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Procedia CIRP 00 (2019) 000–000
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8th CIRP Conference of Assembly Technology and Systems

Maintenance and digital health control in smart manufacturing based on condition monitoring

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Abstract

Smart manufacturing is the modern form of manufacturing that utilises Industry 4.0 enablers for decision making and resources planning by taking advantage of the available data. Therefore, the state of the art technologies are either replaced or improved using the newly introduced manufacturing paradigm. In practice, condition monitoring is an on-going activity that preserves the manufacturing facility capability to deliver its production aims and decrease the production discontinuity as much as possible. Against this background, this paper discusses the state of the art condition monitoring and proposes a framework of fault detection and decision making at different levels namely component and station. The introduced framework relies on Virtual Engineering (VE) and Discrete Event Simulation (DES) in smart manufacturing environments. The application of the suggested methodology and its implementation is demonstrated in a case study of a battery module assembly line.

Keywords: Maintenance; condition monitoring; smart manufacturing; digital health; virtual engineering; discrete event simulation; Industry 4.0

1. Introduction

Decision making is a repetitive procedure that takes place in manufacturing facility at all levels by humans or industrial controllers. In both cases, a "condition" that provokes the decision making has to be reported so that a corrective action is started. However, the suitability of the decision to the situation depends significantly on the input data, and the higher the level of decision making the more crucial the consequences are on the manufacturing and production. Moreover, the responsiveness in terms of the machine downtime reduction is taken into account with the increased production frequency. Therefore, feeding the decision maker with the accurate descriptive data is the best base for optimising manufacturing activities.

Smart manufacturing as it is perceived now is the future of manufacturing and most of the current developments are inspired by its expected fruits. Smart manufacturing is data-driven [1], where the data obtained through the sensors in real time are processed to support decision making. The abundance of data will allow the rise of technologies such as Cyber-physical systems, machine learning and simulation [1]. Thus, the symptoms in terms of the unhealthy conditions can be reported to the operator to diagnose the system digital health, and attempt to respond as soon as possible.

Condition monitoring can lead to a reduction in the maintenance cost when conducted in a smart manufacturing environment [2]. However, companies face some obstacles when designing and building condition monitoring systems [3]:

- The complexity of condition monitoring system.
- The high ratio of variation in the operating machine conditions.
- Finding an effective design method to correspond to the requirements of smart factory operations in terms of self-reconfigurability and recognisability.

The aim of this paper is to explore the recent advancements in smart manufacturing based condition monitoring. Then, to propose a framework to increase the effectiveness of this practice in Industry 4.0 environment. In the following, Section 2 reviews the literature of condition monitoring in smart manufacturing and summarises the research gaps. Then, Section 3 introduces the research methodology. A case study is exemplified in Section 4 and Section 5 concludes the paper.

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2. Literature review

The following literature review explores the research on condition monitoring applications in the smart manufacturing systems for different fields of application.

Shin et al [3] proposed a systematic design method of smart condition monitoring based on ISO/IEC 15288 inspired by the systems engineering processes. Kumar et al [2] developed a big data analytics framework for the purpose of maintenance condition-based schedule optimisation which contributes to cost reduction and equipment reliability improvement. Tedeschi et al [4] acknowledged the role of Industry 4.0, Internet of things (IoT) in particular, in enabling autonomous condition monitoring. To report the electrical machines performance through a user interface, an IoT based method is presented in [5] where the current, voltage, machine temperature and vibration are monitored. Wang et al [6] introduced a production control system based on condition monitoring such as machine degradation and buffer occupancy, and optimised the production rate using Markov decision processes. Referring to the life cycle consideration in smart manufacturing, [7] notes the importance of including the prognostic health and maintenance in the global life cycle of equipment and processes. Both [8, 9] believe that the manufacturing cell should be conceptualised as systems and subsystems so that the failure influence can be traced, and this is achievable in smart manufacturing due to data availability.

