Predictive Maintenance on the Energy Distribution Grid–Design and Evaluation of a Digital Industrial Platform in the Context of a Smart Service System

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***Abstract*—The energy turnaround and the shift towards sustainable mobility threaten the stability of European energy distribution grids due to substantially increasing load fluctuations and power demand. These challenges can critically impact assets in the distribution grid—e.g., switchgears—intensifying the need to plan, conduct, and manage the maintenance of such assets. Predictive maintenance strategies that analyze assets' current and historical condition data have been discussed as promising approaches toward that end. However, the extant research focuses on designing and improving analytical algorithms or information technology (IT) artifacts while not considering how a maintenance service is cocreated by companies with IT. This research article posits that IT and service must be aligned closely, presenting an ensemble artifact comprising a digital industrial platform and a smart service system for predictive maintenance on the distribution grid. The artifact is evaluated by conducting a willingness-to-pay analysis with asset operators, documenting their demand for condition monitoring and predictive maintenance as an integrated solution, although they still struggle with even getting the condition data of their assets. Building on these results, we formalize the knowledge in the form of design principles and implications for managing the maintenance of critical assets in the distribution grid.**

***Index Terms*—Design science research, digital platform, distribution grid, IS design, predictive maintenance, smart services.**

I. Introduction

Climate change is one, if not the most important challenge humanity has to solve over the next century. A major strategy to tackle the amount of carbon dioxide emitted into the atmosphere is to shift the generation of electrical energy from resources outputting greenhouse gases to renewables, e.g., wind power and photovoltaic. In the German energy market, this transition is known as the *Energy Turnaround* [1]. In comparison to fossil energy sources, renewables are distributed and intermittent, forcing the distribution grid to change: The formerly unidirectional and centralized distribution grid has to become bidirectional and highly decentralized [2]. As the mobility sector increasingly builds on electric vehicles to reduce its emissions, too, the demand for electrical energy also has to be satisfied through the distribution grid [3]. Combined, this transformation makes the distribution grid subject to increased load fluctuations and power demand, stressing its central components [2], [4]. Recent studies document that the current distribution grid, thus, becomes increasingly susceptible to failures and blackouts [2], [5]—considered threats to our society.

Critical assets of the distribution grid having to adapt to upcoming stress factors include *switchgears* in medium voltage (MV) settings [6]. Switchgears are in use for up to 40 years by distribution grid operators and, thus, need to be maintained to function properly, distributing electrical energy into different micrograds for long periods [7]. Failures of switchgears are in 90% of cases related to aging [7], requiring sophisticated maintenance activities. Maintaining critical, industrial assets can generally be pursued by different maintenance strategies, mainly categorized as *reactive maintenance*, *preventive maintenance*, and *predictive maintenance* [8]. While reactive maintenance operates assets to the point of failure or required maintenance activities, preventive maintenance utilizes intervals based on, e.g., operating hours before assets are checked, and critical components replaced [8]. Predictive maintenance[1] utilizes real-time and historical condition data to monitor the current status of an asset permanently and predicts its remaining lifetime [10].

Related research has already shown positive results, e.g., increased availability of wind farms [11] and even further optimization models for predictive maintenance of wind farms [12]. However, predictive maintenance is mostly investigated from an engineering perspective, focusing on the design of technical components such as sensors and architectures, e.g., [13] and [14], or improved machine learning methods and algorithms, e.g., [15] and [16]. Especially within the energy distribution grid, this focus shows a lack of integrating the management of the technology and the maintenance strategies that has also been observed in recent research [17]. The technical research on predictive maintenance, thus, needs to be complemented by a management perspective. We make use of *service science* as a domain focusing on the management of services rather than

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[1]In neighboring disciplines, predictive maintenance is also denoted as *condition-based maintenance* [9].

(technical) products [18] to take on this perspective on predictive maintenance. In detail, we view switchgears as integrated *smart products*—physical products, which utilize sensor data to monitor their status and surrounding [19]—for their management from a service science perspective. These switchgears would need to be enriched by engineered technology for data collection, connectivity, and locatability to enable: 1) customers (i.e., distribution grid operators) to monitor their performance and status; and 2) service providers (i.e., asset manufacturers) to analyze the data for product improvements [19]. When taking such a service science perspective, the systems in which value is cocreated through the management of the smart products are defined as *smart service systems* [19]. We posit that combining the technical design perspective with the service science management perspectives enables to consider the cocreation of value combined with the holistic technology engineering and management of predictive maintenance innovations. For this, we aim to design a combination of a smart service system, managing critical assets as smart products, and a digital industrial platform—a class of digital platforms collecting, integrating, and analyzing data of industrial assets [20].

We approach this design goal by adhering to the research paradigm of design science research (DSR)–focusing on building, instantiating, and evaluating our ensemble artifact [21], [22]. We start our research with a prestudy, i.e., qualitative interviews with distribution grid operators, to identify and analyze their current service systems and problems, leading us to define the objectives of our solution [21]. Subsequently, we construct a smart service system and instantiate a prototype for a digital industrial platform to manage critical assets of the distribution grid utilizing predictive maintenance. We evaluate our design by analyzing the willingness-to-pay (WTP) of distribution grid operators to participate in the smart service system–focusing on the value-in-use generated with the service [23], [24] rather than the intention-to-use the platform as an information system. Finally, we discuss the results by formalizing the learning of our DSR endeavor and abstract our result in a set of five design principles [25] for an ensemble of a smart service system and a digital industrial platform [20].

Our results contribute to theory by applying predictive maintenance—an established maintenance strategy—to a new domain, i.e., central assets of the energy distribution grid, and deriving design insights from our study. Therefore, this article extends the technical understanding of predictive maintenance to a holistic understanding–incorporating the management, i.e., value cocreation, of predictive maintenance strategies and services. Additionally, we demonstrate that using a WTP analysis serves as a suitable evaluation method for service design in DSR. From a managerial perspective, our results contribute insights on how to design and instantiate a smart service system and a digital industrial platform enabling predictive maintenance and yielding fruitful insights for distribution grid operators. Furthermore, our WTP analysis provides managerial implications for offering smart service and smart products for distribution grid operators. With these contributions, we answer recent calls for research to investigate feasible revenue models and architectures for platforms managing industrial assets [20], to transition to predictive maintenance for central assets of the distribution grid [6], and to design and engineer smart service systems [19].

The rest of this article is organized as follows. This article summarizes fundamental properties of distribution grids, followed by maintenance strategies and the basics of digital industrial platforms in Section II. Section III illustrates DSR as our research paradigm and justifies our research approach. Section IV reports on the current situation and resulting design objectives derived from interviews with distribution grid operators. Section V covers the design of the ensemble artifact of smart service system and digital industrial platform. In Section VI, we present a WTP analysis to evaluate our ensemble artifact. We discuss our insights by deriving design principles from our ensemble artifact in Section VII. Finally, Section VIII concludes this article.

II. Theoretical Background

A. Energy Transmission and Switchgears

European energy grids are divided into different voltage levels. When energy is produced, for instance in a nuclear power plant, the electricity is transmitted into the extra-high voltage (EHV) grid. This part of the grid handles voltage levels from 220 to 380 kV [26]. To be able to supply large industrial customers, EHV is transformed into high voltage (HV) through a transformer station. The HV grid manages 60–110 kV [26]. Here, power generation facilities, e.g., biogas plants, insert energy. Another transformer station then transforms the HV to MV to provide industrial customers, offices, and service buildings with energy. This part of the grid handles voltage levels from 6 to 30 kV [26] and is also powered by wind energy plants and large photovoltaic systems. The provision of electricity to the population in cities and rural areas is handled by the low voltage (LV) grid, using 230 or 400 V [26]. Through a distribution substation, the MV grid is connected to the LV grid. This LV grid is only fed by houses with their own energy production—mostly photovoltaic systems—and supplies charging stations for electric vehicles, apartment buildings, and houses without own production, trade, retail, and service facilities.

Within distribution substations, there are different assets critical for a continuous supply of energy. Switchgears enable to interrupt electrical circuits through their key component—the circuit breaker—and, thus, embody protective and control functions [6]. The transformation from MV to LV is a key element for providing energy to households. Thus, a failure-free operation of the substations is crucial for grid operators. Zickler et al. [27] investigated failures of switchgears and found 90% of failures to be related to aging, while Zhang et al. [7] identified a decrease of mechanical strength due to material fatigue under cyclic load caused by thermal stress as the main factor to provoke failures. In case of a switchgear failure, the part of the distribution grid being supplied with electrical energy connected to the switchgear will be shut down. Consequences comprise missing electrical energy for multiple households, industries, and potentially critical infrastructure, e.g., hospitals.

