Intelligent decision support for maintenance: An overview and future trends

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Abstract: The changing nature of manufacturing, in recent years, is evident in industry's willingness to adopt network connected intelligent machines in their factory development plans. A number of joint corporate/government initiatives also describe and encourage the adoption of Artificial Intelligence (AI) in the operation and management of production lines. Machine learning will have a significant role to play in the delivery of automated and intelligently supported maintenance decision making systems. While e-maintenance practice provides a framework for internet connected operation of maintenance practice the advent of IoT has changed the scale of internetworking and new architectures and tools are needed. While advances in sensors and sensor fusion techniques have been significant in recent years, the possibilities brought by IoT create new challenges in the scale of data and its analysis. The development of audit trail style practice for the collection of data and the provision of a comprehensive framework for its processing, analysis and use should be a valuable contribution in addressing the new data analytics challenges for maintenance created by internet connected devices. This paper proposes that further research should be conducted into audit trail collection of maintenance data and the provision of comprehensive framework for its processing analysis and use, allowing future systems to enable 'Human in the loop' interactions.

Keywords: Machine learning, Industry 4.0, E-Maintenance, Intelligent Maintenance.

1. Introduction

Increasingly manufacturing industry is adopting network connected intelligent machines in their factory development plans. This has created a new wave of interest in incorporating advances in Artificial Intelligence (AI), which is described and encouraged by a number of international government/industry initiatives. The Industry 4.0 movement is one such initiative, between the German government and national industries, with a role to envisage and promote the use of new technologies and organizational methods for manufacturing (German Federal Government, 2016). Cyber Physical Systems (CPS) are a core theme of Industry 4.0, encompassing the further integration between machines and computing resources, leveraged in part by the Internet of Things (IoT). In addition, the enhanced information processing and analysis opportunities provided by the ubiquity of sensor use in modern machinery to provide data streams and resulting Big Data sets is seen to create potential for new products and new types of manufacturing models. In the US the Industrial Internet Consortium is an initiative setup between the US government and large industrial organizations. While having similarities to the vision provided by Industry 4.0 there is a concentration on three core components: Intelligent Production Machines, Analysis of Sensed Data, People and Machines working together (Posada et al. 2015). The industrial Internet is also much more focused on the visualisation of data at both global and local levels (Industrial Internet Consortium, 2017). The central differentiator between the two visions is that while Industry 4.0 focusses on manufacturing, the remit of the Industrial Internet is much wider bringing in other sectors of the economy as well. In the opinion of the authors of this paper the central challenge is how maintenance can best utilise the opportunities brought by this expansion of AI into the manufacturing arena. The quality and provenance of data are important factors in data management and a key success factor for when engaging in any form of analytics. With maintenance rapidly adopting key Industry 4.0 technologies, such issues attain increased importance for successful applications and services. The path towards Industry 4.0-enabled maintenance has seen developments in Predictive Maintenance, Condition Based Maintenance, Intelligent Maintenance, and E-Maintenance; leading to the introduction of IoT, Context aware computing and Audit Trail concepts for maintenance. This paper offers a critical overview of this evolving landscape, including Industry 4.0 applications in the area of maintenance. The paper concludes by finding that while maintenance is increasingly adopting Industry 4.0 technologies, issues related to data governance, provenance and quality management, are already well appreciated in the Big Data literature; these topics deserve equal attention in this application domain and to this end a discussion of the potential of using the Audit Trail for maintenance data is provided.

2. Intelligent Decision Support

2.1 Condition Based and Predictive Maintenance

Condition Based Maintenance (CBM) is the standard term employed to describe maintenance strategies determined on the basis of the actual condition of assets, as identified by the application of condition monitoring programmes (ISO 13372:2012)(BS EN 13306:2017). While this general viewpoint holds a central role in literature, details on how exactly CBM benefits from individual technologies, methods, has also received significant attention in the literature. In industrial practice, CBM involves the performance of maintenance tasks triggered by the analysis and interpretation of monitored hardware parameters and the associated decision making rules as an integrated process (Liyanage et al., 2009). Peng et al. (2010) describe Condition Based Maintenance (CBM) as a “decision making strategy to enable real-time diagnosis of impending failures and prognosis of future equipment health, where the decision to perform maintenance is reached by observing the “condition” of the system and its components” or additionally on the basis of prognostics about the anticipated future condition. While the diagnostics and prognostics parts of CBM approaches have benefited from incorporated machine intelligence in order to associate measured data and parameters with current and future machinery conditions (Jardine et al., 2006) (Emmanouilidis et al., 2006), an early criticism of machine intelligence use in CBM has been that the research has concentrated on very specific cases with only limited attempts to deliver solutions with generic applicability (Lee et al. 2006). As a response to this Lee et al. (2006) put forward a toolkit for predictive CBM based on sensor data, capable of working with different manufacturing machines and set ups. In their review of machinery diagnostics and prognostics Jardine et al. (2006) indicated a number of research directions for Condition Based Monitoring (CBM) systems for condition based Maintenance, including the development of a new generation of sensors for on-line data collection in real time and investigation into the provision of predictive techniques based on collected data. The next step in the maintenance data processing chain is to produce action recommendations, as highlighted in the OSA-CBM architecture (MIMOSA, 2017). This elevates a CBM strategy to proactive maintenance. Within such an approach, asset events and errors are decomposed in a process flow, arguing that in understanding the conditions leading up to a fault, more accurate estimates of safe operating limits can be identified (Radkowski and Jasinski, 2014). The importance of utilising a range of evidence contained in multiple data sets and streams when making CBM related decisions is highlighted by Niu et al. (2010). Such a data fusion approach can bring benefits through the combination of many condition measurements into a consolidated description of maintenance needs for an individual component or unit under observation. Niu et al. (2010) outline a maintenance system that takes advantage of data fusion and the OSA-CBM standard, providing a platform for the optimised exploration of maintenance decisions and predictions. Building on the availability of Big Data Bousdekis et al. (2015) provides a review of Condition Based Maintenance (CBM) and proposes a framework for maintenance decision making, utilising expert knowledge, which is capable of recommending maintenance actions for implementation.

The question of how much capital to invest in maintenance practice has been addressed in the field of vibration monitoring by Al-Najjar and Alsyouf (2004). These authors concluded that a framework of performance measurement should be utilised to ensure value for money is being obtained from maintenance activities. Further research has been conducted into calculation of the likelihood of failure of assets and the appropriate stage at which to conduct maintenance interventions. Yao et al. (2016) identify two types of failure under CBM where in the first instance an asset may fail before the monitoring threshold is reached and the second where the monitoring threshold is exceeded without asset failure. Goyal et al. (2016) provide a more recent review that includes a number of machine intelligence methods for CBM and predictive maintenance practice and note that while such techniques provide good offline models research scope still exists in harnessing them for real time prediction and decision making. Accorsi et al. (2017) add a set of models to aid the prediction of faults in production systems and explore machine learning techniques such as decision trees utilised for the classification and identification of abnormal operating conditions derived from production machine data streams. Accorsi et al. (2017) go onto propose a framework for data mining and modelling related to CBM.

Prognostic maintenance practice is based on the prediction of likely breakdowns in hardware formed from the analysis of collected parameters and degradation trends. Liyanage et al. (2009) identify three prognostic approaches:

- Model based: Centred on detailed knowledge of a system and its interlinkages; its use is limited due to inherent complexity of modern industrial systems.
- Data-driven: Requires historical parameter collection from monitored assets; requires pattern recognition and machine intelligence techniques to realise actionable decision making outcomes.
- Hybrid: Is a combination of the two aforementioned approaches requiring a joint analysis of both known information about a system in combination with sensed data points.

