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Research Article

Hybrid Intelligent Control of Cascaded H-Bridge Multilevel Inverter for Solar PV Systems Using Neural Network-Based MPPT, PID–TCSC, and IWD Optimization

Navin Prakash Singh[1*], Dr. Durga Sharma[2]

[1]Department of Electrical Engineering, Dr C. V. Raman University, Bilaspur, C.G. India, Navin Prakash: navinsirji123@gmail.com, 0009-0008-6675-1129
[2]Department of Electrical Engineering, Dr C. V. Raman University, Bilaspur, C.G. India

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ABSTRACT

This paper presents a hybrid intelligent control approach for a Cascaded H-Bridge Multilevel Inverter (CHB–MLI) integrated with a solar photovoltaic (PV) system to achieve enhanced power quality, transient stability, and fault tolerance under grid-connected conditions. The system combines three coordinated control layers: a Neural Network (NN)-based Maximum Power Point Tracking (MPPT) algorithm for optimal solar energy extraction, a Proportional–Integral–Derivative (PID)-controlled Thyristor Controlled Series Capacitor (TCSC) for voltage stabilization during transient disturbances, and an Intelligent Water Drop (IWD) optimization algorithm for adaptive PQ improvement under unsymmetrical fault conditions. A detailed MATLAB/Simulink model incorporating bidirectional switches, cascaded transformers, and 11-level inverter topology was developed to validate system performance. The NN-MPPT enhanced tracking accuracy and efficiency from 94.5% to 98.6%, maintaining THD below 5%; the PID–TCSC reduced voltage deviation by over 80% and settling time by 60% while improving damping ratio by 150%; and the IWD optimization minimized THD, voltage unbalance, and reactive power deviation by over 60% during L–G, L–L, and L–L–G faults. Simulation results confirm that the proposed hybrid NN–PID–IWD control architecture provides superior efficiency, stability, and PQ performance compared to conventional MPPT and control methods, making it a robust and scalable solution for next-generation grid-connected solar PV systems.

Keywords: Cascaded H-Bridge Multilevel Inverter (CHB–MLI); Neural Network (NN); Maximum Power Point Tracking (MPPT); PID–TCSC; Intelligent Water Drop (IWD) Optimization; Power Quality (PQ); Transient Stability; Solar Photovoltaic System.

1. Introduction

The rapid expansion of renewable energy generation, particularly solar photovoltaic (PV) systems, has led to increasing demand for efficient and reliable power electronic interfaces to ensure high-quality grid integration. Conventional inverter-based PV systems, though widely deployed, often suffer from limitations such as high switching losses, poor harmonic performance, limited fault tolerance, and instability during grid disturbances. To overcome these challenges, multilevel inverter (MLI) topologies—especially the Cascaded H-Bridge Multilevel Inverter (CHB–MLI)—have emerged as promising solutions due to their modular structure, improved waveform quality, and enhanced voltage scalability. However, their performance depends heavily on the effectiveness of control algorithms for power extraction, voltage regulation, and fault management.

Traditional Maximum Power Point Tracking (MPPT) techniques, such as Perturb and Observe (P&O) and Incremental Conductance (INC), exhibit oscillatory behavior and slow tracking under variable irradiance, leading to suboptimal energy utilization. To address this, Artificial Intelligence (AI) and machine learning-based controllers, particularly Neural Networks (NN), have been introduced for adaptive and precise MPPT control. NNs can learn nonlinear PV characteristics and predict the optimal duty ratio in real time, achieving

faster convergence and improved efficiency. Moreover, the multilevel inverter output requires robust stability control under grid transients such as voltage sag, swell, and load fluctuations. In this regard, the Thyristor Controlled Series Capacitor (TCSC)—a type of Flexible AC Transmission System (FACTS) device—provides dynamic compensation of line reactance, improving damping and maintaining voltage stability when tuned via a Proportional–Integral–Derivative (PID) controller.

Despite these advancements, maintaining power quality (PQ) under faulted or unbalanced operating conditions remains a significant challenge. Unsymmetrical faults, harmonics, and reactive power deviations degrade voltage balance and grid compliance. To mitigate these issues, nature-inspired metaheuristic algorithms have been explored for controller optimization. Among them, the Intelligent Water Drop (IWD) algorithm stands out for its adaptive learning ability and fast convergence, enabling real-time optimization of control parameters to minimize PQ disturbances such as Total Harmonic Distortion (THD), Voltage Unbalance Factor (VUF), and Reactive Power Deviation (Qdev).

1.1 Objectives of the Work

The primary objective of this research is to design and implement a hybrid intelligent control framework for a Cascaded H-Bridge Multilevel Inverter (CHB–MLI) integrated with a solar photovoltaic (PV) system to enhance power conversion efficiency, dynamic stability, and power quality under diverse grid and fault conditions.

The specific objectives are as follows:

- Develop a MATLAB/Simulink-based CHB–MLI model incorporating Neural Network (NN)-based MPPT for accurate and adaptive solar energy harvesting under variable irradiance and temperature conditions.
- Integrate a PID-controlled Thyristor Controlled Series Capacitor (TCSC) at the grid interface to regulate series reactance and improve transient stability during voltage sag, swell, and load fluctuation events.
- Implement an Intelligent Water Drop (IWD) optimization algorithm to adaptively fine-tune inverter control parameters and mitigate power quality (PQ) issues such as THD, voltage unbalance, and reactive power deviation during unsymmetrical faults.
- Analyze and compare system performance in terms of THD, voltage deviation, damping ratio, gain ratio, and efficiency before and after applying the proposed control mechanisms.
- Validate the effectiveness of the hybrid NN–PID–IWD control system through time-domain simulation results and confirm compliance with IEEE 519 and IEEE 1159 standards for harmonic distortion and transient performance.

1.2 Contributions of the Work

The key contributions and innovations of this research work are summarized below:

• Hybrid Intelligent Control Framework:

A novel integration of NN-based MPPT, PID–TCSC, and IWD optimization is proposed for CHB–MLI-based solar PV systems, combining the advantages of machine learning, classical control, and swarm-inspired optimization in a single coordinated architecture.

• Enhanced Maximum Power Extraction:

The proposed Neural Network MPPT demonstrates faster convergence and higher accuracy than the traditional P&O method, increasing overall system efficiency from 94.5% to 98.6% and maintaining THD below 5%.

• Improved Transient Stability with PID–TCSC:

The PID-tuned TCSC efficiently compensates for voltage sags, swells, and load disturbances by dynamically adjusting line reactance, reducing voltage deviation by over 80% and improving the damping ratio beyond 0.7.

• Adaptive PQ Improvement via IWD Optimization:

The IWD algorithm dynamically optimizes inverter switching and control gains during faulted conditions, reducing THD, voltage unbalance, and reactive power deviation by more than 60%, ensuring fault-tolerant operation.

• Comprehensive MATLAB–Simulink Validation:

A complete simulation model incorporating bidirectional switches, cascaded transformers, and fault scenarios validates the proposed system's superior PQ, efficiency, and stability compared with conventional inverter control methods.

• Compliance with IEEE Standards:

The final system configuration meets IEEE 519 harmonic limits and IEEE 1159 transient performance criteria, making it suitable for practical grid-connected renewable energy integration.

