Artificial Intelligence based Asset Management

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***Abstract*—In a System Engineering perspective, asset management (AM) is related to a subset of techniques focusing on the in-service phase, aligned with product life-cycle management discipline. Today, within AM solution market, the integration of Artificial Intelligence (AI) technics above traditional entreprise solution is a key trend. This paper is focusing on how symbolic AI and data driven AI could improve some issues of the AM life cycle, in particular in asset acquisition, performance analysis and forecasting, asset monitoring, predictive and prescriptive maintenance, supply chain optimisation including spare parts management...**

***Index Terms*—Asset Management; Maintenance; Supply Chain Management; Artificial Intelligence; Data driven AI; Machine Learning; Symbolic AI; Knowledge based AI; Multi-Criteria; Decision Making; Planning; Ontology.**

I. A BRIEF INTRODUCTION OF ASSET MANAGEMENT

Non quality, downtime, and sub-optimal performance are related to poor **asset management** (AM), which induce increasing costs, lost market opportunities and trust, lower profits and decrease reputation. AM in a System Engineering perspective is related to a subset of techniques focusing on the in-service phase, aligned with product life-cycle management discipline. For instance, decisions such as the maintenance operations or equipment replacement have critical impact on the overall operation. These losses and costs have given companies the motivation to explore smart AM strategies enhanced by lean approaches [1] and artificial intelligence (AI).

In this paper, assets are defined as follows: "*An asset is an item, thing or entity that has potential or actual value to an organization*". Asset can be tangible such as manufacturing machines, test benches, equipment or intangible such as patent, know-how, processes and can also be resources including human resources. Based on ISO 55000, AM is described as [2], [3] "*coordinated activity of an organization to realize value from assets*". AM is one of the ways to improve the productivity under industrial constraint which may also be seen as the management strategy for different the phases of asset life cycle (see fig. 1), in order to optimize its lifetime, to reduce costs, to improve quality and efficiency, to extend health of assets, to enhance safety and to decrease unplanned downtime. AM is a process of deciding, planning and monitoring acquisition, use, care and/or retirement of assets through service delivery optimization and related risks and costs mitigation over their overall life.

In the last decade, AM was often a practice related to reliability and maintenance, following a cost saving strategy. But, today, it becomes more than just a maintenance approach. AM helps to:

- Reduce operation asset total costs;
- Reduce investment asset costs;
- Improve operating performances (minimizing failure rates, maximizing availability...);
- Reduce health and usage impacts;
- Reduce safety risks;
- Minimise environmental impacts...

Fig. 1. The 5 steps of the asset's lifecycle

This is why, companies such as Thales [4] have shifted views on asset management where the overall AM process integrates life-cycle costing into asset decisions. This AM life-cycle (fig. 1) begins when a business goal is identified. From there the asset is planned, created or acquired, operated and maintained, monitored, and replaced or upgraded when it reaches the end of its life. Thus, it is divided in the five following steps where AI brings add value:

- **Acquisition Phase:** Acquire assets (§III) involve technical and financial analysis and explanation, new asset acquisition planning, as well as acquisition monitoring.
- **Deployment phase**: Deploy assets focus on activities associated with the installation, initialisation, testing, and commissioning of new assets.
- In Service Phase covers both operation and support where operation addresses **utilization** (§IV) and **monitoring** (§IV); and support encompasses asset availability (health), longevity, and capability (quality, performance) **maintenance, repair and overhaul** (§V) in operation.
- **Retirement phase** a.k.a disposal phase (§VI) cover managing assets that are no longer being used. This implies decision to remove from service, to scrap, and demolish. Then, this phase addresses the dismantling activities.

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This paper underlines how the usage of various AI techniques of both symbolic AI and data driven AI, will improve the overall AM life-cycle in a balanced manner, satisfying the continuum of constraints imposed by business strategy, economy, technical and operational integrity, maintenance and regulatory compliance [4]. For example, Predictive maintenance provides alert of a pending failure of a part (§V-A), then prescriptive/corrective maintenance involves planning and tasking tools needed to send a repair operator to replace the equipment before it breaks down and causes further damage or casualties (§V-B). However, we should note that even though efficient maintenance is crutial in AM, it is only one of all issues that AM decision makers have to take into account along the overall asset life-cycle. They have to guaranty that assets perform at peak levels and, at to keep operation and maintenance costs down. Therefore, to ensure effective utilization of an asset, effective decisions will be based on a deep analysis of the all asset life-cycle phases monitoring. Thus, AM also keeps costs down by tooling the supply chain to ensure optimal inventory of parts and materials (§IV-C). Then, an AM support system is a coherent solution for monitoring the asset health and usage, for providing maintenance management, spares, supporting inventory management, and optimizing procurement capabilities.

