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Utilising failure history to improve maintenance planning

Simon Didriksen[1], Kasper B. Hansen[1], Kristoffer V. Sigsgaard[1], Niels Henrik Mortensen[1], Julie K. Agergaard[1], Jingrui Ge[1]

[1]Department of Civil and Mechanical Engineering, Technical University of Denmark
s163881@dtu.dk
kabaha@mek.dtu.dk
krvsig@mek.dtu.dk
nhmo@mek.dtu.dk
jkrag@mek.dtu.dk
jinge@mek.dtu.dk

Abstract

In the literature, improving decision support by utilisation of failure history maintenance data is considered to hold a great potential for enhancing the maintenance planning process, as decisions are based on experience and available information. Five principles were identified to structure maintenance failure history data to support decisions in the maintenance planning process, when having high frequency observations of failures. However, the possibility of utilising the full extent of the available failure history data for all occurring failures and the usefulness of failure history data for decision support in low-frequency observations of failures have not been addressed in the literature. Proposals often tend to present data structures that rely on high-frequency observations of failures on individual equipment with a limited possibility of failure history comparison across the entire system. This paper proposes a principle for linking failure history to a multi-classification model of existing physical systems for supporting key decisions in corrective maintenance when having low-frequency observations of failures. The proposal is a fundamental linkage principle indicated to precede those described in the current literature. It also expands the principles identified from the literature by enabling a comparison of failure history data across the entire system to support decisions when having both high- and low frequency observations of failures. Through a case study, the principle proved useful for supporting key decisions in routine-based maintenance work, complex failures with low frequency observations, and identifying recurrent failures that may require new maintenance plan designs. Its potential benefits were the acceleration of knowledge gathering, improved consistency and quality of maintenance plan designs, comparison of all failures across the entire system when having low frequency observations, and indication and prevention of recurrent failures. However, further studies must be conducted to assess the extent of the identified benefits and the effect of the proposed principle.

Keywords: Decision-making, information retrieval, knowledge sharing, optimisation, data driven design

1 Introduction

When a failure in a system occurs, an appropriate maintenance plan must be designed for the system to function again. In industrial maintenance, this plan is defined through the maintenance planning process, which is one of the five steps of the maintenance management process described by Sigsgaard, Agergaard, Mortensen, et al. (2020B). Maintenance planners must ensure that the proper decisions are made for selecting the right maintenance actions with the correct estimates and more (Duffuaa & Raouf, 2015). This requires experience and expert knowledge within the field and an understanding of the failure. When a new maintenance plan is created, its design is mainly based on the available data and the experience of the maintenance planner. Maintenance planners can access the available data through the company's computerised maintenance management system (CMMS) and use them to guide their decisions. However, the maintenance planner might not be able to locate and translate the relevant data into meaningful knowledge to support the decision-making for a particular problem, as the CMMS links the data to the maintenance work process, which complicates finding the relevant information with a suitable approximation for a specific problem. Collecting the data is time demanding (Hodkiewicz & Ho, 2016), which forces decisions to be based on tacit knowledge rather than on existing information. Applying historical data to support the decision-making process has been shown to hold a great optimisation potential as much valuable knowledge and decisions are layered within the data (Bokrantz et al., 2017; Sigsgaard, Agergaard, Bertram, et al., 2020). Previous studies on decision support based on failure history exist; however, support for decision-making is lacking when the equipment has a low frequency of failures. Large volumes of valuable data are available for physical long-life systems (Hodkiewicz & Ho, 2016), while the equipment in the system can have a low frequency of observations. In this case, historical data can only truly be utilised for decision support if the full volume of data is available and comparable across the entire system for assessment of individual failures. Furthermore, data must be linked, structured, and contextualised to understand them (Stark, 2016; Teixeira et al., 2021).

This paper proposes a principle for linking failure history to a multi-classification model that consists of multiple classes representing similar elements in different hierarchical levels of an existing physical system. Applying this principle can provide a design-thinking approach for using historical maintenance data as decision support in maintenance planning. The proposal expands the study by Sigsgaard, Agergaard, Bertram, et al. (2020A) on improving decision-making in early development by contextualising data through a hierarchical decomposition of existing physical systems. The study presented in this paper focuses on:

1. How can decisions be supported when the frequency of observations is low?
2. How can failure history be linked to a multi-classification model of existing systems?

These questions were used to explore how the proposed principle can support key decisions in corrective maintenance, improving on routine-based failures, complex failures with low frequency observations, and identifying and preventing recurrent failures. The paper is structured as follows: First, the research method is presented, followed by the Background and Motivation section, which discusses the use of failure history as decision support in maintenance. Next, the proposed principle is presented, followed by a case study presenting the application of the approach and scenarios of the key decisions that can be supported. Lastly, a discussion and conclusion are presented.

