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INTELLIGENT ENERGY MANAGEMENT STRATEGIES FOR OPTIMIZING POWER QUALITY AND EFFICIENCY ACROSS INDUSTRIAL ELECTRICAL SYSTEMS

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ABSTRACT
Industrial electrical systems are increasingly required to maintain high energy efficiency, stable power quality, and reliable operation despite growing load complexity, nonlinear equipment, distributed energy resources, and continuously changing production demands. Conventional energy-management approaches often address consumption, power quality, and equipment performance independently, limiting their ability to identify interactions between electrical disturbances and inefficient energy utilization. This study investigates intelligent energy management strategies that integrate real-time electrical monitoring, power-quality assessment, energy-efficiency analysis, and data-driven operational optimization within industrial power systems. The proposed framework evaluates voltage variation, current imbalance, harmonic distortion, power factor, demand patterns, equipment loading, energy consumption, and operational states to construct a unified representation of electrical-system performance. Intelligent analytical models are employed to detect abnormal operating conditions, predict efficiency degradation, identify power-quality risks, and determine suitable corrective strategies. Optimization mechanisms subsequently coordinate load operation, reactive-power compensation, demand management, and equipment utilization while maintaining prescribed electrical constraints. The approach provides an integrated foundation for reducing energy losses, improving power quality, increasing equipment reliability, lowering operating costs, and supporting resilient and sustainable industrial energy management.

Keywords:
Intelligent Energy Management, Power Quality, Energy Efficiency, Industrial Electrical Systems, Predictive Analytics, Energy Optimization

1. INTRODUCTION

1.1 Industrial Electrical Systems, Energy Demand, and Operational Complexity

Industrial production is becoming increasingly electrified as manufacturing facilities expand their dependence on electric motors, variable-speed drives, converters, furnaces, compressors, pumps, automated production equipment, and sensitive electronic loads [1]. Although electrification improves production flexibility and process controllability, it also creates highly dynamic electrical environments in which load magnitude and operating characteristics can change rapidly with production schedules [3]. Simultaneous operation of high-power machinery and electronically controlled loads can produce substantial variations in demand across feeders, production lines, and operating periods [5]. This complexity is further increased by the integration of distributed generation and energy-storage systems, which introduce bidirectional and time-varying power flows into traditionally centralized industrial networks [7]. Consequently, energy consumption, production continuity, equipment reliability, and operating expenditure have become closely interconnected performance concerns [9]. Conventional monitoring based primarily on periodic energy consumption or maximum-demand measurements provides limited insight into these interactions [4]. Industrial energy management therefore requires intelligent, system-wide assessment capable of continuously relating electrical conditions to equipment operation, production requirements, and energy performance [8].

1.2 Coupled Power-Quality and Energy-Efficiency Problem

The principal challenge is that industrial energy efficiency cannot be separated from the quality of electrical power supplied to and consumed by industrial equipment [2]. Voltage deviation, voltage unbalance, current imbalance, harmonic distortion, poor power factor, and excessive reactive-power demand can alter current flow and increase electrical losses without necessarily producing an immediate equipment failure [5]. Nonlinear loads such as converters and variable-speed drives can introduce harmonic currents, while unbalanced loading can increase thermal stress in motors, transformers, cables, and distribution components [7]. Poor power factor further

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increases the current required to deliver a given quantity of active power, contributing to conductor losses and capacity utilization [3]. Under three-phase balanced operation, active power is expressed as

$$P = \sqrt{3} V_L I_L \cos \phi \qquad (1)$$

where Prepresents active power, $V_L$is line voltage, $I_L$is line current, and $\cos \phi$is the power factor [6]. Equation (1) demonstrates that useful electrical-power transfer depends jointly on voltage, current, and power factor rather than energy consumption alone. Power-quality deterioration can therefore increase losses, thermal loading, equipment degradation, peak demand, and production-disruption risk [8]. Treating power quality and efficiency as independent optimization problems may consequently overlook the electrical mechanisms through which poor-quality conditions reduce overall system efficiency [9].

1.3 Research Problem, Objectives, and Contributions

Against this background, the central research question is: How can intelligent energy-management strategies jointly identify, predict, and optimize power-quality and energy-efficiency conditions across dynamically operating industrial electrical systems? Existing monitoring approaches can identify individual electrical variables, but effective industrial optimization requires synchronized interpretation of electrical measurements, equipment loading, production states, disturbances, and controllable resources [1]. Accordingly, the first objective is to reconstruct time-dependent industrial electrical operating states from synchronized voltage, current, power, harmonic, load, and operational measurements [4]. The second is to quantify coupled power-quality and energy-efficiency conditions so that disturbances can be evaluated according to their associated energy and operational consequences [6]. The third objective is to develop intelligent predictive mechanisms for identifying abnormal, inefficient, or deteriorating operating states before they create significant losses or operational disruption [7]. The fourth is to optimize controllable electrical resources while maintaining voltage, current, power-quality, equipment, and production constraints [9]. The resulting contribution is an integrated energy-management framework connecting electrical-state reconstruction, disturbance assessment, efficiency analytics, predictive intelligence, and constrained operational optimization within a unified industrial decision environment [5].

Figure 1. Industrial Electrical Energy, Power-Quality, and Efficiency Interaction Landscape