To maintain their grid, provide the right spare parts for each component, and be aware of the (geographical) structure of the grid, grid operators rely on different information systems. They use geographic information systems (GISs) to manage location information and enterprise resource planning (ERP) systems for asset management and administration processes. Furthermore, there are different tools for strategic management and some grid operators use basic supervisory control and data acquisition (SCADA) systems for their critical assets [28].

B. Maintenance Strategies for the Distribution Grid

Maintenance strategies have shifted from being a cost-driver to enabling success [29]. Thus, a change from reactive to proactive actions can be identified [30]. For maintenance of assets within energy grids, three central maintenance strategies can be identified: 1) *reactive*; 2) *preventive*; and 3) *predictive maintenance*.

Reactive maintenance strategies operate assets until a malfunction or defect occurs. Energy providers pursuing this strategy neglect to plan or schedule inspections. Thus, assets are operated for their maximum lifespan and replacement and spare parts costs are minimized. However, it also enforces downtimes, which occur more often and increase costs due to rapid repairs [8].

Preventive maintenance uses scheduled maintenance activities based on predefined intervals, e.g., specific amounts of operating hours or time intervals. This strategy aims to prevent downtimes by replacing parts before an error occurs. However, preventive maintenance is not able to prevent failures altogether and provokes replacements before the possible maximum lifetime is reached [8].

Predictive maintenance is a sophisticated maintenance strategy that is based on sensors that detect condition changes and failures with the help of advanced signal processing techniques [31]. Predictive maintenance is already one of the most applied scenarios for smart service systems, especially in manufacturing contexts [32]. The implementation of predictive maintenance avoids downtimes by predicting defects before they occur and also prevents unnecessary equipment replacement [8]. Condition monitoring—“a management technique that uses the regular evaluation of the actual operating condition of plant equipment, production systems, and plant management functions, to optimize total plant operation” [33, p. 36]—enables predictive maintenance by acquiring and processing information and data that indicate the status of a machine over time [9].

Combining the advantages of reactive and preventive maintenance by avoiding downtimes and using the maximum lifespan of assets, predictive maintenance has been established as a promising strategy for maintenance activities in the energy grid, being mainly used in LV, HV, and EHV. On the LV grid, smart meters enable to obtain individual data from the household, which can be analyzed for load forecasting, abnormal detection, consumer segmentation, and demand response [34]. In HV grids, condition-based monitoring is used on transformers to identify factors impacting their reliability [35] and to predict their current status [36]. In EHV grids, predictive maintenance is used for nuclear power plants, as they are condition-based, highly advanced industries equipped with different sensors, instruments, and analytical methods to extend the time-to-failure [37]. Concerning MV, predictive maintenance has not yet been applied for central grid components.

Most studies on predictive maintenance in the field of innovation and technology management focus on technically improving [38], [39], comparing [40], optimizing [12], or developing predictive maintenance methods and algorithms [41]. Further, researchers designed IT artifacts, focusing on developing design knowledge on predictive maintenance-based systems [42], e.g., in the field of predictive maintenance through smartphones [43]. This gathered design knowledge [42] can be transferred to the prediction of the future condition of components within the energy distribution grid: A predictive maintenance system “should provide all task-relevant data in a comprehensive manner using appropriate means to attract the user’s perception [...] of important information while keeping him receptive to the overall status” [42, p. 4]. Thus, a system for predictive maintenance on the distribution grid should be able to process data from different sources, e.g., sensors, in real-time and enable storing and processing of historical data. Since there are different areas of interest, e.g., different plants or locations within the grid, the system should prevent data overload and be able to switch attention between different areas of interest [42]. Further, a predictive maintenance system “must provide means to enable the user’s understanding of current business situations [...] to make decisions invariant of errant mental models” and “should present the current status and possible future outcomes in a comprehensive manner enabling the user to anticipate (near) future business situations” [42, p. 5]. For the energy distribution grid, the control center has the overview of the condition data of the assets and about the incidents [28]. To make these data more valuable, a predictive maintenance system should embed the data in a situational context on the one side and a historical context on the other [42]. Within the energy distribution grid, integrating these contexts enables decisions about upcoming maintenance activities, grid planning tasks, and analysis of historical events.

Combining the existing knowledge on predictive maintenance strategies, e.g., [8], and design principles, e.g., [42], within the context of the energy distribution grid, there is a clear focus on technical aspects. What is missing, however, is an integration of the management perspective into the design of predictive maintenance artifacts. This integration is not an easy task, since different groups of stakeholders are involved, e.g., asset manufacturers, distribution grid operators, repair service providers, sensor manufacturers, and industrial customers, who partly operate their own assets [28]. Thus, maintenance strategies do not only need to be applied by enhancing components and methods technically, but need to be transferred into the contexts of the value cocreation. First, steps have been taken to design and describe digital service platforms for predictive maintenance of connected vehicles [44] and the capabilities and solution scenarios of industrial IoT platforms [45]. Thus, the relevance of digital platforms for predictive maintenance has been discovered, but again with a more technical focus, not gaining knowledge on focusing on digital platforms for predictive maintenance.

C. Digital Industrial Platforms

The concept of a digital platform—generally defined as a "mediating entity operating in two- or multisided markets, which uses the internet to enable direct interactions between two or more distinct but interdependent groups of users (e.g., in the case of a two-sided market: Buyers and sellers) to generate value for at least one of the groups [46], [47], [48], [49]" [50, p. 513]—has been discussed as an enabler for complex maintenance strategies for critical assets [20]. The architecture of digital platforms is characterized by multiple layers and modularization [51], [52] that enable controlling the platform while maintaining flexibility [53]. While a multitude of different platform terms and concepts exists in the literature [54], two types can be distinguished in platform research: 1) transaction platforms; and 2) innovation platforms [55]. Transaction platforms, on the one hand, match users and enable them to cocreate value by exchanging information [55], e.g., Amazon, WhatsApp, and Uber. Innovation platforms, on the other hand, enable innovation through applications and services for third parties [55], [56], e.g., SAP and AmazonWebServices.

Digital industrial platforms allow to combine both types of digital platforms [20], [57]. Pauli et al. [20, p. 183] define digital industrial platforms as "platforms that: 1) collect and integrate data from a heterogeneous set of industrial assets and devices; 2) provide this data and additional technical support to an ecosystem of third-party organizations who develop and enable complementary solutions that 3) affect the operation of industrial assets and devices; and 4) provide a marketplace to facilitate interactions between platform owner, third-parties, and business customers." They aim to combine and integrate data from industrial assets in business-to-business (B2B) contexts to enable smart services for complementors [19], [20], [58]. Therefore, digital industrial platforms act as innovation platforms when enabling smart services, whereas they act as transaction platforms when collecting asset data and analyzing or optimizing asset performance [20]. Thus, they are able to connect industrial assets and information systems of users of these assets [20], [59].

The layered modular architecture of digital platforms is also represented in digital industrial platforms. A digital industrial platform consists of the following four layers [20]:

1) device layer (with assets, sensors, and actuators);
2) connectivity layer (for connectivity protocols, gateways, and technologies);
3) platform ecosystem;
4) application layer (for industrial application).

The digital industrial platform connects the platform ecosystem with its manufacturers, software developers, and customers to the connectivity layer and establishes the service layer as a fifth layer [20].

Digital industrial platforms are characterized by four attributes and peculiarities. First, the asset data stored and processed on a platform are heterogeneous [20]. This fits to the distribution grid and its variety of assets applied in substations to enable a continuous energy flow, e.g., switchgears and transformers. Additionally, assets are in use for up to 40 years, thus, different product versions are simultaneously operated. Second, digital industrial platforms are applied in industrial B2B contexts [20]. The distribution grid with its multiple asset manufacturers and product versions is a typical B2B domain. Third, digital industrial platforms are based on multiple actors cooperating to cocreate value for the operator of its assets [20]. Within distribution grids, these actors can include distribution grid operators, asset manufacturers, sensor developers, and data analysts. Fourth, service that is enabled by digital industrial platforms intends to improve the use of the industrial assets [20]. In the case of the distribution grid, most assets are already mature due to their long application range without major technical changes. However, maintenance strategies are still to be improved and optimized based on the data of the assets. Thus, applying a digital industrial platform in the context of the distribution grid seems to be a promising strategy.