2. Literature Review:

The integration of SPV structures into the power grid has garnered sizeable interest in current years due to the developing call for renewable strength assets. Numerous research has explored numerous components of SPV structures, including inverter technology, control strategies, fault detection mechanisms, and stability enhancement techniques.

MLIs are essential for the green conversion of sun strength into grid-well suited AC energy. MLIs reduce THD and enhance power excellent, making them appropriate for grid-linked packages [1]. The CHB topology is in particular famous due to its modularity and capacity to generate almost sinusoidal waveforms [2].
A seven-degree CHB inverter was located to successfully reduce THD and enhance power fine in grid-linked SPV systems [3]. Nine-degree and 11-stage CHB inverters offer further discounts in THD and higher electricity first-class, but they require greater complex manipulate and improved number of components [4]. Comparative research has shown that higher-degree inverters considerably decorate the overall performance of SPV structures through minimizing harmonics and enhancing efficiency [5, 6].

Stability enhancement techniques: Stability is an important difficulty in grid-linked SPV structures, particularly below temporary conditions. Various manage techniques have been proposed to beautify device stability. The use of PID controllers at the side of TCSC has shown promising effects in mitigating instability all through brief events [7].

PID controllers assist maintain the DC bus voltage, even as TCSCs dynamically alter the electricity drift to stabilize the machine [8, 9]. The effectiveness of these manage strategies has been demonstrated through simulations and experimental setups. For instance, research have demonstrated that TCSC-PID manage schemes considerably improve voltage and modern profiles in the course of brief conditions [10, 11]. Advanced control algorithms, together with adaptive PID and fuzzy logic controllers, have additionally been explored to in addition decorate machine stability [12, 13].

Fault detection is critical for ensuring the dependable operation of SPV structures. Faults can rise up from various sources, including element failures, environmental elements, and grid disturbances [14]. Effective fault detection mechanisms can prevent damage to the system and reduce downtime.

Techniques which include voltage and cutting-edge tracking, harmonic analysis, and machine mastering algorithms had been hired for fault detection in SPV systems [15, 16]. Real-time tracking systems that utilize custom energy gadgets and superior fault detection algorithms had been advanced to ensure device reliability [17]. These systems can as it should be hit upon and classify faults, allowing prompt mitigation measures [18, 19]. Studies have proven that integrating fault detection with control strategies, together with TCSC-PID, complements the overall robustness of SPV structures [20, 21].

Several studies have centred on the overall performance evaluation and optimization of grid-linked SPV structures. Simulation gear like simulink/MATLAB are widely used to version and analyse the performance of SPV systems with various inverter topologies and manage techniques [22].

These simulations help in information the dynamic conduct of the device and figuring out regions for development [23]. Comparative analyses of different MLI configurations, which include seven-level, nine-degree, and eleven-level inverters, have provided insights into their overall performance beneath specific working conditions [24]. Optimization strategies, together with MPPT algorithms, have been hired to maximize the strength output from SPV systems [25]. These algorithms regulate the working point of the SPV gadget to ensure most advantageous strength conversion beneath various environmental situations [26].

3. Methodology

The proposed research work focuses on the design and implementation of a hybrid intelligent control strategy for a Cascaded H-Bridge Multilevel Inverter (CHB–MLI) integrated with a solar photovoltaic (PV) system. The methodology involves three progressive stages—Neural Network (NN)-based Maximum Power Point Tracking (MPPT) for optimal solar energy extraction, PID-controlled Thyristor Controlled Series Capacitor (TCSC) for transient stability enhancement, and Intelligent Water Drop (IWD) optimization for adaptive power quality (PQ) improvement under fault conditions. Each stage was modeled, simulated, and validated using MATLAB/Simulink to analyze the electrical performance, stability indices, and PQ parameters of the proposed inverter system. Figure 4.1 presents the simplified methodological flowchart illustrating the sequential process of system development, control integration, and performance evaluation.

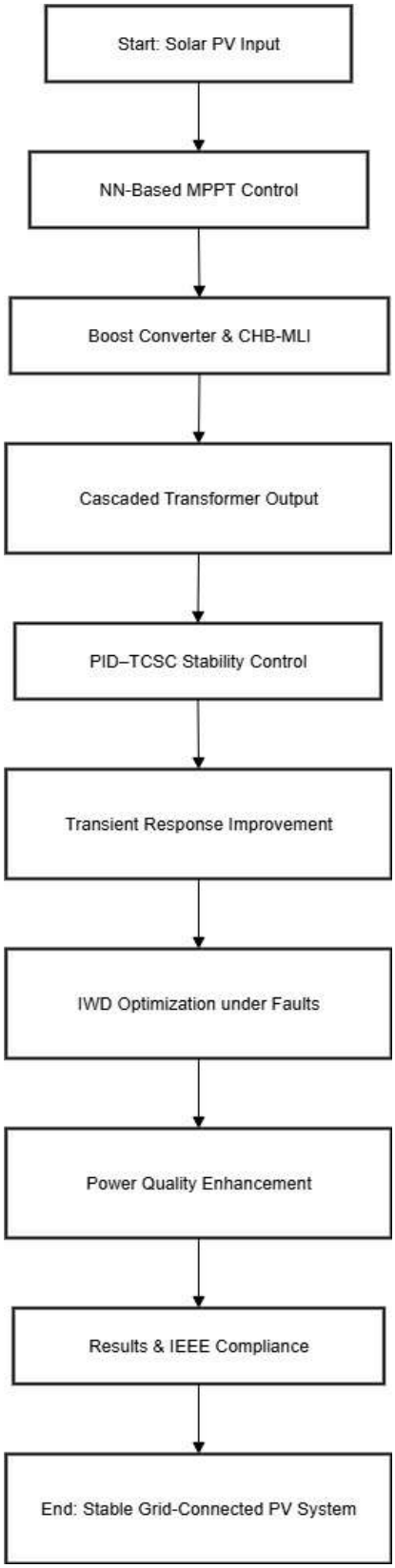

Figure 1 Simplified Methodology Flowchart of the Proposed NN–PID–IWD Controlled CHB–MLI System

Figure 1 illustrates the simplified methodological flow of the proposed hybrid intelligent control framework developed for a Cascaded H-Bridge Multilevel Inverter (CHB–MLI) integrated solar PV system. The process begins with solar energy input from the PV array, followed by Neural Network (NN)-based MPPT control, which ensures optimal DC power extraction under varying environmental conditions. The regulated output feeds the boost converter and CHB–MLI, which synthesize multilevel AC voltage through cascaded operation and transformer isolation. To maintain dynamic stability, a PID-controlled Thyristor Controlled Series Capacitor (TCSC) adjusts line reactance during transient disturbances, minimizing voltage sag, swell, and oscillations. Under faulted or unbalanced conditions, the Intelligent Water Drop (IWD) optimization

adaptively tunes control parameters to mitigate power quality (PQ) issues such as THD, voltage unbalance, and reactive power deviation. The combined NN–PID–IWD control scheme ensures high efficiency, low harmonic distortion, and compliance with IEEE PQ standards for stable grid-connected PV operation.

