Towards Predictive Maintenance as a Service in the Smart Housing Industry

Maximilian Lowin[1] and Cristina Mihale-Wilson[2]

Abstract: Maintenance is a significant cost driver in many industries with tangible assets. Aiming to predict damages before they occur, this paper focuses on predictive maintenance (PdM) for smart buildings and apartments – a multi-billion-dollar market with substantial cost savings potential. Based on stakeholder groups' heterogeneity within the smart housing industry, PdM cannot be a one-fits-all solution. To be effective, practitioners can enrich PdM with Artificial Intelligence (AI). However, to match very heterogeneous environments and the various needs of the stakeholders, PdM must be modular and flexible. Motivated by the challenges and peculiarities for implementing Predictive Maintenance as a Service (PdMaaS) in the smart housing industry, we provide a concept to support managers to overview and optimize complex PdM needs in complex and heterogeneous environments.

Keywords: smart services, predictive maintenance, smart housing industry, visualization.

1 Motivation

Maintenance is a significant cost driver in almost all industries with tangible assets [WY07]. Ineffective maintenance in industrial settings represents a yearly loss of more than $60 billion [Mo02]. Such losses occur because traditional maintenance methods such as **run-to-failure** management and **preventive maintenance** are not optimal. In the case of **run-to-failure** management, for instance, machines only get maintained if they break. Run-to-failure results in low machine availability due to long downtimes until artisans correct machine failures and higher overtime labor costs [Mo02]. On the contrary, in the case of **preventive maintenance**, a machine gets maintained on a time-driven schedule, e.g., based on elapsed time or hours of operation. Such time-driven approaches in maintenance face two significant problems: First, companies replace parts that are not yet broken and would have lasted longer. As a result, preventive maintenance creates regular but sometimes unnecessary repairs. Second, parts may break before their scheduled maintenance. In this case, preventive maintenance generates a similar cost as run-to-failure approaches. Flexible and intelligent forward-looking maintenance promises enormous potential savings. Hence, scholars and practitioners are continually seeking to develop more efficient forms of maintenance. One promising concept is **Predictive Maintenance**

[1] Goethe University Frankfurt, Professur für Wirtschaftsinformatik und Informationsmanagement, Theodor-W.-Adorno-Platz 4, 60629 Frankfurt am Main, lowin@wiwi.uni-frankfurt.de
[2] Goethe University Frankfurt, Professur für Wirtschaftsinformatik und Informationsmanagement, Theodor-W.-Adorno-Platz 4, 60629 Frankfurt am Main, mihale-wilson@wiwi.uni-frankfurt.de

(PdM). PdM concept aims at monitoring the physical conditions of specific objects like manufacturing plants or devices to predict failures in advance using statistical methodologies and Artificial Intelligence (AI). This form of maintenance is particularly cost-effective. However, PdM also requires a high degree of digitalization of the environment that needs high domain-specific expertise and knowledge on leveraging AI techniques in various contexts. After all, many PdM methods originate in industrial settings (e.g., manufacturing facilities and for smaller industrial parts like bearings, engines, electrical motors [So12, WY07], or aviation [Al14]), which are highly digitalized and complex domains.

Interestingly, although repair and maintenance work alone accounts for one-third of the construction sector's output [AO20], and damages in appliances can substantially impact other infrastructure (as in the case of leakages), implementations of PdM for smart buildings and apartments remain challenging to achieve and are very rare. One potential reason, therefore, is the heterogeneity of infrastructure in smart buildings and apartments. Another major obstacle in transferring existing PdM approaches from industrial contexts to smart living areas is that PdM requires a high degree of domain knowledge and appropriate AI knowledge. Building on a systematic approach for PdM service design combined with various expert workshops, this work seeks to support practitioners in the smart housing industry (SHI) by providing a blueprint for realizing PdM for smart buildings and apartments. Our blueprint entails a proposition for a service solution and a decision support monitoring tool. It caters to the heterogeneity and complexity of smart living environments and proposes a **PdM as a Service solution**. After all, due to its stakeholders' group heterogeneity (i.e., building and apartment owners, managing companies, tenants, third party service companies) and their different needs within this context, PdM cannot be a one-fits-all solution. Instead, in the SHI context, PdM requires modularity and flexibility to match the various needs of the housing sector stakeholders.

Formally, this paper is structured as follows: Section two provides a brief overview of PdM in the service and SHI context. Section three presents the key insights from the systematic PdM service approach applied to the SHI – i.e., the challenges, objectives, and potential solutions. Finally, the last chapter summarizes the key insights of this work and gives an outlook for future work.

