



FDaaS: FAULT DETECTION AS A SERVICE IN INDUSTRY 4.0 ENVIRONMENT

Aicha BOUHENTALA ^{1,*} , Rafik MAHDAOUI ² , Leila-Hayet MOUSS ¹ , Ouahiba CHOUHAL ² 

¹ Automation and Manufacturing Engineering Laboratory, Industrial Engineering Department,
Faculty of Technology, Batna2 University, Batna, 05000, Algeria

² ICOSI Lab, Mathematics and Computer Science Department, Faculty of Science and Technology,
Abbas Laghrour University, Khenchela, 40000, Algeria

* Corresponding author, e-mail: aicha.bouhental@univ-batna2.dz

Abstract

Modern industry 4.0 technologies are critical for improving the efficiency of transactions and sharing distributed resources and big data for optimal utilization within manufacturing networks. Therefore, they play a paramount role in various industrial sectors, especially in assets maintenance. The concept of Maintenance as a Service is inspired from the principle of cloud manufacturing, that seeks to provide on-demand manufacturing through the use of manufacturing resources, thereby matching the cloud-computing paradigm's goal of delivering everything as a service. Reliable maintenance refers to the early detection of faults to prevent assets from suffering unexpected downtime, thus reducing the high cost of maintenance. The main objective of this work is to present a fault diagnosis architecture that includes spans from fault detection to the conception of comprehensive and intelligent maintenance architecture. This concept intends to assure asset reliability and availability at the industry level, while also meeting the evolving demands of Industry 4.0 technologies.

Keywords: cloud manufacturing, fault detection, fault detection as a service, Industry 4.0, maintenance, web services

List of Acronyms

AR – Augmented Reality
CC – Cloud Computing
CMfg – Cloud Manufacturing
FDaaS – Fault Detection as a Service
IoT – Internet of Things
MAaaS – Maintenance as a service
SWHSm – Solar Water Heating System
WS – Web Services

1. INTRODUCTION

The present-day industrialized sector faces intense global competition and diverse demands, leading to the circulation of vast amounts of data. Consequently, the adoption of essential technologies, including Machine Learning, Cloud computing, Internet of Things (IoT), among others (Figure 1) has become imperative. These technologies collectively establish an industrial network, and their efficient integration gives rise to the formation of a smart factory, as illustrated in [1]. Industry 4.0 strongly influences all stages of plant operations, from asset installation and condition monitoring to downstream processes such as product sales and marketing. Maintenance 4.0 is amongst the paramount resulting notions of the industrial

revolution 4.0. Specifically, the integration of technologies: Internet of Things, Augmented Reality and cloud manufacturing has revolutionized the practice of maintenance in terms of increasing operational efficiency and reducing costs and downtime.

According to [2], the proactive maintenance approach is considered the first step in implementing maintenance 4.0, as it focuses on monitoring the causes of failures. Such maintenance strategy is characterized by an anticipatory approach, based on monitoring, diagnosis, prognosis and the use of decision support algorithms for data processing. On this basis, many emerging Industry 4.0 maintenance strategies have focused on failure prevention, fault detection and diagnosis, and anomaly prediction. These include predictive maintenance 4.0, maintenance based on machine learning techniques, and Maintenance as a Service, which is grounded in Cloud Manufacturing concepts (CMfg). This research shows that fault detection is the most important part of successful Maintenance-as-a-Service. The study also provides fault detection as a service, which is its main goal. This paper proposes an architecture for Fault Detection as a Service (FDaaS) within the Industry 4.0 framework. The architecture allows users to access the service at

any time and from any location, securely store their data, and utilize the service on a pay-per-use basis.

The remainder of this paper is organized as follows: the second section introduces the state of the art of maintenance in industry 4.0. The third section presents the proposed framework. Section 4 depicts a case study on fault detection as a web service conducted on a solar water heater system, with interpretation of the obtained results.

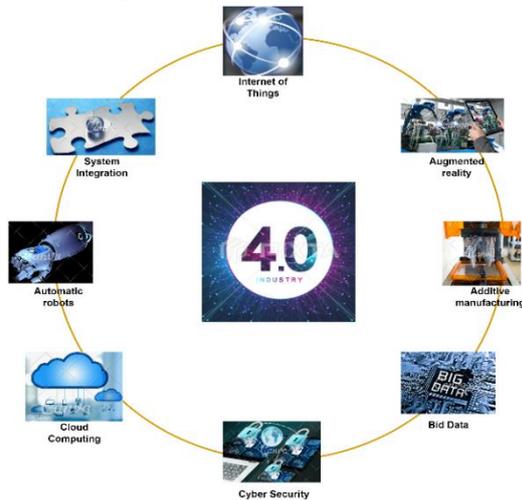


Fig. 1. Presentation of various industry 4.0 technologies

2. LITERATURE REVIEW

Over time, researchers have contributed to Industry 4.0 technologies and implemented them in maintenance, hence giving rise to a new maintenance approach. This shift has transformed maintenance practices from traditional techniques such as cleaning, lubrication, and welding to activities centred around data collection, visualization, analysis, and informed decision-making. It is important to mention that this evolution does not discard the significance of traditional tasks, but rather integrates them synergistically with the new practices [3]. Below we mention some works that have applied these technologies in the field of maintenance and fault detection.