II. A Brief Overview of AI

In the last decades, data, information and knowledge have become extremely important especially with the AI renewal. This branch of computer science aims to embed cognitive capacities in an artificial system. The central principles of AI include such as perception, learning, abstraction, reasoning, decision, dialogue and the ability to move and manipulate objects [5].

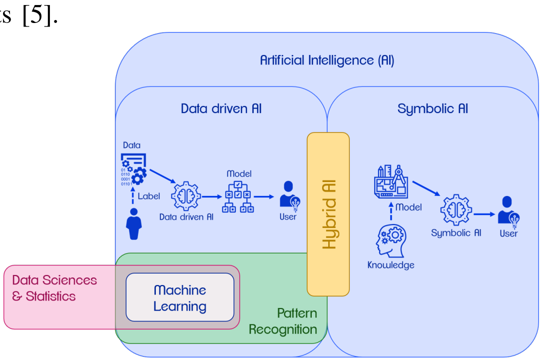

Fig. 2. Data Sciences, Data driven AI and Symbolic AI

AI methods can be divided into two broad categories: (1) **data driven AI** which includes machine learning, statistical learning, evolutionary computing... suitable for pattern matching and recognition, classification and forecasting problems; and and (2) **symbolic AI** which focuses on the development of ontologies and semantics graphs, knowledge-based systems and reasoning for complex problem solving such as resource optimisation, planing and scheduling, multi-criteria decision making... The premises of data driven AI and symbolic AI are fundamentally different. The paradigm of data driven AI is based on brain-style learning such as neural networks, whereas symbolic AI approaches employ model and knowledge reasoning.

- Often used in the context of pattern recognition, classification, clustering or perception, data driven AI such as machine learning infers the inherent structure from a set of examples (data) which can be used for mapping new examples. Supervised learning methods are done using a ground truth, unsupervised learning methods do not use explicitly-provided labels.
- Symbolic AI can be defined as a problem solving system such as resource allocation, planing or decision making, utilizing symbolic (semantic) model and knowledge through a reasoning process. A particular feature of such approaches is based on separation between the knowledge, which can be represented by various approaches such as rules, constraints, or cases, and the inference engine or reasoning algorithm which uses the knowledge base to built a conclusion.

Thus, to be competitive, companies utilize AI to better manage their assets and to anticipate the future by providing actionable information. Achieving this objective requires the use of a combination of symbolic AI and machine learning solutions for tracking, analyzing, modelling, forecasting, and delivering solution to AM stakeholder's issues.

III. Acquire Assets

Acquisition is the first step of the asset life cycle, where asset requirements are defined and verified. This includes asset purchasing with the aim of ensuring cost effective acquisition. Therefore, identification of goal driven and added value management strategies is required in order to include and analyze the need for an asset. Asset managers agree that real-time operational, economic and asset life KPIs are mandatory to measure efficiency and performance. But establishment of such acquisition requirements is based on KPIs evaluation of future assets and their potential to meet business needs. Thus, acquisition KPIs issues come from an analysis disconnected to the asset operation (an estimated capability value of the asset) and the financial acquisition value. Both types of value have the common feature that they depend upon the purpose for which the asset will be used.

In one side, the knowledge of the capacity value forecasting for physical assets is essential to evaluate asset life-cycle risks of both technical and economical nature. Thus, machine learning and more especially NNs approaches can be used when historical data set exists [6]. On the other side, financial value depends on the purpose for which the asset is used. The original cost is appropriate when the aim of the valuation is to identify how funds have been expended. The "value in use" is relevant to determine if an asset should be retained or replaced and to estimate future cash flows. More over yield is an important way to measure the current and future income on the investment based on property's income/market value, running costs and annual income.

