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A new model to compare intelligent asset management platforms (IAMP)

Pablo Martínez-Galán, Adolfo Crespo, Antonio de la Fuente and Antonio Guillén.

** Authors are members of Intelligent Maintenance System research group (SIM) of the University of Seville, Spain. (Tel: +34610-986-672; e-mail: pablomgf93@gmail.com, adolfo@us.es, antoniodela84@gmail.com, ajguillen@us.es).*

Abstract: Nowadays, no business activity escapes the fourth industrial revolution, called industry 4.0, which is characterized by digitalization of processes. The possibility of simultaneously having systems with greater interconnection, more information and greater flexibility, allows companies to have a clearer view of their processes and consequently improve their effectiveness and efficiency. The digital transformation can no longer be based simply on making the processes more efficient, but on creating more sustainable and profitable customer relationships, continuously aligning the value of the product with the changing customer requirements. Even though managing assets over the Internet is increasingly common, much effort is needed to identify the functionality that should be provided by these platforms to enhance existing asset management practices.

The effort of IT vendors is focused on the development of IoT platforms, which allow, among other functions, to create a connection between machinery and digital systems, protect all devices and data against hacking or attacks, control operations and maintenance of equipment or perform different analyses of assets or systems. The aim of this paper is to understand the functionalities of the existing IAMP platforms, providing a system that evaluates these functionalities based on the business objectives from the point of view of asset management. This methodology allows maintenance managers guiding the evolution of the life cycle of their assets according to the business value conception. This makes this methodology especially suitable for supporting new challenging scenarios of maintenance management. In this paper we first talk about the structure of an IAMP, then how they integrate the asset management model and a summary of the features and modules that have the most known IAMP platforms. Finally, an evaluation system of IAMP platforms and a case study is presented based on their content for asset management.

Keywords: Asset Management, Industrial IoT, Digitalization, Predictive Analytics, Intelligent assets management systems.

1. INTRODUCTION

Intelligent Assets Management Platforms (IAMP), from our point of view, can be defined as software platforms for the collection and analysis of data from industrial assets. They can connect and manage smart devices and infrastructure in industrial and manufacturing environments to integrate operational data and control into business processes. They are based on the use of digital technologies in industry and it is a fact that the vendors community have recently increase their R&D which is boosting growth. The maturity that has been reached in communications in the industrial environment supports the adoption of IAMP, as well as numerous CEOs that are launching digitalization strategies in their companies.

Although monitoring and asset management over the Internet are gaining ground, much effort is needed to identify the functionality that these platforms must provide to improve existing AM practices. A better understanding of the functionality of existing Apps for AM decision-making will improve effectiveness and efficiency in management. Finally, once the structure of the platform has been understood, a platform evaluation system based on the evaluation solutions of (Woodhouse, 2001) is proposed with the objective of adjusting it as closely as possible to the asset management requirements of a company.

In this paper we first discuss about the factors explaining IAMP growth, then we explain the structure of general IAMPs and the main parts they usually have and finally, an evaluation system to measure the alignment of business objectives in asset management and the contents of intelligent asset management platforms is presented.

2. FACTORS PROMOTING IAMP GROWTH IN INDUSTRIAL COMPANIES

In reference to the Gartner report, the market growth of IAMPs is mainly boosted by four issues: The industrial IoT, Big Data, Predictive Maintenance Analytics and Digital twins.

2.1. The availability of the 'Internet of Things' (IoT) technologies

The adoption and deployment of modern 'Internet of Things' (IoT) technologies has enabled important advances in the development of these platforms. The efforts of open

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membership organizations like The Industrial Internet Consortium (IIC) has served to promote the development, adoption and widespread use of interconnected machines and devices and intelligent analytics (Industrial Internet Consortium, 2015).

First, for successful implementation of Internet of Things (IoT), the main prerequisites are: dynamic resource demand, real time needs, exponential growth of demand, availability of applications, data protection and user privacy, efficient power consumptions of applications, execution of the applications near to end users and access to an open and inter operable cloud system (Madakam, 2015).

