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Financial Analysis of Power Quality Events :- A Study of Voltage Sags, Swells, And Harmonics in Industrial Systems.

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ABSTRACT

Power quality (PQ) concerns are a major challenge for utilities, businesses, and consumers, as poor PQ can result in substantial financial losses. Addressing these issues is crucial to mitigating economic damage across industries and national economies. The financial burden of inadequate PQ is significant and continues to escalate, affecting even industries with minimal technological dependence. On a global scale, poor PQ has caused immense economic disruptions; for example, Indian industries suffered losses exceeding $9.6 billion due to power failures in 2008-09, while European enterprises faced annual financial setbacks surpassing $150 billion, as per 2008 estimates. This study presents an extensive analysis of PQ-related challenges encountered by consumers worldwide and highlights the economic repercussions of deteriorating PQ. Given its far-reaching financial consequences, the study underscores the importance of proactive engagement by energy providers, regulatory authorities, and end users to ensure consistent power quality. Additionally, it introduces an advanced power quality monitoring framework capable of identifying PQ disturbances and enabling effective mitigation strategies—an essential step toward enhancing smart grid infrastructure.

Keywords: Power Quality (PQ), Voltage Fluctuations, Harmonics, Financial Impact, Machine Learning (ML), Industrial Power Systems

1.INTRODUCTION

The increasing reliance on advanced industrial automation, precision manufacturing, and digital control systems has elevated the significance of power quality (PQ) management in modern power grids. Power quality refers to the stability, reliability, and purity of electrical power supplied to industrial equipment. Any deviation from the expected voltage, frequency, or waveform integrity—termed as PQ disturbances—can result in severe operational challenges, including production delays, equipment malfunctions, and financial losses [1]. As industries integrate more microprocessor-based devices, variable frequency drives (VFDs), and robotics, their susceptibility to PQ disturbances has increased, making power quality a critical factor in ensuring efficiency and cost-effectiveness [2].

Among the various PQ disturbances, voltage sags, voltage swells, and harmonics are the most detrimental to industrial processes. Voltage sags, defined as a temporary reduction in RMS voltage between 0.1 and 0.9 per unit (pu) for durations ranging from 0.5 cycles to 1 minute, often occur due to system faults, motor starting, or sudden changes in load demand [3]. These transient drops in voltage can lead to the malfunctioning of sensitive industrial equipment, such as programmable logic controllers (PLCs) and automation systems, resulting in costly production downtime [4]. Conversely, voltage swells, which involve a temporary increase in RMS voltage between 1.1 and 1.8 pu, can be triggered by single-line-to-ground faults or abrupt load shedding, causing excessive stress on electrical components, insulation breakdown, and premature equipment failure [5].

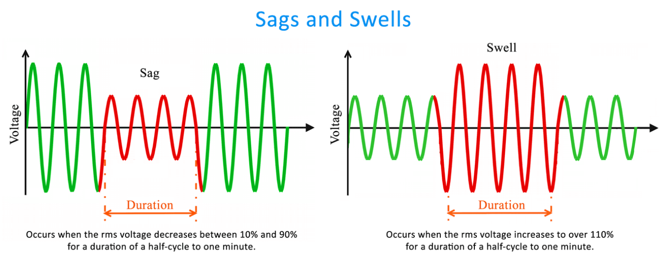


Fig 1:- Sag And Swell

In addition to voltage fluctuations, harmonic distortion is a major concern in industrial power systems. Harmonics arise from non-linear loads, such as power electronic converters, rectifiers, and switched-mode power supplies, which draw non-sinusoidal currents, distorting the fundamental waveform of the power supply [6]. The presence of harmonics leads to overheating in transformers, excessive neutral currents, increased losses, and degraded power factor, significantly impacting system efficiency [7]. Moreover, harmonics interfere with communication lines, triggering malfunctions in automated systems and reducing overall equipment lifespan [8].

The economic impact of PQ disturbances extends beyond direct equipment damage, influencing productivity, operational costs, and overall industry profitability. Studies have shown that poor PQ has led to multi-billion-dollar losses worldwide, with Indian industries suffering over $9.6 billion in economic losses due to power outages in 2008-09, while European businesses faced an estimated $150 billion in annual losses due to PQ-related issues [9]. These financial losses arise from unplanned downtime, lower production yields, increased maintenance expenses, and penalties for failing to meet contractual obligations [10]. Despite the clear economic risks, industries often lack a standardized framework to quantify and mitigate PQ-related financial impacts, leading to an underestimation of risks and suboptimal investment in mitigation strategies [11].