Capability and financial value are related. For example, how much it costs to own and use an asset or how much additional

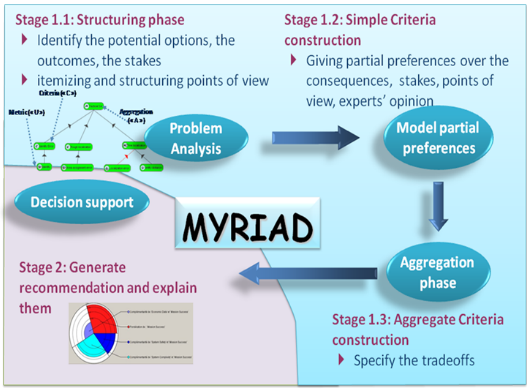

Fig. 3. Myriad© methodology

cost is needed to improve the capability of the asset to satisfy a service delivery requirement change. As Multi-Criteria Decision Making (MCDM) offers several methodologies and tools to provide accurate models for the preference [7] of an expert over several criteria, we propose to use MCDM aggregation for financial and capability KPIs modeling (see fig. 3). For this purpose, the Choquet integral is a very general aggregation function which can take into account not only the importance of each criterion, but also interaction phenomena between the criteria. Therefore, the Choquet integral can model a wide range of decisional behaviors according to well founded elicitation processes [8]. Efficient tools and methodologies have are today available to establish a good multi-criteria model. We use the Thales Myriad© suite [9] to help the asset manager in building relevant KPIs to construct utility functions (capturing the financial/capability value) and determines the Choquet integral coefficients according to the his/her preferences.

IV. Utilize and Monitor Assets

The main goal of an AM support system is business process optimization through monitoring and analysis of KPIs to spot issues before they become bigger. Thus, companies must implement a suitable set of KPIs such as reliability of manufacturing or production processes for monitoring the flawless operation and for measuring the influence of practices implemented in their activities. Establishing such relevant KPIs is highly related to business contexts and strategies.

A. Myriad© methology apply to asset performance evaluation

As asset managers deal with the complex tasks of finding relevant KPIs that can help them to achieve goals, asset performance assessment is broken into 3 phases (see fig. 3):

Phase 1: To develop general conceptual models that highlight all asset management involved criteria.

The challenge is to identify the most appropriate criteria to formulate adequate KPI, which considers the asset management performance in relation to the business goals and strategies. The search for appropriate indicators was conducted by a survey with a number of professionals by inviting key people to participate such as asset managers, facilities managers, decision makers, maintenance operators... in order to investigate which KPIs were perceived as most relevant. One major KPI is reliability which measures of the likelihood an asset will remain in-service for its lifetime based on Mean Time Between Production Loss (MTBL) observation. The longer and more frequent the equipment fails, the less reliable it is. This KPI is not only used to AM but to maintenance performance as well.

Phase 2: To improve the general conceptual models developed in phase 1 by analysing the level of relevance of each criteria and their dependencies.

Since stakeholders have different views and different levels of understanding about asset performance issues, there are no formal rules about which techniques should be used to identify criteria and to analyse and forecast the situation. Assigning relative importance to different criteria impacts and their relationships is then required to build a consistent hierarchical model by composing judgments on the relative importance of the elements at each level of the hierarchy into a set of overall stakeholder's priorities.

Phase 3; To develop a practical model by aggregating criteria

We also propose [10] to use Myriad suite to deliver the most objective measurement possible, by considering a range of asset management issues.

