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A SITUATION AWARENESS DRIVEN DESIGN FOR PREDICTIVE MAINTENANCE SYSTEMS: THE CASE OF OIL AND GAS PIPELINE OPERATIONS

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Prototype

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Abstract

The acquisition and processing of events from sensors or enterprise applications in real-time represent an essential part of many application domains such as the Internet of Things (IoT), offering benefits to predict the future condition of equipment to prevent the occurrence of failures. Many organisations already use some form of predictive maintenance to monitor performance or keep track of emerging business situations. However, the optimal design of applications to allow an effective Predictive Maintenance System (PMS) capable of analysing and processing large amounts of data is only scarcely examined by Information Systems (IS) research. Due to the number, frequency, and the need for near-real-time evaluation systems must be capable of detecting complex event patterns based on spatial, temporal, or causal relationships on data streams (i.e. via Complex Event Processing). At the same time, however, due to the technical complexity, available systems today are static, since the creation and adaptation of recognisable situations results in slow development cycles. In addition, technical feasibility is only one prerequisite for predictive maintenance. Users must be capable of processing this vast amount of data presented without considerable cognitive effort. Precisely this challenge is even more daunting as operational maintenance personnel have to manage business-critical decisions with increasing frequency and short time. Research in Human Factors (HF) suggests Situation Awareness (SA) as a crucial system's design paradigm allowing human beings to understand and anticipate the information available effectively. Building on this concept, this paper proposes a PMS for promoting operational decision makers' Situation Awareness by three design principles (DP): Sensing, Acting, and Tracking. Based on these DPs, we implemented a PMS prototype for a scenario in Oil and Gas pipeline operations. Our finding suggest that the use of SA is of particular interest in realizing effective PMS.

Keywords: Predictive Maintenance, Situation Awareness, Sensing, Acting, Tracking.

1 Introduction

The understanding of maintenance has changed significantly over the last decades; from reactive to proactive maintenance, from being a cost-factor to being a driver for the organisation's success (Fredendall et al., 1997). Predictive maintenance defines a technique that enables organisations to improve the efficiency and effectiveness of their maintenance actions (Tian and Zuo, 2010). In modern organisations, maintenance often is not only perceived as a separate function that performs repairs; it rather represents a vehicle to achieve the firm's strategic goals. Thus, investments in maintenance can result in improved quality, safety, flexibility, and lead times (Teresko, 1992).

However, even today, many maintenance decisions are made due to subjective evaluations based on staff experience and qualification (Christer, 1999). But with increasing shortage of skilled tradespeople, it becomes mandatory to reduce the effects of retiring specialists (Bailey, 2015). Bailey (2015) argues that these employees can be hard to replace and that this problem could be mitigated by leveraging information technology applying techniques like predictive maintenance. Further, Babiceanu and Seker (2015) argue that the Internet of Things (IoT) is greatly enhancing the capabilities of equipment in terms of shared communication and data (e.g. sensor data to measure temperature) to interact and make decisions. According to the authors, IoT offers huge opportunities to collect and process data in order to apply the predictive maintenance concept effectively. For instance, it grants access to an increasing amount of real-time data from various machines, pipeline sections, and vaults as well as provides techniques and computational resources to gain new insights from the data. This offers huge opportunities for the business in terms of flexibility and reliability (Babiceanu and Seker, 2015). Existing research offers much insight about the modelling of maintenance decisions and the employment of sensor data to help in the decision process. However, in-depth reviews of maintenance strategies are scarce in the existing literature and practice (Veldman et al., 2011). Further, the optimal design of the database and real-time applications to allow an effective Predictive Maintenance System (PMS) capable of analysing and processing large amounts of data are not very well researched, although many organisations already use some form of predictive maintenance (White, 2004). Specifically, design efforts need to minimize user's action distance – the time required to capture and process data as well as to determine which action to proceed (Hackathorn, 2002).

