A Methodology for Fast Deployment of Condition Monitoring and Generic Services Platform Technological Design

Santiago Fernandez[1], Christophe Mozzati[2], and Aitor Arnaiz[3]

[1,3]*Intelligent Information Systems, IK4-TEKNIKER, Eibar, 20600, Spain*
santiago.fernandez@tekniker.es
aitor.arnaiz@tekniker.es

[2]*PREDICT, Avenue de la Forêt de Haye 19, CS 10508, 54519 Vandoeuvre lès Nancy, France*
christophe.mozzati@predict.fr

ABSTRACT

Maintenance is a research field that has recently been gaining importance in business and where the study and development of monitoring and predictive technologies has been very active, as the role of these technologies is key in enabling predict and prevent maintenance strategies. Moreover, by means of monitoring features of processes and components, an impact in lifecycle value can be achieved. However, challenges remain in structuring the condition monitoring offer and the technological platform due, in particular, to the variety of potential domains of application, the characteristics of the existing information and the final goals of the monitoring activities. These challenges may impact in the deployment time of a condition monitoring solution. In order to limit these challenges, a methodology for fast deployment of condition monitoring and a technological service platform is presented. The methodology has been obtained from research and analysis of several use cases in the context of product-service systems. The focus is on methodological and technological results, which are presented in a general manner such that they can be applicable to the deployment of condition monitoring and services in various domains. Finally, application of the methodology is presented in two different scenarios.

1. INTRODUCTION

The role of monitoring and predictive technologies in many business areas and industry has been substantial since the advent of these technologies. In recent years, one area where the study and development of these technologies has been very active is that of maintenance, as this area has gained importance in business, especially service-oriented business, and technologies have a crucial role in enabling the change from traditional "fail and fix" practices to "predict and prevent" strategies (Lee, Ni, Djurdjanovic, Qiu & Liao, 2006). Moreover, current trends towards the convergence of digital virtual and physical systems contribute to emphasize further the relevance of monitoring and predictive technologies.

Supported by these technologies, condition-based maintenance (CBM) and prognostics and health management (PHM) maintenance strategies aim to align actions with the real needs of processes and components. This, in turn, will help to decrease maintenance costs and downtimes, thus reducing lifecycle costs and increasing availability, and overall, having an impact in lifecycle value.

At the technical level, a relevant attempt to guide and to bring in a methodological approach for the introduction of these technologies for maintenance is the OSA-CBM architecture (Discenzo, Nickerson, Mitchell, & Keller, 2001). OSA-CBM presents a series of layers or steps on which to base CBM systems, from sensors to signal processing, intelligence and presentation.

The development of algorithms providing functionality within the scope of these layers has been extensive in the last decades, and it is an active area of on-going research (see e.g.: Roemer, Byington, Kacprzynski and Vachtsevanos, 2005; Pandian and Ali, 2010). Whilst OSA-CBM is still a reference methodology cited by researchers (Alves, de Oliveira Bizarria & Galvão, 2009), other alternative or complementary methodologies and approaches have also been proposed during the years. Line and Clements (2005) proposed a systematic method and toolset for applying PHM techniques in an aeronautics domain. The method covers from analysis of prognosis candidates to algorithm definition and description. Muller, Suhner, and Benoît (2008) deal with the prognosis process within an e-maintenance approach, and propose a methodology following three stages: research and development (R&D), engineering, and operational, along with generic steps within the R&D stage from functional modeling to the prognosis model definition. Chen, Yang, and Hu (2012) present, within a technical framework for embedded diagnostics and prognostics, a methodology for system design and integration.

In parallel to this research, work has also been done on areas less directly connected to technical development and implementation but closer to technical analysis and management. At this level, a number of tools have been available and its usage extended, such as Failure Mode and Effects Analysis (FMEA), Fault Tree Analysis (FTA), Functional Hazard Analysis (FHA), etc. Links to business potential have also been sought after by means of introducing existing tools (e.g. Balanced Scorecard (BSC)), developing tools (Life Cycle Cost analysis (LCC)) and/or improving existing techniques, such as for instance (life) cost based FMEA. In cost based FMEA, the traditional factors used to prioritize potential failures (occurrence, severity and detection) are replaced by an evaluation of risk using probability and cost (Kmenta & Ishii, 2000; Rhee & Ishii, 2003).

