Designing for Human-Centred Decision Support Systems in PHM

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ABSTRACT

Prognostics and health management (PHM) represents a paradigm shift from legacy condition based maintenance (CBM) frameworks by expanding the potentials to accurately and robustly detect and diagnose incipient system faults. The ultimate goal of PHM is reliably predicting system failure times to allow for efficient maintenance scheduling either autonomously or by human decision makers (DM). In many industrial settings today the output from PHM systems constitutes a decision support system (DSS) used to aid DM, as entirely autonomous systems have not seen widespread industrial integration. However, there is relatively little support for engineers designing PHM systems in terms of human factors and how to provide the information in a way that actively supports human decision-making and this gap may result in limited use of PHM system by maintainers. The reliability of the information presented is a critical factor in the user acceptance and trust in a system. As a first step in developing such guidance, this paper reviews the implementation of other DSS and presents a design framework whereby PHM reliability levels are mapped against a suggested level of human input to the decision making process regarding required maintenance. The aim is to provide engineers with a guide to the level to which they should consider human factors and the presentation of information in the design of their PHM system. Fundamental to the suggested paradigm is that the uncertainties within a PHM system can be quantified, and as uncertainty increases, the requirement for DM to access additional information not explicitly tied to the PHM output increases. This information can form both explicit and tacit knowledge of a system or indeed industrial contexts

surrounding decision implications, such as acceptable maintenance intervention windows in busy production schedules. As the complexity of a system or component being monitored is likely to affect the uncertainty within the PHM system associated with it, we are considering the overall cumulative uncertainty of a model output as the metric through which the required level of human input can be inferred. Coupled to this is the fact that increased model uncertainty is a causal factor in distrust and potential non-use of the model in industrial applications. It is the authors' belief therefore that designing for increased human-model interaction concurrent with increasing model uncertainty may lead to a better engagement with PHM decision support capabilities, thereby offering the full advantages that PHM has to offer. The framework presented in this paper is an initial step towards facilitating the design of more usable and useful PHM systems.

1. INTRODUCTION

Human factors (HF) considerations remain wholly underutilised within PHM framework design. More specifically, a human factors integration (HFI) approach, as outlined in ISO standard 9241-210 (International Standards Organisation, 2010) is rarely if ever considered as part of the PHM design process. Although much of the technological developments in the field to date relate to mathematical and computational scheme advancements, HF is a discipline which cannot be overlooked if maintenance decision support is to continue its necessary evolution in the coming years.

Recent developments in measurement devices, data storage capacities, data processing, and computational capabilities have occurred concurrently with advancements in industrial internet technologies. These developments are encouraging high risk industries in particular, such as the military,

nuclear, oil and gas, chemical, automotive, pharmaceutical, and aerospace to adopt Prognosis and Health Management (PHM) systems for increasing system availability, minimizing unscheduled shutdowns, reducing maintenance costs, and increasing safety (Walker & Kapadia, 2009). In these high risk industries detecting and isolating faults and subsequently predicting the remaining useful life (RUL) of critical components is a crucial task. If logistical support services, predominantly maintenance activities and associated spare parts inventory management, are to operate as efficiently as possible to achieve this goal, active contributions from multiple disciplines are required. These are typically cited as being from the engineering sciences, computer science, reliability engineering, communications, management sectors etc. (Vachtsevanos, Lewis, Roemer, Hess, & Wu, 2006). The main bulk of current research activity in industry and academia towards PHM focuses on the availability of run-to-failure data, accelerated ageing environments, real-time prognostics algorithms, uncertainty representation and management (URM) techniques, prognostics performance evaluation, and methods for verification and validation (Saxena, Roychoudhury, & Celaya, 2010). Performance assessments of PHM systems currently evaluate the technical and economic feasibility of diagnostic and prognostic technologies (Vachtsevanos et al., 2006), with little to no consideration given to end-user requirements or ergonomic issues. While this work is critical and valid from a technical standpoint, we propose that the human factors discipline also has a key role to play in the efficacy of PHM systems, particularly if they are to have a defining role in new global industrial systems. The authors believe it is necessary to take a holistic view of PHM system design and implementation if they are to enjoy widespread industrial integration in the coming years and lessons can be learned in this regard from DSS developed for other applications. Even though many successful R&D activities in the PHM domain are carried out by numerous major companies such as GE, Boeing, Lockheed, and Honeywell, PHM still lacks widespread acceptance as a technology standard (Vachtsevanos et al., 2006).

2. PHM OVERVIEW

Prognostics and Health Management (PHM) has been defined as 'an approach to system life-cycle support that seeks to reduce/eliminate inspections and time-based maintenance through accurate monitoring, incipient fault detection, and prediction of impending faults' (Kalgren, Byington, Roemer, & Watson, 2006). To do so, different information and data sets relating to the past, present and future behaviour of the equipment in question are required. An accurate PHM system requires the availability of sufficient and relevant statistical equipment failure data. However, the common scarcity of such data, particularly of critical components in the nuclear industry for example, has led to the development of numerous approaches based on

different sources of information and data, modelling and computational schemes, and data processing algorithms (Zio, 2012). A typical PHM scheme consists of three main facets, Fault Detection (D), Fault Diagnosis (FD), and Fault Prediction (FP). Fault detection normally includes fault isolation, which is a task to locate the specific component that is faulty. Fault detection in a broader sense indicates whether something is going wrong in the monitored system, and fault diagnosis determines the nature of the fault after it has been detected. Prognostics deals with fault prediction, and is a task to determine whether a fault is impending and estimate how soon and how likely that fault is to occur. Diagnostics therefore can be defined as posterior event analysis and prognostics as prior event analysis. Prognostics is much more efficient than diagnostics in achieving zero-downtime performance. Diagnostics, however, is required when fault prediction of prognostics fails and a fault occurs, and is important from a root cause analysis (RCA) perspective to avoid future failures of a similar nature (Jardine, Lin, & Banjevic, 2006).

