This is an Accepted Manuscript version of the following article, accepted for publication in Production Planning and Control (ISSN: 0953-7287).

Adalberto Polenghi, Irene Roda, Marco Macchi & Alessandro Pozzetti (2021) A methodology to boost data-driven decision-making process for a modern maintenance practice, Production Planning & Control, DOI: 10.1080/09537287.2021.2010823

It is deposited under the terms of the Creative Commons Attribution-NonCommercial License (http://creativecommons.org/licenses/by-nc/4.0/), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited.

A methodology to boost data-driven decision-making process for a modern maintenance practice

Maintenance is evolving due to the double-sided influence of Asset Management paradigm and digitalisation. In this evolution, assessing the maintenance management process status in terms of process completeness, information and data completeness and integration is paramount to boost a reliable data-driven decision-making. Grounding on Design Science Research, a methodology is realised to favour the comparison of two data models, a reference one and a company specific one, used as a means to evaluate the process status. In particular, the methodology embeds a reference data model for the maintenance management process. Both methodology and data model are artifacts tested and refined during an action research in an automotive company willing to improve the maintenance management process. The application of both artifacts demonstrates that the company is facilitated in planning improvement actions for various time horizons to foster a modern maintenance practice whose decision-making is more data-driven.

Keywords: data; information; methodology; data model; maintenance; Asset Management

1. Introduction

A modern maintenance practice and advanced solutions for increased productivity are today vital for companies in every sector (Macchi, Roda, and Fumagalli 2020). As such, maintenance is evolving due to the double-sided influence of Asset Management (AM) and digitalisation.

On one side, the AM paradigm requires maintenance to broaden its scope including strategy, risk management, safety and environment, and human factors (Amadi-Echendu and Brown 2010). Indeed, maintenance is a pillar of AM (Komonen and Despujols 2013), which fosters increased cross-functional collaboration to guarantee alignment with company strategic objectives towards value creation from assets (Komonen, Kortelainen, and Räikkönen 2012; Roda and Macchi 2018). Hence, maintenance is not anymore a “doer” aiming at chasing company objectives, but it becomes a trigger that influences and determines long-term strategies.

On the other side, digitalisation is pushing maintenance to adopt Industry 4.0-like solutions (Zheng et al. 2018) by redirecting the attention towards diagnostic and predictive tools (Herterich, Uebernickel, and Brenner 2015; Lee, Bagheri, and Kao 2015) for data-driven design improvements and services (Tao et al. 2018a). The final aim is to develop advanced systems that could establish and support a proper decision-making based on data and evidence from the field (Jantunen et al. 2019; Yunusa-Kaltungo and Labib 2020). In the context of this research, a data-driven decision-making is defined as *"the degree to which decisions are based on data"* (Bokrantz et al. 2020a).

These phenomena are relevant and challenging at the same time in manufacturing, which is experiencing an increasing adoption of AM (Polenghi et al. 2021). Furthermore, manufacturing could count on huge amounts of multi-sourced data (Errandonea, Beltrán, and Arrizabalaga 2020). Thus, a modern maintenance practice in manufacturing companies should claim a more tactical and strategic perspectives, rather than only operational, with a through-lifecycle view, leveraging on real-time shop-floor data integrated by cross-functional knowledge.

Overall, suitable information and data management strategies remain a shortfall in the current manufacturing context (Razmi-farooji et al. 2019): data are dispersed in the company (Bousdekis et al. 2015), maintenance relies mainly on CMMS (Computerized Maintenance Management System) that does not fully fit current needs (Polenghi et al. 2020), and performance indicators are still unripe for strategic decisions (del Mar Roldán-García et al. 2021).

Tackling these issues involves a comprehensive approach that embrace maintenance as a whole: technologies, processes and people must be valorised to promote a data-driven decision-making (Bokrantz et al. 2020a). Nonetheless, technologies and advanced analytics are perceived as a critical aspect to be improved to promote a data-driven decision-making by maintenance people (Gallo and Santolamazza 2021). Indeed, it is especially the technical integration of data and information for maintenance purposes that is put at the stack as a critical enabler of a data-driven decision-making. Much effort has been put to cross-functionally integrate available data (Kortelainen et al. 2015); although, many times this effort results in a disorganised ingestion of data and information from the shop-floor and from several information systems (O'Donovan et al. 2015). However, it is integration that unlocks the possibility of judging proper decisions to improve the maintenance management (MM) process (Gopalakrishnan, Subramaniyan, and Skoogh 2020). As noted by (Tretten and Karim 2014), integrating the CMMS with other systems makes the MM process efficient and effective. Also, the integration of information systems enables the completeness of data and information. In this work, completeness is not intended form a technical perspective as from database engineering (Ballou and Pazer 1985), but from a managerial perspective with respect to the decision-making process. For example, to prioritise the assets in terms of criticality, a FMECA is required, which needs failure modes, effects, causes, etc. Thus, these classes of data and information should be available to the decision-maker.

Therefore, the objective of this work is to target data and information completeness and integration, providing a step-by-step guidance to improve them through the analysis of the MM process of a manufacturing company. This brings to the following research question (RQ): *How to support companies in planning MM process-focused improvement actions regarding data and information completeness and integration?*

Indeed, this question intrinsically relates to two sub-questions that operatively push this work: *Are data and information complete with respect to the MM process? Are the required data and information involved in the MM process integrated?*

To answer to these questions, a methodology and a data model are developed, which are generically called artifacts in Design Science Research (DSR). The development of both artifacts is iterative and compels both theoretical contributions and practitioners' viewpoints. The refinement of the artifacts is fostered by action research in an automotive company interested in improving the MM process. The application to the industrial case also allows elaborating over the generalizability.

The paper is organised as follows. Section 2 presents an overview about information and data management is given, pinpointing the extant gaps addressed by this research work. Section 3 introduces and explains the DSR methodology and how it is used. Section 4 proposes the methodology (artifact 1) based on data modelling, while section 5 describes a reference data model for the MM process (artifact 2). Section 6 summarises the application in the company and related results. Finally, section 7 critically discusses the potential generalizability of the proposed artifacts and section 8 draws the conclusions.

2. Data and information integration for the maintenance management process

To get to a data-driven maintenance decision-making process, both the human and technological aspects should be tackled to provide a concurrent and effective improvement of the current MM practice (Bokrantz et al. 2020b). Nonetheless, the latter aspect is many times seen as an enabler to improve also the former. When looking from the technological perspective, effort is put on extracting value from raw data to judge suitable decisions (Tao et al. 2018b). The transformation of data into usable and useful information involves (Polenghi et al. 2021): (i) the generation of data from the physical asset (data collection), (ii) its successive and gradual transformation into information to support the decision-making process (data to information transformation), and (iii) the judgment of a decision based on shared and integrated information (information management and integration) that impacts on the management of the asset, in a virtuous cycle (Amadi-Echendu et al. 2010). Figure 1 reports a summary of the process with details of some specific topics.

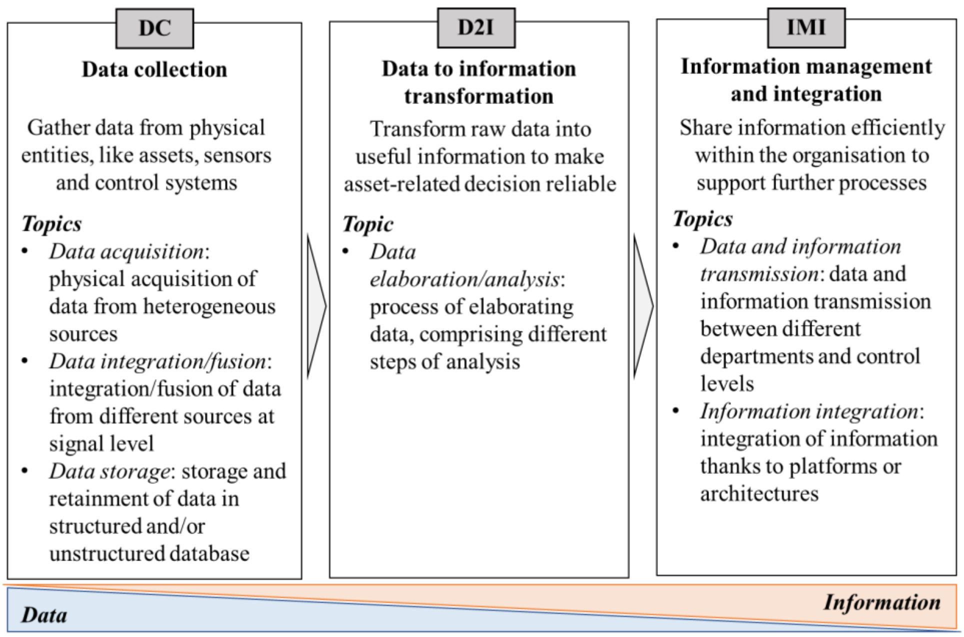

Figure 1. The process from raw data to useful and usable information.

Despite every step is relevant to judge maintenance-related decisions, it is especially the technical integration of data and information that affects the robustness and reliability of the current MM process (Ruschel, Santos, and Loures 2017). In particular:

- *Data integration*: heterogeneous and geographically dispersed data sources generate a huge number of signals to be recorded (often in a different format and sampling frequency) that are not easy to merge in a single and consistent database to enable further elaboration (Sharma et al. 2017; Campos et al. 2017);
- *Information integration*: difficulties in integrating highly specialised, domain-specific systems in a consistent way affect the sharing and integration of information to support decision-making; this is exacerbated by the misalignment between company departments (Mahlamäki et al. 2016; Legat, Neidig, and Roshchin 2011).

Overall, information and data integration mainly refers to the technical issue of letting systems talk each other to create architectures or platforms, thus arising interoperability problems (Bokrantz et al. 2017). However, not all systems are needed to be integrated and interoperable. Before addressing interoperability and IT-related issues, the MM process must be structured (Iung et al. 2009). This is well recognised in the scientific literature but, as reported in subsection 2.1, some gaps could be identified, which are addressed by this research work.

