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► To cite this version:

Maryam Mohammad-Amini, Behnam Einabadi, Armand Baboli, Reza Tavakkoli-Moghaddam. Determination of Health Key Performance Indicators and Their Visualization in the Production System in the Context of Industry 4.0. 2021 IEEE 8th International Conference on Industrial Engineering and Applications (ICIEA), Apr 2021, Chengdu, China. pp.126-131, 10.1109/ICIEA52957.2021.9436703 . hal-03616165

HAL Id: hal-03616165

<https://hal.science/hal-03616165v1>

Submitted on 31 Mar 2022

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Determination of Health Key Performance Indicators and Their Visualization in the Production System in the Context of Industry 4.0

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Abstract—Nowadays, maintenance and supervision of production equipment through health indicators are one of the key issues to improve the efficiency of manufacturing systems. On the other hand, the use of the Internet of Things (IoT), Cyber-Physical System (CPS), and other technologies in Industry 4.0 provide an enormous amount of data; however, the important point is how to analyze the related data and help managers in their decision-making process. The main objective of this paper is to study the problem of monitoring the state of machines and propose a health indicator system. Thus, different Health Key Performance Indicators (HKPIs) are defined and their measurements are discussed. Furthermore, the visualization of HKPIs is represented. The visualization of these HKPIs could be personalized based on the mission of each decision-maker, as top manager, intermediate manager, and technician. These HKPIs are calculated based on the available historical and real-time data and information of FPT Industrial Company.

Keywords—*predictive maintenance; health monitoring; data visualization; health indicator; predictive decision-making; industry 4.0*

I. INTRODUCTION

Industry 4.0 has been found as a potential solution in responding to the integration and optimization complexities of mass production systems through digital transformation. This possibility generates a large amount of data and information that needs to be analyzed. In this context, the main question is how to represent the results to help managers in their decision-making process. From the maintenance perspective, one of the main aspects concerns health monitoring and visualization of production machines. Health Key Performance Indicators (HKPIs) can be very useful to achieve this goal.

The first step in proposing a health monitoring system is to identify appropriate HKPIs. Then, measuring them with different approaches, such as Mathematics, Statistics, and Machine Learning which are considerable challenges. Afterwards, presenting them by using various visualization tools (e.g., different types of plots and charts) is another challenge. The main objective of this research is to propose a general process of having a health monitoring system

based on the information and data visualization. It should be noted that the corresponding and expressive decision levels are proposed for each HKPI. The following of this paper is continued by a review in Section II, the HKPIs methodology in Section III; application of the method in the case study and results in Section IV; and the conclusions and perspectives of future research in the last section.

II. LITERATURE REVIEW

Maintenance policies aim to increase the efficiency and availability of the production system because today, more efficiency, better performance, and lower costs are essential in competitive manufacturing industries [1]. Increasing productivity, reducing equipment downtime, reducing spare parts inventories, and reducing reworks are the various benefits of a proper maintenance system.

A. Maintenance Problems

Maintenance problems are divided into two groups, namely 1-maintenance planning, and 2-health monitoring and visualization. In the first group, four types of maintenance have been distinguished, namely Corrective, Preventive, Conditional, and Predictive Maintenance (PdM) [2]. The main concern is to develop suitable maintenance planning that minimizes maintenance costs and increases the production system availability. PdM deals with predicting defects, failures, or required maintenance actions through monitoring equipment, the Internet of Things (IoT), and digitization..

B. Health Monitoring and KPIs

In this paper, the focus is on the second group of maintenance problems. Health monitoring systems measure many parameters (e.g., vibration, temperature, and pressure) using various sensors to assess the health state of a system. Health monitoring can be used to monitor the integrity of systems in taking better decisions [3]. Health monitoring, fault diagnosis, and condition assessment are used in different industrial cases; for example, in gas turbines [4], in large wind turbines to understand the causes and effects of bearings [5], in rotating machines for diagnosis and prognosis [6].

