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Review

A Survey of Time-Series Prediction for Digitally Enabled Maintenance of Electrical Grids

Hamid Mirshekali, Athila Q. Santos and Hamid Reza Shaker *

SDU Center for Energy Informatics, University of Southern Denmark, 5230 Odense, Denmark; hmir@mmmi.sdu.dk (H.M.); aqs@mmmi.sdu.dk (A.Q.S.)
* Correspondence: hrsh@mmmi.sdu.dk

Abstract: The maintenance of electrical grids is crucial for improving their reliability, performance, and cost-effectiveness. It involves employing various strategies to ensure smooth operation and address potential issues. With the advancement of digital technologies, utilizing time-series prediction has emerged as a valuable approach to enhance maintenance practices in electrical systems. The utilization of various recorded data from electrical grid components plays a crucial role in digitally enabled maintenance. However, the comprehensive exploration of time-series data prediction for maintenance is still lacking. This review paper extensively explores different time series that can be utilized to support maintenance efforts in electrical grids with regard to different maintenance strategies and grid components. The digitization of the electrical grids has enabled the collection of diverse time-series data from various network components. In this context, the paper provides an overview of how these time-series and historical-fault data can be utilized for maintenance purposes in electrical grids. Various maintenance levels and time series used for maintenance purposes in different components of the electrical grid are presented.

Keywords: time-series forecasting; digitally enabled maintenance; electrical grid; artificial intelligence

Citation: Mirshekali, H.; Santos, A.Q.; Shaker, H.R. A Survey of Time-Series Prediction for Digitally Enabled Maintenance of Electrical Grids. *Energies* **2023**, *16*, 6332. https://doi.org/10.3390/en16176332

Academic Editor: Stéphane Grieu

Received: 14 July 2023
Revised: 24 August 2023
Accepted: 29 August 2023
Published: 31 August 2023

1. Introduction

The maintenance of electrical grids holds significant importance as it directly influences the reliability, performance, and cost-effectiveness of the grid [1]. This maintenance process can be categorized into five levels: reactive, planned, proactive, predictive, and prescriptive [2–5]. Among these levels, reactive maintenance stands out as one of the costliest approaches in dealing with electrical systems. In reactive maintenance, when a failure or fault occurs within the system, corrective actions are taken to identify the failure and restore the electricity supply. The main objective is to ensure that the network can continuously deliver electricity. Despite its necessity in urgent situations, reactive maintenance can incur high expenses due to its let us fail and react nature [6–9]. It is crucial to implement a comprehensive maintenance strategy that encompasses planned, proactive, and predictive approaches to minimize costs, enhance reliability, and optimize grid performance. Planned maintenance refers to a structured maintenance program that provides the operations and maintenance team with a designated time frame to carry out maintenance activities on the system. Its primary objective is to reduce failures within the network. In this approach, maintenance actions are scheduled based on predetermined intervals or specific criteria [10–14]. Proactive maintenance, on the other hand, belongs to a higher category of maintenance strategies. It relies on specific conditions within the system to trigger maintenance actions. It can be performed by employing specific devices on the equipment for condition monitoring of the different parts of the system and take action in case of any deviation from predefined thresholds [15–18]. Predictive maintenance, on the other hand, tries to predict failure in the system before it happens. By utilizing the recorded historical data and expert knowledge, a sophisticated platform can be developed to predict potential failures in the system. This predictive approach enables the early detection of anomalies and enables prompt intervention to prevent or mitigate potential issues [19,20]. At the most advanced level, there is prescriptive maintenance. This approach not only predicts failures within the network but also provides suggested corrective solutions. By combining real-time monitoring, predictive analytics, and expert recommendations, prescriptive maintenance equips the operations and maintenance team with actionable insights to respond to failures quickly and accurately. This level of maintenance helps streamline the decision-making process and enables more efficient and effective maintenance actions [21–23]. To enable predictive and prescriptive maintenance, the utilization of digital tools is essential. The cornerstone of these maintenance approaches lies in the ability to accurately predict and prescribe actions based on data analysis. Due to technological advancements and the widespread implementation of smart metering in various network areas, the feasibility of predictive and prescriptive maintenance has increased. This, in turn, facilitates the transition to sustainable energy. The research indicates that Europe will need investments of between 375 to 425 billion euros to support the transition to sustainable energy [24–26]. Smart meters play a crucial role in recording various quantities within the network. These can include measurements such as current, voltage, active and reactive power, temperature, and more. The data collected from these meters typically consist of sequential time series, providing valuable insights into the performance and behavior of the network [27]. The accuracy and correctness of predicting these time-series data have a direct impact on the effectiveness of the maintenance methods. A reliable prediction method and approach are crucial, especially when dealing with diverse types of data in the system [28]. By selecting the most appropriate prediction techniques and leveraging advanced algorithms, maintenance teams can gain valuable foresight into potential issues, enabling proactive intervention. Various time-series prediction algorithms exist, including autoregressive integrated moving average (ARIMA) [29], seasonal ARIMA [30], exponential smoothing [31], prophet [32], long short-term memory (LSTM) [33], and support vector machine (SVM) [34].

The objective of this review paper is to examine various methods, algorithms, and data utilized in maintenance practices related to the electrical grid, considering both maintenance levels and grid components. While certain algorithms are directly applicable to the maintenance tasks, others primarily serve the purpose of predicting the relevant quantities for maintenance purposes. The paper encompasses research studies on the maintenance of various components within the electrical grid, including transmission lines, distribution grids, low voltage lines, overhead lines, underground cables, insulators, and more. The installed measurements enable the prediction and subsequent implementation of maintenance measures. This paper delves into a comprehensive analysis of the different time-series prediction methods for maintenance purposes in the electrical grid domain. Moreover, the paper sheds light on the significance of utilizing the available data sources for maintenance purposes. This may include historical maintenance records, sensor data from network components, and other relevant data sets. Figure 1 illustrates the distribution of the research studies on maintenance across different components of the grid and the severity of grid situations, presented as numbers out of 100 references. The figure highlights a clear emphasis on grid components in studies, rather than addressing severe situations within the grid. This highlights the significance of collecting data from different components in order to establish an intelligent maintenance system, emphasizing the importance of grid digitization. In order to facilitate comparison, Table 1 provides a comprehensive overview of the current review paper alongside other notable state-of-the-art papers in the field. The table highlights key similarities and differences, allowing for a clear understanding of the unique contributions and approaches of each publication. Figure 2 shows the taxonomy of the review paper. This classification simplifies the paper and gives an overall view to the readers for understanding the paper.

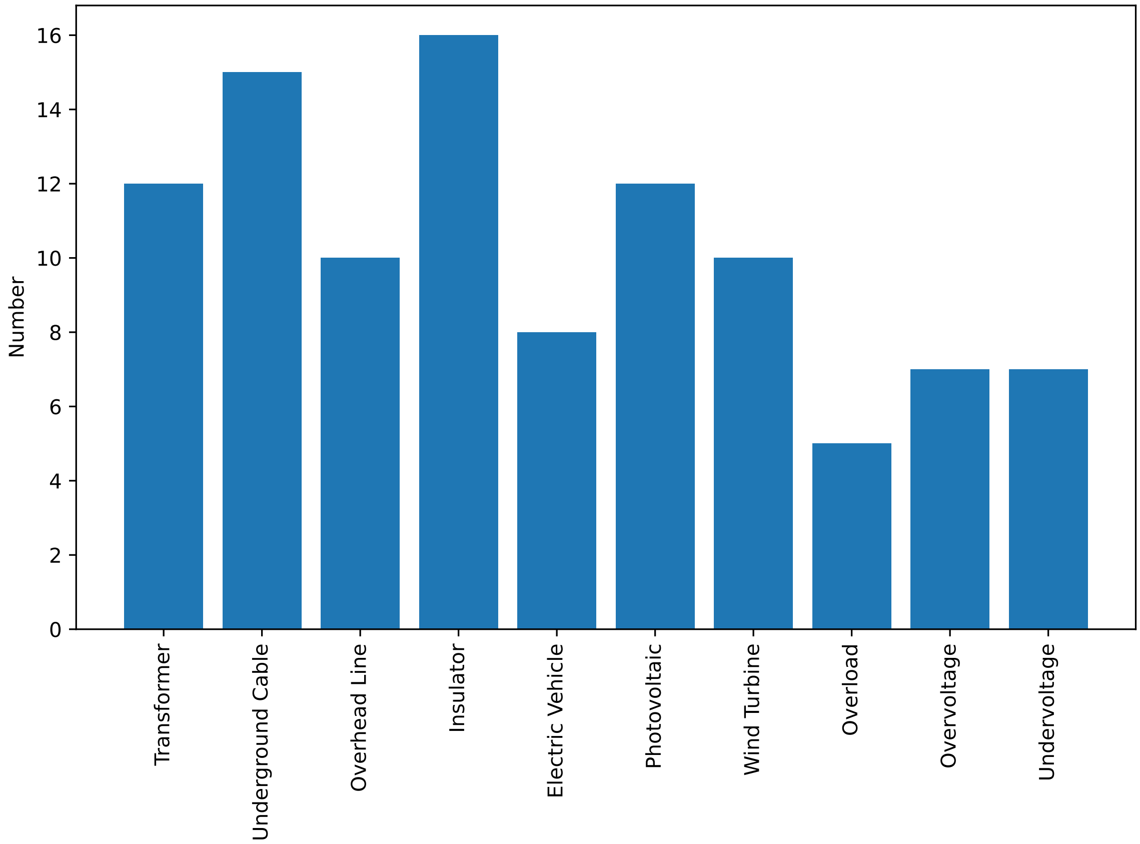

Figure 1. Different studies with regard to grid components and grid severe situations.

