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# Dashboard proposition for health monitoring of production system in the automotive industry

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**Abstract:** In the context of industry 4.0, the predictive maintenance (PdM) approach plays an important role in the optimization of maintenance costs, as breakdowns and over-maintenance costs. Health supervision of production behaviors is one of the critical steps to implement PdM. To do this, specific Maintenance KPIs, called also Health Key Performance indicators (HKPI) must be identified. Furthermore, dealing with real data, finding the right HKPIs, and validating the final proposed solution by the industrial actors, are less seen in theoretical studies. In this paper, based on available historical and real-time data and information, some suitable HKPIs have been proposed, allowing to build the dashboards for monitoring the health state at machine and production system levels. Regarding the variety of real-time data to present in the dashboard, Principal Component Analysis (PCA) method has been applied, allowing to find the most appropriate features. At the production system level, HKPI aggregation and identification of decision levels are rarely studied. We propose also for each HKPI, a suitable decision-level, and an appropriated aggregation methodology. The proposed methodology has been applied to production equipment of the FPT Industrial Company and the results were appreciated by managers.

*Keywords:* Predictive Maintenance, Health Monitoring, Health Key Performance Indicator, Visualization, Real-Time Supervision, Health Indicator, Dashboard, Industry 4.0

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## 1. INTRODUCTION

In the highly competitive global market, the traditional mass production system needs to move toward customized mass production to be able to respond to the customers' demands which are a family of products for the same function. This requires a considerable level of flexibility, agility, efficiency, and a high level of availability of production equipment for manufacturing the client's demands. As a result, the Maintenance sector of the industries becomes crucial. Recently, the advent of Industry 4.0 has brought a new overview for finding solutions to the complexities of new mass customized production systems. Real-time data and systems, IoT, cloud computing, and ICT platforms are important tools that can accelerate achieving to have a smart factory or an intelligent manufacturing system.

One of the main issues in the implementation of Industry 4.0 concerns Predictive Maintenance. Conceptually, PdM follows the objective of cost reduction, and availability augmentation of production machines. This is mainly obtained by minimizing the number of sudden breakdowns on one hand and minimizing the number of excessive preventive maintenance on the other hand. For this objective, there is a necessity to consider the actual operation condition of the equipment by collecting information and data from the condition monitoring process (Ahmad and Kamaruddin, 2012). The monitoring information in practice is often obtained by installing sensors in the equipment (Rabatel et al.,

2011). However, sensor data is not the only source for monitoring the health state of the machine. There is also information about past maintenance activities and breakdowns which are also quite important to consider in the health monitoring of machines.

The main challenge here is to find how to use and to show the high volume of historical and real-time data to help the decision-makers in health monitoring of production systems and their decision making (Pech et al., 2021). In this way studying new approaches and methods to use real-time and historical data is one axis to obtain comprehensible information from the data. The further axis is to identify and propose a visualization dashboard in which decision-makers get helpful visions in their decisions.

For this, HKPI identification, measurement, and visualization are the three principal steps. Traditional maintenance KPIs are already used in the literature, but in this study, some new HKPIs have been proposed along with decision levels for each HKPI. Furthermore, an aggregation method is proposed to monitor the production system rather than each machine separately. In besides, new real-time HKPIs have been proposed based on sensor data. In the end, two dashboards (in the machine and global or production system point of view) are proposed for real-time supervision and health monitoring of the production system. The idea of dashboards is to help decision-makers by taking a quick vision of the machine and system state from the real-time dashboards.

As a real case study, it has been used from maintenance data of some production equipment in FPT Industrial Company such as several sensor data as motor temperature, power consumption, speed ... and also past maintenance information like maintenance costs, stoppages, duration... HKPIs have been measured and depicted in the dashboards.

The rest of this paper is organized as follows: Section 2 describes the last research works; Section 3 proposed the methodology and health monitoring system; Section 4 presents the case study and results; Section 5 presents conclusions and perspectives of future works.

## 2. LITERATURE REVIEW

In general, Health monitoring and real-time supervision systems are proposed to reduce breakdown maintenance costs by actively monitoring the integrity of machines or systems (Xu and Xu, 2017). The main objective of health monitoring systems in predictive maintenance is the evolution from reactive (diagnostic) to proactive (prognostic) maintenance.

