Experiential learning of Prognostics and Health Management and its implementation in MATLAB

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Abstract: Nowadays, smart factories more and more rely on key enabling technologies to optimize the management of operations. In the maintenance context, predictability is a major characteristic required for advanced monitoring and controlling systems, embedded in Cyber-Physical Systems (CPS), which are the building blocks of smart factories. As such, methodologies and tools proper of the Prognostics and Health Management (PHM) body of knowledge, represent the background on which a company should build their competitive advantage. However, promoting the application of PHM in current industrial scenario is not only a matter of digital technologies, but it encompasses engineering methodologies. These methodologies should be made available to learners so to transfer knowledge to industry. Therefore, a learning-by-doing approach is proposed, which aims at showing how the current software tools provide per se a complete platform for PHM for teaching purposes, without a strong requirement of real testbeds, at least at first sight. Also, the selection of MATLAB allows to transfer knowledge to learners with few or no programming skills. It is demonstrated how the engineering methodologies and tools underlying a robust PHM system could be developed during lectures independently from the availability of a laboratory or industry-like environment if the key characteristics of PHM are properly formalised. Therefore, the basic idea is to support the dissemination of a practical background about PHM, both in physical and virtual classrooms, aimed at providing advanced understanding of CPS-based smart factories.

Keywords: Prognostics and Health Management, PHM, maintenance, teaching

1.Introduction

Recently, the growing advances in digitalization of processes and systems have led to the next generation of manufacturing technologies by introducing the concept of smart factories. This concept is framed into the paradigm of Industry 4.0 where the manufacturing systems are defined as intelligent systems that rely on key enabling technologies to optimize the management of operations. Cyber-Physical Systems (CPS) are the building blocks of smart factories and predictability is one of their fundamental characteristics (Lee *et al.*, 2017, Napoleone *et al.*, 2020). As such, they impact on both production and maintenance management. The latter is particularly gaining momentum due to the potentialities offered by the above-cited systems to have a deep and detailed knowledge of the current state of the machine and support diagnostics and prognostics analyses (Guillén *et al.*, 2016). As such, Prognostics and Health Management (PHM) is becoming a relevant engineering discipline on top of which companies are making their competitive advantage. It represents the key to understand the machine health state, hence promoting field-synchronized and automated decision-making (Negri *et al.*, 2020). To fulfil this purpose, PHM consists of two main tasks (Teixeira, Tjahjono and Alfaro, 2012): fault detection, and diagnosis and health management. Due to its importance, PHM has gradually matured to practical field applications receiving attention from both academia and industry. Therefore, a number of literature reviews on this approach have been proposed based on different perspectives (Si *et al.*, 2011; Lee *et al.*, 2014; Vogl, Weiss and Helu, 2016; Weiss *et al.*, 2016; Atamuradov *et al.*, 2017; Javed, Gouriveau and Zerhouni, 2017; Lei *et al.*, 2018; Xia *et al.*, 2018). The design of a framework for PHM implementation is challenging and application-specific, since it depends on the assets to be monitored, or on the criticality of component characteristics. Hence, different aspects such as data acquisition techniques, models and tools, and historical information should be taken into consideration to develop the most appropriate PHM approach. Moreover, PHM is not only a matter of applying digital technologies and advanced analytics to data already available. It requires a deep understanding of the asset of interest, which is a pre-requisite to develop a PHM approach fit for purpose. The hard skills and analytic mind-set should be profound in the learners, being them engineering students, post-graduates, or practitioners, to let them be aware of the need for a strong engineering background. Therefore, it is worth to establish an experiential learning approach that supports transferring the basics of PHM in an easy way.

Given these premises, the goal of this work is to propose a learning-by-doing approach to understand the basics of

PHM. The approach is thought for its application in physical and virtual classrooms. The core idea is to develop an experiential learning to gain conceptual insight and practical expertise without a strong requirement of real testbeds but leveraging on the integrated solutions provided by MATLAB. This experiential learning will be available for all the people involved in the development of PHM, from students to practitioners. After a recall on the basics of PHM in Section 2, the reasons behind the selection of MATLAB are reported in Section 3. Then, Sections 4, 5 and 6 explores some of the functional blocks in the PHM process, explaining how to implement them easily in MATLAB. Section 7 summarises the last steps of PHM. Finally, Section 8 reports first results from a preliminary application in a controlled environment and Section 9 draws some conclusions.

