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Predictive Maintenance assisted by Edge-Computing Augmented Reality and 5G networks

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Abstract

During the last decades numerous innovations and inventions have been presented under the framework of Industry 4.0. The ultimate goal of the latest industrial revolution is the digitalization of modern manufacturing systems. Therefore, several techniques and technologies have been investigated by the academia and the industrial practitioners, such as Edge Computing. The above-mentioned paradigm adheres to the distributed computing paradigm, which is an analogous to the trend of decentralization of manufacturing systems. However, there are still several challenges to be addressed in the integration of such decentralized computing systems in real-life industries. Therefore, in this paper, the design and development of an Edge-computing platform is proposed, in order to distribute the computational load to the nodes and by extension to enable the utilization of machine learning techniques for the calculation of Remaining Useful Life (RUL) of critical machine tool components. Moreover, the proposed framework promotes the utilization of 5G cellular networks, in order to take advantage of the ultra-low latency and increased bandwidth offered by this technology.

1. Introduction

Industrial maintenance when considered as a part of the manufacturing lifecycle, approaches 60–70% of the overall cost of production. Therefore, if the engineering department is able to have good estimates for upcoming malfunctions and equipment faults, followed by the required maintenance and repair operations (MRO) in a scheduled time, can lead to successful troubleshooting, and at the same time increase the availability of machine tools [1]. Currently, the adoption of an inadequate maintenance strategy can result in an approximate reduction of the total productive ability of the plant by between five up to twenty percent (5-20%) according to the research presented by Deloitte in 2017 [2]. Traditionally, maintenance professionals have combined several techniques, both quantitative and qualitative, aiming towards the anticipation of potential equipment failures and minimizing downtime in their production plants. Consequently, Predictive Maintenance, often abbreviated as PdM, enables maintenance engineers to further improve both the time and quality of MRO almost in real time, maximizing the useful life of their equipment while avoiding disruption of operation [3]. PdM increases uptime by

10–20%, while reducing overall maintenance costs by 5–10% and maintenance planning time by 20–50%. Furthermore, due to increased interconnectivity and new opportunities for collecting, processing, and analyzing information, predictive maintenance can be a very powerful strategy. Recent research studies and market analyses have indicated that unplanned downtime is costly, with an estimation of fifty billion US dollars($50 billion) per year for global producers [4].

A significant amount of development work has been made to design and improve real time technical service systems and software focused on mobile apps to prevent unwanted errors and malfunctions [5]. Moreover, the handling of complex cases of smart factories, intelligent maintenance, self-organized adaptive logistics, customer-integrated engineering and smart factory architectures require the integration of production data into modeling that can only be achieved with the use of advanced simulation and Information Technology (IT) [6]. With the advancement of Information and Communication Technology (ICT) and cutting-edge technologies such as Mixed-Reality (MR), Augmented Reality (AR) and Virtual Reality (VR), the academic domain is expanding this strategy by leveraging the advantages of AR for data visualization during maintenance operations [7-9]. Emerging technologies such as the Internet of Things (IoT), cyber-physical networks and cloud computing have enabled the processing of vast volumes of tracking data, which is intended to significantly increase manufacturing productivity [10-12].

Having identified the above-mentioned challenges, this research work presents the design and development of a predictive maintenance framework for industrial equipment based on the utilization of Edge computing and AI algorithms. Further to that the contribution of this research work extends to the presentation of a custom Data Acquisition (DAQ) device and a framework for processing the data via the Digital Twin of the equipment for the calculation of Remaining Useful Life of critical components.

The remainder of the paper is structured as follows. In State of the Art the most pertinent literature is reviewed, and commercial devices are compared. In Section 3, the proposed system architecture, is presented. Then, in Section 4 the system implementation steps are discussed. Finally, in Section 5 “Concluding Remarks and Outlook”, the paper is concluded, and future research points are discussed by the authors.