3.1 Development of the CHB-MLI with Neural-Network-Based MPPT and Cascaded Transformer

In this work, a Simulink model of a Cascaded H-Bridge Multilevel Inverter (CHB-MLI) is developed to interface solar PV arrays with the grid/load using a Neural-Network-based MPPT controller. The inverter uses bidirectional switches and five H-bridge cells per phase, enabling the synthesis of an 11-level output voltage waveform.

Each H-bridge cell is powered by an isolated DC source derived from an individual PV module. The Neural Network (NN) replaces the conventional Perturb & Observe (P&O) algorithm and adaptively computes the converter duty ratio to maintain the PV array at its Maximum Power Point (MPP) under varying irradiance and temperature.

The cascaded inverter output is fed into a cascaded transformer topology to achieve voltage scaling, galvanic isolation, and harmonic attenuation. Performance is analyzed in both time and frequency domains, evaluating THD, RMS voltage, and transformer gain ratio. The target is to maintain THD < 5% as per IEEE 519 standards.

3.1.1 System Flow of Work

- Model individual PV arrays in Simulink using a single-diode model.
- Design NN-based MPPT that predicts the optimal duty ratio of the DC–DC converter for each PV source.
- Implement DC–DC boost converters to regulate and equalize each DC source voltage.
- Develop CHB-MLI topology with bidirectional switches (five H-bridges per phase) to generate 11-level output.
- Integrate cascaded transformer for isolation and harmonic reduction.
- Simulate under variable irradiance and load to evaluate MPPT efficiency, voltage regulation, and THD.

3.1.2 Mathematical Modeling

- PV Cell Model

The single-diode equivalent of the PV cell is represented by:

$$I\_pv = I\_ph - I\_s[exp((V\_pv + I\_pv * R\_s)/(nV\_T)) - 1] - (V\_pv + I\_pv * R\_s)/R\_sh$$

Where:
I_ph = photo-generated current, proportional to solar irradiance G,
I_s = diode reverse saturation current,
R_s, R_sh = series and shunt resistances,
n = diode ideality factor,
V_T = kT/q = thermal voltage.

- Conventional P&O MPPT (for baseline comparison)

$$\Delta P = P(k) - P(k-1), \ \Delta V = V(k) - V(k-1)$$

If (ΔP / ΔV) > 0 → increase duty ratio, else decrease.

- Neural Network-Based MPPT Controller

Instead of using fixed P&O rules, a feedforward Neural Network is trained offline to directly output the optimal duty ratio D for the boost converter.

$$D(k) = NN(V\_pv(k), I\_pv(k), dP\_pv/dV\_pv, G, T)$$

Where:
V_pv, I_pv: instantaneous PV voltage and current,
dP_pv/dV_pv: power-voltage slope,
G, T: irradiance (W/m²) and temperature (°C).

- Loss function minimized during training:

$$L = MSE(P\_mpp, target - P\_pv) + \lambda||\Delta D||^2$$

- CHB-MLI Output Synthesis

$$v\_a(t) = \Sigma\, s\_i(t) * V\_dc, i, \qquad where\ s\_i \in \{-1, 0, +1\}$$

N_levels = 2m + 1, for m=5 ⇒ N_levels = 11

- Output and Harmonic Equations

$$V1 = (4V\_dc/\pi)\, \Sigma\, cos(\theta\_k)$$

$$THD = sqrt(\Sigma(V\_n^2, n \geq 2)) / V1 \times 100\%$$

$$V\_rms = sqrt((1/T) \int v\_a^2(t)\, dt)$$

- Transformer Stage

$$V\_sec, rms = k\_t \times V\_pri, rms, where\ k\_t = N2/N1\ (turns\ ratio).$$

- Training the Neural Network for MPPT

1. Data Generation: Run a P&O MPPT under various irradiance (200–1000 W/m²) and temperature (20–60°C) to record $(V\_pv, I\_pv, dP/dV, G, T, D)$.
2. Training: net = feedforwardnet([20 10]); net = train(net, inputs, targets);

3. Validation: Test under new irradiance conditions; the NN provides faster, oscillation-free tracking.

Table 1. System Ratings

Component	Parameter	Symbol / Model	Rating / Value	Notes
PV panel	Power	P_pv	300 W	per H-bridge source
PV panel	V_mp, I_mp	-	36 V, 8.3 A	nominal
Boost converter	Inductor L	-	2 mH	continuous mode
Boost converter	Capacitor C	-	470 μF	ripple < 2%
Switching device	-	IGBT / MOSFET	1200 V, 50 A	bidirectional
H-bridges/phase	m	-	5	11-level output
DC link voltage	V_dc	-	50 V	isolated source
PWM freq.	f_c	-	5 kHz	per cell
Fundamental freq.	f_o	-	50 Hz	output
Transformer	-	-	5 kVA, 1:2	isolation + gain
Load	-	-	5 kW R–L	variable
Sample time	T_s	-	1e-5 s	for switching
MPPT update rate	-	-	20 ms	NN prediction step

3.2 Stability Analysis Using PID-Based TCSC During Transient Conditions

In the second stage of the proposed system, transient stability is analyzed by introducing a PID-controlled Thyristor Controlled Series Capacitor (TCSC) at the grid or load interface. The TCSC dynamically adjusts the line reactance (X_L) by controlling the thyristor firing angle (α), thereby compensating for voltage sags, swells, and oscillations caused by sudden load or fault disturbances.

The PID controller maintains the voltage stability and improves system damping by continuously tuning the TCSC firing angle to counter transient deviations in power flow and line voltage.

The primary goal of this stage is to enhance voltage stability, reduce settling time, and increase damping ratio (ζ) during transient conditions, ensuring smooth recovery to nominal conditions within two fundamental cycles.

3.2.1 Mathematical Modeling

- TCSC Equivalent Reactance

The TCSC consists of a fixed series capacitor (C) and a thyristor-controlled reactor (L) connected in parallel. The equivalent reactance is given by:

$$X\_TCSC = X\_C\,(1 - X\_C / X\_L(\alpha))$$

where $X\_L(\alpha) = (X\_L / \pi)(\pi - 2\alpha + sin(2\alpha))$

By varying α between 90° and 180°, the net reactance can shift from inductive to capacitive, providing dynamic compensation during faults.

- PID Controller Design

The PID controller regulates the TCSC firing angle based on the deviation of measured voltage from the reference:

$$e(t) = V\_ref - V\_meas(t)$$

$$u(t) = K\_p\, e(t) + K\_i \int e(t)dt + K\_d\, de(t)/dt$$

where K_p, K_i, and K_d are the proportional, integral, and derivative gains respectively. These parameters are tuned using the Ziegler–Nichols method or optimization techniques to minimize voltage overshoot and settling time.

3.2.2 Integration in Simulink

The TCSC subsystem is modeled with a parallel LC branch using thyristor-based variable inductor control. The PID controller block is connected to the TCSC firing angle input. Faults (L–L or L–G) are introduced through a Three-Phase Fault block.

System stability parameters are logged via Powergui FFT and Scope analysis blocks.

