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Context-based and human-centred information fusion in diagnostics

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Abstract: Maintenance management and engineering practice has progressed to adopt approaches which aim to reach maintenance decisions not by means of pre-specified plans and recommendations but increasingly on the basis of best contextually relevant available information and knowledge, all considered against stated objectives. Different methods for automating event detection, diagnostics and prognostics have been proposed, which may achieve very high performance when appropriately adapted and tuned to serve the needs of well defined tasks. However, the scope of such solutions is often narrow and more generic solutions without human - contributed intervention and knowledge are hard to achieve. Appropriate integration of such user-driven contextualisation of such solutions is therefore sought. This paper presents a conceptual framework of integrating automated detection and diagnostics and human contributed knowledge in a single architecture. This is instantiated by an e-maintenance platform comprising tools for both lower level information fusion as well as for handling higher level knowledge. Well structured maintenance relationships, such as those present in a typical FMECA study, as well as on the job human contributed compact knowledge are exploited to this end. A case study presenting the actual workflow of the process in an industrial setting is employed to pilot test the approach.

Keywords: e-maintenance, information fusion, human-centred maintenance, event detection, diagnostics

1. INTRODUCTION

Maintenance management and engineering practice has progressed to adopt approaches which aim to reach maintenance decisions not by means of pre-specified plans and recommendations but increasingly on the basis of best contextually relevant and available information and knowledge, all considered against stated objectives. The need for contextual relevance is emphasised by both the high variability of the circumstances upon which decisions must be taken, as well as by the nature, the different requirements and roles of the various actors, which play a role in the decision making process {El Kadiri, 2016 #1}. The availability of information refers to data originating within an organisation, such as operational, tactical and strategic enterprise data, to data related to the wider production, supply/logistics, customer and overall service chains, but also to external data, which may vary from market and financial data to normative and legislative requirements or even to specific environment data. Relevant information may be composed by historical data, current evidence and future forecasts and predictions, carrying a varying degree of uncertainty. Knowledge may refer to best available and often structured domain knowledge, which is an essential element in making available data contextually relevant. Typical examples of how such knowledge is represented in industrial maintenance include physics-based and simulation models, Fault Modes Effects (and Criticality) Analysis (FMEA/FMECA) studies, domain ontologies, and diagnostic rules, including Fault Tree Analysis (FTA).

The aforementioned direct or indirect knowledge formalisms may not carry a uniform degree of validity across all application cases. For example, recorded monitoring data may carry a varying level of accuracy and uncertainty, even when originating from exactly the same sources, depending on the time context of their acquisition, processing and recording. Furthermore, the availability of all potentially contextually relevant information and knowledge may also be characterised by time-dependence and can range from poor to high availability for different time periods. What is to be understood is that in any case decisions need to be reached on the basis of the best available information and knowledge, but the way these decisions are reached and even the outcome of a decision making process cannot be assumed to be always the same, even for cases that appear to fall under identical circumstances but may yet need to be considered differently due to variations in certain contextually relevant factors.

There are many ways in which maintenance engineering and management can account for the different underlying circumstances upon which to reach decisions. The way in which disparate sources of information can be combined to support the decision making process is often termed to as information fusion. Different layers of data processing involve data of different nature. Low-level information fusion typically aims to produce a synthesis of data and evidence gathered by field measurements, such as sensor readings, typically referred to as sensor fusion. It is typically an automated process without user involvement and has been long studied in the literature (Crowley and Demazeau, 1993). At a higher abstraction layer, information fusion is mostly concerned with knowledge entities synthesis and terms such as High-Level Information Fusion (HLIF) are relevant there (Blasch et al., 2012). In hierarchical representations there can be multiple layers of information fusion, starting from the synthesis of low-level features, moving to the integration of higher-level features, all the way up to synthesis of more abstract concepts and knowledge entities. The increasing penetration of Internet of Things technologies and the explosive growth of data generation processes has driven research towards context-based information fused, in an effort to ground information fusion to contextual relevance (Snidaro et al., 2015).

In maintenance engineering and management, focusing on condition monitoring, the fusion of low to medium - level information can for example be concerned with fusing measured signal features, historical data and data from equipment providers libraries (Esteban et al., 2005). Even for this low-level synthesis the task complexity can vary from single sensor readings on a single component to readings of multiple physical quantities from multiple components and assets in geographically disparate sites. In higher level information fusion the information to be integrated is more abstract and may refer to higher level features, symptoms and fault modes, thus it concerns semantically enriched content, with the JDL multi-level fusion model being highly applicable (Bevilacqua et al., 2015).