2.1 Extant gaps and objective of the research work

The MM process should be aligned with company objectives as well as with international standards, which define the minimum set of criteria to be respected (Selvik and Aven 2011). Therefore, given the process as granted, it is the maintenance platform/architecture that should follow maintenance needs. As such, a process-oriented view should be adopted when tackling information and data integration problem at technical level (Ouyang et al. 2009). To cope with this, graphical notations (like BPMN and IDEF0 for business process modelling and UML from information systemoriented language (Ko, Lee, and Wah Lee 2009; Campos and Márquez 2011)), are used to support improvements in the maintenance platform/architecture in compliance with the MM process.

Nonetheless, extant contributions addressing data and information integration for the MM process are poor and suffer from some gaps worth of mentioning:

(1) Most of the contributions are focused on improving data to information transformation; in some cases, attention is given to data integration so to properly feed the analytics, but generally, the information integration is still open for future research (Borangiu et al. 2019; Forcina, Introna, and Silvestri 2021);

(2) Even though new platforms and architectures are developed to address data and information integration issues, many times the problem is addressed as merely technical (Zeid et al. 2019); this is also driven by the new complexity in gathering, managing and elaborating data (Turner et al. 2019).

Overall, to the best of authors' knowledge, contributions specifically targeting data and information integration for the MM process in manufacturing field and providing a guidance for its improvement under a managerial perspective, are still missing. However, approaches that combine and evaluate simultaneously the business process and the supporting platforms are key (Qu et al. 2018) to ensuring the two work harmoniously to achieve the company objectives.

Therefore, in this work, the objective is to target data and information completeness and integration and improve them through the analysis of the MM process of the company. For this reason, two artifacts are realised, that are a methodology and a reference data model. The artifacts are developed thanks to the DSR methodology explained in section 3.

3. Research methodology

The adopted methodology finds its roots in DSR, which extends knowledge in a pragmatic way, usually with direct involvement of practitioners along the development process (J. E. Van Aken 2005).

DSR is exploratory and iterative in nature (Holmström, Ketokivi, and Hameri 2009; Kuechler and Vaishnavi 2008), and its final aim is to design artifacts that contribute to knowledge under various forms (Gregor and Hevner 2013). The underpinning methodology of DSR, that is, the steps required to provide substantial contribution to knowledge, is even today open for debate. Nonetheless, the nominal process sequence for DSR by (Peffers et al. 2007) is inspirational for the research presented in this article and it is adopted to develop the two artifacts, i.e., methodology and data model, complemented by the guidelines by (Hevner et al. 2004). Figure 2 summarises the steps required by the research methodology. Indeed, the action research plays a relevant role in this DSR-based work because it guarantees to refine the objective, the questions, and the artifacts themselves (Holmström, Ketokivi, and Hameri 2009).

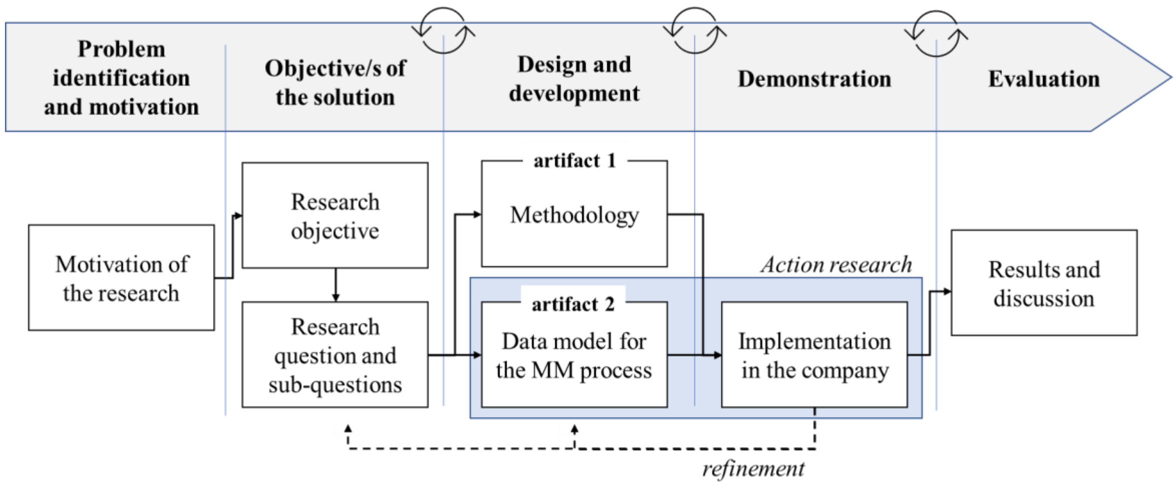

Figure 2. DSR methodology and effects of the action research.

After the problem identification and motivation of the research, the objective of the solution is stated, including the research question and related sub-questions. Then, the artifacts are designed and developed, thus depicting their characteristics and the underlying technological rules. The demonstration deals with the instantiation of the methodology and of the data model for the specific purposes of an automotive company. The results of the artifacts are discussed during the evaluation step. To this end, in this work, an observational and descriptive evaluation method is adopted (Hevner et al. 2004). Furthermore, the evaluation should support the generalizability of the artifacts to other contexts of application (Holmström, Ketokivi, and Hameri 2009).

As for DSR relevant characteristic, the process is iterative (see circular arrows in Figure 2) through the action research in the automotive company. The iteration is fruitful because of two main reasons: (i) at the beginning, the problem was ill-structured (initially, the company manager engaged the researchers to make the MM process more data-driven, but without a clear view on how to do it), then it becomes more structured (with focus on data and information completeness and integration) and so the objective and questions can be better stated; (ii) despite explicitly targeting data and information integration, the action research unveils the capability of the artifacts to suggest improvements also regarding the MM process itself.

As a matter of presentation, this article already presents the finalised artifacts; nevertheless, when valuable, digressions on specific refinements due to action research are reported.

4. Overview on the proposed methodology

The data model-based methodology represents the first artifact of this research work, and it aims at describing a business process under three perspectives: process completeness, information and data completeness and integration. Based on it, company managers could understand the status of their business processes and plan eventual improvement actions. Briefly, the methodology (artifact 1) embeds the reference data model from a scientific and normative literature (artifact 2 in relation to the MM process). The data model is instantiated according to company characteristics. The comparison will then support the planning of improvement actions. The methodology is sketched out in Figure 3 and described in detail in the next subsections.

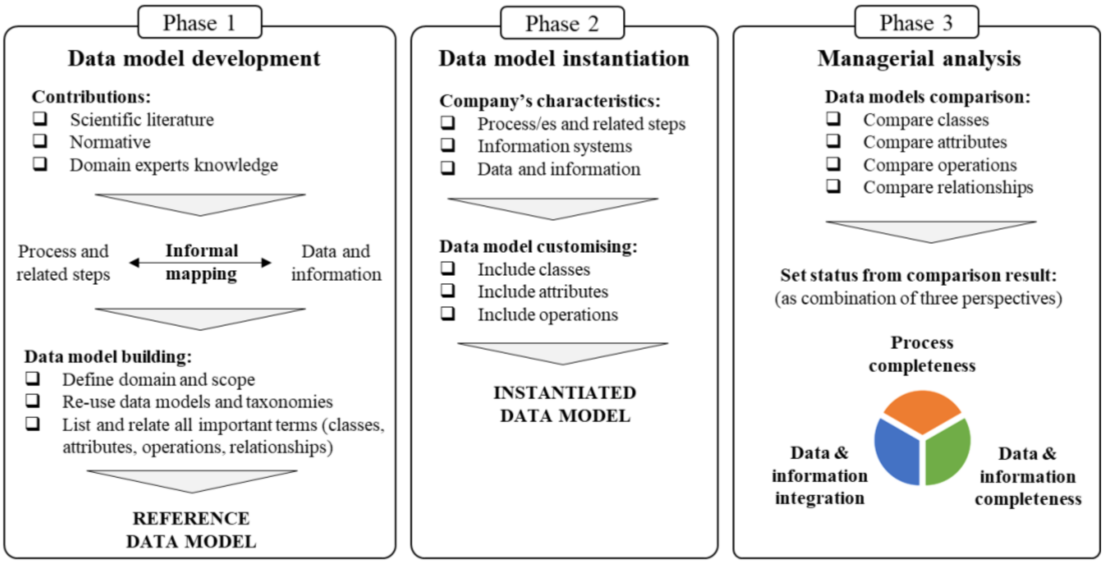

Figure 3. Proposed data model-based methodology.

4.1 Data model development

The first phase of the methodology prescribes to develop a reference data model grounded on theoretical contributions. Data models are selected since they offer modelling flexibility, being they capable of formalising varied concepts (or entities), like an information system, a stakeholder, or a process step, also linked through semantic relationships (West 2011). The output of this phase is a reference data model able to formalise the different facets of the business process of interest, including data and information, relevant analyses to be performed and final decisions to be taken. To this end, theoretical contributions according to the domain of interest, i.e., the targeted business process, need to be investigated. Relevant contributions include scientific literature, already available data models and taxonomies, and domain experts' knowledge. Also, industrial standards are worth to be looked at since they enable an alignment with standardised, agreed-upon, and shared best practices. Once gathered the relevant knowledge, two activities (to be intended as technological rules in DSR) follow:

(1) Informally mapping data and information with the corresponding process steps that allows to unveil needed data to be used and data sources to be integrated; at this point, every informal or formal mapping method could be used;

(2) Data model building according to well-defined steps (Negri et al. 2017):

    (a) Define domain and scope (bounded by the selection of the business process);

    (b) Reuse already existing data model and taxonomies;

    (c) List and relate all relevant terms:

        (i) Classes and their hierarchy/ies;

        (ii) Properties (attributes and operations) of the classes;

        (iii) Relationships among classes.

