

Article

Digital Twin-Driven Dynamic Reactive Power and Voltage Optimization for Large Grid-Connected PV Stations

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Abstract

With the increasing penetration of inverter-based photovoltaic (PV) generation, utility-scale grid-connected PV plants are frequently exposed to voltage regulation and voltage stability challenges driven by intermittent irradiance and limited reactive power flexibility under operating constraints. Conventional static Volt/VAR control schemes are typically designed for quasi-steady conditions and therefore struggle to respond to fast variations in PV output and network states. This paper presents a digital twin (DT)-enabled framework for dynamic Volt/VAR optimization in large PV plants. A four-layer DT architecture is developed to achieve real-time cyber-physical synchronization through multi-source data acquisition, secure transmission, fusion, and quality control. To balance model fidelity and computational efficiency, a hybrid physics–data-driven model is constructed, and a local voltage stability L-index is incorporated as an explicit security constraint. A multi-objective optimization problem is formulated to minimize node voltage deviations and reactive power losses while maximizing the static voltage stability margin. The problem is solved using an adaptive parameter particle swarm optimization (AP-PSO) algorithm with dynamic inertia and learning coefficients. Case studies on modified IEEE 33-bus and 53-bus systems demonstrate that the proposed method reduces the voltage profile index by up to 68.9%, improves the static voltage stability margin by 76.5%, and shortens optimization time by up to 30.3% compared with conventional control and representative meta-heuristic or learning-based baselines. The framework further shows good scalability and robustness under practical uncertainties, including irradiance forecast errors and measurement noise. Overall, the proposed approach provides a feasible pathway to enhance operational security and efficiency of grid-connected PV plants under high-penetration scenarios.

Keywords: grid-connected photovoltaic plants; digital twin; dynamic Volt/VAR optimization; voltage stability; L-index; adaptive particle swarm optimization



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1. Introduction

The large-scale integration of inverter-interfaced photovoltaic (PV) generation has fundamentally altered the operational characteristics of modern power systems [1]. Utility-scale PV plants, increasingly deployed in distribution and sub-transmission networks, often operate under weak grid conditions characterized by low short-circuit ratios [2]. Although the rapid expansion of PV capacity is essential for achieving carbon neutrality targets, it has introduced new operational challenges that cannot be adequately addressed by conventional voltage control paradigms [3].

Unlike synchronous generator-dominated systems, PV plants inherently lack physical inertia and exhibit fast, stochastic power variations driven by intermittent solar irradiance [4]. Consequently, voltage regulation in PV-dominated networks is no longer a quasi-static problem but becomes tightly coupled with voltage stability [5]. Rapid changes in active power injection modify reactive power flows through network impedances, giving rise to non-monotonic voltage–power relationships at the point of common coupling (PCC) [6]. Under such conditions, voltage deviation and stability margin degradation often occur simultaneously, particularly during high irradiance or fast cloud-transient events [7]. This dynamic voltage–stability coupling invalidates the implicit assumption adopted by many traditional Volt/VAR schemes that voltage regulation and voltage stability can be treated as largely independent problems [8].

Conventional rule-based and static control strategies, including fixed power factor operation, on-load tap changers (OLTCs), and discrete capacitor switching, are primarily designed for steady or slowly varying operating conditions [9]. Their limited response speed and coarse regulation granularity render them fundamentally incapable of tracking rapid PV-induced transients, frequently resulting in voltage violations or excessive control actions [10]. More critically, these approaches lack explicit mechanisms to guarantee a sufficient voltage stability margin, leaving PV-rich systems vulnerable to instability under high penetration levels [11].

To address these limitations, extensive research has investigated optimization-based Volt/VAR control methods. Meta-heuristic algorithms, such as particle swarm optimization and genetic algorithms, have demonstrated improved voltage profiles and reduced reactive power losses in offline or quasi-static settings [12,13]. However, these methods typically rely on fixed network models and periodic optimization, implicitly assuming slow system evolution between control intervals [14]. In practical PV-dominated grids, where operating conditions may change within seconds, the absence of real-time model synchronization significantly limits their effectiveness [15].

Learning-based control strategies have recently been proposed to enhance adaptability by directly mapping system states to reactive power commands [16]. Despite their ability to handle nonlinearities, these methods suffer from limited interpretability, uncertain generalization capability, and insufficient safety guarantees [17]. In particular, voltage stability constraints are rarely embedded explicitly, raising concerns regarding their reliability in safety-critical power system applications [18].

Digital twin technology has emerged as a promising paradigm for managing the growing complexity of cyber-physical energy systems [19]. By enabling high-fidelity virtual representations of physical assets through continuous data synchronization, DTs offer a potential bridge between real-time system dynamics and decision-making processes [20]. Existing DT applications in power systems have primarily focused on asset monitoring, predictive maintenance, and state estimation [21]. Although recent studies have begun to explore DT-assisted control and optimization, most current frameworks do not explicitly incorporate voltage stability constraints, nor do they provide a systematic mechanism for integrating dynamic optimization with real-time cyber-physical synchronization at the plant level [22].

To this end, this paper proposes a digital twin (DT)-driven dynamic reactive power and voltage optimization framework for large grid-connected PV plants. A four-layer DT architecture is developed to enable real-time cyber-physical synchronization and predictive scenario analysis [23]. A hybrid physics-informed and data-driven modeling approach is adopted to balance accuracy and computational efficiency, while the local voltage stability L-index is explicitly integrated as a security constraint [24]. Furthermore, a DT-oriented

adaptive PSO strategy is designed to enhance convergence speed and robustness in dynamic operating environments.