In the field of machining, [10] shows the possibility of using cloud-based parallel machine learning algorithms to predict tool wear depending on the condition monitoring data. Also in the field of machine tools, the management of the manufacturing system's events and alarms is accomplished by a cyber-physical system in [11, 12] by using the cloud and its services to process CNCs monitored conditions data. In [13], a condition monitoring strategy, particularly energy consumption, is introduced for the purpose of optimising the energetic behaviour of machine tools based on its resultant accurate description. Arellano et al [14, 15] employed the machining tool data as an input to the deep learning Convolutional Neural Networks (CNN) algorithm to predict the tool wear. Soualhi et al [16] proposed the use of a health indicator for a robot cutting tool that is a combination of many signals such as torque, current, force and vibration. In [17], a module for monitoring the vibration induced when using drill tools of different diameters was developed with a transmission network functionality. Lee et al [18] aimed at minimising the machining process waste through condition monitoring especially surface machining, therefore, product quality inspection is performed by a statistical learning theory tool.

According to Vogl et al [19], the field of Prognostics and Health Management (PHM) is still emerging. Also, among the PHM challenges is the integration of Programmable Logic Controller (PLC) information and PHM capabilities [19]. In a cyber-physical systems (CPS) context, Lee et al [20] suggest an approach of PHM in CPS based on having a machine-cyber interface that enables the interconnection between machine health analytics. However, Fleischmann et al [21] state that developing a condition monitoring system and CPS is difficult because of the distribution of computational tasks among heterogeneous industrial IT-architectures.

To summarise, the following points are recognised in the state of the art previewed earlier:

- Condition monitoring is of a vital importance for the maintenance process.
- The recent trend is to employ Internet of Things (IoT) for data collection so that further processing and decision making are possible.
- Condition monitoring is also useful for production control.
- Much work has been done in the field of machining, but less for assembly lines.
- The considerations of life cycle assessment in smart manufacturing are not given enough attention, and new opportunities exist under Industry 4.0.

Therefore, the research questions this paper discusses are:

Q_1 What are the condition monitoring strategies to consider in the assembly line design phase?

Q_2 What is the architecture of a condition monitoring system in smart manufacturing environment?

Q_3 What are the obstacles that would restrict the use of such condition monitoring system?

To answer the previous research questions, a research methodology is constructed and explained in the following section.

3. Methodology

In this paper, condition monitoring is considered as an essential aspect in the manufacturing system life cycle, and the decisions made based on it are vital. To achieve this, a robust infrastructure in terms of software, hardware and models have to be constructed [7]. Generally, maintenance can be classified into four main categories: preventive maintenance, corrective maintenance, planned maintenance and condition-based maintenance [2]. Currently, there is a clear trend to transform form "fail-and-fix" to "predict-and-prevent" [22]. However, this requires modelling the involved components and the manufacturing units. To this end, the proposed framework considers two levels: the component and the station. The term "station" is used to describe multiple components performing a certain process e.g. welding station, so it is possible that many stations are doing the same action.

3.1. Proposed framework

Based on the recommendations in both [8, 9], it is useful to follow the decompositional approach when assessing system