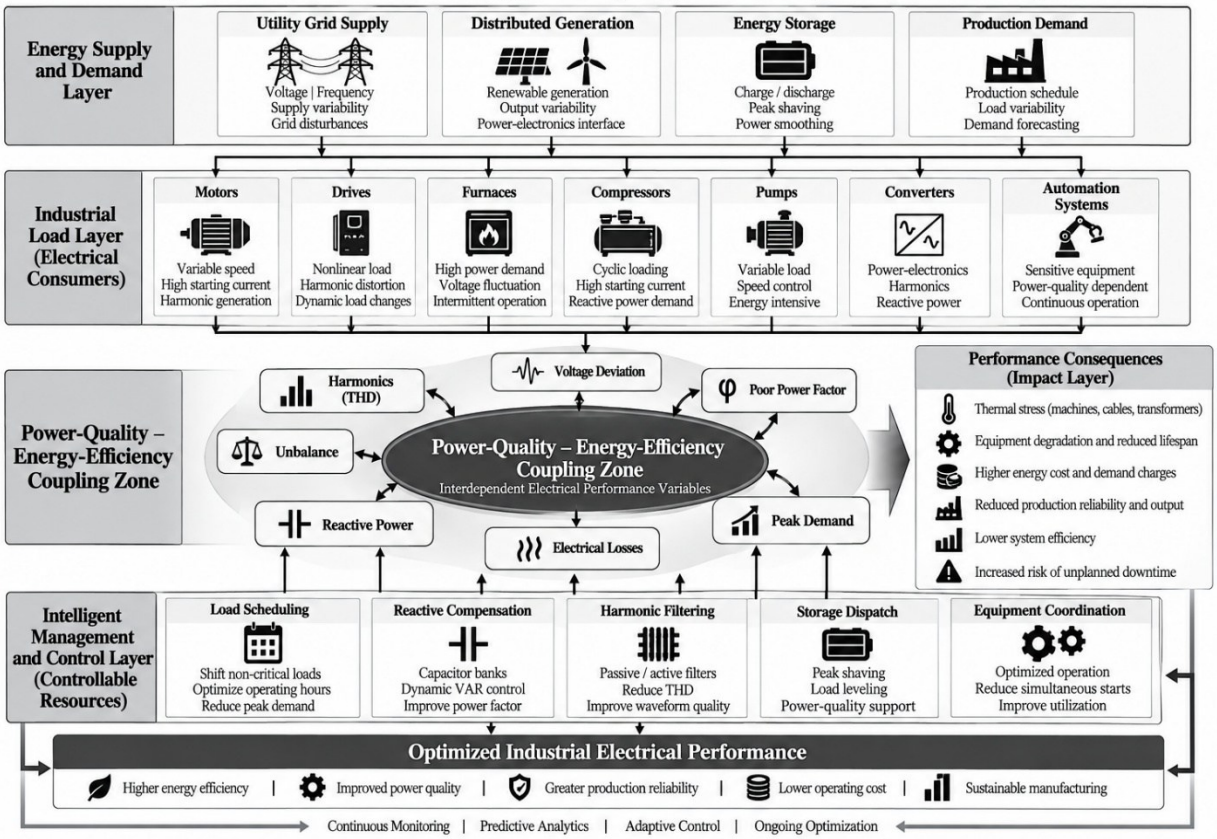

Figure 1. Industrial Electrical Energy, Power-Quality, and Efficiency Interaction Landscape

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2. INDUSTRIAL ELECTRICAL DATA ACQUISITION AND SYSTEM-STATE RECONSTRUCTION

2.1 Multi-Source Electrical and Operational Data Acquisition

Effective intelligent energy management requires electrical measurements to be interpreted together with the operational conditions under which energy is consumed [6]. Accordingly, the acquisition framework combines three-phase voltage, phase and line currents, active and reactive power, frequency, power factor, harmonic components, and accumulated energy consumption with equipment loading and production-state information [8]. Smart meters provide interval-level demand and energy measurements, while power-quality analyzers capture waveform disturbances, harmonic spectra, voltage variation, and phase imbalance at critical electrical nodes [10]. Intelligent electronic devices extend monitoring to feeders, transformers, protection systems, and major industrial loads [12]. PLC and SCADA records provide complementary operational variables including machine status, production mode, set points, switching events, and equipment utilization [14]. Equipment-level sensors additionally capture temperature, vibration, speed, pressure, and other condition variables that can explain changes in electrical behaviour [9]. Integrating these heterogeneous sources therefore enables observed electrical variations to be associated with specific equipment, production processes, operating regimes, and environmental conditions rather than being interpreted as isolated plant-level consumption changes [15].

Table 1. Industrial Electrical Measurement and Operational Variable Framework

Variable Group	Representative Variables	Measurement Level	Typical Resolution	Unit	Analytical Function
Voltage	Phase voltage, line voltage, RMS voltage, positive- and negative-sequence voltage	Equipment, feeder, distribution	Cycles to seconds	V, kV	Voltage deviation, sag, swell, and imbalance assessment
Current	Phase current, line current, RMS current, sequence current	Equipment, feeder	Cycles to seconds	A, kA	Equipment loading, current imbalance, and conductor-stress assessment
Power	Active power, reactive power, apparent power	Equipment, feeder, plant	Seconds to minutes	kW, kVAR, kVA	Demand, reactive-power burden, and electrical-capacity assessment
Power Quality	Frequency, power factor, harmonic components, THD	Equipment, feeder, distribution	Cycles to seconds	Hz, %, dimensionless	Harmonic distortion and electrical-quality assessment
Energy	Interval energy consumption, cumulative energy consumption	Equipment, production line, plant	Minutes to hours	kWh, MWh	Consumption, energy-intensity, and efficiency analysis
Equipment Operation	Equipment loading, utilization, operating state, switching condition	Machine, production line	Seconds to minutes	%, state	Operating-regime identification and efficiency characterization
Production	Production mode, throughput, production output	Process, production line, plant	Minutes to hours	units, kg, tonnes	Production-normalized energy-performance assessment
Condition and Environment	Temperature, vibration, pressure, rotational speed, ambient conditions	Equipment, local environment	Seconds to minutes	°C, mm/s, bar, rpm	Electrical-condition correlation and equipment-state assessment

2.2 Power-Quality Parameter Computation

Raw waveform measurements are transformed into indicators that quantify the electrical disturbances experienced by industrial equipment [7]. Harmonic analysis separates the fundamental-frequency component from higher-order frequency components generated principally by nonlinear electrical loads [10]. Voltage total harmonic distortion is calculated as

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$$THD_V = \frac{\sqrt{\sum_{h=2}^{H} V_h^2}}{V_1} \times 100 \qquad (2)$$

where $V_1$is the RMS magnitude of the fundamental voltage and $V_h$represents the RMS magnitude of harmonic order h[13]. Increasing THD_Vindicates greater waveform distortion and provides an interpretable basis for locating distortion-intensive operating states. Three-phase asymmetry is quantified through the voltage unbalance factor,

$$VUF = \frac{V_{\text{negative}}}{V_{\text{positive}}} \times 100 \qquad (3)$$

where the negative- and positive-sequence components are obtained through symmetrical-component decomposition [11]. These indicators are evaluated alongside RMS voltage deviation, current imbalance, frequency variation, power factor, and disturbance duration [8]. Their combined evaluation distinguishes persistent electrical-quality deterioration from short-duration deviations associated with equipment switching, startup, or production transitions [15].

