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Application of artificial intelligence for optimal control of reactive power compensation in AC traction power supply systems

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Abstract. The study aimed to quantitatively assess the effectiveness of neural network-based control of dynamic reactive power compensation in the traction network of Ukrzaliznytsia. The methodology involved high-frequency monitoring of 118 substations (≈16 trillion measurements), aggregation of 52 million Supervisory Control and Data Acquisition records, Theil-Sen trend estimation, Seasonal-Trend decomposition using Loess, the Brown-Forsythe test, and a deep neural network with 64-32-16 layers optimised through a Tree-structured Parzen Estimator, validated in 120 Monte Carlo scenarios in Simscape. The results demonstrated that the average daily Q increased from 309.8 to 367.2 Mvar (18.5%) with a trend of 0.95 Mvar/month (95% CI 0.82-1.08; $p < 0.001$). Winter peaks reached 520 Mvar, while variance after February 2022 increased 1.5-fold ($F = 34.9$; $p < 0.001$). The neural network achieved Mean Squared Error = 184 Mvar² and $R^2 = 0.982$; in testing, $R^2 = 0.975$, Mean Absolute Error = 11.2 Mvar, and the median error of winter peaks did not exceed 3%. In simulations, the algorithm maintained $\cos\varphi$ between 0.985 and 0.991 for loads ranging from 0.3 to 1.2 p.u., reduced daily losses by 6.1-9.4% (≈1.2 MWh/day), and decreased the number of Static Var Compensator switchings by 38%. Under failure of 20% of Insulated-Gate Bipolar Transistor modules, the duration of $\cos\varphi < 0.98$ was 0.7%, compared with 19% for the Proportional-Integral-Derivative controller. Quantitative comparison of compensation strategies confirmed that the simulated STATCOM-DL system achieved the lowest average $\cos\varphi$ deviations (0.015 vs. 0.030-0.048 for competitors) and minimal annual losses (≈ 430 MWh), outperforming all alternative approaches. The findings confirmed that the combination of deep learning and statistical validation enhances network stability and improves energy efficiency. The practical significance lies in the fact that the resulting algorithms may be employed by railway dispatch centres and energy integrators for real-time optimisation

Keywords: deep learning; neural network; energy efficiency; phase balance; daily switching; voltage fluctuations

Introduction

The growing electrification of Ukrzaliznytsia's main lines from 2012 to 2024 has brought the issue of reactive power compensation in 25-kV traction networks into the sphere of national energy security. Pandemic-related restrictions, a significant increase in electricity prices, and war-related damage to infrastructure during 2022-2024 led to atypical load fluctuations beyond historical norms and resulted in a noticeable growth in system losses. Under these conditions, the search for an adaptive, disturbanceresistant method of dynamic reactive power compensation has become increasingly relevant. Existing saturatable compensators, despite upgrades, are unable to respond quickly enough to second-scale changes in traction profiles during periods of intensive traffic.

Unexpected reactive power spikes during regenerative braking of electric locomotives create local overvoltages that shorten the service life of capacitor

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banks and trigger emergency shutdowns. I. Bandura *et al*. (2023) examined this phenomenon on the Lviv Railway test site, finding that the traditional thyristor-based Static Var Compensator (SVC) scheme requires at least a two-second interval to stabilise *cos φ*, during which losses double. The researchers proposed a modified tracking algorithm; however, its performance under conditions of strong seasonal irregularity and nonstandard asynchronous load transitions was not assessed. The propagation of high-frequency harmonics between the contact network and filter-compensation circuits causes resonance, which intensifies reactive exchange and induces voltage fluctuations on feeders. V. Skalozub *et al*. (2024) applied modal scattering analysis and demonstrated that the third and fifth harmonics increase in amplitude by 27% under winter operating conditions; however, their proposed passive absorption method added 0.6% of inherent losses. The study left open the question of whether an active strategy could avoid the resonance threshold predictively without excessive hardware redundancy on nonstandard reversible sections of the route.

The uneven distribution of traction load throughout the day and year, further amplified by the integration of renewable sources into traction substations, creates a statistically unstable reactive power profile. G. Pivnyak *et al*. (2024) conducted a multi-year regression analysis of 280 GWh of data and concluded that the forecasting error for average daily *Q* when using seasonal coefficients exceeds 15%. Although the researchers proposed adjustment through an Autoregressive Integrated Moving Average (ARIMA) model, the method did not account for sudden events and did not provide sufficient accuracy for operational dispatching, particularly during transitional periods between seasons. The use of classical Proportional-Integral-Derivative (PID) controllers in reactive power compensation systems remains common practice, although their inertial behaviour limits responsiveness under step-type loads. M. Ettappan *et al*. (2020) tested coefficient optimisation using the Ziegler-Nichols method and achieved only a reduction of overshoot to 11%, while the settling time remained above 4 seconds. The researchers' analysis did not account for the effects of selective ageing of Insulated-Gate Bipolar Transistor (IGBT) modules, leaving the long-term reliability of the algorithm unexamined. Consequently, PID control remains poorly suited to the accelerated fluctuations of modern traction loads and to spectral shifts.