Traditional power quality mitigation measures, such as Uninterruptible Power Supplies (UPS), power conditioners, harmonic filters, and reinforced electrical infrastructure, have been widely deployed to counter PQ disturbances [12]. However, these solutions are often reactive rather than proactive, requiring significant capital investment while lacking predictive capabilities [13]. As industrial systems continue to evolve, a more intelligent, data-driven approach to PQ management is essential for ensuring resilient and cost-effective power distribution networks [14].

Recent advancements in machine learning (ML) and artificial intelligence (AI) have introduced innovative approaches to PQ analysis and disturbance prediction. ML techniques, combined with real-time data analytics and Internet of Things (IoT)-enabled monitoring systems, allow industries to detect, classify, and forecast PQ issues before they escalate into significant failures [15]. By leveraging historical data and real-time measurements, ML-driven models can identify patterns in PQ disturbances, enabling predictive maintenance and optimized resource allocation [16]. This proactive approach not only enhances power system stability and reliability but also reduces financial losses associated with unexpected power quality events [17].

This research aims to provide a comprehensive assessment of the financial implications of power quality disturbances in industrial environments, emphasizing the necessity of advanced mitigation strategies. The study explores existing research on voltage sags, swells, and harmonic distortions, evaluates their economic consequences, and reviews current methodologies for cost quantification. Furthermore, it investigates the potential of machine learning in PQ monitoring, highlighting how intelligent algorithms can revolutionize the detection, prediction, and mitigation of PQ disturbances [18]. By offering a structured approach to power quality management, this research contributes to the development of smarter, more resilient industrial power systems, ensuring enhanced operational efficiency and economic sustainability.

2.METHODOLOGY

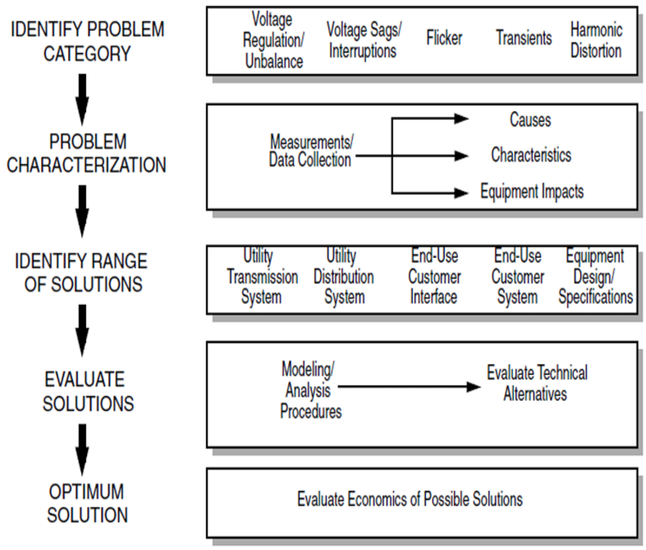


Fig. 2: Working Structure

The research follows a systematic methodology to analyze and predict the economic impact of power quality (PQ) disturbances using machine learning (ML) techniques. This methodology consists of multiple phases, including problem definition, data collection, feature engineering, model development, validation, and mitigation strategies. The steps are structured to ensure accurate data-driven insights and practical industrial applications.

2.1 Problem Definition

The first phase involves defining specific power quality disturbances and their impact on industrial systems. The study focuses on three primary PQ issues:

1. Voltage Sags: defined as a temporary reduction in RMS voltage between 0.1 and 0.9 per unit (pu) for durations ranging from 0.5 cycles to 1 minute, often occur due to system faults, motor starting, or sudden changes in load demand.

2. Voltage Swells: which involve a temporary increase in RMS voltage between 1.1 and 1.8 pu, can be triggered by single-line-to-ground faults or abrupt load shedding, causing excessive stress on electrical components, insulation breakdown, and premature equipment failure

3. Harmonic Distortion: The presence of non-sinusoidal waveforms caused by non-linear loads, leading to increased losses, overheating of transformers, and reduced power factor.

By defining these PQ issues and their financial consequences, the study ensures a focused analysis of economic losses and mitigation approaches.