The main contributions of this work are summarized as follows:

- (1) A plant-level digital twin architecture is established to achieve real-time synchronization between physical PV systems and their virtual counterparts, enabling dynamic and predictive Volt/VAR decision-making.
- (2) A security-aware multi-objective optimization model is formulated by jointly considering voltage deviation, reactive power loss, and voltage stability margin through explicit L-index constraints.
- (3) A DT-oriented adaptive PSO strategy is tailored to meet real-time stability-constrained optimization requirements, emphasizing system-level integration and engineering applicability rather than standalone algorithmic novelty.
- (4) Comprehensive case studies on modified IEEE 33-bus and 53-bus systems validate the effectiveness, scalability, and robustness of the proposed framework under high PV penetration and practical uncertainties.

2. Materials and Methods

2.1. Digital Twin Framework and Multi-Source Data Processing

To enable security-aware and time-consistent Volt/VAR optimization under fast-varying operating conditions, a four-layer Digital Twin framework is established, explicitly designed to maintain continuous cyber-physical synchronization rather than static model mirroring. The framework integrates multi-source data acquisition, transmission, fusion, and quality control as intrinsic components to ensure data reliability and model fidelity under measurement uncertainty and communication latency.

The proposed DT framework forms a closed-loop adaptive control system (Figure 1) and comprises the Perception, Transmission, Modeling, and Decision-Making layers. The Perception layer serves as the data foundation, employing a heterogeneous sensor network to capture high-resolution, time-synchronized data streams. In contrast to conventional SCADA-based monitoring, both meteorological parameters (solar irradiance, ambient temperature, and wind speed) sampled at 1–5 min intervals and high-frequency inverter-level measurements are collected. System-wide operational states are monitored by the SCADA system at the PCC and by DTUs at key internal collector nodes, enabling node-level observability of voltage and reactive power dynamics. A PMU deployed at the PCC ensures precise phasor acquisition in compliance with synchrophasor measurement standards [25].

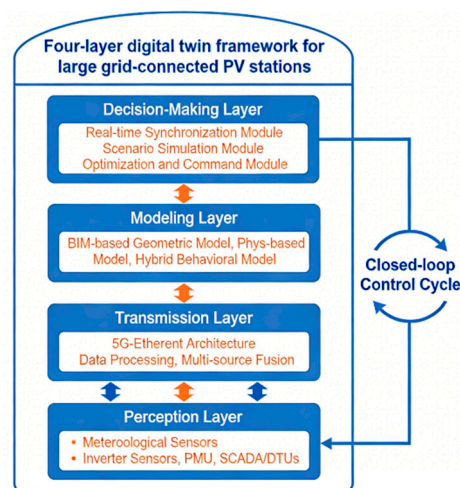


Figure 1. Four-layer digital twin framework for large grid-connected PV stations.

The Transmission layer facilitates secure and low-latency data delivery through a hybrid 5G–Ethernet architecture, where latency-sensitive operational data are transmitted via 5G and lower-frequency streams via Ethernet. An embedded preprocessing module performs initial data refinement, employing wavelet-based denoising to suppress high-frequency measurement noise [26] and LSTM-based temporal reconstruction for intelligent imputation of missing values [27,28]. To resolve inconsistencies among heterogeneous data sources, an improved Dempster–Shafer evidence theory-based fusion method is adopted [29,30]. This fusion mechanism explicitly accounts for source credibility and temporal consistency, enhancing data robustness. For quality control, an isolation forest algorithm is employed to detect abnormal samples [31], which are subsequently corrected using fused historical information.

The Modeling layer constructs a high-fidelity digital replica of the PV plant through three complementary sub-models. A BIM-based geometric model provides a spatially consistent three-dimensional representation of the station layout [32]. A physics-based model describes the operational characteristics of key components, including PV array electrical behavior, collector line impedance, and inverter reactive power capability [33]. To address unavoidable parameter drift and modeling mismatch, a hybrid behavioral model integrates first-principles equations with data-driven learning modules, such as GRU networks, enabling adaptive correction of model parameters under dynamic conditions [34,35].

The Decision-Making layer translates DT insights into executable control actions and constitutes the core of the cyber-physical loop. It integrates:

- (1) a Real-time Synchronization Module that continuously calibrates the digital model using preprocessed measurements;
- (2) a Scenario Simulation Module that performs short-horizon predictive analyses under anticipated disturbances; and
- (3) an Optimization and Command Module that solves the Volt/VAR optimization problem and dispatches optimal setpoints to PV inverters, OLTCs, and capacitor banks. This closed-loop architecture ensures that optimization decisions remain consistent with the evolving physical system states, thereby avoiding control obsolescence.

2.2. Dynamic Modeling and Real-Time Simulation

Dynamic modeling and real-time simulation are essential to ensure that the digital twin accurately reproduces the physical system behavior under rapidly changing operating conditions.

For PV generation, the single-diode model is employed to characterize the nonlinear I–V relationship:

$$I = I_{sc,ref} [1 - C_1 (e^{V/(C_2 V_{oc,ref})} - 1)] - \frac{V}{R_p} \quad (1)$$

where $I_{sc,ref}$ and $V_{oc,ref}$ are the short-circuit current and open-circuit voltage at reference irradiance, C_1 , C_2 are characteristic constants, and R_p is the parallel resistance. To enhance accuracy under dynamic conditions, parameters C_1 and C_2 are dynamically corrected via a GRU neural network based on real-time irradiance and temperature data, mitigating modeling errors from parameter uncertainties.