Márquez, de León, Fernández, Márquez and González (2009) introduced a process for maintenance management, and within this process, they classify a number of those aforementioned maintenance engineering techniques and tools. Gilabert, Fernandez, Arnaiz and Konde (2015) introduced a methodology oriented to predictive maintenance that integrates existing reliability and analysis techniques. In addition to this, they introduce simulation of maintenance strategies, thus establishing a link between the methodology and reliability information on components and predictive technologies. In recent years simulation has received considerable attention for maintenance optimization (Alrabghi & Tiwari, 2013). Nonetheless, it is also worth noticing the efforts in parallel to gather real data (Puttini & Fitzgibbon, 2008).

Bengtsson (2007) emphasizes the role of "general enabling factors" in implementing CBM, citing management support, training, communication and motivation, among others.

Challenges remain in structuring the condition monitoring offer and the technological platform due, in particular, to the variety of potential domains of application, the characteristics of the existing information and the final goals of the monitoring activities. These challenges may impact in the deployment time of a condition monitoring solution. In order to limit these challenges, a methodology for fast deployment of condition monitoring and a technological service platform is presented (section 2).

Because, beyond components, systems and processes are considered, a fleet perspective naturally emerges in the platform and services to be provided. Technologies and capabilities in the platform become needed in order to help managing a fleet of machines, as well as individual components and systems (section 3).

Finally, in section 4 the application of the methodology is illustrated in two scenarios. And conclusions are presented in section 5.

2. METHODOLOGY FOR CONDITION MONITORING

Challenges observed in structuring the condition monitoring offer have shaped the idea behind the methodology. In order to consolidate the offer, a methodology is proposed aiming to draw the big picture and to help to apprehend the link between final goals and technology, and vice versa. This shall, in turn, facilitate iterative feedback (e.g. from customers), meant to speed up the process and overcome fast the difficulties (i.e. variety of potential domains, characteristics of existing information). In sum, the methodology illustrates a stepped approach to the full deployment of a condition monitoring for specific business needs and asset types. This tool serves as a roadmap that, in the hands of maintenance and reliability professionals, will help to guide customers in the search of the optimal solution for their needs.

2.1. Framework

As starting point a reference framework is selected that is structured in three levels. The upper level is a typology for different scenarios. The typology helps to identify the main objectives and the scope of activities.

The second level is a process-activity model. Conceptually it follows this sequence of steps: assessment, objectives, analysis, actions and implementation. For supporting these steps a novel methodology tool has been devised (section 2.3). Finally, the lower level is methods and tools. A comprehensive set of existing tools are available for supporting activities and methodology steps in the upper levels and for providing more detailed insight if needed.

2.2. Methodology

Following the framework, the methodology has been structured as shown in Figure 1. In level 1, the typology has been hierarchically structured, from more goal-oriented scenarios to more technically-oriented scenarios. At the top the typology is close to goals. Overall Equipment Effectiveness (OEE) is one of the main indicators; it includes availability, quality and performance. Down in the hierarchy, and more balanced between goal and technical orientation, the typology includes aspects such as external factors, condition, remote diagnosis, load/parts produced, usage/operation time and energy efficiency, among others. These are related to the typology in the upper level but are more specific about the scenario.