Different graphical notations for data modelling could be used but UML (Unified Modelling Language) is suggested since it is the de-facto standard (Negri et al. 2016), it has the ISO 19505 reference standard, and it is understandable by different-skilled stakeholders, from the IT technician to the maintenance manager (Thimm, Lee, and Ma 2006).

4.2 Data model instantiation

The second phase entails the instantiation of the reference data model according to the company characteristics. A preliminary preparatory phase is needed, involving:

(1) Mapping of the business process of interest, whose result is the formalisation of each step;

(2) Mapping of the information systems, whose goal is listing the set of software tools, databases, and data sources in general, for each formalised business process step;

(3) Mapping of data and information, which determines the data and information that shall be used or produced in every step of the process.

For the first step, the BPM (Business Process Modelling) methodology could be adopted, which encompasses different techniques according to process characteristics or manager’s needs (Aguilar-Savén 2004); each technique implies high interaction with company experts to assess the process. Then, for the second and third step, the following activities are envisaged: (i) interviews with company experts involved in the process, as well as those supporting it, like the IT managers; (ii) documents analysis, including paper-based documents and e-documents; (iii) direct on-field observations for getting how the day-by-day process is carried out. The second step has been introduced due to the refinement driven by the action research. It has been seen that directly asking which data and information operators/technicians/managers use is hard at first sight and a link via the daily used information systems eases the mapping activity in the third step.

Upon the completion of this preparatory phase, the data model could be instantiated, which means to include all concepts (classes, attributes, operations, and relationships) of the reference data model that hold for the company as well. In principle, the instantiated data model should be less extended than the reference one; this enables assessing the status of the company business process of interest.

4.3 Managerial analysis

The third and last phase of the methodology involves the comparison between the two data models, following a flowchart of rules as expressed in Figure 4. To ease the comparison of concepts, the logical schema is reported in Figure 5.

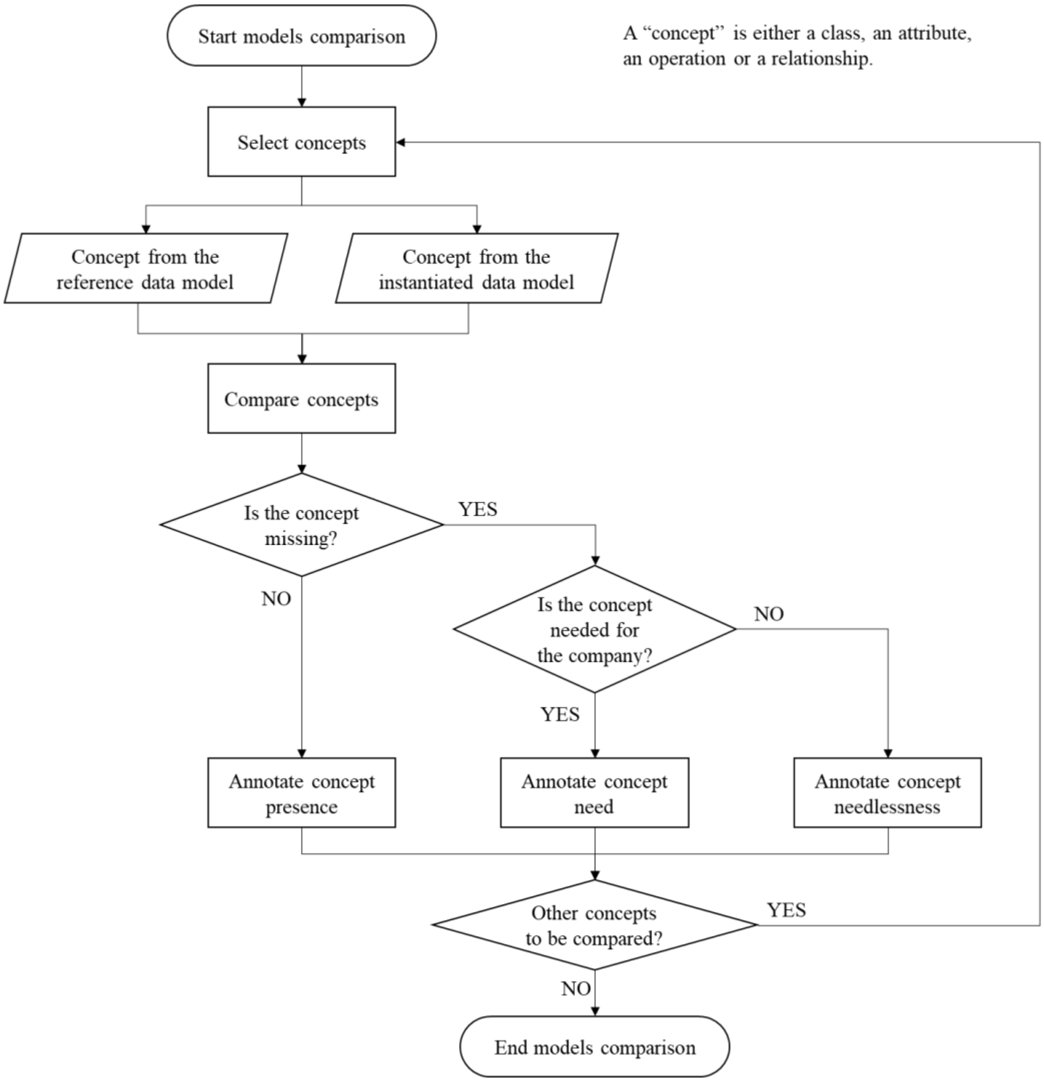

Figure 4. Flowchart for data models comparison.

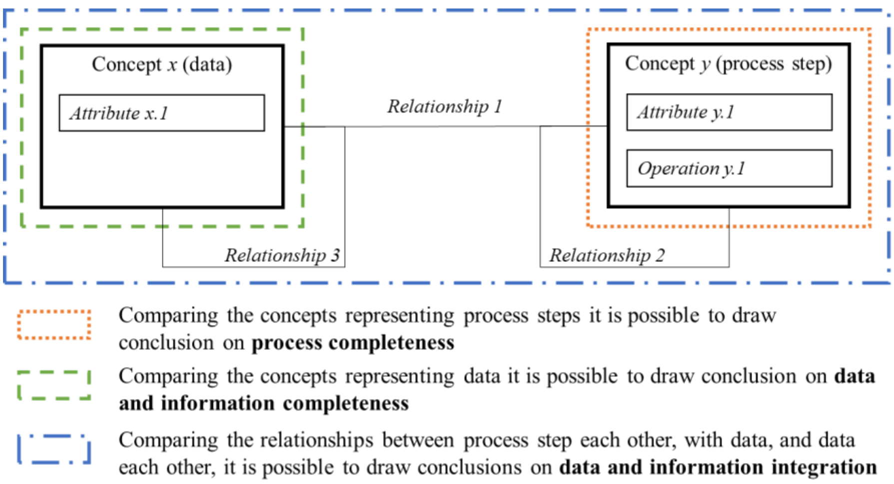

Figure 5. Logical schema for concepts' comparison.

The outputs of the comparison are the annotations regarding the presence of the concept, the absence of a needed concept, the absence of an unneeded concept. To clear out what this means, if a concept is a process step, e.g., an analysis to be performed, it could be that:

- Process step is present (the company is compliant with the reference process formalised in the reference data model);
- Process step is absent and:
  - Needed (the business process does not have that step, but its introduction is deemed useful to improve the process);
  - Not needed (the business process does not have that step, but its introduction is seen as non-critical to improve the process).

On the whole, the comparison allows to set the status of the company process according to the three perspectives of process completeness, information and data completeness and integration. This may lead the company to take short, medium, and long-term improvement actions. In the long run, a (re-)structuring of the IT ecosystem could be envisaged to adhere with the business process requirements thus boosting the related decision-making. This happens because information and data integration reflects on the integration of available information systems forming the IT ecosystem, towards a complete interoperability.

To demonstrate the applicability of the methodology, it must be field-tested. To this end, a one-year action research project is activated in a company willing to improve their MM process (as targeted business process) to comply with their long-term objectives of increased market share. The action research does not only show that the methodology can suggest improvement actions in regards of the MM process, but it also serves to iteratively refine the phases and technological rules of the methodology itself as for DSR guidelines. Thus, the research methodology is applied. In section 5 the reference data model for the MM process is described, whereas in section 6 the instantiated data model and comparison are summarised.

5. Reference data model formalising the maintenance management process

In the first phase, the methodology implies to realise a reference data model, in this case for the MM process. Despite being a company problem-driven artifact, that is, it is realised because of a need of the company, the data model is general enough to be used in other projects likewise. To this end, scientific literature and international normative are screened; for the latter Table 1 summarises relevant standards to be considered.

Industrial standards	
Standard scope	*References*
Data and information management	ISO 14224 (2016) on collection and exchange of lifecycle data ISO 13372 (2012), ISO 13374 (2015) and ISO 17359 (2018) on condition monitoring and diagnostics of machines
Asset Management	ISO 5500x body of standards (2014 and 2018) on AM PAS 55 (2008) later incorporated in ISO 5500x ISO 16646 (2014) on maintenance within AM
Maintenance Management	ISO 15341 (2019) on maintenance key performance indicators ISO 13306 (2017) on maintenance terminology
Failure / Reliability analysis	ISO 16602 (2014) and IEC 60812 (2018) on FMEA/FMECA methodologies

Table 1. Relevant industrial standards used for the development of the data model.

As suggested by the proposed methodology, an informal mapping with mind map is realised to get the picture of information and data required to the MM process. In Figure 6, two examples are shown, one related to asset data and the other to the FMECA.

