Approaching Interoperability and Data-Related Processing Issues in a Human-Centric Industrial Scenario

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Abstract. Industry 4.0 industrial automation paradigm and the related new Operator 4.0 role and pool of competencies are playing a critical role in bringing forth the Digital Transformation to manufacturing industry and SMEs in particular. The human-centric aspect of Industry 4.0 in combination with resilience, sustainability and circularity of manufacturing processes is gaining wider acceptance in Europe and across the globe while the transition towards Industry 5.0 starts to gain momentum as well as the integration of human centric solutions in Industry 4.0 automation systems. The current work uses a three-pronged approach to wearable sensors integrated with existing Industry 4.0 automation systems, by addressing sensor heterogeneity, data interoperability and network latency issues under the umbrella of a single unified and harmonised solution. Such a solution is realised in a realistic industrial scenario showcasing adaptive Human-Robot collaboration and leverages open-source software and open reference architectures.

Keywords: Human in the loop · Operator 5.0 · 5G · IIoT · NGSI-LD · CPPS

1 Introduction

The so called "Industry 4.0" has gained significant popularity since its introduction in the year 2011. This primary talking point in this new era of manufacturing has been the digitization of industries. With the adoption of this new industrial revolution, concepts like Cyber-Physical Production Systems (CPPS) and Industrial Internet of Things (IIOT) are helping in the transformation of the traditional Factories into "Smart Factories" [1]. Along with the evolution of industries, the role of the operators has also evolved. The term "Operator 4.0" has been used in the context of Industry 4.0 to signify the latest iteration of this evolution [2]. This paradigm calls for the development of "Human-centric Technologies" in a bid to improve the collaboration between humans and technologies/machines. Operator 4.0 typologies like "Healthy Operator", "Super Strength Operator", "Analytical Operator", "Collaborative Operator" can be used to classify terminology for such solutions [3].

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In continuation of Industry 4.0, Industry 5.0 and the corresponding Operator 5.0 can be seen as the next logical evolution. The need for such an evolution was primarily triggered by the COVID-19 pandemic and it exposed several fault lines within the existing systems particularly with respect to the resilience of the production systems. This new phase, while relying on the foundations of the earlier phase, calls for a renewed focus on the operator aspect of the industry [4], also considering that in recent years the attention on the "Social" dimension in the so-called "Triple Bottom Line" [5] has grown in terms of attention [6], in particular following the introduction of the "2030 Agenda for Sustainable Development" [7]. In this sense, the focus on the operators can highly impact these goals, thanks to the technology-assisted approach which can decrease the physical and mental stress of operators, improving their health condition and well-being, and reducing inequalities in accessing certain tasks even for operators with physical inequalities.

With the renewed focus of the industry on the operator, operator-centric technologies and their seamless integration with the existing systems has become of critical importance. One such aspect that the current work deals with is the integration of multivendor, operator-worn sensors in a Human-Robot collaborative workspaces and paced assembly-work scenarios.

The remaining part of the paper is structured as follows: Sect. 2 provides a brief overview of the state of the art and problem description, Sect. 3 briefly describes the testing scenario, Sect. 4 defines the proposed software architecture, Sect. 5 describes the test bed setup, Sect. 6 presents an open-source implementation of the proposed architecture. Section 7 presents the conclusion and future work.

2 Problem Description

The aforementioned industrial evolutions bring forth the importance and demand for human-centric solutions which significantly enhance the capabilities and the general wellbeing of the operators at multiple levels. A well-known work [3] made a significant attempt at classifying and formalizing the different typologies to be used for the different categories of operator enhancement. In that context, the current work primarily falls under the banner of "Healthy Operator". Solutions of this kind are aimed at improving the occupational health of the operators (e.g., by reducing fatigue and stress levels). This is achieved by monitoring and processing the biometric signals to evaluate and manage the cognitive and physical stress levels of the operators. To capture the biometric signals, the use of different wearable sensors has been suggested. In this context the use of sensors like Electroencephalograph (EEG), Electromyograph (EMG), Galvanic Skin Response (GSR), Heart Rate (HR), skin temperature, Electrocardiograph (ECG), Heart Rate Variability (HRV), Blood Volume Pulse (BVP), Photoplethysmography (PPG) has been reported in the literature [8]. However, single biometric signal is usually not sufficient to accurately evaluate the stress levels of a person [9] therefore a combination of multiple sensors is commonly used and suggested in literature, in a bid to improve the ability to detect stress [10].