2.1. Fault Detection

Within fault detection, several empirical signal reconstruction models have been explored to estimate the expected values of measured variables under both changing and steady state process conditions, such as: Auto-Associative Kernel Regression (AAKR) (Baraldi, Di Maio, Pappaglione, Zio, & Seraoui, 2012); Artificial Neural Networks (ANNs) (Hines & Garvey, 2006); Evolving Clustering Method (ECM) (Zhao, Zio, & Baraldi, 2011); Principle Component Analysis (PCA) (García-Alvarez, 2009; Jain, Duin, & Mao, 2000); Independent Principle Component Analysis for redundant sensor validation (Ding, Hines, & Rasmussen, 2003); Support Vector Machines (SVMs) (Laouti, Sheibat-Othman, & Othman, 2011); and Fuzzy Similarity (Baraldi, Di Maio, Genini, & Zio, 2013).

For robust determination of anomaly detection certainty several methods can be found in the literature. For example, in threshold-based methods (Montes de Oca, Puig, & Blesa, 2012; Puig, Quevedo, Escobet, Nejjari, & de las Heras, 2008), the process of an anomaly is concluded when the residual values exceed a predefined threshold. Another example is using statistical methods such as sequential probability ratio test (SPRT) (Hines & Garvey, 2006) in which anomaly detection is concluded if the probability distribution function of the residual differs from the probability distribution function calculated during normal conditions. However, these methods have some practical difficulties such as setting of the threshold value in threshold-based methods and some parameters (e.g., SPRT), and when no information about the confidence on FD outcomes (e.g., threshold-based) is provided.

2.2. Fault Diagnostics

System diagnostics lead to increased overall equipment effectiveness (OEE) in a number of ways. This is because when an alarm is triggered due to an identified system event, a decision must be taken to (Zio, 2012):

- Ignore the alarm. This increases the chances for potential accidents and catastrophic equipment failure in the case of a true alarm event.
- Stop the equipment. This will lead to additional utilised manpower resources, lost production time, and extra costs in the case of a false alarm.
- Further manual investigations without stopping the system, which, in the case of false alarms, again leads to extra costs and manpower.

An automated event diagnosis system is therefore used after an event detection module concludes that there are sufficient abnormal conditions in a system at a time t, in order to identify the root cause(s) of the occurred abnormality, on the basis of the observed signals which are representative of the system behaviour. This can be considered as a classification problem in which specific classes of event are associated with specific values of observed measured variables (Baraldi, Di Maio, Rigamonti, & Zio, 2013; Venkatasubramanian, Rengaswamy, Yin, & Kavuri, 2003).

2.3. Fault Prognosis

Upon fault detection and diagnosis, prognostics becomes a fundamental task of a PHM system which aims to reliably and accurately forecast the RUL of the equipment/system (Kalgren et al., 2006) so that it may function for as long as its design intended (Zio, 2012). RUL is typically a time, cycle, or some other specific context driven expression. The RUL is the prediction of a component or systems functional/operational usage expectancy based on measured, detected, modelled, and/or predicted health state. The RUL is dependent on the intended set of operating conditions or mission to be performed (Kalgren et al., 2006).

It is not pertinent within this work to give a further detailed treatise of PHM and its constituents. For this purpose the interested reader is referred to the work of Zio (2012) and Vachtsevanos et al (2006).

3. PHM AND THE FOURTH INDUSTRIAL REVOLUTION

PHM must meet the challenge facing industry in the first half of the 21st century. This challenge, commonly labelled 'Industry 4.0', (German Federal Ministry of Education and Research, 2013) is what has been termed as the fourth industrial revolution, where future industrial production will be characterised by industrial internet driven smart factories

centred around adaptability, resource efficiency and ergonomics. ProcessIT Europe, an innovation centre focusing on manufacturing automation solutions for EU process industries, outline the elements expected to be key in the expansion of large-scale automation systems required to drive Industry 4.0 (ProcessIT Europe, 2013). Among these are improvements in automation system functionality to enable the integration of traditionally separated systems, along with greater internet compatibility and open standards, such as those developed under EU funded projects SIRENA, SODA, SOCRADES, and AESOP (Bohn, Bobek, & Golatowski, 2006; Deugd, Carroll, Kelly, Millett, & Ricker, 2006; Souza, Spiess, Guinard, Moritz, & Karnouskos, 2008; Karnouskos, Colombo, Jammes, Delsing, & Bangemann, 2010). Machine to machine communications (M2M) using Internet of Things (IoT) principles will form the so called Cyber-Physical Systems (CPS) predicted to enable new automation archetypes and improve plant operations in terms of increased OEE. One component of this is a need for improvement in human-machine interface development, which must continue to improve the possibilities for efficient plant operations through the visualisation, virtualisation, and simulations of a plant and its automation systems (ProcessIT Europe, 2013). GE outlined their own similar initiative titled 'The Industrial Internet' (Evans & Annunziata, 2012). Central to this initiative is an integration of three fundamental elements which embody the essence of the Industrial Internet, 'Intelligent Machines', 'Advanced Analytics', and 'People at Work'. Evans and Annunziata (2012) argue that human-machine interaction will be a critical step in blending the hardware and software components required to support the minimal input and undesired output of future industrial automation systems.

Lee and Lapira (2014) argue that adoption of the IoT ideology within Industry 4.0 presents a unique opportunity for organisations to create tools and technologies that can identify and quantify organisational uncertainties, to determine an objective estimation of the assets and processes and the resultant manufacturing readiness of the organisation. The authors argue that interactive PHM systems are the next phase in the industry's evolution that will provide transparency in the factory, giving DM the opportunity to proactively implement mitigating or countermeasure solutions to prevent production losses.

Tying into this, ISO 9241-210 (International Standards Organisation, 2010) describes six key principles to ensure that the design of such interactive systems are user centred, which are:

- The design is based upon an explicit understanding of users, tasks and environments.
- Users are involved throughout design and development.

- The design is driven and refined by user-centred evaluation.
- The design process is iterative.
- The design addresses the whole user experience.
- The design team includes multidisciplinary skills and perspectives.

In terms of addressing the whole user experience, the standard outlines the following: 'the concept of usability used in ISO 9241…can include the kind of perceptual and emotional aspects typically associated with user experience'. This is an important point, as for a system to be fully utilised, it has to be more than 'easy to use', it has to engage with users in multiple ways. One of the best examples of this is through operator trust in a system. This concept is discussed later in the paper.