While the fusion of information across multiple sources has been an active target for research over very long time, one particular aspect of integration, that of integrating human contributed knowledge originating from the field with collected data but also with other available structured knowledge, has only started to become the focus of more in depth studies, following the increasing penetration of collaborative and socially enabled applications, which were brought by the shift to Web 2.0 technologies (El Kadiri et al., 2016). Most efforts to deal with the integration of human-contributed information target to manage human observations, often referred to as soft readings (Snidaro et al., 2015). However, the nature of human observations is typically more abstract and distinctively dissimilar to that of sensor readings. During operations, inspections or maintenance tasks, technical staff may observe patterns of equipment behaviour which they can describe in relatively vague terms. Such observations are often not recorded and even if they do in terms of textual notes and reports, they are not taken into account in a structured computational manner. On the other hand, efficient event detection, diagnostics and prognostics techniques have been developed and applied in maintenance practice but they are typically over-specified and applicable to a very narrow range of monitoring tasks, or when of generic nature, they may lack sufficient grounding not only to the specific problem of interest but also to the underlying circumstances of the monitoring task. Providing a valid contextual reference for better tailoring them to the task in hand would be desirable but not easy to achieve, as the overall context space may be particularly wide, especially for technical systems and assets of significant complexity.

This paper argues that fusing human-contributed knowledge, with automated data processing techniques, such as those typically employed in event detection and diagnostics, with the support of a sound underlying knowledge construct can constitute a viable path towards customisable and adaptive condition monitoring. An e-maintenance platform with maintenance support tools applicable to both the operational, as well as tactical level (Pistofidis et al., 2012) offers the basis upon which to pilot test the concept of bridging lower-level automated data processing (Katsouros et al., 2015) with semantically enriched entities, such as those available in a typical Failure Modes, Effects and Criticality Analytics (FMECA) studies (Pistofidis et al., 2016) to drive context-adaptive maintenance services and support (Papathanasiou et al., 2014; Pistofidis and Emmanouilidis, 2013). The information processing cycle includes data acquisition, date pre-processing and feature extraction, application of event detection and diagnostics algorithms, as well computer-supported FMECA knowledge management and integration and management of human contributed observations and knowledge. The rest of the paper is structured as follows. Section 2 presents the overall e-maintenance platform. Section 3 outlines the integrated detection and diagnostics approaches. The model and tool for integrating human-contributed knowledge is presented in section 4. A case study employed to pilot the information fusion processing cycle is presented in section 5. The final section summarises the main outcomes of the work, its limitations and provides pointers for further research.

2. ARCHITECTURE AND FUSION CONTEXT

The main enabling information and communication technologies (ICT) for e-maintenance are web-based and semantic maintenance, context-adaptive computing, internet of things (IoT) and smart sensing technologies, including smart data processing and analytics for detection, diagnostics and prognostics, often ported down to the level of smart sensing with wired and wireless sensors, appropriately design to make it possible also to offer relevant services over the cloud. An e-maintenance architecture has been developed that seeks to employ such technologies to vertically integrate data and processes from the shop floor up to the level of maintenance management (Papathanasiou et al., 2014; Pistofidis and Emmanouilidis, 2013) (Figure 1). At the lower level the architecture's main functional block is that of a smart node in a wireless sensor network (WSN) infrastructure, carrying sensor embedded maintenance intelligence. Data acquisition, initial processing and transmission is handled by the Sense-MI module and is developed on top of the WSN operating system (OS) and middleware. Further pre-processing for analysing the sensor readings at the sensor board is undertaken by the SENSE-PRE module. The actual embedded detection and diagnostics functionality is performed by the SENSE-MI-DETECT module. A common data model, adopting a subset of the MIMOSA schema with some extensions is unifying data exchange between lower layer and higher layer components, such as the intelligent maintenance advisor (IMA), undertaking maintenance support services. IMA exploits data and knowledge to export services via context-adaptive interfaces to web or mobile clients. Contextualised-support is offered to users via an e-support and training component (WCTP) (Papathanasiou et al., 2014). Knowledge management and fusion services are offered through the FMECA-IMA module (Pistofidis et al., 2016). Finally, following processing by the condition monitoring modules and the FMECA-IMA and WCTP services, the outcome of the recommendation services is fed through the IMA-Planner, which is interfaced with a Computerised Maintenance Management System (CMMS) to prioritise planning.

