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PERSPECTIVE

Toward Cognitive Assistance and Prognosis Systems in Power Distribution Grids–Open Issues, Suitable Technologies, and Implementation Concepts

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ABSTRACT In recent times, both geopolitical challenges and the need to counteract climate change have led to an increase in generated renewable energy as well as an increased demand for clean electrical energy. The resulting variability of electricity production and demand as well as an overall demand increase, put additional stress on the existing grid infrastructure. This leads to strongly increased maintenance demands for distribution system operators (DSOs). Today, condition monitoring is used to address these challenges. Researchers have already explored solutions for monitoring critical assets like switchgear and circuit breakers. However, with a shrinking knowledgeable technical workforce and increasing maintenance requirements, mere monitoring is insufficient. Already today, DSOs ask for actionable recommendations, optimization strategies, and prioritization methods to manage the growing task backlog effectively. In this paper we propose a vision of a grid-level cognitive assistance system that translates the outcome of diagnosis and prognosis systems into actionable work tasks for the grid operator. The solution is highly interdisciplinary and based on empirical studies of real-world requirements. We also describe the related work relevant to the multi-disciplinary aspects and summarize the research gaps that need to be closed over the next years.

INDEX TERMS Renewable energy, electrical grid infrastructure, maintenance planning, condition monitoring, AI, explainable AI, large language models, cognitive assistance system, service engineering.

I. INTRODUCTION

Without a doubt, the climate crisis is chief among the most pressing problems of our time. Recently, additional geopolitical crises have imposed further difficulties. Both challenges imply that it is in the interest of nations like Germany to react by decoupling from fossil fuels. However, replacing fossils like coal, gas, and oil results in massive changes in the electrical grid (see Figure 1).

On the demand side, both the quantity and the volatility are changing. Electrical vehicles add new peaks when they are loaded in the evening. Industries (e.g. chemical) that switch from fossil fuels to electricity increase demand. On the supply side, the steady input from coal and gas plants is replaced

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by often weather-dependent renewable energies like solar and wind. One consequence is a high level of additional stress on the assets in the electrical distribution grid, resulting in additional efforts of service and maintenance for distribution system operators (DSOs).

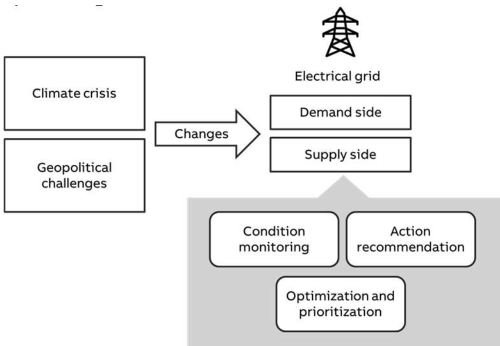

FIGURE 1. The near-future challenges in the electrical grid.

The current approach to solve this problem is condition monitoring. Suitable solutions to monitor assets like switchgear have been explored by the authors in recent years (cf. [37], [98]). In this context, they developed sensor systems for medium-voltage switchgear that detect technical problems at the component level. However, with shrinking technical work forces and increased maintenance demand, it is necessary to provide action recommendations and optimization and prioritization of the generated task backlog. In this paper we describe a vision of a grid-level cognitive assistance and prognosis system supporting maintenance activities of DSOs that we plan to develop in the context of the German public-funded project AProSys. The assistance system is based on both existing and to-be-developed elements as shown in Figure 2.

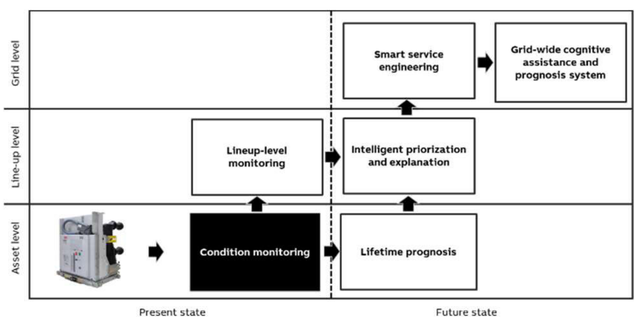

FIGURE 2. Journey from component-level to an intelligent system on the grid level.

Sensor-based condition monitoring is a solid foundation for the further system elements. The data generated by these systems can be used as input for a lifetime prognosis that goes beyond an analysis of the current condition. Sensors on the line-up level augment the asset-level sensors and with intelligent sensor fusion allow the discovery of problems such as partial discharge or worker safety problems. A lifetime prognosis on the asset level can be used for an intelligent prioritization and explanation of maintenance tasks. The results can be presented to field technicians by an assistant system that is designed along principles from the field of smart service engineering.

The rest of this paper explains our interdisciplinary vision in detail and has the following structure. In section II, we show related work that forms the foundation of our next steps. In section III, we discuss the requirements of a grid-level assistance system that we will address in this paper. In that section we also examine how to best embed the system into service processes. The actual vision for the system is discussed in section IV. In section V, we explain our piloting concepts. We end with a conclusion.

The purpose of this paper is to provide a holistic vision for an intelligent grid-wide maintenance assistance system and to identify the research gaps that need to be addressed. It is of interest for readers who are looking for an industry-driven problem description and concepts to solve this issue developed by an interdisciplinary team of researchers.

II. RELATED WORK

In this section, we examine the related work that is relevant to our vision. First, we examine literature, which can serve as a foundation of the envisioned assistance system. Works from several academic disciplines are of interest: Assistance and prognosis systems including digital twins, the state of the art in the field of smart service engineering, approaches to lifetime prognosis, techniques for prioritization and recommendation, as well as a series of enabling technologies. The other category of related work are projects with a similar scope. We will discuss them in the last subsection and explain their difference to the vision proposed in this paper. The key findings related to research gaps and useful foundations from all subsections are shown in Figure 3.

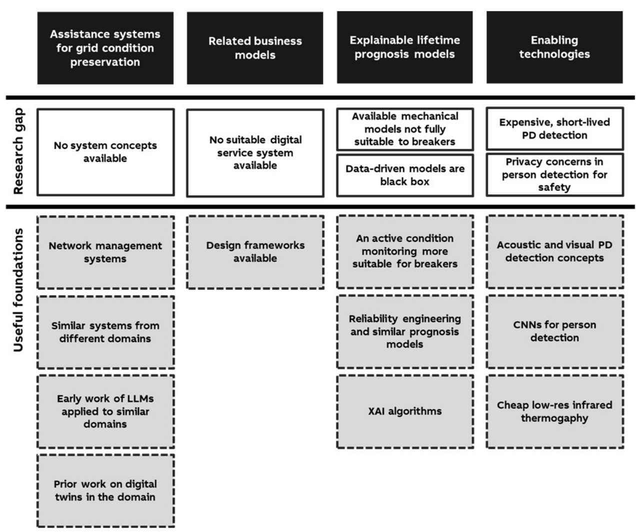

FIGURE 3. Related work overview.

