AI-Based Predictive Maintenance Strategies for Improving the Reliability of Green Power Systems

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Abstract The adoption of AI-based predictive maintenance techniques increases the dependability of green power systems. Using AI, researchers are examining a vast array of potential approaches to revamping the maintenance of renewable energy systems. The use of supervised learning algorithms enables the classification and prediction of faults using historical data from green power systems, enabling the detection and categorization of distinct failure types. In addition, sensor data collected from renewable energy sources can be utilized by unsupervised learning algorithms for anomaly detection and failure identification. Moreover, reinforcement learning algorithms optimize the scheduling and allocation of maintenance resources by utilizing the system's current state. The combination of Internet of Things (IoT) sensors and data analytics tools makes real-time monitoring of renewable power systems feasible. To better predict the likelihood of equipment failure and the remaining useful life, it is necessary to analyze sensor data for patterns, trends, and anomalies that may indicate impending failures or performance degradation. In addition, there is an increase in the use of digital twin technology, which creates digital duplicates of green energy systems to model and foresee their operation in order to facilitate condition monitoring, predictive maintenance planning, and performance enhancement. Integrating real-time sensor data with digital twin models enables continuous system monitoring and diagnostics, providing the groundwork for timely maintenance interventions. Predictive maintenance of hydraulic systems is the primary focus of this paper, which demonstrates the practical application of AI-based predictive maintenance strategies via intriguing case studies and results. The dependability and performance of renewable energy sources illustrate the effectiveness and advantages of AI-driven maintenance procedures.

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W. Leal Filho et al. (eds.), *Digital Technologies to Implement the UN Sustainable Development Goals*, World Sustainability Series,
https://doi.org/10.1007/978-3-031-68427-2_2

Keywords Artificial Intelligence · Green Power Systems · Machine Learning · Predictive Maintenance

1 Introduction

Renewable energy has replaced fossil fuels since their depletion. We use more alternative energy each year. Complex and hybrid energy-generating technologies are being developed to fulfill requirements and secure energy. Infrastructure must be improved to use renewable energy. AI can improve energy infrastructure and decision-making. Predictive maintenance using AI, machine learning, and sensor data makes data-driven decisions. AI algorithms can find trends in real-time and historical data to forecast green power system failures. Preventive maintenance reduces unforeseen problems and optimizes resource utilization. AI-based solutions can also illuminate issue sources, enabling more targeted interventions and better system performance (Afridi, Ahmad, & Hassan, 2022; Bangroo, 2023).

Machine learning algorithms applied to sensor data analytics have optimized energy distribution networks and systems in recent years. These algorithms have shown promise in AI-based preventative maintenance plans for green power installations (Jha et al., 2023; Sayal et al., 2023). Machine learning is used to renewable energy sector concerns including fault classification, anomaly detection, predictive modeling, and the recently proposed Digital Twin technology. Machine learning algorithms applied to sensor data analytics have optimized energy distribution networks and systems in recent years. These algorithms are promising for AI-based green power facility preventative maintenance programs. Machine learning is used to renewable energy sector concerns including fault classification, anomaly detection, predictive modeling, and the recently proposed Digital Twin technology. IoT sensors and data analytics platforms provide real-time green power system monitoring. The Internet of Energy (IoE) can connect the energy sector to the growing ICT sector. This chapter discusses how the renewable energy business may use IoT to better monitor assets, discover abnormalities, and optimize system performance.

The chapter also examines sensor data for patterns, trends, and anomalies that may indicate imminent breakdowns or reduced performance. Machine learning and deep learning identify and classify abnormalities, reducing outages and repair time. This chapter covers sensor data prediction models, an important issue. Predictive maintenance uses real-time data analysis to evaluate machinery lifespan. Machine learning and historical data optimize maintenance plans, save costs, and prevent unplanned outages. Digital Twin technology models and predicts system performance. Stakeholders may better understand green power systems, analyze situations, and make choices by modeling real-world infrastructure in a digital environment.

The chapter's last case study applies data analysis and machine learning to hydraulic system predictive maintenance. The study provides in-depth data purification, exploratory analysis, preprocessing, model training, assessment, and performance analysis. This chapter discusses AI-based predictive maintenance's future.

These include machine learning algorithm improvements, peripheral computing and artificial intelligence integration, sensor technologies, big data analytics, digital twin applications, and cybersecurity precautions. These advancements may increase fault classification, prediction accuracy, system dependability, and long-term viability in green power systems.

This chapter primarily focuses on the utilization of artificial intelligence (AI) for forecasting and upkeep of sustainable energy systems. The Sustainable Development Goals (SDGs) that are relevant to this context are SDG 11: Sustainable Cities and Communities, SDG 13: Climate Action, SDG 7: Industry, Innovation and Infrastructure, and SDG 9: Affordable and Clean Energy. Implementing predictive maintenance techniques can improve the reliability and effectiveness of renewable energy sources like wind and solar power. Advocating for the adoption of sustainable energy sources is a means to contribute to the attainment of SDG 7. A technological infrastructure that combines sensor data analytics and machine learning can provide additional support in achieving SDG 9 by efficiently distributing and monitoring energy. To effectively achieve SDG 11, which focuses on creating environmentally sustainable and resilient urban areas, the adoption of solar-powered smart grid systems offers a practical solution. Utilizing artificial intelligence, and green power infrastructure optimization solutions can assist in achieving SDG 13, which seeks to address climate change by promoting the adoption of cost-effective clean energy systems.

2 Machine Learning Algorithms

Current trends suggest autonomous software will oversee energy distribution and decision-making. This program will be customized for these tasks. The program will control energy demand and supply. Optimizing energy distribution networks and systems requires advanced ML technology. Wide area monitoring systems (WAMS) use AI to analyze synchronized data from phasor measuring devices in smart grids. Machine-learning technologies use supervised, unsupervised, and reinforcement learning. These methods train and improve machine-learning models. Labeled examples help the model understand patterns and make predictions. Unsupervised learning trains the model using unlabeled data to reveal hidden patterns and structures. Reinforcement learning uses incentives and punishments to teach the model. Labeled data is used during supervised learning training. Unsupervised learning groups incoming data based on preset criteria without using training data labels. The analysis's clustering criterion determines the number of clusters. Reinforcement learning is a computational approach that includes an agent interacting with an environment, getting rewards or penalties, and utilizing this knowledge to enhance its performance through iteration. These three learning concepts have inspired many theoretical procedures and implementations (Qiu et al. 2016). Neural networks, decision trees, support vector machines, and deep learning assess power system transient stability. These techniques are used to generate mapping functions from offline data. This permits online time series and fresh instance analysis.

2.1 Supervised Learning Algorithms for Fault Classification and Prediction Based on Historical Data from Green Power Systems.

Random Forest (RF) is a popular ensemble learning technique that is being used more and more in the fields of economics and health. Collaborative learning surpasses solitary learning in terms of the ability to apply knowledge to a wide range of situations. Many students worked on this. Random Forest (RF) training involves generating distinct subsets through bootstrapping sampling. Each student receives personalized instruction. A new training set is generated by constructing a regression tree and randomly selecting m features from each of the w training subgroups. The regression tree decision tree model is a powerful tool for conducting regression analysis. In his 2001 paper, Breiman demonstrates the correlation between the division of the input space and the resulting output value at each node of a regression tree partition. Finding the most suitable values for the parameters of an RF model is a difficult task. This issue can be resolved by leveraging the out-of-bag (OOB) error. The reliable and accurate measure for quantifying error in the process of generating random forests is the out-of-the-box (OOB) error. Finding the most suitable values for the parameters of an RF model is a difficult task. This issue can be resolved by leveraging the out-of-bag (OOB) error. The reliable and precise metric for assessing the error in the process of generating a random forest is the out-of-the-box (OOB) error. The online prediction of TSM was examined by Gao, Mi, and Wang. The Random Forest (RF) algorithm was utilized for conducting regression analysis. The ensemble regression trees model utilizes multiple base learners to establish a correlation between initial conditions and CCTs. To address the dimensionality catastrophe problem, one can utilize bootstrapping and randomly select variables during the training process, even without employing feature selection. The study conducted by Mi et al. (2021) evaluated power engineering solutions using ridge regression and step lasso.

Solar and wind energy availability has been predicted using several methods. Support vector machines outperform other modeling methods in precision prediction, according to the study. SVMs are notable for their efficiency, reliability, and accuracy (Zendehboudi, Baseer & Saidur 2018; Cortes & Vapnik 1995). Statistical learning theory and structural risk minimization underpin this technique. Nonlinear mapping translates the input space, which is nonlinear, into a higher-dimensional space. This method locates a hyperplane in newly generated space. SVMs are recommended for classification, pattern recognition, and regression analysis. They supplanted traditional statistical models. SVMs may approximate functions and regression. SVR is achievable (Huang et al., 2002). SVM models have several kernel functions. Polynomial, Exponential, Radial, Sigmoid, and Linear functions are offered.

