No Time to Crash: Visualizing Interdependencies for Optimal Maintenance Scheduling

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***Abstract*—With the digital transformation in manufacturing, Predictive Maintenance (PdM) is increasingly proposed as an approach to increase the efficiency of manufacturing processes. However, system complexity increases due to mass customization, shorter product life cycles, and many component variants within a manufacturing system. So far, PdM mainly focuses on a single component or system-level and thus neglects the complexity by not considering the interdependencies between components. In a Multi-Component System (MCS) perspective, models covering interdependencies between components within a complex system are established and used for the prediction. Even if the predictive accuracy is superior, modeling interdependencies is a complex and laborious task that prevents the broad adoption of the MCS perspective. A potential way to tackle this challenge is using visualizations to discover and model the interdependencies. This paper evaluates different visualization approaches for PdM in the context of MCSs using a crowd-sourced study involving 530 participants. In our study, we ranked these approaches based on the participant's performance that aimed to identify the optimal timing for maintenance within an MCS. Our results suggest that visualization approaches are suitable to identify interdependencies and that the stacked-area approach is the most promising approach in this regard.**

Keywords*—*Multi-Component System; Predictive Maintenance; Visualization Analytics; Optimization; Stochastic Interdependencies

I. Introduction

Predictive Maintenance (PdM) focuses on managing maintenance actions based on the prediction of component or system conditions. Currently, PdM significantly impacts not only the manufacturing process but also the whole industrial product life cycle [1]. Hence, high-quality products and more reliable manufacturing processes are provided. In practice, PdM is applied either on the level of an entire system or a single component, thus neglecting the interdependencies between components within a system [2]–[4]. However, with the digital transformation in manufacturing, more complex processes, shorter product life cycles, and a wide variety of product variants emerged. This transformation not only increases the complexity of manufacturing systems; it also decreases the time to interact with the system and to learn and understand its behavior. Thus, it is more challenging to model the health indicators accurately and leads to the application of the more simple single component approaches on the one hand. But on the other hand, the grown complexity increases the demand for approaches taking this complexity sufficiently into account, such as Multi-Component System (MCS) view.

MCS models describe interdependencies between components within a system and can be used to improve predictive results and decision support. In the literature, it has been shown that the presence of interdependencies between the components impacts the deterioration process of the components, subsystems, and system [4] [2]. For instance, an old worn-out component will accelerate the wear out of the newly replaced components that interact with it. Therefore, identifying and understanding interdependencies between components helps to extract this additional knowledge, which could contribute to a better understanding of system performance in terms of component and system degradation and improve predictive results. However, this process is not straightforward and requires incorporating human cognitive reasoning and decision-making. Hence, more cognitive approaches applicable to such complex systems with a variety of properties and factors that could influence the decisions are required [5]. In particular, current research within the topic of MCS lacks proper methods to identify interdependencies, thus, failing to build MCS within complex production systems [1]. A promising way to tackle these challenges is through using visualization approaches which provide intuitive and faster ways to understand and identify interdependencies [6].

Visual Analytics (VA) has been applied in PdM for MCSs, aiming to show the presence of interdependencies within an MCS [4] [7] [8]. Nevertheless, the usefulness of visualization aiming to identify interdependencies within an MCS has not been evaluated in these studies. Recently, Gashi et al., [6] evaluated different visualization approaches regarding their suitability for maintenance scheduling. However, to the best of our knowledge, visual approaches with respect to optimal timing were neither analyzed nor ranked so far in the existing research within the field of PdM.

 ISBN: 978-1-61208-950-8

This research work evaluates different visualization approaches based on stochastic interdependencies. In particular, we rank visualization approaches aiming to identify the optimal timing for maintenance, i.e., replace point. Moreover, we discuss difficulties in integrating such approaches in the context of MCS. Additionally, factors that motivate users' decisions for maintenance actions are discussed.

This paper is organised as follows: The second section gives a brief overview of theoretical background. The third section describes materials and methods used for the research experiments. Furthermore, the forth section discusses the results and contribution of this research work, whereas the last section highlights the conclusions and future work.

II. Theoretical Background

In the age of big data, PdM is gaining a lot of attention due to the ability to use predictive models to determine when maintenance actions are required [3]. PdM application provides many benefits, such as decreased maintenance costs and downtime, and increased production performance, sustainability, and quality. In particular, superior predictive results for maintenance help to improve maintenance decisions, such as maintenance scheduling or resource optimization [3]. So far, PdM solutions are acceptable, but in practice, the increased complexity of manufacturing processes and the products leads to the need for more precise results. Moreover, PdM is mainly applied solely on system level or single components, thus neglecting the interdependencies between components completely. In the literature, the presence of interdependencies between components within an MCS can be found [4] [2]. Modeling interdependencies between components could help improve predictive results and understand the deterioration behavior of the components and the system.