The collector circuit is modeled using a π -type equivalent to account for distributed parameters, with impedance corrected via measured data. The voltage drop is derived as:

$$\Delta V = \frac{PR + QX}{V_N} \quad (2)$$

where R and X denote line resistance and reactance, P and Q are transmitted powers, and V_N is the rated voltage. An auxiliary data-driven sub-model predicts impedance variations with temperature and load, improving adaptability.

The inverter reactive power model follows a PQ control strategy, with its capability constrained by active power output [36]:

$$-\sqrt{S_N^2 - P_{inv}^2} \leq Q_{inv} \leq \sqrt{S_N^2 - P_{inv}^2} \quad (3)$$

where S_N is the inverter's rated capacity. A first-order inertia link models the dynamic response, with the time constant identified in real-time via a recursive least squares algorithm to accurately reflect the sub-100 ms response [37].

Real-time simulation is implemented in MATLAB/SimulinkR2023b with a 100 ms time step. A feedback correction mechanism compares simulated outputs with physical measurements and updates model parameters accordingly, maintaining key indicator errors within $\pm 2\%$, which is sufficient for real-time optimization.

2.3. Optimization Model with Explicit Stability Constraints

A multi-objective optimization model is formulated to jointly improve voltage regulation performance, reactive power efficiency, and static voltage stability. Unlike conventional Volt/VAR formulations that focus solely on voltage deviation, the proposed model explicitly incorporates voltage stability as a security constraint. The objective function integrates three goals:

$$f_1 = \sum_{i=1}^N |V_i - V_{rated}| \quad (4)$$

where N is the total node count, V_i is the voltage at node i , and $V_{rated} = 1.0 \text{ p.u.}$

Minimize Reactive Power Loss: Enhances operational efficiency of collectors and transformers.

$$f_2 = \sum_{l=1}^L \frac{P_l^2 + Q_l^2}{V_l^2} R_l \quad (5)$$

where L is the number of branches, and P_l, Q_l, V_l, R_l are the active power, reactive power, voltage, and resistance of branch l .

Maximize Static Voltage Stability Margin: Characterized by the local voltage stability L-index L_i [38].

$$f_3 = \max \left(\min_{i=1}^N (1 - L_i) \right) \quad (6)$$

A weighted sum method converts this into a single-objective problem:

$$\min f = \omega_1 f_1 + \omega_2 f_2 - \omega_3 f_3 \quad (7)$$

where ω_1, ω_2 , and ω_3 are dynamically adjusted weighting coefficients summing to 1. Priority is given to the most critical objective in real-time: ω_1 increases if voltage deviation exceeds 5%, ω_2 increases for reactive power loss $> 3\%$, and ω_3 increases if the stability margin falls below 0.1.

The model incorporates four constraint categories:

The model incorporates four essential categories of operational and safety constraints to ensure the feasibility and reliability of the optimization results. The voltage constraint complies with national standards [39] mandating that 110 kV PCC node voltages remain within 0.97–1.07 p.u. and 10 kV collector circuit node voltages within 0.93–1.07 p.u. The reactive power output of each PV inverter is constrained by its instantaneous apparent power capacity, expressed as $-\sqrt{S_N^2 - P_{inv}^2} \leq Q_{inv} \leq \sqrt{S_N^2 - P_{inv}^2}$. For discrete compensation devices, the number of switched capacitor bank groups n_c is restricted to an integer

within $[0, N_{c,\max}]$ while the on-load tap changer (OLTC) is limited to integer tap positions within $\pm 10\%$ of its rated setting. Lastly, the system must satisfy the AC power flow balance equations at all nodes to ensure physical consistency [40].

To explicitly enhance static voltage stability, the L-index is introduced as a direct constraint:

$$L_i = \left| 1 - \sum_{k \in G} \frac{Z_{ik}^* S_k}{V_i V_k^*} \right| \leq 0.85 \quad (8)$$

where G is the set of generator nodes, Z_{ik} is the mutual impedance, S_k is the complex power, and V_i, V_k are voltages. This ensures a minimum stability margin of 0.15. For computational efficiency in dynamic optimization, an L-Q sensitivity formula is derived to predict index changes with reactive power adjustments, avoiding repeated full power flow calculations.

2.4. Adaptive Parameter Particle Swarm Optimization Algorithm

An Adaptive Parameter Particle Swarm Optimization (AP-PSO) algorithm is proposed to efficiently solve the formulated dynamic optimization problem, enhancing adaptability and convergence speed.

In the standard PSO, each particle's velocity v_{id} and position x_{id} in dimension d at iteration t are updated as:

$$v_{id}(t+1) = \omega v_{id}(t) + c_1 r_1 (p_{id}(t) - x_{id}(t)) + c_2 r_2 (g_d(t) - x_{id}(t)) \quad (9)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (10)$$

where ω is inertia weight, c_1, c_2 are acceleration coefficients, r_1, r_2 are random numbers in $[0,1]$, p_{id} is the particle's personal best, and g_d is the global best.