However, connecting multiple sensors for the purpose of developing a stress evaluation system may require a significant integration effort. This is because such a solution demands reliance on multiple sensor manufacturers, and they often rely on different modalities of data transmission and payload formats. The resulting data heterogeneity and data interoperability issues are quite well known and have already been highlighted as one of the challenges for realising Industry 5.0 vision [11]. In this context, efforts to tame the heterogeneity of multivendor devices has already been reported in literature. As an example, a previous work [12] provided an open-source solution integrating multi-vendor Automated Guided Vehicles (AGVs) however, it lacked to address the aspect of cross platform data interoperability.

Up to this point the current section has concentrated on the challenges related to gathering biometric data from multi-vendor wearable devices. However, development of a successful Healthy Operator solution also involves the processing of this data to gain meaningful insights namely the stress or fatigue levels of the operator. Typically, this involves the use of some form of Machine Learning (ML) or Artificial Intelligence (AI) Algorithms [13]. However, running AI or ML workloads often requires significant computational resources which may not be feasible for the CPPS, and there is a need to rely on software and networking architectures which make it feasible to leverage higher computational assets. These computational assets may be available onsite or alternatively through cloud based computational service providers.

Pushing the computational workloads to more computationally capable devices can lead to improvements in the processing capabilities [14] thereby reducing the computational latency. However, it can also introduce significant network related latencies. One solution to this problem that can be seen in the literature is to use fog computation [15]. Similarly slicing of 5G Networks can also be utilised to provide low latencies in critical applications in Industrial settings [16].

The goal of the current work is to provide a solution which addresses the three aspects of wearable sensor integration, which include data interoperability, data heterogeneity, and latency. To address all these points under the umbrella of a single solution, a series of decisions and suggestions related to the selection of software tools, networking, and computational hardware has been used to address each of these issues. Before delving into the intricacies of the proposed solution, a brief discussion about the testing scenario has been provided to set the context of the proposed applications.

3 Testing Scenario

To test the developed solution, an experimental scenario has been realized inside a semi-industrial test bed setting. The semi-industrial nature of the test bed has been used here because it facilitates more robust testing and evaluation of the developed solution. This would be more difficult in a real factory because of the potential disruptions to production. The test bed in question hosts two industrial use cases representing two distinct industrial scenarios.

The first use case consists of an independent workstation where an operator equipped with wearable sensors, is supposed to perform a multi-stage repetitive assembly task with adaptive support provided by two collaborative robots. The assembled component in question is composed of 3 parts: a base, a midsection and a threaded top part. The assembly operation consists of following 4 steps:

1. Retrieve assembly components from close by storage areas.
2. Assemble Middle part to the base
3. Assemble the threaded top part
4. Place the finished assembly in the final storage buffer area.

Under the normative conditions steps 2 and 3 are carried out by the operator and collaborative robots are engaged in steps 1 and 4. However when the operator becomes fatigued, the collaborative robots also perform step no 3, relieving him/her from further effort and allowing recovery.

In the second use case the operator works on a workstation which is a part of a paced assembly line for manufacturing of valves. The stations preceding this workstation feed this station at a defined rate and the operator is supposed to keep pace with the feed rate to prevent the line from getting stopped due to pooling up of material at the station input side. The station is fed using two main methods; with an AGV which supplies the main components of the valve assembly at defined intervals, and a set of *gravity flow racks* [17] which feeds standard parts like nuts, bolts etc. The valve assembly consists of 19 sub-components of which 12 are unique. To facilitate fault free assembly, an *Arkite Operator guidance system* [18] is deployed to assist the operator during the complex assembly operation. Under high stress situations, supportive intervention in this scenario is in the form of reduction in the overall takt time of the assembly line.