In addition, there are three components, which required for Internet of Things (IoT) computing: hardware (sensors, embedded hardware, fitness devices, etc.), middleware as mediator between the hardware and application layers and application layer for visualization and interpretation tools that can be designed for the different applications.

IIoT platforms originated in the form of IoT middleware in industry. It is expected to support integration with almost any connected device and blend in with third-party applications used by the device. This independence from underlying hardware and overhanging software allows a single IoT platform to manage any kind of connected device in the same straightforward way (Kaa IoT platform, 2019).

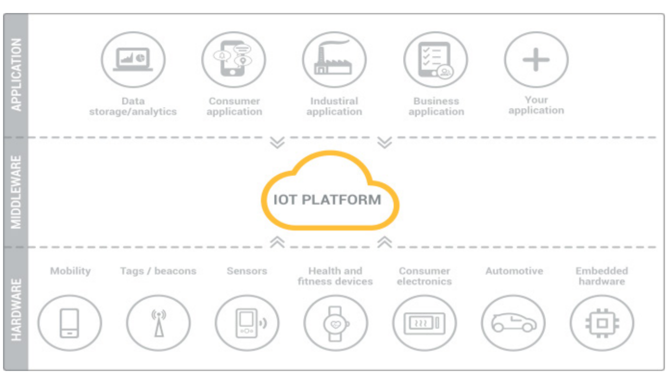

Figure 1. IIoT Platform

Modern IoT platforms go further and introduce a variety of valuable features into the hardware and application layers as well. They provide components for frontend and analytics, on-device data processing, and cloud-based deployment. Some of them can handle end-to-end IoT solution implementation from the ground up. Nowadays, primary functionality needed for developing connected devices and smart things in a top-of-the-range platform includes:

Connectivity to connect devices directly or via gateways using all modern connectivity types; Data collection and storage; Creation of virtual machines; Remote device configuration and control; Device management to manage devices and their credentials individually or in groups and over-the-air firmware updates.

Importantly, the best IoT platforms allow you to add your own industry-specific components and third-party applications. Without such flexibility adapting an IoT platform for a particular business scenario could bear significant extra cost and delay the solution delivery indefinitely.

2.2. The Improvements in big data management

The data required for critical decisions and/or reports must be collected, evaluated and analyzed with a high degree of quality. This data can come from both, within and outside the organization, and both sources must typically be consulted to make informed decisions.

As shown in Figure 2, efforts in data preparation accounts for about eighty percent of the work of data scientists. It is by far the most time-consuming aspect of the typical data scientist's workflow (Medium, 2018).

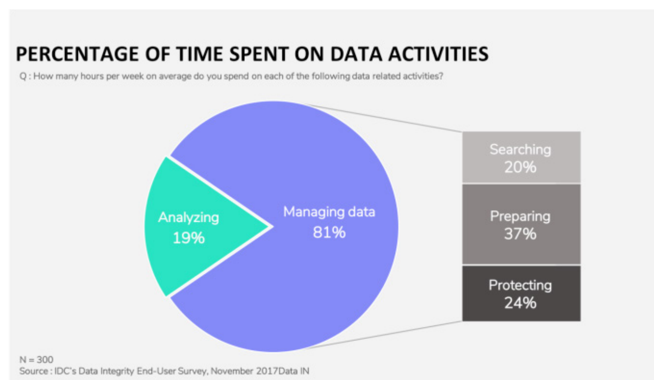

Figure 2. Percentage of time consumed by data scientists

For system health monitoring and predictive maintenance purposes, data in modern IoT platforms differs from traditional data storage and processing applications in five ways (ISO/IEC JTC 1 Information technology, 2015): Volume is too big, Velocity is too fast, Variability is high, Veracity is low (too much noise) and Variety is also high (too diverse). To support these application scenarios, diverse big data analytics functions can be performed, including but not limited to:

- Complex aggregation analysis: to profile information of different time periods or locations,
- Multi-dimensional query and analysis: to examine and deep-mine the machine data from different perspectives,
- Log data analysis: to monitor system and operational health,
- Time-window based stream data analysis: to identify temporal features and trends and
- Complex event processing: to detect patterns and anomalies.