2.Prognostics and Health Management basics

The PHM process consists of different functional blocks or levels as reported in OSA-CBM (ISO-13374-1, 2003) specification (Figure 1). The firsts two levels, named L1 and L2, are data acquisition (DA) and data manipulation (DM), respectively. The former is the process of data collection and storage through sensor-based technology enabling physical connection with relevant data sources (asset, systems, controllers, etc.) to monitor their status. The latter involves data pre-processing (i.e., denoising, cleaning, integration, normalization) and feature extraction and selection to improve both quality and reducing redundancy (i.e., dimensionality) of data, aimed at converting it into a proper space for future analysis. The third level L3 is the state detection (SD). It is the process of detecting the asset' state to identify the failure mechanism and it involves two different stages: (i) an ex-ante analysis of the working states based on determining the relationship between cause and effect of a failure event; (ii) an ex-post analysis (after models' application) of working states based on defining the rules for alerting and isolate the failure when is detected.

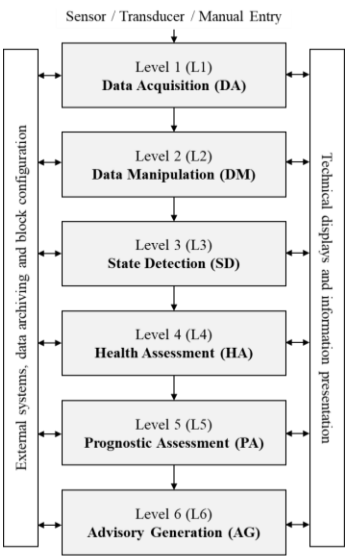


Figure 1: PHM architecture from ISO 13374-1, 2003

The level L4 is health assessment (HA), which consists of the analysis of current asset' health state combined with assessment reports to support the implementation of a proper maintenance plan for the monitored systems. The L5 is the prognostic assessment (PA) level, which aims to predict the remaining useful life (RUL) according to the future health state and usage trends of the monitored systems to support proactive decision making. Finally, the level L6 is the advisory generation (AG). It consists of the analysis of the information content for each alert, based on the diagnostics and/or prognostics results, to generate recommended actions for maintenance tasks and to define normative-based KPIs (Key Performance Indicators). Conversely, the SD is the core block of PHM resulting propaedeutic to next ones since it allows the identification of working states useful to normalise HA and PA results. It is in the scope of the proposed learning-by-doing approach to retrace the blocks from DA to SD, given their relevance. The experiential learning is favoured using MATLAB, whose selection is cleared out in Section 3.

3.Reasons behind the selection of MATLAB

The selection of MATLAB to support the experiential learning experience in PHM is due to several methodological and technological reasons:

1. MATLAB can follow all the six levels of the PHM (Figure 1), from DA to AG. Especially, in relation to DA, MATLAB has the OPC Toolbox (link), which allows to leverage upon the OPC-UA protocol (Open Platform Communications – Unified Architecture), and MQTT (Message Queuing Telemetry Transport) via the ThingSpeak IoT platform (link) by MathWorks.

2. MATLAB has a set of toolboxes and apps that allows even beginners to apply advanced analytics and get insights on the data, (almost) without the need to know how to program in MATLAB, for example: Signal Processing Toolbox (link) Classification Learner Toolbox (link), Predictive Maintenance Toolbox (link), Curve Fitting Toolbox (link).

3. MATLAB has a free trial with full potentials, and it is also available for free with downgraded performance. In the latter case, the functioning is online only (link), with few cores reserved and adequate storage, accessible via browser for PCs, tablets, and smartphones. Moreover, for tablets and smartphones the MATLAB Mobile app (link) is available, used in the remainder, too.

Besides, it is worth underlining that the selection of MATLAB is grounded on the availability of all these solutions in a single and standalone software tool. For the purposes of this work, it is possible to collect real-field data from sensors without the need to generate random ones through algorithms. Eventually, also Python could be used, even though more programming skill is required. Therefore, the proposed approach is especially fitted for those classes that require a fast understanding on the topic (e.g., maintenance engineers from industry) or students with few programming basics that anyhow need a to get a flavour on PHM.

