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AI-driven UPQC control for dynamic power quality enhancement in railway transportation systems

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Abstract

Metro railway systems exhibit nonlinear and rapidly varying load characteristics, which can significantly affect the quality of electrical power supplied to the traction system. Variations in traction power demand, voltage fluctuations, harmonic distortion, and other disturbances can adversely affect the stability, efficiency, and reliability of railway power systems. To address these challenges, an artificial intelligence (AI)-based control strategy was applied to a Unified Power Quality Conditioner (UPQC) for power-quality improvement. Three advanced control approaches were developed and evaluated using MATLAB/Simulink: an Artificial Neural Network (ANN) controller, a Nonlinear Autoregressive-Moving Average with Exogenous Inputs (NARMA-L2) controller, and a Proportional-Integral (PI) controller optimized using the Adaptive Lizard Algorithm (ALA). Their performance was assessed primarily based on the reduction of total harmonic distortion (THD) in the source current. The results demonstrated that all three proposed AI-based control strategies significantly improved power quality compared with the uncompensated system. Among the investigated techniques, the ANN controller achieved the best performance, followed by the NARMA-L2 controller and the ALA-optimized PI controller. These findings demonstrate the potential of AI-based UPQC control for mitigating power-quality disturbances and improving the reliability and efficiency of modern metro railway traction systems. The study also highlights the importance of intelligent and adaptive control techniques for future railway power-quality management.

This paper investigates power-quality improvement in metro railway networks using an artificial intelligence (AI)-based Unified Power Quality Conditioner (UPQC) control strategy. Three advanced control schemes are developed and comparatively evaluated using the MATLAB/Simulink environment: **(i)** a Proportional-Integral (PI) controller optimized using the Adaptive Lizard Algorithm (ALA), **(ii)** a Nonlinear Autoregressive-Moving Average with Exogenous Inputs (NARMA-L2) controller, and **(iii)** an Artificial Neural Network (ANN) controller. The performance of these controllers is evaluated based on their ability to mitigate power-quality disturbances, particularly source-current total harmonic distortion (THD). The comparative analysis demonstrates the effectiveness of AI-based UPQC control techniques for improving power quality in metro railway systems.

Keywords: Metro Railways, Power Quality Unified Power Quality Conditioner (UPQC), Artificial Intelligence (AI) Control, Adaptive Lizard Algorithm (ALA)

The effectiveness of the proposed controllers is evaluated based on their ability to reduce the total harmonic distortion (THD) of the source current. The main contributions of the study can be summarized as follows:

1. Optimization of the PI controller: The PI controller parameters used for DC-link voltage regulation of the UPQC are optimized using the Adaptive Lizard Algorithm (ALA) to improve dynamic response and compensation performance.
2. Application of AI-based controllers: Advanced artificial intelligence techniques, including Artificial Neural Networks (ANN) and the Nonlinear Autoregressive-Moving Average with Exogenous Inputs (NARMA-L2) controller, are incorporated into the UPQC control system to enhance power-quality compensation.
3. Comparative evaluation: The performance of the proposed control strategies is investigated and compared to demonstrate the effectiveness of AI-based UPQC control in mitigating power-quality disturbances associated with metro railway traction systems.

Numerous studies have been conducted to address power-quality problems in modern railway transportation systems. Therefore, the Literature Review section presents and critically discusses relevant previously published research. The UPQC Controller Modeling section describes the

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configuration and control methodology of the proposed UPQC. The System Description section explains the metro railway power-supply system and its operating characteristics. The Results and Discussion section presents the simulation results and compares the performance of the proposed control strategies with previously reported methods. Finally, the Conclusion section summarizes the major findings and highlights potential directions for future research.

2. Literature Review

Several research studies have investigated advanced optimization and intelligent control techniques for improving the performance of Unified Power Quality Conditioners (UPQCs). One recent study introduced the Adaptive Lizard Algorithm (ALA) as an optimization technique for determining suitable PI-controller parameters for the DC-link voltage-control loop of an active filter [1]. The adaptive nature of ALA-based control can improve UPQC performance under varying load conditions and may therefore be suitable for the rapidly changing loads encountered in metro railway systems. The combination of optimization algorithms with intelligent control techniques provides an opportunity to exploit the advantages of different approaches and achieve improved power-quality (PQ) compensation.

Inadequate compensation performance can limit the effectiveness of UPQC systems, particularly when the load varies rapidly and exhibits nonlinear characteristics. Although the application of artificial intelligence (AI) in metro railway power systems is still relatively limited, existing studies demonstrate considerable potential. AI-based approaches have been investigated for predicting power-quality disturbances associated with railway traction loads [3] and for optimizing train schedules to improve energy utilization [9]. These studies indicate that intelligent algorithms can effectively address complex and dynamic operating conditions in railway transportation systems.