The AP-PSO introduces key adaptive mechanisms:

Dynamic Inertia Weight ω : Balances global exploration and local exploitation. It adapts based on the particle's relative fitness within the swarm:

$$\omega = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \times \frac{f - f_{\min}}{f_{\max} - f_{\min}} \times \frac{t}{T_{\max}} \quad (11)$$

where $\omega_{\max} = 0.9$, $\omega_{\min} = 0.4$, f is the particle's fitness, $f_{\max/\min}$ are the swarm's extreme fitness values, t is the current iteration, and $T_{\max}$ is the maximum iteration.

Adaptive Acceleration Coefficients (c_1, c_2): c_1 (cognitive) decreases linearly from 2.5 to 1.5, while c_2 (social) increases from 1.5 to 2.5, shifting focus from individual to social learning as the search progresses.

Constraint-Handling via Penalty Function: Infeasible solutions violating constraints are penalized by adjusting their fitness:

$$F_{\text{penalty}} = F + \lambda_Q \sum \Delta Q^2 + \lambda_V \sum \max(0, |\Delta V| - 0.05)^2 \quad (12)$$

where λ_Q, λ_V are penalty coefficients.

The AP-PSO solution flow is:

- (1) Initialize swarm (population = 50, random positions within bounds);
- (2) Evaluate fitness via the objective and penalty functions;
- (3) Update personal best (p_{id}) and global best (g_d) positions;
- (4) Adaptively adjust parameters ω, c_1, c_2 ;
- (5) Update particle velocities and positions;
- (6) Repeat steps 2–5 until convergence or reaching $T_{\max} = 100$ iterations, then output the global optimal solution.

2.5. Validation Setup and Performance Metrics

A systematic validation framework is established to comprehensively evaluate the effectiveness, scalability, and robustness of the proposed DT-driven dynamic Volt/VAR optimization method. The validation is conducted on modified IEEE 33-bus and 53-bus test systems, integrating hardware-in-the-loop compatible modeling, multi-dimensional performance metrics, and comparative analysis against state-of-the-art control strategies to ensure the reliability and practical relevance of the findings.

2.5.1. Test System Configuration

The core validation is performed on a modified IEEE 33-bus distribution system. A 30 MW grid-connected PV plant is integrated at Node 18, which serves as the point of common coupling. The plant comprises thirty 1 MW PV generation units, each connected to a 10 kV collector network via a 0.27/10 kV step-up transformer. The collector network is interfaced with the main 12.66 kV distribution grid through a 10/12.66 kV transformer equipped with an on-load tap changer. Reactive power support is provided by six 1 Mvar shunt capacitor banks located at the low-voltage side of the main transformer and the OLTC with 17 tap positions ($\pm 10\%$ range), reflecting typical configurations of utility-scale PV plants. To assess scalability, an extended 53-bus test system is developed, featuring five 10 kV collector circuits with ten 1 MW PV units each, while maintaining identical grid-connection and compensation configurations.

2.5.2. Experimental Scenarios and Comparative Strategies

Three characteristic operational scenarios are designed to encapsulate the typical challenges faced by large PV plants. Scenario parameters are calibrated using actual irradiance data recorded at a PV station in Northwest China.

- (1) **Steady Irradiance:** Simulates clear-sky conditions with stable irradiance between 800 and 1000 W/m².
- (2) **Dynamic Irradiance:** Introduces a cloud-transient event, modeling a 30% irradiance drop from 900 W/m² to 630 W/m² over a 5 min period.
- (3) **High-Penetration:** Evaluates system stress by increasing the PV installed capacity to 45 MW in the 33-bus system and 75 MW in the 53-bus system.
- (4) The proposed method is benchmarked against four representative control strategies:
- (5) **Traditional Control (TC):** A conventional industry strategy employing constant power factor control, fixed OLTC taps, and discrete capacitor switching.
- (6) **Standard PSO:** A static Volt/VAR optimization method utilizing a fixed-parameter PSO algorithm without DT support.
- (7) **GWO-based Optimization:** A static optimization approach using the Gray Wolf Optimizer, recognized for its performance in power system applications.
- (8) **AI-based Control (AI):** A data-driven strategy using an LSTM network for reactive power dispatch, devoid of explicit stability constraints.

2.5.3. Performance Metrics and Evaluation Standards

Five key metrics are defined to comprehensively assess voltage quality, stability, efficiency, and real-time performance, aligned with IEEE standards [1547-2018] [41] and industry practices:

- (1) **Voltage Profile Index (VPI):** Measures the average absolute voltage deviation across all system nodes, expressed as a percentage. Lower values indicate superior voltage regulation:

$$VPI = \frac{1}{N} \sum_{i=1}^N \left| \frac{U_i - U_{i,n}}{U_{i,n}} \right| \times 100\% \quad (13)$$

- (2) Average L-Index (ALI): The mean value of the nodal voltage stability L-indices, serving as a direct indicator of the system-wide proximity to voltage collapse. A lower ALI denotes a greater stability margin.
- (3) Reactive Power Efficiency (RPE): Quantifies the effectiveness of reactive power utilization by calculating the percentage reduction in reactive power losses relative to the total reactive power input.

$$RPE = \frac{P_{loss,before} - P_{loss,after}}{Q_{input}} \times 100\% \quad (14)$$

- (4) Optimization Time (OT): Quantifies the effectiveness of reactive power utilization by calculating the percentage reduction in reactive power losses relative to the total reactive power input.