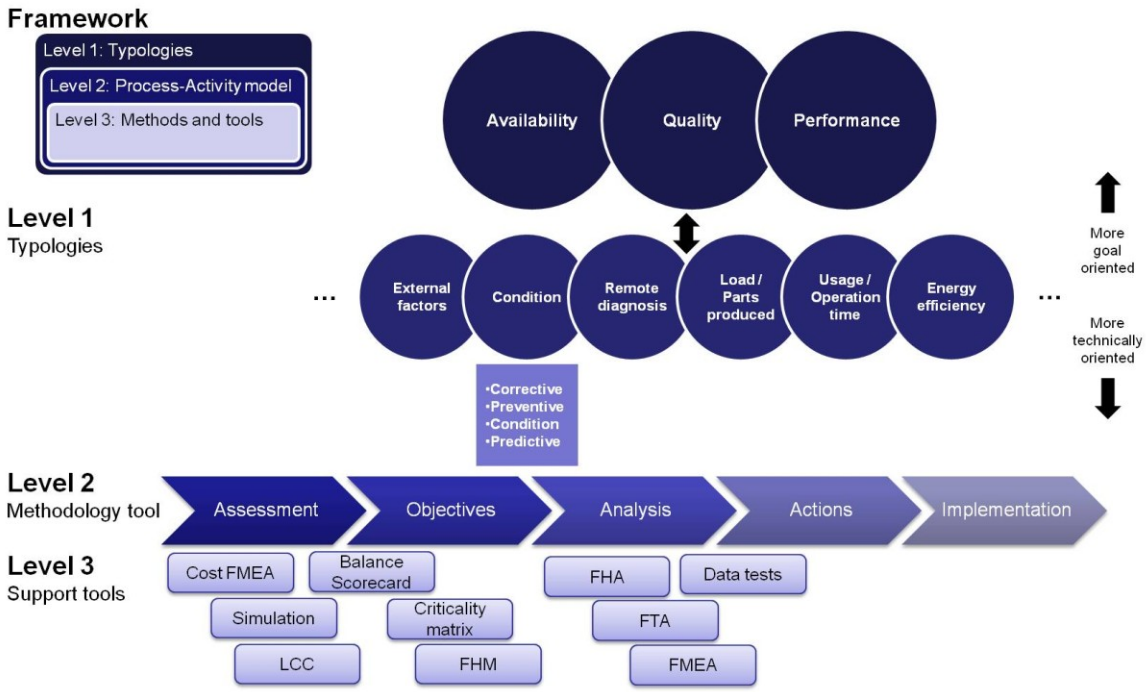

Figure 1. Condition monitoring methodology framework.

A third level in the hierarchy will be more technically oriented. For instance, for condition various aspects have been defined for identifying competitive maintenance strategies in this scenario.

Level 2 defines the process-activity model. A novel methodology tool has been developed for facilitating and guiding the application in practical scenarios. The next section (section 2.3) is devoted to it.

Finally, level 3 consists of a comprehensive set of (existing) tools to provide support to activities and methodology steps in the upper level, along with additional, more detailed insight, if needed. A number of tools have been considered and aligned with the corresponding steps in the process-activity model. This is further described in the next section along with the methodology tool.

2.3. Methodology Tool

This section presents a methodology tool for supporting the process-activity model of the methodology. From the methodological needs identified, it was argued that there is room for a higher level formulation. The methodology tool aims to capture that perspective and to focus on: addressing the big picture, showing key information at the right level of detail, and facilitating faster iterations. Existing support tools are applied when deemed necessary (e.g. criticality matrix, FMEA, etc.).

The steps defined within the methodology tool are: business perspective, technical objective, technical analysis and data monitoring. Within each step, focus and value are stated. The first step, business perspective, is associated to the assessment step in the process-activity model. The next step, technical objective is related to the step objectives in the process-activity model. The steps technical analysis and data monitoring are related to step analysis. Finally, from the information available, the step actions in the process-activity model is related to the decision on needed actions, such as technology/process adoption/implementation. Finally, the step implementation on the process-activity model corresponds to the actual implementation of those decisions.

It is envisaged that methodology results shall be refined and improved iteratively, supported by the new knowledge/information acquired/analyzed in the process or by using the support tools, and by the feedback from customers/scenarios.

A diagram for the methodology tool is shown in Figure 2. Each color corresponds to one of the steps within the methodology tool. For each step, two columns are available for stating both focus and value. Information in rows is aligned, and therefore linked across steps. A number of potential support tools are shown at the bottom and aligned with each step in the methodology.

The methodology tool is presented in a wider context, linking on the left hand side to means for evaluation of final outcomes, and on the right hand side to CBM hardware and software implementation.

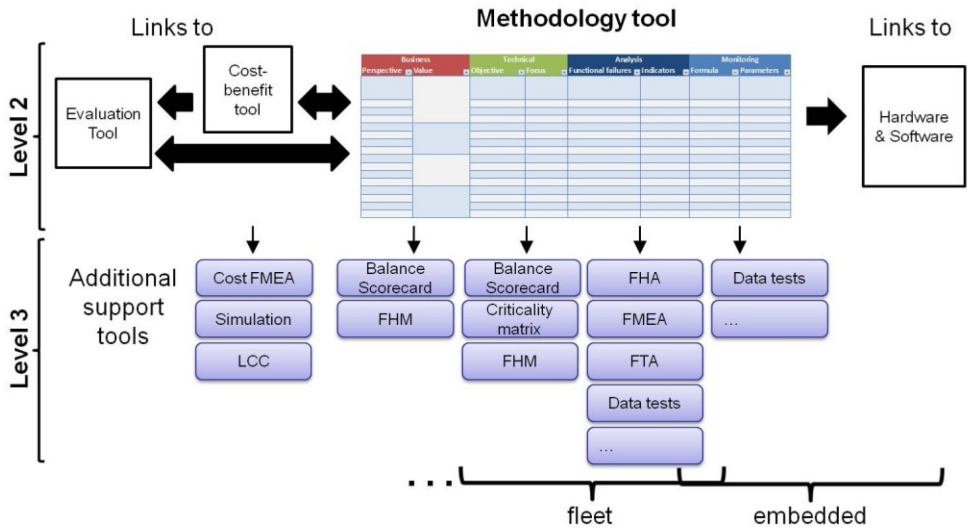

Figure 2. Methodology tool within a wider context. Context includes, on one hand evaluation, and on the other hand hardware and software implementation. A number of potential support tools are also shown at the bottom.