2.3. The Emerging Predictive Maintenance Analytics

Business leaders have increasingly recognized the importance of 'predictive analytics' to increase the efficiency in the industry. A recent survey shows that almost 70% of the surveyed business leaders or industry analysts consider industrial analytics crucial for their businesses, (Lueth et al., 2016). The same survey found that analytics on physical objects and machines rank high in importance. Predictive and prescriptive maintenance of machines (at 79% of surveyed considering it extreme or very important) ranks at the top.

Descriptive analytics detect irregular behavior of the asset within milliseconds of the actual event. The data used to perform these analytics is usually local to the asset under consideration and relies on data acquired from the asset when it was working normally. Diagnostic analytics that identify the root cause of the anomaly such as a failing bearing in a motor requires previous knowledge of fault states. Diagnostics results can be returned in the order of minutes. Prognostic and Prescriptive analytics tell you the remaining useful life of a bearing can take in the order of hours to return a result and requires access to multiple types of data and from multiple sources to make the prediction.

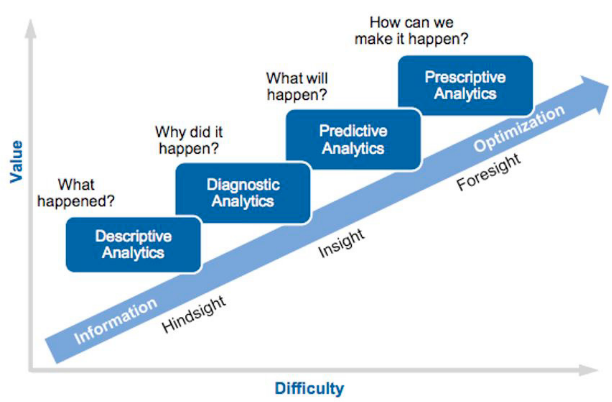

Figure 3. Types of analytics based on its applications, from Gartner (2012).

Deployment of analytics typically consists of three steps: train a (predictive) analytics model, test and validate the model on previously unseen data and deploy the model to make predictions on real (streaming) data.

To gain prediction accuracy, intelligence and flexibility need to be incorporated into prediction models, and that's why the application of Artificial Intelligence (AI) – Machine Learning (ML) techniques is gaining more and more adepts in this field. AI-ML techniques consist of fitting the parameters of a model from observed data (experience) and are best suitable to discover behavioral patterns from data series in the presence of randomness. This property of machine learning algorithms is invaluable in anomaly detection problems (Rodríguez et al., 2018). In diagnostic analytics, data must be examined to answer the question "Why did it happen?", techniques such as drill-down, data discovery, data mining and correlations are used to take a deeper look at data to attempt to understand the causes of events and behaviors.

In prognostic analytics, data-driven approaches are gaining ground, especially when the understanding of first principles of system operation is not comprehensive or when the system is sufficiently complex such that developing an accurate model is prohibitively expensive. The main disadvantage is that data driven approaches may have wider confidence intervals than other approaches and that they require a substantial amount of data for training. Data-driven approaches can be further subcategorized into fleet-based statistics and sensor-based conditioning. The two basic data-driven strategies involve (1) modeling cumulative damage and then extrapolating out to a damage threshold (Vachtsevanos et al., 2007), or learning directly from data the remaining useful life (Mosallam et al., 2015, 2016) (Jia et al., 2018).

2.4. Digital Twin Simulations

The vision of the Digital Twin (DT) refers to a comprehensive physical and functional description of a component, product or system, which includes all information which could be useful in all lifecycle phases (Boschert and Rosen, 2016). DT is considered as a virtual entity, relying on the sensed and transmitted data of the IoT infrastructure, as well as on the capability to elaborate data through data analytics and simulation technologies, with the purpose to allow optimizations and informed decision-making. The potentials for decision support along the asset lifecycle offered by DT modeling are highly promising (Roda and Macchi, 2018), leading to think of future applications built on the DTs of Physical Assets.