The overarching goal of both scenarios from an industrial perspective is to make required interventions under high stress or fatigue situations to promote operator well-being, avoiding high risk situations and hence contribute to the prevention of workplace accidents [19].

4 Software Architecture

This section describes the proposed software architecture and brief overview of the functional aspects of each of the architectural layers. The overarching goal of the proposed architecture is to present a solution which enables efficient computation by enabling the use of necessary computational resources while also addressing the issues of data interoperability and heterogeneity. The proposed architecture consists of the following main layers:

- Physical layer.
- Gateway layer.
- Middleware and Data persistence layer.
- Service layer.

The physical layer consists of an array of industrial assets like wearable sensors, robots, workstations and other industrial assets. These assets rely on a wide array of communication protocols which pose challenges related to integration and interoperability.

The Gateway layer consists of an application or a set of applications which are responsible for communicating with the assets in the physical layer. These applications may also include protocol bridge elements which are responsible for translating from the native communication protocol of the sensors to industrial protocols compliant with

RAMI 4.0 specifications which include OPC-UA, MQTT, DDS, AMQP [20] and many others. This consequently helps to addresses the issues related to the heterogeneous data transmission resulting from the use of multi-vendor sensors.

The Middleware layer primarily consists of a message broker [21] which stores the context data in a standardised format to promote cross platform interoperability. The layer also allows connecting and interfacing with different industrial protocols to receive northbound sensor data and send southbound messages for actuation of the physical layer elements. Additionally, the layer also hosts one or more types of Databases for different storage requirements.

The Service layer consists of analytics, AI/ML algorithms, event processing and visualisation services which can be derived from the data stored in the underlying layer.

With a proper choice of implementation tools, the middleware and the service layers can be flexibly deployed at different computational resources at edge or cloud infrastructure (Fig. 1).

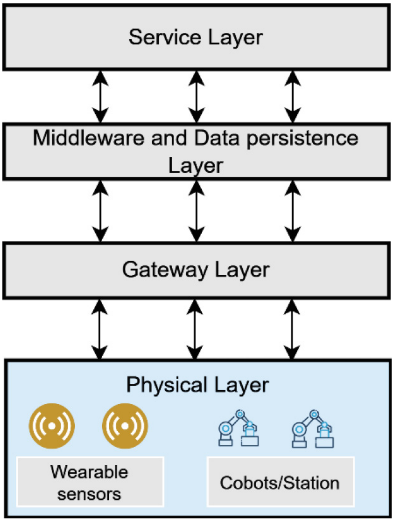

Fig. 1. Proposed software Architecture

The proposed software architecture is partly inspired from similar implementations dealing with the integration of industrial assets [22]. However, offers an advancement in terms of added service layer and inclusion of a data persistence to the middle ware layer. Another related implementation of software architecture which specifically deals with human-centric production scenarios is reported in [23]. Although there are some similarities with the current work, however, there are also significant differences. In particular the current work strongly focusses on the use of open-source tools and furthermore solves the interoperability aspects by implementing concepts like linked data. Which is further addressed in Sect. 6 which deals with the implementation of the Architectural model.

5 Test Bed Description

The current section provides an in-depth overview of the test bed setup and resources used for validating and testing the proposed solution. In terms of solving identified issues this section primarily focused on addressing the issue of network/computational latency. Figure 2 presents the hardware, and the network diagram used for testing. There are four main elements of the test setup:

- The Shopfloor assets
- The Gateway hardware
- Private 5G system
- An on-premise server

The Shopfloor assets consist of a workstation with two collaborative robots and an operator who is equipped with two sets of wearable sensors. 8 surface EMG (sEMG) sensors are placed on major muscles – The bicep, triceps, trapezius and brachioradialis on either side of the body. The use of specific muscle groups is inspired in part from literature references and based on actual trial experiences [24]. Additionally, Polar H10 sensor is used for capturing ECG and related features like HR, R-R interval and HRV. The latter has been selected because ECG and related features are amongst the most widely studied in the industrial context [25].