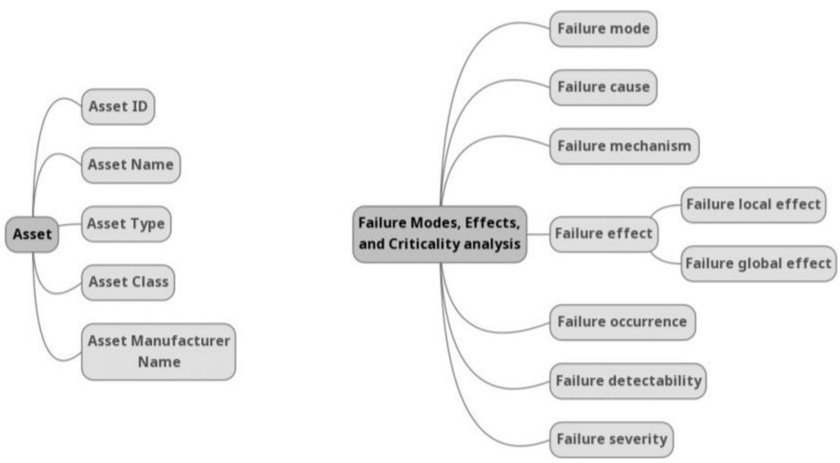

Figure 6. Information/data and process with mind mapping.

The mind map speeds up the creation of the data model. By listing all concepts and relating them accordingly, the data model is finally realised (Figure 7), adopting UML.

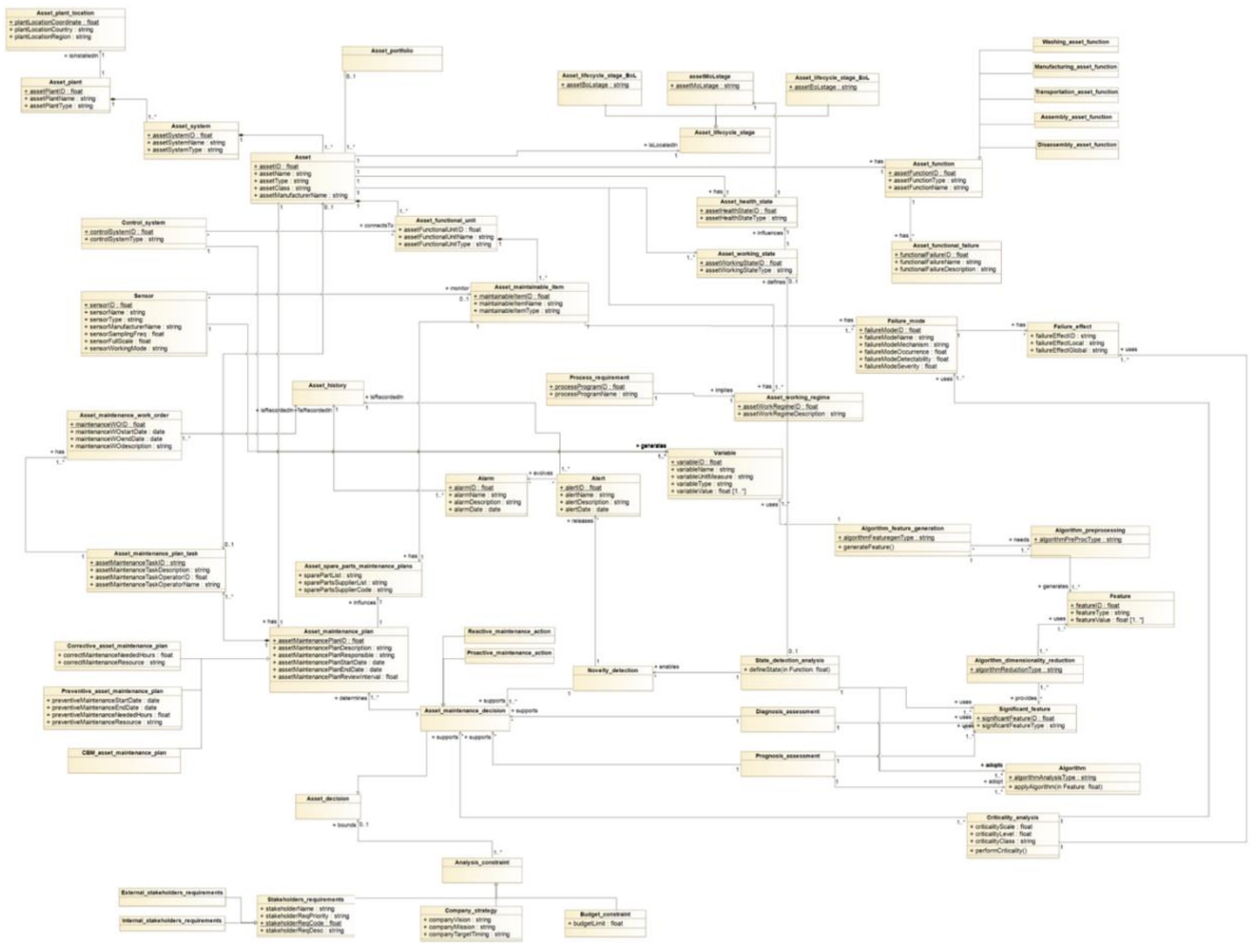

Figure 7. Reference data model for MM process.

The data modelling activity is also accelerated by a conceptual framework, specific for AM and MM decision-making (Polenghi et al. 2019), leading to arrange the data model in five blocks, described in the next subsections.

5.1 Physical description

This block collects any class describing the physical objects composing the production plant. The central class is *Asset*, which represents an entity "that has potential or actual value to generate value for the organisation" (ISO 55000 2014), so it models any machinery or equipment, as milling or turning machine. The *Asset* is decomposed in one or more *Asset_functional_unit* (called "subunit" in the ISO 14224), that performs a specific task, like water supply unit, cooling unit or scrap removal unit. Each *Asset_functional_unit* is further decomposed in more *Asset_maintainable_item* that are those items on which the maintenance action is performed according to ISO 13306, like a pipe for the water supply or the collector of scraps from the machining unit. More *Asset*(s) could compose an *Asset_system*, which may be thought as a department in the job shop (*Asset_system* as a group of assets homogenous for technological characteristics) or a production line (*Asset_system* as a group of assets homogenous in production goal). One or more *Asset_system* compose the *Asset_plant* that is the whole production plant, which is installed in a specific *Asset_plant_location*. Also, *Asset_portfolio*(s) are relevant for companies since they collect information about heterogenous assets (Petchrompo and Parlikad 2019).

Moreover, there are two relevant classes from which data will be extracted: *Control_system* and *Sensor*. *Control_system* represent those systems, like PLC (Programmable Logic Controller) or CNC (Computer Numerical Control), that are connected to the *Asset_functional_unit* and govern its work and/or retrieve feedback signals. *Sensor* could be used to monitor an *Asset_maintainable_item* and measure a certain quantity.

5.2 Logical description

This block describes how the *Asset* is and how it works.

Firstly, the *Asset* is located in a specific *Asset_lifecycle_stage*, which could be *Asset_lifecycle_stage_BoL*, *Asset_lifecycle_stage_MoL*, or *Asset_lifecycle_stage_EoL*. Then, within each lifecycle stage it could be in a specific sub-stage, like design or commissioning for BoL (Beginning of Life), production or maintenance for MoL (Middle of Life), and disposal for EoL (End of Life).

Thereafter, the *Asset* has an *Asset_health_state*, which could be (*AssetHealthStateType*) healthy, abnormal, or faulty state (or more states depending on the needs). Coherently with

Prognostics and Health Management (PHM) theory, the *Asset_health_state* experiences in *Asset_lifecycle_state_MoL*, thus during operations.

Eventually, the *Asset* has one or more *Asset_function* that could be of different types, like manufacturing, transportation, assembly, and so on. An *Asset_functional_failure* may arise, which represents the inability to perform a specific *Asset_function*. Related to *Asset_maintainable_item*, a *Failure_mode* could occur, which is the manner in which the inability of an *Asset* to perform a required function occurs, as by IEC 60812. The *Failure_effect* describes the consequences of a *Failure_mode*, within or beyond the boundary of the failed *Asset_maintainable_item*.

5.3 Information sources

This block collects all classes that are sources of data and information.

Firstly, from the *Control_system* or *Sensor*, some *Variable*(s) are derived/generated, which will be used for different analyses. Among those data useful to MM, *Alarm* and *Alert* are fundamental sources as they represent a portion of indications on events the *Asset* went through. The *Asset_history* collects *Alarm* and *Alert* along with other data and information, such as the *Asset_maintenance_work_order*. It includes all details of a maintenance action, regarding starting date, ending date, description and others, in both structured and unstructured way.

Moreover, the *Process_requirement* represent the production cycles the *Asset* must respect, including which products it must realise. When a product comes to the *Asset*, it starts a certain *Asset_working_regime,* that includes all the details (alias parameters setting) required to perform certain programs on the product. For example, the tightening force for screws is a variable within the *Asset_working_regime* that, together with others, completely define the set of operations to be performed, in compliance with the *Process_requirement.*

5.4 Relevant analyses

This block collects analyses relevant for MM decision-making.

On one side, the criticality analysis is modelled, being one of the most adopted techniques in maintenance planning (Crespo Márquez et al. 2016) in MoL and BoL. Indeed, the *Criticality_analysis* supports the identification of critical *Asset* or *Failure_mode* depending on the interested granularity. The inputs of the *Criticality_analysis* are several but, in maintenance common practice, they are almost all related to the FMEA, like *Failure_mode* and *Failure_effect*.