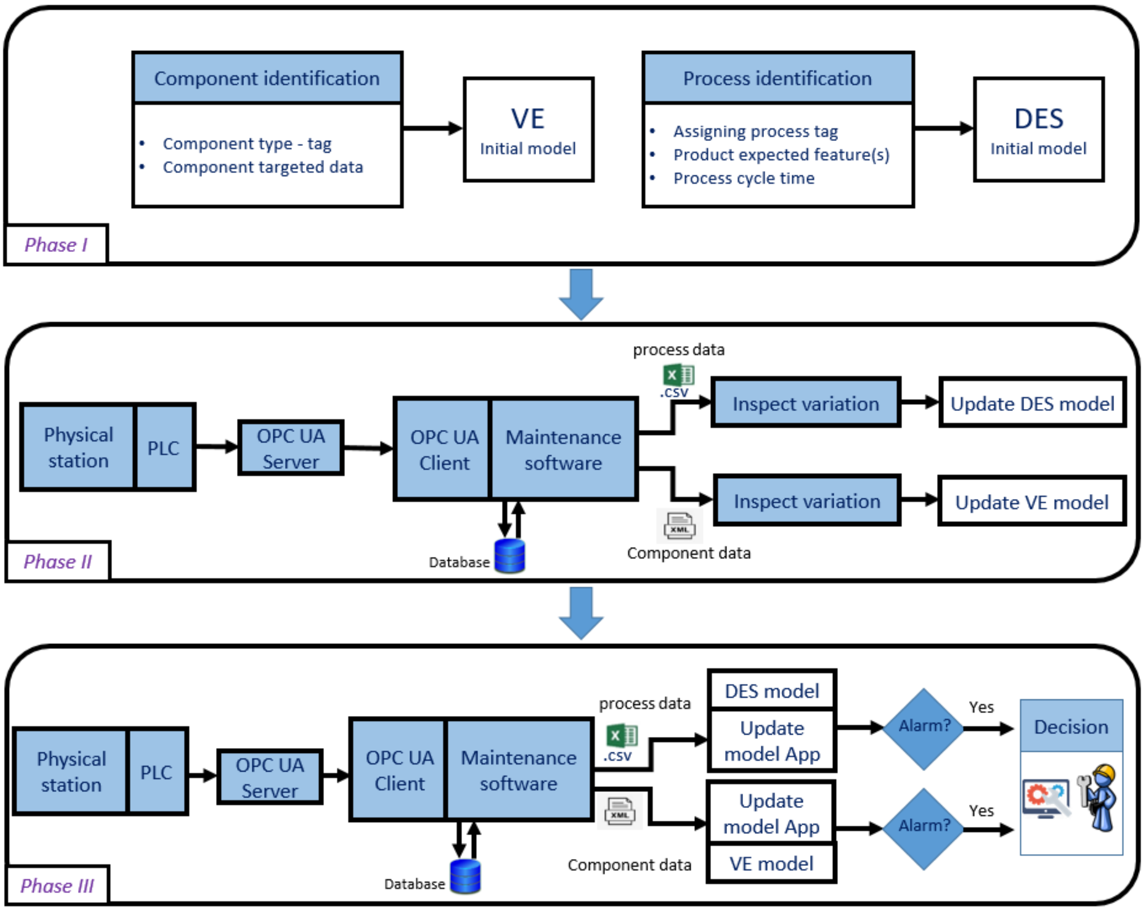

Fig. 1. A framework of condition monitoring in smart manufacturing environment

health conditions. Then, the view is introduced from the cyber-physical systems perspective. To construct a system architecture, the type of the components to be monitored should be specified in order to decide the technology that suits them the best, and the type of data that are useful for the diagnosis. The typical components of an assembly line are classified into the following categories based on the design domains in the Component-based Automation Systems (CBAS) approach [23]:

- Mechanical: e.g. gear, belt, bearing ... etc.
- Electrical: e.g. electrical motor, circuit breaker ... etc.
- Control: e.g. sensor, servo motor ...etc.
- Hydraulic: e.g. hydraulic pump, hydraulic valve ... etc.
- Pneumatic: e.g. air valve, pressure regulator ... etc.

Thus, depending on the component's classification, the associated conditions are monitored. Then, VE software tool receives the components data. Please note that the human operator in addition to the machines that require human-machine collaborative work are not included in this study. Also, for flexible assembly lines (i.e. with robots), a mechatronic component such as a robotic arm can be broken down to a group of the aforementioned basic components.

On the other hand, for the process, when more than one component is involved in adding the feature to the product, two major quantities express the process quality that are the cycle time (productivity) and the energy consumption (sustainability). The Discrete Event Simulation model is capable of describing the flow and thus the cycle time change. Consequently, an accurate DES model supports the system operator in identifying the irregular system behaviour. It should be noted that VE model can perform the tasks DES model does, but DES model is easier to create and analyse.

The standard ISO 13374-4:2015 and MIMOSA (Machinery Information Management Open System Alliance) in Annex A of ISO 13374-2:2007 define a condition monitoring and diagnosis architecture composed of the following functional layers: Data Acquisition (DA), Data Manipulation (DM), State Detection (SD), Health Assessment (HA), Prognostic Assessment (PA), Advisory Generation (AG). Comparing these functional layers with the proposed framework, it can be noticed that this framework fulfils the functions requirement except for the advisory generation which may be studied in future work. This framework is also consistent with the best practices recommended by [19] in terms of flexible middleware software that minimises hardware and software infrastructure dependencies.

3.2. Data acquisition

Data collection is a vital step towards diagnosing the manufacturing system health status. In smart manufacturing, the physical assets conditions data are influenced by the technologies available in the communication layer [24]. Among the communication technologies, the following are able to satisfy the data acquisition quality requirements [24]:

- PROFINET (Process Field Net) IRT (Isochronous Real-Time): with a sampling rate down to 32.15 μs.
- OPC UA (Open Platform Communications Unified Architecture): suitable for the communication with the Internet and the Cloud (vertical communication).
- Time synchronization with PTP (Precision Time Protocol): wide data synchronisation and a precision of 100 ns and less.

