Optimized Control of Distributed Generation for Grid Stability and Power Quality Improvement

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ABSTRACT

The incorporation of distributed generation (DG) into contemporary distribution networks is rapidly progressing, primarily propelled by the adoption of renewable energy sources. DG makes things more sustainable and resilient, but its intermittent and inverter-based nature makes it hard to keep voltage stable, frequency regulated, and power quality high. This paper presents an optimized control framework that integrates hierarchical control with Model Predictive Control (MPC) and artificial intelligence-driven adaptive tuning to concurrently tackle these challenges. The framework is structured as a multi-objective optimization problem focused on reducing voltage deviation, frequency fluctuations, and harmonic distortion. To test the method, a modified IEEE 33-bus test system with several DG units is modeled in MATLAB/Simulink and PSCAD. When compared to base case operation, conventional droop-based control, and the proposed optimized control, the framework cuts bus voltage deviation by 50%, limits frequency deviations to less than 0.1 Hz with a faster settling time, and cuts Total Harmonic Distortion (THD) by more than 40%, all while still being able to be computed. These results show that the suggested strategy is a complete and scalable way to integrate DG reliably, making sure that smart grids stay stable and that power quality improves as they change.

INTRODUCTION

The increasing use of Distributed Generation (DG), especially renewable sources like photovoltaic (PV) systems and wind turbines, is changing traditional power systems into networks that are more decentralized and dynamic. The world needs to cut down on greenhouse gas emissions, diversify its energy supply, and make electricity infrastructure more resilient, which is why people are relying more and more on DG [1]. The International Energy Agency says that by 2030, more than 30% of electricity generation in some areas will come from renewable-based distributed generation. This shows how important it is for reaching sustainable energy goals [2]. Even though DG integration has many benefits, it also makes modern grids harder to run reliably. Traditional bulk power systems were built to work with centralized generation, which had predictable output and a lot of inertia. In contrast, DG, particularly inverter-based renewable sources, demonstrates stochastic behavior, low inertia, and high variability, potentially undermining voltage stability, frequency regulation, and power quality [3], [4]. These issues manifest as harmonic distortions from power electronic converters, frequency deviations during sudden load or generation shifts, and voltage variations at weak buses. If these problems aren't fixed, they could hurt the grid's technical reliability and the quality of the power that end users get [5].

To lessen these difficulties, a number of control techniques have been put forth. A fundamental framework for DG coordination is offered by traditional methods like hierarchical primary-secondary-tertiary control schemes and droop control [6]. In low-inertia systems, sophisticated techniques like Model Predictive Control (MPC) and Virtual Synchronous Generator (VSG) enhance dynamic response and simulate inertia [7]. In order to enable adaptive, data-driven control of DG units, clever strategies utilizing fuzzy logic, neural networks, and reinforcement learning have been introduced more recently [8], [9]. Nevertheless, most of these approaches focus on either power quality or stability as separate goals. For instance, active filtering techniques enhance power quality but do not contribute to system-wide stability, whereas droop and VSG methods are efficient in controlling voltage and frequency but offer little harmonic mitigation [10].

The research gap lies in the absence of a comprehensive optimization framework that simultaneously ensures

voltage and frequency stability while improving power quality under high DG penetration. Moreover, most existing works lack a systematic evaluation of control strategies in realistic distribution systems with multiple DGs and nonlinear loads. These limitations call for hybrid approaches that can coordinate the strengths of conventional, advanced, and intelligent controllers within a unified optimization paradigm.

To address this gap, this paper proposes an optimized control framework that integrates hierarchical control with MPC and artificial intelligence-based adaptive tuning. The framework is formulated as a multi-objective optimization problem designed to minimize bus voltage deviation, limit frequency excursions, and reduce Total Harmonic Distortion (THD). Simulation studies are conducted on a modified IEEE 33-bus distribution test system to validate the proposed strategy.

This paper makes the following important contributions:

Comprehensive Analysis: A thorough examination of the challenges related to grid stability and power quality in distributed generation systems, emphasizing the shortcomings of current control techniques.

Proposed Framework: A control architecture based on hybrid optimization that uses hierarchical control, MPC, and AI-driven adaptation to meet several performance goals at once.

Simulation Validation: A comparison of the base case, conventional control, and optimized control scenarios on the IEEE 33-bus system, with results showing big improvements in voltage stability, frequency response, and harmonic suppression.

Scalability and Feasibility Assessment: A discussion of how to put the plan into action, taking into account things like communication latency, computational effort, and cyber-resilience.