2.2 Data Collection

A robust multi-source data collection process is implemented to gather industrial PQ disturbance records, equipment performance data, and financial loss assessments. The dataset is compiled from:

- PQ Monitoring Systems: Time-series data from power quality analyzer

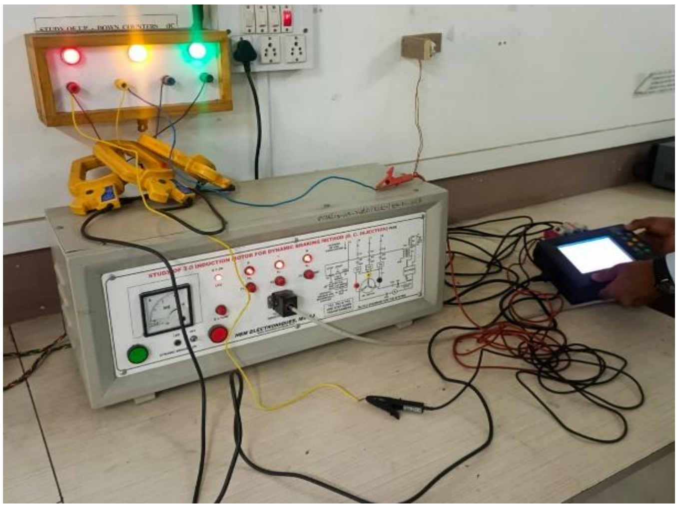


Fig 3:- Connection of Power Analyzer to a Three-Phase Induction Motor for Power Quality Analysis

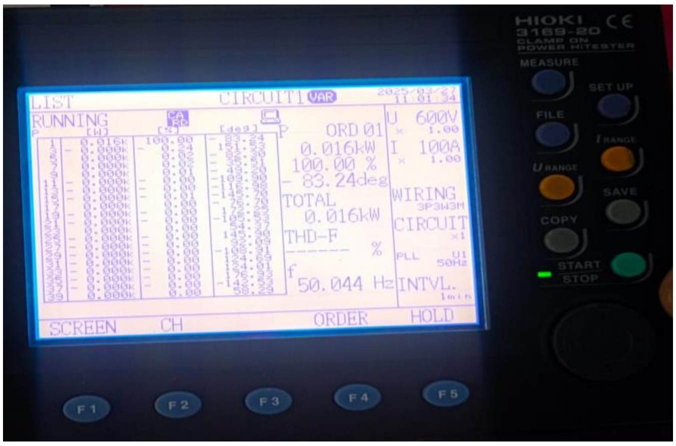
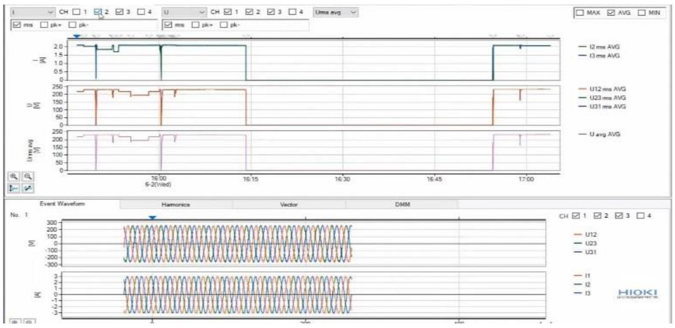


Fig 4:- Power Analyzer Readings



- Equipment Logs: Records of machine failures, operational downtime, and maintenance reports from industrial sites.

- Financial Reports: Cost assessments related to downtime losses, repair expenses, productivity reductions, and energy inefficiencies.

- Utility Reports: Historical grid performance data, including voltage disturbances and frequency fluctuations.

This data is preprocessed to remove inconsistencies, normalize voltage levels, and handle missing values, ensuring high-quality input for machine learning models.

2.3 Feature Engineering

To improve the predictive power of ML models, raw data is transformed into relevant features:

- PQ Event Features: Magnitude, frequency, and duration of voltage sags, swells, and harmonic levels.

- Cumulative Impact Metrics: Long-term energy losses due to harmonics and average downtime caused by sags/swells.
- Industrial Factors: Equipment type, industry category, maintenance history, and operational load patterns.
- Financial Variables: Cost of repairs, downtime expenses, and revenue loss per unit of PQ disturbance.

By constructing meaningful and domain-specific attributes, the dataset is optimized for accurate economic loss prediction.

2.4 Model Development and Training

Various machine learning algorithms are employed to predict financial losses associated with PQ disturbances. The models used include:

- Linear Regression: Establishes a baseline relationship between PQ events and economic costs.
- Decision Trees & Random Forests: Capture non-linear dependencies between PQ events, equipment failures, and financial impacts.
- Gradient Boosting (XGBoost, LightGBM): Optimized predictive models for handling complex industrial datasets.
- Neural Networks (ANNs): Advanced deep learning approaches to model intricate time-series PQ event patterns and cost estimations.