2 Research method

The background and motivation of this paper were focused on maintenance and built around the existing body of literature for the use of failure history as decision support in maintenance. The proposal in this paper is based on the principle of Sigsgaard, Agergaard, Bertram, et al. (2020A) on how to structure and contextualise historical data by linking them to a hierarchical decomposition of systems. This paper is mainly built around a case study. The case study approach was chosen to provide a better understanding of the utilisation of failure history as decision support in the maintenance planning process. This approach is chosen as theory and research are in the forming stages, which is where case studies can bring value in the formation (Voss et al., 2002).
The case study presented was based on approximately 11 years' worth of failure history maintenance data acquired for the period 2010–2021 from the CMMS of a major offshore oil and gas production company. This case covers approximately 50 installations distributed over 16 offshore oil and gas fields. The historical maintenance data applied for this case study included all failure notification data, maintenance work order plan data, and general location and equipment data for all 50 offshore installations over the stated period. In this period, the volumes of notified failures and maintenance work order plans were 99.336 and 93.836, respectively. The data were extracted using three standardised extraction codes from the CMMS that the company use to store all maintenance related data, where the volume from the three extractions was more than 1.5 million rows of data.

3 Background and motivation

This section presents five failure history decision support principles for improving decision support based on maintenance failure history data, focusing on the linkage of the data. These principles are identified as the most relevant proposal for utilising failure history as decision support in maintenance planning and they form the background and motivation of this study. Principle 1 is on comprehensive information framework creation, principle 2 is on the evaluation of maintenance policies, principle 3 is on cause-and-effect mapping, principle 4 is on data structuring for condition-based maintenance decision support, and principle 5 is on risk assessment visualisation for maintenance planning.

3.1 Principle 1: Comprehensive information framework creation

Hao et al. (2010) proposed a comprehensive decision support framework for corrective-, preventive-, and condition-based maintenance that includes failure history data, real-time project management, and condition monitoring system. The framework organises the content of the physical system as CMMSs do, but it allows for accessing varied information in a multi-faceted view, with both prescriptive and descriptive information for all levels of a system. However, the data linkage only enables decision support for high-frequency observations. The data structure is not presented to enable comparison between similar types of equipment and failures, but it contains prescriptive knowledge and rules that may enable alternative types of support.

3.2 Principle 2: Evaluation principle for maintenance policies

Morant et al. (2016) presented a decision support data modelling principle for maintenance by analysing the current maintenance to help determine better actions for improving future maintenance policies. The study focused on failure frequency from a holistic perspective by reviewing the effect on the corrective maintenance performance based on changes in maintenance policies. The model shows great potential for the analysis of maintenance plans for the overall system, but as the failure history is linked to the highest level of the system, the failure history could not be reviewed for the individual equipment.

3.3 Principle 3: Cause-and-effect mapping

Fischer et al. (1996) and Galley (2004) both presented accumulative malfunction and experience database models consisting of cause-and-effect diagrams that enhance the amount of experience in which the employee can rely on. The causes of the malfunctions can be located and solved faster, and time can be saved for finding the right information to solve the failures. However, both proposals do not provide a principle for linking the data, and the core principle is only supported by having high-frequency observations of failures.

3.4 Principle 4: Data structuring for condition-based maintenance

Teixeira et al. (2021) proposed a principle for structuring and standardising failure history data and combining them with preventive maintenance event and equipment monitoring data to analyse equipment failures to support decisions for condition-based maintenance implementations. The proposed data structure is a hierarchical composition of a production line, where the failure history data are linked to the low-level equipment in the machines of the line. The study focused on data analysis and machine learning methods, and shows a potential for providing detailed information for the failure history of individual equipment. However, this paper does not present a principle for linking the equipment to the totality of the system and between different production lines to compare failure similarities across the system.

3.5 Principle 5: Risk assessment visualisation for maintenance planning

Sarshar and Haugen (2018) presented a risk-assessment decision support concept for the maintenance planning process in the offshore petroleum industry. The concept was developed to establish and manage maintenance plans while identifying hazards in relation to the maintenance actions. This is accomplished through location visualisation, external condition data, and failure history data. It provides context to planned activities, in contrast to enterprise resource planning systems, and it can be used to review all activities in one or multiple maintenance plans. However, the study focused on the application and use of the concept, rather than on the structuring of the underlying data. Whether the proposal provides a linkage of the data that can enable comparison of similar failures and equipment across the entire system is not indicated, compromising the overview that can be provided in the case of low-frequency observations.

The five principles can provide varied valuable information for high-frequency observations of failures. However, in the case of low-frequency observations of failures, the principles cannot utilise the full range of available failure history data for decision support because they lack a clear classification and data linkage that enable comparison of similar failures or equipment across the system. Either the classification and linkage were not presented in previous studies or they lack the ability to enable cross comparison in the system.

