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APPLIED RESEARCH

A Condition and Fault Prevention Monitoring System for Industrial Computer Numerical Control Machinery

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ABSTRACT Nowadays, the integration of smart systems within the modern industrial scenario is a continuously growing paradigm. Computer Numerical Control (CNC) machinery can heavily benefit from the introduction of Artificial Intelligence (AI) based monitoring applications. In this paper, we present an industrial condition and fault prevention monitoring system for CNC tools. The developed system is the result of an industrial project aimed at realizing a multi-purpose machine which is currently in pre-commercial stage. The results of this work represent the base platform for the further commercial development, which will be carried on from the industrial partners in accordance with clients feedbacks and specifications. This work presents the hardware architecture of the system, the web-based monitoring platform for remote management, and the AI framework used for fault monitoring. The multi-purpose machine is equipped with accelerometer units to monitor the vibration in multiple points of the structure. The control unit of the machine is connected to the sensing nodes and is used to communicate the actual machine state to a remote web platform. The accelerometric data are analyzed through an AI algorithm to perform fault detection. The fault detection algorithm was trained with the measurements performed on the machine under controlled environment faulty operation. The Internet of Things (IoT) based architecture has proven to be effective to facilitate the supervision of the machining processes, and the AI-based classification shows good classification performances for the fault detection tests.

INDEX TERMS Artificial intelligence, CNC, digital twin, fault detection, Industry 5.0, Internet of Things, sensors, remote monitoring.

I. INTRODUCTION

A. THE MODERN INDUSTRIAL SCENARIO

The industrial production sector is facing a transformation period due to the development of new technologies. The new industrial approach is commonly named Industry 5.0, focusing on the development of a more sustainable, human-centric, and resilient industry with respect to the previous Industry 4.0 paradigm. As a matter of fact, nowadays machines, structures, and, in some cases, workers are equipped with sensing devices, which allows to gather a large quantity of information [1]. The introduction of novel techniques has radically changed the production processes, increasing productive efficiency, particularly in the supply

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chain networks [2], while supporting the industry to move towards more sustainable operations. Historically, data was locally processed, and the output was available for in-situ monitoring [3], while in the modern industry, the tendency is to enable the remote monitoring of industrial machines by adding remote control [4].

The application of connected electronic systems has introduced an increased capability of information extraction [5]. Some widely used technological solutions are machine-to-machine (M2M) communication, radio frequency identification (RFID), Internet of things, Artificial Intelligence (AI), and Decision Support Systems (DSS). The development of these new-generation information technologies allows collecting more data. As a result, the concept of digital twin has arisen [6] to represent a virtual model designed to reflect a physical object, in our case an industrial machine. The sensors equipped onboard produce data about the object's performance. Data are then processed, and the virtual model is helpful to study performance, run simulations and find issues, with the aim of generating continuous improvements.

In particular, the failure of industrial equipment has various consequences that can vary from a simple part replacement to severe accidents [7]. In the best-case scenario, a part replacement can be executed in a small amount of time, without introducing a relevant service disruption. However, in the worst cases, there is the possibility of a large machine downtime, with relevant production losses, as well as other events, such as pollution or fatal injuries [8].

Clearly, the early detection of a fault is very useful since it can prevent the malfunctioning from becoming a bigger issue [9]. A faulty machine may not present evident signs of an unhealthy condition at all stages of the fault, since the damage can be of a non-critical nature: from an operative point of view, the machine condition is nominal but during the operation the failure can lead to sudden malfunctioning and possible damage. Hence, early detection and condition monitoring help identifying the faulty parts of the system in advance, thus leading to several benefits such as increased safety, limited-service disruptions, and economical benefits. In this context, AI is a widely spread computational tool adopted both for predictive diagnosis and problem recognition [10].

The applied research is a necessary element in the industrial world to develop more complete and efficient systems.

B. SUMMARY OF THIS WORK

This paper presents the case study of a condition and fault prevention monitoring system developed in a real industrial scenario. It presents the main technological enhancements related to the so-called ASSIOMI project, funded by the Italian Ministry of Education, Universities and Research (MIUR). A multi-purpose machine is part of the system together with smart electronic equipment. Condition monitoring and fault prevention and recognition are enhanced by the application of an AI technique. Moreover, the system exploits the IoT capabilities to allow the remote management of the structure. More in detail, the paper reports details at the various levels of implementation to illustrate the complete development of the whole system, differently from other research contributions, which commonly propose the developed technical solution for a detailed case study.

The paper structure is as follows: Section II analyzes the literature contributions on IoT and AI based fault detection and diagnosis systems in the industrial context. The basic concepts behind a fault detection (FD) algorithm design are described in Section III. Section IV presents the hardware and IoT-related architecture of the system while Section V describes the applied AI algorithms for fault detection along with the obtained results. Finally, Section VI summarizes the conclusions.

II. RELATED WORKS

The implementation solutions for an industrial application based on IoT are various, but every system has a common general architecture, as shown in Figure 1.

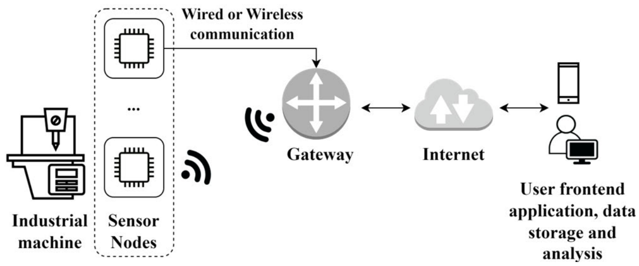


FIGURE 1. The general architecture of an IoT-based industrial system for machinery monitoring.

