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Predictive Maintenance in Power Networks: AI-Powered Solutions for Electrical Systems

[1] Dr. R. Rajasekar, [2]T. Nedunchezhian, [3]Dr. Beulah Jackson, [4]P. Vinoth Kumar, [5]T.N. Sudhahar, [6]T. Sakthi Sree

[1]Associate Professor, Department of Computer Science & Engineering (Data Science), Sri Venkateswara College of Engineering & Technology (Autonomous), Chittoor, Andhra Pradesh, India, email:rajasekar.sept@gmail.com.

[2]Associate Professor, Department of Computer Science & Engineering (Data Science), Sri Venkateswara College of Engineering & Technology (Autonomous), Chittoor, Andhra Pradesh, India,

email:tnchezhian79@gmail.com

[3]Professor, Department of Electronics and Communication Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India, email:beulah.jack@gmail.com

[4]Assistant Professor, Department of Artificial Intelligence and Data Science, St Joseph's Institute of Technology, Chennai, Tamil Nadu, India,

email: vinothkumar5251@gmail.com

[5]Assistant Professor, Department of Artificial Intelligence and Data Science, Rajalakshmi Institute of Technology, Chennai, Tamil Nadu, India, email: sudhahar81@gmail.com

[6]Assistant Professor, Department of Information Technology, Hindusthan College of Engineering and Technology, Coimbatore, Tamil Nadu, India, email: sakthisree.it@hicet.ac.in

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Abstract:

Predictive Maintenance (PdM) has revolutionised power network maintenance, especially electrical system maintenance. Predictive Maintenance and artificial intelligence (AI) may revolutionise power network maintenance, according to this article. Past reactive maintenance practices in power networks have caused expensive downtime and unanticipated breakdowns. AI analyses massive volumes of data from sensors, IoT devices, and past maintenance records to provide Predictive Maintenance. Predictive Maintenance uses powerful machine learning algorithms to find data patterns, trends, and anomalies to help utilities and operators forecast equipment problems. AI-powered Predictive Maintenance has several benefits. Monitoring equipment health and performance helps utilities optimise maintenance plans, decrease downtime, and prolong asset lifetime. Early identification of possible faults permits preventative maintenance, reducing catastrophic failures and guaranteeing power network stability. This article examines AI-powered Predictive Maintenance in power networks and electrical systems. Case studies and real-world examples show how AI-driven initiatives improve asset dependability and operational efficiency. The report also examines data quality, system integration, and regulatory compliance issues related to AI technology adoption in maintenance. AI-powered Predictive Maintenance trends and future directions are also examined in the report. AI can integrate with edge computing, 5G connectivity, and sophisticated analytics methods like predictive modelling and digital twins. Utility power networks may improve resilience and performance by adopting these advances. To conclude, this article provides a complete review of Predictive Maintenance in power networks and shows how AI-powered solutions have transformed electrical system maintenance. AI helps utilities optimise asset management, cut costs, and assure power infrastructure dependability and efficiency in the face of changing challenges.

Keywords: Predictive Maintenance, Power Networks**,** AI-Powered Solutions, Electrical Systems, Artificial Intelligence, Maintenance Strategies

Introduction

Electrical system stability and efficiency are crucial in the continually changing power network environment. Predictive Maintenance (PdM), enabled by AI, is a major improvement over conventional maintenance procedure. Power network maintenance used to respond to problems, resulting in unexpected outages and high repair costs [1]. Predictive Maintenance uses AI to analyse massive information from network sensors and IoT devices. This method detects possible difficulties early, enabling for prompt interventions before failures cause expensive repairs or disruptive outages. Figure 1 Illustrates Revolutionizing power network reliability: AI-driven predictive maintenance for optimized electrical systems.

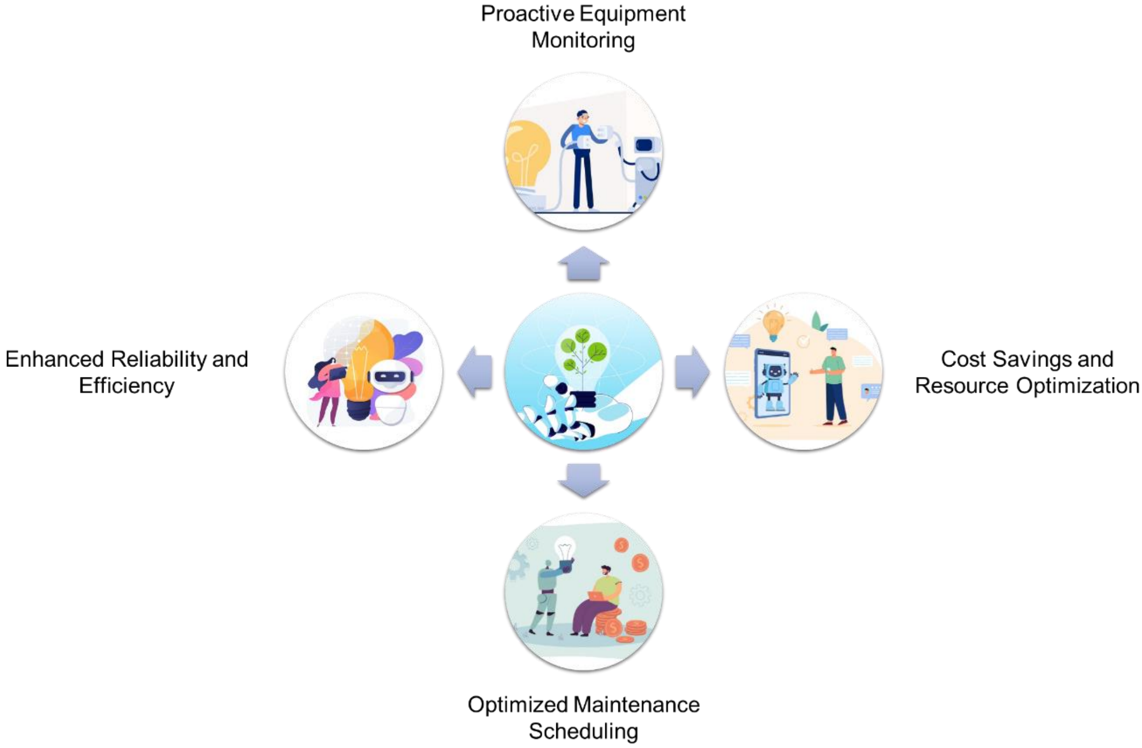

Figure 1. Revolutionizing power network reliability: AI-driven predictive maintenance for optimized electrical systems.

To illustrate, imagine monitoring a high-voltage transformer, a vital power network component. AI algorithms can analyse temperature, voltage, and cooling system efficiency data in real time using sensors [2]. These algorithms are taught to detect flaws and deterioration, such as insulation failure due to anomalous temperature rises. If the AI system detects irregularities, maintenance crews may undertake targeted inspections and interventions to avert transformer failure. This strategy optimises maintenance scheduling, resource allocation, and power supply dependability, lowering operating costs. AI's capacity to learn from previous data and increase its forecast accuracy strengthens power networks' resistance to unexpected outages. Thus, AI-powered Predictive Maintenance in electrical systems is a strategic move towards more sustainable and efficient power network management, promising to reduce equipment failure risks and provide continuous power supply to customers. This study uses thorough case studies and empirical data to demonstrate how AI-driven Predictive Maintenance transforms power network operating dynamics, making electrical systems more dependable, cost-effective, and efficient.