2.1. Maintenance Based on Augmented Reality (AR)

Augmented reality is an emerging technology that has been around for a decade, but still has a significant impact on complex operations, especially in the field of maintenance [4]. Several research studies concerning maintenance based on AR have proven this impact. In 2018, [5] have developed an application on a portable mobile phone based on AR for preventive maintenance. The application enables real-time control of assets, leading to minimized intervention costs and prevention of asset faults or breakdowns, while Mourtzis in [6] have developed a maintenance strategy based on augmented reality. To this end, remote repair operations through communication channels between maintenance operators and experts was carried out,

where the application managed to minimize Mean Time To Repair (MTTR).

2.2. IoT/Cloud Based Maintenance and Fault Detection

Many companies have chosen to implement IoT across various industrial sectors due to its numerous benefits. Web protocols and the Internet of Things (IoT) have made predictive maintenance easier to implement, as proven in [7]. The authors proposed an online monitoring system for polishing and sanding machines through devices based on software that translates the equipment status into web protocols and saves it in an IoT platform, alerting users with messages when parameters degrade.

In [7], an IoT-based predictive maintenance methodology on medical equipment is used to diagnose and predict failures to increase reliability in critical systems. Saily and Bourezza [8], [9] have developed an intelligent predictive maintenance platform allowing diagnosis and health monitoring of equipment in order to guarantee their availability and minimize maintenance costs. Furthermore, Dong have opted for big data applications and IoT in road maintenance to increase their performance [10].

The cloud also is a maintenance solution for connecting widely dispersed data in different repositories [11]. Through the cloud, users can benefit from data collection, distribution, and storage services, thereby enhancing maintenance efficiency. Some researchers have also combined the cloud with the IoT. For example, the idea proposed in [12] aims to monitor equipment online and in real time, and was effective with a large number of equipment. The same combination was made in [13][14], where both opted for a cloud-based IoT solution for fault detection and localization performing the more computationally intensive tasks, data storage and decision-making. Wang et al. [15] proposed an innovative predictive maintenance model based on mobile agents capable of dynamically deploying different services via cloud computing. This approach relies on distributing analysis algorithms directly to cloud nodes, rather than transmitting raw data from sensors, in order to optimize information sharing and strengthen interaction mechanisms within the maintenance architecture. A monitoring system has been proposed in the form of a web application developed on the cloud, which informs maintenance experts about the status of the equipment in real time [16]. Amr have proposed a Cloud Computing platform, which receives unlabelled data to generate online decision and collect the historical data to improve the maintenance system [17].

Kadhun et al. propose a scalable IoT framework for predictive maintenance of electrical equipment, utilising real-time data collection and automated algorithms for fault detection, which significantly improves maintenance efficiency [18]. Similarly, Bindushree's research on renewable energy systems demonstrates a fault diagnosis system achieving high detection accuracy (96.7% for solar PV and 93.5% for

wind), reducing maintenance costs by 29.4% and unplanned downtime by 37.8% [19]. Muthu et al. emphasise the importance of prompt fault detection in power systems, utilising AWS cloud technology for real-time fault isolation [20]. Furthermore, Ul Mehmood et al. present a robust cloud-based solution for fault localisation in power distribution systems, effectively managing data transmission and enhancing fault detection capabilities [15]. Lastly, Aljadani et al. introduce Elevint, a cloud-based system for elevator fault detection that ensures real-time monitoring and communication between stakeholders, achieving 98% accuracy in fault identification [21]. Collectively, these studies highlight the transformative impact of IoT and cloud technologies on maintenance strategies across diverse applications.

2.3. Maintenance based on Web Services (WS)

Maintenance using information technology, or e-maintenance, was established in the 1990s. A Dynamic Neural Network Architecture has been proposed in [22] to ensure remote equipment monitoring using web services and yields more autonomous and intelligent maintenance approach. Ricardo in [23] have created a predictive maintenance service and deployed it in an

Amazon Web Service cloud platform. An improvement in maintenance efficiency and a decrease in costs was noticed in [24], where the authors proposed an electronic maintenance framework based on web technologies to plan maintenance actions and avoid breakdowns in supervisory assets.

A web platform dedicated to maintenance management, gathering the collected information related to cultural heritage, as well as diagnostic reports has been elaborated in [25]. This platform is accessible to all stakeholders involved in computerised industrial systems, facilitating the scheduling of maintenance operations and cost estimation based on data obtained from supervision and control systems. Table 1 compares the three main maintenance strategies in the context of Industry 4.0 technologies, each characterised according to the availability criteria of industrial systems and assets, where each method is defined in terms of availability, fault tolerance, scalability, and challenges encountered during installation. From this definition, the most suitable methods can be selected according to the indications of the industrial systems.

Table 1. Comparative Evaluation of Maintenance Methods Based on Industry 4.0 Technologies

	Maintenance based on IoT	Maintenance based on RA	Maintenance based on WS
Principle	Based on equipment connectivity and data collection via intelligent sensors.	AR allows the technician to view operations step by step and be guided remotely by experts.	Maintenance actions carried out as a web service using a cloud platform for data processing and storage.
Infrastructure	Sensors and IoT software and communication networks.	AR software, applications and hardware (AR glasses).	Servers, applications, web services, network connection, Cloud platform and IoT sensors.
Fault tolerance	The processing and analysis of data is done immediately in real time so the tolerance for faults is very high.	Depending on the reliability of RA devices.	Depends on the reliability of services, internet connection and the robustness of the platform.
Mobility	By dint of portable devices and reliable networks, availability and mobility are ensured.	Depends on the presence of AR device users.	Accessible via an internet-enabled portable device, users can access their data.
Scalability	Extremely scalable: IoT systems have the ability to expand by integrating new sensors and devices.	Constricted by the total number of augmented reality devices (tablets, headsets).	Strongly scalable: thanks to the cloud, users can increase or decrease resources and capacities.
Interoperability	Interoperability in IoT systems is critical and relevant and considered as the most difficult challenge to solve [26].	Moderately weak and requiring a high degree of interoperability due to device and platform incompatibility.	Very high: interoperability in web services running in the cloud is essential because it facilitates communication between applications and the platform in a seamless manner.
Challenges	Data security, high installation costs.	Need for significant investment in AR equipment and ongoing user training.	Requires significant storage space and a high internet connection. Response time linked to the presence of the internet, as well as the confidentiality problem.
Area of application	Fault detection, proactive and predictive maintenance.	Real-time monitoring, corrective and predictive maintenance.	Fault detection, proactive, preventive and predictive maintenance.

