Investigating information and data criticality in Asset Management decision-making process

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Abstract: Asset Management (AM) is increasing in attention among researchers and practitioners since it aims at creating an integrated and holistic methodology to manage physical assets, as production systems or machineries. The development of such holistic methodology is founded on several AM fundamentals, which are: asset control levels (operational, tactical, and strategic), asset lifecycle stages (BoL, MoL, EoL), and AM principles (Lifecycle, System, Risk, and Value). Thus, the AM decision-making process must rely on the AM fundamentals to properly support every decision belonging to AM, e.g. capital investment, operations and maintenance and others. This being the situation, information and data become critical: every decision needs suitable information and data to support it and to respect the AM fundamentals. On one side, scientific literature is producing data models, mainly confined within the maintenance field, that schemes out the flow of information and data within the decision-making process. On the other side, the industrial world is pushing towards the creation of standards that allows formalising an information and data management strategy. However, in both cases, there is no clear way on how to improve AM decision-making through a better information and data management, while considering the AM fundamentals. Therefore, the goal of this work is to propose a framework able to support data modelling in AM. The proposed framework serves as a checklist when creating data models for AM since it provides guidelines on how to comply with AM theory.

Keywords: information, data, framework, asset management, manufacturing

1.Introduction

The current competitiveness of the market environment is pushing companies to optimise every aspect of their business. In this view, the management of the physical assets (intended as machineries or production systems (Amadi-Echendu *et al.*, 2010)) is at the top of the agenda in the industrial debate. Increasing reliability of the production system by acting on assets reliability while reducing operational cost may provide help in being competitive on the market (Campbell *et al.*, 2016). In this context, Asset Management (AM) is a discipline that is attracting both researchers and practitioners since it aims at creating an integrated and holistic methodology to manage physical assets.

At the beginning, the endeavour to optimise the management of assets was undertaken by the maintenance function. Its shift from "merely" traditional maintenance to AM (Amadi-Echendu, 2004) guarantees company competitiveness. Over the year, AM becomes central in the strategy of many companies willing to optimise their production systems, also at organisational structure (El-Akruti *et al.*, 2013).

The manufacturing has demonstrated to be restrictive in adopting AM methodology for long time. Nevertheless, the recent publication of the ISO 5500x body of standards in 2014 (with revisions for ISO 55002 in 2018) fosters and underlines the importance of the implementation of an AM system to realise value from assets, balancing cost, performance, and risk (ISO 55000:2014(E), 2014).

These three drivers (cost, performance, and risk) are becoming central in supporting a suitable AM decision-making process: which is the best maintenance policy for this asset? Should I need to buy another asset or repair the one I own? These decisions must not only be supported by a suitable AM system, but also they must hinge on reliable information and data, as every decision-making should be (Haider, 2009).

Suitable information and data management has always recognised a criticality also for the "restricted" function of maintenance (Tsang *et al.*, 2006). Then, AM has stepped up the game: information and data management must consider different decisions, integrating different organisational functions and be adherent with AM theory.

Being this the current situation, the present work aims at investigating information and data for AM in manufacturing. The final result is a high-level framework that guides data modelling for the AM decision-making. So, section 2 states the basics of the AM decision-making process. Then, section 3 performs a literature review to understand which is the current state-of-the-art in AM when addressing information and data criticality. Then, section 4 analyses some data models that have been developed to support the decision-making process for maintenance and AM; a synthesis of the data models and the consequent house-like framework are proposed in section 5. Finally, section 6 states some conclusions and future works.

2.Background on AM decision-making

AM is currently a hot topic for researchers, and many works are shedding light on the principles that must be considered. A consensus on terms and definitions has not been reached yet, but it is possible to find some commonalities in literature and in international standards.

A robust AM decision-making process must be developed on some fundamentals that are summarised by (Roda and Macchi, 2016, 2018), also supported by other scientific literature:

- Asset control levels (operational, tactical, and strategic) (El-Akruti, 2013);
- Asset lifecycle stages (BoL Beginning of Life, MoL Middle of Life, and EoL End of Life) (Ouertani *et al.*, 2008).