The use of prognostic maintenance practice to estimate the remaining useful life of a component has been investigated by Van Horenbeek and Pintelton (2013). This work takes into account inter-component dependencies in the degradation calculation approach and prognostic maintenance policy developed (Van Horenbeek and Pintelton, 2013). Prognostic maintenance practice can benefit from advances in data capture and the availability of big data for a range of applications. Lee et al. (2013) describe the use of a Digital Twin whereby a machine may be represented in digital form utilising CAD models and sensor streams from the machine. Lee et al. (2013) also describe the possibility for similar machines to communicate with each other to check and compare status to form more accurate feedback to the maintenance monitoring system along with the use of self-aware sensors with built in decision making capabilities. Lee et al. (2013) conclude with an outline of a cloud based cyber physical model of machine data capture, analysis and use. The capture and integration of expert knowledge to support and validate predicted routines is very much an active subject of research. The use of prognostics in condition based maintenance through the construction of a hybrid model incorporating expert knowledge is investigated by Galar et al. (2015). In this work a combination of discrete data and semantic feedback (provided by experts) is combined to provide decision support in relation to issues of component degradation (Galar et al. 2015). Baysian approaches to prediction in maintenance are not new; McNaught and Zagorecki (2009) have explored the use of a Bayesian network approach to prognostic modelling of equipment in terms of maintenance. A more recent technique drawing on Bayesian theory for prediction is put forward by Desforges et al. (2017) is described as a support system for maintenance planning activities with the aim of modelling fault prorogation in subsystems for improved prediction. In addition the technique aims to reduce the downtime of systems enabling further efficiencies in planning to take place (Desforges et al., 2017). Niu and Jiang (2017) propose a technique for prognostic control at a component level within a system while enabling the optimisation of the system as a whole at a global level. This enables the development of a suitable overall maintenance interval schedule based on sub system level health prognostics (Niu and Jiang, 2017). Ragab et al. (2017) put forward a way of pattern selection from condition monitoring data to support prognostic maintenance, a method that does not rely on expert judgement and statistical base assumptions on initial set up. A case study on prognostic techniques relating the maintenance of railway infrastructure is presented by Marugan and Marquez (2016). Binary Decision Diagrams are used with fault trees to provide an Internet based decision making process for problem diagnosis in railway points. Recent work by Belkacem et al. (2017) investigated the combined approach of integrating diagnostic and prognostic maintenance policies to provide a dynamic maintenance system; a technique these authors aim to extend and develop further, in terms of its scalability, in future research. The practice of prognostic maintenance must of course be viewed within a wider maintenance system composed of the latest hardware and software. Such a system is envisaged within the field on E-maintenance, which is the subject of the following section of this paper. Xia et al. (2018) provide a concise summary of predictive techniques in use for maintenance practice in a range of digital manufacturing activities; these authors note that innovative manufacturing techniques, such as 3D printing, bring new challenges to the way maintenance is performed, demanding new research into how supply chains support products manufactured in this way. Vafaei et al. (2019) have investigated CBM from the perspective of providing an approach for an early warning system. In this work Vafaei et al. (2019) utilise a fuzzy inferencing approach to enable a system capable of developing what-if scenarios based on generated rulesets regarding the potential for break downs in monitored production lines. In their survey paper on CBM and prognostic techniques in industry Sakib and Wuest (2018) make the case that a combination of such techniques is increasingly seen as the most likely future path for maintenance practice, involving a multiphase approach to problem detection, diagnosis and corrective/mitigating actions.

2.2 E-maintenance

Incorporating predictive maintenance approaches within E-maintenance aims to integrate developments in web enabled communication technologies with semantically described data resources, sensing technologies and artificial intelligence algorithms to realise new capabilities for remote and ubiquitous maintenance. Levrat et al. (2008) state that inherent in the concept of e-maintenance is the remote monitoring and management of assets though

Internet-based technology. Levrat et al. (2008) go onto propose a framework for e-maintenance encompassing issues such as infrastructure, business processes and information architecture, noting that further research is needed in terms of unified standards for e-maintenance and the communication protocols required for effective operation. A particular feature of e-maintenance, enabled though its framework, is the facilitation of fault prediction in order to pre-emptively schedule mitigating maintenance activity. Voisin et al. (2010) proposes a prognosis business process as a formalisation of the predictive feature of e-maintenance practice in their proposed model. Muller et al. (2008) provides a review of the main research works in the area of e-maintenance, focussing on definitions of e-maintenance ranging from a maintenance strategy to a type of maintenance planning. Muller et al. 2008) state that the combination of the latest ICT developments, especially with regard to prognostics, with maintenance practice has led to the emergence of e-maintenance. However, a more accurate assessment would see e-Maintenance as an enabling factor for more efficient maintenance, which would also include prognostics, rather than the other way round. The utility of machine learning in the successful delivery of e-maintenance has been noted by Ucar and Qiu (2005). These authors also note the rise of wireless communications technology (networks, sensors etc.). Arnaiz et al. (2010) provide a review of communication technology use in e-maintenance and point to two trends; that of the use of wireless web enabled communication technologies and the miniaturisation of sensing devices. The potential value of RFID and other associated smart tagging technologies is noted by Adgar et al. (2010) along with the rise of ubiquitous computing, a movement describing the almost universal availability of miniaturised computing power in a range of, often, portable devices (Arnaiz et al., 2010; Krommenacker et al. 2010). The prominence of one particular approach has been identified by several authors (Arnaiz et al., 2010; Campos, 2009; Vogel-Heuser et al. 2014); that of Agent technology, where sometimes geographically distributed software modules are able to cooperate in order to autonomously fulfil a given objective or set of objectives. When used with machine learning techniques this approach is particularly relevant to the field of e-maintenance. Overall, e-maintenance is considered an umbrella term to include a range of enabling technologies which facilitate the whole data process chain in maintenance, from data acquisition through sensor miniaturisation, smart tags, and sensor networks, to wireless communications and mobile devices, all the way to web-based and semantic computing for offering maintenance services and decision support, including technology enablers for maintenance training (Holmberg et al., 2010).

Holgado et al. (2016) identify a range of functionalities provided by e-maintenance applications listing 10 categories of tools. These focused on provided diagnostic and prognostic functionality were rated more highly for usefulness than those than were based on model simulation. A recent evaluation work comparing diagnostic and prognostic maintenance policies is provided by Belkacem et al. (2017). The use of AR (Augmented Reality), where animations and graphics are overlaid on actual scenes in real time, is identified by Azuma (1997) and Azuma et al. (2001) as an aid to maintenance activities. Henderson and Fiener (2011) explore the use of AR for engineer knowledge assistance in maintenance and repair activities. These findings are interesting as Turner et al. (2016) envisages the development of AR with simulation, allowing models of production systems to be fed with data in real time and overlaid on the actual physical view of the plant/assets in question. Such a combination of technologies could act as a context relevant visualisation to aid 'in-field' maintenance decisions. Ceruti et al. (2019) examine the use of AR within case studies drawn from aviation maintenance practice, concluding that such an approach can streamline part identification tasks and on the job training and support of maintenance technicians.

Real world case studies of e-maintenance systems in action can be found in industries such as aerospace and rail and road maintenance where sensed data about both static and mobile assets may be collected and analysed to make decisions about present and future maintenance actions. (Ben-Daya et al., 2016). Ben-Daya et al. (2016) charts the rise of e-maintenance, from manual systems, and CBM into web connected systems.

Increasingly industry is witnessing the gradual introduction of Cyber Physical Systems (CPS). Such CPS systems are composed of deeply interconnected hardware and software systems with sensing capabilities and are often able to provide intelligent decision support and decision making functionalities to users (NIST, 2013). Holgado et al. (2016) notes the importance of CPS and the increasing potential of machines to interact with their maintenance systems and influence the works carried out and their timing. As a tangent to this Ruiz-Arenas et al. (2014) explores many of the e-maintenance issues that pertain to CPS systems themselves and provide the case study of a CPS enabled greenhouse as an example. Penna et al. (2014) and Botelho et al. (2014) describe an approach for the visualisation of CPS integration in maintenance systems and the development of maintenance scenarios using 3D modelling tools. The aforementioned visualisation approach focusses on Human Computer Interaction issues taking into account and designing interfaces for the support of human operators within the maintenance process (Penna et al., 2014). One of the central components of e-maintenance is the ability to freely collect, exchange and process data. One approach to this is through the use of semantic technology and ontology use. Nuñez and Borsato (2017) explore the potential of semantic technologies to describe machine health management and prognostic forecasting of potential failure. The semantic framework built by Nuñez and Borsato (2017) is provided in the form of prototype software to allow experimentation with a wide variety of plant and machinery. Zhou et al. (2017) provide a potential augmentation to the aforementioned semantic framework through their research of fault diagnosis and provision of a requisite knowledge model. This work also utilises a semantic approach and envisages the use of pattern recognition approaches such as Neural Network to better identify and classify a fault through data analysis (Zhou et al., 2017). Li et al. (2017) in a review of artificial intelligence/machine learning use in manufacturing discuss programmes for proactive and preventative maintenance that would be possible within an intelligent manufacturing system. The interconnected nature of organisational management systems and manufacturing production machines in combination with accessible rich data and information sets is leading to this new role for machine learning in industry (Li et al. 2017). In applications with high maintenance needs there is a requirement to coordinate the supply chain responsible for spare parts delivery. This subject has been researched by Espíndola et al. (2012) who put forward a conceptual approach to combining an intelligent maintenance system with supply chain coordination and planning processes. In addition da Silva et al. (2014a) also investigate the integration of parts supply chain and planning with an intelligent maintenance system touching on the use of ontology to describe communication within the combined architecture; along with Saalmann et al. (2016) who propose a multi-layer ontology incorporating existing semantic approaches to supply chain and intelligent systems. A particular use of ontology is in the potential integration of spare parts supply chains and the field of CBM, where the two entities possess distinct knowledge sets and express their data and parameters in different levels of granularity and importance (Saalmann et al., 2016). Saalmann et al. (2016) make the case for a common terminology and utilise DPWS (Device Profile for Web Services) in order to obtain metadata from physical devices (DPWS is a standardised middleware for exposing parameters about and data from physical hardware devices).