Shamshirband et al. (2016) provide a novel approach for estimating daily diffuse solar radiation on a flat surface. SVM and WT are combined in the method. These two methods are intended to increase estimation precision and reliability. The clarity index is the sole measure used to evaluate dispersed radiation. This study assessed

MABE, RMSE, and R. After a thorough investigation, SVM-WT outperformed SVM-RBF, ANN, and an empirical model in predicting diffuse solar radiation.

Baser and Demirhan introduced a novel worldwide horizontal sun radiation estimation method. They use fuzzy regression and SVM. Their model improves solar radiation computation precision and reliability. Researchers hope to improve predicting performance by combining both strategies. This unique solar radiation estimating approach might improve energy systems and solar radiation estimation. FRF-SVM uses linear, polynomial, Gaussian, and sigmoidal kernel functions to boost performance and versatility. This study compared FRF-SVM models to adaptive neuro-fuzzy system (ANFIS) and robust coplot-supported genetic programming (GenProg) models. This study employed temperature, humidity, longitude, latitude, and altitude. FRF-SVM and ANFIS input these variables. This page describes local weather and geographical features. Coplotting the variables ensured a full examination. This study found that the FRF-SVM method, utilizing a Gaussian kernel function, estimated horizontal global solar radiation more accurately than previous models. This analysis used Turkey-specific data (Baser & Demirhan 2017).

Time series prediction is difficult. Our study used deep neural networks to solve this problem. We forecasted well using numerous trials and meticulous analysis. SVR and other models were compared. This paper's case studies show that support vector regression performs similarly to deep neural networks in accuracy and error. The result highlights support vector machines' generalization potential. Meteorological data, projections, and power generation have been used to estimate solar energy system performance (Sharma et al. 2011).

Jiang and Dong developed QKSVM-FR forward regression. This technique primarily addressed variable selection while predicting global horizontal radiation in the Tibet Autonomous Region. Quadratic regression was used to find the most important input factors for an accurate estimate. The suggested technique generated predictions with more precision than existing reference models (Jiang & Dong 2017).

In addition to linear regression, Urraca et al. used random forests and support vector regression (SVR). The investigation was conducted at 39.11°38′N and 26°13′W in Southeast Spain. The researchers examined 1-h data at this site. Static and dynamic models were used to assess the research topic. SVMs forecast solar irradiance better than other models (Urraca et al. 2016).

Abbas et al. optimized renewable energy generating capacity with genetic algorithms and storage systems. Chance-constrained modeling handled renewable energy system challenges. Genetic algorithms addressed the problem. A Western China scenario proved the model's validity (Abbas et al. 2018).

Chen et al. developed an ensemble learning system to estimate home power usage. The researchers used an ensemble learning model to predict household energy use in this data-driven design. This study used ridge regression, feed-forward deep networks, and an extreme gradient-boosting forest (Chen et al. 2018).

2.2 Unsupervised Learning Algorithms for Anomaly Detection and Early Fault Identification in Sensor Data Collected from Renewable Energy Sources

Gallagher et al. investigated how machine learning may reduce energy savings measurement and verification mistakes. Machine learning algorithms are being studied for energy savings in industrial operations. Fine-tuning the model's parameters improved its forecasts. Machine learning (ML) models outperformed conventional approaches in the research (Gallagher et al. 2018).

The researchers presented a novel approach for achieving power stabilization and generation scheduling in a hybrid system consisting of wind turbines and marine current. This study presents novel approaches for reducing wind-induced damage. Oceanic currents exhibit a higher level of predictability compared to atmospheric winds. The methods provided endorse the efficient scalability of the hybrid arrangement. The Harmonic Analysis Method employed ocean current velocities as a model to enhance the training of artificial neural networks. A variety of neural networks were trained to forecast wind speeds at various time intervals. The model ensures the scheduling of power generation dispatch, leading to cost reduction and the mitigation of power fluctuations (Anwar et al., 2016).

To project global radiation time series, one can utilize the innovative Kalman filter models developed by Voyant et al. Their approach eliminates the necessity of prior data to attain accurate predictions. Unlike these methods, these studies employed data-driven models that incorporated variable time intervals. The root mean squared error (RMSE) has emerged as the prominent metric. The findings confirmed the enhanced predictive capacity of the model (Voyant et al. 2017).

This research demonstrates that the predictive accuracy of the ARIMA and ANN models is influenced by temporal patterns. By examining the error distributions of both models, the empirical cumulative distribution function yielded valuable insights. The outcomes illustrate the differences among the models. During the first week of testing, the ANN model exhibited superior performance in comparison to the ARIMA model. The artificial neural network (ANN) model consistently produced cumulative errors that were consistently below 5%. When it comes to resuming data analysis after interruptions, Artificial Neural Networks (ANNs) perform better than traditional methods. To enhance the precision of ARIMA predictions, it is imperative to train the model using a substantial amount of historical load data. An Artificial Neural Network (ANN) can gain information about the desired output solely based on the input data models. ANN demonstrates higher accuracy than ARIMA, as stated by Tarmanini et al. (2023).

2.3 Reinforcement Learning Algorithms for Optimizing Maintenance Scheduling and Resource Allocation Based on Real-Time System Conditions.

Reinforcement learning (RL) is a branch of machine learning that focuses on how autonomous agents can maximize their overall reward by optimizing their interactions with the environment. This study examines the degree to which agents can gain knowledge from their surroundings by receiving positive or negative reinforcement after their actions. The agent is driven to enhance its performance and decision-making within the environment as a result of this procedure.

Through the utilization of a reinforcement learning algorithm, an intelligent agent acquires the capacity to adapt its decision-making process in accordance with changing environments. The essential elements of the algorithmic framework enhance the agent's learning process. The agent's decision-making is influenced by tactics, regulations, and rules, while its performance is evaluated through incentive systems (Arulkumaran et al., 2017). Enhancing the agent's efficiency and adaptability can be achieved by developing improved decision-making skills.

1. The intelligent agent learns from its surroundings and makes educated judgments. The agent seeks to maximize benefits from its interactions.
2. The agent operates in a physical domain, simulated realm, or any system with specified states and behaviors.
3. An agent's current status or perception of the environment informs decision-making.
4. Using its learning process and current state, the agent chooses an action to change states.
5. After an action, the agent receives numeric input from the environment called a reward, which can be positive, negative, or neutral, indicating the action's desirability and consequences. This dynamic interaction between agents, environment, states, actions, and rewards underpins a complicated and goal-oriented system of intelligent decision-making.

Reinforcement learning algorithms find an optimum policy that matches states and actions to maximize cumulative rewards over time (Sutton & Barto, 2018). The algorithm investigates the environment, assesses its effects, and modifies its policy depending on rewards.

Below are reinforcement learning methods used to optimize maintenance schedules and resource allocation depending on system conditions:

1. Q-Learning is an environment-independent reinforcement learning algorithm. It seeks an environment-optimal decision-making policy. Q-tables record the predicted cumulative rewards for each state-action combination in the algorithm. Q-Learning iteratively refines the policy by exploring and exploiting Q-values. This iterative procedure lets the program assess the current state and choose actions, improving performance over time (Sutton & Barto, 2018).

2. Deep Q-Network (DQN) advances reinforcement learning by handling complex state spaces. DQN enhances Q-Learning with deep neural networks. The Q-network, a complex neural network, approximates Q-values in DQN. Experience replay and a target network helps the algorithm stabilize and accelerate learning. DQN reduces correlation by replaying prior events. The target network, independent from the Q-network, stabilizes learning by providing a stable reference point. DQN uses this integrated technique to navigate complicated state spaces and optimize reinforcement learning (Mnih et al., 2015).
3. PPO optimizes policy functions directly. Iteratively changing the policy to maximize projected cumulative reward while putting limits prevents major policy changes. PPO uses sample data effectively, especially in continuous action spaces (Schulman et al., 2017). PPO optimizes policy in a variety of situations by balancing exploration and exploitation.
4. Trust Region Policy Optimization (TRPO) optimizes policies within a trust region restriction. This limitation helps TRPO avoid instability and sudden, harmful policy changes by keeping policy updates close to the prior one. TRPO is prominent in continuous control optimization due to its theoretical guarantees. It works well in such situations and is widely accepted (Schulman et al., 2015).
5. Model-based reinforcement learning method Proximal Value Iteration (PVI) combines value and policy iteration. It uses value iteration to estimate the state-value function using a learned environment model. PVI also improves policy using value estimations. This approach is useful when system dynamics are well understood or modeled. PVI optimizes reinforcement learning when system dynamics are understood or can be properly modeled (Richardson, Berant, & Kuhn, 2018).
6. Monte Carlo Tree Search (MCTS) is a tree-based decision-making technique. Iteratively extending alternative actions and modeling their results develop a search tree. MCTS excels in complex fields like game-playing and planning. MCTS effectively navigates the search tree to help solve complicated issues by making smart decisions (Winands & Lee, 2019).

