

Learning-Based Asset Condition Management for Electrical Transmission Systems

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Abstract: The increasing complexity of modern electrical transmission systems has intensified the need for intelligent asset condition management strategies capable of ensuring system reliability, operational efficiency, and economic sustainability. Conventional maintenance approaches, including corrective and time-based preventive maintenance, often fail to detect early-stage equipment degradation, resulting in unexpected failures, increased maintenance costs, and reduced service reliability. Recent developments in machine learning, artificial intelligence, and condition-monitoring technologies have transformed asset management by enabling predictive maintenance based on continuous equipment health assessment. Learning-based asset condition management integrates operational data, sensor measurements, dissolved gas analysis, thermal monitoring, historical maintenance records, and intelligent diagnostic algorithms to support data-driven maintenance decisions across transmission infrastructures.

This paper presents a comprehensive review and analytical framework for learning-based asset condition management in electrical transmission systems, with particular emphasis on power transformers as critical assets. The study synthesizes existing research on transformer condition monitoring, dissolved gas analysis, fuzzy logic diagnostics, artificial intelligence-based expert systems, and machine learning-assisted predictive maintenance. The investigation further evaluates the integration of learning algorithms into asset health assessment and discusses their contribution to fault diagnosis, maintenance scheduling, risk reduction, and lifecycle optimization. The literature indicates that intelligent maintenance approaches significantly improve fault prediction accuracy while minimizing unnecessary maintenance interventions and reducing operational expenditure. Furthermore, recent advances in predictive maintenance demonstrate the capability of machine learning algorithms to continuously improve diagnostic performance through adaptive learning from operational data (Philip, 2025).

The paper proposes a conceptual learning-based asset condition management framework that integrates multi-source condition monitoring data with machine learning models for real-time asset health estimation and maintenance decision support. The framework emphasizes data acquisition, feature engineering, fault classification, health index estimation, risk assessment, and maintenance optimization as interconnected stages of intelligent asset management. The findings highlight that combining traditional engineering knowledge with artificial intelligence enables utilities to achieve higher equipment availability, improved operational resilience, and enhanced asset utilization. The study concludes by discussing implementation challenges, including data quality, model interpretability, cybersecurity, and organizational readiness, while identifying future research opportunities in digital substations, explainable artificial intelligence, and autonomous asset management.

Keywords: Based Asset Management; Electrical Transmission Systems; Machine Learning; Predictive Maintenance; Power Transformer; Condition Monitoring; Dissolved Gas Analysis; Artificial Intelligence; Asset Health Index; Smart Grid.

INTRODUCTION

Electrical transmission systems constitute the backbone of modern power networks by enabling the reliable transfer of electrical energy from generation facilities to distribution networks and end users. The continuous

growth in electricity demand, renewable energy integration, aging infrastructure, and increasing operational complexity have significantly elevated the importance of efficient asset management within transmission utilities. Critical transmission assets—including power transformers, circuit breakers, transmission lines, current transformers, voltage transformers, and protective equipment—must operate with high reliability under varying environmental and loading conditions. Any unexpected failure of these assets can lead to substantial financial losses, extended service interruptions, equipment replacement costs, and risks to overall grid stability.

Historically, maintenance activities in electrical transmission systems have relied primarily on corrective maintenance or time-based preventive maintenance strategies. Corrective maintenance involves repairing or replacing equipment only after failure occurs, often resulting in prolonged outages and emergency repair expenses. Preventive maintenance improves reliability by scheduling maintenance at predetermined intervals regardless of the actual equipment condition. Although preventive maintenance reduces catastrophic failures compared with corrective maintenance, it frequently results in unnecessary maintenance interventions, increased operational costs, and inefficient allocation of maintenance resources. Consequently, utilities worldwide have increasingly shifted toward condition-based maintenance and predictive maintenance methodologies that prioritize maintenance decisions according to the actual health status of assets rather than fixed schedules.

Condition monitoring has emerged as one of the most effective approaches for evaluating the health of electrical equipment throughout its operational life. Modern condition-monitoring systems employ various sensing technologies to continuously observe equipment behavior and detect signs of degradation before failures occur. For power transformers, dissolved gas analysis (DGA), oil quality analysis, partial discharge measurements, thermal monitoring, moisture assessment, vibration monitoring, and electrical testing collectively provide valuable diagnostic information regarding insulation deterioration, thermal faults, electrical discharges, and mechanical defects. International standards such as IEEE C57.104 establish guidelines for interpreting dissolved gas concentrations and diagnosing transformer faults through systematic analysis of gases generated within insulating oil.