To answer this call, this paper suggests a PMS leveraging Situation Awareness (SA) as a crucial design paradigm for increasing decision-making and performance of such a system (Endsley and Jones, 2012). SA is defined as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future" (Endsley, 1988, p. 97). From the perspective of HF research, PMS shall support decision makers in their SA perception, understanding, and anticipation of the current situation. This research approach examines the applicability of SA on the design of PMS. In particular, useful lessons can be expected with regard to the construction of a human-centred user interface (Limberger and Mühlhäuser, 2008). Although the relevance of SA-driven design has been confirmed in areas like Military operations and Aviation (Endsley and Jones, 2012), research has only made little effort on applying SA (1) in the field of Information Systems (IS) development and (2) in predictive maintenance research. Specifically, we will suggest a PMS for Oil and Gas pipeline operations. In this industry required information can be hard to detect or available due to the variety of admissible situations or the inaccuracy of data. In addition, the complexity and dynamic nature of pipeline operations could make an operational specialist fail to comprehend the significance of information (e.g. tank venting) and consequently hinder the user to anticipate future events (e.g. in case of overfill of tanks). For instance, in 2010 a leaking oil pipeline near Marshall, Michigan, remained undetected for 17 hours (Munroe, 2012). Although the responsible personnel recognised a major pressure decrease, neither the operator nor the control centre in Edmonton was aware of the situation. A PMS drawing the attention of the operator to a possible leak as the probabilistic reason could have significantly reduced the extent of the disaster. Thus, a SA-oriented PMS can offer the possibility to standardise the maintenance decision process and help to model the condition of the monitored equipment. In order to tackle the aforementioned obstacles in Oil and Gas pipeline operations, we have identified three design principles (DP): (a) autonomously sensing abnormal readings of pump locations, (b) enable the operational decision maker to act appropriately with an equipment repair or replacement order, and (c) support him to track the success of the triggered response in real-time as well as estimate probable future states of the process. The remainder of this paper is as follows: Firstly, we describe the evolvement of predictive maintenance. Secondly, based on extant HF research results, we analyse software requirements and suggest DPs. Thirdly, we instantiate our design principles by implementing a running software prototype, before we conclude our paper.

2 Evolvement of Predictive Maintenance

Historically, reactive maintenance or corrective maintenance (Tsang et al., 2006) – maintenance actions after the occurrence of issues to resolve these – was the dominating form of maintenance (Pun et al., 2002). Pun et al. (2002) argue that a shift to a proactive-based, cost effectiveness, and high service level type of maintenance has taken place in the last decades. The authors state that this led to the introduction of preventive maintenance – maintenance actions to prevent the occurrence of issues. Predictive maintenance takes this view even one step further, as it concentrates on predicting the future condition of equipment to prevent the occurrence of failures (Camci, 2014; Faiz and Edirisinghe, 2009). Faiz and Edirisinghe (2009) state that the characteristics of predictive maintenance are the mitigation of failure, the detection of the causes of failure, and the uncovering of hidden failure. Compare and Zio (2014, p. 135) state that "predictive maintenance (…) is founded on the possibility of monitoring equipment to obtain information on its condition". The authors elaborate that this information is used to identify problems before they occur and predict their impact on the remaining useful life of the equipment. Predictive maintenance focuses on the prediction of the future development of the equipment's condition and the threshold which determines the occurrence of the failure (Compare and Zio, 2014). According to Faiz and Edirisinghe (2009), predictive maintenance provides guidance for maintenance decision-making.

Condition-based maintenance is "an advanced maintenance strategy to achieve the reliable, cost-effective operation of engineering systems" (Tian and Zuo, 2010, p. 700). Data about the condition of equipment is gathered to predict the equipment's actual state (also called health condition) and make maintenance decisions thereupon (Liu et al., 2013).When making maintenance decisions, it can be implied that inspection costs are weighed against possible failure costs (Faiz and Edirisinghe, 2009; Golmakani, 2012). Through condition monitoring existing problems can be detected and it can be analysed how serious these are and how long it would take before the equipment experiences failure (Tsang et al., 2006). The ultimate goal is to extend the remaining useful life (Compare and Zio, 2014) of the equipment (Mosallam et al., 2014; Tsang et al., 2006). Ionescu (2013) argues that predictive maintenance is part of condition-based maintenance. Following this argumentation, predictive maintenance, as used in this paper, complements condition-based maintenance.

3 Designing Predictive Maintenance Systems

SA describes an operational decision maker's state of knowledge with respect to a set of three ascending levels (Endsley, 2015): (a) Level 1 is described as the user's perception of the characteristics, status, and dynamics of relevant elements in a situation, (b) Level 2 is defined as the user's comprehension of the meaning of the objects and events for its situation, and (c) Level 3 is characterised as the user's ability to project (near) future actions of the elements in the environment. These three levels of SA are determined by task or system factors (e.g. interface design, process complexity) on the one hand and individual factors (e.g. working memory, goals) on the other side (Endsley and Jones, 2012). Thus, SA is achieved through an iterative process of searching for and evaluating of information until adequate decisions can be made (Endsley, 2015). IS should support decision-making and especially decision preparation by assisting the user in obtaining the above mentioned three levels of SA (Lambert, 2009; Yang et al., 2009). Based on this theoretical foundation, we analyse the requirements (R) for a PMS in Oil and Gas operations and subsequently present our deviated DPs. The requirements are derived from extant HF research outcomes. We argue that the three levels of SA can be synthesised to deduce three DPs.