Table 1. Comparison of this study with other state-of-the-art review papers.

References	[35]	[36]	[37]	[38]	[39]	[40]	[41]	This Paper
ReM	✓	×	×	✓	×	×	✓	✓
PlM	×	×	×	×	×	×	✓	✓
ProM	×	×	×	×	×	×	✓	✓
PredM	×	✓	✓	×	✓	✓	✓	✓
PresM	×	×	✓	×	×	×	×	✓
UCFP	×	×	×	✓	×	×	×	✓
IFP	✓	×	×	×	✓	×	×	✓
OLFP	✓	×	×	✓	×	✓	×	✓
TFP	✓	✓	×	×	×	✓	✓	✓

ReM: reactive maintenance, PlM: planned maintenance, ProM: proactive maintenance, PredM: predictive maintenance, PresM: prescriptive maintenance, UCFP: underground cable fault prediction, IFP: insulator fault prediction, OLFP: overhead line fault prediction, TFP: transformers fault prediction.

The rest of the paper is organized as follows. In Section 2, the different types of maintenance are described. Section 3 presents time-series applications for the maintenance of different grid components, followed by Section 4, which presents the challenges, advantages, and limitations of maintenance in the electrical grid. Finally, the conclusion is presented in Section 5.

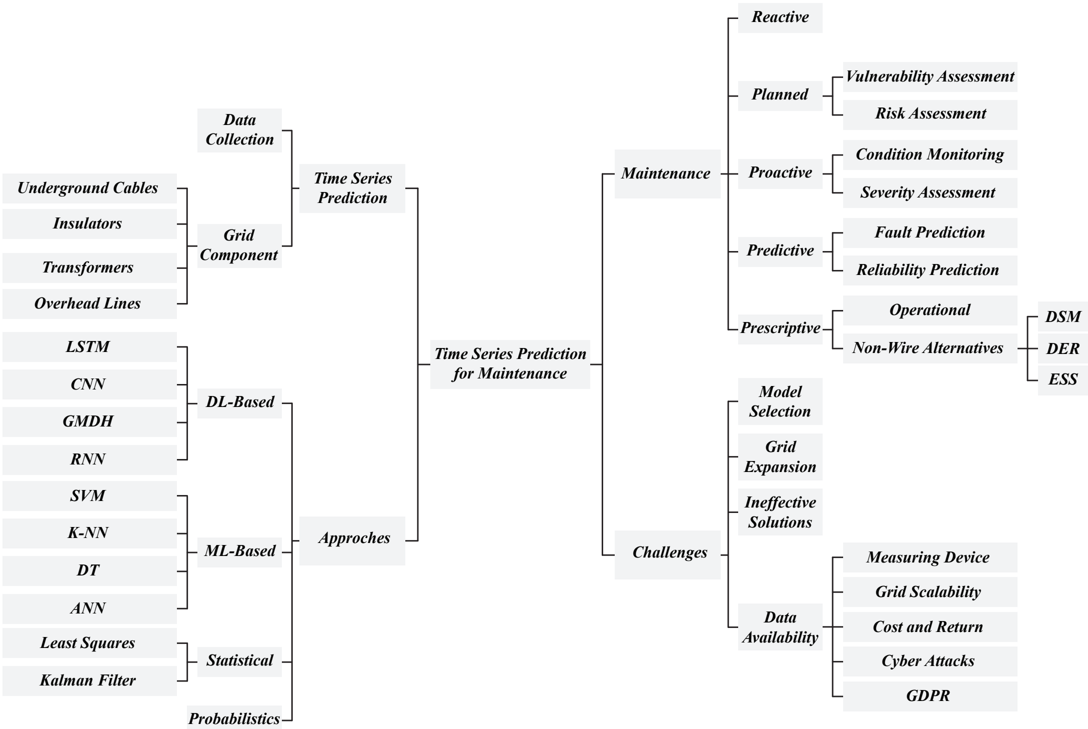

Figure 2. Taxonomy of the surveyed research works.

2. Electrical Grid Maintenance

In electrical grids, there exist five distinct types of maintenance. Figure 3 illustrates each type of maintenance along with its unique characteristics. As can be seen from Figure 3, the reliability of the electrical grid improves progressively as maintenance shifts from reactive to prescriptive levels. To implement prescriptive maintenance in the electrical grid, it is vital to install sensors across various sections of the grid. These sensors enable accurate measurements and facilitate the prediction process [42]. Furthermore, when prescribing corrective actions, considering non-wires alternatives (NWAs) [43], which utilize the existing network infrastructure, can be a favorable choice.

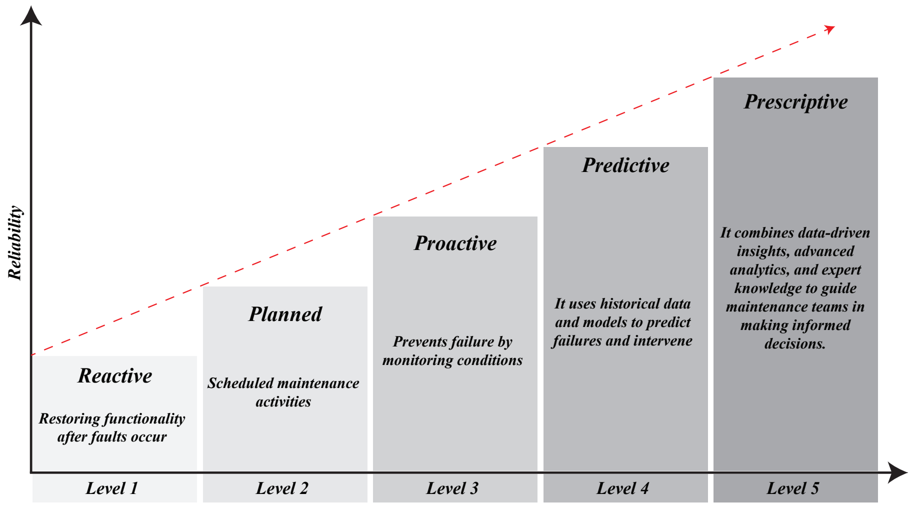

Figure 3. Five levels of maintenance in electrical grids.

2.1. Reactive Maintenance

An electrical grid can experience various types of failures, including line failure [44], insulator failure [45], transformer failure [46], and underground cable failure [47]. In a recent study by [48], a novel methodology is introduced for fault location detection in smart distribution networks. This method utilizes the recorded voltage and current measurements at the beginning of the feeder, along with the load values of consumers. Notably, this approach relies on limited measurement information, making it suitable for real-world network applications. To overcome the potential variation of line parameters caused by aging and weather conditions, [49] propose a new mixed gradient descent particle swarm optimization (PSO) algorithm to estimate line parameters for fault location purposes. However, it is important to note that deploying this algorithm requires additional measuring devices, leading to increased deployment costs. In [50], a novel matching index is introduced to address the challenges posed by varying fault locations in impedance-based algorithms. These algorithms often lead to increased downtime and confusion within the maintenance group. The proposed matching index utilizes the recorded active power at the beginning of the feeder to accurately differentiate the actual faulty point from other potential candidates. Machine learning algorithms have gained significant popularity for fault identification in distribution grids [51,52]. In [53], a deep learning algorithm is employed specifically for fault determination in the distribution network. This algorithm solely relies on the recorded post-fault voltage at the beginning of the feeder. One notable advantage of this approach is the exclusion of the fault current, which can compromise fault location accuracy due to cumulative error and CT saturation. Fault area detection, fault type diagnosis, and location in the transmission line are addressed in [54], where a long-short term memory (LSTM) model is utilized for these tasks. The application of a Bayesian network, optimized by PSO, for fault diagnosis is investigated in [55].

2.2. Planned Maintenance

Planned maintenance, which is a step above reactive maintenance, involves proactive measures taken for the electrical network components. Distribution system operators (DSOs) conduct regular inspections of these components to determine if any repairs or replacements are needed before they fail and cause power outages in the network. Planned maintenance often involves establishing a routine maintenance schedule, as these components cannot be checked externally. For example, when maintaining electric motors, inspections such as temperature monitoring, vibration analysis, and electrical checks may not be sufficient. Proper lubrication and cleaning are sometimes necessary, which can take more time and require the process or power generation to be stopped [56]. The routine of maintenance can be determined based on the factors such as vulnerability, risk, cost, and inspection. The diagram of planned maintenance is depicted in Figure 4. Vulnerability and risk are associated with cost, and inspections are important in maintenance planning.

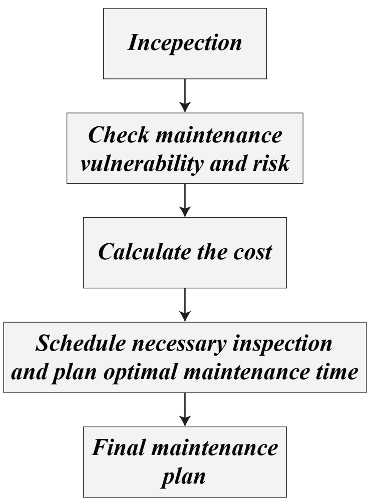

Figure 4. Planned maintenance diagram based on vulnerability and risk assessment.