In literature, MCS interdependencies are analyzed from different perspectives. Hence, interdependencies are grouped into four different categories: stochastic, economic, structural, and resources based interdependencies. Whereby, stochastic interdependencies analyze the deterioration effect between components within an MCS. For instance, Assaf et al. [4] proposed a deterioration model for MCS, which aims to describe stochastic degradation processes. Economic interdependencies, on the other side, focus on the effect of the costs that can be assured through performed maintenance within an MCS [9]. Structural interdependencies, however, take into account components that are structurally dependent and use this knowledge to improve maintenance processes [10]. Finally, resource-based dependencies aim to model dependency between components and spare parts or other required maintenance resources [11]. In general, modeling and presenting interdependencies within an MCS is a complex and challenging process, which helps to improve predictive results and decision-making processes when performing maintenance. Therefore, presenting and understanding interdependencies to the end-user is a crucial aspect that could help to improve the results. However, the process of identifying interdependencies is not straightforward and requires human cognitive reasoning and decision-making.

Cognitive computing, in general, aims to develop coherent, suitable, adaptable techniques based and inspired in the human mind, which can adapt to new situations [12]. More specifically, cognitive computing is a term used by IBM to describe techniques that can learn from a wide range of datasets, can provide reasons, interact with humans, and learn over time within the context [13]. In particular, understanding and extracting knowledge from big data is an important aspect of handling new emerging data-based decision problems. Therefore, in the context of our work, it is crucial to provide approaches that help facilitate human cognitive reasoning, which could increase shop floor workers' performance and system reliability. One promising approach in this regard is VA.

Visualizations help to understand and extract knowledge from data, thus, improving the decision-making process. Data visualization was applied in various contexts in the manufacturing process, e.g., to identify quality derivations and machine failures in a data-driven way [14], for anomaly detection [15] or for causal analysis [16]. Moreover, visualization for decision making in the context of PdM has been extensively applied [17] [18] [19]. Additionally, extensive research works focusing on PdM for MCSs used visualizations to demonstrate the existence of interdependencies within an MCS [4] [7] [8]. For instance, Assaf et al. [4] used line charts to present the interdependencies between components. Whereby, Shahraki et al. [7] used multi-line to visualize interdependencies within an MCS. Yet, the usefulness of visualization to identify and present interdependencies has not been evaluated.

Nevertheless, Gashi et al. [6], evaluated and ranked visualization approaches for MCSs use-cases in terms of functionality using a crowd-sourced study. In this case, the aim was to identify the best visualization approach that helps users conduct a successful maintenance strategy, i.e., the system will not crash. However, various critical systems, along with the aim to avoid crashes, require to operate at their optimal level. In this case, optimal timing is crucial and a must requirement. To the best of our knowledge, this challenge was not evaluated. Therefore, in this work, we aim to analyze and rank visual approaches in terms of optimal timing for maintenance.

III. Materials and Methods

A. Visualization approaches

Based on a literature review, we first identified candidate visualization approaches for modeling interdependencies: line-based approach [4], matrix-based approach [20] [8], multi-line approach [21], bar-based approach [22], and stacked area approach [23]. Next, in close collaboration and in multiple iterations, we pre-selected the suitable approaches in discussion sessions with three domain experts. As a result, we defined the appropriate rule to pre-select the relevant approaches which are evaluated within this study. A visualization is considered relevant if it fits the following requirements: First, visualization highlights interdependencies over time, emphasizes the performed maintenance actions, and space reduction, i.e., less space is required for visualization, is an important feature.

Multi-line visualizations are suitable approaches for pattern and relationship analysis of multiple time series data [21]. In a nutshell, deterioration of the components as a physical parameter evolves over the distance and this is shown in multi-line visualization on the x-axis (see Fig. 1). The deterioration rate, on the other side, is shown on the y-axis. Consequently, 1 represents a thoroughly worn-out component and 0 a new component. Furthermore, each line shows the deterioration over distance for a specific component, e.g., chain.

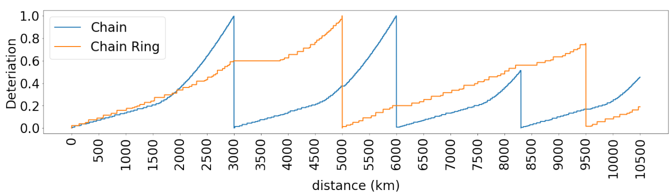

Fig. 1. MCS interdependencies are presented using a multi-line visualization approach. The x-axis represents the distance information in km, and the y-axis represents the deterioration time.