4. UNCERTAINTY IN PHM

The ultimate goal of PHM is to increase component availability, reduce maintenance costs, minimise unscheduled shutdowns, and increase safety. The importance of uncertainty quantification in this context should not be understated. Monitoring the health state of systems, subsystems, and components, the classification of the different types of faults that may occur in these components, and estimating the RUL along with other prognostic metrics such as the End-of-Prediction (EoP) time index, can be extremely helpful to support DM in assessing whether maintenance intervention is necessary or not. In ever more complex environments, operators need to quickly make thousands of decisions to maintain optimal decision performance. Although this challenge can be overcome by enabling a DSS to perform select operations with human consent (Evans & Annunziata, 2012), without quantifying the associated uncertainties, remaining life projections have little practical value within PHM systems (Engel, Gilmartin, Bongort, & Hess, 2000). It is the comprehension of the corresponding uncertainties that is at the heart of being able to develop a business case that addresses prognostic requirements. The assumption of data monitoring without uncertainty is particularly problematic, as this forces maintenance planning to become an exercise in decision making under uncertainty with sparse data (Sandborn, 2005).

As stated previously, PHM systems are usually implemented in three stages for the holistic health state management of a component of interest: fault detection, fault diagnosis, and system lifetime prognosis. Several methods have been widely developed in the last few decades to increase the reliability of PHM systems. In this paper, we define the reliability of the PHM system models as the cumulative reliability of the following;

Fault Detection: the ability to confidently monitor the health condition of a system with low false and missing alarm rates with respect to the detection of normal or abnormal conditions.

Fault Diagnosis: the ability to identify the fault type/class with a low misclassification rate

Fault Prediction: the ability to predict the probability of system failure and the RUL with low inaccuracies, taking into account the set of missions needed to be completed.

This cumulative information will provide the organisation with the information required to decide if maintenance intervention is necessary and if so, when to perform maintenance actions (Zio, 2012). It is worth mentioning that assessing the reliability of the PHM system is made a priori during model development using the previously mentioned methods dedicated to each part of the PHM system. In this respect, the different sources of uncertainty which exist within the varied fault detection, diagnosis, and prognosis methodologies have to be taken into account. For example, those sources may influence the performance of the PHM system, causing false or missing alarms, and hence impact the overall reliability. In the false alarm case, the output of the PHM system indicates that a healthy component is experiencing abnormal conditions, causing potential unwarranted downtime, whereas in the missing alarm case the output of the PHM system indicates that an unhealthy component is operating under normal conditions, potentially leading to catastrophic unexpected failures of the component/system with associated large downtimes, high cost, as well as possible safety and environmental implications (Zhao et al., 2011).

For these reasons, it is necessary to manage the different sources of uncertainty that may arise in the PHM system stages. In practice, the possible sources of uncertainty that may arise in a PHM system are:

- Uncertainty in the signal measurements: incomplete, noisy, and imprecise measurements
- Uncertainty in the models adopted at each data management stage, such as:
- Model Structures: un-modelled phenomena, approximations, simplifications, hypotheses, assumptions, etc.
- Model parameters: the Kernel Bandwidth in Auto Associative Kernel Regression (AAKR) methods, the threshold parameter in threshold-based methods classification and detection algorithms such as Support Vector Machines (SVM) etc.
- Uncertainty due to the inherent stochasticity of the physical processes: stochasticity in the current and

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future states of the system, unforeseen future loads and environmental conditions etc.

- Human decision errors relating to the decisions made given the PHM system output

Uncertainty quantification research currently, both in industry and academia, focuses on the shortcomings in the availability of run-to-failure data, accelerated ageing environments, real-time prognostics algorithms, uncertainty representation and management (URM) techniques, prognostics performance evaluation, and methods for verification and validation (V&V) (Saxena et al., 2010).

Essentially, the inherent uncertainties which propagate through PHM systems mean that the PHM output can never be perfectly reliable (Aven, Baraldi, Flage, & Zio, 2014; Gertler, 1998; Jardine et al., 2006; Sankararaman & Goebel, 2012). Even if it were, in practice a PHM system is being applied in complex industrial environmental contexts and there will almost always be human DMs at the system interface who may choose not to follow the guidance of the PHM system, because of a possible lack of trust in the system output or because they have knowledge extraneous to the modelled parameters. Context drivers in this regard include financial pressures to delay maintenance activities, unexpected environmental conditions which could affect the reliability/uncertainty of the algorithms, a change in the maintenance policies of the organisation, cost of shutting down at a particular time, resource availability, time available for production intervention activities (including time of the year), audit timing within regulated industries, management interests, corporate politics etc. With this in mind, it is important to consider the application of the PHM system within the overall socio-technical system of the maintenance organisation. Only by providing a PHM system that is calibrated against the actual usage of the system can the full benefit be achieved.

Sandborn (2005) asks; given that the forecasting ability of PHM is fraught with uncertainties in the sensor data collected, the data reduction methods, the models applied, the material parameters assumed in the models, etc., how can PHM results be interpreted so as to provide value? Sandborn argues that this problem partly reduces to one of determining optimal safety margins and prognostic distances for health monitoring. This determination is intrinsically contextually driven. Engel, Gilmartin, Bongort, and Hess (2000) also argue that the calculation of system RUL in PHM systems alone does not provide sufficient information to form a decision or to determine corrective action. They state that without comprehending the corresponding measures of the uncertainty associated with the calculation, DSS outputs have little practical value.

5. HUMAN FACTORS OVERVIEW

Human factors is defined as 'the scientific discipline concerned with the understanding of the interactions among humans and other elements of a system, and the profession that applies theoretical principles, data and methods to design in order to optimize human well-being and overall system performance' (International Ergonomics Association, 2000). Within multiple high risk industries such as nuclear, oil and gas, and the medical domains, there is an existing recognition of the importance of HF, not just from a safety perspective, but also from a systems performance perspective. A recent directorate of the Nuclear Installations Inspectorate (NII) of the Health and Safety Executive (HSE) of Great Britain (2010) outlines how HF needs to be incorporated in all industrial projects in the field, throughout the full project lifecycle, to achieve both the aims of increased safety and reliable energy production. The objective is again reiterated about considering HF as an integral part of all projects, and not just an afterthought. The issue that we see repeated is that if the requirements of system operators are only accounted for at the end of system design, then it is unlikely that it will be a useable system.