Reinforcement learning methods can optimize maintenance schedules and resource allocation in real time. Each algorithm has pros and downsides, therefore choosing one depends on the situation and needs. Algorithm selection is crucial to effective maintenance scheduling and resource allocation.

3 Sensor Data Analytics

In the era of the Internet of Things (IoT) and the proliferation of networked devices, sensor data analytics has become a crucial topic. Sensors play a crucial role in the acquisition of real-time data in a variety of contexts, including environmental conditions, industrial operations, infrastructure monitoring, and personal devices.

Massive opportunities exist to optimize system performance, make better decisions, and obtain actionable insights from the abundance of sensor data.

3.1 Integration of IoT Sensors and Data Analytics Platforms for Real-Time Monitoring of Green Power Systems

The Internet of Energy (IoE) is an innovative concept in energy research that combines the information and communication technology (ICT) revolution with conventional energy infrastructure. The Internet of Things is commonly abbreviated as IoE. The Internet of Things (IoT) facilitates the connection of various devices and systems through the internet, in combination with other modern methods. The Internet of Things marks the onset of the third wave of informatization. The Internet of Things (IoT) improves the automation and intelligence of various systems. Real-time monitoring of intricate systems is feasible. Power grids serve as the central hubs of energy ecosystems. Components of the Internet of Everything are essential for the functioning of smart grids. Having conducted an inquiry into the Internet of Things (IoT) as it pertains to the electrical grid. Renewable energy sources (RES), commonly known as green energy, can potentially reduce greenhouse gas emissions, cleanse air pollution, and reduce reliance on fossil fuels. The specific publication being referred to is Saleem et al. (2019). Investing in solar and wind farms in the renewable energy industry is expensive. An abundant supply of quickly deployable power generation is equally important. The Internet of Things (IoE) greatly revolutionizes wind and solar energy initiatives. A considerable proportion of grid components, especially renewable sources, are not under the control of individuals unless they have access to an internet connection and a communication platform. Real-time data transmission from all components to national and regional hubs is necessary. Data supervision is essential. A wind and solar farm comprises a variety of wind turbines and solar panels. Within a system characterized by an excessive abundance of moving components, executive operators may experience a state of being overwhelmed. Time, fuel, and remuneration are necessary to maintain everything in operational condition. These elements undermine the resilience of the grid. RES issues are resolved using real-time status monitoring. Implementing end-to-end Internet of Everything (IoE) systems can be achieved by utilizing cellular modules, such as routers that are equipped with integrated Subscriber Identity Modules (SIMs). The primary objective of this is to provide a source of energy for wind and solar farms. The ubiquity of the Internet of Everything (IoE) can be addressed by companies specializing in Renewable Energy Solutions (RES). Many of these challenges can be easily and inexpensively addressed by implementing the Internet of Things (IoT) in the renewable energy sector, particularly in wind and solar power. A cohesive and user-friendly system is necessary for the grid. They possess a high level of skill in promptly recognizing problems and swiftly finding resolutions. The deployment of IoT technology has facilitated the remote surveillance of solar and wind resources (Zhang et al., 2021; Shahinzadeh et al., 2019).

Intelligent power systems can manage energy consumption and delivery. Intelligent power systems help provide and conserve energy. Real-time environmental monitoring automates energy allocation and conservation. Grid-connected power plants are often located near diesel or renewable energy sources in rural locations. Thus, bulk transmission networks carry power across long distances, often across countries. Thus, grid electrical voltage rises. Energy reduction is difficult. Internet and smart city gadgets may be energy efficient. IoT sensors and other devices collect crucial data about urban infrastructure including roads, bridges, railroads, communications, water systems, electricity grids, and skyscrapers. Data science and predictive analysis help people make better judgments. Smart cities integrate renewable energy sources like the utility grid to an autonomous and widespread IoT platform. IoT and AI determine energy distribution. Eliminating heat loss saves electricity. Allocation and demand balancing algorithms using machine learning (Hossein Motlaghet al., 2020; Sagiroglu, Terzi, Canbay, & Colak, 2016).

The "Green smart grid" study develops AI-assisted electrical infrastructure management. Smart grid systems are large, sophisticated networks that need regulation, monitoring, tracking, and management of numerous networked devices and assets. Smart grid systems can help clients, estimate future demands, and generate new ideas using big data. Smart meter faults and use statistics are further instances. Recent big data analytics breakthroughs are thought to solve these issues. "Big data" refers to data collections that are too large to gather, handle, or analyze using typical methods (Moradi et al., 2019).

Big data analytics has revolutionized the power systems business by collecting, analyzing, and interpreting massive amounts of data. AI, ML, DM, and time-series forecasting are used. When dealing with large-scale, real-world instances, power system decision-makers have faced many variables, complex procedures, huge computing loads, inconsistent findings, mistakes, and low model accuracy. Big data analytics seeks relevant information from enormous datasets. Its various uses include electricity markets, microgrid operation, active distribution network control, energy theft detection, renewable energy use, and stability evaluation. Big data analytics requires widespread IoT device adoption, easy cloud storage, and blockchain technology. Smart sensor networks will boost data volume and variety in electricity infrastructures. This data requires continual management and interpretation, but it can improve the electricity grid (Jaradat et al., 2015; De Benedetti et al., 2018).

3.2 Analysis of Sensor Data to Identify Patterns, Trends, and Anomalies that Can Indicate Potential Failures or Performance Degradation.

The study (Himeur et al., 2021) proposed finding anomalies by comparing the actual and predicted AC power supplied by a PV system. An ANN model trained using data from the under-observation PV facility predicted AC power production. Comparing real-time PV system data with model output and examining the residual vector for abnormalities yielded daily predictive maintenance warnings. The program collected all residuals and ran them through the Triangular Moving Average (TMA) method with an algorithmically derived window size to find out-of-threshold samples and system deterioration trends throughout the day. The investigations' positive predictive detection rate approached 90%, showing high anomaly identification. By highlighting abnormalities and sending maintenance notifications, the algorithm supported decision-making.

Sub-meters and smart sensors in homes can reveal energy usage abnormalities and save money. Unsupervised detection approaches assume anomalies are less than 20% of the data and aim to find previously unknown abnormal consumption patterns. Supervised anomaly detection, which requires labeled datasets for machine learning classifier training, is limited by the absence of labeled data. Ensemble approaches may manage power consumption data complexity and discover abnormalities by applying many models to progressively smaller groups of observations. Using proper measurements and modeling consumption patterns in new areas, feature extraction improves anomaly identification. Hybrid or semi-supervised anomaly detection uses normal footprint annotations and deep autoencoder architectures to find outliers (Zaher et al., 2009).

Plant owners can achieve operational goals with CM systems. These devices help operators make maintenance choices by delivering vital machinery data. This extreme departure from standard maintenance approaches is a major step toward condition-based maintenance, which detects and fixes early symptoms of degradation or new issues before catastrophic breakdowns. Well-maintained turbines can run without planned maintenance to decrease downtime. Many sectors use Supervisory Control and Data Acquisition (SCADA) to identify, diagnose, and prognosticate equipment failures. High-tech algorithms automatically identify turbine degradation, compressor leak band failure, fuel supply system faults, combustion liner burn-through, and sensor faults within acceptable limits in turbine engine diagnostics. Real-time SCADA data helps monitor turbine effectiveness. Performance monitoring can also isolate component defects for more accurate maintenance (Kim et al., 2011; Abu-Samah et al., 2015).

3.3 Development of Predictive Models Based on Sensor Data to Forecast Equipment Failure Probabilities and Remaining Useful Life.

Maintenance should only be done when necessary, such as when warning indications suggest system failure. Predictive or condition-based maintenance is this method. Unlike preventative maintenance, this strategy adapts maintenance periods to the system state. Predictive maintenance research has grown due to the industrial Internet of Things and sensor technology. Predictive maintenance limits maintenance staff to essential tasks to cut expenses, system downtime, and maintenance time. Predictive maintenance requires continuous machinery status data. These sensors improve wind turbine maintenance and reduce unscheduled outages (Zhang & Zhang, 2015; Yurek & Birant, 2019).

Machine learning (ML) can help predictive maintenance embrace new approaches. Predictive models identify components by their likelihood to fail within a certain time period and utilize past data to forecast RUL. Predicting with a continuous input and outcome requires regression. Thus, several RUL estimation studies have used it. One research (Yurek and Birant, 2019) predicts RUL using regression analysis. On the C-MAPSS dataset, one of two ways computes the RUL before running the regression models. First, the machine's current time is calculated by subtracting the fault time. RUL maximum value for each failure determines runtime in the second procedure. Azure Learning Machine used many feature selection and machine learning methods. The investigation includes 72 models with different feature selection and machine learning methods. After examining the data, Decision Forest Regression gave the most accurate estimates (Ouda, Maalouf, & Sleptchenko, 2021).