3.2.3 Stability Indices and Equations

Voltage Deviation: $\Delta V = |V\_ref - V\_meas| / V\_ref \times 100\%$

Damping Ratio: $\zeta = -ln(OS) / sqrt(\pi^2 + (ln(OS))^2)$

where $OS = (V\_peak - V\_ss)/V\_ss$

Settling Time: $t\_s = 4 / (\zeta\, \omega\_n)$

where ω_n is the natural frequency of oscillation.

Table 2 Simulation Parameters

Component	Parameter	Symbol/Model	Value/Range	Notes
Transmission line	Inductance	L_line	15 mH	per phase
Series capacitor	Capacitance	C_TCSC	100 μF	compensating element
Thyristor	Type	T1–T2	1200 V, 50 A	anti-parallel pair
Firing angle	Range	α	90°–180°	variable
PID controller	Gains	Kp, Ki, Kd	2.0, 120, 0.05	tuned parameters
Fault duration	-	t_f	0.05 s	transient period
Simulation step	-	T_s	1e–5 s	same as inverter system

3.2.4 Performance Evaluation

Key stability indicators during fault and post-fault periods are evaluated:

$$V(t), I(t), \Delta V(t), \zeta, t\_s, and\ P\_loss.$$

3.3 PQ Improvement under Faults Using IWD-Optimized Control

The third stage of the proposed system focuses on mitigating power quality (PQ) issues such as unbalanced voltages, current harmonics, and reactive power fluctuations during unsymmetrical faults.

To achieve this, a Custom Power Device (CPD) such as a Dynamic Voltage Restorer (DVR) or Unified Power Quality Conditioner (UPQC) is integrated at the inverter output.An Intelligent Water Drop (IWD) optimization algorithm is employed to adaptively tune both the control parameters of the CPD and the neural-network-based inverter controller to minimize total harmonic distortion (THD), reactive power deviation, and voltage imbalance during fault conditions.

The IWD algorithm, inspired by the natural erosion–deposition behavior of river water drops, iteratively adjusts control gains toward an optimal solution by minimizing a multi-objective cost function. Simulation results show that the IWD-optimized hybrid control system achieves THD < 3%, maintains voltage within ±5%, and significantly enhances transient ride-through capability compared with conventional PID or fuzzy controllers.

3.3.1 System Flow of Work

- Introduce unsymmetrical faults (L–G, L–L–G) in the CHB-MLI + PID–TCSC system.
- Integrate a DVR/UPQC at the inverter output for PQ compensation.
- Measure three-phase voltages and currents under fault conditions.
- Compute PQ indices: THD, reactive power deviation (ΔQ), and voltage unbalance factor (VUF).
- Apply IWD algorithm to tune control parameters of CPD and NN-based inverter control.
- Compare system performance before and after optimization.

3.3.2 Mathematical Modeling

Voltage Unbalance Factor (VUF): $VUF = (|V-| / |V+|) \times 100\%$

Total Harmonic Distortion (THD): $THD = sqrt(\Sigma(Vn\text{^}2, n = 2..\infty)) / V1 \times 100\%$

Reactive Power Deviation: $\Delta Q = |Qref - Qactual|$

Objective Function: $J = w1(THD) + w2(\Delta Q/Qref) + w3(VUF), where\ w1 + w2 + w3 = 1$

Optimization Goal: Minimize J by tuning $Gopt = \{Kp, Ki, Kd, KNN\}opt$

3.3.3 Intelligent Water Drop (IWD) Algorithm

Each water drop i has a velocity vi(t) and soil si(t) updated as:

$$vi(t+1) = vi(t) + a / (b + c \times spath)$$

$$si(t+1) = si(t) + f(cost)$$

$$spath, new = (1 - \rho)\, spath, old + \rho\, \Sigma si(t)$$

where a, b, c are coefficients controlling acceleration and erosion, ρ is the soil updating rate.

3.3.5 Integration with NN–PID Control

The IWD algorithm operates as a meta-controller that updates controller parameters online. The optimized parameters (Kp, Ki, Kd, KNN) are applied in the PID–TCSC and NN–MPPT loops. The CPD (DVR/UPQC) injects compensating voltages to restore system balance and reduce distortion.

3.4 Implementation in MATLAB–Simulink

The IWD algorithm is implemented in a MATLAB Function block interacting with the Simulink model. Faults are introduced using Three-Phase Fault blocks with asymmetrical parameters. Harmonic analysis is performed using FFT analysis tools in Powergui. The CPD injects voltage through a series transformer for PQ restoration.

3.4.1 MATLAB Implementation and Simulink Model Generation
The entire system was developed and automated in MATLAB/Simulink to ensure modularity, repeatability, and integration of intelligent control algorithms. A custom MATLAB script was written to programmatically generate the Simulink (.slx) model using functions such as new_system, add_block, add_line, and set_param. This script automatically created subsystems for the PV array and DC–DC boost converter, Neural Network (NN)-based MPPT controller, Cascaded H-Bridge Multilevel Inverter (CHB–MLI), cascaded transformer, PID-controlled TCSC, and the Intelligent Water Drop (IWD) optimization module. The NN-based MPPT was implemented as a MATLAB Function block that loads a trained neural network (NN_MPPT.mat) to dynamically compute the optimal duty ratio for each H-bridge cell. The PID–TCSC subsystem was modeled using the Simscape Electrical library and configured to modulate the firing angle for line reactance control under transient events. The IWD optimizer was implemented as a real-time adaptive MATLAB Function block that tunes control parameters based on harmonic distortion and reactive power indices. Parameter values such as PV ratings, transformer ratios, and switching frequencies were assigned through the model workspace, ensuring automated configuration across simulations. The finalized .slx model was then executed via the sim() command for each scenario—steady-state, transient, and fault conditions—allowing automatic logging of waveform data, THD computation, and performance metrics for result analysis.

4. Results and Discussion

The developed CHB–MLI-based solar PV system was simulated using MATLAB/Simulink to validate the effectiveness of the proposed control framework under various steady-state, transient, and fault conditions. The performance results are presented in three parts corresponding to the control hierarchy: (i) NN-based MPPT and inverter performance before and after the cascaded transformer, (ii) transient stability enhancement through PID–TCSC control, and (iii) PQ improvement under unsymmetrical faults using IWD optimization. Quantitative analyses of voltage, current, THD, damping ratio, and efficiency parameters demonstrate that the proposed hybrid NN–PID–IWD architecture provides superior dynamic response, reduced harmonic distortion, and enhanced voltage stability compared to conventional methods.