2. Fundamentals of Predictive Maintenance

Predictive Maintenance (PdM) is a cornerstone of proactive asset management across sectors, comprising a variety of methods to forecast and avoid equipment problems. The systematic collection, analysis, and interpretation of important asset status and performance data is central to PdM. PdM uses sensors, data analytics, and machine learning to help organisations switch from reactive or time-based maintenance to anticipatory and cost-effective maintenance. A key part of PdM is setting baseline asset performance measurements to identify and evaluate variations. Consider a factory that uses industrial equipment. Sensors in these machines monitor temperature, vibration, and lubricant quality using PdM. These sensors provide baseline performance profiles for each machine over time, indicating typical operating circumstances and performance criteria. An increase in vibration or a decrease in lubricant quality may indicate equipment failure. Monitoring these anomalies in real time allows maintenance teams to schedule inspections and repairs, reducing unexpected downtime and improving asset dependability. Table 1 Illustrates Unlocking efficiency: mastering the fundamentals of predictive maintenance.

Fundamentals	**Definition**	**Example**	**Importance**	**Implementation**	**Reference**
Data Collection	Gathering relevant data from sensors and systems to monitor equipment health.	Using vibration sensors to collect data on machine vibrations to predict bearing failures.	Essential for identifying patterns and trends that indicate potential equipment failures.	Deploying IoT sensors and integrating with data management systems to collect and store data.	[3]
Condition Monitoring	Continuous monitoring of equipment parameters to detect deviations from normal operating conditions.	Monitoring temperature, pressure, and vibration levels in rotating machinery.	Allows for early detection of anomalies, facilitating timely maintenance interventions.	Installing sensors and implementing real-time monitoring systems to track equipment condition.	[4]
Predictive Analytics	Utilizing algorithms and statistical models to analyze data and predict equipment failures.	Using machine learning algorithms to predict when a pump is likely to fail based on historical data.	Enables proactive maintenance planning and optimization of resources.	Implementing predictive analytics software and training models on historical data.	[5]
Fault Detection	Identifying abnormalities or deviations in equipment	Detecting abnormal vibration patterns in a motor,	Facilitates early detection of potential failures,	Setting up alarms and alerts based on predefined thresholds to	[6]

	performance that may indicate underlying faults.	suggesting bearing wear or misalignment.	minimizing downtime and repair costs.	notify maintenance teams of potential faults.	
Asset Health Assessment	Evaluating the overall health and condition of assets based on collected data and analysis results.	Assessing the remaining useful life of a transformer based on oil analysis and thermal imaging.	Provides insights into asset performance, degradation trends, and maintenance requirements.	Conducting regular inspections and assessments using advanced diagnostic techniques and technologies.	[7]

Table 1. Unlocking efficiency: mastering the fundamentals of predictive maintenance.

PdM also helps implement condition-based maintenance methods, which trigger maintenance based on asset condition rather than timetables. This method avoids needless maintenance and extends asset life by reducing wear and tear. An important part of PdM is using sophisticated data analytics to get actionable insights from sensor data. Machine learning algorithms can discover failure types and deterioration processes in past maintenance records and sensor data. Predictive models may accurately anticipate future failures by comparing these patterns to real-time sensor data. Consider a fleet of commercial aeroplanes having engine performance sensors. Machine learning systems can forecast engine component problems using past maintenance data and sensor readings, enabling airlines to intervene before in-flight crises. PdM integration with asset management systems lets organisations prioritise maintenance based on asset criticality, operational impact, and cost-effectiveness. Maintenance efforts are focused on assets with the highest risk of interruption or economic loss due to this strategic allocation. Predictive Maintenance uses data analytics, machine learning, and domain knowledge to predict and prevent equipment breakdowns. Companies may increase asset dependability, maintenance schedules, operational efficiency, and profitability by adopting PdM concepts.

2.1 Technologies Enabling Predictive Maintenance

PdM uses innovative technology to predict and prevent equipment breakdowns, revolutionising maintenance management. Several essential technologies allow precise equipment health prediction and timely maintenance, making PdM effective. Sensors, IoT devices, data analytics platforms, machine learning algorithms, and cloud computing infrastructures help gather, analyse, and interpret PdM data [8]. Predictive Maintenance relies on sensors and IoT devices to monitor temperature, vibration, pressure, and acoustic emissions across assets. These devices provide real-time, high-fidelity data on equipment status and performance. Industrial pump vibration sensors may detect misalignment or bearing wear, indicating the need for maintenance before a catastrophic failure. Process and analyse massive sensor and IoT data using data analytics tools. These platforms use statistical and analytical methods to uncover equipment faults by integrating data sources. Data analytics may uncover blade damage or gearbox faults in wind farm turbine performance data. By comparing deviations to past failure data, operators may plan maintenance proactively to maximise turbine uptime and efficiency. Predictive Maintenance relies on machine learning techniques to create accurate equipment failure prediction models. Based on previous maintenance records and real-time data, these computers uncover complicated correlations and failure patterns that people cannot. The railway sector uses machine learning to anticipate rail problems using track monitoring system data. Railway operators can prioritise maintenance and improve safety by precisely predicting problem locations and severity. Cloud computing provides the scale and computational capacity needed for data-intensive Predictive Maintenance. Cloud systems allow organisations to store and analyse enormous datasets, run complicated machine learning models, and obtain forecast insights anytime, anywhere. Global manufacturing enterprises benefit from cloud-enabled PdM systems, which centralise equipment monitoring and maintenance across various locations, maintaining uptime and performance while decreasing maintenance costs. Finally, Predictive Maintenance relies on sensors, IoT, data analytics, machine learning, and cloud computing. These solutions help organisations across industries switch from reactive or planned maintenance to data-driven maintenance. Predictive Maintenance boosts asset dependability, performance, operational efficiency, and cost reduction by using these technologies.

2.2 Comparing Reactive, Preventive, and Predictive Maintenance

comprehending predictive maintenance fundamentals is crucial to comprehending the change from conventional to proactive maintenance. To distinguish Reactive, Preventive, and Predictive Maintenance techniques, compare their features and uses. Reactive Maintenance is "fix-it-when-it-breaks" that starts when equipment breaks. This strategy may appear cost-effective at first, but it typically causes unforeseen downtime, expensive repairs, and operational interruptions. In a reactive maintenance regime, the abrupt breakdown of a major equipment might stop output in a manufacturing facility, resulting in considerable financial losses owing to idle labour and missed production objectives. However, preventive maintenance involves planned maintenance at set times regardless of equipment condition. This strategy prevents unexpected downtime by proactively replacing or fixing components, although it may increase maintenance costs. Consider a fleet of delivery vehicles that gets oil changes every 5,000 miles. Other trucks may not need an oil change at this time, wasting resources and wasting asset utilisation. Predictive Maintenance uses real-time data and analytics to predict equipment health and breakdowns, changing reactive and preventative methods. Predictive maintenance systems use sensors and IoT devices to monitor machine factors like temperature, vibration, and fluid levels for small changes that may indicate problems. Consider a commercial aeroplane having engine performance sensors. Airlines can forecast engine component failures using machine learning algorithms from sensor data, enabling for targeted maintenance before problems arise. By prioritising maintenance actions based on equipment condition and operational needs, predictive maintenance optimises maintenance schedules and resource allocation. This prioritises repair on high-risk assets, reducing downtime and improving dependability. In conclusion, reactive maintenance reacts to faults as they occur, preventive maintenance follows schedules, and predictive maintenance uses real-time data and sophisticated analytics to avoid failures [9].