2. State of the Art

Among the latest trends in the modern manufacturing world,is Artificial Intelligence, denoted as AI. AI can be considered as a superset of different learning approaches such as Machine Learning (ML). Globally AI adoption is surging at enormous rates, according to new research [13], stressing out that AI adoption will hit 270% increase within a time horizon of 4 years along with an increase in global spending of around eighty US billion dollars (US$ 80 billion).

The implementation of ML frameworks can lead to major cost savings, higher predictability, and increased availability of the systems. Therefore engineers have focused their efforts on the development of new technologies and techniques for facilitating the prediction of manufacturing equipment malfunctions and therefore to further optimize existing maintenance policies as well as to introduce more adaptive maintenance policies. Some of the most common problems that can be addressed with PdM include, the calculation of Remaining Useful Life (RUL), which aims at the suitable scheduling of future Maintenance and Repair Operations (MRO), Flagging Irregular Behavior, which is based on anomaly detection by the utilization of time series analysis, and

Failure Diagnosis and Recommendation of Mitigation after failure [14,15]. Moreover, in recent research works SCADA systems are integrated with ML algorithms, in order to extend their usability as well as to shift towards prognostics [16-18].

Besides the technologies and techniques examined so far, Edge Computing has emerged the last decade and based on the systematic literature review presented by the authors in reference [19], this technological branch in conjunction with the accompanying key concepts, including Fog computing, will play a key role in the development of Industry 4.0 solutions. In their research work, Deng et al. have proposed an adaptive framework for the sequential offloading of mobile networks, achieving great efficiency and scalability as the Edge network expands [20]. Similarly, Hsu et al. in [21], have presented a framework based on the implementation of Edge Computing in conjunction with Deep Learning, enabling the estimation of the degradation rate of critical components. Similarly, in the literature review of [22], where the Edge Computing architectures have been investigated, one of the key findings/conclusions of the authors, is that the combination of Edge Computing with AI techniques, such as Reinforcement Learning poses a powerful tool, capable for addressing the increased complexity of the real-world systems. Miori et al. in 2017 [23] have based their research on the integration of Raspberry Pi single board computers for creation of an Edge network/cluster. The authors in [24] have presented an interesting framework based on Edge Computing, which was applied in an automotive case study, indicating the increased capabilities offered by this technology. Moreover, one of the main concerns/challenges expressed by the authors is the need for secure communication between the individual nodes of the Edge Network. In the paper presented by Zhang et al. in 2021 [25], a three-tier framework for the detection of abnormalities in data derived from Edge Nodes and are fed to the Digital Twin of the corresponding cyber-physical system has been proposed. Modern manufacturing relies on the collaboration of multiple technologies, resulting in the generation of large data sets. With the ultra-low latency and high bandwidth capacity offered by 5G technology, this massive increase in data collection can be transmitted and analyzed much faster. The addition of multiple sensors to industrial facilities machine monitoring is generating more data than before [26]. While the production floor is the most obvious location where 5G can benefit manufacturing, there are other ways in which 5G can contribute to the manufacturing environment in a non-direct [27]. The goal of Industry 4.0 is to increase efficiency by incorporating the features of cutting-edge technologies into all processes and assets, as well as to provide a better understanding of manufacturing processes across their manufacturing sites in near real-time. The deployment of 5G has raised expectations that it will open new opportunities for manufacturing business models, given the expected increase in data requirements ranging from mission-critical to massive machine connectivity.

3. Proposed PdM system architecture

The proposed system architecture is based on the utilization of a microcontroller unit (MCU), such as the STM32F429Discovery board for the development of the prototype Data Acquisition device (DAQ). Then, the data gathered from each DAQ, i.e. the MCU with the integrated sensors, the data are transmitted either via hardwire or wirelessly, to the Edge Node, which is realized a Raspberry Pi computer. Consequently, the data processing procedure is initiated at the Edge Node level, in order to process the transmitted data, for the creation of spectrograms which are then fed to a Support Vector Machine (SVM), for the classification of the data. This classification will determine the message to be passed to the Cloud Server, where the Digital Twin of the equipment/machine is stored and ran as a Cloud Service. By extension if the message transmitted to the Cloud Server is not reporting any type of malfunction, then the Digital Twin remains de-activated. However, if the Cloud Server receives a report for machine malfunctioning, then a data pull request for the corresponding Edge Node is granted from the Cloud Server. Consequently, the data transmission from the Edge Node is initiated. In Figure 2, the data sequence diagram depicts the information flow, starting from the sensors through the Edge Nodes and finally to the Digital Twin of the physical system. The SVM mentioned in the previous paragraph has been trained prior the implementation on the Edge Node.