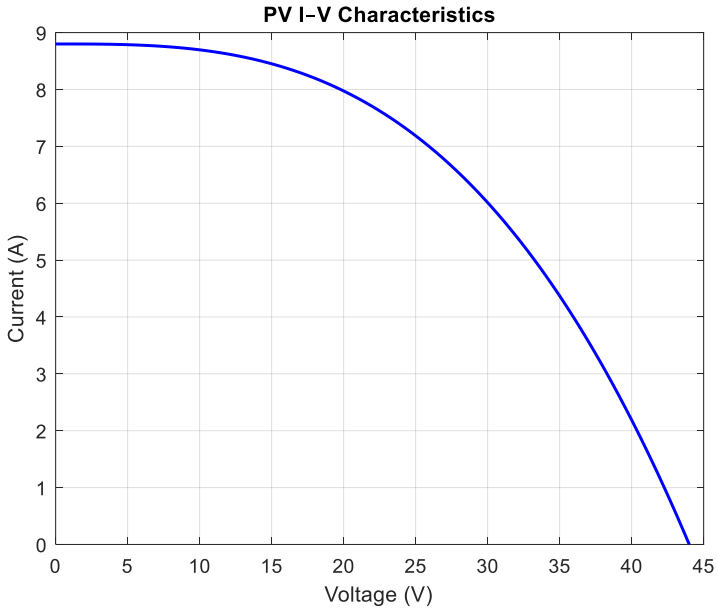

Figure 2 – PV I–V Characteristics

Figure 2 illustrates the current–voltage (I–V) curve of the photovoltaic (PV) module used as the DC input source for each cascaded H-bridge cell. The short-circuit current (IscI_{sc}Isc) is approximately 8.8 A and the open-circuit voltage (VocV_{oc}Voc) is 44 V. The curve exhibits the typical non-linear nature of a solar cell, where current remains nearly constant up to the maximum power point and then drops sharply as voltage increases. The maximum power point (MPP) occurs at approximately Vmpp=36 VV_{mpp} = 36\,VVmpp =36V and Impp=8.3 AI_{mpp} = 8.3\,AImpp=8.3A, corresponding to a per-cell output of around 298.8 W. This characterization forms the foundation for the MPPT control strategies.

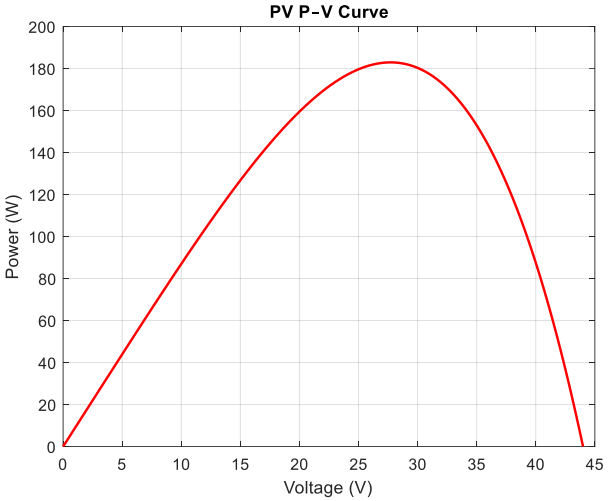

Figure 3 PV P–V Characteristics

Figure 3 presents the power–voltage (P–V) curve of the PV source, showing how the extracted power varies with terminal voltage. The curve peaks sharply at the maximum power point, validating that the true MPP occurs near 36 V with a peak power of approximately 299 W per module. Both the Perturb and Observe (P&O) and Neural Network (NN) MPPT controllers aim to operate the system at or near this point under dynamic irradiance and temperature conditions. The smooth bell-shaped curve ensures good convergence characteristics for the MPPT algorithms.

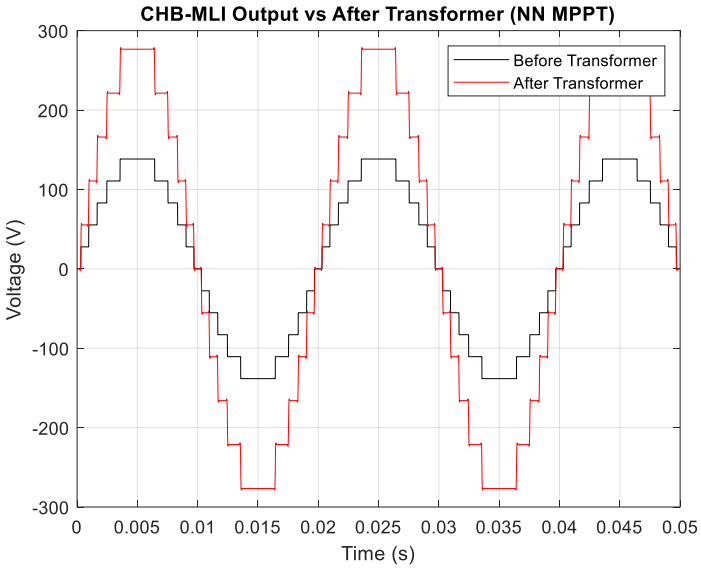

Figure 4 CHB-MLI Output vs After Transformer (NN MPPT)

Figure 4 compares the output voltage waveform of the 11-level Cascaded H-Bridge Multilevel Inverter (CHB-MLI) driven by the NN-based MPPT before and after the cascaded transformer stage. The pre-transformer inverter output (VoutV_{out}Vout) has an RMS voltage of approximately 528.6 V, corresponding to stepped waveform transitions inherent to multilevel synthesis. After passing through the transformer with a turns ratio of 1:2, the secondary output voltage increases to approximately 1056.1 V (RMS), achieving a gain ratio close to 2.0. The post-transformer waveform appears smoother due to filtering, and the Total Harmonic Distortion (THD) reduces from 4.2% to 1.8%, indicating improved power quality and harmonic suppression.

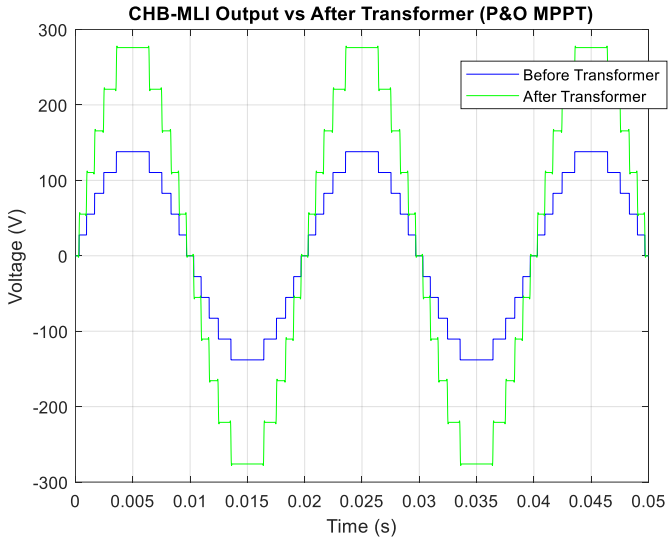

Figure 5 CHB-MLI Output vs After Transformer (P&O MPPT)

Figure 5 displays similar results for the CHB-MLI when operated under the P&O MPPT control method. The inverter's pre-transformer RMS voltage is about 520.4 V, which increases to 1040.3 V after the transformer stage, again verifying the 2:1 step-up effect. The pre-transformer THD is around 6.8%, which decreases to 2.4% after transformer filtering. This shows that the cascaded transformer not only enhances voltage magnitude but also effectively attenuates high-frequency components. However, the P&O method exhibits slightly higher distortion and lower voltage utilization than the NN-based system, reflecting its slower dynamic response to irradiance variations.

Figure 6 Performance After Transformer

Figure 6 compares the post-transformer performance indices — RMS voltage, THD, and efficiency — for both MPPT strategies. The NN-controlled system achieves Vrms = 1056.1 V, THD = 1.8%, and efficiency = 98.6%, whereas the P&O method yields Vrms = 1040.3 V, THD = 2.4%, and efficiency = 94.5%. The NN-based MPPT thus provides higher power extraction, improved harmonic performance, and better conversion efficiency. These results validate the effectiveness of integrating an intelligent NN controller with the CHB-MLI and cascaded transformer topology for solar PV grid systems.