2 Theoretical Background and Research Setting

Motivated by the current shift in consumer consumption away from products towards solution-based services [Li06], this work posits that successful PdM in the SHI must follow a service approach. Services allow that individuals enjoy benefits through a temporary possession rather than ownership per se [LG04]. Moreover, individuals can book services to get work done for them, e.g., by outsourcing work to machines [Go99].

2.1 Product Service Systems

The concept of Product Service Systems (PSS) brings services and products together [Go99]. By definition, a PSS refers to a set of products and services that jointly fulfill users' needs. Furthermore, because PSS extends manufacturers' responsibility to the use phase until the end of product life [Zh12], it can achieve a range of benefits such as greater diversity of choices for customers, (mass) customization, additional value, and higher product quality [Mo02b]. Based on the benefits it provides, several scholars adapted and refined the PSS concept in various industries, e.g., aviation [Zh12], automotive industry [Wi06], or manufacturing [CBL06].

Notably, [CBL06] distinguish between product-orientated PSS, use-orientated PSS, and result-orientated PSS. **A product-orientated PSS** is characterized by the ownership of a material artifact being transferred to the buyer. An application of the PSS concept is product maintenance [CBL06, Wi06, Zh12]. As a product-orientated PSS, PdM can be an inherent service function of the product itself. Thus, PdM can support existing warranty and maintenance contracts and minimize costs [Le09]. An example would be house owners buying a boiler, including a PdM service that automatically notifies them if something is abnormal. In contrast, **a use-orientated PSS** is characterized by transferring only the rights of use to the customer, while the material artifact's ownership remains with the service provider [CBL06]. For instance, house owners rent a PdM solution for their existing boiler. This solution includes sensor hardware belonging to the services provided. The house owners only use the PdM services, which include the sensors for the time of the service contract. Besides, in the case of **result-orientated PSS**, a customer purchases the utility and not the use of a product. Following our example, the house owner would purchase a service for warm water without taking care of the respective infrastructure and maintenance solution.

To date, there is a trend towards smart PSS, as they combine smart digital technologies with physical, tangible products, intangible services, and business models of PSS [CHP18]. Digital technologies such as IoT, Cloud Computing, and Analytics enable the required input for PSS and their information management capabilities [Ar16]. In addition, modular smart PSS solutions can foster remote monitoring and forecast possible failures and maintenance needs because of PdM services' high degree of automation [CHP18].

To date, the literature on PdM applications in the industry is extensive [Al14, So12, We11, WY07]. However, scholarly work on PdM-related services is scarce. One notable scholarly effort on PdM-related services is the work of Lee and colleagues [Le09]. In their work, [Le09] present a methodology for PdM service design. Although Lee and colleagues' approach is a product-oriented PSS, we can also transfer it to other PSS types. Their approach for PdM service design [Le09] envisions eight steps that build our work's basic framework.

2.2 Systematic Approach for PdM Service Design

We follow [Le09] systematic approach for PdM service design and implement Predictive Maintenance as a Service (PdMaaS) in SHI. [Le09] structured PdM service design in eight steps: problem formulation; abstraction level and performance metrics identification; prognostic method selection; measurement selection and sensor strategy; monitoring strategy evaluation; experimental design planning; solution feasibility/selection; cost-benefit analysis (see Fig. 1).

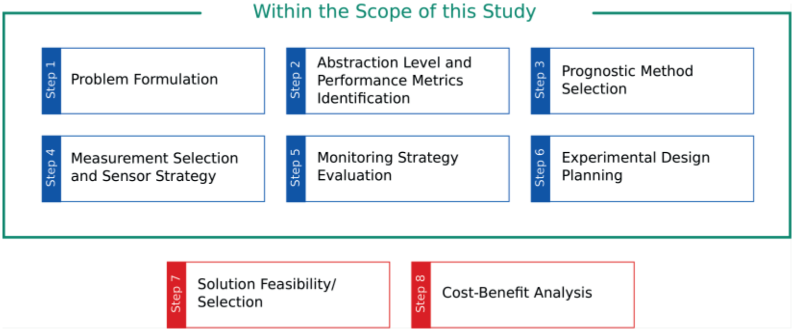

Fig. 1. Research methodology of our PdMaaS concept following [Le09].

Problem formulation represents one of the most crucial steps within this method. As the authors concede, successful PdM design requires that consumers' and companies' service needs are identified and translated into precise maintenance requirements. Accordingly, the problem formulation step intends to articulate companies' or consumers' service needs at its core. Such service needs can include service uptime needs; service to failure prevention; service for system streamlining; service for productivity improvement; service for information management; and closed-loop life cycle product management [Le09].