Within the methodology tool diagram the separate steps have been proposed as follows.

The step on business perspective states the focus and the impact expected from the technologies in terms of the value introduced with respect to the (business) goals. The perspective or focus of the value improvement could be financial or maintenance perspective, but other aspects might be relevant as well (e.g. customer, product, service, learning, marketing,…). In turn, the value expected from the technology can be stated in terms of maintenance, lifecycle, unavailability, risks, among others.

As regards the step on technical objectives, it is the highest technical level in the methodology. Thus, the overall objective of the technology is stated, in relation to the business perspective. Main drivers could be condition monitoring, remote diagnosis, prognosis and maybe usage, performance, among others. The technical focus is also stated, indicating the technical rationale and approach to be pursued. Various technological approaches may jointly contribute to achieving the same target (business) value.

The next step, technical analysis, states the critical functional aspects and the means to pinpoint them. This is a technical and complex phase where supporting tools are expected to be needed. This phase can lead to the development and implementation of advances in diagnostic and prognostic technologies. As its main focus, functional failures and functional critical aspects to be tackled are stated. In general, any condition needing attention. As value, potential indicators are formulated, describing the data used and their attributed examined. It is a higher level of data description than monitored data/signals, from which indicators are derived. Some examples are statistics, characteristic frequencies, etc. from which, for instance, health condition can be determined directly or derived.

The final step within the tool is data monitoring. In this step, the parameters and processing leading to the extraction of relevant indicators are stated. This is the closest stage to hardware level and some interaction is expected in order to clarify and refine options. First, parameters (the raw data or signal to be monitored) are indicated. Typical examples are physical sensors (temperature, accelerometer, current, and so on) but other possible sources of data can be included (for instance counters). Then the formula is stated, this is to say, the processing needed to derive useful indicators for the analysis. Examples are calculations related to signal processing and simple condition algorithms.

The methodology tool is meant to serve as a guideline supporting the application of the methodology. In practice, some variation can be observed on the usage of the aforementioned terminology depending on the scenario/customer, and still obtain a clear, consistent picture.

3. PLATFORM TECHNOLOGIES

In recent years there have been significant advances in both embedded and cloud systems, increasing the power and capabilities of the former, expanding the scope and increasing the services provided by the later.

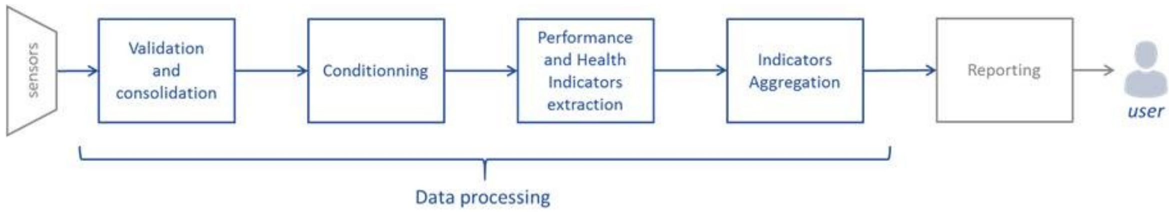

Figure 3 : Data processing structure

The platform proposed is devised as incorporating local condition monitoring and remote fleet management. The local, embedded system specializes in monitoring and communication capabilities. Certain data processing can be achieved such as certain event detection and local alarms. The remote system, on the cloud, specializes in global management and services, mainly rooted in their data organization, processing and analysis capabilities from data gathered by, typically many, local systems. A communication link between local and remote systems must be established for them to act in a coordinated manner.

A number of capabilities are needed in the platform and are presented below.

3.1. Data acquisition

The data acquisition layer has to be flexible in order to accommodate for the variety of available formats and protocols. Data can be collected:

- Periodically or on demand: in this case, batch data (i.e. several data files) are extracted from mobile or embedded devices and transferred, manually or automatically to the platform. The transfer may require some specific import / export tools.
- Continuously: in real or delayed time (i.e. file by file), data are transferred from the machine, PLC or local storage units to the platform.

Whatever the acquisition method used, data transfer and integration principles are:

- “Push”: Client-server communication mode where dialog is initiated by the server. The data source is considered as the server and the platform is the client. While running, the client subscribes to the notification service in order to get informed when new data are available. In this case, the sampling period is not constant because of the notification system.
- “Pull”: Client-server communication mode where dialog is initiated by the client that “pulls” the information from the server. While running, the client connects to the server regularly and reads available data. In this case, the sampling period could be constant because it is fixed by the client.