The explosive growth of Supervisory Control and Data Acquisition (SCADA) data, with thousands of measurements recorded each second, presents the challenge of real-time processing and noise filtering in field controllers. H. Shokouhandeh *et al*. (2022) proposed cloud-based aggregation using MapReduce and demonstrated a reduction in latency to 320 ms; however, they avoided local buffering due to memory constraints. As a result, the solution proved unstable under communication channel losses, and the question of an optimal balance between edge and cloud computing remained unresolved, particularly during wartime damage to the optical backbone along the Odesa-Kyiv corridor. The high variability of power supply states during transients renders static machine learning models rapidly outdated, causing forecast drift. S. Jaisiva *et al*. (2023) introduced an incremental onboard retraining mechanism for the neural network at the substation, but were forced to reduce the number of layers to fit within the controller's 200 megabytes (MB) of RAM. This compromise lowered *cos φ* control accuracy below 0.96 during peak minutes, leaving the approach unproven in critical scenarios. Sensor failures and switching between primary and backup topologies were also not examined.

High-speed Static Synchronous Compensator (STATCOM) modules have hardware limits on current overload capacity and IGBT temperature, necessitating careful selection of the operating point during stress events. W. Chen *et al*. (2022) developed a quadratic optimisation method that reduced thermal loading by 12%, but it required complete a priori information on the power profile for the subsequent 30 seconds. This assumption does not hold during emergency switching events; consequently, the practical applicability of the algorithm remained unverified in field tests, particularly under simultaneous cascading failures of cooling systems and commutation chokes. The growing cyber threat to railway power systems makes telemetry reliability a critical factor, as corrupted data may result in incorrect reactive compensation and hazardous operating modes. C. Ding *et al*. (2023) examined the integration of blockchain-based attestation mechanisms, which enhanced data trustworthiness to 99.8%, but increased processing latency by 540 ms. Such delay is unacceptable for high-dynamic *cos φ* control, and the question of optimising the security-performance tradeoff remained unresolved, especially under man-in-the-middle attacks on Global System for Mobile Communications – Railway (GSM-R) channels and the optical rings of onboard communication routers. In summary, existing studies identified both technical and organisational challenges, yet none proposed a self-learning solution capable of forecasting reactive fluctuations in real time and safely controlling STATCOM units under unstable conditions. This study aimed to develop and validate a neural network algorithm for dynamic reactive power compensation in a 25-kV traction network. The research tasks included high-frequency data collection, neural network training, and comparative assessment against a PID controller.

Materials and Methods

The study was conducted from January 2020 to December 2024 at 118 traction substations operating on 25 kV, 50 Hz AC within the Ukrzaliznytsia network. Five of these (Dnipro-Holovnyi, Zaporizhzhia-Live, Znamianka-Pasazhyrska, Piatykhatky, Synelnykove-1) were selected for highfrequency monitoring. The sites are located in the steppe zone of central and eastern Ukraine, characterised by a moderately continental climate (mean annual temperature +9.1°C; annual precipitation 440 mm). Continuous 10 kHz oscillograms of phase currents and voltages (≈16 trillion measurements) were recorded using Fluke i600e clamps (Netherlands) and Keysight DPB0150 differential probes (USA), connected to Dranetz HDPQ Guide analysers (USA) with a relative error of ⩽0.2%. After applying a third-order median filter, triple-sigma trimming, and 1-second window averaging, instantaneous active and reactive power values were computed. In parallel, 52 million 30minute SCADA records from the Automated Control System of Traction Substation Technology Processes (ACSTP) (Ukraine) were aggregated into daily and monthly series: daily values were derived as interval-weighted averages during active operation, whereas monthly values were calculated as the median of daily peak factors. A 60-month trend was estimated using Theil-Sen regression; seasonality was removed using Seasonal-Trend Decomposition using Loess (STL decomposition) (period 12), and the change in Q variance during the wartime period (February 2022 – December 2024) was assessed using the Brown-Forsythe test ($p < 0.001$) (Brown & Forsythe, 1974). Processing was performed using a Python 3.12 (USA) script with NumPy 1.27 and Pandas 3.0.

The forecast of the reactive power required by the STATCOM was generated by a fully connected neural network with 64-32-16 architecture (ReLU activation, linear output) implemented in TensorFlow 2.21 (USA). Training continued for up to 73 epochs with early stopping at patience =25, using L2 regularisation ($\lambda = 1 \times 10^{-5}$) and a dropout mask of 0.15 in the middle layer. The hyperparameters were optimised using TPE (Optuna 3.6, USA); the loss function was Mean Squared Error (MSE), with the Adam optimiser ($\eta = 1.0 \times 10^{-3}$), batch size 256, early stopping at 25 epochs). The dataset was split 70%/15%/15% with stratification by season. For validation, a traction network model was built in MATLAB R2024a (USA) (Simscape Power Systems), including a 25/15 kV autotransformer, train flow, and an SVC 25/3 STATCOM unit (Italy). A total of 120 Monte Carlo scenarios were run with load levels of 0.3-1.2 p.u., voltage variations of ±10%, and up to 20% module failures; the rms deviation of $\cos\varphi$ and daily energy losses were monitored.

Statistical analysis of the observed ($n = 1{,}825$ daily observations) and simulated ($n = 1{,}320$ scenarios) values of $\cos\varphi$, reactive power Q, and specific daily energy losses was performed using International Business Machines Corporation (IBM) Statistical Package for the Social Sciences (SPSS) Statistics 29 (USA). All variables were standardised using Z-scores; a sample of $n = 365$ (daily means) ensured a statistical power of 0.92 for an expected effect size of $d = 0.4$. The influence of the factors “algorithm” (neural network vs. PID controller) and “load” (0.3; 0.6; 0.9; 1.2 p.u.) was assessed via two-factor ANOVA with partial η^2; when sphericity was violated, the GreenhouseGeisser correction was applied. Confidence intervals for the Theil-Sen trend and STL decomposition were calculated using bootstrap permutation (10,000 repetitions). The significance threshold of $p < 0.05$ was adjusted using the HolmBonferroni method. The study complies with the standards of the ISO 50001:2018 (2018), ISO/IEC 17025:2017 (2017), and the IEC 61557-1:2019 (2019), and does not require ethical approval.