The gateway hardware consists of a set of fan-less industrial PCs which host all the applications related to the control of the robotics and the assembly line station. A windows 10 operating system is used on these devices primarily due to the dependencies of the hosted applications. Additionally, an Android phone is used to host a data logger application for connecting the Polar H10 sensor.

A DELL R740 server is used to provide the necessary computational resources for the resource intensive applications. It hosts the elements of the middleware layer and the service layer. The Server runs a Redhat Enterprise Linux OS and OpenShift container platform is used for deployment of the Middleware and Service layer elements.

For establishing connectivity, the test bed relies on a private 5G network deployment, which relies on 3rd Generation Partnership Project (3GPP) compliant hardware and Open-source software for implementation of the RAN and Core functionalities. To allow non-5G native devices to connect to the access network, Customer Premise Equipment (CPE) is used for relaying the 5G signals to Wi-Fi.

Figure 2 shows how both testbed setup relies on a mixture of both wired, 5G network along with the ability to use Wi-Fi networks. Since the testbed uses an on-premises server with high computational capabilities network and computational latency issues are not expected however given the diversity of connectivity options available it opens the opportunity to make a comparative analysis of network latencies of the three modes. In a more general scenario where on-premises computational capability is limited, the use of cloud services is needed. Under such scenarios, if network latency requirements are quite stringent, Ultra-Reliable Critical Communication service (URCC) public 5G network slice can be utilized. Conversely, Enhanced Mobile Broadband Connectivity slice (eMBB) could be leveraged for high data rates or if the situation demands, a customized network slice could be tailored to cover specific scenarios [26].

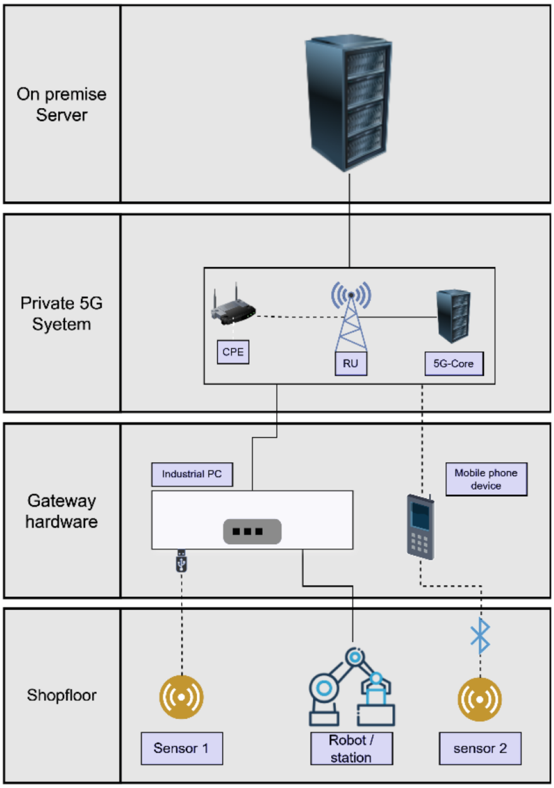

Fig. 2. Experimental setup and network architecture

6 Software Architecture Implementation

This section provides details about implementation tools used to realize each architectural layer. The implementation relies heavily on the use of open-source implementation tools and tries to satisfy each of the requirements and characteristics described in Sect. 4.

Gateway layer – The gateway layer has been implemented using 3 sets of applications dedicated to each of the hardware elements. For sEMG sensors, a custom application was developed in C++ to connect to the sensors and publish the data to an MQTT Topic. Two programs were developed for collaborative robots which represent two levels of support to the operator. A Node-RED workflow was used to expose an MQTT subscriber client which is used to switch between the two levels of support. Finally, The Polar H10 sensor uses a mobile phone application which publishes data to MQTT topics. As an alternative to the mobile phone app, an additional Python application has also been created to connect the Polar H10 sensor using the Industrial PCs. This has been done to allow a one-to-one comparison of network latencies of the 5G system and the traditional wired system.

Apart from MQTT, OPC-UA protocol was also considered initially, however, MQTT was chosen as a preferred protocol because of its lightweight nature and generally lower latency in comparison to OPC-UA. This however is in neither meant to negate the inherent advantages of OPC-UA protocol [27], nor to exclude the possibility to make these two communication protocols to co-exist [21].