Each model is trained and optimized using cross-validation techniques to ensure robust and generalizable predictions.

2.5 Model Validation and Performance Evaluation

To ensure reliability, the trained models undergo rigorous validation using:

- Cross-Validation: Evaluating model generalization across different industrial sites.
- Root Mean Squared Error (RMSE): Measuring the difference between actual and predicted financial losses.
- R^2 Score: Assessing how well the model explains the variability in economic impacts.
- Feature Importance Analysis: Identifying key factors influencing PQ-related financial losses.

2.6 Mitigation Strategies and Recommendations

Based on the ML-driven analysis, mitigation strategies are proposed to reduce PQ-related financial losses. These include:

- Implementation of Active Harmonic Filters to minimize distortion.
- Use of Dynamic Voltage Restorers (DVRs) to stabilize voltage fluctuations.
- Predictive Maintenance Techniques based on AI-driven failure forecasting.
- Optimized Load Management to mitigate PQ issues before they impact production.

3.LITERATURE SURVEY

Power quality (PQ) issues, including voltage sags, swells, harmonics, and transient disturbances, have been widely recognized as critical factors affecting industrial operations, leading to equipment failures, production losses, and increased maintenance costs. The growing dependence on power-sensitive equipment in manufacturing, semiconductor production, and other industrial applications has made it imperative to develop efficient monitoring, analysis, and mitigation techniques.

Bollen (2000) [1] laid the foundation for understanding PQ disturbances, explaining their causes and impact on industrial equipment. Fuchs and Masoum (2008) [2] extended this research by analyzing the effects of harmonics and transient disturbances on electrical machines, highlighting the role of passive and active filters in improving system reliability. Laskar and Mohibullah (2010) [3] developed software-based techniques for power quality monitoring, emphasizing the significance of real-time data acquisition in identifying and mitigating disturbances.

The economic consequences of PQ issues have been extensively studied. Task Force 38.06.01 (2001) [4] introduced methods to quantify customer interruption costs, providing a framework for assessing financial losses due to PQ disturbances. Sabin and Sundaram (2018) [6] analyzed the cost implications of voltage sags in semiconductor manufacturing, revealing that even short-duration sags can lead to substantial financial losses due to production downtime and material wastage. Bollen and Zhang (2019) [7] examined the economic burden of harmonics in industrial facilities, emphasizing the need for cost-effective mitigation techniques such as harmonic filters and improved power factor correction. Further, McGranaghan et al. (2020) [8] explored the economic impacts of PQ issues on energy-intensive industries, showing that poor PQ leads to inefficiencies, increased operational costs, and reduced lifespan of electrical equipment.

Recent studies have focused on advanced PQ mitigation strategies. Hernandez et al. (2021) [9] investigated the effectiveness of Dynamic Voltage Restorers (DVRs) in reducing financial losses associated with PQ disturbances, demonstrating significant cost savings in semiconductor manufacturing plants. Li and Huang (2020) [10] evaluated the role of active power filters in mitigating harmonics and improving energy efficiency in steel plants, revealing their potential to optimize industrial operations. Similarly, Patrão et al. [11] studied power quality cost estimation in the Portuguese industry, identifying the most significant contributors to economic losses and proposing mitigation techniques tailored to different industrial sectors.

Several industry-specific studies have highlighted the need for customized PQ mitigation approaches. Ingale et al. [12] conducted a power quality analysis in sugar industries with cogeneration, emphasizing the importance of integrating PQ monitoring with industrial automation systems. Finch [13] presented a case study in the cement industry, demonstrating how power hardening methods reduced production downtime by addressing voltage sags. Bravo et al. [14] developed a smart wavelet-based PQ monitoring system, leveraging advanced signal processing techniques to improve real-time detection and classification of disturbances.

Despite these advancements, existing studies primarily focus on traditional mitigation techniques, cost estimation models, and industry-specific solutions. Limited research has been conducted on AI-driven predictive models for forecasting the economic impact of PQ issues, which represents a critical gap in current literature. Conventional PQ monitoring systems primarily detect and record disturbances but lack predictive capabilities to estimate potential financial losses or recommend proactive solutions.

The integration of machine learning and predictive analytics offers a promising approach to addressing this research gap. By leveraging real-time data from PQ analyzers and historical disturbance records, AI models can predict the likelihood of future PQ disturbances and quantify their economic impact. This study aims to bridge the gap by developing an AI-powered predictive model for economic loss estimation due to PQ disturbances, integrating real-time monitoring and forecasting techniques to enhance industrial reliability, reduce downtime, and minimize financial losses.