2.3 Energy-Efficiency and Electrical-Loss Characterization

Power-quality measurements become operationally meaningful when their relationship with useful energy utilization is established [6]. Overall electrical-system efficiency is represented as

$$\eta = \frac{E_{\text{useful}}}{E_{\text{input}}} \times 100 \qquad (4)$$

where E_{input}represents supplied electrical energy and E_{useful}represents energy effectively converted into productive output [12]. Efficiency characterization additionally considers energy intensity, load factor, demand factor, equipment utilization, distribution losses, reactive-power burden, idle consumption, and individual equipment contributions to plant peak demand [9]. These indicators distinguish high consumption caused by legitimate production requirements from consumption associated with underloaded equipment, excessive reactive current, electrical losses, prolonged idling, or inefficient scheduling [14]. For example, rising current without proportional productive output can indicate deteriorating utilization even when total energy consumption remains within historical limits [7]. Linking efficiency measures with power-quality indicators therefore establishes whether electrical disturbances coincide with increased losses, reduced productive energy use, or excessive infrastructure loading [15].

2.4 Temporal Synchronization and Industrial Electrical-State Reconstruction

Because electrical and operational data originate from systems with different sampling frequencies, meaningful analysis requires reconstruction of a common time-dependent operating state [8]. Measurements are aligned according to timestamp, equipment identity, feeder location, production condition, and predefined operating intervals, while aggregation procedures preserve fast electrical disturbances separately from slower energy and production variables [11]. The reconstructed state at time $t$is defined as

$$S_t = f(V_t, I_t, P_t, Q_t, H_t, L_t, O_t) \qquad (5)$$

where $V_t$and $I_t$represent three-phase voltage and current states, $P_t$and $Q_t$denote active and reactive power, $H_t$represents harmonic conditions, $L_t$captures equipment loading, and $O_t$identifies the corresponding operational state [13]. This reconstruction preserves the context necessary to determine whether similar electrical measurements represent normal production demand or inefficient and abnormal operating behaviour [15].

3. POWER-QUALITY AND ENERGY-EFFICIENCY FEATURE ENGINEERING

3.1 Electrical Disturbance and Power-Quality Features

Power-quality features were constructed over defined operating windows so that persistent deterioration could be distinguished from isolated switching transients [13]. RMS voltage deviation quantified departure from the nominal supply level, while sag and swell frequency represented the number and persistence of voltage excursions within each observation interval [15]. Current imbalance characterized unequal phase loading, whereas voltage and current THD captured aggregate waveform distortion generated by nonlinear industrial loads [17]. Individual harmonic magnitudes were retained because equivalent THD values can originate from different harmonic spectra

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and consequently represent different equipment conditions [19]. Frequency deviation measured departures from nominal system frequency, particularly during rapidly changing load or distributed-generation conditions [14]. Power-factor deterioration was calculated relative to equipment- or feeder-specific normal operating levels, while reactive-power excursions identified intervals of unusually high non-active power demand [18]. Window-level statistics—including mean, maximum, variability, duration, and exceedance frequency—therefore preserved the temporal severity of disturbances that individual instantaneous measurements could conceal [20].

3.2 Load Behaviour and Energy-Performance Features

Load-performance features were developed to distinguish productive energy demand from consumption associated with poor utilization or inefficient operating behaviour [14]. Peak-to-average demand ratio characterized demand concentration, while load variability quantified fluctuations within comparable production periods [16]. Base-load consumption represented persistent demand independent of production variation, and the idle-energy ratio identified electricity consumed while equipment remained non-productive [18]. Equipment loading percentage provided additional evidence of underloading or sustained operation near rated capacity [20]. Demand ramp rate captured rapid increases or reductions associated with equipment sequencing and production transitions [15]. Specific energy consumption and production-normalized consumption enabled facilities with different output volumes to be compared on a common operational basis [17]. Energy intensity for operating interval $t$was expressed as

$$EI_t = \frac{E_t}{Y_t + \varepsilon} \qquad (6)$$

where $E_t$denotes electrical energy consumed, $Y_t$represents useful production output, and εprevents numerical instability when output approaches zero [19]. Consequently, increasing consumption caused by increased production can be separated from genuine deterioration in energy performance.

3.3 Coupled Power-Quality–Efficiency Indicators

Rather than modelling power quality and efficiency as independent dimensions, coupled indicators were constructed to determine when electrical disturbances coincide with inefficient energy utilization [13]. THD was evaluated against equipment and distribution losses to identify operating periods in which waveform distortion accompanied increased energy dissipation [16]. Power factor was associated with current demand to distinguish productive loading from excessive current required by reactive-power conditions [18]. Similarly, voltage imbalance was examined against motor loading because comparable imbalance levels can produce different operational consequences depending on machine utilization [20]. Reactive-power demand was related to energy intensity, while peak electrical demand was normalized against simultaneous production output to identify demand increases unsupported by equivalent productive activity [15]. These relationships were consolidated using a normalized composite deterioration index:

$$CEI_t = \sum_{j=1}^{m} w_j \, z_{j,t}, \quad \sum_{j=1}^{m} w_j = 1 \qquad (7)$$

where $z_{j,t}$represents the standardized deviation of the j-th coupled electrical-performance indicator and $w_j$represents its assigned importance [17]. The index therefore increases when multiple power-quality and efficiency conditions deteriorate concurrently rather than responding disproportionately to a single high-magnitude variable [19].

3.4 Feature Selection and Operating-Regime Differentiation

Feature selection was performed within defined industrial operating regimes because the electrical characteristics of efficient operation are not constant across production states [14]. Correlation filtering first removed strongly redundant variables, while multicollinearity assessment prevented closely related electrical quantities from disproportionately influencing model estimation [16]. Mutual information was then used to retain nonlinear associations between candidate predictors and deterioration outcomes, complemented by model-based feature importance for identifying variables with consistent predictive contribution [18]. Regime labels differentiated normal production, peak production, partial loading, idle operation, startup or shutdown, and disturbance conditions [20]. This distinction prevents high startup current, for example, from being incorrectly interpreted using steady-production thresholds [15]. Regime-sensitive predictors consequently characterize deterioration relative to the electrical and production context in which it occurs, producing a more defensible input space for subsequent intelligent detection and predictive modelling [19].