Middleware Layer – This layer was implemented using elements from FIWARE [28] ecosystem. The layer is essentially composed of FIWARE Orion-LD context broker, which is based on the de-facto ETSI-NGSI-LD [28] specification. Mongo-DB is used to hold the latest values of the data in the form of NGSI-LD entities. Additionally, Timescale-DB is used for storing historical data with the help of FIWARE Mintaka. FIWARE Mintaka also exposes APIs which enables external applications to retrieve data from Timescale-DB. Finally, a web server application has been used to hold a static file (namely, "@context", as per Fig. 3) which is used by the Orion-LD context broker for NGSI operations. Since the Data from Gateway layer was transformed to MQTT protocol, it is possible to leverage the IoT agent for JSON from the FIWARE ecosystem. This agent can be configured to subscribe/publish to different MQTT topics corresponding to the sensors and the industrial systems. The use of FIWARE and, more specifically, Orion-LD-based architecture is inspired by two factors, the first one being the open-source nature of the ecosystem. Secondly, the entities which represent different objects like sensors and robots within the context broker follow the JSON-LD format with the addition of context definition which is a set of URIs where detailed semantic definition of the different attributes can be found. This enables high degree of data Interoperability [29, 30].

In the current implementation all the field devices and sensors communicate using MQTT protocol with JSON payloads, with the same elements and minor changes in environmental variables of the IOT agent for JSON it is possible to switch to AMPQ or HTTP protocols. It is also possible to interface with other protocols like OPC-UA, or different payloads like Ultralight 2.0. Alternatively, it is also possible to develop some custom IoT agents in case the protocol/payload combination is not currently supported by the available list of pre-existing solutions.

Service layer – The service layer consists of mainly 2 elements. A Stress detector and a Complex event processing element. Which are both implemented using Python (Fig. 4).

The stress detector element evaluates the operator's stress/fatigue levels based on the historical sensor data queried from the Timescale-DB using the FIWARE Mintaka APIs of the Middleware layer. Our implementation uses sEMG sensor data for fatigue prediction and. Figure 5 shows a pictorial representation of the sequence of steps which are involved in the processing and prediction of Fatigue state of the operator. In essence we are implementing an infinite while loop which carries out the following main steps:

- Data Filtering
- Feature extraction
- Fatigue prediction.

A 5 s initial delay, is introduced at the beginning to ensure that at least 5000 datapoints are available in the Timescale-DB. The data filtration process consists of a 50 Hz notch filter corresponding to AC frequency and 4th order Butterworth band pass filter of 20–450 Hz. Subsequently, 4 frequency domain features namely mean frequency, median frequency, mean power frequency, and zero crossing frequency are extracted from the