2.2.1. Maintenance Routine Determination Based on Vulnerability

It is crucial to determine an optimal routine maintenance interval to minimize unnecessary maintenance costs and energy consumption [57,58]. The optimization of routine maintenance allows the operation and maintenance group to focus on the more susceptible areas of the system.

In a study focused on the underground electrical system of the New York City network [59], statistical models known as reactive point processes (RPPs) are utilized to predict discrete events over time. RPPs demonstrate various crucial characteristics of power failures in the grid. The vulnerability to future serious events instantaneously increases following past serious events, and then gradually returns to a baseline level, indicating self-exciting properties. Conversely, vulnerability can decrease instantaneously due to inspections, repairs, or corrective actions, and this effect diminishes over time, illustrating self-regulating properties. The cumulative impact of events or inspections can reach a saturation point, preventing vulnerability levels from deviating too far from the baseline level and exhibiting diminishing returns. The baseline vulnerability can be altered if there was at least one previous event. Entities with similar characteristics exhibit similar vulnerability patterns. Ultimately, a decision-making algorithm is developed to propose routine inspections for optimal planned maintenance. This work provides a solution that introduces intelligent inspections for entities within the underground electrical systems.

2.2.2. Maintenance Routine Determination Based on Risk

Maintenance planning for a large, widespread, and aging power infrastructure poses a significant challenge. The authors of [60] introduce a new approach for assessing the risk associated with power line infrastructure. The method incorporates inspection data, reliability models for component aging, and maintenance costs to provide a comprehensive risk assessment and associated expected costs, depending on the chosen maintenance strategy. By overlaying the visual representation of risk on map data, decision-makers can grasp the risk profile and make informed investment decisions accordingly. The developed model helps DSOs to make optimal and cost-effective decisions for grid planned maintenance based on the risk assessment.

In [14], static security risk assessment during planned maintenance in the electrical grid is the main concern. During planned maintenance, there is a high probability of power flow violations, which can potentially lead to disruptions or failures in the system. The proposed method aims to address the challenges associated with risk assessment during planned maintenance. It recognizes that the existing risk assessment indicators used in this context are often single and subjective, limiting their effectiveness. Therefore, the paper introduces a new approach that incorporates multi-source heterogeneous information to assess the static security risk. By analyzing factors such as equipment failure rate, electrical characteristics, and grid topology, the method takes into account various aspects of the power system's condition. The selected indicators are then preprocessed to enhance their relevance and accuracy. The deep belief neural network (DBNN) is utilized to evaluate the risk by considering the relationships and patterns among the multiple indicators. The goal is to provide a comprehensive risk assessment during planned maintenance. By enabling risk self-assessment, it allows dispatchers to have a better understanding of the potential risks associated with their maintenance decisions. This assists dispatchers in making informed choices when adjusting equipment to avoid power flow violations or other limitations during maintenance operations.

The paper [61] introduces a novel maintenance schedule for power plants and wind farms. The primary objective is to identify the generators that should be temporarily shut down for maintenance, with the aim of minimizing downtime and reducing the risk of generator failure, which can lead to significant costs. In a broader context, the goal is to maximize the system's reliability. The research paper presents the optimal routine for the maintenance of generators in power plants and wind farms as its key outcome.

2.3. Proactive Maintenance

Proactive maintenance refers to a type of maintenance strategy that involves monitoring specific conditions within a system and taking preventive actions based on predetermined thresholds [62]. Condition monitoring and severity assessment are two essential factors for efficient proactive maintenance. The proactive maintenance triangle diagram is shown in Figure 5. As can be seen, condition monitoring of the electrical grid, which needs specific devices, is involved with the severity assessment block to determine effective thresholds for maintenance actions.

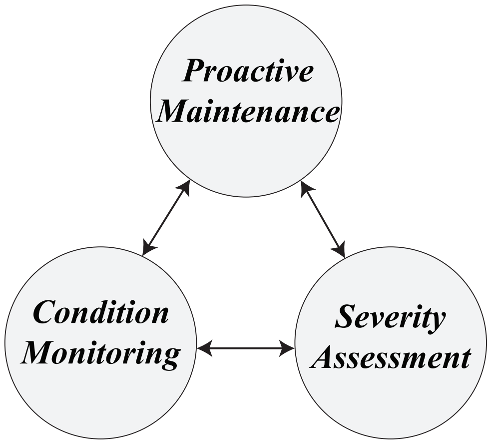

Figure 5. The triangle diagram of proactive maintenance.

2.3.1. Condition Monitoring

Proactive maintenance utilizes sensors or measurements placed strategically throughout the system to monitor its health and performance. When certain conditions exceed the predefined thresholds, maintenance actions are triggered to prevent system failures and minimize downtime [63]. It is necessary to have coordinated measuring devices that have the same timetags, which facilitate the maintenance objective. The authors of [64] introduce a novel measuring device that incorporates real-time communication capabilities. This device is specifically designed for the condition monitoring of wind turbines, with the goal of enabling proactive maintenance. In [65], the authors propose a new scheme for the condition monitoring of underground cables, made possible by the development of partial discharge measuring devices. This scheme enables the maintenance group to continuously monitor the condition of the cables, facilitating the creation of an optimized maintenance routine. Specifically, the paper focuses on assessing the severity of insulator damage in underground cables, as insulator health is crucial for the reliable operation of the entire cable system. Regular data recording plays a crucial role in ensuring effective condition monitoring and proactive maintenance practices. The authors of [66] introduce a new and innovative data processing mechanism designed specifically for the condition monitoring of railway switches. This mechanism incorporates various types of data, including control data, physical data, systematic drifts, and deviations from expected behavior. By analyzing and processing these data sets, the mechanism enables the implementation of proactive maintenance strategies.

2.3.2. Severity Assessment

Determining the appropriate conditions to monitor and setting the thresholds can be challenging, especially considering the unique maintenance requirements of each component in the electrical grid. By conducting a severity assessment, the operation and maintenance group can gain insights into the health status of the cables. This information empowers them to make informed decisions regarding maintenance priorities and budget allocations. For instance, if the severity assessment indicates a higher risk of failure in certain cables or insulators, the maintenance group can prioritize their inspection and replacement, thereby reducing the chances of costly failures and improving overall system reliability [67]. Moreover, the severity assessment enables the operation and maintenance group to optimize their resource allocation. By identifying cables or insulators with higher severity levels, they can allocate resources such as manpower, equipment, and materials more effectively. This approach minimizes unnecessary maintenance activities on components with lower severity levels, thereby optimizing the utilization of maintenance resources and reducing operational costs [68].

In [69], a novel intelligent and proactive maintenance system is introduced with the aim of effectively identifying critical faults in wind turbines. Additionally, a prediction analysis tool is developed to forecast the generation status of small wind turbines. This innovative approach utilizes a sensor-based IoT system to monitor crucial parameters that directly impact the operational condition of the wind turbines. These parameters encompass wind speed, vibration, temperature, and output power. Through the continuous monitoring of these parameters, the intelligent maintenance system can successfully detect significant faults in the turbines and facilitate prompt repairs or corrective measures. Moreover, the prediction analysis tool harnesses the collected data to predict the generation status of small wind turbines. This valuable insight enables the optimization of their performance and maintenance scheduling. By leveraging the forecasted generation status, the maintenance group can allocate resources more efficiently, ensuring optimal resource utilization. This proactive maintenance approach not only enhances the overall performance of the wind turbines but also aids in streamlining maintenance operations for improved efficiency.

2.4. Predictive Maintenance

Predictive maintenance approaches are commonly employed to predict potential future failures in a system by utilizing collected time-series data in conjunction with historical fault statistics [70]. These techniques provide a valuable tool set for the maintenance group, enabling them to proactively respond to potential issues. Two of the main applications of predictive maintenance on the electrical grid are fault prediction and reliability assessment.

2.4.1. Fault Prediction

A fault prediction tool set can aid the O&M group to react before the fault happens, which results in improving reliability. One area particularly susceptible to faults is the cable sheath in overhead lines, especially during adverse weather conditions. In the research paper [71], a novel prediction method based on artificial neural networks (ANN) is presented to forecast the maximum induced voltage in the cable sheath. To generate the necessary data for training the ANN, various scenarios are simulated, allowing for accurate predictions. It is worth noting that the prediction accuracy relies not only on the voltage time series but also on other parameters, such as tower footing resistance, sheath ground resistance, and the severity of weather conditions. These factors collectively contribute to achieving high prediction accuracy and ensuring effective maintenance planning. When a fault occurs in an electrical grid, it is important to determine whether it will result in system stability or instability [72]. This knowledge empowers the maintenance group to prioritize different parts of the network based on their significance and potential impact on grid stability, enabling the efficient allocation of resources for renewal or budget planning. In [73], a novel approach is implemented to assess network stability during fault occurrences. The data collected from phasor measurement units across the network are leveraged to train a stacked sparse autoencoder. This trained model is then applied in real transient situations to determine potential instability. The probability of divergence from a stable baseline is calculated using Kullback–Leibler divergence [74], which is incorporated into the loss function.