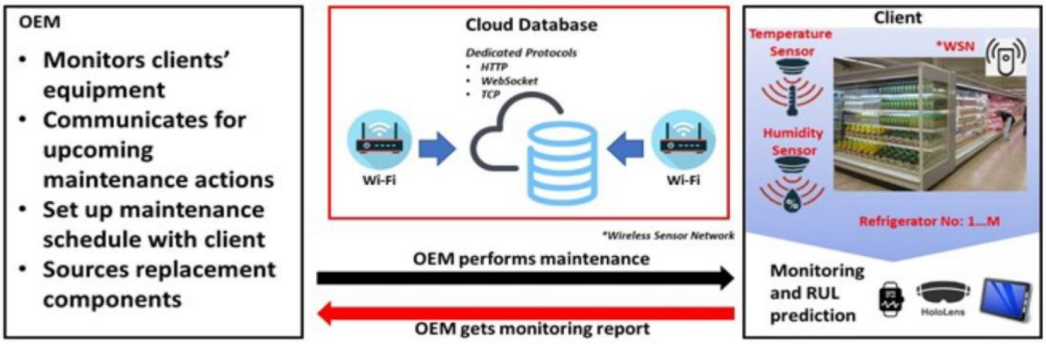

Figure 1: Proposed System Architecture

In order to successfully connect the physical counterpart of the system, which in the scope of this research work is a professional refrigerator group, to the Digital Twin of the system, a UML based modelling approach has been adopted. The main entity of the UML model is the Refrigeration facility, which consists of refrigerator entities. The Refrigerator entities, in turn, consist of two different classes, namely "compressor" class and the "cooling chamber" class. The OPC-UA communication protocol has been utilized during the initial development of the proposed framework. More specifically, the authors have examined the semantics of OPC-UA elements in order to create a mapping between OPC-UA and Unified Model Language (UML). As a result, the digital twin of the industrial system is designed with a layered hierarchy. The subcomponents and elements of the resources are also modelled hierarchically. Following the OPC-UA notations, the Digital Twin (DT) of the Refrigerator is modelled as a set of nodes that will be exposed to clients through the address space. The modelling of the DT utilises mainly the "Object" and "Variable" node notations, and the "HasComponent" and "HasSubtype" reference notations. Therefore, the various industrial components and their subcomponents are modelled using a high-level element analysis.