III. Research Method

The goal of this research endeavor is to design and evaluate an ensemble artifact for managing critical assets of the distribution grid utilizing predictive maintenance. We focus on switchgears as exemplary, critical assets because of their vulnerability to aging and the need for maintenance [7], [27]. The ensemble artifact should serve as a single point of contact for different roles at a distribution grid operator. While control center agents use the artifact to supervise the status of assets and plan maintenance activities, distribution grid engineers use its data, insights, and transactions to maintain and repair assets. Furthermore, distribution grid planners build on the data and insights to plan and optimize the future distribution grid.

The artifact to be designed classifies as an ensemble of IT artifacts in the sense of Hevner et al. [21]. Therefore, we apply design science research (DSR) as our research paradigm. DSR is focused on designing and evaluating artifacts in organizational contexts while using established foundations and methodologies from the knowledge base [21]. DSR aims to provide actionable and useful artifacts to solve relevant problems in their applied organizational context, paired with scientific knowledge [21], thus, characterized by "learning through building" [60]. Design knowledge in this article is embodied in the form of design principles–"prescriptive statements that show how to do something to achieve a goal" [25, p. 1622]. A set of design principles depicts the principles of form and function of a design theory [25].

In this article, we apply the DSR methodology by Peffers et al. [22]. Our research consists of six proposed steps (Fig. 1). We start with *identifying the problem and motivating* our research, describing that central assets of the distribution grid, especially, switchgears, will be stressed harder in the future due to increasingly flexible energy production and demand. For our *objective of a solution*, we aim to apply predictive maintenance as an advanced maintenance strategy to overcome the stated problems. Ultimately, failures and blackouts of the distribution grid caused by faulty assets should be predicted and prevented through maintenance activities. To further investigate the objectives and structure our goals, we interviewed six distribution grid operators of different voltage ranges (MV to HV),

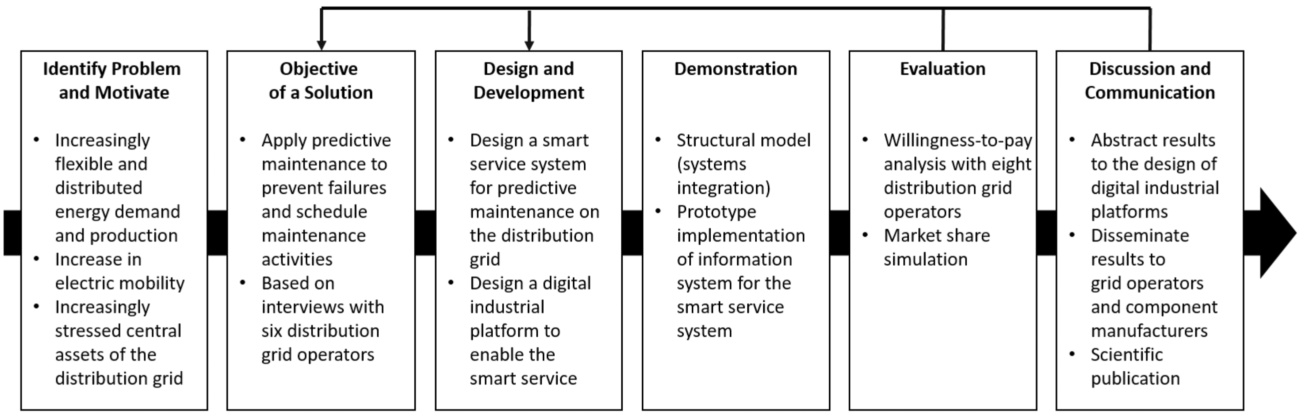

Fig. 1. Instantiated research process building on the DSR methodology [22].

sizes (<250 to >10 000 substations), and employees (<250 to >1000). We interviewed a minimum of two representatives of each distribution grid operator, lasting between 90 and 180 min. We used qualitative methods to identify and map the distribution grid operators' maintenance and repair processes, acquired their IT artifacts and status data currently available, outlined the value cocreation network, and analyzed the major tasks, pains, and gains [61].

The third step—*design and development*—builds on the insights from the qualitative interviews to derive design knowledge. Utilizing the objectives of our solution, enriched by design knowledge, e.g., [42], we design an ensemble artifact consisting of a smart service system and a digital industrial platform. To *demonstrate* our design results, we implement a prototype of our digital industrial platform by conceptualizing systems integration and data models. As this research does not focus on improving algorithms and data transfer between assets and the system itself, we blackbox both the sensors and the machine learning system. However, we are able to use experimental data for the condition of switchgears in our prototype implementation.

The *evaluation*—a central component of DSR studies [21]—aims to validate whether the design actually helps to solve the problems identified in the first step. Ideally, the proposed smart service system and digital industrial platform would be implemented at a distribution grid operator and applied over a longer time period. Afterwards, downtimes and costs could be analyzed to evaluate the success of the ensemble artifact and maintenance strategy. However, such an evaluation in the form of a field study would take vast amounts of resources (costs for sensors, costs for proper implementation, training of personnel) and be subject to a risk of early failures of the system—leading to potentially drastic consequences such as blackouts.

Therefore, we make use of a willingness-to-pay (WTP) analysis to evaluate our designed ensemble artifact. A WTP analysis generally aims to quantify the utility function of a customer in monetary units—i.e., the willingness to pay for a service or prodct [62], [63], [64]. Thus, it is able to determine the value-in-use, i.e., "individual judgment of the sum total of all the functional and emotional experience outcomes" [65, p. 120]. Value-in-use can only be determined by service customers [24], [65], fitting to the WTP approach. The quantified benefit from a customer's perspective can also be assessed through the technology acceptance model, allowing conclusions about why individuals use a technology [66]. Here, *perceived usefulness* describes the judgment of the performance benefit for the user resulting from the technology, whereas *perceived ease of use* describes the freedom or effort of (physically and mentally) using a system [66]. WTP analyses have been applied to both consumer goods and industrial goods [67]. While not yet applied as evaluations in DSR studies, we posit that WTP analyses are a suitable means to evaluate IT artifacts from a value cocreation perspective because they enable us to determine whether a service would be accepted on a market. In our case, we take a management and service science perspective to investigate the perceived usefulness for the participating organization, i.e., distribution grid operators using critical assets. Our WTP analysis serves as an agile evaluation strategy so that we can evaluate our service and artifact design before fully implementing IT artifacts in organizations.

Estimating the WTP is a challenging task, since customers are not yet able to determine the exact value of our designed service and might not want to disclose their real WTP. As customer groups differ drastically for B2B-relations in comparison to B2C relationships, there is a catalog of different methods available for a WTP analysis [62]. Due to the low number of possible customers—only distribution grid operators and few businesses buy switchgears—combined with an impediment to disclose real numbers, we opt for a conjoint analysis to measure indirect preference structures [62], [68]. We define different attributes and levels to design the stimuli and perform interviews to gather data for the preferences. To evaluate our findings, we determine the impact on the decision for each attribute and perform a market share analysis.

Finally, for *discussion and communication*, we incorporate the learning of our evaluation by deriving a set of five design principles [25] for an ensemble artifact comprising a smart service system and a digital industrial platform for predictive maintenance on the distribution grid. We already disseminated our results to manufacturers of assets and the distribution grid operators involved in both our interviews at the beginning of the research and our WTP analysis.

TABLE I
OBJECTIVES OF OUR ENSEMBLE DESIGN

No.	Objective	Reasoning	Additional references
1	Condition monitoring	Lack of condition data and asset state, assets are operated for up to 40 years, increasing reaction and repair times.	Davies [33], ISO 13372 [9], Hashemian [31]
2	Predictive maintenance	Outdated maintenance strategies, increasing risks of outages and blackouts, cost pressure requiring increased maintenance intervals.	Hashemian [31]. Hoffmann et al. [6], Mobley [8]
3	Knowledge management	Distribution grid operators use multiple information systems (e.g., GIS and ERP), knowledge on assets is scattered across these systems, high amount of implicit and tacit knowledge.	Kumar and Jayantilal [70]
4	Systems integration	Different information systems in use, lack of integration between these information systems, redundant data storage and use.	Farhangi [71]

IV. OBJECTIVES FOR PREDICTIVE MAINTENANCE ON THE DISTRIBUTION GRID

Distribution grid operators have multiple tasks in their daily business. The highest prioritized task of all distribution grid operators interviewed in our study is to secure a permanent energy supply to customers. This task includes fixing errors or disturbances that hinder a continuous energy delivery, but does not include maintenance activities. Operators are informed about disturbances and errors either by voltage drops or by customers complaining about failures in their energy supply. Currently, distribution grid operators do not have condition data of their central assets available, making them unable to directly locate error sources and causes. Instead, they have to assess multiple substations or assets locally.