2.4.2. Reliability Assessment

Determining customer reliability can provide great information for optimizing investment in order to maximize overall grid reliability. The authors in [75] introduced a novel approach aimed at determining customer reliability within the distribution system. The method incorporates various factors, including component failure frequency, downtime, and weather conditions. By examining the relationship between equipment failures and weather conditions, an index is developed to assess the reliability of each customer connected to the distribution grid. The analysis takes into consideration different types of failures, such as transformers, overhead lines, and underground lines, with their respective failure frequencies serving as parameters for the prediction model. The primary objective of determining customer reliability is to identify areas within the network that are more susceptible to failures compared to others. By estimating the probability of failure for individual customers, maintenance teams can prioritize their attention to the most vulnerable parts of the network. This approach helps in optimizing maintenance efforts and reducing downtime. To achieve this, fault tree analysis is employed as a methodology in this study, enabling a systematic evaluation of the potential failure scenarios. The proposed method integrates the comprehensive analysis of component failure frequency, downtime, and weather conditions to provide a great understanding of customer reliability within the distribution system. By considering the interactions between these factors, the model can generate valuable insights into the network's vulnerability and guide maintenance strategies effectively.

2.5. Prescriptive Maintenance

Prescriptive maintenance, driven by predictive analysis, plays a crucial role in forecasting potential failures within the electrical grid [76]. Prescriptive maintenance is one level higher than predictive maintenance in terms of equipment condition and reliability for the electrical grid, as can be seen in Figure 6. It can be seen that prescriptive maintenance is faster than other maintenance strategies and more cost-effective. However, planned maintenance can be faster than prescriptive maintenance or slower than proactive maintenance, which is completely related to the maintenance routine.

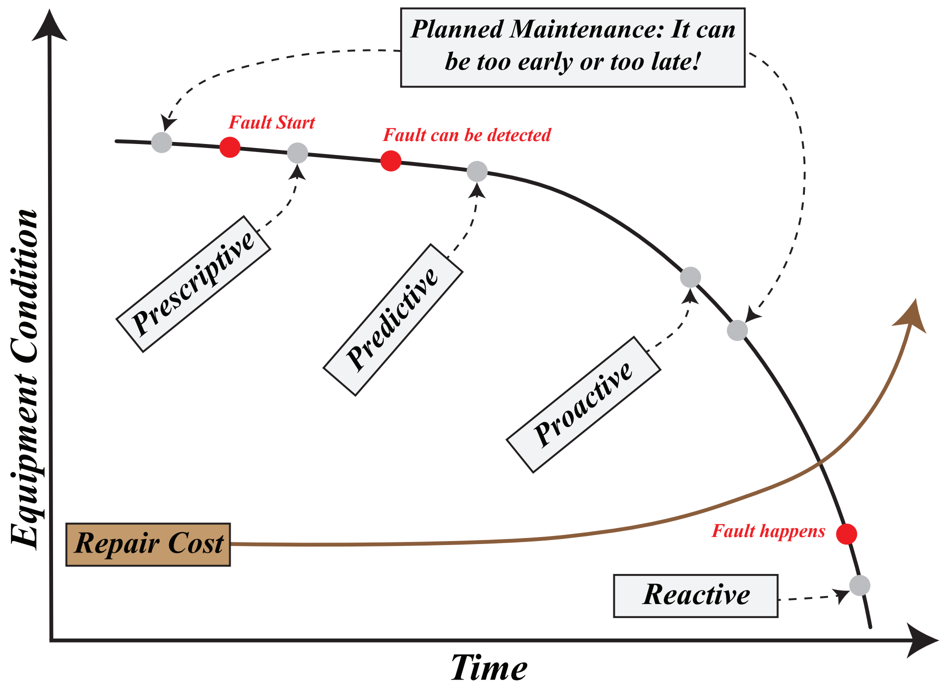

Figure 6. Different types of maintenance with regard to equipment condition and repair cost over time.

2.5.1. Non-Wires Alternatives

Utilizing advanced techniques and algorithms, it enables proactive decision-making and the implementation of smart NWAs [77]. These NWAs apply digital applications and innovative solutions to address grid vulnerabilities without resorting to extensive infrastructure investments. By leveraging the existing grid infrastructure, prescriptive maintenance offers several distinct advantages, including cost-effectiveness, efficient decision-making, and a proactive approach to identifying and resolving potential failures before they occur [78]. This proactive manner helps to ensure uninterrupted power supply, minimize downtime, and enhance the overall reliability of the grid. Similar to predictive maintenance, prescriptive maintenance relies on the analysis of recorded time-series data. By analyzing historical patterns, trends, and fault statistics, predictive models can accurately forecast potential failures within the electrical grid [79].

To prevent predicted faults in the electrical grid, two primary strategies emerge. The conventional approach involves investing in hardware upgrades and expanding the grid's capacity by adding more infrastructure [80]. While this method can be effective, it often incurs substantial costs and may not be the most efficient or sustainable solution in the long term in terms of optimal budgeting. On the other hand, NWAs provide a more forward-thinking and innovative alternative [81]. By embracing advanced technologies, demand-side management techniques [82], distributed energy resources (DERs) [83], energy storage systems (ESSs) [84], and other creative solutions, NWAs present a paradigm shift in grid management. Rather than solely relying on traditional methods to increase grid capacity, NWAs prioritize the optimization of existing assets and the integration of localized energy resources. This approach aims to enhance the reliability, stability, and efficiency of the grid by leveraging advanced tools such as real-time monitoring, intelligent load balancing, and demand response programs. By actively managing grid operations and integrating renewable energy sources, NWAs offer a sustainable and resilient grid infrastructure. They enable the grid to adapt to changing energy demands, incorporate distributed generation, and develop a more dynamic and responsive energy ecosystem. By adopting NWAs and embracing prescriptive maintenance, the electrical grid can achieve significant benefits. It can improve its performance, reduce costs associated with infrastructure expansion, enhance grid resilience, and contribute to a more sustainable energy future. The integration of NWAs into grid management strategies empowers operators and maintenance teams to make informed decisions, prioritize system upgrades, and ensure the reliable delivery of electricity to end consumers [85].

2.5.2. Distributed Energy Resources

DERs have emerged as viable NWAs for managing peak load and potentially delaying or avoiding the need for conventional grid expansion projects [86]. However, the inherent value derived from utilizing DERs as NWAs is often not explicitly considered in the planning process for DER deployment. Ref. [87] addresses this gap by investigating a planning problem that simultaneously optimizes the investment and operation of DERs alongside the timing of the capacity expansion. By introducing the timing of capacity expansion as a decision variable, this approach naturally incorporates the value stream associated with DERs as NWAs in the planning problem. Despite the resulting optimization problem being non-convex and potentially involving millions of variables, it is demonstrated that an optimal solution can be obtained by iteratively solving a series of smaller linear problems. To illustrate the practical application of the approach, a case study involving NWAs planning is proposed that uses real data collected from the Seattle Campus of the University of Washington. By leveraging this dataset, the potential benefits of integrating DERs as NWAs are analyzed within the campus grid, considering factors such as demand profiles, renewable energy generation potential, and operational constraints. The planning of DERs can be effectively carried out by employing the distribution locational marginal prices (DLMP) strategy. In [88], a novel methodology is introduced to address the challenge of overloading in electrical grids in the absence of DERs. The research proposes a solution that involves the integration of DERs into the grid to proactively prevent overload situations while simultaneously optimizing the associated costs. To establish a prescriptive platform for DER planning, it becomes imperative to accurately predict the potential overload conditions. By incorporating the concept of DLMP, the optimal locations for deploying DERs within the grid are determined. This approach enables the mitigation of marginal loading conditions without the need for extensive infrastructure expansion, thereby offering a cost-effective and efficient solution.

Although DERs offer the potential to lower operational expenses and postpone system upgrades, determining the appropriate economic incentive to encourage DER investors to install a capacity that benefits both themselves and the system operator is challenging. In an effort to address this, ref. [89] propose a bilevel optimization framework that aims to identify the least costly solution for alleviating overloads in distribution systems. By incorporating the framework's co-optimal price signal, system operators can incentivize DER investors to deploy a capacity that not only benefits their own interests but also contributes to cost savings and grid reliability. This research highlights the importance of accurately valuing DERs and provides a comprehensive framework to determine the optimal economic signal. By considering both the needs of DER investors and the system operator, the proposed approach aligns incentives, reduces capital and operational expenses, and maximizes the benefits of DER integration. The core element in implementing a prescriptive solution within an electrical grid lies in accurate prediction. The ability to forecast loading conditions, voltage fluctuations, and other maintenance-related parameters plays a crucial role in prescribing effective corrective measures to mitigate future grid challenges. By precisely anticipating these factors, it becomes feasible to proactively address potential grid constraints and develop appropriate solutions.

3. Time-Series Forecasting Application for Maintenance

The primary focus of digitally enabled maintenance in electrical grids centers around the concept of forecasting, which is possible when there is a measuring device to record the data for each component. The components in electrical grids are susceptible to different types of severe situations such as potential faults, overload, overvoltage, undervoltage, frequency fluctuations, and more, which can potentially lead to power outages, resulting in customer dissatisfaction and financial losses [90]. In the subsequent sections, the various research studies focusing on data collection and maintenance-related time-series prediction in different components of the electrical grid with respect to prediction methods are briefly reviewed. These studies aim to enhance the understanding of effective maintenance practices and enable proactive decision-making based on predictive insights.