From a cognitive perspective, PMS should support a user's perception of all relevant data and information of the system environment, its elements and their relationships (SA Level 1). As a first step in providing such perception, data needs to be made available (Endsley, 2008). However, the continuously increasing heterogeneity of data elements perceived by users represents a major challenge to achieve a high level of perception (Kokar et al., 2009). Consequently, our PMS should be able to process data from various sources (e.g. real-time or historical data) without having to reformat or migrate that data (**R1**). In other cases, data is available, but data detection and discrimination is problematic. This phenomenon is often associated with misplaced salience (Endsley, 1995). Salience is defined as the compellingness of specific shapes of information which largely depend on its physical characteristics (Endsley and Connors, 2008). Certain signal characteristics like the colour red, movement, and larger noise are more likely to attract a user's perceptual system (Endsley and Jones, 2012). Salient properties are important system features to promote SA. However, if such properties are utilised too often or inappropriately, it may lead to users' confusion and errors since the user would not be able to identify the critical information (Endsley and Jones, 2012). An alert of a predicted breakdown of a valve in two weeks needs to be treated differently than one of an actual breakdown (i.e. with different alert modes) while still drawing the user's attention to it. Current trends in salience utilise dashboards to display a dense array of information immediately and clearly in a small amount of space (Mortenson et al., 2015). Accordingly, our PMS design should leverage salience without overemphasising to support a user's ability to detect and discriminate data (**R2**). Our third requirement facilitates a user's ability to monitor and observe data by tackling attention tunnelling. Operational decision makers have to switch their attention between different sources of information to maintain a high SA level (Endsley and Connors, 2008). However, users often lock their attention on certain aspects of the environment that they attempt to process, while unintentionally neglecting their scanning behaviour. As a result, operational decision makers will achieve a high SA in the area of their concentration, while becoming out-dated elsewhere (Bolstad et al., 2006). Consider an alert of a (predicted) defect in one area: a relevant alert must not monopolise the attention of the user from upcoming ones or the overall status of the system. Thus, dynamically switching attention between different areas of interest remains a challenge for users and needs to be considered explicitly in our system (**R3**). The volume and frequency at which data is changed generate the need for fast information absorption which quickly exceeds the sensory and cognitive abilities of a user. In a given state, a user can only receive and process information to a certain degree at a time. Given abstract information (e.g. temperature or pressure) such dissolution may occur in 20-30 seconds (Endsley and Jones, 2012). When the auditory or visual information exceeds the cognitive threshold of a user, the decision maker's SA will generate gaps or become outdated (Bolstad et al., 2006). Often such issues arise in areas where systems fail to provide a fair degree of accuracy of the relevant cues in data sampling (Endsley, 1995). For instance, a screen showing all sensor data of all pumps and valves of a pipeline would overwork the perceptual capacity of any user. Thus, the system has to prevent such data overload (**R4**). We combine the requirements into our first DP:

DP 1 *– Sensing: A PMS should provide all task-relevant data in a comprehensive manner using appropriate means to attract the user's perception (SA Level 1) of important information while keeping him receptive to the overall status.*

The dynamics of operational decision-making situations usually require a timely integration and provision of necessary knowledge (Watson, 2009). Only if this goal is met, users can achieve an understanding of the current situation (SA Level 2). To provide a high comprehension of perceived data, errant mental models (MM) need to be addressed. MMs represent large knowledge units in the long-term memory which support the user's understanding how something works (Endsley and Jones, 2012). However, errant MMs might cause errors during the execution of a task. Such errors are typically insidious since an operational decision maker might not recognise that the utilised MM is incorrect. For instance, human beings tend to use even far-fetched explanations to fit conflicting information to their incorrect MM (Endsley and Connors, 2008). Providing recommendation support along the workflow of an operational decision maker implies a high value (Bucher et al., 2009) as it may automatically identify data needed for a decision or indicate alternatives for actions (**R5**). With ever growing computer processing power, the analysis of data can be obtained in (near) real-time (Mortenson et al., 2015). Of particular interest is the fact that current process flow data only makes sense in the context of process history, e.g. in relation to previous state descriptions (Gluchowski et al., 2009). Thus, information delivers more value when it is embedded in the course of the day (situational context) and visualised in comparison to the history of bygone days (historical context) (**R6**). With such knowledge, users could achieve immediately and even intuitively a high understanding of the situation and reduce the probability of forming and maintaining errant MMs. In addition, context information would support the user in assessing alternative decisions (i.e. recommendations) by taking also cost, risk, or other correlates into consideration. We combine these requirements to our second DP:

DP 2 *– Acting: A PMS must provide means to enable the user's understanding of current business situations (SA Level 2) to make decisions invariant of errant mental models.*