A. IoT MONITORING SYSTEMS IN INDUSTRIAL MANUFACTURING

In literature, several applications of IoT-based AI systems for different industrial scenarios are presented [11], [12], [13], [14]. A comprehensive survey on fault diagnosis and early warning for manufacturing equipment is carried out in [15].

The study presented in [16] reports a theoretical analysis of an intelligent monitoring system for manufacturing by processing statistical data. Based on the calculations, authors estimate the feasibility of a real time monitoring chain for a workshop, proving the applicability of IoT technologies in industrial processes. An experiment of remote management of a Programmable Logic Controller (PLC) is reported in [17]. Periodical tests on manufacturing pieces report the local parameters to a monitoring system, which stores and analyzes data to assess the manufacturing qualities with respect to employed time.

The authors of [18] focus on the integration of wireless technology and a Computer Aided Manufacturing (CAM) system for Computer Numerical Control (CNC) workshop development. The focus of the case study is to show a complete phase of manufacturing, starting from Computer Aided

TABLE 1. Related works comparison and features.

Ref.	System stage	Monitored element	Hardware implementation reported	Digital twin	Classification algorithm
[19]	Test prototype	Cutting chatter vibration	No	Yes	DNN
[20]	Prototype	Tool wear	No	Yes	DNN
[21]	Test prototype	Machine case vibration	Yes	No	Unspecified Machine Learning method
[22]	Simulation	Spindle center point variation	No	No	RS
[23]	Test prototype	Bearing vibration	No	No	CNN
This work	Industrial implementation	Machining vibration	Yes	Yes	Regression trees

Design (CAD) modeling, machine processing, and data gathering. The machining process is monitored using temperature sensors and an Inertial Measurement Unit (IMU).

B. ARTIFICIAL INTELLIGENCE FOR CNC MACHINES

The development of IoT structures, in synergy with AI-based methods, gives new opportunities for data analysis and remote monitoring [12]. In fact, the combination of IoT-based systems for monitoring and AI algorithms enables more advanced solutions. For instance, the authors of [19] use a deep learning Neural Network (DNN) for the remote monitoring of a CNC machine. The cutting process is supervised to ensure the cutting stability so as to achieve an increased quality of products. In this case, the authors classify the cutting process by measuring the cutting forces in three dimensions. The data elaboration and processing is performed externally to the CNC machine by means of a dedicated calculator.

Edge-intelligence driven systems are the frontier of industrial AI applied to CNC machines. The contribution in [20] provides a preliminary discussion on the construction method and deployment of a system used for tool wear prediction based on vibration analysis. The authors report that the proposed architecture of CNC systems still needs to be improved.

A prototype for anomaly detection based on commercial electronic boards is presented in [21]. The researchers study the feasibility of process monitoring by using vibrational analysis with Fast Fourier Transform (FFT) integration. Obtained results are promising for an application to a real industrial process.

The authors of [22] propose a decision support model of fault diagnosis for a CNC grinding machine based on the advantages of redundant information reduction and rough set (RS) model. The model is applied into an example of fault diagnosis for a specific type of grinding machine.

Bearing fault is particularly interesting in CNC anomaly detection, as shown in [23]. The authors use a single set of microphone and accelerometer to monitor the vibration and noise data of an industrial machine. The information is used to feed a Convolutional Neural Network (CNN) in order to obtain the classification of the recognized fault.

Several machine types have been considered in previous research works, covering one or more specific aspects of a CNC machine workflow that can lead to machine break-down, motivating the design of ad-hoc Fault Identification algorithms and the relative IoT monitoring infrastructures. The literature reports both theoretical and practical approaches to the introduction of AI-based systems in the Industry 5.0 framework. From the above discussion on the literature contributions on this topic, mathematical models applicable to CNC machinery for fault detection have been widely studied in the past. Prototype monitoring systems have been integrated along with the existent industrial equipment, but the industrial field still needs efforts to properly make the next generation machines fully integrated with modern information technologies.

The aim of this work is to fill this gap, presenting a case study in real industrial scenario, with the development of a production ready machine integrated with an AI-based tool for fault detection and a web digital twin for remote management. As we can observe by taking into consideration the literature, the fault detection systems for industrial applications have been studied in the past. These implementations often are carried on at simulation or preliminary testing level. The industrial field can benefit at commercial level from applied research works to develop more complex and efficient systems, as in the case of this work.

Table 1 reports a comparison of the features of this work with the related works.

III. BASICS ON AI SYSTEMS FOR FAULT DETECTION

In the next section, some guidelines for a general Fault Identification algorithm are presented, investigating aspects such as the theoretical approach for classifiers design, the data collection strategies, and the data preprocessing steps.

The implementation of an AI-based system consists of building an automatic procedure that, by elaborating machine sensor data, can supply information about one or more specific state variables of the process defined by the machining workflow.

The decision process behind the implementation of an AI model for fault detection purposes is sketched in Figure 2.