Notably, consumers' and companies' service needs are unique to companies' assets and products. Against the background that successful PdMaaS must closely mimic the industry's idiosyncrasies and companies' assets and products [Le09], we conduct our research in the context of an ongoing SHI research project (please see next section – Research Setting). At this point, we adopt Lee and colleagues' methodology because it is tailored specifically for the PdM setting. This way, we strive to address everything needed for PdM service design. We omit the last two steps of the systematic approach to leave it open for further discussions (e.g., within the MOC workshop) and future research and concentrate on a practice motivated PdM concept prototype. Within the next methodological step, we propose a proper experimental design and suitable prototypical artifact.

We carried out this work as part of a research project sponsored by the German government. Below we explain the goal, structure, and stakeholders in the research project ForeSight.

2.3 Research Setting

The research project ForeSight aims to develop and establish an Artificial Intelligence (AI)-based service platform for smart living [Ba19]. Within ForeSight, PdM is a central element for the smooth, optimal, and sustainable realization of Smart Living. The project's team entails experts from original equipment manufacturers (OEM) (for both smart and traditional products), smart home solution providers, research entities, and housing companies. We harness organizations' diversity within the project and their specific domain knowledge to conduct various workshops that help us articulate an SHI-specific PdM service design. Based on the input, we develop ideas on how PdM could look like and identify challenges and solutions for implementing the envisioned PdM for SHI. We invited 12 experts from various industries to participate in our workshops: Five participants work for housing companies that own and rent out a large number of "traditional" and smart apartments in the German housing market. Seven participants were domain experts working for smart housing solution providers or OEM vendors for smart home goods and devices. We designed and organized the workshops based on a modified version of the nominal group technique (NGT) to ensure timely and valuable results.

The NGT is a robust methodology for idea generation and prioritization and addresses the necessity of stakeholder involvement in a very early stage of the project [DVG75]. The topics of the four workshops were (1) identification of service needs for PdM in SHI, (2) objectives for a solution, (3) a smart service marketplace design for PdMaaS, and (4) the testing of our artifact. By combining ideas of the Improved Nominal Group Technique (INGT) proposed by [Fo89], we ensure proper preparation of all participants before the meetings. This preparation took place in the form of a short briefing on the workshops' topic several weeks before the workshops. Although we performed the workshops online, the NGT methodology ensures proper workshops and meaningful results [La07].

3 Predictive Maintenance as a Service in SHI

3.1 Problem Formulation

The first workshop's goal was to identify smart housing environments' service needs and formulate problems occurring when transferring a PdM solution to the SHI. We define smart houses as complex PSS systems of a plethora of interconnected sensors, actuators, hardware devices, and Artificial Intelligence (AI)-enabled software components. Our results reveal that **failure prevention, system streamlining, productivity improvement, and information management** stand out to be the most pressing SHI-related maintenance needs. While failure prevention adheres to the companies' needs to ensure that the complex systems of smart housing do not fail and thus bring the entire system down, system streamlining refers to companies' goal to prolong the functional life of components by continuously and intelligently monitoring and maintaining them. Similarly, service for productivity improvement relates to companies' goal of improving their productivity through continuous operation readiness. In this context, companies strive to achieve reduced energy consumption and enhanced safety. Finally, companies' service for information management relates to maintaining operational readiness and requires optimal information flows for the stakeholders involved. Therefore, we will primarily focus on the information management in our prototype design to properly manage our AI-based service solution.

Out of these service needs, particular problems occur in the SHI context. SHI products and goods are often mass-produced and lack the option of customization. White goods such as washing machines or ovens rarely include PdM solutions. Other facilities such as elevators or HVAC systems that offer PdM do so in proprietary (silo) solutions that are product-related and lack interoperability. This way, current PdM solutions do not harness the plethora of information that (interconnected) sensors, actuators, hard- and software components can provide. The segregation of PdM solutions for single products or product solutions is surprising. After all, PdM in industries such as manufacturing and aviation reveals, there is much to be gained from combining data from various sources (e.g., sensors, hard- and software components) to improve the availability of machines, the cost of maintenance, productivity, and machine profitability [Mo02].

Regarding the predictive power of PdM, experts also agree that rich data from various sources is central for reliably detecting anomalies and thus predicting failures. Given that SHI is an emergent market, we focus on its peculiarities regarding the data measurement selection and sensor strategy in detail in a later section.