Many approaches can be adopted for automated detection and diagnosis. Two typical scenarios are (i) to detect when observed behaviour deviates from expected or known behaviour (detection) (ii) to assign the monitored condition to one or more known condition (diagnosis). In the first case, observed signal and/or features characteristics are compared against recorded ones or are fused through models which model the known or expected patterns of behaviour. These two cases are handled by the SENSE-MI-DETECT module which performs event detection (Katsouros et al., 2015) and assigns cases that fall under previously known patterns to conditions, including Fault Modes (diagnosis).

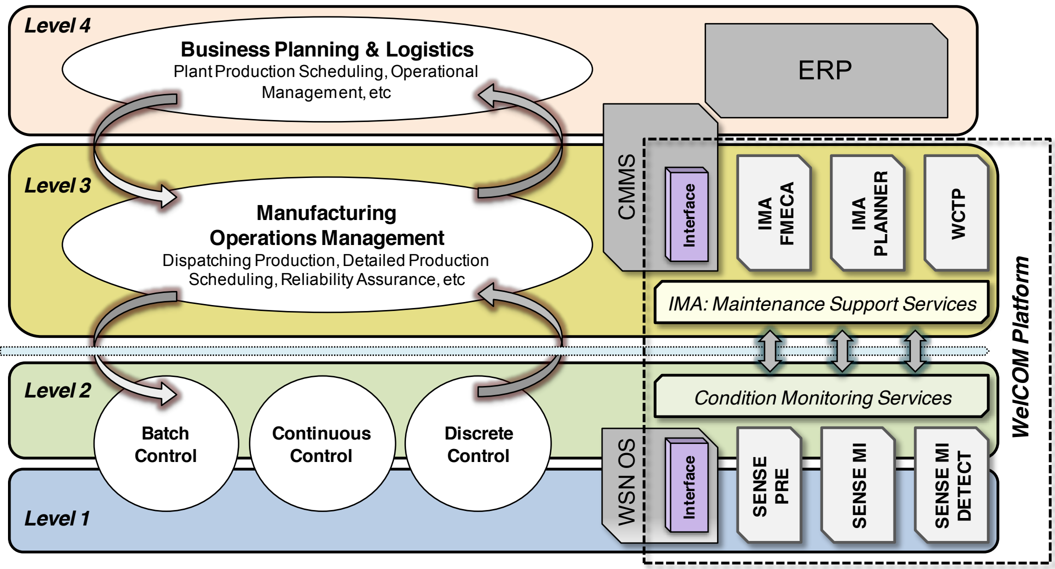

Fig. 1. e Maintenance architecture

There are typically two further scenarios to consider: (i1) there is a mostly complete record of historical data which cover the expected behaviour or there exists a model which captures most aspects of expected behaviour (i2) only limited historical data or a narrow scope model are available at most, which only partially capture the observation space of the expected behaviour. Clearly scenario (i1) is unrealistic in most practical monitoring situations. Therefore a realistic application case would focus on scenario (i2). The data processing workflow would go as follows. Measurements can be assigned to known or unknown status. Those assigned to known status can be further processed and classified to one of the known classes (conditions or Failure Modes). Those identified as deviating significantly from the known patterns may correspond to one of the already modelled conditions, to a condition for which the previously available data cover only part of the observation space, to a condition which has not been mapped against observation data at all, or even to a new condition which was not recorded for example in an FMECA study (Emmanouilidis et al., 2006). In this scenario human expert contribution is sought to (a) assign detected unknown data to known conditions (b) analyse the situation and identify a new condition to be included in the knowledge pool (Figure 2). Lower level information fusion is performed by SENSE PRE and SENSE MI DETECT modules. The first undertakes signal pre-processing and fusion at the features level. The second performs fusion for detection and diagnosis tasks. The low-level information fusion which handles features extracted from measurements taken from different locations, components and assets is not the focus of this paper and has been studied substantially in the literature. For this we employ algorithms earlier reported (Katsouros et al., 2015) with some extensions briefly outlined in the next section. The interest in this paper is in the integration of human contributed knowledge and automated data and signal processing for detection and diagnosis. Higher level information fusion is performed by IMA-FMECA, wherein human contributed knowledge is recorded and fused to drive recommendations or refine/extent existing knowledge (Pistofidis et al., 2016). In this setting the concept of context can be employed to enable information fusion and drive adaptation, that is to support the delivery of relevant data and services to the apparent context of each service request. In mobile asset and maintenance management, context can fall under different categories, namely user, social, environment, system and service context. IMA-FMECA and WCTP were designed and developed having this view of context modeling in order to offer context-adaptive services (Papathanasiou et al., 2014; Pistofidis et al., 2016).