The second group of tasks distribution grid operators uniformly reported are maintenance activities. The current market situation for distribution grid operators shows that they are facing ambiguity. On the one hand, their processes, information systems, and maintenance strategies are sound and they do currently not face many issues with their distribution grids [7]. On the other hand, the challenges distribution grid operators face—caused by the transition to renewable energies and an increase in the demand for electrical energy—combined with unknown conditions of central assets require proactive actions. Subsequently, we state the main objectives of the interviewed distribution grid operators for future scenarios concerning maintenance on their distribution grids (cf. Table I).

First, current maintenance strategies of distribution grid operators are not based on actual data of critical assets, but based on either waiting for failures (i.e., reactive maintenance) or maintenance intervals recommended by manufacturers of assets (i.e., preventive maintenance). The interviewed operators mainly make the lack of condition data on their assets responsible for their outmoded maintenance strategies, but assured us that these strategies are common for distribution grid operators. A reason for this lack of data is the operating life of these assets—switchgears are in use for up to 40 years. To counteract the problems distribution grids will face, therefore, a permanent monitoring of condition data of central assets is necessary. In the case of switchgears on the distribution grid, required data can be collected by multiple types of sensors, i.e., current sensors to determine the flow of electricity, thermal sensors to identify overheating, air quality sensors to determine contamination levels (e.g., from dust or soot), and camera sensors to identify animal intruders (possibly causing short circuits).

Identifying the current status of assets can decrease reaction times in failures, possibly prevent outages, and reduce costs, e.g., in cases where maintenance activities can be postponed. However, condition monitoring serves as a prerequisite for predictive maintenance [9], [31]. Therefore, the second objective for distribution grid operators is to be able to predict problems, errors, and outages of their critical assets, i.e., transition to predictive maintenance. Predictive maintenance requires pattern recognition [31] by machine learning models and algorithms, which can predict remaining lifetimes of assets and resulting windows for maintenance activities [8]. Additionally, predictive maintenance requires vast amounts of test and training data, which (as well) is currently sparse [6]. With condition monitoring and eventually predictive maintenance, distribution grid operators expect to improve their knowledge of conditions of critical assets on their distribution grid, extend maintenance intervals, reduce errors, and ultimately save costs while maintaining a healthy distribution grid.

As a central aspect of both condition monitoring and predictive maintenance revolves around the collection of sensor data, distribution grid operators need to easily store, access, and manually inspect the data. The goal is to accumulate knowledge on their critical assets. However, current knowledge about assets and their history and peculiarities is only stored as master data in GIS or ERP systems, or as implicit knowledge of experienced technicians on the distribution grid. Thus, the third objective for our ensemble artifact to be designed is to build a knowledge base on assets of a distribution grid operator, including current and historical sensor data as well as transactional data of maintenance activities.

Our interviewed distribution grid operators further raised nonfunctional requirements, e.g., permanent system availability, data and process security, and reliability. These requirements are fulfilled by established SCADA systems [69] and do not contribute new design knowledge to our smart service system to be designed. One particular nonfunctional objective, however, stood out with every interviewed distribution grid operator complaining. Currently, information systems used by distribution grid operators seem to lack integration to other information systems, leading to redundant data sources and overlapping information. Therefore, the fourth objective our ensemble artifact aims to achieve is providing a singular data source and storage with an integrated suite of information systems and applications. The main benefits are lowered search and update times for gathering information.

V. DESIGN OF OUR ENSEMBLE ARTIFACT

Based on the objectives of a solution, we design and instantiate an ensemble artifact for enabling and managing predictive maintenance of assets on the distribution grid. We start with focusing on assets of the distribution grid that are smart products in our smart service system [19]. Specifically, we refer to switchgears as one essential class of asset, while our conceptualization is transferable to other assets including transformers and relays. We then describe the avenues for value cocreation that are enabled by the smart service system. From a technical perspective, we present the conceptualization and software prototype of a digital industrial platform that enables data flows and information management in the smart service system.

A. Smart Service System Design

Subsequently, we build on Beverungen et al. [19] to conceptualize our smart service system. The central actors involved in our smart service system are service consumers—i.e., distribution grid operators—and service providers—i.e., manufacturers of central assets of the distribution grid. In smart service systems, *smart products*—using sensors, connectivity, unique identifier, localization, data storage and processing capabilities, actuators, and interfaces—take the role of boundary objects that establish value cocreation among the actors [19]. In our case, these smart products are switchgears, but could also be other components that are digitally networked.

Different types of *sensors* can be used for condition monitoring, including temperature sensors for heat monitoring [72], electrical field (D-dot) sensors for partial discharge monitoring [73], and acceleration and vibration sensors for breaker drive monitoring in switchgears [6]. As data collected by sensors needs to be distributed in (near) real-time, switchgears require *connectivity* in the form of a central BUS system for aggregating the data and an internet connection to transfer the data to software applications for analyzing the asset's condition and predicting maintenance activities. For assets in the distribution grid, connectivity is the enabling technology to integrate condition data with external data (e.g., weather, pollution), especially since distribution grid assets are often stationed in remote locations [19].

Many information systems used by distribution grid operators already feature certain characteristics of switchgears as smart products. Master data records of switchgears often have *unique IDs* in ERP systems that enable enterprise asset management, for instance, as equipments or functional locations. Similarly, *locations* of switchgears (and other assets) inside substations are often stored in a GIS to visualize energy grids and navigate technicians during maintenance operations. Combining locations of assets with external information and knowledge can enable value cocreation further [74]. For instance, data on weather forecasts, animal populations, and (natural or man-made) pollution—all impacting the lifetime of switchgears—can only be meaningful if interpreted with switchgears' location data.

Although smart products should be offering their service "locally and autonomously, beyond the full control of a central system" [19, p. 10], we design switchgears to not incorporate *data storage and processing capabilities* locally. Instead, data will be send to an application system for storage and data processing, to enable condition monitoring and predictive maintenance on the level of the installed base. One reason for this decision is that switchgears often remain in operation for more than 40 years, whereas Moore's law predicts costs for storage and data processing to decrease at much greater pace. Further, external data can be integrated more efficiently and data analytics can be performed on the entire data repository when using a central system. The main *actuator* in a switchgear is its breaker drive for breaking electrical circuits. *Interfaces* enable a switchgear to interact with further assets in the distribution grid, mainly in the same substation.

The resulting smart service system is depicted in Fig. 2, contextualizing the broader smart service system conceptualization [19] for our application scenario. From a technical perspective, distribution grid operators deploy these assets into their physical distribution grids, i.e., electrical substations. From the perspective of value cocreation, the data gained from these devices is then used to inform value creating activities of customers [32]. More specifically, value is cocreated based on the four capabilities of smart, connected products [19], [75]: Monitoring, control, optimization, and autonomy. First, distribution grid operators are able to *monitor* the condition of their assets to derive insights about possible failures, risks, and reactive maintenance activities. This capability relates with condition monitoring as the first objective identified. Second, operators can *control* functions of the product and, thus, inspect functions–e.g., in the case of switchgears, distribution grid operators can break electric circuits remotely. Third, by analyzing assets' performance, distribution grid operators can *optimize* their use of these assets, while asset manufacturers can optimize the design of their assets based on hard field evidence. This capability aligns with our objective to implement predictive maintenance on the distribution grid. Fourth, *autonomy* might even be possible in future scenarios, enabling switchgears to react to state changes of nearby assets or the distribution grid. Still, this capability is yet to be conceptualized and implemented, as evidenced by our interviews.