It is possible to build a space to understand the complexity of the AM decision-making, as depicted in Figure 1.

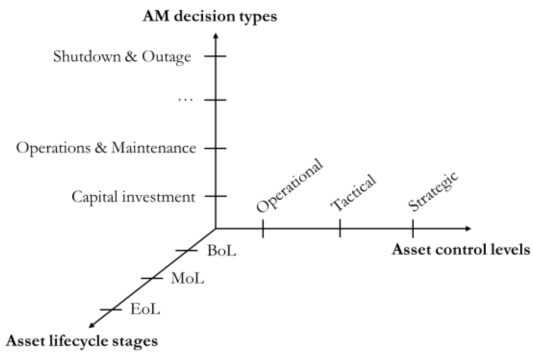

Figure 1: AM decision-making features

Information and data should fulfil the space proposed in Figure 1 in a way that allows to suitably manage the asset. When it is time for an asset-related decision, the information and data must be available and should be aligned with: the asset control level (if operational some information is needed, while if strategic other types are), the asset lifecycle stage (if in BoL the decision-maker needs some information and data that are different from MoL and EoL), and the current decision (specific information and data are necessary for a capital investment decision, while different ones are required for a maintenance decision).

Moreover, the AM decision-making must introduce the AM principles defined in the literature (Roda, Parlikad, *et al.*, 2016; Roda *et al.*, 2017):

- System orientation;
- Lifecycle orientation;
- Risk orientation;
- Value orientation.

Overall, the AM decision-making is complex, but a founding concept could be stated: all decisions in all asset lifecycle stages must be aligned with the asset control levels and driven by the AM Principles.

This gives an overview on the complexity of the field of information and data in AM, and it underlines the need to put effort in this direction to sustain the holistic and integrated methodology promoted by AM for managing the physical assets. Next section 3 reviews information and data in AM, so as to understand current state-of-the-art of the knowledge.

3.Literature review on information and data in AM

This literature review is performed looking at documents adherent in scope to AM, and specific for manufacturing. The literature analysis reveals that information and data are currently a criticality in the scientific literature (Kiritsis, 2013; Petchrompo and Parlikad, 2019). More in the details, it is possible to relate the information and data criticality to three main levels, which are identified in (Polenghi *et al.*, 2019) and supported by other literature:

i) Data collection (Amadi-Echendu, 2010; Campos *et al.*, 2017);
ii) Data to information transformation (Amadi-Echendu, 2010; Campos, 2017; Golightly *et al.*, 2017);
iii) Information management and integration (Amadi-Echendu, 2010; Kangilaski and Shevtshenko, 2017).

The level (i) is the one related to the data gathering activities from the shop floor and the storage into databases. Then, level (ii) promotes the asset-related decisions by transforming raw data into useful information that may be already used to take local decisions (e.g. a corrective action on a broken machine). This level could support a first decision-making, but not in an integrated and holistic view as the one of AM. Finally, level (iii) enhances the AM decision-making process by properly managing and integrating the information. The decision-maker is helped in choosing the best option, relying on AM fundamentals. This level enables the spread of information to all stakeholders interested in the decision-making process.

This levelled view of information and data in the AM decision-making process can be summarised in Figure 2, which also presents how data evolves towards information. Passing from one level to the next one, a comprehensive information is built step-by-step.

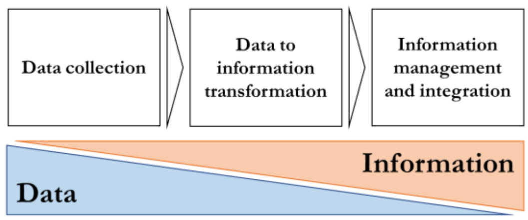

Figure 2: Information and data levels

The information and data criticality (and its levels i), ii), iii)) in AM identified by the literature review must be fulfilled in order to create a suitable AM system, whose decision-making process is reliable.

Before addressing this criticality in section 4, subsection 3.1 proposes an overview on the international standards that deal with how managing information and data in industrial companies.