There is a wide range of data and information that can be considered here as historical maintenance activities and failures, operating parameters, condition sensors... Regarding the methodology of health monitoring systems, they can be categorized as 1-Model-based, 2-Data-driven, and 3-Hybrid models (Tahan et al., 2017). There are several studies of health monitoring and supervision systems in different industrial cases as (Mohtasham Khani et al., 2019) in gas turbines, (Abdel Fatah et al., 2019) in centrifugal pumps, (Hernández-Muriel et al., 2020) in bearing and rotatory machines, and (Lebel et al., 2020) in the high-speed train suspension system.

### 2.1 Health indicators:

For the real-time supervision of the state of the machine, it is necessary to have health indicators. These indicators can come whether from expert knowledge or some methodologies based on the input data (Lei et al., 2020). Maintenance KPIs can be regarded as a health indicator of machine and maintenance systems and can help the maintenance team to track and detect failures (Kronz, 2006).

The following KPIs have been studied in the literature: Operation, Control Performance, Maintenance, and Planning KPI (Aceto et al., 2020), RUL based KPIs (Wu et al., 2018), Reliability, Availability, Maintainability, and Safety KPIs (Raza et al., 2016). There are fewer studies in the literature regarding HKPIs. In this study, some HKPIs as Cost, Control Performance, and Planning have been proposed, which are found very interesting and missed in the literature.

Each HKPI could be suitable for a certain organizational level. Proposing the right aggregation methods for the overall HKPIs in the production line or organizational level is less considered in the literature to the best of our knowledge. In PdM the focus is on component state indicators, but it is interesting to have a global view of multi-level systems for decision-makers in different hierarchical levels (Shafiq et al., 2019).

### 2.2 Data-driven methods for RUL and state prediction:

Likely, the same as health monitoring systems, RUL and state prediction methods in the literature are in three categories of physical model-based, data-driven, and hybrid models (Einabadi et al., 2019) and its methodology is challenging and important to review. Physical model-based methods are more accurate since in this model the failure mechanism is studied, but it is hard to apply. On the other hand, data-driven methods can be implemented easier. Hybrid methods attempt to use the advantages of both physics-based and data-driven approaches (Wu et al., 2020) (Chen et al., 2020). Many researchers have used data-driven techniques for RUL and state prediction and health monitoring systems. The data-driven learning techniques are categorized in (Fig 1.)

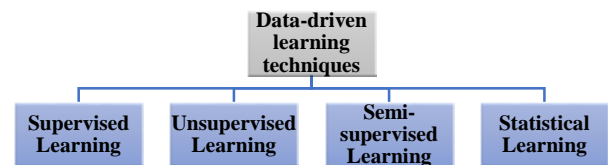


Fig 1. Data-driven learning methods

Regarding supervised learning, (Utah and Jung, 2020) have applied k-nearest neighbors, decision trees, random forest, and support vector classification for RUL prediction in the case of industrial valves. (Yang, 2012) Have used of Support vector machine for performance degradation of rotating machinery. (Zhang et al., 2018) Have also used SVM for the fault diagnosis in diesel engines. There are some researches regarding the combination of supervised and unsupervised learning as semi-supervised as (Li and Zhou, 2014) Have worked on semi-supervised learning for the fault diagnosis of bearings. Concerning statistical learning, (Babbar et al., 2009) have studied advanced diagnostic and prognostic with RMS analysis for determining aircraft engine performance.

Machine learning methods are widely applied in literature, however, using PCA methods for an HKPI has been rarely addressed in the health monitoring of sensor data. As of today, many visualization tools have been proposed to monitor the sensor data in machines, however, in practice, it may be useless to monitor all the sensor data, in this way a real-time HKPI by PCA analysis has been proposed to be used instead. This has been rarely considered in the literature for the visualization of real-time data.

### 2.3 Visualization in the form of a Dashboard:

Data visualization helps humans to take a quick vision of the system or process. It helps to uncover hidden information in the data. Data visualization is the main key in data analytics (Lebanon and El-Geish, 2018) (Huynh et al., 2017). Different kinds and types of plots could be used in data visualization, as single variables, bi-variables, ... and Strip Plots, Histograms, Line Plots (Liu et al., 2017) (Thomas and Cook, 2006).

Creating dashboards particularly for maintenance activities has been less studied by researchers, for example (Okoh et al., 2017) have just presented some visualization techniques to monitor maintenance events. (Green et al., 2020) have presented some process KPIs and their visualization. (Moens

et al., 2020) have presented a real-time dashboard for visualization of sensor data. Thus, the dashboard proposition that comprises maintenance-specific HKPIs, and real-time health indicators from sensor data is one of the contributions of this study that has not been found earlier in the literature.