Neural-network-based control has also attracted considerable attention for power-quality improvement in railway systems. Conventional linear controllers, such as proportional-integral (PI) and proportional-integral-derivative (PID) controllers, may experience limitations when applied to highly nonlinear and rapidly changing systems. To address these limitations, the Nonlinear Autoregressive-Moving Average with Exogenous Inputs (NARMA-L2) model has been investigated for nonlinear dynamic-system identification and control [16]. Artificial Neural Networks (ANNs) are capable of learning complex nonlinear relationships from input-output data and can therefore provide effective approximations for nonlinear system modelling and control [17]. The combination of ANN-based system identification with NARMA-L2 control provides a potential framework for controlling nonlinear dynamic systems under varying operating conditions [8]. Typically, an ANN is trained using measured or simulated input-output data to identify the nonlinear system behaviour. Training procedures may involve back propagation and other learning algorithms. Once the nonlinear model has been established, the NARMA-L2 approach can be used to develop a suitable feedback-control strategy through techniques such as feedback linearization or inverse-system control [18].

Other intelligent-control approaches have also been investigated for power-quality compensation. Fuzzy-logic controllers have been applied to shunt active filters to improve voltage and current quality in complex distribution systems [19]. In addition, genetic algorithms and multi-objective optimization techniques have been employed to optimize UPQC configurations and control parameters for simultaneous voltage- and current-harmonic mitigation [20]. Evolutionary optimization methods have also demonstrated potential for improving the compensation performance of UPQC systems under different operating conditions [20].

The UPQC is particularly attractive for railway applications because it can simultaneously compensate voltage- and current-related power-quality disturbances [21]. However, its effectiveness strongly depends on the control strategy, especially when the system is subjected to rapidly changing metro-train loads [22]. Consequently, intelligent control methods such as neural networks and fuzzy-logic controllers have received increasing attention because of their adaptability to nonlinear and dynamic power-quality problems [22], [23]. Machine-learning techniques, particularly Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs), offer additional opportunities for power-quality monitoring, prediction, and optimization. Neural networks can be employed for dynamic control tasks such as adaptive reference-signal generation, harmonic detection, and compensation-current estimation.

Despite these developments, the application of AI-driven UPQC control specifically to metro railway power-quality problems remains comparatively underexplored. There is therefore a need for systematic investigation and comparison of different intelligent control strategies under realistic and rapidly varying railway traction-load conditions. This research addresses this gap by investigating ALA-optimized PI, NARMA-L2, and ANN-based UPQC controllers and comparing their effectiveness

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in reducing source-current THD and improving overall power quality in metro railway systems.

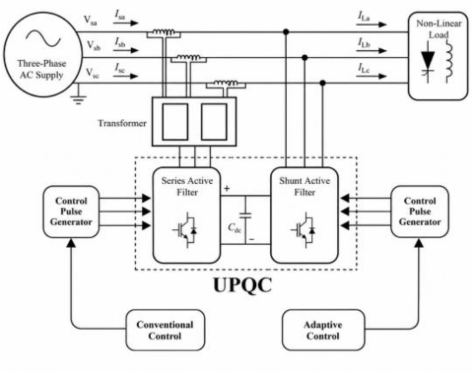

Figure 1. UPQC schematic diagram

AI-based techniques have demonstrated considerable potential for harmonic mitigation because they can accurately identify individual harmonic components and generate appropriate compensation references for active power filters and UPQC systems [27]. Similarly, AI-based controllers incorporated into UPQCs and Dynamic Voltage Restorers (DVRs) can provide rapid responses to voltage-sag and voltage-swell disturbances [28]. Intelligent methods can also improve reactive-power management and power-factor correction by dynamically determining the required compensation level, thereby improving energy utilization and potentially reducing distribution losses [29]

Modelling of series active power filter (SAPF)

A Series Active Power Filter (Series-APF) protects sensitive loads by injecting a voltage in line with the supply. Tis mitigates voltage sags and swells, ensuring a stable voltage. Its control system responds within 2–10 ms during oscillations. The Series-APF compensates for faults on other lines, restoring the load's voltage level pre-fault. A single vector model derived from the distorted supply forms the basis of the Series-APF design. Its primary functions include eliminating voltage sags/swells and reducing harmonic distortion. Figure 2 shows a block diagram depicting the configuration where the bus voltage (verb) is sensed and converted to a d-q reference frame for control as per Eq. (1) [30]

$$i_{pf(ref)}^{(ref)} = T_{rdqo}{}^{ref} \times \ i_{\mathrm{pf\ (dq0)}}{}^{(ref)} \quad (1)$$

$$Vt_{dq0} = T_{rdqo}{}^{ref} \times V_{\mathrm{tryb}} = V_{\mathrm{t1p}} + V_{\mathrm{t1n}} + V_{\mathrm{t10}} + V_{\mathrm{thd}} \quad (2)$$

V_{t1p}, V_{t1n}, V_{t10} and V_{thd} are frequency elements positive, negative, zero sequence elements and harmonic bus voltage.

$$V_{\mathrm{t1p}} = [V_{t1(\mathrm{p-d})}\ V_{t1(p-q)}\ 0\ ]^T \quad (3)$$

$$[V_{t1n} = \ V_{t1(n-d)} V_{t1(n-q)}\ o]\ T \quad (4)$$

$$V_{t10} = [0\ 0\ V_{t10}]^T \quad (5)$$

$$V_{thd} = [V_{t(h-d)} V_{t1(h-q)}\ Vt1_{(h-0)}\ ]^T \quad (6)$$

$$V_{\mathrm{Ldq0}}^{exp} = T_{\mathrm{ryb}}^{(\mathrm{ref})} \times V_{\mathrm{Lryb}}^{\mathrm{exp}} = \begin{bmatrix} Vm \\ 0 \\ 0 \end{bmatrix} \quad (7)$$

Compensating reference voltage is given as

$$V_{sfdqo}^{ref} = V_{\mathrm{tdq0}} - V_{\mathrm{Ldq0}}^{\mathrm{exp}} \quad (8)$$

Assume a balanced three-phase system and the desired load voltages are pure sinusoidal waveforms.