4 Principle for linking failure history to a multi-classification model

In the literature, no studies were identified to utilise the full volume of available failure history data for failures with low-frequency observations. To expand on the reviewed studies and achieve a full utilisation of failure history data for support of the key decision in maintenance planning, a principle for linking failure history to a multi-classification model is proposed in Figure 1. It is based on the principle of linking data to the hierarchical decomposition of existing physical systems presented by Sigsgaard, Agergaard, Bertram, et al. (2020A), which originates from the Theory of Technical Systems (Hubka & Eder, 1988). Furthermore, the proposal is based on the principle of assessing a piece of data and comparing it with all other similar pieces of data, and the structure of the physical system is reflected in the data structure to bring it into context (Stark, 2016). The principle presented in Figure 1 is composed of a one-to-many comparison, where the model contains two views of the same system, which means that the two sides consist of identical data sets and hierarchical structures of the system. Each side of the model contains a hierarchical structure, where the data are linked between the failure history, equipment, subsystem, and system. The link and link direction enable the comparison of specific equipment with all similar equipment in different subsystems of the same system. As presented in the figure, a system may contain a multitude of different subsystems and equipment, but with the right classification and structure, comparable equipment can be identified by applying a bottom-up search followed by a top-down search through the same system.

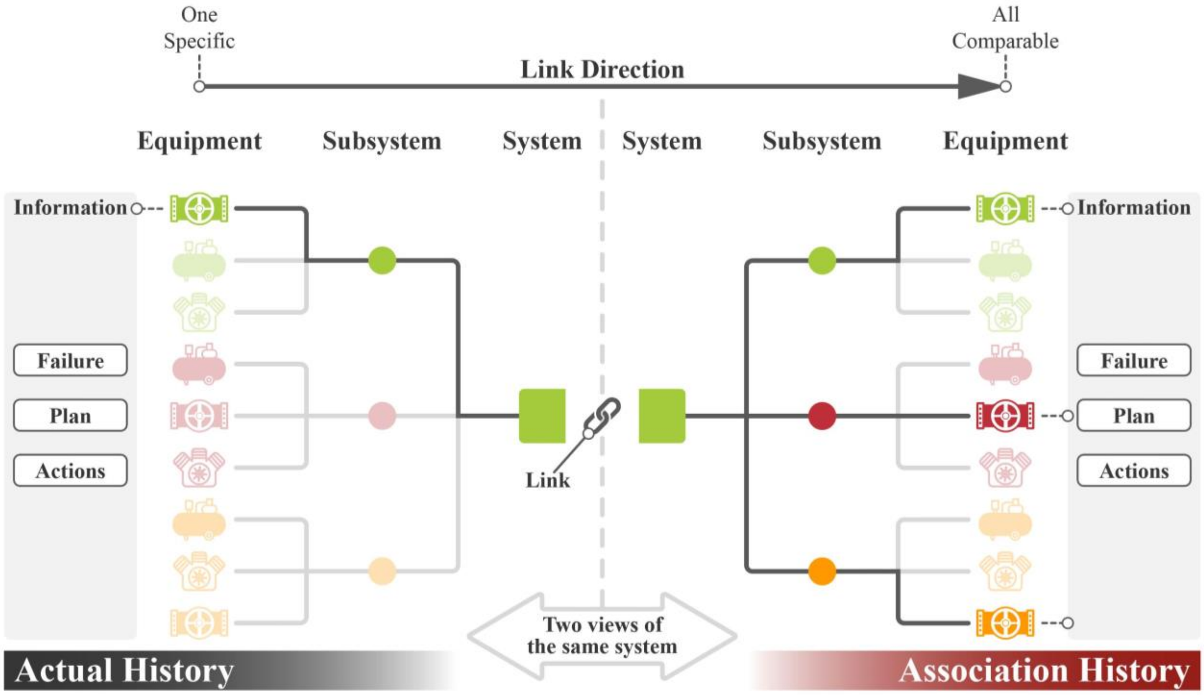

Figure 1. Principle for linking failure history data to a multi-classification model. The failure history is made available for a specific equipment and for all comparable equipment in the system by linking two views of the same system.