GenAI usage declaration: ChatGPT (GPT-4, OpenAI) was only used for grammar and spelling checks. All outputs were reviewed and edited by the authors, who take full responsibility for the content. No GenAI tools were used for study design, data collection, analysis, or result interpretation.

3. Results and Analysis

3.1. Voltage Quality and Static Voltage Stability

Voltage quality and stability are core indicators for PV station grid integration, directly affecting grid security and power supply reliability. The proposed method's performance in these aspects is analyzed across all scenarios, with key results summarized in Table 1 and Figure 2.

Table 1. Key Performance Metrics of Different Strategies for 33-Bus System with 30 MW PV Installed Capacity.

Strategy	VPI	ALI	VOF	RPE	OT
TC	4.56	0.76	8.3	10.5	-
Standard PSO	2.89	0.71	3.1	24.2	315
GWO	2.67	0.69	2.7	26.8	330
AI	2.43	0.73	2.2	25.1	275
Proposed Method	1.42	0.60	0	34.7	230
TC	4.56	0.76	8.3	10.5	-

In the steady irradiance scenario, the proposed method reduces VPI by 68.9% compared to TC, 50.9% compared to standard PSO, and 41.6% compared to AI, achieving a uniform voltage distribution across all nodes. The ALI is minimized to 0.60, 15.5% lower than that of GWO, which confirms that the L-index constraint and DT-driven dynamic optimization effectively enhance stability margins. This performance advantage stems from the DT model's accurate mapping of PV output and grid states, which enables precise reactive power allocation.

In the dynamic irradiance scenario with a 30% drop in irradiance, the TC strategy exhibits severe voltage fluctuations with a voltage over-limit frequency of 12 times per hour, primarily due to its slow response to transients. In contrast, the proposed method maintains VPI at 1.78% and completely eliminates voltage over-limits, with a voltage over-limit frequency of 0. This is enabled by the DT framework's real-time synchronization

with a synchronization error of no more than 500 ms and the adaptive parameter adjustment of AP-PSO, which together facilitate rapid reactive power regulation. The voltage waveform at Node 18, shown in Figure 3, indicates that the fluctuation amplitude of the proposed method is 52.3% smaller than that of standard PSO, verifying its robust dynamic adaptation capability.

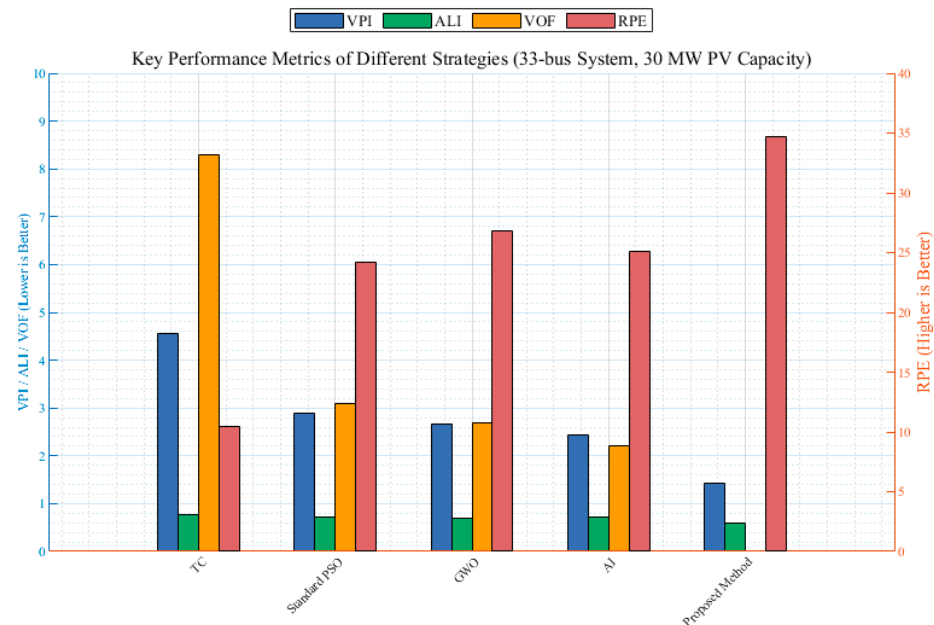


Figure 2. Key Performance Metrics of Different Strategies in 33-Bus System (30 MW PV Capacity).