Forecasting the future health of facilities plays an important role in PdM. Prognostics and Health Management (PHM) apply Key Performance Indicators (KPIs) to track the equipment health state [7]. KPIs generally play an important role in monitoring the performance of a company regarding its objectives, thus KPIs can influence the decision-makers. They can be used in different areas, such as energy, raw materials, control, operation, and maintenance [8]. Some standards have defined KPIs; for example, energy KPIs in ISO 50006 [9].

Several KPIs can be used to measure maintenance performance. [10] discussed different methods of measuring maintenance performance through KPIs, such as reliability, availability, maintainability, and safety at different levels. In general, maintenance KPIs are one of the topics, which are rarely discussed in the literature [11].

C. Industry 4.0

In the context of Industry 4.0, the equipment can communicate with computers because intelligent devices could integrate tools, organizations, and information systems for data sharing and exchange and real-time monitoring. Industry 4.0 refers to a wide range of concepts and technologies that include Cyber-Physical Systems (CPS) [12], self-organization, IoT, virtual manufacturing, and intelligent robotics and Artificial Intelligence (AI) [13].

D. Visualization

In a CPS, different sensors can be used to communicate between physical and computational parts. The application of IoT and CPS will provide access to data and information that will allow maintenance to evolve towards PdM. As the system has a lot of data for analysis and decision-making, managers expect a better visualization or analysis of the data. Data visualization helps humans to easily understand the data by using a variety of methods to interact with the data to discover hidden patterns in them [14]. One of its benefits is the incorporation of human capabilities into an intuitive visual interface. [15] introduced a visualization technique for the intuitive detection of anomalies which allows monitoring the machine state.

III. METHODOLOGY

To create an equipment health monitoring system, different HKPIs are required. In health monitoring, the use of HKPIs is essential. It should be noted that the indicators cannot provide the causes of failures; instead, they will display alerts to draw attention. In this section, the identification of HKPIs, their measurement and visualization will be discussed.

A. Identification of HKPIs

It is important to select and identify appropriate KPIs in manufacturing and processing operations. There are many KPIs in the literature [16,17]; however, in this paper, only those related to health monitoring are considered. In Table I, several new HKPIs are also added, such as planning, control, and equipment HKPIs.

The first and second columns show the name of the HKPIs and their description, respectively. The third column represents the data type needed for having the HKPIs, which can be maintenance historical data and information, or real-time sensor data. The fourth column is about the HKPIs measurement methodologies. The fifth column presents different types of plots and charts that can be used to visualize the HKPIs. And, the last column shows the most appropriate level of decision-making for each one of them. It is important to define the decision levels because each HKPI may not be appropriate for all levels.

1. Level one is related to the top manager, who is at the strategic level,
2. Level two is linked to the intermediate managers (maintenance managers and production supervisors), who are at the tactical level,
3. Level three is linked to the technician, who is at the operational level.

Note that in Table I, input data and information can be Maintenance Historical Data & Information (MHD&I), Real-time sensor data (RTSD), and Production & Quality Information (P&QI) and methodologies could be Mathematical Approach (MA), Statistical Approach (SA) and Machine Learning (ML) approach.

B. Measurement Methodology of HKPIs

HKPIs can be calculated using mathematical, statistical, and ML approaches. Simple mathematic formulas are used in mathematical approaches, while statistical approaches are mostly based on statistical data modeling. ML is an AI technique that attempts to help machines and learns from data and makes decisions with minimal human intervention [18]. ML approaches have been classified into three groups, namely: supervised learning, unsupervised learning, and reinforcement learning [19].

Planning HKPIs can be calculated using mathematical approaches. The main operational HKPIs is the Overall Equipment Effectiveness (OEE), which is based on three criteria: availability, performance, and quality (1). Availability indicates the level of uptime for each machine (2); uptime is the time when the machine is ready to operate. Performance is the percentage of produced parts number per its capacity (5), and Quality indicates the ratio of confirmed produced parts per total produced items (7). OEE is an appropriate productivity indicator of machines or systems.

The Mean Time to Repair (MTTR) is the average time spent on the repair process in the case of failure. It is different from the meantime to replace (MTTr), which is the average time it takes to repair/replace a defective component in preventive maintenance (8). Mean Time Between Failures (MTBF) is the average time between two failures of repairable equipment. It also refers to the average amount of time that a device or product functions before failing (9).