4 Digital Twin Technology

Through the utilization of digital twin technology, it is possible to create a highly precise digital copy of an object, process, or system, including all of its components, behavior, and characteristics. A digital twin is a virtual version of a physical object that closely mimics its behaviors and characteristics. They can be used to gain deeper insights, perform comprehensive analyses, and optimize the actual system over its entire lifespan. By implementing a novel approach, we can improve our understanding of the physical object being portrayed, carry out a thorough examination of it, and maximize its efficiency, all with the goal of achieving its highest potential (Grieves & Vickers, 2017).

A digital twin is made up of numerous parts, including:

1. The physical system embodies the tangible entity, whether it be a machine, structure, or infrastructure, which finds its reflection in the Digital Twin.

2. Sensors strategically integrated within the physical system perform the vital task of capturing real-time data, encompassing measurements, conditions, and operational parameters. This valuable information is then transmitted to the Digital Twin, where it undergoes meticulous analysis and forms the foundation for modeling.
3. Leveraging the wealth of collected data, the Digital Twin constructs a virtual model that faithfully mirrors the intricacies and characteristics of the physical system. The fidelity of the model can range from a simplified representation to a sophisticated simulation, tailored to meet the specific requirements and desired level of detail.
4. The process of data integration and analytics plays a pivotal role in the realm of Digital Twins. By amalgamating and analyzing the data gathered, a comprehensive understanding of the behavior, performance, and condition of the physical system can be obtained. This integration and analysis not only provide insights but also facilitates real-time monitoring, predictive maintenance, optimization, and informed decision-making.
5. Moreover, Digital Twins often offer interactive interfaces and visualization tools, empowering users to engage with the virtual model, explore various scenarios, and gain valuable insights into the system's behavior. This interactive capability fosters improved decision-making processes and enables the formulation of effective optimization strategies (Jones et al., 2020).

4.1 Creation of Virtual Replicas (Digital Twins) of Green Power Systems to Simulate and Predict System Behavior.

To accurately depict green power systems in digital form, it is crucial to create accurate digital models, simulate system behavior, acquire a thorough understanding of the system, and collect real-time data (Grieves, 2019). The digital siblings have unmatched analytical, optimization, and decision-making abilities.

1. Consider the broad picture: the green power system is comprised of solar panels, wind turbines, energy storage devices, inverters, and grid connections; therefore, it is essential to understand as much as possible about each of these components and how they interact.
2. By accumulating data from sensors and monitoring equipment, measurements of solar irradiance, wind speed, energy generation, battery state, and grid characteristics can be obtained in real-time.
3. Using mathematical equations, physics-based models, or machine learning techniques, develop precise digital models that accurately represent the dynamics of the green power system.
4. To ensure the model's accuracy and dependability in simulating the behavior of the physical system, its parameters must be calibrated and validated using historical data.

5. Utilize the calibrated digital twin model to simulate the behavior of the green power system, taking into consideration variables such as weather, load profiles, and control techniques, in order to make performance predictions and identify potential issues in advance.
6. Applying cutting-edge algorithms to the digital twin model and deducing optimal configurations, control techniques, and resource allocation will maximize energy output, system efficiency, and stability.
7. Utilize the information provided by the digital counterpart to aid in system expansion, maintenance planning, investment estimation, and performance evaluation.

By utilizing digital twins to enhance the performance, efficiency, and dependability of green power systems, stakeholders can enhance the sustainability, efficiency, and effectiveness of renewable energy infrastructure (Bae et al., n.d).

4.2 Utilization of Digital Twins for Condition Monitoring, Predictive Maintenance Planning, and Performance Optimization.

Digital twins have numerous applications, including condition monitoring, predictive maintenance, and efficiency improvements. To monitor the physical world in real-time, digital siblings incorporate sensors. The Digital Twin performs an analysis of the data and compares it to expected thresholds and patterns. By continuously monitoring critical variables such as temperature, vibration, and pressure, the Digital Twin can detect irregularities, deviations from normal operation, and impending failures. This form of preventative condition monitoring can reduce maintenance expenses and disruptions.

Digital siblings employ sophisticated analytics to forecast when physical systems may require maintenance. By analyzing both historical and real-time data, component failure or degradation trends can be uncovered. Businesses can plan preventive maintenance in advance to make better use of available resources and decrease the likelihood of disruptions. Utilizing Digital Twins for predictive maintenance improves machine utilization, lowers maintenance costs, and increases asset dependability (Gupta et al., 2023).

With the aid of their digital counterparts, physical systems can be improved. The models and algorithms of Digital Twin can enhance a variety of environments. Variable configurations, operational strategies, and parameter modifications are attempted as part of this procedure. The Digital Twin is an exact replica of the actual system that demonstrates how various configurations affect key performance indicators such as efficiency, throughput, and quality. Digital twins enable data-driven decisions, optimized operational settings, and enhanced system performance (Kim et al., n.d).

4.3 Integration of Real-Time Data from Sensors with Digital Twin Models for Continuous System Monitoring and Diagnostics.

Real-time sensor data and digital twin models provide system monitoring and diagnosis. Data from physical sensors in the system is continuously sent to their digital twins. Thus, real-time system performance analysis, monitoring, and diagnostics are available.

1. To start this process, strategically placed physical sensors in the real-world system measure variables like temperature, pressure, vibration, humidity, or other relevant characteristics dependent on the system being studied. These sensors capture data on measurements, circumstances, and system behavior and performance (Sana Kazilbash). The digital twin concept receives raw sensor data through wired or wireless networks.
2. Preprocessing sensor data ensures its quality and compliance with the digital twin model. The digital twin approach may need data cleansing, filtering, or transformation. The digital twin then uses preprocessed sensor data to update its internal state and imitate the real-world system's behavior (Drobnjakovic et al., 2023).
3. After integration, the digital twin model monitors. It rigorously compares real-time sensor data to its model's predicted behavior and performance. The digital twin can detect physical system abnormalities, deviations, and difficulties through constant examination. It diagnoses, notifies, or initiates actions based on rules or algorithms.
4. User interfaces, dashboards, and reports may exhibit digital twin evaluation findings and analysis. These visual representations help operators, engineers, and decision-makers understand the system's performance, identify areas for improvement, and make educated decisions to improve operations (Kim et al.).

5 Case Study: Predictive Maintenance of Hydraulic Systems

The purpose of the model is to perform data cleansing, generate and compare diverse classification models, and graphically display the results (Schneider, Helwig, & Schütze, 2017; Helwig, Pignanelli, & Schutze, 2015a; Helwig, Pignanelli, & Schütze, 2015b). In addition to Scikit-learn and Seaborn, the tpot, scipy, zipfile, numpy, pandas, matplotlib, and os libraries are also utilized. This predictive maintenance case study aims to analyze sensor data to predict the health of the hydraulic system and identify potential failure points. According to available information, the following steps comprise the procedure:

	PS1	PS2	PS3	PS4	PS5	PS6	ESP1	FS1	FS2	TS1	...	TS4	VS1	CE	CP	SE	Cooler_Condition	Valve_Condition	Internal_Pump_Leakage	Hydraulic_Accumulator	Stable_Flag
0	160.673492	109.466914	1.991475	0.0	9.842169	9.728098	2538.929167	6.709815	10.304592	35.621983	...	31.745250	0.576950	39.601350	1.862750	59.157183	3.0	100.0	0.0	130.0	1.0
1	160.603320	109.354890	1.976234	0.0	9.635142	9.529488	2531.498900	6.715315	10.403098	36.676967	...	34.493867	0.565850	25.786433	1.255550	59.335617	3.0	100.0	0.0	130.0	1.0
2	160.347720	109.158845	1.972224	0.0	9.530548	9.427949	2519.928000	6.718522	10.366250	37.880800	...	35.646150	0.576533	22.218233	1.113217	59.543150	3.0	100.0	0.0	130.0	1.0
3	160.188088	109.064807	1.946576	0.0	9.438827	9.337429	2511.541633	6.720565	10.302678	38.879050	...	36.579467	0.569267	20.459817	1.062150	59.794900	3.0	100.0	0.0	130.0	1.0
4	160.000472	108.931434	1.922707	0.0	9.358762	9.260636	2503.449500	6.690308	10.237750	39.803917	...	37.427900	0.577367	19.787017	1.070467	59.455267	3.0	100.0	0.0	130.0	1.0
5	159.920210	108.887682	1.913285	0.0	9.301160	9.206877	2501.007067	6.699023	10.178720	40.659450	...	38.212067	0.572683	19.149683	1.072083	59.563333	3.0	100.0	0.0	130.0	1.0
6	159.672675	108.676466	1.888100	0.0	9.233942	9.143320	2494.416900	6.698573	10.140810	41.463633	...	38.932100	0.573033	18.666383	1.081683	59.789900	3.0	100.0	0.0	130.0	1.0
7	159.614452	108.651745	1.874894	0.0	9.194159	9.105058	2489.421533	6.678027	10.095978	42.215267	...	39.558967	0.572000	18.178433	1.078700	59.590617	3.0	100.0	0.0	130.0	1.0
8	159.475745	108.529738	1.858120	0.0	9.144616	9.057067	2484.419067	6.671652	10.039710	42.891983	...	40.080533	0.567067	18.334867	1.115083	59.608883	3.0	100.0	0.0	130.0	1.0
9	159.437997	108.510885	1.841063	0.0	9.104831	9.019265	2480.434867	6.659990	9.997762	43.532833	...	40.612550	0.571683	18.205733	1.129133	59.473733	3.0	100.0	0.0	130.0	1.0

Fig. 1 Portion of the data frame

5.1 Data Preparation

To begin, numpy arrays containing data from multiple files are imported. The sensors gather data regarding pressure (PS1, PS2,…), temperature (TS1, TS2,…), vibrations (VS1), and additional parameters (EPS1, FS1, FS2, CE, CP, SE). To create a DataFrame (df) containing the average values, the mean of each array is calculated along the rows. To include target labels, the DataFrame is expanded by adding extra columns that represent various hydraulic system conditions. The columns contain the values Stable_Flag, Cooler_Condition, Valve_Condition, Internal_Pump_Leakage, and Hydraulic_Accumulator (Fig. 1).