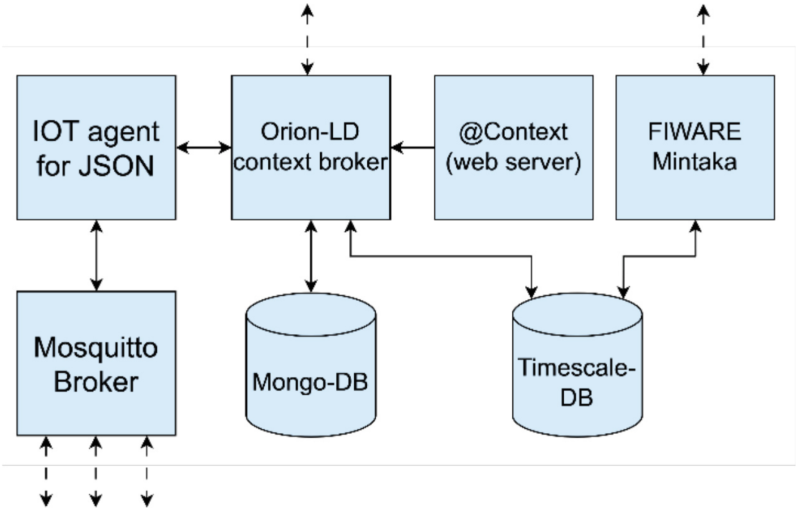

Fig. 3. Middleware layer Implementation

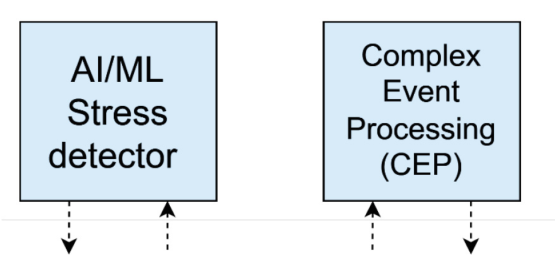

Fig. 4. Service Layer Implementation

filtered signal which is used to predict the fatigue state of the different muscles of the operator. The predicted fatigue state is stored in the databases hosted in the Middleware layer through an http PATCH request to the relevant NGSI-LD entity every 1 s. A similar logical workflow has been used to implement the detection of stress using the heart rate sensor. For the sake of simplicity just one of the two is presented here.

The complex event processing directly interacts with the Orion-LD context broker to obtain the latest fatigue and stress state of the operator and based on this an MQTT message sent to the relevant topic is used to switch the operating mode of the robot system. A more detailed logic of the CEP can be seen in Fig. 6. Contrary to the Stress detector logic seen in Fig. 5, an initial delay block is missing in CEP. In order to facilitate this, the NGSI-LD entity holding the fatigue state and stress is always initialized with the lowest values. The alternative use case where production line speed is being changed in response to the operator stress/fatigue state, the downstream communication uses an http POST in place of the MQTT message this is based on the constraints of the system in question.

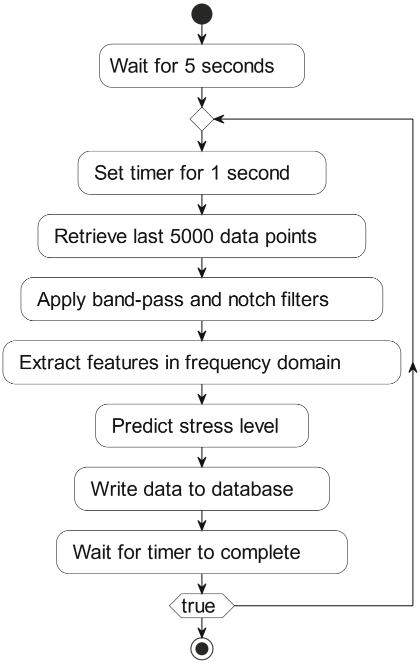

Fig. 5. Stress Detector Logic

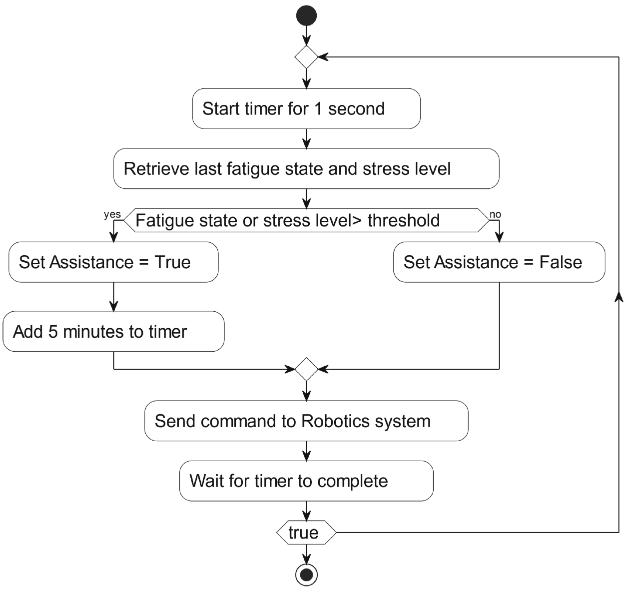

Fig. 6. CEP logic

To ensure a user-friendly experience, a simple web interface has also been created which allows the operator to easily start and stop the application. Figure 7 shows some snapshots of the Web interface.