3.2. Data storage

Once collected data are processed and stored into knowledge base describing the system.
Typically, an architecture of the knowledge base is decomposed as follows:

- Structural / functional / dysfunctional representation: corresponding to the static definition of the system. This description contains the decomposition of the system in terms of sub-systems, components, relation between them and also some system intrinsic characteristics (i.e. location, serial number, etc.).
- Behavioral representation corresponding to the evolution of the dynamic of the system all along its lifecycle. Both internal (i.e. system) and external (i.e. environment) behaviors that characterize usage and condition of use of the system can be represented by three relevant information groups: signals, operating modes and indicators.

All collected and processed information are stored in the knowledge base in order to combine them to obtain further information about the system.

3.3. Data processing structuring

Data processing consists of four mains phases depicted in Figure 3. Outputs of the last phase can then be used to perform reporting task. The four main phases are:

1. Validation and consolidation phase that aims at improving raw data reliability, i.e. to eliminate and replace outliers.
2. Conditioning phase that allows to detect the operating modes of the system in order to enable and disable some indicators’ computation.
3. Performance and health indicators extraction phase which consists in computing the indicators.
4. Indicators aggregation phase which is the fusion of indicators to have an overall view of the components, sub-systems, systems...

Following sections detail each phase of data processing, in a generic point of view.

3.4. Validation and consolidation

First step of the validation and consolidation phase consists in detecting periods where data is present in order to know when all the algorithms have to be run.

Once data presence is computed, the second step validation and consolidation phase is to detect outliers in measurements. Firstly, for each collected data it is checked if the measurement value is in the sensor measuring range. Then according to the measured quantity dynamic, signal is filtered and smoothed by using robust method as a median filter for example.

Second phase of data processing consists in the identification of the different operating modes of the system. An operating mode is assumed to represent a state of a system where different constraints from environment and operation imposed on the system are considered constant. For each sub-system and for the system itself operating modes are extracted from the different input signal.

Once each operating condition of the system identified, relative indicators can be computed.

3.5. Indicators computation

The third phase of data processing consists in processing the different systems' indicators. An indicator represents an information about system usage, performance or health during a specific operating mode.

Different types of indicators can be represented like counters and operating times, for example. Mainly, indicators represent cumulative values over operating modes periods. They can be used either as Key Indicators, or for computing Key Indicators or they can be used as information's for HMI and reporting.

3.6. Indicators aggregation

Indicators aggregation is a process synthesizing in a global value (an aggregated value) the information coming from various sources which could be from various entities. This aggregated value must satisfy some preferences of a group of individuals or some properties, thus helping decision making in look for a consensus. Indicators being of different natures and scales, the phase of indicators aggregation is split in 2 steps: notation which is a normalization process and aggregation.

3.6.1. Notation

Notation consists in normalizing a quantitative variable. Hence a notation function $N(x)$ is defined like:

$$N: \mathbb{R} \rightarrow [0; 1]$$

There are several ways to define these functions:

1. Using data resulting from experience feedback. A history of data of the indicators taken during identified working period (good behavior, degradation mode) makes possible to identify range of values or specific working point linked to working modes. The drawback of this method is that it requires a learning period during which it is mandatory that phases of good behavior are identified and bad behavior as well.
2. Using requirement from expert knowledge on the system. These requirements define critical values for which the system will not be able to match expectations required. It is possible to define directly with the expert "ideal" ranges of values or working point. The drawback of this method is that the expert knowledge is not always sufficient to define quantitatively these characteristic values of utility function.

Many forms of notation functions exist from the simplest that is directly a mathematical function such as Gaussian curves or Mexican hats to the composed functions or piecewise defined functions.

3.6.2. Aggregation

Aggregation consists in merging a set of information's notes thanks to aggregator operators defined as:

Several aggregation operators exist, for instance: mean type operators (arithmetic mean, weighted arithmetic mean), Connectors, Uninorms, O.W.A. (Ordered Weighted Averaging) are among the most used.

Usually, maps are drawn in order to visualize the behavior of these operators. A map illustrates the result of a two notes merging. An example of the map of Max operator (connector type) is shown in Figure 4. Pure green correspond to the maximal value (i.e. note equals to one), and pure red correspond to the minimal value (i.e. note equals to zero). The horizontal and vertical scales correspond to the two input notes. The example can be read like:

- The two inputs are good (green or equals to 1) then the result will be good.
- At least one input is bad (red or equals to 0) then the result will be bad.