3.1. Data Collection

It is evident that each component necessitates specific measuring devices tailored to the maintenance level for data collection that results in detecting or predicting faults. Smart metering for prescriptive maintenance in grid components is connected to the type of maintenance, considering the parameters that influence the health index of the components. To facilitate predictive and prescriptive maintenance, specialized measurements need to be installed on different pieces of equipment within the grid. These measurements enable the implementation of smart planning systems, planned maintenance approaches, and proactive maintenance strategies [91]. It is crucial to recognize that different components in the network exhibit distinct types of time-series data, necessitating the careful selection of appropriate prediction methods for accurate forecasting [92]. Time series in different grid components can help the maintenance process. Table 2 presents different time series that can be collected from underground cables, insulators, overhead lines, and transformers. Various components and parts of the network yield diverse datasets that can be utilized for predictive and prescriptive maintenance purposes. For example, insulators can provide measurements of leakage current, flashover incidents, and contamination levels. These data points can be collected over time to generate a sequential time-series dataset, facilitating intelligent maintenance strategies.

Table 2. Different times series from grid components that can help the maintenance process [93–99].

<table>
<tr><th>Underground Cable</th><th>Insulator</th><th>Overhead Line</th><th>Transformer</th></tr>
<tr>
<td>Temperature variations along the cable's length over time.
Electrical load fluctuations and power consumption patterns.
Voltage and current measurements at different points along the cable.
Partial discharge (PD) activity indicating insulation degradation.
Cable fault records, such as fault occurrence timestamps and fault location data.</td>
<td>Leakage current measurements indicating the electrical integrity of the insulator.
Flashover events and associated timestamps for evaluating insulator performance.
Pollution severity data to assess the level of contamination on the insulator surface.
Environmental conditions, including temperature and humidity, affecting insulator behavior.
Visual inspection records noting the condition of insulators and any observed defects.</td>
<td>Line current measurements to assess load profiles and detect abnormal current patterns.
Line temperature data for monitoring conductor heating and identifying hotspots.
Line sag measurements to monitor changes in the line's mechanical properties.
Weather data (e.g., temperature, humidity, wind speed) to assess environmental conditions.
Lightning strike records for evaluating the line's exposure to lightning-induced surges.</td>
<td>Dissolved gas analysis (DGA) results indicating the concentration of gases in transformer oil, which can indicate potential faults.
Temperature measurements at various points within the transformer, including winding and oil temperatures.
Load profiles to evaluate transformer utilization and assess stress on the transformer.
Oil quality parameters, such as moisture content, acidity, and breakdown voltage.
Vibration data to monitor mechanical integrity and detect abnormal vibration patterns.</td>
</tr>
</table>

3.2. Underground Cables

Predicting faults in underground cables plays a critical role in the maintenance and operation of electrical systems. This section includes the benefits and drawbacks of utilizing underground cables, special measuring devices, and environmental condition, along with an exploration of the various forecasting methodologies applied to the maintenance of underground cables.

3.2.1. Advantages and Limitations of Underground Cables

One of the main challenges associated with these cables is their inaccessibility for regular inspections [100]. However, despite this limitation, underground cables offer several advantages that make them a preferred choice in certain contexts, particularly in urban areas. One significant advantage is their environmental friendliness. Underground cables eliminate the need for unsightly overhead lines, minimizing visual impact and preserving the aesthetics of the surrounding environment. This is especially important in densely populated areas where preserving the visual appeal of the landscape is crucial. Another key benefit of underground cables is their enhanced resilience to severe weather conditions. By being installed below the surface, these cables are less vulnerable to damage caused by high winds, ice storms, and falling trees. Consequently, they experience fewer outages compared to overhead lines, ensuring a more reliable power supply to consumers. Furthermore, underground cables contribute to improving safety. With no exposed wires, the risk of accidental contact or interference from external factors is significantly reduced. This makes them a safer option, especially in areas with high foot traffic or where aesthetic considerations necessitate the removal of overhead lines [101–103].

There are some disadvantages associated with underground cables. One major drawback is the high installation cost. The extensive excavation and specialized equipment required for installation significantly increase the upfront expenses compared to overhead lines. Additionally, the complex nature of underground cable systems can pose challenges during maintenance and repairs. Locating and diagnosing faults underground often require sophisticated equipment and expertise, leading to increased maintenance complexity and potentially longer restoration times. Another limitation is the reduced flexibility and expanding capability of underground cables compared to overhead lines. Underground systems are less adaptable to changes in demand or network expansion, as adding or modifying cables underground is a more complex and costly process. This can pose challenges in terms of scalability and accommodating future growth [104,105].

3.2.2. Partial Discharge Measuring Device

The nature of underground installations necessitates the development of specialized measuring devices capable of detecting partial discharge and collecting sequential time-series data. In recent studies such as [106,107], novel mechanisms and topologies for measuring partial discharge in low voltage underground cables were proposed. These devices utilize clamps that can be conveniently installed at the cable's entry point without the need for excavation or cable damage. By capturing partial discharge, which manifests as small defects in cable insulation without immediate fault occurrence but with potential failure risks, these devices generate time-series data that can be leveraged for prediction and maintenance purposes. The acquisition and analysis of such time-series data facilitate efficient maintenance strategies for underground cables. The overall schematic of measuring partial discharge in underground cable can be seen in Figure 7. The figure illustrates a device that applies a high voltage between the cable insulator and the core wire, while a measuring device is employed to monitor partial discharge. This process generates a time-series dataset of leakage current. Such data can be utilized in predictive tool sets to facilitate predictive maintenance.

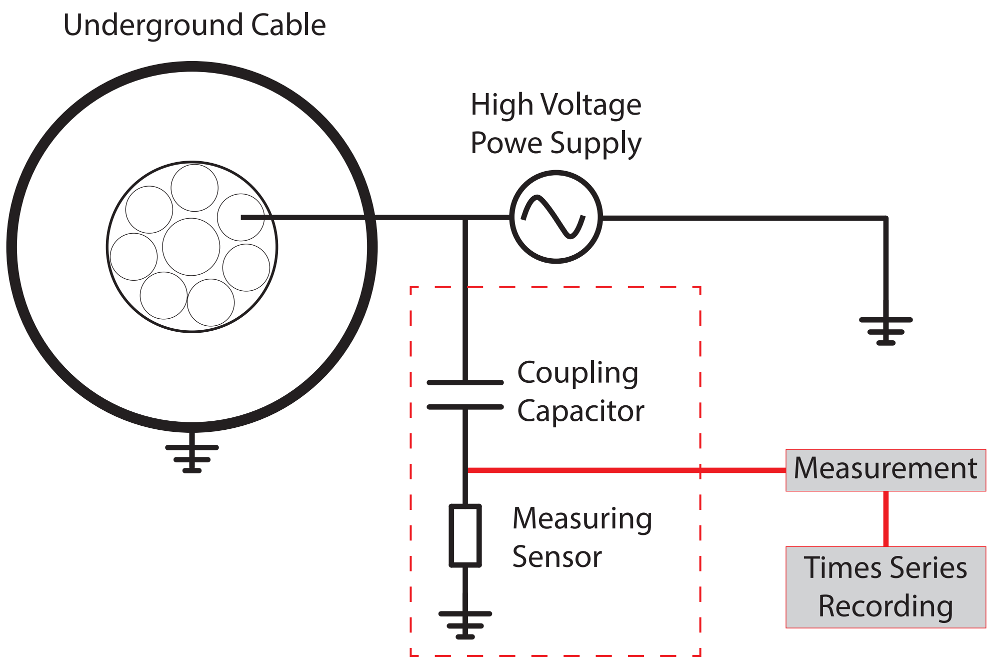

Figure 7. Schematic of partial discharge measuring in underground cables.

3.2.3. Environmental Condition

The underground cables' insulators are susceptible to various environmental factors that can have adverse effects. In [94], the impact of loading burden on the cables, soil temperature and moisture, as well as heat waves, particularly during the summer season, are investigated. The goal is to establish a relationship between these environmental factors and cable faults. Statistical models are developed to correlate the occurrence of failures with the specific features representing the effects of each factor. This analysis provides valuable insights for the maintenance team, enabling them to assess the health index of different network parts and prioritize their examination and maintenance efforts accordingly. Utilizing machine learning techniques for predictive maintenance entails addressing the complexities that arise when dealing with diverse time-series data, each with its own unique resolution. The research paper [108] focuses on the prediction of fault vulnerability in distribution grids equipped with underground cables. Various parameters such as soil type, road proximity, land-use, and depth to anaerobic soil conditions are used as features for the fault vulnerability prediction. These features, along with fault statistics, are combined to predict the vulnerability of the functioning cables. The paper introduces a virtual sample generation method to enhance the prediction accuracy. This method involves randomly altering the features associated with each cable, resulting in a new dataset. The new dataset is then fed into the model to determine the ranking of fault vulnerability for the underground cables across the studied electrical grid. This ranking provides valuable insights for the management group in terms of optimizing their budget for cable renewal in the distribution grid.