For instance, Tesla has a digital twin for every car manufactured. Every day, thousands of miles of data from the cars, are fed into the simulation models back in the factory. That's a thousand and more ways to learn and optimize from the real-world, which wouldn't be possible with simulation models only. By feeding real-world data collected from the twin back into designs, engineers can improve future models of a product or even its current operation in the field.

With the benefit of IoT data, actual operating conditions can be simulated with confidence, quickly yielding actionable insights. For instance, one of the most interesting possibilities is using simulation to assess how long the product will remain operational. A DT can keep track of its own failures, its own wear and degradation. Using simulation, the twin can then estimate its remaining useful-life (RUL) and report back to maintenance.

3. IAMP STRUCTURE

According to principles of software hierarchy design, we will support the structure of an IAMP on three different levels, defined below on Figure 4. From now on, we will use these terms to refer to each level of the structure. The first level is logically the intelligent asset management platform that encompasses everything else, facilitating an abstract for global management, an example of these platforms could be GE APM, property of General Electric, SAP Hana, property of SAP or Siemens Mindsphere of Siemens. The second level that

we find within the platform are the M modules with different functions on asset management, developing the different domains of asset management that can be dependent among them and so interrelation is crucial. For example, reliability module, health module, strategy module, etc. In addition, each module "M" contains "x" applications that will have different purposes according to the scope of the decision-making process that they support and providing rapid developments. They are more specific, and some examples of applications are RCM, criticality analysis or preventive maintenance optimization. Finally, each application contains a data model that, as explained below, thanks to a predefined schema configures the databases where the relevant data will be stored with k-level scalability. The ontology links different data models, correlating data tables structurally and guiding the data models, similar to human reasoning, towards
their decision-making processes, without the necessity to know the complexity of the low-level software.

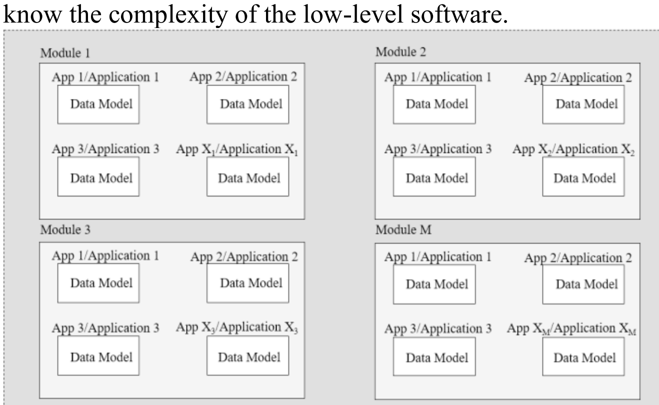

Figure 4. IAMP structure

4. EVALUATION SYSTEM OF IAMP

After analysing the reasons that have promoted the digitalization of companies through the IAMPs and the structure they present, we develop a system to evaluate the different IAMPs based on the functions or applications they include for asset management. Although it seems that all the IAMPs developed by large companies have the same functions and the implementation process is the same, it is not so. Each IAMP presents its own functions with a certain structure and grouping, although it is logical that some of these applications are repeated on several platforms, for example the most recurring applications in asset management such as criticality analysis or reliability centered maintenance (RCM).

In the process of digitalization that the companies carry out and in which they invest millions of dollars, it seems interesting to study which platform is the one that best fits the company's asset management strategy. We have developed an evaluation system to try to evaluate these platforms and to choose the one that best suits the companies' asset management requirements. This evaluation of platforms has been based on the evaluation of solution model of Woodhouse (Woodhouse, 2001) and the asset management model of Crespo (Crespo, 2007).

Table 1 shows the requirements or applications that a platform should have in order to carry out a good asset management strategy. The first block refers to the design phase of the project, and it includes all the capabilities that an intelligent platform may have related to cost benefit analysis and life cycle cost analysis.