2.3 Benefits of Predictive Maintenance

Fundamentals of Predictive Maintenance include its many advantages across sectors. Explaining how Predictive Maintenance (PdM) improves asset dependability, optimises maintenance schedules, and lowers operating costs is crucial. PdM helps organisations avoid equipment breakdowns by being proactive. Predictive maintenance systems use real-time data from sensors, IoT devices, and previous maintenance records to identify possible faults and schedule preventative maintenance. A wind farm with turbine sensors is one option. Operators may detect turbine component problems like gearbox or blade deterioration before they cause expensive downtime by analysing sensor data using machine learning techniques. This proactive strategy reduces unexpected outages and extends key equipment lives, boosting asset dependability and operating efficiency. Predictive Maintenance prioritises maintenance actions based on equipment condition and operational needs to optimise schedules and resource allocation. Organisations may save downtime, maintenance costs, and asset utilisation by prioritising urgent assets. Predictive maintenance systems may analyse vehicle performance data to forecast component failures in a fleet of commercial vehicles, allowing maintenance staff to arrange repairs during off-peak hours to minimise interruptions. PdM encourages data-driven decision-making, enabling organisations to make strategic asset management and investment choices. Predictive analytics helps organisations optimise asset lifecycle management and resource allocation by identifying equipment performance data trends, patterns, and correlations. This strategy boosts operational efficiency, corporate performance, and competitiveness.

3. Introduction to Artificial Intelligence

Introduction to AI provides a basic understanding of the multidisciplinary area that is changing society. AI involves a wide range of approaches, algorithms, and procedures to create computer systems that can do human-like activities. Machine learning is a key idea in AI, where computers analyse large information to find patterns, forecast, and get insights [10]. Image recognition is an example of how machine learning algorithms can analyse massive collections of photos and effectively categorise items. NLP, which lets computers perceive, interpret, and synthesise human language, is another key part of AI. Siri and Alexa employ NLP algorithms to understand and react to human requests. Figure 2 Illustrates Embark on the journey into the realm of Artificial Intelligence.

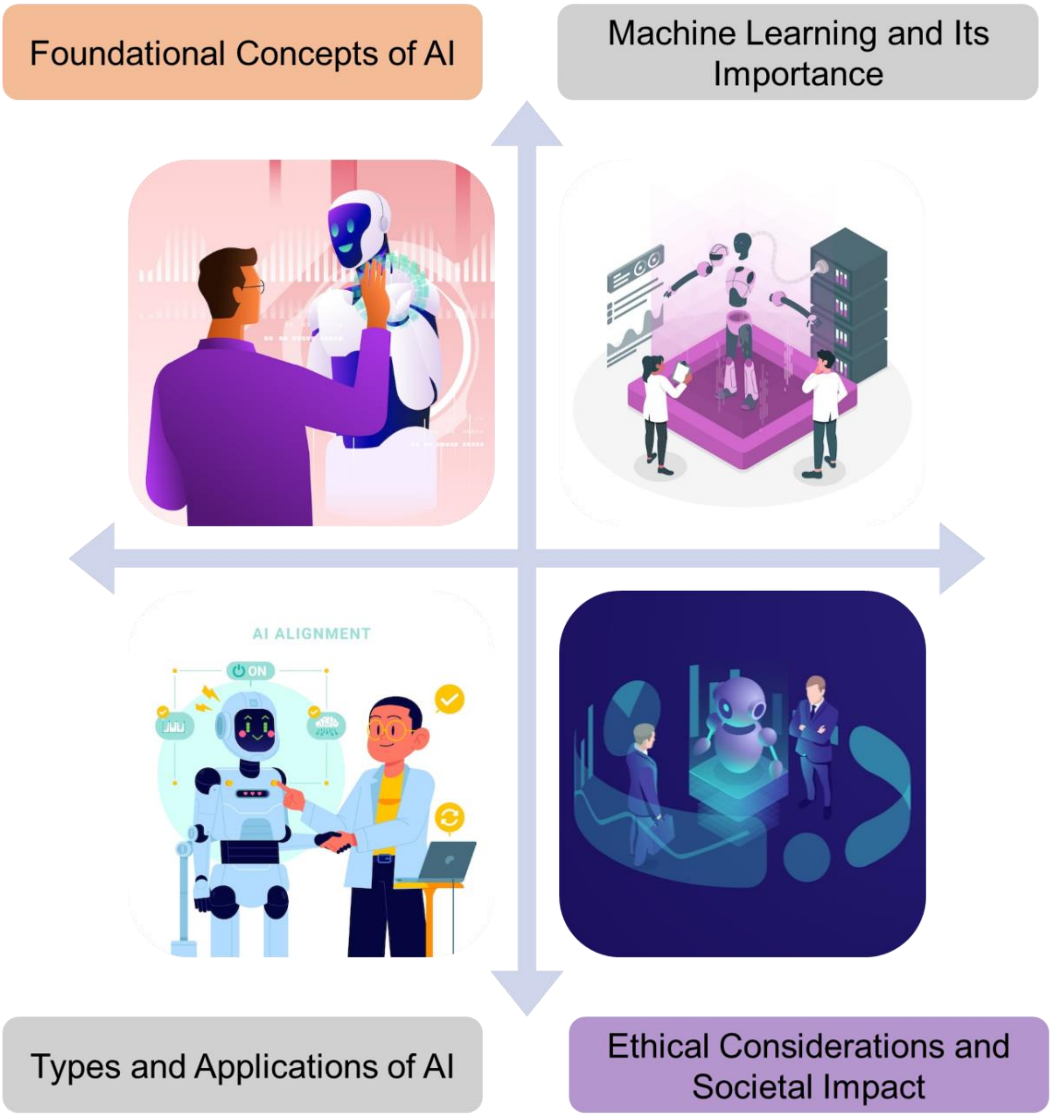

Figure 2. Embark on the journey into the realm of Artificial Intelligence.

AI also includes sophisticated methods like deep learning, inspired by the brain's neural networks. Deep learning algorithms do voice recognition, language translation, and picture production with exceptional accuracy and efficiency. AI includes robotics, where intelligent devices execute activities independently, such as autonomous cars managing traffic or robotic arms building things in factories. Another significant field of AI, reinforcement learning, trains computers to make judgements via trial and error to maximise rewards in a particular environment. Reinforcement learning methods can teach AI bots to play chess or Go like pros. Healthcare uses predictive analytics and machine learning algorithms to analyse medical data to aid diagnosis and treatment. AI-powered diagnostic tools can identify anomalies in X-rays and MRI scans and help doctors interpret data. Finance uses AI algorithms for fraud detection, algorithmic trading, and personalised financial advising. AI-powered fraud detection systems may spot suspicious transaction patterns, while AI-driven trading algorithms can execute trades quickly depending on market circumstances and trends. AI has also transformed the entertainment business by personalising Netflix and Spotify content suggestions using machine learning algorithms. In conclusion, Introduction to Artificial Intelligence covers the many methods and applications that are shaping the rapidly evolving landscape of AI, highlighting its transformative potential in healthcare, finance, transportation, and entertainment.

