\Delta P > 0$ and $\Delta V < 0$	Increase D
$\Delta P < 0$	Reverse the last adjustment

3.2. Mathematical expression for PSO

PSO is a global optimization algorithm where particles explore the search space to find the optimum D. The particles with random positions D_i and velocities V_i are initialize. The power P for each particle position D_i is evaluated in equation (5). Each particle's velocity and position are updated using equation (6) and this process is repeated until convergence on the MPP. The updated duty cycle $D(k+1)$ at the next iteration is calculated by equation (7)

$$\mathbf{P_i = V(D_i) \times I(D_i)} \tag{5}$$

$$\mathbf{V\_i\ (k+1) = w * V\_i\ (k) + c\_1 * r\_1 * (P\_"\boldsymbol{best}" - P\_i\ (k)) + c\_2 * r\_2 * (G\_"\boldsymbol{best}" - P\_i\ (k))} \tag{6}$$

$$\mathbf{D_i(k+1) = D_i(k) + V_i(k+1)} \tag{7}$$

where, w is the inertia weight, c_1 and c_2 are cognitive and social factors, and r_1 and r_2 are random numbers.

3.3. Mathematical expression for CSA

The CSA is inspired by the brood parasitism of some cuckoo species. The power output function $P(D_i)$, and Fitness(D_i) function is given by equation (8) and equation (9) respectively. The new duty cycle D_{new} is calculated using equation (10)

$$\mathbf{P(D_i) = V_{pv}(D_i) \cdot I_{pv}(D_i)} \tag{8}$$

Where $V_{pv}(D_i)$ and $I_{pv}(D_i)$ are voltage and current measured when the duty cycle is given to the converter so that the nonlinear I–V characteristic is respected.

$$\mathbf{D_i = |\ P_{ref} - P(D_i)\ |} \tag{9}$$

$\mathbf{P_{ref}}$ is the measured power at the first evaluation and updated during iterations to obtain maximum reference power.

$$\mathbf{D_{new} = D_i + \alpha \times L\acute{e}vy(\beta)} \tag{10}$$

where D_i is the current duty cycle (position) of a nest (solution), α is a scaling factor or step size and $L\acute{e}vy(\beta)$ is a random step from the $L\acute{e}vy$ distribution.

3.4. Mathematical expression for GWO

GWO simulates the hunting behavior of grey wolves. The rank wolves (solutions) based on their power values, and assigning them as alpha (D_α), beta (D_β), and delta (D_δ) wolves. The duty cycle is updated based on these leader positions given by equation (11) and equation (12). Each wolf's position using distance control is updated using equation (13).

$$\begin{cases} \mathbf{D_1(t+1) = D_\alpha\,(t) - A_1\ * |\ C_1 * D_\alpha(t) - D(t)|} \\ \mathbf{D_2(t+1) = D_\beta\,(t) - A_2\ * |\ C_2 * D_\beta(t) - D(t)|} \\ \mathbf{D_3(t+1) = D_\delta\,(t) - A_3\ * |\ C_3 * D_\delta(t) - D(t)|} \end{cases} \quad (11)$$

$$\mathbf{D_i = \frac{D_\alpha + D_\beta + D_\delta}{3}} \quad (12)$$

$$\mathbf{D_i(k+1) = [D_{leader} - A *|\ C * D_{leader} - D_i(k)|]} \quad (13)$$

where A and C are coefficient vectors for controlling convergence.

3.5. Proposed MLP Based MPPT for MPP

The MLP network is used to optimize tracking of the MPP under PSC, focusing specifically on duty cycle prediction based on voltage and current inputs. The input to the neural network consists of the PV voltage (V) and current (I), and the output is the variable "D". The following mathematical equation represents the system:

The input vector x consists of V and I is given by equation (14). For each layer l, the general transformation is given by equation (15).

$$\mathbf{x = [V, I]^T} \quad (14)$$

$$\mathbf{a^{(l)} = tanh\left(W^{(l)} a^{(l-1)} + b^{(l)}\right)} \quad (15)$$

where $a^{(l)}$ = x (input to the first layer is the voltage and current),$W^{(l)}$: Weight matrix of layer l, $b^{(l)}$: Bias vector of layer 1, tanh (z): Hyperbolic tangent activation function applied element-wise and z is simply the input to the activation function. Input to layer 1 to output layer D is given from equation (15) to equation (20).