3.1 Overview on international standards

Different international standards have been developed to support companies in their effort to define an information and data management strategy for AM. In general, two main dimensions of analysis may be recognized: one that deals with interoperability between machines to enable interconnection and exchange (Cousin *et al.*, 2015; Backman *et al.*, 2016; Lee *et al.*, 2016; Petchrompo, 2019), and one that guarantees quality (Lin *et al.*, 2007; Woodall *et al.*, 2013). These two dimensions are used to map different industrial standards according to the dimension they consider. The industrial standards define the scope they want to address at the very beginning of the relative documents, so it is possible to identify the dimensions they are going to analyse (if interconnection/exchange or quality).

Thus, Table 1 collects the main industrial standards dealing with information and data management, and classifies them according to the field (maintenance, AM, general) and the dimension (interconnection/exchange, quality). If there are more standards of the same family, the family is first highlighted and then, for each standard, the scope is better specified.

Table 1: Industrial standards for information and data management

Industrial standards	Field	Dimension
ISO 8000 – Data quality	G	Quality
Industrial automation systems and integration:		
ISO 10303 – Product data representation and exchange	G	Interconnection / Exchange
ISO 15531 – Industrial manufacturing management data	G	Interconnection / Exchange
ISO 15926 – Integration of life-cycle data for process plants including oil and gas production facilities	AM	Interconnection / Exchange
ISO 18876 – Integration of industrial data for exchange, access and sharing	AM	Interconnection / Exchange
Condition monitoring and Diagnostics of machines:		
ISO 13374 – Data processing, communication and presentation	M	Interconnection / Exchange
ISO 13379 – Data interpretation and diagnostics techniques	M	Quality
ISO 19650 - Organization and digitization of information about buildings and civil engineering works, including building information modelling BIM	AM	Interconnection / Exchange
MIMOSA OSA-CBM (see also ISO 13374)	M	Interconnection / Exchange
MIMOSA OSA-EAI	AM	Interconnection / Exchange
M = Maintenance, AM = Asset Management, G = General		

Table 1 demonstrates that there are industrial standards that can be used as guidelines to address the problem of information and data management in different sectors, as manufacturing. Generally, these standards adopt an object-oriented modelling with different formalisms, e.g. UML (Unified Modelling Language), XML (eXtensible Markup Language), and OWL (Web Ontology Language) (see (Negri *et al.*, 2016) for additional information). However, these standards are intended to support software developers when coding interoperable IT applications. Nevertheless, modelling decision making processes adopting concepts from those standards could help both the decision-makers and the software developers. The decision-makers could rely on well-structured processes that could be followed to integrate information and data, while software developers could take advantage from the high-level representation of relationships between different entities.

Thus, to overcome the criticality identified in the literature and to help companies in facing the information and data management in a suitable way, section 4 analyses data models developed in the scientific literature, whose aim is the management of physical asset.

4.Data models formalising decision-making process

Before dealing with data models, it is necessary to define them: *[data model is] a method of organizing data that reflects the basic meaning of data items and the relationships among them* (Gartner, 2019). Being this the basics, for this work a data model represents any object-oriented model that deals with information and data, eventually including also the formalisation of the decision-making process for which those information and data are used.

In the scientific literature, data models are demonstrated to be successful in suitable addressing the problem of formalisation of information and data (Colledani *et al.*, 2008; Negri, 2016). For this reason, a set of four data models have been selected from the literature, considering those that describes the decision-making process in maintenance or AM. Maintenance is selected as important field due to its engagement in the adoption of an AM perspective (Amadi-Echendu, 2004), and the central role in correctly supporting AM (BS EN 16646:2014, 2014).

Among the analysed data models, (Campos *et al.*, 2010) develops a data model with the final aim of supporting the generation of an alert based on a condition monitoring system, resulting in some recommendations on the management of the item under analysis. Similarly, (Lopez-Campos *et al.*, 2013) wants to plan the maintenance for the system. It also integrates maintenance-related nomenclature and methods, as the decomposition of the system according to the ISO 14224, and the clear description of information extraction from system failure according to maintenance concepts, aligned with ISO 17359.