One particular challenge relating to e-maintenance data is that of missing values, where connectivity issues and faulty sensors can lead to incomplete data recordings (Loukopoulos et al., 2017). The research of Loukopoulos et al. (2017) explores the process of imputing missing values in data relating to the e-maintenance practice required for compressors used in the oil industry. This work investigates the use of computational intelligence approaches such as self-organising map (SOM) Neural Network learning, K nearest neighbours classifier and Bayesian techniques. Lou found that while SOM and KNN produced reasonable results the best result was produced by Multiple Imputation MI (an uncertainty method used to introduce simulated data based on Bayesian theory). Beyond missing values, Liyanage et al. (2009) makes the point that there is also a need to keep experts in the loop; networks of people are required to enrich data from systems and sensors with their own contributed observations or knowledge. Djurjanovic et al., (2003) outline a watchdog agent which has been designed to convert sensor data into health management information and Liyanage et al. (2009) place this within an overall e-Maintenance framework. In combination with decision management functionality the agent is designed as a semi-autonomous software module capable of interaction and coordination with enterprise maintenance and manufacturing systems.

In line with Muller et al. (2008) definition of e-maintenance as a combination of 'telemaintenance principles with Web services and modern e-collaboration principles' enabling knowledge exchange and intelligence based on the ability to identify and collect relevant and timely parameters, a more recent wave of technologies presents a step change and the possibility for real time proactive maintenance. This paradigm addressed existing practices that were much more focussed on the improved management of maintenance, from reactive to proactive activities, through prognostics based on largely disconnected datasets with potential for data quality and timeliness penalties. The increasing importance of maintenance as a service in industry is highlighted by Akkermans et al. (2019); these authors highlight that the product service methodology has evolved into the provision of smart maintenance services to complement products, made possible by more accurate quantifications of service needs and costs based on real-time analytics.

2.3 IOT

Developments within hardware have increasingly leveraged the availability of almost ubiquitous network connectivity provided by internet based communication protocols. This has now culminated in IoT whereby hardware from sensors to entire machines may be web addressed as interactive objects providing raw and often intelligently filtered data points to client software applications. Cloud implementations utilise both network technologies and big data production capabilities of IoT connected hardware to provide new distributed manufacturing forms and the opportunity for prognostic flexible maintenance based on intelligent near real-time analysis of live operating environments. The utilisation of cloud technologies to enable CBM is one of the more recent research strands within e-maintenance. Karim et al. (2016) make the case for what they term 'Maintenance Analytics', where four time related perspectives of practice are defined in the utilisation of data provided by industrial application cloud platforms. In a rail related case study, 'Rail Cloud', Karim et al. (2016) find that a systematic treatment of maintenance data is required with its synthesis and integration required for decision making in order to support the next generation of digitally monitored plant and machinery. In the research of Truong (2018) it is acknowledged that the inherent complexity of modern machinery IoT enabled cloud platforms require additional analysis of interactions between system components, and that this analysis also requires human intervention and decision making capabilities. Truong (2018) go onto propose a system capable of automatically recognising when human expertise is required and alerting the correct expert for input of knowledge and decision making capability. While this research outlines an architecture for distributed analytics processing Truong (2018) notes that much research is still required in the correct mapping of analytics to domain knowledge derived from experts an in the facilitation of the 'Human in the Loop'. Mourtzis et al. (2016) propose a shop floor monitoring approach that includes CBM functionality delivered via a cloud infrastructure. The approach of Mourtzis et al. (2016) highlighted the possibility of near real time data acquisition and monitoring for maintenance decision making. In later work Mourtzis et al. (2018) provide a cloud based model for IoT sensor data collection from a manufacturing production line; highlighting the potential of such a system in its ability to interconnect the shop floor with enterprise IT software, these authors elude to the possibility of fine grain control and prediction at the individual machine tool sensor pack level. Wang et al. (2017) provide an example model of cloud based prognostic maintenance practice outlining the advantages of local processing of data on mobile devices in order to manage the overall analytics load within the system and reduce the communications bandwidth required. In their work Wang et al. (2017) cite the need for further research in the development of distributed data analysis practice and co-ordination of heterogeneous data streams and for improved security for data communication. The question of enhanced security practice for cloud based CBM practice is one explored by Tedeschi et al. (2017) who propose a structured approach to the assessment of security requirements within a cloud based CBM system. In more recent work Bowden et al. (2019) propose a 'plug and Play' end to end cloud architecture for predictive maintenance. The architecture utilises Docker containers (an open source software that is used to 'wrap' up unites of code into generically compatible container compliant with common software as a service and platform as a service implementations) to provide flexibility in the implementation and deployment of the completed analytics system. A case study is provided by these authors, based on the monitoring of a Comau industrial robot, with initial results demonstrating a range of predictive and near to real time alerting functionalities expected of a future industry 4.0 maintenance system (Bowden et al., 2019). Predictive maintenance architectures such as Bowden et al. (2019) often rely on data streams provided by IoT compliant sensing packs composed sensors and Edge data processing devices. It is the opinion of certain research works that there are limitations in the utilisation of Cloud platforms for industrial applications in that the sheer volume of data transfer that must take place between facility and Cloud infrastructure means that more localised processing is necessary (Anaya et al. 2018). Patel et al. (2017) also acknowledge the data transfer limitation of Cloud platforms along with the need for near to real time processing of data, a factor that is also difficult to achieve in such platforms.

In such circumstances the ability of Edge devices to pre-process data streams emanating from production and machine tool sensors takes on additional importance; as such decentralised processing of data using Edge devices is an active stream of research within Industrial IoT analytics programs to support maintenance activities (Uhlmann et al. 2017). Parpala & Iacob (2017) describe how IoT enabled Edge technologies can be used to allow data collection from legacy machinery. This work also demonstrates a simple data communication interface to complement the sensor and Edge device hardware implementations required (Parpala & Iacob, 2017). Jantunen et al. (2018) provide a case study drawn from research of a proactive maintenance approach within a power plant. This work examined the output of vibration sensors monitoring flue gas blowers within a power plant; the research concluded that a six month time difference between component replacement times suggested by use of this approach and manual assessments of the same data (Jantunen et al., 2018). A wider exploration of Edge computing in the manufacturing domain is provided by Wan et al. (2018) who propose an architecture for IoT enabled production. In their maintenance based case study Wan et al. (2018) the authors found that the packing of confectionary boxes by robots could be performed autonomously with self-organisation and planning undertaken at the production line level, made possible by the inherent advantages of co-located processing provided by Edge computing devices. The connection and synergies achievable with the combined use of IoT, predictive maintenance and 3D printing are elicited by Yamato et al. (2017a). Such linkages are explored with regard to aircraft maintenance, and an analytics platform is proposed (Yamato et al., 2016) along with a case examining the potential of sound stream analysis in maintenance utilising edge devices (Yamato et al., 2017). In terms of machine learning use with data streams Tran and Yang (2012) propose a platform for CBM utilising intelligent techniques such as Principal Component Analysis (PCA) and Support Vector Machine (SVM) in particular to extract features from data and then diagnose faults in rotating machinery, respectively. In further studies involving the maintenance practice relating to rotating machinery, Yunusa-Kaltungo and Sinha (2017) make the case that while analysis of big data obtainable from such equipment is potentially transformative, in the case of vibration based parameters more streamlined techniques can hold the potential for lower cost and simplified e-maintenance practice. These authors provide an approach utilising classification and optimisation techniques for use in the monitoring of such machines (Yunusa-Kaltungo and Sinha, 2017). Kanawaday and Sane (2017) explore the use of a forecasting method, AutoRegressive Integrated Moving Average (ARIMA), on data streams generated by IoT sensorised production line machinery. This approach has been used to improve maintenance planning and in future research may be adapted to predict remaining useful life of a production machine and detect operational anomalies (Kanawaday and Sane, 2017). The concept of tele maintenance (remote maintenance) is highlighted by Selcuk (2018) as a future direction for prognostic maintenance, made possible by IoT connected sensors, intelligent products and machines. This author also points to the emergence of maintenance as a full integrated service provided to customers, leveraged through IoT technology (Selcuk, 2018). It is also the case that Digital Twins, providing virtual replicas of real world production lines and assets, may be used in IoT (Koulamas and Kalogeras, 2018) for connected predictive maintenance practice (Qi & Tao, 2018) and administered from both inside and outside the customer organisation. A number of interesting new business models for IoT based service provision are outlined by Ju et al. (2016). These authors propose a generic framework for the enablement of IoT business model development (Ju et al., 2016). Khan et al. (2017) also provide a methodology for IoT sensing in industry, illustrated by a use case based on a process to facilitate predictive maintenance within an organisation. It is clear that localised processing of data streams can provide real benefits in terms of real time decision making and the enablement of intelligent automation; for an additional commentary on the mining of streaming data for maintenance activities Munir et al. (2018) provide a concise summary. At this point it should be noted that newer IoT enabled maintenance techniques are perhaps not a complete replacement for existing techniques such as root cause failure analysis and preventative maintenance practice; existing and new techniques can be complimentary in their use, a point made by Bengtsson and Lundstrom (2018).