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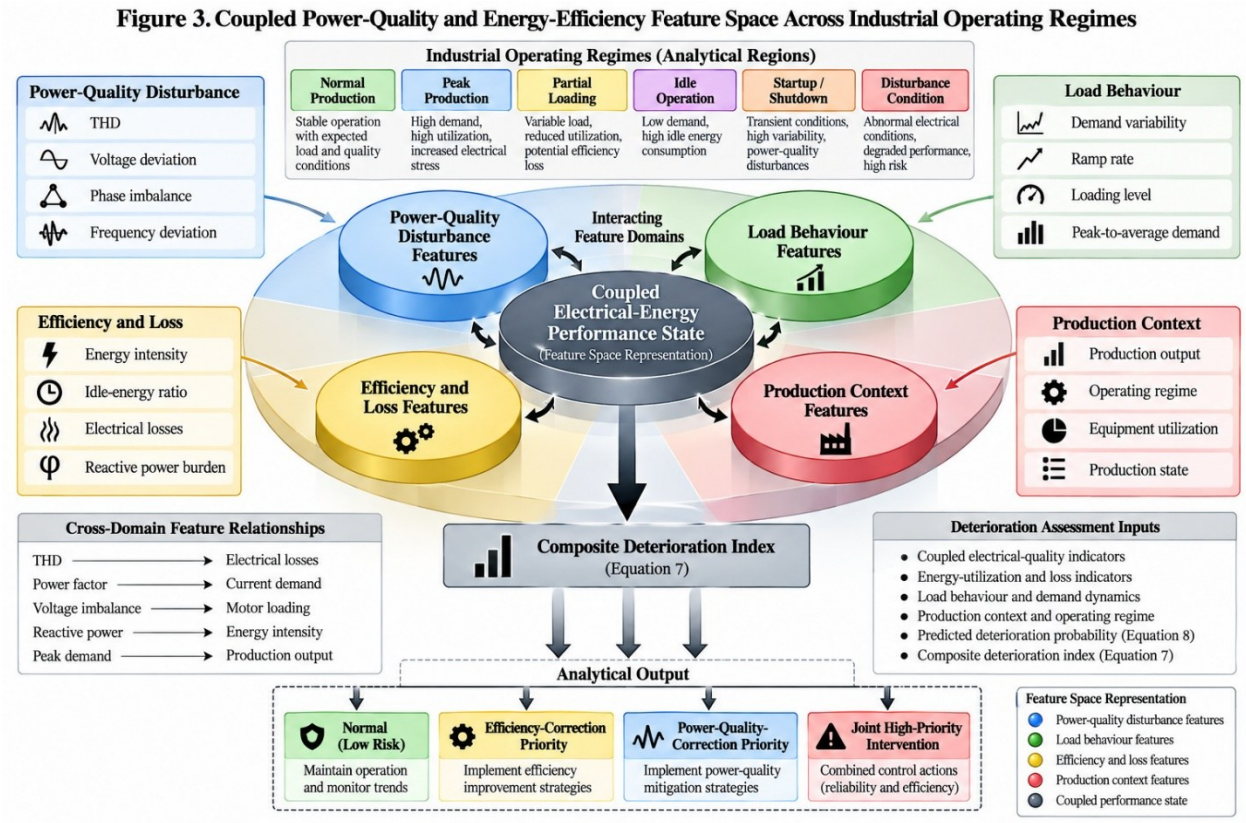

Figure 3. Coupled Power-Quality and Energy-Efficiency Feature Space Across Industrial Operating Regimes

4. INTELLIGENT DETECTION AND PREDICTION OF ELECTRICAL-ENERGY PERFORMANCE

The coupled indicators developed in Section 3 provide a basis for moving beyond retrospective monitoring toward anticipating when industrial electrical conditions are likely to become inefficient, unstable, or operationally undesirable [18]. The modelling stage therefore combines anomaly detection, predictive risk estimation, temporal validation, and explainability so that emerging deterioration can be identified early enough for corrective energy-management action.

4.1 Detection of Abnormal Power-Quality and Efficiency States

Abnormal-state detection was performed relative to equipment-specific and operating-regime-specific behaviour rather than applying identical thresholds throughout the industrial system [18]. Harmonic anomalies were identified when THD or individual harmonic magnitudes departed materially from distributions associated with comparable production conditions [20]. Reactive-power anomalies captured unusually high non-active demand relative to simultaneous active loading, while consumption anomalies represented energy use inconsistent with production output, equipment utilization, or historical operating patterns [22]. Equipment-specific inefficiency was characterized by increasing energy intensity, current demand, or losses without corresponding increases in productive loading [24]. Phase-level features additionally identified persistent load imbalance that could remain obscured within aggregate plant demand [19]. Multivariate anomaly assessment was particularly important because deteriorating conditions can emerge through moderate simultaneous changes in harmonics, power factor, loading, reactive power, and energy intensity rather than through a single extreme measurement [23]. Consequently, anomaly severity reflected both individual deviation and the concurrence of abnormal electrical-efficiency characteristics across synchronized operating windows [25].

4.2 Predictive Modelling of Energy and Power-Quality Risk

Following abnormal-state identification, predictive models estimated whether the present electrical-operational condition was likely to develop into a deteriorated state within a defined future horizon [19]. Regression models provided interpretable baselines for continuous energy and loss estimation, whereas Random Forest models accommodated nonlinear relationships and interactions among electrical variables [21]. Gradient-boosting models were considered for progressively learning complex deterioration patterns, while support-vector approaches

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provided an alternative for separating normal and abnormal states within high-dimensional feature spaces [23]. Neural networks were reserved for cases where sufficient sequential data justified modelling longer temporal dependencies among loading, disturbances, and production transitions [25]. For feature vector x_t, the probability of deterioration within prediction horizon Δwas expressed as

$$P(D_{t+\Delta} = 1 \mid x_t) = \sigma\left(\beta_0 + \sum_{j=1}^{p} \beta_j x_{j,t}\right) \qquad (8)$$

where $D_{t+\Delta}$denotes the future deterioration state, $x_{j,t}$represents the j-th predictor, and $\sigma(\cdot)$transforms the model score into a probability [20]. Prediction horizons were selected to provide sufficient intervention time before unacceptable power-quality or efficiency conditions developed [24].