The literature study of different maintenance techniques based on various Industry 4.0 technologies is well enriched, and researchers have achieved important advances in extracting significant profits in the field of maintenance in terms of failure anticipation and increasing asset availability. The main challenges are associated with the high investment costs related to equipment acquisition, system installation, and supporting infrastructure, as well as concerns about data security. Consequently, there is a growing need for an autonomous maintenance service that, unlike conventional solutions, can be accessed at any time, from any location, and through any Internet-connected device. To the best of our knowledge, there is still a lack of notable contributions regarding these maintenance services deployed on the cloud, more precisely detection as a service and this is the core of this research. Furthermore, Existing research indicates that Industry 4.0 technologies such as augmented reality, Internet of Things, cloud computing, and web-based services, have significantly improved maintenance by providing connectivity, real-time monitoring, and predictive capabilities. AR-based approaches primarily improve maintenance execution and reduce MTTR through operator training, while IoT and cloud solutions enable large-scale data collection and highly accurate fault detection. However, most existing solutions rely on local, threshold-based detection and output generic non-prioritised warnings. Diagnostic reasoning and maintenance decision support are often scattered or poorly structured. Historical data and machine learning methods are not sufficiently leveraged for continuous improvement. Moreover, a trade-off exists between low-latency edge response and intelligent cloud-based analytics. This study presents a hybrid FDaaS architecture that distinguishes between rapid local alarm detection and centralized cloud-based diagnostics. The proposed approach combines information from multiple data sources, assesses the most likely causes of failures, and provides contextual explanations. As a result, system failure diagnoses are translated into clear, prioritised, and data-driven maintenance actions, thereby improving the efficiency of maintenance decision-making.

3. PROPOSED FRAMEWORK

After presenting an overview of industrial maintenance techniques based on Industry 4.0 technologies, we propose a vision of the general architecture of industrial maintenance as a service in the context of Industry 4.0, more precisely fault detection as a service (FDaaS). The architecture of our application has taken its roots from the notion of cloud manufacturing, and the use of cloud platforms in different manufacturing sectors has favourably influenced the management of the company, including all processes [27].

In establishing the architecture of the fault detection service, it is essential to clarify the following concepts:

- A. From an industrial perspective, web services are applications that enable connectivity between users and industrial assets through hardware and software resources. It facilitates real-time data exchange and sharing, providing several advantages for industrial systems, including continuous remote monitoring, real-time equipment supervision, and the automation of industrial operations, which reduces downtime and operational costs.
- B. Cloud manufacturing is an innovative platform that uses Cloud Computing and IoT technologies, which allows the storage and analysis of data. In maintenance, the platform hosts different web services dedicated to fault detection, predictive maintenance, intervention planning, and from there comes the principle of "everything is provided as a service". This access facilitates users' remote supervision, resource management, operation planning and several other advantages, consequently reducing field trips and maintenance costs.

As mentioned in [28], the different service models provided by the CMfg are based on IaaS, PaaS and SaaS, including the following models:

- Design as a Service (DaaS): The Design Resources and Capabilities are provided as a service;
- Manufacturing as a Service (MFGaaS): Manufacturing resources and capacities are provided as a service;
- Experimentation as a service (EaaS): The resources and the capacities for experimentation are provided as a service;
- Simulation as a service (SIMaaS): The simulation resources and capacities are provided as a service;
- Management as a service (MaaS): Management resources and capacities (MR&Cs) are provided as a service;
- Maintenance as a service (MAaaS): The maintenance resources and capacities are provided as a service.

The last service is our search field, it aims to provide on-demand services and achieve full sharing, free circulation, on-demand usage and optimal allocation of various management resources and capacities. The principle of maintenance as a service is adopted from the concept of remote maintenance, where equipment diagnosis is achieved by integrating smart sensors, IoT technology, web services, etc.

Maintenance as a service MaaS is a commercial approach that aims to outsource all maintenance activities to a third party with a usage-based contract. The service provides several services according to customer demand namely: information on equipment, spare parts, supplier, history, planning ...etc.