The second block encompasses asset management in the operation and maintenance phase, which may be the most important for asset management and therefore the most comprehensive evaluation. This block includes:

- KPIs related to previously defined O&M objectives and for a defined strategy and responsibilities.
- The study of the performance of assets in terms of performance and reliability.
- The hierarchy of assets through a criticality analysis with the possibility of selecting the algorithm.
- The study of preventive maintenance, through which the optimized maintenance plan of the installation will be created.
- The use of predictive maintenance when it is useful, with the definition of possible variables to be monitored and the rules of interpretation for each variable. In addition, if there are learning algorithms that can predict failures or not.
- The asset health analysis that allows you to evaluate the health of an asset through an indicator and then relate it to a probability of failure.

Finally, the third block refers to spare parts and materials, also an important issue in asset management and that is becoming increasingly important. This block includes a series of functions to set the spare parts strategy and another section to manage the spare parts according to their criticality.

For a better understanding, a case study is shown in which two platforms with different features are compared. Table 1 evaluates platform A and the methodology for evaluating platform B would be the same. The results comparing both platforms are shown in Figure 5.

In view of table 1, each capability or function of the platform is evaluated with a "yes" or "no" depending if the platform presents an application or a function that gives such capability to the platform. For each platform, all capabilities will be evaluated. We propose a vision of the results for each section of asset management, valuing each of them over 10 points. The capabilities that the platform contains are evaluated with 10 points and those that it does not contain with 0 points. A weight evaluation system is proposed in which, depending on the needs of the company, certain weights are given for each capability within a section. With the score (0 or 10) of each capability and the weight it represents of the section, the score of the section of that platform is calculated. Notice that it is important to maintain the criteria of the weights to compare different platforms. In the case study, it has been assumed that the weight is the same for all capacities within the same section.

TABLE 1
CRITICALITY AND SEVERITY DETAILS PER ASSET

AM Feature	Check whether the platform…	Platform capability	(y/n)
Group 1: Project, Design and Modifications			
1.1. Current Assets Configuration Cost/Benefit Analysis	Contains an App or functionality supporting a cost/benefit analysis for:	1.1.1. Equipment upgrades	N
		1.1.2. Process changes	N
		1.1.3. Procedure changes	N
		1.1.4. Technology updates	Y
		1.1.5. Efficiency improvements	Y
		1.1.6. Problem priority/urgency	N
		1.1.7. Problem solving efforts	N
1.2. Life Cycle and Asset Replacement	Contains an App or functionality supporting decision- making on:	1.2.1. Equipment Selection	Y
		1.2.2. Vendors comparison	Y
		1.2.3. Capex/Opex Trade-off	Y
		1.2.4. Repair vs. replacement	Y
		1.2.5. Life extension projects	Y
Group 2: Operations & Maintenance Strategy			
2.1. Defining O&M Objectives	Registers & updates the:	2.1.1. O&M Objectives	N
		2.1.2. Strategy & responsibilities	N
		2.1.3. O&M KPIs	Y
2.2. Expected Asset's Performance / Reliability	Optimize actual asset's, process' or system's efficiency profile, allows:	2.2.1. The simulation of scenarios	Y
		2.2.2. The optimization of the TBM (services, overhauls, Etc.)	Y
2.3. Assets' criticality analysis	AC analysis includes the possibility of:	2.3.1. Indenture level setting	Y
		2.3.2. Criteria selection	Y
		2.3.3. AC algorithm selection	N
2.4. Preventive maintenance	Contains an App or functionality supporting:	2.4.1. PM set by assets' criticality	Y
		2.4.2. Methods: RCM, RCA, MTA,	Y
		2.4.3. PM interval optimization	Y
		2.4.4. Time vs. usage-based PM	Y
		2.4.5. Optimum shutdown interval	N
		2.4.6. Repair vs. replace options	Y
2.5. Predictive maintenance / Condition monitoring / CBM	Contains an App or functionality which supports easy predictive / CBM introduction by:	2.5.1. Descriptor variables plug-in	Y
		2.5.2. Links FF-FM-Symptoms-Var	Y
		2.5.3. Interpretations rule definition	Y
		2.5.4. Detect-Diagnose-Prognose	Y
		2.5.5. CBM program performance, safety-risk exposure metrics	Y
2.6. Asset Health Analysis	Contains an App or functionality to:	2.6.1. Calculates AHI	Y
		2.6.2. Correlates AHI to PoF	N
		2.6.3. Project Capex/Opex Trade-off	N
Group 3: Spares and Materials			
3.1. Spares parts Strategy	Has an App or functionality defining each spare part's management strategy, according to part criticality and management complexity:	3.1.1. Defines stock holding strategy	Y
		3.1.2. Whole unit vs. component	Y
		3.1.3. Shared or dedicated for an asset	Y
		3.1.4. Supplier A vs. B benchmark	Y
		3.1.5. Pooled access contracts	Y
		3.1.6. Supplied held spares	Y
3.2. Spares Criticality	Includes spare part criticality analysis:	3.2.1. Links part to in service assets	N
		3.2.2. Considers part demand per asset	N
		3.2.3. Define the criteria for criticality	N
		3.2.4. Includes an algorithm for CA	N