In relation to data acquisition, [24] recommends the use of modular hardware and software for the successful monitoring. Fortunately, both VE and DES allow such a functionality.

3.3. Data analysis

According to the proposed framework, condition monitoring and data analysis take place at two levels:

Component level: A first step is data cleaning and filtering, and then statistical analysis follows in order to extract statistical features. Also, it is possible to have predefined Key Performance Indicators so that the indicators resultant from the current data analysis are compared with the provided ones. Finally, the data has to be logged for further future analysis and documentation.

Station level: As mentioned earlier, energy consumption and cycle time are the top priorities. Further, if the features added to the product are measurable, they can be compared to the set values. This way, if the added feature does not correspond to the standard, this signifies an error in the involved components' behaviour. Similar to the component level, some KPIs, like the ones introduced in [25], can be evaluated.

4. Case study

4.1. Layout and description

The study case chosen to investigate the applicability of the proposed methodology is a battery module assembly line in Warwick Manufacturing Group (WMG) - University of Warwick. The layout of the case study assembly line is illustrated in Figure 2. This system is composed of:

- Transportation system (St0)
- Robotic assembly stations (St1,St2,St3).
- Robotic stacking station (St4).
- A welding station (SSW).
- An inspection station (SSI).

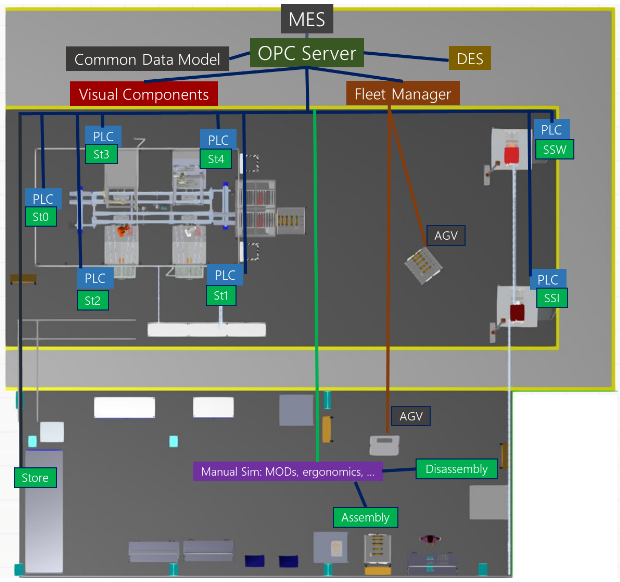

Fig. 2. Battery assembly smart manufacturing environment

- An assembly & disassembly manual stations.
- Autonomous Guided Vehicles (AGVs).

OPC UA scan-based protocol with a minimum scan rate of 10 ms is used in this study. This testing environment was used to provide the preliminary results introduced in the following subsection. The VE modelling tools used are: Visual Components, WinMOD, Siemens Process Simulate and VueOne, and for DES, WITNESS from Lanner Group. Also, the PLC tags necessary to capture cycle times were assigned. All PLC to the virtual model communications were done using OPC UA client-server communication platform over TCP.

4.2. Implementation and results

Component level: The VE model was built and specific tags were dedicated for the different components types so that the system health signals are received, analysed and recorded (Phase I). As an example of the component level, a bearing (mechanical element) is monitored using an accelerometer (Phase II), and the signals are sent to the VE model to be updated and to recognise the abnormality in the component behaviour (Phase III). Figure 3 shows the monitored component.