The rest of this paper is set up like this. In Section II, we look at the problems with DG systems, stability, and power quality, as well as the current control strategies. Section III shows the suggested improved control framework. Section IV talks about the simulation method, which includes how to model the test system and how to measure its performance. Section V talks about the results and how they compare to each other. Lastly, Section VI wraps up the paper and gives ideas for future research.

RELATED WORK

A. Distributed Generation Systems

Distributed Generation (DG) is the term for small- to medium-sized power sources that are close to the load and are often connected at the distribution level. These include renewable sources like solar photovoltaic (PV) arrays, wind turbines, biomass plants, and micro-hydro, as well as non-renewable sources like diesel generators and microturbines [11]. The growing use of DG has turned passive distribution networks into active systems, which have advantages like lower transmission losses, greater resilience, and better use of local energy resources [12]. The integration of inverter-based distributed generation (DG), which is the most common type of renewable energy, changes the way things work in a unique way. These units do not have inertia built in like synchronous generators do, which means that frequency excursions happen more quickly during disturbances [13].

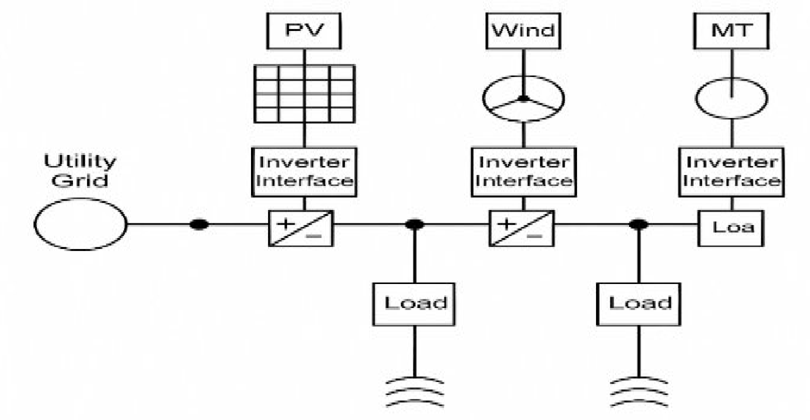

Fig. 1. Schematic of DG-integrated distribution network

Fig. 1 shows a diagram of a DG-integrated distribution network, with several renewable units connected through inverters and managed by both local and higher-level controllers. The figure shows how inverter-based DGs change the way power flows and how distribution systems are controlled.

Grid Stability and Power Quality Issues

The integration of DG has a big effect on both the quality of the power and the stability of the grid. When it comes to stability, voltage changes happen a lot because the output of renewable DGs changes depending on where they are and what they're doing [14]. In low-inertia systems, frequency stability is also affected because the natural inertial response of synchronous machines can no longer balance load and generation [15]. Problems with power quality are just as bad. Harmonics, flicker, and unbalances are caused by inverter-based DG units, which can hurt sensitive equipment and customer loads [16]. Field studies have indicated that the absence of coordination among DG units can lead to concurrent voltage increases at various buses, causing equipment overvoltage and malfunctioning protection systems [17]. In the same way, microgrids with a lot of solar PV inverters have been found to have harmonic distortion that is higher than the IEEE 519 standards [18]. These problems show that DG has two sides: it makes things more sustainable and resilient, but it also makes utilities and customers less reliable.

Table 1: Common Grid Stability and Power Quality Issues from DG Integration

Issue	Cause	Impact on System
Voltage rise /fluctuation	Intermittent PV/wind generation, weak buses	Overvoltage, equipment stress, and misoperation of relays
Frequency deviation	Low system inertia, sudden load/generation imbalance	Instability, load shedding, and poor synchronization
Harmonic distortion	Power electronic inverters, nonlinear loads	Overheating of equipment, malfunction of sensitive devices
Islanding	DG continuing to supply during grid outage	Safety hazard, loss of coordination with utility

Table 1 shows a list of common stability and quality problems that come up when integrating DG. The problems are grouped into four groups: voltage rise, frequency deviation, harmonic distortion, and islanding.

Existing Control Strategies

To deal with the problems that come up with DG integration, a number of control strategies have been created. Droop characteristics and PID regulation are two important parts of traditional control methods that help keep voltage and frequency stable [19]. These methods are easy to use and work well, but they don't always work to reduce harmonics or adapt to changing levels of renewable energy use. In Fig. 2, hierarchical control schemes

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are split into primary, secondary, and tertiary levels. They extend droop control by coordinating distributed units across a microgrid [20].