A. ASSISTANCE AND PROGNOSIS SYSTEMS

Assistance systems for interventions in the technical environment (e.g. maintenance work) are already the subject of current research ([61], [87]). Such assistance systems can be classified as mobile systems with a high level of support (decision making and recommendation) and cognitive-sensory support [61]. Cognitive assistance systems support people in decision-making by providing predictive and adaptive recommendations for action or planning based on condition assessment ([61], [87]). Similar concepts can be found under the names *Smart Management System* or *Smart Protection System* (cf. [24]) or as an idea for distribution network automation [2], which are to be distinguished here from cognitive assistance systems.

Some of these systems share a focus on managing the electrical grid's increasing load under scenarios similar to those described in section I (e.g. [2], [24], and [43]). However, unlike our proposed solution, these approaches focus on monitoring and planning energy flows (network management) and not on improving the condition of the network at the component or resource level.

Even existing work focusing on evaluating condition data favors bypassing defective components ([18], [22]) or maintenance of "smart" components instead of the timely repair of the physical distribution network ([101], [102]). In other industries, such as oil production, there are approaches to solve problems at the equipment or component level [6] but they are not directly transferable due to the technical differences.

However, there are useful aspects to be found in the preliminary work. Especially the aspect of distribution network digitalization (e.g. [24]) provides an important basis for cognitive assistance systems. In a position paper, Bitcom explicitly calls for the digitalization of the distribution network to enable reliability without further increasing redundancies [10]. Many of the visions described (e.g. decisions based on the overall status of the network) are not yet implemented by DSOs ([10], [86]).

The rise of highly capable user assistance system such as ChatGPT [76], driven by large language models (LLMs) as a specific type of generative AI, possibly revolutionizes the way we work [25]. These systems have potential to decrease costs and increase efficiency ([4], [59]). LLMs such as GPT3 [16], GPT4 [77] or Codex [19] powering text-based assistants such as ChatGPT [76] or GitHub Copilot [27] raised a special interest in LLM-driven assistance systems [94]. LLMs contain billions of parameters and are trained on billions of tokens ([16], [94]). These generative models aim to generate meaningful text based on an input sequence of tokens (context) and are trained to autoregressively predict the next token t_{n+1} based on the conditional probability distribution $P(t_{n+1}|t_1 \ldots t_n)$ [89]. Such pre-trained LLMs can be adapted to various downstream tasks and domains ([12], [25]). Therefore, they are often called foundation models. Foundation models can be adapted for domain-specific downstream tasks using various techniques. For example, prompt engineering approaches can be used to adapt LLMs to the downstream tasks, providing unambiguous instructions, called prompts, to the model [56]. Also, the models can be trained further (so-called fine-tuning) to solve downstream tasks based on human demonstrations and feedback [78].

Although modern LLMs are highly capable, they can generate incorrect, discriminating, or harmful content under certain circumstances [94]. These are examples of the AI alignment problem, occurring when an AI agent's actual behavior differs from that intended by its relevant stakeholders [34]. Many approaches to LLM alignment exist, ensuring more factually correct and unbiased LLM-based assistance systems [91]. However, especially the mitigation of factual incorrectness in LLMs in form of hallucinations remain as challenge [45]. While the first LLM-driven assistance system attempts exist regarding maintenance in the energy sector [22], they are usually in a prototypical state and often do not provide production ready attempts.

Besides classical assistance systems, digital twins can advance the monitoring and prognosis of part failures. The purpose of digital twins is to provide a virtual representation of a physical instance, such as a switchgear or a complex networked system. Digital twins themselves usually do not provide additional value, however, they provide the base data for value-generating digital applications. Physical asset, digital twin, and digital application form a so-called cyber-physical system [37]. The components of the cyber-physical system can also be cut differently, as e.g. described by the triad of digital / hybrid / cognitive twins [1]. All digital twin concepts have in common that in the digital twin the information is managed. For the industrial usage this requires standardized information models and interfaces, e.g. the Asset Administration Shell (AAS) [17] and the Digital Twins Definition Language (DTDL) [72].

Industrial applications of digital twins span all phases of a product lifecycle: from the design phase, over manufacturing to service and asset retirement [56]. In the context of this paper the service phase, and especially fault detection and diagnosis as well as predictive maintenance and state monitoring are most relevant. A review of such applications is given by Liu et al. [56], and an example for predictive maintenance of medium-voltage switchgear is provided in [37] and shown in Figure 4. Digital twins also build a key component to enable autonomy of industrial systems [28]. Digital-twin-based AI-functionalities can enable the ability to react autonomously to predicted but also unexpected situations with adapted recommendations [1]. In this case, the autonomy is not based on the automated action or control logic, but in the situationally adapted prioritization of recommendations for action.

The development and operation of value-generating cyber-physical systems requires the collaboration of multiple disciplines, covering its various technological aspects such as sensors, digital services, modeling, data management, cyber security and not least artificial intelligence [37].

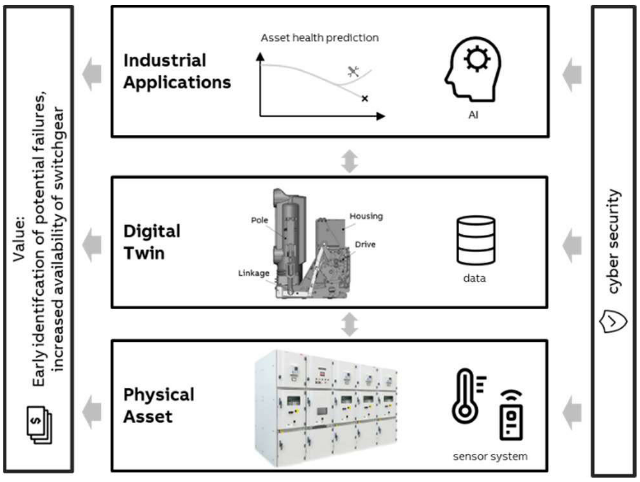

FIGURE 4. Cyber-physical system of a medium voltage switchgear enabling predictive maintenance to increase the availability of of the switchgear. Figure adapted from [37].

B. SMART SERVICE ENGINEERING

The development of novel business solutions as service systems is described in the literature as service systems engineering ([8], [11]).