2.3.1 Data fusion from multiple sensor outputs

The IoT opens up disparate physical plants and machinery to the potential for ubiquitous and real time data connectivity. While much work still remains to be completed on the establishment of unified data exchange standards and semantics progress has been made in terms of data networking and management approaches for this recent paradigm shift in connectivity.

2.3.1.1 Large scale data internetworking

Emmanoulidis et al. (2009) make the case for the take up of advanced communication networks in conjunction with mobile computing solutions in order to support maintenance activities. A reliance on locally available data and resources provided by LAN (local Area Network) often means that organisations must undertake manual data mining tasks on disconnected data sets in order to make planning decisions on maintenance activities (Emmanoulidis et al., 2009). Sayafar et al. (2016) add that the real time optimisation of maintenance activity planning, in part enabled through mobile networked devices, will lead to universal access to vital asset data for involved workers. The production of data by intelligent products provides another IoT enabled source of data. Intelligent products may produce data while in operation ‘in the field’ or even while in production while being assembled in a factory. McFarlane et al. (2012) investigate the state of the art in intelligent products point to the use of RFID (Radio-frequency identification) tags to trace products through the supply chain and also note the rise of IOT and its potential to network connect intelligent products. Cuthbert et al. (2016) make the case for product intelligence in domestic appliances suggesting that low cost electronics could be integrated into such products to enable health tracking for maintenance purposes. Improvements in communications networks especially mobile networks are helping to leverage interest in IOT. The 5G mobile standard promises bandwidths capable of serving the requirements for the wireless connection of IOT devices with greater energy efficiency (Andrews et al., 2014). Papakostas et al. (2016) outlines 5G in a manufacturing context pointing to the possibility for ubiquitous connectivity and potential for plug and play hardware on the shop floor.

2.3.1.2 Large scale data management and analytics

The volume of data sets and streams available with networked hardware in manufacturing leads to changes in the way that data analysis takes place. Cloud technologies have been assessed for this purpose and the concept of Cloud Manufacturing has been put forward as a potential analytics solution. The Cloud Manufacturing paradigm is based on the use of distributed Cloud Computing technologies for sustainable manufacturing while integrating distributed Internet technologies such as IoT (Zhang et al., 2014). Sustainability in maintenance practice is a theme explored by Franciosi et al. (2018) who surveyed literature and found that proactive and predictive maintenance practices could lead to reduced environmental impact in many cases, noting that improved end of life estimation and failure modes that take account of emission/environmental damage due to machine breakdown hold much potential. The distributed processing of data envisaged by Cloud Manufacturing is one way to address the analytics need created by the challenge of continuous maintenance particularly of high value long lifecycle products (Roy et al., 2016). Truong (2018) provide a predictive analytics approach for maintenance utilising IoT and Big Data Cloud resources.

More efficient methods of maintenance are required as many high value products are sold as product-service offerings whereby maintenance is delivered as part of the retail offer (Baines et al., 2009). Cyber Physical Systems (CPS) in manufacturing are entities that both produce and consume vast quantities of data in their operation. While encompassing such entities as cybernetic extensions to humans CPS systems in terms of manufacturing are more likely to be formed of the following components: production capable machines; sensing functionality (both hardware and software); intelligent computer processing functionality. With CPS there is a need for both local data processing (within the CPS hardware entities), for autonomous operation within a shop floor perhaps, and remote analytics for monitoring and global coordination. Gubbi et al. (2013) notes that both Cloud and IoT technologies are required to fully enable CPS and link together intelligence at both local and global levels; it is this, in the authors’ of this paper opinion, that will help to deliver the next generation of manufacturing solutions including those focussed at the maintenance level. While realising interconnectivity at a hardware and digital communications level is key to the latest maintenance practice an often overlooked concept, though one that is gaining in acceptance, is that of context awareness in relation to maintenance.

2.4 Context aware computing

The area of context awareness in systems has been growing over recent years. Dey et al. (2001) describe the context awareness of systems as being provided through the intelligent characterisation and interaction of computer applications with their surrounding environment. In the view of Dey et al. (2001) context awareness acquisition by a system may be manual as well as automatic. The research of Bettini et al. (2010) advises that applications should be abstracted away from the context related functionality that they utilise, meaning that changes in context data and models should not break the software systems built upon them. To this end Bettini et al. (2010) survey the field of context modelling with the aim of identifying good practice in order to reduce the complexity of context aware application development; recommendations are also made as to the use of formal modelling techniques such as Object-Role Modelling (ORM) in the development of context models. Blasch et al. (2012) highlights the importance of context in the development of a data fusion architecture noting that the use of technologies such as simulation in combination with context based information can provide further efficiencies at the analysis stage. One key driver for increased interest in context awareness is the rise of pervasive computing. Ye et al. (2012) identify pervasive computing as a type of computing that through the use of sensors is able to interact with the world with minimal or no human intervention. Perera et al. (2014) provide an overview and a taxonomy of a lifecycle approach to context awareness for utilisation in conjunction with IoT linked middleware, highlighting a progression from context acquisition through processing and analysis to its eventual distribution though API (Application Programming Interfaces) and appropriate data formats.

Hong et al. (2009) provide a classification framework for context aware systems in their survey of the area identifying five distinct layers: Concept and research layer; Network layer; Middleware layer; Application layer; User intrastate layer. Focusing on Enterprise Information Systems, El-Kadiri at al. (2016) argue that the multi-networked nature of physical entity supported IoT empowers physical products and assets to become intelligent; but in order to cope with the breadth, depth, rate, and sheer volume of produced data a context aware approach is needed. El-Kadiri at al. (2016) identify abstract context categories (e.g. user, environment, system, service and social context) as relevant to a wide range of applications but they indicate that such high-level context abstraction needs to be supplemented by domain-specific context modelling, providing examples relevant to maintenance and asset management.

Of most interest to this paper are the application and middleware layers. While benefitting from the other layers the application and middleware layers contain the logic required to establish context and provide intelligent processing and presentation of data to the user while holding the potential as a platform for automated decision making. In the research put forward by Perera et al. (2014) these authors also sought to examine appropriate data collection frequency levels and establish responsible components for data collection and decision making within context aware IoT systems. The importance of context in data fusion is highlighted by a number of authors (Khaleghi et al. 2013, Fernández-de-Alba et al. 2015, Snidaro et al. 2015, Linas et al. 2016). In particular the fusion of context related data is interesting in the work of Fernández-de-Alba et al. (2015) who put forward a framework to combine senor data from different sensors and platforms; the framework is demonstrated through a case study that guides users to meetings within an organisation. An important facilitator of context aware computing is semantic technology.