### 3. METHODOLOGY

As the main objective of this study is to propose suitable supervision and health monitoring systems, in the first step, it is focused on proposing a data visualization dashboard for the maintenance vision of industrial equipment. In this way, several types of HKPIs have been used and some of the most important HKPIs are explained. In the second step, it is concentrated on real-time data of sensors to identify and propose HKPIs for better supervision of the equipment. It has been used from ML techniques as PCA method to identify the most important sensor parameters and visualize the variations trend. This can be an indicator of a component health state.

#### 3.1 Visualization dashboard

In this part, a brief presentation of the HKPIs and measurement methods for the most important HKPIs are presented:

##### 3.1.1 Health Key Performance Indicators (HKPIs)

There are some maintenance-related KPIs in the literature, while the important point is to identify suitable HKPIs (Bhadani et al., 2020). In table 1 HKPIs of health monitoring are presented. Since each HKPI could be suitable for certain decision levels, it is important to segregate the HKPIs for the suitable one as following:



**Strategical:** At this level, top management is engaged.



**Tactical:** At this level, maintenance managers and supervisors are engaged.



**Operational:** At this level, lower-level supervisors and technicians are engaged.

For the *Maintenance cost HKPIs*, three important costs in maintenance are the maintenance operation (labor), spare part, and downtime cost. The ratio of these costs per total produced items over a defined period could be a very interesting indicator for the management point of view. *Performance Control HKPIs* are more related to the type of maintenance activities and type of failures per machine and components in more detail to give a good vision of the maintenance situation. *Planning HKPIs* gives a quick vision of the state of the machine in terms of maintenance dates. The main *Operational HKPI* is the OEE that is based on three criteria of Availability, Performance, and Quality. Availability shows the uptime level of each machine, uptime is the time when the machine is ready for operation. Performance is the percentage of produced items number per capacity of production. Quality indicates the ratio of confirmed produced items per total produced items. *Equipment HKPI* as RUL and state prediction which is defined as the useful duration of a component, part or machine from the current time to the end of its useful life. It is critically important to assess the RUL of an asset because of its impacts on maintenance planning, spare parts provision, and

operational performance (Qiu et al., 2020). Monitoring all the presented HKPIs over time and tracing the evolution of them is determinant for getting a vision.

**Table 1. Various HKPIs**

KPI	Description	Decision Level
Planning HKPIs	Number of days without failure (Last failure)	
	Number of days to next maintenance	
	Last inspection or maintenance	
Operational HKPIs	Overall Equipment Effectiveness (OEE)	
	Availability	
	Reliability	
	MTTR	
Maintenance cost HKPIs	Maintenance operation cost per production output over a period	
	Maintenance Spare part cost per production output over a period	
	downtime cost per production output over a period	
Performance Control HKPIs	Level of inspections, inspection repairs, and interventions	
	Corrective & Preventive maintenance level	
	Technological group failure level	
	Number of Intervention per machine function	
	Maintenance duration per machine function	
Equipment HKPI	RUL and state of the main component	

##### 3.1.2 Measurement methodology of HKPIs

The measurement of HKPIs is normally based on mathematical, statistical, and ML approaches. Some of the most important HKPIs are explained in the following: For the calculation of OEE, generally in the literature, the formula is like equation (1). However, in the WCM standard and professional maintenance book of knowledge, it is offered to add another managerial factor (M) that indicates the losses due to other causes (S. D'APRILE, 2020). The idea is to separate the losses due to the machine problem and the other losses. Calculation of availability requires some other criteria as Mean Time Between Failure (MTBF) and Mean Time to Repair (MTTR). MTBF considers only the operational times (not the calendar times) and the number of failures.

$$OEE = Availability \times Performance \times Quality \quad (1)$$

$$Availability \% = \frac{Operating Time}{Planned Production Time} = \frac{MTBF}{MTBF + MTTR} \quad (2)$$

$$Operating Time = Planned Production Time - Unplanned Downtime \quad (3)$$

$$Planned Production Time = Shift Length - Planned Downtime \quad (4)$$

$$MTBF = \frac{Total Hours of Operation}{Total Number of Failures} \quad (5)$$

$$MTTR = \frac{Total Hours of Maintenance}{Total Number of Repairs} \quad (6)$$



$$\text{Performance}\% = \frac{\text{Total Parts Produced}}{\text{Capacity}} \quad (7)$$

$$\text{Capacity} = \frac{\text{Operating Time}}{\text{Ideal Cycle Time}} \quad (8)$$

$$\text{Quality}\% = \frac{(\text{Total Produced items} - \text{Total Scrapped items})}{\text{Total Produced items}} \quad (9)$$