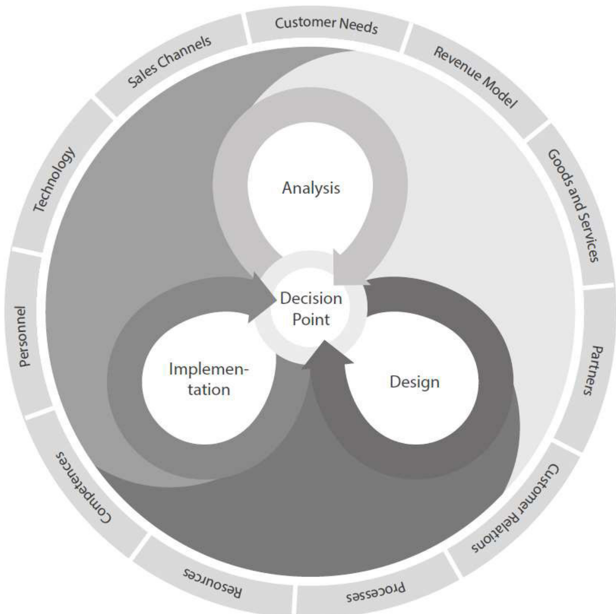

FIGURE 5. Reference process for the development of digital service systems according to DIN SPEC 33453.

In service systems engineering, knowledge about the design of service systems is particularly relevant to deal with the disruptive influence of new technologies, new types of collaboration, and peculiarities of a certain context [11]. New technologies, e.g., high precision sensor systems, can open up new collaboration opportunities between actors, e.g., component manufactures and DSOs. This constellation enables smart services, a special form of service that is focused on digitalized objects, functioning as boundary objects between different actors [9]. In the case of a high precision sensor system acting as a smart object, any communication and interaction between component manufacturers and DSOs is streamlined through the smart object and related IT systems. Thus, the smart service system (comprising the smart objects, actors, and IT systems) is putting an emphasis on an entire value creation system instead of a marketable service, leading to an accessible interactive and collaborative innovations through digital technologies [37].

The DIN SPEC 33453 for the development of digital service systems [21] details a coherent process for the development of digital service systems. Figure 5 shows the basic model, highlighting the three phases of analysis, design, and implementation. During the digital service system development process, these phases can occur in any order to ultimately establish a digital service system, allowing for an agile development approach.

C. LIFETIME PROGNOSIS

In the context of medium-voltage substations, the majority of faults/failures occur in grid components. 85% of these faults can be attributed to material fatigue of mechanical components (cf. [65], [66], [67]). In comparison, electrical faults/failures in grid components generally play a minor role. In this section, we examine both the prior work on models as well as the role of explainability in understanding the predictions.

1) PROGNOSIS FOR GRID COMPONENTS

The reliable sensor-based and network-adaptive monitoring of critical grid components is a basic requirement for the future power grid. However, AI-supported lifetime prognosis systems for grid components mostly focus on the precise prediction of the remaining electrical service life during continuous operation [3], which can only make conditionally valid predictions on a long-term time scale when there are significant load changes at the grid level. Although there is some preliminary work on the subject of mechanical remaining lifetime estimation ([40] and [92]), the physically-based analysis of the cause of the error, taking into account material fatigue effects, and the AI supported generation of prioritized action recommendations remain widely ignored. In addition, according to current knowledge, there is also a lack of sustainable approaches to designing sensor systems that can simultaneously monitor several components, including their function, or directly networked systems.

For electrical grid components, there are hardly any approaches to model simulation-based digital twins with the possibility of synchronizing them with the underlying sensor-based monitoring system. Here, approaches from other technical applications can possibly be modified so that they can be applied to the problem at hand. In these approaches, the synchronization with the real object is carried out using Kalman filters. The main benefit is that the synchronization is not only used for the non-parametric comparison of the system states [47], but it can be also applied to estimate further key performance indicators from a parameter identification based on a physical model. Practical examples, successfully validated for other technical applications, are given for model-based mechanical diagnosis [48] and hydraulic components of vehicle transmissions [50]. A possible extension of this approach is to use several models in parallel for the monitoring where the procedure is described in various publications (cf. [35], [63], [64], [73], [74]) and successfully applied for the development of active vibration-reducing systems [5].

When applying the methods described above to grid components, however, it must be considered that the circuit breakers are closed in the normal state and are only operated relatively rarely and at irregular times. Monitoring and diagnostics represent a particular challenge because in the closed state there are no or only insufficient measurement signals available for system monitoring. This problem has not yet been addressed in the literature for electrical grid components. However, research and methods from other technical applications can possibly be transferred, for instance from the workflow developed for screw connections with the design of the (especially pulse-like) excitation signals and the signal analysis of the system response measured [14]. The methods developed can be referred to as active condition monitoring and can in principle be transferred to switches and circuit actuation systems. This also applies if there are several components to be monitored in a mechanical structure (e.g. a housing) [15].

With active condition monitoring, a small, negligible change in condition or fault is deliberately caused by an additional or system-specific actuator. The effect of this process is recorded and analyzed in the same way as with conventional condition monitoring. A key advantage of this method is that active condition monitoring is also possible for systems that are not continuously operated. When actively monitoring the condition, particular care must be taken to ensure that the normal functionality of the system is not disrupted.

Active condition monitoring has so far only been used very sporadically in grid components. One example is electromagnetically driven circuit breakers, in which the driving motors can be actively monitored for each pole individually. In mechanically driven systems, active condition monitoring is usually more difficult because the additional functionality cannot be easily implemented due to the complex mechanisms for the actuation of the switching operations.

2) INTELLIGENT PRIORIZATION AND EXPLANATION

Many AI algorithms, especially in deep learning, are inherently black boxes. However, for a cognitive assistance system it is essential to provide some justification for recommendations, e.g. to understand the root cause of the problem and therefore the severity. This will increase the trust in AI algorithms by industrial users, which is a major requirement of the adaption of AI in industry [38].

The field of Explainable AI (XAI) covers research on how to explain the decisions of black box models (e.g., [51], [52], [55], [62], and [105]). There are two general directions. One explains the mechanisms of the model itself (e.g., [32]). The other provides tools to understand the solution to a particular set of inputs (e.g., [53] and [83]). A cognitive assistance system can profit from the latter, especially if the solutions assess the importance of individual features ([53], [83]), which can be mapped to physical components in many cases. A related concept is the assessment of uncertainties to understand the robustness of results ([46], [88], [103], and [105]).