As the most recent work, (Guillén *et al.*, 2016) expands what developed before to the overall maintenance decision-making process involved in CBM (condition-based maintenance) program definitions. Particularly, it relies on different industrial standards (e.g. ISO 13374, see also MIMOSA at www.mimosa.org) and assessed methodologies (FMECA-Failure Modes, Effects, and Criticality Analysis, RCM-Reliability-Centered Maintenance). However, a more asset-oriented data model is the one presented by (Koukias *et al.*, 2013). The focus is the asset, understanding the relationships with possible status, data, managers, and specification (intended as the collection of asset maintenance strategy, asset operation specification and asset configuration specification).

These data models are composed by a set of classes, defined as the "things" that compose the data models, and a set of relationships that highlights the relation/s between two classes: for instance, an asset can be composed by units, so there is a composition relationship; further information about relationships between classes and object-oriented modelling may be found in the IBM Knowledge Center at https://www.ibm.com/support/knowledgecenter/it/SS5JSH_9.5.0/com.ibm.xtools.modeler.doc/topics/cclassd.html).

Table 2 proposes a grouping of the data models classes into three layers: Physical asset, Information and data, Decision-making.

Table 2: Grouping of data models

Grouping	**Maintenance**			**Asset Management**
	(Campos, 2010)	(Lopez-Campos, 2013)	(Guillén, 2016)	(Koukias, 2013)
Physical asset description and logical description of asset / asset system	Item Function HypotheticalEvent	System Subsystem MantenibleItem RequiredSubfunction FunctionalFailure FailureMode FailureEffect	System Equipment Unit Maintainable Item Function Functional Failure Failure Model	Asset Asset Function
Information and data collection and organisation	MeasLoc DataEvent ItemRequestForWork Eventhistory	Signal Sensor WorkOrder History	Sensor Measurement Technique Variable Monitoring Variable	Asset_Operational_Data Asset_Configuration_Data Asset_Maintenance_Data Maintenance_Schedule Maintenance_Activity Asset_Event
Decision-making process	AlertRegion Alert ItemRecommedation	ConditionMonitoringManager RCMAnlysis Alarm MaintenancePlanning	Symptom Descriptor Interpretation Rules Detection Diagnosis Prognosis Maintenance Decision	Asset_State (Normal_State, Degrad_State, Failure_State) Asset_Specification

Overall, the analysed data models try to formalise the decision-making process. Firstly, the asset description is done. The asset is identified by the classes *Item*, *System*, or *Asset*. The relative functioning and logical aspect are also described (see classes *Function*, *FailureMode*, and *AssetFunction*). Then, the asset status needs to be formalised: sensors, variables, data, events are formalised through the classes *Signal*, *Sensor, DataEvent*. Finally, the decision is schemed out through different classes as *ItemRecommedation*, *MaintenancePlanning*, *Maintenance Decision*, or *Asset_Specification*. From an AM perspective, (Koukias, 2013) proposes the more AM-oriented model since it is not limited to maintenance as the other ones, but it enlarges the scope towards other possible decisions related to the asset. This enlargement in the scope is represented by the class *Asset_Specification* that collects the strategy, the operation and configuration specification of the asset.

5. Synthesis of the data models

The above description shows that the classes can be grouped together since they present some commonalities: there are three layers through which the data models develop through (see Table 2). The first layer is characterised by the physical description of the asset and the relative logical description of the asset functioning. In this layer all the classes describing the item/system/asset and functions are collected. Then, the second layer deals with the information and data coming from the asset. Those data are structured and organised for future use and so all the classes related to sensors/variables/data/events are gathered in this layer. Finally, layer three collects the classes describing or supporting the decision-making process. In this layer all classes dealing with recommendation/planning/decision are grouped.

Note that the information and data levels (section 3, Figure 2) are not comprised within the information and data layer only, but: data collection represents the interface with the physical asset, so it partially belongs to this layer; then, information management and integration level spread also in the decision-making layer since it depends on the final decision to be taken.

However, what is still missing in this synthesis of the data model classes is how to integrate AM theory (related to the AM fundamentals). In so doing, this work could provide a support for the development of data models for the AM decision-making process.