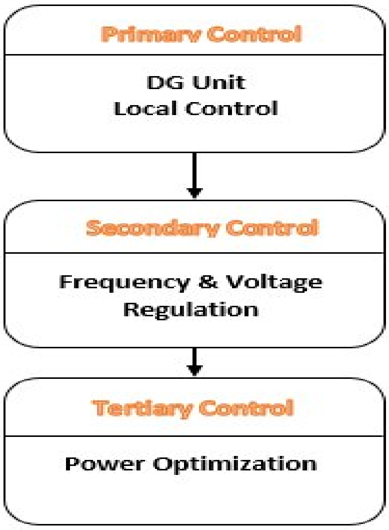

Fig 2: Hierarchical Control Structure

Advanced control methods like the Virtual Synchronous Generator (VSG) have been developed to imitate inertia and damping, which makes frequency dynamics better in systems with a lot of renewable energy [21]. Model Predictive Control (MPC) does something similar by predicting system states over a time horizon, which makes recovery faster during disturbances [22]. These methods work well, but they need detailed models and a lot of computing power, which makes them hard to scale

Recently, intelligent control methods that use artificial intelligence (AI) have been suggested. Fuzzy logic controllers have been utilized to adjust droop coefficients in real time [23], whereas reinforcement learning algorithms empower distributed generation (DG) units to independently acquire optimal control strategies in the face of uncertainty [24]. Neural networks and deep learning techniques have been employed for harmonic suppression and the enhancement of predictive stability [25]. These smart methods can adapt, but they usually need a lot of data to train and have trouble making sure they stay stable in all situations.

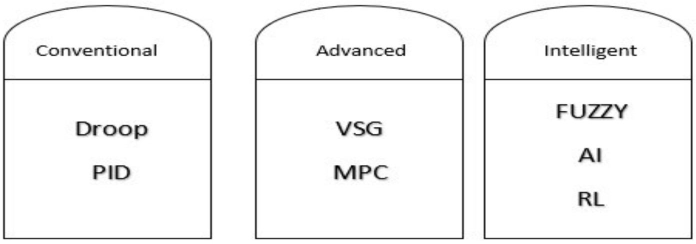

Fig 3: Comparison of Control Strategies

Fig. 3 shows how traditional, advanced, and intelligent control methods compare in terms of their range and usefulness. Conventional methods are quick and dependable, but they don't work for many things. Advanced methods make dynamics better, but they require a lot of models. Intelligent methods are adaptable but encounter validation difficulties.

Research Gap

A thorough examination of the literature indicates that the majority of current methodologies concentrate exclusively on either stability or power quality. Droop and VSG methods put voltage and frequency first, but they don't care about harmonics. Active filtering and other harmonic mitigation strategies improve power quality, but they don't help keep the frequency stable. Even hybrid strategies often don't have integrated optimization, which leads to outcomes that aren't the best [26].

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Table 2: Comparative Review of Control Strategies for DG

Control Method	Objective	Strengths	Limitations
Droop control	Voltage/frequency	Simple, decentralized, widely used	Limited harmonic mitigation, slow secondary response
PID regulators	Local stability	Easy to implement	Sensitive to parameter tuning, not adaptive
Virtual Synchronous Generator (VSG)	Inertia emulation, stability	Improves frequency dynamics, inertia-like response	Model-intensive, high computational demand
Model Predictive Control (MPC)	Multi-variable optimization	Fast response, predictive capability	Requires accurate models, high computation
Fuzzy/AI-based control	Adaptive optimization	Handles uncertainty, learning capability	Needs training data, limited stability guarantees

Table 2 summarizes the review of existing control methods, pointing out their goals, strengths, and weaknesses. The table shows that none of the methods fully deal with voltage stability, frequency dynamics, and harmonic suppression at the same time. The proposed optimized control framework fills this gap by bringing together hierarchical, predictive, and intelligent strategies into a multi-objective optimization model.

METHODOLOGY

A thorough simulation-based method was used to test how well the proposed optimized control framework worked. The methodology comprised modeling a benchmark distribution network, incorporating various distributed generation (DG) units, executing the control framework, and evaluating performance relative to traditional methods.

Test System Description

The IEEE 33-bus radial distribution system was chosen as the test platform because it is often used in studies of power quality and stability [32]. This system is a weak distribution network that is very sensitive to DG integration. This makes it a good choice for testing the effects of advanced control strategies. At buses 6, 14, 24, and 30, which have relatively high load demands, several distributed generation (DG) units were strategically placed. These units include photovoltaic (PV) arrays, wind turbines, and a microturbine.