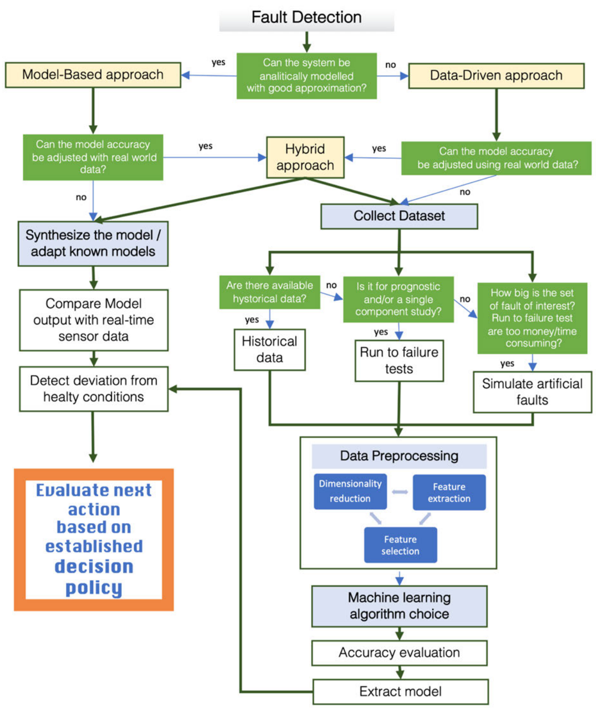


FIGURE 2. Decision process flowchart for the implementation of a Digital Twin model for fault detection.

Predictive Maintenance (PM) tasks are accomplished by using one or more mathematical models that can evaluate the value of a set of observable quantities, which are related to the machinery process with respect to the work conditions and functional parameters.

The model-building phase can follow a Model-Based (MB) approach or a Data-Driven (DD) approach, depending on the specific faulty entity.

A. CLASSICAL APPROACHES FOR FAULT DETECTION

The traditional MB approach makes use of known mathematical models by establishing physics-based equations with respect to measurable components. A MB approach is the best choice for processes that can be mathematically modelled with good approximation [24] because it enables the possibility to determine the system behavior with respect to specific production inputs. An anomaly in the system can be detected when the determined output does not match the real-time sensor data.

The pertinent literature reports research that deals with MB fault detection. For instance, in [25] the authors survey the methods and possibilities for fault detection in robotic machines by the application of physical models of their dynamics.

The number of variables involved in industrial processes are difficult to be treated in an analytical way. This is the main limitation for the adoption of MB methods in fault diagnosis [26].

Conversely, DD approaches do not require the deep knowledge of the mathematical representation of the system under study. Machine Learning (ML) algorithms are employed to measure the similarity between real-time sensor data with respect to a carefully built training dataset. The dataset contains ground truth labeled data related to a specific healthy or faulty condition of the system.

The DD approach can be less reliable with respect to the MB approach, which is ruled by equations, furthermore the employment of these methods can require a more complex infrastructure for data storage and analysis.

However, the availability of new Machine Learning frameworks and cheaper computational units, marked the application of AI in specific diagnostic problems.

In this work we adopt a DD fault detection method. The focus of this work is not predicting outputs of the sensors, but to process real-time data and classify them. To this aim, we use a Machine Learning model.

Before detailing the proposed approach, in the following subsection, we first describe the main steps that are generally applied when developing a DD fault detection algorithm.

B. DATA COLLECTION STRATEGIES

The purpose of data collection is to build a dataset intended for an AI algorithm training by performing experiments. This process is not trivial: complex machines can work in numerous ways, making the experiment planification one of the most complex steps for DD predictive maintenance in multiconfiguration machines.

There are several ways to construct an ad-hoc dataset for PM.

When historical data are available, they can be processed to study recent deviation from the previous behaviors. Historical data can be difficult to use for generalized applications, as those are usually relative to a specific set of operations.

Run-to-failure test is the most common way to build prognostic datasets, forcing the machine to constantly work until a failure appears. This kind of test is very helpful in the study of prognostics, since it allows observing the evolution of recorded data along with the defect growth dynamics. Run-to-failure tests can be expensive and time consuming, and in some cases don't allow to deal with a specific fault of interest, but only with fault that naturally arises along the degradation test.

In the artificially simulated faults approach instead, specific problems of interest are artificially induced in the system, allowing the analysis with full a-priori knowledge of the fault. The economic effort related to the execution of this kind of test can be higher respect to run to failure tests, but the data collection phase is surely faster.

C. DATA PREPROCESSING

Data Preprocessing operation converts data in a more suitable format for AI modelling, either enhancing the information content and/or reducing data size.

Data cleaning is a crucial step, usually employing denoising, normalization, spike removing techniques.

Feature Extraction (FE) is the operation that applies a certain function or a certain transformation to the measured data to obtain non explicit information. An example is the computation of motor torque starting from electrical measurements. Fourier Transformation is another tool that can also supply important information signal retrieved from a machine [27].

Feature Selection (FS) is an operation that estimates the information content of each component of the datasets by finding a subset of the original feature-set that can still contain enough information for classification purposes, while decreasing the computational effort for the model training phase.

Finally, Feature Compression (FC) is based on the same concept of feature extraction, with the difference that FE processes sample applying a known transformation that completely change the shape and the physical meaning of data. FC techniques instead focus on the data size reduction, removing or combining features to reduce the amount of data without a sensible loss of information.

In this work we applied a Fast Fourier Transformation (FFT) as FE technique, in order to extract frequency domain information from accelerometry data. The features are subsequently compressed by an Empiric Moving Avarage (EMA) technique, as reported in Section V.

D. MACHINE LEARNING ALGORITHM

The last step for developing an ML algorithm consists in choosing a proper classifier. It is difficult to find an analytic way to a-priori identify the ML algorithm that best suits a specific application.

In general, Neural Network algorithms are the most popular in AI fault detection [28]. Nonetheless, several literature contributions adopt other ML algorithms [29].