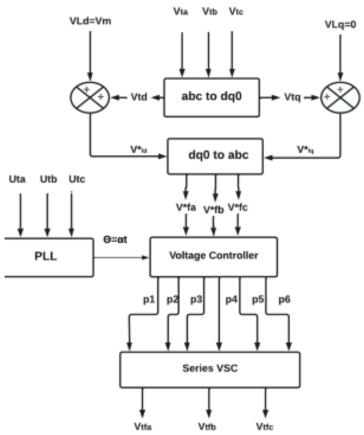

Figure 2. Control scheme of series compensator

Reference and Actual Load Voltages

$$V_{1pa} = Vm \times sin(\omega t) \quad (9)$$

$$V_{1pb} = Vm \times sin(\omega t - 120^0) \quad (10)$$

$$V_{1pb} = Vm\ \times sin(\omega t + 120^0) \quad (11)$$

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Where V_{lpa},V_{lpb}, and V_{lpc} are the desired load voltages on phases a, b, and c, Vm is the peak voltage amplitude.

$$V_{ac} = V_{1a} - V_{1pa} \tag{12}$$

$$V_{bc} = V_{\mathrm{lb}} - V_{\mathrm{lpb}} \tag{13}$$

$$V_{cc} = V_{lc} - V_{\mathrm{lpc}} \tag{14}$$

Power flow

$$P_{sr} = V_{\mathrm{lpa}} \times \mathrm{I}_{\mathrm{sha}} + V_{\mathrm{lpb}} \times I_{\mathrm{shb}} + V_{\mathrm{lpc}} \times I_{\mathrm{shc}} \tag{15}$$

Modeling of shunt active power filter (ShAPF)

Employing d-q theory, a shunt active power filter's control approach objectives the reactive component of load current (I_L) and targets to regulate the DC-link capacitor voltage, as shown in Fig. 3. This results in improved dynamic performance and reduced THD (39)

The control structure of the shunt compensator is shown in fig.3

$$i_{\mathrm{L(d-q)0}} = T_{\mathrm{(d-q)0}}\, r_{yb} \times i_{\mathrm{Lryb}} \tag{16}$$

Transformation values from equation (14)

$$T_{ryb}^{(d-q)0} = \frac{2}{3}\begin{bmatrix} \cos wt & \cos(wt - 120^0) & \cos(wt + 120^0) \\ \sin wt & \sin(wt - 120^0) & \sin(wt + 120^0) \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix}$$

(17)

Positive sequence component to dc values in d-q axis

$$i_{Ld} = \bar{\iota}_{Ld} + \hat{\iota}_{Ld} \tag{18}$$

$$i_{Lq} = \bar{\iota}_{Lq} + \hat{\iota}_{Lq} \tag{19}$$

Shunt VSC's d-q component elements

$$i_{pfd}^{r} = \bar{\iota}_{Ld} \tag{20}$$

$$i_{pfq}^{r} = \hat{\iota}_{Lq} \tag{21}$$

The feeder current of the d-q element is

$$i_{sd} = \bar{\iota}_{dL} \tag{22}$$

$$i_{pd}^{r} = \bar{\iota}_{Ld} + \Delta\, i_{dc} \tag{23}$$

$$i_{pfq}^{r} = \hat{\iota}_{Lq} \tag{24}$$

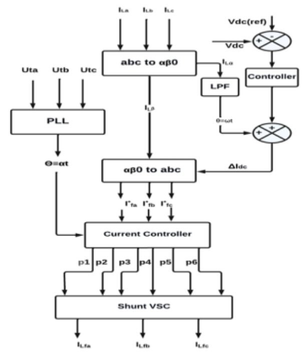

Figure 3. Control structure of shunt compensator

Controllers

This paper applies three controllers: a PI controller, a NARMA-L2 controller, and an ANN controller. Adaptive lizard algorithm used by PI controller. The Shunt active Power Filter uses a PI controller to regulate reactive power.

Reference reactive power (Qref) .This value is often set to zero to achieve a unity power factor and ensure most of the source current is used for real power transmission. Measured reactive power (Q) This value is calculated from the source voltage and current by using the p-q theory.