On the other side, classes modelling the PHM are introduced, including state detection, diagnosis and prognosis (Guillén et al. 2016). In these processes, the *Variable* is used by an *Algorithm_feature_generation* that generates one or more meaningful *Feature*, eventually supported by a preliminary *Algorithm_preprocessing*. After the application of an *Algorithm_dimensionality_reduction*, one or more *Significant_feature* are provided, which are at the basis of *State_detection_analysis*, *Diagnosis_assessment*, and *Prognosis_assessment*; all may require the adoption of a proper *Algorithm*. The *State_detection_analysis* enables *Novelty_detection* that, if properly implemented, bring to an *Alert* if the *Asset* is not working properly and this may evolve into an *Alarm*.

5.5 MM decision-making

This block collects all decisions (*Asset_decision*) interesting for MM within AM. The *Asset_decision* is subjected to one or more *Analysis_constraint* that may be related to *Budget_constraint*, *Company_strategy*, and *Stakeholders_requirements*. A specific type of *Asset_decision* is *Asset_maintenance_decision*, which is supported by the analyses in the previous block. This decision determines the identification of a proper *Asset_maintenance_plan* for the *Asset* that could be *Corrective_asset_maintenance_plan*, *Preventive_asset_maintenance_plan*, or *CBM_asset_maintenance_plan*. These plans affect the *Asset_spare_part_management_plan* that must be properly established to comply with the requirements of the associated maintenance plan (Roda et al. 2014). The *Asset_maintenance_plan* is composed by one or more *Asset_maintenance_plan_task* that are field-related tasks to carry out. When the task needs to be performed, an *Asset_maintenance_work_order* is established that is recorded in the *Asset_history* at its completion. Related to PHM, *Reactive_maintenance_action* and *Proactive_maintenance_action* decisions could be taken, dictated by *Novelty_detection* and *Prognostics_assessment*, respectively.

6. Industrial case: action research in an automotive company

The action research is performed during a one-year project in a multinational company active in the automotive sector, which allows to use and refine both the methodology and the reference data model. The strategic plan sets an increase in the actual production in the coming years; hence, maintenance becomes a central function to guarantee machine availability.

The company is organised in departments, each further divided into units. The production system is composed by two areas, whose characteristics are reported in Table 2, decoupled by means of a buffer: a mechanical machining area, which receives the inbound raw material flow, and an assembly area, which performs the operations before delivery.

Characteristics	**Mechanical machining area**	**Assembly area**
Configuration	Job-shop	Cells
Machine/station	Milling, turning, and washing machines (generic machines)	Specialised cells with drilling and turning operations plus manual ones
Handling system	Semi-automatic	Automatic
Age	High average age (up to 20/25 years old)	Very wide (new and up to 10 years old)
Obsolescence	Low impact	High impact due to customer's demand

Table 2. Company production system.

Due to the high customisation of products, the assembly area is often renewed, and it offers the most heterogeneous ensemble of old and recent technologies. This leads to several consequences on how the MM process is carried out and with which tools, as described in the remainder. The first step of the methodology has been already described (data model development) in section 5. Thus, subsections 6.1 to 6.4 represent the second step of the methodology (data model instantiation), while subsection 6.5 the third (managerial analysis).

6.1 Identification of processes and related steps

Together with the maintenance manager of the company, the corrective and preventive maintenance processes are selected as the scope of the project, with special attention to the latter. Despite the various benefits preventive maintenance could bring, the shortcomings recognised by the maintenance manager mainly come from premature interventions on healthy asset, reducing the availability, with increasing operational and hidden costs.

The BPMN (Business Process Modelling Notation) is selected to map the processes since it offers a perspective on the internal departments involved with consequently easy identification of organizational roles to interview for further insights. Figure 8 shows the preventive maintenance process of the assembly area.

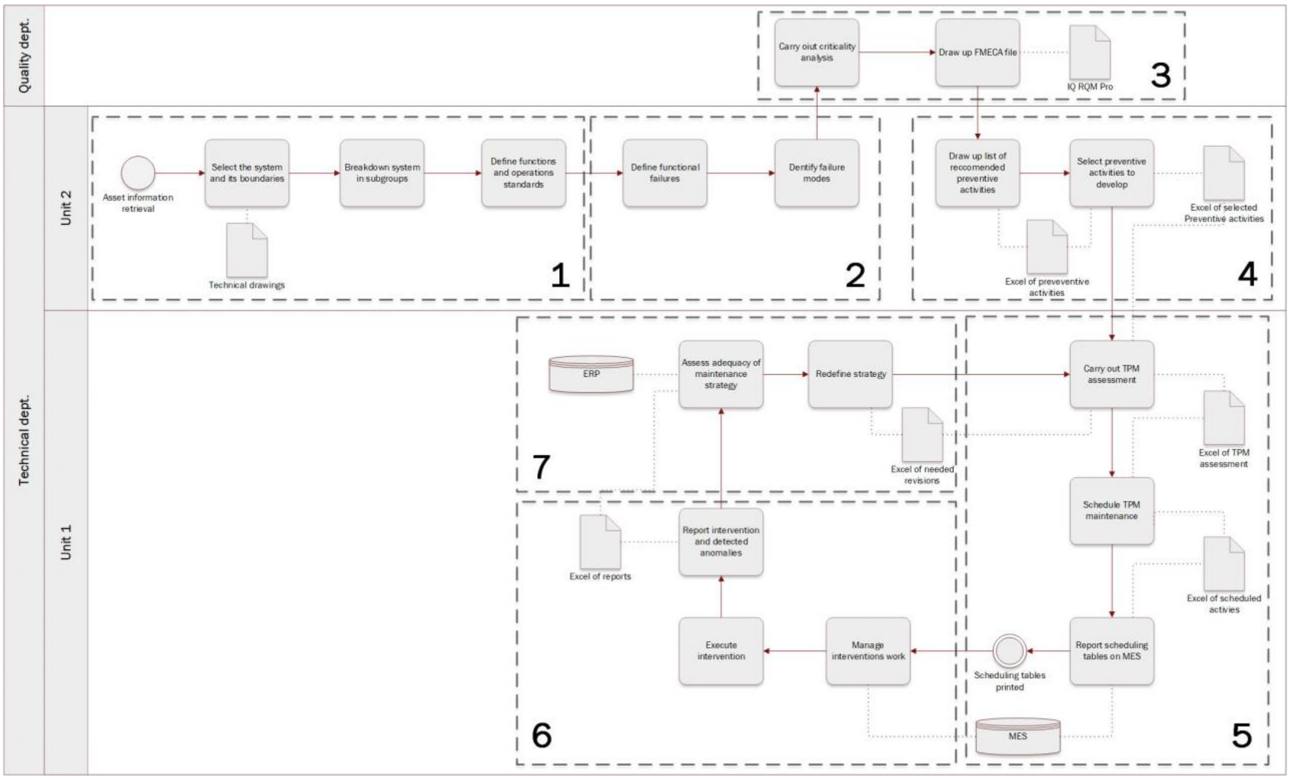

Figure 8. BMPN for the assembly area preventive maintenance process.

An important result is already achieved, that is the formalisation and comparison of the company MM processes. Indeed, the preventive maintenance process is carried out differently between the mechanical machining and assembly areas of the company while the corrective is consistent. It is due to the relevant technological divide between the areas, but also due to the wide attention for the assembly area which is more critical. The two preventive MM processes share sub-processes 1, 2, and 3, while the process for the machining area is less structured from the 4th onwards, counting more on operator's experience.

The identification of 7 sub-processes guides the next mapping activities of information systems, and data and information.

6.2 Mapping of information systems

This activity aims at identifying those information systems used to perform the maintenance process, especially by mapping the used software tools. The systems differ between company departments and units, and integration and interoperability problems arise. Usually, the transformation in spreadsheet or comma-separated values files is mandatory to guarantee data exchange within and outside departments. E-mails and unstructured general-purpose databases are today the most used means. In Table 3, the software tools used for the preventive maintenance process of the assembly area are listed, divided per company department.

Department	Software tool type	Type
Quality	FMEA Software	Commercial
	Spreadsheet	Commercial
Technical	ERP (Enterprise Resource Planning)	Commercial
	MES (Manufacturing Execution System)	Proprietary
	FMEA Software	Commercial
	Spreadsheet	Commercial

Table 3. Current software tools used in the company for preventive maintenance.

Most used software tools are commercial solutions for industrial application. The exceptions are spreadsheets as generic software tools and the proprietary MES that is developed in-house; this implies a high degree of flexibility to introduce new required functionalities.

Concerning the mechanical machining area, the preventive maintenance process is entirely built on the ERP, while the MES is not present. This is a crucial problem recognised by the maintenance manager since the MES is built in-house and is continuously updated according to the company needs. On the other side, the ERP is a system forcing the company to adapt to the ERP built-in processes and structures, and its flexibility to changes is low.

6.3 Mapping of data and information

All data and information for each MM process step need to be retrieved. During this activity, a data taxonomy may play a key-role since it could guide the interviews by stating the important data classes to be explored. Table 4 shows an extract of the document provided to the company reporting this analysis for the preventive maintenance of the assembly area. To contextualise the needed data and information, they are associated with the corresponding process step (see numbering in Figure 8) and software tools.

Process step	**Software tools**	**Information and data**	
		Taxonomy class	**Specific data/info**
1	Spreadsheet	Asset data	Asset class Asset type Asset identification Asset location Asset description Manufacturer’s name Manufacturer’s model designation Functioning standards Normal operating parameter Start date of current service Technical drawings
2	Spreadsheet FMEA software	Failure data	Failure record Equipment identification code Equipment location Failure mode Failure cause Failure probability Failure severity Failure detectability Failure occurrence

Table 4. Extract of the report: process steps, related software tools, data and information.

6.4 Instantiated data model

The instantiated data model builds upon the results already achieved, namely the BPMN diagram, the software tools and the relevant information and data for the MM process. As advisable since the beginning, the reference data model is wider than the instantiated one since it considers the MM process in all its steps, information and data. The instantiated model is not shown for privacy issues.

6.5 Managerial analysis

Finally, the proposed methodology prescribes to compare the reference data model with the instantiated one to identify the status of the MM process. It is worth remarking that the reference data model is developed so that its classes represent data or process steps; the classes within the physical description, even though they refer to real entities, are also seen as information or data.