In this work the chosen ML algorithm is based on Regression Trees. A performance comparison is reported with respect to other ML algorithms often used for classification in industrial fault diagnosis, namely k-Nearest Neighbor (k-NN), Support Vector Machine (SVM) and Multilayer Perceptron Neural Networks (MLP) [30].

IV. SYSTEM ARCHITECTURE

In this section we describe the system architecture of the considered case study. The system is composed of a local physical part and a cloud infrastructure for the remote management through the digital twin representation. The first includes the machine, the sensors, and the electronic devices for data gathering, as well as the local monitoring platform. The local devices are connected to the internet and transmit the data in packets towards a web application where the digital representation of the machine is reported. The data are also analyzed and used for early warning in case of compromised status of a part of the machine. Figure 3 shows a block scheme of the considered system.

The sensor node is a stand-alone unit equipped with onboard accelerometers. The local unit (labeled as A in

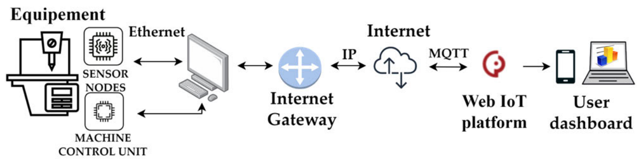


FIGURE 3. The application scheme of the proposed system.

Figure 4) is a calculator where a custom-made software is used to monitor and program the CNC machine (labeled as B in Figure 4).

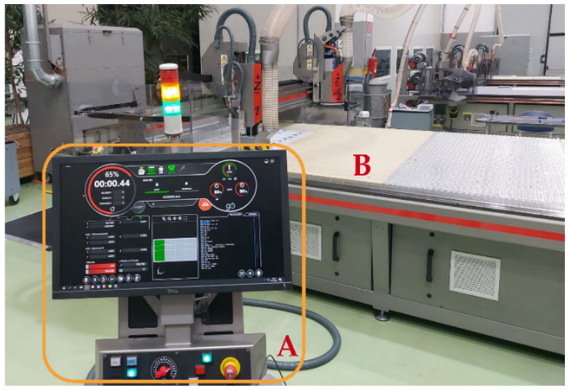


FIGURE 4. The CNC machine of the considered case study.

The machine designed in the ASSIOMI project is multifunctional, having the possibility to process a wide variety of materials, such as cardboard, rubber, sponge, plastics, composites, aluminum, brass, wood, and other hard materials. The machine is equipped with an automatic planar tool changer. At the same time, it is also a 3D milling machine capable of working plastic, wood, light alloys, composites, and real plan plotter for cutting and creasing multi-layered and alveolar corrugated elements. Figure 5 shows the scheme of the CNC machine with the reference frames for the accelerometric units.

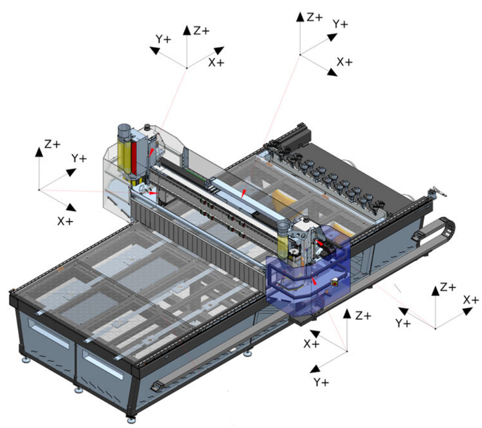


FIGURE 5. The ASSIOMI CNC machine 3D model with accelerometers placement.

A. NODE HARDWARE

The sensor node is a microcontroller-based unit that is used to obtain data from an accelerometer. The gathered information is transmitted to the local calculator on an RS-485 bus, managed by a transceiver unit. The programming and debugging port is available on Serial Peripheral Interface (SPI). The device is powered by a 12 V direct current line, connected to internal regulators for voltage regulation. Figure 6 shows the block schematic of the circuit and Figure 7 reports the three-dimensional model and the realized unit.

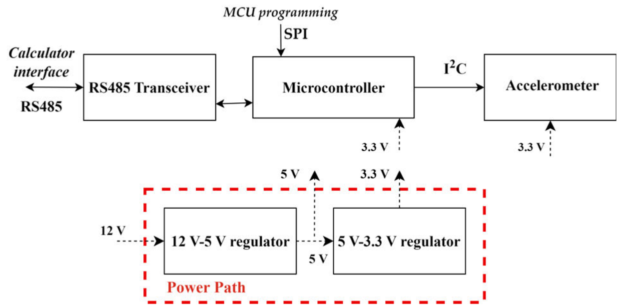
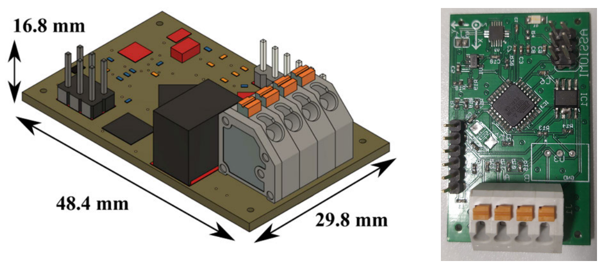


FIGURE 6. Hardware scheme of the accelerometer nodes.



(a) (b)

FIGURE 7. The realized sensor node: (a) 3D view. (b) Printed Circuit Board.