Reliability is the likelihood that a system will perform properly during a specific period (12). In other words, there are no repairs during operation. The reliability distribution function is calculated based on failure rate λ , which is the frequency of component failure per unit of time.

More details and calculation methods of operational HKPIs are given below:

$$OEE = \text{Availability \%} \times \text{Performance\%} \times \text{Quality\%} \quad (1)$$

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

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

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

$$\text{Performance\%} = \frac{\text{Total Parts Produced}}{\text{Capacity}} \quad (5)$$

$$\text{Capacity} = \frac{\text{Operating Time}}{\text{Ideal Cycle Time}} \quad (6)$$

$$\text{Quality\%} = \frac{(\text{Total Produced parts} - \text{Total Scrapped parts})}{\text{Total Produced parts}} \quad (7)$$

TABLE I. VARIOUS HKPIS

KPI	Description	Input Data & Information	Methodology	Form of visualization	Decision Level
Planning HKPIs	Number of days without failure (Last failure)	MHD&I	MA	Digit	3
	Number of days to next intervention (maintenance)	MHD&I	MA	Digit	3
	Number of Intervention per machine function per year	MHD&I	MA	Bar chart, Pie chart, Doughnut chart	3
	Percentage of the technological group (Mechanical, Hydraulic, Electrical...) failure	MHD&I	MA	Column chart, Pie chart, Doughnut chart	3
	Last inspection or maintenance	MHD&I	MA	Digit	3
Operational HKPIs	Overall Equipment Effectiveness (OEE)	MHD&I, P&QI	MA, SA	Pie chart, Doughnut chart, Gauge chart	1,2
	Availability	MHD&I	MA	Area plot, Gauge chart, Pie chart, Doughnut chart	1,2,3
	Reliability	MHD&I	SA	Density plot, Probability distribution plot	1,2,3
Control performance HKPIs	Number of inspections, inspection repairs & interventions (%)	MHD&I	MA	Bar chart, Column chart, Pie chart, Doughnut chart	1,2,3
	Over maintenance	MHD&I	MA	Bar chart, Gauge chart, Pie chart, Doughnut chart	1,2,3
	Reaction time	MHD&I	MA	Bar chart	1,2,3
	Percentage of corrective & preventive maintenance	MHD&I	MA	Bar chart, column chart, Pie chart, Doughnut chart	2,3
General HKPIs	Maintenance operation cost over a period	MHD&I	MA	Histogram, Line plot, Bar chart	1,2
	Maintenance Spare part cost over a period (inventory holding, shortage, obsolescence, etc.)	MHD&I	MA	Histogram, Line plot, Bar chart	1,2
	Downtime cost over a period	MHD&I	MA	Histogram, Line plot, Bar chart	1,2
	MTTR or Average of maintenance time	MHD&I	MA	Histogram, Box plot, Line plot, Bar chart, Gauge chart	2,3
	Maintenance duration per machine function	MHD&I	MA	Bar chart, Pie chart, Doughnut chart	3
	Number of alarms over a period	MHD&I	MA	Digit, Bar chart	3
Equipment HKPIs	RUL of the main component	MHD&I, RTSD	ML, SA	Density plot, Probability distribution plot	2,3
	RUL of machine	MHD&I, RTSD	ML, SA	Density plot, Probability distribution plot	2,3
	Equipment degradation	MHD&I, RTSD	ML, SA	Histogram, Line plot, Bar chart, Density plot, Probability distribution plot	2,3

$$MTTR = \frac{\text{Total Hours of Maintenance}}{\text{Total Number of Repairs}} \quad (8)$$

$$MTBF = \frac{\text{Total Hours of Operation}}{\text{Total Number of Failures}} \quad (9)$$

$$A(t) = \frac{MTBF}{MTBF + MTTR} \quad (10)$$

$$\lambda = \frac{1}{MTBF} \quad (11)$$

$$R(t) = e^{-\lambda t} \quad (12)$$

$$\text{Over maintenance} = \frac{(MTBF - TBTSI)}{MTBF} \quad (13)$$

$$\text{Reaction time} = \text{stoppage date of machine} - \text{starting date of maintenance} \quad (14)$$

Control performance HKPIs: These indicators are related to production speed and product quality. Inspection is a careful examination of a machine and/or a component to check its proper functioning. The inspection consists of visually checking the equipment; however, the intervention consists of acting after visually checking the equipment, such as repairing and replacing the defective part.