3.1 MATLAB for PHM

In the following sections, the goal is to retrace the first three functional blocks of the ISO 13374. Details on how each block could be performed in MATLAB are provided. As a support throughout this work, in Figure 2 a mapping between the MATLAB functionalities and the PHM process is realised.

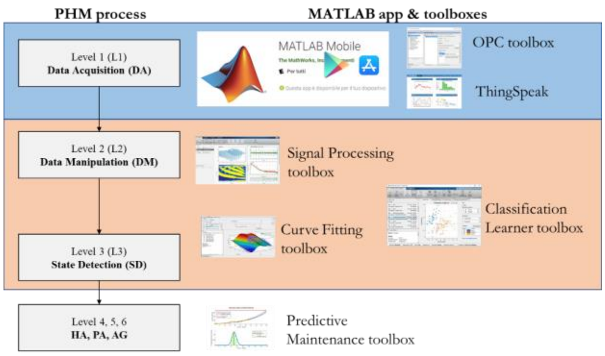


Figure 2: Mapping MATLAB functionalities with PHM functional blocks

As anticipated, in this research only the DA, DM, and SD are tackled for their relevance in PHM. Furthermore, some theoretical tips for each block are provided to complement the usage of MATLAB. Therefore, in this work the authors stop at SD, but the lecturer could go far beyond to improve the learning experience.

4. Level L1 - Data acquisition

The acquisition of data is the first and fundamental block since raw data from various sources are identified and collected. It is crucial to let the learners understand that different kinds of data could be collected from the field. Understandably, the effectiveness of a PHM process implementation strongly depends on the choice of this set of variables to be monitored. According to (Jardine, Lin and Banjevic, 2006), *"data collected in a PHM program can be categorised into two main types: the so-called event data and condition monitoring data"*. Event Data (ED) includes the information on what happened (e.g., installation, breakdown, overhaul, etc.) and what the causes were and/or what was done (e.g., minor repair, preventive maintenance, oil change, etc.) to the selected physical asset, i.e., the machine. Condition Monitoring Data (CMD) includes instead the measurements related to the health condition/state of the physical asset (e.g., vibration data, acoustic data, temperature, pressure, humidity, environmental data). Said CMD types are the following: Value Type, when data collected at a specific time epoch is a single value (e.g., temperature, pressure); Waveform Type, when data is a time series (e.g., vibration data, acoustic data); and finally, Multidimensional Type, when it is, trivially, multidimensional (e.g., image data such as infrared thermographs, visual images, X-ray images). Given the possibilities offered by MATLAB, only CMD could be reproduced and used for PHM purposes since invented ED could be only speculative and misleading. Therefore, the lecturers and the learners should be aware that in this learning-by-doing approach, it is only possible to get in touch with CMD and elaborate over it. Thus, the MATLAB Online app for smartphone is used as data acquisition system, installed on an Android mobile phone with 6 GB of memory and 64 GB of storage. The app allows to activate several sensors of the mobile phone, like accelerometers, gyroscope, magnetic field sensors and even camera. Figure 3 provides a screenshot of the app, whose documentation could be found at the following link. The sampling frequency is set to 10 MHz but is tuneable depending on the final purposes.

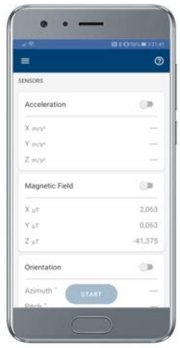


Figure 3: MATLAB Online app

As far as this approach concerns, the OPC Toolbox and ThingSpeak could not be adopted since they require a real asset with installed sensors. However, these toolboxes and applications should be known by the learners since they ease the data collection in real industrial scenarios.

Before to proceed with the description of the data collection, an excursus on how the simulated behaviour of a general machine could be realised is needed, as explained in subsection 4.1.