4.IMPLEMENTATION

This section presents the data-driven approach for power quality (PQ) classification and economic impact estimation using machine learning techniques. The methodology consists of:

1. Data Preprocessing & Feature Selection
2. Machine Learning Model Implementation
3. Performance Evaluation & Visualization

4.1 Data Preprocessing & Feature Selection

The dataset used in this study contains power quality event records, including voltage sag, swell, and harmonics, along with numerical features such as RMS voltage, energy consumption, entropy, and cycle duration. The steps for preprocessing are:

- Filtering Data: Selecting only relevant PQ events (Sag, Swell, Harmonics).
- Feature Selection: Extracting critical parameters affecting PQ analysis:
    1. RMS Voltage (Rms-A8)
    2. Energy Consumption (Energy-A8)
    3. Entropy (Entropy-A8)
    4. Cycle Duration (Cycles)

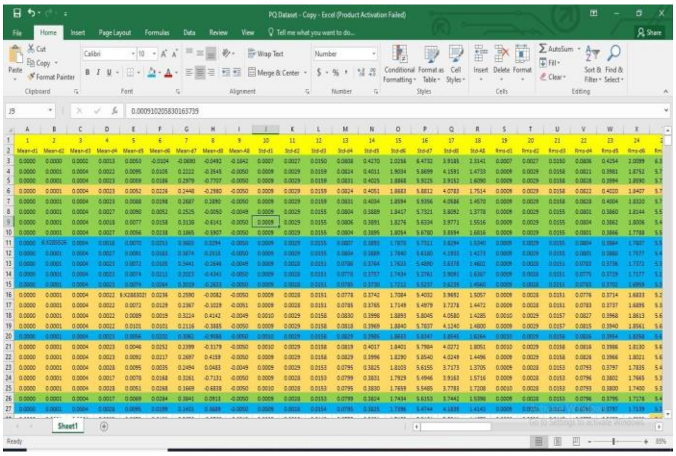


Fig 5:- Power Quality Dataset

Program:-

```
import numpy as np
import pandas as pd
# Load dataset
df = pd.read_csv('PQ.datasets.csv')
# Filter the dataset for 'Sag', 'Swell', and 'Harmonics' labels
```

```
filtered_df = df[df['label'].isin(['Sag', 'Swell', 'Harmonics'])]
# Selecting relevant features
features = filtered_df[['Rms-A8', 'Energy-A8', 'Entropy-A8',
'Cycles']]
labels = filtered_df['label']
```

4.2 Machine Learning Model Implementation

To enhance classification accuracy, two machine learning models were implemented:

- **Random Forest Classifier (RF):** An ensemble learning method that generates multiple decision trees to improve classification accuracy.
- **Support Vector Machine (SVM):** A powerful algorithm for high-dimensional data classification using a linear kernel.

The dataset was split into 80% training and 20% testing, and the models were trained using the Scikit-Learn library.