3.2.4. Approaches for Fault Prediction in Underground Cables

Artificial Neural Network:

An artificial neural network (ANN) is a computational model inspired by the brain's neural structure. It comprises interconnected nodes that process information using weighted connections and activation functions. ANNs are utilized for tasks such as pattern recognition and data analysis. However, the effective training of complex networks demands a substantial amount of data and resources, necessitating precautions to prevent overfitting. In [109], the measuring partial discharge of the underground cable is used to predict the dielectric parameters of an aged medium voltage cable. Three machine learning algorithms of curve fitting, ANN, and decision tree are applied and compared with each other. The data are created in a high power laboratory. One of the most important parts is how to use the time-series data that can have the most effect on the maintenance. The way of formulation can make the use of the data able to highly impact the maintenance efficiency. This paper uses the equivalent circuit parameters as given in the following equations:

$$\tan\delta = DF = \frac{I_R}{I_C} = \frac{\frac{U}{R}}{U.\omega.C} \tag{1}$$

$$P_k = \omega.C.U^2.\tan\delta \tag{2}$$

where R, C, U, I_R, I_C, I, and δ are the resistance representing P_k, capacitance of insulation, applied voltage, current causing P_k, current flowing through the capacitance of the cable, total current flow, and phase angle between I_C and I. By following the trend of P_k, it is feasible to establish a health index that can assess the condition of underground cable insulators. The data collected from measurements play a crucial role in determining the aging characteristics of cables. By analyzing these data, it becomes possible to establish a model that can predict the future trends of the insulator's health index, enabling predictive maintenance strategies. The findings of this study demonstrate the superior performance of ANN compared to other techniques such as decision trees and curve fitting in this context.

Long Short Term Memory:

LSTM is designed to manage sequences and time-dependent data. It is particularly skilled at retaining long-term dependencies in data, making it useful for tasks such as time-series prediction. The quantities such as voltage, current, and power combined with fault statistics can give information about possible faults in the grid. In [110], an advanced fault prediction algorithm utilizing LSTM models is employed specifically for underground cables in distribution networks. The algorithm categorizes cable conditions into three main states: normal, early warning, and critical situations. Recorded measurements of voltage, current, and active power are utilized to formulate the prediction problem. By defining three goal states based on this formulation, the algorithm aims to accurately identify and anticipate potential faults in the underground cables, enabling proactive maintenance actions to mitigate potential failures. This approach enhances the reliability and longevity of underground cable networks in distribution systems. The three goal states are defined based on the following formulation:

$$V_g = \begin{cases} 1 - \frac{|V-\bar{V}|}{V_{\max}-V_{\min}}, & \text{if } V_{\max} \neq V_{\min} \\ 0, & \text{if } 1 - \frac{|V-\bar{V}|}{V_{\max}-V_{\min}} < 0 \end{cases} \tag{3}$$

$$I_g = \begin{cases} 1 - \frac{|I-\bar{I}|}{I_{\max}-I_{\min}}, & \text{if } I_{\max} \neq I_{\min} \\ 0, & \text{if } 1 - \frac{|I-\bar{I}|}{I_{\max}-I_{\min}} < 0 \end{cases} \tag{4}$$

$$P_g = \begin{cases} 1 - \frac{|P-\bar{P}|}{P_{\max}-P_{\min}}, & \text{if } P_{\max} \neq P_{\min} \\ 0, & \text{if } 1 - \frac{|P-\bar{P}|}{P_{\max}-P_{\min}} < 0 \end{cases} \tag{5}$$

where V_g, I_g, and P_g are the goal states of voltage, current, and active power, respectively. $\bar{V}$, $\bar{I}$, and $\bar{P}$ stand for the mean values. This is a creative way to convert the input raw data to a more meaningful pattern that is easier for machine learning models to learn. It shows that if the recorded quantities can be converted to another form, it can be helpful for predictive analysis. In order to address the issue of limited training samples, a sample generator technique is employed. The generated dataset is then utilized to train an LSTM model.

Kalman Filter:

The Kalman filter is a math tool for predicting future values in a sequence. It uses both predictions and real-time data to adjust its estimates, giving accurate and updated predictions for how a system will behave. Detecting incipient faults in underground cables is crucial for maintenance purposes. Conventional protection relays are unable to detect these minor faults, which can negatively impact cable insulation and eventually lead to permanent faults. Therefore, it is essential for maintenance teams to proactively detect these faults to prevent failures. In [111], a novel method based on the Kalman filter is presented to estimate the voltage waveform and compare it with the measured waveform. If the divergence exceeds a predefined threshold, it indicates the presence of an incipient fault in the cable. This method utilizes the voltage at the sending end of the cable during the fault. Modeling the arc in the cable is necessary for voltage waveform generation. The Mayr and modified Mayr arc models are as follows:

$$\frac{1}{g}\frac{dg}{dt} = \frac{1}{\tau}\left(\frac{u^2}{U_c^2} - 1\right) \tag{6}$$

$$\frac{1}{g}\frac{dg}{dt} = \frac{1}{\tau}\left(\frac{ui}{P_0 + C_i|i|}\right) \tag{7}$$

where g, τ, U_c, C_i, and P_0 are electrical conductance of the arc, time constant of the model, a constant specifying voltage level, current constant, and a constant that is equal to 1, respectively. Equations (6) and (7) stands for Mayr and modified Mayr arc models. The state space representation of the dynamic model for the fundamental component of voltage signal estimation with the aid of a Kalman filter is as follows:

$$\begin{aligned} X_{n+1} &= MX_n + b\psi_n \\ y_n &= h^T X_n + v_n \end{aligned} \tag{8}$$

where

$$X_n = \begin{bmatrix} S_n & S_{n-1} \end{bmatrix}^{-1}, \quad M = \begin{bmatrix} 2\cos(\omega_0) & -1 \\ 1 & 0 \end{bmatrix}, \quad b = \begin{bmatrix} 1 & 0 \end{bmatrix}^T, \quad h = \begin{bmatrix} 1 & 0 \end{bmatrix}^T \tag{9}$$

By creating an iterative formulation, the estimation of the voltage can be derived by these equations. Finally, the standard deviation can be calculated by the following formulation:

$$STD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(VSR_n - V\hat{S}R)} \quad (10)$$

where VSR_n and $V\hat{S}R$ are the voltage signal residual at sample n and the measured voltage signal residual. By employing this method and following the trend of standard deviation, it is possible to detect the defected underground cables before creating a permanent failure.

3.3. Insulators

The condition of insulators is directly linked to the overall safety and reliability of the grid. When insulators are clean and in good health, they effectively isolate the conductive components, minimizing the risk of electrical accidents, short circuits, and other electrical mishaps [112–114]. Therefore, maintaining healthy and well-maintained insulators is of paramount importance. In the subsequent section, the phenomenon of flashover, which frequently occurs in insulators, and the application of the leakage current in flashover prediction are examined. This is followed by an exploration of the various deep learning techniques applied to predict flashovers.

3.3.1. Flashover

In outdoor environments, insulators are particularly susceptible to a phenomenon known as flashover. Flashover occurs when a disruptive discharge or electrical breakdown happens across the surface of the insulator, typically due to factors such as pollution, humidity, or adverse weather conditions. Flashovers can lead to insulator failures, compromising the integrity of the grid and potentially causing power interruptions. To address these challenges and enhance network reliability, predictive measures can be employed [115–117]. By utilizing the recorded maintenance data and historical information, it becomes possible to analyze patterns and identify potential flashover incidents in insulators. By predicting when flashovers are likely to occur, the appropriate maintenance and preventive measures can be taken proactively. This proactive approach allows for timely intervention, such as cleaning or replacing insulators before failures happen, reducing the likelihood of faults caused by insulator failure and improving the overall reliability of the network.

In [118], the prediction of insulator flashover voltage is performed using electric field measurements. This research focuses on both clean and polluted insulators. The relationship between the measurement data and the flashover voltage is established using logarithmic regression. Although this study utilizes a specific device, its findings can be applied to the maintenance of insulators. It can be employed in periodic inspections to measure the values and predict the flashover voltage. If the predicted voltage deviates from the standard, proactive actions can be taken to prevent catastrophic situations caused by insulator faults, which can result in power outages.

3.3.2. Leakage Current

Leakage current can create localized heating, which can contribute to the breakdown of insulation and increase the risk of flashover, where a sudden electrical discharge occurs through the insulator, potentially leading to equipment damage or failures. It is shown in Figure 8 where a sensor can be installed to measure leakage current value over time and send the values to the control center after processing through the communication link. The study conducted in [119] focuses on predicting the flashover occurrence of outdoor polluted insulators by analyzing the harmonic components of the leakage current. The researchers measured the leakage current in various scenarios, encompassing different pollution levels, weather conditions, and water conductivity. By assessing the different levels of harmonics present in the leakage current, the study aimed to evaluate and predict the flashover phenomenon in the insulators. Ref. [120] focuses on predicting faults in insulators by analyzing the leakage current, which occurs due to contamination. The study records the leakage current data for various levels of contamination and utilizes these recorded time series for machine learning-based prediction. Ensemble learning methods are employed to tackle the prediction task, enabling the combination of multiple models for improved accuracy and robustness.

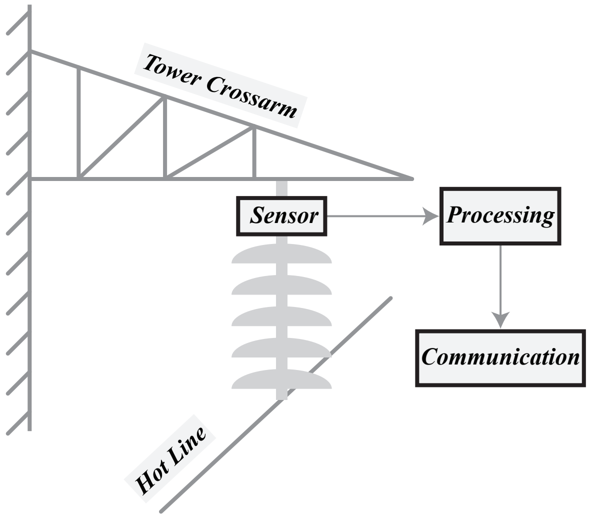

Figure 8. A sensor measures the leakage current and sends it to the control center through the communication link.