B. CLOUD STRUCTURE

The ASSIOMI web platform is used as a Digital Twin of the ASSIOMI CNC machine in a user-friendly environment, so that a high level of specialization is not required. The web interface is composed as follows. A set of machines and users can be assigned to an organization. Users are divided into two categories: base users and administrators. These two types of users differ from the permissions that are assigned to them: base users can only view and interact with the dashboard of a machine, while administrators can modify dashboards and machines assignment and can grant permissions to other users. Machines have two main features: the state indicators and the anomaly signals. The state indicators represent the current status of the machinery, such as motors speed, positions, and temperatures. Anomaly signals are warnings that are enabled when the AI algorithm detects an abnormal work condition. In Figure 8 a structure of the Organization, Users and Machines is reported.

The dashboard of a machine can be divided into two environments: the login page, where an enabled user can access the web panel, and the user dashboard page, which includes a set of all the aforementioned indicators and warnings, representing the digital twin of the machine. The online data can be gathered from the user in a specific file format for external analyses. Figure 9 shows the screenshots and structure of the dashboard.

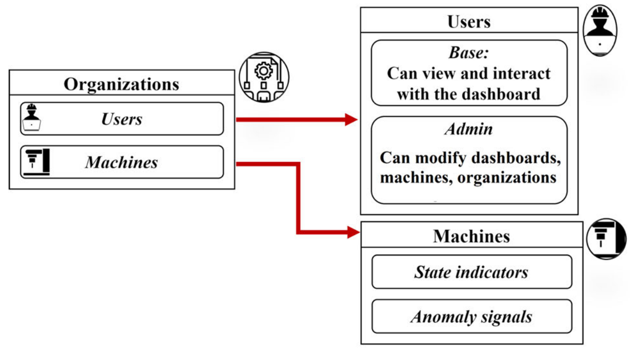


FIGURE 8. Structure of the web portal for the management of the CNC machines digital twin.

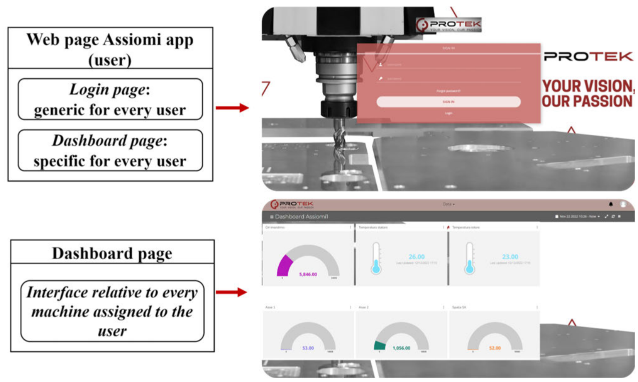


FIGURE 9. The ASSIOMI digital twin web page.

V. THE PROPOSED METHODOLOGY

The considered system is a multi-purpose CNC machine; hence the fault detection unit is required to be flexible and generalizable, allowing each customer to replicate the procedure of FD model-building for the specific fault of interest, and to add the new entities without interfering with other pre-existing models.

A faulty model library can be collected and grown over time, as explained in Section III. In this work, an artificial simulation approach is used, executing several maneuvers of the machine in both healthy and faulty conditions, see Figure 10. During the experiments, the vibration profile was acquired using a sample frequency of $F_s = 391$ Hz.

The system is supposed to work for any possible machining job that the user wants to operate, so the trajectories of the Tool Center Point (TCP) have been carefully planned to produce different geometries for the data collection tests, as Figure 10 shows. The same trajectories have been used for all the testing procedures, both in healthy and faulty conditions.

Each geometry of the machine elements for a different trajectory obliges the mechanical system to assume different joint configurations and different dynamics in the joint-space. These behaviors are linked to the vibrational response of the structure. The experimental data supply information on the vibrational response in all the working area of the machine's branches in terms of position, velocity, and acceleration of the TCP.

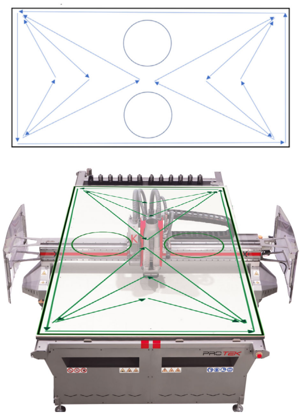


FIGURE 10. **Test trajectories for the data gathering.**

Faults have been simulated by modifying the mechanical structure of the machine by untightening and unscrewing some fastening bolts on the side panels of the tool.

The CNC machine is controlled by the proprietary software, which allows the user to directly select the desired spindle velocity, allowing the tool to move with constant rotation speed along the programmed trajectories.

All the test trajectories have been performed at three different velocities, that is, low, moderate, and high speed.

The time duration of the experiment is around 1,632 seconds, so all the row data acquisition has been divided into 3,264 segments of 0.5 second each.

Figure 11, Figure 12, and Figure 13 show sample acquisitions of the accelerometer data, at the electro-spindle rotation speed of 16,000 Revolutions Per Minute (RPM), in the three different faulty conditions. The health states have been labeled as GREEN (i.e., no damage), YELLOW (i.e., light damage), and RED (i.e., severe damage).

On the horizontal axis, the time is reported, while vertical axes gX, gY, and gZ (in different colors as labeled in each figure) respectively represent the x, y, and z accelerations, expressed in units of gravitational acceleration (g).

The dataset has been randomized and a classification tree algorithm has been trained with the acquisitions recorded at electro-spindle velocities $V_1 = 8000$ RPM and $V_3 = 24000$ RPM (66% of the dataset), leaving the data record at trajectory velocity $V_2 = 16000$ RPM as validation-set. The RPM range was chosen in accordance to the rotation speeds used for aluminum and fiber-reinforced plastics machining.