4.1 Replication of machine behaviour

The behaviour of a machine highly depends by the current type of machine under analysis. For example, industrial centrifugal pumps have generally a design point. Thus, apart from very specific needs, plant owners typically set the pump to work at specific rpm (revolutions per minute) and head (H, related to the kinetic energy of the fluid). Again, CNC (Computer Numerical Control) machine tools have several part programs that could be realised, and the axes and the spindle could work at various speeds, orientations and so forth. These are two examples of machines whose behaviour is radically different. However, independently from the machine type, the PHM must be able to discern between the different operations in which the machine could be (Wang *et al.*, 2019).

Therefore, it is worth assuming a machine that has four different operations. The operations are represented by emulating four different movements of the mobile phone, whose sensors allow to register some relevant variable useful for PHM. Thus, the data collection performed with MATLAB is organized in such a way. In this work, only the accelerations are reported for the sake of simplicity, but as anticipated, multiple sensors could be activated on the mobile phone. The emulated movements start from the origin of the reference system (see Figure 4). Movements 1, 3 and 4 are performed in a similar way, that is, replicating the same accelerations. Movement 2 is the same as movement 1 but its accelerations are doubled.

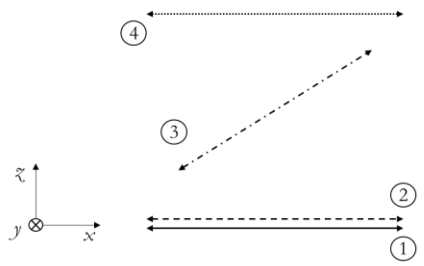


Figure 4: Schematic representation of the movements, i.e., the operation, reproduced by moving the phone

Once the MATLAB Online app is activated, i.e., the embedded sensors are ready to collect data, the movements have been reproduced in series, from 1 to 4. Indeed, it is a given some noise due to the movement by hand, but noise is typical also of industrial applications. Therefore, the CMD of waveform type is collected, namely, the acceleration signals from the accelerometers, reported in Figure 5 for the three axes.

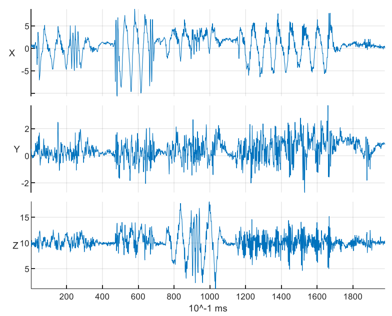
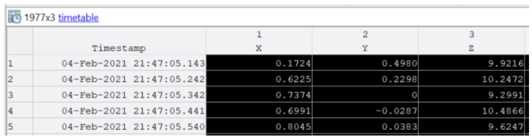


Figure 5: accelerations measured on the x, y, and z axes through the mobile phone

The collected signals are of "timetable" format in MATLAB, but, if needed, they could be converted to array for easier manipulation. The generated table has the following variables:

- **Timestamp**, which includes date and time of the sample, e.g., 04-Feb-2021 21:47:05.143.
- **X**, which includes the sample of the acceleration on the x axis.
- **Y**, which includes the sample of the acceleration on the y axis.
- **Z**, which includes the sample of the acceleration on the x axis.

Each **X**, **Y**, and **Z** could be understood as time-series and timestamp and axes are presented as a matrix, as shown in Figure 6. If additional sensors are activated, then other timetables are generated, one for each type of sensor (see Figure 7), always with the associated timestamp for each sample. As shown in the remainder, even in this simple practical experience, the learners will understand the impact of missing sensors and the importance of avoiding a complete data-driven approach to the problem: the engineering and industrial experience remains a cornerstone of PHM applications, translated in this case in the knowledge of the different operations.


1977x3 timetable

	Timestamp	1 X	2 Y	3 Z
1	04-Feb-2021 21:47:05.143	0.1724	0.4980	9.9216
2	04-Feb-2021 21:47:05.242	0.6225	0.2298	10.2472
3	04-Feb-2021 21:47:05.342	0.7374	0	9.2991
4	04-Feb-2021 21:47:05.441	0.6991	-0.0287	10.4866
5	04-Feb-2021 21:47:05.540	0.8045	0.0383	9.6247

Figure 6: The generated "timetable" in MATLAB when collecting the accelerations on the three axes

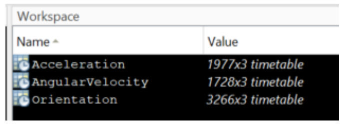


Figure 7: Each timetable includes signals for each type of sensor e.g., accelerometers for Acceleration

Indeed, thanks to this a priori knowledge, it is possible to manually associate a categorical variable (in this case 0, the setup, and from 1 to 4, for the movements, respectively) so to establish a supervised experiment for the subsequent SD phase (see Section 6).