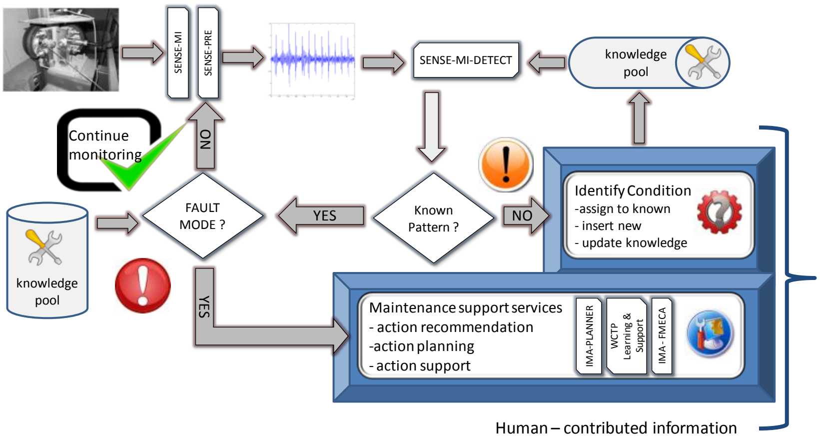

Fig. 2. Workflow of data processing, showing human-contributed information

3. AUTOMATED DETECTION AND DIAGNOSIS

The SENSE-MI-DETECT module implements event detection for asset condition monitoring by embedding relevant algorithms in a WSN node. It involves data processing on a sliding window of measurements and when cases are identified as falling under 'known' patterns, the node is capable of assigning each case to pre-specified classes (conditions). Two basic approaches were developed for event detection. The first one is applied on the raw signal and determines state changes by examining the statistical properties of the signal via the so called Martingale framework (Ho and Weschsler, 2010). The second approach implements outlier detection via Gaussian multivariate distribution modelling applied on extracted signal features (Katsouros et al., 2015). The Gaussian approach to detection is extended to diagnosis so that for each set of extracted features both a novelty vector for outlier detection, as well as a distance vector for classification are calculated. The difference is that now it is not the distance of the extracted features from the overall batch of data which is of concern, but the different distances calculated over each set of data belonging to a pool of approved data for each Fault Mode. Specifically, if $\boldsymbol{\mu}_k$ is the d-dimensional mean vector of the k-th class for a d-dimensional data set $T_{n-1} = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \ldots, (\mathbf{x}_{n-1}, y_{n-1})\}$, and $\boldsymbol{\Sigma}$ be its $d \times d$ co-variance matrix. The (i, j) th entry of the covariance matrix is equal to the covariance between the i^{th} and the j^{th} dimensions. The probability distribution $f(\mathbf{x}_k)$ for a d-dimensional data point $\mathbf{x}_k$ of the k-th class can be modelled with the Gaussian distribution:

$$f(\mathbf{x}_k) = \frac{1}{(2\pi)^{d/2}\sqrt{|\boldsymbol{\Sigma}|}} \exp\left(-\frac{1}{2}(\mathbf{x}_k - \boldsymbol{\mu}_k)\boldsymbol{\Sigma}^{-1}(\mathbf{x}_k - \boldsymbol{\mu}_k)^T\right)$$

where $|\boldsymbol{\Sigma}|$ denotes the determinant of the covariance matrix. The term in the exponent is proportional to the Mahalanobis distance between the data point $\mathbf{x}_k$ and the mean $\boldsymbol{\mu}_k$ of the available representative data of class k and therefore each data can be assigned to the nearest class c:

