Available online at www.sciencedirect.com

ScienceDirect

IFAC-PapersOnLine 49-28 (2016) 220–225

Context-based and human-centred information fusion in diagnostics

Christos Emmanouilidis*, Petros Pistofidis/***, Apostolos Fournaris**, M. Bevilacqua*, I. Durazo-Cardenas*, Pantelis N. Botsaris ***, Vassilis Katsouros**, Christos Koulamas** and Andrew G. Starr***

Cranfield University, School of Aerospace, Transport and Manufacturing, Cranfield, Bedfordshire MK43 0AL, UK (email: {christosem; m.bevilacqua; i.s.durazocardenas; a.starr}@cranfield.ac.uk)

***ATHENA Research and Innovation Centre, Athens, Greece & Democritus University of Thrace, Greece (email: pistofid@ceti-athena.innovation.gr; fournaris@isi.gr; vsk@ilsp.gr; koulamas@isi.gr)*

****Democritus University of Thrace, Greece (email: {pistofid;panmpots}@duth.ac.uk)*

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 without a mechanism to include human contributed intervention and knowledge contribution. 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 the most 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 the roles of the various actors in the decision making process (El Kadiri, 2016). 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 environmental 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 the best available and often structured domain knowledge, which is an essential element in making 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. While decisions need to be reached on the basis of the best available information and knowledge, the way these are reached may vary depending on variations in 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 aims to produce a synthesis of data and evidence gathered by field measurements, such as sensor readings, and it is typically referred to as sensor fusion. It is usually 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

10.1016/j.ifacol.2016.11.038

be multiple layers of information fusion, starting from the extraction 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 fusion, 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 various physical quantities from multiple components and assets in geographically disparate sites. In higher level 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 (Joint Directors of Laboratories) 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, pre-processing and feature extraction, application of event detection and diagnostics algorithms, computer-supported FMECA knowledge management and integration as well as 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 (edge analytics) or appropriately offered as services over the cloud. An e-maintenance architecture has been developed that seeks to employ such technologies to vertically integrated data and processes from the shop floor up to the level of maintenance management (Pistofidis et al., 2012; 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 are handled by a module acting on top of the WSN operating system (OS) and middleware (SENSE-MI). Pre-processing for analysing 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. 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.

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. The IMA consumes data and knowledge and exports services via context-adaptive interfaces to the web or to mobile clients. Contextualised-