5. Level L2 - Data manipulation

In this case, the data are collected so to have very low random noise, no missing data and outliers. Nevertheless, if interested, these classic and general characteristics impacting on data quality could be reproduced in the dataset for learning purpose. Therefore, the only relevant phase within the DM block is feature engineering. In this block, it could be possible to use the Signal Processing Toolbox in MATLAB to study more thoroughly the collected signals. However, in authors' teaching experience, it may be better to implement some very basic coding operations. For example, with very few programming lines (the used functions are mean() and std(), whereas the CV, coefficient of variation, is the ratio of the two, i.e., std()./mean()), it is possible to make an explorative analysis of the data, as reported in Table 1.

Table 1: Explorative analysis

	Mean [m/s^2]	**Standard deviation** [m/s^2]	**CV**
Axis x	0.6593	2.8617	4.3405
Axis y	0.4333	0.7177	1.6562
Axis z	10.1230	1.8509	0.1828

It is relevant to underline the relevance of an explorative analysis since signals with high CV are likely to hide additional information content. To this end, additional elaborations are needed, and new and more complex features could be adopted.

5.1 Details for feature engineering

Despite expecting to apply a supervised or an unsupervised method in the SD phase, the feature engineering remains pivotal for a well-performing PHM process. Therefore, the learners should be aware of the importance of extracting and selecting the correct features from the signals. There are two "directions" on which to act: i) the domain (time, frequency, time-frequency), and ii) the type of feature (mean, standard deviations, Kurtosis, FFT, etc.). Even in this learning experience, the selection of a specific domain brings to different results. The selection of some features among all the possible ones, could be made in various way, e.g., by applying the PCA (Principal Components Analysis). It is not in the scope of this learning experience to deep dive into this feature engineering phase, that resides under the hat of "signal processing", so the attention is given to a simpler case, in which selection is made a priori. Indeed, in the time domain, as an easy, yet meaningful feature, the RMS is adopted since it is well used in scientific and industrial literature given its capability to represent the energy dissipated via increasing vibrations (Cattaneo and Macchi, 2019). Therefore, for the three signals, one per axis (x, y, and z), the RMS is calculated, leading to three features: RMS_x, RMS_y, and RMS_z. In Figure 8, the RMS is calculated after a proper partitioning of the signals, based on the available knowledge of the operations.

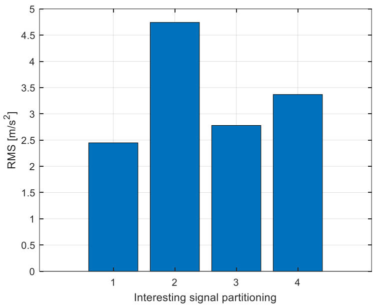


Figure 8: RMS_x evaluated for the four operations (identified via the additional labels during DA)

The RMS on the x axis shows that there are at least two main "families", called working states: the first one groups together 1, 3 and 4, while the second group has 2, only. Therefore, it is possible to assume at least two working states since, within the first group, there is no statistical difference between RMS for 1, 3, and 4.

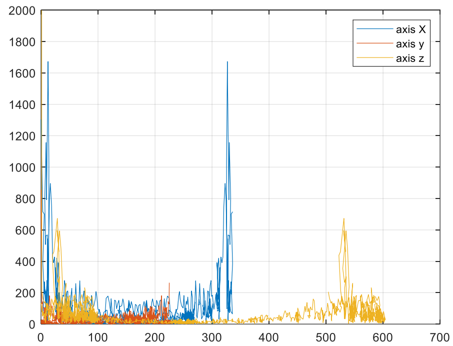


Figure 9: Frequency spectrum

On the other side, when analysing the frequency spectrum, thus in the frequency domain, reported in Figure 9, it is possible to see three main peaks, two on the x axis and one on the z axis. Thus, it is possible to conclude that there are at least three main working states the machine experiences in this case. Therefore, the analyses show different pitfalls:

- Movements 1, 3 and 4 are not distinguished by the RMS.
- Movements 1 and 4 are not distinguished by the frequency analysis.