5.2 Exploratory Data Analysis (EDA):

The subsequent procedure entails employing a heatmap, as depicted in Fig. 2, for the purpose of ascertaining the interdependencies among the various features present in the DataFrame df_final. By sorting the correlation matrix according to how it correlates with the target labels, the state of the system can be better understood.

5.3 Data Preprocessing:

The data undergoes preprocessing procedures to be adequately prepared for both model training and evaluation. A partition exists between the DataFrame and the desired features and labels. In order to obtain the desired labels, the data is partitioned into two distinct sets: the training set and the testing set. The StandardScaler module is employed for the purpose of feature scaling, wherein the data is normalized by ensuring uniformity in the size of all features. Subsequently, the anticipated labels are forecasted employing multiclass classification methodologies such as Logistic Regression, k-Nearest Neighbors, Support Vector Machine, Naive Bayes, Decision Tree, and Random Forest. In the given code, there are four target variables being considered. These targets are:

Cooler_Condition, represents the condition of the cooler.

Valve_Condition, represents the condition of the valve.

Internal_Pump_Leakage, represents the internal pump leakage.

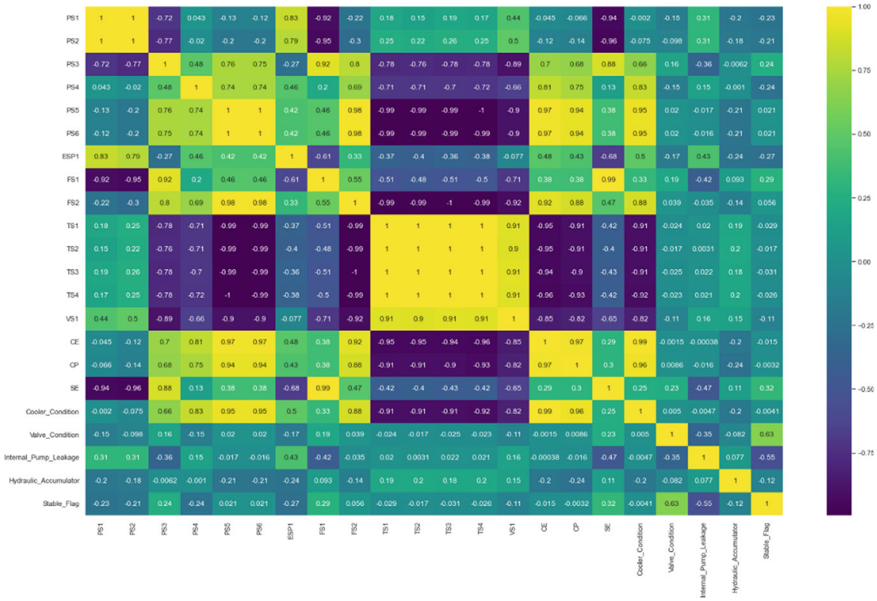

Fig. 2 Heatmap of the data

Hydraulic_Accumulator, represents the hydraulic accumulator.

5.4 Model Evaluation

The evaluation procedures employed in modeling encompass:

1. Logistic Regression (logistic_regression method): The program utilizes the Logistic Regression classification algorithm to evaluate its functionality across multiple metrics. The F1 score, accuracy, precision, and recall are computed using two distinct datasets, one allocated for training and the other for testing. By examining these indicators. System maintenance specialists can evaluate the accuracy of the model in accurately representing the current state of the system. The code computes the mean F1 score, recall, precision, and accuracy for each data fold using cross-validation. The utilization of seaborn allows for the creation of a confusion matrix, which visually represents the model's predictions and misclassifications.
2. k-Nearest Neighbors (knearestneighbors method): The code utilizes and assesses the efficacy of the k Nearest Neighbors (kNN) classification algorithm. Similar to Logistic Regression. It calculates accuracy, precision, recall, and F1 score for both the training and testing datasets. Cross-validation is employed to obtain standard evaluation metrics for various data folds. Additionally. Seaborn is

utilized to generate a confusion matrix. Enabling visual inspection of the model's predictions.

3. Decision Tree (decision_tree method): The algorithm that has been implemented makes use of a Decision Tree structure. This structure employs entropy as the main criterion when constructing a classifier. When computing both the training and testing sets. Various metrics are utilized, including but not limited to F1 score, accuracy, precision, and recall. To obtain the average metrics for multiple testing folds. Cross-validation is employed. In order to visually represent the models' predictions Seaborn is used to generate a confusion matrix.
4. Random Forest (random_forest method): The Random Forest algorithm's classification performance is evaluated by the code. The accuracy, precision, recall, and F1-score for both the training and testing sets are calculated. To obtain standard evaluation metrics across multiple folds, cross-validation is used. Seaborn is utilized to generate a confusion matrix displaying the model's predictions and classification errors.
5. Support Vector Machine (SVC method): The classification algorithm utilized in this study is the Support Vector Machine (SVM). Which has been shown to be a reliable method for pattern recognition tasks. To evaluate the performance of the SVM, a radial basis function (RBF) kernel is employed within the code. In order to determine how well the model performs. Cross-validation techniques are utilized. This involves splitting our dataset into training and test sets and calculating various evaluation metrics such as accuracy, precision, recall, and F1 score. By utilizing cross-validation. We obtain a more robust estimation of the model's performance on unseen data. Furthermore in order to gain insights into the SVM's predictive capabilities and identify any misclassifications a confusion matrix is plotted using the Seaborn library.
6. Naive Bayes (naive_bayes method): The employed code utilizes the Gaussian Naive Bayes classification algorithm and assesses its performance using precision, recall, and F1-score on both training and testing data sets. Cross-validation is utilized to calculate average metrics for evaluation across multiple folds. Seaborn generates a confusion matrix to provide a visual representation of the model's predictions and misclassifications.
7. best_model method: The best_model method combines the evaluation results of all classification models into a dataframe for comparison purposes. For each model, the dataframe contains evaluation metrics such as accuracy, precision, recall, and F1-score. By analyzing these metrics collectively, maintenance professionals can determine which model predicts the condition of the hydraulic system most accurately (Figs. 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13).

The Cooler_Condition, Valve_Condition, Internal_Pump_Leakage, and Hydraulic_Accumulator target variables' predicted K-Nearest Neighbors (KNN) values are displayed in a dataframe (refer to Fig. 14).

In conclusion, the code's model evaluation section ranks the quality of each classifier using metrics such as accuracy, precision, recall, and F1 score. Confusion matrices can be visually examined to gain an in-depth understanding of the model's

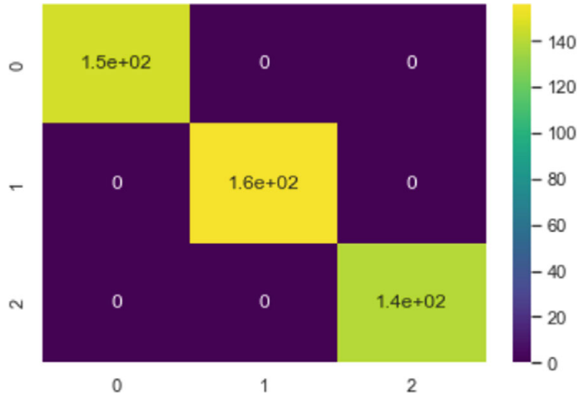

Fig. 3 Understanding the Confusion Matrix of the TPOTClassifier Model (target-1)

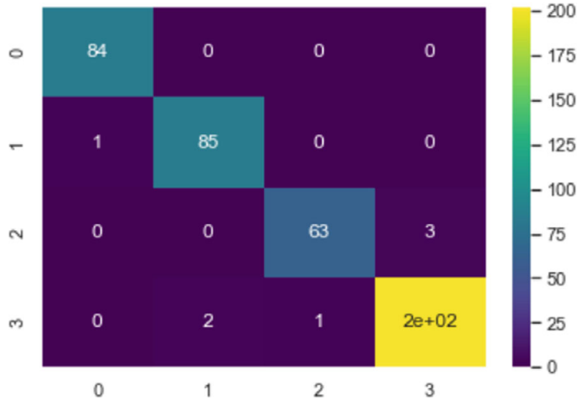

Fig. 4 Understanding the Confusion Matrix of the TPOTClassifier Model (target-2)

