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Mitigating Harmonic Distortion in Urban Distribution Networks Using Hybrid AI-Based Control Models

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Abstract

This study examines the escalating challenge of power quality degradation in contemporary urban electricity distribution systems, driven by rapid urbanisation, high penetration of nonlinear loads, and widespread deployment of power-electronic interfaces. The primary purpose is to critically evaluate existing harmonic mitigation approaches and to assess the suitability of hybrid artificial intelligence–based control models for managing harmonics under dynamic urban operating conditions. A structured review methodology was adopted, synthesizing theoretical foundations, industry standards, empirical studies, and recent advances in monitoring, modelling, and intelligent control. Particular attention was given to the interaction between harmonic phenomena, urban network complexity, and emerging digital infrastructures.

The analysis reveals that conventional mitigation techniques, including passive and active filtering strategies, remain technically effective but are increasingly constrained by static design assumptions, limited scalability, and reactive operational paradigms. In contrast, hybrid AI-based control models demonstrate superior adaptability by combining physics-based control structures with data-driven learning and optimisation. These models enable real-time harmonic detection, predictive compensation, and coordinated control across distributed urban assets, while also supporting resilience, cybersecurity, and governance requirements. Performance evaluation evidence indicates that successful implementation depends on robust data acquisition, computational efficiency, explainability, and alignment with regulatory frameworks, particularly in developing urban contexts.

The study concludes that intelligent hybrid control represents a transformative pathway for sustainable power quality management in urban distribution networks. It recommends the integration of adaptive AI controllers with advanced monitoring infrastructure, the evolution of standards toward performance-based compliance, and the development of institutional capacity to support secure and responsible deployment. Collectively, these measures provide a foundation for resilient, efficient, and future-ready urban electricity systems. The findings are relevant to utilities, regulators, researchers, and city planners seeking data-driven solutions for complex urban energy environments in worldwide contexts.

Keywords: Harmonic Distortion, Urban Distribution Networks, Hybrid AI Control, Power Quality Management, Smart Grids, Infrastructure Resilience

1. Introduction

Urban distribution networks are undergoing a profound transformation driven by rapid urbanisation, electrification of transport, the proliferation of power-electronic devices, and the increasing penetration of distributed energy resources. These developments have significantly altered the electrical characteristics of distribution systems, particularly through the widespread introduction of nonlinear loads such as electric vehicle chargers, variable-speed drives, switched-mode power supplies, and inverter-interfaced renewable generation. While these technologies enhance efficiency, controllability, and system flexibility, they also intensify harmonic distortion, posing serious challenges to power quality, equipment lifespan, and overall system reliability (Zenhom *et al*., 2024; Adefarati & Bansal, 2016) [54, 3]. In dense urban environments, where load diversity and network complexity are high, harmonic interactions can accumulate and propagate across feeders, substations, and customer installations, making mitigation increasingly difficult using conventional approaches (Farhangi, 2010) [15]. Harmonic distortion refers to the deviation of voltage and current waveforms from their ideal sinusoidal form due to nonlinear system behaviour. Excessive harmonics are associated with overheating of transformers and cables, increased technical losses, misoperation of protection and metering devices, and electromagnetic interference with communication systems (Akagi, 2017; Singh, Al-Haddad & Chandra, 1999) [4, 45]. Comprehensive treatments of power quality phenomena further emphasise that harmonic effects are often cumulative and spatially distributed, particularly in networks with high concentrations of nonlinear loads (Dugan *et al*., 1996) [11]. Regulatory frameworks such as IEEE Std 519-2014 establish recommended limits for harmonic levels; however, maintaining compliance in modern urban networks remains challenging due to rapidly fluctuating load conditions and decentralised generation (IEEE Power & Energy Society, 2014) [21]. These challenges are especially pronounced in developing economies, where infrastructure constraints and limited monitoring capabilities compound harmonic-related risks, as observed in Nigerian distribution networks with high penetration of nonlinear loads (Ogunyemi & Adetona, 2020).

Traditional harmonic mitigation techniques, including passive filters, active power filters, and hybrid filter configurations, have been widely deployed to address power quality issues. Although effective under relatively stable operating conditions, these methods often suffer from inherent limitations such as fixed tuning, susceptibility to resonance, high capital and maintenance costs, and reduced effectiveness under dynamic operating scenarios (Bollen & Hassan, 2011; Akagi, 2017) [7, 4]. Signal-processing-based analyses of power quality disturbances indicate that such static mitigation approaches struggle to cope with the non-stationary harmonic behaviour typical of contemporary urban grids (Bollen & Gu, 2006) [8]. As urban distribution systems become increasingly dynamic and data-rich, there is growing recognition that rule-based or fixed-parameter control strategies are insufficient for managing complex harmonic interactions in real time. This has motivated increasing interest in artificial intelligence (AI) and data-driven control approaches capable of adapting to changing network conditions and learning from historical and real-time data streams (Xu, Wang & Yang, 2020; Taghvaie *et al*., 2025 [48]).

Hybrid AI-based control models represent a promising paradigm for harmonic mitigation in urban distribution networks. These models combine the robustness and interpretability of classical control techniques with the adaptability and predictive capabilities of AI algorithms, including machine learning and optimisation-based intelligence. Recent studies demonstrate that intelligent controllers can dynamically adjust compensation strategies to improve harmonic suppression in distribution systems with high variability and uncertainty (Abbas *et al*., 2021) [1]. By leveraging high-resolution monitoring data, hybrid controllers can modify filter parameters, inverter switching strategies, and compensation schemes in response to evolving load and generation conditions, thereby enhancing power quality performance (Zahid *et al*., 2025) [53].

However, the effectiveness of such systems depends not only on algorithmic accuracy but also on the quality of decision-making frameworks that govern how AI outputs are interpreted and applied in operational contexts. Research on AI-driven decision-support systems indicates that performance gains are realised only when intelligent models are embedded within transparent, goal-oriented, and human-supervised decision architectures (Okafor *et al*., 2023) [35]. In harmonic mitigation applications, this implies that AI controllers should augment, rather than replace, engineering judgement, particularly in safety-critical urban power networks.

Explainable artificial intelligence (XAI) has therefore emerged as a critical enabler of trust and transparency in AI-assisted control systems. Ogbuefi *et al*. (2023) [32] argue that acceptance of AI in high-stakes environments depends on operators' ability to understand and interrogate algorithmic recommendations. Within the context of harmonic distortion mitigation, explainability is essential for enabling system operators to evaluate why specific control actions are proposed, especially when these actions affect regulatory compliance or involve trade-offs between competing operational objectives. Lack of transparency may lead to operator resistance or conservative overrides that diminish the benefits of AI-based control.

The deployment of hybrid AI-based control models also relies heavily on robust analytics engineering infrastructures. Obuse *et al*. (2023) [31] emphasise that effective operational decision-making requires end-to-end analytics pipelines capable of handling data acquisition, preprocessing, model execution, and real-time visualisation. In urban distribution networks, this necessitates the integration of smart meters, power quality analysers, communication networks, and digital control platforms. Inadequate analytics infrastructure can undermine even advanced AI models by introducing latency, data quality degradation, or integration failures.

Globally, these challenges are evident across both developed and developing power systems. While advanced economies face increasing complexity due to electrification and decentralisation, many African and other emerging economies contend with additional constraints related to ageing infrastructure, limited investment, and technical capacity gaps (Ogunyemi & Adetona, 2018) [34]. Nevertheless, reviews of intelligent power quality control indicate that AI-based approaches can deliver meaningful improvements even in constrained environments by optimising the use of existing assets and data (Wang *et al*., 2020) [50].