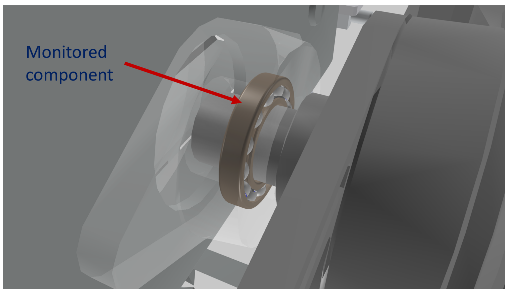

Fig. 3. Bearing in the VE model

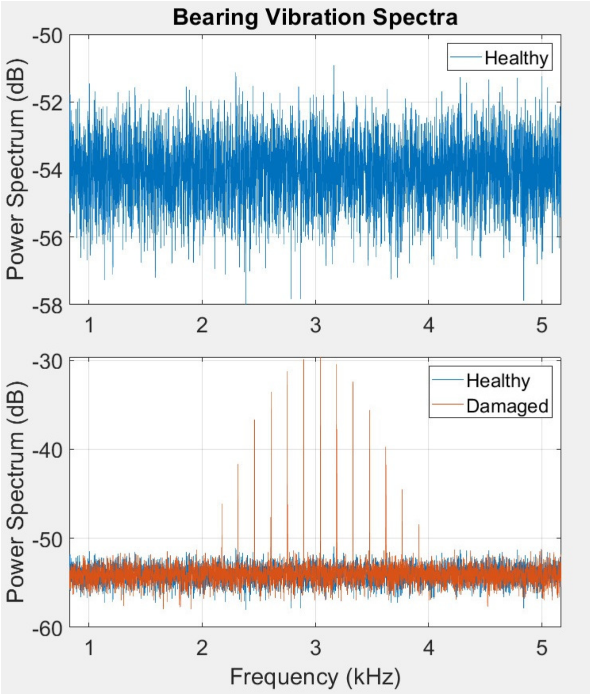

Fig. 4. A comparison between the bearing behaviour before and after damage

As mentioned earlier in the methodology, in Phase II, the healthy component behaviour is identified. In the case of a bearing, following the appropriate data filtering and processing, this can be identified in terms of the power spectrum in the frequency domain. The decision whether the bearing is faulty or not depends on the range of the produced frequency which is in turn dependent on the defect location: outer rings or inner rings for example. The reason is that each of them has its own natural frequency [26]. Filtering techniques are needed to trace certain ranges of frequencies. It is often the pattern of the bearing defect frequencies that is most significant in determining the defect severity [26]. The aim is to find the envelope of the signal whose frequency corresponds to the repetition rate of the defect. For this reason envelop spectrum is used to process the received signal. Figure 4 shows the results of processing the captured data where the damaged bearing could be identified after analysing the bearing power spectrum and comparing it with the healthy bearing power spectrum.

Station level: For the processes monitoring, in Phase I, a DES model was created (Figure 5). The simulation model attempts to accurately reflect the operation of real system through time so that it gives a behavioural dynamic movie of the system it represents. Such a representation should be sufficient to ensure that the outputs from the actual modelled manufacturing line serves as an accurate predictor of reality. This way, once a change in the outputs is detected, the reason has to be investigated. Also, the impact on the costs and risk reduction may be associated with the model. Lee et al [20] define the critical change as the dramatic variation in machine health value that provokes a maintenance action.

After capturing the processes' cycle times, the data were fed into to the DES model (Phase II) where the appropriate

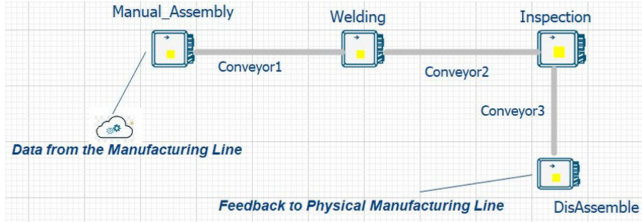

Fig. 5. DES model of the assembly line

mathematical distributions are chosen. Figure 6 illustrates a station whose cycle time is attributed to the normal distribution. In this case the alarm is chosen to be triggered once the cycle time is out of the range $[\bar{x} - \sigma, \bar{x} + \sigma]$ where σ, $\bar{x}$ stand for the standard deviation and mathematical mean respectively (Phase III).

Although there are some stand-alone devices that can be linked to the Programmable Logical Controller (PLC) to report the component/station behaviour, having short-term reports of the components diagnostics with the assistance of DES/VE models makes the decision making process more efficient especially when it comes to production planning or logistical issues. Further, performance analytics and predictions that rely on big data would be easier to obtain.