Heatmap approaches are suitable for cross-examination, patterns, or similarity analysis of multivariate data [20]. Heatmap visualizations are built using a matrix format and coloring of cells based on the magnitude of variables. Moreover, space reduction is a crucial feature of this approach. In the heatmap visualization, shown in Fig. 2, the deterioration of the components is encoded visually using a variety of colors for each cell. A cell over the x-axis represents a specific distance ride in km. The color within a specific row represents the corresponding deterioration state of the component. A white color reveals a new component, whereas a black indicates a fully worn-out component. Finally, a row represents a single component's deterioration and maintenance state.

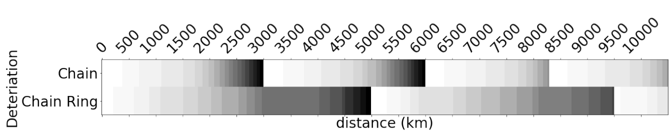

Fig. 2. MCS interdependencies are presented using the heatmap visualization approach.

Stacked-area visualizations (shown in Fig. 3) aim to represent multiple time-series data by stacking filled shapes (single time-series) on top of each other [24]. This approach is relevant for pattern, causal, and comparison analysis. The distance is shown on the x-axis, and the deterioration rate is shown on the y-axis. For each component, the deterioration rate of 1 represents a fully worn-out component, respectively 0 a new component. In contrast to the multi-line approach, the stacked-are approach accumulates the deterioration rate of all components at every specific distance point.

All these approaches can visualize data over time, e.g., over distance, are appropriate for pattern recognition or relationship analysis. Moreover, an advantage of these approaches is the space reduction feature, thus, increasing the relevance of these approaches in use cases, such as MCS, where space is an important aspect due to a large number of components. This work is an extension of previous research work [6]; therefore, further details are explained and published in [6].

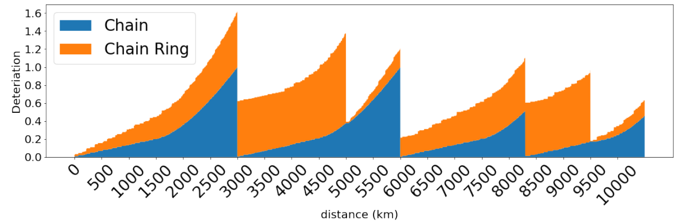

Fig. 3. MCS interdependencies are presented using the stacked-area visualization approach.

B. Procedure and user study

This design study aims to identify which visualization/-s is/are the most appropriate ones for visualizing and identifying the interdependencies of an MCS. For this purpose, a crowd-sourced study is designed to evaluate different visualization approaches. The visualizations are evaluated using a bike example as a common MCS use case that most people are aware of and understand. In particular, the bike has a small number of components, and strong interactions between these components are present; therefore, the bike is an appropriate MCS. In particular, we focus on two specific components based on domain experts' knowledge: chain and chain-ring. Moreover, we used resorted synthetic data to describe the deterioration process and interdependencies between components based on the mathematical model introduced in [6].

In the design study, each participant had to evaluate only one specific visualization in detail, which has been assigned randomly, thus avoiding the presence of biased data [25]. Moreover, the order of answers to all questions within the design study was randomized. As a first step, a description and purpose of the study altogether with the information about confidentiality regarding the data are provided to each participant. Second, the participant is asked to answer some demographic questions, such as expertise on visualization or education level. Further demographic information is collected directly from the platform used to conduct the study. Third, the MCS use case and the definition of interdependencies are presented through short video animation. Next, the participant performed the task to evaluate the assigned visualization approach. This task was designed based on the suggestion from Kittur et al. [26], thus motivating the participants to analyze the visualizations accurately and prevent random answers.

The task was designed as follows: (1) a short description of the visualizations was shown to the participant, (2) two different scenarios of component deterioration over time and performed maintenance actions using the corresponding visualization were shown to the participant. Next, the participant is asked to analyze these scenarios in detail and try to identify the interdependencies between components. As a next step, the participant is asked to rank the recognized level of interdependencies. Finally, the participant is asked to design a maintenance strategy for a distance ride of 10 000 km having a limited budget of 600 €. Whereby chain costed 20 € and chain-ring 200 €. Next, we performed a usability evaluation based on the System usability scale framework [27]. Moreover, the participant is asked to provide subjective feedback through a post-task questionnaire based on NASA TLX [28] six dimensions of workload: mental demand, physical demand, temporal demand, effort, frustration, and perceived performance. Finally, to each participant, all three approaches are shown, and the participant is asked to select the approach that they would use to identify interdependencies between components.