4.3 Model Training, Hyperparameter Optimization, and Temporal Validation

Model development preserved the chronological structure of industrial operation because random partitioning could allow future production behaviour to influence estimates of historical performance [18]. The earliest 60% of observations formed the training period, the subsequent 20% supported validation and hyperparameter selection, and the final 20% remained locked for independent out-of-time testing [21]. All preprocessing parameters—including missing-value treatment, normalization, feature filtering, operating-regime baselines, and variable selection—were estimated using training information without reference to the independent test period [23]. Tree-based models were tuned across maximum depth, number of estimators, learning rate, minimum observations per terminal node, and feature subsets [25]. Regularization parameters were optimized for regression, support-vector, and neural-network models to constrain unnecessary model complexity [20]. Classification thresholds were selected from temporal validation performance rather than automatically adopting a probability threshold of 0.5 [22]. This design prevents information leakage and tests whether learned relationships among harmonics, loading, reactive demand, energy intensity, and deterioration remain predictive under genuinely later industrial operating conditions [24].

4.4 Model Evaluation and Explainability

Performance evaluation considered both statistical discrimination and the operational consequences of prediction error [19]. For deterioration classification, precision quantified the reliability of predicted abnormal states, while recall measured the proportion of actual deterioration events detected before or during their development [22]. F1-score balanced these objectives, whereas ROC-AUC evaluated ranking performance across classification thresholds and PR-AUC emphasized performance when deterioration events were relatively infrequent [24]. Continuous predictions of consumption, energy intensity, or electrical losses were evaluated using mean absolute error, root mean squared error, mean absolute percentage error, and mean deviation [20]. Model performance was additionally compared across normal production, peak production, partial loading, idle operation, startup or shutdown, and disturbance regimes to identify condition-specific weaknesses [25]. Feature-attribution analysis then determined whether individual predictions were predominantly associated with harmonic distortion, voltage or current imbalance, reactive-power demand, equipment loading, production conditions, or interacting variables [23]. Explainability therefore converts a deterioration probability into evidence that can support the selection of an appropriate corrective strategy [21].

Table 2. Intelligent Model Training, Hyperparameter, and Performance-Evaluation Framework

Model Family	Primary Analytical Role	Principal Inputs	Hyperparameters / Configuration	Validation Measures	Industrial Interpretation
Regression	Continuous energy, loss, and efficiency estimation	Energy intensity, loading, reactive power, production output, disturbance indicators	Regularization strength, predictor subset, interaction terms	MAE, RMSE, MAPE, mean deviation	Quantifies expected consumption or efficiency deviation from operating conditions
Random Forest	Nonlinear deterioration classification and variable interaction detection	Power-quality, load, efficiency, and operating-regime features	Number of trees, maximum depth, minimum leaf size, feature subset	Precision, recall, F1, ROC-AUC, PR-AUC	Detects nonlinear combinations associated with inefficient or abnormal states

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Model Family	Primary Analytical Role	Principal Inputs	Hyperparameters / Configuration	Validation Measures	Industrial Interpretation
Gradient Boosting	High-resolution deterioration-risk prediction	Coupled indicators, temporal statistics, loading and production context	Estimators, learning rate, tree depth, subsampling, regularization	Precision, recall, F1, ROC-AUC, PR-AUC	Identifies incremental combinations of electrical conditions preceding deterioration
Support-Vector Model	Separation of normal and abnormal electrical-energy states	Standardized multidimensional electrical-performance features	Kernel, penalty parameter, kernel scale, class weighting	Precision, recall, F1, ROC-AUC	Defines boundaries between acceptable and deteriorated operating regions
Neural Network	Temporal and complex nonlinear pattern modelling	Sequential electrical, equipment, and production states	Network depth, hidden units, learning rate, regularization, sequence length	F1, PR-AUC, MAE, RMSE	Captures time-dependent deterioration where sufficient sequential data are available
Integrated Selected Model	Final predictive decision support	Selected power-quality–efficiency features and regime context	Validation-selected model parameters and decision threshold	Independent out-of-time performance across all relevant metrics	Provides deterioration probability and supporting feature attribution for energy-management intervention

5. MULTI-OBJECTIVE INTELLIGENT ENERGY OPTIMIZATION AND CONTROL

5.1 Controllable Industrial Energy-Management Resources

Industrial energy management was formulated around resources whose operating states can be modified without violating production requirements [23]. Load scheduling determines when flexible electrical processes operate, whereas equipment dispatch selects combinations of parallel machines capable of satisfying production demand at more efficient loading levels [25]. Reactive-power compensation and capacitor-bank switching regulate reactive demand and power factor, reducing unnecessary current circulation and associated losses [27]. Harmonic-filter utilization provides targeted mitigation when nonlinear loads produce unacceptable waveform distortion [29]. Energy-storage dispatch introduces additional flexibility by charging during lower-demand periods and discharging during peak or electrically constrained conditions [31]. Demand-response participation allows eligible loads to be shifted or curtailed when external network or tariff conditions justify intervention [24]. Controllable production loads are similarly coordinated according to process flexibility, equipment availability, and production priority [28]. These resources constitute the decision space through which predicted deterioration can be converted into physically implementable energy-management actions rather than remaining solely an analytical warning [32].

5.2 Multi-Objective Optimization Formulation

Because no single control action simultaneously minimizes every industrial performance criterion, corrective decisions were formulated as a constrained multi-objective optimization problem [24]. The control vector $u$contains feasible settings for load schedules, equipment dispatch, compensation devices, harmonic filters, storage operation, and other controllable resources [26]. The optimization objective is expressed as

$$\min_{u} J(u) = \alpha C_E(u) + \beta P_{\text{loss}}(u) + \gamma PQI(u) + \delta P_{\text{peak}}(u) \qquad (9)$$

where $C_E$represents energy cost, P_{loss}denotes electrical losses, PQIrepresents power-quality deterioration, and P_{peak}captures peak-demand exposure [29]. The weighting coefficients $\alpha, \beta, \gamma, \delta$determine the relative operational importance of these objectives and can be adapted to production or tariff conditions [31]. Candidate solutions remain subject to electrical and operational feasibility:

$$V_{\min} \le V_i \le V_{\max},\ I_i \le I_i^{\max},\ THD_i \le THD^{\max}$$
$$PF_i \ge PF^{\min},\ P_{\text{demand}} \le P_{\text{contract}} \qquad (10)$$

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for monitored location i[27]. Production requirements, equipment availability, storage limits, switching restrictions, and process dependencies provide additional constraints [30]. Optimization therefore seeks an economically and electrically preferable operating point without improving one criterion by creating unacceptable deterioration elsewhere [32].