The service also envelops maintenance sub-services including fault detection, diagnosis, prognosis and prediction. This model is based on the use of innovative Industry 4.0 technologies such as the IoT for data collection, AI techniques for processing and analysis, and the Cloud for storage, enabling companies to increase flexibility and reliability

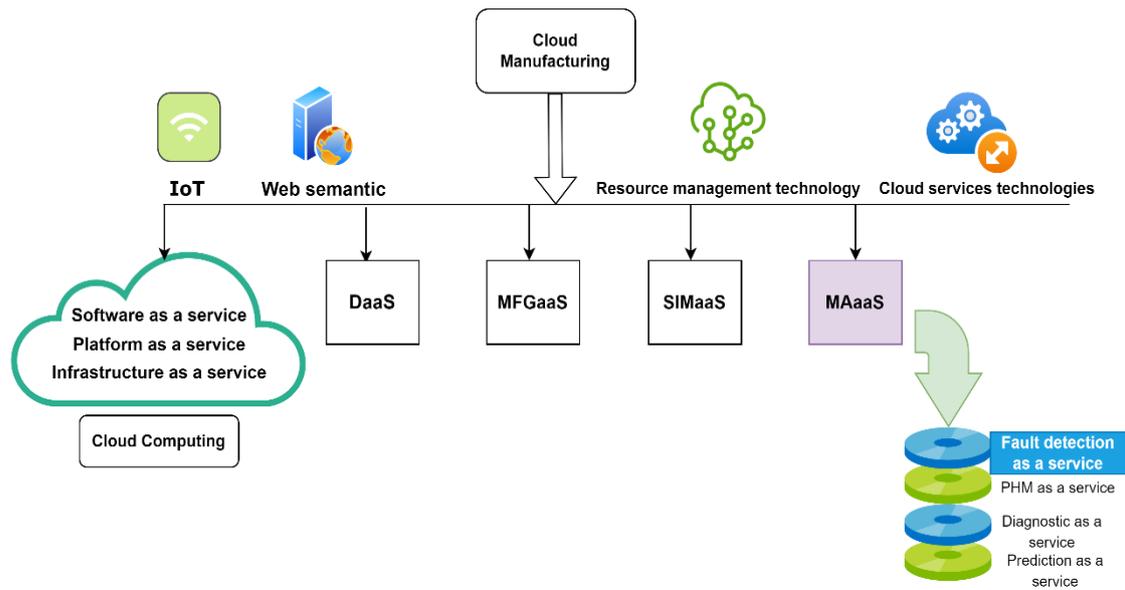


Fig. 2. Different services offered by Cloud Manufacturing

Within this framework, different users are allowed to find and request the necessary services from the cloud to complete the required tasks to carry out maintenance operations in real time while ensuring the availability of equipment and the efficiency of human/machine interaction in which the user may be a maintenance operator or an expert on the system under surveillance. The figure 3 illustrates our framework, which starts with the implementation of a standalone application. This application aims to monitor the system status in real-time. It is characterized by a set of implemented features to detect faults, diagnose failures, and anticipate degradation. Each application is dedicated to a specific system and generally operates in real-time. However, like any application, it has limitations, sometimes requiring the use of shared solutions such as access to remote procedures, web applications, and web services available on the internet. Fault Detection as a Service (FDaaS) constitutes a pivotal solution within contemporary maintenance paradigms, recognizing fault detection as a critical enabler of operational success. This service model facilitates the identification of equipment anomalies through a network of intelligent sensors. The data acquired by these sensors is subsequently transmitted to a cloud-based platform for comprehensive processing and analytical evaluation. By employing integrated performance monitoring and advanced detection algorithms, the system enables precise fault identification.

In this work, we propose a Fault Detection as a Service (FDaaS) solution, recognizing fault detection as the cornerstone of effective maintenance operations. Our approach enables the identification of equipment anomalies via smart sensors. The collected data are transmitted to a cloud platform for processing and analysis, where integrated performance monitoring and detection algorithms support facilitate precise fault identification. The FDaaS framework is designed

based on a modular web services architecture. Our methodology begins with the creation of discrete, single-function web services, each dedicated to a specific task.

One service acquires data, another processes it and alerts users of system status and anomalies, while a third performs diagnostic analysis to infer probable fault causes. This structure ensures that maintainers can make timely and appropriate maintenance decisions. This system is implemented by first developing and validating these server-side web services within a local PC environment under a WWW directory. To coordinate the individual components, we then compose them into an orchestrated workflow. This service composition is essential for achieving an autonomous and optimized fault detection system, integrating all operations into a unified service. Finally, the composite service is hosted on a cloud platform to ensure accessibility for users.

4. CASE STUDY APPLICATION

In this case study (Shown in figure 4), we analyse a specific industrial system to illustrate the application of fault detection as a service. Starting with a detailed description of the system, detailing its operation and the types of anomalies that may occur. Then, we discuss the creation of the web service that monitors the operation of the system in real time paradigm, and any deterioration of the defined parameters, the user will be notified by an alert.

4.1. System presentation

We opted for a health monitoring application for a Solar Water Heating System (SWHSm) developed in the LabVIEW programming environment [29][30][31]. The SWHSm works by absorbing solar energy via flat collectors. The heat is transferred to the heat transfer fluid circulating in the absorber of the solar collector in a closed circuit via a circulation