Error signal (e)

$$e(t) = Q_{ref} - Q(t) \tag{25}$$

PI Controller Output (u):

$$u(t) = Kp \times e(t) + Ki \times \int e(t)dt \tag{26}$$

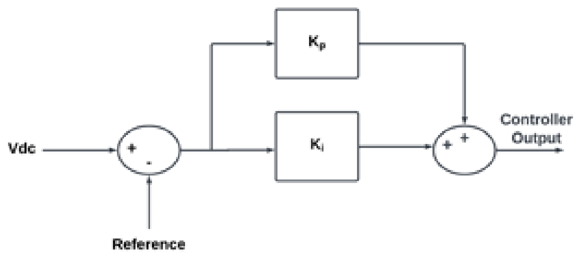

Figure 4. Schematic diagram of PI controller

This work employs the Adaptive Lizard Algorithm (ALA) to determine the optimal Kp and Ki parameters of the PI controller. The optimization

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aims to improve the overall system performance. Figure 5 shows the parameter flowchart of the ALA.

Name	K_p	K_i	Par limits	I_{nit}	T_s
Discrete PID controller	8	0.987	[1e6−1e6]	0	5.00E−06

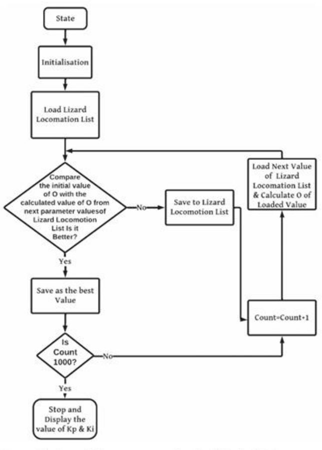

Figure 5. Flow chart to find the parameters using adaptive lizard algorithm (ALA)

Initially, the values of Kp and Ki are arbitrarily set to 8 and 0.9, respectively. The ALA technique systematically modifies these parameters in a step-by-step manner, without real-time interaction, to achieve the optimal mix, as shown in Table 2. The algorithm produces a value of 10 for Kp and 0.987 for Ki after doing the calculation. The reference value is 700. The method continues to iterate until it reaches 1000 iterations, which marks the conclusion of the optimization phase.

Quadrant	K_p	K_P
i	Reduce	Rise
ii	Rise	Rise
iii	Rise	Reduce
iv	Reduce	Reduce

Table1. $K_p$and K_i variations

This approach demonstrates the efficiency of utilizing bio-inspired optimization techniques to address complex control challenges 1000 iterations, which marks the decision of the optimization phase.

The AALF method employed to ascertain the optimal PI controller values for system performance without relying on a formula or manual adjustment.

$$D + A + S = 1$$

The priority coefficients assigned to each metric are 0.33 for settling time and rising time and 0.34 for % overshoot. ALA optimization is performed offline, lowering the computational load in real time. The ALA is attractive because of its simplicity and low computational requirements. Its offline implementation reduces processing time. Simulation results confirm its effectiveness and demonstrate its suitability as a promising optimization technique. The eigenvalue theorem is used to analyze the stability of the system. The AC source and AC bus are assumed to have a phase difference. The proposed model is validated through signal analysis of a small-scale power system using ALA-optimized parameters. ALA optimizes the PI controller parameters to improve the power-step response, voltage-loop bandwidth, and system stability. It provides a flexible and efficient alternative to conventional parameter selection.

NARMA-L2 controller

The NARMA-L2 controller converts nonlinear system dynamics into a simplified linear form using a neural-network model. In this work, it is applied to the shunt component of the UPQC to improve current quality by reducing harmonics and reactive-power imbalance. The d–q synchronous reference frame is used to simplify control and compensation. Figure 6 shows the complete NARMA-L2 control structure, including the reference model, controller, plant, feedback paths, and tapped delay lines (TDLs).

ANN controller

The ANN controller effectively handles the nonlinear and varying operating conditions of metro train power systems. It generates control signals for the UPQC shunt active filter to reduce current

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harmonics, compensate reactive power, and correct load unbalance.

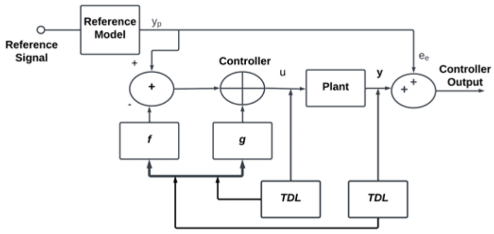

Figure 6. NARMA-L2 controller

The ANN consists of interconnected neurons arranged in layers, with adjustable synaptic weights. A back propagation algorithm is used to train the network by mapping error signals to appropriate control signals. The d–q reference frame is used for efficient control. The synchronous d–q reference frame simplifies three-phase signal analysis, enabling the ANN controller to effectively compensate harmonics and reactive power. Compared with conventional PI control, ANN offers better adaptability and faster response. Figure 7 shows the ANN-based UPQC control structure. Two ANNs are used: one extracts voltage harmonics for the series APF reference, while the other extracts current harmonics for the shunt APF reference. ANN consists of three layers.

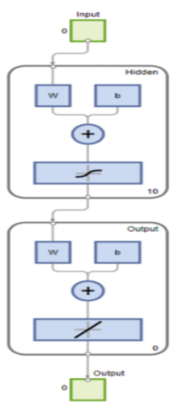

Figure 7. ANN controller

The ANN architecture consists of 20 neurons in the first hidden layer and 10 in the second. The networks are trained offline using the Levenberg–Marquardt algorithm with 10,000 field-data samples. The trained ANNs generate accurate harmonic reference signals for the series and shunt APFs. The AI-based controller then controls the switching states of the series and shunt VSCs while regulating the DC-link voltage. The proposed system includes a 25 kV traction power system, NPC-based UPQC inverters, and ANN-based reference generation.