From a cognitive perspective, our system also needs to support the projections of probable future states of an environment (SA Level 3). Users may fully understand the current situation, without being able to anticipate the (near) future (Endsley, 1995). Mental projection represents a challenging task as many decision makers overly confide on their mental simulation abilities. Thus, our system needs to prevent overreliance on a user's mental simulation abilities (**R7**). For instance, the application of predictive business process monitoring could be leveraged to identify abnormal patterns and to make empirical predictions about business situations (Metzger et al., 2015). Such practice includes techniques of statistical process control, data mining, and simulation and offers support for the analysis of the impact of various alternative actions to a user. Thereby, the user should be enabled to not only perceive information on an aggregated level (e.g. average cycle time of a business process), but also to drill down into the individual process instance to track down its progress and to identify the bottlenecks of the respective process before they become a problem. Such capabilities could be enabled by key performance indicators (KPI) and metrics implemented on the process instance level (**R8**). Accordingly, the operational decision maker could anticipate immediately the perceived trends without being highly dependent on its mental simulation abilities. We formulate these requirements as our third DP:

DP 3 *– Tracking: A PMS should present the current status and possible future outcomes in a comprehensive manner enabling the user to anticipate (near) future business situations (SA Level 3).*

4 Instantiating the Design Principles - The PMS Prototype

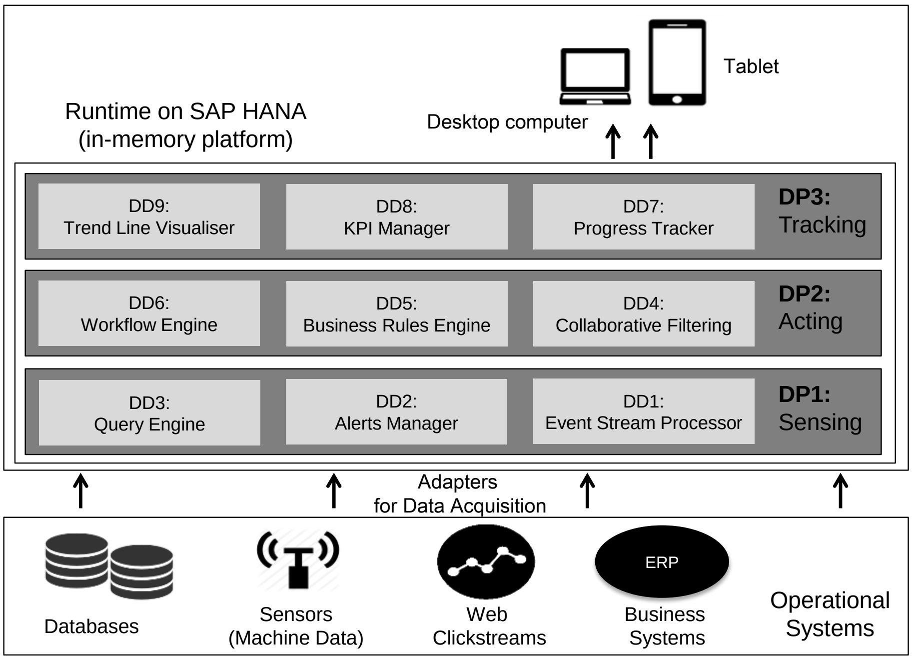

Fig. 1 Design Principles and Design Decisions

Following the design suggestions, we discuss the chosen design decisions (DD) and present a prototypically instantiation of our DPs in the Oil and Gas pipeline operations context. We illustrate our software prototype also in a screencast.[1] Figure 1 summarises our deviated DPs and chosen DDs.

4.1 Sensing Business Situations

The first step in gaining SA is the perception of the different elements in the current situation. Following our first DP, our PMS supports **SA Level 1** by both collecting and filtering a vast amount of various data types as well as visualising them in a comprehensive manner. We decided to use an Event Stream Processor to (a) steadily sense and acquire streams of event data from diverse sources into a SAP HANA in-memory computing platform and (b) to systematically identify imminent breakdowns (so called business situations) that represent unusual or abnormal system behaviour (**DD1**). We define a business situation as a significant change in state worthwhile for user notification. Research distinguishes between three types of sensing: physical (e.g. position data), virtual (e.g. database trigger), and logical sensing (i.e. data combined from various sensors). Our Event Stream Processor entity supports all three sensing types leveraging several adapters to acquire data in real-time. The underlying operational systems include databases, business systems like ERP, machine data from a variety of sensors, and clickstream data capturing user activity on websites. In case the Event Stream Processor identifies a business situation (e.g. pump sensors report a drop in pressure), an Alert Manager (**DD2**) entity forwards and visualises the warning on the operational decision maker's screen for subsequent actions that range from simple filtering and analysing to triggering multi-layered assemblage of error handling and other related routines. The operational decision maker in charge will use a dashboard where the respective notification is visualised on a tablet or desktop computer with a geographic view of the pipeline including the pump locations and details of the business situation. Alerts can be distinguished by differing colours, sizes, and effects. As shown in Figure 1, severe alerts are displayed at the location of the event through red flashing circles; less severe ones are coloured in yellow. While the user drills into a specific issue, our system helps him not to lose attention to the overall status of the system and new alerts. The left side of the screen is reserved for an overview using a three-colour-scheme to indicate the overall status of all relevant parts and showing some key figures to avoid attention tunnelling. Further, we complement the Sensing component with a Query Engine for running interactive queries for high-speed analytics at scale (**DD3**). A single query can include data from various sources (i.e. relational or proprietary data stores), enabling analytics across the company's ecosystem. Our Query Engine targets users who require response times ranging from sub-seconds to minutes. For instance, the user can trace down which areas are most affected by pump failures.