Figure 9 reports the reference data model with the differences highlighted. Colours are used as proxies to identify levels of misalignment in the MM process: missing classes in red, missing attributes in red, not formalised attributes in grey, missing relationships in red.

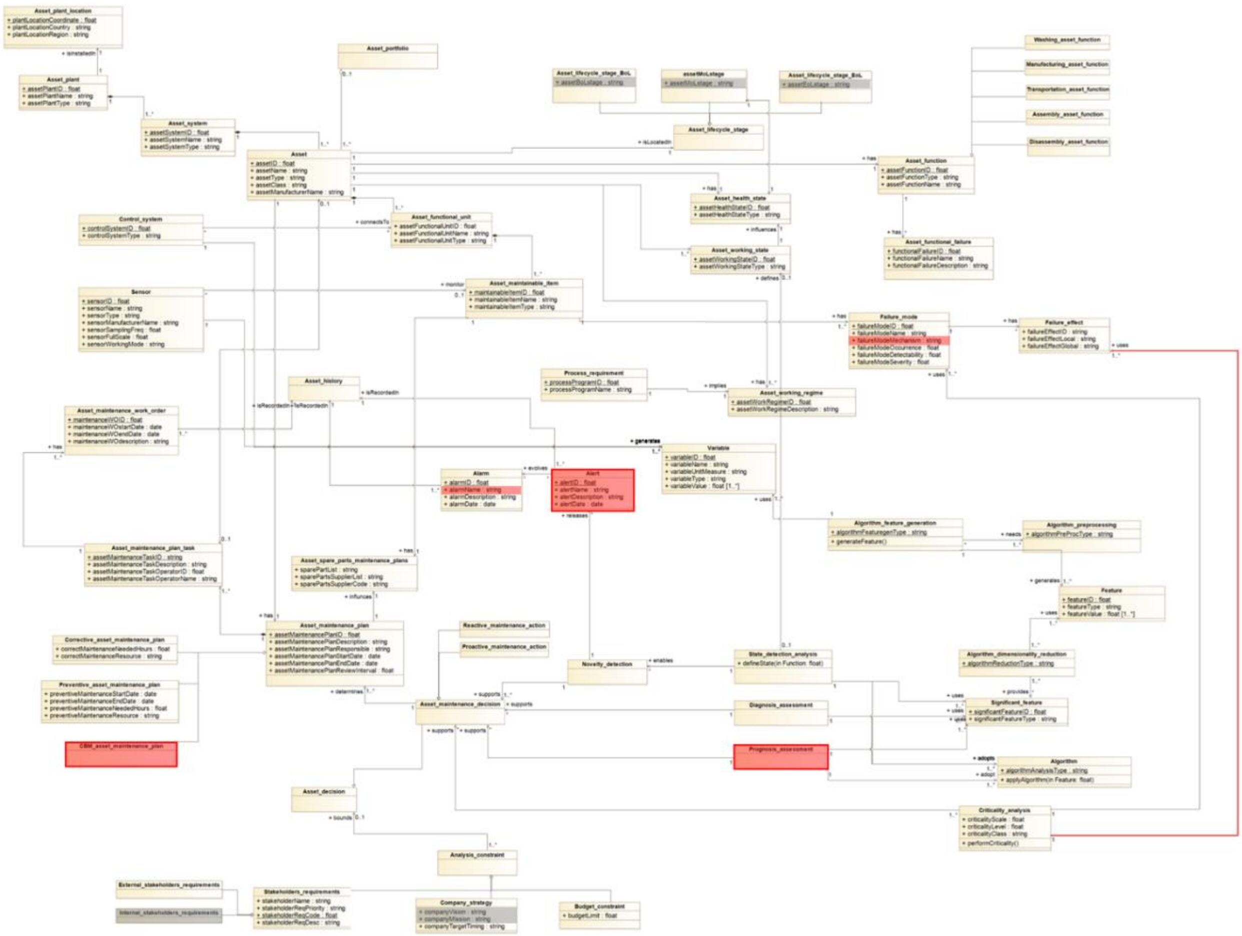

Figure 9. Reference data model with highlighted differences.

The managerial implications are analysed together with the maintenance manager, according to the three perspectives of interest.

Process completeness. Absence of some steps in the MM process. However, it is worth noting that a missing step does not necessarily imply a criticality to be solved, as agreed by the maintenance manager. The identification of absent steps is important to make informed decisions: 1) the step is important for the process and it must be immediately established and formalised; 2) the step is important, but it is not a primary concern, and the implementation could be planned; 3) the step is not important.

A relevant example is the prognosis step in the MM process. The maintenance manager underlines that only diagnosis is carried out to solve eventual customers' claims. However, the new trends have pushed the management to commit towards an advancement in the maintenance practice through investments in digitalisation. Thus, prognosis is enabled, even though it is not yet carried out, but planned to be fully exploited in the next years.

Data and information completeness. Identification of lacks in data and information. These consist of the following matters:

(1) The missing data and information are spread in different process steps. This is symptom of not robust and unreliable decision-making, which could result in misleading analyses that misdirect the final decisions regarding the assets;

(2) Even though some data and information are present in the process, they are not properly formalised. Such data may come in different formats, may not be updated, and be dispersed in company databases; consequently, the analyses must adapt to the available data, but the vice-versa is advisable.

Two examples are useful. The first one considers the failure mechanism of the asset, which is not analysed and registered, preventing to realise a complete reliability-centred analysis of the asset. For the second one, internal stakeholders' requirements are not formalised as done for the external stakeholders (customers); consequently, the asset criticality, whose definition depends on stakeholders' requirements (Pistofidis et al. 2016), may be erroneous, with several implications on what maintenance strategy to adopt and how it is carried out.

Data and information integration. Most MM process steps, that should have related each other in terms of needed data and information, cannot count on integrated information systems. Thus, when the data need to be transferred between classes for a certain purpose, the data must be transformed in auxiliary formats.

A peculiar example of such missing integration is represented by the exchange of FMECA-related results. Even though FMECA is recognised a backbone of a proper maintenance strategy planning, the exchange of related data is cumbersome. In the company, the results obtained in a commercial solution for FMECA need to be transformed into spreadsheets and delivered through e-mail or internal databases; this leads to a risk of loss of control on data quality.

Apart from these three perspectives, during the action research, the methodology allows the maintenance manager to reason over the involved stakeholders in the MM process. Even though the stakeholders are not formalised, it is worth to summarise the key insights the maintenance manager underlines:

(1) Missing stakeholders: some process steps are so far performed without including all the interested stakeholders, implying that some perspectives on the asset are missing;
(2) Redundancy of stakeholders: as opposed to the previous case, there are some steps characterised by an overabundance of stakeholders, leading to erroneous balancing of all needs and thus biased decisions.

Having depicted the MM process status, the company is undertaking different improvement actions under various time horizons:

- In the short-term:
    - Two best practices on the corrective and preventive maintenance processes are realised so that newly acquired assets will undertake consistent processes;
    - Despite keeping paper-based and spreadsheet-based information, more data and information will be considered in the analysis so to come up with complete results;
- In the medium-term, a transition from spreadsheet-based information to more standardised and structure-fixed formats will be pursued, trying to make interoperable the required information systems. In particular, the in-house MES will increase its role as the backbone to comply with interoperability requirements;
- In the long-term, a more interoperable architecture is envisioned even though it is difficult to forecast one possible way since many stakeholders are involved, not only maintenance.

A final reflection is on the process-oriented interoperability the company aims to pursue in the coming years. Instead of fostering a more technical-driven integration of already available information systems, the company prefers to opt for enhancing and extending MES functionalities that provide flexibility. In so doing, the maintenance manager could formalise the MM process at best and then the required functionalities are implemented.

7. Discussion on artifacts' generalizability

In the present work, two artifacts are developed based on the DSR methodology, which is built upon action research, and constitute the main difference with explanatory approaches (Van Aken 2005; Van Aken, Chandrasekaran, and Halman 2016). Even though the two artifacts, i.e., the data modelling-based methodology and the reference data model, are contextualised for the specific company case, thy could claim generalizability, even though bounded, i.e., not willing to be complete and ground explanatory theories (Holmström, Ketokivi, and Hameri 2009).

Thus, on one side, the reference data model (artifact 2) may claim generalizability since it is extensively based on scientific contributions and normative literature, which represents an agreed-upon knowledge. As such, the data model could be assumed generalizable by design; the methodology aims at being of enough high-level to be reused in other context, but this should be verified.

On the other side, the generalizability of the proposition this research work promotes (the methodology with the reference data model could enable MM process in becoming more data-driven) is still to be proven. To this end, additional scientific studies, based on case studies and action research, are envisioned so to identify a causality relationship, grounded on empirical evidence, between the introduction of the proposed data modelling-based methodology and an improved capability of the company to plan short, medium, and long-term improvement towards an improved data-driven decision-making.

8. Conclusions

This research work aims at boosting the data-driven decision-making process for a modern maintenance practice. This need stems from the wider scope fostered by AM and the technological evolution induced by the digitalisation. In this context, data and information integration are put at the stack as critical enablers of suitable decision-making. Extant literature on the use of graphical notations to tackle information and data management at large, shows some pitfalls and mainly focuses on improving the transformation of data into information rather than on integrating them, while looking at interoperability problems majorly from a merely technical rather than a managerial perspective. For this reason, two artifacts are developed according to DSR: a methodology and a reference data model; the latter is specific for the MM process. The data-model based methodology enables to assess the process itself, namely its completeness, the information and data completeness and integration. The methodology leverages on the capability of data models to represent multi-nature concepts, like process and related data, and on its ease of comprehension by different skilled stakeholders. The core of the methodology is the comparison between a reference data model and an instantiated data model adapted to company characteristics. The reference data model is realised through an action research and finds its roots in scientific and normative literature as well as it underwent refinement according to company feedbacks.