$$\mathbf{a^{(1)} = tanh\left(W^{(1)} \begin{bmatrix} V \\ I \end{bmatrix} + b^{(1)}\right)} \quad (16)$$

$$\mathbf{a^{(2)} = tanh\left(W^{(2)} a^{(1)} + b^{(2)}\right)} \quad (17)$$

$$\mathbf{a^{(3)} = tanh\left(W^{(3)} a^{(2)} + b^{(3)}\right)} \quad (18)$$

$$\mathbf{a^{(4)} = tanh\left(W^{(4)} a^{(3)} + b^{(4)}\right)} \quad (19)$$

$$\mathbf{a^{(5)} = tanh\left(W^{(5)} a^{(4)} + b^{(5)}\right)} \quad (20)$$

$$\mathbf{D = W^{(6)} a^{(5)} + b^{(6)}} \quad (21)$$

The final output, D, can be directly used to control the converter for tracking the MPP given in equation (22).

$$\mathbf{D = f(V, I; \theta)} \quad (22)$$

where $\theta = \{W^{(l)}, b^{(l)}\}_{l=1}^{6}$ represents the set of all trained network parameters (weights and biases) for the six-layer MLP. Equation 22 shows that the output duty cycle D is determined by the input PV voltage and current through this fixed parameter set. During simulations, θ is fixed after training, and the network uses it to infer the optimal duty cycle for MPPT under partial shading conditions.

4. Results and Discussion

The simulation consists of a 3×1 PV string with a boost converter and MPPT algorithm. The PV module parameters are given in Table 2. The specifications of the boost converter (inductance = 3 mH, filter capacitors C1 = C2 = 100 µF, switching frequency = 50 kHz) and the sampling time (1e-6 s) are used.

Table 2. PV parameters used in simulation

Parameter	Symbol	Value	Unit
Module rating	–	83.28	W
Modules in series	–	3×1	–
Cells per module	Ncell	20	–
Open-circuit voltage	Voc	12.64	V
Short-circuit current	Isc	8.62	A
Maximum power voltage	Vmp	10.32	V
Maximum power current	Imp	8.07	A
Series resistance	Rs	0.0986	Ω
Shunt resistance	Rsh	82.116	Ω
Temp. coefficient Voc	–	–0.33969	%/°C
Temp. coefficient Isc	–	0.063701	%/°C

The simulation results demonstrate the enhancement of power using various MPPT techniques under PSC. The uniform (1000 W/m²) and non-uniform cases ([1000, 800, 600]) at fixed Temperature 25°C is used in the simulation as shown in table 3. Table 3 summarises the peak to peak (P2P), mean ($\overline{X}$), Standard Deviation (σ), variance (σ^2), median ($\widetilde{X}$), RMS and mean square ($\overline{X^2}$) data at different irradiation. Solar Power and Load power comparison for non-uniform irradiation is shown in figure 3.

Figure 4 and 5 show the comparison of source and load power under random irradiation [1000, 960, 850]) at fixed Temperature 25°C. The P&O method was used as the base model for comparison. Advanced optimization techniques, including PSO, CSA, GWO, and MLP-based ML, were applied to achieve similar or better performance. Among these, the MLP-based ML method showed superior results in both power

(SPV and Load) and settling time compare to others.

Table 3. Statistical comparison for Solar and Load Powers in uniform and non-uniform irradiation conditions