5.1 AM fundamentals introduction

The AM decision-making process is summarised in Figure 3. The house-like framework wants to summarise the pillars on which the AM decision-making should be built on.

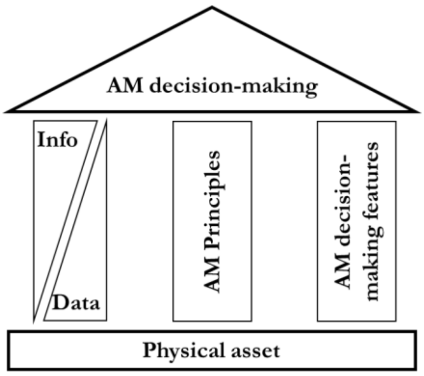

Figure 3: AM house-like framework

At the roots, there is the Physical asset since every decision must be aligned with actual state of the asset.

The first pillar is the Information and data level: the data coming from the asset must be transformed into suitable information to support the decision-maker.

Then, the second pillar is the AM Principles. While making a decision, these principles (System, Lifecycle, Risk, and Value orientation) must be considered. System orientation involves the logical description of the asset, either the description of its functioning either its relationship with other assets. The Lifecycle orientation means to consider the long-term perspective when taking a decision in a specific asset lifecycle stage: this is enabled by the logical description of the system before explained. Moreover, according to the AM theory, cost, performance, and risk must be considered and balanced in order to realise value from the asset. For this reason, also Risk and Value are inserted in this pillar.

Finally, the third pillar involves the AM decision-making features described in Figure 1. The Asset lifecycle stages are introduced since the asset could be in any of the three stages (BoL, MoL, EoL). The Asset control levels represent where the decision is taken (operational, tactical, strategic): they are somehow related to how information and data are stored and managed by different software tools, overall called IT ecosystem. The software tools can be organised in a pyramid way to better support the management of the asset over the lifecycle (Tucci and Bettini, 2006). The last feature deals with the AM decision types that could span from capital investment to shutdown and outage.

The roof of the house-like framework, that is the AM decision-making, is sustained by the afore-described pillars. In so doing, it is possible to build an effective decision-making process that will consider the AM theory, and so building an integrated and holistic methodology to manage the physical assets of the company.

6.Conclusions

The present work aims at investigating information and data criticality in AM decision-making process. The literature review shows that this criticality is recognised as significant by the scientific community. In addition, international standards are developed in order to help practitioners in implementing a suitable information and data management strategy in their companies, even though those standards are not AM-oriented.

The recognised gap in the literature and the difficulty for companies firstly facing the information and data criticality bring to the need of improvement in such a direction. For this aim, data models formalising mainly the maintenance decision-making process are analysed. This analysis allows to understand that there is a three-layer structure underlying these data models. The three layers are: Physical asset, Information and data, and Decision-making. The decision-making process goes from the former one and finishes in the latter one.

This represents a first outcome of this work, but it is completed by a further analysis on how the AM fundamentals could be introduced in the AM decision-making. Thus, a house-like framework is proposed. The roots of the house are composed by the Physical asset, whose management is the scope of the AM decision-making. The pillars are: Information and data level to guarantee providing suitable information to the decision-maker; AM Principles to guide the AM decision-making; and the AM decision-making features to understand the context of the decision (Asset lifecycle stages, Asset control levels, and AM decision types)

This house-like framework claims to serve as a rough basis on which researchers could rely for data modelling of the AM decision-making process. The framework identifies where the AM fundamentals should come out, so the developed data models could be checked against possible misalignment with respect to the AM theory.

Moreover, this work aims at underlining the need to explore other decisions within AM, e.g. capital investment, since many of the works are focused on maintenance only.

6.1 Future works

Future researches will be devoted to specifying more the framework, introducing more details to better guide data modelling for AM. Moreover, further studies will be focused on enlarging the analysis to other decisions within AM, as capital investment, and shutdown and outage.

References

Amadi-Echendu, J. E. (2004) 'Managing physical assets is a paradigm shift from maintenance', in *2004 IEEE International Engineering Management Conference (IEEE Cat. No.04CH37574)*, pp. 1156–1160. doi: 10.1109/IEMC.2004.1408874.