The application of the methodology in a real context enables the maintenance managers in understanding the MM process status. As such, the methodology supports the drafting of a set of requirements that will guide improvement actions, mainly related to guarantee interoperability between proper information systems, and the consistency of process steps and used data to support decisions. The integration requirements between information systems are based on process needs, and not vice-versa. This will lead to a more reliable decision-making process driven by data exchanged seamlessly intra-department and inter-department to exploit cross-functional knowledge.

Overall, the artifacts support the definition of improvement actions for a business process. The application in an automotive company demonstrates that they enable:

(1) Standardisation and formalisation of the process of interest;
(2) Standardisation and formalisation of the needed information and data;
(3) Identification of interoperability requirements, in terms of data and information integration, to guarantee seamless intra and inter-department data exchange.

Future research should focus on proving the generalizability of the proposed artifacts by applying them in different contexts. Also, it is possible to foresee some extensions:

(1) Extension of the portfolio of processes being formalised through data modelling, to guarantee a wider spectrum of reference processes for comparison;
(2) Realisation of multi-process data models to guarantee understanding of interoperability requirements also between the various business processes taking place in the company;
(3) Formalisation of the process maturity (in terms of the three perspectives of interest) in a pre-defined scale to allow internal and external benchmarking.

Building on these three directions, it is our particular interest to study the MM process and its connection to other processes in the wider scope of asset lifecycle management.

References

Aguilar-Savén, Ruth Sara. 2004. "Business Process Modelling: Review and Framework." *International Journal of Production Economics* 90 (2): 129–149. doi:10.1016/S0925-5273(03)00102-6.

Amadi-Echendu, J. E., and K. Brown. 2010. *Definitions, Concepts and Scope of Engineering Asset Management*. Edited by Roger Willett and Joseph Mathew. *Springer*. doi:10.1007/978-1-84996-178-3.

Amadi-Echendu, J E, R Willett, K Brown, T Hope, J Lee, J Mathew, N Vyas, and B -S Yang. 2010. "What Is Engineering Asset Management?" *Engineering Asset Management Review*. doi:10.1007/978-1-84996-178-3_1.

Ballou, Donald P., and Harold L. Pazer. 1985. "Modeling Data and Process Quality in Multi-Input, Multi-Output Information Systems." *Management Science* 31 (2). INFORMS: 150–162. doi:10.1287/mnsc.31.2.150.

Bokrantz, Jon, Anders Skoogh, Cecilia Berlin, and Johan Stahre. 2017. "Maintenance in Digitalised Manufacturing: Delphi-Based Scenarios for 2030." *International Journal of Production Economics* 191. Elsevier B.V.: 154–169. doi:10.1016/j.ijpe.2017.06.010.

Bokrantz, Jon, Anders Skoogh, Cecilia Berlin, Thorsten Wuest, and Johan Stahre. 2020a. "Smart Maintenance: An Empirically Grounded Conceptualization." *International Journal of Production Economics* 223. Elsevier: 107534.

Bokrantz, Jon, Anders Skoogh, Cecilia Berlin, Thorsten Wuest, and Johan Stahre. 2020b. "Smart Maintenance: A Research Agenda for Industrial Maintenance Management." *International Journal of Production Economics* 224: 107547. doi:https://doi.org/10.1016/j.ijpe.2019.107547.

Borangiu, Theodor, Damien Trentesaux, André Thomas, Paulo Leitão, and Jose Barata. 2019. "Digital Transformation of Manufacturing through Cloud Services and Resource Virtualization." *Computers in Industry* 108: 150–162. doi:https://doi.org/10.1016/j.compind.2019.01.006.

Bousdekis, Alexandros, Babis Magoutas, Dimitris Apostolou, and Gregoris Mentzas. 2015. "A Proactive Decision Making Framework for Condition-Based Maintenance." *Industrial Management & Data Systems* 115 (7). Emerald Group Publishing Limited: 1225–1250.

Campos, Jaime, Pankaj Sharma, Unai Gorostegui Gabiria, Erkki Jantunen, and David Baglee. 2017. "A Big Data Analytical Architecture for the Asset Management." *Procedia CIRP* 64: 369–374. doi:10.1016/j.procir.2017.03.019.

Campos, M. A.López, and A. Crespo Márquez. 2011. "Modelling a Maintenance Management Framework Based on PAS 55 Standard." *Quality and Reliability Engineering International* 27 (6):

805–820. doi:10.1002/qre.1168.

Crespo Márquez, Adolfo, Pedro Moreu De Leõn, Antonio Sola Rosique, and Juan F. Gõmez Fernández. 2016. "Criticality Analysis for Maintenance Purposes: A Study for Complex In-Service Engineering Assets." *Quality and Reliability Engineering International* 32 (2): 519–533. doi:10.1002/qre.1769.

del Mar Roldán-García, María, José García-Nieto, Alejandro Maté, Juan Trujillo, and José F. Aldana-Montes. 2021. "Ontology-Driven Approach for KPI Meta-Modelling, Selection and Reasoning." *International Journal of Information Management* 58 (June). Elsevier: 102018. doi:10.1016/j.ijinfomgt.2019.10.003.

Errandonea, Itxaro, Sergio Beltrán, and Saioa Arrizabalaga. 2020. "Digital Twin for Maintenance: A Literature Review." *Computers in Industry* 123: 103316. doi:https://doi.org/10.1016/j.compind.2020.103316.

Forcina, Antonio, Vito Introna, and Alessandro Silvestri. 2021. "Enabling Technology for Maintenance in a Smart Factory: A Literature Review." *Procedia Computer Science* 180: 430–435. doi:https://doi.org/10.1016/j.procs.2021.01.259.

Gallo, Tommaso, and Annalisa Santolamazza. 2021. "Industry 4.0 and Human Factor: How Is Technology Changing the Role of the Maintenance Operator?" *Proceedings of the 2nd International Conference on Industry 4.0 and Smart Manufacturing (ISM 2020)* 180 (January): 388–393. doi:10.1016/j.procs.2021.01.364.

Gopalakrishnan, M, M Subramaniyan, and A Skoogh. 2020. "Data-Driven Machine Criticality Assessment–Maintenance Decision Support for Increased Productivity." *Production Planning and Control*. doi:10.1080/09537287.2020.1817601.

Gregor, Shirley, and Alan R Hevner. 2013. "Positioning and Presenting Design Science Research for Maximum Impact." *MIS Quarterly* 37 (2). Management Information Systems Research Center, University of Minnesota: 337–355.

Guillén, A. J., A. Crespo, M. Macchi, and J. Gómez. 2016. "On the Role of Prognostics and Health

Management in Advanced Maintenance Systems." *Production Planning and Control* 27 (12). Taylor & Francis: 991–1004. doi:10.1080/09537287.2016.1171920.

Herterich, Matthias M, Falk Uebernickel, and Walter Brenner. 2015. "The Impact of Cyber-Physical Systems on Industrial Services in Manufacturing." *Procedia CIRP* 30: 323–328. doi:https://doi.org/10.1016/j.procir.2015.02.110.

Hevner, Alan R, Salvatore T March, Jinsoo Park, and Sudha Ram. 2004. "Design Science in Information Systems Research." *MIS Quarterly* 28 (1). Management Information Systems Research Center, University of Minnesota: 75–105. doi:10.2307/25148625.

Holmström, Jan, Mikko Ketokivi, and Ari-Pekka Hameri. 2009. "Bridging Practice and Theory: A Design Science Approach." *Decision Sciences* 40 (1). John Wiley & Sons, Ltd: 65–87. doi:https://doi.org/10.1111/j.1540-5915.2008.00221.x.

ISO 55000. 2014. "Asset Management — Overview, Principles and Terminology." *BSI Standards Publication*. International Organisation for Standardization.

Iung, Benoît, Eric Levrat, Adolfo Crespo Marquez, and Heinz Erbe. 2009. "Conceptual Framework for E-Maintenance: Illustration by e-Maintenance Technologies and Platforms." *Annual Reviews in Control* 33 (2): 220–229. doi:10.1016/j.arcontrol.2009.05.005.

Jantunen, Erkki, Giovanni Di Orio, Csaba Hegedűs, Pal Varga, Istvan Moldovan, Felix Larrinaga, Martin Becker, Michele Albano, and Pedro Maló. 2019. "Maintenance 4.0 World of Integrated Information." In *Enterprise Interoperability VIII*, 67–78. Springer.

Ko, Ryan K L, Stephen S G Lee, and Eng Wah Lee. 2009. "Business Process Management (BPM) Standards: A Survey." *Business Process Management Journal* 15 (5). Emerald Group Publishing Limited: 744–791. doi:10.1108/14637150910987937.

Komonen, Kari, Helena Kortelainen, and Minna Räikkönen. 2012. "Corporate Asset Management for Industrial Companies: An Integrated Business-Driven Approach." In *Asset Management*, edited by T. Van der Lei, P. Herder, and Y. Wijnia, 47–63. Springer, Dordrecht.