4.2 Acting on Business Situations

Our second DP (Acting) refers to supporting an operational decision maker to invoke an appropriate adaptation to business situations. An appropriate response, however, demands for a precise understanding of the situation (**SA Level 2**). Next to high level information such as flashing alerts, our PMS fosters the understanding of its users by giving background information on the reasoning process. By clicking on an alert, the PMS provides a filtered list of the relevant data and events that caused the alert. The user will then have the possibility to drill down to respective abnormal pump readings and predicted failure rates as well as maintenance records. In addition, cost data, such as diverse risk scenarios for e.g. a pipeline break or a pump failure, will be provided to the user. The user can thus examine the system's reasoning and draw his own conclusion about the current status. Our PMS further supports the operational decision maker in his understanding by proposing next best actions to deal with business situations based on two techniques: Collaborative Filtering (**DD4**) and a Business Rule Engine (**DD5**). Collaborative filtering represents a technique leveraged by recommender systems to propose recommendations –

[1] Software information including a screencast for the upstream incident management scenario are available at https://www.youtube.com/watch?v=jjmltuUikVg

in our case, next best actions – based on past user behaviour. In case of a pump failure the system informs the user of his option to repair or replace the pump. While giving additional information such as costs based on the designated pump vendor, the PMS might immediately suggest to replace the pump instead of a repair if the user usually reacts in this way (cf. Figure 2). The Business Rule Engine enables domain experts, who possess tacit knowledge about Oil and Gas pipeline operations, to use a text-based IF-THEN rule construct or decision tables to codify business rules for certain situations. Based on these findings, the operational decision maker can invoke a suitable action, e.g. in form of an equipment repair or replacement action, to respond appropriately. The user could create a rule to immediately alert the local staff if a certain error occurs. Once an alert is displayed, the operational decision maker can access not only sensor data but gets immediate access to a responsible employee at the critical station. Enabled by a Workflow Engine (**DD6**), the user can trigger previously integrated mitigation workflows as well as receive contact information about the person in charge in order to reduce the reaction time.

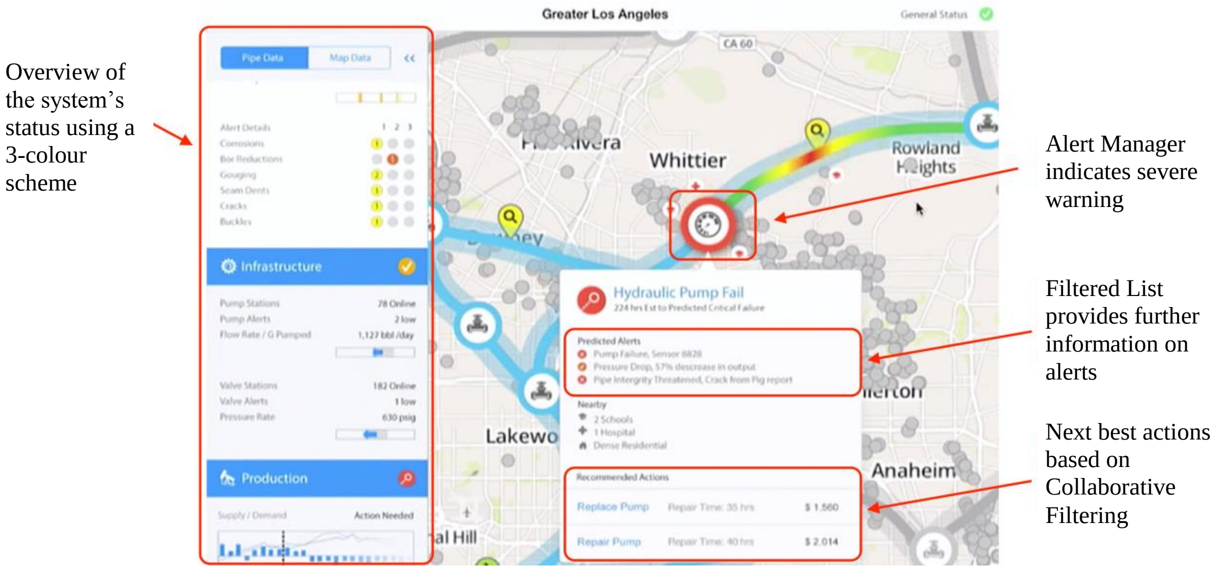

Fig. 2 *Screenshot of the User Interface for Sensing and Acting on Business Situations*