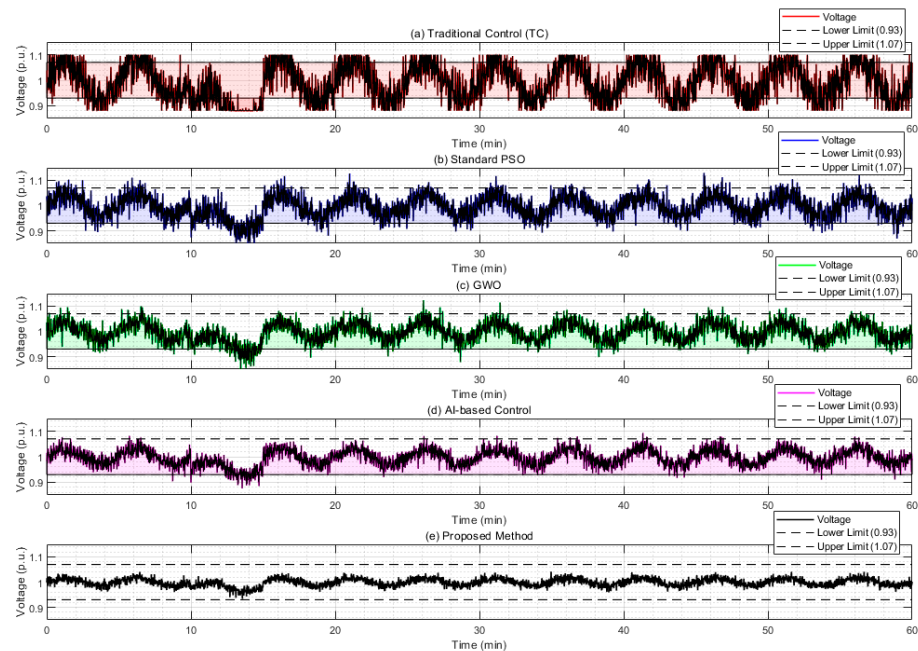


Figure 3. Voltage waveform at Node 18 (dynamic irradiance scenario).

In the high PV penetration scenario featuring a total installed capacity of 45 MW, the TC strategy's ALI reaches 0.83, corresponding to a stability margin of 0.17 and approaching the critical stable state. The proposed method increases the stability margin to 0.30 with an ALI of 0.70, representing a 76.5% improvement, while reducing VPI to 2.31%. This improvement is achieved because the DT-driven optimization fully exploits the reactive

power regulation potential of PV inverters and capacitor banks, and the L-index constraint prevents the system from operating near the voltage collapse point.

3.2. Reactive Power Efficiency and Real-Time Performance

Reactive power efficiency and real-time performance are critical for engineering application, directly affecting operational costs and control responsiveness.

The proposed method achieves the highest Reactive Power Efficiency (RPE) with 34.7% in steady scenarios and 30.2% in dynamic scenarios among all strategies, as shown in Table 1. This performance advantage is attributed to two key mechanisms. One is the digital twin-driven coordinated optimization of PV inverters, on-load tap changers (OLTC), and capacitor banks, which avoids redundant reactive power flow and reduces associated losses. The other is the adaptive parameter adjustment of the Adaptive Parameter Particle Swarm Optimization algorithm, which enhances the optimization precision of reactive power allocation. For instance, in the 33-bus system, the proposed method reduces reactive power loss by 38.6% compared to the traditional control strategy and 24.4% compared to the standard PSO strategy, as the DT model predicts reactive power demand in advance based on irradiance trends

3.2.1. Real-Time Performance

The optimization time (OT) of the proposed method is 230 milliseconds, which is 27.0% shorter than that of standard PSO and 30.3% shorter than that of GWO. A visual comparison of the optimization time of different strategies is provided in Figure 4. This performance meets the real-time control requirement for large PV stations, where the response time must be no more than 300 milliseconds. Two key optimizations contribute to this advantage. One is the hybrid modeling approach of the DT model, which combines physics-based and data-driven techniques to balance accuracy and computational efficiency. This reduces simulation time by 35% compared to pure physics-based models.

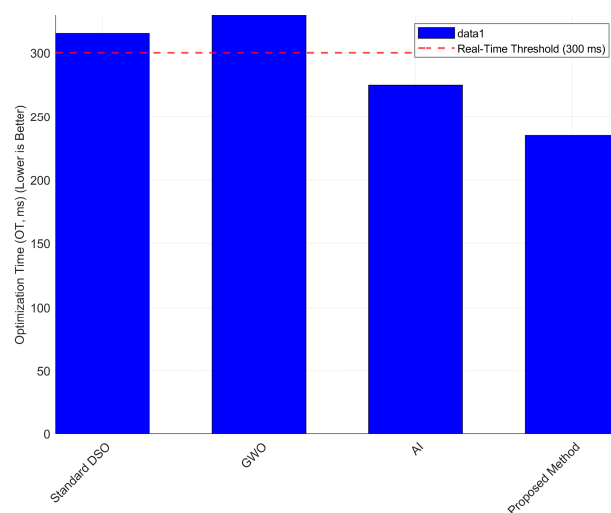


Figure 4. Optimization Time Comparison of Different Strategies (33-bus System, 30 MW PV).

3.2.2. Impact of Reactive Compensation Device Combination

Verification in the 53-bus system shows that the coordinated control of PV generation units (PVGUs), on-load tap changers (OLTC), and capacitor banks (CBs) proposed in this method outperforms single-device control strategies, as shown in Table 2 and Figure 5. When only PVGUs are used for reactive regulation, the RPE is limited to 22.3% due to insufficient capacity. When only OLTC and CBs are used, the ALI remains at 0.72 because of the discrete adjustment characteristic of these devices. The coordinated control strat-

egy achieves an optimal trade-off between efficiency and stability, confirming the DT framework's capability to synergize multiple reactive power sources for comprehensive performance improvement.

Table 2. Performance of different reactive compensation combinations (53-bus system, high penetration scenario).