By starting from one specific equipment at the lowest level of the hierarchy with a bottom-up approach and then applying a top-down approach from the highest level of the hierarchy in the same system, comparable equipment can be located at the lowest level of the hierarchy on the basis of a single equipment. The related information of all the located equipment can then be accessed by structuring and contextualising the historical data, where information for failures, plans, and actions are linked to each equipment. To explore a specific failure of an equipment in a system, all the relevant historical failure information for that specific equipment would be accessible through the left side of the model, identified as the actual history in Figure 1. The link then combines the equipment to the rest of the system and makes all available data for equipment and related failures in the system accessible through the right side of the model, identified as the association history in Figure 1. Thereby, the failure at multiple levels of the hierarchy and across the entire system can be compared. This enables maintenance planners to start further ahead in the maintenance plan design process, apply previous and successful designs for new designs, and avoid creating a new design that might be identical to an already existing design for an equipment with multiple recurrent failures. Furthermore, it enables the utilisation of all available failure history data as decision support for failures with low-frequency observations.

The proposed principle enables the maintenance planner to specify how precise the match should be between the actual history and the comparable association history to review relevant data at multiple levels across the system. The proposal is a fundamental maintenance data linkage principle that precedes what currently exists in the identified literature for maintenance decision support systems and can provide flexible data to be used as decision support and evaluation for new designs of maintenance plans. The principle expands on the principles presented in the literature by enabling a comparison of equipment failure history across the entire system for supporting key decisions regarding both high- and low-frequency observations. However, it requires a right classification of the system and a sufficient quality level of the data for the proposal to enable decision support through association history.

5 Case study

The data acquired for the case study were utilised in accordance with the proposed principle through the business intelligence software Power Bi. The case study is divided into three sections: the first section presents the realised data structure based on the proposed principle, the second section presents a dashboard application realised from the data structure, and the third section presents scenarios for three key decisions in corrective maintenance planning that the proposed principle can support.

5.1 Data structure realised from the proposed principle

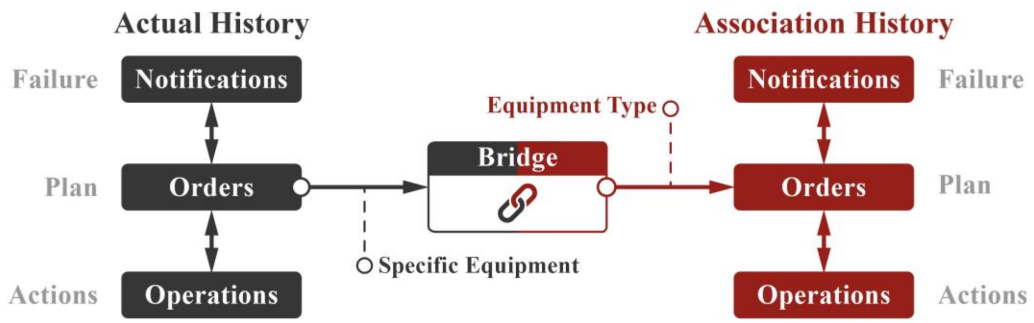

Figure 2. The data structure realised from the proposed principle. The two sides contain the same datasets, the bridge links the sides by matching specific equipment with the equipment type, and the link direction enables searching all levels of the system hierarchy.

The data from the case company consist of three separate datasets. The notification dataset contains all historical data for notified failures. The order dataset contains all historical data for the maintenance plans. Lastly, the operations dataset contains all historical data for how the maintenance plans were designed with actions that should mend the notified failures. The data structure presented in Figure 2 was created on the basis of the proposed model in Figure 1, where the three datasets are duplicated, so the actual history side consist of the same data as the association history side. The three datasets in each side are double-directionally linked to each other based on the order number present in all the datasets. The order dataset contains equipment and equipment type data that were extracted and used to generate the bridge data table in the middle. The equipment data in the order dataset of the actual history side is one-directionally linked to the equipment data in the bridge table. The equipment data in the bridge are matched to the equipment type data, which are then linked to the equipment type data in the order dataset of the association history side. One equipment can only match one equipment type, while one equipment type can match multiple equipment. The one-directional linkage through the bridge enables the data structure to provide data for multiple equipment belonging to a single equipment type based on the search of one specific equipment.

5.2 Dashboard application realised from the data structure

The presented data structure can be utilised for creating the failure history dashboard, which is divided into Figures 3 and 4. Figure 3 presents the dashboard area realised by the actual history side of the proposed principle and data structure.