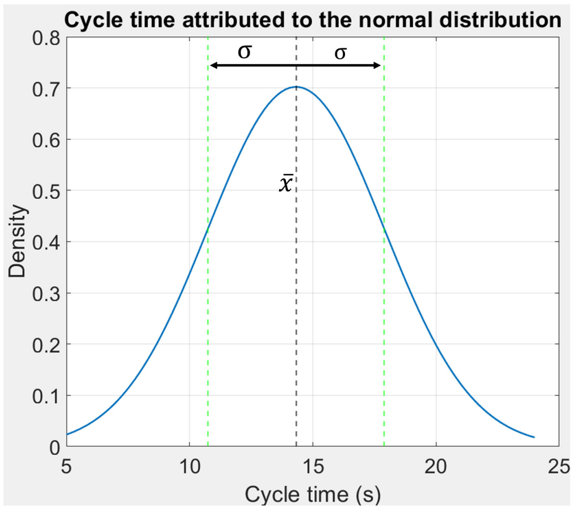

Fig. 6. Cycle time as a Gaussian function

4.3. Limitations and challenges

The main challenge with this in-progress work is data logging into the VE and DES models especially in Phase II where this activity is performed every pre-specified period of time. Besides, some additional algorithms should be developed to judge the stability of the component/station model based on the fed data. In fact, the availability of data does not constrict this, however, data extraction, filtering, storing and processing need further effort to be put.

On the technical side, DES model response is faster than the VE model as the computational capabilities it needs are less than the VE one. However, the alarm triggered by the VE model (after stability in Phase III) might be more effective as it detects the problem at the component level (prior to DES) which will eventually result a problem at the station level.

Another challenge is related to the huge number of the tags related to the components. As it can be imagined, a modern production line has a great number of components to be monitored, which requires a well-prepared infrastructure of information and communication networks.

5. Conclusion and future work

The current work addresses condition monitoring in a smart manufacturing environment where Industry 4.0 technologies allow more amounts of data to be captured and greater potential of correct decision making. Although the data can be invested in maintenance and system health evaluation, the vision is not completely clear yet. This paper proposed a framework that addresses two levels: the component and station. The solution approach utilises VE and DES to tackle the problem from a CPS perspective. The preliminary results are promising, however, further improvements are still needed, and many challenges need to be overcome.

This paper did not address the complexity resulting from installing additional smart components to the system in addition to the complexity of the maintenance system itself. Moreover, decision making algorithms are not discussed due to the multiplicity of artificial intelligence solutions that might be used. Therefore, future research will look into these issues in addition to the aforementioned limitations.

Acknowledgement

The authors would like to acknowledge the support of the Warwick Doctoral College - University of Warwick and High Value Manufacturing Catapult project for funding this work.

References

[1] O'Donovan, P., Leahy, K., Bruton, K., O'Sullivan, D. T., An industrial big data pipeline for data-driven analytics maintenance applications in large-scale smart manufacturing facilities. *J Big Data*, 2015. 2(1): p. 25.

[2] Kumar, A., Shankar, R., Thakur, L. S., A big data driven sustainable manufacturing framework for condition-based maintenance prediction. *J Comput Sci*, 2018. 27: p. 428-439.

[3] Shin, K.-Y., Shin, N.-H., Choi, S.-W., Choi, S.-H. Systems engineering approach to designing smart condition monitoring systems for smart manufacturing (iccas 2016). in *2016 16th International Conference on Control, Automation Systems (ICCAS)*. 2016. IEEE.

[4] Tedeschi, S., Rodrigues, D., Emmanouilidis, C., Erkoyuncu, J., Roy, R., Starr, A., A cost estimation approach for IoT modular architectures implementation in legacy systems. *Procedia Manuf*, 2018. 19: p. 103-110.

[5] Barksdale, H., Smith, Q., Khan, M. Condition Monitoring of Electrical Machines with Internet of Things. in *SoutheastCon 2018*. 2018. IEEE.

[6] Wang, F., Lu, Y., Ju, F. Condition-based real-time production control for smart manufacturing systems. in *2018 IEEE 14th International Conference on Automation Science Engineering (CASE)*. 2018. IEEE.

[7] Weiss, B. A., Vogl, G., Helu, M., Qiao, G., Pellegrino, J., Justiniano, M., Raghunathan, A. Measurement science for prognostics health management for smart manufacturing systems: key findings from a roadmapping workshop. in *Proceedings of the Annual Conference of the Prognostics Health Management Society. Prognostics Health Management Society Conference*. 2015. NIH public Access.

[8] Sharp, M. Weiss, B. A., Hierarchical modeling of a manufacturing work cell to promote contextualized PHM information across multiple levels. *Manuf lett*, 2018. 15: p. 46-49.