Over-maintenance involves performing maintenance activities more frequently than recommended by the supplier or replacing parts that still have considerable useful lives. In equation (13), TBTSI is the Time Between Two Successive Interventions on the same equipment.

It is important to mention that HKPIs could be calculated using data or knowledge (experience). In other words, many HKPIs can be calculated using data; however, others cannot. In these cases, the definition of upper and lower limits for each HKPIs based on the experience of experts may be an appropriate solution. In general, companies attempt to reduce over-maintenance to lower their costs.

Reaction time is defined as the time from receiving the request of maintenance till the starting time of maintenance. Decreasing the reaction time will result in downtime costs reduction and increasing availability (14).

The percentage of preventive and corrective maintenance can help to establish an objective rate for each machine to monitor and control the health state of each machine.

General HKPIs: Cost is one of the most important HKPIs, especially at the strategic level. There are three types of maintenance costs, such as the costs of maintenance operation (or labor), spare parts, and downtime. The downtime cost is related to the losses cost of production capacity and production resource due to sudden failures. For damaged or failed items, spare parts can be replaced. The cost of maintenance operation and the cost of spare parts are considered separately because, in the case of obsolescence of the spare parts, the cost could be higher, which shows the importance of those parts.

The number of alarms over a period is important as well. Some types of machines automatically send alarms related to different problems. It is important to track the correlation between alarms and failures, i.e. which type of alarm will cause which type of failure. These alarms also allow planning the maintenance activity. Thus, monitoring the number of these alarms could be an interesting HKPI for the operational level.

Equipment HKPIs: This type of HKPIs is quite important, while the calculations are more complex.

RUL is one of the most critical HKPIs in the health monitoring of equipment or machinery. There are different approaches for RUL prediction, such as model-based methods, data-driven methods, and hybrid methods [20].

C. HKPIs Visualization

Today, data visualization techniques are developing because of the constant change in data and the importance of transforming raw data into useful information. Data visualization is important for effective data analysis. Different types of plots can be used for KPI visualization [21]. For instance, a scatter plot or joint plot is a classic type of visualization allowing to visualize two numerical variables along two axes (Figure 1). Box plots illustrate ranges, minimum, maximum, and median values of a dataset, as well as first and second quartiles and outliers (Figure 2). The line plot, line chart, or seismograph chart displays information as a series of data points connected by a straight line. Time series are line plots that are useful for understanding trends over time (Figure 3).

The area plot is used when the area covered under a line plot is important. The greater the area is covered, the bigger the importance is (Figure 4). A bar chart shows categorical data with rectangular bars. The bar chart can be used to compare numerical values or data from several groups (Figure 5). A column chart is used to show a comparison between different attributes (Figure 6). A histogram divides data into several bins, then plots the frequency of data points in each bin (Figure 7). Pie charts show the proportions and percentages between categories using slices (Figure 8). The doughnut chart is similar to the pie chart, but with a hole in the middle. In the pie chart, the emphasis is on the size or area of the slices; however, in the doughnut one, the emphasis is on the length of the arcs (Figure 9). Gauge charts are a combination of pie and doughnut charts. They show the maximum, minimum, and current values of the data. There are different types of Gauge charts, such as the Speedometer (Figure 10), Rating meter (Figure 11), etc. A density plot is similar to an abstracted histogram, but instead of each bin, it has a smooth curve (kernel) through its top (Figure 12). Probability distribution plots are used to understand the distribution of data for a continuous variable. In prediction, forecasting, or finding trends, this kind of plot can be used (Figure 13). The heat map shows the correlation between all the features in a dataset using different colors (Figure 14). Pair plots are used to plot all possible joint plots for each pair of variables. In other words, it shows which variables are dependent or interdependent (Figure 15).