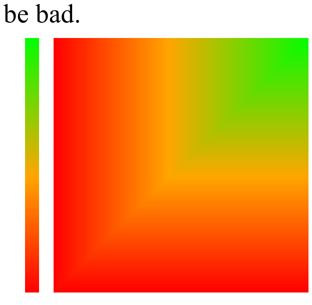

Figure 4 : Map example of Max Connector aggregation operator

3.7. Reporting

Reporting services goals are to offer different ways of visualize various indicators according to a selected fleet. Users should have the possibility to query the remote database in order to access relevant information about systems that share common characteristics. The user interface has to present dynamic reporting services according to user's needs.

According to the platform specificities and tools, two ways of data visualization are available:

- Interactive visualization tool: This application allows users to visualize variables in time (signals, operating modes, indicators either computed or acquired). Within this application it is possible to compare multiple variables, create contexts and analyze histograms or plot X/Y graphs as depicted in Figure 5. The application offers the possibility to analyze historical periods of the remote database content as real time data flow too.

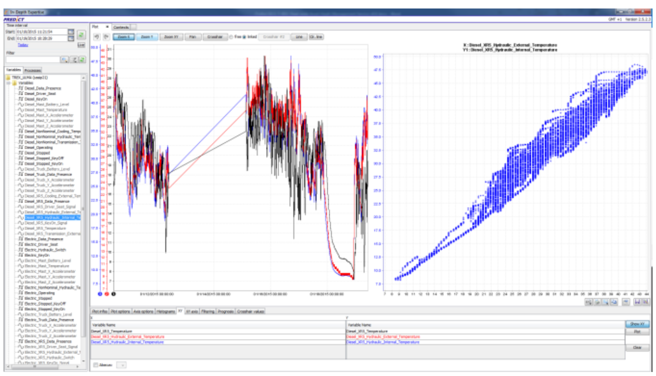

Figure 5: Interactive Data Visualization

- Static reporting contents: models which outputs are custom static document (".pdf", ".doc"). The content of such document is customised according to users' needs or systems' specificities and can be generated automatically for defined periods. These reports can contains charts such as boxplots, pie charts, radar charts, or other graphs.

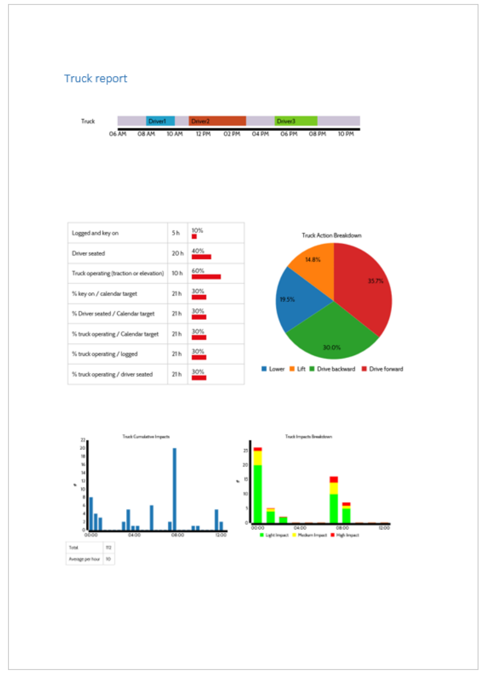

Figure 6 : Daily report of a truck

- Dynamic web designed HMI: Customized according to the users' needs, HMI offers the possibility to visualize dynamically information from the remote platform by querying the database. The web format offers a huge panel of possibilities and solutions in terms of data visualization (HTML, CSS, JS, SVG, etc.) and supported format (Computer, Smartphone, gear, etc.).

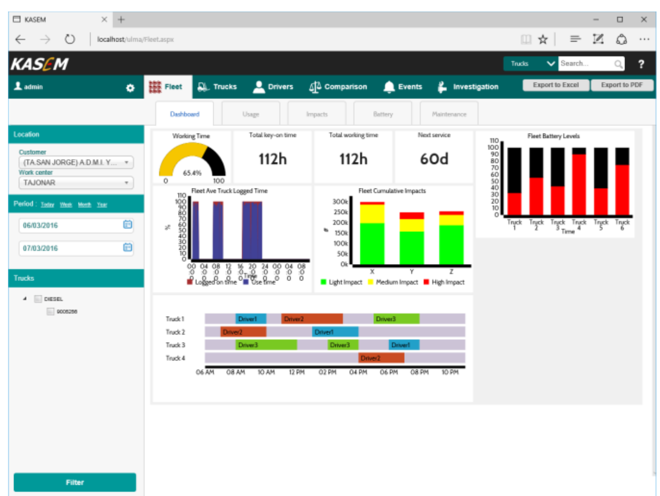

Figure 7 : Custom fleet-wide HMI

4. METHODOLOGY APPLICATION TO INDUSTRIAL CASES

The context for the application of the methodology to industrial cases was research on product-service solutions, where companies offer a mix of product and services and not only the traditional product solution. Maintenance, among other services, can provide an added value and a source of income.