The survey of Snidaro et al. (2015) underlines the increasing role of machine learning in the analysis and use of context based data, in addition these authors also note the need to provide context processing functionality as part of a shared middleware layer that applications utilise for information processing. Linas et al. (2016) go onto formalise the roles of context and information fusion in their combined use. These authors also promote the JDL (Joint Directors of Laboratories) data fusion model which defines five fusion levels their roles in applications and the algorithmic approaches associated in their realisation. Smirnov et al. (2015) introduce a number of context based knowledge fusion patterns. The seven patterns aim to encapsulate the different context based effects that occur in decision support systems when integrating new knowledge and changes in semantic mappings to related ontologies. The role of ontology in the collection and analysis of context related data has been researched by a number of authors (Perera et al. 2014; Sminov et al. 2015, Sminov et al. 2016, Linas et al. 2016). From literature it is clear that semantics and metadata descriptions will play a significant part in the development of context awareness, as raised by Sminov et al. (2015) the ability to arrive at and distribute processed data with a recognised shared meaning will be key. Perera et al. (2014) identify six wider research challenge areas for context aware computing for IoT that in the opinion of the authors of this paper also relate to IoT enabled maintenance applications:

1. Automated configuration of Sensors
2. Context discovery
3. Acquisition, modelling, reasoning and distribution
4. Selection of sensors in sensing as a service model
5. Security, privacy and trust
6. Context sharing

Establishing and describing context for data is an important subject for the further development of maintenance practice, though perhaps it still lacks a holistic containing formalisation to enable its universal take-up in industry. It is the opinion of the authors of this paper that underlying many of the aforementioned IoT, Context, and prognostic maintenance research challenges outlined by Perera et al. (2014) it is perhaps that there is a need for an audit trail framework to be applied to data collection and semantic description methods, particularly for its use with maintenance applications taking into account their transactional nature and need for integrated scheduling.

2.5 The audit trail for maintenance

The quality and provenance of data are important factors in data management and a key success factor for engaging in any form of analytics. With maintenance rapidly adopting key Industry 4.0 technologies, such issues attain increased important for successful applications and services. Product and asset lifecycle data are increasingly acknowledge as a valuable asset (Kubler et al., 2015). Therefore their own lifecycle needs to be appropriately managed and this could become a key factor in establishing a credible audit trail for maintenance activities and data. Lin et al. (2007) conducted a survey into data quality relating to asset management information. The survey found that processes and software for asset related data quality management were missing in a majority of organisations interviewed; in addition organisations did not have a strategy in place regarding data quality (Lin et al., 2007). In a review of standards relating to Asset Management, Koronios et al. (2007) noted the increasing use of XML (eXtensible Markup Language) as a data description standard along with OPC UA (OPC Unified Architecture) for industrial system intercommunication. The OPC UA standard, while comprehensive in its specification, can be complex and expensive for an organisation to implement. The work of Henßen and Schleipen (2014) examines the role that the AutomationML mark-up language can play in simplifying the use of OPC UA models with existing data sets and streams expressed in XML. According to Henßen and Schleipen (2014) use of OPC UA directly is a complex task, utilising AutomationML mapping to OPC UA opens up the opportunity of streamlined connectivity with OPC UA compliant systems and manufacturing systems. Liyanage et al. (2009) mention the semantic web, ontology and use of XML metadata descriptions for information exchange in e-maintenance. Grangel-Gonzalez et al. (2016) take the semantic communication notion a step further by producing a metadata software shell for Industry 4.0 components. The approach is based on RDF (Resource Description Framework) and OWL (Web Ontology Language) and allows for new functionality, described by ontological elements, to be integrated into the communication framework with minimum disruption (Grangel-Gonzalez et al., 2016). In combination with machine intelligence such a framework could acts as an enabling protocol for automation efforts in maintenance activities and factory operations alike.

Many enterprise systems in organisations, such as ERP (Enterprise Resource Planning), possess event logging capabilities. Such event logs may be mined in order to reconstruct a chain of activities that have taken place within the organisation and administrated by the system (Tiwari et al. 2008, IEEE Task Force on Process Mining 2011, Turner et al. 2012) and then further analysed by automated techniques to provide optimised processes (Tiwari et al. 2010, Vergidis et al. 2015). Similar event logging based audit trails have been utilised in the field of cyber threat detection within networked software systems. Bass (2002) details efforts made in the development of intrusion detection systems utilising a data fusion approach. In this work Bass (2002) highlights the use of pattern detection utilising templates. In later research Vaughn et al. (2005) examine the possibility for automated cyber vulnerability recognition where sensor data is used to trigger security warnings. The aim of automated cyber security is also sought by Abreu et al. (2015) with the use of audit trail data. With this work Abreu et al. (2015) and others such as Nehinbe (2014) employ machine learning techniques to derive patterns and insights to, in principle, enable automated actions and decisions to be made. Duncan and Whittington (2016) advise on the regular analysis of audit trails in the effective securing of Cloud based systems. While useful in countering intrusions into maintenance systems it is also the case that such approaches provide much of the rigor and data management practise required to ensure quality and enforce standards within an organisation and its supply chain and linked parties. The use of such audit trail techniques in manufacturing has been much less evident though its use with IoT has in outline been explored by Lomotey et al. (2018) in research exploring the need for visualisation of Internet connected devices. In addition Lomotey et al. (2018) propose a provenance methodology to allow for improved traceability and identification of routes through a network that specific data points may take. Efforts towards a unified metadata syntax and model for provenance are embodied in the work of Moreau et al. (2011) who put forward the Open Provenance Model (OPM), enabling the unified and secure exchange of such data between networked systems and entities. Park et al. (2011) also explore issues surrounding the location of provenance data for an entity (local vs global storage) and the rights of access to the provenance data by other network connected entities.

Use has been made of audit type data in industrial applications. A sensor fusion approach has been used by Payan et al. (2016) in the development of proactive safety metrics for Helicopters. In this research Payan et al. (2016) fuse the outputs of flight data monitoring to form the basis for predictive safety measures, with the potential to advise preventative actions. Such an approach may also inform the development of audit trail compilation and use to enhance the scheduling and performance of maintenance activities. An approach to combining multi sensor data has been put forward in the information fusion technique of Basir and Yuan (2007), who utilise Dempster-Shafer theory evidence theory with an industrial case based on engine testing on an automotive production line. Basir and Yuan (2007) found that their approach was able to successfully address decision conflicts pertaining to engine fault diagnosis with an improved level of accuracy.

With the use of such audit trail based intelligent data mining there arises the potential need to explain the reasoning behind automated decisions to humans for the purposes of evaluating/ensuring provenance of maintenance data. Duncan and Whittington (2016) make a number of recommendations on how the audit trail for Cloud computing could be improved; the following are an adaptation of a subset of those recommendations with relevance to the maintenance field:

- Insufficient logging of data within Cloud environments and manufacturing systems, data logging is not set to 'on' by default
- A proper regime of data log migration to data storage is required
- Further understanding on information flow within a manufacturing system is required
- Enhanced data security is required to safeguard collected audit trail data and digital entry points to manufacturing systems from cyber attackers

It is the case that a 'human in the loop' is also required as their expert knowledge and overview capability can be leveraged, in particular, to help ensure data and process security. A vital step along the road to automation is the inclusion of human expertise along with standards such as the MIMOSA open system architectures for CBM and EAI (Enterprise Application Integration) (MIMOSA, 2017), which potentially provide a wider underlying structure for the concept of maintenance audit trails.

Figure 1 illustrates the concept of the audit trail with an example drawn from railway maintenance activities. In Figure 1 it can be seen that for a section of track there are a range of maintenance activities that may involve: maintenance workers, feeding back reports via mobile devices; rail maintenance vehicles with sensors; passenger trains fitted with track and infrastructure monitoring sensors. In addition a number of trackside sensors may also stream back data to a control centre concerning a range of environment specific parameters. IoT hubs may be co-located with trackside equipment and within train vehicles. Edge devices on standard passenger services may be linked to sensors and process and store data for forwarding to the IoT hub (allowing for when the passenger service may be out of communication range with the advantage of possibly reducing the amount of data to be communication due to built-in intelligent processing and filtering stage). The OPC/UA (Open Platform Communications – Universal Architecture) standard and message queuing telemetry transport protocol (MQTT) would provide the data transfer format to and from IoT hubs.