Against this backdrop, this study aims to review and synthesise existing research on mitigating harmonic distortion in urban distribution networks using hybrid AI-based control models. The objective is to examine the technical foundations, decision-making frameworks, and analytics infrastructures that underpin these approaches, with particular attention to explainability, adaptability, and operational feasibility. The study adopts a global perspective, with specific relevance to developing urban power systems in Africa, and focuses on how hybrid AI-based control can enhance power quality, regulatory compliance, and system resilience in increasingly complex urban distribution environments.

1.1 Evolution of Urban Distribution Networks

Urban distribution networks have evolved significantly over the past few decades in response to rapid urbanisation, technological advancement, and changing energy consumption patterns. Traditionally, distribution systems were designed as passive, unidirectional networks delivering power from centralised generation plants to end users. These networks were characterised by predictable load profiles, limited power electronics, and relatively simple protection and control schemes. However, contemporary urban environments now demand distribution infrastructures that are flexible, adaptive, and capable of accommodating diverse and rapidly changing electrical loads (Bollen & Hassan, 2011) [7].

The integration of distributed energy resources (DERs), such as rooftop photovoltaic systems, battery storage, and small-scale wind generation, has fundamentally altered the structure and operation of urban distribution networks. These resources introduce bidirectional power flows and increase the prevalence of inverter-interfaced devices, which significantly affect network dynamics. Adefarati and Bansal (2016) [3] note that while DERs enhance system resilience and sustainability, they also introduce new operational challenges related to voltage regulation, protection coordination, and power quality management. In dense urban settings, where DER penetration is often high, these challenges are magnified by limited network redundancy and space constraints.

Electrification of transport and the proliferation of power-electronic-based consumer devices have further accelerated the transformation of urban distribution systems. Electric vehicle charging stations, data centres, and smart buildings impose highly variable and nonlinear load profiles that differ substantially from traditional residential and industrial loads. As a result, urban networks are increasingly data-intensive and require advanced monitoring and control infrastructures to maintain reliable operation. This shift has driven the adoption of smart grid technologies, including advanced metering infrastructure, real-time sensors, and digital communication platforms, enabling more granular visibility and control over network conditions.

In developing economies, including many African cities, the evolution of urban distribution networks has occurred alongside persistent infrastructure limitations. Ogunyemi and Adetona (2018) [34] highlight that Nigerian distribution networks face the dual challenge of accommodating modern nonlinear loads while operating with ageing assets and limited investment capacity. This context underscores the need for intelligent, adaptive solutions that can enhance power quality and operational efficiency without extensive physical network upgrades. Consequently, the evolution of urban distribution networks has created a compelling case for hybrid AI-based control models capable of addressing emerging complexities, particularly harmonic distortion, in a scalable and context-sensitive manner.

1.2 Nature and Significance of Harmonic Distortion

Harmonic distortion arises in power systems when nonlinear devices draw currents that are not proportional to the applied sinusoidal voltage, resulting in waveform distortion and the presence of frequency components at integer multiples of the fundamental frequency. In modern urban distribution networks, the widespread use of power-electronic converters in consumer electronics, industrial drives, renewable energy interfaces, and electric vehicle chargers has significantly increased harmonic injection into the grid (Zenhom *et al*., 2024) [54]. Unlike traditional linear loads, these devices distort current waveforms even under normal operating conditions, making harmonics an inherent feature of contemporary power systems.

The significance of harmonic distortion lies in its wide-ranging technical and economic impacts. Excessive harmonics increase thermal stress in transformers, cables, and rotating machines, leading to accelerated ageing and reduced equipment lifespan. Akagi (2017) [4] explains that harmonics also contribute to additional power losses and can cause resonance phenomena that amplify distortion levels beyond acceptable limits. In urban networks with dense load concentrations, such effects can propagate across feeders and substations, affecting multiple customers and complicating fault diagnosis.

From a system operation and regulatory perspective, harmonic distortion directly influences compliance with power quality standards. IEEE Std 519-2014 establishes recommended limits for current and voltage harmonics to ensure acceptable power quality at the point of common coupling (IEEE Power & Energy Society, 2014) [21]. Failure to meet these limits can result in penalties, customer dissatisfaction, and increased operational costs for utilities. In smart city contexts, where critical infrastructure such as hospitals, data centres, and transport systems depend on high-quality power supply, the consequences of harmonic-related disturbances are particularly severe.

The growing significance of harmonic distortion has elevated it from a secondary power quality issue to a central concern in urban distribution planning and operation. As networks become more complex and dynamic, harmonics interact with other phenomena such as voltage fluctuations and unbalance, necessitating holistic and adaptive mitigation strategies. This complexity highlights the limitations of static approaches and reinforces the need for intelligent control frameworks capable of responding to real-time harmonic conditions.

1.3 Gaps in Conventional Harmonic Mitigation Strategies

Conventional harmonic mitigation strategies have historically relied on passive filters, active power filters, and hybrid configurations designed to suppress specific harmonic frequencies. While these solutions have proven effective in controlled and relatively stable environments, their limitations have become increasingly apparent in modern urban distribution networks. Passive filters, for example, are typically tuned to fixed frequencies and can suffer from detuning and resonance when network conditions change, reducing their effectiveness and potentially worsening harmonic distortion (Singh, Al-Haddad & Chandra, 1999) [45].

Active power filters offer greater flexibility by dynamically injecting compensating currents; however, their performance is highly dependent on accurate system modelling and fast control algorithms. In complex urban networks with variable loads and distributed generation, maintaining accurate models in real time is challenging. Bollen and Hassan (2011) [7] observe that conventional control schemes often struggle to cope with bidirectional power flows and rapidly changing harmonic profiles introduced by inverter-based resources. As a result, active filters may operate sub-optimally or require frequent retuning, increasing operational complexity and cost.

Another critical gap in conventional approaches is their limited scalability and adaptability in resource-constrained environments. In many African urban distribution systems, including Nigeria, utilities face constraints related to ageing infrastructure, limited monitoring, and insufficient technical capacity (Ogunyemi & Adetona, 2018) [34]. Deploying and maintaining sophisticated filtering hardware across widespread urban networks is often economically unfeasible. Moreover, traditional mitigation strategies generally operate in isolation, lacking the system-wide coordination required to address harmonics arising from multiple interacting sources.

These gaps highlight a fundamental mismatch between static mitigation technologies and the dynamic nature of modern urban distribution networks. Conventional strategies are largely reactive, addressing harmonic issues after they manifest rather than anticipating and adapting to changing conditions. This limitation underscores the need for hybrid AI-based control models that integrate real-time data analytics, adaptive learning, and coordinated control to overcome the shortcomings of traditional harmonic mitigation methods.

1.4 Motivation for Hybrid AI-Based Control Models

The increasing complexity of urban distribution networks has created a strong motivation for transitioning from conventional harmonic mitigation techniques to hybrid AI-based control models. Modern urban grids are characterised by high penetration of nonlinear loads, inverter-interfaced distributed energy resources, and rapidly fluctuating demand patterns. These factors introduce non-stationary harmonic profiles that vary across time and network locations, rendering static or rule-based mitigation approaches increasingly inadequate. Traditional controllers are typically designed around fixed system assumptions and deterministic models, which struggle to cope with the uncertainty and variability inherent in contemporary urban power systems (Zahid *et al*., 2025) [53].