It is important to note that the XAI methods mentioned above are domain-independent and often quite abstract. Enhancing XAI with domain knowledge (cf. [44]) would greatly benefit a system specific to a problem such as maintenance management. There is some work on explaining maintenance activities (e.g., [93]) that might be adaptable to our problem domain.

The logical next step from explanations is to allow the user to give feedback to the system if they are in disagreement. Concepts from active learning [41] could be combined with explainability tools. Another solution from the literature is interactive ML (cf. [41] and [84]), which explore human input that affects the learning of models.

D. ENABLING TECHNOLOGIES

In addition to the main fields, there are several adjacent technologies relevant to our work.

1) PARTIAL DISCHARGE

Partial discharge (PD) diagnostics is an essential part of the evaluation of electrical insulating materials. It is also possible to use PD diagnostics for condition monitoring. PD diagnostics are used in practice for many power engineering components, such as transformers, gas-insulated switchgear (GIS) or power cables [7]. In the past, the focus of PD diagnostics was predominantly on components at the high-voltage level. However, partial discharges also occur at the medium-voltage level. At the high voltage level PD diagnostics are not carried out during operation but in the laboratory or directly on the disconnected component. Only in individual cases, PD diagnostics is carried out as an online measurement over a longer period of time.

At the MV level, online measurements are less complex and can certainly be considered. However, despite its utility in condition monitoring, PD diagnostics for the monitoring of medium-voltage switchgears has been only rarely investigated at this time [106]. PD detection provides several benefits:

- Preventive measures avoid further damage and can reduce impending efficiency losses of electrical equipment through early PD detection.
- It can potentially also be used to monitor neighboring components at the line-up level.

The challenge is to develop cost-effective methods for online PD measurement. In addition, a meaningful and easy-to-understand signal for users is desirable. For this, several points must be taken into consideration:

- It must be investigated whether already installed sensors can be used for PD detection.
- The sensors used must be highly reliable, as the monitoring systems are intended to increase system availability.
- An evaluation of the sensor functionality in a monitoring system should be included to detect sensor failures and prevent associated damage.

A PD monitoring system usually consists of two components: a unit for the physical detection of PD signals and a unit for data analysis. The PD signal detection module comprises various sensors that are designed and used to detect these diverse signal transmission paths. The data analysis unit is often equipped with advanced pattern recognition techniques that can distinguish PD from ambient (industrial) noise and possibly detect and localize the specific PD source.

It is generally known that PD emits signals in a very broad spectrum. Electrical or acoustic methods, for example ([42] and [60]), are suitable for diagnostics on medium-voltage switchgear. The detection of ozone can also be considered in indoor areas. The simultaneous acquisition of acoustic sensor signals also enables the localization of partial discharge by means of triangulation. Nowadays, advanced sensor technology and data analysis techniques enable automatic detection of PD activity.

2) PERSON DETECTION

In the context of switchgear and breaker maintenance, worker safety is of key importance and automated person detection is a key feature of our proposed system.

In the last decades, impressive advancements have been made in the field of Computer Vision (CV), especially in object detection and tracking. Object detectors can fundamentally be distinguished in one-stage detectors and two-stage detectors: Two-stage detectors are provided with Regions of Interest (RoI) by an algorithm denoted proposal generator. The detector then evaluates whether an instance of the object of interest exists in that region or not. A classical algorithm used in this context is a Histogram of Oriented Gradients (HOG) [75].

Among the first two-state detectors based on Convolutional Neural Networks (CNN) is the Region-based Convolutional Neural Network (R-CNN) [30], which suffers from long training time and slow inference. Pooling regions of interest together, like SPP-Net [58] and Fast R-CNN [29], and incorporating the proposal generator into the network, like Faster R-CNN [82] and Mask R-CNN [36], significantly sped-up training and inference times.

A further speed-up in inference was enabled by one-stage detectors. These detectors do not rely upon region proposals but work on a grid and formulate the object detection problem as a regression problem rather than a classification problem as usual. This enables one-stage detectors to process the whole image in a single pass. However, the speed-up in inference is usually at the expense of localization precision. Well-known one-stage detectors are You Only Look Once (YOLO) [80] [81], [95] and the Single Shot Detector (SSD) [57].

In conclusion, these more complex models were the major driver of progress in the field of Computer Vision. These models are only trainable and inferable in reasonable time due of the development of never seen before high-performance graphics processing units (GPUs). In addition to that, all the models and methods mentioned above were only developed and tested on visual images with at least moderate resolution (e.g. 256 × 256 pixels). These requirements imply that environments with low computational resources cannot use these solutions. Furthermore, not all environments have enough light for regular cameras to work and require infrared images, which are often low resolution (e.g. 32 × 32 pixels). This requires the use of algorithms that work with low-resolution infrared images ([49], [90], [104]).

E. RELATED RESEARCH ACTIVITIES AND NOVELTY

The project envisioned in this paper addresses the increased strain of distribution network assets through an AI-based forecasting and assistance system. It is based on residual life forecasts that are used for prioritized maintenance action recommendations. It also touches on aspects of knowledge and workforce management. Given the high relevance of the topic, there is a series of related projects, which we discuss below.

As the changes caused by the energy transition and e-mobility are not yet understood in detail, activities are taken to model the effects to understand their impact (project extremOS [71]). Other public funded projects do not go into this level of detail but focus on concepts to support the transition instead. Some examples are smart grid integration [20], i-Automate [85], and Green Access [69]. The typical approach to deal with the problem is load management, which is complementary to our focus on maintenance.

Currently, there are no other projects that focus on an AI-generated maintenance strategy as part of an assistance system for the distribution network. However, for related areas such as wind farms (SmartWind [23]) similar concepts exist. There are also projects that address high-voltage assets but focus on the condition monitoring part instead of the recommendations (iMonet [100] and Monalisa [99]). Monalisa focuses on offshore systems or on systems from the oil and gas industry. Somewhat close to our vision is the Reliability Design project [97], which deals with the service life prediction aspect of switching devices. However, it focuses on devices specially developed for PV and battery storage systems, which can only with difficulty be transferred to the much more highly stressed control and protection components of the medium voltage level.

One other project of relevance, DARE [96], uses reinforcement learning and simulation with synthetic data. Their focus is microgrids. Despite some common keywords, it is not comparable to AProSys in terms of both its objectives and its methodology.

Sensors are an important fundament of this work that have been explored in the Fleming project ([39], [98]). Key sensor technologies explored in the context of Fleming are thermal monitors for switchgear [31] and vibration-based circuit breaker drive monitoring [13]. Other related sensing projects are FONA, which avoids local sensors by drawing conclusions from the high-frequency properties of the network [68] or INTEGRIS, which develops new sensors [70]. What all these projects have in common is that they do not have the holistic, decision-centric nature of the vision described in this paper.