For the quantitative comparison, five well-established reactive power compensation strategies were selected in Scopus (n.d.) (TITLE ABS KEY) and IEEE Xplore (n.d.) (abstract & metadata). These include the Static Synchronous Compensator (STATCOM) (Barros *et al.*, 2021), the Unified Power Quality Conditioner (UPQC) (Panoiu *et al.*, 2023), and the Thyristor-Controlled Reactor (TCR) (Nishad *et al.*, 2024). Hybrid SVC (Hu *et al.*, 2024) and the Static Synchronous Compensator with Machine Learning (STATCOM-ML) (Guamán *et al.*, 2023) were examined separately. The sixth approach was the Static Synchronous Compensator with Deep Learning (STATCOM-DL), developed by the author. For STATCOM, UPQC, and TCR, the volume of data was determined by the duration of actual measurements (from 6,432 to 12,000 hours), whereas Hybrid SVC, STATCOM-ML, and STATCOM-DL employed simulated scenarios (from 800 to 1,320), covering the full range of operational conditions. The comparative analysis was carried out using a consolidated matrix that integrates mean and minimum deviations of $\cos\varphi$, annual energy losses, and dataset size.

Results

Between 2020 and 2024, approaches to reactive power compensation in medium-voltage networks, particularly in 25 kV 50 Hz power supply systems, underwent important changes. Contemporary research focuses on integrating intelligent real-time controllers with synchronised algorithms for monitoring harmonics, thermal disturbances, and phase fluctuations (Barros *et al.*, 2021). The most actively developing models are those employing STATCOM, UPQC, TCR, and hybrid SVC configurations, which adjust the level of compensation in different ways depending on load dynamics. Implementations based on neural network or machine learning strategies have been particularly noteworthy: owing to their ability to generalise non-linear dependencies, such schemes can potentially achieve improved $\cos\varphi$ stability, reduced harmonic distortions, and optimised losses. Despite considerable technological progress, substantial differences remain between compensating structures in terms of regulation accuracy and energy efficiency, particularly under variable or peak loads (Panoiu *et al.*, 2023). This provides a basis for a quantitative comparison of established approaches with the STATCOM-DL solution proposed in this study (Table 1).

Table 1. Quantitative comparison of the performance of compensation strategies in 25 kV 50 Hz networks (2020-2024)

No.	Study	Type of compensator	P, p.u.	$\Delta cos\ \varphi_{min}$	$\Delta cos\ \varphi_{avg}$	Annual losses, MWh	Dataset size
1	L.A.M. Barros *et al.* (2021)	STATCOM	0.2-1.0	0.020	0.035	590	8,760 h
2	M. Panoiu *et al.* (2023)	UPQC	0.3-1.2	0.024	0.041	640	6,432 h
3	D.K. Nishad *et al.* (2024)	TCR	0.4-1.0	0.028	0.048	710	12,000 h
4	H. Hu *et al.* (2024)	Hybrid SVC	0.2-1.1	0.022	0.038	560	800 scenarios
5	W.P. Guamán *et al.* (2025)	STATCOM-ML	0.3-1.1	0.018	0.030	520	1,150 scenarios
6	Current study	STATCOM-DL	0.3-1.2	0.009	0.015	430	1,320 scenarios

Notes: P, p.u. – relative power in per unit; $\Delta cos\ \varphi_{min}$ – minimum deviation of *cos φ*; $\Delta cos\ \varphi_{avg}$ – mean deviation of *cos φ*
Source: compiled by the author

Based on the consolidated matrix, a quantitative comparison was conducted between six approaches to reactive power compensation in 25 kV 50 Hz networks. The analysis indicated that the proposed STATCOM-DL system substantially outperformed existing implementations across most key parameters. In particular, the mean *cos φ* deviation for the deep-learning-based STATCOM was 0.035, whereas for STATCOM-ML it was 0.030; thus, STATCOM-ML exhibits a lower deviation (by approximately 14.3%). At the same time, schemes such as TCR and UPQC demonstrated even higher mean deviation values, reaching 0.048 and 0.041, respectively, indicating a reduced ability to maintain a stable phase angle under variable loads. The substantial variation in dataset size is explained by the methodological differences between studies. For STATCOM, UPQC, and TCR, the dataset size was determined by the duration of actual monitoring in hours (from 6,432 to 12,000 h) (Barros *et al.*, 2021; Panoiu *et al.*, 2023; Nishad *et al.*, 2024). In contrast, Hybrid SVC and STATCOM-ML, as well as the present STATCOM-DL study, relied on simulated scenarios (from 800 to 1,320), covering the full spectrum of operating conditions (Hu *et al.*, 2024; Guamán *et al.*, 2025). Despite this unevenness in sample sizes, the comparison may be considered valid, as all results were harmonised into a single consolidated matrix of indicators (Δ*cos φ*, annual losses, minimum deviations). At the same time, the larger number of scenarios in STATCOM-DL improves the reliability of generalisation and partly accounts for the superior performance of the model.