The proposed system integrates AI-based control with a UPQC to improve power quality in a metro railway system. The major nonlinear loads include traction induction motors and power electronic converters used for motor control. These loads can produce harmonics and other power-quality disturbances. Accurate modeling of these nonlinear characteristics is therefore essential for designing effective UPQC compensation. Figure 8 shows the metro railway load, while Figure 9 presents the MATLAB/Simulink UPQC model for the OCS metro train system. System parameters are provided in Tables IV–VIII in the Appendix.

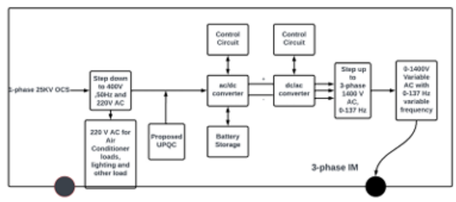

Figure 8. Proposed load model for metro rail supply system

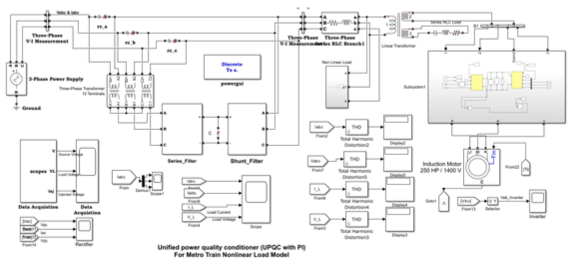

Figure 9. Complete MATLAB setup diagram of UPQC for OCS metro train load.

Nonlinear Loads in Metro Railway System

- **Traction Load:** The three-phase induction motor provides traction for the metro train. Its nonlinear magnetic characteristics can contribute to power-quality disturbances.
- **Power Converter:** PWM inverters and variable-frequency converters used for motor control generate harmonic currents, including 5th, 7th, and 11th harmonics.
- **Auxiliary Loads:** On board auxiliary systems such as SMPS units and rectifiers

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also introduce nonlinear currents and harmonics.

- **Variable Voltage Supply:** The power converter provides a 6–1600 V variable AC supply at 50–60 Hz to the three-phase induction motor. This variation enables speed and torque control but also introduces nonlinearities and power-quality disturbances into the system.

Simulation Parameters

The Three-Phase Programmable Voltage Source (TPPVS) is set to 400 V line-to-line and 50 Hz, with a simulation duration of 1 s. Harmonics are introduced during 0.3–0.4 s and 0.5–0.6 s. The MATLAB/Simulink ode23tb solver is used with a relative tolerance of 1e−6, refine factor of 1, maximum order of 5, and zero-crossing detection enabled. These settings provide accurate and stable simulation of the moderately stiff system dynamics.

These parameters control the accuracy and efficiency of the variable-step solver. The implicit **ode23tb** solver is suitable for accurately simulating the moderately stiff dynamics of the proposed system.

The simulation parameters provide a suitable balance between accuracy and computational speed for the UPQC model. A low relative tolerance improves numerical accuracy, while the implicit solver effectively handles system stiffness. The three-phase series RL branches use equal values of(R = 1Ω and C = 1mH.The shunt active filter consists of a hysteresis-band controller, a three-phase IGBT/diode inverter with a DC voltage source, and a compensating-current calculation block with unity gains. The series active filter consists of a three-phase transformer for voltage injection, a series RL branch, and a UPQC controller with a discrete three-phase PLL and unity gain.

Control of DC link

The DC-link voltage Vdc is continuously measured and compared with its reference Vdc*.The resulting error is processed by the PI controller to generate the reference current isp(n). A limiter ensures sufficient active power is supplied to both the load and the UPQC DC bus. Thus, the DC link is self-supported by a portion of the source active power and provides energy support to the series and shunt inverters.

Results and Discussion

The proposed AI-based UPQC controllers were evaluated in MATLAB/Simulink under different power-quality disturbances in the metro railway system. The main performance indicator was the Total Harmonic Distortion (THD) of the source current. A sampling time of (Ts) of 5.00E−06 s (5 microseconds) was used for the discrete three-phase PLL in the UPQC control subsystem, as listed in Table VIII.

THD Performance Comparison

Figure 10 show the uncompensated metro railway system, where the source current THD reached 19.74%. The high harmonic distortion indicates poor power quality and can increase losses, heating, and reduce system efficiency.