III. CONTEXTUAL PROBLEM MOTIVATION

A cognitive assistance and prognosis system is a new, additional element in the context of distribution grids and DSOs that needs to fit in with the existing ecosystem. This section describes the context consisting of actors, the relevant processes for DSOs concerning the introduction of assistance and prognosis systems, their IT systems, and problems that DSOs are facing. We have interviewed six DSOs in a series of workshops, focusing on identifying their value co-creation network and their pains and gains. We also identified the key pain points to be addressed by a new system.

A. CONTEXT OF THE DISTRIBUTION GRID

On the distribution grid, the deployment of assistance and prognosis systems is influenced by a myriad of stakeholders within the DSOs' operational sphere. A critical assessment of the internal and external agents reveals a landscape where influence is bidirectional, and the stakes are significant. The following actors are the main stakeholders either influencing or influenced by an assistance and prognosis system:

- Service providers: Internal and external operational partners provide services such as maintenance, inspection, disposal, commissioning, and telecommunications. They contribute to the value co-creation of stakeholders through upkeeping functionalities and systems, thus, directly affecting their reliability and performance. Especially maintenance service providers (both internal or external) will be the main users of the assistance and prognosis systems.
- Project managers and department heads: These actors execute and lead the projects of implementing, evaluating, and establishing assistance and prognosis systems.
- Decision makers: Executive board, management, and controlling departments orchestrate the integration of advanced systems to meet corporate visions and ensure that the systems align with the strategies of the DSOs and their long-term goals.
- End-users: Consumers of electricity and up- or down-stream network operators demand a continuous energy supply. Accordingly, they favor maintenance activities as long as they do not interfere with a steady power supply.
- Regulatory entities: In Germany, the Federal Network Agency alongside state regulatory authorities and pivotal industry associations like the Federal Association of Energy and Water Industries (BDEW), wield regulatory power in the form of policies and compliance directives that constrain and shape the operational environment of the DSOs.
- Research institutions: By enabling (digital) innovation of DSOs, research institutions contribute to the development of innovative systems through rigorous research and the piloting of emerging technologies.

There are several business processes that will be sustainably influenced by establishing an assistance and prognosis system. The first is fault management, which encompasses activities for the rapid identification, analysis, and rectification of grid problems, and serves to ensure the security and quality of the electricity supply for end-users [110]. Maintenance management focuses on activities associated with the maintenance of grid equipment. This includes the commissioning and work preparation of maintenance measures as well as their implementation and processing. An assistance and forecasting system can also have implications for procurement and accounting processes [109]. This includes processes associated with ordering materials or the commissioning of specialized service personnel. Processes and tasks in quality management will also become relevant. While these processes will have to be adapted, they also offer enormous potential to be supported by assistance and forecasting systems as well as to be automated or simplified [110].

The implied business processes provide information on users and beneficiaries of an assistance and prognosis system, i.e., end-users. Asset managers are the ones responsible for managing operating resources and optimizing their service life [26]. Distribution grid technicians can benefit from working directly on the equipment. In addition, such a system can also have implications for employees in work preparation, logistics or network planning & control. This means that they can be the central providers of requirements and designers of such an assistance and forecasting system.

Various IT systems, applications or technologies support the maintenance of components in the distribution grid and must be considered during the development of an assistance and forecasting system. These include geographic information systems (GIS) from various providers, which are used to record, manage, analyze, and visually display geographic data of the distribution grid and its components [109]. Furthermore, enterprise resource planning (ERP) systems are used to integrate and manage all business processes, such as finance, human resources, procurement and asset management. ERP systems mostly store master and transaction data of all relevant components [108]. DSOs use ERP systems from various providers as on-premise software or as cloud-based software-as-a-service systems. Other important systems include reporting and results systems, which are used particularly in fault management. The implications of supervisory control and data acquisition (SCADA) systems must also be considered. These systems are directly related to the operating processes and equipment on the distribution grid.

B. CURRENT CHALLENGES OF DSOs

In the context of analyzing the workshops with six DSOs from Germany, five primary challenges have emerged, which will be described below in prioritized order, starting with the most urgent challenge for all DSOs.

The most urgent problem is a shortage of trained staff (C1). Currently available specialists such as network technicians are retiring in large numbers (due to demographic change and the high age structure in the field). This is compounded by declining numbers in newly-trained technicians, changing employee expectations such as home office, and higher rates of employee fluctuation. Additionally, new employees require significant time for training. Distribution network operators infer from this problem the risk of knowledge loss due to departing employees, including local, partially implicit experiential knowledge. Furthermore, staff shortages lead to long-term neglect of maintenance and repair issues.

Another problem identified as urgent by all DSOs is a lack of comprehensive knowledge management and associated information systems (C2). In many cases, information on maintenance and repair is only implicitly available to distribution network operators, for example, in Excel sheets, as individual employees experience, or in local operating facilities. Due to the lack of company-wide knowledge databases and outdated system documentation, there is a lack of knowledge, especially about non-routine tasks, such as maintenance of components that are used in small numbers in the network. Additionally, gaps in data collection arise from media breaks, different templates, and insufficiently standardized data entry. All these factors lead to a lack of systematic capture of local knowledge and experience, ultimately also due to the absence of knowledge management systems.

The increasing complexity of the network was identified by DSOs as an increasing challenge (C3). It was particularly lamented that the components in the networks consist of a multitude of different products from various manufacturers. Thus, responsibilities are unclear about which facilities and components are worthwhile to exchange or modernize, with the need to balance economic benefits against the current and foreseeable condition. This increasing network complexity also has negative effects on knowledge within the company, as more knowledge about more components, products, and types would need to be available.

The fourth identified problem describes the lack of information about the condition of the network (C4). Components and facilities do not fail as frequently, and primary technology lasts a long time, but secondary technology and associated sensor systems are significantly more susceptible, so deploying them is often not worthwhile. Thus, the installation of sensors often competes with network expansion. Here too, there are effects on knowledge management, as information from the network would be needed currently so that maintenance and repair measures can be carried out with precisely tailored preparation.

As a perceivable but not strongly prioritized problem, risks for network (partial) failures could also be identified (C5). Due to staff shortages (cf. C1) and insufficiently documented peculiarities of individual components and facilities, there are delays in maintenance and repair measures. Consequently, components may fail, which can ultimately result in a complete network failure.