3.3.3. Approaches for Fault Prediction in Insulators

Least Squares Support Vector Machine:

The least squares support vector machine (LSSVM) is a machine learning technique that seeks to find an optimal linear or nonlinear function to approximate data points while minimizing prediction errors. It is particularly effective for tasks such as regression and classification. In [121], a new method is introduced for estimating the flashover voltage of insulators. This method incorporates various factors such as diameter, height, creepage distance, form factor, and equivalent salt deposit density. The estimation is performed using a combination of LSSVM and PSO. The prediction task involves three main steps. First, the training samples are normalized. Second, the model hyperparameters are optimized using PSO and the training samples. Finally, the optimized model and the validation data are utilized for the prediction task. The authors of [122] proposed a novel approach utilizing LSSVM for predicting the flashover voltage of transmission line insulators. Unlike the research conducted by [121], this paper focused on determining the parameters of a dynamic model specifically designed for insulator flashover voltage prediction. The key parameters of LSSVM were tuned using grid search methodology. It should be noted that this study used data from contaminated insulators, as contamination, especially in polluted areas, can lead to the creation of leakage current. Monitoring this situation can greatly assist maintenance teams in devising intelligent repair plans.

Convolutional Neural Network:

A convolutional neural network (CNN) is a type of deep learning model designed for tasks involving images and visual data. It employs specialized layers that automatically learn and identify features from the input data, enabling it to recognize patterns, objects, and structures within images. In [123], CNN is employed for the classification of insulators based on the analysis of time series-records of the leakage current. Their research was conducted in the mountainous region of Taiwan, providing valuable insights to maintenance teams regarding the extent of contamination affecting insulators in that specific area. This classification approach enables the grouping of insulators based on different levels of contamination. Such categorization proves useful in identifying potential faults in insulators. The classes can be divided into various levels, ranging from low and safe levels to high and severe levels, indicating the likelihood of failure. The authors of [124] introduced a novel algorithm based on one-dimensional CNN for predicting the leakage current of insulators using environmental data. The authors conducted an analysis using historical data and demonstrated that a set of 21 weather condition samples served as an adequate number of features for the regression task, resulting in accurate predictions.

Group Method of Data Handling:

The group method of data handling (GMDH) is a machine learning technique that creates and optimizes a network of mathematical models to predict or analyze complex patterns in data. It employs a self-organizing approach to iteratively build and refine these models, enhancing their accuracy and capturing intricate relationships within the dataset. The authors of [96] employed the wavelet group method to predict faults in electrical power insulators. Ultrasound inspection was utilized to assess the power insulators, which generated time-series data associated with audible noise. The researchers employed the GMDH to forecast the time series derived from ultrasound measurements. This approach holds promise for maintenance purposes, as it enables inspections to generate data that can be compared with the existing data. By leveraging prediction techniques, maintenance actions can be performed based on the forecasted outcomes, aiding in the proactive management of insulator faults.

3.4. Transformer

Transformers play a crucial role in electrical grids, enabling voltage conversion for the efficient distribution and transmission of electrical energy. They are vital for transferring power from the generation sources to consumers. The subsequent content discusses various faults that can occur in transformers, along with the utilization of dissolved gas analysis data for predicting these faults.

3.4.1. Faults in Transformers

Transformers are susceptible to various types of faults such as overheating, insulation breakdown, winding short circuit, core faults, oil leakage, tap changer malfunctions, cooling system failures, voltage regulation issues, and mechanical failures. By monitoring different parameters of transformers and analyzing the recorded data, it is feasible to proactively predict potential faults. This proactive approach to maintenance allows for timely actions to be taken on transformers, ensuring their optimal functioning and preventing potential issues. In the research conducted in [125], the transient overvoltage occurring in transformers as a result of power plant switching is calculated using a transient model. This calculation serves as a valuable tool for predictive maintenance. By predicting the timing of power plant switching or other events leading to transients, the corresponding overvoltage values can be determined. This information can then be utilized for short-term maintenance actions on transformers. Ref. [126] propose a novel control algorithm that leverages the charging time of electric vehicles (EVs) to mitigate the overload effect on transformers. This algorithm offers a practical solution to alleviate the burden on transformers caused by the increased load demand from EV charging.

3.4.2. Dissolved Gas Analysis Data

The dissolved gas analysis data provide insights into potential issues or faults within the transformer, as certain gas types and concentrations can indicate specific problems. The authors in [127] introduced an algorithm based on regression and classification techniques using dissolved gas chromatography data to predict faults in transformers. They employ the Mish-SN temporal convolutional network for the regression task. In [128], SVM and dissolved gas analysis data are employed to predict faults in transformers. The study explores the use of SVM in conjunction with dissolved gas analysis for effective fault prediction. In [129], the focus is on diagnosing faults in transformers using dissolved gas analysis. The research addresses the challenges associated with the dissolved gas analysis data, such as imbalance, insufficiency, and overlap, which can affect the diagnostic process.

To overcome these challenges, various machine learning algorithms, including decision trees, k-nearest neighbors, SVM, ensemble methods, naive Bayes, and discriminant analysis, are compared to identify the most effective approach for handling these issues.

3.5. Overhead Line

Overhead lines are a part of the electrical grid. Fault prediction in overhead lines is a critical aspect of maintaining the reliability and safety of electrical grids. Overhead lines are vulnerable to various types of faults, including short circuits, insulation breakdowns, and conductor failures. Predicting these faults in advance allows for proactive maintenance actions, minimizing downtime and ensuring the continuous supply of electricity. Fault detection, diagnosis, identification, and location are crucial to improve the sensitivity and reliability of system protection. This maintains the power systems continuous proper operation; however, it is challenging in large-scale multi-machine power systems. The research paper [130] introduces three deep learning classification and regression models based on deep recurrent neural networks (DRNN) for fault region identification, fault type classification, and fault location prediction. The recorded current and voltage by phasor measurement units at different terminals are used as input features for the models. This gives the maintenance group a reactive conservation. In [131], the magnetic field from power overhead lines in transmission and distribution grids is measured. The correlation between the load consumption and magnetic field is then obtained for the prediction scenario. This magnetic field can be the reason for the fault in the system. It would be important to measure its value then. Ref. [132] propose a method to predict the thermal situation of the overhead power lines. It actually predicts the conductor temperature over different conductor overload conditions. The Echo State Network is used to adaptively determine the nonlinearity of the overhead conductor thermal dynamics under different weather conditions.

4. Challenges, Advantages, and Limitations of Electrical Grid Maintenance

This section examines the advantages and limitations of maintenance in electrical grids. It is noted that reactive maintenance is the least reliable level, whereas prescriptive maintenance is the most reliable. Table 3 presents the characteristics, requirement, advantages, and limitations associated with different maintenance levels. Reactive and planned maintenance typically require fewer measuring devices compared to proactive, predictive, and prescriptive maintenance. There are some challenges in model selection for the prediction task, mostly for predictive maintenance, hardware requirements and ineffective recommendations in prescriptive maintenance, and, most importantly, data availability, which is the main key of grid maintenance. Figure 2 gives a quick view of maintenance challenges.

4.1. Model Selection

Machine learning models can be used for the prediction of time-series data. While predictive and prescriptive maintenance frameworks offer DSOs the chance to proactively respond to potential failures, the efficacy of these frameworks relies heavily on the strength of the predictive algorithms employed. In [133], a novel control strategy is introduced to address overvoltage issues in wind farms caused by reactive power demand. The authors utilize a CNN model to forecast reactive power values, which are subsequently used in the control algorithm to proactively respond and ensure a smooth transition, thereby preventing overvoltage. However, a significant challenge lies in selecting the appropriate prediction algorithm. In this study, a CNN model is employed for the prediction task, which may exhibit limitations and prediction errors, thereby potentially impacting the controller's performance.

The integration of prediction analytics can offer valuable insights for long-term generation decision-making processes. In this context, ref. [134] introduces a novel model that leverages the generation data from the existing PV sites, taking into account topographical and meteorological information, to predict the generation potential of new PV sites. However, this approach poses a complex challenge as it heavily relies on the accuracy of the model and input data. Furthermore, the utilization of weather data introduces an additional level of uncertainty compared to other types of data due to its inherently volatile nature. Short-term time-series predictions play a crucial role in facilitating short-term decision-making processes. In the publication [135], a novel approach utilizing wavelet analysis is introduced for wind speed prediction, particularly in the context of wind turbine power generation. This method holds potential for enabling a predictive system capable of forecasting power generation in wind power plants. The obtained data can be applied to address predictive maintenance issues related to power generation, such as overloading. However, it is important to note that selecting an appropriate model for predicting wind speed, given its highly fluctuating nature, can pose a significant challenge.

Table 3. Some main advantages and limitations of different maintenance levels [21,136–138].