5.3 Adaptive Selection of Corrective Energy Strategies

Corrective strategies were selected according to the predicted deterioration mechanism, its severity, the prevailing production regime, and the available control flexibility [23]. When declining power factor accompanied increasing reactive demand, compensation capacity could be introduced through appropriately controlled capacitor banks or other reactive-support resources [26]. Harmonic deterioration associated with converter-intensive operation could activate filtering or coordinate nonlinear loads to reduce simultaneous distortion-producing conditions [28]. Excessive peak demand could instead trigger flexible-load rescheduling, equipment sequencing, or energy-storage discharge where production constraints permitted [30]. Low equipment utilization accompanied by high specific consumption could favour consolidation of production across fewer machines operating nearer efficient loading regions [32]. Persistent phase imbalance could require redistribution of controllable single-phase or unevenly allocated loads [25]. Where deterioration resulted from the interaction of several conditions, candidate interventions were evaluated jointly rather than applying independent corrective rules [29]. Intervention priority was therefore determined from predicted severity, expected efficiency improvement, electrical feasibility, production impact, and implementation cost, allowing the optimization mechanism to distinguish urgent electrical-quality correction from lower-priority efficiency opportunities [31].

Figure 4. Intelligent Power-Quality and Energy-Efficiency Decision Surface

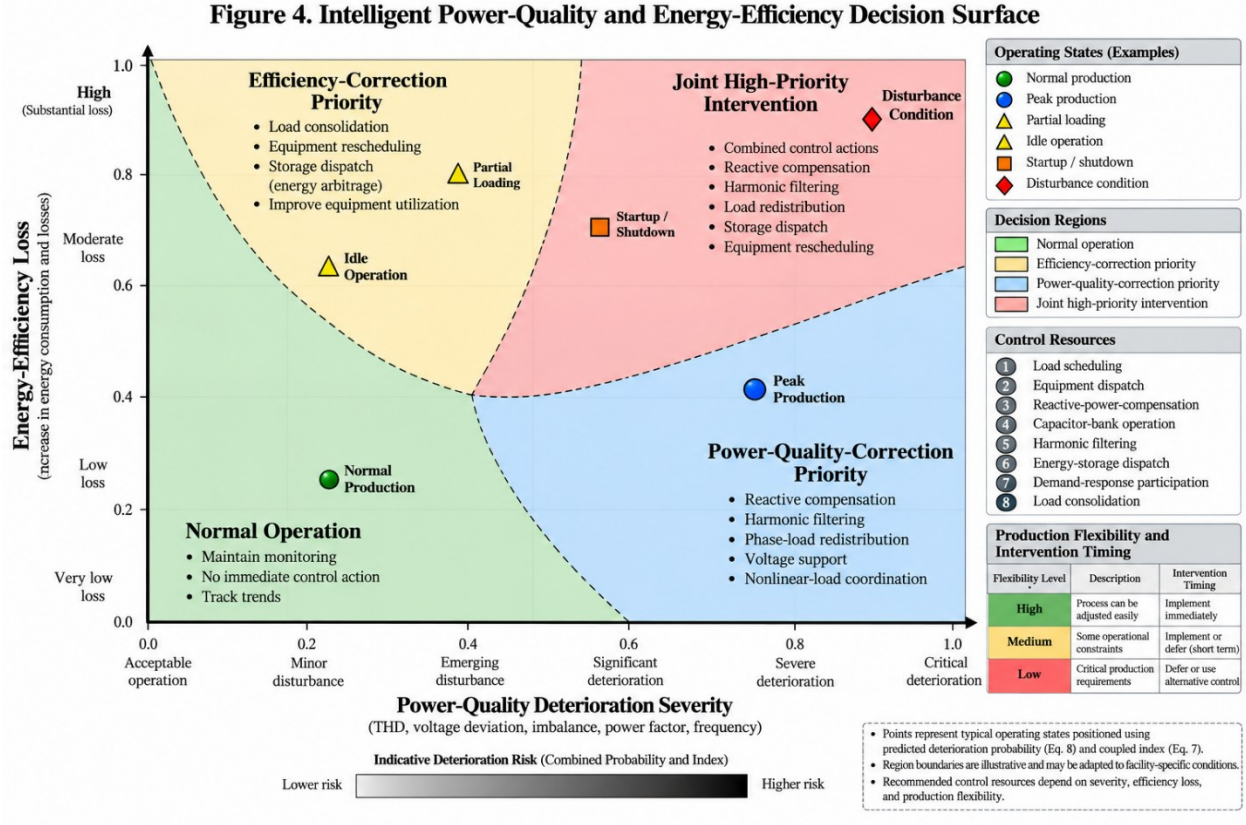

Figure 4. Intelligent Power-Quality and Energy-Efficiency Decision Surface

5.4 Closed-Loop Monitoring and Adaptive Energy Management

Optimization was implemented as a closed-loop process in which every intervention was evaluated against the electrical state that motivated it [24]. The pre-intervention state retained measured power-quality conditions, energy-performance indicators, production regime, deterioration probability, and selected control settings [27]. After the recommended strategy was implemented, synchronized measurements reconstructed a new post-control electrical-operational state [29]. The effectiveness of intervention $a$can be quantified by the normalized performance improvement:

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$$\Delta J_a = \frac{J_{\text{pre}} - J_{\text{post}}}{J_{\text{pre}} + \varepsilon} \qquad (11)$$

where J_{pre} and J_{post} represent the multi-objective performance measure before and after intervention, respectively [31]. A positive ΔJ_a indicates net improvement under the selected objectives, whereas negligible or negative values indicate ineffective or counterproductive control [26]. Deviations between predicted and observed outcomes are retained as feedback for model recalibration, control-weight adjustment, and subsequent intervention selection [28]. This feedback is particularly important as production schedules, equipment condition, tariffs, and load composition change over time [30]. The resulting architecture therefore closes the loop from monitoring and prediction to intervention and verified performance improvement, enabling energy management to adapt continuously rather than relying on permanently fixed operating rules [32].