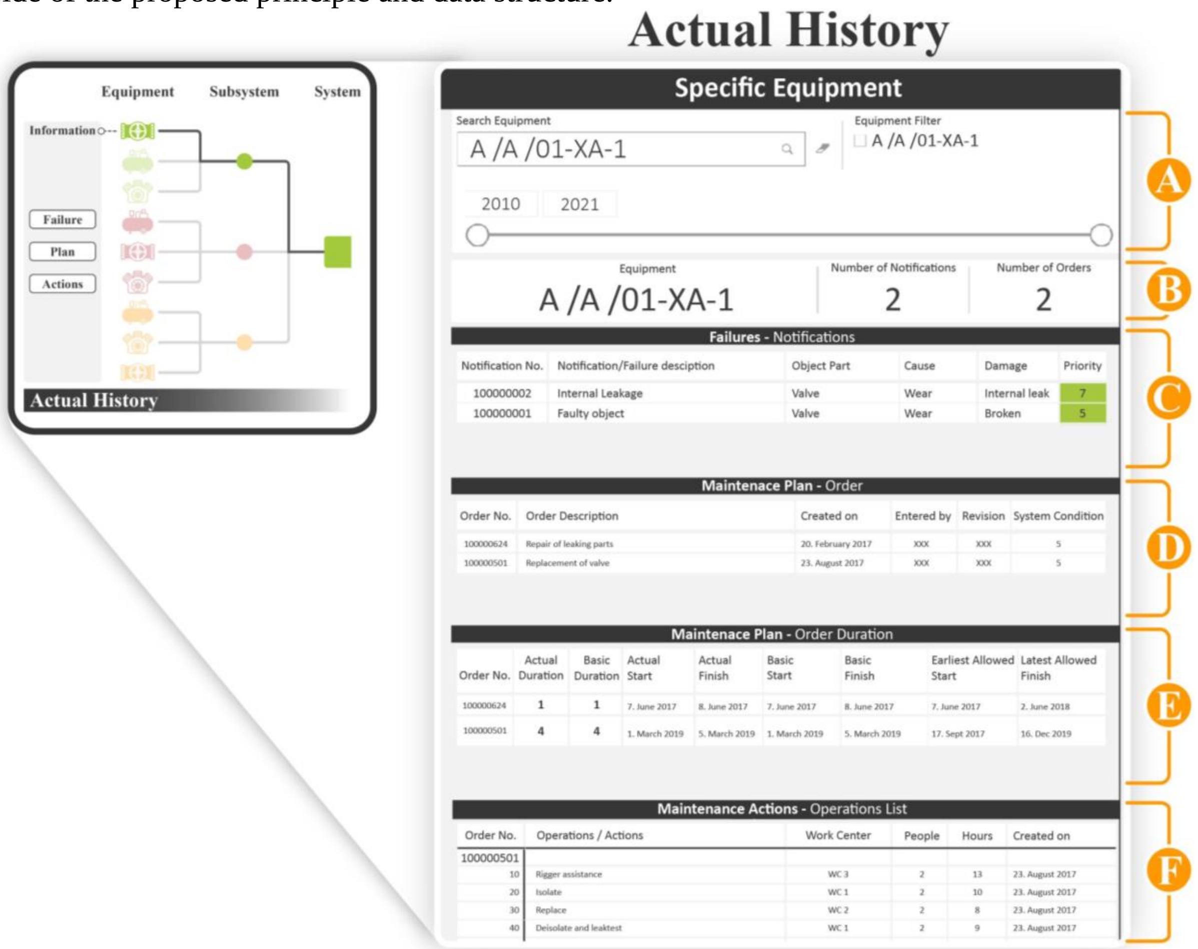

Figure 3. The actual history area of the dashboard showing failure history data for a specific equipment. A) Equipment search field and time filter. B) Failure and plan frequency. C) Failure data. D) Maintenance plan data. E) Maintenance plan timestamps. F) Maintenance plan operation list with planned actions.

The areas marked with letters in Figure 3 indicate all available failure history data for individual equipment. A) shows where the maintenance planner can search for specific equipment to access all available data and furthermore filter the time frame. B) shows the observation frequency of the notified failures and maintenance plans for the specific equipment. C) is a table containing data related to the notified failures of the specific equipment. D) presents a table with all the maintenance plans. E) presents a table containing the relevant timestamps for the maintenance plans. In F), the operation lists, which contain the planned actions with all the estimated resources and materials for maintenance plans, are shown.

Figure 4 presents the dashboard area realised by the association history side of the proposed principle and data structure. This provides the maintenance planner with all associated maintenance data across the system for the same equipment type as the one that has been searched for. The areas marked A, B, and F in Figure 4 provide the same type of information as that in Figure 3, but for all associated equipment across the entire system.

