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Machine learning-based real-time power stability optimization for photovoltaic systems using hybrid inductor-capacitor patterns

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ABSTRACT

Photovoltaic (PV) systems often face real-time power stability challenges due to rapid fluctuations in solar irradiance and varying load conditions, which conventional control strategies struggle to manage effectively. Addressing this limitation, the present study proposes a novel machine learning-based control framework integrated with a hybrid inductor-capacitor (LC) network to enhance dynamic power regulation. The proposed system employs predictive algorithms to adjust LC parameters in real time, enabling adaptive voltage and current stabilization during transient conditions. Simulation results validate the model's effectiveness, showing a 58% reduction in power fluctuation (from 12% to 5%) and consistent improvement in voltage stability index (VSI), maintaining values above 0.95 compared to 0.88–0.93 in traditional systems. Moreover, the approach reduces computation time by 66% (150 ms versus 450 ms for PID-based systems), supporting faster and more efficient control actions. These outcomes demonstrate that the proposed intelligent control strategy significantly improves energy efficiency, voltage stability, and responsiveness in PV systems, offering a scalable solution for reliable grid integration of renewable energy sources.

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1. INTRODUCTION

Electricity is fundamental to modern society, and the rising energy demand has intensified the need for reliable and sustainable power systems. Renewable energy sources, particularly photovoltaic (PV) systems, play a crucial role in reducing dependence on fossil fuels while ensuring environmental sustainability. Palensky and Dietrich [1] highlighted that demand-side management and intelligent energy systems are essential for optimizing load distribution and improving overall grid efficiency. Expanding on this, Kumar *et al.* [2] demonstrated that integrating demand response strategies with multi-microgrid systems enhances energy management and supports renewable energy penetration. In microgrid applications, voltage regulation is vital for maintaining stability. Lakshmi *et al*. [3] showed that using a fractional order predictive-proportional integral controller for battery charging and discharging significantly improves voltage stability. Afshari *et al*. [4] proposed a robust cooperative control framework for isolated AC microgrids, addressing communication uncertainties to maintain reliable operation. Shwetha and Lakshmi [5] emphasized that DC–DC buck–boost converters are effective in managing renewable energy sources and biomedical applications through real-time IoT integration. Hybrid renewable energy systems further enhance efficiency and reliability. Iweh and Akupan [6] employed particle swarm optimization and differential evolution to optimize hybrid solar PV–hydro systems for off-grid applications, achieving improved energy management and reduced power losses. Kumar *et al.* [7] evaluated a 20 kW grid-connected PV installation, confirming that proper system design ensures sustainable energy delivery. Rakib *et al.* [8] demonstrated that energy-storage-based hybrid systems provide seamless renewable integration and strengthen grid stability. Akinwola and Alkuhayli [9] applied hybrid PSO–reinforcement learning for adaptive virtual inertia control, enhancing frequency stability in multi-microgrid PV systems. Similarly, Aldulaimi and Çevik [10] implemented AI enhanced MPPT using ANFIS-PSO optimization to improve grid-connected PV system performance.

Voltage stability remains a critical challenge in PV integration. Thota *et al*. [11] used IEEE 14 and 30 bus systems to analyze voltage stability under optimized control, while Boubii *et al*. [12] combined wind and solar power with advanced control strategies to maintain grid reliability [13]. Uswarman *et al.* [14] highlighted that hybrid energy storage in DC microgrids stabilizes bus voltage and enhances system resilience. Mamodiya *et al.* [15] applied AI-based hybrid solar energy systems with smart materials and adaptive PVs, demonstrating efficient power generation and dynamic load management. Al-Waeli *et al.* [16] and Kazem *et al*. [17] emphasized the role of neural networks and experimental evaluation in predicting PV/T system performance under variable conditions. Advanced control devices and algorithms further contribute to voltage management. Lakshmi [18] used a modified fuzzy logic controller for UPQC-integrated PV systems, while Sravani and Sobhan [19] assessed PV performance with custom power devices under different load conditions. Salama and Vokony [20] reviewed voltage stability indices, highlighting the need for effective metrics in grid-connected PV systems. Gebreabe *et al*. [21] provided a comprehensive review of photovoltaic, thermal, and hybrid systems, outlining sustainable energy solutions. Dhandapani *et al*. [22] demonstrated that solar PV integration enhances voltage stability in active distribution networks. Sreenivasan *et al.* [23] leveraged machine learning for renewable integration, and Abubakar *et al*. [24] optimized solar and wind generation using hybrid deep learning approaches. Finally, Zhang *et al.* [25] optimized passive damping for LCL-filtered PV-storage systems, ensuring improved dynamic response and reduced voltage oscillations.