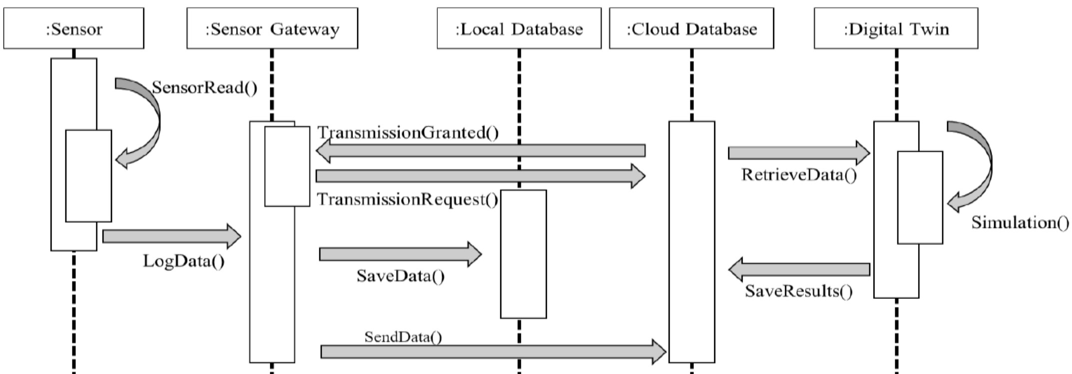

Figure 2: Data sequence diagram of the proposed Edge Computing architecture

An AR module is provisioned in order to facilitate the monitoring process of the industrial equipment. This module can be realized as a multi-platform application, from which the customers can either remotely or on-site visualize crucial information about their equipment and interact with it, easily and intuitively with the use of this cutting-edge digital technology. Concretely, the current implementation of the framework supports handheld Android-based platforms, e.g. mobile phones and tablets, as well as Head Mounted Displays (HMD), such as the Microsoft HoloLens. User tracking and pose estimation for the Android-based devices is based on the recognition of a feature-rich image target, as in the one presented in Figure 3.

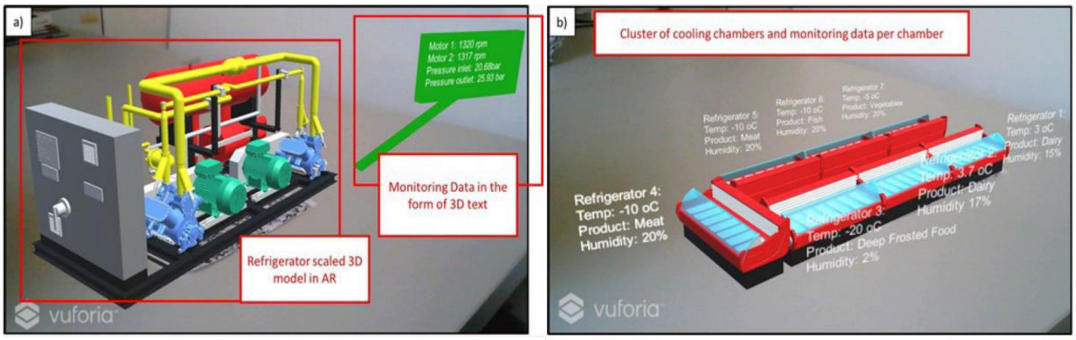

Figure 3: a) AR visualization of compressor and its working parameters; b) cooling chamber cluster and the current working conditions.

4. System Implementation

The proposed architecture can be realized as a multi-sided application. The first aspect of the application is a desktop-based application, which communicates with the server in order to retrieve the data from the server and process them through the predictive algorithm. The predictive algorithm is responsible for the identification of patterns within the processed data. Each of these patterns represents a classification of the possible situations of the under-examination machine, or cluster of machines. A predictive algorithm will have to analyze the data gathered from the sensors so that a prediction of unforeseeable machine malfunctions can be identified. However, since the data are available on the server, it is of great importance to create an application for monitoring the current situation of the machines. In the following figure, the developed prototype for the DAQ device is presented along with the setup used for the WSN and the Edge nodes of the system.

For the development of GUIs as well as the AR module of the proposed framework, the Unity 3D game engine is utilized. As regards the code scripts, the Microsoft Visual Studio IDE is used. More specifically, for the development of the main functionalities of the application, the code scripts are written in C# programming language. Since the application supports two user groups, one for the OEM supplier/service provider and one for the customers, a common login/register system is implemented. Upon installation of the application on the end-user's device, the user is prompt to register a new account.

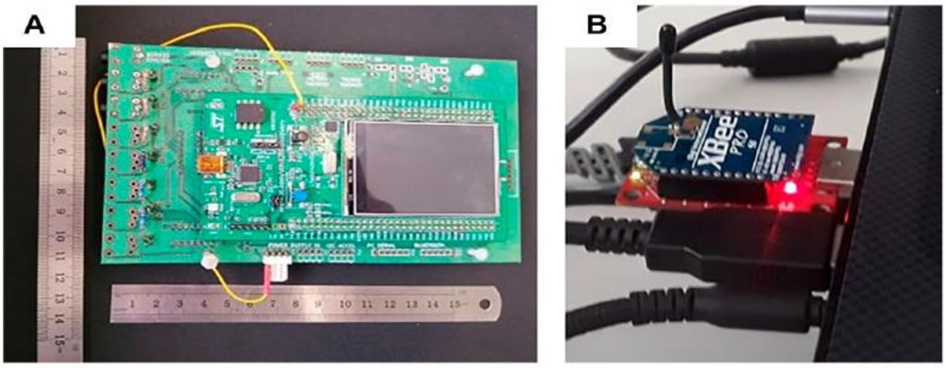

Figure 4: a) Prototype DAQ device; b) Setup of edge node and WSN.