[9] Weiss, B. A Qiao, G. Hierarchical decomposition of a manufacturing work cell to promote monitoring, diagnostics, prognostics. in *ASME 2017 12th International Manufacturing Science Engineering Conference collocated with the JSME/ASME 2017 6th International Conference on Materials Processing*. 2017. American Society of Mechanical Engineers Digital Collection.

[10] Wu, D., Jennings, C., Terpenny, J., Kumara, S., Gao, R. X., Cloud-based parallel machine learning for tool wear prediction. *J Manuf Sci Eng*, 2018. 140(4): p. 041005.

[11] Villalonga, A., Beruvides, G., Castaño, F., Haber, R. Industrial cyber-physical system for condition-based monitoring in manufacturing processes. in *2018 IEEE Industrial Cyber-Physical Systems (ICPS)*. 2018. IEEE.

[12] Villalonga, A., Beruvides, G., Castaño, F., Haber, R. E., Novo, M., Condition-Based Monitoring Architecture for CNC Machine Tools Based on Global Knowledge. *IFAC-PapersOnLine*, 2018. 51(11): p. 200-204.

[13] Gontarz, A. M., Hampl, D., Weiss, L., Wegener, K., Resource consumption monitoring in manufacturing environments. *Procedia CIRP*, 2015. 26: p. 264-269.

[14] Martínez-Arellano, G., Terrazas, G., Ratchev, S., Tool wear classification using time series imaging deep learning. *Int J Adv Manuf Technol*, 2019. 104(9-12): p. 3647-3662.

[15] Martínez-Arellano, G., Ratchev, S. Towards an active learning approach to tool condition monitoring with Bayesian deep learning. in *Proceedings - European Council for Modelling and Simulation, ECMS*. 2019.

[16] Soualhi, M., Nguyen, K., Medjaher, K., Lebel, D., Cazaban, D. Health Indicator Construction For System Health Assessment in Smart Manufacturing. in *2019 Prognostics System Health Management Conference (PHM-Paris)*. 2019. IEEE

[17] Hsu, C.-N., Lin, Y.-C., Yang, C.-C., Tsai, H.-Y., Huang, K.-C., Tseng, S.-F., Hsiao, W.-T. Low-Cost Vibration Acceleration Sensors Module for the Drilling Processes Monitoring. in *2019 IEEE Sensors Applications Symposium (SAS)*. 2019. IEEE.

[18] Lee, W. J., Mendis, G. P., Sutherl, J. W., Development of an Intelligent Tool Condition Monitoring System to Identify Manufacturing Tradeoffs Optimal Machining Conditions. *Procedia Manuf*, 2019. 33: p. 256-263.

[19] Vogl, G. W., Weiss, B. A., Helu, M., 2019. A review of diagnostic and prognostic capabilities and best practices for manufacturing. *J Intell Manuf*. 30(1): p. 79-95.

[20] Lee, J., Bagheri, B., Kao, H.-A., 2015. A cyber-physical systems architecture for industry 4.0-based manufacturing systems. *Manuf Lett*. 3: p. 18-23

[21] Fleischmann, H., Kohl, J., Franke, J., 2016. A modular architecture for the design of condition monitoring processes. *Procedia CIRP*. 57: p. 410-415.

[22] Sezer, E., Romero, D., Guedea, F., Macchi, M., Emmanouilidis, C. An industry 4.0-enabled low cost predictive maintenance approach for smes. in *2018 IEEE International Conference on Engineering, Technology Innovation (ICE/ITMC)*. 2018. IEEE.

[23] Alkan, B., Harrison, R., 2019. A virtual engineering based approach to verify structural complexity of component-based automation systems in early design phase. *J Manuf Syst*. 53: p. 18-31.

[24] Maier, A., Schriegel, S., Niggemann, O., Big Data Machine Learning for the Smart Factory—Solutions for Condition Monitoring, Diagnosis Optimization, in *Industrial Internet of Things*. 2017, Springer. p. 473-485.

[25] Assad, F., Alkan, B., Chinnathai, M., Ahmad, M., Rushforth, E., Harrison, R., A framework to predict energy related key performance indicators of manufacturing systems at early design phase. *Procedia CIRP*, 2019. 81: p. 145-150.

[26] Lacey, S., 2011. The role of vibration monitoring in predictive maintenance. *Asset Management & Maintenance Journal*. 24(1): p. 42.