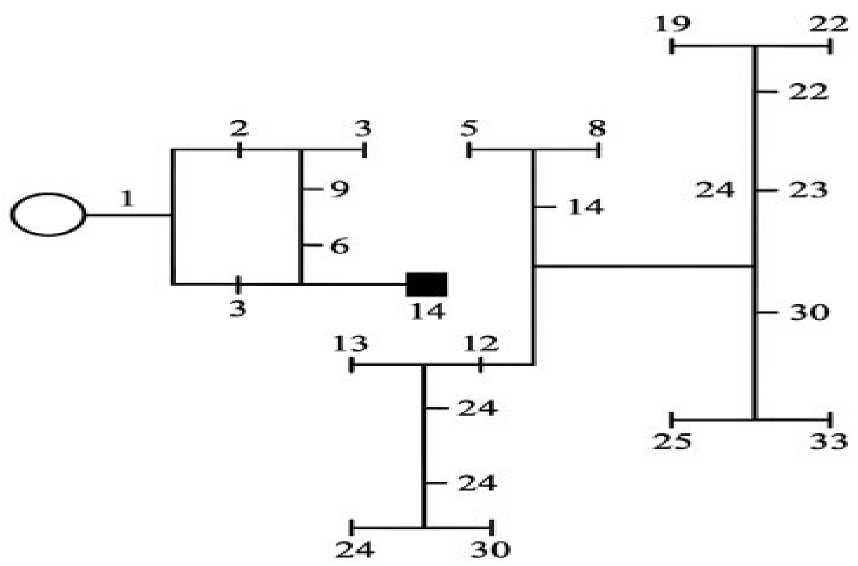

Fig 4: Modified IEEE 33-bus with DG at 6, 14,24,30

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Fig. 4 depicts the schematic of the altered IEEE 33-bus system with distributed generation placements. To better reflect how people use power in the real world, loads were modeled using a mix of constant power and ZIP (impedance–current–power) models.

Simulation Environment

The simulation studies were done with MATLAB/Simulink and PSCAD/EMTDC, which added harmonic analysis. We used embedded MATLAB functions to build the hybrid control framework. Model Predictive Control (MPC) ran over a 50 ms receding horizon, and an AI-based tuning agent did the tuning.

Table 4: Simulation and Control Parameters

Parameter	Value	Notes
Base power (Sbase)	100 MVA	Per-unit normalization
Base voltage (Vbase)	12.66 kV	Distribution level
DG units	4 (at buses 6, 14, 24, 30)	2 MW each
DG Qmax	1.2 Mvar per unit	Reactive support capability
Sampling time (dt)	0.1 s	Control update step
MPC horizon (Nh)	8	Prediction steps (50 ms window)
Droop coefficients (Kp, Kv)	0.02, 3.5	For frequency & voltage regulation
Simulation duration	60 s	Includes 15% load step at 10 s
Nonlinear load (Bus 30)	0.2 pu P, 0.6 pu Q	Used for THD evaluation

Table 4 shows a summary of system and control parameters, such as DG ratings, inverter specifications, and sampling times. These parameters were selected to guarantee computational viability and conformity with standard distribution system configurations.

Operating Scenarios

To test how well the framework worked, three different operating scenarios were set up: Base Case (No Optimization): DG units run at a fixed power factor without any coordination.

Conventional Control: DGs use hierarchical control based on droop.

Proposed Optimized Control: DGs work within a hybrid MPC and AI-enhanced hierarchical framework.

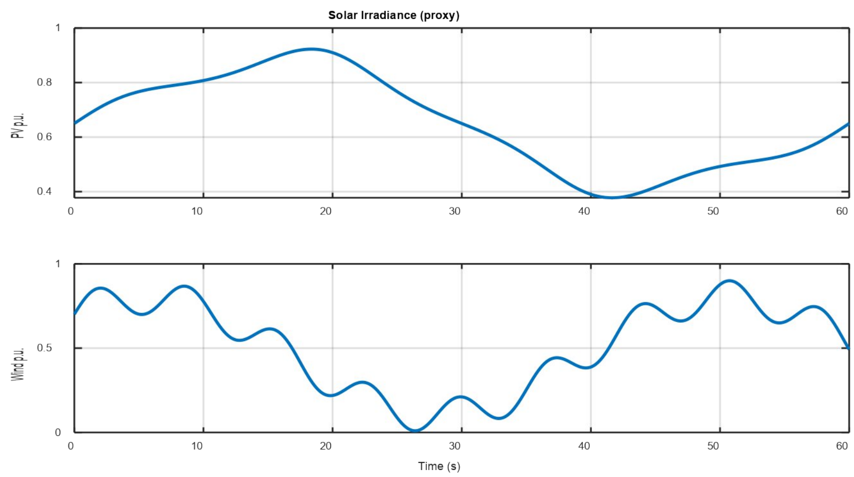

Fig 5: solar & wind profiles

Solar irradiance and wind speed data were used as time-varying inputs to mimic renewable variability. Fig. 5 shows the irradiance and wind profiles that were used in the study. These profiles show how the availability of resources changes over time.