3.2 Abstraction Level and Performance Metrics Identification

Contrasting the challenges mentioned above in SHI (i.e., no PdM for certain goods, the existence of proprietary silo PdM solutions, and the heterogeneity of the SHI stakeholders) to the SHI service needs (i.e., failure prevention, system streamlining, productivity improvement, and information management), the workshop participants agree that efficient PdM in SHI should be overarching, intelligent and flexible.

In the industrial context, the basic idea of PdM is to determine the actual mean-time-to-failure of machines and other complex systems. Therefore, several aspects like the availability of machines, the cost of maintenance, the quality, productivity, and the machines' profitability can be optimized [Mo02]. For PdM in the industrial setting, modern methods use the information given by a system to determine the system's condition and predict when maintenance should be performed [Al14].

However, there are no clear, distinct aims for PdM in the SHI as in the producing industry, for example. Due to the sheer amount and heterogeneity of stakeholder groups involved, each stakeholder assesses the PdM performance differently and often displays competing interests. In this respect, PdM in SHI must serve the housing owners, the managing companies, the tenants, and third-party service companies. Performance metrics must incorporate both efficiency (e.g., accuracy) and effectiveness, but also additional evaluation metrics like tenants' satisfaction with the solution, their perceived intrusiveness due to the digitalization, trust in the system, and the control of respective conditions and countermeasures. Thus, PdM in SHI requires modularity and flexibility to match the various needs of the housing sector's stakeholders. Ultimately, in the SHI context, getting the correct information at the right time to the right person is as crucial for PdM in SHI as identifying service needs at the optimal point in time.

3.3 Prognostic Method Selection

To be able to predict potential failures, PdM relies on detecting outliers in data sets. To this end, PdM commonly uses methods such as clustering or anomaly detection algorithms. In general, outliers can be errors or events. Errors are noisy data that may originate from a faulty sensor. Events refer to a change of a consistent state of the real world (Nesa et al., 2018). Outliers can be an extreme sensor reading, for instance, and such algorithms often work independently of the type of sensor. In this sense, the higher the amount of historical and real-time data and the higher accuracy of such outlier detection algorithms, the better the predictions of PdM routines. The presence of labeled data – i.e., on data that document failure events – improves the predictions' accuracy and interpretability. Due to the high availability of labeled historical data in the manufacturing setting, anomaly detection and failure prediction use mainly supervised machine learning techniques (SL) which learn from labels of failures (e.g., time series anomaly detection algorithms using neural networks like RNNs or LSTMs). In contrast to the manufacturing setting, the smart housing sector is a relatively young emergent market in which smart sensors and devices have relatively short life cycles (often not more than five years). Accordingly, historical data is almost inexistent.

Similarly, smart houses typically do not register anomalies. Thus, they do not produce labeled data, so the implementation of anomaly detection based on supervised learning is not feasible. A potential solution for the missing historical and labeled data is to use domain knowledge to verify whether the data at hand are non-anomalous or anomalous and use semi-supervised learning (SSL) instead of supervised learning. For SSL, not all data used to train algorithms needs to be labeled. Instead, SSL requires just a few labels that were made manually by domain experts. Potential algorithms include LSTM Autoencoders.

Another essential difference between the industrial and SHI setting is the environment and context in which PdM methods operate. For manufacturing sites, processes are usually standardized and follow a predefined schedule. In the residential context, there is no preschedule for activities. For instance, in SHI, different residents are using the laundry room and are washing their laundry at different times by using various washing cycles with different lengths. A PdM solution in the SHI must be aware of this status and must be able to recognize current situations and contexts as additional information besides the pure sensor measurements. Furthermore, PdM methods must operate on contextual data.

In this sense, anomaly detection algorithms need to monitor the data and the context itself. A contextual anomaly occurs, for instance, if users change their behavior. Imagine, for example, that residents of a specific apartment always turn on the ceiling lamp when they come home from work. If they suddenly stop turning on the ceiling lamp but turn on another lamp instead, PdM might erroneously label the ceiling lamp as a defect.

3.4 Measurement Selection and Sensor Strategy

The quality of anomaly detections and predictions about failure depends on the amount of data available. In general, the more data PdM systems can access, the more accurate its predictions are. Again, PdM in SHI hinges on several challenges unique to the smart housing context. One challenge is that the SHI often does not have the database necessary to conduct such predictions. SHI does not possess sensor densities as high as manufacturing and digitalization are scarce. Also, SHI does not always allow for retrofitting activities. While sensors can be retrofitted and attached closely meshed almost everywhere in a manufacturing plant in the industrial setting, new sensors in buildings and apartments can easily interfere with the tenants' aesthetics and living comfort. Besides esthetic reasons, the SHI does not allow retrofitting specific sensors and devices after completing a house's construction process. For instance, one can retrofit a leakage sensor to a production machine, but one cannot install it in a house where the walls and piping have already been built.