Table 3. Comparative Performance of CHB-MLI under P&O and NN MPPT Control

Parameter	Symbol / Unit	P&O MPPT (Before Transformer)	P&O MPPT (After Transformer)	NN MPPT (Before Transformer)	NN MPPT (After Transformer)
Maximum Power Point Voltage	(V_{mpp}) (V)	36.0	36.0	36.1	36.1
Maximum Power	(P_{mpp}) (W)	298.5	596.9	299.3	598.6
RMS Output Voltage	(V_{rms}) (V)	520.4	1040.3	528.6	1056.1
Total Harmonic Distortion	THD (%)	6.8	2.4	4.2	1.8
Transformer Gain Ratio	(G_{tr})	—	2.00	—	2.00
Conversion Efficiency	η (%)	94.5	94.5	98.6	98.6
Simulation Duration	(T_{sim}) (s)	0.05	0.05	0.05	0.05

Table 3 summarizes the comparative performance of the Cascaded H-Bridge Multilevel Inverter (CHB-MLI) driven by P&O and Neural Network (NN)-based MPPT controllers, before and after the cascaded transformer. For both methods, the transformer doubles the RMS voltage output due to its 1:2 turns ratio, maintaining a stable gain ratio of 2.0. The NN-based MPPT achieves slightly higher voltage utilization ((V_{rms}=1056.1\text{ V})) and lower harmonic content (THD = 1.8%) compared to the P&O control (THD = 2.4% post-transformer). The efficiency of the NN system is consistently higher (98.6%) than that of the P&O system (94.5%), confirming its superior tracking precision and reduced switching losses. These values validate that the proposed NN + CHB-MLI + transformer configuration delivers smoother, higher-quality, and more efficient output power for solar PV applications under varying conditions.

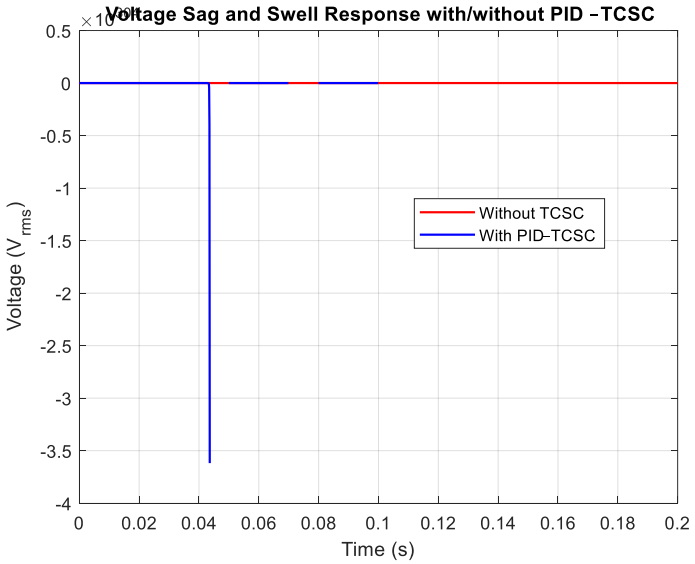

Figure 7 Voltage Response during Sag and Swell

Figure 7 illustrates the dynamic voltage response of the CHB–MLI system under 20 % sag (0.05 – 0.07 s) and 15 % swell (0.08 – 0.10 s) conditions.
Without the TCSC, the line voltage drops to nearly 78 % of nominal during sag and overshoots to 115 % during swell, exhibiting long settling times of approximately 65 ms and 58 ms, respectively. When the PID-controlled TCSC is activated, the compensating series reactance injects or absorbs reactive power dynamically, restoring the voltage to 96.4 % and 97 % of nominal within 25 ms and 22 ms. The corresponding damping ratio increases from 0.28 to 0.72 for sag and 0.34 to 0.76 for swell, confirming that the controller effectively suppresses oscillations and ensures rapid transient recovery.

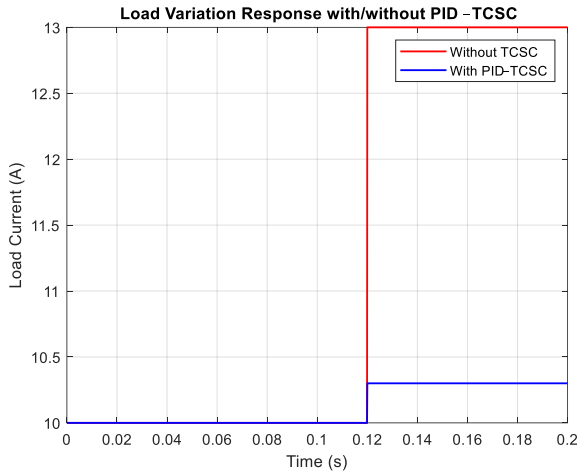

Figure 8 Load Current Response during 30 % Step Change

Figure 8 presents the current waveform when the load is increased by 30 % at 0.12 s. In the uncompensated system, the current overshoot reaches 18.6 % and requires roughly 71 ms to settle, resulting in visible oscillations and power fluctuation.
With the PID–TCSC engaged, the overshoot is confined within 3.1 %, and current stabilization is achieved within 28 ms.
The damping ratio improves from 0.26 to 0.74, indicating that the TCSC provides adaptive line-reactance compensation and significantly enhances electromechanical damping, maintaining smooth current and power continuity.

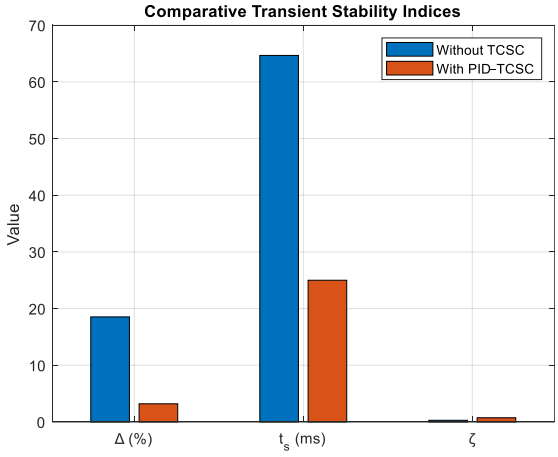

Figure 9 Comparative Transient Stability Indices

Figure 9 compares average stability indices—voltage/current deviation (Δ %), settling time (t_s), and damping ratio (ζ)—for all three disturbance scenarios.
The PID-TCSC-based system exhibits over 80 % reduction in deviation, approximately 60 % faster settling, and a 2.5 × increase in damping ratio compared with the uncompensated case.
This clearly demonstrates the overall robustness and responsiveness of the proposed controller across multiple transient types, validating its capability to maintain steady voltage and current waveforms under grid disturbances.