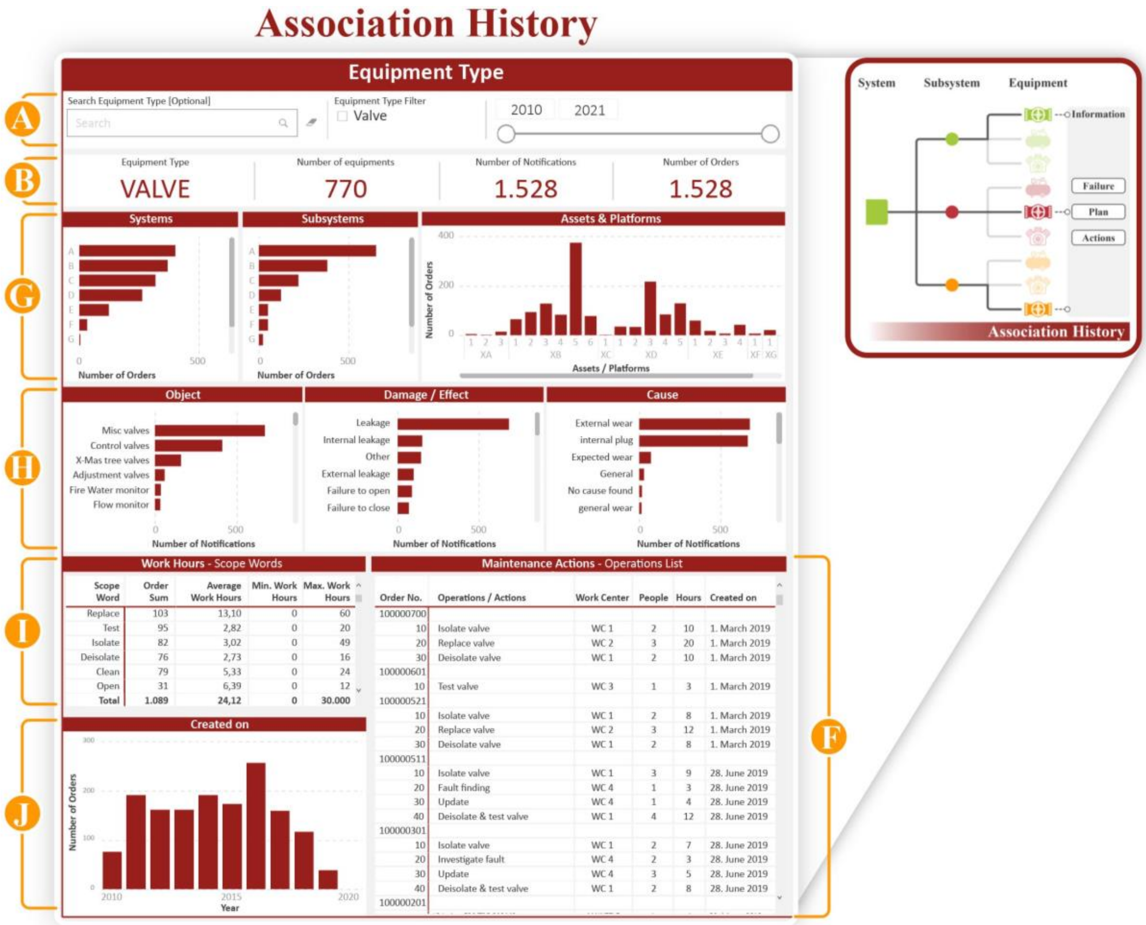

Figure 4. The dashboard area realised by the association side of the proposed principle. All available data across the entire system are accessible for the equipment type linked to the searched specific equipment.

In Figure 4, G) provides an overview of the frequency of maintenance plans in the different systems, subsystems, assets, and platforms for the equipment type. H) provides the frequency of notified failures related to different objects, damages, and causes for the equipment type. I) provides the possibility to filter for specific scope words related to the type of maintenance plans. By using scope words, the type of maintenance that is mostly designed for the specific equipment type can be identified. J) is an overview for the frequency of maintenance plans created at different times. One or multiple tables and graphs in the dashboard can be clicked to filter the data and find an exact match for the failure at hand, such as filtering for a specific cause or/and maintenance action.

5.3 Key decision scenarios supported by the proposed principle

Three scenarios are presented to reveal how the proposed principle can support key decisions in maintenance planning. The first scenario presents routine-based maintenance work with high-frequency observations, the second scenario presents decision support for complex failures with low-frequency observations, and the third scenario presents decision support for recurrent failures that may require a different maintenance plan design. The three scenarios reflect failures and maintenance plans that have been identified to occur in the offshore installations of the case company. The principle was in this case applied for selecting whether to replace or repair a valve given various failures and historical data. Valves were selected for the scenarios, as it is central flow control equipment in offshore oil and gas production installations. They are equipment with increased fragility, as they consist of movable parts that results in high-frequency observations for some failures and low-frequency observations for other failures.