The application of the methodology is carried out from interviews and interactions with the companies, and also from analysis and research of the various aspects identified, the results of which are reflected in the methodology tool. In successive iterations the content is refined and improved.

A potential impact is identified in terms of maintenance costs reduction, lifecycle costs reduction, lifecycle extension and components/systems re-use increase. Overall, the main indicators identified can be grouped in one of the following categories. Usage: such as time of operation/use and anomalous usage. Condition and diagnosis: based on various physical sensors measurements. And performance: associated for instance to energy consumption, number of operations, among others.

Tools such as FMEA where applied in some cases in order to understand and/or clarify certain aspects of the system. Data collection was applied too, for understanding the systems, defining algorithms, configuring and adjusting technologies, and in general for development.

A first typology of generic algorithms was defined for structuring the monitoring needs in the use cases, as follows. Counters: used on data for obtaining usage, time durations, number of certain events. Events: for determining normality or anomalies in one parameter's data. Condition: for detecting, among others, anomalous conditions in various parameters data. Some alarms/actions that could be triggered according to the results of algorithms were identified as well.

The following sections describe two use cases. The first one is on the transport domain and the second one on the machine-tool domain.

4.1. Transport Domain

In the transport domain, the focus was on a provider of forklift trucks and services for handling and logistics. In recent years the interest in rental services has been increasing, and among their efforts to offer the best service, research has been performed on the application of monitoring technologies, condition-based maintenance and fleet management capabilities. In particular, since this is one of the levers considered for enabling improved short-term rental service, a type of service increasingly demanded by customers.

From the application of the methodology, nine potential business added value impacts were identified, affecting aspects such as lifecycle extension, re-use increase, maintenance cost reduction and lifecycle cost reduction. From monitoring technologies nine main indicators were identified that include information in relation to usage and operational time, and condition monitoring, among others.

Condition-based maintenance is proposed as including local condition monitoring and remote fleet management tools and technologies. Development of the system includes, among others, communication capabilities to instantiate this architecture, along with embedded capabilities for monitoring and detection of events. Availability of services and asset management capabilities can contribute to inform and to improve the application of the technologies.

4.2. Machine-Tool Domain

In the machine-tool domain, the focus was on a machine-tool manufacturer and seller with an interest in adding services to their portfolio such as maintenance. This is a market with a high value and specialized product, where efforts have been done in terms of, among others, research on new designs and on monitoring technologies as an enabler of condition-based maintenance services.

From the application of the methodology, three potential business added value impacts were identified, affecting mainly maintenance cost reduction, and in turn, life cycle cost reduction. Further analysis, identified more than five potential indicators from monitoring technologies, providing information in relation to usage, performance and condition.

System development makes an emphasis on new designs, and additionally on embedded monitoring and event detection with capabilities for remote fleet management.

5. CONCLUSION

Special-purpose tools exist for technical analysis and guidance in relation to condition monitoring activities. Nonetheless most with few or none links to final goals on the one hand, and/or on the other hand, to implementation. Our research has lead to the methodology introduced in this paper, and encapsulates knowledge on an overall view and a methodology from goals perspective to condition monitoring technologies. The methodology helps to structure the condition monitoring offer. In addition to this, it guides the potential need and selection of more specific methods and techniques, in relation to the final goals. A methodology serves as a guideline, and as such it is a tool or set of tools for facilitating the way so as to assess and clarify needs, limit challenges, and in doing so, to favour fast development.

The methodology was applied to industrial use cases, for supporting industry in adopting new or alternative maintenance strategies, a process facilitated by the broader perspective that should contribute as well to involve actors from various areas/departments (business, technical, etc.). As the project is not yet finished the final impact in the business is to be assessed. The methodology main added value is in strengthening the link between condition monitoring activities and final goals. The content is iteratively studied and refined in order to understand and clarify needs. As this is an iterative procedure further advances can be possible as it evolves, eventually affected by progress in both business models and technologies.

Maintenance is gaining relevance in business, especially as they transition towards providing services in their portfolio. For this reason, technologies such as condition monitoring and services platform are appealing, along with the development of supporting methodologies.

ACKNOWLEDGEMENT

The work presented in this paper is part of the research work still in progress in the project T-REX, funded under FP7 under grant agreement no. 609005, as part of the Factories of the Future initiative.