In order to extract faulty information, a frequency domain feature extraction technique is used, due to the oscillatory nature of accelerometry data.

The obtained spectrum still contains a lot of information according to the prefixed resolution, so the features of this classification problem can be further restricted to reduce the computational effort for the model training and the model inference, and to decrease the required memory.

To this aim, Empiric Moving Average (EMA) is a simple technique that can resume information stored in a generic ordered vector. Being r the reduction factor, N the vector size, and w the moving window size, the vector size can be decreased of $r = N/w$. The algorithm takes the first w samples of the vector and computes the average, then shifts the window to the next block of w-elements and repeats the process until the end of the vector. This technique is suitable for spectrum processing because it supplies qualitative information about the energy distribution of the vibration spectrum, with respect to r different segments of the accelerometer sensor band width. Hence, the data dimension of the input vector has been compressed again by applying an EMA transformation, thus reducing data of a factor of 10, and obtaining a classification input vector for the Classification and Regression Trees Algorithm (CART) of 12 components.

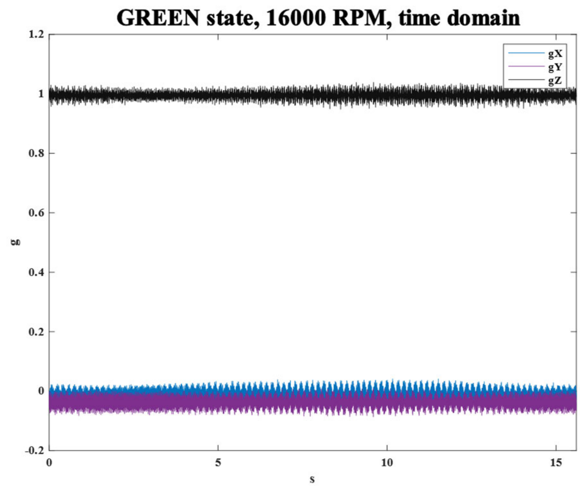


FIGURE 11. **Sample of measured acceleration in the no fault state.**

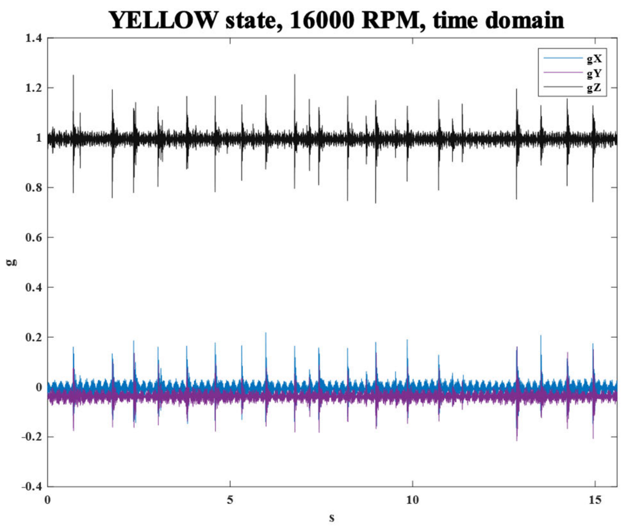


FIGURE 12. **Sample of measured acceleration in the light fault state.**

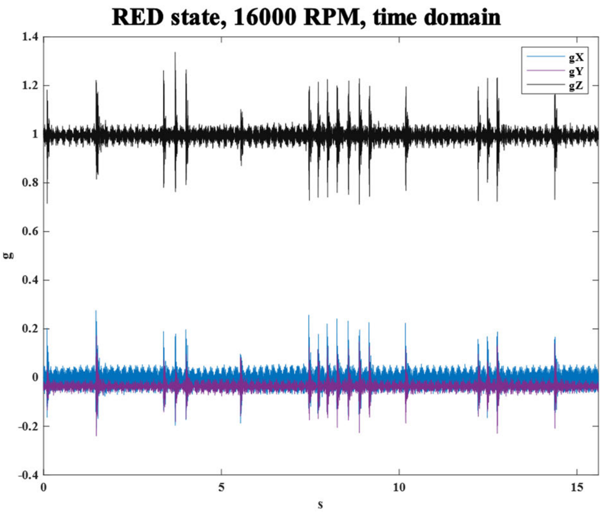


FIGURE 13. Sample of measured acceleration in the severe fault state.

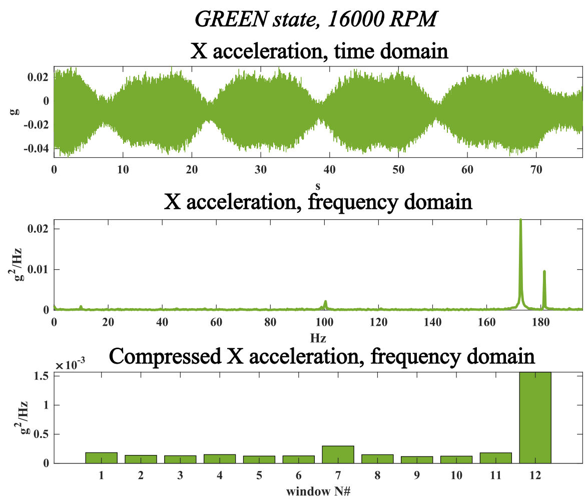


FIGURE 14. Data elaboration on x axis, no fault.