Hybrid AI-based control models are motivated by the need for adaptive, data-driven decision-making capabilities that can respond dynamically to changing harmonic conditions. By integrating classical control methods with artificial intelligence techniques such as machine learning and deep learning, these models leverage both physical system knowledge and empirical data patterns. Taghvaie *et al*. (2025) [48] demonstrate that learning-based approaches can identify complex harmonic signatures and predict distortion trends with higher accuracy than conventional signal-processing techniques. When embedded within hybrid control architectures, such predictive capabilities enable proactive mitigation strategies that adjust compensation actions before harmonic levels exceed acceptable thresholds.

Another key motivation lies in the limitations of infrastructure and monitoring capabilities, particularly in developing economies. In many African urban distribution networks, including those in Nigeria, utilities operate under constraints such as ageing assets, limited real-time measurement, and restricted capital for extensive hardware-based mitigation solutions. Ogunyemi and Adetona (2018) [34] highlight that these constraints exacerbate power quality challenges and limit the scalability of traditional filtering technologies. Hybrid AI-based control models offer a pathway to enhance harmonic mitigation performance without proportionate increases in physical infrastructure, by maximising the value extracted from available data and existing control devices.

Furthermore, hybrid AI-based approaches support system-wide coordination and learning, which are essential in dense urban environments where harmonic sources interact across multiple feeders and substations. Unlike isolated mitigation devices, AI-enabled controllers can learn network-wide patterns, coordinate responses among distributed compensators, and continuously improve performance as operating conditions evolve. This learning capability is particularly valuable in urban grids undergoing rapid transformation due to electrification and decentralisation.

2. Harmonic Distortion in Urban Distribution Systems

Harmonic distortion has emerged as a defining power quality challenge in contemporary urban distribution systems, largely as a consequence of rapid technological transformation and increasing urban densification. Urban electricity networks are now characterised by high concentrations of nonlinear loads, including power-electronic converters, electric vehicle charging infrastructure, renewable energy inverters, and digitally controlled consumer appliances. These devices draw non-sinusoidal currents from the grid, resulting in voltage and current waveforms that contain frequency components at integer multiples of the fundamental frequency (Zenhom *et al*., 2024) [54]. Empirical studies of metropolitan power systems further show that the aggregation of such loads produces persistent and spatially distributed harmonic emissions that vary with time, usage patterns, and network configuration, making harmonic distortion a continuous operational challenge rather than an occasional anomaly (Dufour & Bélanger, 2014) [10].

The technical mechanisms through which harmonics affect urban distribution systems are well documented. Harmonic currents flowing through network impedances generate distorted voltage profiles that propagate across feeders and substations, often affecting large numbers of end users simultaneously. Akagi (2017) [4] explains that these distortions increase thermal stress in transformers, cables, and capacitors, accelerating insulation ageing and raising the probability of premature equipment failure. In densely populated urban areas, where network assets frequently operate close to their thermal limits, harmonic-induced losses can significantly degrade reliability and increase lifecycle maintenance costs. Additionally, harmonics interfere with sensitive electronic equipment and communication systems, which are increasingly embedded within smart city infrastructures and digitally managed public services (Meyer, Klatt & Schegner, 2011) [26].

From a system-level perspective, harmonic distortion undermines both the operational efficiency and regulatory compliance of urban utilities. IEEE Std 519-2014 establishes recommended limits for harmonic levels at the point of common coupling to ensure acceptable power quality for all connected users (IEEE Power & Energy Society, 2014) [21]. However, maintaining compliance is particularly challenging in urban networks characterised by heterogeneous load profiles, decentralised generation, and bidirectional power flows. Bollen and Hassan (2011) [7] observe that inverter-interfaced resources complicate harmonic assessment because dominant distortion sources may shift dynamically across time and network locations. Large-scale monitoring studies of European and Asian cities further confirm that static compliance assessments are insufficient for such environments, reinforcing the need for continuous monitoring and adaptive mitigation strategies (Ravi & Sathish Kumar, 2022) [41].

In developing urban contexts, the significance of harmonic distortion is amplified by infrastructural and institutional constraints. Nigerian distribution networks, for instance, experience high levels of nonlinear load penetration alongside ageing assets, limited automation, and sparse power quality monitoring infrastructure. Ogunyemi and Adetona (2018) [34] report that these conditions exacerbate voltage distortion, increase technical losses, and heighten the vulnerability of critical network components, resulting in frequent outages and reduced service quality. Similar patterns are observed across other African cities, where rapid urban growth outpaces investment in distribution infrastructure and power quality management. In such contexts, harmonic distortion constitutes not only a technical problem but also a socio-economic challenge, with direct implications for industrial productivity, public service delivery, and consumer confidence in electricity providers (Khalid *et al*., 2019) [23].

The increasing integration of smart city technologies further elevates the importance of understanding harmonic distortion within urban distribution systems. Smart lighting, intelligent transport systems, data centres, and digital public services rely heavily on power-electronic interfaces that both generate and are sensitive to harmonic disturbances. Okojie *et al*. (2023) demonstrate that predictive analytics can be used to assess infrastructure risk in complex urban environments, an approach that is directly transferable to power quality management. Treating harmonic distortion as a quantifiable infrastructure risk within broader urban analytics frameworks enables utilities to anticipate degradation trends, prioritise interventions, and optimise maintenance planning (Music *et al*., 2012) [28].

Harmonic distortion also intersects with emerging governance and sustainability agendas. Okojie *et al*. (2023) situate energy system performance within environmental, social, and governance (ESG) frameworks, highlighting the role of digital technologies in improving transparency and accountability. Persistent harmonic distortion can therefore be interpreted as a governance and compliance risk, reflecting inefficiencies, weak asset stewardship, and regulatory shortcomings within urban energy systems. Integrating harmonic monitoring indicators into ESG-oriented reporting structures strengthens regulatory oversight and supports evidence-based, sustainable urban energy planning (Pérez-Lombard *et al*., 2019) [40].

Recent advances in data-driven and AI-based techniques have enhanced the ability to characterise and manage harmonic distortion in complex urban networks. Deep learning models have demonstrated strong performance in identifying harmonic patterns and predicting distortion trends under variable operating conditions (Taghvaie *et al*., 2025) [48]. When combined with real-time analytics pipelines and distributed sensing infrastructures, these approaches enable utilities to transition from reactive fault-based responses to proactive power quality management strategies (Xu, Wang & Yang, 2020). Nevertheless, the effectiveness of such methods depends on a detailed understanding of urban harmonic behaviour, including interactions among multiple distortion sources, feeder topology, and load diversity.

Resilience considerations provide an additional lens through which harmonic distortion in urban distribution systems can be understood. Ogbuefi *et al*. (2025) [33] conceptualise resilience as the capacity of interconnected infrastructures to absorb disturbances while maintaining essential functions. Unmitigated harmonic distortion erodes this capacity by increasing component stress, narrowing operational margins, and accelerating asset degradation. In highly interconnected urban systems—where electricity underpins communication, transportation, healthcare, and emergency services—the cascading impacts of poor power quality can be severe. Effective management of harmonic distortion is therefore integral to enhancing the resilience, reliability, and sustainability of urban critical infrastructure systems.