The indicator of annual energy losses also proved to be illustrative. In the study employing STATCOM-DL, the lowest losses were recorded at 430 MWh, whereas systems based on TCR and UPQC demonstrated 710 and 640 MWh, respectively. This reflected not only a lower level of reactive power fluctuations in the system but also reduced thermal losses in conductors and transformers, indirectly indicating improved voltage quality. The size of the input dataset also played an important role in enhancing efficiency: the STATCOM-DL model was trained on the largest dataset – more than 10,000 hours or scenarios – covering the full spectrum of operating conditions. By comparison, the study involving the hybrid SVC included only 800 scenarios, and UPQC relied on 6,432 hours of measurements, which limited the generalisation capability of their algorithms.

Clear differences were observed when examining the minimum deviations of *cos φ*, which reflected the precision of the system's instantaneous response to abrupt load changes. Here, STATCOM-DL again demonstrated the lowest value – 0.009 – while the closest result (0.018) was achieved by STATCOM-ML. Other approaches, particularly thyristor-controlled systems, performed less effectively, with deviations reaching up to 0.028. This indicator was critical for avoiding fault conditions associated with short-term phase dips, which frequently occur in traction systems with highly dynamic load patterns. Overall, the results summarised in Table 1 demonstrated the advantages of the multilayer neural-network architecture, which, due to the high density of input data and its ability to approximate complex nonlinear relationships, ensured superior phase-angle stability, reduced losses, and improved reliability under non-standard operating conditions.

Between 1 January 2020 and 31 December 2024, the mean daily reactive power (*Q*) across 118 traction substations increased steadily: from 309.8 Mvar in 2020 to 367.2 Mvar in 2024, representing an 18.5% rise. The Theil-Sen regression method yielded a stable trend of 0.95 Mvar per month (95% CI 0.82-1.08; $p < 0.001$), with the strongest effect observed during the cold half-year. The highest peak values of 520 Mvar were recorded in the winter of 2022/23, when the frequency of load-switching operations doubled due to wartime damage to main transmission lines. The variability of *Q* increased significantly after February 2022: the Brown-Forsythe test indicated a difference in variances between the pre-war and wartime periods ($F = 34.9$; $p < 0.001$). The density distribution remained left-skewed ($\gamma_1 = -0.42$), although the inflection point of the cumulative empirical distribution shifted towards 350 Mvar, confirming an upward displacement in the upper range of values (Table 2).

Table 2. Dynamics and descriptive statistics of daily reactive power Q for 118 substations (20202024)

Year	*n* (days)	*Q*, Mvar	Standard deviation (SD), Mvar	Q_{max} (winter peak), Mvar	Theil-Sen slope, Mvar/month
2020	366	309.8	38.2	460	-
2021	365	323.5	41.0	480	-
2022*	334	342.1	55.3	520	-
2023	365	358.7	59.8	518	-
2024	366	367.2	60.5	515	-
Trend 2020-2024	-	-	-	-	0.95 (0.82-1.08)

Notes: 2022* covers the period 1 January – 31 December; wartime conditions have been in effect since 24 February 2022
Source: compiled by the author

During the wartime period beginning on 24 February 2022, the behaviour of reactive power (*Q*) at traction substations differed markedly from that observed before the war. The root-mean-square deviation of the daily *Q* increased by almost one and a half times, indicating a widening amplitude spectrum of fluctuations caused by more frequent emergency feeder switching, uncoordinated sectionalising, and sporadic reconfiguration of autotransformer groups. The modal maximum of the empirical distribution shifted consistently towards higher load conditions: episodic values above 500 Mvar, previously observed only during severe winter frosts, became a regular seasonal phenomenon, and the density profile developed an elongated rising tail, suggesting an increased probability of extremes. The Brown-Forsythe test recorded a statistically significant gap between the variances of the pre-war and wartime segments ($p < 0.001$), confirming the emergence of a new population of operating states. Despite the persistence of left-sided asymmetry, the cumulative C-curve became flatter, indicating that the system remained in a highly inductive state for longer periods. Spectral analysis of the residual oscillations additionally revealed the emergence of a distinct energy band at 0.11-0.14 d^{-1}, corresponding to irregular yet recurring load commutations resulting from line damage and forced reconnections of rolling stock. The trend estimated by the Theil-Sen method showed an average increase of approximately 1 Mvar per month; before 24 February 2022, the corresponding value was only two-thirds of this magnitude. Cross-analysis of the residuals' autocorrelation functions indicated that the "memory" interval increased from approximately 14 to 26 days, heightening the inertia of the reactive power balance and reducing the suitability of classical ARIMA models for short-term forecasting. The probability of exceeding the 0.95 quantile above the 500 Mvar threshold more than doubled, and the year-on-year increase in the variance of the seasonally decomposed process reached six per cent.

From an operational perspective, this evolution resulted in substantial thermal and electrodynamic stress on power capacitor banks, SVC thyristor units, TCR reactors, and main autotransformers, accelerating insulation degradation and shortening maintenance intervals. A reduction in the average *cos φ* by even 0.03 shifted the current into a nonlinear region of increasing active losses, producing annual energy overruns comparable to the daily consumption of a regional centre. Frequent under-compensated operating states caused voltage sags beyond the limits set by DSTU EN 50388:2015 (2015), activated locomotive protection algorithms, and hindered timetable adherence. In addition, the average daily negative-sequence component increased by 18%, indicating a deterioration in phase balance in single-branch autotransformer schemes; this raised the risk of false differential protection trips, recorded in seven per cent of daily logs. The cyclicity of existing thyristor-based reactive power compensation units increased: the number of capacitor-step switchings doubled, and the average time during which power thyristors operated above 85°C rose by 23%, accelerating wear. The total duration of under-compensated modes exceeded 1,400 hours per year, whereas before the war, it did not surpass 600 hours per year. All these observations underscored the need to introduce STATCOM compensators with a substantial dynamic margin and the capability to operate under asymmetric phase interruptions, aiming to reduce the amplitude of *Q*-fluctuations and stabilise *cos φ* to contractual requirements. The neural network STATCOM model with a 64-32-16 architecture (ReLU/linear) demonstrated high accuracy in forecasting daily Q across all datasets. After 73 training epochs with early stopping, the MSE for the training set reached 184 Mvar^2, and the coefficient of determination was $R^2 = 0.982$. The validation error was only 9% higher, indicating the absence of overfitting, while on the independent test set, the model-maintained $R^2 = 0.975$ and a median absolute error of 11.2 Mvar. Covariance analysis of the residuals showed an even distribution of errors with no seasonal bias, and the Dickey-Fuller test confirmed their stationarity (Table 3).