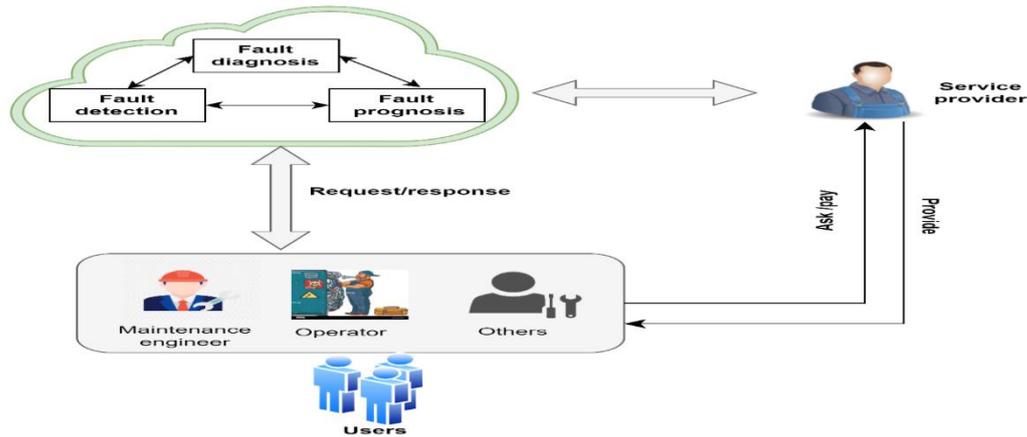


Fig. 3. Service Workflow in a Cloud Manufacturing Environment

pump. The cold water stored in a storage tank will be heated thanks to the thermal change, and the hot water is ready to be consumed. Therefore, LabVIEW user interface is developed to implement the functionalities of each component in the SWHSm (Figure 5). This interface aims to simulate the system's operation and monitor the measurements from the installed sensors (temperature, pressure, and flow) in real time, allowing timely intervention when necessary [33], [36]. The installed sensors measure the temperature values at the solar collector and the two tanks. Pump 2 (see Figure 5) is activated when the difference between the temperature measured at the level sensor and the temperature of the second tank exceeds a specified threshold ($\Delta T=10^{\circ}\text{C}$) and deactivated once this difference is reduced. The is greater than ΔT , allowing heat exchange until the water continues to circulate as long as this difference desired temperature is reached. Moreover, another peripheral that must be added is obviously the data acquisition card (DAQ) whose role is to connect the sensors to the system. This process is based on the continuous measurement of various parameters using the installed sensors, and on the comparison of these measurements with predefined thresholds. Hence, this makes it possible to know the state of the system at any time and to detect anomalies originating from the tank leaks, solar energy collection problems or sensor failures

4.2 Malfunction mode and parameters monitoring

The solar water heating system can experience different types of malfunctions; we can identify them and analyse their causes and effects one by one through the Failure Modes, Effects Analysis (FMEA). To supervise the Solar Water Heating System, we take a few main elements and we monitor the parameters considered for each element so that these parameters always remain within the acceptable ranges. In the event of being exceeded, an alarm goes off indicating a fault in the system, which allows supervisors to cope with the problem in real time by restoring the system to a good condition. Through the dashboards developed in LabVIEW, it is possible to monitor the measured parameters of the solar water heating system

in real time through a user-friendly visual interface (see Figure 6), which displays current measurements, such as temperature, circuit pressure, water flow, etc. Parameters measured in real time are displayed as graphs, gauges or numerical values, enabling up-to-date, continuous and efficient control of the system status and performance.

Sensors are installed to collect relevant data and the specified thresholds for each measurement (temperature, pressure, flow, etc.) corresponding to the normal behaviour of the system are defined as follows: maximum water temperature for solar collectors: 70°C - 90°C , minimum water temperature threshold for solar collectors: 5°C - 10°C to prevent excessively cold conditions.

Minimum water temperature threshold in the storage tank: 40°C - 50°C to ensure comfortable domestic hot water usage and maximum system pressure: 6-10 bars. It is crucial to carefully monitor abnormal operating modes to ensure the proper performance of the solar water heater and to avoid any interruption or loss of hot water production. In addition to real-time monitoring of parameters, the monitoring program also displays if there is a blocking fault or an unexpected shutdown indicating the fault location and its probable causes (Figure 7).

When a fault occurs, an alarm message is displayed in the LabVIEW environment, indicating the type of fault and its probable causes. This alert notifies the diagnostic system about detected problems, such as leaks, sensor failures or circuit malfunctions.

So that maintenance operators can tackle the issue at the right time and diagnose the malfunctions and restore the system to good condition [34],[35].

4.3. Fault detection as a web service

4.3.1 Creation of the fault detection web service

To meet the specific requirements of the experimental setup, web services were developed using LabVIEW. Real-time parameter measurement functionalities were incorporated, enabling rapid system updates while maintaining continuous online operation. Communication with multiple instruments was

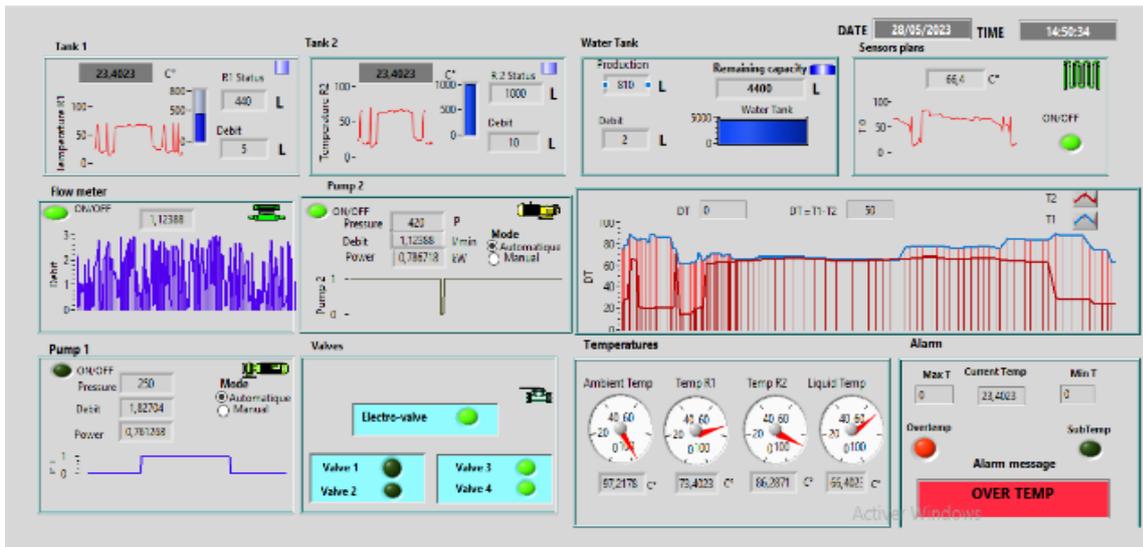


Fig.4. BPMN Model of the Fault Detection Workflow as a Service in Cloud Manufacturing