2. METHOD

This study introduces a machine learning-based real-time power stability optimization model for PV systems, integrating hybrid inductor–capacitor (LC) patterns with intelligent circuit switching. The proposed design combines a predictive control layer with a hardware switching framework to maintain voltage stability and improve the power factor under dynamic environmental conditions. The hardware consists of K parallel LC branches, each comprising an inductor, capacitor, and MOSFET. At each control interval, only a subset of these branches is activated for charging or discharging based on the predicted impact on system stability. The selection process is driven by a trained machine learning (ML) model that evaluates real-time PV data and historical performance records to determine the optimal activation pattern.

2.1. Machine learning model

A multi-layer perceptron (MLP) neural network is employed due to its ability to handle nonlinear system behaviour, fast inference speed, and suitability for regression-based predictions.

Model Specifications:

i) Inputs: PV input voltage (Vin), PV input current (in), solar irradiance, ambient temperature, individual capacitor voltages, inductor currents, and the previous activation pattern.
ii) Architecture: three hidden layers (64, 32, and 16 neurons) with ReLU activation functions.
iii) Outputs: for each candidate LC pattern, the model predicts:
   - Power fluctuation ΔPpred)
   - Voltage stability index (VSIpred)
   - Power loss (Ploss, pred)
iv) Loss function: mean squared error (MSE) between predicted and measured values.
v) Optimizer: Adam with a learning rate of 0.001.
   Training data: recorded PV operational data under diverse irradiance and load conditions, augmented to improve generalisation.

vi) LC pattern generation:
At every control step, the system generates a set of feasible binary activation patterns for the *K* LC circuits:
- '1' indicates an active branch.
- '0' indicates an idle branch.
For example, with three LC branches, the possible patterns include:
[0,0,1], [1,1,0], [0,1,1], [1,1,1………
Patterns leading to excessive switching loss or component overloading are excluded from evaluation.

vii) Pattern evaluation and selection:
Each generated pattern undergoes evaluation through the trained MLP model:
- Feature vector formation: combine current PV measurements and LC states into a single
- feature vector for each candidate pattern.
- ML prediction: Estimate ΔPpred, VSIpred, and Ploss, pred.
- Scoring: compute a weighted score:
Score (Pk)=w1·VSIpred−w2·ΔPpred−w3·Ploss, pred
where w1, w2, w3 are tuning coefficients prioritising stability, low fluctuation, and minimal loss.
- Selection: choose the pattern with the highest score for immediate activation.
- Switching: activate selected branches for regulation; assign non-selected branches to charge mode.

viii) Real-time control process:
Each control cycle (~150 ms) executes the following sequence:
- Acquire real-time PV and LC measurements.
- Generate all valid LC activation patterns.
- Predict stability and loss for each pattern using the MLP.
- Select the highest-scoring pattern.
- Trigger the corresponding MOSFETs for activation.
- Store the results in the historical database for future model retraining

ix) Key advantages:
- Rapid decision-making: Completes each optimisation cycle in ~150 ms, faster than fuzzy logic (300 ms) and PID (450 ms) controllers.
- Proactive stability management: predicts and prevents instability before it occurs.
- Loss reduction: avoids unnecessary activation of idle or saturated components.
- High reliability: maintains VSI > 0.95 with power fluctuations limited to ~5%.