	Irr	P2P	$\bar{X}$	σ	σ^2	$\tilde{X}$	RMS	$\bar{X}^2$
ML_LOADPOWER	Uniform	244.30	242.72	16.03	257.01	244.29	243.25	59170.22
ML_SPVPOWER	Uniform	249.83	246.33	22.98	528.04	249.83	247.40	61208.83
ML_LOADPOWER	Non-uniform	159.11	157.89	11.03	121.73	159.03	158.27	25050.19
ML_SPVPOWER	Non-uniform	163.89	161.42	15.51	240.47	163.84	162.16	26296.62
PO_LOADPOWER	Non-uniform	159.14	155.54	14.47	209.28	158.85	156.21	24401.30
PO_SPVPOWER	Non-uniform	164.68	159.67	20.02	400.69	164.49	160.92	25894.63
PSO_LOADPOWER	Non-uniform	157.59	156.16	12.28	150.70	157.59	156.64	24537.04
PSO_SPVPOWER	Non-uniform	163.62	160.57	17.49	305.83	163.62	161.52	26087.40
CSA_LOADPOWER	Non-uniform	156.27	153.42	14.78	218.35	156.18	154.13	23755.15
CSA_SPVPOWER	Non-uniform	161.26	157.99	16.38	268.38	161.25	158.84	25229.47
GWO_LOADPOWER	Non-uniform	159.45	147.03	17.65	311.61	151.36	148.09	21929.75
GWO_SPVPOWER	Non-uniform	163.04	150.01	20.82	433.39	155.05	151.45	22936.84

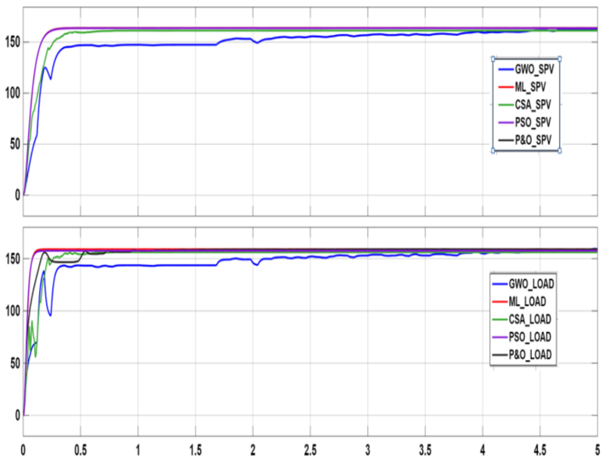

Figure 3. Solar Power and Load power comparison for non-uniform irradiation

The MLP-based approach achieved the highest power output compared to the base P&O and other optimization techniques, as shown in Table 4. The comparison of settling time (Ts) using different optimization techniques is presented in Table 5. The faster settling time demonstrates its ability to adapt quickly to changes in shading conditions, making it the most efficient method for MPPT. While metaheuristic techniques such as PSO, CSA, and GWO also enhanced power output, their settling times were comparatively longer.

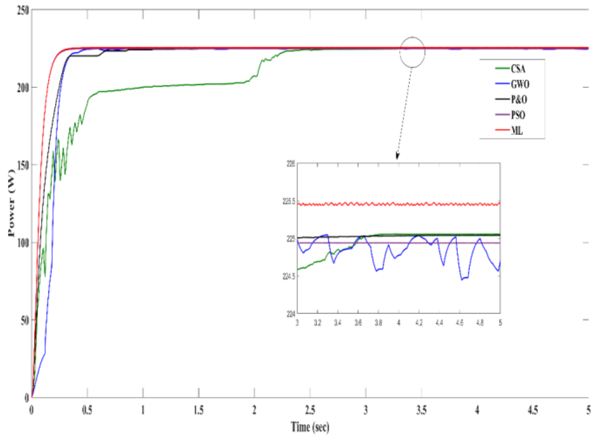

Figure 4. SPV power estimation using various optimization techniques under PSC

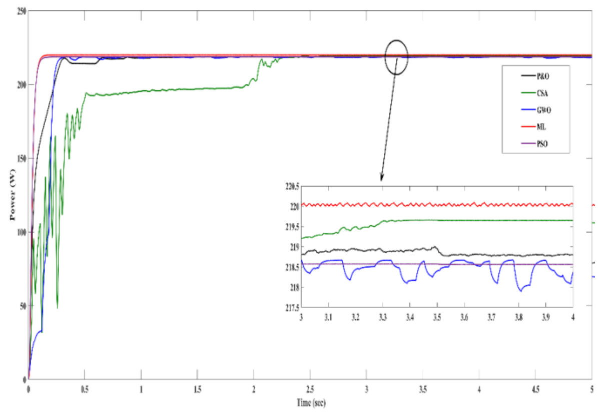

Figure 5. Enhancement of power on load side using various optimization techniques under PSC