Therefore each time the user is connected, after getting authorized, their user group is automatically retrieved by the Cloud database and the suitable GUIs are loaded. As long as the login is successful, if the user is listed as a client, then the available options are to create a new cluster of refrigerators or process/monitor an existing cluster. The "Set Up New Line" functionality is targeted for new customers, or customers that acquired new equipment, i.e. new refrigerator group(s) or new DAQ device(s). The core functionality of the developed framework lies within the monitoring functionalities. In the corresponding GUIs, the customer can visualize in 3D a scaled version of their refrigerator group and upon request to visualize the available information, which are automatically fetched by the Cloud database. Then, in continuation, if requested, the data can be transformed into statistical figures, so that the client can visualize the current status of their equipment. All of the above-mentioned data can also be visualized in the form of augmentations in case the customer is close to the refrigerator. In order to further notify the customer about an upcoming maintenance action or if any piece of equipment requires special attention, certain alerts have been implemented. Regarding the communication interfaces between the DAQ device, the end-user application and the Cloud Platform, RESTful API services have been developed. As regards the communication interface between the DAQ device and the Cloud Database, the DAQ device as a client can send POST, and PUT requests to the Cloud Platform, so as to enable the data to be posted on the database if they are not existent or updated as needed. On the contrary, the majority of the services implemented on the end-user application send only GET requests, in order to fetch data to the end-user's device, with the exception of user registration, where a POST request is sent in order to record the user's data on the database. However, due to the large volumes of sensitive data that are circulated within the proposed framework, a set of security measures are taken. Initially, all the HTTP requests are of type HTTPS (Hypertext Transfer Protocol Secure). Secondly, DELETE requests are not allowed for anyone trying to connect to the Cloud Platform. Therefore, in order to delete any records from the database, this process has to be undertaken manually by the authorized system administrator. In an attempt to make the proposed framework more general, a custom editor has been developed for supporting the functionalities of the framework itself. More specifically, the development team assisted by the editor can create virtually any configuration of systems and functionalities, so that the framework can be adapted to the actual needs of the corresponding company. From a hardware point of view, a desktop PC has been utilized for the development of the application as well as the Cloud Database and its services. For the implementation of the developed AR-based application, an Android-based tablet and a Microsoft HoloLens HMD are used. As regards, the DAQ device, an Arduino Mega 2560 microcontroller is paired with the custom board presented in the previous paragraphs. In addition to that for the XBee RF modules, the Arduino XBee shield and the Adafruit explorer shield were used.

From a software point of view, for the setup of the DAQ device, the Arduino IDE was used. Moreover, for the setup of the WSN the X-CTU application from Digi has been utilized. The implementation of the Edge computing network is based on the utilization of a cluster of Raspberry Pi 3 single-board computers, running on Linux operating system. Concretely, for gathering useful data from the machine tools, a DAQ device is connected to the machine tool and its Programmable Logic Controller (PLC). The selected firmware of the XBee devices is based on the XBee 802.15.4 protocol in order to enable the above-mentioned functionality. Additionally, the Raspberry Pi is preferred since it is a micro-processor (MPU) versus the STM32F429 which is a micro-controller unit (MCU). Consequently, the MPU has increased computational capabilities (as a result of the integrated hardware, processor, RAM etc.) thus, enabling the creation and operation of the edge nodes.