Maintenance Level	Reactive	Planned	Proactive	Predictive	Prescriptive
Characteristics	Fixing after failure	Scheduled based on time or usage	Conduct with early sign of equipment deterioration	Conduct before equipment failure based on the prediction analysis	Predict the failure and recommend solution
Requirements	Quick response team and emergency equipment	Maintenance schedule and regular inspection	measuring device installment, communication link, and trend tracking	Real-time data collection, predictive tools, and machine learning	Advanced analytic and integration with operational system
Advantages	Minimal planning	Unplanned downtime reduction	Equipment lifetime enhancement and major failure risk reduction	Cost-effective and optimized maintenance schedule	Increased uptime and optimized resource allocation
Limitations	Increased overall maintenance cost, safety risks, and high downtime	Missed or unnecessary maintenance due to scheduling constraints	Initial investments and false alarms	Need accurate data, specialized expertise, and investment on predictive technology	Complex data analysis and incorrect or ineffective recommendations

4.2. Grid Expansion Requirement

Prescriptive maintenance has the capability to predict the failures within the electrical grids and recommend solutions using existing infrastructures. Nonetheless, its effectiveness could be compromised by the necessity for expanding the grid. The research paper [139] introduces a prescriptive maintenance framework aimed at predicting transmission line overload and proposing generation rescheduling as a corrective measure. While this approach can effectively predict overload situations and provide recommendations for mitigating them through N-1 contingency generation plans, it may not be applicable in cases of severe overload. One significant limitation of prescriptive maintenance is its restricted ability to address extensive grid expansion requirements. In [140], a novel approach is introduced to address overvoltage issues in low voltage feeders caused by high solar generation and low consumption. This prescriptive maintenance procedure incorporates the main controller of the inverter and employs an active power curtailment strategy. This method offers the advantage of mitigating the negative impact of excessive generation by implementing a NWAs solution, simply by adjusting the behavior of the inverter controller in specific scenarios. However, it should be noted that in cases of highly unbalanced generation and demand, the controller may struggle to deliver power to the grid accurately, potentially resulting in power outages or damage to components. In this case, grid expansion is inevitable.

4.3. Ineffective Solutions

The solutions provided by a prescriptive maintenance system could be ineffective. The publication [141] introduces a novel management strategy for EV charging to address the issue of undervoltage caused by the large-scale fast charging of EVs. This method can be categorized as a prescriptive maintenance strategy. By formulating an optimization problem, various charging scenarios are considered to determine the optimal charging strategy that prevents the grid from experiencing undervoltage conditions. However, a significant challenge lies in the practical implementation of the proposed charging scenarios. In real-world scenarios, there is no guarantee that consumers will adhere to the optimized plans, even with the incentive of electricity pricing.

4.4. Data Availability

The availability of data is essential for enabling predictive capabilities. The methodology, data type, advantages, limitations, and maintenance type of different research papers in the field of electrical grid maintenance are presented in Table 4 to give a quick picture of the most recent studies in the field to readers. The table reveals that many of the limitations stem from issues regarding the availability and reliability of data. The primary factor for effective maintenance is the digitization of the grid, which can be both challenging and expensive. Understanding the extent of grid digitization is crucial as it plays a significant role in maintenance activities. Determining the level of digitization is crucial as it helps find a middle ground between grid expansion and the integration of predictive analytics into grid maintenance, thereby reducing costs. While grid expansion is necessary in certain instances, relying solely on prescriptive solutions may not address all potential issues in the grid [22,142,143]. Various forms of time-series data are employed to facilitate the predictive and prescriptive maintenance of grid components. As evidenced by the references in Table 4, historical load data, wind speed, and solar generation measurements serve as primary time series for digitally enabled maintenance in the electrical grid. However, challenges related to the data availability within electrical grids are outlined as follows.

Table 4. Advantages and limitations of different research papers.

Reference	Method	Data	Maintenance Level	Advantages	Limitations
[144]	Probabilistic	Current	Prescriptive	Predicting EVs impact on residential load, Considering Different types of DGs and seasonal effects, providing re-schedule charging plan	No solution for high DG penetration, large-scale EV charging, and smart EV charging
[145]	Electrical and Electro-acoustic	Leakage Current	Proactive	Using acoustic sensors, enabling wide range of frequency, cost-effective	No predictive procedure, not available for HV cables, not detecting PD level
[146]	Probabilistic	Failure rate, Age, Length	Predictive	Prediction of underground cable failures, five models for failure estimation, piecewise constant model	Limited availability of age data, practical implementation, and long-term prediction
[147]	ANN	Solar radiance, Temperature	Predictive	predicting anomalies and faults in PV systems, power prediction	Not robust against different conditions and need available data and real-time monitoring

Table 4. *Cont.*

Reference	Method	Data	Maintenance Level	Advantages	Limitations
[148]	FFT	Vibration, Temperature	Proactive	IoT system, predicting abnormal conditions, using FFT algorithm	Need communication link, vulnerable to cyber attacks, needs additional technical resources for IoT system
[149]	Optimization	Power	Prescriptive	No need for infrastructure expansion, provide solution to minimized aggregate load, prevent overload	Accurate load prediction is needed, trade-off between charging efficiency and charging speed is not investigated

4.4.1. Measuring Device Installation

Measurement installation could be challenging in order to collect data from different components of the grid. For instance, in order to perform predictive analysis, it is essential to install measuring devices on insulators to capture time-series data. Contamination levels in insulators pose a significant concern as they can lead to failures. However, installing sensors in all insulators for predictive maintenance purposes would be a daunting task. Nevertheless, there are alternative approaches to address this challenge. Studies can be conducted in different environments to analyze the contamination patterns of insulators over time, considering various environmental conditions. This approach allows for a better understanding of the contamination levels and facilitates predictive maintenance strategies specific to each environment. In [150], a novel approach is introduced for load forecasting that can support predictive maintenance. This method aids in the decision-making process; however, it necessitates access to recorded historical data, which may require a substantial initial investment for the installation of measuring devices. As the network expands, it becomes imperative to invest in the installation of measuring devices to establish an effective predictive maintenance system.

4.4.2. Grid Scalability

The primary challenge lies in the scalability of the grid concerning digitization. Introducing predictive maintenance throughout the extensive and intricate electrical grid presents difficulties in consistently gathering data, creating tailored models for various equipment, handling substantial data volumes, and coordinating multiple stakeholders. This requires robust infrastructure, advanced data management systems, and efficient communication protocols to handle the growing data demands effectively [151,152].

4.4.3. Cost and Return

It is crucial to consider the costs and return on investment associated with the maintenance development in the electrical grid. While implementing maintenance solutions incurs initial expenses for infrastructure and technology deployment, it offers long-term cost savings by reducing downtime, optimizing resource allocation, minimizing emergency repairs, and enhancing reliability, ultimately yielding a positive return on investment [153].

4.4.4. Cyber Attacks

Another challenge encountered in the implementation of predictive maintenance is the establishment of reliable and secure communication links. Creating a communication infrastructure that is resistant to cyber attacks is crucial to transmit the recorded data to the monitoring center for further analysis [154,155].

4.4.5. General Data Protection Regulation

Compliance with the general data protection regulation (GDPR) is essential when utilizing personal data for predictive maintenance in the electrical grid. Several key considerations, including data protection, lawful basis, purpose limitation, data minimization, data security, data subject rights, data transfer, privacy impact assessment, and accountability and documentation, must be taken into account. DSO companies seeking to enhance grid maintenance levels must comprehend and adhere to the GDPR requirements to ensure the lawful and responsible processing of personal data. Seeking guidance from legal professionals or data protection authorities can provide further assistance in fulfilling specific compliance obligations [156,157].

5. Conclusions

This review paper has provided a comprehensive analysis of the application of time-series prediction methods for maintenance in electrical grids. The integration of digital technologies and the availability of diverse time-series data have opened up new possibilities for enhancing maintenance practices in electrical systems. Through an exploration of statistical models, machine learning algorithms, and artificial intelligence approaches, this paper has demonstrated the potential of these techniques in supporting maintenance efforts. The reviewed literature has highlighted the significance of time-series data and historical-fault data for maintenance purposes. These datasets offer valuable insights into the condition of electrical grid components and enable proactive maintenance actions to ensure reliability, performance, and cost-effectiveness. Furthermore, the study has shed light on the diverse range of time-series algorithms used in different components of the electrical grid, including underground cables, overhead lines, transformers, and insulators. The findings emphasize the importance of digitization in collecting, analyzing, and leveraging time-series data for maintenance decision-making. By applying advanced data analytics and predictive modeling, utilities can enhance their maintenance strategies, reduce downtime, and optimize resource allocation. It is worth noting that while significant progress has been made in the field of time-series prediction for maintenance in electrical grids, there are still challenges to overcome. These include data quality issues, algorithm selection, model interpretability, and scalability. The future research should focus on addressing these challenges to further improve the effectiveness of time-series prediction methods in supporting maintenance practices.

Author Contributions: H.M., Conceptualization, formal analysis, investigation, writing—original draft. A.Q.S., conceptualization, supervision, writing—review and editing. H.R.S., conceptualization, funding acquisition, project administration, supervision, writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This work is supported by the "Leveraging Smart Meter Data to Optimize Grid Investments" project, funded by the Danish Energy Agency under the Energy Technology Development and Demonstration Program, ID number: 64022-1049.

Data Availability Statement: No new data were created or analyzed in this study.

Conflicts of Interest: The authors declare no conflict of interest.

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