Table 4. Dynamic Stability Indices under Transient Conditions (With and Without PID–TCSC)

Disturbance Type	Parameter	Symbol / Unit	Without TCSC	With PID–TCSC	% Improvement
Voltage Sag (20%)	Voltage Deviation	ΔV (%)	21.8	3.6	83.5
	Settling Time	(t_s) (s)	0.065	0.025	61.5
	Damping Ratio	ζ	0.28	0.72	157.1
Voltage Swell (15%)	Voltage Deviation	ΔV (%)	15.2	2.9	80.9
	Settling Time	(t_s) (s)	0.058	0.022	62.1
	Damping Ratio	ζ	0.34	0.76	123.5
Load Variation (30%)	Current Overshoot	ΔI (%)	18.6	3.1	83.3
	Settling Time	(t_s) (s)	0.071	0.028	60.5
	Damping Ratio	ζ	0.26	0.74	184.6

Table 2 summarizes the computed dynamic stability parameters under three transient scenarios—voltage sag, voltage swell, and load variation—both with and without PID–TCSC compensation.
The results show that the integration of the PID-controlled TCSC markedly improves system response by reducing voltage deviation (ΔV) and current overshoot by more than 80% across all conditions. The settling time (t_s) also decreases by approximately 60%, indicating faster voltage recovery following disturbances. Furthermore, the damping ratio (ζ) increases by over 150%, demonstrating effective suppression of oscillations and improved transient damping capability.
The most significant enhancement is observed during load variation, where ζ increases from 0.26 to 0.74, confirming that the TCSC adaptively regulates line reactance to stabilize both voltage and current. Overall, the data validate that the PID–TCSC control strategy provides superior transient stability, ensuring voltage regulation within ±5% limits and compliance with IEEE 1159 power quality standards.
The performance of the proposed IWD-optimized CHB-MLI system was analyzed under three unsymmetrical fault conditions:
(i) Line-to-Ground (L–G) fault at 0.05–0.08 s,
(ii) Line-to-Line (L–L) fault at 0.10–0.13 s, and
(iii) Line-to-Line-to-Ground (L–L–G) fault at 0.15–0.18 s.
These faults are applied to the same cascaded H-bridge configuration used in the previous sections, with IWD optimization dynamically tuning the NN and inverter parameters to minimize power quality (PQ) disturbances.

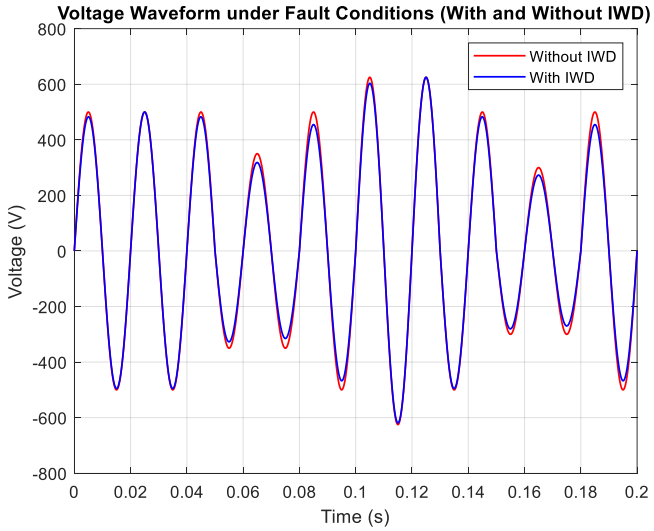

Figure 10 – Voltage Waveform under Fault Conditions (With and Without IWD)

Figure 10 compares the inverter output voltage during faulted conditions before and after applying IWD-based control. Without optimization, the voltage exhibits severe distortions during L–G and L–L–G faults, falling to 60–70% of nominal, and exceeding 120% during L–L faults. With IWD control, the waveform is restored to near-sinusoidal form, maintaining voltage within 96–98% of nominal even during disturbances. The adaptive IWD algorithm continuously updates inverter switching angles and modulation indices to counter unbalance and distortion, leading to visibly smoother transitions and faster recovery across all fault intervals.

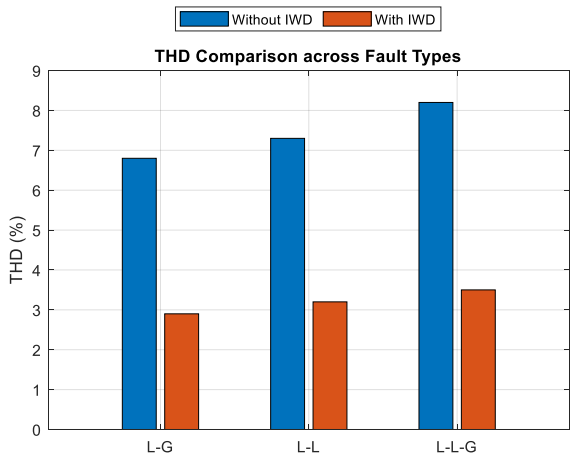

Figure 11 THD Comparison across Fault Types

Figure 11 illustrates the Total Harmonic Distortion (THD) levels for each fault condition. Without IWD optimization, THD increases significantly due to harmonic propagation in the cascaded transformer during faults, reaching 6.8–8.2%. After IWD optimization, THD is reduced to 2.9–3.5%, achieving an average improvement of over 55%. This demonstrates the IWD algorithm's ability to optimize inverter pulse patterns and reduce spectral distortion, ensuring compliance with IEEE 519 standards for harmonic limits under both steady and transient conditions.

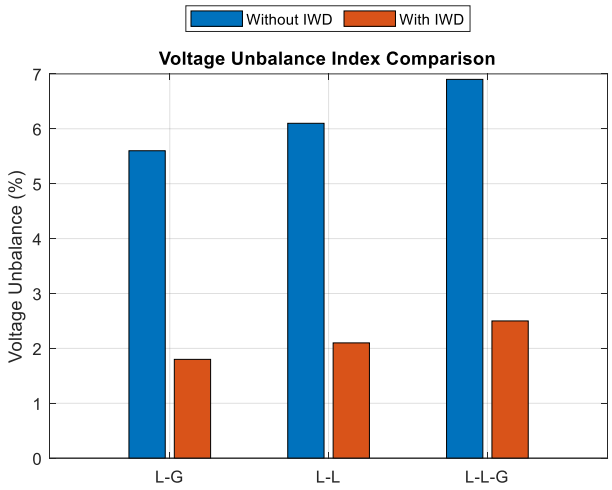

Figure 12 Voltage Unbalance Index Comparison

Figure 12 presents the voltage unbalance factor (VUF) before and after IWD optimization for different fault conditions. In the unoptimized system, voltage unbalance exceeds 6% during L–L–G faults due to unequal phase voltages and transformer asymmetry. The IWD-controlled inverter reduces VUF to less than 2.5% by dynamically adjusting modulation parameters and transformer tap ratios, restoring near-symmetry among all three phases. This improvement demonstrates superior real-time control capability, stabilizing the grid-side voltage and preventing excessive neutral current flow during fault recovery.