In this specific case, the frequency analysis shows better results if compared to the time-domain analysis with the RMS. However, the working states are anyhow confused since 1 and 4 would have required an altimeter to be distinguished.

Moreover, it is worth underlining the different results an unsupervised or a supervised approach could lead to:

- In an **unsupervised approach**, there is no way to evaluate the goodness of the two analyses since the operations are not labelled. The only conclusions that could be drawn is that the frequency spectrum distinguishes more working states than the RMS. This case is more challenging, but it represents a real case when the production plans are not available for the machine, and so it is not possible to identify the different operations from the very beginning.
- In a **supervised approach**, it is possible to evaluate the goodness of fit since the operations are identified and labelled. Therefore, it is possible to conclude that none of the two features is able to correctly characterise the operations, since the identified working states are less in number. However, the analysis in the frequency domain outperforms the one in time. This approach could be adopted when the production plan is clearly retraceable in the company and, also, when the maintenance reports are available since some working states could represent abnormal operations.

Therefore, it is possible to understand that, even in the controlled environment in which this experiment is carried out, the data analysis reveals some shortfalls that are important lessons learnt for unexperienced students. According to authors' industrial experience, it is important the learner could manage both unsupervised and supervised approaches; he/she should be aware of the shortfalls each approach has. Indeed, it is relevant to understand that a complete data-driven approach must be supported by an adequate understanding of the industrial/engineering problem. Maintenance engineers and operators' knowledge is fundamental to implement a well-performing PHM since they could help in assessing the results of the feature engineering and then the identified working states could be verified. The knowledge of the working states unleashes the development of a Novelty Detection (ND) approach in the SD phase, which allows to identify anomalies in the current behaviour of the machine.

6. Level L3 - State detection

Fixed the results in level L2, the ND approach by (Pimentel *et al.*, 2014) could be retraced. The health of the asset is modelled to represent its normal state, to detect, in such a way, any novelty (or abnormality) once it appears in the system. The learner should be aware, at this point, of the importance of knowing and considering the different working states. Indeed, a novelty in the system could arise for different reasons: it could be due to a new operation the machine is performing and therefore the machine's state is different from all the ones previously registered. Or, conversely, the novelty could be caused by a degradation process in evolution, that again, results in a different machine's state. Assuming the labelled working states, that is, connected with the machine's operations, a supervised learning approach could be established. As for this experiential learning, it is suggested to follow this approach at first since the unsupervised one is more challenging (remind that the operations should be manually associated to the gathered signals in MATLAB for the supervised approach). Therefore, the Classification Learner Toolbox of MATLAB is adopted to develop a classification algorithm. The selected and extracted classification algorithm can be used in a ND way. Indeed, if the algorithm is misclassifying an observation, this could be because the observation is moving away from its normal behaviour. In the following, Figure 10 reports a picture to visualize one of the results when the RMS feature is used for running the Classification Learner toolbox.

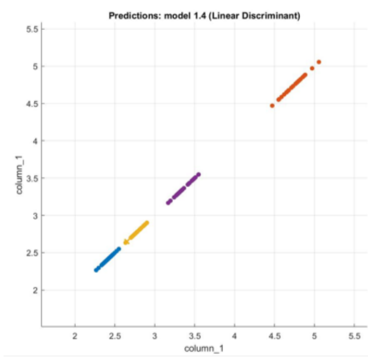


Figure 10: Classification Learner results considering the RMS in the x direction. The linear discriminant algorithm has reached an accuracy of the 99.2%

In this case the learner can use some simple functions present in MATLAB (i) to prove the normality of data, for example using the kstest() function (link) and (ii) to build a control chart (link).