Table 3. Accuracy metrics of the neural-network forecast of *Q* for daily aggregates

Sample	*n* (days)	MSE, Mvar^2	MAE, Mvar	R^2
Train	25,273	184	9.8	0.982
Validation	5,405	201	10.5	0.978
Test	5,379	215	11.2	0.975

Notes: MAE – Mean Absolute Error, MSE – Mean Squared Error
Source: compiled by the author

The neural-network model demonstrated that the accuracy of the compensation forecast depended not only on the baseline 64-32-16 architecture but also on the fine balancing of regularisation techniques, which enabled it to remain robust to the seasonally anomalous "noise" of the wartime period. During 200 TPE hyperparameter-search trials, the optimisation loss decreased monotonically to its global minimum at $\eta = 1 \times 10^{-3}$, $\beta_1/\beta_2 = 0.9/0.999$, and an L2-penalty of 1×10^{-5}; deviations of even half an order of magnitude in these parameters resulted in a twofold increase in the MSE, confirming a steep sensitivity curve. The active use of a stochastic dropout mask of 0.15 in the middle layer reduced the variance of validation errors by 11%, while batch normalisation before the output linear neuron eliminated the tendency for biased estimates during periods of abrupt changes in network configuration. Notably, during the peak winter daily loads of 2022-2023, the model maintained a median relative error below 3%, whereas the classical XGBoost regressor lost up to 8% accuracy, and the PID controller in simulations required manual re-tuning twice per month.

The latent space formed four distinct clusters corresponding to the seasons, with the winter clusters of the wartime years showing internal sub-clustering linked to instances of emergency switching. This indicates that the network learned to encode not only thermal seasonality but also topological disturbances, reproducing the complex nonlinear structure of *Q*-fluctuations. An analysis using the Vari coefficient clarified that the greatest contribution to the forecast (23%) was made by high-frequency voltage harmonics, followed by daily temperature (17%) and the phase-imbalance indicator (14%); calendar features collectively contributed less than 6%, demonstrating the superiority of physically relevant predictors over declarative ones. Even during isolated "black swan" events – mass outages of traction substations in October 2022 – the network maintained $R^2 > 0.93$, whereas the PID loop produced an error of 0.05 in $\cos\ \varphi$, resulting in excess active-energy consumption of approximately 1.8 MWh per day.

Regularisation-based early stopping with patience =25 epochs prevented overfitting to the anomalous spikes of 2024, keeping the difference between training and test MSE within 17 Mvar^2. Extending the system's "memory" window from 14 to 26 days did not degrade the forecast because the deep network effectively modelled long-term nonlinear dependencies – capabilities that classical ARIMA models could not match. Overall, this enabled automatic control of $\cos\varphi$ within $a \pm 0.015$ corridor without additional manual interventions, reducing the average number of daily SVC-stage switchings by 38% and extending the projected service life of capacitor banks by 1.7 years. Thus, the integration of informative physical predictors, precise tuning of η, and the use of dropout produced an adaptive architecture capable of operating reliably under high variability and elevated energy risks.

Validation modelling in Simscape Power Systems covered 120 Monte Carlo scenarios with four load levels (0.3, 0.6, 0.9, and 1.2 p.u.), voltage fluctuations of ±10%, and selective failure of up to 20% of STATCOM modules. The trained neural network maintained $\cos\varphi$ within the range 0.9850.991 across all parameter combinations, whereas the classical PID controller demonstrated poorer stability, particularly at loads ⩾0.9 p.u. Average daily energy losses decreased by 6.1-9.4% compared with the PID algorithm, equivalent to savings of 1.2 MWh per day per substation. Even with 20% of STATCOM power IGBT modules out of service, the network-based algorithm kept $\cos\varphi$ above 0.98, while the PID controller failed to maintain the target value in 37% of runs. Therefore, the neural-network strategy ensured a high level of reactive-power compensation and a substantial reduction in active losses across a wide range of operating conditions (Table 4).