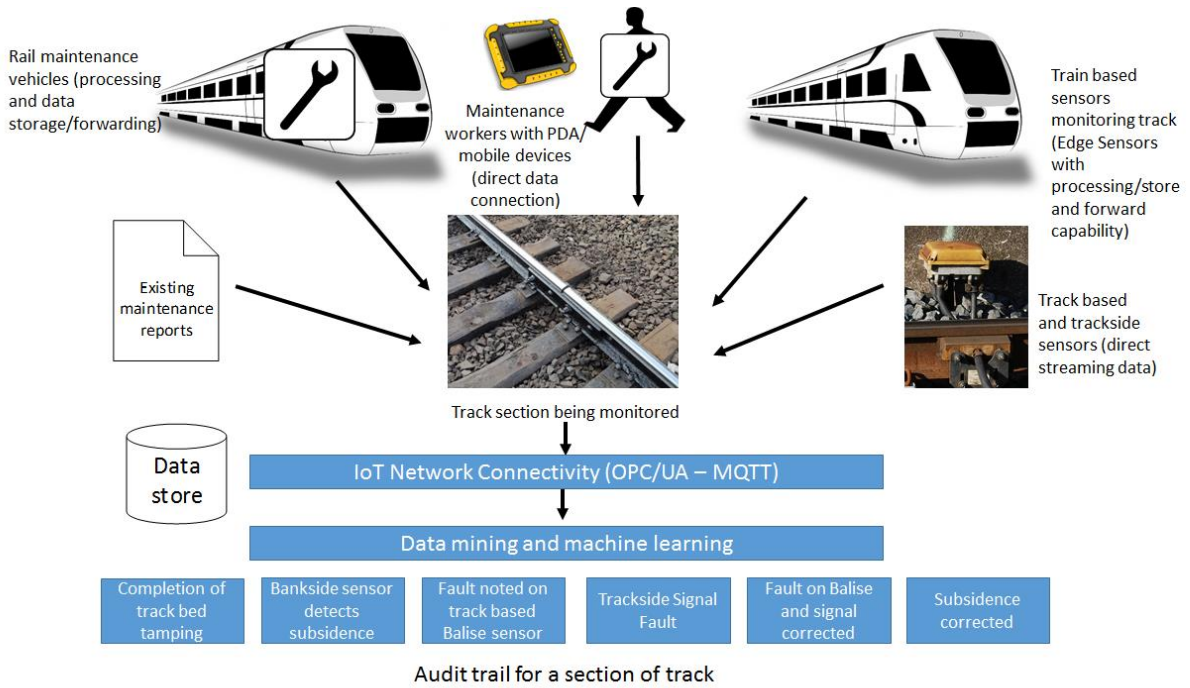

Figure 1: An audit trail drawn from rail maintenance activities and sensor streams for a section of track

The scenario depicted in Figure 1 relates to the possibility that sensors have registered faults with a Balise (track based forming part of an automatic train protection (ATP) system) and trackside signals in a period of time after the section of track has been tamped (where the ballast bed of the track is adjusted). In addition a bankside sensor has noted some occasional subsidence in the past. All these data streams are recorded at a central control centre. The use of data mining may establish a causal link between these events taking into account the outlier measurement from the bankside sensor leading to the root cause of the fault. The audit trail establishes the order of events via timestamps and the output from data mining/machine learning. Such audit trails once established can help in the decision making and may also advise trackside workers, undertaking maintenance in future scheduled activities, to make additional checks based on the history of the track section.

3. Related Work and Discussion

It is clear that Industry 4.0 enabling technologies are changing attitudes towards digital connectivity and automation in manufacturing, though it is also the case that there is a need for a holistic understanding of the use of machine intelligence in the achievement of automated and autonomous manufacturing visions of the near future. It is also clear from this review that standardised data collection processes and intelligent analysis techniques are the subject of current investigation by many research groups around the world. As part of this review, using the search tool Scopus, it was possible to identify the amount of papers published in the period 2000 to 2018. Of interest were the findings for papers published involving the subject of E-maintenance and that of predictive maintenance. Figure 2 shows that predictive maintenance papers have shown a gradual increase of the period peaking in 2018. For the same time period Figure 3 shows that E-Maintenance papers peaked in 2010 and then have stabilised at around 15-23 publications per year for the most recent 5 year period. From this review it was possible to identify a number of works that best typify the sub areas highlighted in this paper. Table 1 summarises these papers in terms of intelligent decision challenges and approaches taken.

From Table 1 it is clear that there is a wide range of potential solutions and approaches to intelligent maintenance, though it is the authors' opinion this field would benefit from clear processes to support audit trail style collection of data and clear framework for its processing, analysis and use. There will be a necessity to capture and store data streams from production machinery and the audit trails of decision making within Semantic technologies may provide a way of describing maintenance data so it may be shared across the manufacturing enterprise and potentially within the supply chain. The case for a metadata layer capable of semantically describing maintenance data is made in part by Pistofidis et al. (2016) who put forward a methodology for maintenance metadata management involving the incorporation of expert knowledge. Such technology may be the cornerstone of evolving context awareness in maintenance systems to enable automated decision making and scheduling for maintenance activities.

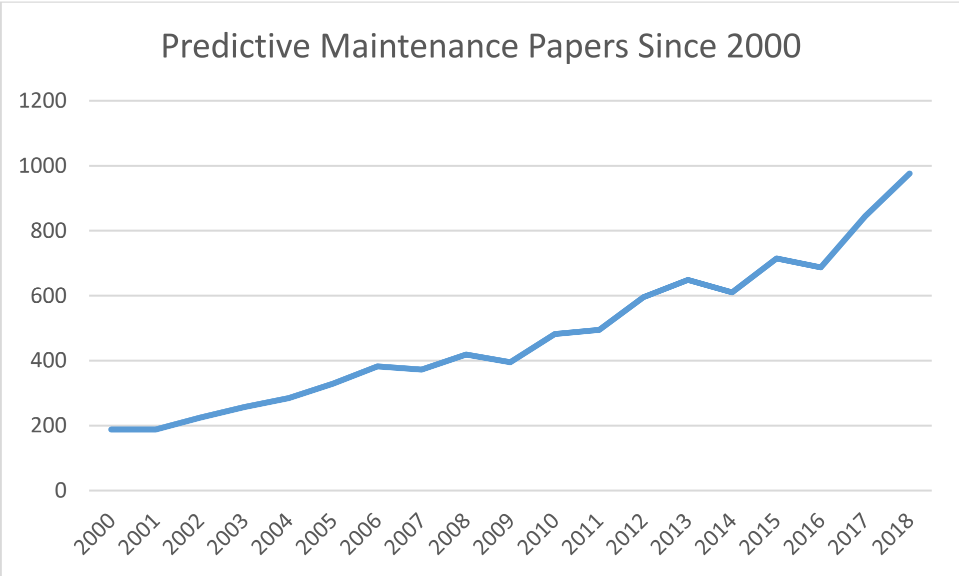

Figure 2: Papers published involving predictive maintenance between 2000 – 2018 (Source: Scopus)

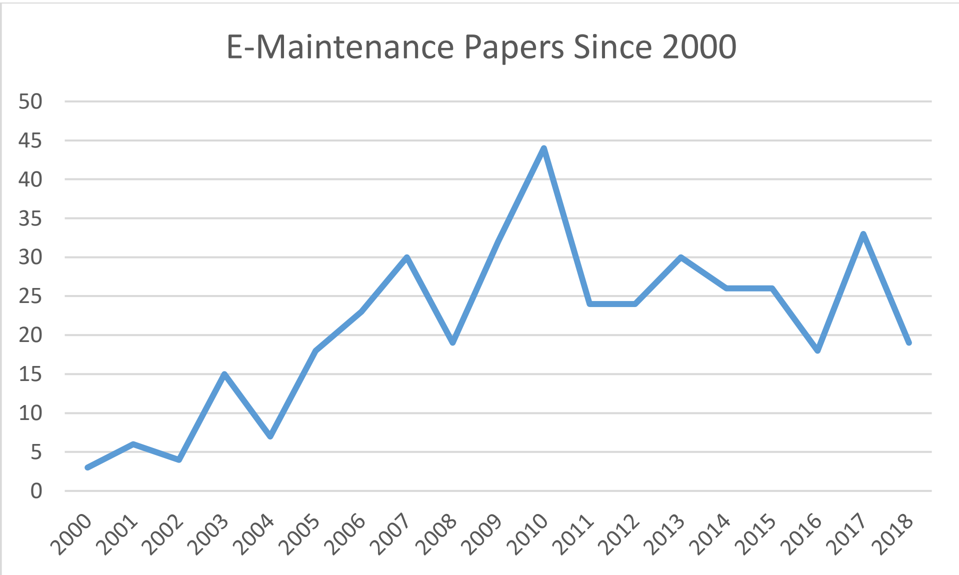

Figure 3: Papers published involving the subject of e-maintenance between 2000 – 2018 (Source: Scopus)

It is clear that machine learning will have a significant role to play in the delivery of future automated and intelligently supported maintenance decision making systems. Predictive maintenance programmes will increasingly rely on machine learning techniques in order to deliver proactive and dynamic maintenance plans. The extension of the manufacturing enterprise to digitally link with its supply chain has gained another potential benefit in the ability to order spare parts in advance of potential breakdowns, when predictive forecasting techniques are employed.