The aggregation methodology of the operational HKPIs is based on the dedicated weights to each machine. These weights are calculated based on two factors: 1. Production and 2. Profit level of product types that the machine is capable to process. Supposing to have two machines as A, B, and four types of products (Table 1), machine A produces type 1 and 2, machine B produces type 2,3 and 4.  $Prd_i$  and  $Prf_i$  are the general production and profit level of products.  $WF_j$  is the sum of the average value of two factors for the specified product types of each machine. Example: for machine B:  $WF_B: Prd_2 + Prf_2/2 + Prd_3 + Prf_3/2 + Prd_4 + Prf_4/2$ . Finally, the percentage of each  $WF$  is calculated regarding the two machines. This weight is dedicated to each machine for the calculation of global HKPI.

	Type1	Type2	Type3	Type4
<b>Machine A</b>	$\frac{Prd_1 + Prf_1}{2}$	$\frac{Prd_2 + Prf_2}{2}$		
<b>Machine B</b>		$\frac{Prd_2 + Prf_2}{2}$	$\frac{Prd_3 + Prf_3}{2}$	$\frac{Prd_4 + Prf_4}{2}$

Table 2. Example of the calculation methodology of global HKPI

**Reliability** is the probability that a system performs correctly during a specific time duration. The reliability distribution function is calculated based on failure rate  $\lambda$  (Woo, 2017):

$$\lambda = \frac{1}{MTBF} \quad (10)$$

$$R(t) = e^{-\lambda t} \quad (11)$$

### 3.2 RUL and State prediction

The overall process of data-driven methods for RUL prediction is based on (Fig. 2.)

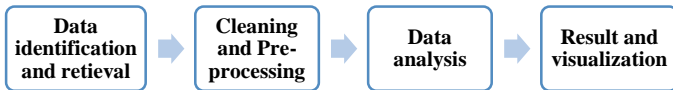


Fig. 2. Data science process

Normally, in the first step, the relating raw data is identified, then some pre-analysis and cleaning are implemented to make the data ready for the core analysis and getting valuable results. In general, there is  $n$  number of observations for  $m$  number of variables. The main source of data for RUL and state prediction is sensor data that are only a set of variables or features  $X_1, \dots, X_m$  and there is no associated response  $Y$ . It is proposed to use of PCA (which is a non-supervised approach) to pre-process the sensor data and identify most influencing parameters which represent the most variations. PCA method has been briefly explained in the next part.

#### 3.2.1 Principal Component Analysis

PCA tool is used to analyze multi-dimensional data to reduce the dimensions so as the dimensions represent as much as possible the variation (Jolliffe and Cadima, 2016). Each dimension of PCA analysis is a linear combination of the  $m$

variables (features). As an example, the equation for the first component (dimension) is:

$$Z_1 = \varphi_{11}X_1 + \dots + \varphi_{m1}X_m \quad (12)$$

$$\sum_{j=1}^m \varphi_{j1}^2 = 1 \quad (13)$$

Where  $\varphi_{11} \dots \varphi_{m1}$  are the loading of each feature for the first component. This is a normalized linear combination of  $m$  features. In order to find the best  $\varphi_{11} \dots \varphi_{m1}$  for the first component, PCA uses the optimization problem to maximize the variance of the observation that is subjected to  $\sum_{j=1}^m \varphi_{j1}^2 = 1$ . In the following linear combination of the observations for the first component and the optimization equation are presented:

$$Z_{i1} = \varphi_{11}x_{i1} + \dots + \varphi_{m1}x_{im} \quad i=1, \dots, n(\text{number of observations}) \quad (14)$$

$$\max \left\{ \frac{1}{n} \sum_{i=1}^n \left( \sum_{j=1}^m \varphi_{j1}x_{ij} \right)^2 \right\} \quad \text{st.} \quad \sum_{j=1}^m \varphi_{j1}^2 = 1 \quad (15)$$

The process for identifying the second and other components ( $Z_2, Z_3 \dots$ ) is the same, while there is a difference that the linear combination of  $Z_2$  should be uncorrelated to the  $Z_1$  and so on (James et al., 2013).