B. Digital Industrial Platform Instantiation

To support our smart service system and to fully incorporate the objectives of our solution, there is a need for a central information system aggregating data and information flows [76]. In detail, our third objective captures that our ensemble artifact should enable building a knowledge base on assets of distribution grid operators, including current and historical sensor data, as well as transactional data of maintenance activities. However, switchgears are only one type of a distribution grid's central assets, with others being, e.g., transformers, relays, and cables. Additionally, our interviewed distribution grid operators stated that they apply different switchgear types and even switchgears of different manufacturers—which is highly likely due to switchgears lasting up to 40 years. Each type of switchgear produces different data, some types varying only in detail, but some systems requiring completely different machine learning models to analyze resulting data. Thus, specific information systems for single manufacturers or asset types would not satisfy the requirements for a holistic predictive maintenance solution on the distribution grid.

The concept of a digital industrial platform seems fruitful to enable different types of assets to be analyzed by their manufacturers using different data and machine learning algorithms. Digital industrial platforms usually act as "integration middleware" [20], [77], bridging industrial assets and

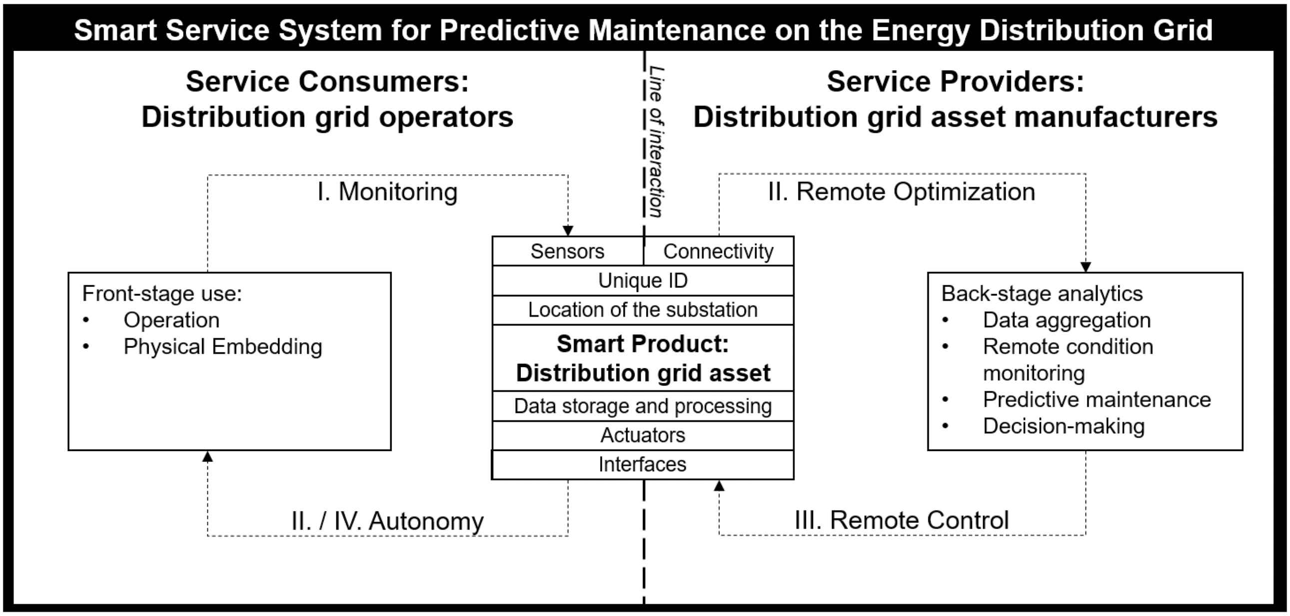

Fig. 2. Smart service system [19] for predictive maintenance on the energy distribution grid.

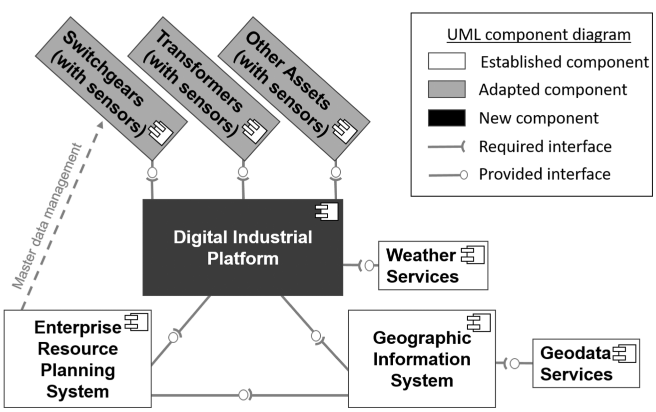

Fig. 3. UML component diagram of our digital industrial platform and related systems.

different applications [20], e.g., condition monitoring and predictive maintenance. As the central information system in our ensemble artifact, the digital industrial platform enables the presented smart service system by collecting, aggregating, and analyzing data of different assets and information systems. An overview of the digital industrial platform integrating with an ERP and GIS system of distribution grid operators, as well as with different assets, is outlined in Fig. 3 in an UML component diagram.

The device layer as the lowest platform layer in a digital industrial platform [20] will be taken by assets of the distribution grid and their sensors. Both sensors and assets are heterogeneous, fitting a central characteristic of a digital industrial platform [20]. The connectivity layer lies on top of the device layer and contains communication protocols, gateways, and connectivity technologies in the form of a BUS system to pass the generated data from the sensors to the digital industrial platform. The digital industrial platform itself works as the service layer [20]. It connects the platform to its ecosystem, comprising in our case manufacturers of assets and sensors, software developers providing algorithms and models to analyze the data, and distribution grid operators as customers. The application layer is embodied by our service for condition monitoring and predictive maintenance.

For demonstration purposes, we developed a prototype of our designed digital industrial platform for the distribution grid, named DigiGrid. DigiGrid was developed using Python, PyRFC for connecting SAP as an ERP system, and ArcGIS as its GIS. We further used Docker for server distribution and different communication protocols, i.e., REST and JSON. DigiGrid was developed in multiple iterations over 6 months and enables three roles of a distribution grid operator to apply condition monitoring and predictive maintenance: 1) control center agent; 2) distribution grid engineer; and 3) distribution grid planner.

The control center agent of a distribution grid operator supervises the status of assets and plans maintenance activities. DigiGrid enables control center agents to manage current service orders and error reports from its automatic data analysis and failure detection (cf. Fig. 4). Control center agents can also inspect details of a service order and its referenced asset (cf. Fig. 6). The main tasks distribution grid engineers have to fulfill are to maintain and repair assets. Preparing these tasks can be improved by having information about the current and historic condition of assets available, as DigiGrid provides (cf. Fig. 6). Distribution grid engineers can, e.g., show historic condition data, view prognosis data for an asset, and compare the historic data to other assets of the same type. The third role—distribution grid planner—needs the data available by both sensors and machine learning prognosis to plan and optimize the future distribution grid. Therefore, DigiGrid presents a dashboard of assets and statistical analyses of their performance (cf. Fig. 5). As visualization through maps enables an easier understanding of geographic relations, GIS maps are integrated into the condition monitoring and predictive maintenance views on DigiGrid (cf. Figs. 4 and 5).

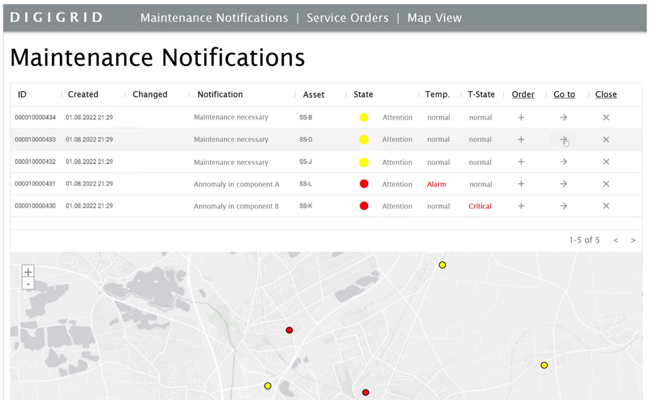

Fig. 4. DigiGrid: Overview for control center agents.

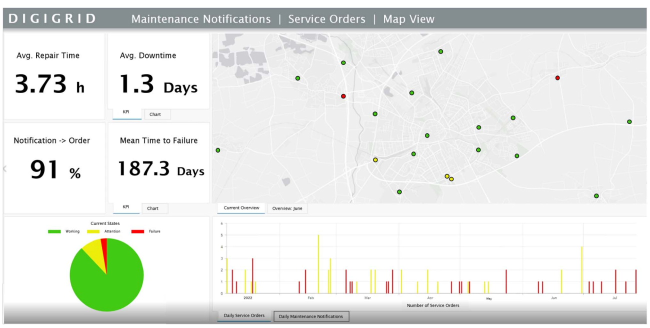

Fig. 5. DigiGrid: Dashboard for distribution grid planners.