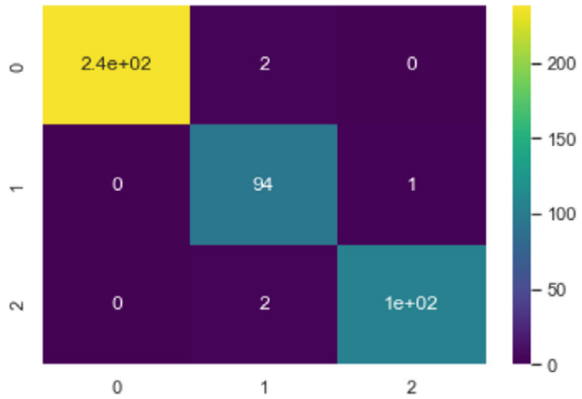

Fig. 5 Identifying the Confusion Matrix of the Logistic Regression Model (target-3)

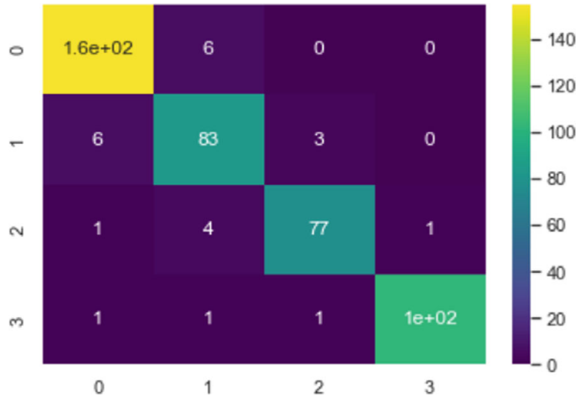

Fig. 6 Identifying the Confusion Matrix of the K-Nearest Neighbors (KNN) Classifier Model (target-4)

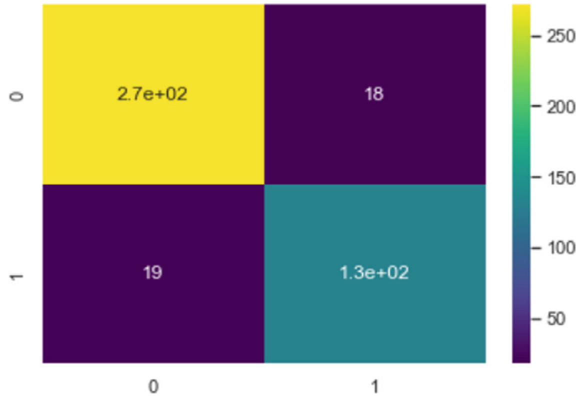

Fig. 7 Exploring the Confusion Matrix of the Decision Tree Classifier (DTC) on Final Target Variables

	Valve_Condition	Internal_Pump_Leakage	Hydraulic_Accumulator
0	100.0	0.0	90.0
1	73.0	1.0	90.0
2	80.0	0.0	115.0
3	100.0	0.0	90.0
4	90.0	2.0	90.0

Fig. 8 Final Data for Testing with Final Target

predictive abilities and misclassifications, and cross-validation ensures accurate evaluation outcomes. Using these evaluation metrics and visuals, maintenance professionals can determine which predictive maintenance model for hydraulic systems is most appropriate.

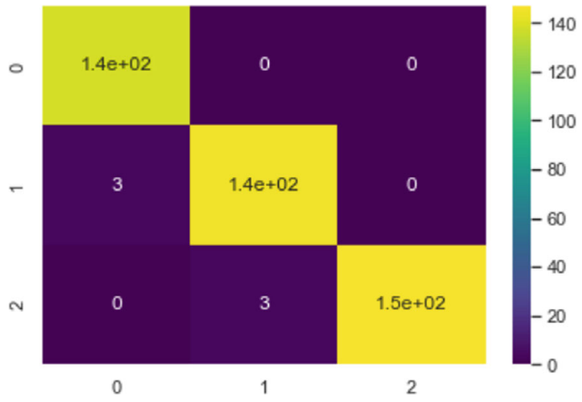

Fig. 9 Exploring the Confusion Matrix of the K-Nearest Neighbors (KNN) on Target 1

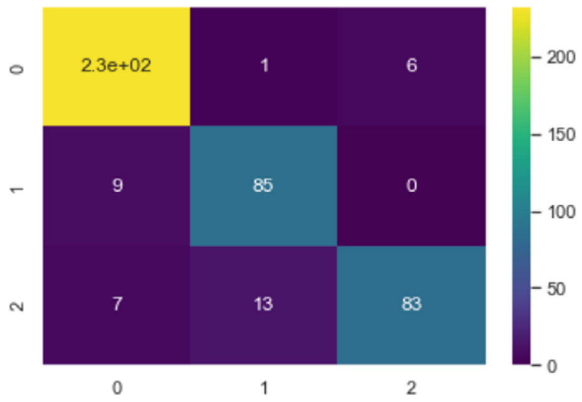

Fig. 10 Analysis of Confusion Matrix for Multiclass Classification Model on Target 3

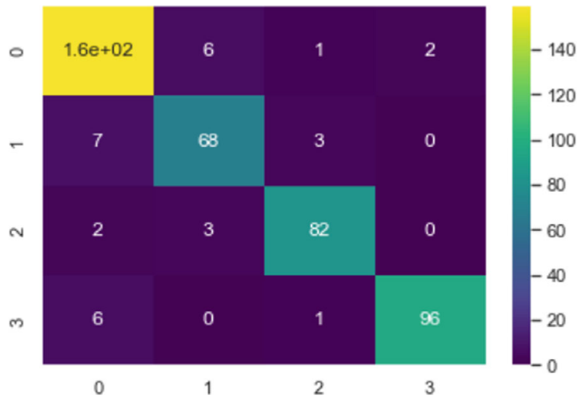

Fig. 11 Exploring the Confusion Matrix of the Multiclass Classification Model on Target 4

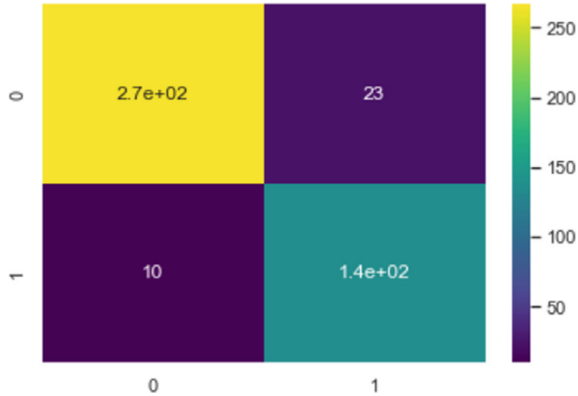

Fig. 12 Analysis of Confusion Matrix for Single-class Classification Model on Final Target

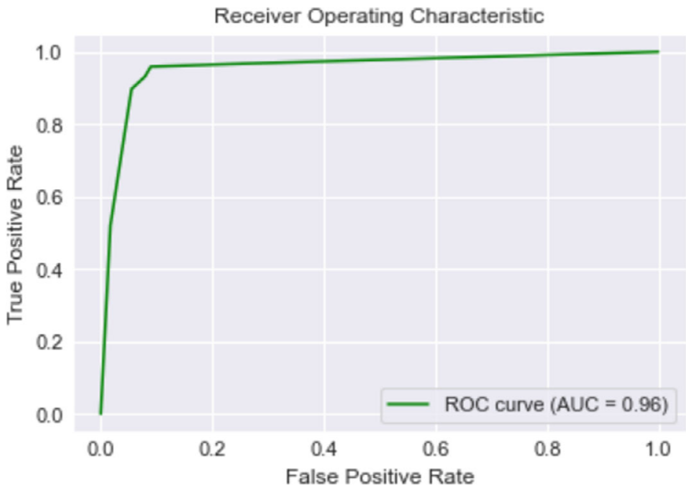

Fig. 13 ROC curve for K-Nearest Neighbors (KNN) Classifier

	Cooler_Condition	Valve_Condition	Internal_Pump_Leakage	Hydraulic_Accumulator
0	100.0	90.0	2.0	115.0
1	3.0	100.0	1.0	100.0
2	20.0	73.0	2.0	100.0
3	20.0	100.0	1.0	100.0
4	3.0	90.0	0.0	100.0

Fig. 14 Final predicted values for Cooler Condition, Valve Condition, Internal Pump Leakage, and Hydraulic Accumulator based on the model

The final results of the Stable Flag prediction are as follows:

Percentage of predicted values classified as "0" (Stable): 67.20%

Percentage of predicted values classified as "1" (Unstable): 32.79%

The research produced a dataset containing 2,177 rows and 5 columns. The columns indicate the status of the vehicle's cooler, valves, internal pump leakage, hydraulic accumulator, and stable flag.