Combination	VPI	ALI	RPE
PVGUs only	3.12	0.68	22.3
OLTC + CBs only	2.87	0.72	25.6
PVGUs + OLTC + CBs	2.31	0.65	32.1

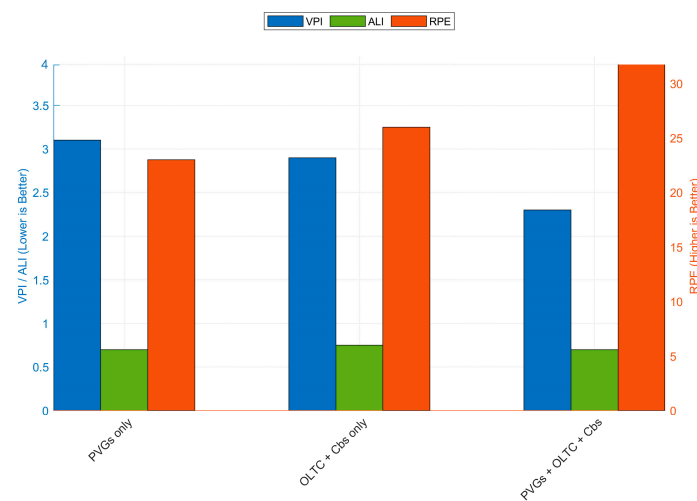


Figure 5. Performance of Different Reactive Compensation Combinations (53-bus System, High Penetration).

3.3. Scalability and Robustness

3.3.1. Scalability to Large-Scale PV Stations

In the 53-bus system with a total PV installed capacity of 75 megawatts, the proposed method maintains superior performance. Its voltage profile index is 2.53 percent, average L-index is 0.65, reactive power efficiency is 32.1 percent, and optimization time is 250 milliseconds. Compared to the 33-bus system, the performance degradation is negligible and less than 10 percent, which verifies the method's scalability. This scalability is attributed to the DT framework's modular modeling approach consisting of perception, transmission, modeling, and decision-making layers. This design reduces the growth of complexity with system scale. Additionally, the adaptive parameters of the AP-PSO algorithm can adapt to the increased optimization dimensions of larger systems.

3.3.2. Robustness to Uncertainties

Sensitivity analysis demonstrates that the proposed method exhibits strong robustness against irradiance forecast errors and measurement noise. For irradiance forecast errors, when the error is no more than 10 percent, the voltage profile index increases by only 0.15 to 0.23 percent. This is because the DT model's real-time data feedback mechanism effectively corrects forecast deviations. When the forecast error exceeds 15 percent, the AP-PSO algorithm's global search capability mitigates the degradation of performance. Additionally, regarding measurement noise, when the noise level is no more than 3 percent, the voltage profile index increases by less than 0.1 percent. This is due to the DT system's integrated data preprocessing techniques, including wavelet transform denoising and

LSTM-based missing value filling. These results confirm the method's strong adaptability to practical data quality issues in real-world operations.

3.3.3. Algorithm Comparison

The AP-PSO algorithm proposed in this method outperforms both standard PSO and GWO in terms of convergence speed and optimization effect, as illustrated in Figure 6. AP-PSO converges within 35 iterations, which is 30 percent faster than standard PSO and 23 percent faster than GWO. This enhanced convergence speed stems from its dynamically adjusted inertia weight and acceleration coefficients. In the 53-bus system, AP-PSO achieves a lower fitness value of 0.78 compared to GWO's 0.81, which further confirms its superior global optimization capability.

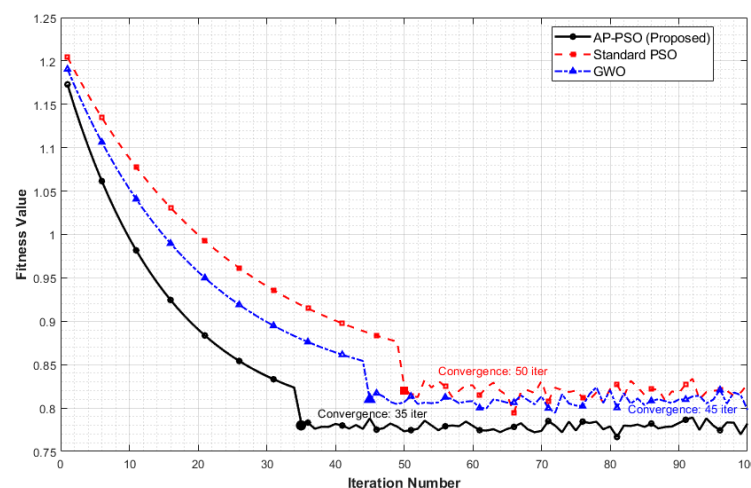


Figure 6. Convergence curve of optimization algorithms (high penetration scenario).

3.4. Ablation Study and Component Contribution Analysis

To explicitly quantify the contribution of each major component within the proposed digital twin-driven framework, an ablation study was conducted on the IEEE 33-bus system under the dynamic irradiance scenario described in Section 2.5.2. All experiments use the same system configuration, optimization horizon, and control constraints to ensure fair comparison.

Four representative variants were evaluated (Table 3):

- (1) DT-AP-PSO (Proposed Method): the complete framework including data quality control, adaptive hybrid modeling, and real-time DT synchronization;
- (2) DT without Data Quality Control: removing LSTM-based missing data reconstruction, Dempster–Shafer fusion, and isolation forest-based anomaly detection, while retaining DT synchronization and optimization;
- (3) DT without Adaptive Modeling: disabling GRU-based parameter correction and using fixed physical model parameters;
- (4) Static Optimization without DT: applying AP-PSO on a static network model without real-time digital twin synchronization.