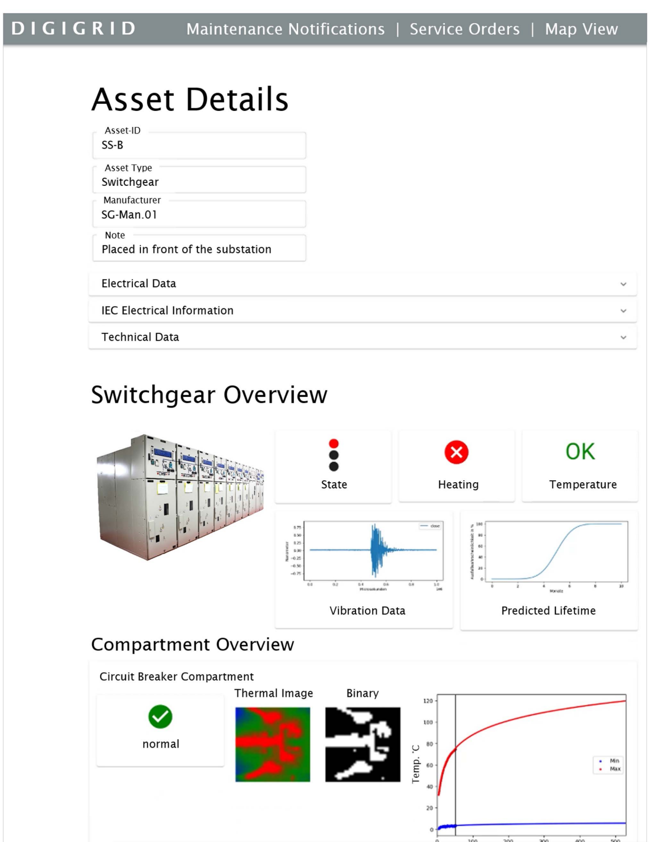

Fig. 6. DigiGrid: Details of switchgear data for multiple roles.

VI. Evaluation Through WTP Analysis

To evaluate our ensemble of the smart service system and the digital industrial platform, we decide to perform a choice-based conjoint analysis (CBCA). A conjoint analysis is based on a customer's evaluation of a product as a sum of its individual attributes [63], mainly used for consumer goods, but also for industrial goods [67]. Thus, customers are able to holistically view a product or service, rather than reduce it to its functions [78]. The CBCA allows customers to hide their real price imagination but show their preferences instead, making CBCA an indirect method [64], [79]. Also named discrete choice analysis [80], we applied a CBCA by conducting eight interviews with different distribution grid operators and using the tool Sawtooth Discover as recommended by Eggers et al. [68].

A. Design of the Stimuli

The first step to prepare the CBCA is to design the stimuli [68]. Here, different attributes of our service as well as different levels of these attributes need to be defined to be able to design different variations of the service in the next step. All attributes and their specific levels are summarized in Table II. We included three attributes based on three times intervals: 1) reporting (historical data); 2) condition monitoring (current data); and 3) forecasting of maintenance requirements (prognosis of future status). For each attribute, we defined the status quo as the level 0. For example, for forecasting, currently maintenance requirements cannot be predicted. Subsequently, we define further levels based on our service, delivering increasing value with each increment.[2] For instance, for prediction, level 1 describes a prognosis of the expected remaining service life per switchgear. The ultimate level for this attribute is a prognosis of the expected remaining service life per switchgear including the consideration of further predictions, e.g., load fluctuations and seasonal changes. In addition to the three attributes that are based on the use cases, we use availability of geodata, ERP automation, and price structure as further attributes. We take availability of geodata to get insights on the operators' WTP for GIS integration, whereas ERP automation aims at integration of ERP systems. Thus, we cover the two information systems classes used by all distribution grid operators. Having a price structure in a CBCA is necessary to determine the WTP [67], [79]. For price structure, we assumed a price increase of 5% per level, increasing up to a 20% increase of the usual asset price.

Next, we designed the choice situations. We included three offers and specified 16 rounds of choices for each participant (as recommended by our tool). For each offer, we combined different levels of all attributes. Our CBCA additionally includes a none-option, which means that the participants in each round can either choose one of the given offers or decide not to buy any of the offers—if they are not willing to accept any of the three given offers.

For a WTP analysis, it is recommended to include budget limitations [68]. Since grid assets are expensive goods and real

[2]The only exception of this increasing value with each increment is the attribute ERP automation. Levels 1, 2, and 3 display different possibilities of ERP automation, while level 4 combines all possibilities.

TABLE II
ATTRIBUTES AND LEVELS FOR THE WTP ANALYSIS

Attribute	Level 0	Level 1	Level 2	Level 3	Level 4
Reporting	No storage and analysis of historical data.	Storage of historical data, manual view and analysis.	Storage of historical data, manual view and standard reports (e.g., for investment decisions, failure statistics).	Storage of historical data, manual view and automated, customizable, and expandable analyses.	-
Condition monitoring	No provision of raw data of the current state.	Provision of sensor data of the current state.	Provision of sensor data and calculation of a "health state" in the form of a traffic light system.	Provision of sensor data and calculation of a "health state" in the form of a percentage value in 10 % intervals.	Provision of sensor data and calculation of a "health state" as accurately as possible, identification of causes of errors and anomalies.
Prediction	No prognosis of maintenance requirements.	Prognosis of expected remaining service life per asset.	Prognosis of expected remaining service life per asset, incl. consideration of further data (e.g., load fluctuations, seasonal changes).	-	-
Availability of geodata	No integration of geodata.	Geodata provided as coordinates.	Geodata and results provided in a separate GIS application.	Geodata and results integrated into existing GIS application.	-
ERP automation	No additional automation of ERP processes	Automatic material ordering (in case of defects and maintenance requirements).	Automatic service order management.	Automatic personnel planning for maintenance and in events of errors.	Automatic material ordering, automatic service order management, automatic personnel planning (best possible ERP integration).
Price structure	100 %	+5 %	+10 %	+15 %	+20 %

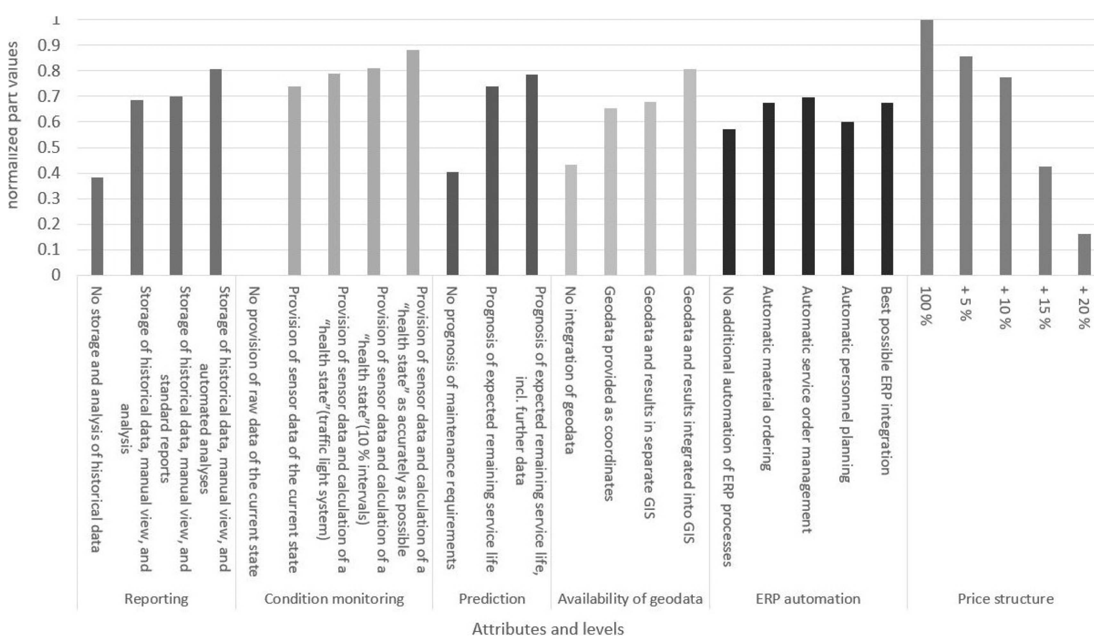

Fig. 7. Normalized part values for all attributes and levels.

budgets cannot be assessed easily, we ensured to invite at least one person with budget responsibility as an expert for the budget limitations within the company. In most interviews, we had multiple interviewees with different roles and knowledge.