B. Machine learning to predict asset performance

Forecasts with the highest possible degree of accuracy, to design the basis for the planning of maintenance and supply chain, are probably the biggest challenge in AM. Defined as a set of methods and algorithms to gain knowledge, predict outcomes, and make decisions by constructing models from a data set [11], data driven AI utilizes approaches from statistics, it also includes methods which are not entirely based on previous work of data scientists or statisticians such as evolutionary algorithms and deep learning (fig. 2). Most predictive models have relied on historical operating asset data. Principal component analysis (PCA) was used to identify key factor values and machine learning (ML) approach is utilized to forecast KPIs using the identified key asset factor values. NN's ability to forecast comes directly from the induced capability to generalise and find the hidden relationships between input and output data. After training, NN is able to predict the future value of a certain sequence on the basis of several previous values and/or any current factors. Furthermore, as the state-of-the-art deep learning algorithms have been focused on either classification or regression problems, such method has not been widely applied to AM. Deep convolutional neural network based regression approach could be also proposed for predictive maintenance (§V-A) to estimate remaining useful life (RUL) [12] of a system component. [13] presents a fairly complete state of the art of RUL estimation methods, including regression techniques, the Hidden Markov Models and Hidden Semi-Markov Models. [14] uses a *Multi-objective Deep Belief Network Ensemble approach based on unsupervised machine learning*. Moreover, Long Short Term Memory (LSTM) could also be a good candidate to learn the past dependencies in the sequential data that may influence future events. However, the most promising methods are those which combine several approaches, as underlined [15]. Therefore, based on [16]; we use with successful results, a combination of a LSTM layer and a deep neural network on historical asset data to provide an end-to-end asset performance prediction model.

C. Advanced planning to support supply chain management

In an AM perspective, supply chain is key as it enable to provide spare and repairs, and more generally equipment, in timeliness against support plans. Consequently, the supply chain flows in their planning and scheduling is key for the overall support and consequently for the overall asset management. The aim of **supply chain management** (SCM) is to optimize the supply chain which covers a "*network of organizations that are involved, through upstream and downstream linkages, in the different processes and activities that produce value in the form of products and services in the hands of the ultimate consumer*" [17]. It encompasses identifying goals of the supply chain, and also outlining policies, strategies, and controls for an efficient deployment. Broadly speaking, SCM consists of the management of the flow of goods and services, involving the movement and storage of assets, the work-in-process inventory from point of origin to point of production.

Symbolic AI approaches combining (two or more) different problem solving are suitable to optimize SCM. Thus, to support SCM, advanced (long, mid and short term) planning. Designing such advanced planning system, to complete existing classical ERP (enterprise resource planning systems), requires specific skills in operation research and symbolic AI methods. Alternative modes of operations may be evaluated to reduce costs and improve profits. For example, a relevant functionality is the ability to validate a (new) customer order with a new due date. In case of insufficient stocks, a tentative planning has to be done by inserting the new customer order into the current one where it fits best. Obviously, this feature allows a supply chain to better be conform with due dates, to become more flexible and to operate with more efficiency. Thus, the added value is managing assets to meet demand and deal with variations in both demand and operations where effective AM planning requires accurate RUL (§V-A) and asset KPI forecasting (§IV-B), but also the ability to translate forecasts into capacity requirements, and anticipated demand supply chain operations.

V. Maintain assets

MRO (Maintenance Repair and Overhaul) is one of the important phases of asset life cycle that can be focused to improve the productivity. This phase may extend the equipment life, improves availability and retains them in healthy positions. But at the same time, recurrent maintenance actions may increase the maintenance cost thereby increase the life cycle cost of a product. Such cost only includes the preventive and prescriptive maintenance cost. Thus, a trade-off between maintenance actions and operational objectives (e.g. availability) is required to minimize the overall maintenance cost. Therefore, a MRO solution is a key component of the global AM strategy which facilitates the service and asset life cycle from production to maintenance including predictive and prescriptive maintenance, logistics, and configuration management to optimize supply chain logistics and overall production cost. This MRO process can be improved by data driven and symbolic AI [15].

In addition, for any MRO activities, in order to execute a task, resources need to be allocated, including human resources. Human resources are subject to availability as any other resources but in addition, we need to consider competences that refer to skills (including soft skills), experience, knowledge and attitude. Consequently, there is also a need for a matching competences versus activities (and associated prerequisite in terms of competencies) in order to guarantee the adequacy.