3.1 Basics of Artificial Intelligence

Introduction to AI provides a basic understanding of the multidisciplinary area that is changing society. AI involves a wide range of approaches, algorithms, and procedures to create computer systems that can do human-like activities. The Basics of Artificial Intelligence subtopic of Introduction to Artificial Intelligence explains the fundamentals of AI systems. The Basics of Artificial Intelligence include the essential principles and methods used to imitate human intelligence in computers. Intelligent agents, which use sensors and actuators to sense and act on their surroundings, are important. Predefined goals or objectives guide these agents' choices. A self-driving automobile with sensors for obstructions, traffic lights, and pedestrians is one example. The car's AI system processes sensor data to steer, brake, and accelerate safely in traffic. The creation of algorithms and techniques to solve complicated issues and make optimum judgements in uncertain or dynamic contexts is another essential component of AI. Search algorithms, which systematically choose the best answer, are a traditional AI problem-solving method [11]. A chess-playing AI programme utilises search algorithms to explore move sequences and choose the best one based on preset assessment criteria. Machine learning, a cornerstone of artificial intelligence, lets computers learn from data and improve without scripting. Machine learning models include supervised, unsupervised, and reinforcement learning. Using labelled data, supervised learning algorithms are taught. Consider a spam email filter trained on labelled datasets of spam and non-spam emails. The filter uses email content elements to identify spam and non-spam. In unsupervised learning, computers uncover patterns or structures in unlabeled data. Clustering methods aggregate related data elements by properties. Marketing customer segmentation uses clustering algorithms to combine clients with similar buying habits or preferences without supervision. Reinforcement learning trains agents to make consecutive choices to maximise cumulative rewards. Trial and error teach agents, who get rewards or punishments. Imagine teaching a computer to play chess. The programme learns by playing against itself or humans, gaining prizes for winning and punishments for failing. The Basics of AI include intelligent agents, problem-solving, decision-making, and machine learning. AI systems are founded on these notions, allowing computers to sense their surroundings, make choices, and learn from experience, imitating human-like intelligence in diverse fields.

3.2 AI in the Industrial Sector

Introduction to Artificial Intelligence (AI) covers AI's many applications and ramifications across sectors, with an emphasis on its revolutionary influence on industry. AI in manufacturing, production, and supply chain management is transforming efficiency, productivity, and operational performance. This subtopic discusses how AI-driven solutions are changing manufacturing processes in industrial environments. Predictive maintenance uses AI algorithms to forecast equipment breakdowns, reducing downtime and optimising maintenance schedules. Imagine a factory with a fleet of industrial machines. AI-powered predictive maintenance solutions can identify irregularities in equipment health in real time, allowing maintenance personnel to avert production interruptions. AI is also improving quality control and fault identification. AI algorithms can accurately and efficiently detect product flaws and abnormalities in photos and sensor data. In car production, AI-powered vision systems can examine vehicles for scratches, dents, and misalignments to ensure high-quality goods. AI optimises inventory, demand forecasts, and logistics, revolutionising supply chain management. Machine learning algorithms can reliably estimate product demand using past sales data, market trends, and external variables. Organisations can optimise inventory, eliminate stockouts, and boost customer satisfaction. In logistics, AI-driven route optimisation algorithms may optimise delivery routes, cut transportation costs, and reduce carbon emissions. AI-enabled robots automate repetitive activities, boost productivity, and improve worker safety in manufacturing. Cobots using AI algorithms may assist humans in assembly, packing, and material handling. Cobots using computer vision and machine learning may help electronics workers assemble circuit boards, enhancing efficiency and quality. AI is also advancing autonomous cars and drones in industry. Artificial intelligence helps autonomous vehicles and drones traverse complicated landscapes, avoid obstacles, and move and check materials. In warehouses, autonomous forklifts with AI guidance algorithms save labour costs and increase throughput.

3.3 Machine Learning and Deep Learning Essentials

Introduction to AI provides a basic understanding of the multidisciplinary area that is changing society. AI involves a wide range of approaches, algorithms, and procedures to create computer systems that can do human-like activities. Introduction to Artificial Intelligence covers Machine Learning and Deep Learning Essentials, which explains these revolutionary methods. Artificial intelligence's machine learning subset develops methods that allow computers to learn from data and make predictions or judgements without being programmed. Machine learning relies on training algorithms to recognise patterns and draw conclusions from datasets. Using example input-output pairs from training data, supervised learning algorithms translate input data to output labels. For instance, a supervised learning system can categorise handwritten digit pictures into their number labels (0–9). The system adjusts its internal settings to minimise the difference between expected and actual labels from hundreds of labelled photos. Another important machine learning paradigm, unsupervised learning, trains algorithms on unlabeled datasets. In contrast, unsupervised learning algorithms seek hidden data patterns or structures. Clustering methods, for instance, group comparable data points by features without class labels. Market segmentation uses clustering algorithms to find groups of consumers with similar buying habits or preferences based on transaction data. Reinforcement learning, the third key machine learning category, trains agents to make consecutive choices to maximise cumulative rewards. Trial and error teach agents, who get rewards or punishments. Imagine teaching a computer to play chess. The programme learns by playing against itself or humans, gaining prizes for winning and punishments for failing. Deep learning, a type of machine learning inspired by the human brain's neural networks, may solve complicated issues in image and audio recognition, natural language processing, and autonomous driving. Artificial neural networks, or deep learning algorithms, make predictions by processing and transforming incoming data using numerous layers of neurons. Computer vision activities like picture categorization and object recognition require CNNs. However, RNNs are ideal for sequential data processing applications like language translation and audio recognition. Artificial intelligence relies on Machine Learning and Deep Learning Essentials to help computers learn, recognise patterns, and make smart judgements. These methods have revolutionised healthcare, banking, driverless cars, and personalised recommendations, fostering digital innovation and transformation.

4. AI Techniques for Predictive Maintenance

AI Predictive Maintenance uses innovative algorithms and methods to predict equipment breakdowns and optimise maintenance schedules. AI analyses sensor, IoT, and historical maintenance data to enable predictive maintenance interventions to reduce expensive downtime and operational disturbances. Anomaly detection, which identifies anomalies from typical operating circumstances that may suggest equipment breakdowns, is an important AI tool for predictive maintenance Anomaly detection often uses SVMs or Isolation Forests. Table 2 Illustrates Empowering reliability: Harnessing AI for proactive maintenance strategies.

AI Techniques	Description	Application	Advantages	Implementation	Reference
Machine Learning	Utilizes algorithms to analyze historical data and identify patterns indicative of equipment failures.	Predicting when a motor is likely to fail based on vibration data collected over time.	Enables proactive maintenance planning, reduces downtime, and optimizes resources.	Training machine learning models on historical maintenance data and sensor readings.	[12]
Deep Learning	Employs artificial neural networks with multiple layers to extract complex patterns from data.	Using deep learning models to analyze images from thermal cameras to detect overheating components.	Capable of handling large and unstructured datasets, leading to more accurate predictions.	Training deep learning models on annotated image datasets and optimizing network architectures.	[13]
Anomaly Detection	Focuses on identifying deviations from normal operating conditions that may	Detecting unusual temperature spikes in a power transformer, signaling potential	Provides early warnings for potential failures, enabling proactive maintenance	Implementing anomaly detection algorithms and setting up thresholds for abnormal	[14]

	indicate equipment faults or failures.	insulation degradation.	interventions.	behavior detection.	
Prognostics	Predicts the remaining useful life of equipment based on current condition and operating parameters.	Estimating the remaining lifespan of a bearing based on wear and tear data.	Allows for proactive replacement of components before they fail, minimizing unplanned downtime.	Developing prognostic models based on physics-based models or empirical data analysis.	[15]
Natural Language Processing (NLP)	Analyzes text data, such as maintenance reports or equipment manuals, to extract insights and identify maintenance patterns.	Extracting maintenance recommendations from equipment manuals and correlating them with sensor data.	Facilitates the integration of unstructured data sources into predictive maintenance workflows.	Developing NLP models to extract relevant information from maintenance documents and integrating them with predictive maintenance systems.	[16]

Table 2 .Empowering reliability: Harnessing AI for proactive maintenance strategies.