B. Results of the WTP Analysis

To assess the WTP, we determined the attribute influence and performed a market share simulation. First, our results indicate that *condition monitoring* (26.3%) and *price structure* (25.0%) have the highest influence on a potential buying decision. In comparison, *ERP integration* (13.5%), *reporting* (12.6%), *prediction* (11.4%), and *availability of geodata* (11.3%) have a significantly lower influence. The normalized values (cf. Fig. 7) allow to make assumptions about the benefits of each level for each attribute compared to the other attributes. Noticeably, all attributes except for ERP integration and price structure have higher influence when increasing the service. For example, for the attribute condition monitoring, the status quo has a value of 0, while the provision of raw data and the calculation of a health

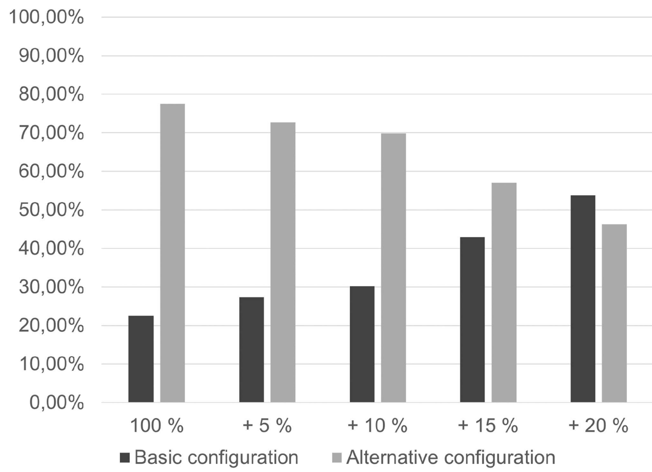

Fig. 8. Market share simulation for second level of condition monitoring.

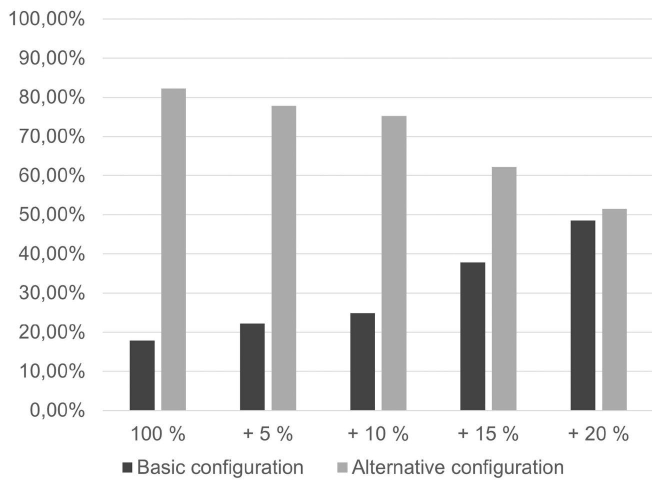

Fig. 9. Market share simulation for fifth level of condition monitoring.

state as accurate as possible has a normalized influence value of 0.9. This result indicates that this level has a high impact on the decision and, thus, on the WTP for the service. For the price structure, the values reveal a gap between 10% and 15%, showing that the price of the smart service should not exceed a price increase of 10% of the current asset price.

Second, we performed a market share simulation to make assumptions about the probability of different configurations of the service having a higher or lower market share than the current product configuration without the smart service. We determined a basic configuration, choosing level 0 for each attribute, i.e., the current status quo. Then, we compared different configurations of the levels against this basic configuration. Since the attributes condition monitoring and price structure have the highest influence on the buying decision, we created a new configuration by changing the levels of the attributes condition monitoring and price structure (Figs. 8 and 9).

The results of the simulations show that the market share decreases with an increasing price level in both configurations. For level 1, which includes a provision of raw data of the current state, the simulated market share value is 77.5% compared to the basic configuration, which has only a market share of 22.5%. The market share of level 1 configuration decreases with increasing price and after a 20% price increase, the basic configuration receives a higher market share. This indicates that the decisions to buy a product including the provision of condition monitoring raw data will be taken by most customers up to a price increase of 15%.

For the highest level of condition monitoring (provision of sensor data and calculation of a "health state" as accurately as possible), the market share value is 82.2%, compared to the basic configuration holding only a market share of 17.8%. The trend between level 1 and the highest possible condition monitoring configuration is similar from 0% to 15% price increase. However, when it comes to a price increase of more than 15%, the provision of raw data and the calculation of a "health state" as accurately as possible, including the identification of causes of errors and anomalies, still has a higher market share compared to the basic configuration. Thus, there is a higher WTP for a more advanced condition monitoring configuration even if the price is 20% higher than the current product price.

In most of the simulations, the biggest change of market share regarding the price is between 10% and 15% compared to the basic configuration. Thus, we found that there is a WTP for the predictive maintenance service that is to be provided with our smart service system.

VII. Discussion: Formalizing the Knowledge

We generalized the findings from our design project by abstracting our results to the level of design principles [25]. Design principles refer to implementer, aim, user, context, mechanism, and rationale [25]. For our design principles, the operator of the digital platform and the provider of the smart service are considered as *implementers*. We abstract the *context* to a holistic perspective on managing (predictive) maintenance of critical assets in a value-creation network. Therefore, our design knowledge is not limited to the energy distribution grid, but can also apply to similar contexts involving assets that require sophisticated maintenance strategies. The *users* of the design principles are asset manufacturers and asset operators–instantiated by distribution grid asset manufacturers and distribution grid operators in the design of our ensemble artifact. Table III summarizes the remaining attributes constituting our five design principles. We outline our learning from the design and evaluation of our ensemble artifact and the reason for each design principle as follows.

Multiple manufacturers of different assets that require maintenance could provide their own information systems to asset operators for managing assets [20]. However, digital platforms connect actor groups for mutual benefit [46], [56]. Thus, a digital platform can enable both sides of the market—including asset manufacturers and asset operators—to cocreate value for mutual benefit [46], [56], as framed in DP1. Asset operators can use a single system for access and insights into their assets to enable predictive maintenance. Asset manufacturers can gather data on the application and usage of their assets. Thus, implementing a digital industrial platform [20] enables indirect network effects [46], [50], i.e., manufacturers being attracted by a high

TABLE III
DESIGN PRINCIPLES RESULTING FROM OUR DESIGN AND EVALUATION

No.	DP and aim	Mechanisms	Rationale
1	Establish a digital platform to enable both sides of the market to co-create value within a value-creation network for mutual benefit.	- asset operator: central information system for access and insights into asset data and states - asset manufacturer: gather data on the usage of assets at multiple operators - indirect network effects fostering the intention to use the platform	- objectives knowledge management and system integration - integrate data of different sources for predictive maintenance systems [42] - distribution grid operators are willing to pay for such a platform (WTP) - avoid individual systems for every asset manufacturer [20] - connect actors through smart products in smart service systems [81] - indirect network effects [46], [50]
2	Model business relationships in a smart service systems to enable actor groups to interact via assets as smart products.	- asset operator: monitor condition of assets and insights on prediction - asset manufacturer: remote optimization through asset usage at multiple operators	- smart service system serves as a useful framework for value co-creation [81] - integration of IT and business perspective - distribution grid operators are willing to pay more for such a service (WTP) - current research on predictive maintenance is not considering business value
3	Provide historical data (reporting), current data (condition monitoring), and predictions on the future status of assets to enable predictive maintenance and resilient asset management for asset operators and insights about product applications for asset manufacturers.	- store, process, and visualize historical asset data - apply condition monitoring to monitor the current status of assets permanently - predict necessary maintenance activities based on historical data and condition data (machine learning models)	- objectives condition monitoring and predictive maintenance - predictive maintenance requires historical and real-time data [42] - present possible outcomes to derive decisions about upcoming maintenance activities [42] - differentiation of condition-based predictive maintenance (real-time data) and statistical-based predictive maintenance (historical data) [82] - condition monitoring and the price are the most important attributes (WTP) - condition monitoring will be accepted on the market even ta low levels (WTP) - level 1 is the most important for reporting, condition monitoring, and prediction (WTP)
4	Integrate multiple systems and data types to allow for smoothly transitioning processes of asset operators.	- integrate ERP systems (for master and transaction data), GIS external geodata services (if assets are wide-spread, even for immovable objects), machine learning models and techniques for prediction of maintenance activities - integrate sensor data from assets, master and transaction data (from ERP systems), location information (for presentation and visualization), and relevant external data (e.g., weather)	- objectives of knowledge management and system integration - include all task-relevant data for maintenance [42] - include means to enable users to understand the current business situations [42] - ERP integration and geodata were relevant attributes (WTP) - integration of location information is key (WTP)
5	Present the data in different degrees of complexity to enable multiple user groups of asset operators to derive valuable implications for operation and planning of assets.	- present a dashboard as a high-level overview of the state of different assets (if assets are wide-spread, use GIS) - enable to access the raw data for specific analyses in detail views	- include all task-relevant data in predictive maintenance artifact [42] - provide means to enable the user to understand the current business situations [42] - allow users to derive decisions about upcoming maintenance activities [42] - condition monitoring will be accepted even at low levels, thus, accessing the data is important (WTP) - level 1 is the most important for prediction, reporting, and condition monitoring (WTP)