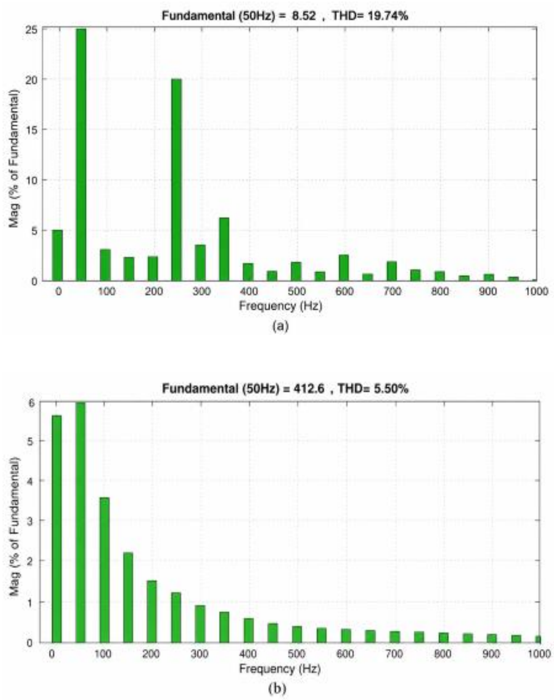
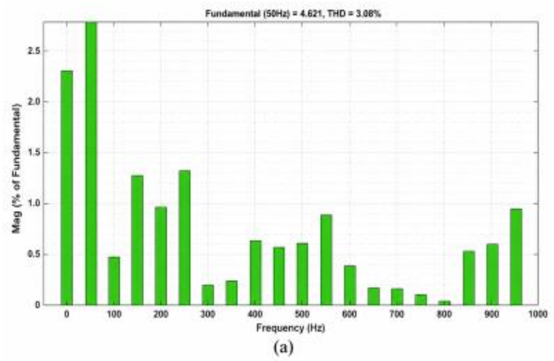


Figure10. (a) Uncompensated source current THD (b) Uncompensated load voltage THD

PI Controller Optimized Using Adaptive Lizard Algorithm Figure 11. Shows the performance of the ALA-optimized PI controller. The source current THD decreased to 3.08%, demonstrating effective harmonic reduction and improved power quality through optimized controller parameters.



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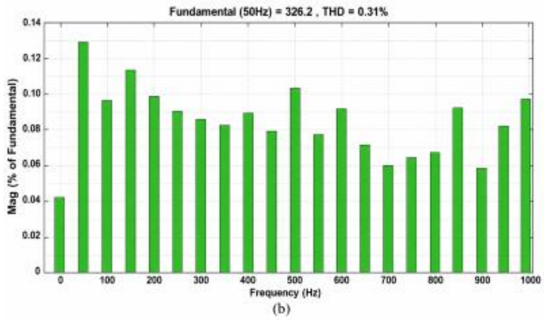

Figure 11. (a) Source current THD PI controller with adaptive lizard algorithm (b) Load voltage THD PI controller with adaptive lizard algorithm

NARMA-L2 Controller

The NARMA-L2 controller further improved the system performance, reducing the source current THD to **2.02%**, as shown in Figure 12. Its ability to handle nonlinear system dynamics provided better compensation than the optimized PI controller.

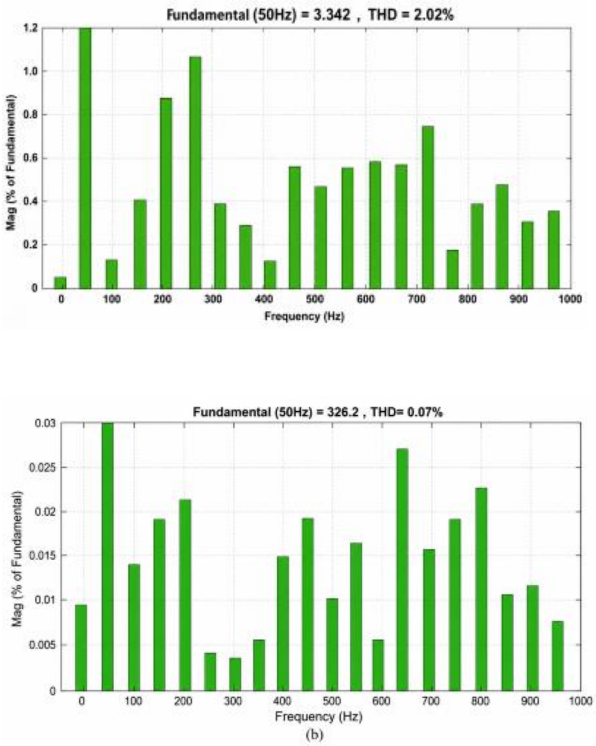

Figure 12. (a) Source current THD with NARMA-L2 controller. (b) Load voltage THD with NARMA L2 controller

ANN Controller

Figure 13 presents the ANN-based UPQC performance. The source current THD was reduced to 1.51%, giving the best result among the three controllers. The ANN effectively learned the nonlinear characteristics of the metro railway load and provided improved harmonic compensation.

Results and Discussion Based on Voltage and Current Profiles

The AI-based UPQC controllers were evaluated in MATLAB/Simulink based on voltage sag/swell compensation, current quality, and response time. The Series Active Power Filter (SAPF) effectively injected compensating voltage to maintain the required load voltage.

The ALA-optimized PI controller compensated the voltage sag occurring from 0.3–0.4 s and voltage swell from 0.5–0.6 s, as shown in Fig. 14. The compensating voltage restored the load voltage to its desired level. The NARMA-L2 controller further improved sag and swell compensation, as demonstrated in Fig. 16.

Voltage Swell Mitigation

The ANN-based UPQC effectively mitigates the voltage swell occurring from **0.3–0.4 s**, maintaining a stable load voltage. Figure 16 shows the system response and the injected compensating voltage during both sag and swell conditions, demonstrating the effectiveness of the ANN controller.