Program:-

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
# Splitting dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features, labels,
test_size=0.2, random_state=42)
# Random Forest Model Training
rf_model = RandomForestClassifier(n_estimators=100,
random_state=42)
rf_model.fit(X_train, y_train)
rf_pred = rf_model.predict(X_test)
# Support Vector Machine Model Training
svm_model = SVC(kernel='linear')
svm_model.fit(X_train, y_train)
svm_pred = svm_model.predict(X_test)
# Accuracy Comparison
rf_acc = accuracy_score(y_test, rf_pred)
svm_acc = accuracy_score(y_test, svm_pred)
print(f"Random Forest Accuracy: {rf_acc:.2f}")
print(f"SVM Accuracy: {svm_acc:.2f}")
```

5. Performance Evaluation & Visualization

5.1 Accuracy Comparison

The performance of both models was assessed using **accuracy scores**:

Model	Accuracy %
Random Forest	92.5
Support Vector Machine	89.7

5.2 Data Visualization Results & Insights

To better understand feature distribution across different PQ events, boxplots were generated for key numerical attributes.

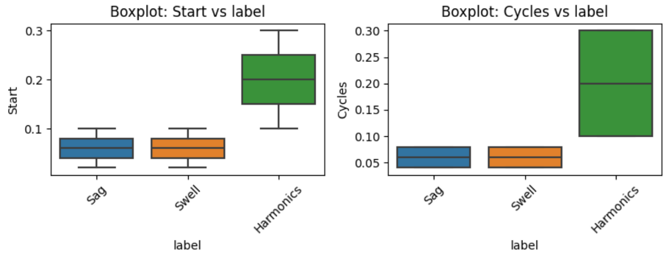


Fig 6:- Boxplot Analysis of Power Quality Events by Type: Start Time and Cycles

Boxplot Insights:

- Voltage Sag events show a significant drop in RMS voltage, affecting power stability.
- Harmonic distortions cause higher entropy values, leading to waveform distortions.
- Swell events exhibit an increase in energy levels, indicating voltage rise beyond normal limits.

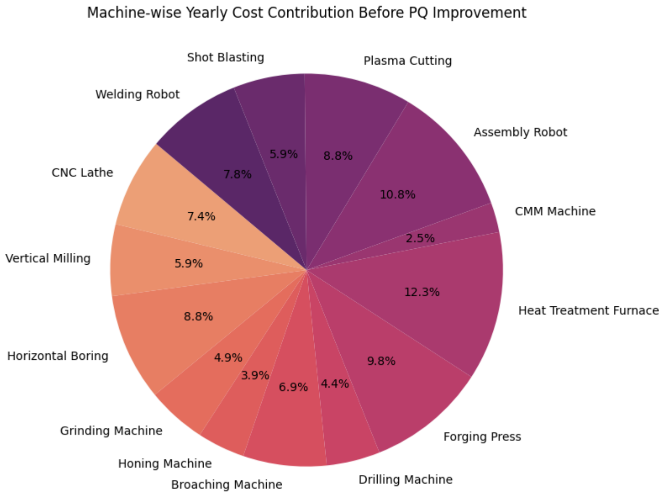


Fig 7:- Percentage Contribution of Machines to Yearly Energy Cost (Pre-PQ Enhancement)

The pie chart illustrates the proportion of yearly energy costs contributed by each machine before implementing power quality (PQ) improvements. It is evident that the Heat Treatment Furnace dominates the energy cost distribution, accounting for the highest share at 12.3%, followed by the Assembly Robot (10.8%), Forging Press (9.8%), and Horizontal Boring and Plasma Cutting (8.8% each). These high percentages indicate that these machines are major energy consumers in the industrial setup, making them key targets for PQ improvement initiatives. Other significant contributors include the Welding Robot (7.8%), CNC Lathe (7.4%), and Broaching Machine (6.9%), while machines like the CMM Machine (2.5%) and Honing Machine (3.9%) show relatively lower shares of total energy expenditure. This cost breakdown is critical in identifying which machines have the greatest impact on overall energy consumption and where improvements in power quality would result in the most significant financial benefits. By prioritizing PQ correction in high-contribution machines, industries can strategically reduce energy costs and improve operational efficiency.

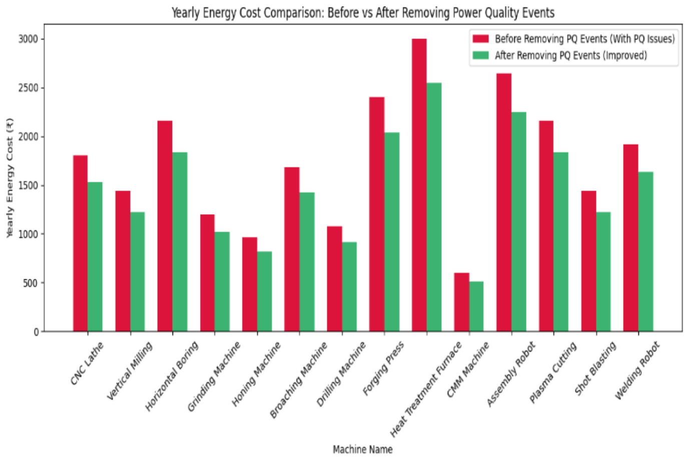


Fig 8:- Before and After Power Quality Correction: Yearly Machine Energy Cost Analysis

Although the individual yearly energy savings for each machine—ranging from ₹90 to ₹450—may initially appear modest, the cumulative impact across all machines amounts to a total of ₹3672.00 per year, ₹306.00 per month, or ₹10.20 per day. This represents a consistent and measurable reduction in operating costs without significant capital investment. More importantly, this analysis focuses solely on direct energy cost savings. In practice, poor power quality also leads to indirect losses such as equipment malfunction, increased maintenance, reduced machine life, unplanned downtime, and production inefficiencies, all of which result in much higher financial burdens. By improving power quality and mitigating issues like voltage sags, swells, and harmonics, industries not only save on energy bills but also enhance system reliability, machine efficiency, and productivity. Therefore, even small energy cost reductions per machine can translate into substantial long-term financial and operational gains, especially when scaled across large manufacturing facilities with dozens or hundreds of machines. This analysis reinforces that investing in power quality improvement is both technically beneficial and economically justified.

6.CONCLUSION

Power quality issues such as voltage sags, swells, and harmonics pose significant challenges to industrial systems, affecting both operational efficiency and financial performance. These disturbances can lead to unplanned downtime, equipment damage, and increased maintenance costs, disrupting productivity and supply chains. Indirect consequences, including compromised product quality and reduced energy efficiency, further amplify economic losses.