When data quality control is removed, the Voltage Profile Index (VPI) increases from 1.42% to 1.72%, and intermittent voltage violations reappear during fast irradiance changes, indicating that data preprocessing is critical for robust control under measurement noise. Disabling GRU-based adaptive modeling degrades the Average L-index (ALI) from 0.60 to 0.71, corresponding to an 18.7% reduction in voltage stability margin, which confirms the importance of adaptive parameter correction under dynamic operating conditions. When real-time DT synchronization is removed, the VPI increases to 1.92% and the optimiza-

tion response becomes noticeably slower, demonstrating that DT-based cyber-physical consistency is essential for maintaining control effectiveness.

Table 3. Summarizes the corresponding performance metrics.

Method	VPI	ALI	RPE	OT
Proposed Method	1.42	0.6	34.7	230
DT w/o Data Quality Control	1.72	0.63	29.8	235
DT w/o Adaptive Modeling	1.59	0.71	31.2	232
Static Optimization w/o DT	1.92	0.74	27.6	290

These results confirm that the performance improvements reported in Sections 3.1–3.3 are not attributable to any single algorithmic module, but rather to the coordinated interaction of data quality control, adaptive modeling, and digital twin synchronization within the proposed framework.

4. Discussion

The findings of this study confirm that the proposed digital twin-driven dynamic Volt/VAR optimization method effectively mitigates the core operational challenges of large grid-connected PV plants, including voltage fluctuations, inadequate stability margins, and low reactive power efficiency. By integrating real-time cyber-physical synchronization, adaptive control, and stability-explicit constraints, the method demonstrates superior performance across multiple metrics compared to traditional and state-of-the-art optimization strategies, offering significant implications for both research and practical grid operation.

The enhanced voltage quality and static stability, evidenced by a reduction in the Voltage Profile Index of up to 68.9% and a minimized Average L-index of 0.60, result from the synergy between the DT framework and the stability constraint. The four-layer DT architecture enables high-fidelity, real-time mapping of system dynamics through multi-source data fusion and hybrid modeling. This capability allows for proactive voltage management during rapid transients such as irradiance drops. The explicit incorporation of the L-index constraint ensures operation within a secure stability margin, a critical advancement over data-driven strategies that often neglect stability for voltage regulation.

The method also achieves high reactive power efficiency, up to 34.7%, and meets real-time requirements with an average optimization time of 230 ms. This engineering applicability stems from the DT-coordinated control of all reactive resources and the enhanced convergence of the AP-PSO algorithm. AP-PSO outperforms standard PSO and GWO, converging 30% and 23% faster while attaining a superior solution quality. The use of an L-Q sensitivity formula for stability assessment avoids computationally expensive power flow recalculations, which is vital for the real-time control of large-scale systems.

The proposed framework demonstrates notable scalability and robustness. Performance degradation was negligible when applied to a larger 53-bus system with 75 MW of PV capacity, confirming the adaptability of its modular DT design and optimization algorithm. The method maintained stable performance under realistic uncertainties like irradiance forecast errors and measurement noise, attributable to robust data preprocessing and the global search characteristics of AP-PSO. This addresses a common gap in studies that overlook practical data imperfections or scalability.

From a practical standpoint, the method delivers clear benefits. Grid operators gain from eliminated voltage violations and a 76.5% improvement in stability margins under high penetration, enhancing system security and renewable integration capacity. Plant managers benefit from reduced operational losses and extended equipment lifespan due to minimized switching actions from coordinated control.

This study acknowledges certain limitations. The present model focuses on PV-dominated systems; future work should integrate energy storage and other generation types. While robust to normal fluctuations, the framework's response to extreme weather events and grid faults requires further development. Additionally, computational demands for ultra-large stations warrant investigation into lightweight modeling techniques. In addition, the present study does not claim universal optimality of all adopted modules, and alternative data-driven or optimization techniques may be substituted within the DT framework depending on system characteristics and computational constraints.

Future research will therefore focus on extending the DT framework for multi-energy systems, incorporating resilience mechanisms against extreme contingencies, developing computational optimizations for very-large-scale deployment, and validating performance through hardware-in-the-loop experiments.

5. Conclusions

This paper presented a digital twin-driven dynamic Volt/VAR optimization framework tailored for large-scale grid-connected photovoltaic plants operating under high penetration and fast variability. By integrating real-time cyber-physical synchronization, adaptive hybrid modeling, and stability-explicit optimization, the proposed approach bridges the gap between static optimization methods and practical operational requirements.

The results demonstrate that the performance improvements are not attributable to a single algorithmic component, but rather to the coordinated interaction of digital twin synchronization, data quality control, adaptive modeling, and optimization. Beyond numerical performance gains, the framework offers practical value for grid operators by enhancing voltage security, reducing operational risk, and supporting more informed planning and regulatory decision-making.

While the study focuses on PV-dominated systems, future work will extend the framework to multi-energy systems and extreme-event resilience, further strengthening its applicability to real-world power system operations.

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Abbreviations

The following abbreviations are used in this manuscript:

PV	Photovoltaic
DT	Digital Twin
AP-PSO	Adaptive Parameter Particle Swarm Optimization
OLTC	On-Load Tap Changer
CBs	Capacitor Banks
PVGUs	PV Generation Units
VPI	Voltage Profile Index
ALI	Average L-Index
RPE	Reactive Power Efficiency
OT	Optimization Time

PMU	Phasor Measurement Unit
SCADA	Supervisory Control and Data Acquisition
BIM	Building Information Modeling
GRU	Gated Recurrent Unit
HIL	Hardware-in-the-Loop
SVG	Static Var Generator
SVC	Static Var Compensator

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