6. BENCHMARKING, ROBUSTNESS, AND INDUSTRIAL VALIDATION

6.1 Baseline and Strategy Benchmarking

Benchmarking compared six progressively more capable energy-management configurations under equivalent electrical and production conditions [30]. Conventional monitoring represented passive observation of consumption and electrical variables without automated intervention, while threshold-based control initiated predefined actions only after selected limits were exceeded [32]. Energy-only optimization minimized consumption, demand, or cost without explicitly accounting for power-quality deterioration [34]. Conversely, power-quality-only management prioritized voltage, harmonic, imbalance, and power-factor conditions without directly optimizing energy utilization [36]. Predictive energy management incorporated forecast information but did not necessarily coordinate power-quality and efficiency objectives simultaneously [31]. The proposed integrated intelligent strategy combined reconstructed electrical states, coupled deterioration indicators, predictive risk, and constrained multi-objective control [33]. Comparisons were performed using identical evaluation periods and production requirements so that improvements could not be attributed merely to differences in industrial output [35]. Benchmarking consequently determined whether joint power-quality–efficiency optimization provided incremental benefits beyond monitoring, reactive control, or optimization of either performance dimension independently [36].

6.2 Robustness Across Industrial Operating Conditions

Robustness testing examined whether the proposed strategy maintained reliable decisions when industrial conditions departed from those represented during model development [31]. Load variability was introduced across low, normal, and peak-demand regimes, while sudden production changes tested adaptation to rapid transitions in equipment utilization [33]. Missing sensor measurements evaluated dependence on individual electrical variables, and controlled measurement noise assessed sensitivity to imperfect metering and communication conditions [35]. Harmonic disturbances and voltage variations tested whether deterioration remained detectable when power-quality conditions changed independently or concurrently [30]. Equipment switching scenarios examined short-duration transients that could otherwise be mistaken for persistent deterioration [32]. Seasonal demand variation was evaluated to determine whether changes in baseline consumption weakened prediction or optimization performance [34]. Robustness was quantified through changes in prediction error, deterioration-event recall, constraint violations, and achieved objective value relative to the undisturbed condition [36]. This approach distinguishes a strategy that performs well under stable historical conditions from one capable of sustaining useful control decisions across changing industrial environments [35].

6.3 Standards-Based Power-Quality and Energy-Management Assessment

Standards-informed assessment examined whether the analytical framework addressed recognized requirements associated with industrial energy management, power quality, electrical measurement, and system operation [30]. Power-quality assessment considered voltage magnitude, frequency, harmonic distortion, imbalance, and related disturbance characteristics, while the energy-management dimension examined systematic measurement, performance evaluation, efficiency improvement, and continual monitoring [32]. Measurement assessment considered the consistency, synchronization, and reliability of electrical variables used for decision-making [34]. Electrical-system assessment additionally examined whether optimization respected equipment ratings, voltage boundaries, current limits, power-factor requirements, and operational constraints [36]. These comparisons were used to identify correspondence between the proposed framework and relevant technical principles rather than to declare formal certification [31]. Standards conformity ordinarily requires defined testing procedures, documented implementation evidence, applicable jurisdictional requirements, and potentially independent assessment [33]. Accordingly, the study treats standards mapping as a structured validation mechanism for identifying technical

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coverage and implementation gaps while preserving the distinction between analytical alignment and formally demonstrated compliance [35].

Table 3. Benchmarking and Standards-Based Industrial Energy-Management Assessment Matrix

Assessment Dimension	Conventional Monitoring	Threshold-Based Control	Energy-Only Optimization	Power-Quality-Only Management	Predictive Energy Management	Proposed Integrated Strategy
Energy-performance visibility	Consumption observation	Limited	High	Limited	High	**Integrated with electrical state**
Power-quality assessment	Mostly observational	Limit-triggered	Limited	High	Model-dependent	**Coupled with efficiency assessment**
Predictive capability	None	None	Limited	Limited	High	**High, deterioration-oriented**
Reactive-power and PF management	Observed	Rule-based	Secondary	High	Predictable	**Prediction-linked optimization**
Harmonic and imbalance response	Diagnostic	Threshold-triggered	Usually limited	Primary	Model-dependent	**Risk- and severity-dependent**
Peak-demand management	Recorded retrospectively	Limit-based	Primary	Secondary	Forecast-based	**Jointly optimized**
Operating constraints	Monitored	Fixed limits	Optimization constraints	PQ limits	Model constraints	**Electrical and production constraints**
Adaptive intervention	None	Fixed response	Objective-specific	Disturbance-specific	Forecast-informed	**Closed-loop and state-dependent**
Standards-informed assessment	Partial	Limit-oriented	Energy-focused	PQ-focused	Variable	**Energy, PQ, measurement and electrical-system coverage**
Primary limitation	No active optimization	Reactive rather than anticipatory	PQ trade-offs may be missed	Efficiency trade-offs may be missed	Objectives may remain separated	**Higher data, modelling and implementation requirements**

6.4 Technical and Economic Performance Assessment

Final assessment determined whether improved prediction and control translated into practically meaningful industrial benefits [31]. Energy reduction was calculated relative to production-normalized baseline consumption, while electrical-loss reduction quantified decreases in avoidable distribution and equipment losses [33]. Power-factor improvement and THD reduction measured changes in electrical quality following intervention, and peak-demand reduction quantified relief of maximum demand exposure [35]. Prediction reliability was evaluated alongside intervention frequency because excessive corrective actions could increase switching, maintenance, and operational burden despite acceptable predictive accuracy [30]. Equipment utilization determined whether scheduling decisions moved machines toward more productive loading regions rather than simply reducing total consumption [32]. Avoided operating cost incorporated energy savings, peak-demand reductions, and other quantifiable operating benefits while accounting for intervention requirements [34]. The integrated strategy was therefore considered superior only when it produced a defensible combination of improved power quality, reduced energy intensity and losses, reliable prediction, feasible intervention frequency, and economic benefit without compromising production requirements [36].