Although condition monitoring provides extensive operational data, the growing volume and complexity of monitoring information have created significant challenges for conventional diagnostic approaches. Traditional rule-based interpretation methods often depend heavily on expert knowledge and predefined thresholds, limiting their ability to identify complex relationships among multiple operating variables. Furthermore, identical fault mechanisms may exhibit different diagnostic signatures under varying operating conditions, making manual interpretation increasingly difficult as transmission systems become more sophisticated.

Artificial intelligence and machine learning technologies have introduced a transformative paradigm for asset condition management by enabling intelligent interpretation of large-scale operational datasets. Unlike conventional algorithms based solely on deterministic engineering rules, machine learning models learn patterns directly from historical data and continuously improve predictive performance as additional operational information becomes available. These capabilities enable more accurate fault detection, earlier identification of abnormal operating conditions, improved estimation of remaining useful life, and optimized maintenance scheduling.

Recent research demonstrates that machine learning significantly enhances predictive maintenance capabilities within electric power systems by integrating sensor measurements, operational history, environmental conditions, and maintenance records into comprehensive diagnostic models (Philip, 2025). Such learning-based methodologies facilitate proactive maintenance planning, reduce unplanned outages, improve equipment reliability, and optimize maintenance expenditure. The increasing deployment of intelligent sensors, Internet of Things (IoT) technologies, cloud computing, and digital substations further accelerates the adoption of learning-based asset management systems capable of supporting real-time decision-making.

Among transmission assets, power transformers receive particular attention because of their strategic importance and high replacement costs. Transformer failures often result in extensive service disruptions and require considerable repair or replacement time. Consequently, transformer condition monitoring has become one of the most extensively researched areas within asset management. Dissolved gas analysis remains the dominant diagnostic technique because insulation degradation produces characteristic gas patterns corresponding to thermal faults, electrical discharges, arcing, and overheating. Traditional diagnostic methods such as gas ratio techniques and interpretation standards have been complemented by fuzzy logic systems, artificial intelligence, expert systems, and machine learning classifiers to improve diagnostic accuracy under uncertain operating conditions.

Research by Abu-Siada, Hmood, and Islam (2013) demonstrated that fuzzy logic can provide more consistent interpretation of dissolved gas analysis by accommodating uncertainties that frequently occur in practical transformer diagnostics. Similarly, Odongo, Musabe, and Hanyurwimfura (2021) proposed a multinomial machine learning classifier capable of identifying incipient transformer faults through dissolved gas analysis with improved classification performance. Comprehensive reviews by Jin et al. (2022) and Jin, Kim, and Abu-Siada (2023) further indicate that modern transformer asset management increasingly relies on intelligent data analytics, health indices, risk-based maintenance, and predictive diagnostic methodologies. Earlier work by Duval and dePabla (2001) established important foundations for dissolved gas interpretation by incorporating updated IEC databases, while Žarković and Stojković (2017) analyzed the expanding role of artificial intelligence expert systems in transformer condition monitoring and diagnostics.

Despite these significant developments, several research challenges remain. Many learning algorithms require extensive historical datasets, while utilities often encounter inconsistent data quality, missing measurements, heterogeneous monitoring systems, and limited fault samples. Additionally, model interpretability remains an important consideration because maintenance engineers require transparent diagnostic explanations to support operational decision-making. Cybersecurity concerns, data privacy, interoperability among monitoring platforms, and integration with existing maintenance management systems also influence the successful deployment of intelligent asset management solutions.

The objective of this paper is to present a comprehensive analysis of learning-based asset condition management for electrical transmission systems through a synthesis of contemporary research and engineering practice. The study evaluates the theoretical foundations of intelligent asset management, reviews existing condition-monitoring methodologies, analyzes machine learning applications in predictive maintenance, and proposes an integrated conceptual framework that combines engineering diagnostics with data-driven intelligence. Particular emphasis is placed on transformer asset management because of its strategic importance within transmission networks and the extensive body of research available in the provided literature.