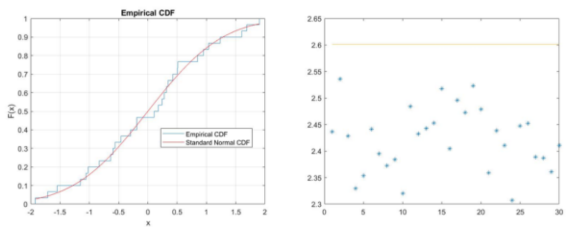


Figure 11: Empirical distribution of RMS in x direction (left) and a control chart for eventual alerting (right)

In this experiential learning, the RMS of each working state is described through a normal distribution and a control chart is properly established. See Figure 11 for details. If an observation falls over the threshold, an outlier (so, an anomaly/abnormality) has appeared in the system and the "machine" is likely experiencing a new state in terms of health. Therefore, with these approaches, the learner is aware that several ways could be followed to implement a SD and ND. Conversely, a probabilistic ND approach is applicable, trying to describe each working state using a probabilistic distribution function. The distribution is then used to set up a control chart for controlling the health state of the system, see for example (Fumagalli *et al.*, 2019). In practice, the selection of the approach could be bounded by some limits of the data and of the available engineering knowledge of the problem.

7. Completing the PHM process

In the scope of this work, the learning-by-doing approach stops at SD. However, the lecturers could complete the PHM overview by listing some takeaways for the learners, hereinafter summarised according to authors' industrial experience. The next functional block of the ISO 13374 includes the HA. Indeed, so far, none has been said about the asset be in healthy, abnormal, or faulty state. Two options are available:

- If the data are collected under controlled conditions, it could be known a priori if the working states refer to the healthy state.
- If the data are collected during the normal asset operations:
    - If maintenance-related knowledge, e.g., reports, is available, then it may be possible to correlate some working states with some ED (events).
    - If no additional knowledge is available, then nothing could be said about the health state of the asset.

Therefore, for the HA, the knowledge of the asset and of the surrounding industrial context is fundamental. For PA, in MALTAB there exist some built-in functions that could be used to project the features in the future and to forecast their behaviour. In this case, the Predictive Maintenance Toolbox could be used, upon the establishment of an extensive data gathering campaign together with real time collection. Finally, the AG is fostered in MALTAB by the usage the MATLAB App Designer that allows fast prototyping of a graphic user interface. However, these functional blocks are outside the scope of this work, but could be implemented if required, with suitable assumptions.

8. Considerations from a controlled application

The approach was tested in the research group, with the involvement of three researchers. The main goal was to identify technical pitfalls that may arise, that have been identified as:

- The saving of the data on the mobile phone could fail for various reasons (Internet connections, problems with MATLAB account).
- Since the realised dataset is built as a structure in MATLAB, some command line / hints must be provided to support learners in the experience.
- For the supervised approach (classification), the collected dataset must be manually modified by adding operations' labels (0, 1, 2, 3, 4).

It is worth to take into account this before starting this learning experience. Moreover, there are some additional organisational shortfalls and constraints that need to be tested in class. These will be explored for future works.

9. Conclusions

In this work, a learning-by-doing approach for PHM is described and implemented. It could serve as a basis on which to develop an experiential learning at various levels, from university students to practitioners. The proposed approach is implemented in MATLAB as it is a standalone software tool capable to exploit all the functional blocks of the ISO 13374-1 without strong coding skills. The idea finds its root in the current situation where virtual classrooms are mandatory due to pandemic. However, this change may be less temporary than thought since long-distance courses have been favoured, e.g., in other countries, and is even expected to increase over time. Moreover, the willingness behind this paper is to promote also an adequate experiential learning without the strong requirements of real physical assets. The proposed MATLAB-powered approach is independent from machines from which to collect data. Undoubtfully, gathering data in industrial context is an incomparable value-added to teaching and learning PHM. Hopefully, this work could be of help to professors and lectures active in maintenance and related new technologies. The overall underlying idea is to support the dissemination of a practical background, framed into new technologies techniques and approaches, aimed at providing advanced understanding of CPS-based smart factories. The authors claim this work also as a possible source to inspire some innovative approach to make learning in SMEs (Small and Medium Enterprises), because it works with the possibility to use limited resources.

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