number of asset operators and vice versa. The need for a digital platform is also shown in our objectives, as asset operators seek integrated solutions that enable knowledge management. Further, Nadj et al. [42] emphasized that data from different sources has to be integrated in predictive maintenance systems, i.e., contributed by different asset manufacturers to a digital platform. Also, digital industrial platforms allow for connecting multiple stakeholders in a value-creation network [20] and our WTP also shows that asset operators are generally willing to pay a price premium for joining a digital platform.

In contrast to recent research on IT artifacts for predictive maintenance [41], [42], [82], our research focuses on management and value cocreation across companies for predictive maintenance. We conceptualized our smart service system by building on the well-known framework of Beverungen et al. [19]. Thus, DP2 encompasses modeling a smart service system to enable different actors to interact based on deploying their assets as smart products as boundary objects that constitute a smart service system. Asset operators can then monitor their assets' conditions, while asset manufacturers can remotely optimize their assets based on field evidence on how their assets are used by multiple operators. The WTP confirmed that asset operators are willing to pay a price premium for this service, thus, we can infer that they intend to cocreate value in a smart service system.

DP3 refers to the distinction of three time intervals. Maintenance on asset-intense industries should be supported by historical data (reporting), current data (condition monitoring), and predictions on the future status of assets (predictive maintenance). This distinction is already reflected in the literature [42], [82] and serves as a key characteristic for predictive maintenance. Our WTP underlines the need for basic reporting, condition monitoring, and predictive maintenance functionality, as the first level of all three attributes providing basic functionality had the highest increase in normalized part values (cf. Fig. 7). Asset operators, however, do not seem to be willing to pay much more for higher service levels, indicating that they need the basic functionality to be implemented first.

DP4 refers to the need to integrate different application systems and data types. In our prestudy to determine the objectives of our ensemble artifacts, asset operators already emphasized the integration of multiple systems. Asset operators use ERP systems for master and transaction data management, GIS, and external geodata systems for distributed infrastructures—even if they have a static location, such as switchgears—and machine learning models and other analytical information systems to analyze and interpret historical and current device data. As for the data types, different assets generate a variety of data, e.g., sensor data, transaction data from ERP systems, location information, and other external data. Integrating information to enable users to understand current and future business situations was also considered by Nadj et al. [42] as a design principle for predictive maintenance. Although the integration of geodata and ERP automation were not among the most important attributes in our WTP analysis, they still account for roughly 12% of the price. Thus, integrating different data and different systems was important for our informants and influenced their purchase decisions.

Integrating multiple data types (DP4) for different time periods (DP3) results in a vast amount of task-relevant data available [42]. Thus, DP5 argues that data has to be presented in different degrees of complexity to enable user groups to derive valuable implications for operating and maintaining assets. Asset operators need a dashboard as a high-level overview of their assets that is best displayed on an integrated map based on GIS functionalities. For specific analyses, raw data has to be available in more detailed views that refer to individual devices. Our WTP analysis emphasizes the need for both raw data and high-level dashboards, as level 1 is the most important for the three attributes related to the time intervals, i.e., showing that raw data is needed.

VIII. Conclusion

This article presented a design study for a combined smart service system and a digital industrial platform to enable predictive maintenance for critical assets on the distribution grid. Through a WTP evaluation, we were able to test the prototype and extract feedback in terms of monetary promising services and characteristics. Finally, we derived five design principles for predictive maintenance that are not specific to the energy distribution grid, but can also be applied to other contexts. Thus, we contribute both theoretical and managerial knowledge to the domain of technology and engineering management.

For theoretical contributions, first, we provide five design principles that bundle the derived knowledge for predictive maintenance of critical assets in a smart service system. Second, we combine multiple streams of literature for new insights, i.e., service science [18] and predictive maintenance (as done in different engineering domains, e.g., [13], [14], [15], and [16]), by bundling a smart service system with a digital industrial platform. Thus, we are able to extend the understanding of predictive maintenance from a rather technical perspective to an integrated perspective, covering multiple disciplines to allow for the fruitful application of predictive maintenance [17]. This theoretical knowledge answers recent calls for the design of revenue models and service systems for maintenance on the distribution grid [6] and the design of digital industrial platforms [20], [83]. Third, from a methodological perspective, we introduce the idea to use a WTP analysis as a means for assessing the managerial value of an IT artifact. In our case, this evaluation enables managerial decisions based on the (technical) design of a predictive maintenance information systems architecture.

For managerial contributions, we provide practitioners with an example how to design, instantiate, operate, and manage a predictive maintenance artifact on the energy distribution grid. The design principles enable to transfer the insights, while the instantiation itself is most helpful for practitioners from the energy domain. Especially, managers and engineers of switchgears can make their products "smart" and expect customers to be willing to spend 10% to 15% more on them, as the WTP results show.

Still, we acknowledge that more research is required to establish a full business model for predictive maintenance on the distribution grid. First, the question of which actor of the value-creation network should take the role of the platform owner and platform provider has remained unanswered. Platform owners manage the core of a digital platform, whereas platform providers control the infrastructure of a digital platform [84]. If an asset manufacturer sets out to implement a digital industrial platform, they would have the benefit of setting higher entry barriers for competitors, but face difficulties of other asset manufacturers joining the platform. Thus, other actors than the asset manufacturers and asset operators might take the role of a platform owner. Further research needs to elicit different scenarios to propose suitable governance scenarios. Second, we see a need to evaluate the ensemble artifact's benefits in a natural evaluation that goes beyond performing an ex ante WTP analysis. Related research has investigated multiple strategies to launch digital platforms in ways that overcome cold-start problems [85]. Considering the distinct assets for industries, e.g., the distribution grid, focusing these efforts on a single domain could be useful, combined with single target groups [85].

Methodological limitations of our study mainly refer to the evaluation using a WTP analysis. First, we did not include actors outside of the immediate value-creation network, e.g., experts of price structures of MV assets, and did not expand our survey to an international setting. While only eight distribution grid operators participated in our WTP analysis, the results indicate that saturation was reached, since the last interviews did not provide any additional insights. Second, an evaluation of our smart service system in form of an implementation of a digital industrial platform for predictive maintenance in the context of an existing value-creation network has still to be done, especially with a focus on the artifact's perceived usefulness and perceived ease of use [66]. For this purpose, we propose conducting multiple evaluation cycles following our WTP analysis [86]. Third, we did not integrate real prices in the survey, but referred to percentage values instead. This decision was made to protect data confidentiality interests of our corporate partners. Still, performing the WTP analysis remained a sensitive issue and we acknowledge that not referring to a realistic asset price might have weakened the participants' willingness to disclose realistic data themselves.

We call on future research and managerial activities to implement smart service systems and digital industrial platforms to evaluate the proposed ensemble artifact in a natural context. A natural evaluation can shed light on the artifact's perceived usefulness and perceived ease of use [66] as well as on other business figures, including WTP, return on investment, and total cost of service. Beyond carrying on this work, we posit that introducing and evaluating the artifact in other contexts can serve to triangulate and extend our design principles. We see continuous work on these topics as a crucial contribution our discipline has to offer towards successful climate action.

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