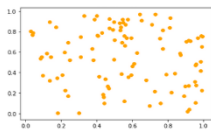


Figure 1. Scatter plot

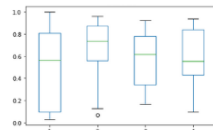


Figure 2. Box plot

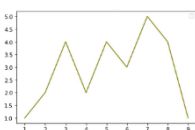


Figure 3. Line plot

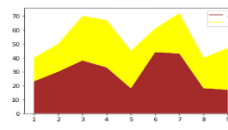


Figure 4. Area plot

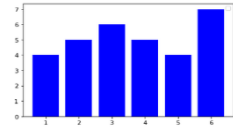


Figure 5. Bar chart

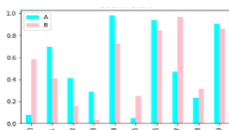


Figure 6. Column chart

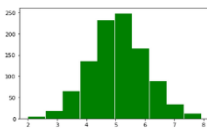


Figure 7. Histogram

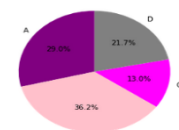


Figure 8. Pie chart

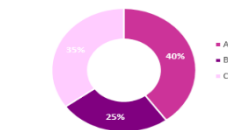


Figure 9. Doughnut chart

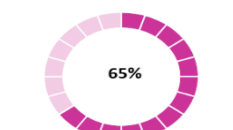


Figure 10. Speedometer

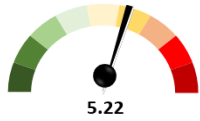


Figure 11. Rating meter

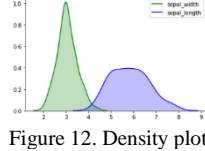


Figure 12. Density plot

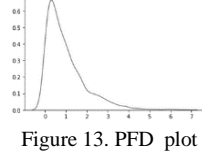


Figure 13. PFD plot

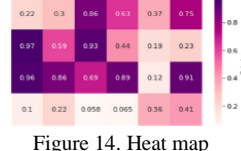


Figure 14. Heat map

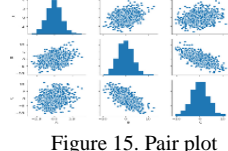
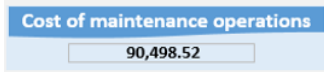


Figure 15. Pair plot

IV. CASE STUDY

This paper uses the data and information of FPT Industrial Company. FPT Industrial is a CNH Industrial Group company and is specialized in the design and production of diesel engines. Three machines of a cylinder head production line of FPT Industrial are considered for proposing a health indicator system. It is necessary to note that in each company different HKPIs could be considered due to the available data and information, which come from Enterprise Resource Planning, Manufacturing Execution System, and Maintenance Management System with various formats. Therefore, data cleaning and pre-processing are required. Note that some HKPIs cannot be shown by charts and graphs, they will be shown by digits because they are numeric values. For instance, the cost of maintenance operations (labor) based on information from previous years are visualized by digits.



In the following, some of HKPIs are calculated based on some example data and the already presented methods.

$$MTTR = \frac{\text{Total Hours of Maintenance}}{\text{Total Number of Repairs}} = \frac{5415}{94} = 5.76 \text{ h} = \quad (15)$$

$$\frac{5.76}{8} = 0.72 \text{ day}$$

The MTTR can be displayed as a gauge chart (Figure 16) that can be dynamic. The gauge chart shows not only the Min and Max values but also the current position.

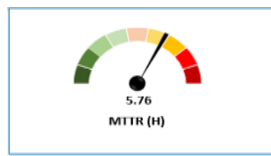


Figure 16. MTTR

For all the machines in the cylinder-head line, the number of working days in four years from 2017 to 2020 is 667. It should be noted that the MTTR and MTBF are also calculated based on four years' information.

$$MTBF = \frac{\text{Total Hours of Operation}}{\text{Total Number of Failures}} = \frac{667}{89} = 7.49 \text{ day} \quad (16)$$

As the MTTR and MTBF values are calculated, the availability of the machine is computed as follows:

$$\text{Availability} = \frac{MTBF}{MTBF + MTTR} = \frac{7.49}{7.49 + 0.72} = 0.91 \quad (17)$$

Availability can be displayed as a gauge chart (Figure 17).