In total, 704 users participated in the crowd-sourced study. 530 (M=435, F=84, N/A=11) participants, age 18-65 were approved. The approve rule is built based on the strategies provided by participants, thus considering only serious attempts. For instance, strategies containing only random numbers were rejected. As a result, 72 submissions were rejected. Moreover, 89 users returned their submission, i.e., they interrupted the participation and did not submit the result. Finally, 13 participation were rejected from the platform for exceeding the time limit, which was 45 minutes (m) by default. The participants had experience with visual- and data analytic tools. Moreover, all participants had experience in the industry and were well educated (529 participants with at least a bachelor's degree). Participants needed 12 m and 42 seconds (s) on average to analyze the heatmap approach successfully. Participants successfully analyzed stacked-area visualization in 13 m and 42 s on average and the multi-line approach in 12 m and 50 s on average.

C. *Evaluation of maintenance strategies*

For the analysis, all valid strategies (non-crash strategies) are considered and evaluated based on the mathematical model introduced in [6]. To estimate the optimal timing (replace-point detection) for maintenance, we estimated the average deviation to the optimal replace-point for every maintenance replacement entry with respect to provided strategies. In this case, the best point is 0, which indicates no deviation; respectively, maintenance was performed at optimal timing. Consequently, positive deviation indicates that participants replaced the component after the optimal timing exceeded, thus indicating that the optimal timing was not recognized. Negative deviation indicates that the participants performed maintenance before the optimal timing was reached. Bar plots with confidence intervals are used to visually quantify and evaluate the results. This helps to easily identify and compare the distributions' mean and the confidence intervals. Moreover, the non-parametric Mann-Whitney U test [29] was used as a statistical approach to estimate the difference between distributions. Results with p-value < 0.05 are considered as significant differences.

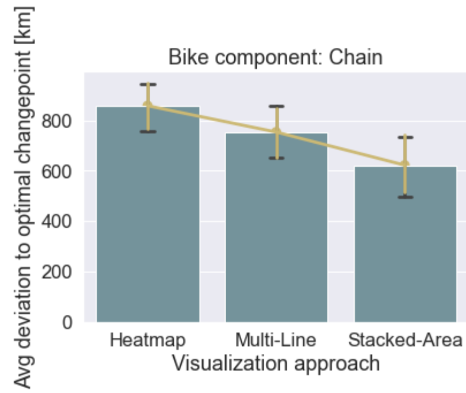

Fig. 4. Bike Chain: Estimated average deviation to change-point (optimal timing) overall participants concerning each visualization approach.

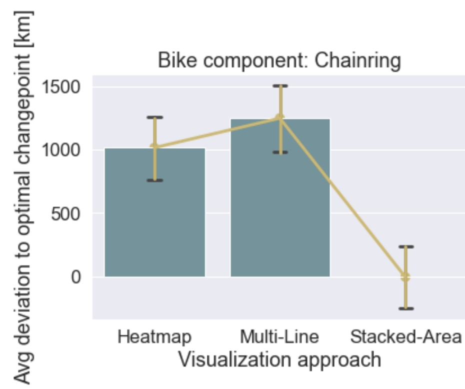

Fig. 5. Bike Chainring: Estimated average deviation to change-point (optimal timing) overall participants concerning each visualization approach.

IV. Discussion of Results

In Fig. 4 and 5, results concerning optimal timing for both chain and chain-ring are shown. Whereby 0 represents the optimal deterioration time. The positive deviation indicates a defensive approach (replacement performed after optimal timing), respectively, negative deviation indicates a more offensive approach (replacements performed before optimal timing). In this case, all three approaches are compared with each other. As a result, the multi-line and heatmap approach show similar behavior with respect to both components, i.e., chain and chain-ring. Consequently, the stacked-are approach outperforms both approaches significantly, see confidence intervals. Moreover, the Mann-Whitney U test results demonstrate the significance of this result with $p < 0.05$. Furthermore, every participant who analyzed a visualization approach in this study was asked to provide qualitative feedback regarding the identification level of interdependencies they manage to identify as shown in Fig. 6.