Another critical challenge is that in SHI, infrastructural objects or appliances are often black box solutions, and users rely on functionalities offered by the appliance manufacturers. Plants and machines are often customized to the factory's special needs or production line in the manufacturing context. Thus, factories can also require to receive the information needed to pursue PdM activities. However, in SHI, the hardware is typically not customizable. Washing machines, for instance, are white goods and cannot be modified easily. Therefore, information and data created by sensory in the washing machines cannot be accessed nor processed quickly for PdM.

Thus, one must use alternative data sources and AI-based PdM technologies to solve these challenges and to digitalize the SHI. For example, one can monitor refrigerators by analyzing the temperature or electricity flow [Ku18]. However, in SHI, adding those sensors to non-smart devices is cumbersome and expensive. A more straightforward solution would be to make use of so-called smart plugs that measure energy consumption. While in some use cases adding smart plugs can work well, this strategy is not appropriate for large energy consumers or appliances. Since smart plugs are often limited to standard socket sizes and a maximum power of around 4,000W, standard smart plugs do not work combined with three-phase current devices. In such cases, PdM could exploit aggregated energy consumption data provided by smart meters. After all, more and more residential buildings are installing smart meters that can capture energy and water consumption.

Smart meter disaggregation helps to break down the accumulated consumption data by using AI. Koutitas and Tassiulas [KT15] define smart meter disaggregation as a 'methodology for recognizing individual appliance signal signatures from aggregated circuit readings' (p. 1665). In other words, by using disaggregation methods, the energy consumption of specific devices within a building can be extracted from the total consumption. The same applies to the disaggregation of smart water meters. [CS13] use disaggregation to understand water consumption profiles for various activities (e.g., showers) and appliances (e.g., dishwashers or washing machines). If the disaggregation is approximately accurate, one can use the data to monitor specific devices and their consumption without needing to attach sensors in or next to the device. Thus, using disaggregation saves costs [KT15], is non-intrusive, and is generalizable to multiple households [Ko16].

Another helpful approach to generating a comprehensive data basis is substituting sensors. Combining several installed sensors can approximate another particular sensor's value. The sensors used to approximate one particular sensor's value can be either the same or a different type of sensor. For example, temperature sensors can approximate other temperature sensors in the same and adjacent room. Similarly, activity and motion detection, usually done by one individual infrared (IR) sensor, can be monitored by following activities in the context and actuators of other devices and furnishings. For example, without an IR sensor, an algorithm can deduce activity and motion from actuators in light switches, a refrigerator door, or a window panel.

3.5 Monitoring Strategy

AI-based PdM services are an excellent opportunity to optimize the sustainability of smart homes. However, without integrating decision support and control systems, this information is only helpful for theory and technicians. Decision-makers need to monitor and assess the failures and maintenance works' impact and urgency. Hence, monitoring several different residential complexes and infrastructural objects associated with them requires dedicated monitoring solutions. Without a suitable visualization interface, it is almost impossible to keep track of AI-based computations on a wide array of different devices, apartments, and residential complexes. Additionally, in case of failures, one can take appropriate action by just notifying responsible persons for various events occurring within a complex and unstructured way.

Current software solutions like building management systems (BMS) or computer-aided facility management (CAFM) solutions often lack predictive features. To date, there is – according to our best knowledge – no suitable non-proprietary solution on the market. Solution providers of existing BMS and CAFM software could add a programmable interface to their software to integrate predictive features through external services. A critical drawback in doing so, however, is that integrating external information to existing software is cumbersome and adds more complexity to already very complex systems. Furthermore, it might not be possible to track and explain why an event occurs accurately.

Thus, instead of patching up legacy visualization products, it would be more suitable to implement a dedicated modular visualization dashboard that displays specific predictive and non-predictive events and physical conditions of the various entities and objects in a smart building. Such a decision tool would also display proper explanations of events – an increasingly important topic for AI. Also, a dedicated modular visualization dashboard can better address the needs of multiple stakeholders. After all, tenants, landlords, property managers, and external service providers such as artisans, water suppliers, or delivery services have different informational needs. Besides the pure visualization of events, a dedicated modular dashboard can also link to a marketplace, where stakeholders can also book and manage PdM services that best fit their needs in those use cases most relevant to them.