The result of PCA analysis is normally depicted in a bi-plot as in (Fig. 3) (Two components in 2D). As it is seen, green vectors represent variables loading vectors based on component 1 (PC1) and component 2 (PC2). Based on the loading vectors, the correlation of variables could be found. Furthermore, it shows the impact level of each variable (in terms of variations) based on proximity to the principal components. It should be noted that in PCA analysis, the raw data variables should be scaled before PCA analysis since each variable has its measurement units and variance. Without scaling, the interpretation will be biased.

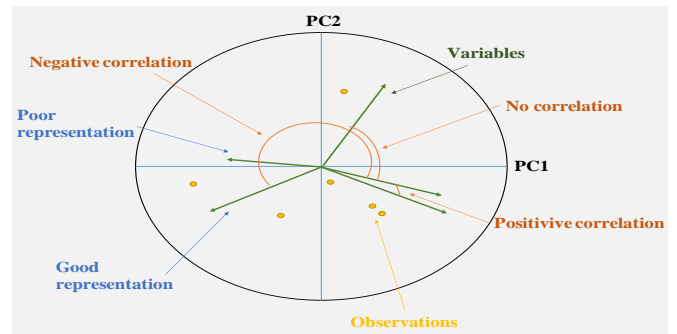


Fig. 3. PCA bi-plot and the interpretations

## 4. CASE STUDY AND RESULTS

FPT Industrial Company is a brand of CNH industrial and one of the leading world players in the 2-20 liter Diesel engines. This company has two main production lines as machining and assembly. In this study, three machines of cylinder head machining lines are considered for proposing the visualization dashboards in the machine and global point of view. It's important to notice that these dashboards are dynamic which means by changing data the dashboard will change automatically.

#### 4.1 Dashboard at Machine Level

Regarding the HKPIs in Table 1, the proposed dashboard at the machine level is illustrated in (Fig. 4). This is more pertinent to the operational and tactical levels. The component state indicator is discussed later. Here, the choice of HKPIs have been done mostly based on the experts views and literature study, however, there is a necessity for a study to be carried out to analyze the importance of HKPIs. It should be defined based on which criteria, HKPIs have to be classified and ranked. Then, based on this ranking the HKPIs should be presented in the dashboard.



Fig. 4. Dashboard at Machine Level

#### 4.2 Dashboard at Global or System Level

In global health monitoring, aggregation of HKPIs is quite important. Based on the aggregation methodology, Production level and profit level are two important factors as it is very important to give more weights to the machines that are producing more quantity. Furthermore, the machines that are manufacturing the products with more profit levels, can have more importance in terms of the production line. Aggregated HKPIs are calculated based on the present method in the previous section. The proposed Dashboard for the global level can be found in (Fig. 5).



Fig. 5. Dashboard at Global or System Level

#### 4.3 State prediction and RUL

As it is proposed in the methodology, PCA method has been used to monitor the state of components, in this study. With the application of PCA into the cleaned sensor data, the results have been obtained in terms of charts and information. It has been understood from the PCA bi-plot (Fig. 6) that the first and second principal components represent 71% and 17% (78% cumulated). This shows a considerable amount of variations within these two components that are acceptable. For this reason, it is proposed to monitor the PC1, PC2, and important sensor data in real-time to supervise the variations and stability of components. This is the state indicator that is included in the machine level dashboard and can be seen in (Fig. 7). Initially, we can bring raw data, however, it may not be necessary to bring all the raw data. We can get an aggregated HKPI by getting a correlation between the data with PCA method. This HKPI has been smoothed and various units of sensor data have been removed. This is a good basis for condition monitoring and further RUL or state prediction.

As discussed, the importance of RUL indicator formerly, the approach of this research is to include RUL indicator in the dashboard, however, due to some difficulties as lack of data and information (Like Run to failure data) RUL is not yet calculated and only the schematic vision of RUL is presented in (Fig. 7).

In terms of correlation, the bi-plot shows the high correlation between the speed and power consumption of the motor. The motor temperature has less correlation with speed and power, however, the motor current has more correlation. In (Fig. 7), it is seen the two important principal components of variations. In This case, real-time data displays a stable state of the CNC motor. Big deviations from the normal state that is continued for a considerable duration could represent mechanical or electrical problems in CNC motor.