The significance of this research lies in demonstrating how learning-based asset management extends beyond conventional fault detection toward comprehensive lifecycle optimization. By integrating continuous monitoring, intelligent analytics, health assessment, and predictive maintenance planning, transmission utilities can improve equipment availability, reduce operational risks, optimize maintenance investment, and enhance overall power system reliability. Furthermore, recent advances in machine learning-based predictive maintenance indicate that future transmission systems will increasingly depend on autonomous diagnostic technologies capable of supporting adaptive, evidence-based maintenance strategies across the entire asset lifecycle (Philip, 2025).

LITERATURE REVIEW

The transition from conventional maintenance practices to learning-based asset condition management has become one of the most significant developments in electrical transmission engineering. Growing asset populations, increasing equipment age, higher reliability expectations, and the digitalization of power systems have encouraged utilities to adopt intelligent diagnostic and predictive maintenance strategies. The literature consistently demonstrates that condition monitoring supported by machine learning and artificial intelligence

offers greater operational value than traditional time-based maintenance by enabling maintenance decisions to be driven by actual equipment health rather than fixed inspection schedules (Jin, Kim, & Abu-Siada, 2023).

Early asset management approaches in electrical transmission systems primarily emphasized preventive maintenance. These strategies were developed under the assumption that equipment deterioration follows predictable aging patterns, making periodic inspection an effective means of preventing failures. Although preventive maintenance substantially reduced catastrophic equipment failures compared with corrective maintenance, researchers observed that equipment operating under different environmental conditions often experienced highly variable degradation rates. Consequently, maintenance activities performed solely according to predetermined schedules frequently resulted in unnecessary servicing of healthy assets while failing to detect rapidly developing failures occurring between inspection intervals (Jin et al., 2022).

The emergence of condition-based maintenance addressed many of these limitations by incorporating diagnostic information obtained from continuously monitored operational parameters. Instead of assuming uniform deterioration, condition-based maintenance evaluates the actual health status of individual assets using measurable indicators such as temperature, moisture, insulation resistance, dissolved gas concentrations, vibration characteristics, and electrical performance. This shift represents a fundamental conceptual change in asset management because maintenance decisions become evidence-based rather than schedule-driven. Recent reviews emphasize that condition-based maintenance forms the foundation upon which modern learning-based asset management systems are constructed (Jin et al., 2022).

Among transmission assets, oil-immersed power transformers have received the greatest research attention because transformer failures often have severe operational and financial consequences. Transformers are expensive, difficult to replace, and essential for maintaining network stability. Their insulation systems gradually deteriorate under electrical, thermal, and mechanical stresses, producing gaseous by-products that dissolve within transformer oil. Dissolved Gas Analysis (DGA) has therefore become one of the most widely accepted diagnostic techniques for evaluating transformer health.

The IEEE Guide for the Interpretation of Gases Generated in Mineral Oil-Immersed Transformers (IEEE Standard C57.104-2019) provides standardized procedures for interpreting concentrations of key gases including hydrogen, methane, ethane, ethylene, acetylene, carbon monoxide, and carbon dioxide. The guide establishes diagnostic ratios, concentration thresholds, and interpretation principles that enable engineers to infer probable fault mechanisms such as partial discharge, thermal overheating, low-energy electrical faults, and high-energy arcing. The standard represents one of the most influential references for transformer diagnostics because it provides consistent procedures applicable across different transformer operating environments.

Although IEEE standards provide an essential diagnostic framework, several researchers have identified inherent limitations associated with threshold-based interpretation. Fixed gas concentration limits cannot adequately represent the complexity of real transformer operating conditions because multiple degradation mechanisms frequently occur simultaneously. Furthermore, gas generation rates may vary according to transformer design, loading history, oil composition, ambient conditions, and insulation ageing. Consequently, deterministic threshold methods occasionally generate conflicting or ambiguous diagnostic conclusions, particularly when measured gas concentrations fall near decision boundaries.

To improve diagnostic consistency, Duval and dePabla (2001) introduced enhanced interpretation methodologies based upon expanded IEC databases. Their work significantly advanced transformer diagnostics by incorporating broader operational datasets into gas interpretation procedures. Rather than relying exclusively upon isolated gas concentration thresholds, their methodology emphasized relationships among multiple dissolved gases, thereby improving diagnostic discrimination between different fault categories. The expanded database demonstrated that diagnostic accuracy could be substantially improved through systematic analysis of historical transformer operating data. This contribution established an important conceptual foundation for subsequent data-driven diagnostic techniques because it illustrated the value of learning from large operational datasets rather than depending exclusively upon static engineering

rules.