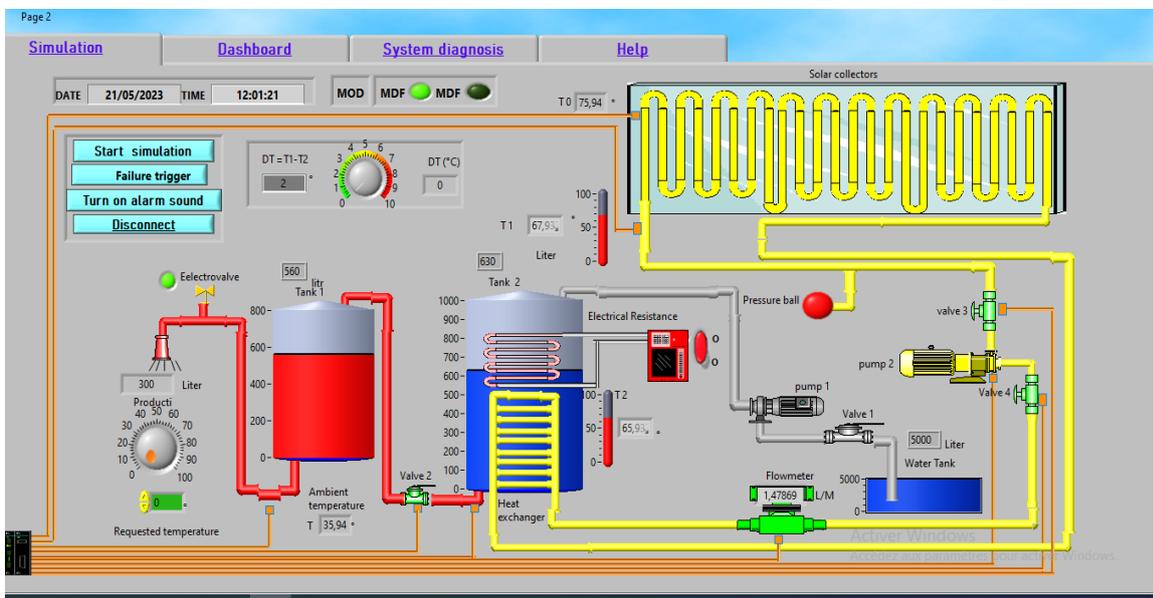


Fig. 5 Global User Interface of the SWHSM

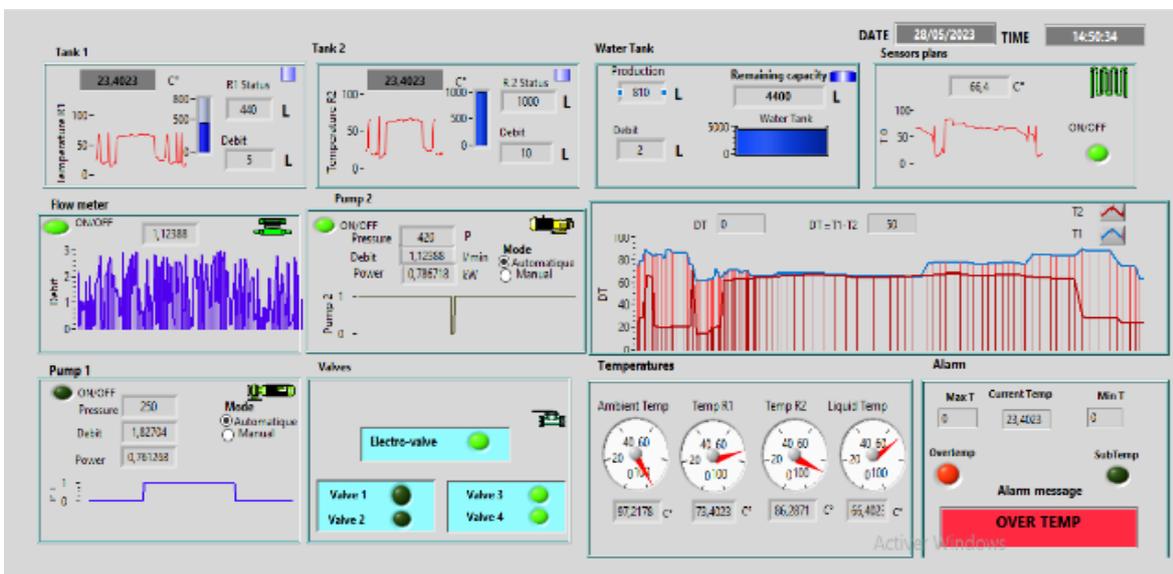


Fig. 6 Real-time parameter monitoring

achieved through HTTP-based protocols implemented within LabVIEW's integrated framework. In addition, interactive dashboards were designed using LabVIEW's graphical interface to display parameter variations during the experiments. A monitoring mechanism was also configured to detect system malfunctions and generate immediate alerts indicating the type of fault, thereby enabling rapid intervention and reducing downtime during experimental activities. Figure 8 presents an overview of our contribution, which indicates the concept of Fault Detection as a Web Service whose mission is to detect and discover anomalies in the solar water heater system early to satisfy the availability requirement and high-quality service demand.