IV. BUILDING BLOCKS OF A COGNITIVE ASSISTANCE SYSTEM FOR THE GRID

At a conceptual level, there are several building blocks to address the challenges identified in the previous section. The overall concept shown in Figure 6 helps us to understand the research gaps we need to fill.

The concept of cognitive assistance systems (CAS), which has not yet been researched in the context of distribution network technology, represents the next logical step in the digitalization of energy technology systems. Based on the first box (fault detection) which represents the state of the art, a CAS will actively forecast the development of faults (prediction of fault severity development) and understand the root causes of the fault to make useful recommendations (diagnosis and recommendation). This information enables a prioritized list of actions that will leverage the limited workforce of the network provider. Combined with classical scheduling software, the list can be turned into a work assignment plan for the technicians.

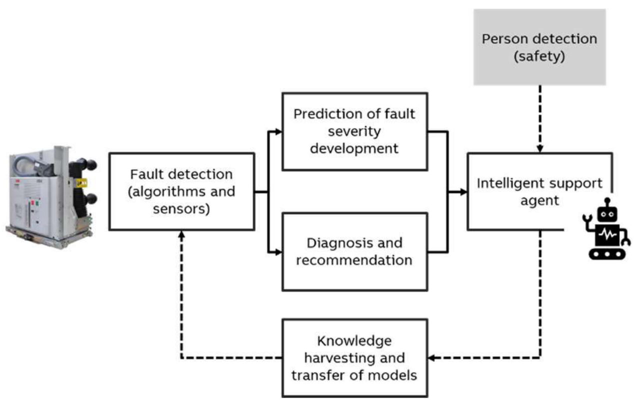

FIGURE 6. Overall concept of a cognitive assistance system at grid level.

On the other hand, long-term predictions can help avoid unscheduled downtime even if the task is not critical yet. Inherent to our concept is the safety of the maintenance technicians (via person detection) which needs to be integrated with the work order management.

To make all relevant information accessible to service technicians, a conversational intelligent support agent aggregates the information from all the modules and presents them in a form accessible to humans. Due to the conversational nature of the agent, it is also possible to collect feedback and continually improve the system.

Figure 7 shows how the solution elements address the challenges identified in the interviews in section III. The intelligent support agent will assist less experienced staff (C1) to deal with the highly complex network of today (C3). The person detection feature will ensure safety even for less experienced people who are less familiar with safety protocols (C1).

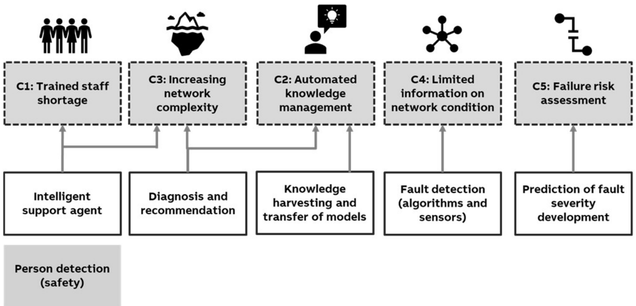

FIGURE 7. **Proposed solutions to the challenges identified.**

The diagnostics feature will provide structured access to answers for even complex situations (C2, C3) and a feedback loop will ensure that any learnings are retained (C2).

Sensors and fault detection provide more insights into the current state of the network (C4) and predictions of fault severity developments allow improved risk management (C5). Most of the elements in Figure 6 require further research at this stage. We will discuss these items in the following subsections.

A. NOVEL FAULT DETECTION CONCEPTS

To understand the current state and health of the grid (C4), a well-designed real-time sensor network is needed. The data generated by the sensors can be interpreted by AI/ML algorithms and passed on to a user via an intelligent support agent. Pivotal for the grid's health are its key components in substations such as MV switchgear and the circuit breakers installed in them. We have explained the central role of such mechanical components for the reliability of the grid in section II-C. Therefore, we focus on this type of asset in this paper.

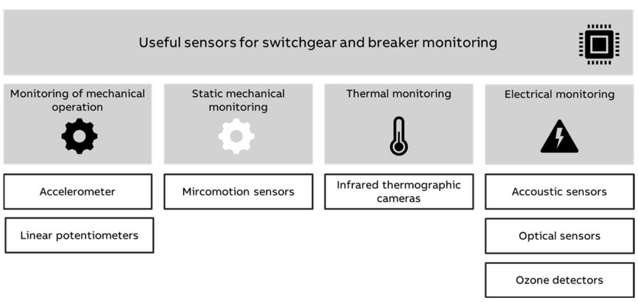

FIGURE 8. **Fault detection sensors.**

Novel fault detection concepts should comprise a sensor system that is capable of simultaneously monitoring various switchgear components and functions. An overview of monitoring challenges and suitable sensors is given in Figure 8.

1) MONITORING OF THE MECHANICAL OPERATION

The opening and closing operations of a breaker imply a movement of parts that can be measured with different sensors. One option is to measure the resulting vibrations. For this purpose, an accelerometer is used. It is usually placed on the circuit breaker housing to monitor several components of the circuit breakers such as the operation mechanism, the spring charging motor or external environmental conditions (e.g. vibrations induced by earthquakes). Linear potentiometers can be used to monitor the co-called travel curve, which can show problems in the correct motion.

These sensors represent the state of the art of breaker monitoring. One of their drawbacks is that they can only detect faults as the breaker operates. Substantial time can pass between breaker operations, so faults might remain undetected for quite some time. Also, the fault is detected at a time when it might be too late (i.e. at the critical point when the circuit needs to be interrupted quickly). Even though the energy transition with more renewables and the e-mobility revolution will lead to more switching operations, it is expected that the number of operations will not be high enough to allow continuous monitoring.

2) STATIC MECHANICAL MONITORING

To address this drawback, novel methods have to be proposed and to be further developed in research to permit the assessment of the health status for the grid components during electrical operation without the need for a switching operation. One approach to static mechanical monitoring is to introduce a negligible excitation of the grid components that does not affect the electrical operation but enables the prediction of the health status by sensing the response of the system.

This novel type of fault detection concept can be referred to as an active monitoring and diagnostics system since it does not only rely on passive sensor information but also excites the system in an active way without the need for a switching operation. In addition to the sensor, the active monitoring system requires an actuator allowing the excitation of the system. One typical example for such an active monitoring and diagnostics system is the micromotion concept for circuit breakers.

3) THERMAL MONITORING

Many electrical faults in a switchgear such as lose contacts or damaged conductors result in overheating scenarios. A good technique to monitor heat problems are infrared thermographic (IRT) cameras. In addition to their original purpose of measuring the temperature inside the switchgear, IRT cameras can be further enabled to perform person and animal detection for providing more safety as described below in section IV-D.