2.1 Fundamentals of Harmonic Phenomena

Harmonic phenomena in power systems arise from nonlinear relationships between voltage and current, leading to waveform distortion and the presence of frequency components at integer multiples of the fundamental system frequency. In ideal power systems, voltage and current waveforms are purely sinusoidal; however, the widespread use of nonlinear devices in modern distribution networks disrupts this condition. Arrillaga and Watson (2003) [5] explain that when nonlinear loads draw current in a non-proportional manner relative to applied voltage, harmonic currents are injected into the network, which then interact with system impedances to distort voltage waveforms.

Harmonics are typically classified by their order, with lower-order harmonics (such as the 3rd, 5th, and 7th) generally having the most severe impact on system performance due to their relatively high magnitude and resonance potential. Zenhom *et al*. (2024) [54] note that triplen harmonics, which are odd multiples of the third harmonic, are particularly problematic in three-phase four-wire systems because they accumulate in the neutral conductor, leading to overheating and insulation stress. The severity of harmonic distortion is commonly quantified using indices such as Total Harmonic Distortion (THD), which provides a measure of waveform deviation from the fundamental component.

The behaviour of harmonics is strongly influenced by network topology and impedance characteristics. Akagi (2017) [4] highlights that resonance between network inductance and capacitance can amplify specific harmonic components, resulting in distortion levels far exceeding those produced by individual loads. In urban distribution networks, where cable capacitance and power-factor correction capacitors are prevalent, resonance conditions are more likely to occur. This makes harmonic phenomena highly location-specific and sensitive to changes in network configuration and loading.

From a regulatory and analytical standpoint, standards such as IEEE Std 519-2014 provide a framework for understanding acceptable harmonic limits and measurement practices (IEEE Power & Energy Society, 2014) [21]. However, these standards assume a level of system predictability that is increasingly challenged in modern urban grids. In developing contexts, including Nigeria, limited monitoring and modelling capabilities further complicate harmonic analysis, making it difficult to characterise distortion accurately (Ogunyemi & Adetona, 2018) [34]. Understanding the fundamental mechanisms of harmonic phenomena is therefore essential for designing adaptive mitigation strategies suited to complex urban environments.

2.2 Sources of Harmonics in Urban Power Networks

Urban power networks host a diverse array of harmonic sources, primarily driven by the increasing penetration of power-electronic-based technologies. One of the most significant contributors is consumer and commercial electronics, including computers, LED lighting, and uninterruptible power supplies, which employ rectifiers and switched-mode power supplies that generate characteristic harmonic currents (Zenhom *et al*., 2024) [54]. In dense urban settings, the cumulative effect of millions of such devices can result in substantial distortion even at medium-voltage levels.

Electric vehicle charging infrastructure represents another rapidly growing harmonic source. Fast chargers rely on high-power converters that introduce high-frequency and low-order harmonics into distribution networks. As urban electrification accelerates, the temporal clustering of charging activities further intensifies harmonic levels during peak demand periods. Taghvaie *et al*. (2025) [48] show that the stochastic nature of such loads complicates harmonic prediction and necessitates advanced detection techniques.

Distributed generation, particularly inverter-interfaced photovoltaic systems, also plays a critical role in harmonic generation. Bollen and Hassan (2011) [7] observe that while modern inverters are designed to meet harmonic standards individually, their collective interaction within urban feeders can lead to unexpected distortion patterns. Variations in inverter control strategies, switching frequencies, and grid conditions contribute to harmonic diversity and complexity.

Industrial and commercial facilities within urban areas introduce additional harmonic sources through variable-speed drives, arc furnaces, and welding equipment. In developing urban contexts such as Nigeria, inadequate enforcement of power quality standards and limited filtering at customer premises exacerbate the impact of these loads (Ogunyemi & Adetona, 2018) [34]. Akagi (2017) [4] emphasises that the multiplicity and interaction of harmonic sources in urban networks distinguish them from traditional radial systems, underscoring the need for coordinated and adaptive mitigation approaches.

2.3 Impacts of Harmonics on Urban Grid Performance

Harmonic distortion adversely affects urban grid performance across technical, economic, and operational dimensions. One of the most immediate impacts is increased thermal stress on network components. Harmonic currents increase copper and core losses in transformers, cables, and rotating machines, leading to overheating and accelerated insulation degradation (Akagi, 2017) [4]. In urban networks where assets often operate close to their thermal limits, these additional losses can significantly reduce equipment lifespan and increase failure rates.

Harmonics also degrade voltage quality, affecting sensitive loads and digital infrastructure common in modern cities. Distorted voltage waveforms can cause malfunction of control systems, data corruption, and nuisance tripping of protection devices. Singh, Al-Haddad, and Chandra (1999) [45] note that harmonics interfere with power-factor correction equipment and can induce resonance conditions that amplify distortion levels. Such phenomena are particularly problematic in urban feeders with extensive capacitive compensation.

From an operational standpoint, harmonics complicate system planning and regulatory compliance. IEEE Std 519-2014 defines acceptable harmonic limits, but persistent distortion increases the difficulty of maintaining compliance under varying load conditions (IEEE Power & Energy Society, 2014) [21]. In developing urban grids, limited monitoring infrastructure further constrains utilities' ability to detect and manage harmonic-related risks (Ogunyemi & Adetona, 2018) [34].

The economic impacts of harmonics include higher maintenance costs, increased technical losses, and reduced reliability for industrial and commercial customers. Zenhom *et al*. (2024) [54] emphasise that these costs are often underestimated, as harmonic-related degradation accumulates gradually. In urban environments that support critical services such as healthcare and transport, harmonic-induced disturbances can have far-reaching societal consequences.

2.4 Standards, Codes, and Compliance Challenges

Standards and codes play a central role in managing harmonic distortion and ensuring acceptable power quality in urban distribution systems. IEEE Std 519-2014 is the most widely referenced guideline, specifying recommended limits for current and voltage harmonics at the point of common coupling (IEEE Power & Energy Society, 2014) [21]. Complementary standards such as IEC 61000-3-6 provide methodologies for allocating harmonic emission limits among multiple users connected to medium- and high-voltage networks. Together, these frameworks establish technical benchmarks for design, operation, and compliance.

Despite their importance, applying these standards in modern urban networks presents significant challenges. Bollen and Hassan (2011) [7] note that traditional compliance approaches assume relatively stable network conditions and clearly identifiable harmonic sources. In contrast, contemporary urban systems feature dynamic load behaviour, bidirectional power flows, and multiple interacting distortion sources, complicating responsibility allocation and enforcement. As a result, utilities often struggle to determine whether non-compliance arises from specific customers, distributed generation units, or broader network interactions.

Compliance challenges are particularly acute in developing economies. In Nigeria, limited deployment of power quality monitoring equipment and weak regulatory enforcement hinder systematic compliance with harmonic standards (Ogunyemi & Adetona, 2018) [34]. Utilities may lack the technical and financial capacity to implement continuous monitoring or corrective measures, leading to persistent distortion levels that exceed recommended limits. Zenhom *et al*. (2024) [54] argue that such gaps undermine the effectiveness of standards and highlight the need for adaptive, data-driven compliance mechanisms.

As urban networks continue to evolve, standards must be interpreted and applied in conjunction with advanced monitoring and control technologies. Static compliance assessments are increasingly insufficient, reinforcing the case for intelligent systems capable of tracking harmonic performance in real time and supporting dynamic compliance strategies in complex urban environments.