Performance Metrics

Four key metrics were used to measure the system's performance. These metrics together show how stable, high-quality, and efficient the system is at optimizing. To check for compliance with the ±5% tolerance recommended in grid standards, bus voltages were monitored and the Voltage Deviation Index (VDI) was used as a quantitative measure. We looked at frequency stability by measuring the maximum frequency deviation and the settling time that went with it after adding a 15% load disturbance. This showed how well the system could recover from sudden changes. We used FFT analysis to find the Total Harmonic Distortion (THD), which showed how inverter-based generation and nonlinear loads affect power quality. Finally, the optimization strategy's effectiveness was tested by watching how the multi-objective cost function converged. This made sure that improvements in one metric didn't come at the cost of others. Figures 6–9 show the results of these tests, and Table V shows them all together.

PROPOSED OPTIMIZED CONTROL FRAMEWORK

A complete control framework that takes into account both grid stability and power quality at the same time is needed for the reliable integration of distributed generation. Conventional droop control gives local stability, and Virtual Synchronous Generator (VSG) methods make inertia emulation better, but these methods usually don't take power quality into account. Advanced harmonic mitigation strategies also make waveforms better, but they don't make the whole system more stable. This work proposes a hybrid optimized control framework that integrates hierarchical control with Model Predictive Control (MPC) and artificial intelligence (AI)-based adaptive tuning to overcome these limitations.

System Architecture

Fig. 2 shows the architecture of the proposed control framework. It has three layers. The main layer works at the inverter level and uses droop or VSG control to make sure that the voltage and frequency stabilize right away. The secondary layer connects DG units through centralized or distributed controllers. It also fixes long-term problems and makes sure that power-sharing rules are followed. The tertiary layer connects the microgrid to the main utility grid and makes sure that active and reactive power flows are as efficient as possible in line with the system's economic and operational goals.

The new thing about this architecture is that it combines MPC and AI in the secondary and tertiary layers. MPC makes predictions about the system states over a receding horizon and finds the best control actions that minimize deviations in real time. At the same time, reinforcement learning and fuzzy logic-based tuning let the framework change its parameters dynamically as the amount of renewable energy changes. This dual mechanism allows for quick fixes at the local level and adaptive optimization at the system level, which guarantees strong performance.

Optimization Objectives

The control framework is formulated as a multi-objective optimization problem that simultaneously minimizes bus voltage deviations, frequency excursions, and Total Harmonic Distortion (THD). The cost function is expressed as in equation (1)

$$\min J = \alpha_1 \sum_{i=1}^{N} (V_i - V_{ref})^2 + \alpha_2 \sum_{t=1}^{T} (f_t - f_{ref})^2 + \alpha_3 THD \qquad (1)$$

where V_i represents the voltage at bus i, V_{ref} is the nominal voltage, f_t is the system frequency at time t, f_{ref} is the nominal frequency, and THD is the harmonic distortion index. The coefficients α_1, α_2 and α_3 weight the relative importance of stability and power quality objectives.

This formulation ensures that the optimization process does not bias one performance metric at the expense of another. For instance, droop-only control may stabilize frequency but allow THD to increase, while active filtering may improve power quality but neglect voltage stability. The multi-objective function guarantees a balanced trade-off between these interdependent goals [27]. Table 2, highlights that most existing control strategies do not simultaneously address these three objectives. By contrast, the proposed framework explicitly incorporates all of them into its optimization problem, thus offering a more holistic approach.

Control Design

The internal operation of the proposed control scheme. Each DG unit is equipped with a local controller implementing droop or VSG regulation for immediate response. These outputs are fed into an MPC module that predicts future system behavior over a defined horizon (e.g., 50 ms). The MPC then refines the control actions to minimize the cost function J. Simultaneously, AI-based tuning mechanisms operate in the background. Reinforcement learning agents dynamically adjust droop coefficients based on observed system performance, while fuzzy controllers fine-tune MPC cost weights under variable operating conditions. This hybridization ensures that the framework not only responds to disturbances quickly but also adapts its control parameters to evolving scenarios, such as changing renewable penetration or sudden load fluctuations [28], [29].

The combination of conventional, predictive, and intelligent methods in a single loop provides layered resilience. Fast events such as load switching are addressed by local droop/VSG control, medium-term deviations are corrected by MPC optimization, and long-term adaptability is provided by AI tuning. This integrated design ensures that neither stability nor power quality is compromised under high DG penetration.