A. Data driven AI to improve predictive maintenance

Thales have developed a capability to the diagnosis of failures based on NNs [15]. This includes both the detection of a fault or faultless state, and the identification of a likely cause of the fault symptom from a database of learned faults. Moreover, having an accurate estimation of the Mean time between failures (MTBF) of a piece of equipment is a very important part of AM, and can save organisations a lot of money. With Internet of Things (IoT) and Industry 4.0, prognostic and health management (PHM) systems are now used to collect massive real-time data from mechanical equipment in order to estimate MTBF. Such PHM systems try to optimize asset efficiency and reliability. Then, an opportunity to AM is the adoption of ML, in particular for **predictive maintenance**. Historical data becomes the sediment of future predictions. Even with this IoT wave, it still happens that the measuring equipment does not fit on to the equipment that needs to be measured which causes a lack of historical data. Even if this concept is not new [18], predictive maintenance has evolved to AI methods that use pattern recognition, including neural networks, fuzzy logic, and data-driven AI. It reduces uncertainty in diagnoses through an accurate estimation of the RUL (Remaining Useful Life), where RUL calculus is based on sufficient prior knowledge of critical components degradation process to perform a maintenance operation, whether an equipment repair or replacement, in order to minimize the production system total breakdowns and maximize its industrial performance.

Application of various data driven AI algorithms to design predictive maintenance policy and capabilities improve maintenance plannings to avoid failures and save the resultant costs. Historical degradation data-set has to be collected before applying data driven AI techniques [19]. In this context, let us mention:

- NN [20] and more especially deep learning or deep convolution neural network [21] is adopted to forecast the spare-part consumption of packaging machinery, with very positive results.

- Support vector machine (SVM) [22], is often used to forecast the reliability of mechanical or electronic assets, with positive results along with some potential threats.
- Hidden Markov models (HMM) [23] allows modelling the time duration of the hidden states and therefore is capable of prognosis.
- Random forest algorithm was implemented to remote monitor a cutting machine reliability assessing the different occurring alarms.

B. Knowledge based AI to enhance prescriptive maintenance

An other capability of AM is **prescriptive maintenance** [24] which addresses on what should be done, focusing on decision making for resource allocation and repair action planing based on input of diagnostic data, prediction of future component states but also on prior maintenance knowledge and practices. Due to the complexity of the various assets in terms of data sources, information and knowledge availability, it is hard to provide generic prescriptive maintenance support.

Ontologies are explicit formal specifications of concepts and feature properties in a specific domain, which are used to share information and reuse domain knowledge. In Thales, [25] proposes to use semantic technologies to model the domain at a conceptual level through ontology [26] or conceptual graph [27], abstracting from the data sources and the maintenance operators' uses and jobs. Remind that ontology or conceptual graph is a way of representing knowledge applied in various domains to various maintenance problem domains. Therefore, relevant knowledge to characterize failures and maintenance events is encapsulated. Moreover, generally, maintenance and spare parts inventory policies are two different processes. However, since the stock level of spare parts is related with maintenance policies, addressing these two problems simultaneously is more efficient.

Such a formal model implement decision logic and business policies to drive prescriptive maintenance solutions. Let us mention some symbolic AI technologies to address such problem, including decision trees [28], 0-1 integer linear programming [29], resource-constraints mixed integer linear programming [30], genetic algorithmic [31], constraint solving [32] or knowledge based reasoning [25] like those today use by Thales. This last approach is based on the user's understanding of the underlying prescriptive maintenance scheduling issue and the spare part stock level. Here, models are declarative through business rules or operational knowledge, ellicitating the business logic, as close to the operational maintenance practice as possible, without modeling execution method. The operating procedure policies embedded in business rules are derived from many sources, including maintenance reports and manuals and operators. Then, MCDM method aims to aggregate the cost function made of spare parts, the cost of the preventive actions and the cost of the additional repair activity in case of unplanned failure, even the cost of the personnel of the producer and/or the maintenance service provider.

VI. Retire assets

When an asset reaches the end of its useful life, it is considered as an under performing asset. Management of end-of-life assets and disposal become important not only because of environmental effects of waste but also economical factors. Reuse, repair, refurbishing, recycling, cannibalization and remanufacturing are among the most end-of-life used strategies. Moreover, in recent years, there has been significant interest in the sustainable processes for this retirement phase to reduce resource consumption and landfill wastes by recycling and re manufacturing these assets in order to maximize the economic benefits while minimizing the environmental costs. Thanks to the KPIs monitoring (based on a MCDM approach as mentioned in §III), an end of life asset notification can be generated when the MRO costs are above replacement costs combined with the disposal costs.