4) ELECTRICAL MONITORING

Partial discharge (PD) is a common problem in electrical grid components. It is a localized dielectric breakdown in the electrical insulation system. These discharges can erode the insulation over time, eventually leading to its failure. Some existing sensors could be used to detect the problem, but new sensor types are needed to achieve greater detection accuracy. Promising candidates are acoustic and optical sensors as well as sensors for the detection of ozone. The complex phenomenon of PD has to be translated into an easy-to-understand signal that is routed to the users/network operators.

B. PREDICTION AND FORECASTING

Using the monitoring solutions from the previous section, it is possible to detect problems as they occur. Many of these faults do not lead to immediate failure but worsen over time and it is possible to act before major problems occur. Network operators are interested in understanding which of these problems to prioritize and how much time remains to fix them (C5).

For the sensors and data preprocessing discussed so far, there is a series of machine learning algorithms (classification and/or anomaly detection) that can detect the presence of faults that will eventually cause failures. However, with this information represents only a snapshot in time. It is non-trivial to compute the remaining useful lifetime based on the mere presence or absence of a fault. Other models are needed to predict the further development of such faults.

1) STATISTICAL PREDICTION MODELS

Traditional statistical predictive models like Reliability functions use historical data to predict the probability and time of failure. There are two weak points in such approaches. First, it is hard or even impossible to obtain representative data for expensive industrial assets. However, such data is needed to determine the model parameters. Second, while a time-dependent probability of failure is useful for larger fleets, they have little meaning for individual units. In other words, the models can predict how many of circuit breakers of a certain condition will fail. They cannot provide the identity of those that will fail, though, so it is hard to derive meaningful maintenance instructions from this information.

We need to develop a way to turn the fault detection snapshots into a health index that can be tracked over time and extrapolated to find a possible end of life. Anomaly detection algorithms represent the degree of degradation through the anomaly score. However, any solution in this area will most likely be tied closely to the particular type of asset it is developed for. A significant challenge we anticipate is defining meaningful thresholds, given that many anomaly scores are normally not directly linked to physical properties.

2) DIGITAL TWINS

Digital twins of electrical grid components are another major branch for prediction and prognostics of the future health status. Digital twins represent a model of a key component (switchgear and/or breaker) that can be used to simulate and predict its behavior. While some data is needed to create the model in the digital twin, it does not need as much data as statistical models. Also, a digital twin can be used for prediction even in the long dormant phases between successive operations. However, digital twins are expensive and difficult to build, so care needs to be taken to invest in the best solution for a particular problem.

The most important type of digital twins consists of one or more physics-based simulation models, in our case of the embedded kinematic chain within switchgears and circuit breakers. The physics-based mechanical model of the system can be supplemented with physics-based and/or data-based statistical ageing models (see previous subsection). The models enable simulations of the underlying mechanism to capture changes in mechanical behavior due to degradation of components and joints. For spring-action based circuit-breakers, mechanism failure can be attributed to one or a combination of the factors shown in Figure 9.

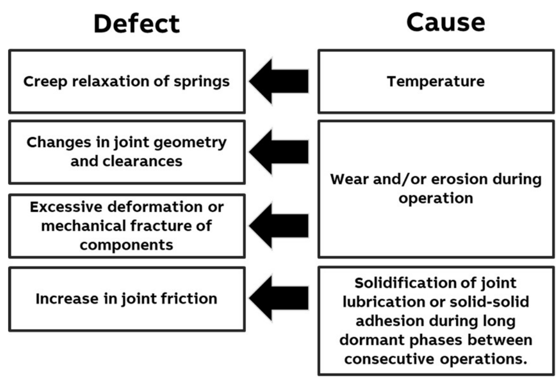

FIGURE 9. Key defect mechanisms in breakers.

Physical models which describe the evolution of mechanical system parameters with time and cycles of operation could be verified offline with experimentation using test-rigs. Initialization of these models for circuit-breakers in the field would require calibration using sensor-data.

An alternative to this concept based on forward-simulation of the physical model is given by online parameter identification. In this case a starkly simplified model of the entire mechanical system is used as a digital twin. This model is capable of reproducing the behavior of the mechanism in terms of time evolution of a physical quantity of interest. The significantly reduced parameter space is suitable for real-time parameter identification using filtered sensor data. In an enhanced monitoring and diagnostics system, the parameter identification from the physical model can be used to extract key performance indicators for the health assessment of the electrical grid components.

C. INTERPRETATION, AND RECOMMENDATIONS

The methods of XAI have been discussed in the related work section. In the context of a cognitive assistant system, algorithms that explain a particular decision based on the input data are of great interest. In an ideal world, maintenance decision support would be a white-box model built bottom up where all details and physical interpretations are available. However, the creation of such a model might be prohibitively expensive. It is much easier to train a data-driven model in particular if it is an anomaly detection model.

When an XAI model is applied to a result produced by a black-box ML model, typically the values that were the most influential for the final decision are identified. If the physical meaning of these elements as well as their relationship to components of the underlying asset is well-understood, a model/process can be created that is able to trace fault warnings back to the components that caused them. This effort (as shown in Figure 10) is not trivial and requires the support of domain experts.

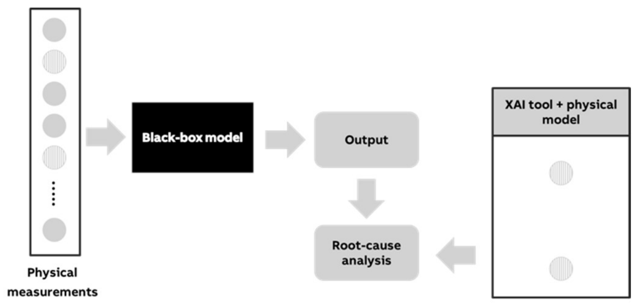

FIGURE 10. Interpretation and recommendations.

D. PERSON DETECTION

Despite the overall high safety standards in electricity distribution networks in general and the numerous safety features implemented in switch gears especially, serious injuries and fatal accidents still do occur. Identifying persons in the vicinity of a switchgear via person detection adds an additional safety layer in preventing or detecting potentially life-threatening events.

Today's state of the art would suggest using a visual light camera to capture the scene and a deep learning-based algorithm to detect humans in that image. However, for several reasons, we propose the use of low-resolution infrared thermographic (IRT) cameras and classical computer vision (CV) algorithms instead.

First, in the context of an employer-worker relationship, privacy is a major concern. A low-resolution infrared sensor instead which makes identifying an individual nearly impossible, preventing a violation of privacy [104]. Privacy is preserved by design. Second, infrared is less prone of changes in illumination and will work equally well in a wide range of scenarios, e.g. nighttime or bright day ([49], [90]).