The participant ranked the approaches between 0 and 5, where 0 indicates that no interdependencies were identified and 5 that strong interdependencies were obvious from the corresponding approach. Correspondingly, participants who analyzed the stacked-area approach seem more confident that they were able to identify interdependencies. These results are statistically significant. In general, the results demonstrate that the stacked-area visualization approach significantly outperforms the other visualization approaches with respect to optimal timing. In this regard, stacked-area visualization is a more offensive approach compared to the other approaches. Still, it is not clear what contributes to these early decisions, and more in-depth research is needed. But one possible factor could be the accumulated deterioration degree showed within a stacked-area approach. This could trigger early decisions and thus reaction on time. The stacked-area approach as an offensive approach could be appropriate in sensitive settings, where breakdown should be prevented due to safety or cost demand. However, in the previous study [6], stacked-area approaches showed the highest error rate (around 44%) with respect to strategies that lead the system to crash. This could be related to the background knowledge level of the participants or the required training; however, there were no significant results from this study in this regard. In particular, the accumulated deterioration state shown as staked areas on top of each other (multiple components) within a stacked-area approach could increase the distortion effects while interpreting results within stacked-area visualization [30], thus, leading to a higher error rate. Thus, our study delivered the first evidence that visualization approaches could be used to identify interdependencies in the context of PdM. We found that the visualization approaches perform differently. More research seems promising to identify the suitability of the different visualization approaches for different PdM settings and MCS modeling approaches.

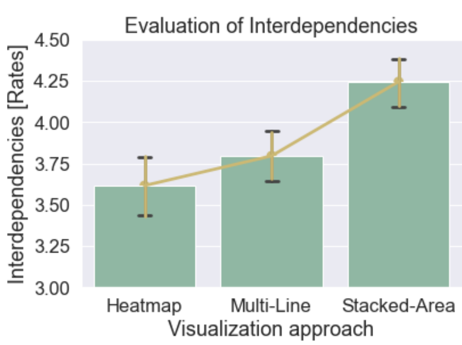

Fig. 6. The results of subjective feedback with respect to interdependencies are shown.

Predominantly, the evaluation of visualization approaches for complex systems, such as MCSs is not a trivial process due to the many factors influencing the process and users' decisions. Factors, such as domain expertise on maintenance or visualization approaches could lead to different results. The results within this study with respect to the background of participants show a trend, where the more experienced the users are, the better they perform; however, the results are not significant, and yet further research in this regard remains feasible. Moreover, depending on the goal of business concerning the sensitivity of the manufacturing process that requires maintenance, different approaches might be suitable. For instance, Gashi et al., [6] showed that the Multi-line is a suitable approach to perform maintenance that avoids downtime but does not necessarily perform at the optimal time. In contrast, in this work, we showed that the stacked-area approach is appropriate when aiming for maintenance at optimal timing. This leads to the conclusion that different perspectives potentially lead to different results. As Plaisant [31] suggests, it requires studying and manipulating data repetitively from multiple perspectives over a long time in order to discover new knowledge. Similarly, Roberts [32] encourages the analysis of data from multiple views while using visualization approaches in order to avoid false conclusions or misinformation. Therefore, researchers could be encouraged to consider these results as a further avenue for future research. In general, this research work demonstrated that simple visualizations could identify the interdependencies concerning optimal timing. In the future, we plan to explore more complex visualizations and xAI approaches in terms of VA, which seem promising in this regard.

V. Conclusion

This research work showed that visualization approaches are suitable to identify interdependencies in the context of PdM. Our key finding bases on a design study to analyze and rank visualization approaches involving 530 participants. The stacked-area approach turned out to be the best approach in terms of optimal timing, thus, being a relevant approach in more sensitive cases, where downtime should be avoided due to safety or cost reasons. Finally, we discussed that the context and business goals within a complex MCS impact the selection of the appropriate visualization approach and that more research is needed to inform the selection of visualization approaches.

In this design study, participants had to generate strategies for the short term, i.e., 10 000 km; therefore, in the future, it will be interesting to compare these approaches in the long term (longer than 10 000 km). Moreover, user interviews in such a study could help understand user behavior regarding maintenance decisions. Furthermore, we evaluated visualization approaches using a simple MCS containing only two components. In the future, an evaluation of these approaches against a complex MCS (larger number of components) is required. Furthermore, synthetic data are used to model the scenarios for all three approaches; therefore, in the future, evaluating these approaches using data from a real use case could provide new insights. For this purpose, we plan to integrate these approaches within a DSS and evaluate them in a real industrial use case.

Acknowledgment

This work has been supported by the FFG, Contract No. 881844: Pro^{2}Future is funded within the Austrian COMET Program Competence Centers for Excellent Technologies under the auspices of the Austrian Federal Ministry for Climate Action, Environment, Energy, Mobility, Innovation and Technology, the Austrian Federal Ministry for Digital and Economic Affairs and of the Provinces of Upper Austria and Styria. COMET is managed by the Austrian Research Promotion Agency FFG.

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