As an example, Reliability is calculated for one of the machines, based on the following equations:

$$\text{Reliability} = e^{-\lambda t} \quad (18)$$

$$\lambda = \frac{1}{MTBF} = \frac{1}{7.49} = 0.13 \quad (19)$$

Reliability can be displayed as a probability distribution plot. (Figure 18) shows the probability of machine reliability as a function of the operation days.

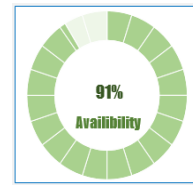


Figure 17. Availability

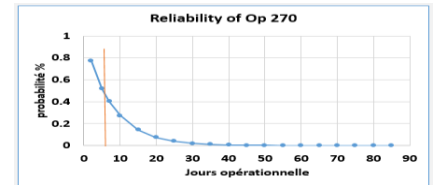


Figure 18. Reliability

The number of interventions per machine function per year indicates the most important functional group of the machine that has led the most maintenance operations. It can be shown as a horizontal bar chart (Figure 19).

The percentage of technological group (e.g., Mechanical, Hydraulic, and Electrical) failure is displayed as a pie chart (Figure 20).

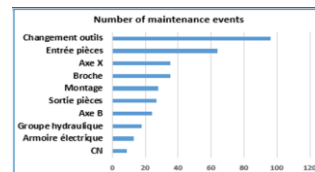


Figure 19. Horizontal bar chart

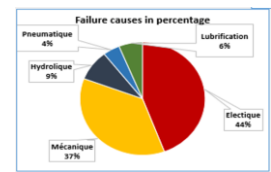


Figure 20. Pie chart

Time series data can be visualized as line charts. (Figure 21) shows the monitoring of power consumption (sensor data) over two weeks.

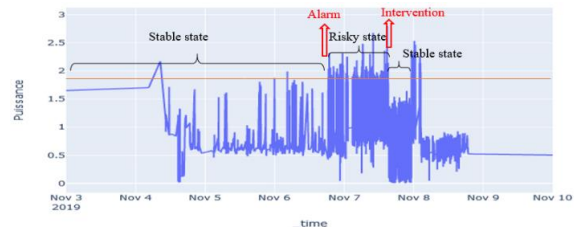


Figure 21. Time series

V. CONCLUSION

Nowadays, not only the flexibility and agility but also the efficiency of a manufacturing system is important to meet customer demands and market competition. In this context, the availability and reliability of the manufacturing system play an important role. It is attracting attention to implement health monitoring systems and predictive maintenance using historical data and information. Industry 4.0 could provide access not only to historical data and information but also to real-time data [22]. This paper focuses on proposing a health indicator system and finding the process for its monitoring using historical and real-time data and information. This involves identifying the best HKPIs for health monitoring, proposing the measurement methods, and considering various plots and charts for their visualization

Health monitoring and predictive maintenance approach have attracted the attention of industry decision-makers and researchers to improve the efficiency and availability of the production system. There are many articles on maintenance planning, however, visualization and monitoring have rarely been discussed before. The first step in equipment health monitoring concerns the identification of health monitoring indicators, so, HKPIs are key elements not often discussed in the PdM literature [8]. In this paper, first of all, many HKPIs were presented and appropriate HKPIs were identified according to the industrial requirement. Then, the measurement methodology, including mathematical, statistical, and ML approaches, was discussed. Afterward, different types of data visualization in the form of plots and charts were presented. The best plots for the visualization of each HKPI were even proposed. It should be noted that the simultaneous consideration of the identification, measurement, and visualization of HKPIs, as well as the definition of decision levels for them, is a new research topic. This approach was applied in the automotive industry. Data and information from FPT Industrial were used in this study.

Following this study, the dashboard proposition can be an interesting subject for future work. As already mentioned, the RUL is one of the most important HKPIs in health monitoring and PdM. The application of various methods to predict the RUL and their comparison can also be considered in future studies.

ACKNOWLEDGEMENT

We would like to thank FPT Industrial Company for their help, allowing us to use their data and information. We would also like to thank Pania BABOLI for her help in editing of this paper.

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