5.3.1 Scenario 1: Routine-based maintenance work

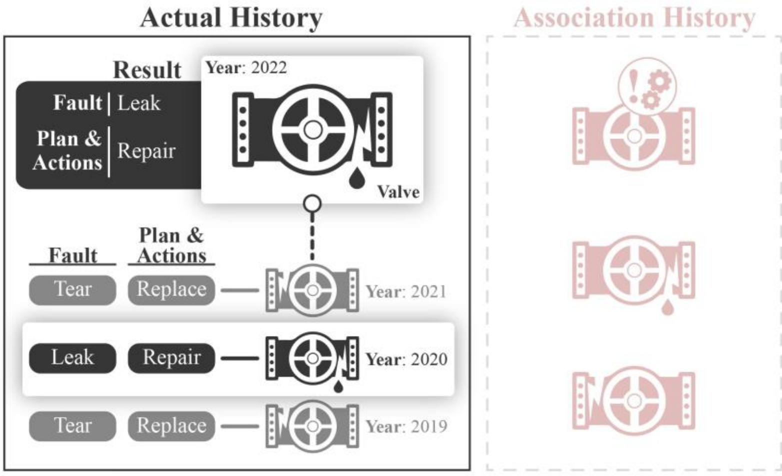

Figure 5. Routine-based maintenance work scenario for both high-frequency observations. The actual failure history can be reviewed to see how maintenance plans for the same fault were designed in the past.

The scenario in Figure 5 presents a valve with a leakage failure that needs maintenance. By applying the proposed principle, the maintenance planner is provided with the actual history of the valve, which shows high-frequency observations of failures. By reviewing the actual history, the exact same failure of the valve 2 years prior can be identified. The maintenance planner can reuse the maintenance plan design from the previous identical fault, which was repair. By doing so, it enables the maintenance planner to not start from scratch and it accelerate the knowledge gathering. Furthermore, it supports the maintenance planner in selecting the best solution that has been effective in the past. This is useful for developing a high-quality maintenance plan design and maintaining consistency in handling routine-based failures.

5.3.2 Scenario 2: Complex failures with low-frequency observations

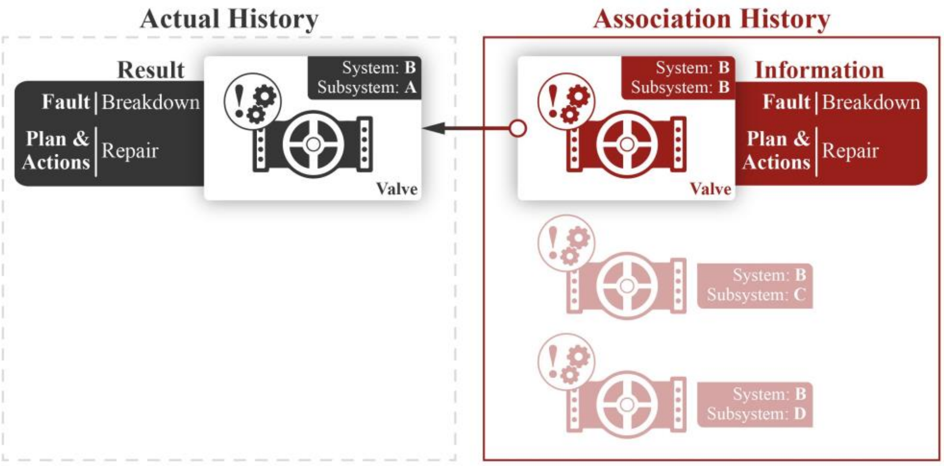

Figure 6. Scenario of a complex failure with low-frequency observations in the actual history of a specific piece of equipment. The association history can be used to find exact matches of similar equipment and failures and as an inspiration to create an adequate maintenance plan with correct actions.

The scenario in Figure 6 presents a complex breakdown failure of a valve in subsystem B, which needs a maintenance plan. As it is a case with low-frequency observations, the maintenance planner can apply the proposed principle and use the association history to search across the system and locate similar historical failures for similar valves. The maintenance planner locates three similar valves with the same failure as the one at hand in three different subsystems. The maintenance planner can use the maintenance plan designs from the association history as an inspiration for the new maintenance plan. In this case, return of experience through historical data can provide guidance and inspiration for failures, where no data are available in the actual history of the specific equipment.