3.6 Prototypical Design for the Visualization of PdM

In this work, we limit ourselves to propose an artifact for the visualization of PdM. We do so since this artifact is of particular importance for decision-makers as an input for an AI-based management and process optimization. Additionally, the implementation of the monitoring tool is independent of the concrete anomaly detection and the preceding data generation process. A smart service marketplace offers different services that perform several PdM tasks in the smart housing context. A smart service can be, for instance, the monitoring of water pipes by using pre-installed hardware or PdM solutions for kitchen appliances. Such a marketplace is a multisided market, where different providers can offer their solution to a customer. Such a solution can be a PSS or product-independent service. Additionally, provided PSS solutions can be product-, use-, and result-based. Therefore, a possible provider can be an appliances manufacturer or a PdM software specialist, for example. Customers can be tenants, property and facility managers, or infrastructure providers. To ensure the required PdMaaS modularity, customers can choose smart services according to their preferences. Furthermore, the smart service marketplace is also a suitable platform for managing and monitoring such smart services. It should display and forecast the health status of an infrastructural object in the form of a central dashboard.

The dashboard's primary goal is to display the most critical or most common events regarding infrastructural objects' physical conditions while avoiding information overload. In addition, modularity and abstraction of various detail levels ensure a customizable solution to meet further information needs.

Based on a third workshop with the stakeholders of the ForeSight project, we prepared a design proposal for a monitoring tool (i.e., PdM dashboard) and a smart service marketplace. Finally, within a fourth expert workshop, the initial prototypical design was discussed and improved. Herein, we present the results from the fourth expert workshop. The experts in the workshop agreed that due to the multitude of stakeholders involved, the initial design of the core PdM dashboard should focus on three main stakeholder groups and their specific (informational) needs: landlords and property managers, tenants, and third-party technicians.

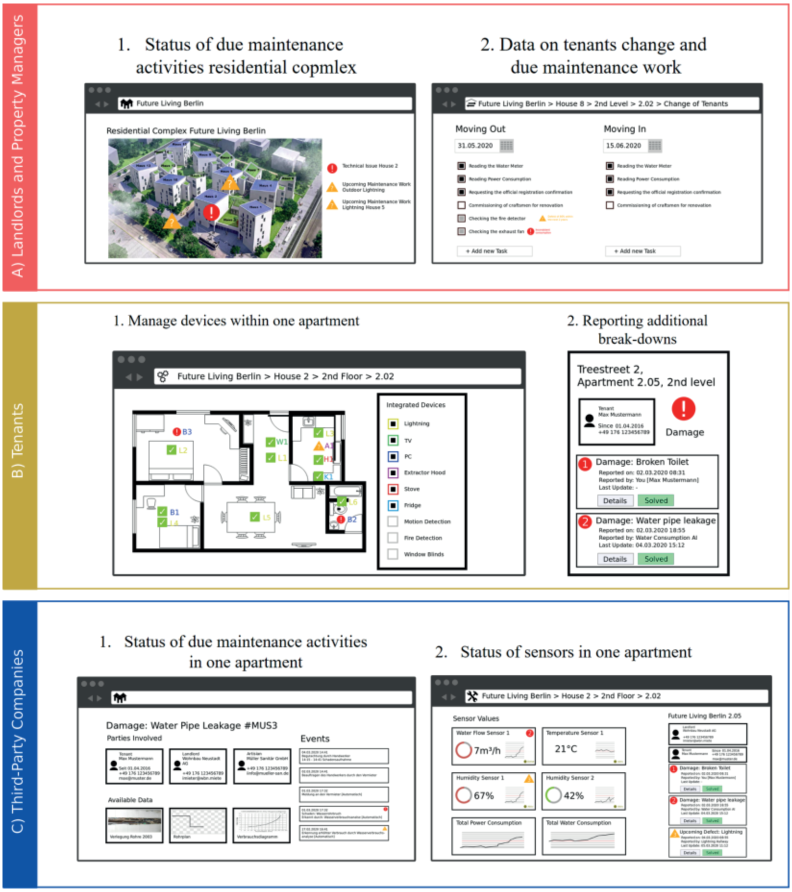

Fig. 2. PdM Visualization Prototype for Different Stakeholders

Landlords and property managers are in the first place interested in the physical conditions of an entire residential complex or building and in aggregated instead of single and detailed failures. The smart service marketplace's dashboard can help these stakeholders keeping an overview of due maintenance work and help them optimize their maintenance processes. Knowing when tenants will change apartments, for instance, will allow landlords and managers to plan and execute upcoming maintenance works "in-between" tenants (see A in Fig. 2). While this procedure is typical for preventive maintenance work, it is often part of a standardized process to repair and renovate an apartment between different tenants. Therefore, we propose conducting PdM works also during the time intervals between tenant changes. Such PdM works would include any maintenance work that would be necessary in the upcoming few months. This procedure minimizes contact with the tenants and prevents any scheduling conflicts.