4.3 Tracking Successful Outcomes of Actions

Our third DP demands comprehensive and easily conceivable tracking and prediction possibilities. Process tracking and prediction "refers to the problem of providing analysts with information about the outcome of a running process instance, or even information about instances yet to be started" (Castellanos et al., 2004, p. 252). We argue that predictive tracking capabilities can help operational decision makers to examine the success of the action taken (i.e. equipment repair or replacement action) in order to increase SA by anticipating future events (**SA Level 3**). The incident case of the action and its details such as tasks assigned or escalation procedures can then be monitored in real-time via a Progress Tracker entity (**DD7**). The Progress Tracker observes the advancement of the mitigation workflows and records outcomes of the actions in a phase model along the status: on time (green), overdue (yellow), or at risk (red). Thereby the user has the possibility to drill down to the respective instance and observe the emerging bottlenecks. For instance, aggregates of incident cases supply the quantity of cases at risk or those which are heading to deadlines (overdue). These insights, in turn, can be leveraged for incident clustering in order to detect contributing factors. A KPI Manager entity (**DD8**) ensures the successful outcome of an action by means of measuring KPIs about the running mitigation process and showcasing of abnormal behaviour. For instance, the KPI manager could calculate KPIs such as total as well as initial response times. If a critical threshold is undergone or if a member of the staff is falling short in response, the KPI will change its colour to red to indicate an imminent issue (cf. Figure 3). This way the user is repeatedly prompted to pay attention to a situation instead of relying on his own mental prediction. In addition, the operational decision maker can leverage a Trend Line Visualiser to predict cycle times of the running process instances (**DD9**). This offers the user the possibility to immediately undertake corrective actions. The user can also leverage various forms of charts (bar, column, line or table) in order to adjust the trend line visualisation comprehensively.

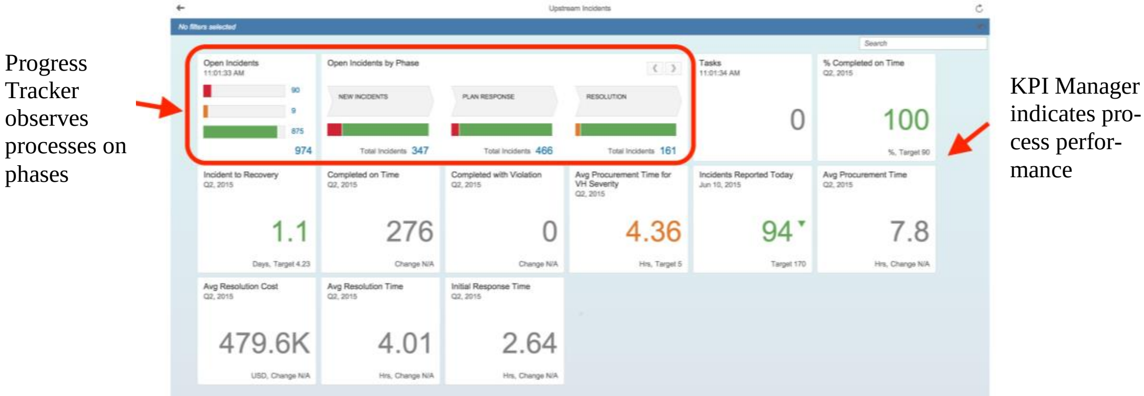

Fig. 3 Screenshot of the User Interface for Tracking Successful Outcomes of Actions