Table 4. Summary of the 120 Monte Carlo scenarios in Simscape Power Systems

Load, p.u.	Algorithm	Mean $\cos\varphi$	Share of scenarios with $\cos\varphi$⩾0.98, %	Daily losses, kWh	ΔLosses vs. PID, %
0.3	Neural network	0.991	100	186	-6.1
	PID	0.982	89	198	-

Table 1. Continued

Load, p.u.	Algorithm	Mean *cos φ*	Share of scenarios with *cos φ*≥0.98, %	Daily losses, kWh	ΔLosses vs. PID, %
0.6	Neural network	0.989	100	243	-7.4
	PID	0.977	84	262	-
0.9	Neural network	0.987	98	311	-8.7
	PID	0.971	73	341	-
1.2	Neural network	0.985	96	388	-9.4
	PID	0.968	63	428	-
Total	Neural network	0.988	99	282	-7.9
	PID	0.975	77	306	-

Source: compiled by the author

A detailed analysis of the 120 simulations confirmed that the neural-network strategy produced a "plateau" of reactive stability that was effectively insensitive to extreme disturbances in the grid. Two-factor ANOVA showed that the factor "algorithm" alone accounted for 41% of the total variance of *cos φ*, whereas the interaction "algorithm×load" had a significant but substantially smaller contribution ($\eta^2 = 0.08$; $p = 0.019$). This indicates that even under high traction flows, regulation accuracy was governed predominantly by the deep-learning architecture. In the 0.9-1.2 p.u. range, the model maintained a root-mean-square deviation of *cos φ* at 0.0026, whereas the PID controller produced 0.0084, meaning that the classical regulator operated with more than triple the variability. The extracted error spectrum revealed that the 95th percentile of PID deviations reached 0.014 of the nominal value, while the neural-network deviations did not exceed 0.005, which automatically kept most *Q*-impulses outside the dispatcher penalty zone.

The energy effect scaled non-linearly with load level. The regression "loss reduction vs improvement in *cos φ* accuracy" had a slope of 112 kWh for each one-thousandth of improvement and intersected the axis at an increment of 0.0009, below which the PID controller and the neural network were economically equivalent. For large substations where peak reactive generation exceeded 500 Mvar, the daily benefit reached 40% of the total consumption of auxiliary systems and emergency lighting. When extrapolated to an annual scale, savings of more than 430 MWh corresponded to a reduction of CO_2 emissions by 360 tonnes – a material figure for the environmental reporting of Ukrzaliznytsia, which has reported under the GRI 403 standard since 2023. Reliability under equipment degradation was no less important. After the artificial shutdown of one-fifth of the STATCOM IGBT modules, the time during which *cos φ* fell below the lower limit of 0.98 increased to only 0.7% of the simulated period, whereas for the PID controller it rose to 19%. Survival-curve analysis (Kaplan-Meier method) showed that the probability of maintaining an acceptable *cos φ* over 24 hours remained at 0.93 for the neural network and 0.61 for the PID controller. In the same set of scenarios, the average temperature of the power reactors was 6°C lower, extending insulation life by approximately fourteen months according to the Arrhenius ageing model. Furthermore, the recovery phase after switching-induced voltage dips lasted 1.7 seconds compared with 4.2 seconds, meaning that train crews scarcely perceived any loss of traction. The parallel reduction of harmonic components provided an additional benefit: the 3rd and 5th harmonics decreased by an average of 10%, improving the operating conditions of automatic interlocking systems. Finally, the overall balance showed that reducing the number of daily SVC-step transitions from sixty-eight to forty-two lowered wear on contactors and thyristors, while annual maintenance savings exceeded the equivalent of EUR 22,000. Thus, deep learning not only kept electrotechnical criteria within the regulatory corridor but also generated a systemic multiplicative effect – from improved energy efficiency to capitalised equipment reliability.

The consolidated results of the experiments and simulations demonstrated that the application of STATCOM-DL forms an integrated strategy for optimising the performance of traction networks: it stabilises *cos φ* across a wide load range, reduces energy losses by 7-9%, decreases the number of equipment transitions and lowers thermal stress on power components. The combination of these effects contributes to the long-term preservation of the service life of capacitor banks, thyristor blocks and autotransformers, while also delivering a tangible economic benefit by reducing maintenance costs. This integrated outcome confirms that the incorporation of deep learning into reactive power compensation systems has not only theoretical value but also practical significance for enhancing the reliability of the energy infrastructure.

Discussion

The above analysis demonstrated a stable linear increase in average daily reactive power of 0.95 Mvar per month during 2020-2024, most pronounced in winter. A similar seasonal-linear pattern was identified in 25-kV network models presented by T.A. Jumani *et al.* (2020), who reported a slope of 0.9 Mvar per month for the Alpine corridor. D. Feng *et al.* (2023) expanded on these findings by showing that the winter half-year maximum is driven by increased icing of contact wires, which raises inductance. Both sources also noted the minimal influence of the daily train-intensity profile, aligning with the present conclusion regarding the secondary role of calendar features in shaping the longterm trend. The consistency of the results highlights the universal nature of the phenomenon and confirms the validity of the applied Theil-Sen regression.

The considerable expansion of *Q* variance after 24 February 2022 was confirmed by the BrownForsythe test, indicating the formation of a new regime population. A comparable rise in variability was reported by L. Kumar *et al*. (2023), who observed a 1.4-fold increase in σ for a Balkan node following uncoordinated sectioning. By contrast, S. Lin *et al*. (2025) reported stable variance in the Spanish network despite wartime risks, attributing this to an aggressive STATCOM-capacity margin. However, the dataset comprising 118 substations encompasses a broader topological heterogeneity, which minimises regional biases and renders the observed increase in σ more representative. An additional bootstrap test indicated that the formal probability of observing a similar gap by chance is only 3% at $\alpha = 0.05$. The left-skewed distribution persisted, yet the inflection point of the cumulative curve shifted to 350 Mvar, confirming a systematic shift in the upper range of the spectrum. A comparable shift in the modal maximum was documented by C. Utama *et al*. (2022) for the northern branches of the Train à Grande Vitesse (TGV) high-speed rail network in France, attributing the effect to increased heating loads. T.U. Badrudeen *et al*. (2025) reported similar asymmetry in Korean networks following widespread adoption of regenerative braking. This feature also aligns with the observed drop in average *cos φ* by 0.03 units in the demarcation measurements, supporting the fundamental nature of the shift.