In a manufacturing facility, anomaly detection algorithms may analyse sensor data from production machines to identify odd vibrations or temperature changes that may indicate equipment breakdown. Regression analysis models the link between operational factors and equipment performance for predictive maintenance using AI. Based on past data, regression models like Linear Regression or Random Forest Regression anticipate equipment deterioration or failure. Regression analysis can forecast the lifespan of important power plant components like turbines and boilers based on running hours, temperature, and pressure. For predictive maintenance, machine learning algorithms may classify equipment conditions into classes or states. Decision Trees and Neural Networks are trained on labelled data to categorise equipment as normal, malfunctioning, or in need of repair. An aeroplane maintenance facility may use classification algorithms to categorise sensor data from aircraft engines as "healthy," "faulty," or "critical," allowing staff to prioritise repairs by severity. Machine learning subset deep learning is also being used for predictive maintenance. Deep learning algorithms like CNNs and LSTMs can analyse enormous volumes of sequential data, making them ideal for predictive maintenance applications that analyse time-series sensor data. To forecast wind farm failures and maintenance requirements, deep learning systems can analyse historical wind speed, temperature, and turbine performance data. Reinforcement learning, a branch of AI, is being investigated for predictive maintenance jobs that require sequential judgements. Through trial and error, reinforcement learning algorithms like Q-learning or Deep Q Networks (DQN) optimise maintenance strategies to maximise long-term rewards and minimise maintenance expenditures. Reinforcement learning algorithms can optimise vehicle maintenance schedules based on use, fuel economy, and repair costs in fleet management systems.

4.1 Data Collection and Preprocessing

AI Techniques for Predictive Maintenance analyse equipment health and anticipate breakdowns using many methods. Data Collection and Preprocessing, which gathers data from sensors, IoT devices, and other sources and prepares it for AI analysis, is a major subtopic in this subject. Data collection is the cornerstone of predictive maintenance since AI models need accurate and complete data to generate correct predictions. Sensor readings, equipment performance metrics, maintenance records, and environmental parameters may be included. Production equipment sensors may measure temperature, pressure, vibration, and energy usage in a factory. Fleet management systems may collect engine performance, fuel consumption, and vehicle use data via vehicle sensors. Data is preprocessed to clean, transform, and organise it for analysis. Data integrity and AI algorithm optimisation depend on this phase. Handling missing values, eliminating outliers, normalising or scaling features, and encoding categorical variables are data preparation methods. When a sensor fails to capture a reading, interpolation or imputation may fill the gap. Data outliers, such as sensor faults or abnormalities, may be discovered and deleted to avoid skewing the analysis. To improve AI model prediction, data preparation may include feature engineering, which creates new features or variables from existing data. A predictive maintenance programme for aviation engines may use raw sensor data to calculate engine load, altitude, and flight time to better understand operational conditions. Predictive maintenance data generally includes time-series metrics. Time-series data needs particular handling to accommodate for temporal relationships and trends. In a wind turbine predictive maintenance system, sensor data may show seasonal or long-term trends owing to weather or equipment wear. Autocorrelation, seasonal decomposition, and trend analysis may reveal data insights. Data Collection and Preprocessing are essential to AI Techniques for Predictive Maintenance, ensuring accurate and dependable forecasts. By preprocessing sensor and other data to clean and organise it, organisations can use AI algorithms to analyse equipment health, predict failures, and optimise maintenance schedules, improving operational efficiency and reducing downtime

4.2 Anomaly Detection using Machine Learning

AI Techniques for Predictive Maintenance include several methods to predict equipment breakdowns. This domain's key subtopic, Machine Learning Anomaly Detection, alerts maintenance personnel to abnormal operating circumstances that may predict approaching breakdowns. In anomaly detection, machine learning algorithms analyse sensor data to find patterns or behaviours that differ considerably from norms. Unsupervised learning algorithms learn data structure without labelled examples, making them a frequent anomaly identification method [17]. Clustering and density estimation may find data points outside the normal distribution. In a manufacturing facility, sensors monitor equipment temperature. An unsupervised anomaly detection programme might detect temperature changes or thresholds that indicate equipment failure. When labelled data is available, supervised learning systems can discover anomalies. In supervised anomaly detection, the algorithm is trained on a dataset of normal and anomalous behaviour to learn about normal functioning and discover abnormalities. In predictive maintenance for aviation engines, supervised learning algorithms may be trained on past sensor data to identify engine failure indications such anomalous vibrations or temperature spikes. Ensemble approaches, which mix various base algorithms to boost performance, may also improve anomaly detection model accuracy and resilience. Random Forests or Gradient Boosting may combine model predictions to examine aberrant behaviour more thoroughly. Ensemble anomaly detection methods may blend machine learning algorithms learned on several sensor data streams to more accurately identify equipment problems in power plants. Deep learning approaches like autoencoders have potential in anomaly identification, especially for tiny deviations in complicated data. Learning to recreate input data from compressed latent space is the goal of autoencoder neural networks. Anomalies occur when recovered data drastically varies from input. Cybersecurity autoencoder-based anomaly detection algorithms may recognise anomalous network traffic patterns that indicate cyber assaults or security breaches.

4.3 Predictive Modelling with Deep Learning

AI Methods for Predictive Maintenance predict equipment breakdowns and optimise maintenance plans. Predictive Modelling using Deep Learning works well in this sector, using neural network designs to analyse complicated data and forecast equipment health. Deep learning trains neural networks with numerous layers of linked nodes to learn hierarchical data representations. Deep learning methods like CNNs and RNNs are ideal for analysing time-series sensor data and predicting equipment performance in predictive maintenance. Predictive maintenance often analyses rotating equipment vibration data using predictive modelling with deep learning. Sensors on rotating equipment like motors, pumps, and turbines may gather vibration data to assess its health. Engineers can forecast equipment breakdowns like bearing defects and unbalance by training deep learning models using past vibration data. Consider a manufacturing plant's predictive maintenance system. Deep learning models trained on pump vibration data may identify trends and forecast pump failure due to bearing wear or misalignment. To avoid expensive downtime and production delays, maintenance staff may plan repairs or replacements in advance. For predictive maintenance jobs that gather data over time, recurrent neural networks (RNNs) are excellent for sequential data analysis. RNNs can analyse flight data recorder (FDR) data on aircraft characteristics including altitude, airspeed, and engine performance in the aviation sector. By training an RNN model using historical FDR data, engineers may forecast engine and hydraulic system failures based on data trends.

5. Implementing AI in Power Network Maintenance

Power network maintenance using AI is a revolutionary way to improve grid reliability and efficiency. AI technologies like machine learning, deep learning, and data analytics detect and prevent problems, lowering downtime and maintenance costs. This connection improves power network efficiency and enables smart grids, where AI-driven insights optimise energy distribution and consumption [18]. AI in power network maintenance begins with massive data collecting and analysis from grid sources. This data contains real-time sensor readings, maintenance history, weather reports, and load demand estimates. Transformers, transmission lines, and substations may be monitored by smart sensors throughout the network for temperature, voltage variations, and equipment vibrations. Figure 3 Illustrates Transforming power networks with AI-driven maintenance solutions.