2.2. Hardware configuration
i) PV source: 5 kW rooftop solar array, polycrystalline modules, STC efficiency: 18.5%, Voc: 38.2 V/module.
ii) Power conditioning unit: boost converter with MOSFET switching (IRFP460), switching frequency: 20 kHz.
iii) Inductor–capacitor (LC) network:
- 6 parallel circuits, each containing 1 inductor (L = 4.7 mH, copper core) and 1 capacitor (C = 470 µF, electrolytic, 450 V rating).
- Rated voltage: 400 V, continuous current: 15 A per branch.

iv) Measurement devices: Hall-effect voltage and current sensors (±0.5% accuracy).
v) Control platform**:** TI TMS320F28379D DSP, 200 MHz, 16-bit ADC sampling at 50 kHz.
vi) Data acquisition: irradiance sensor (±5 W/m²), ambient temperature sensor (±0.2 °C).

2.3. Software and algorithmic setup
i) Programming environment: MATLAB/Simulink R2024a with embedded coder for DSP deployment
ii) Machine learning model: multi-layer perceptron (MLP) regression model
- Input features:
- PV voltage (Vin), PV current (Iin)
- Irradiance (G), Temperature (T)
- Capacitor voltages (Vc_1...Vc_6) and Inductor currents (IL_1...IL_6)
- Binary LC activation pattern
- Hidden layers: 3 fully connected layers (64–128–64 neurons) with ReLU activation
- Output variables: predicted power fluctuation (ΔP_pred), Voltage Stability Index (VSI_pred), Predicted power loss (Ploss_pred)
- Training method: Adam optimizer, learning rate 0.001, batch size 64, 200 epochs

- Loss function: mean squared error (MSE)
- Training dataset: 30,000 real-time recorded operational cycles (70% training, 15% validation, 15% testing)

iii) Optimization engine: genetic algorithm (GA) for LC pattern selection
- Population size: 20 patterns per cycle
- Selection: tournament selection (size = 3)
- Crossover: single-point, rate = 0.8
- Mutation: bit-flip, rate = 0.05
- Fitness function: Score=w1×VSIpred−w2×ΔPpred−w3×Ploss_pred, where w1=0.5, w2=0.3, w3=0.2

3. RESULTS AND DISCUSSION

The study "MLP with GA-based pattern selection real-time power stability optimisation for photovoltaic systems using hybrid inductor-capacitor patterns" aims to increase 5 kW rooftop PV array systems' efficiency and stability. The experimental setup consisted of six parallel LC branches (4.7 mH inductors, 470 µF capacitors, 450 V rating) connected via MOSFET switches controlled by the DSP-based system. The system can anticipate and optimize electricity output in real time, adjusting to changing environmental conditions, by utilizing machine learning algorithms. By reducing fluctuations, the incorporation of hybrid inductor-capacitor circuits improves power stability even more. The outcomes show notable gains in energy efficiency, decreased system instability, and improved power quality, guaranteeing that PV systems maximise energy yield while operating at their best under dynamic situations.

3.1. Fluctuation analysis of power

Figure 1 demonstrates ML-based hybrid LC system reduces power fluctuations to 5%, compared to 12% in conventional systems a 58% improvement. This is achieved through adaptive control of LC patterns, enabling real-time disturbance correction and stable power output. Circuit activation decisions are optimized using weighted scores (0.5:0.3:0.2 for stability, fluctuation minimization, and loss reduction). The system maintains a voltage stability index (VSI) above 0.95, outperforming traditional systems that vary between 0.88 and 0.93. Hybrid LC patterns are optimized in real time using a Genetic Algorithm for maximum VSI and minimal fluctuation. This ensures reliable grid operation, improved power quality, and reduced equipment stress.