PHM systems aim to be highly autonomous up until the point that a decision is required regarding maintenance intervention. In this way PHM systems can assist maintainers to determine the optimum time to perform maintenance given a host of constraints, providing the operator with confidence bounds on the availability of critical assets to meet production schedules. Ideally autonomous diagnostic and prognostic capabilities are to be implemented within an integrated maintenance and logistics system that supports critical complex systems throughout their lifetimes (Vachtsevanos et al., 2006). However, there is little to no evidence that it has as yet proven possible in practice to achieve this level of autonomy, and some degree of human intervention is typically required. In fact, a complete prognostic health management system still does not exist (Saxena et al., 2010). For this reason this paper draws on the human factors discipline in order to propose a set of design rules for the incorporation of human factors into PHM, particularly with regards to data visibility during the decision making process.

5.1. Human Factors in PHM

The application of human factors has traditionally been in safety critical industries, where a variety of methods and techniques are applied to understand human interactions within a system and the potential for human error, and recommendations are made to improve the system, environment, organisation or tasks to improve human performance. It has long been recognised that maintenance tasks are vulnerable to human error, particularly in the aircraft maintenance domain (Australian Government Civil Aviation Authority, 2013; Ben-Daya, Duffuaa, Raouf,

Knezevic, & Ait-Kadi, 2009; International Civil Aviation Organization (ICAO), 2003; Latorella & Prabhu, 2000; Rankin, Hibit, Allen, & Sargent, 2000) and maintenance of the protection systems in nuclear industries (Khalaquzzaman, Kang, Kim, & Seong, 2011; Rasmussen, 1975). In these instances human factors principles have been applied in order to reduce both the rate and impact of human errors.

However, there has not been a strong input from human factors in the domain of PHM. Most of the PHM literature, when it considers human interactions within the system at all, considers that a benefit of PHM is the potential reduction in required maintenance interventions, thereby reducing the opportunity for human errors in the maintenance process (Leão, Fitzgibbon, Puttini, & de Melo, 2008). While true, this view of human factors does not consider the possibility of harnessing human intelligence and reasoning abilities to improve the overall maintenance system, or of modelling human interactions with the system to improve both the prediction of faults and effectiveness of the system output. Only Zhao, Tian, and Zeng (2013), and Yu, Syed Zubair, and Yang, (2013) suggest that human factors could be included as an uncertainty in the PHM system itself, although ultimately both works neglected to use HF as a modelling parameter. Research in this area could investigate the feasibility of incorporating some of the existing HRA techniques in a PHM model, or could use another approach whereby there is feedback from the maintainer/installer in order to generate a confidence interval for the possibility of human error having occurred.

Despite the potential in these areas, in this paper, we propose a more general framework for the level of human interaction with a PHM system based on the calculated reliability (or inversely speaking the calculated uncertainties) of the PHM system, and from this the requirements for the outputs from the PHM algorithms and the feedback to the human maintainer. There are several papers that consider the important issue of the user interface through which PHM analysis is displayed to the maintenance staff (Bechhoefer & Morton, 2012; Mathur, Cavanaugh, Pattipati, Willett, & Galie, 2001; Saxena et al., 2010). Mathur et al (2001) recognise that human factors considerations need to guide the development of interface components and accessibility requirements. They provide an example of a web-based design of servers which support a distributed, multi-platform, three-tier architecture. Saxena et al (2010) detail four key parameters driving the requirements for prognostics from a technical engineering perspective, but alludes to the fact that classifying software requirements based on functionality, e.g. feature set, capabilities, generality, security, and usability e.g. human factors, aesthetics, consistency, and documentation, is also important. Bechhoefer and Morton (2012) studied the lack of adoption of condition monitoring systems relating to wind turbines in the renewable energy sector. They

concluded that as no single condition indicator (CI) can detect all failure modes, a user display requirement is necessary to view, threshold, and trend information that incorporates more than just spectral data or one CI. They specify the need for a data reduction methodology that is intuitive and user friendly, citing the use of the health indicator (HI) concept, which is the integration of several condition indicators into a single value. The HI provides the health status of the component to the end user. In contrast to these works, which focus on providing a user friendly interface at the end of the system, we propose that early consideration of how the operator will use system outputs in practice should drive the whole philosophy of the PHM system and hence influences not just the design of the interface, but the decisions on what data to present and at what level of detail.

5.2. PHM as a Decision Support System

Sandborn (2005) states that methods used to obtain and store large amounts of information has largely been perfected, and as a result, a sort of information overload is prevalent, where it is not uncommon that a lot more information exists than organisations know how to use. Sandborn states that the trick now is to figure out how to make decisions based on that information. The goal of applied PHM technology is to provide decision support. Therefore, the final form of the output from a PHM system, driven by the context of the user, is actionable information that supports improved decision making (Kalgren et al., 2006). Decision Support Systems (DSS) are designed to support the intelligence, design, or choice phases of human decision makers (DM) (Mintzberg & Simon, 1977).

A comprehensive study was conducted by Ketteler (1999) on the requirements for equipment monitoring and decision support systems in the machining/manufacturing domain regarding their reliability, flexibility, and user friendliness, using the input of industries from Japan, the USA, Canada, and Europe. Data from machine builders, end-users, and monitoring system suppliers was collected and analysed. The main conclusions are applicable across multiple industries, dealing with the theme of industrial integration, and lack thereof, of online decision support capabilities aiding maximum throughput. Ketteler concludes that less than 38% of end-users were at the time satisfied with available monitoring systems, the main reasons for this being the lack of system reliability, too many false alarms, and the complicated nature of the monitoring systems. Reliability was defined as high detection rates with low false alarms. While the number of satisfied end-users may have increased in the preceding decade, Ketteler's conclusions on end-users general expectations leading to their satisfaction in monitoring systems and DSS are still applicable today. The most important expectations for end-users when using DSS were less downtime of the production equipment, less scrap production, higher

productivity, easier DSS operability, and less false alarms. Given the need for greater operability, DSS and associated technologies need to move out of the realm of esoterica, enabling full implementation and management environments within organisations. Many analytics technologies still focus on the technical aspects with insufficient regard for the monitoring of model performance and the sharing of information in a collaborative environment. Although this is one of the less glamorous aspects of predictive technologies, in many ways it is one of the most important, as without the establishment of the confidence levels in predictive models the technology will always be underexploited and untrusted (Butler, 2013).