For each of the machines monitored, a Raspberry Pi computer is utilized and handles the data gathered from the sensors. The STM32Discovery boards have been programmed to use the freeRTOS, which, is a free real-time operating system and is compatible with the Arm Cortex-M4 processor of the MCU. As far as the sampling rate is concerned, the DAQ device collects feedback from the installed sensors on a varying rate. The sampling rate for the accelerometer sensor is set to one (1) second or 1 Hz. The sampling rate for the temperature sensor is set to five (5) seconds and for the pressure sensor is set to 10 ms (milli-second) as soon as a surge event is detected. Each of the Edge Nodes is assigned the task of processing the data, in order to offload the central Cloud computer system. Subsequently, the results are transmitted to the central Cloud Computer, which is responsible for fusing the data received from the Edge Nodes and run the simulations/feed the digital twin in order to estimate the RUL. For the communication of the Edge nodes, XBee radio frequency (RF) modules are implemented on each Edge Node. In order to provide a more robust communication network, an API protocol is setup and implemented. More specifically, the data logged from the DAQ devices are automatically split into binary packets. Each of the packets carries a set of additional information regarding the ID of the transmitted device, and the RSSI (Received Signal Strength Indication). The volume of data in the current implementation status is approximately 9.7 Gigabytes per hour and could be increased as the number of the edge nodes increases. A cellular network for the data transmission is selected, in order to ensure that data can be acquired from equipment located in difficult to reach points. On the other hand, Zigbee is a low-power, low data rate, and close proximity wireless ad hoc network with a physical coverage of a few meters (< 100m). Furthermore, powerline communication is a good and acceptable solution, however, the installation of the DAQ equipment requires additional infrastructure. Therefore, system's adaptability and agility are compromised. From a software point of view, the SVM is implemented as a Python application. the same applies also for the rest of the components of the Edge Node, as discussed in the previous paragraphs. As regards the Digital Twin side, used for the simulation of the equipment, it is implemented as a functional block diagram via MATLAB Simulink. Further to that, the usability of the above-mentioned Simulink model extends to the generation of fault data. The faulty datasets are mainly useful in the initial implementation of the system, in order to facilitate the population of the Cloud database with false operating data and assist during the calculation of the RUL of the components. From a hardware point of view, for the current developments, as presented in this research work, for the

Cloud server, a PC have been utilized, equipped with an Intel Core i7 processor, 16Gb of RAM memory and a Nvidia GPU with 6Gb of dedicated memory.

5. Conclusions and Outlook

The scope of this research work was to present a novel framework that will facilitate engineers to constantly monitor the status of the manufacturing equipment and in advance to predict the forthcoming maintenance activities. By extension, the prediction of malfunctions will enable companies to schedule their production more efficiently, whilst it makes them more adaptive to any disturbances caused within the company limits. From the implementation in the industrial partner, it became evident that the refrigerator downtimes can be reduced by approximately 20%, since both the clients and the OEM were capable to monitor the status of their equipment and by extension, with the use of the AI algorithm, the RUL prediction for crucial components of the refrigerator system, the client got a trustworthy estimation of when their equipment should be maintained. In addition to that, since the customer, could get an estimation of the upcoming failure, they are able to schedule a maintenance session with the OEM much faster and fitted to both ends' schedule without creating great disturbances. An equally important finding is that the maintenance costs can be reduced by approximately 10% since the OEM can order and acquire the needed components beforehand, thus eliminating overnight delivery costs.

The most important implication faced, is that the calculation of the RUL cannot be performed in real-time thus inducing a certain amount of latency in the AR visualizations. The amount of latency is affected by two major issues, first the network speed and second the computational power of the system handling the Digital Twin. Another implication is the authoring of the AR visualizations in the field of view of the end-users. Currently, this is a manual task, which in the future must be addressed, so that AR applications can become useful tools in the modern manufacturing environment rather than increasing the complexity of the systems, by increasing the time and effort to prepare the so called "AR scenes". In the future, the Digital Twin of the equipment will be improved. It is estimated that following the implementation of the proposed framework in similar equipment, i.e. a fleet of assets, will enable the creation of data ensembles. Essentially, this will facilitate the use of similar datasets in order to improve the predicting accuracy of the Digital Twin. Another issue that will be addressed in a future research work, is the integration of an Edge security framework, in order to improve the security of the developed framework under cyberattacks.

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