Tenants: Due to privacy regulations and different needs, tenants will have a different landing view on the smart service marketplace than landlords or property managers (see B in Fig. 2). Since their apartment is their central point of life, they are primarily interested in being informed on their own apartment's status, but sometimes also in the status of the common building (e.g., the status of the smart door at the entrance, status of the smart elevator). Additionally, they need to manage their smart service subscriptions and the individual sensors and devices within the apartment. Tenants require an intelligent interface to report anomalies or failures and get information about the repair status. Therefore, the tenant's view is more detailed. What is also crucial to tenants is that if failures are not detected automatically, they can still report issues manually.

Third-party companies: Like the landlords/managers and the tenants, third-party companies like external artisans and other service providers will be able to view information about the site and the mutual connections between devices and sensors. Especially the latter is helpful to detect the broken critical devices more efficiently. Therefore, service providers should see real-time and short-time historical data (i.e., data from the last hours before defect) of dedicated sensors. Additionally, service companies should have the opportunity to mark all problems as solved for all assigned problems. It can be beneficial for third-party companies to see further anonymized data of similar sites and sensors for further troubleshooting. With the help of digitalization, third-party companies can also remotely support tenants and monitor infrastructure.

4 Conclusion

The monitoring of a building's physical conditions and the prediction of upcoming maintenance work are essential for operating residential complexes – both estimations base on a distinct but related methodology. Although the idea of predicting failures originates from the manufacturing industry, this work transfers the PdM concept to the SHI by conceptualizing it as a Service (PdMaaS). Based on four interdisciplinary workshops with various domain experts from the SHI, this work presents a systematic evaluation of challenges and solutions of the application of PdMaaS in the SHI.

By closely considering the key objectives of a PdMaaS for SHI – i.e., modularity, flexibility, and applicability on different devices and appliances – we propose a prototype concept to visualize smart services in the context of PdM in the SHI. We limit our work to the visualization only as it is independent of the concrete implementation but enables an early demonstration to evaluate it among the different stakeholders independently of a specific underlying methodology. Nevertheless, this monitoring solution is crucial for decision-makers as an input for AI-based management and process optimization and needs a thorough evaluation.

Within the next step, we need to evaluate the feasibility of several algorithmic solutions for PdM in the SHI needs. Additionally, following [Le09], future research should also consider the economic aspect of PdM in SHI by conducting comprehensive cost-benefit analyses for various PdM services in different residential contexts (e.g., large versus smaller housing developments, luxury versus social housing). Altogether, our work presents valuable insights that can serve as input in subsequent considerations on designing and implementing predictive maintenance as a service for the smart housing industry. Further, the insights presented in this paper can also directly enter into practitioners' ongoing efforts to adopt PdM for their industry- and business-specific needs. After all, by predicting damages and repairing or exchanging devices before damage occurs, any type of business can save substantial amounts of time and money.

Acknowledgment

This work is funded by the German Federal Ministry for Economic Affairs and Energy (BMWi) as part of the ForeSight project (Grant: 01MK20004J).

Bibliography

[Al14] Alestra, S., Brand, C., Erofeev, P., Bordry, C., Burnaev, E., Papanov, A.: Rare Event Prediction Techniques in Application to Predictive Maintenance of Aircraft. In: Proceedings of ITaS conference. pp. 32–37, 2014.

[AO20] Allcoat, J., Office for National Statistics: Output in the Construction Industry, https://www.ons.gov.uk/file?uri=/businessindustryandtrade/constructionindustry/datasets/outputintheconstructionindustry/current/previous/v64/bulletindataset2v2.xlsx, last accessed, 2020/06/15.

[Ar16] Ardolino, M., Saccani, N., Gaiardelli, P., Rapaccini, M.: Exploring the Key Enabling Role of Digital Technologies for PSS Offerings. Procedia CIRP 47, pp. 561–566, 2016.