5.2.1. Human Factors Considerations in Decision Support Systems

Human interaction with automation as a whole, of which PHM can be considered a branch, and the use of DSS has been widely researched in human factors. Many lessons can be learned by PHM system designers from the introduction of automated systems in the aviation industry for example, and there is a large volume of knowledge which exists in the HF literature on the subject. One of these lessons is whether total system safety is always enhanced by allocating functions to automatic devices rather than human operators (Wiener & Curry, 1980). Research on DSS information output indicates that DSS which indicate the status of a system are preferable to those that advise operators on how to respond (Crocoll & Coury, 1990). Similar findings in high-risk industries where the information is imperfect suggest that status displays are better than command displays (Sarter & Schroeder, 2001). DSS which incorporate a high degree of decision autonomy have failed frequently in industrial settings, as discussed earlier. In theory, a DSS acts as a 'prosthesis' to aid a human DM who is purportedly characteristically flawed and inconsistent in his/her decision making. As such, more precise algorithms are the preferred research objectives of PHM, as opposed to a greater understanding of the power of human cognition (Salvendy, 2012). This type of reasoning is common in the PHM literature. However, the level of automation required with such an approach conflicts in reality with the amount of situations the algorithms must face. The great danger here is that a DSS will make wrong decisions about situations it has not been modelled to compute. Tied to this is the fact that removing the responsibility of decision making from a human DM in high-risk industrial settings has been shown to have negative consequences as people will simply blame erroneous decisions on the automation.

This phenomenon has been labelled as automation bias (AB), essentially the tendency to over-rely on automation, and has been studied in various academic fields. Although most research shows overall improved operator and system performance with the use of automation, there is often a failure to recognise the new errors that DSS can introduce.

This problem can also be described as automation-induced complacency or insufficient monitoring of automation output. User factors which directly influence AB include operator trust and confidence in the DSS. Environmental mediators include workload, task complexity, and time constraints, which pressurise the cognitive resources of the end users. Mitigating factors of AB includes implementation factors such as training and emphasising user accountability, and DSS design factors such as the position of the advice on the screen, updated confidence intervals of the DSS output, and the provision of information versus recommendation (Goddard, Roudsari, & Wyatt, 2012). The 'information versus recommendation' degree of automation where the DM is used to critique the output of a DSS has met with more success in terms of industrial integration, particularly in high-risk situations (Salvendy, 2012). For example, Guerlain et al. (1999) created a DSS for blood type identification in a blood bank. When used as a critiquing tool, where the DSS presented the users with different hypotheses regarding the data available rather than defined solutions, the operators made correct decisions 100% of the time. This was in contrast to a DSS which did not allow the operators to critique the decisions, which led to wrong decision being made between 33% and 63% of the time.

This gives us an interesting insight into the power of human cognition, one of a number of seemingly intangible elements important for successful businesses (Pecht, 2008). With regard to the power of human cognition in the decision making process, it has been written that the human recognition process relies heavily on context, knowledge, and experience. The effectiveness of using contextual information in resolving ambiguity and recognizing difficult patterns is therefore the major differentiator between the recognition abilities of humans and systems (Jain et al., 2000). With this in mind, the fundamental research issue in building intelligent DSS should centre on linking the domain-specific knowledge of experts with the normative power of analytical decision techniques to improve the quality of decisions (Yam, Tse, Li, & Tu, 2001). It has been said that the complex human decision process largely follows a Bayesian approach, as given a set of information, human decision makers tend to duplicate Bayesian predictions if they are provided adequate information in appropriate representations (Martignon & Krauss, 2003). The strength of this approach is demonstrated in recent research which illustrated that human reasoning in complex situations, in this case complex ribonucleic acid (RNA) folding schemes related to HIV and cancer research, outperformed specifically formulated RNA folding algorithms almost by an order of magnitude. The research focused on allowing humans to come up with complex folding patterns for RNA through a crowdsourcing application, and not only were humans able to develop better models of RNA folding than previous computer algorithms, but design rules formulated by the online

community have even been used to construct a new algorithm, EteRNABot, and in some cases represent completely new understandings about RNA folding that have yet to be explained mechanically (Lee et al., 2014).

Formal methodologies have been developed, called knowledge-based expert systems, in an attempt to capture human knowledge to draw conclusions in a formal methodology framework. An expert system is a DSS that essentially mimics the cognitive behaviour of a human expert. It consists of a knowledge base, a set of if–then–else rules, and an inference engine which searches through the knowledge base to derive conclusions from given facts (Venkatasubramanian, Rengaswamy, & Kavuri, 2003). This essentially forms a sort of indirect fusion approach, which uses information sources like a-priori knowledge about the environment and human input into a DSS (Teti, Jemielniak, O'Donnell, & Dornfeld, 2010). Again we see however that the problem with this kind of knowledge representation is that it does not have any understanding of the underlying physics of the system, and therefore fails in cases where a new condition is encountered that is not defined in the knowledge base. Therefore, this kind of knowledge is referred to as 'shallow' since it does not have a deep, fundamental understanding of the system which it is attached to (Venkatasubramanian, Rengaswamy, & Kavuri, 2003).

Similarly Billings (1991) describes what he terms as 'human-centred automation' in the aviation industry. Automation systems in Billings definition include systems which have intelligence, or some capacity to learn and then to proceed independently to accomplish a task. Such reasoner systems are evidenced frequently in PHM literature. Billings argues that the quality and effectiveness of an automation system depends largely on the degree to which the system takes advantage of the combined strengths of humans and automation technologies, and equally compensates for the weaknesses of both elements. Though Billings admits that humans are far from perfect sensors, decision-makers and controllers, he argues that they possess a number of vital attributes which automation systems do not. These are that humans are excellent detectors of signals in the presence of noise, can reason effectively given uncertainties, are capable of abstraction and conceptual organisation, can cope with failures not envisioned by system designers, possess the ability to learn from experience and thus the ability to respond quickly and successfully to new situations, recognise and bound the expected, cope with the unexpected, and to innovate and to reason by analogy when previous experience does not cover a new problem. Humans thus provide a degree of flexibility with regards to decision making and system control that cannot be attained by computational DSS alone, except in narrowly and well defined, well understood domains and situations. These uniquely human attributes each provide a reason to retain the human in a central position in systems

which are neither directly controllable nor fully predictable (Billings, 1991).