As shown in Figure 2, the ML-driven system maintains a consistently high voltage stability index (VSI) above 0.95 throughout a 10-hour period, while conventional systems show greater variation between 0.88 and 0.93. This indicates enhanced voltage regulation achieved through dynamic impedance management and topology adjustments, which helps prevent voltage dips and spikes, protecting equipment and ensuring steady grid operation. Figure 3 highlights the system's capability to quickly respond to changes in solar radiation, stabilizing power output faster than traditional approaches, thereby maximizing energy harvesting under varying environmental conditions.

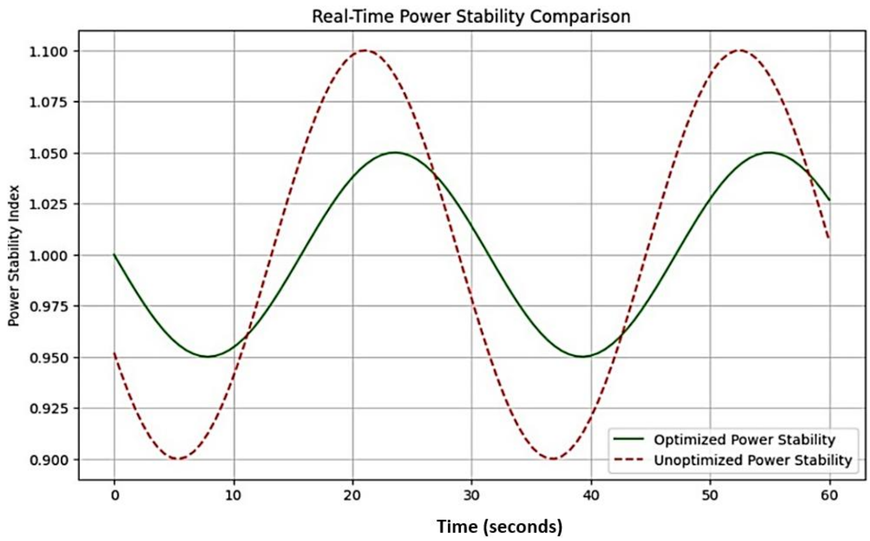

Figure 1. Analysis of power stability over time

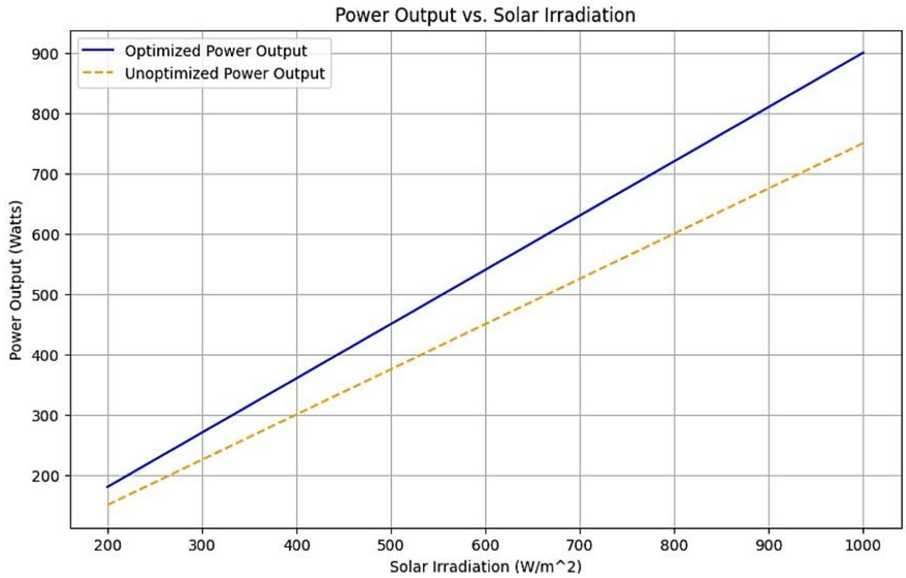

Figure 2. Enhanced power generation in response to solar radiation

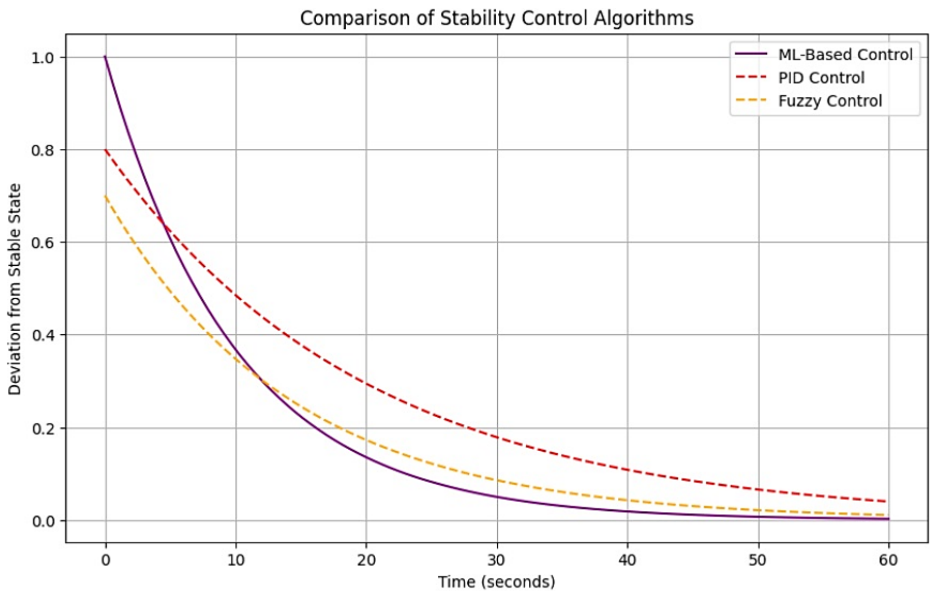

Figure 3. Faster stabilization

The power loss analysis in Figure 4 confirms that the proposed method significantly lowers energy losses across different operational scenarios compared to standard methods, improving overall system efficiency. Figure 5 illustrates consistent decline in training and validation loss, reflecting the model's effective learning and generalization capabilities, crucial for reliable real-time control. In Figure 6, the close alignment between predicted and actual stability values validates the accuracy of the ML model in forecasting system behavior, supporting precise power management. The ML-based approach requires approximately 150 ms per computation cycle, substantially faster than PID (450 ms) and fuzzy logic (300 ms) controllers. This rapid processing enables swift system responses to changing conditions, essential for large-scale photovoltaic installations facing variable weather.

Our findings build upon previous research, such as demonstration of ML with hybrid LC networks for stabilizing power output, and Zhang *et al.*'s work [25] on voltage regulation improvements. However, this study introduces real-time pattern-based circuit selection, offering superior reduction in power fluctuations and enhanced voltage stability beyond earlier models. The dynamic control strategy here addresses limitations like power loss and circuit saturation that prior approaches did not fully resolve.