REFERENCES

Alrabghi, A., & Tiwari, A. (2013). A Review of Simulation-based Optimisation in Maintenance Operations. *15th International Conference on Computer Modelling and Simulation (UKSim)*, pp. 353–358.

Alves, M. R. J., de Oliveira Bizarria, C., & Galvão, R. K. H. (2009). Trend analysis for prognostics and health monitoring. *Proceedings of the 2009 Brazilian Symposium on Aerospace Engineering and Applications / 3rd CTA-DLR Workshop on Data Analysis and Flight Control*. S. J. Campos, SP, Brazil.

Bengtsson, M., (2007). *On Condition Based Maintenance and its Implementation in Industrial Settings.* Doctoral dissertation. Mälardalen University, Sweden.

Chen, Z. S., Yang, Y. M., & Hu, Z. (2012). A technical framework and roadmap of embedded diagnostics and prognostics for complex mechanical systems in prognostics and health management systems. *IEEE Transactions on Reliability*, 61(2), pp. 314-322.

Discenzo, F. M., Nickerson, W., Mitchell, C. E., & Keller, K. J. (2001). Open systems architecture enables health management for next generation system monitoring and maintenance. Development Program White Paper, The OSA-CBM Development Group.

Gilabert, E., Fernandez, S., Arnaiz, A., & Konde, E. (2015). Simulation of predictive maintenance strategies for cost-effectiveness analysis. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture.*

Kmenta, S., & Ishii, K. (2000). Scenario-based FMEA: A life cycle cost perspective. *Proceedings of DETC 2000 / 2000 ASME Design Engineering Technical Conferences*. Baltimore, Maryland, U.S.A.

Lee, J., Ni, J., Djurdjanovic, D., Qiu, H., & Liao, H. (2006). Intelligent prognostics tools and e-maintenance. *Computers in Industry*, 57, pp. 476-489.

Line, J. K., & Clements, N. S. (2005). A systematic approach for developing prognostic algorithms on large complex systems. *Proceedings of IEEE Aerospace Conference*, pp. 1-7.

Márquez A. C., de León P. M., Fernández J. F. G., Márquez C. P. & González V. (2009). The maintenance management framework: A practical view to maintenance management. *Safety, Reliability and Risk Analysis: Theory, Methods and Applications*, Martorell et al. (eds), Taylor & Francis Group, pp. 669-674.

Muller, A., Suhner, M-C., & Benoît, I. (2008). Formalisation of a new prognosis model for supporting proactive maintenance implementation on industrial system. *Reliability Engineering and System Safety*, 93(2), pp.234-253.

Pandian, A., & Ali, A. (2010). A review of recent trends in machine diagnosis and prognosis algorithms. *International Journal of Computer Information Systems and Industrial Management Applications*, 2, pp.320-328.

Puttini, L. C., & Fitzgibbon, K. T. (2008). An overview of testing methodologies for the development of PHM solutions. *Proceedings of the 2008 International Conference on Prognostics and Health Management*.

Rhee, S. J., & Ishii, K. (2003). Using cost based FMEA to enhance reliability and serviceability. *Advanced Engineering Informatics*, 17, pp. 179-188.

Roemer, M. J., Byington, C. S., Kacprzynski, G. J., & Vachtsevanos, G. (2005). An overview of selected prognostic technologies with reference to an integrated PHM architecture. *Proceedings of the First International Forum on Integrated System Health Engineering and Management in Aerospace*.

BIOGRAPHIES

Dr Santiago Fernandez received his B.Sc. in Physics from the University of Santiago de Compostela in 1996, and M.Sc. (equiv.) in 1997. In 2001 he received his Ph.D. degree for work in the area of speech perception and acoustic phonetics. After having worked as a post-doctoral researcher in the University College London and at the Dalle Molle Institute for Artificial Intelligence, Switzerland, he joined Tekniker, where he works on intelligent information systems unit.

Christophe Mozzati graduated from Telecom Nancy (formerly ESIAL) school of engineering specialized in IT in 2006**.** He works in PREDICT, a SMB specialized in predictive maintenance solutions. He is responsible for the development of the KASEM® platform and has been participating in multiple national and European R&D projects related to predictive maintenance in various fields of application.

Dr. Aitor Arnaiz is head of the intelligent information systems unit at IK4-Tekniker. He holds an MSc on 'Applied

Artificial Intelligence' at Aberdeen University and a PhD at Sunderland Univ. with the thesis 'Development of Artificial Intelligence Technologies to support automation of condition monitoring tasks'. During last 5 years he has also been head of the diagnostics and prediction unit and responsible of the research line in maintenance and reliability at Tekniker.