Finally, a strong computational platform is not a given in the context of a substation for various reasons such as technological legacy as well as cost. Low-resolution images induce a low computational burden on the image processing hardware, thereby reducing costs [104]. Using strong deep learning image processing algorithms requires large amounts of memory and CPU/GPU to function. Classical CV methods on the other hand are not end-to-end but modular: In contrast to a two-stage detector, where the CNN itself first performs feature extraction on the given RoI and then classification, CV methods employ a dedicated feature extraction method. I.e. the engineer chooses an appropriate feature extraction method rather than relying upon the CNN to find useful features itself. While this may hamper performance a bit, it also greatly increases interpretability, maintainability, and computational efficiency. For example, the Histogram of Oriented Gradients (HOG) [75] divides an image into a grid of cells and calculates a normalized histogram of the orientation and magnitude of the local gradients. It is therefore a representation of edges in an image. While developed for the visual spectrum, it can be expected to perform even better in the infrared spectrum for the following reason: In visual images HOG is only useful because persons have a distinct contour by means of which they can be identified. Their clothing and therefore the edges on their body will be very different and not useful for detection. In the infrared spectrum however, the temperature distribution over the human body becomes visible, which is very useful information for classification.

E. COMMUNICATION OF RECOMMENDATIONS

The intelligent support agent, as the main communication module of the cognitive assistance system shall communicate the recommendations generated by the fault detection to service technicians, answer their questions, and provide (didactically prepared) information from the DSO's documents or knowledge bases. It can help both inexperienced technicians (C1) as well as veterans who have to work on new or unusual parts of the network infrastructure (C3).

While some organizations or individuals might have concerns about them, existing research suggests Large Language Model (LLM)-based user assistance systems as an appropriate technology for communication with users via chat or speech (see Section II-A). LLM-based assistance systems with human-level capabilities in processing and generating textual and speech inputs can address multiple recipients with different knowledge levels of maintenance, while they are able to process and integrate the feedback provided by users [78]. As mentioned, an important challenge is the mitigation of LLM hallucinations. LLM hallucinations are factually incorrect or off-topic generations by LLMs [45]. These random statements can cause damage to the assets or potentially even lead to harm for technicians, if they provide wrong recommendations that cause them to ignore safety procedures. Additionally wrong recommendations can lead to additional technical problems up to system failures.

While addressing these challenges remains complex, there are various approaches to mitigate hallucinations [91], that will be considered during the LLM-training and implementation of the LLM-based assistance system. As the assistance system will use the DSO's documents to answer questions and use recommendations provided by the fault detection and analysis, the retrieval augmented generation (RAG) [54] or retrieval augmented fine-tuning (RAFT) [107] are possible candidates for the implementation. Additionally supervised fine-tuning (SFT) [78], where high quality human demonstrations are used to fine-tune LLMs and methods of incorporating human preferences such as reinforcement learning from human feedback (RLHF) [78], or direct preference optimization (DPO) [79] can incorporate human feedback to improve the LLMs outputs.

F. KNOWLEDGE HARVESTING

The integration of human feedback addresses the lack of knowledge management by the DSOs (C2). Classical implementations of knowledge management are mostly rejected by experienced workers. They are perceived as useful mainly to new or unexperienced workers while causing additional effort for experienced workers. Conversely, LLM-based assistants are more widely accepted due to their public availability [94]. The assistance system enables the technicians to process additional information during maintenance. This information includes possible annotations and changelogs for existing manuals, internal documents, or assets that enable other technicians to improve the maintenance efficiency. LLMs enable the didactical preparation and language improvement of technician feedback and annotation to the documents and assets due to their high language understanding and restructuring capabilities [94]. As human knowledge is mostly expressed in an unstructured manner through language, LLMs can process and structure this knowledge. The LLM-based assistant can process the technician's feedback on a specific document, restructure it as an annotation to the document and store it as an annotation text file, to prevent AI-interventions on the documents. While this annotation process can also include the problem of hallucinations, an additional approval-loop can ensure that the LLM-annotation contains the technician's intended knowledge.

Besides the alignment problem, the acceptance of the human-in-the-loop architecture for the LLM-based assistance system is an additional challenge. Like most user technologies, the acceptance of users is very important for assistance systems. This can be addressed by an early inclusion of the knowledge workers and mechanics that will use the system. They decide on the features to in- or exclude and decide on the assistance system from an initial prototype to the pilot version.

V. PILOT SCENARIO

The technology concepts for the forecast-based assistance systems developed in the previous work packages are to be tested and demonstrated under real operating conditions. Based on the feedback of service personnel, the system will be adapted and improved further.

The pilot scenarios are to be tested in cooperation with the network operator Westfalen Weser Netz GmbH (WWN). WWN is a municipal company servicing the German regions of Ostwestfalen-Lippe, Südniedersachsen, and Sauerland and is involved in various research projects to address future energy supply requirements and to create an intelligent and sustainable electricity grid. The distribution grid operated by the company covers a cable length of around 30,000 km.

At the time of writing, the pilot phase is being carried out at a substation in the WWN grid area. A substation is a facility that acts as an interface with transformers to enable the transmission and distribution of electricity between different voltage levels (110 kV high voltage to 10 kV low voltage in this case).

In the first step of the pilot project, circuit-breakers are equipped with a sensor system and monitored in order to generate real data from the switching operations carried out. The various solution elements described in section IV will be tested with this data. In particular, diagnosis, prognostics, and digital twins can be tested using the recorded data and service technicians can provide feedback to the assistant system.

Following successful integration in this area, the assistance and forecasting system will then be extended to other systems and equipment. Due to the high IT requirements of a distribution grid operator, the conceptual assistance system will be implemented as an isolated edge system and designed for a retrofit to enable simple integration into existing systems.

VI. CONCLUSION

In this paper, we have presented a comprehensive and interdisciplinary vision for an intelligent grid-wide maintenance assistance system. We have provided a comprehensive review of the various technologies needed to realize our concept as well as its need in the context of other scientific activities that are currently underway.

We have conducted empirical studies to determine the current pain points of electrical grid operators. Our proposed vision addresses all these points and describes a multi-layered system that can make fault prognoses and safety assessments and communicate those to service technicians in a didactic and understandable way. The algorithms and sensors can deal with a series of fault types both electrical and mechanical. Based on our initial prototypes and the pilot installation at WWN, we will continue to refine the algorithms, digital twins, and sensors to show the feasibility of our vision.

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