[Ba19] Bauer, J., Hoffmann, H., Feld, T., Runge, M., Hinz, O., Mayr, A., Förster, K., Teske, F., Schäfer, F., Konrad, C.: ForeSight - Platform Approach for Enabling AI-based Services for Smart Living. In: International Conference on Smart Homes and Health Telematics. pp.204–211. Springer, Cham, 2019.

[CBL06] Cook, M.B., Bhamra, T., Lemon, M.: The transfer and application of Product Service Systems: from academia to UK manufacturing firms. Journal of cleaner production 14, pp. 1455–1465, 2006.

[CHP18] Chowdhury, S., Haftor, D., Pashkevich, N.: Smart Product-Service Systems (Smart PSS) in Industrial Firms: A Literature Review. Procedia CIRP 73, pp. 26–31, 2018.

[CS13] Cole, G., Stewart, R.A.: Smart meter enabled disaggregation of urban peak water demand: precursor to effective urban water planning. Urban Water Journal 10, pp. 174–194, 2013.

[DVG75] Delbecq, A.L., Van de Ven, A.H., Gustafson, D.H.: Group techniques for program planning: A guide to nominal group and Delphi processes. Scott, Foresman, 1975.

[Fo89] Fox, W.M.: The improved nominal group technique (INGT). Journal of management development 1989.

[Go99] Goedkoop, M.J., Van Halen, C.J., Te Riele, H.R., Rommens, P.J., others: Product service systems, ecological and economic basics. Report for Dutch Ministries of environment (VROM) and economic affairs (EZ) 36, pp. 1–122, 1999.

[Ko16] Kong, W., Dong, Z.Y., Ma, J., Hill, D.J., Zhao, J., Luo, F.: An extensible approach for non-intrusive load disaggregation with smart meter data. IEEE Transactions on Smart Grid 9, pp. 3362–3372, 2016.

[KT15] Koutitas, G.C., Tassiulas, L.: Low cost disaggregation of smart meter sensor data. IEEE Sensors Journal 16, pp. 1665–1673, 2015.

[Ku18] Kulkarni, K., Devi, U., Sirighee, A., Hazra, J., Rao, P.: Predictive maintenance for supermarket refrigeration systems using only case temperature data. In: 2018 Annual American Control Conference (ACC). pp.4640–4645. IEEE, 2018.

[La07] Lago, P.P., Beruvides, M.G., Jian, J.-Y., Canto, A.M., Sandoval, A., Taraban, R.: Structuring group decision making in a web-based environment by using the nominal group technique. Computers & Industrial Engineering 52, pp. 277–295, 2007.

[Le09] Lee, J., Chen, Y., Al-Atat, H., AbuAli, M., Lapira, E.: A systematic approach for predictive maintenance service design: methodology and applications. International Journal of Internet Manufacturing and Services 2, pp. 76–94, 2009.

[LG04] Lovelock, C., Gummesson, E.: Whither services marketing? In search of a new paradigm and fresh perspectives. Journal of service research 7, pp. 20–41, 2004.

[Li06] Lindahl, M., Sundin, E., Shimomura, Y., Sakao, T.: An outline of an interactive model for service engineering of functional sales offers. In: International Design Conference-DESIGN 2006. Bubrovnik, Croatia, 15-18 2006. pp. 897–904, 2006.

[Mo02] Mobley, R.K.: An introduction to predictive maintenance. Elsevier, 2002.

[Mo02b] Mont, O.K.: Clarifying the concept of product–service system. Journal of cleaner production 10, pp. 237–245, 2002.

[So12] Soualhi, A., Clerc, G., Razik, H., Lebaroud, A.: Fault detection and diagnosis of induction motors based on hidden Markov model. In: 2012 XXth International Conference on Electrical Machines. pp. 1693–1699. IEEE, 2012.

[We11] West, S.R., Guo, Y., Wang, X.R., Wall, J.: Automated fault detection and diagnosis of HVAC subsystems using statistical machine learning. In: 12th International Conference of the International Building Performance Simulation Association, 2011.

[Wi06] Williams, A.: Product-service systems in the automotive industry: the case of micro-factory retailing. Journal of cleaner production 14, pp. 172–184, 2006.

[WY07] Widodo, A., Yang, B.-S.: Support vector machine in machine condition monitoring and fault diagnosis. Mechanical systems and signal processing 21, pp. 2560–2574, 2007.

[Zh12] Zhu, H., Gao, J., Li, D., Tang, D.: A Web-based Product Service System for aerospace maintenance, repair and overhaul services. Computers in Industry 63, pp. 338–348, 2012.