It is clear that industry is still missing an overall framework for digital maintenance. Advances in sensors and sensor fusion techniques have run-ahead of suitable processes and systems capable of fully harnessing their outputs. This is evident in the introduction of Cyber Physical Systems (CPS) within manufacturing, though progress is being made in the area of worker interactions with shop floor machinery. Both simulation and visualisation technologies, especially Mixed Reality, provide a new platform for enhanced machine assistance for human engineers and raise the potential for maintenance related Cobot development. Much research has concentrated on the further development and use of more readily available data streams such as those provided by SCADA systems. Increasingly though papers may be found exploring the role IoT can play in the provision of data streams from both new and even legacy equipment. This move is especially evident in the area of Condition Based Maintenance (CBM) and predictive approaches. Utilisation of Digital Twin systems to replicate industrial production assets are now being introduced; a significant focus in Digital Twin development is that of health monitoring and prediction of maintenance needs/breakdowns with many organisations adopting this virtual representation for the specific goal of increased uptime. For many organisations the use of existing systems in combination with new sensor technologies and software will provide many of the potential advantages promised by e-maintenance and visions such as Industry 4.0.

Table 1: Intelligent Decision Support Challenges and Approaches

Publication	Approach outline	Problem targeted
Prognostic maintenance		
de Novaes et al. (2017)	A review of prognostic techniques relating to remote field maintenance of wind turbines including discussion of Hidden Markov Model, Neural Networks and use of SCADA data.	Prognostic maintenance practice relating to remote field maintenance of wind turbines
Djurdjanovic et al. (2003)	Describes ‘Watchdog agent’ capable of sensor assessment and prediction of machine performance. Utilises Neural Network, Hidden Markov Model, Particle Filter	Product performance degradation prognostics

Fumagalli and Macchi (2015)	E-maintenance platform utilising web services approach and statistical techniques.	E-maintenance platform for rapid integration of maintenance activities
Katsouros et al. (2013)	Bayesian approach for maintenance action recommendation based on historical cases	Intelligent decision support/recommendation
Kiritsis (2011),	Closed loop product lifecycle approach for Intelligent products Definition, Semantic model and ontology for data interchange respecting IoT connectivity possibilities.	Intelligent products and product service model and data usage for improved product lifecycle including maintenance practice.
Lee et al. (2006)	Tools for prognostics utilising Self-Organizing Map (SOM),Hidden Markov Model, illustrated with case studies	Machine health prognostics
Lee et al. (2014)	A position paper and case study detailing. Discussion of Self-Organizing Map (SOM), Gaussian Mixture Model (GMM), Bayesian Belief Network (BBN), Fuzzy Logic for maintenance	Machine health prognostics
Leitao et al. (2016)	A survey of Smart Agent use in combination with machine intelligence within manufacturing and maintenance	Intelligent Maintenance Systems and CPS Integration
Leite et al. (2017)	Holistic prognostics to support maintenance of wind turbines utilising an approach incorporating Neural Network and Particle Filter (maintaining assets located in inaccessible/remote sites)	Maintenance Prognostics
Liyanage et al. (2009)	An outline of an integrated e-maintenance approach and description of the Watchdog (Agent-Based Real-time Remote Machinery Prognostics and Health Management) toolbox application. Utilisation of Software agent and custom algorithms.	Framework for E-maintenance with prognostic maintenance application.

McNaught and Zagorecki (2009),	Development of a model for Prognostic maintenance decision making and policy evaluation utilising Bayesian Networks	Prognostic modelling for reliability and maintenance policy experimentation
Niu and Jiang (2017)	Custom algorithm for dynamic maintenance incorporating both local health prognostics for combination with global optimisation approach	Health Prognostics and maintenance optimisation
Papathanassiou et al. (2013)	E-learning approach to support maintenance management proposing a toolkit for training delivery.	E-learning for maintenance management
Peng et al. (2010)	Classification of common prognostic models for maintenance. Discussion of neural network, Bayesian-related methods, hidden Markov models for maintenance.	Machine health prognostics – residual useful life
Selcuk (2018)	Prognostic maintenance, made possible by IoT connected sensors, intelligent products and machines. The emergence of maintenance as a full integrated service provided to customers, leveraged through IoT technology.	Maintenance as an IoT enabled service
Vafaei et al. (2019)	Fuzzy inferencing for rule set composition and maintenance scenario generation.	Maintenance decision support for CBM.
Voisin et al. (2010)	Custom algorithm for proactive maintenance, framework for ‘predict and prevent ‘.	Generic prognostic approach and methodology for maintenance decision support
Xia et al. (2018)	Concise summary of predictive techniques in use for maintenance practice in a range of digital manufacturing practices.	Predictive maintenance review of techniques
Yunusa-kaltungo and Sinha (2017)	Big data and optimisation techniques for simplified e-maintenance practice; utilisation of classification and optimisation for production machine monitoring.	Classification and optimisation technique for maintenance prognostics
Zhou et al. (2017)	Custom algorithm statistic for performance degradation forecasting of power	Performance Degradation Prognostics

	machinery based on historic and monitored datasets	
Remaining useful life prediction		
Belkacem et al. (2017)	Prognostic and diagnostic architecture for industrial system maintenance using a custom approach based on hybrid automata modelling.	Remaining useful life prognostics and diagnostics
Desforges et al. (2017)	Prognostic function for maintenance planning support. Proposes extensions to Object Oriented Bayesian Networks for Remaining Useful Life calculation	Proposes co-operative planning between production and maintenance to promote their synchronisation.
Fan et al. (2015)	Remaining Useful Life prediction and prognostics approach for LED lights utilising a particle filter approach based on Sequential Monte Carlo (SMC) and Bayesian techniques.	Remaining useful life prediction and prognostics
Galar et al. (2015)	Residual useful life predicted through data aggregation and context awareness using fuzzy approaches and clustering	Residual useful life prediction for condition based maintenance
Kanawaday and Sane (2017)	Use of the forecasting method, AutoRegressive Integrated Moving Average (ARIMA), on data streams generated by IoT sensorised production line machinery. Used to improve maintenance planning with possible future application to RUL.	Forecasting method utilising IoT data streams, with application to RUL.
Marugan and Marquez (2015)	Approach for the monitoring of rail track points utilising binary decision diagram and fault tree analysis. An online decision making system based on this research is envisaged as a next stage.	Diagnostic and prognostic maintenance decision making
McNaught and Zagorecki (2009)	Development of a model for Prognostic maintenance decision making and policy evaluation modelling with utilising Bayesian Networks	Prognostic modelling for reliability and maintenance policy experimentation
Niknam et al. (2015)	Prognostic based approach for maintenance decision	Residual life prognostics approach

	making based on remaining life prediction using a custom algorithm	
Ragab et al. (2017)	Pattern based approach utilising a logical analysis of data (LAD) and Kaplan–Meier (KM) estimator; provides an estimated reliability curve for a given monitored asset.	Prognostic technique for Condition based maintenance
Van Horenbeek and Pintelon (2013)	Dynamic maintenance policy development based on prognostics using a custom algorithm and degradation model.	Prognostic approach for component lifetime extension
Zhou et al. (2017)	Combination of forecasting and statistic based method to provide a combined time and condition based maintenance approach.	Degradation trend prognostics and fault diagnosis
Intelligent products and assets		
Barbosa et al. (2016)	Envisages the combination of both intelligent products with Cyber Physical systems (CPS), outlining the additional combined use of agent based systems to provide prognostic maintenance and decision making.	Intelligent products in use data combined with Cyber Physical Systems (CPS) for prognostic maintenance.
Brintrup et al. 2011	Intelligent agent platform based on a web service approach to leverage in field assets data generation.	Autonomous intelligent products in-use data harvesting with maintenance application.
Cuthbert et al. (2016)	Framework for domestic products health monitoring describing the potential for automated self-repair of assets based. A future research challenge section is set out by this paper	Intelligent product data use and maintenance with self-repairing assets
Dhall and Solanki (2017)	IoT based predictive car maintenance where the connected car is able to communicate health data so that service scheduling is streamlined.	Predictive Car maintenance scheduling
Katsouros, et al. (2015)	Embedded event detection within intelligent products though feature extraction and statistical time series data analysis.	Self-aware assets and analysis of their generated data streams