Injected Voltage during Sag/Swell

Figure 17 shows the injected compensating voltage during voltage sag and swell conditions using the ANN-based UPQC controller.

Compensating Current

The Shunt Active Power Filter (ShAPF), controlled by AI-based strategies, injects compensating currents to reduce current harmonics, reactive power, and load unbalance, thereby improving overall power quality.

(i) The PI controller optimized using the Adaptive Lizard Algorithm (ALA) effectively reduced the source-current THD. Figure 17 presents the source, load, and compensating current waveforms obtained with the ALA-optimized PI controller. Before compensation, the source current exhibited a THD of **19.74%**. After UPQC compensation, the THD was reduced to **3.08%**, demonstrating significant improvement in power quality. The compensating current effectively mitigated the current harmonics and improved the source-current waveform.

The **NARMA-L2 controller** provided further improvement, reducing the source-current THD to

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2.02%. Figure 18 illustrates the source, load, and compensating current waveforms obtained with the NARMA-L2-based UPQC controller.

(ii) The **ANN controller** achieved the best performance, reducing the source-current THD to 1.51%. Figures 19 and 20 present the corresponding source, load, and compensating current waveforms after compensation. Compared with the ALA-optimized PI controller, the ANN controller reduced THD by approximately 50.97%, while achieving a 25.25% reduction compared with the NARMA-L2 controller. These results demonstrate the superior harmonic-compensation capability of the ANN-based UPQC controller.

Response Time

Fast response is essential for effective power-quality compensation. The Series-APF control system responds within approximately **2–10 ms** during power-quality disturbances.

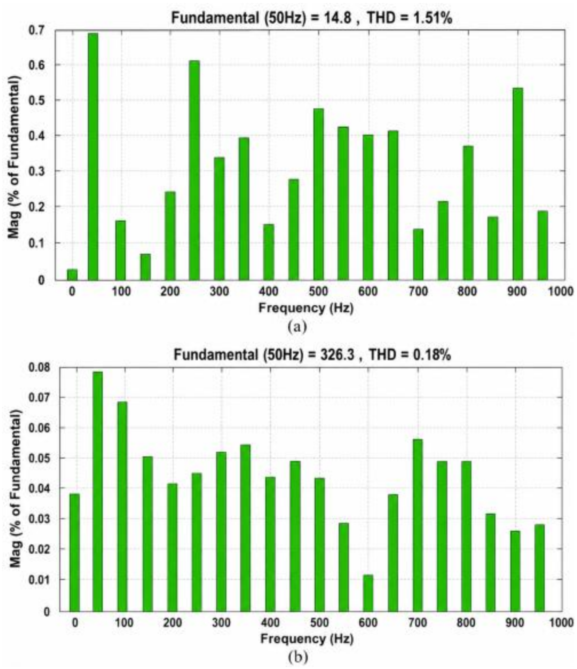

Figure 13. (a) Source current THD with ANN controller. (b) Load voltage THD with ANN

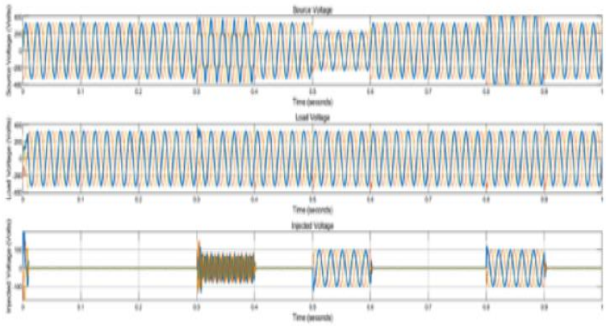

Figure 14. Simulation results of (a) source voltage, (b) load voltage (c) injected voltage during sag/ swell with PI-ALA controller.

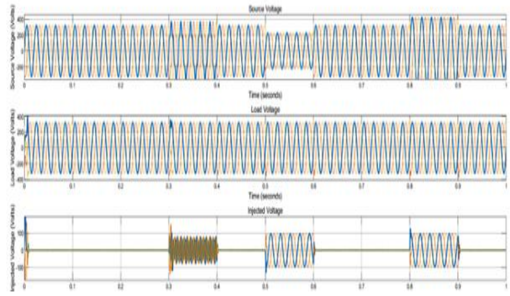

Figure 15. Simulation results of (a) Source voltage, (b) load voltage during sag/swell, (c) injected voltage during sag/swell with NARMA-L2 controller.

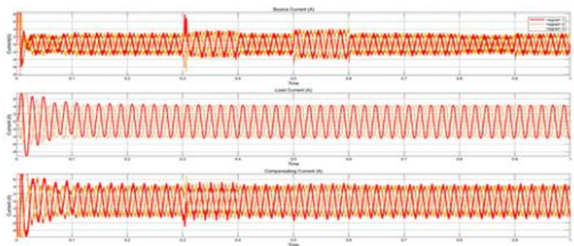

Figure 16. Simulation result of source voltage, load voltage, and injected voltage during sag/swell with ANN controller

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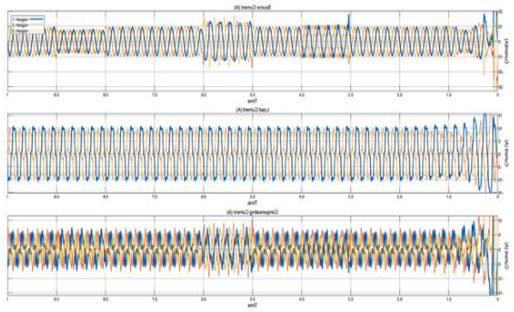

Figure 17. Simulation results of source current, load current and compensating current.