5 Conclusion

In this paper, we present our research on the design of a PMS as an emerging area for interdisciplinary research that tie IS research with insights from HF. We believe that such an approach offers new opportunities for IS scholars to produce influential research results beyond its traditional emphasis. We identified DPs for a PMS by analysing extant HF literature discussing related concepts such as SA. We argue that the antecedent three SA levels can be synthesised to deduce three DPs: (a) sensing data to facilitate a user's perception of environmental change of a given situation (Level 1), (b) acting, i.e. helping an operational decision maker to invoke an appropriate decision based on a clear understanding of the current situation (Level 2), and (c) tracking, i.e. facilitating a user's ability to track the success of the chosen response in order to anticipate future events (Level 3). Based on the identified DPs, we implemented a PMS prototype. We are aware that our research comes with some limitations: Yet, the DPs are derived from HF findings and applied within an Oil and Gas pipeline case. However, to strengthen the generalizability of the developed DPs, further research in terms of reviewing various contexts is required. In addition, the functionality of our prototype needs to be contrasted against the functionality of existing PMS software used by organisations. As a next step, this prototype will be developed further with a glance on performance to strengthen its usability and ease of use following the call of Peffers et al. (2012) for more practice relevant research. Subsequently, we plan to resume our results in a first version of a design knowledge for SA-driven design. Although our study shows some shortcomings, we consider it as a valuable contribution for both, scholars and practitioners. From an academic point of view, each DP and requirement indicate how to acquire a precise goal extending the existing body of knowledge for PMS. To our knowledge, there are currently only scarce attempts to design PMS in research (Schwegmann et al., 2013a). For instance, Schwegmann et al. (2013b) showcase a prototype to illustrate "how process-aware information systems can work together with analytical systems in near real-time" (p. 453). However, our presumption was confirmed that there is no derived artefact so far, that explicitly considers cognitive concerns, such as SA, in the design of PMS to support operational decision makers. From a practical perspective, we perceive the implementation of such software as beneficial, as studies confirm that the average maintenance cost on pumps of energy companies are 50% lower for plants operating a predictive maintenance program instead of reactive maintenance (Sullivan et al., 2010). These benefits, although limited to the energy industry, show the huge potential of employing PMS in practice. Besides, our PMS prototype is also relevant for PMS designers in practice as, up to date, no alternative system addresses the identified requirements and DPs in a holistic fashion, although organisations already utilise some form of predictive maintenance. We believe that using our software will facilitate to tackle the risk of pump breakdowns and oil leakage due to a higher SA of the operational decision maker in charge.

References

Babiceanu, R.F. and Seker, R. (2015). “Service Orientation in Holonic and Multi-agent Manufacturing.” *Service Orientation in Holonic and Multi-Agent Manufacturing* 594, 157–164.

Bailey, J. (2015). “6 strategies to bridge the skills gap.” *Plant Engineering* 69 (2), 16–17.

Bolstad, C.A., Costello, A.M. and Endsley, M.R. (2006), “Bad Situation Awareness Design: What Went Wrong and Why?” *International Ergonomics Association 16th World Congress*, 1–6.

Bucher, T., Gericke, A. and Sigg, S. (2009). “Process-centric business intelligence.” *Business Process Management Journal* 15 (3), 408–429.

Camci, F. (2014). “The travelling maintainer problem: integration of condition-based maintenance with the travelling salesman problem.” *Journal of the Operational Research Society* 65 (9), 1423–1436.

Castellanos, M., Casati, F., Dayal, U. and Shan, M.C. (2004). “A comprehensive and automated approach to intelligent business processes execution analysis.” *Distributed and Parallel Databases*, 16 (3), 239–273.

Christer, A.H. (1999). “Developments in delay time analysis for modelling plant maintenance.” *Journal of the Operational Research Society* 50 (11), 1120–1137.

Compare, M. and Zio, E. (2014). “Predictive Maintenance by Risk Sensitive Particle Filtering.” *IEEE Transactions on Reliability* 63 (1), 134–143.

Endsley, M.R. (1988). “Design and Evaluation for Situation Awareness Enhancement.” *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 32, 97–101.

Endsley, M.R. (1995). “A taxonomy of situational awareness errors.” In: *Human Factors in Aviation Operations*. Ed. by R. Fuller, N. Johnston and N. McDonald. Aldershot, England: Ashgate Publishing Ltd., 287–292.

Endsley, M.R. (2008). “Situation Awareness: A Key Cognitive Factor in Effectiveness of Battle Command.” In: *Battle of Cognition: The Future Information-Rich Warfare and the Mind of the Commander*. Ed. by A. Kott. Westport, Conn.: Praeger Security International, 95–119.

Endsley, M.R. (2015). “Situation Awareness Misconceptions and Misunderstandings.” *Journal of Cognitive Engineering and Decision Making* 9 (1), 4–32.

Endsley, M.R. and Connors, E.S. (2008). “Situation awareness: State of the art.” *Proceedings of Power and Energy Society General Meeting: Conversion and Delivery of Electrical Energy in the 21st Century*, IEEE, 1–4.

Faiz, R.B. and Edirisinghe, E.A. (2009). “Decision making for predictive maintenance in asset information management.” *Interdisciplinary Journal of Information, Knowledge and Management*, 4, 23–36.

Fredendall, L.D., Patterson, J.W., Kennedy, W.J. and Griffin, T. (2011). “Maintenance: Modeling Its Strategic Impact.” *Journal of Managerial Issues* 9 (4), 1–14.

Gluchowski, V.P., Kemper, H. and Seufert, A. (2009). “Was ist neu an Operational BI? Innovative Prozess-Steuerung.” *Bi-Spektrum* 1 (4), 8–12.