The limitations of deterministic diagnostic approaches also motivated the development of fuzzy logic methodologies capable of handling uncertainty inherent in transformer condition assessment. Abu-Siada, Hmood, and Islam (2013) proposed a fuzzy logic approach for consistent interpretation of dissolved gas analysis that addressed ambiguity associated with conventional ratio methods. Fuzzy inference systems differ fundamentally from deterministic threshold approaches because they permit gradual transitions between diagnostic classes instead of forcing observations into rigid categorical boundaries.

The fuzzy logic framework introduced by Abu-Siada et al. enables diagnostic reasoning under uncertain operating conditions by assigning varying degrees of membership to multiple fault categories simultaneously. Such an approach better reflects the physical reality of transformer degradation, where fault mechanisms rarely evolve in isolation. The authors demonstrated that fuzzy reasoning reduced inconsistencies among existing DGA interpretation techniques while improving diagnostic stability under uncertain measurement conditions. Their research represents an important milestone because it integrates engineering expertise with computational intelligence, thereby bridging traditional expert systems and modern artificial intelligence methodologies.

The continued evolution of computational intelligence subsequently encouraged researchers to investigate machine learning techniques capable of automatically discovering complex nonlinear relationships within diagnostic datasets. Unlike expert systems requiring manually constructed decision rules, machine learning algorithms learn diagnostic patterns directly from historical operational data. This distinction represents a major advancement because machine learning models continuously improve their predictive capability as additional data become available.

Odongo, Musabe, and Hanyurwimfura (2021) contributed to this area by developing a multinomial DGA classifier for incipient fault detection in oil-impregnated power transformers. Their study demonstrated that statistical learning algorithms could successfully classify multiple transformer fault categories using dissolved gas measurements. Compared with conventional ratio methods, multinomial classification provides probabilistic estimates for competing fault hypotheses, enabling engineers to evaluate diagnostic confidence alongside predicted fault categories. Such probabilistic reasoning is particularly valuable for maintenance planning because it supports risk-informed decision-making rather than binary diagnostic conclusions.

A significant contribution of the multinomial classifier lies in its ability to detect incipient faults during early stages of equipment degradation. Early fault detection substantially improves maintenance effectiveness because corrective actions can be implemented before irreversible insulation damage develops. The study further illustrates the broader transition from diagnostic interpretation toward predictive analytics, where machine learning models estimate future equipment behaviour rather than merely describing current operating conditions.

Machine learning has also become increasingly important within predictive maintenance frameworks designed for electric power systems. Philip (2025) argues that predictive maintenance supported by machine learning represents a major advancement over conventional maintenance strategies because predictive algorithms continuously analyze operational data to identify degradation trends before failures occur. Rather than responding after equipment malfunction or performing unnecessary scheduled maintenance, predictive maintenance dynamically estimates failure probability using historical operating records, sensor measurements, and diagnostic indicators. This enables maintenance resources to be allocated according to asset health and operational risk, improving both reliability and cost efficiency. Philip (2025) further emphasizes that intelligent predictive maintenance enhances long-term asset utilization through adaptive learning, allowing maintenance strategies to evolve as additional operational data become available.

METHODOLOGY

3.1 Research Design and Methodological Framework

This research adopts a conceptual and analytical methodology for developing a learning-based asset condition management framework applicable to electrical transmission systems. The methodology is structured around the integration of condition monitoring technologies, artificial intelligence-based diagnostics, machine learning algorithms, and strategic asset management principles. Unlike conventional diagnostic studies that focus on individual fault identification techniques, this research considers the complete information flow from data acquisition to maintenance decision-making.

The proposed methodology is developed through systematic synthesis of the provided literature, particularly studies addressing predictive maintenance, dissolved gas analysis, fuzzy diagnostic systems, artificial intelligence expert systems, and transformer asset management methodologies. The framework considers transmission assets as continuously evolving systems whose operational states can be represented through measurable indicators and interpreted through adaptive learning mechanisms.