2.5 Harmonic Measurement and Monitoring Technologies

Accurate measurement and continuous monitoring of harmonics are foundational to effective power quality management in urban distribution networks. Harmonic phenomena are inherently dynamic, varying with load behaviour, network configuration, and operating conditions. Traditional measurement approaches relied on periodic assessments using portable power quality analysers, which provided only snapshot views of harmonic conditions. While useful for diagnostic purposes, such methods are inadequate for modern urban systems where distortion levels can change rapidly due to stochastic load patterns and distributed generation (Arrillaga & Watson, 2003) [5].

Advances in digital measurement technologies have significantly improved harmonic monitoring capabilities. Modern power quality meters and intelligent electronic devices are capable of capturing high-resolution voltage and current waveforms and computing harmonic indices such as total harmonic distortion in real time. IEEE Std 519-2014 provides guidance on measurement locations, aggregation intervals, and interpretation of harmonic data, forming the basis for consistent monitoring practices across utilities (IEEE Power & Energy Society, 2014) [21]. In urban networks, these devices are increasingly deployed at substations, feeders, and critical customer connection points to enable granular visibility of harmonic propagation.

The integration of harmonic monitoring with smart grid infrastructures has further expanded analytical capabilities. Advanced metering infrastructure and communication networks allow continuous data streaming from distributed sensors to centralised or cloud-based analytics platforms. Xu, Wang & Yang (2020) note that such data-driven architectures enable utilities to move beyond threshold-based alarms towards predictive monitoring, where emerging harmonic trends are identified before they escalate into compliance violations or equipment damage. This shift is particularly relevant in urban environments with high load diversity and frequent operational changes.

Recent research has explored the use of artificial intelligence to enhance harmonic measurement and detection. Taghvaie *et al.* (2025) [48] demonstrate that deep learning models can extract harmonic features from noisy measurement data with greater robustness than traditional signal-processing techniques. These approaches are well-suited to urban networks, where measurement signals may be affected by electromagnetic interference and complex waveform interactions. When embedded within monitoring systems, AI-based detection algorithms can improve the accuracy and responsiveness of harmonic assessment.

Despite these advances, significant challenges remain in many developing urban networks. Ogunyemi and Adetona (2018) [34] highlight that limited deployment of advanced meters and insufficient data management infrastructure constrain harmonic monitoring in Nigerian distribution systems. Similar conditions exist in other African cities, where financial and institutional barriers limit large-scale instrumentation. Addressing these gaps is critical for enabling the data-driven and AI-assisted mitigation strategies required to manage harmonic distortion effectively in urban distribution networks.

2.6 Modeling and Simulation of Harmonics

Modeling and simulation play a critical role in understanding harmonic behaviour and evaluating mitigation strategies in urban distribution networks. Harmonic models provide a mathematical representation of nonlinear loads, network impedances, and their interactions, enabling engineers to analyse distortion propagation and resonance phenomena. Classical harmonic analysis techniques typically employ frequency-domain models, where harmonic sources are represented by current injections at specific frequencies (Arrillaga & Watson, 2003) [5]. These methods are computationally efficient and widely used for planning studies, but they assume steady-state conditions that may not reflect the dynamic nature of urban loads.

Time-domain simulation approaches address some of these limitations by capturing transient and non-stationary behaviour associated with power-electronic devices and switching events. Zenhom *et al.* (2024) [54] note that time-domain models are particularly useful for analysing interactions between harmonics, control systems, and protection devices. However, their application to large urban networks is often constrained by computational complexity and the need for detailed component models. As network size and heterogeneity increase, maintaining model accuracy becomes increasingly challenging.

The integration of distributed generation has further complicated harmonic modeling. Bollen and Hassan (2011) [7] observe that inverter-based resources introduce harmonics that depend on control algorithms, switching strategies, and grid conditions. Accurately modeling these effects requires a detailed representation of inverter dynamics, which may not be readily available due to proprietary designs. In urban environments with diverse inverter technologies, model uncertainty can significantly affect simulation outcomes.

Recent advances in data-driven and AI-based modeling offer new possibilities for harmonic analysis.Taghvaie *et al.* (2025) [48] demonstrate that machine learning models can learn complex harmonic patterns directly from measurement data, reducing reliance on detailed physical models. Such approaches are particularly attractive for urban networks where load behaviour is highly variable and difficult to characterise analytically. However, data-driven models require high-quality datasets and careful validation to ensure generalisability.

In developing urban systems, including those in Nigeria, limited access to accurate network data and modeling tools remains a major barrier (Ogunyemi & Adetona, 2018) [34]. Hybrid modeling approaches that combine simplified physical models with data-driven corrections may offer a pragmatic pathway, supporting the design of adaptive harmonic mitigation strategies suited to resource-constrained urban environments.

2.7 Urban-Specific Challenges in Harmonic Mitigation

Harmonic mitigation in urban distribution networks presents challenges that extend beyond those encountered in traditional radial systems. One defining characteristic of urban grids is their high load density and diversity, which results in multiple, interacting harmonic sources distributed across relatively short electrical distances. Zenhom *et al.*

(2024) [54] note that this proximity increases the likelihood of harmonic aggregation and resonance, making local mitigation measures insufficient to address system-wide distortion.

Urban networks are also characterised by frequent reconfiguration to accommodate maintenance, load growth, and fault management. Bollen and Hassan (2011) [7] highlight that such operational changes alter network impedance and harmonic propagation paths, potentially rendering fixed mitigation devices ineffective or even counterproductive. In this context, harmonic mitigation strategies must be adaptive and responsive to changing system conditions, a requirement that conventional passive solutions struggle to meet.

Socio-economic and institutional factors further complicate harmonic mitigation in many cities, particularly in developing regions. Ogunyemi & Adetona (2018) [34] show that Nigerian urban distribution systems face constraints related to ageing infrastructure, limited monitoring, and insufficient technical capacity. These challenges limit the feasibility of widespread deployment of advanced filtering equipment and reduce the effectiveness of regulatory enforcement. Similar issues are observed across other African urban centres, where rapid urbanisation outpaces investment in power quality management.

Urban harmonic mitigation is increasingly intertwined with broader smart city and sustainability agendas. Okojie *et al.* (2023) argue that predictive analytics can enhance urban infrastructure risk management, an approach that is directly applicable to power quality. Integrating harmonic mitigation within smart city platforms requires coordination across multiple stakeholders and infrastructures, increasing organisational complexity. From a resilience perspective, unmanaged harmonic distortion undermines the ability of urban systems to absorb disturbances and maintain critical services (Ogbuefi *et al.*, 2025) [33]. These urban-specific challenges underscore the need for hybrid AI-based control models capable of addressing technical, organisational, and contextual complexities simultaneously.

3. Conventional Harmonic Mitigation Techniques

Conventional harmonic mitigation techniques have long formed the foundation of power quality management in distribution networks. These approaches were originally developed for power systems characterised by relatively predictable load behaviour, unidirectional power flows, and limited penetration of power-electronic devices. In such environments, harmonics were commonly treated as localised disturbances that could be mitigated through dedicated compensation equipment installed at specific points in the network. However, the rapid transformation of urban distribution systems—driven by nonlinear loads, distributed generation, and network reconfiguration—has exposed both the enduring value and the inherent limitations of these traditional techniques (Arrillaga & Watson, 2003; Zenhom *et al.*, 2024; Dugan *et al.*, 1996) [5, 54, 11].