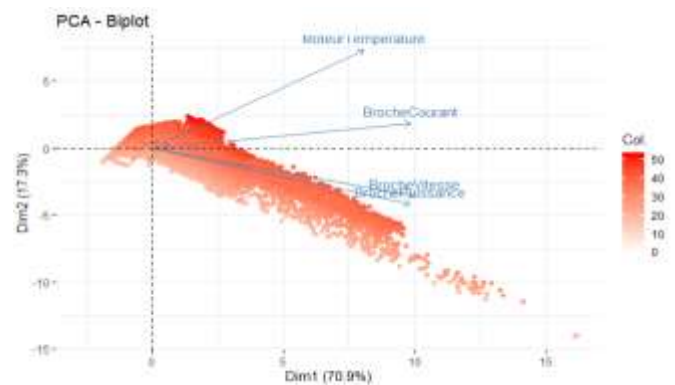


Fig. 6. The PCA bi-plot for the sensor data of CNC motor

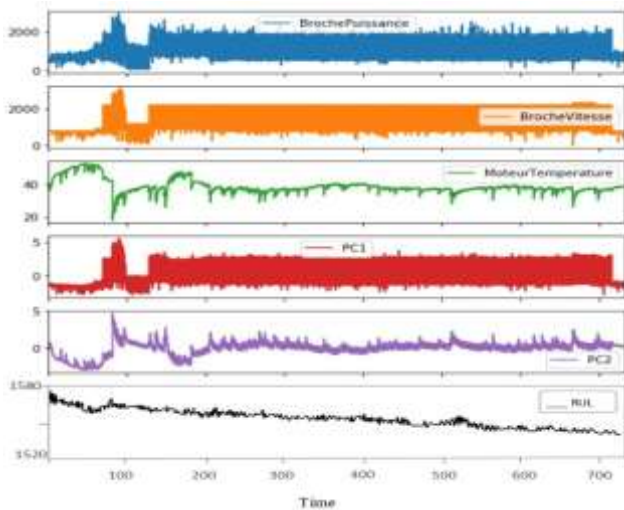


Fig. 7. PCA visualization regarding component state

## 5. CONCLUSIONS

Health monitoring and predictive maintenance approach have taken the attention of industries to optimize their production system. This study proposes an applicable methodology to support the industrial deciders in maintenance management. For this, it has been focused on the papers which are applied to a real case or could be useful for the devolvement of the new methods especially for the case of this work. Maintenance Key Performance Indicators is one of the topics, which are rarely discussed in the PdM literature. More challenges as, data acquisition from the existing databases, HKPI identification, and presentation, and the validation of proposed solutions by the industrial manager must also be met in an industrial case. Some important aspects in the HKPIs that have been less studied to the best of our knowledge are i) HKPIs aggregation for the global or system view and ii) Dedication of suitable decision level for each HKPI. In this paper, some new and pertinent HKPIs have been proposed, the appropriate decision levels have been allocated. In continue, the aggregation method is developed to have a valuable global vision of the production system.

Due to the necessity of access to real-time data, existing health monitoring systems are more applied in the continuous production systems and this is less considered in discrete production systems. ML techniques have been getting more and more attention in the literature on PdM topics, particularly in RUL or state prediction. However, reliable and accurate methods or algorithms are the challenge area of the researchers. One of the initial steps toward this objective is developing the right HKPI from real-time data. Based on this, a new HKPI has been proposed by using of PCA machine learning method to monitor the health state of components regarding the variations.

Regarding the HKPIs and the above-mentioned contributions, two dashboards have been proposed at the machine and system level for health monitoring of some chosen equipment. Comparing to the literature, the proposed dashboards benefit from both maintenance HKPIs and real-time health indicators and have been found more helpful for the decision-makers and validated by them.

The proposed approach can help decision-makers at different levels make the best decisions after tracking and evaluating the results represented by the dashboards, which saves time and money. While, the creation of a dashboard system is tied to the availability of data and data management system, which means if they are missing, the measurement and displaying an HKPI in the dashboard would not be possible.

As an overview of future works, finding suitable data-driven methodologies for the RUL prediction is still the challenging part of PdM and should be followed for the optimization of maintenance planning and spare part replenishment. In this way, transforming the dashboard into a decision support system that gives alarms and decision suggestions could be interesting points to be investigated.

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