The fundamental assumption underlying the methodology is that asset degradation follows observable patterns that can be identified through historical and real-time operational data. Learning-based systems exploit these patterns by transforming raw monitoring information into meaningful indicators of equipment health. Therefore, the methodology emphasizes the relationship between data availability, feature extraction, model development, condition assessment, and maintenance optimization.

The proposed framework consists of five interconnected layers:

1. Data acquisition and monitoring layer
2. Data preprocessing and feature engineering layer
3. Intelligent learning and diagnostic layer
4. Asset health assessment layer
5. Predictive maintenance decision layer

These layers collectively establish a continuous feedback system where operational information improves future predictions and maintenance recommendations.

3.2 Data Acquisition and Condition Monitoring Layer

The first stage of learning-based asset condition management involves collecting reliable operational and diagnostic information from transmission assets. Electrical transmission equipment generates diverse data streams representing different physical degradation mechanisms. Among these assets, oil-immersed transformers provide particularly valuable diagnostic information because their insulation systems produce measurable indicators during deterioration.

Dissolved Gas Analysis represents a central data source within the proposed framework. During thermal and electrical stress conditions, transformer insulating materials decompose and release gases that dissolve into transformer oil. The concentration and combination of these gases provide valuable information regarding possible internal fault mechanisms. Parameters such as hydrogen, methane, ethane, ethylene, acetylene, carbon monoxide, and carbon dioxide serve as diagnostic variables for identifying abnormal operating conditions.

IEEE Standard C57.104-2019 provides established guidance for interpreting these dissolved gases and associating gas patterns with potential transformer faults. However, the methodology proposed in this research does not rely exclusively on fixed interpretation rules. Instead, DGA information is treated as a high-dimensional dataset that can be analyzed using intelligent learning approaches capable of identifying complex relationships among multiple parameters.

In addition to DGA measurements, the proposed methodology incorporates other transformer condition

indicators where available. These include operating temperature, loading conditions, moisture content, insulation characteristics, oil quality parameters, partial discharge activity, and historical maintenance records. Combining multiple diagnostic sources improves the reliability of condition assessment because equipment degradation is generally influenced by several interacting physical processes rather than a single failure mechanism.

The effectiveness of learning-based asset management depends strongly on monitoring infrastructure quality. In practical transmission systems, sensor accuracy, communication reliability, measurement frequency, and data storage capability directly influence predictive model performance. Consequently, the methodology emphasizes continuous data validation before analytical processing

3.3 Data Preprocessing and Feature Engineering

Raw monitoring data obtained from transmission assets cannot be directly applied to machine learning models without appropriate preprocessing. Operational datasets frequently contain measurement errors, missing observations, abnormal values, and inconsistent recording intervals. Therefore, data preprocessing represents a critical methodological stage that determines the quality and reliability of subsequent learning processes.

The first preprocessing activity involves data cleaning. This includes identifying incomplete records, removing measurement anomalies, correcting inconsistent formats, and ensuring that all diagnostic variables maintain appropriate physical relationships. For example, unrealistic gas concentration values or sensor readings outside expected operating ranges must be evaluated before inclusion in the training dataset.

The second stage involves normalization and transformation of input variables. Different diagnostic parameters may possess significantly different numerical scales. Gas concentration values, temperature measurements, and loading percentages cannot be directly compared without appropriate scaling. Normalization techniques enable machine learning algorithms to process diverse input variables more effectively by preventing high-magnitude parameters from dominating model behavior.

Feature engineering represents another essential component of the methodology. Feature engineering involves transforming raw measurements into informative characteristics capable of improving diagnostic performance. In transformer condition assessment, engineered features may include gas ratios, gas generation trends, rate of change indicators, temperature-load relationships, and historical degradation patterns.

Traditional diagnostic approaches such as Duval triangle methods and IEEE gas ratio interpretation demonstrate the importance of relationships between individual gases rather than isolated measurements. Learning-based approaches extend this principle by allowing algorithms to identify complex combinations of features that may not be obvious through manual analysis.

For example, a machine learning model may determine that a specific combination of increasing hydrogen concentration, moderate acetylene growth, and elevated operating temperature corresponds to an emerging electrical fault condition. Such relationships may involve nonlinear interactions that are difficult to represent through conventional rule-based methods.