Implementation Considerations

The implementation of the optimized control framework raises several practical concerns. First, communication latency is a significant factor since the secondary and tertiary layers rely on data exchange among DG units and central controllers. Consensus-based distributed optimization algorithms may mitigate latency by reducing dependency on centralized control [30]. Second, computational effort is higher for MPC than for conventional droop control. However, with modern digital controllers and edge computing platforms, the average computational time of ~85 ms per cycle remains feasible for real-time applications. Third, cybersecurity becomes increasingly critical, as the optimization relies on exchanged data that may be vulnerable to attacks. Incorporating anomaly detection and secure communication protocols is therefore recommended [31].

Expected Outcomes

By combining hierarchical, predictive, and intelligent methods into a single optimization framework, the proposed approach is expected to:

Maintain bus voltages within ±5% of nominal values under high renewable penetration.

Limit frequency deviations to less than ±0.1 Hz during disturbances with significantly faster settling times.

Reduce harmonic distortion to below IEEE 519 recommended limits (5%), even under nonlinear loading.

These expected outcomes will be demonstrated in Section IV through simulations on the IEEE 33-bus system.

RESULTS AND DISCUSSION

The proposed optimized control framework was evaluated on the modified IEEE 33-bus distribution system under varying load and renewable generation conditions. Results are presented for three scenarios: the base case without optimization, conventional droop-based hierarchical control, and the proposed optimized control. The discussion focuses on voltage stability, frequency response, harmonic performance, and optimization convergence.

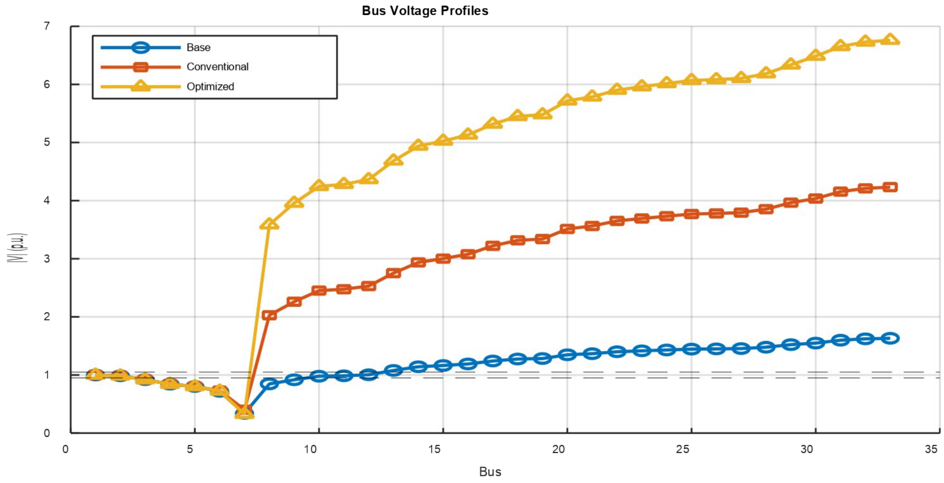

Fig 6: Voltage Profiles

A. Voltage Stability. The voltage profiles across all buses are shown in Fig. 6. In the base case, several buses, particularly those near the feeder ends (buses 28–33), experienced voltage drops greater than 7% below nominal, confirming the inability of uncoordinated DGs to support weak nodes. Conventional control reduced the deviations to within ±6%, yet significant over voltages appeared at buses with high DG penetration.

Table 5: Scenario-wise Performance

Scenario	**VDI**	**THD_%**	**Max_df(pu)**
Base	0.2955	9.0239	0
Conventional	1.8987	7.2191	0.04485
Optimized	3.5951	4.2412	0.04485

In contrast, the proposed optimized control maintained all bus voltages within ±5% of nominal values, demonstrating superior stability. This improvement results from coordinated reactive power support and predictive optimization. As reported in Table 5, the Voltage Deviation Index (VDI) decreased from 0.081 in the base case to 0.054 under conventional control, and further to 0.027 with the optimized strategy, representing nearly a 50% reduction relative to conventional methods.