Cannibalization, where a component of an asset is utilized to provide spare parts for another, is commonly utilized to maintain readiness when spares are not available. This can be beneficial in maintaining asset readiness and reducing spare part demands since is it allows any shortage of spares to be consolidated into a small number of inoperative assets. Nevertheless, cannibalization is a complex problem for asset managers. Genetic algorithms based simulation-optimisation approach could be employed to find the optimal solutions of asset spare provisioning and replacement to minimise the cost.

VII. Conclusion

AM support system provides to business manager means to monitor an accurate global picture of their industrial assets at any time in order to anticipate any future AM decision. Today, within EAM (Entreprise AM) solution market, the AI integration above traditional entreprise solution is a key trend. Let us mention, for IBM the couple MAXIMO© and Watson© [33], and respectively for SAP, ECC© and HANA© [34]. This bird's-eye view aids in asset allocation, performance monitoring, maintenance planning and supply chain optimisation. To guaranty asset management objectives are aligned with the strategic objectives, an AM system is needed. Thanks to AI both data driven AI such as machine learning and symbolic AI, advanced EAM (see fig. 4) optimises the translation of the organization's objectives into asset-related decisions for acquisition, analytics for asset performance monitoring, predictive and prescriptive maintenance activities, supply chain planning, spare parts optimisation and end-of-life asset management.

References

[1] Paolo Perico, Emrah Arica, Daryl J Powell, and Paolo Gaiardelli. Mes as an enabler of lean manufacturing. *IFAC-PapersOnLine*, 52(13):48–53, 2019.

[2] Robert Davis. An introduction to asset management. *Retrieved November*, 20, 2016.

[3] Nicholas Anthony John Hastings. Introduction to asset management. In *Physical Asset Management*, pages 3–23. Springer, 2015.

[4] Juliette Mattioli, Sarah Lamoudi, and Pierre-Olivier Robic. La gestion d'actifs augmentée par l'intelligence artificielle. *APIA : Application Pratique en Intelligence artificielle*, page 67, 2019.

[5] Stuart J. Russell and Peter Norvig. *Artificial intelligence: a modern approach*. Malaysia; Pearson Education Limited, 2016.

Fig. 4. An AI based Asset Management Support System

[6] Shihao Gu, Bryan Kelly, and Dacheng Xiu. Empirical asset pricing via machine learning. *The Review of Financial Studies*, 33(5):2223–2273, 2020.

[7] Fabien Le Huédé, Michel Grabisch, Christophe Labreuche, and Pierre Savéant. Integration and propagation of a multi-criteria decision making model in constraint programming. *Journal of Heuristics*, 12(4-5):329–346, 2006.

[8] Christophe Labreuche and Michel Grabisch. The choquet integral for the aggregation of interval scales in multicriteria decision making. *Fuzzy Sets and Systems*, 137(1):11–26, 2003.

[9] Christophe Labreuche and Fabien Le Huédé. Miriad: a tool suite for mcda. In *EUSFLAT Conf.*, pages 204–209, 2005.

[10] César Duarte Freitas Gonçalves, José António Mendonça Dias, and Virgílio António Cruz Machado. Multi-criteria decision methodology for selecting maintenance key performance indicators. *International Journal of Management Science and Engineering Management*, 10(3):215–223, 2015.

[11] Amy JC Trappey, Charles V Trappey, Lin Ma, and Jimmy CM Chang. Intelligent engineering asset management system for power transformer maintenance decision supports under various operating conditions. *Computers & Industrial Engineering*, 84:3–11, 2015.

[12] Giduthuri Sateesh Babu, Peilin Zhao, and Xiao-Li Li. Deep convolutional neural network based regression approach for estimation of remaining useful life. In *International conference on database systems for advanced applications*, pages 214–228. Springer, 2016.

[13] Xiao-Sheng Si, Wenbin Wang, Chang-Hua Hu, and Dong-Hua Zhou. Remaining useful life estimation–a review on the statistical data driven approaches. *European journal of operational research*, 213(1):1–14, 2011.

[14] Chong Zhang, Pin Lim, A Kai Qin, and Kay Chen Tan. Multiobjective deep belief networks ensemble for remaining useful life estimation in prognostics. *IEEE transactions on neural networks and learning systems*, 28(10):2306–2318, 2016.

[15] Juliette Mattioli, Pierre-Olivier Robic, and Thomas Reydellet. L'intelligence artificielle au service de la maintenance prévisionnelle. *APIA : Application Pratique en Intelligence artificielle*, 2018.