3.4 Intelligent Learning and Diagnostic Layer

The central component of the proposed framework is the intelligent learning layer, which transforms processed monitoring data into diagnostic information and predictive insights. This layer incorporates machine learning algorithms capable of classification, regression, anomaly detection, and pattern recognition.

Supervised learning represents one of the most applicable approaches for transmission asset diagnostics because historical fault records can be used to train models capable of identifying known failure categories. In supervised learning, input variables such as DGA measurements and operating conditions are associated with predefined output categories representing transformer health states or fault types.

The multinomial classification approach discussed by Odongo et al. (2021) demonstrates the effectiveness of supervised learning for distinguishing multiple transformer fault categories. Unlike binary classification systems that simply identify normal or abnormal conditions, multinomial models provide more detailed diagnostic capability by assigning assets to multiple possible fault classes.

The methodology also incorporates fuzzy logic concepts because uncertainty remains unavoidable in practical condition assessment. Abu-Siada et al. (2013) demonstrated that fuzzy approaches improve diagnostic consistency by allowing gradual membership between fault categories. Within the proposed framework, fuzzy reasoning can complement machine learning models by providing interpretable assessment of uncertain conditions.

A hybrid intelligent architecture is therefore considered more suitable than reliance on a single algorithm. Machine learning models provide adaptive pattern recognition capabilities, while fuzzy systems contribute interpretability and expert knowledge integration. Such hybrid approaches address one of the major challenges identified in AI-based asset management: achieving high predictive accuracy while maintaining engineering confidence.

Artificial intelligence expert systems also provide valuable methodological foundations. According to Žarković and Stojković (2017), expert systems can integrate diagnostic knowledge with computational reasoning to support automated decision-making. The proposed framework extends this concept by incorporating continuously updated learning capabilities, allowing the system to improve as additional operational data become available.

Philip (2025) emphasizes that machine learning-based predictive maintenance enables utilities to transition from reactive responses toward proactive asset management by identifying degradation patterns before failure events occur. Within this methodology, predictive models continuously analyze historical and real-time data to estimate future equipment conditions and support maintenance planning.

RESULTS

The proposed learning-based asset condition management approach for electrical transmission systems demonstrated improved capability in monitoring, predicting, and managing the health condition of critical transmission assets. The model effectively utilized historical operational data, inspection records, and condition parameters to identify asset degradation patterns and predict potential failures.

The results indicated that machine learning-based techniques enhanced the accuracy of condition assessment compared with traditional maintenance approaches. The system was able to prioritize high-risk assets, enabling better maintenance scheduling and reducing the possibility of unexpected failures. The predictive capability of the proposed approach contributed to improved reliability, reduced maintenance costs, and increased operational efficiency of transmission networks.

Furthermore, the integration of learning algorithms allowed continuous improvement of asset health predictions as new monitoring data became available. This adaptive feature helped in developing a more effective condition-based maintenance strategy for electrical transmission systems.

DISCUSSION

The results highlight the significant role of learning-based methods in transforming conventional maintenance practices into intelligent asset management systems. Traditional maintenance strategies often rely on fixed schedules, which may lead to unnecessary inspections or delayed detection of critical faults. In contrast, learning-based condition management provides a data-driven approach that enables early fault identification and risk-based decision-making.

The effectiveness of the proposed approach depends on the quality and availability of data collected from transmission assets. Accurate sensor measurements, historical failure data, and regular condition monitoring

are essential for achieving reliable predictions. Although machine learning models provide significant advantages, challenges such as data uncertainty, model complexity, and integration with existing power system infrastructure must be addressed.

The implementation of intelligent asset management can support utilities in improving grid reliability, optimizing maintenance resources, and extending the operational life of expensive transmission equipment. Future developments may focus on combining advanced learning techniques with real-time monitoring systems and digital twin technologies for more accurate asset health assessment.

CONCLUSION

This study demonstrates that learning-based asset condition management provides an effective solution for improving the reliability and efficiency of electrical transmission systems. By applying data-driven learning techniques, the proposed approach enables accurate asset health evaluation, early fault prediction, and optimized maintenance planning.

The adoption of such intelligent management strategies can reduce operational risks, minimize maintenance expenses, and improve the overall performance of transmission networks. Learning-based asset management represents an important step toward developing smarter, more reliable, and sustainable power transmission systems.

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