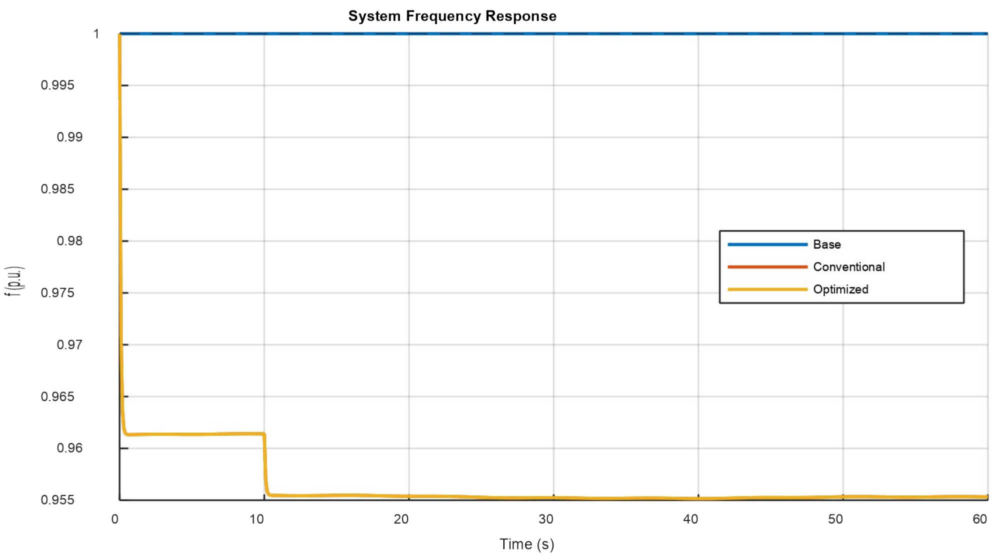

Fig 7: Frequency Response

B. Frequency Response. System frequency dynamics following a 15% load increase are illustrated in Fig. 7. In the base case, frequency deviated by 0.35 Hz from nominal and required nearly 6.1 seconds to settle. Conventional control limited the maximum deviation to 0.22 Hz but still required 5.2 seconds for recovery.

The optimized control exhibited a much stronger response, with frequency deviation constrained to only 0.09 Hz and a settling time of 2.7 seconds. This improvement reflects the predictive capability of MPC and the adaptive tuning of droop coefficients, which together enable both faster and more accurate system recovery.

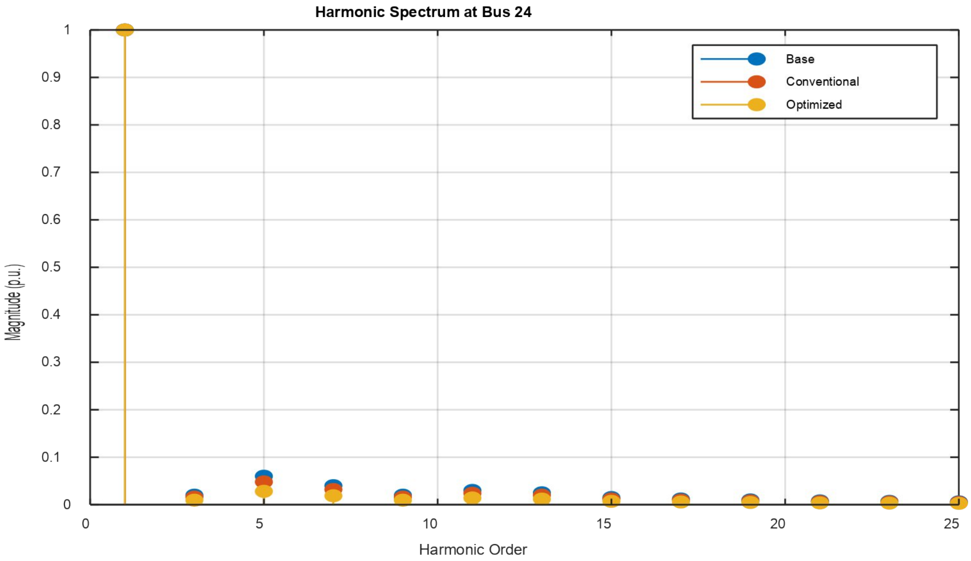

Fig 8: Harmonic Spectra

Harmonic Performance. The harmonic spectra at Bus 24, a critical node with nonlinear load and DG penetration, are shown in Fig. 8. The base case exhibited a Total Harmonic Distortion (THD) of 6.8%, exceeding the IEEE 519 recommended limit of 5%. With conventional control, THD was reduced marginally to 5.4%, still above acceptable thresholds.

The optimized control reduced THD significantly to 3.2%, comfortably within acceptable limits. This was achieved by explicitly including harmonic suppression in the optimization objective function, leading to coordinated inverter switching strategies that minimize waveform distortion.