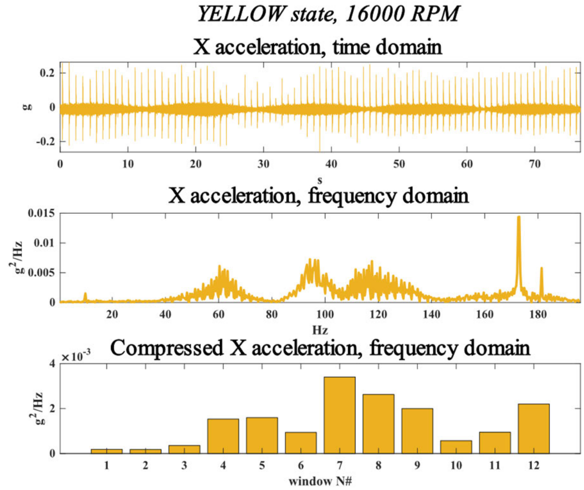


FIGURE 15. Data elaboration on x axis, light fault.

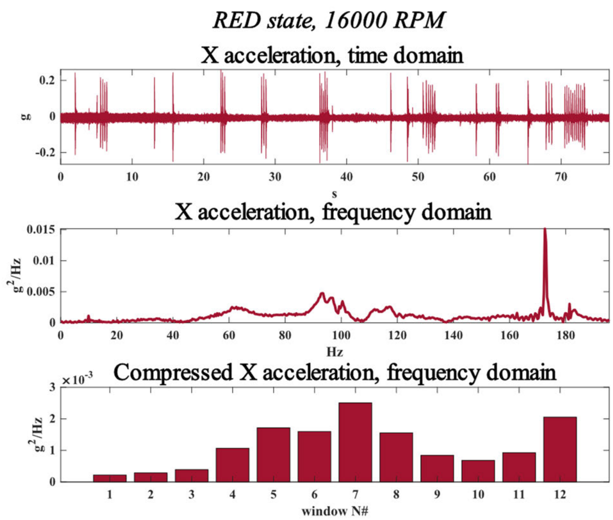


FIGURE 16. Data elaboration on x axis, severe fault.

The CART includes 12 EMA processed components, and the spindle angular velocity, which is assumed to be always known.

Figure 14, Figure 15, and Figure 16 show the FFT and compression results for a sample of acceleration data over one axis in the three fault cases.

Figure 14 shows the time domain and frequency domain values of the measured acceleration during an operation time slot relative to a healthy state of the machine.

The FFT plot shows two peaks located at the frequency of the main vibrational components. The compressed frequency domain plot shows the results of the EMA processing applied to the FFT processing resulting vector.

The vibrational influence of the faulty component is observable by taking into consideration the peaks in the time domain vibration signal. In the acceleration plot of Figure 15, we can observe that the acceleration values suggest that the component where the sensor is placed vibrates with a periodic behavior. In the time domain acceleration plot of Figure 16 we can observe that the vibration peaks are not found at regular intervals.

The FFT applied to the YELLOW and RED states shows the changes in the vibrational signature with respect to the GREEN state of operation. The EMA results allow maintaining the shape of the original energy distribution while reducing the data amount.

This application considers a classification problem represented by twelve continuous features associated with a set of three possible categorical labels, namely GREEN, YELLOW, and RED. To improve accuracy the problem was split into three different subproblems, one for each class. The obtained subproblems approach the classification in a binary way, telling whether the input vector belongs or not to the i-th class, also known in literature as a ONE VS ALL strategy.

The three sub-problems are still characterized by twelve continuous features, but the binary set of labels became

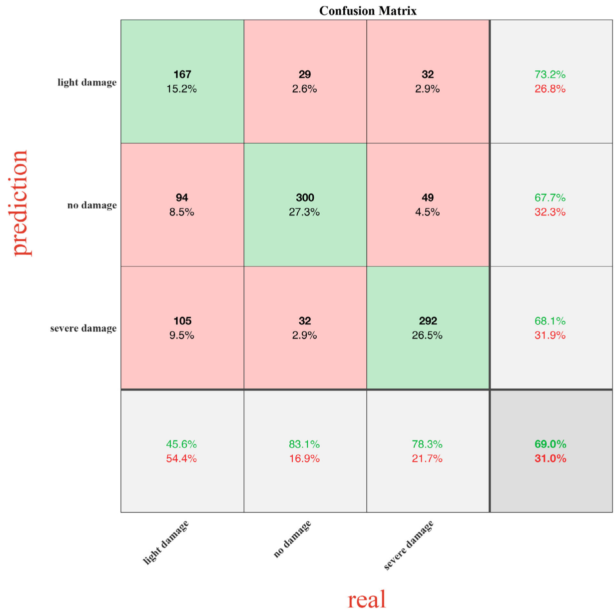


FIGURE 17. Confusion matrix obtained using k-NN classification algorithm.

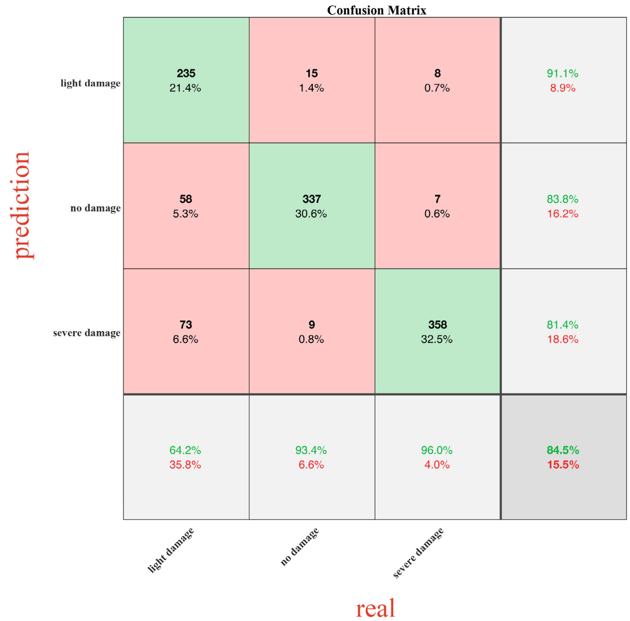


FIGURE 19. Confusion matrix obtained using a MLP Neural Network classification algorithm.