$$c: ArgMin_D, D = \{(\mathbf{x} - \mu_k)\Sigma^{-1}(\mathbf{x} - \mu_k)^T\}$$

The embedded implementation is described in more detail in (Katsouros et al., 2015). It performs: (a) data acquisition, including sampling and storage management; (b) data pre-processing, namely the extraction of key signal features upon which to base the detection decision; and (c) the final detection algorithms, now extended to diagnosis tasks. All parameters and results from each functional block are also exposed as network variables to a ZigBee or 6LoWPAN networking infrastructure. The system has been implemented over 3 different sensor node hardware platforms, namely the TelosB/TinyOS platform, the NXP Jennic platform over its own API and over the Contiki OS, as well as for the PrismaSense development kit platform and API, using ZigBee, 6LoWPAN and raw IEEE802.15.4 protocol stacks.

4. FUSING HUMAN INPUT AS LINKED KNOWLEDGE

Fusing structured domain knowledge with human-contributed field knowledge in industrial maintenance has been the primary target of the IMA-FMECA module. The underlying concept is that maintenance metadata are valuable knowledge units which enable the definition, instantiation and integration of relationships between maintenance knowledge entities. Starting from a well established maintenance knowledge construct, namely FMECA, the tool implements a knowledge enrichment and validation loop via engaging field personnel. To make this really applicable to shop floor practice, staff interaction with the system is kept minimal, facilitated with adaptive, touch-friendly interfaces and consisting of mostly simple interaction mechanisms for confirming and voting relevant to firmly established knowledge entities, such as fault modes, observations, symptoms etc. In this way, both 'soft sensor readings', ie. human observations, as well as metadata relevant to the maintenance entities and concepts are collected, managed and fused. Overall, the system enables active involvement of maintenance staff in enriching maintenance knowledge, making it a valuable tool for improving asset lifecycle management and is implemented with cloud-oriented technologies (Node.js, JSON, MongoDB NoSQL, HTML-5, CSS-3.3 and Javascript)(Pistofidis et al., 2016). Furthermore, it enables an instantiation of the "Failure Context", which stands as the combined knowledge about a specific failure mode, enriched with time-relevant feedback regarding the event circumstances obtained from maintenance practice.

6. CASE STUDY

A case study was carried out in a manufacturing industry that delivers complete lift solutions to pilot test the concepts of information fusion. It involved industrial personnel and three different assets, namely an Electrical Testing Lift facility, a Service (operational) Hydraulic Lift and an Air Compressor. These were assets that fall under different categories. The first is a testing facility for a key company products, aimed at global markets with installation based on high storey buildings, and is considered a tesbed for product customisation, thus a case of one of a kind asset. The second is a typical case of a company's product aimed at domestic installation and as such more representative of case of an asset with a very wide installation base, but still accepting some customisation. Finally, the third is a case of general purpose machinery, very often met in industry.

The key research question we wanted to test were "*How can we include both low level and high level information fusion in a single case of vertically integrating monitoring and maintenance support tools in industrial practice*?".

The low level information fusion is performed entirely in the embedded system on the sensor node (SENSE-MI PRE and SENSE-MI-DETECT modules) (Figure 3), while higher level fusion is undertaken by IMA-FMECA. To illustrate the process we present an example of the piloting workflow on the hydraulic lift case (Figure 4). The steps are as follows:

1. Initial FMECA knowledge for the lift filled in the system.

2. Distinct noise is observed inside the lift cabin by a staff member. The system does not contain an adequate FMECA entry for this. The employee uses the system to "tag" the lift with an "issue" (denoting something irregular observed), adding a textual note describing the noise.

3. Signal data are fused by SENSE-MI-PRE and SENSE-ME DETECT identifies an unknown event.

4. An engineer tags the lift with an issue and a textual note describing the observed vibration, similar to (2).

5. Two days later, another engineer felt a tremble in the cabin, feeling poor movement of the cabin on the guides. The corresponding FMECA events were tagged as confirmed.

6. A maintenance expert is alerted by the system which fuses the lower level event (3) with the higher level information from (2), (4) and (5) and hypothesises a problem with the roller wheels and asks for inspection. The inspection confirms that due to the lifts' glass exterior and exposure to sun-heat and dust, dirt on the roller wheels damaged their rubber. The FMECA events were as confirmed by the expert.

6. The maintenance supervisor, aided by the system to fuse the information by (2)-(6), issues a maintenance action to replace the wheels.