Amadi-Echendu, J. E., Willett, R., Brown, K., Hope, T., Lee, J., Mathew, J., Vyas, N. and Yang, B.-S. (2010) 'What is engineering asset management?', *Engineering Asset Management Review*, pp. 3–16. doi: 10.1007/978-1-84996-178-3_1.

Backman, J., Vare, J., Framling, K., Madhikermi, M. and Nykanen, O. (2016) 'IoT-based interoperability framework for asset and fleet management', *IEEE International Conference on Emerging Technologies and Factory Automation, ETFA*, 2016-Novem, pp. 0–3. doi: 10.1109/ETFA.2016.7733680.

BS EN 16646:2014 (2014) 'Maintenance — Maintenance within physical asset management', *BSI Standards Publication*.

Campbell, J. D., Jardine, A. K. S. and McGlynn, J. (2016) *Asset management excellence: optimizing equipment life-cycle decisions*. CRC Press.

Campos, J., Sharma, P., Gabiria, U. G., Jantunen, E. and Baglee, D. (2017) 'A Big Data Analytical Architecture for the Asset Management', *Procedia CIRP*. The Author(s), 64, pp. 369–374. doi: 10.1016/j.procir.2017.03.019.

Campos, M. A. L., Fumagalli, L., Fernandez, J. F. G., Marquez, A. C. and Macchi, M. (2010) 'UML model for integration between RCM and CBM in an e-Maintenance architecture', in *IFAC Proceedings Volumes*, pp. 110–115. doi: 10.3182/20100701-2-PT-4012.00020.

Colledani, M., Terkaj, W., Tolio, T. and Tomasella, M. (2008) 'Development of a Conceptual Reference Framework to Manage Manufacturing Knowledge Related to Products, Processes and Production Systems', *Methods and Tools for Effective Knowledge Life-Cycle-Management*. Berlin, Heidelberg: Springer Berlin Heidelberg, 1(1), pp. 259–284.

Cousin, P., Serrano, M. and Soldatos, J. (2015) 'Internet of things research on semantic interoperability to address manufacturing challenges', *Enterprise Interoperability: Interoperability for Agility, Resilience and Plasticity of Collaborations (I-ESA 14 Proceedings)*. John Wiley & Sons, p. 280.

El-Akruti, K. O., Dwight, R. and Zhang, T. (2013) 'The strategic role of Engineering Asset Management', *International Journal of Production Economics*. Elsevier, 146(1), pp. 227–239. doi: 10.1016/j.ijpe.2013.07.002.

Gartner (2019) *Gartner IT Glossary*. Available at: https://www.gartner.com/it-glossary/ (Accessed: 23 March 2019).

Golightly, D., Kefalidou, G. and Sharples, S. (2017) 'A cross-sector analysis of human and organisational factors in the deployment of data-driven predictive maintenance', *Information Systems and e-Business Management*. Springer Berlin Heidelberg, pp. 1–22. doi: 10.1007/s10257-017-0343-1.

Guillén, A. J., Crespo, A., Gómez, J. F. and Sanz, M. D. (2016) 'A framework for effective management of condition based maintenance programs in the context of industrial development of E-Maintenance strategies', *Computers in Industry*. Elsevier, 82, pp. 170–185. doi: 10.1016/J.COMPIND.2016.07.003.

Haider, A. (2009) 'Evaluation of Information Systems Supporting Asset Lifecycle Management', in *International Conference on Enterprise Information Systems*. Springer, Berlin, Heidelberg, pp. 906–917. doi: 10.1007/978-3-642-01347-8_75.

ISO 55000:2014(E) (2014) 'Asset management — Overview, principles and terminology', *BSI Standards Publication*. International Organisation for Standardization.

Kangilaski, T. and Shevtshenko, E. (2017) 'Do we need capabilities in our management system?', *Journal of Machine Engineering*. Publishing House of Wroclaw Board of Scientific Technical Societies Federation, 17(1), pp. 88–100.