This study included the training of multiple models for independent target variables. For the target variable "Cooler Condition," a k-nearest neighbors' model was developed and evaluated with an accuracy of 99.36% on the training set and 98.62% on the test set. A TPOT classifier was trained for the target variable "Valve Condition," and a precision score was calculated using test data. For additional targets, knn also produced the outcomes shown in the table below, with accuracy, precision, and recall measurements taken from both training and testing sets (Table 1).

According to the findings of this study, the k-nearest neighbors and TPOT classifier models performed well in predicting the Cooler Condition and Valve Condition variables. These models can be used to assess the condition of hydraulic system components such as coolers and valves.

This research yields several significant conclusions that can be inferred:

1. Model Performance: The findings indicate that the Cooler_Condition classification problem was effectively addressed using the K-Nearest Neighbors algorithm. This information can be utilized by technicians to ascertain the optimal models that accurately forecast the state of specific components within the hydraulic system. One can perform a comparative analysis of multiple models in parallel and opt for the most suitable one that aligns with their specific requirements.
2. Suitable Models: To successfully implement predictive maintenance strategies for hydraulic systems cooler. Professionals must have a thorough understanding of both their strengths and weaknesses. Multiple factors such as precision, comprehensibility, and computational demands need to be considered when determining the best approach.

Table 1 Performance Metrics for Multiple Target Variables and Models

Target	Train Accuracy	Test Accuracy	Train Precision	Test Precision	Train Recall	Test Recall
Cooler_ Condition	0.9937	0.9862	0.9937	0.9864	0.9937	0.9862
Valve_ Condition	1.0	0.8303	1.0	0.8381	1.0	0.8302
Internal_ Pump_Leakage	0.9362	0.9174	0.9359	0.9182	0.9362	0.9174
Hydraulic_ Accumulator	0.9511	0.9289	0.9518	0.9296	0.9511	0.9289
Final Target (Stable Flag)	0.9299	0.9243	0.8637	0.8553	0.9380	0.9315

3. Decision Support: This research aims to improve current maintenance procedures by introducing a systematic approach that incorporates machine learning techniques. By utilizing these techniques for failure prediction and optimization of maintenance procedures. Teams can expect improved system reliability along with reduced downtime and expenses.

The study concludes with an application of machine learning models that predict potential failures as well as assess the operational condition of hydraulic systems. A structured methodology consisting of data preprocessing exploratory data analysis allows valuable insights regarding system condition extraction through model development evaluation fostering effective decision-making in choosing the ideal predictive maintenance strategy. However, it is not recommended to use global variables for storing evaluation metrics in larger projects despite their utilization in the given code. As they can limit the establishment of a predictive maintenance framework for hydraulic systems. The utilization of various data storage and management techniques facilitates enhanced stability and scalability of responses. The implemented approach in the code optimizes operational efficiency, minimizes downtime, and mitigates maintenance expenses for hydraulic systems (mayank1897, 2020, 2021).

6 Future Scope

The future of AI-based predictive maintenance in green power systems holds immense potential for advancements across various domains. One significant area lies in the continuous development and enhancement of machine learning algorithms. Researchers can explore sophisticated algorithms, such as deep learning architectures, ensemble methods, and hybrid models. By doing so, they can further improve fault classification, prediction accuracy, and overall system reliability (Hamid and Ganne, 2023).

Another promising avenue lies in the integration of artificial intelligence with edge computing. The emergence of edge computing offers an opportunity to directly incorporate AI algorithms into edge devices that are employed in green power systems. This integration facilitates real-time data analysis, thereby reducing latency and enhancing the responsiveness of predictive maintenance strategies. The fusion of edge computing and AI algorithms empowers the system to detect anomalies, predict failures, and optimize maintenance operations more efficiently (Rao et al., 2023).

In summary, the future scope of AI-based predictive maintenance in green power systems encompasses advancements in machine learning algorithms, edge computing and AI integration, enhanced sensor technologies, integration of big data analytics, improved digital twin applications, and strengthened cybersecurity measures. These advancements hold the promise of more accurate, efficient, and reliable maintenance strategies, ultimately leading to improved system reliability, performance, and sustainability (Salehi, 2023).

7 Conclusion

This chapter explored the capacity of artificial intelligence-driven predictive maintenance solutions to improve the reliability of green power systems. Reinforcement learning, supervised learning, and unsupervised learning are the fundamental components of machine learning, as stated earlier. The application of these methodologies is essential for optimizing energy distribution networks and infrastructure.

Supervised learning techniques, such as Random Forest and Support Vector Machines, have shown significant effectiveness in defect classification and prediction for green power systems. These algorithms leverage tagged data to improve the performance and reliability of the system through precise prediction and pattern recognition. Unsupervised learning techniques have been successfully applied to detect anomalies and diagnose early failures in sensor data collected from renewable energy sources. By analyzing unannotated data to uncover hidden patterns and rectifying measurement errors, these algorithms enhance the efficiency of power generation scheduling and promote power stability. The integration of the current system state into reinforcement learning algorithms has successfully optimized the maintenance schedule and resource allocation. These algorithms make mistakes as part of their learning process and then correct or strengthen them. They gather data from their surroundings and utilize it to make well-informed choices that improve the system's availability by optimizing resource allocation and carrying out preventative maintenance.

The possibility of combining data analytics platforms with internet of things (IoT) sensors to facilitate immediate monitoring of renewable power systems has also been considered. A digital twin is a visual representation of a system that helps in understanding, monitoring, and making informed decisions about its behavior, modeling, and prediction in real-time. Predictive maintenance solutions based on artificial intelligence (AI) have the capacity to greatly enhance the reliability, effectiveness, and longevity of green power systems. Organizations that utilize machine learning algorithms to analyze sensor data through the Internet of Things can potentially achieve a decrease in unscheduled outages, improved system performance, and reduced expenses. These advancements have the potential to significantly improve the reliability and environmental sustainability of the power grid, thereby greatly enhancing the renewable energy industry.

References

Abbas F, Habib S, Feng D, Yan Z (2018) Optimizing generation capacities incorporating renewable energy with storage systems using genetic algorithms. Electronics 7(7):100

Abu-Samah A, Shahzad MK, Zamai E, Said AB (2015) Failure prediction methodology for improved proactive maintenance using Bayesian approach. IFAC-PapersOnLine 48(21):844–851

Afridi YS, Ahmad K, Hassan L (2022) Artificial intelligence based prognostic maintenance of renewable energy systems: A review of techniques, challenges, and future research directions. Int J Energy Res 46(15):21619–21642

Anwar MB, El Moursi MS, Xiao W (2016) Novel power smoothing and generation scheduling strategies for a hybrid wind and marine current turbine system. IEEE Trans Power Syst 32(2):1315–1326

Arulkumaran K, Deisenroth MP, Brundage M, Bharath AA (2017) A brief survey of deep reinforcement learning. ArXiv https://doi.org/10.1109/MSP.2017.2743240

Assouline D, Mohajeri N, Scartezzini JL (2017) Quantifying rooftop photovoltaic solar energy potential: A machine learning approach. Sol Energy 141:278–296

Bae KH, Feng B, Kim S, Lazarova-Molnar S, Zheng Z, Roeder T, Thiesing R (n.d.). A CASE STUDY OF DIGITAL TWIN FOR A MANUFACTURING PROCESS INVOLVING HUMAN INTERACTIONS.

Bangroo IS (2023). AI-based Predictive Analytic Approaches for safeguarding the Future of Electric/Hybrid Vehicles. arXiv preprint arXiv:2304.13841.

Baser F, Demirhan H (2017) A fuzzy regression with support vector machine approach to the estimation of horizontal global solar radiation. Energy 123:229–240

Breiman L (2001) Random forests. Mach Learn 45:5–32

Chaithra N, Jha J, Sayal A, Gupta V, Gupta A (2023). A Paradigm Shift towards Computer Vision. In 2023 International Conference on Device Intelligence, Computing and Communication Technologies, (DICCT) (pp. 54–58). IEEE.

Chen K, Jiang J, Zheng F, Chen K (2018) A novel data-driven approach for residential electricity consumption prediction based on ensemble learning. Energy 150:49–60

Cortes C, Vapnik V (1995) Support-vector network-. machine learning20: 273–297. Portfolio Select J Global Optim 43:2–3

De Benedetti M, Leonardi F, Messina F, Santoro C, Vasilakos A (2018) Anomaly detection and predictive maintenance for photovoltaic systems. Neurocomputing 310:59–68

Drobnjakovic M, Shao G, Nikolov A, Kulvatunyou B, Frechette S, Srinivasan V (2023). Towards Ontologizing a Digital Twin Framework for Manufacturing. In IFIP International Conference on Advances in Production Management Systems (pp. 317–329). Cham: Springer Nature Switzerland.