Kiritsis (2011)	Closed loop product lifecycle approach for Intelligent products Definition, Semantic model and ontology for data interchange respecting IoT connectivity possibilities.	Intelligent products and product service model and data usage for improved maintenance practice and product lifecycle management.
McFarlane et al. (2013),	A review of intelligent product and RFID tag data use.	Review of intelligent products field including RFID technologies for active participation of products in their manufacture and in field use
Meyer et al. (2009)	A review of intelligent products giving reference to maintenance practice that may be envisaged/leveraged through the paradigm. Discussion of agent based approach for potential combination with machine intelligence algorithms is provided.	Intelligent products in-use data and system interaction and interconnectivity, data provision potential for prognostics and maintenance decision support systems.
Parpala & Iacob (2017)	Utilisation of IoT hardware and protocols to link legacy machine tools to internet services for the provision of automated maintenance and status alerts to production line operators.	IoT connectivity to legacy machine tools with software interface and edge hardware implementation.
Selcuk (2018)	Prognostic maintenance, made possible by IoT connected sensors, intelligent products and machines. The emergence of maintenance as a full integrated service provided to customers, leveraged through IoT technology.	Maintenance as an IoT enabled service.
Truong (2018)	Predictive analytics approach for maintenance utilising IoT and Big Data Cloud resources.	Analytics framework for IoT connectivity with cloud resources and big data for maintenance.
Wuest et al. (2018)	Analysis of work and expert opinion synthesis regarding the present and future of intelligent products.	Future intelligent products are projected to move beyond providing information or decision support by becoming more proactive.
IoTStreaming Data and Intelligent Decision making		

Accorsi et al. (2017)	Model set to aid the prediction of faults in production systems, framework for data mining and modelling related to condition based maintenance.	Framework for data mining and modelling related to CBM decision making.
Barbosa et al. (2016),	Envisages the combination of both intelligent products with Cyber Physical systems (CPS), outlining the additional combined use of agent based systems to provide prognostic maintenance and decision making.	Integration of Cyber Physical Systems and Intelligent Products for improved decision making in maintenance practice
Bowden et al. (2019)	A ‘plug and Play’ end to end cloud architecture for predictive maintenance, utilising IoT Edge processing and open source Docker containers. Case study based on industrial robot autonomous operation.	IoT enabled predictive maintenance utilising IoT Edge devices and a cloud platform.
Chen et al. (2018)	IoT Edge computing for manufacturing based maintenance practice, case study and architecture.	IoT Edge computing architecture for manufacturing based maintenance practice.
Jantunen et al. (2018)	IoT based framework for maintenance, detailing a case study drawn from research of a proactive maintenance approach within a power plant.	Industry 4.0 compliant IoT based framework for maintenance.
Karim et al. (2016)	Knowledge discovery framework for cloud based maintenance analytics platforms with a rail industry case study	Knowledge discovery framework for cloud based maintenance analytics platforms
Katsouros, et al. (2013)	A Bayesian approach to maintenance action recommendation. The technique utilises past maintenance event data in its classification of problem types and probability estimation.	Intelligent decision support for maintenance actions.
Kiritsis (2011),	Closed loop product lifecycle approach for Intelligent products Definition, Semantic model and ontology for data	Intelligent products and product service model and data usage for improved product lifecycle including maintenance practice.

	interchange respecting IoT connectivity possibilities.	
Liyanage et al. (2009)	An outline of an integrated e-maintenance approach and description of the Watchdog (Agent-Based Real-time Remote Machinery Prognostics and Health Management) toolbox application. Utilisation of Software agent and, custom algorithms.	Framework for E-maintenance and with CBM prognostic maintenance application.
Mattila et al. (2016),	Agent based approach to decision making utilising data from intelligent products respecting the product life cycle.	A distributed agent based information architecture for decision making utilising intelligent product data.
Meyer et al. (2009),	A review of intelligent products giving reference to maintenance practice that may be envisaged/leveraged through the paradigm. Discussion of agent based approach for potential combination with machine intelligence algorithms is provided.	Intelligent products in- use data and system interaction and interconnectivity, data provision potential for prognostics and maintenance decision support systems.
Trappey et al. (2016),	Underlying standards supporting IoT technology with relevance to maintenance systems including data linkages between hardware and software systems for the realisation of intelligent maintenance practice.	A review of standards supporting IoT use in industry with relevance to intelligent maintenance systems.
Uhlmann et al. (2017)	Maintenance analytics approaches for decentralised IoT Edge platforms; Edge devices pre-processing data streams emanating from production and machine tool sensors.	Maintenance analytics approaches for decentralised IoT Edge platforms.
Data description and visualisation		
Botelho et al. (2014)	Maintenance skill capture for use in intelligent maintenance systems for improved automated decision making with regard to assets degradation	Method for improved Intelligent decision making for maintenance with inclusion of contextual data represented by maintenance

	monitoring using virtual reality environment and simulation system.	skill capture from human operators.
Ceruti et al. (2019)	AR based visualisation of maintenance manual instructions and spare parts identification and information provision within an aviation maintenance setting.	Visualisation of spare parts and maintenance instructions using AR.
Fumagalli and Macchi (2015)	E-maintenance platform utilising web services approach and statistical techniques.	E-maintenance platform for rapid integration of maintenance activities
Krempl et al. (2014)	Mining of data streams open challenges highlighting the potential role of classification and machine learning algorithms for pre-processing of streamed data.	Open challenges for mining of data streams provided by sensors.
Loukopoulos et al. (2017)	Technique to impute missing values in data used for maintenance prognostic approaches using K Nearest Neighbour and Self-Organising Map algorithms.	Method to impute missing e-maintenance data for use in prognostic maintenance systems.
Nunez and Borsato (2017)	Semantic framework expressed through OWL2 language and interoperability with SPARQL for decision making in prognostic maintenance practice.	Ontology based framework for data communication between systems promoting P-prognostics for machine maintenance.
Penna et al. (2014)	3D visualisation and simulation tool using Augmented Reality to allow for user editing of maintenance scenarios to support intelligent maintenance practice.	Interactive visualisation, simulation and planning of intelligent maintenance scenarios.
Turner et al. (2016)	VR and AR visualisation and DES simulation for potential use in visualising the decision making process for maintenance actions when used in combination with machine intelligence.	Visualisation of intelligent maintenance decisions with VR, AR and DES Simulation.
Zhong et al. (2017)	Framework proposed for mining and analytics of manufacturing shop floor data utilising a custom algorithm.	Mining RFID data for internet based intelligent manufacturing.

Conclusions

This paper has charted the evolution of intelligent decision support for maintenance practice from Condition Based Maintenance (CBM) then prognostic use all the way to the e-maintenance paradigm and the introduction of IoT and Cloud-enabled solutions. It is arguable that the ability to digitally interconnect manufacturing plant and machinery provides many new opportunities to raise productivity and efficiency within a production line and in itself leads to a potential new era for intelligent maintenance though adoption of Industry 4.0 technologies. Many challenges still remain in the provision of intelligent decision support for manufacturing maintenance activities. While progress continues to be made in the area of prognostics for maintenance and whole life considerations of manufacturing assets it is still the case that there is a need for a holistic understanding of the use of machine intelligence in the achievement of automated and autonomous manufacturing visions of the near future. The provision of appropriate security measures for use in not just digital maintenance systems but throughout the manufacturing organisation and its supply chain is a topic that will prompt much research over the coming years. IoT technologies and their connectivity potential must be supported by standards but also shared semantic descriptions, with OPC/UA (Open Platform Communications – Universal Architecture) seen by many as a valid starting point in such efforts. Further work remains to be completed on understanding data flows within manufacturing and how digitisation of systems and information will impact maintenance activities.

The quality and provenance of data are important factors in data management and a key success factor for when engaging in any form of analytics. With maintenance rapidly adopting key Industry 4.0 technologies, such issues attain increased importance in the delivery of successful applications and services. It is put by the authors that clear processes to support audit trail style collection of maintenance data and the provision of a comprehensive framework for its processing, analysis and use should be important goals for the work that must be completed in the near future for full enablement of digital maintenance practice. The concept of ‘Human in the loop’ is also reinforced with the use of audit trails, allowing streamlined access to decision making and the ability to mine decisions (and the reasoning behind decisions for both machine assisted workers and managers). The ability to provide procedural structure to data for reuse and communication within an Industry 4.0 maintenance system will be vital for any future move towards semi or fully autonomous maintenance activities.

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