4.3.2 Remaining useful life estimation by web services composition

Among the solutions also approved for monitoring devices the estimation of the remaining life, in this

section we suggest a solution based on the composition of web services that estimates the RUL [31], which is considered as a basic element for the implementation of predictive maintenance. This composition of web services aims to simplify the communication between components and increase their availability at a lower cost. Therefore, we created a composite web application, where we first created a Wsd files (Web Services Description Language) from the XSD (XML Schema Definition file) [32]. Then, we tried to create the partner web services namely RUL and MIN (minimum value of all RULs of the subsystems). The third step is based on the integration of these files into our BPEL (Business Process Execution Language) business process after configuring each activity. Finally, we tested this application in an industrial system, which is a cement kiln of the Ain Touta Batna cement plant. Using web service composition, these services interact with the BPEL process to estimate the remaining useful life of our studied system.

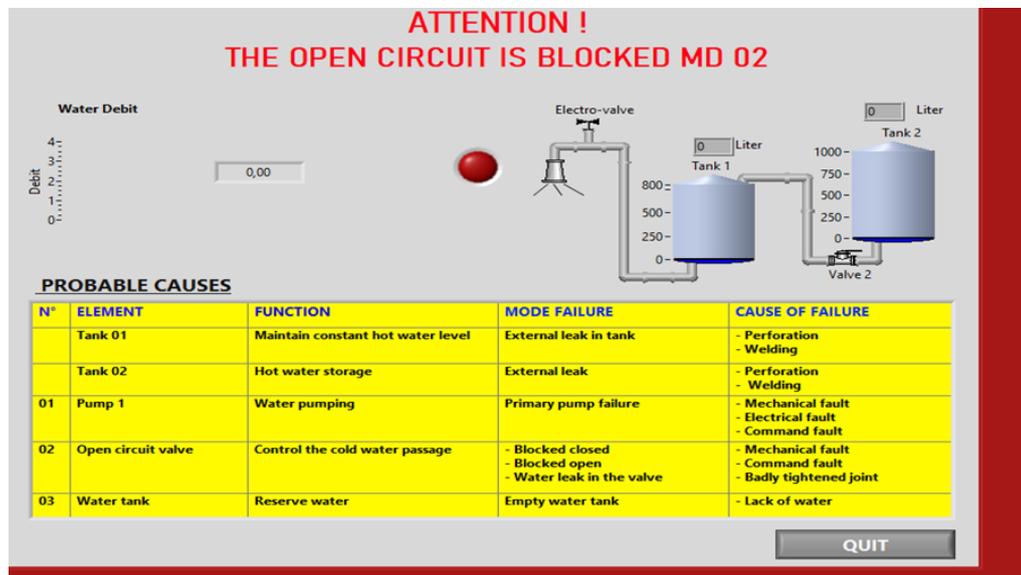


Fig. 7. Display of an alarm message

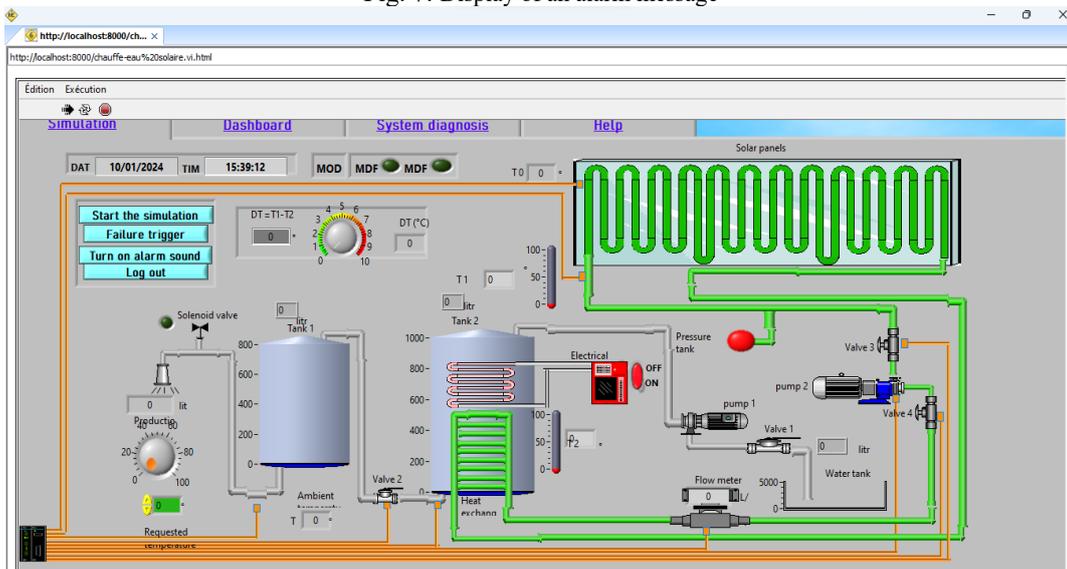


Fig. 8. Publishing fault detection function as a web service

4.4 Results and Discussion

The results obtained from our system demonstrate its effectiveness in detecting faults in a solar water heating system, with a reasonable level of accuracy. The system successfully identified anomalies related to temperature deviations, providing real-time monitoring capabilities via a web service-based interface. However, some limitations remain, such as sensor inaccuracies, potential delays in data transmission, and external environmental factors influencing temperature readings. The two principal fault diagnosis paradigms are clearly distinguished. The Local diagnostic model operates as a real-time alarm generation module, providing immediate detection of abnormal system behavior and ensuring low-latency fault notification. The Cloud-based FDaaS model functions as an intelligent diagnostic decision-support system systematically transforming raw alarms into a structured, contextualized, and prioritized maintenance strategy. It performs fault cause ranking, integrates operational and historical data, and supports an optimized, data-driven maintenance decision for the technician assigned to resolve the identified fault (e.g., MD-02). It performs fault cause ranking, integrates operational and historical data, and supports an optimized, data-driven maintenance decision for the technician assigned to resolve the identified fault (e.g., MD-02). In our case we see that after the invocation of web service as a FDD tools: an active over temperature alarm is present, despite the displayed current temperatures (24.48°C, 64.6°C) being below a typical critical threshold. This suggests the alarm is generated