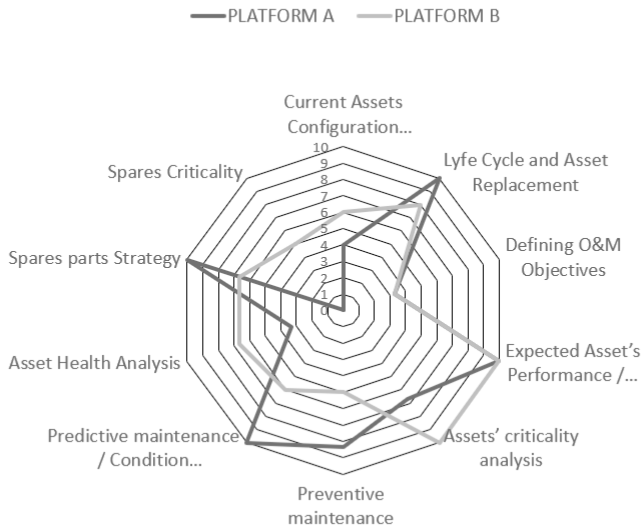

Figure 5. Results by sections of asset management

In view of the results we obtain a quick and simple comparison between two platforms, which allow us to choose the one that has more potential in the section that the company gives more importance to asset management. In this case platform A may be worse in the design phase than platform B, so if a company is assumed with continuous changes in the operation, in which there are many redesign phases we will opt for the option B.

Secondly, in the operation and maintenance block they are similar except in the preventive and predictive maintenance sections, in which platform A presents more capacity than platform B. In the case that we had a company such as the railway sector in which preventive and predictive maintenance is essential, we would opt for the A platform that offers us better features.

Finally, with respect to the block of the spare parts, in the management of spare parts the platform A is better, but does not take into account any of the criticality of the spare parts, while the platform B has spare parts management functions and also in their criticality function. In the same way as the previous ones, if our company manages critical spare parts with high supply times or with high cost, we will opt for the B platform that takes these factors into account.

5. CONCLUSIONS

The purpose of this methodology is to align assets management to business value through the digitalization of the companies and the choice of the intelligent asset management platform that best fits with the organisation. This choice is made through a simple evaluation of the platforms where all the functions or applications that a platform should have to review a good asset management strategy are reviewed. Our methodology also uses graphics to show the results and in a visual way to compare different platforms.

This methodology allows maintenance managers guiding the evolution of the life cycle of their assets according to the business value conception. This makes this methodology especially suitable for supporting new challenging scenarios of maintenance management characterized for a high technological level and great interaction between assets. In addition, it will generate a great amount of data and information for the decision making.

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