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Figure 5. Power-Quality–Efficiency–Cost Optimization Frontier Across Energy-Management Strategies

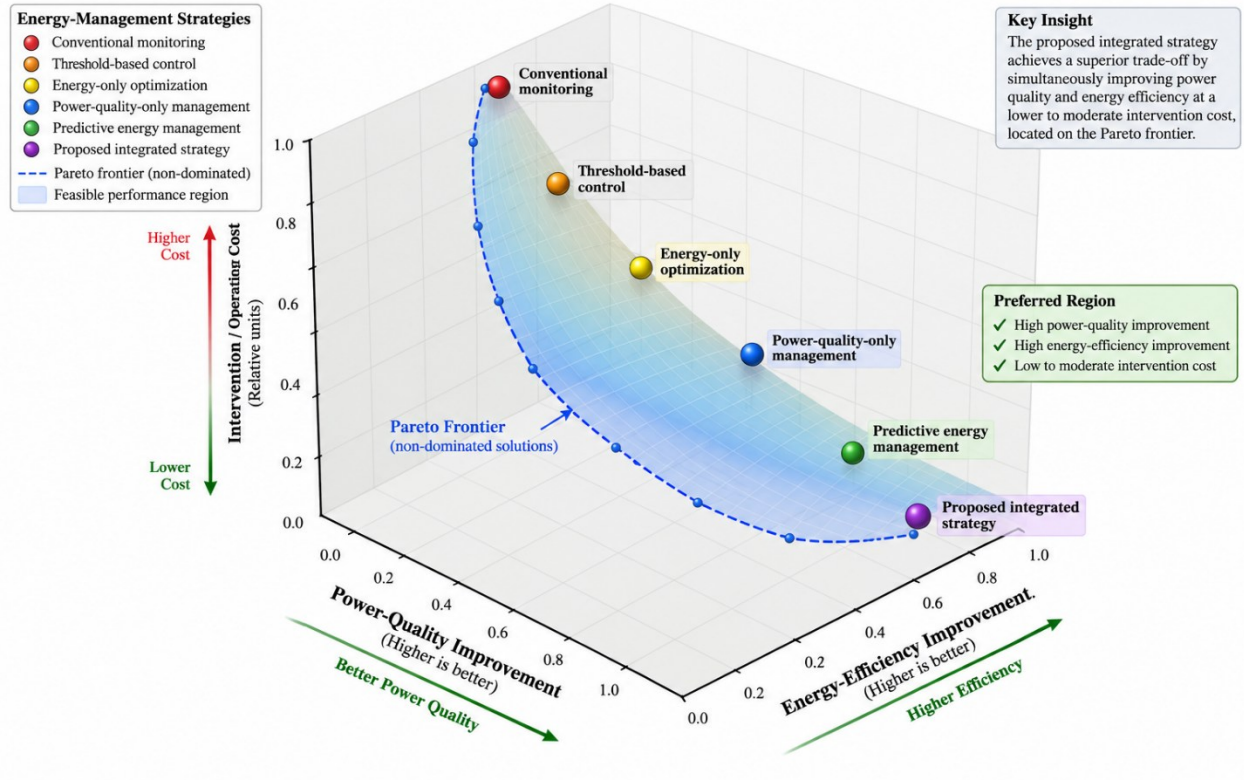

Figure 5. Power-Quality–Efficiency–Cost Optimization Frontier Across Energy-Management Strategies

7. DISCUSSION AND CONCLUSION

7.1 Integrated Interpretation and Industrial Implications

The proposed framework demonstrates that effective industrial energy management depends on connecting measurement, electrical-state reconstruction, predictive intelligence, and operational optimization within a unified decision structure [35]. Multi-source measurements establish electrical and production context, while synchronized state reconstruction determines the conditions under which disturbances and inefficient consumption emerge [37]. This contextual representation enables predictive models to distinguish normal production-driven demand from abnormal electrical-energy behaviour requiring intervention [39]. Importantly, power quality and energy efficiency should be interpreted as coupled industrial performance conditions rather than independent objectives [36]. In nonlinear and dynamically loaded systems, harmonic distortion, voltage imbalance, reactive-power demand, and poor power factor can increase current loading, losses, thermal stress, and inefficient capacity utilization [38]. Conversely, aggressive energy reduction without consideration of electrical quality or production requirements can create undesirable operating conditions [40]. Integrating predictive risk with constrained optimization therefore enables industrial facilities to select interventions according to both the electrical cause of deterioration and its efficiency, reliability, and production consequences [37].

7.2 Practical Deployment, Limitations, and Scalability

Practical deployment depends on the availability and quality of synchronized electrical and operational measurements [35]. Older industrial facilities may lack sufficiently distributed sensors or may operate legacy equipment that cannot communicate directly with modern energy-management platforms [38]. Missing measurements, inconsistent timestamps, sensor drift, and communication interruptions can consequently reduce state-reconstruction and prediction reliability [40]. Computational requirements may also increase when high-frequency waveform measurements and large equipment populations are analysed continuously [36]. Model transferability presents another limitation because relationships learned in motor-intensive manufacturing may not directly represent furnaces, process industries, or highly automated production environments [39]. Deployment therefore requires sector- and facility-specific calibration while maintaining interpretable recommendations for

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operators [37]. Cybersecurity is equally important because increased connectivity expands the interaction between measurement, control, and production systems [40]. Integration with existing SCADA and energy-management systems should consequently preserve access control, operational safety, explainability, and compatibility with established industrial control practices [38].

7.3 Conclusion and Future Research

This study establishes an integrated intelligent energy-management framework for jointly improving power quality and energy efficiency across industrial electrical systems. By connecting multi-source electrical monitoring with synchronized state reconstruction, coupled performance indicators, predictive modelling, and constrained multi-objective optimization, the framework moves industrial energy management beyond isolated consumption monitoring and reactive disturbance correction. Its principal contribution lies in recognizing that energy losses, power-quality deterioration, equipment loading, production requirements, and operating costs are interconnected conditions requiring coordinated assessment and control. The resulting approach provides a foundation for reducing inefficient energy consumption and electrical losses, improving power quality and equipment utilization, strengthening industrial reliability, lowering operating costs, and supporting predictive maintenance and sustainable manufacturing. Future research should extend the framework through industrial digital twins, reinforcement-learning-based control, renewable-generation coordination, advanced energy-storage integration, and real-time adaptive optimization. Large-scale deployment across different industrial sectors should further examine model transferability, long-term equipment behaviour, economic performance, and resilience under changing electrical and production environments.

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