Passive filtering remains one of the earliest and most widely applied harmonic mitigation techniques. Passive filters typically consist of combinations of inductors, capacitors, and resistors tuned to specific harmonic frequencies. When deployed at strategic locations, they provide low-impedance paths for targeted harmonic components, thereby reducing distortion levels in the surrounding network. Singh, Al-Haddad, and Chandra (1999) [45] note that passive filters are relatively simple, cost-effective, and robust, making them attractive for industrial and commercial applications. However, their effectiveness is highly sensitive to system impedance variations, and detuning can occur as network conditions evolve. In urban distribution networks with frequent reconfiguration and variable load patterns, passive filters may introduce resonance phenomena that amplify harmonics rather than suppress them, particularly when multiple nonlinear sources interact (Rohouma *et al.*, 2020) [44].

Active power filters (APFs) were developed to overcome several limitations associated with passive solutions. APFs employ power-electronic converters to inject compensating currents that actively cancel harmonic components generated by nonlinear loads. Akagi (2017) [4] highlights that active filters offer superior adaptability and can respond dynamically to changing harmonic profiles, making them well-suited to environments with highly variable demand, such as urban commercial centres and mixed-use developments. Nonetheless, active filters are associated with higher capital and maintenance costs, increased control complexity, and sensitivity to measurement accuracy and control delays. Practical deployment studies indicate that these factors often constrain large-scale adoption of APFs in extensive urban networks, particularly where financial and technical resources are limited (Blaabjerg, Teodorescu & Liserre, 2011) [6].

Hybrid filter configurations combine passive and active elements in an effort to balance mitigation performance with economic feasibility. By assigning passive filters to handle dominant lower-order harmonics and using active filters to compensate residual or time-varying components, hybrid solutions seek to achieve improved harmonic suppression with reduced converter ratings (Singh, Al-Haddad & Chandra, 1999) [45]. Although hybrid filters offer enhanced robustness compared to purely passive systems, they continue to rely on predefined design assumptions and fixed coordination strategies. As a result, their effectiveness may deteriorate under rapidly changing urban load conditions unless frequent retuning or controller reconfiguration is undertaken (Guerrero *et al.*, 2014) [18].

Beyond filtering technologies, conventional harmonic mitigation also encompasses network-level measures such as phase balancing, transformer derating, feeder reconfiguration, and the strategic placement of shunt capacitors. These measures are typically implemented within distribution planning and asset management frameworks. Bollen and Hassan (2011) [7] observe that while such approaches can alleviate secondary harmonic effects—including overheating, voltage distortion, and neutral overloading—they do not address the root causes of harmonic generation. In urban networks with high penetration of inverter-based distributed generation, these indirect mitigation measures are increasingly insufficient when applied in isolation (Dulău, Abrudean & Bică, 2014) [12].

Monitoring and assessment play a critical supporting role in conventional harmonic mitigation frameworks. Utilities traditionally rely on periodic measurements and compliance checks against standards such as IEEE Std 519-2014 to identify harmonic issues and trigger corrective actions (IEEE Power & Energy Society, 2014) [21]. However, this approach is inherently reactive, as mitigation actions are initiated only after distortion exceeds acceptable thresholds.

In dynamic urban environments, where harmonic levels can fluctuate rapidly due to changing load behaviour and distributed generation output, delayed responses significantly reduce mitigation effectiveness and may allow cumulative equipment damage to occur (Ribeiro *et al*., 2012).

Recent advances in data analytics have begun to augment conventional mitigation strategies, even prior to the widespread adoption of fully AI-based control systems. Filani *et al*. (2022) [16] demonstrate how real-time risk assessment dashboards, supported by machine learning techniques, can enhance decision-making in complex operational systems. Although their work focuses on supply chain contexts, the underlying principles are directly transferable to power quality management. Real-time dashboards that visualise harmonic levels, temporal trends, and risk indicators can improve situational awareness and support more informed deployment of conventional mitigation devices in urban distribution networks.

Similarly, network analytics approaches provide methodological insights relevant to harmonic mitigation. Nnabueze *et al*. (2022) [30] show how network-based forecasting techniques can identify vulnerabilities and anticipate disruptions in interconnected systems. When applied to urban distribution networks, such methods can assist utilities in understanding how harmonics propagate through network topology and in identifying critical nodes where conventional mitigation measures may yield the greatest benefit. Nevertheless, these analytical enhancements do not fundamentally alter the static and reactive nature of traditional harmonic mitigation technologies.

In developing urban contexts, the limitations of conventional harmonic mitigation techniques are further accentuated by resource constraints. Ogunyemi and Adetona (2018) [34] report that Nigerian distribution networks face persistent challenges related to ageing infrastructure, limited monitoring coverage, and insufficient technical capacity, which restrict the deployment and maintenance of advanced filtering solutions. Under such conditions, utilities often depend on minimal or ad hoc mitigation measures, resulting in sustained power quality problems that negatively affect industrial productivity, service reliability, and customer satisfaction. These constraints underscore the growing need for more adaptive and intelligence-driven approaches capable of complementing or superseding conventional harmonic mitigation strategies.

4. Role of Artificial Intelligence in Harmonic Control

Artificial intelligence has emerged as a transformative enabler in the control and mitigation of harmonic distortion within modern urban distribution networks. The increasing penetration of nonlinear loads and inverter-interfaced resources has introduced levels of complexity that exceed the practical limits of traditional deterministic and model-based control methods. AI offers the ability to learn from large volumes of data, recognise complex nonlinear patterns, and adapt control actions in real time, making it particularly well suited to environments characterised by uncertainty, variability, and high-dimensional interactions (Xu, Wang & Yang, 2020). Recent global studies on intelligent power system operation further indicate that AI-based control frameworks are especially effective in distribution networks with high variability and limited observability, conditions typical of dense urban grids (Ozcanli, Yaprakdal & Baysal, 2020) [39].

One of the most significant contributions of AI to harmonic control lies in advanced detection and classification. Conventional harmonic analysis techniques rely heavily on fixed signal-processing algorithms, such as Fourier- and wavelet-based methods, which may perform poorly under noisy or non-stationary conditions commonly encountered in urban distribution systems. Taghvaie *et al*. (2025) [48] demonstrate that deep learning models can identify harmonic components with greater robustness and accuracy by learning directly from raw waveform data. Complementary research shows that convolutional and recurrent neural networks are particularly effective in capturing time-varying harmonic signatures, enabling early identification of emerging distortion patterns before regulatory thresholds are exceeded (Yu *et al*., 2021) [52]. Such capabilities support a shift from reactive mitigation towards predictive and preventive power quality management.

Beyond detection, AI plays a critical role in adaptive control and optimisation. Hybrid AI-based controllers integrate machine learning algorithms with classical control structures to dynamically adjust filter parameters, inverter switching strategies, and compensation schemes in response to changing system conditions. Zahid *et al*. (2025) [53] show that such hybrid architectures outperform conventional controllers under variable load scenarios by continuously updating control policies based on observed system behaviour. Similar findings from intelligent DSTATCOM and active filter studies confirm that reinforcement learning and adaptive neural controllers can significantly improve harmonic suppression in distribution networks with fluctuating loads and distributed generation (Gong & Lam, 2025) [17]. This adaptability is particularly valuable in urban environments, where load profiles can change rapidly due to electric vehicle charging, commercial activity, and renewable energy intermittency.

AI also enhances system-level decision-making by enabling predictive and risk-informed control strategies. Okafor *et al*. (2023) [35] emphasise that AI-driven decision-making frameworks deliver performance improvements only when aligned with clearly defined objectives and supported by reliable data pipelines. In harmonic control applications, predictive models can forecast distortion trends, evaluate the consequences of alternative mitigation actions, and support prioritisation of interventions that minimise operational risk and cost. Studies on intelligent grid management further show that such AI-enabled foresight improves coordination between local controllers and system operators, representing a fundamental shift from rule-based to intelligence-driven power quality management (Vargas *et al*., 2019).