by a different sensor (e.g., the "Junction Temp" reading between 81-100°C) or a system fault. Pump 1 is off, while Pump 2 is in CHF (Command/Control) mode and operational. The system is in automatic mode with a low level status indicator.

6. CONCLUSION

This study proposed a Fault Detection as a Service (FDaaS) architecture that uses fundamental Industry 4.0 concepts to monitor simple and complex industrial systems. Real-time monitoring of a solar water heating system was used as an appropriate case study to validate the suggested method. The proposed solution effectively detects anomalies and errors in the system and alerts users in real time by providing the observed anomaly and its potential causes, allowing for prompt and suitable corrective measures. The proposed FDaaS uses a web service-based architecture, allowing diverse users, such as managers and maintenance operators, to monitor assets at any time and from any device, as well as get fast notifications when abnormal situations develop. To improve the flexibility and intelligence of the fault detection process, future research will concentrate on combining machine learning and advanced learning algorithms. In particular, the estimation of the Remaining Useful Life (RUL), a critical component of predictive maintenance, will be thoroughly investigated as a promising improvement on the suggested architecture.

Table 2. Diagnosis Local and Cloud FDaaS evaluation

Metric	Diagnosis Local	Cloud FDaaS
Time to Initial Alert	< 100 ms from sensor data acquisition	1.5 – 3 seconds (data transmission latency + cloud processing queue)
Fault Detection Accuracy	<70% (high rate of false positives/negatives)	> 95% (enhanced by pattern recognition, historical data correlation, and advanced analytics)
Data Transmitted per Day	~10 MB (only essential alert logs and status changes)	~500 MB – 1 GB (includes full high-frequency sensor streams for deep analysis and storage)
Computational Resource Use	Minimal (runs on embedded processor with < 5% average CPU utilization)	High but elastic (utilizes scalable cloud compute; may use 10+ virtual CPU cores during intensive diagnostic analysis)
Diagnostic Precision (Cause Ranking)	Not applicable (presents static list without prioritization)	Quantifiable probability scores (e.g., Valve Command Fault: 65%, Mechanical Blockage: 30%, Pump Failure: 5%)
MTTR Impact	Potential increase of 25 – 40% due to troubleshooting with an unprioritized cause list	Potential reduction of 15 – 30% due to targeted, prioritized maintenance actions

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Declaration of competing interest: *The authors declare that they have no known competing financial interests or*

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Recherche”, in *Electrical and Computer Engineering*, from the University of Batna. This is the Highest French degree. Dr. MOUSS is a Member of the IEEE Industrial Electronics, Industry Applications, Dr MOUSS is currently working on prognosis and health management (PHM) using learning techniques and other predictive maintenance topics such as fault detection and diagnosis. The Researches are conducted in the LAP Lab (Laboratoire d’Automatique et Productique) at Batna.

E-mail: h.mouss@univ-batna2.dz

Aicha BOUHENTALA Received her Master’s degree in Industrial engineering in 2016, and her Engineer degree in Hygiene and Industrial Safety in 2014, from the Institute of Hygiene and Safety of Batna University. She is currently a PhD student in LAP Lab (Laboratoire d’Automatique et Productique) at Batna. Her Research interests include Industrial Systems fault diagnosis and systems safety.

E-mail : aicha.bouhental@univ-batna2.dz



Rafik MAHDAOUI

Received Ph.D. degree in Industrial Engineering Sciences from Batna University in 2013 for his thesis titled “Contribution to the dynamic monitoring of evolving production systems using Temporal Neuro-Fuzzy systems”. He is currently a Professor in mathematics and computer science department, and a IT security team leader in ICOSI laboratory at the University of Abbes Laghrour Khenchela., Algeria. His research interests include computer science, software Security and Industrial systems.

E-mail: mahdaoui.rafik@univ-khenchela.dz

Ouahiba CHOUHAL

Received Ph.D. degree in Industrial Engineering Sciences from Batna University in 2018 for his thesis titled “Contribution to the dynamic monitoring of evolving production systems using Temporal Neuro-Fuzzy systems”. He is currently a Professor in mathematics and computer science department, and a IT security team leader in ICOSI laboratory at the University of Abbes Laghrour Khenchela., Algeria.

E-mail : haouassi.hichem@univ-khenchela.dz



Leial-Hayet MOUSS

was born in Batna, Algeria. He received the B.Sc. degree in Electrical Engineering from the National Polytechnic School of Algeria, Algeria; the M.Sc. degree in Electrical and Computer Engineering, from the ENSERB, France; and finally the Ph.D. degree also in Electrical and Computer Engineering, from Bordeaux University, France. After

graduation, he joined the University of Batna, Algeria. In 2005, Dr. MOUSS Held the “Habilitation à Diriger des