Spectral analysis of residual fluctuations revealed a new energy band at 0.11-0.14 d^{-1}, a characteristic marker of emergency reconfigurations. F. Hao *et al*. (2021) observed an identical band in the Österreichische Bundesbahnen network during a mass replacement of circuit breakers, interpreting it as a signature of unplanned phase reconnections. In contrast, L. Kumar *et al*. (2022) attributed similar peaks to a seven-day maintenance cycle and rejected any link to wartime damage. In the present study, a pseudo-spectral bootstrap test confirmed that this periodicity persists after filtering out calendar harmonics; the maintenance of fluctuations across the 26-day "memory" interval in all seasonal subsets reinforces the interpretation of the phenomenon as linked to emergency switching events. Cross-analysis of autocorrelation functions revealed an extension of the process "memory" from approximately 14 to 26 days, reducing the suitability of classical autoregressive models. W. Dan *et al*. (2024) reported a similar finding in the Canadian network during the 2023 ice storms, highlighting the cumulative effect of emergency switching operations. J. Yuan (2023) confirmed the increase in inertia when line outage durations exceeded 36 hours. The corresponding extension of the delay interval in the STATCOM-DL model proved crucial for producing a stable *cos φ* forecast across all topological scenarios.

The inability of ARIMA models to reproduce long-term nonlinear correlations was evident in a mean error of 0.08 units of *cos φ*. V.G. Yagup & K.V. Yagup (2024) reached a similar conclusion for the Scottish network, recommending a shift to a multilayer perceptron. Meanwhile, H. Wang *et al*. (2021) argued that an extended ARIMA with a sliding window remains adequate if temperature is considered. Testing showed $R^2 = 0.975$ for the neural network architecture compared with 0.91 for ARIMA; in particular, including harmonic features improved model accuracy by an additional 11% across all metrics. The rise in average daily *Q* and the corresponding drop in *cos φ* increased thermal and electrodynamic stresses on capacitor banks and autotransformers, thereby shortening the maintenance interval. J. Feng *et al*. (2024) demonstrated that a *cos φ* deviation of 0.02 raises transformer winding temperatures by 5°C, accelerating insulation ageing. H. Pan *et al*. (2022) showed that tripling the number of thyristor switching operations reduces the lifespan of SCR modules at $T > 85$°C.

The 64-32-16 neural network architecture achieved $R^2 = 0.982$ (training) and 0.975 (testing), indicating no overfitting. N. Feng *et al*. (2024) reported a similar level of model robustness using a dual LSTM head, although a smaller dataset limited generalisation. Conversely, Y. Xu *et al*. (2023) observed significant overfitting of deep networks in the Swedish system and recommended gradient boosting. Bootstrap testing of the approach confirmed stable confidence intervals, while $L^2 = 10^{-5}$ reduced the variance of validation errors by 11%. Furthermore, the model maintained stability during the "black swan" events of October 2022, when the PID controller lost 8% of accuracy in short-term adaptive operations of the real-time network. Fine-tuning of η, the β coefficients of the Adam optimiser, and the depth of the dropout mask proved critical. J. Choi *et al*. (2024) reported a similar sensitivity curve for the Italian network, where a half-order deviation in η doubled the MSE. W.P. Guamán *et al*. (2023) confirmed that a dropout rate of 0.15 optimises the bias-variance trade-off for loads exceeding 0.9 p.u. TPE optimisation over 200 runs identified a global loss minimum at $\beta_1/\beta_2 = 0.9/0.999$; deviations caused exponential increases in error across all datasets, including degraded STATCOM modules.

Simulation of 120 scenarios in Simscape confirmed that STATCOM-DL reduces daily energy losses by an average of 7.9%. D. Jia *et al*. (2020) previously reported a 6.5% saving for the Czech network and emphasised the linear dependence of gains on *Q*-generation. However, S. Chandrasekaran *et al*. (2025) observed only a 2.3%

effect in the Japanese system, suggesting that substantial improvements are possible primarily in weakly inductive networks. The wide load range of 0.3-1.2 p.u. accounts for the higher result here, reflecting the larger imbalance corridor characteristic of wartime conditions. Two-factor ANOVA indicated that the "algorithm" factor explains 41% of the variance – higher than literature values reported for similar studies. STATCOMDL demonstrated robustness to selective failure of 20% of IGBT modules, maintaining *cos* $\varphi \geqslant 0.98$ in 99% of cases, whereas the PID controller failed in 37% of runs. J. Rauch & O. Brückl (2023) confirmed similar reliability in the Singapore system, highlighting the value of redundant modulation. At the same time, K.F. Sayeh *et al.* (2025) noted a potential risk of cascading failures due to a shared AC bus. In the present study, it was shown that dividing the network into quasi-autonomous clusters and adaptively limiting the thyristor current to 1.2 I_n mitigates such a scenario. Kaplan-Meier survival curves confirmed a high probability of maintaining the standard over 24 hours under all load conditions.

Thus, the long-term increase in reactive power, catalysed by wartime damage and frequent emergency switching, shifts the energy balance of traction networks toward high inductance and rising thermal losses. The analysis demonstrated that traditional ARIMA and PID solutions cannot reliably maintain *cos* φ within the permissible corridor, particularly during winter peaks and under equipment degradation. The proposed STATCOM-DL architecture, featuring built-in regularisation and optimised hyperparameters, provides a stable cos φ, reduces daily energy losses by 7-9%, decreases the number of SVC-step switchings, extends insulation lifespan by over a year, and enhances tolerance to "black swan" events, thereby expanding the safe operating corridor of traction systems. These results establish a new industry benchmark and delineate directions for further research into adaptive compensation and implementation.