Komonen, Karl, and Antoine Despujols. 2013. "Maintenance within Physical Asset Management: A

Standardization Project within CEN TC319.” *Proceedings of COMDEM, Helsinki*, 11–13.
Kortelainen, Helena, Susanna Kunttu, Pasi Valkokari, and Toni Ahonen. 2015. “Asset Management Decisions—Based on System Thinking and Data Analysis.” In *Proceedings of the 8th World Congress on Engineering Asset Management (WCEAM 2013) & the 3rd International Conference on Utility Management & Safety (ICUMAS)*, 1083–1093. Springer, Cham. doi:10.1007/978-3-319-09507-3_92.
Kuechler, Bill, and Vijay Vaishnavi. 2008. “On Theory Development in Design Science Research: Anatomy of a Research Project.” *European Journal of Information Systems* 17 (5). Taylor & Francis: 489–504. doi:10.1057/ejis.2008.40.
Lee, Jay, Behrad Bagheri, and Hung An Kao. 2015. “A Cyber-Physical Systems Architecture for Industry 4.0-Based Manufacturing Systems.” *Manufacturing Letters* 3. Society of Manufacturing Engineers (SME): 18–23. doi:10.1016/j.mfglet.2014.12.001.
Legat, Christoph, Jörg Neidig, and Mikhail Roshchin. 2011. “Model-Based Knowledge Extraction for Automated Monitoring and Control.” In *IFAC Proceedings Volumes*, 44:5225–5230. Elsevier. doi:10.3182/20110828-6-IT-1002.03700.
Macchi, M, I Roda, and L Fumagalli. 2020. “On the Focal Concepts of Maintenance in the Digital Era.” *IFAC-PapersOnLine* 53 (3): 84–89. doi:https://doi.org/10.1016/j.ifacol.2020.11.013.
Mahlamäki, K, A Niemi, J Jokinen, and J Borgman. 2016. “Importance of Maintenance Data Quality in Extended Warranty Simulation.” *International Journal of COMADEM* 19 (1): 3–10.
Negri, Elisa, Luca Fumagalli, Marco Garetti, and Letizia Tanca. 2016. “Requirements and Languages for the Semantic Representation of Manufacturing Systems.” *Computers in Industry* 81 (September): 55–66. doi:10.1016/j.compind.2015.10.009.
Negri, Elisa, Sara Perotti, Luca Fumagalli, Gino Marchet, and Marco Garetti. 2017. “Modelling Internal Logistics Systems through Ontologies.” *Computers in Industry* 88: 19–34. doi:10.1016/j.compind.2017.03.004.
O’Donovan, P., K. Leahy, K. Bruton, and D. T.J. O’Sullivan. 2015. “An Industrial Big Data

Pipeline for Data-Driven Analytics Maintenance Applications in Large-Scale Smart Manufacturing Facilities." *Journal of Big Data* 2 (1). Springer International Publishing: 1–26. doi:10.1186/s40537-015-0034-z.

Ouyang, Chun, Marlon Dumas, Wil M P Van Der Aalst, Arthur H M Ter Hofstede, and Jan Mendling. 2009. "From Business Process Models to Process-Oriented Software Systems." *ACM Trans. Softw. Eng. Methodol.* 19 (1). New York, NY, USA: Association for Computing Machinery. doi:10.1145/1555392.1555395.

Peffers, Ken, Tuure Tuunanen, Marcus A Rothenberger, and Samir Chatterjee. 2007. "A Design Science Research Methodology for Information Systems Research." *Journal of Management Information Systems* 24 (3). Routledge: 45–77. doi:10.2753/MIS0742-1222240302.

Petchrompo, Sanyapong, and Ajith Kumar Parlikad. 2019. "A Review of Asset Management Literature on Multi-Asset Systems." *Reliability Engineering and System Safety* 181 (March 2018). Elsevier Ltd: 181–201. doi:10.1016/j.ress.2018.09.009.

Pistofidis, Petros, Christos Emmanouilidis, Aggelos Papadopoulos, and Pantelis N. Botsaris. 2016. "Management of Linked Knowledge in Industrial Maintenance." *Industrial Management and Data Systems* 116 (8): 1741–1758. doi:10.1108/IMDS-10-2015-0409.

Polenghi, Adalberto, Irene Roda, Marco Macchi, and Alessandro Pozzetti. 2019. "Conceptual Framework for a Data Model to Support Asset Management Decision-Making Process." In *Advances in Production Management Systems. Production Management for the Factory of the Future. APMS 2019. IFIP Advances in Information and Communication Technology*, edited by F. Ameri, K. Stecke, G. von Cieminski, and D. Kiritsis, 566:283–290. Springer, Cham. doi:10.1007/978-3-030-30000-5_36.

Polenghi, Adalberto, Irene Roda, Marco Macchi, and Alessandro Pozzetti. 2020. "A Conceptual Model of the IT Ecosystem for Asset Management in the Global Manufacturing Context." In *Advances in Production Management Systems. Towards Smart and Digital Manufacturing*, edited by Bojan Lalic, Vidosav Majstorovic, Ugljesa Marjanovic, Gregor von Cieminski, and David

Romero, 711–719. Cham: Springer International Publishing. doi:10.1007/978-3-030-57997-5_82.

Polenghi, Adalberto, Irene Roda, Marco Macchi, and Alessandro Pozzetti. 2021. "Information as a Key Dimension to Develop Industrial Asset Management in Manufacturing." *Journal of Quality in Maintenance Engineering* ahead-of-p (ahead-of-print). Emerald Publishing Limited. doi:10.1108/JQME-09-2020-0095.

Qu, Yuanju, Xinguo Ming, Yanrong Ni, Xiuzhen Li, Zhiwen Liu, Xianyu Zhang, and Liuyue Xie. 2018. "An Integrated Framework of Enterprise Information Systems in Smart Manufacturing System via Business Process Reengineering." *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture* 233 (11). IMECHE: 2210–2224. doi:10.1177/0954405418816846.

Razmi-farooji, Arian, Hanna Kropsu-vehkaperä, Janne Härkönen, Harri Haapasalo, Arian Razmi-farooji, Hanna Kropsu-vehkaperä, Janne Härkönen, and Harri Haapasalo. 2019. "Advantages and Potential Challenges of Data Management in E-Maintenance." *Journal of Quality in Maintenance Engineering* 25 (3): 378–396. doi:10.1108/JQME-03-2018-0018.

Roda, Irene, and Marco Macchi. 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): 368–378. doi:10.1177/1748006X17753501.

Roda, Irene, Marco Macchi, Luca Fumagalli, and Pablo Viveros. 2014. "A Review of Multi-Criteria Classification of Spare Parts: From Literature Analysis to Industrial Evidences." *Journal of Manufacturing Technology Management* 25 (4). Emerald Group Publishing Limited: 528–549.

Ruschel, Edson, Eduardo Alves Portela Santos, and Eduardo de Freitas Rocha Loures. 2017. "Industrial Maintenance Decision-Making: A Systematic Literature Review." *Journal of Manufacturing Systems* 45 (October). Elsevier: 180–194. doi:10.1016/J.JMSY.2017.09.003.

Selvik, J T, and T Aven. 2011. "A Framework for Reliability and Risk Centered Maintenance." *Reliability Engineering and System Safety* 96 (2). Elsevier: 324–331. doi:10.1016/j.ress.2010.08.001.

Sharma, Pankaj, David Baglee, Jaime Campos, and Erkki Jantunen. 2017. “Big Data Collection and Analysis for Manufacturing Organisations.” *Big Data & Information Analytics* 2 (2): 127–139. doi:10.3934/bdia.2017002.

Tao, Fei, Qinglin Qi, Ang Liu, and Andrew Kusiak. 2018a. “Data-Driven Smart Manufacturing.” *Journal of Manufacturing Systems* 48 (January). The Society of Manufacturing Engineers: 157–169. doi:10.1016/j.jmsy.2018.01.006.

Tao, Fei, Qinglin Qi, Ang Liu, and Andrew Kusiak. 2018b. “Data-Driven Smart Manufacturing.” *Journal of Manufacturing Systems* 48 (January). The Society of Manufacturing Engineers: 157–169. doi:10.1016/j.jmsy.2018.01.006.

Thimm, G, S G Lee, and Y.-S. Ma. 2006. “Towards Unified Modelling of Product Life-Cycles.” *Computers in Industry* 57 (4): 331–341. doi:https://doi.org/10.1016/j.compind.2005.09.003.

Tretten, Phillip, and Ramin Karim. 2014. “Enhancing the Usability of Maintenance Data Management Systems.” *Journal of Quality in Maintenance Engineering* 20 (3). Emerald Group Publishing Limited: 290–303.

Turner, C J, C Emmanouilidis, T Tomiyama, A Tiwari, and R Roy. 2019. “Intelligent Decision Support for Maintenance: An Overview and Future Trends.” *International Journal of Computer Integrated Manufacturing* 32 (10). Taylor & Francis: 936–959. doi:10.1080/0951192X.2019.1667033.

Van Aken, Joan Ernst, Aravind Chandrasekaran, and Joop Halman. 2016. “Conducting and Publishing Design Science Research: Inaugural Essay of the Design Science Department of the Journal of Operations Management.” *Journal of Operations Management* 47–48: 1–8. doi:https://doi.org/10.1016/j.jom.2016.06.004.

Van Aken, Joan Ernst. 2005. “Management Research as a Design Science: Articulating the Research Products of Mode 2 Knowledge Production in Management.” *British Journal of Management* 16 (1). John Wiley & Sons, Ltd: 19–36. doi:https://doi.org/10.1111/j.1467-8551.2005.00437.x.

West, Matthew. 2011. *Developing High Quality Data Models*. Elsevier.

Yunusa-Kaltungo, Akilu, and Ashraf Labib. 2020. "A Hybrid of Industrial Maintenance Decision Making Grids." *Production Planning & Control*, March. Taylor & Francis, 1–18. doi:10.1080/09537287.2020.1741046.

Zeid, Abe, Sarvesh Sundaram, Mohsen Moghaddam, Sagar Kamarthi, and Tucker Marion. 2019. "Interoperability in Smart Manufacturing: Research Challenges." *Machines*. doi:10.3390/machines7020021.

Zheng, Pai, Honghui Wang, Zhiqian Sang, Ray Y Zhong, Yongkui Liu, Chao Liu, Khamdi Mubarok, Shiqiang Yu, and Xun Xu. 2018. "Smart Manufacturing Systems for Industry 4.0: Conceptual Framework, Scenarios, and Future Perspectives." *Frontiers in Mechanical Engineering* 13 (2): 137–150. doi:10.1007/s11465-018-0499-5.