The role of AI in harmonic control extends beyond algorithms to encompass the digital infrastructures required for reliable deployment. Secure, scalable, and auditable implementation of AI-based controllers is essential in safety-critical power systems. Adebayo *et al*. (2023) [2] provide a conceptual model for secure DevOps architectures that supports continuous integration, deployment, and monitoring of intelligent applications. In smart grid environments, comparable frameworks are required to ensure that AI control models can be validated, updated, and scaled without compromising system integrity or operational availability. International experience indicates that weak digital infrastructure and poor model governance are among the primary barriers to successful AI adoption in power system control (Lazaroiu *et al*., 2022) [25].

Cybersecurity and resilience considerations further shape the role of AI in harmonic control. As distribution networks become more digitised, AI-enabled controllers are increasingly exposed to cyber threats capable of disrupting sensing, communication, and control functions. Soneye *et al*. (2024) [47] highlight the importance of AI-augmented threat detection frameworks for protecting institutional networks, an insight directly transferable to smart grids. Integrating cybersecurity intelligence alongside harmonic control functions enhances the resilience of urban power systems and safeguards the reliability benefits promised by AI-driven automation (Hewett, Rudrapattana & Kijsanayothin, 2014) [20].

In developing urban contexts, AI offers particular advantages by enabling more efficient use of limited technical and financial resources. Nigerian distribution networks, for example, face persistent challenges related to ageing infrastructure, sparse monitoring coverage, and limited automation, all of which exacerbate harmonic distortion problems (Ogunyemi & Adetona, 2018) [34]. AI-based approaches can partially offset these constraints by extracting actionable insights from sparse or noisy data and optimising the operation of existing mitigation devices. Evidence from emerging economies suggests that data-driven control can deliver meaningful power quality improvements even in the absence of extensive physical upgrades (Renga *et al*., 2020) [42].

The integration of AI into harmonic control also builds on decades of experience with active filtering technologies. Akagi (2017) [4] and Singh, Al-Haddad and Chandra (1999) [45] document the evolution of active filters as flexible and effective harmonic mitigation tools. AI enhances these technologies by embedding adaptive intelligence that tunes control actions in response to real-time system conditions and long-term behavioural patterns. Rather than replacing established methods, AI augments them, giving rise to hybrid solutions that combine proven power-electronic hardware with advanced analytics and learning-based optimisation.

5. Hybrid AI-Based Control Models for Harmonic Mitigation

Hybrid AI-based control models for harmonic mitigation have gained increasing attention as a response to the limitations of purely model-based or purely data-driven approaches in complex urban distribution networks. Conventional controllers depend heavily on accurate mathematical models of system dynamics, which are difficult to maintain in environments characterised by nonlinear loads, distributed generation, and frequent operating changes. Conversely, standalone AI models, while adaptive, may lack stability guarantees and physical interpretability. Hybrid control models address these shortcomings by combining the robustness of classical control with the learning and adaptation capabilities of artificial intelligence.

A central motivation for hybrid approaches is their ability to embed physical system knowledge into learning-based frameworks. In power quality applications, classical controllers such as proportional–integral (PI), resonant, or model predictive control provide well-understood stability and performance characteristics. AI components, including neural networks or fuzzy logic systems, are then layered onto these controllers to compensate for modelling uncertainties and unmeasured disturbances. Nasyrov and Aljendy (2018) [29] demonstrate that hybrid fuzzy–PI controllers significantly improve harmonic compensation performance compared to fixed-parameter controllers by adapting control gains in real time based on system conditions.

In the context of active and distributed compensation devices, hybrid AI-based control has proven particularly effective. El-Habrouk, Darwish and Mehta (2000) [14] highlight that active power filters are inherently dependent on fast and accurate control strategies. Hybrid controllers enhance these systems by enabling dynamic reference generation and adaptive current tracking, which are essential in urban networks where harmonic profiles vary rapidly. By learning from historical and real-time measurements, AI-enhanced controllers can anticipate distortion trends and adjust compensation actions proactively rather than reactively.

Recent advances have integrated model predictive control with machine learning techniques to further enhance harmonic mitigation. Zhang, Wang and Xia (2021) show that neural-network-assisted model predictive controllers achieve superior performance in tracking harmonic references while respecting system constraints. Such hybrid architectures are particularly suitable for urban distribution systems, where multiple objectives—such as harmonic reduction, voltage regulation, and loss minimisation—must be balanced simultaneously under operational constraints.

Hybrid AI-based control models also offer advantages in scalability and transferability across different network contexts. Deng *et al*. (2024) [9] argue that combining data-driven learning with reduced-order physical models allows controllers to generalise across varying network topologies and load conditions. This capability is critical in urban environments, where feeders may serve mixed residential, commercial, and industrial loads with diverse harmonic characteristics. Hybrid controllers can be trained on representative datasets and then fine-tuned locally, reducing deployment complexity.

In developing economies, hybrid AI-based control provides a pragmatic pathway for improving power quality under resource constraints. Nigerian distribution systems, for example, face persistent harmonic challenges due to high nonlinear load penetration and limited monitoring infrastructure. Edafe and Nicholas (2024) [13] demonstrates that advanced control of DSTATCOM devices can significantly reduce current harmonics in such contexts. When augmented with AI-based adaptation, these solutions can further enhance performance without requiring extensive physical upgrades, making them attractive for rapidly urbanising regions across Africa.

Another strength of hybrid AI-based control models lies in their ability to support coordinated, system-wide mitigation strategies. Rather than operating as isolated local controllers, hybrid models can incorporate network-level information to coordinate multiple compensation devices. Mishra, Ghosh and Joshi (2012) show that intelligent control of distribution-level compensators improves overall voltage and power quality performance. Extending such frameworks with AI enables learning-based coordination that accounts for interactions among harmonic sources and mitigators distributed across urban networks

6. Performance Evaluation and Practical Considerations

Performance evaluation is a critical aspect of deploying advanced harmonic mitigation strategies in urban distribution networks, particularly when hybrid and AI-based control models are involved. Unlike conventional mitigation techniques, intelligent controllers operate under dynamic conditions and adapt their behaviour based on real-time data, making systematic and transparent evaluation essential for ensuring reliability, safety, and regulatory compliance. Effective performance assessment must therefore extend beyond static harmonic indices to include robustness, scalability, and operational resilience.

A primary dimension of performance evaluation involves quantitative power quality metrics. Traditional indicators such as total harmonic distortion, individual harmonic magnitudes, and voltage unbalance remain fundamental benchmarks for assessing mitigation effectiveness. However, in urban distribution networks with highly variable load profiles, these metrics must be evaluated over time and across multiple operating scenarios. Hafezi *et al.* (2016) [19] emphasise the importance of benchmark networks and scenario-based testing to capture the spatial and temporal variability of power quality phenomena. Such benchmarks enable comparative evaluation of control strategies under realistic urban conditions, including peak demand, distributed generation fluctuations, and network reconfiguration.

Dynamic performance and stability constitute another key evaluation dimension. Intelligent harmonic controllers interact with network dynamics, power-electronic devices, and protection systems, raising concerns about control interactions and transient behaviour. Classical stability concepts from power system engineering remain relevant in this context. Kundur (2007) [24] argues that any advanced control scheme must be evaluated for its impact on system stability margins, particularly under disturbances and parameter uncertainty. For AI-based harmonic mitigation, this implies testing controller responses to sudden load changes, faults, and communication delays to ensure that adaptive behaviour does not introduce oscillations or instability.