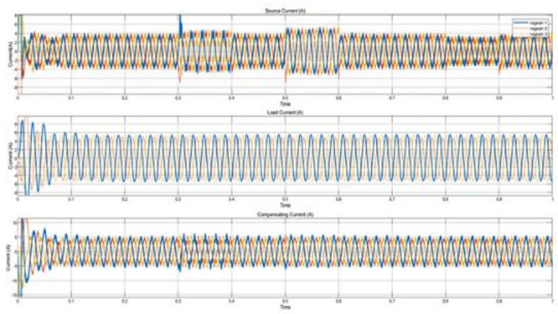

Figure 18. Simulation results of source current, load current and compensating current respectively

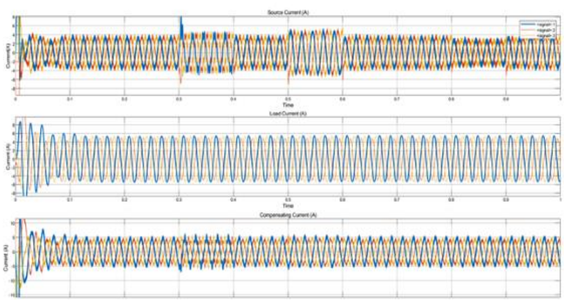

Figure 19. Simulation result of source current, load current and compensating current

The PI controller optimized using the Adaptive Lizard Algorithm (ALA) achieved a response time of 5 ms, while the NARMA-L2 and ANN controllers achieved 10 ms and 2 ms, respectively. As shown in Table 3 and Fig. 20, the ANN controller provided the fastest and most effective response, followed by the ALA-optimized PI and NARMA-L2 controllers. These results confirm the potential of AI-based UPQC control for improving power quality and reliability in metro railway systems. Future research can focus on advanced AI algorithms and the integration of UPQC with renewable energy sources for efficient and sustainable power-quality management. Controllers Parameters.

Controllers	Parameters			
	Source current THD (%)	Load voltage THD (%)	Source current THD (%) Hina Mahar et al.36	Load voltage THD (%)Hina Mahar et al.36
Uncompensated	19.74	5.50	23.76	14.27
Adaptive Lizard Algorithm with PI controller	3.08	0.31	8.63	3.61
NARMA-L2	2.02	0.07	NA	NA
ANN Controller	1.51	0.18	2.87	0.71

Table 3. Performance comparison of THD

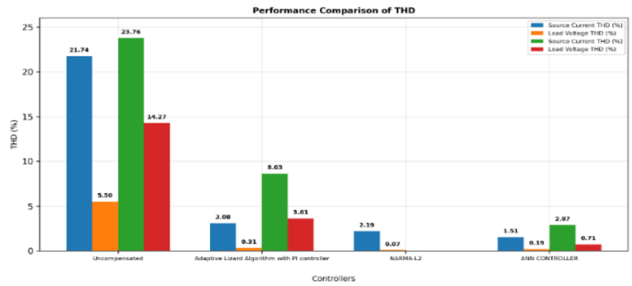

Figure 20. Performance analysis of comparisons of THD.

Conclusion

This study investigated AI-driven control strategies for a Unified Power Quality Conditioner (UPQC) to improve power quality in metro railway networks. Three control techniques—ALA-optimized PI, NARMA-L2, and ANN—were evaluated based on their ability to reduce source-current THD. The ANN controller achieved the best performance, reducing THD from 19.74% in the uncompensated system to 1.51%. The NARMA-L2 and ALA-optimized PI controllers achieved THD values of 2.02% and 3.08%, respectively.

The results confirm that AI-based UPQC control can significantly mitigate power-quality disturbances and improve the reliability and dynamic performance of metro railway systems. Future work should focus on validating the proposed controllers in practical metro systems and investigating advanced techniques such as reinforcement learning and deep learning to improve robustness, scalability, and real-time performance. Integrating UPQC systems with renewable energy sources in metro railway networks can further enhance power quality while supporting sustainable transportation. Future research should focus on practical validation of the proposed AI-driven UPQC controllers in real metro systems to assess their scalability, robustness, reliability, and cost-effectiveness under varying operating conditions. Advanced AI techniques, including reinforcement learning and deep learning, can also be explored to improve real-time control

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performance. Furthermore, collaboration among electrical engineers, AI researchers, and urban planners can facilitate the development of robust and innovative power-quality solutions that support smart-city infrastructure and public safety. Thus, practical validation, renewable-energy integration, advanced AI techniques, and interdisciplinary collaboration represent important directions for future development of intelligent power-quality management in modern transportation networks.

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