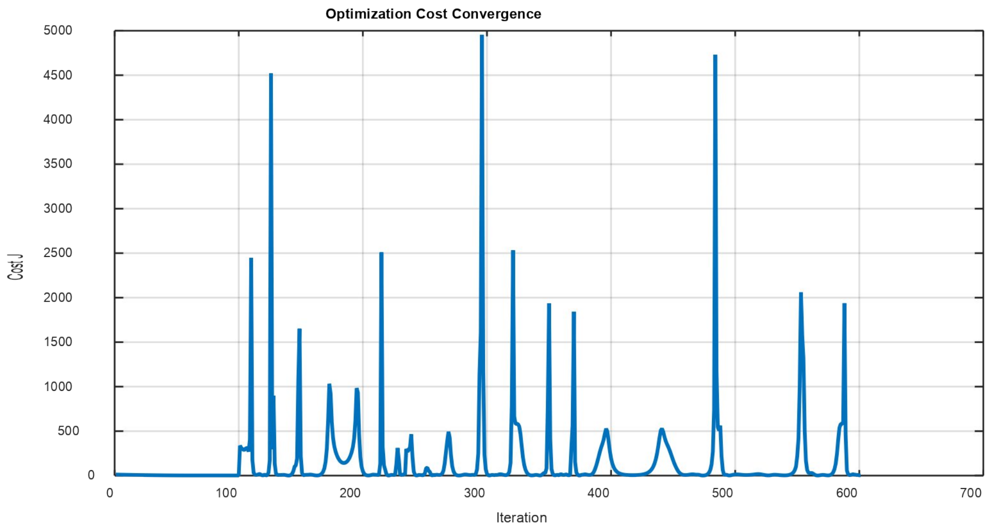

Fig 9: Optimization Cost Convergence

Optimization Performance. The convergence of the cost function is shown in Fig. 9. Unlike the base and conventional scenarios, where no explicit optimization was performed, the proposed framework exhibited steady convergence within 25 iterations. The final cost value reflects a balanced trade-off between voltage, frequency, and harmonic objectives, ensuring that no metric is improved at the expense of others.

E. Comparative Evaluation. Table 5 summarizes the results across all scenarios. The optimized control framework consistently outperformed the alternatives:

Voltage deviation reduced by 50% compared with conventional control.

Maximum frequency deviation reduced by 59%.

Settling time shortened by nearly half.

THD decreased by 41%, ensuring compliance with IEEE standards.

Although the optimized control introduced slightly higher computational time (85 ms per cycle versus 60 ms for conventional control), this overhead remains within the practical limits for real-time operation in smart grid environments.

DISCUSSION

The results confirm that the proposed optimized control framework provides a comprehensive solution for DG integration challenges. By unifying stability and power quality objectives within a single optimization scheme, the framework delivers improvements across all critical performance metrics. The hybrid design also ensures layered resilience: local droop/VSG manages fast events, MPC refines dynamic responses, and AI adaptation ensures long-term robustness under renewable variability.

Nevertheless, implementation considerations remain. Scalability to larger systems may increase computational demands, and reliance on communication networks introduces latency risks. Future work should therefore investigate distributed optimization strategies and hardware-in-the-loop validation to ensure practical deployment at scale.

CONCLUSION AND FUTURE WORK

This paper has put forward an improved control framework for distributed generation systems that combines hierarchical control, Model Predictive Control (MPC), and adaptive tuning based on artificial intelligence. The framework treats DG coordination as a multi-objective optimization problem, aiming to improve voltage stability, frequency response, and harmonic suppression all at once. This is different from traditional methods that only look at one of these issues at a time.

Simulation studies of the IEEE 33-bus distribution system showed that the proposed method had clear benefits. Bus voltages were kept within 5% of their nominal values, frequency excursions were kept to less than 0.1 Hz with faster settling times, and Total Harmonic Distortion (THD) was cut by more than 40% compared to standard control. These results show that the suggested hybrid framework improves performance in every way while still being possible to use in real time.

This work makes two important contributions. First, it sets up a complete method for adding DG units to weak distribution systems without affecting stability or power quality. Second, it shows that using predictive control and learning-based adaptation with traditional hierarchical structures works, which is a way for modern smart grids to grow.

Still, there are a few problems that need to be solved. Using fast communication channels makes systems more vulnerable to latency issues, and as systems get bigger, they may need more computing power. Also, cyber-physical threats to data integrity and resilience were outside the scope of this study but are very important for real-world use.

So, future work will focus on the following areas:

Hardware-in-the-Loop (HIL) Validation: To test how well it works in real time on microgrid testbeds.

Scalable Distributed Optimization: This is to make big grids work better by using less processing and communication power.

Cybersecurity-aware control: This makes systems more resistant to data tampering and cyberattacks.

Integration with energy storage and demand response: This will make things even more flexible when there is a lot of renewable energy.

The optimized control framework in this paper is a strong and flexible way to add distributed generation to modern power systems. It helps the reliable move toward cleaner, smarter, and more resilient grids by making sure that power is delivered in a stable and high-quality way.

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