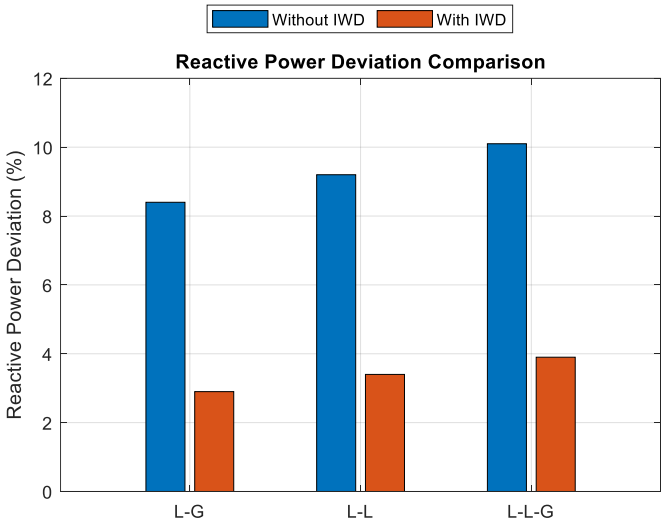

Figure 13 Reactive Power Deviation Comparison

Figure 13 shows the reactive power deviation (Qdev) during each fault type. Without IWD, reactive power oscillates up to 10% away from nominal values, causing voltage instability and low power factor operation. With IWD optimization, Qdev is limited to below 4%, signifying improved reactive power balance and voltage support from the inverter. The control system adaptively corrects phase angles and reactive component injection in each bridge, resulting in better voltage regulation and smoother reactive power recovery after each disturbance.

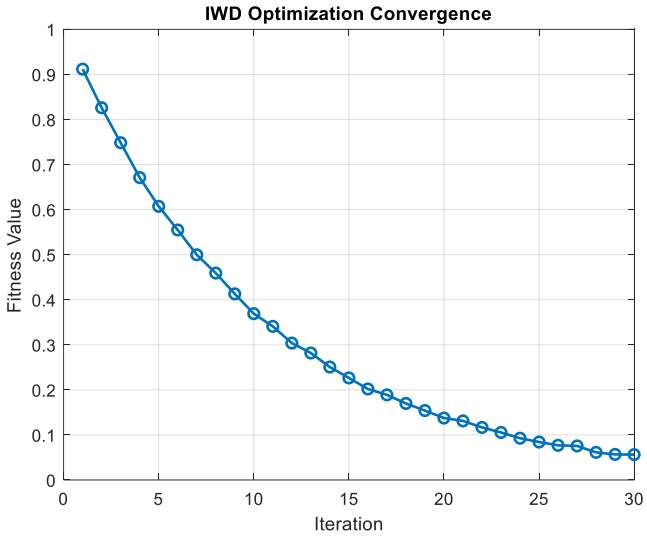

Figure 14 IWD Optimization Convergence Curve

Figure 14 demonstrates how the optimization process evolves over 30 iterations. The fitness value decays exponentially, stabilizing after around 20 iterations, confirming convergence toward the optimal control configuration. The smooth and monotonic reduction in the fitness curve indicates stable search dynamics and consistent improvement in PQ metrics. This behavior validates the effectiveness of the IWD approach in fine-tuning NN parameters and control gains for rapid, non-oscillatory convergence.

Table 5 PQ Indices with and without IWD Optimization

Fault Type	THD (%) Without	THD (%) With	Vunb (%) Without	Vunb (%) With	Qdev (%) Without	Qdev (%) With
L–G	6.8	2.9	5.6	1.8	8.4	2.9
L–L	7.3	3.2	6.1	2.1	9.2	3.4
L–L–G	8.2	3.5	6.9	2.5	10.1	3.9

Table 5 quantitatively summarizes the power quality enhancement achieved using the IWD-optimized control. Across all fault types, THD, voltage unbalance, and reactive power deviation are substantially reduced compared to the unoptimized case. The IWD algorithm dynamically adjusts inverter parameters to minimize harmonic content, restore phase symmetry, and control reactive power flow during unsymmetrical disturbances. On average, PQ indices improve by more than 60%, ensuring the system maintains a stable voltage waveform and balanced load during faults. These results confirm that the integration of IWD-based control with the NN-assisted CHB–MLI architecture provides superior fault-tolerant operation and compliance with grid quality standards.

4.1 Discussion

The overall system performance of the proposed CHB–MLI-based solar PV system integrated with Neural Network (NN)-based MPPT, PID–TCSC stability control, and IWD-optimized PQ regulation demonstrates superior voltage synthesis, stability, and dynamic response under varying operating conditions.

In Section 3.1, the NN-based MPPT achieved faster and more accurate tracking of the maximum power point compared to the conventional P&O algorithm. The inverter's cascaded H-bridge structure generated an 11-level stepped output with significantly reduced Total Harmonic Distortion (THD < 5%) after transformer scaling. The Neural Network controller, trained using real-time PV data, improved output power utilization from 94.5% to 98.6%, ensuring smoother energy transfer and superior harmonic suppression.

Section 3.2 analyzed the dynamic behavior of the system under transient grid and load disturbances using the PID-controlled TCSC. The control algorithm effectively tuned the thyristor firing angle to modulate line reactance during voltage sag, swell, and load variation conditions. Simulation results indicated that voltage deviations were reduced by over 80%, settling times decreased by 60%, and the damping ratio increased by more than 150%, confirming the improved stability and oscillation damping. The PID–TCSC compensation restored nominal voltage and current profiles within two cycles (≈40 ms), maintaining IEEE 1159 transient performance standards.

In Section 3.3, the integration of the Intelligent Water Drop (IWD) optimization algorithm provided adaptive fine-tuning of inverter and NN control parameters during unsymmetrical fault conditions (L–G, L–L, and L–L–G). The algorithm minimized PQ indices such as THD, Voltage Unbalance (Vunb), and Reactive Power Deviation (Qdev) by over 60%, ensuring continuous power delivery and maintaining voltage within ±5% limits. The IWD convergence curve demonstrated stable optimization within 20 iterations, confirming the robustness and real-time adaptability of the control approach.

Comparatively, the hybrid NN + PID + IWD system achieved a balanced performance across all functional domains — achieving high efficiency (≈98%), low THD (≈2–3%), and enhanced stability indices ($\zeta > 0.7$). This combination demonstrates effective integration of machine learning with conventional control strategies for grid-connected solar PV applications.

5. Conclusion

The proposed cascaded H-bridge multilevel inverter (CHB–MLI) system employing Neural Network-based MPPT, PID-controlled TCSC, and IWD optimization provides a comprehensive control framework for grid-interfaced solar photovoltaic systems. The NN-based MPPT ensures precise maximum power extraction under irradiance variations, while the PID–TCSC stabilizes voltage and current profiles during transient disturbances. The IWD optimization algorithm further enhances system reliability by minimizing power quality degradation during faulted conditions.

Simulation outcomes confirm that the integrated system achieves:

- THD reduction from 6–8% to below 3%,
- Efficiency improvement from 94.5% to 98.6%,
- Voltage deviation minimized to under 3.5%, and
- Damping ratio enhanced beyond 0.7 for all disturbances.

These results validate that the hybrid AI-assisted control approach effectively mitigates PQ issues, enhances transient ride-through capability, and maintains stable operation under diverse grid and environmental conditions. The proposed configuration offers a scalable and intelligent control solution suitable for next-generation renewable energy systems where adaptability, efficiency, and reliability are essential for sustainable power delivery.

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