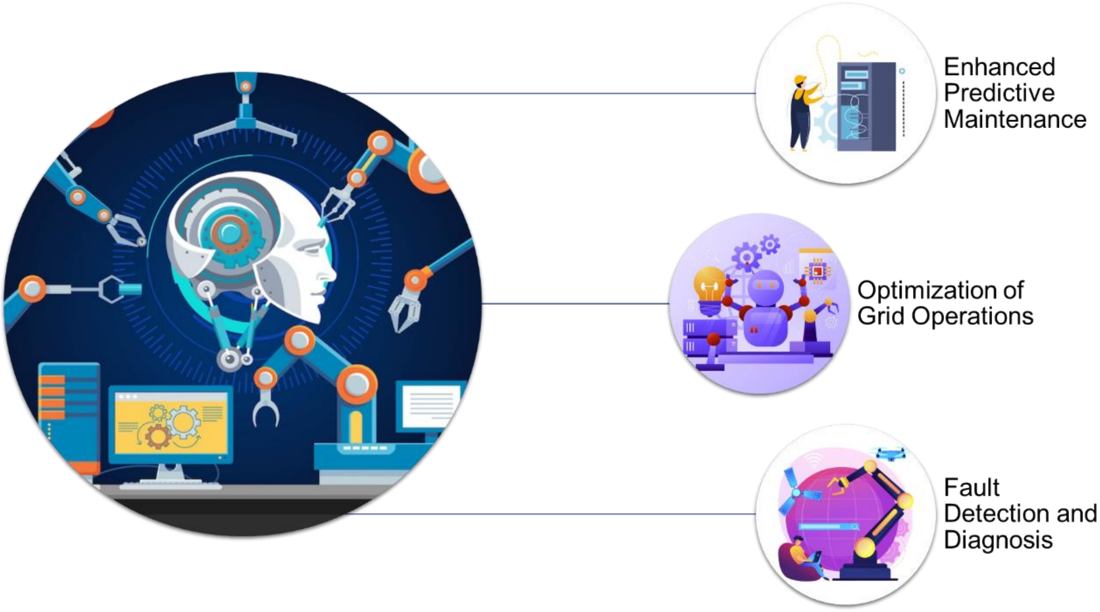

Figure 3. Transforming power networks with AI-driven maintenance solutions.

Machine learning algorithms are crucial to data processing and analysis. Utility models trained on historical data may find patterns and connections that analysts may miss. Predictive models may foresee equipment breakdowns or suboptimal operating conditions that might cause service interruptions. Using temperature changes and loading circumstances, machine learning algorithms may anticipate transformer breakdowns. By forecasting such failures, utilities may arrange maintenance or replacements in advance, preventing interruptions. AI in power network maintenance may analyse more complicated data patterns using deep learning, a subset of machine learning. Deep neural networks can capture temporal relationships that impact equipment health by processing sequential data from time-series sensors. Recurrent neural networks (RNNs) might analyse circuit breaker performance data to detect small indicators of wear or malfunction before failure. AI algorithms aid power network maintenance and operating decisions beyond predictive maintenance. Reinforcement learning, which sequentially makes judgements, may optimise maintenance schedules and techniques using rewards. Simulating maintenance activities and their results helps the algorithm identify ones that minimise costs and maximise power network dependability. Reinforcement learning algorithms may incorporate weather, demand projections, and equipment status to schedule maintenance tasks to minimise power supply disturbance. Data privacy, cybersecurity, and computing resources are other issues when integrating AI into power network maintenance. The quality and granularity of data and staff competence in understanding AI-generated insights also affect AI adoption effectiveness. AI in power network maintenance is a proactive way to manage electrical grid health and efficiency. Machine learning and deep learning algorithms help utilities detect breakdowns, optimise maintenance, and assure electricity reliability. This shift towards AI-driven maintenance procedures is crucial to smart grids, where data analysis drives operational choices.

5.1 Infrastructure Requirements

Power network maintenance using Artificial Intelligence (AI) requires strong infrastructure to gather, process, and analyse massive volumes of electrical grid data. Data collection methods, communication networks, computer resources, and cybersecurity are needed to integrate AI into power network maintenance. Data Acquisition Systems enable AI-powered maintenance by delivering real-time power network component health and performance information. Sensors, metres, and monitoring devices around the grid collect data on voltage, current flows, temperature, humidity, and other characteristics. Transformer smart sensors monitor oil, winding, and load currents, giving data for predictive maintenance algorithms. Communication networks provide sensor and device data to centralised data warehouses and analytical platforms. Data is sent throughout the grid reliably and quickly via fiber-optic cables or 5G wireless technologies. This allows operators to quickly address problems by monitoring and analysing crucial infrastructure components in real time. In a smart grid deployment, scattered sensors and smart metres provide data to central control centres across communication networks, where AI algorithms identify abnormalities and forecast breakdowns. Processing and analysing power network monitoring systems' huge data sets need computing resources. HPC clusters, cloud computing platforms, and edge computing devices manage AI algorithm computations. These resources provide real-time data processing, model training, and inference for power network maintenance decision-making. In predictive maintenance, cloud-based servers or edge devices analyse sensor data and propose repair using machine learning models built on past data. AI-enabled power network maintenance systems need cybersecurity to prevent cyberattacks. Data breaches, malware outbreaks, and DoS assaults grow more likely as electricity networks become more linked and digitised. Data and infrastructure assets are protected by strong cybersecurity techniques including encryption, authentication, access control, and intrusion detection. For instance, encryption algorithms safeguard data flows via communication networks, and access control measures secure vital infrastructure components. To secure and maintain AI-enabled power network maintenance systems, industry standards and regulations like the North American Electric Reliability Corporation (NERC) Critical Infrastructure Protection (CIP) standards and the European Union's General Data Protection Regulation (GDPR) must be followed.

5.2 Integrating AI with Existing Systems

Power network maintenance using AI integrates AI technology with current systems to improve grid reliability and efficiency. To achieve compatibility and maximum advantages, AI integration with current systems involves rigorous design, collaboration, and adaptation. This subtopic discusses the problems and solutions of incorporating AI into power network maintenance using current infrastructure and technologies. Legacy hardware and software compatibility is a major issue when implementing AI. Many power companies use older systems that may not support AI applications. Thus, utilities must evaluate their infrastructure and discover compatibility concerns during integration. Legacy SCADA systems used to monitor and operate power networks may not have the interfaces or standards for AI-driven analytics. Utilities may need to update or retrofit to support AI technology. AI system compatibility with data sources and procedures is another issue. Power utilities create massive volumes of data via sensors, metres, and operational databases. Integrating AI into current systems demands smooth data interchange across platforms and apps. To get meaningful insights, AI systems must interpret and analyse grid sensor data. To aid decision-making, utilities must guarantee that AI systems can consume data from current sources and integrate with other systems like asset management and outage management. Integrating AI with current systems demands data quality and governance improvements. Training AI models and making accurate predictions requires data quality including correctness, completeness, and consistency. To guarantee AI system data correctness and integrity, utilities must evaluate their data and establish data cleaning and validation methods. Data governance rules and processes must also control data collection, storage, and usage in accordance with regulations and industry standards. Despite these obstacles, numerous methods to integrate AI into power network maintenance systems. A flexible and scalable framework enables AI to be gradually integrated into processes. Utility systems may progressively replace outdated components with AI-enabled analytics modules. This stepwise strategy minimises operational interruption and lets utilities use AI-driven insights immediately. APIs and middleware platforms may let utilities share data and integrate AI systems with existing infrastructure. AI systems may smoothly connect with other apps and services because to APIs' standardised data access and manipulation interfaces. Integration hubs like middleware platforms transform, route, and synchronise data across systems. To speed up integration, utilities might cooperate with AI and power system technology and service companies. These agreements may provide utilities access to specialised tools, algorithms, and domain expertise to solve technical obstacles and apply AI. Finally, incorporating AI into power network maintenance systems involves careful consideration of compatibility, interoperability, data quality, and governance. Modular architectures, APIs, middleware platforms, and technology vendor partnerships allow utilities to integrate AI technologies into their workflows and use AI-driven insights to improve electrical grid reliability and efficiency [19].