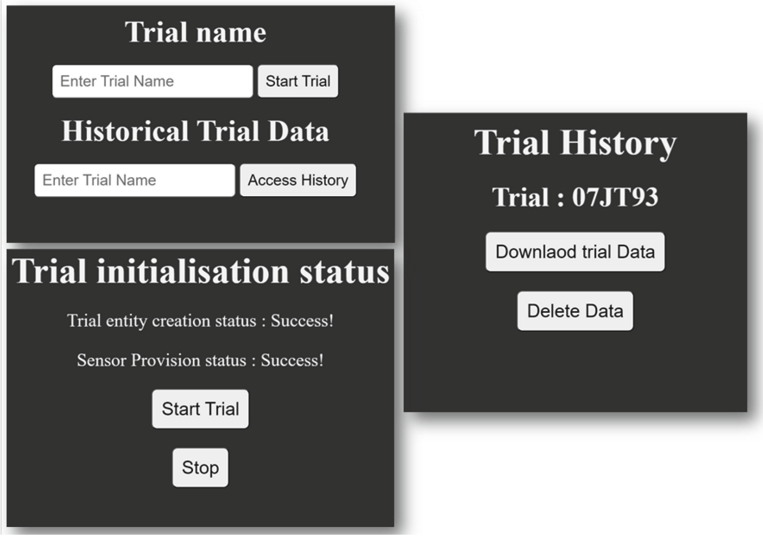

Fig. 7. Snapshots from the application web interface

7 Conclusion and Future Work

In the recent years the focus of the manufacturing industry has been increasingly shifting towards the adoption of technologies which are directed towards enhancing the well-being of the operator in this direction, the concept of Industry 5.0 has been put forth which essentially renews the focus of the manufacturing world towards the important role of human element in the production sphere. Wearable sensor technology is amongst the key enablers which allows the manufacturing world to advance in the development of human-centric solutions. Integrating these sensors and deriving meaningful and supportive interventions based on the sensor data compels us to deal with the eminent challenges of data interoperability, data heterogeneity and network/computational latencies. To solve the issue of data interoperability and data heterogeneity, the current work outlines an enabling software architecture. And furthermore, takes advantage of the open-source tools like the FIWARE ecosystem to develop some initial implementations of the software architecture. Similarly, the latency issues are managed using a suitable combination of computational resources and the use of low latency 5G network slices.

Although the current works addresses some of the issues related to development and deployment of Human-centric solutions in the industry, solution deployment at an industrial scale still has several challenges. Dealing with biometric data is always associated with General Data Protection Regulation (GDPR) compliance and privacy issues.

This issue has previously been highlighted in literature however, a conclusive solution still eludes us. This is in part due to the inability of the current legislation to properly deal with this issue [31]. As a result, the applications that were developed as a part of the current work primarily focus on a deployment under research settings. The current applications were in fact designed to work in sync with an independent, pre-existing GDPR compliance system that is currently in place in our institution. An extension to the current applications could involve integrating the existing GDPR compliance system into the application itself. On a separate note, while an initial version of the applications has been developed, the applications have seen very limited testing. Therefore, a robust and exhaustive testing needs to be performed to ensure that the applications can be safely deployed. Furthermore, there are several features which remain to be integrated. This as an example includes the addition of role-based access and on a lighter note, a more elegant interface could also be a positive addition. Also, as an extension to the current scope of work the gateway layer could be implemented to intentionally use more than one communication protocol at the same time in a bid to introduce more diversity to the testing scenario and to compare the advantages and disadvantages of using different protocols.

From a purely development perspective, the primary goal of the current stage of work has been to create a working platform using open-source tools. Looking from the perspective of human-centric manufacturing, the current implementation only integrates 2 wearable sensors. Additional sensors like EEG, GSR, Skin temperature etc. could greatly improve the utility of the platform for its potential use by a wider audience. Extending on the same line of thought, creation of Open-source libraries for processing bio signals is an important research tool that can potentially reduce the implementation time and effort of potential adopters. As such it is intended to publish an extended form of the currently developed processing tools in the form of python libraries.

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