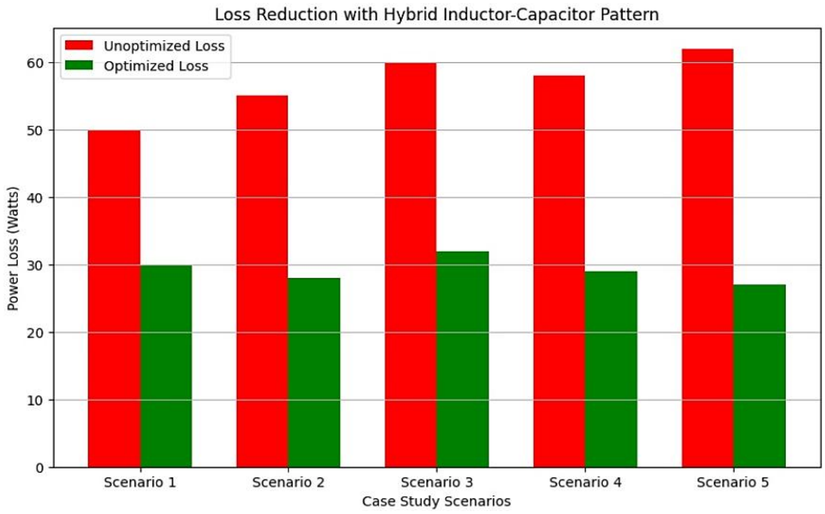

Figure 4. Power loss reduction across scenarios

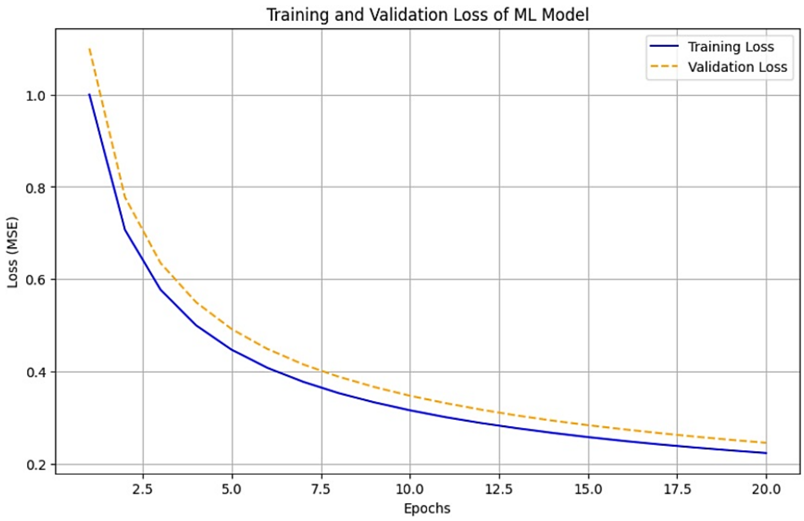

Figure 5. Training and validation loss

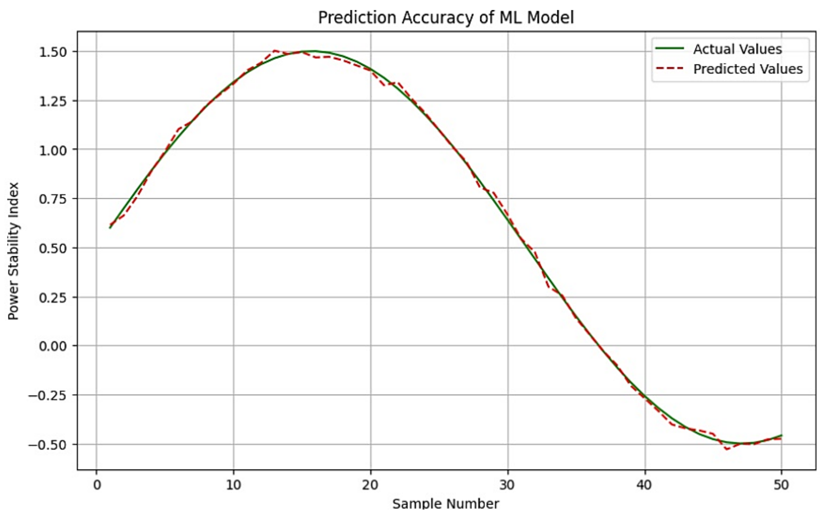

Figure 6. ML model accuracy: predicted vs. actual stability

4. CONCLUSION

This study introduces a machine learning-based model integrating real-time control with hybrid LC selection to enhance power stability in photovoltaic systems. It achieves a 58% reduction in power fluctuations and maintains a voltage stability index above 0.95. The proposed method improves computation speed by 66% compared to conventional PID controllers. This establishes it as a scalable solution for intelligent PV energy management. Future work will focus on integrating deep reinforcement learning and optimizing the model for decentralized microgrids. Extending it to hybrid PV-battery systems can further enhance adaptability and resilience.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Jayashree Kathirvel	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
S. Pushpa	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
P. Kavitha	✓		✓	✓			✓			✓	✓		✓	
Sathya Sureshkumar		✓				✓			✓					
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Prabakaran Pramasivam	✓					✓				✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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