5.3.3 Scenario 3: Recurrent failures requiring new solutions

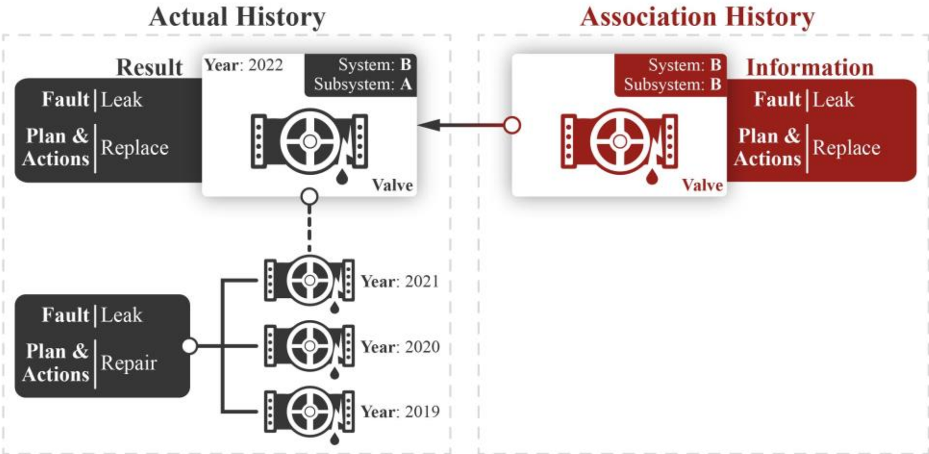

Figure 7. Scenario of a recurrent failure that may require new solutions to end the repetition. By reviewing the actual history, recurrent failures can be identified. By examining the association history, alternative maintenance plan designs can be identified and used as inspirations for new solutions to a recurrent failure.

The scenario in Figure 7 presents a valve in subsystem A with a leakage failure that needs maintenance. By applying the proposed principle, the maintenance planner can, through high-frequency observations, identify that the failure has occurred three times before at continuous intervals and that the maintenance plan for each failure was to repair it. By accessing the actual history, the maintenance planner can identify that the failure is recurrent, which may be due to continuous application of incorrect maintenance plan designs. By examining the association history, whether similar valves with the same failure across the system have a recurrence of the failure can be known. In the scenario, a similar failure occurred in a valve in subsystem B with no recurrent failures, and the maintenance plan was to replace the valve. Thus, the maintenance planner can use the proposed principle to identify recurrent failures and as an inspiration for new solutions to prevent a continuous occurrence of a failure.

6 Discussion

6.1 Implications for research

Five principles have been identified to propose the utilisation of data that can provide valuable failure history information for the maintenance planner to apply as decision support when having high-frequency observations of failures in a system. Different elements from the identified principles were applied in the development of the proposed principle. These elements were data organising and hierarchical structuring of physical systems, application of failure cause and effect frequency observations, and application of failure history data for maintenance plan designs. However, the proposals in the literature lack the ability to utilise the full volume of the available failure history for failures with low-frequency observations and for comparison of failures across the entire system. Either the proposed data structures are not capable of providing this possibility or it is not indicated in the studies. The proposed principle in this paper allows for the use of the full volume of failure history data for each occurring failure by linking failure history to a multi-classification model. Applying this principle expands the accessibility of failure history data to support maintenance planning for a larger variety of failures in complex systems, which extends the current research by enabling new application areas for failures with low-frequency observations.

6.2 Implications for practitioners

The case study scenarios present potential benefits for the maintenance planner by the application of the proposed principle. These benefits include acceleration of knowledge gathering, improved quality and consistency of maintenance plans, comparison across the system in cases of low-frequency observations, and prevention of recurrent failures. Utilising the full volume of the available failure history data in the maintenance planning process for past failures can potentially provide an adequate level of information that the maintenance planner can rely on as a basis for the decision-making for future maintenance plan designs.

6.3 Limitations and further research

The usability of the full volume of failure history data can be limited by having low-quality data and an incorrect classification of the system. As Janssen et al. (2017) and Hussin et al. (2010) reported, obtaining quality data is an important factor in ensuring the quality of the decisions derived from the data. The data made accessible to maintenance planners through the proposed principle are based on previous designed maintenance plans. Therefore, these data will be relevant to future maintenance plan designs, as the same type of data input is required. Whether additional types of data should be included can only be evaluated by testing the proposal in collaboration with maintenance planners in future studies. Some study limitations and problems were uncovered regarding the access to and identification of the relevant data points and the quality of the data. The principle is only applicable for old systems, as a large volume of historical data is required. The single-case study formed the basis, which limited the study to provide only an indication for potential. To assess the extent of the identified potential benefits, further studies on the effect of the principle must be conducted. Furthermore, studies on the generalisation of the principle to other industries and the implementation of the principle in generic systems such as configuration systems could be beneficial extensions of the research.

7 Conclusion

A principle for linking failure history to a multi-classification model of existing physical systems is presented in this paper. Indications of potential for the principle to support key decision in maintenance planning for low-frequency observations were found by enhancement of the comparability of failure history across the entire system. The case study reveals that data structures and decision support applications can be developed on the basis of the principle to support the key decision for routine-based maintenance work, complex failures with low-frequency observation, and identification and prevention of recurrent failures. The principle is not indicated to be unique, but the fundamental linkage principle is identified to precede what currently exists in maintenance literature for the utilisation of failure history data. It is a steppingstone to enhance the use of historical data and design-thinking approaches in maintenance planning.

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