FIGURE 18. Confusion matrix obtained using SVM classificationn algorithm.

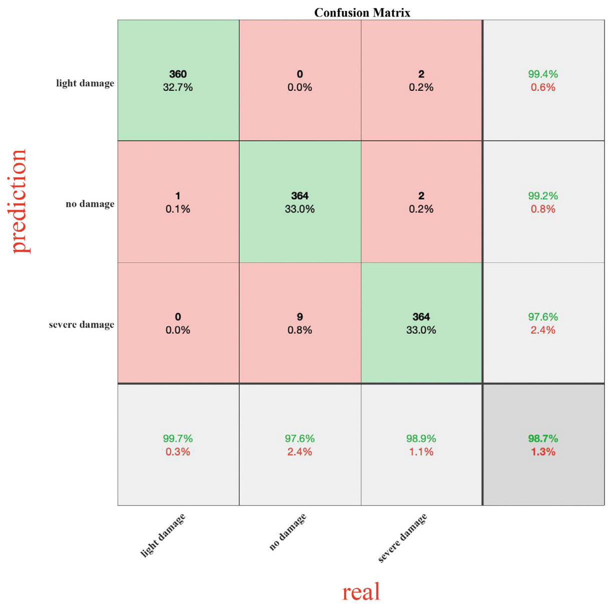


FIGURE 20. Confusion matrix obtained using regression-trees in a ONE VS ALL strategy.

respectively: ("YES GREEN", "NOT GREEN"), ("YES YELLOW", "NOT YELLOW"), ("YES RED", "NOT RED").

By training three different models, according to the new formulation of the problem, we can combine three different outputs and get the classification results. This strategy presents one issue: every instance of the dataset should always produce two "NOT" results and one "YES" result. This is not assumable in practice.

To deal with collision, the three subproblems were formulated using labels with continuous values, more specifically 0 for "NOT" and 1 for "YES". By doing this, the collision can be solved by a comparison of the three outputs. The model producing an output closer to 1 is selected as the classification label.

The training dataset storing the twelve EMA components of the acquisitions taken at 8000 and 24000 RPM has been used to train three different regression tree algorithms.

The regression tree training has been imposed without a maximum tree depth, in order to get only pure leaf with a minimum sample split value of five. The split criterion is the Mean Square Error (MSE) and an amount of ten minimum number of parents per node was selected.

The chosen classification algorithm has been compared with other ML classification algorithms: k-NN, SVM, and MLP Neural Networks.

The k-NN classifier has been trained using the Ball Tree search algorithm using Euclidean distance and a batch size of 100. The SVM was used again in a ONE VS ALL strategy employing 3 different regression algorithms (one per fault) using the Sigmoid kernel and a value of gamma equal to 0.08.

Finally, the MLP neural network was chosen with one hidden layer, the used layer's transfer function is the tangent-sigmoid logistic function, trained with the Levenberg-Marquardt training algorithm using MSE as loss function.

From the confusion matrices in Figure 17, Figure 18, Figure 19, and Figure 20 we can see that all the algorithms achieved a tolerable global accuracy of 70%. As expected, k-NN algorithm shows the lowest precision, probably due to the low complexity of the method. Neural Network and SVM reached the same global accuracy. The classification results suggest that the ONE VS ALL strategy improves the accuracy in the ''light damage'' case, which counts 24% of misclassification error in the SVM, against the 35.8% in the MLP classification.

The regression trees method chosen for this work reports better classification accuracy with respect to the other methods. All the classes have been correctly sorted with an error rate inferior to 3.5%. Those are close (MICA TANTO) to the MLP classification performances in case of ''severe damage'' (RED) and ''no damage'' (GREEN), but the performances in the ''light damage'' (YELLOW) case are consistently higher, underlining the effect of the ONE VS ALL strategy.

VI. CONCLUSION

Although failures in CNC machinery are not a daily expectation in high-end machinery, a tool for fault detection and fault prognosis is certainly beneficial to the user. In this paper, a real scenario implementation of an industrial, AI-based, IoT system for fault detection is presented. The system is currently in pre-commercial stage. The industrial partners can benefit from the research carried out and will include the clients feedbacks and needs, in order to further tune and increase the system capabilities.

This work reports the full implementation of the AI-based system developed within a research project (namely ASSIOMI), including the hardware implementation, the web-based digital twin, and the AI-based methods for fault detection. The AI model was tested by introducing different faults during different test runs of the machine, proving to be effective in the classification of each tested anomaly.

Among the further developments of this work, we find the introduction of materials and methods for energy analytics and management in order to increase the energetic efficiency of the industrial machinery.

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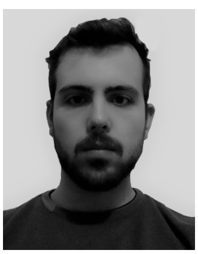

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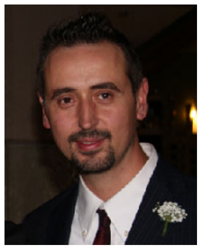

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