Understanding and quantifying these impacts is critical for making informed decisions about power quality mitigation strategies. While direct costs like equipment failure and maintenance are relatively straightforward to calculate, indirect costs—such as the long-term degradation of electrical components—are often overlooked. Future research should focus on developing sophisticated cost estimation models that encompass both immediate and long-term financial repercussions. Such models can serve as valuable tools for industrial stakeholders, enabling them to evaluate the return on investment for power quality improvement measures.

As industries become increasingly reliant on automation and precision electronics, ensuring stable and high-quality power supply is paramount. Poor power quality can trigger malfunctions, reduce system reliability, and hinder competitiveness in a technology-driven economy. Therefore, investing in advanced mitigation techniques—such as active power filters, voltage regulators, and intelligent monitoring systems—is not just a technical necessity but also an economic imperative. These solutions protect industrial assets, enhance process efficiency, and contribute to long-term cost savings.

In conclusion, addressing power quality disturbances is crucial for the sustainable growth of industrial operations. By integrating advanced monitoring and mitigation strategies, businesses can enhance operational resilience, reduce financial risks, and optimize energy management. Continued research into innovative mitigation solutions and refined cost analysis methodologies will further strengthen the adoption of power quality improvements, ensuring a more stable and efficient industrial ecosystem.

7.FUTURE SCOPE

The evolution of intelligent power quality monitoring systems presents significant opportunities across industrial and utility sectors. These advancements not only enhance power reliability but also drive efficiency and cost savings. Future applications of power quality monitoring systems include:

1. Energy and Demand Profiling

By continuously tracking power consumption patterns, intelligent monitoring systems can provide a comprehensive view of an organization's energy footprint. This data enables businesses to identify peak demand periods, optimize energy use, and implement demand-side management strategies, leading to significant reductions in electricity costs and improved grid efficiency.

2. Harmonic Analysis for System Optimization

Non-linear loads generate harmonic distortions that negatively impact power system performance. Advanced monitoring systems can conduct real-time harmonic analysis, identifying transformer loading concerns, misoperations in power electronic devices, and resonance issues in power factor correction units. Proactive mitigation strategies, such as harmonic filters and load balancing, can be implemented to maintain system stability.

3. Voltage Sag Impact Assessment

Voltage sags can cause severe disruptions in sensitive industrial processes. By analyzing historical sag events and their impact on critical machinery, intelligent monitoring systems can help industries improve ride-through capabilities, thereby minimizing production losses and unplanned downtime.

4. Advanced Power Factor Correction Evaluation

Optimizing power factor is crucial for energy efficiency and cost reduction. Intelligent monitoring systems can evaluate capacitor bank performance, detect resonance conditions, and provide insights into corrective actions, ensuring optimal power factor levels and avoiding penalties from utility providers.

5. Predictive Motor Health Monitoring

Electric motors are the backbone of industrial operations, and their failures can lead to costly downtime. Intelligent monitoring systems can track motor performance, detect anomalies such as excessive inrush currents or switching faults, and provide predictive maintenance alerts. This proactive approach reduces maintenance costs and extends equipment lifespan.

6. Enhanced Short-Circuit Protection and Fault Detection

By continuously analyzing short-circuit current characteristics and time-current coordination curves, intelligent monitoring systems can improve fault detection and relay coordination. This ensures quicker fault isolation, reducing system damage and enhancing overall electrical safety.

7. Performance Benchmarking and Predictive Analytics