Kiritsis, D. (2013) 'Semantic technologies for engineering asset life cycle management', *International Journal of Production Research*. Taylor & Francis, 51(23–24), pp. 7345–7371. doi: 10.1080/00207543.2012.761364.

Koukias, A., Nadoveza, D. and Kiritsis, D. (2013) 'Semantic data model for operation and maintenance of the engineering asset', *IFIP Advances in Information and Communication Technology*, 398(PART 2), pp. 49–55. doi: 10.1007/978-3-642-40361-3_7.

Lee, J., Bagheri, B. and Jin, C. (2016) 'Introduction to cyber manufacturing', *Manufacturing Letters*. Society of Manufacturing Engineers (SME), 8, pp. 11–15. doi: 10.1016/j.mfglet.2016.05.002.

Lin, S., Gao, J., Koronios, A. and Chanana, V. (2007) 'Developing a data quality framework for asset management in engineering organisations', *International Journal of Information Quality*, 1(1), p. 100. doi: 10.1504/IJIQ.2007.013378.

Lopez-Campos, M. A., Marquez, A. C. and Fernandez, J. F. G. (2013) 'Modelling using UML and BPMN the integration of open reliability , maintenance and condition monitoring management systems : An application in an electric transformer system', *Computers in Industry*, 64(5), pp. 524–542. doi: 10.1016/j.compind.2013.02.010.

Negri, E., Fumagalli, L., Garetti, M. and Tanca, L. (2016) 'Requirements and languages for the semantic representation of manufacturing systems', *Computers in Industry*, 81, pp. 55–66. doi: 10.1016/j.compind.2015.10.009.

Ouertani, M. Z., Parlikad, A. K. and Mcfarlane, D. (2008) 'Towards an approach to select an asset information management strategy', *International Journal of Computer Science and Applications*, 5(3), pp. 25–44.

Petchrompo, S. and Parlikad, A. K. (2019) 'A review of asset management literature on multi-asset systems', *Reliability Engineering and System Safety*. Elsevier Ltd, 181(March 2018), pp. 181–201. doi: 10.1016/j.ress.2018.09.009.

Polenghi, A., Roda, I., Macchi, M. and Pozzetti, A. (2019) 'Asset Management in manufacturing: a systematic literature review', *International Journal of Production Economics (submitted).*

Roda, I. and Macchi, M. (2016) 'Studying the funding principles for integrating Asset Management in Operations: an empirical in production companies', in *IFAC-PapersOnLine*, pp. 1–6. doi: 10.1016/j.ifacol.2016.11.001.

Roda, I. and Macchi, M. (2018) 'A framework to embed Asset Management in production companies', *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 232(4), pp. 368–378. doi: 10.1177/1748006X17753501.

Roda, I., Macchi, M., Parmigiani, C. and Arata, A. A. (2017) 'System-Oriented Reliability-Based Methodology for Optimal Joint Maintenance and Production Planning', in *IFIP International Conference on Advances in Production Management Systems*. Springer, Cham, pp. 92–100. doi: 10.1007/978-3-319-66923-6_11.

Roda, I., Parlikad, A. K., Macchi, M. and Garetti, M. (2016) 'A Framework for Implementing Value-Based Approach in Asset Management', in *Proceedings of the 10th World Congress on Engineering Asset Management (WCEAM 2015).* Springer, Cham, pp. 487–495. doi: 10.1007/978-3-319-27064-7_47.

Tsang, A. H. C., Yeung, W. K., Jardine, A. K. S. and Leung, B. P. K. (2006) 'Data management for CBM optimization', *Journal of Quality in Maintenance Engineering*. Emerald Group Publishing Limited, 12(1), pp. 37–51. doi: 10.1108/13552510610654529.

Tucci, M. and Bettini, G. (2006) 'Methods and tools for the reliability engineering: a plant maintenance perspective', *Proceedings of the 2nd maintenance management MM2006, Sorrento, Italy, April.*

Woodall, P., Borek, A. and Parlikad, A. K. (2013) 'Data quality assessment: The Hybrid Approach', *Information and Management*. Elsevier B.V., 50(7), pp. 369–382. doi: 10.1016/j.im.2013.05.009.