Gallagher CV, Bruton K, Leahy K, O'Sullivan DT (2018) The suitability of machine learning to minimise uncertainty in the measurement and verification of energy savings. Energy and Buildings 158:647–655

Grieves M, Vickers J (2017). Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. Transdisciplinary perspectives on complex systems: New findings and approaches, 85–113.

Grieves MW (2019). Virtually intelligent product systems: Digital and physical twins.

Gupta A, Chaithra N, Jha J, Sayal A, Gupta V, Memoria M (2023). Machine Learning Algorithms for Disease Diagnosis using Medical Records: A Comparative Analysis. In 2023 4th International Conference on Intelligent Engineering and Management (ICIEM) (pp. 1–6). IEEE.

Hamid M, Ganne A (2023). ARTIFICIAL INTELLIGENCE IN ENERGY MARKETS AND POWER SYSTEMS.

Helwig N, Pignanelli E, Schutze A (2015). Condition monitoring of a complex hydraulic system using multivariate statistics. 2015 IEEE International Instrumentation and Measurement Technology Conference (I2MTC) Proceedings. https://doi.org/10.1109/i2mtc.2015.7151267

Helwig N, Pignanelli E, Schütze A (2015). D8.1 - detecting and compensating sensor faults in a hydraulic condition monitoring system. Proceedings SENSOR 2015. https://doi.org/10.5162/sensor2015/d8.1

Himeur Y, Ghanem K, Alsalemi A, Bensaali F, Amira A (2021) Artificial intelligence based anomaly detection of energy consumption in buildings: A review, current trends and new perspectives. Appl Energy 287:116601

Hossein Motlagh N, Mohammadrezaei M, Hunt J, Zakeri B (2020) Internet of Things (IoT) and the energy sector. Energies 13(2):494
Huang C, Davis LS, Townshend JRG (2002) An assessment of support vector machines for land cover classification. Int J Remote Sens 23(4):725–749
Jaradat M, Jarrah M, Bousselham A, Jararweh Y, Al-Ayyoub M (2015) The internet of energy: smart sensor networks and big data management for smart grid. Procedia Computer Science 56:592–597
Jha J, Vishwakarma AK, Chaithra N, Nithin A, Sayal A, Gupta A, Kumar R (2023). Artificial Intelligence and Applications. In 2023 1st International Conference on Intelligent Computing and Research Trends (ICRT) (pp. 1–4). IEEE.
Jiang H, Dong Y (2017) Global horizontal radiation forecast using forward regression on a quadratic kernel support vector machine: Case study of the Tibet Autonomous Region in China. Energy 133:270–283
Jones D, Snider C, Nassehi A, Yon J, Hicks B (2020) Characterising the Digital Twin: A systematic literature review. CIRP J Manuf Sci Technol 29:36–52
Kim K, Parthasarathy G, Uluyol O, Foslien W, Sheng S, Fleming P (2011). Use of SCADA data for failure detection in wind turbines. ASME 2011 5th International Conference on Energy Sustainability, Parts A, B, and C. https://doi.org/10.1115/es2011-54243
Kim S, Feng B, Smith K, Masoud S, Zheng Z, Szabo C, Loper M BUIDING A DIGITAL TWIN FOR ROBOT WORKCELL PROGNOSTICS AND HEALTH MANAGEMENT.
mayank1897. (2021). Predictive_maintenance_of_hydraulic_system. Kaggle. https://www.kaggle.com/code/mayank1897/predictive-maintenance-of-hydraulic-system
mayank1897. (2020). Predictive maintenance of Hydraulics System. Kaggle. https://www.kaggle.com/datasets/mayank1897/condition-monitoring-of-hydraulic-systems
Mi D, Wang T, Gao M, Li C, Wang Z (2021) Online transient stability margin prediction of power systems with wind farms using ensemble regression trees. Int Trans Electr Energy Syst 31(11):e13057
Mnih V, Kavukcuoglu K, Silver D, Rusu AA, Veness J, Bellemare MG, Hassabis D (2015) Human-level control through deep reinforcement learning. Nature 518(7540):529–533
Moradi J, Shahinzadeh H, Nafisi H, Marzband M, Gharehpetian GB (2019). Attributes of big data analytics for data-driven decision making in cyber-physical power systems. In 2020 14th international conference on protection and automation of power systems (IPAPS) (pp. 83–92). IEEE.
Ouda E, Maalouf M, Sleptchenko A (2021). Machine Learning and Optimization for Predictive Maintenance based on Predicting Failure in the Next Five Days. In ICORES (pp. 192–199).
Qiu J, Wu Q, Ding G, Xu Y, Feng S (2016) A survey of machine learning for big data processing. EURASIP J Adv Signal Process 2016:1–16
Rao PS, Yaqoob SI, Ahmed MA, Abdinabievna PS, Yaseen SM, Arumugam M (2023) Integrated artificial intelligence and predictive maintenance of electric vehicle components with optical and quantum enhancements. Opt Quant Electron 55(10):1–19
Richardson K, Berant J, Kuhn J (2018). Polyglot semantic parsing in APIs. arXiv preprint arXiv:1803.06966.
Sagiroglu S, Terzi R, Canbay Y, Colak I (2016). Big data issues in smart grid systems. In 2016 IEEE international conference on renewable energy research and applications (ICRERA) (pp. 1007–1012). IEEE.
Saleem Y, Crespi N, Rehmani MH, Copeland R (2019) Internet of things-aided smart grid: technologies, architectures, applications, prototypes, and future research directions. IEEE Access 7:62962–63003
Salehi M (2023). AI-Enhanced Renewable Energy: Revolutionizing Monitoring & Driving Sustainable Progress. Available at SSRN 4416913.
Sayal A, Jha J, Chaithra N, Gupta V, Gupta A, Memoria M (2023, April). Blockchain: Its Applications And Challenges. In 2023 International Conference on Computational Intelligence, Communication Technology and Networking (CICTN) (pp. 96–100). IEEE.

Schneider T, Helwig N, Schütze A (2017) Automatic feature extraction and selection for classification of Cyclical Time Series Data. Tm - Technisches Messen 84(3):198–206. https://doi.org/10.1515/teme-2016-0072

Schulman J, Levine S, Abbeel P, Jordan M, Moritz P (2015). Trust region policy optimization. In International conference on machine learning (pp. 1889–1897). PMLR.

Schulman J, Wolski F, Dhariwal P, Radford A, Klimov O (2017). Proximal policy optimization algorithms. arXiv preprint arXiv:1707.06347.

Shahinzadeh H, Moradi J, Gharehpetian GB, Nafisi H, Abedi M (2019, February). Internet of Energy (IoE) in smart power systems. In 2019 5th Conference on Knowledge Based Engineering and Innovation (KBEI) (pp. 627–636). IEEE.

Shamshirband S, Mohammadi K, Khorasanizadeh H, Yee L, Lee M, Petković D, Zalnezhad E (2016) Estimating the diffuse solar radiation using a coupled support vector machine–wavelet transform model. Renew Sustain Energy Rev 56:428–435

Sharma N, Sharma P, Irwin D, Shenoy P (2011, October). Predicting solar generation from weather forecasts using machine learning. In 2011 IEEE international conference on smart grid communications (SmartGridComm) (pp. 528–533). IEEE.

Sutton RS, Barto AG (2018) Reinforcement learning: An introduction. MIT press, Cambridge

Tarmanini C, Sarma N, Gezegin C, Ozgonenel O (2023) Short term load forecasting based on ARIMA and ANN approaches. Energy Rep 9:550–557

UNITED NATIONS. (2023). Retrieved from https://sdgs.un.org/goals

Urraca R, Antonanzas J, Alia-Martinez M, Martinez-de-Pison FJ, Antonanzas-Torres F (2016) Smart baseline models for solar irradiation forecasting. Energy Convers Manage 108:539–548

Voyant C, Motte F, Fouilloy A, Notton G, Paoli C, Nivet ML (2017) Forecasting method for global radiation time series without training phase: Comparison with other well-known prediction methodologies. Energy 120:199–208

Winands MH, Lee N (2019). Monte-Carlo Tree Search.

Yurek OE, Birant D (2019, October). Remaining useful life estimation for predictive maintenance using feature engineering. In 2019 Innovations in Intelligent Systems and Applications Conference (ASYU) (pp. 1–5). IEEE.

Zaher ASAE, McArthur SDJ, Infield DG, Patel Y (2009) Online wind turbine fault detection through automated SCADA data analysis. Wind Energy 12(6):574–593

Zendehboudi A, Baseer MA, Saidur R (2018) Application of support vector machine models for forecasting solar and wind energy resources: A review. J Clean Prod 199:272–285

Zhang Z, Zhang P (2015) Seeing around the corner: an analytic approach for predictive maintenance using sensor data. J Manage Anal 2(4):333–350

Zhang X, Manogaran G, Muthu B (2021) IoT enabled integrated system for green energy into smart cities. Sustain Energy Technol Assess 46:101208