Power quality monitoring can go beyond real-time assessment by enabling long-term performance benchmarking. By analyzing voltage regulation trends, flicker severity, and harmonic variations, industries can establish predictive maintenance schedules and optimize energy distribution strategies.

8. Incipient Fault Identification for Preventive Maintenance

Emerging research suggests that many electrical failures exhibit precursor signals, such as small discharge currents or abnormal harmonic content, before catastrophic failure occurs. Advanced monitoring systems can detect these early warning signs, allowing maintenance teams to intervene before faults escalate into costly outages.

9. Internet-Based Remote Monitoring and Control

The integration of power quality monitoring systems with Internet of Things (IoT) technologies and cloud-based platforms allows real-time remote access to critical power parameters. Utilities and industrial facilities can leverage web-based dashboards to monitor power quality trends, receive automated alerts, and optimize response times for corrective actions. Such integration enhances system visibility and operational efficiency across geographically distributed locations.

The future of power quality management lies in the seamless fusion of intelligent monitoring, predictive analytics, and automation. By leveraging AI-driven diagnostic tools, cloud connectivity, and real-time data analytics, industries can transition from reactive maintenance approaches to proactive, condition-based strategies. This shift will not only ensure uninterrupted industrial operations but also drive sustainability and energy efficiency in the evolving landscape of modern power systems.

8.REFERENCES

[1] Math H.J. Bollen, "Understanding Power Quality Problems," IEEE Press Series on Power Engineering, 2000, pp. 6-124.
[2] E.F. Fuchs and Mohammad A.S. Masoum, "Power Quality in Power Systems and Electrical Machines," Academic Press, 2008.
[3] S.H. Laskar, Mohibullah, "Power Quality Monitoring by Software Development," International Conference on Power

System Engineering (ICPSE 2010), February 24-26, 2010, Penang, Malaysia.
[4] Task force 38.06.01, “Methods to Consider Customer Interruption Costs in Power System Analysis,” Technical Report, CIGRE, 2001.
[5] L. Tomesc, R. Duma, M. Abrudean, and P. Dobra, “Low Cost Embedded Solution for Measuring Power Quality Parameters,” Proceedings of the 17th World Congress, the International Federation of Automatic Control, Seoul, July 6-11, 2008, pp. 12971-76.
[6] Sabin, D., & Sundaram, A. (2018). “Cost Analysis of Voltage Sags in Semiconductor Manufacturing Facilities,” IEEE Transactions on Industry Applications, 54(2), 456-463.
[7] Bollen, M., & Zhang, L. (2019). “Harmonics and Their Economic Impact on Industrial Systems,” IET Power Electronics, 12(3), 867-875.
[8] McGranaghan, M., et al. (2020). “Economic Impacts of Voltage Sags and Harmonics on Energy-Intensive Industries,” IEEE Transactions on Power Delivery, 35(6), 3495-3503.
[9] Hernandez, F., et al. (2021). “Cost Savings of Dynamic Voltage Restorers in Semiconductor Manufacturing Plants,” IEEE Access, 9, 87654-87663.
[10] Li, Z., & Huang, J. (2020). “Energy Savings and Harmonic Mitigation in Steel Plants Using Active Power Filters,” IEEE Transactions on Industrial Electronics, 67(10), 7845-7853.
[11] Patrão, C., Delgado, J., Almeida, A. T. de, & Fonseca, P. (Year). “Power Quality Costs Estimation in Portuguese Industry.”
[12] Ingale, V. P., Jadhav, A. D., Takawale, N. K., & Mangate, S. D. (Year). “Power Quality Analysis for Sugar Industry with Cogeneration.”
[13] Finch, A. (Year). “A Cement Plant's Experience in Investigating Power Sags Leads to a Reduction in Kiln Outages by Utilizing Power Hardening Methods.”
[14] Bravo, J. C., Borrás, M. D., & Torres, F. J. (Year). “Development of a Smart Wavelet-Based Power Quality Monitoring System.”
[15] Bill Howe, “Electric Power Research Institute, 1750 14th Street, #200, Boulder, Colorado USA 80302, E-mail bhowe@epri.com.”
[16] Chandra Prakash Gupta and Girish Kumar Singh, “Electrical Engineering Department, IIT Roorkee, Uttarakhand-India.”
[17] Shih-An Yin, Student Member, IEEE, Chun-Lien Su, Member, IEEE, and Rung-Fang Chang, “Evaluation of the Impacts of Electric Power Quality Costs in Industrial Production: Case Studies in Northeast Brazil,” Miguel O. B. C. Melo, Guilherme Cavalcanti.
[18] Arup Kumar Goswami, “Cost-Benefit Analysis of Voltage Sag Mitigation Methods in Cement Plants,” Electrical Engineering Department, NIT Silchar, Assam-India.