[16] Linxia Liao and Hyung-il Ahn. Combining deep learning and survival analysis for asset health management. *International Journal of Prognostics and Health Management*, 16, 2016.

[17] M Christoffer. Logistics and supply chain management–strategies for reducing cost and improving service. *Financial Times Professional Limited*, 1998.

[18] R Keith Mobley. *An introduction to predictive maintenance*. Elsevier, 2002.

[19] Gian Antonio Susto, Andrea Schirru, Simone Pampuri, Seán McLoone, and Alessandro Beghi. Machine learning for predictive maintenance: A multiple classifier approach. *IEEE Transactions on Industrial Informatics*, 11(3):812–820, 2014.

[20] Nagi Gebraeel, Mark Lawley, Richard Liu, and Vijay Parmeshwaran. Residual life predictions from vibration-based degradation signals: a neural network approach. *IEEE Transactions on industrial electronics*, 51(3):694–700, 2004.

[21] Xiang Li, Qian Ding, and Jian-Qiao Sun. Remaining useful life estimation in prognostics using deep convolution neural networks. *Reliability Engineering & System Safety*, 172:1–11, 2018.

[22] Tarak Benkedjouh, Kamal Medjaher, Noureddine Zerhouni, and Saïd Rechak. Remaining useful life estimation based on nonlinear feature reduction and support vector regression. *Engineering Applications of Artificial Intelligence*, 26(7):1751–1760, 2013.

[23] Ming Dong and David He. A segmental hidden semi-markov model (hsmm)-based diagnostics and prognostics framework and methodology. *Mechanical systems and signal processing*, 21(5):2248–2266, 2007.

[24] Setrag Khoshafian and Carolyn Rostetter. Digital prescriptive maintenance. *Internet of Things, Process of Everything, BPM Everywhere*, pages 1–20, 2015.

[25] Luis Palacios, Gaëlle Lortal, Claire Laudy, Christian Sannino, Ludovic Simon, Giuseppe Fusco, Yue Ma, and Chantal Reynaud. Avionics maintenance ontology building for failure diagnosis support. In *KEOD*, volume 2, pages 204–209, 2016.

[26] Barry Smith and Christopher Welty. Ontology: Towards a new synthesis. In *Formal Ontology in Information Systems*. ACM Press, USA, 2001.

[27] John F Sowa. Conceptual graphs. *Foundations of Artificial Intelligence*, 3:213–237, 2008.

[28] Changjun Wei and Susan Tighe. Development of preventive maintenance decision trees based on cost-effectiveness analysis: an ontario case study. *Transportation research record*, 1866(1):9–19, 2004.

[29] JF Dopazo and HM Merrill. Optimal generator maintenance scheduling using integer programming. *IEEE Transactions on Power Apparatus and Systems*, 94(5):1537–1545, 1975.

[30] Riccardo Manzini, Riccardo Accorsi, Teresa Cennerazzo, Emilio Ferrari, and Fausto Maranesi. The scheduling of maintenance. a resource-constraints mixed integer linear programming model. *Computers & Industrial Engineering*, 87:561–568, 2015.

[31] M Ali Ilgin and Semra Tunali. Joint optimization of spare parts inventory and maintenance policies using genetic algorithms. *The International Journal of Advanced Manufacturing Technology*, 34(5-6):594–604, 2007.

[32] Safaai Deris, Sigeru Omatu, Hiroshi Ohta, Lt Cdr Shaharudin Kutar, and Pathiah Abd Samat. Ship maintenance scheduling by genetic algorithm and constraint-based reasoning. *European Journal of Operational Research*, 112(3):489–502, 1999.

[33] Arun Hampapur, H Cao, A Davenport, WS Dong, Don Fenhagen, Rogério Schmidt Feris, G Goldszmidt, ZB Jiang, Jayant Kalagnanam, Tarun Kumar, et al. Analytics-driven asset management. *IBM Journal of Research and Development*, 55(1.2):13–1, 2011.

[34] Christof Bornhövd, Robert Kubis, Wolfgang Lehner, Hannes Voigt, and Horst Werner. Flexible information management, exploration and analysis in sap hana. In *DATA*, pages 15–28, 2012.