Practical deployment considerations also necessitate evaluation of data quality and signal processing performance. Harmonic monitoring and control depend on accurate, high-resolution measurements, which are often subject to noise, latency, and data loss in urban environments. Ribeiro *et al.* (2013) [43] highlight that signal processing techniques play a crucial role in extracting reliable harmonic information from measurement data. Performance evaluation must therefore assess how control algorithms perform under degraded data conditions, a particularly important issue in developing urban networks where sensor coverage and communication reliability may be limited.

Computational efficiency and scalability are additional practical considerations. Urban distribution networks can comprise thousands of nodes and devices, requiring control solutions that scale without excessive computational or communication overhead. Zhang, Dong, and Zhang (2020) show that intelligent controllers must balance performance gains against computational complexity, especially when deployed in real-time environments. Evaluation frameworks should therefore include metrics such as execution time, communication bandwidth usage, and controller convergence speed, ensuring that harmonic mitigation strategies remain feasible as network size and complexity increase.

From a socio-technical perspective, contextual factors strongly influence performance outcomes. In Nigerian urban distribution systems, for example, infrastructure ageing, limited automation, and constrained investment environments shape the practical effectiveness of advanced control strategies. Osamika *et al.* (2025) [38] demonstrate that power quality performance in such contexts is influenced as much by institutional and infrastructural factors as by control technology. Performance evaluation must therefore consider local operational realities, including maintenance capacity, operator expertise, and regulatory enforcement, to avoid overestimating achievable benefits.

Finally, alignment with broader smart grid objectives is an important practical consideration. Farhangi (2010) [15] argues that intelligent control technologies should be evaluated not in isolation but as components of integrated smart grid architectures. For harmonic mitigation, this means assessing how control models interact with voltage regulation, demand response, and asset management systems. Performance evaluation frameworks that incorporate these interactions provide a more holistic understanding of value creation and system impact.

7. Future Research Directions

Future research on mitigating harmonic distortion in urban distribution networks using hybrid AI-based control models must respond to the accelerating complexity of modern power systems, increasing decentralisation, and evolving governance expectations. One critical research direction lies in the development of distributed and privacy-preserving learning architectures for harmonic mitigation. As urban grids increasingly rely on data collected from geographically dispersed substations, feeders, and customer endpoints, centralised AI training approaches raise concerns related to data ownership, cybersecurity, and scalability. The concept of federated learning, as articulated by Soneye *et al.* (2025) [46], offers a compelling pathway for harmonic control research. By enabling local controllers at substations or feeders to train models collaboratively without sharing raw data, federated learning can support adaptive harmonic mitigation while preserving data privacy and reducing communication burdens.

Another important avenue for future investigation concerns the coordination of hybrid AI-based controllers in networks with high penetration of distributed energy resources. Adefarati and Bansal (2016) [3] and Bollen and Hassan (2011) [7] highlight that distributed generation fundamentally alters power flow patterns and harmonic interactions in distribution systems. Future research must therefore focus on multi-agent and cooperative control frameworks in which AI-enabled compensators and inverter controllers learn to coordinate their actions across urban networks. Such frameworks should explicitly address the interactions between harmonic mitigation, voltage regulation, and frequency support to avoid conflicting control objectives and unintended system responses.

The integration of advanced power-electronic hardware with intelligent control algorithms also warrants further exploration. While active harmonic filters remain a cornerstone of mitigation strategies, their future evolution depends on tighter integration with AI-based decision-making and optimisation mechanisms. Akagi (2017) [4] underscores the technical maturity of active filters but also points to the need for more adaptive and predictive control strategies. Research efforts should investigate how hybrid AI-based controllers can dynamically reconfigure filter topologies, switching strategies, and control parameters in response to real-time network conditions, particularly under high load variability typical of urban environments.

Standardisation and regulatory alignment represent another critical research frontier. Existing harmonic standards, such as IEEE Std 519-2014, were developed primarily for static compliance assessment and may not fully account for the adaptive behaviour of AI-driven control systems (IEEE Power & Energy Society, 2014) [21]. Future studies should examine how regulatory frameworks can evolve to accommodate intelligent, self-learning mitigation technologies while maintaining transparency, accountability, and safety. This includes the development of performance-based compliance metrics that reflect time-varying harmonic behaviour and the adaptive nature of hybrid control models.

Policy and governance dimensions are increasingly recognised as central to the successful adoption of AI in critical infrastructure. Kalu-Mba, Mupa and Tafireniyika (2025) [22] argue that AI innovation in the public sector requires clear policy guidance, risk management strategies, and institutional capacity building. Applied to urban energy systems, this perspective suggests that future research should extend beyond technical optimisation to examine governance models that support responsible AI deployment in harmonic mitigation. Topics such as algorithmic accountability, stakeholder engagement, and public trust are likely to influence the pace and scale of adoption in urban distribution networks.

Finally, future research must address the growing interdependence between power systems and other urban infrastructures. As cities evolve into tightly coupled socio-technical systems, harmonic distortion in electricity networks can have cascading effects on transportation, communication, and public services. Hybrid AI-based control models should therefore be studied within a broader resilience framework that considers cross-sectoral interactions and systemic risk. This aligns with emerging views that harmonic mitigation is not merely a power quality issue but a component of urban infrastructure resilience and sustainability.

8. Conclusion

The work presented offers a comprehensive and systematic response to the growing challenge of harmonic distortion in modern urban distribution networks, fulfilling its aims through a rigorous synthesis of technical, analytical, and governance-oriented perspectives. The study set out to examine the evolving nature of urban power systems, assess the limitations of conventional harmonic mitigation techniques, and evaluate the suitability of hybrid AI-based control models as a forward-looking solution. These objectives were met by progressively linking foundational harmonic theory with contemporary developments in monitoring, modeling, artificial intelligence, and urban infrastructure resilience.

Key findings demonstrate that harmonic distortion in urban networks is no longer a peripheral power quality issue but a structural consequence of load digitalisation, distributed generation, and dense power-electronic penetration. Conventional mitigation techniques—while technically sound—were shown to be increasingly constrained by their static design assumptions, limited adaptability, and reliance on reactive monitoring. In contrast, hybrid AI-based control models emerged as a robust and scalable alternative, capable of integrating physical system knowledge with data-driven intelligence to deliver adaptive, predictive, and context-aware harmonic mitigation. The analysis further highlighted that performance effectiveness depends not only on algorithmic accuracy but also on practical considerations such as data quality, computational scalability, cybersecurity, regulatory alignment, and local infrastructural capacity.

The study concludes that hybrid AI-based control models represent a decisive shift in how harmonic mitigation can be conceptualised and operationalised in urban distribution systems. Their ability to respond dynamically to changing conditions, coordinate distributed resources, and align with broader smart grid and resilience objectives positions them as a cornerstone technology for future urban energy systems. However, successful deployment requires deliberate attention to governance frameworks, standard evolution, and capacity building, particularly in developing urban contexts.

Based on these findings, the study recommends prioritising the development of adaptive, explainable, and secure AI-driven control architectures; investing in advanced harmonic monitoring infrastructure; and fostering regulatory frameworks that support intelligent, performance-based compliance. Collectively, these measures will enable more resilient, efficient, and sustainable urban power networks in the face of accelerating technological change.

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