Golmakani, H.R. (2012). “Condition-based inspection scheme for condition-based maintenance.” *International Journal of Production Research* 14, 3920–3935.

Hackathorn, R. (2002). “Minimizing Action Distance”. *DM Review* 12, 22-23.

Ionescu, D. (2013). “Predictive Maintenance for intensive energy consuming plants , serviced by under-qualified staff . Case study.” *Renewable Energy and Power Quality Journal* 11, 3–6.

Kokar, M.M., Matheus, C.J. and Baclawski, K. (2009). “Ontology-based situation awareness.” *Information Fusion* 10 (1), 83–98.

Lambert, D. (2009). “A blueprint for higher-level fusion systems.” *Information Fusion* 10 (1), 6–24.

Limberger, T., Mühlhäuser, M. (2005). “Infobionik — Entwurf einer menschzentrierten Benutzerschnittstelle.” In: *Bionik*. Ed. by T. Rossmann and C. Tropea. Berlin/Heidelberg: Springer-Verlag, 63–80.

Liu, X., Li, J., Al-Khalifa, K.N., Hamouda, A.S., Coit, D.W. and Elsayed, E.A. (2013). "Condition-based maintenance for continuously monitored degrading systems with multiple failure modes." *IIE Transactions* 45 (4), 422–435.

McKeown, C. (2013). Designing for Situation Awareness: An Approach to User-Centered Design, Ergonomics, 2nd Edition, Vol. 56, London: Taylor & Francis.

Metzger, A., Leitner, P., Ivanovic, D., Schmieders, E., Franklin, R., Carro, M., Dustdar, S., Pohl, K. (2015). "Comparing and Combining Predictive Business Process Monitoring Techniques." *IEEE Transactions on Systems, Man, and Cybernetics: System* 45 (2), 276–290.

Mortenson, M.J., Doherty, N.F. and Robinson, S. (2015). "Operational research from Taylorism to Terabytes: A research agenda for the analytics age." *European Journal of Operational Research* 241 (3), 583–595.

Mosallam, A., Medjaher, K. and Zerhouni, N. (2014). "Data-driven prognostic method based on Bayesian approaches for direct remaining useful life prediction." *Journal of Intelligent Manufacturing*, 1-12.

Munroe, R. (2012). Enbridge's Kalamazoo Disaster: Straight from the Files. URL: http://thetyee.ca/News/2012/08/27/Kalamazoo-Disaster-Files/ (visited on 01/21/2016).

Peffers, K., Rothenberger, M., Tuunanen, T. and Vaezi, R. (2012). Design Science Research Evaluation. *Proceedings of the 2012 Conference on Design Science Research in Information Systems and Technologies*, 398–410.

Pun, K., Chin, K., Chow, M. and Lau, H.C.W. (2002). "An effectiveness- centred approach to maintenance management." *Journal of Quality in Maintenance Engineering* 8 (4), 346–368.

Schwegmann, B., Matzner, M., and Janiesch, C. (2013a). "A Method and Tool for Predictive Event-Driven Process Analytics." *Wirtschaftsinformatik Proceedings*, 721-735.

Schwegmann, B., Matzner, M., and Janiesch, C. (2013b). "preCEP: Facilitating Predictive Event-Driven Process Analytics. " *Proceedings of the 8th International Conference on Design Science Research in Information Systems and Technologies*, 448–455.

Sullivan, G.P., Pugh, R., Melendez, A.P. and Hunt, W.D. (2010). Operations & Maintenance Best Practices. A Guide to Achieving Operational Efficiency.

Teresko, J. (1992). "Time Bomb or Profit Center?" *Industry Week* 241 (5), 52–57.

Tian, Z. and Zuo, M.J. (2010). "Health Condition Prediction of Gears Using a Recurrent Neural Network Approach." *IEEE Transactions on Reliability* 59 (4), 700–705.

Tsang, A.H.C., Yeung, W.K., Jardine, A.K.S. and Leung, B.P.K. (2006). "Data management for CBM optimization." *Journal of Quality in Maintenance Engineering* 12 (1), 37–51.

Veldman, J., Klingenberg, W. and Wortmann, H. (2011). "Managing condition-based maintenance technology." *Journal of Quality in Maintenance Engineering* 17 (1), 40–62.

Watson, H.J. (2009). "Tutorial: Business Intelligence – Past, Present, and Future." *Communications of the AIS* 25 (39), 487–510.

White, T. (2004). "An Exploratory Study of the Role of Internet Technologies in the Field of Industrial Maintenance: Is Knowledge Management the Way Forward?" *Journal of Information Systems and Technology Management* 1 (1), 94–110.

Yang, S.J., Stotz, A., Holsopple, J., Sudit, M. and Kuhl, M. (2009). "High level information fusion for tracking and projection of multistage cyber attacks." *Information Fusion* 10 (1), 107–121.