5.3 Case Studies: Successful Implementations

Several successful AI deployments in power network maintenance have shown how AI technology may alter electrical grid reliability and efficiency. This subtopic examines success stories of AI deployments in power network maintenance, including difficulties, solutions, and results. Southern Company, one of the leading US electric utilities, utilised AI-driven predictive maintenance for its power producing assets. Southern Company identified imminent problems in gas turbine, boiler, and other key equipment sensor data using machine learning algorithms. Southern Company cut downtime, improved equipment performance, and saved millions by proactively resolving maintenance concerns. Southern Company scheduled turbine blade maintenance during planned outages to minimise interruptions and prevent expensive emergency repairs by forecasting failures. UK Power Networks, a significant UK power distribution network operator, used AI-enabled predictive analytics to increase network reliability and resilience. UK Power Networks used machine learning algorithms to detect failures and optimise maintenance plans using historical outage data, weather predictions, and asset health data. UK Power Networks minimised power outages and improved customer satisfaction and regulatory compliance by prioritising maintenance based on AI data. UK Power Networks replaced ageing transformers at risk of failure to reduce unexpected outages and improve network reliability. Using sophisticated analytics and digital twin technologies, General Electric (GE) introduced AI-driven predictive maintenance solutions for its gas turbine and power production fleet. GE analysed turbine sensor data using machine learning algorithms to detect equipment faults and optimise maintenance plans. GE increased equipment dependability, maintenance costs, and operational efficiency by using AI-generated insights for proactive maintenance. GE scheduled gas turbine blade replacements during planned maintenance outages by identifying early blade deterioration, saving expensive downtime and maximising turbine performance. Pacific Gas and Electric Company (PG&E), one of the leading US natural gas and electric energy corporations, used AI-driven predictive analytics to optimise vegetation management and decrease wildfire risks. PG&E identified vegetation-related outage hotspots using machine learning algorithms using satellite images, geographic data, and historical wildfire data. According to AI-generated risk evaluations, PG&E prioritised vegetation management actions to decrease power outages caused by vegetation encroachment, wildfire hazards, and public safety. PG&E cleared thick vegetation near power wires to reduce wildfire danger and system stability.

6. IoT and Sensors in Predictive Maintenance

IoT and sensor integration into predictive maintenance techniques advances system management and optimisation, from industrial equipment to infrastructure networks. This technological synergy allows real-time monitoring, data collecting, and analysis to forecast equipment breakdowns, reducing downtime and increasing asset life. This article explains the technical aspects of predictive maintenance using IoT and sensors with examples. Modern predictive maintenance solutions rely on IoT and sensors. Such systems monitor vibration, temperature, pressure, and humidity via sensors. These sensors are growing more sophisticated and may detect even minor irregularities that might signal equipment breakdown. For instance, vibration sensors may identify atypical equipment patterns, indicating maintenance before a catastrophic collapse. Vibration sensors monitor bearings and gearboxes in wind turbines, which may cause considerable downtime and replacement costs. Table 3 Illustrates Seamlessly integrating IoT and sensors to pioneer predictive maintenance.

IoT and Sensors	Description	Example	Benefits	Implementation	Reference
Sensor Technologies	Various sensors are deployed to monitor equipment parameters such as temperature, vibration, and pressure, enabling real-time condition monitoring.	Installing vibration sensors on rotating machinery to detect abnormal vibration patterns indicative of bearing wear.	Early detection of equipment faults, proactive maintenance planning, and improved asset reliability.	Deploying sensors strategically across critical equipment and integrating them with IoT platforms for data collection and analysis.	[20]
Data Acquisition	IoT technology is utilized to collect data	Gathering temperature and pressure	Real-time monitoring, centralized	Implementing IoT-enabled data acquisition	[21]

	from sensors deployed on equipment, transmitting it to centralized systems for analysis and decision-making.	data from sensors installed on a hydraulic system and transmitting it to a cloud-based analytics platform.	data management, and enhanced decision-making capabilities.	systems with wireless communication capabilities and cloud-based analytics platforms.	
Condition Monitoring	Continuous monitoring of equipment parameters to detect deviations from normal operating conditions, enabling early detection of potential faults.	Monitoring temperature, pressure, and vibration levels in rotating machinery to identify abnormal behavior indicative of impending failures.	Early detection of equipment anomalies, proactive maintenance planning, and improved reliability.	Installing sensors on critical equipment and integrating them with condition monitoring systems for real-time data analysis.	[22]
Predictive Analytics	Utilizing advanced analytics techniques, such as machine learning and statistical modeling, to analyze sensor data and predict equipment failures.	Using machine learning algorithms to analyze vibration data from a motor and predict when it is likely to fail.	Proactive maintenance planning, reduced downtime, and optimized resource allocation.	Developing predictive analytics models and algorithms tailored to specific equipment and operational conditions.	[23]
Integration with Maintenance Systems	IoT-enabled sensors are integrated with existing maintenance management systems to	Integrating sensor data with a computerized maintenance management system	Improved visibility into equipment health, streamlined maintenance processes, and	Integrating IoT-enabled sensors with CMMS platforms through application programming	[24]

	streamline maintenance workflows and facilitate data-driven decision-making.	(CMMS) to generate work orders based on equipment health status.	enhanced collaboration between maintenance teams.	interfaces (APIs) or middleware solutions.	

Table 3. Seamlessly integrating IoT and sensors to pioneer predictive maintenance.

IoT sensors are connected to a cloud-based central processing system where data analytics and machine learning algorithms analyse the data in real time. This connection lets distant assets' data be analysed together, improving predictive maintenance methods. A worldwide manufacturing corporation may employ IoT to centralise equipment data from numerous locations into one analytics platform. Thus, the organisation can spot trends and forecast breakdowns throughout its processes, allowing proactive maintenance and lowering downtime. Digital twins, virtual clones of physical assets that match their real-time state, functioning, and performance, may be created using IoT and sensors. These digital twins may simulate numerous situations to forecast how the real asset would perform and detect trouble areas. Digital twins of jet engines are used in aerospace to simulate and analyse their performance under various operating circumstances. This method optimises maintenance plans based on real wear and tear rather than predetermined timetables, lowering costs and boosting aircraft availability. IoT and sensors in predictive maintenance provide data security, interoperability, and large data management difficulties. Security is crucial for sensor data transmission and storage since breaches might disclose important operational data. When combining sensors and IoT devices from multiple manufacturers, standardised protocols are needed to assure interoperability. To get relevant insights from sensor data, complex algorithms and computer power are needed for data management and analysis. In energy, utility firms employ hundreds of sensors throughout power producing and distribution networks to overcome these issues. These sensors monitor equipment and the environment, providing data into sophisticated analytics systems that forecast maintenance requirements and optimise repair schedules. These organisations maintain power supply dependability and grid safety by tackling security, interoperability, and data management concerns, demonstrating the transformational potential of IoT and sensors in predictive maintenance.