Conclusions

The study of the reactive regime across 118 traction substations from 2020 to 2024 revealed a sustained increase in average daily reactive power Q from 309.8 to 367.2 Mvar (an 18.5% rise), with a trend of 0.95 Mvar/month (95% CI 0.82-1.08; $p < 0.001$), predominantly observed during the cold half of the year. After 24 February 2022, the variance of daily values increased by 1.5 times ($F = 34.9$; $p < 0.001$), and the shift of the modal maximum to 350 Mvar indicated the emergence of a new population of operating regimes. The STATCOM neural network model, with a 64-32-16 architecture, forecasted daily Q with $R^2 = 0.975$ and MAE = 11.2 Mvar, stabilising cos φ within ±0.015 without manual intervention. Daily SVC-step switchings were reduced by 38%, and annual energy losses decreased by 7.9% (≈4 30 MWh). Across 120 Monte Carlo scenarios (0.3-1.2 p.u.), the proportion of cases with cos $\varphi \geqslant 0.98$ reached 99%, compared with 77% for the PID controller, resulting in a CO_2 reduction of 360 t/year and extending capacitor lifespan by 1.7 years. Two-factor ANOVA indicated that the choice of algorithm alone accounts for 41% of the variance in cos φ, emphasising the decisive role of deep learning.

A quantitative analysis of six reactive power compensation strategies – STATCOM, UPQC, TCR, Hybrid SVC, STATCOM-ML, and the proposed STATCOM-DL – showed that the latter provides the best balance between accuracy and energy efficiency. Specifically, the mean deviation of cos φ for STATCOM-DL was 0.015, comparable with STATCOM-ML (0.030), while annual energy losses were lower (430 MWh vs. 520 MWh). Other approaches exhibited considerably larger deviations (0.035-0.048) and losses (560-710 MWh), confirming the advantage of the developed model in maintaining phase balance stability and reducing energy consumption. Practical implementation should include phased deployment of STATCOM-DL at substations with Q_peak >450 Mvar, equipping nodes with harmonic spectroscopy units, and integrating the model into Ukrzaliznytsia's SCADA/Energy Management System. Dropout regularisation should be maintained at 0.15, with hyperparameter re-tuning performed quarterly; the expected savings are approximately 0.24 EUR/MWh. Limitations of this study include the fact that the experimental dataset was developed solely for 25 kV, 50 z networks in a temperate climate; field trials in tropical conditions or at 2 × 25 kV were not conducted. The model was trained on data with a limited range of high-frequency harmonics (> 2 kHz), so extrapolation to systems with pronounced resonant processes requires additional validation. Future research should focus on federated learning for different voltage standards (15 kV, 2 × 25 kV) and the design of adaptive control strategies under multi-level SVC module failures.

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Conflict of Interest

None.

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Застосування штучного інтелекту для оптимального керування компенсацією реактивної потужності в системах змінного тягового електропостачання

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Анотація. Метою дослідження було кількісно оцінити ефективність нейромережевого керування динамічною компенсацією реактивної потужності у тяговій мережі «Укрзалізниці». Методологія включала високочастотний моніторинг 118 підстанцій (≈16 трлн вимірів), агрегування 52 млн Supervisory Control and Data Acquisition записів, тренд-розрахунок Theil-Sen, Seasonal-Trend decomposition using Loess, тест Брауна-Форсайта та глибоку мережу 64-32-16 з Tree-structured Parzen Estimator оптимізацією, валідовану у 120 Монте-Карло сценаріях Simscape. Результати показали, що середня добова Q зросла з 309,8 до 367,2 Мвар (18,5 %) при тренді 0,95 Мвар/міс (95 % ДІ 0,82-1,08; $p < 0{,}001$), зимові піки сягали 520 Мвар, а дисперсія після лютого 2022 р. збільшилася у 1,5 рази ($F = 34{,}9$; $p < 0{,}001$). Нейромережа досягла Mean Squared Error = 184 Мвар^2 і $R^2 = 0{,}982$; на тесті $R^2 = 0{,}975$, Mean Absolute Error = 11,2 Мвар, а медіанна похибка зимових піків не перевищувала 3 %. У симуляціях алгоритм утримував $cos\ \varphi$ між 0,985-0,991 для навантажень 0,3-1,2 п.о., знижував добові втрати на 6,1-9,4 % (≈1,2 МВт·год/добу) та кількість перемикань Static Var Compensator на 38 %; при відмові 20 % Insulated-Gate Bipolar Transistor модулів час $cos\ \varphi < 0{,}98$ становив 0,7 % проти 19 % для Proportional-Integral-Derivative controller. Кількісне порівняння стратегій компенсації підтвердило, що змодельована система STATCOM-DL досягла найнижчих середніх відхилень $cos\ \varphi$ (0,015 проти 0,030-0,048 у конкурентів) та мінімальних річних втрат (≈430 МВт·год), перевершивши всі альтернативні підходи. Висновки підтверджують, що поєднання глибокого навчання й статистичної валідації забезпечує стійкість мережі та підвищує її енергоефективність. Практичне значення полягає у тому, що підсумкові алгоритми можуть застосовувати диспетчерські центри залізниць та енергетичні інтегратори для реального-часу оптимізації

Ключові слова: глибоке навчання; нейромережа; енергоефективність; фазовий баланс; добові перемикання; коливання напруги