7. The wheels were replaced at the next scheduled maintenance, 6 days later. Thanks to the fused information, the team was ready and all necessary parts for the replacement were timely available.

8. The monitoring system now measures lower vibration.

9. An expert issues an observation tag to note that the system record of step 3 was a typical case of worn rubber on roller wheels and the state of step 8 is normal operation. In the future these will become exemplars in the monitoring system for event detection. This is another case of where higher level fusion is fed to lower level to increase the "knowledge capacity" of the diagnostics system.

The above example offers evidence of the ability of the system to aid fusion of lower with higher level information.

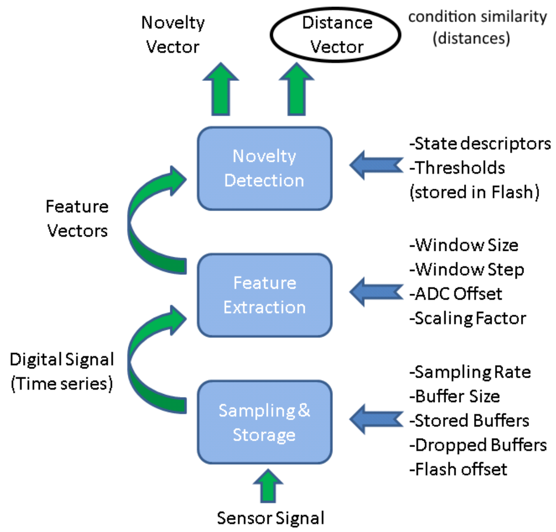

Fig. 3. Embedded event detection and diagnosis

7. CONCLUSIONS

This paper discussed issues relevant to higher and lower level information fusion in diagnosis and introduced a conceptual framework for performing such a synthesis. The concept is implemented via an e-maintenance platform, comprising tools for lower (monitoring) and higher (maintenance support) level maintenance services. The system workflow is currently limited to human intervention required to close the loop between event detection and diagnostics and needs to be further piloted in broader and more extensive applications. Although the system implementation employs technologies which facilitate scaling up, making it applicable to cloud porting, more research effort is needed to implement this porting ensuring computational, security and robustness concerns are addressed.

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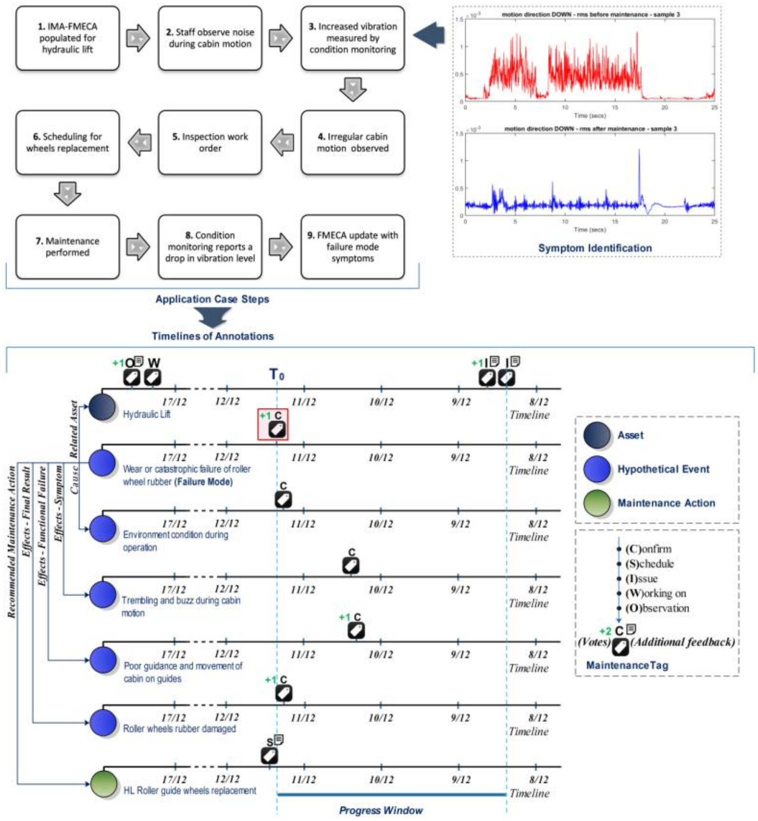

Fig. 4. Case study fusion workflow (Pistofidis et al., 2016)

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