The reliability of automation and decision support tools has long been understood to be a key factor in the success of the tool (Wickens & Dixon, 2007). Madhavan and Wiegmann (2007a) and Wickens and Dixon (2007) both conducted a meta-analysis of numerous research studies relating the reliability of diagnostic automation and its effect on the performance of human operators. The main conclusion from both studies indicates that below an optimal threshold of 70% reliability, performance degrades to the point that DSS are largely disused. Balfe et al (2012) describe a set of principles for automation systems, designed for rail automation but applicable to other domains. Among these are the importance of reliability of the automation, and feedback to the human operator in terms of making the base information, raw data that has been transformed in to useful information, visible and providing understandable outputs to the operator. Bechhoefer and Morton (2012) explicitly mention the need for end-user confidence in PHM systems to be high in order to preserve the value of the system. They refer to the need to reduce false alarm rates (type I errors) and increase the sensitivity to actual faults (type II errors), i.e. increasing PHM system reliability. They also specify that to achieve widespread deployment of CMS, it is necessary to change the perception of end-users by convincing them of the value proposition supporting PHM. One of the facets enhancing a strong proposition that they note is an improved user interface, greater system reliability, and greater access to more actionable information.

5.2.2. Trust in Decision Support Systems

A review of trust in automation systems was conducted by Balfe (2010), of which DSS can be considered a branch. Table 1 below outlines the key findings from research on the factors leading to operator trust in automation systems. It can be argued that the usage of DSS under uncertainty relies on the same tenets to realise integration into the working environment. Balfe (2010) concludes that the effect of system uncertainty on trust and subsequent usage has been conclusively proven, and that evidence exists to support the notion of human competence as a key dimension in trust as understanding automation systems can improve the rating of trust.

Table 1: Summary of key research on trust in automation, adapted from (Balfe, 2010)

Key Finding	Author
There is a correlation between trust in and usage of automation.	(De-Vries, Midden, & Bouwhuis, 2003; Muir & Moray, 1989)
High reliability and competence are fundamental requirements for trust in automation.	(Muir & Moray, 1989; Wiegmann, Rich, & Zhang, 2001)
Operator self-confidence and the usefulness of the automation also influence usage.	(Lee & Moray, 1992, 1994)
For complex systems, explicit feedback is required to develop trust.	(Dzindolet, Peterson, Pomranky, Pierce, & Beck, 2003; Sarter, Woods, & Billings, 1997; Sheridan, 1999)
Trust must be well calibrated to ensure optimal use of automation.	(Lee & See, 2004; Madhavan & Wiegmann, 2007b)
Accurate mental models are important to ensure correct calibration of trust.	(Sheridan & Parasuraman, 2006)
Individual differences influence trust.	(Merritt & Ilgen, 2008)

Decision making given large uncertainties has been widely studied in the medical literature, many of whose conclusions on DSS integration into the working environment agree with those of Balfe (2010). One example of this is evidence based medicine (EBM), where clinicians integrate individual clinical expertise with the best available external clinical evidence from systematic research. Combining both individual expertise with external evidence allows clinicians to improve the accuracy and precision of diagnoses and prognoses (Sackett, Rosenberg, Gray, Haynes, & Richardson, 1996). EBM has led to the creation of clinical decision support systems (CDSS), interactive computer software systems designed to aid doctors with medical decisions, designed to impact clinician decision making about individual patients at the point in time that decisions are made (Berner, 2007). They are similar in scope and design to their industrial counterparts, albeit the system inputs are clinical metrics related to the human body. This same approach can be utilised by maintenance and management personnel involved in decision making related to defective components or equipment. Uckun, Goebel, and Lucas (2008) and Popov, Fink, and Hess (2013) draw similar comparisons.

While CDSS have many proven benefits, their uptake by GPs (general practitioners) is limited. Shibl, Lawley, and Debuse (2013) researched how and why GPs accept DSS via a UTAUT (Unified Theory of Acceptance and Use of Technology) based model. The insights into the reasons why GPs do not use DSS are transferable to other industries for the development of strategies to enable greater widespread adoption of DSS. Shibl et al. (2013) conclude that the four main factors influencing DSS acceptance and use include usefulness, facilitating conditions (including training), ease of use, and trust in the DSS output. Similarly, Alexander (2006) concludes that a clinician's level of trust in CDSS is affected by how knowledge is represented, the CDSS' ability to make reasonable decisions, and how they are designed. Again, usage issues arise if end-users do not understand how to use the CDSS.

Dreiseitl and Binder (2005) investigated how physicians react when faced with DSS suggestions that contradict their own diagnoses. They found that in 24% of the cases in which the physicians' diagnoses did not match those of the DSS, the physicians changed their diagnoses. Physicians were significantly less likely however to follow the decision system's recommendations when they were confident of their initial diagnoses. They conclude that given uncertainties, people are most likely to trust their own judgement. False trust leads to wrong diagnoses, therefore uncertainty quantification is critical. Quality assurance and validation of such systems is therefore of paramount importance.

The challenge of increasing system reliability concurrent with decreasing system complexity allowing greater usability cannot be understated. For while the algorithms and methods behind the three facets of PHM, detection, diagnosis, and prognosis, must become more robust and potentially more complex as they seek to reduce and ultimately eliminate uncertainties, so too must their outputs become flexible, reconfigurable, and subjectively easy to interpret. While one can argue that this approach would dictate the use for a 'black box' style methodology to DSS, this too is also not favourable. This is because the complexity of the mathematical models involved, coupled with end-user perception of high missed detection and false alarm rates, leads to mistrust and eventual non-use of DSS. Consequently a more open interface is required where PHM outputs are viewed as non-esoteric. This essentially means the transformation of data to usable information, useable information being context driven. As such the management of DSS must be addressed to providing the right information in the right form to the right people at the right time in the right place to support maintenance-related decision-making across different organisational levels (ProcessIT Europe, 2013). Uckun et al. (2008) similarly state the need for PHM to become less of an art and more of a science. They conclude that one of the main issues with PHM today is the lack of standardisation governing the research, and that it is often impossible to derive actionable conclusions based on the research results.