6.1 Role of IoT in Modern Power Networks

IoT transforms how utilities monitor, operate, and repair essential infrastructure in modern power networks. Power utilities may use IoT technology and sensors to monitor their networks in real time and use predictive maintenance tactics to reduce downtime, optimise asset utilisation, and improve grid dependability. This subtopic discusses IoT's many roles in current power networks with examples. Modern power networks use IoT for remote grid asset monitoring and condition-based maintenance. IoT sensors on transformers, switchgear, and other equipment continually measure temperature, voltage, and current. This data is wirelessly sent to centralised monitoring systems for real-time equipment health assessment and anomaly detection [25]. Distribution transformer sensors can identify overheating and overloading before they cause breakdowns. Utility companies may avoid expensive downtime and increase asset life by proactively addressing these concerns. By offering real-time monitoring and management, IoT helps integrate renewable energy sources like solar and wind into the power system. IoT sensors on solar panels, wind turbines, and battery storage devices track energy output, consumption, and storage. Grid operators utilise this data to optimise energy delivery and balance supply and demand. Solar inverter sensors monitor solar irradiance and panel efficiency, enabling operators to optimise output and energy production. Battery storage system sensors can monitor charge/discharge cycles and state of charge, helping utilities optimise energy storage and grid stability. IoT also helps optimise and manage grid assets by giving performance and utilisation information. With sensors and smart metres throughout the grid, utilities can monitor voltage, power flows, and equipment health in real time. The data is analysed to detect congestion, voltage fluctuations, and equipment breakdowns, helping utilities optimise grid operations and prioritise repairs. Sensors on distribution feeders can detect voltage sags and surges and rectify them to guarantee dependable power supply. IoT also improves grid resilience and outage management with early warning and fast response solutions. Power lines, poles, and substations include sensors that can detect temperature, humidity, and wind speed that might damage grid infrastructure. This data is analysed to detect threats like tree branches and ice accumulation that might cause outages or equipment damage. Acoustic and vibration sensors can detect power line arcing or sparking, allowing utilities to deploy staff to resolve fire dangers before they cause widespread outages. IoT and sensors may provide utilities real-time grid performance information, enabling predictive maintenance, and improve grid resilience and dependability. IoT will become more important in contemporary power networks, pushing energy sector innovation and efficiency [26].

6.2 Sensor Technologies for Condition Monitoring

Sensor technologies help predictive maintenance by giving real-time equipment data to identify flaws and probable breakdowns. Each sensor technology used for condition monitoring in predictive maintenance applications may identify distinct abnormalities and performance deviations [27]. This subtopic discusses predictive maintenance condition monitoring sensor technology and their applications. Vibration sensors are widely utilised for condition monitoring in rotating equipment such motors, pumps, and turbines. These sensors detect equipment vibrations, which may indicate misalignment, imbalance, bearing wear, or structural flaws. A manufacturing plant's vibration sensors on a motor may detect anomalous vibrations produced by worn bearings, enabling maintenance crews to arrange repairs before a catastrophic failure. Wind turbine vibration sensors identify early gear wear and fatigue that might cause downtime. Condition monitoring in predictive maintenance also requires temperature sensors. These sensors detect equipment and component overheating, insulation deterioration, and thermal runaway. Temperature sensors in electrical switchgear may detect hotspots created by faulty connections or high current, signalling fire threats. Temperature sensors in HVAC systems monitor refrigerant lines and compressor motors for leaks or malfunctions. Pressure sensors monitor hydraulic and pneumatic systems for leaks, blockages, and pressure variations. These sensors monitor system fluid pressure, revealing fluid flow rates, system integrity, and performance. Pressure sensors on a hydraulic system can detect leaks or obstructions that cause pressure decreases or spikes. Pressure sensors monitor compressed air line pressure to detect leaks or pressure dips that might impair equipment performance or energy efficiency. Acoustic sensors can detect aberrant equipment noises or vibrations that may signal mechanical or operational concerns. These sensors analyse equipment-generated sound waves or vibrations to find irregularities. Acoustic sensors on a conveyor belt may detect aberrant noises from worn bearings or misaligned rollers, signalling maintenance needs. In rotating equipment like pumps and compressors, acoustic sensors may detect vibration patterns or frequencies that indicate bearing or rotating component failure [28].

6.3 Data Acquisition and Management

IoT and sensor-based predictive maintenance systems gather, store, and analyse massive volumes of sensor data to find equipment irregularities and anticipate problems. This subtopic discusses predictive maintenance data collecting and management technique and instances of its use. Data collection includes gathering sensor data from the monitored equipment or system. This data may include temperature, vibration, pressure, current, and voltage, depending on the sensors used. Industrial equipment sensors measure motor temperature, bearing vibration, and oil pressure. After transmission, a central data collecting system aggregates and analyses sensor data. Data acquisition systems use Wi-Fi, Bluetooth, or cellular networks to send sensor data to centralised data repositories for IoT-enabled predictive maintenance [29]. Real-time equipment health monitoring and analysis is possible regardless of asset location or size. In commercial fleets, IoT sensors on engines may send diagnostic data, fuel usage, and vehicle performance indicators to a central management system via cellular networks. This lets fleet managers track vehicle health, maintenance requirements, and operating efficiency in real time. Sensor data is stored, organised, and analysed to provide actionable insights and aid predictive maintenance decision-making. Sensor data is stored in organised databases or data lakes and queried and analysed using modern analytics tools and algorithms. To discover equipment irregularities and forecast breakdowns, power utilities store sensor data from substations, transformers, and distribution lines in a centralised data repository and process and analyse it. Data is analysed using machine learning and statistical modelling to provide predictive maintenance suggestions. Throughout sensor data's lifespan, data management systems must assure security, integrity, and dependability. To safeguard sensitive data, encryption, access restrictions, and data validation are used. In healthcare institutions, IoT sensors on medical equipment must follow tight data privacy and security rules to protect patient data [30].

Conclusion

Finally, AI-powered Predictive Maintenance in Power Networks improves electrical system dependability, efficiency, and safety. AI can help utilities move from reactive and preventative maintenance to proactive techniques that predict and prevent equipment problems. This revamped maintenance method reduces downtime, costs, and grid vulnerability while extending asset life. AI-powered predictive maintenance can analyse massive volumes of data from sensors, metres, and operational records to find trends and anomalies that indicate equipment deterioration or potential breakdowns. AI systems can forecast transformer failures in power utilities by analysing historical transformer performance, weather, and load demand data. This allows maintenance crews to arrange repairs or replacements in advance. By doing so, utilities may reduce unplanned outages, optimise maintenance schedules, and prolong essential equipment lifespans. AI-powered predictive maintenance helps utilities allocate resources and prioritise maintenance based on equipment criticality and chance of failure. Utility prediction models can prioritise maintenance jobs based on equipment age, condition, and operating history using machine learning algorithms. This optimises maintenance resources to prioritise important assets and save downtime and costs. AI-powered predictive maintenance also improves grid stability and resilience by detecting possible hazards and vulnerabilities in advance and enabling utilities to manage them. A distribution network's smart metres, weather predictions, and previous outage records may be used by AI algorithms to detect voltage sags and equipment breakdowns. To increase grid stability and dependability, utilities might install voltage regulation devices or replace equipment. AI-powered predictive maintenance allows real-time grid monitoring, management, and optimisation, supporting smart grids. Utility operators may improve grid performance, find optimisation possibilities, and react rapidly by integrating AI technologies with grid infrastructure. AI algorithms can optimise energy distribution, minimise losses, and balance supply and demand in real time using smart metre and sensor data, providing efficient and dependable power delivery to customers.

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