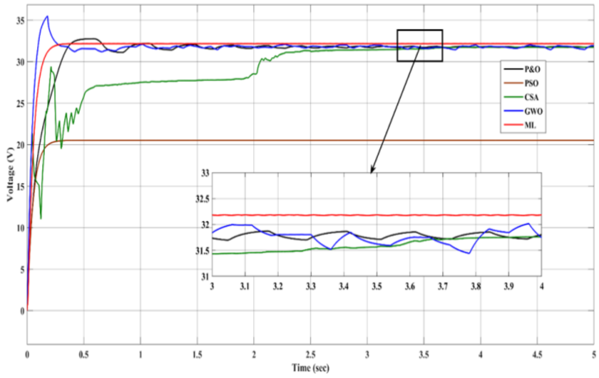

Figure 6. SPV voltage estimation using various optimization techniques under PSC

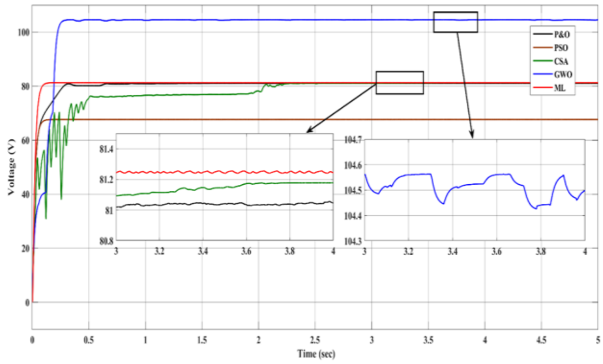

Figure 7. Load voltage estimation using various optimization techniques under PSC

The MLP-based approach, as shown in figures 6 and 7, demonstrates a significant improvement in maintaining stable voltage across shading conditions. This method achieved rapid convergence to the optimal voltage level, minimizing fluctuations and ensuring that the voltage remained close to the desired MPP.

The metaheuristic techniques PSO, CSA, and GWO also improved voltage stability, with occasional deviations during transient conditions. Among these, GWO showed better load voltage performance compared to PSO and CSA but fell short of the precision offered by the MLP-based method.

Table 4. Comparison of SPV power using different optimization techniques

	P&O	PSO	CSA	GWO	MLP
SPV Power	225.0427	224.9422	225.0586	225.0481	225.50
Load Power	219.01	218.57	219.66	218.69	220.11
SPV Voltage	32.78	20.53	31.76	35.51	32.18
Load Voltage	81.05	67.60	81.17	104.57	81.26

Table 5. Comparison of settling time (Ts) using different optimization techniques

	Ts_ P&O	Ts_ PSO	Ts_ CSA	Ts_ GWO	Ts_MLP
SPV Power	0.6048	0.2307	2.2123	0.3449	0.233
Load Power	0.6023	0.0949	2.2093	0.254	0.0988
SPV Voltage	0.8534	0.1973	2.3001	0.6763	0.2013
Load Voltage	0.2659	0.0812	2.0427	0.2407	0.0849

5. Conclusion

The study demonstrates the effectiveness of various MPPT techniques in enhancing power output and stabilizing voltage under PSCs. While the traditional P&O method provided a baseline for comparison, advanced optimization techniques such as PSO, CSA, GWO, and MLP-based ML showed significant improvements in both power and voltage performance. Among these, the MLP-based ML method emerged as the most effective, achieving the highest power output and the most stable load voltage with minimal settling time.

The MLP-based MPPT technique's ability to adapt to dynamic environmental conditions and converge quickly to the optimal operating point highlights its superiority over traditional and metaheuristic approaches. These findings emphasize the importance of leveraging ML for efficient SPV system management, especially in challenging scenarios such as PSCs. Future work can focus on real-time hardware implementation and scaling MLP-based methods for large-scale solar energy systems to maximize efficiency and reliability.

Conflict of Interests

The authors declare that they have no conflict of interest.

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