6. PROPOSED DESIGN FRAMEWORK

The aim of PHM systems is to provide information for maintenance decisions and ideally, the information would be totally reliable. However, although a perfectly reliable PHM system is a noble aim, it is unfortunately unlikely to always be possible. The uncertainties within any system mean that a PHM methodology acting as a DSS can never be perfectly reliable, either due to technical difficulties in creating an accurate model or external factors which influence the reliability of the output. With this in mind, it is important to consider the application of the PHM system within the overall socio-technical system of the maintenance organisation and develop the system against a design philosophy appropriate for the context of use.

The design framework presented here is intended to assist the developer of a PHM system in considering the feedback requirements based on the expected reliability of the PHM algorithms and hence set a design philosophy. This is a crucial first step in correctly setting the user requirements and designing the HMI. We propose that as the level of reliability of the algorithm increases, the required feedback to the operator decreases as per a simple proportional relationship. It is important to note that in this paper we deal with this concept purely in the notional sense. The reliability of the PHM system is intended to be calculated after it has been developed, and before the detailed design of the user interface for presenting the results. This is an adaptation of the well-known pilot control and management continuum developed by Billings (1991) for NASA, which directly relates levels of automation and human involvement in flight control systems for pilots.
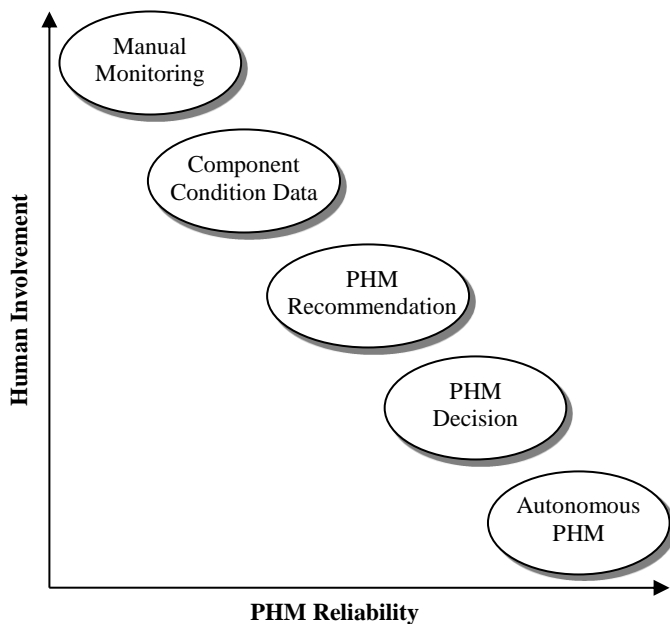

Figure 1: Proposed Design Framework

Figure 1 describes this proportional relationship and suggests five categories of PHM system. The categories begin with a low PHM reliability and a corresponding high level of human involvement. In this case the system would probably not benefit from a PHM system at all; however this decision must be made at a local level. At the other end of the scale, very high PHM reliability (e.g. very low levels of model uncertainty) could successfully achieve an autonomous PHM system in which human input is not required.

The lower level of reliability considered in this model is suggested to be 70%, on the basis of the previously discussed research (Madhavan & Wiegmann, 2007a; Wickens & Dixon, 2007) which provides evidence that automation below this level is not useful. The same research by Wickens & Dixon (2007) describes how the benefits of automation increase as the reliability level increases and on the basis of their analysis, we describe a suggested banding of the reliability levels to support the model in Table 2. The banding is intended as a guide and not a hard and fast rule.

Table 2: Banding of Reliability Levels

Reliability	Feedback Required
< 70%	Manual Monitoring
70-80%	Component Condition Data
80-90%	PHM Recommendation
90-99%	PHM Decision
>99%	Autonomous PHM

Each of these bandings is described below:

- Manual Monitoring – below a 70% reliability threshold it is proposed that traditional methods of system maintenance are employed, such as corrective and/or scheduled maintenance approaches. The development of a PHM system with such an amount of present uncertainties is unlikely to add significant value to the maintenance decision process;

- Component Condition Data – between 70% and 80% reliability, it is proposed that a PHM DSS use component condition data in conjunction with traditional methods of system maintenance to provide an additional data source to aid human decision makers. This generates requirements in terms of the data presented to the decision maker which must be at a sufficient level of detail for them to interpret. A combination of these two elements might take the form of scheduled maintenance intervals, in which maintenance will always be performed, interspersed with the use of CBM technologies to help ensure the component does not fail between maintenance windows.

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- PHM Recommendation – when reliability levels are expected to reach 80%, the PHM system can provide a primary recommendation on proposed maintenance actions, and there is no need for the inclusion of traditional maintenance approaches. The recommendation should be provided in conjunction with supporting information for a final decision by the human decision maker, and at the lower levels of the reliability band should be presented alongside alternative hypotheses. Again, this suggests requirements on presentation of the PHM analysis in a manner which facilitates the human decision maker in interpreting the data;

- PHM Decision – above 90% reliability, a decision can be made by the DSS and be provided to the human decision maker for confirmation. Supporting information is not required at this stage and the human decision maker would be expected to seek out additional information if they believed it was necessary with regard to a particular decision. The interface requirements are perhaps less demanding in this case, but is still necessary to provide access to interpretable data when required;

- Autonomous PHM – if the reliability of the PHM system is proven to be above 99%, the system can be considered for implementation as an autonomous system, with directions for maintenance interventions passing directly from the system to the maintenance team, without the involvement of any human decision maker. There is also scope in such a system to coordinate with inventory management systems and/or a logistics knowledgebase for complete synchronisation of the maintenance effort. Such a system would be particularly efficacious in the self-maintaining systems envisioned as the next generation in intelligent industrial equipment enabling the fourth industrial revolution (Lee, Ghaffari, & Elmeligy, 2011)

Identification of the correct banding is key to developing the correct design philosophy and presenting the PHM data to the human decision maker in a way which optimises operator trust in and use of the system. However, regardless of the banding, the system should still facilitate the user in 'drilling-down' in to the source data in order to support understanding and trust in the system. Again, this is to avoid the use of a 'black-box' style approach. The design framework detailed here proposes that the source data can become gradually more hidden as reliability increases. We believe this framework can act as a useful guide for PHM system designers, and that further research is needed in the area if PHM is to continue its advance to becoming a standard industrial methodology in the coming years.

7. CONCLUSION

In this paper we conducted a comprehensive review tying together for the first time the literature within the HF, automation, decision support, and PHM domains. We have presented unique findings from these disciplines across multiple domains that will aid in the acceptance, widespread industrial integration, and ultimate end-use of PHM systems which act as maintenance DSS. Some of the key findings in this paper include the factors which govern the acceptance of automation and DSS technologies in multiple applications, including presentation of information considerations and developing operator trust in those systems. From the knowledge and insights gained we demonstrated how such HF elements must be considered from the outset of system development, and why it is important to consider the application of a PHM system within the overall complex socio-technical-economic contexts existing within today's organisations. We presented a theoretical blueprint which is a useful first step in designing and deploying successful PHM systems in industry, where using a quantitative assessment of PHM reliability, based on PHM system uncertainties, one can alter the system outputs to cater for the needs of both end-users and the organisation as a whole.

While an important step in bridging the gap for the first time between human factors and PHM, this work represents early theoretical research. Further research activity can be focused towards the identification of applicable industrial case studies to provide empirical evidence in support of the model, generating a more detailed model of guidance for implementation of PHM systems, and combining HF metrics as inputs into PHM systems in order to increase the reliability of decision outputs. In addition, the different types of uncertainty (e.g. false positive and false negative rates in diagnosis, accurate prognosis horizons in prediction, receiver operating curves, etc.) may have different implications for how the information is presented. Future work will look at the sources of uncertainty in terms of detection, diagnosis, and prognosis and expand the model presented here to include guidance on the human factors concerns relating to different types of uncertainty.

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BIOGRAPHIES

Darren McDonnell graduated from the Dublin Institute of Technology, Ireland, with a B.Eng.Tech in Mechanical Engineering (2008) and a B.Eng (Hons.) in Manufacturing and Design Engineering (2010), for which he won the Institute of Engineering and Technology Manufacturing Engineering Student Prize 2010. He completed his M.Sc. Master's degree by research in Mechanical and Manufacturing Engineering (2013) in collaboration with Trinity College Dublin, Ireland, and Daimler AG, Ulm, Germany. He worked as the lead Daimler AG researcher to oversee the completion of the EU FP7 funded project ADACOM (Adaptive Control for Metal Cutting). The research centred on developing state of the art manufacturing and decision support methodologies for the machining of freeform gear geometries to single digit microns of accuracy. Between 2008 and 2013 he also worked in industry as a maintenance engineer within the pharmaceutical sector and as a mechanical design engineer in the maritime sector. He is currently studying for his Ph.D. in Mechanical and Manufacturing Engineering as an Early Stage Researcher in the EU FP7 Marie Curie ITN project InnHF, in collaboration between Trinity College Dublin and Pfizer Ireland Pharmaceuticals. His current research interests focus on the development of a Decision Support System for an industrially integrated data driven predictive maintenance program for complex pharmaceutical equipment.

Dr. Nora Balfe completed her Ph.D. research on human factors issues in design of automation systems in a railway signaling context in 2009 at the University of Nottingham. She also holds an MSc in Human Factors and Safety Assessment from Cranfield University (2003) and a BEng in Aeronautial Engineering from Queen's University Belfast (2001). She has experience working in industrial human factors teams in the rail and aviation industries and is currently working as an Experienced Researcher on the Marie Curie ITN InnHF project at Trinity College Dublin. With a strong background in research on automation design and use, her current research interests focus on identification of innovative ways of managing risk through human factors methods and techniques in safety critical industries.

Sameer Al-Dahidi (B.Sc. in Electrical Engineering, The Hashemite University, 2008; M.Sc. in Nuclear Energy - Operations and Maintenance Specialty – Ecole Centrale Paris and Université Paris-Sud 11, 2012) is pursuing his Ph.D. in Energetic and Nuclear Science and Technology at Politecnico di Milano (Milano, Italy). He is an Early Stage Researcher (ESR) in the European Union Project INNovation through Human Factors in risk analysis and management (INNHF, www.innhf.eu) funded by the 7th framework program FP7-PEOPLE-2011- Initial Training Network: Marie-Curie Action. His research aims at analyzing the uncertainty in Condition-Based Maintenance (CBM); developing maintenance decision making taking into account uncertainty and Human Factors; and optimizing the maintenance activities in industrial plants and components which can increase the safety and productivity of industrial plants, while reducing the overall operational and maintenance costs. In 2008-2010, he worked as an Electrical & Instruments Engineer at CCIC in Oil & Gas and petrochemical mega projects in Kuwait and UAE. In 2010 and 2011, he did his internships at AREVA NP in France.

Dr. Garret E. O'Donnell is Assistant Professor in the Manufacturing Technology and Systems group within the School of Engineering at Trinity College Dublin, Ireland. He completed his Ph.D. research on sensor technologies for process monitoring in flexible machining systems at University College Dublin (2006). He is a member of the Institute of Physics, MInstP, the Institute of Engineers of Ireland, MIEI, the International Academy of Production Engineering (CIRP) of which he also an associate member. His current research interests are based around advancing manufacturing technology, including manufacturing technology that underpins ICT and bio-medical technologies, and high performance machining in biomedical, automotive and aerospace applications. Specific research interests include: Sensing, process monitoring and control of manufacturing and high performance machining and grinding operations; micro-manufacturing including the machining, handling, assembly and inspection of micro-components; automation of manufacturing operations and the automation of laboratory testing; sustainable and energy efficient manufacturing; development and characterisation of sensor systems and adaptive control. He is the author or co-author of over 60 peer-reviewed publications and other research outputs to date.