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A FOG COMPUTING APPROACH FOR PREDICTIVE MAINTENANCE

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Abstract. Technological advances in areas such as communications, computer processing, connectivity, data management are gradually introducing the internet of things (IoT) paradigm across companies of different domain. In this context and as systems are making a shift into cyber-physical system of systems, connected devices provide massive data, that are usually streamed to a central node for further processing.In particular and related to the manufacturing domain, Data processing can provide insight in the operational condition of the organization or process monitored. However, there are near real time constraints for such insights to be generated and data-driven decision making to be enabled.In the context of internet of things for smart manufacturing and empowered by the aforementioned, this study discusses a fog computing paradigm for enabling maintenance related predictive analytic in a manufacturing environment through a two step approach: 1. Model training on the cloud, 2) Model execution on the edge.The proposed approach has been applied to a use case coming from the robotic industry.

Keywords: Internet of things · Predictive analytics · Cyber-physical system.

1 Introduction

The Industrial IoT (IIoT) will massively increase the amount of data available for analysis by organizations in a manufacturing ecosystem. In this context, data analytics hold the promise for manufacturing companies of better understanding their production processes and systems. In addition, predictive analytics enable insight into machinery condition through the analysis of past data to predict future breakdowns. This would reduce the production and/or product failure rates, and as a result, bring down the operation costs of the manufacturer.

IoT requires an end-to-end infrastructure which is a challenge, especially for small enterprises. Cloud solutions may provide centralized storage and higher processing power, enabling batch processing of large amounts of data, thus suitable for the development and training of complex predictive models, such as recurrent neural networks. On the other hand, this approach introduces latency, depending on the network architecture and bandwidth, hence increasing the response time of analytics-driven decision making, assuming the later is located at an edge node in a factory. With respect to the aforementioned and towards enabling predictive analytics at the edge, the current study discusses a two-step approach integrating cloud and edge functionalities through a fog network where multiple devices could be connected to the same or multiple gateways on a fog network. First, the data aggregation and analysis is performed on a cloud node. Then the trained models are pushed down on an edge gateway, allowing insight generation in little time.

2 Related work

Recent advances in ICT with the emergent rise of CPSs [10] and cloud computing [22], enable new opportunities for manufacturing enterprises [23]. Industry 4.0 has increased the significance of the maintenance process in production systems [2]. In the literature, several approaches on predictive maintenance platforms have been introduced (e.g. [19], [12]), but they fail to adequately address the fundamental tension between flexibility to host many applications, the need of security privacy, data transmission and the user is permitted with limited control and management. Condition-based predictive maintenance represent the maintenance approach supported by sensor measurements [4].

An integrated predictive maintenance platform was proposed in [6], consisting of three main pillars.A semantic framework for predictive maintenance in a cloud environment was introduced in [17]. On a similar manner, a condition-based maintenance policy approach was introduced in [18], that made a diagnosis of the asset status based on wire or wireless monitored data, predicting the assets abnormalities and executing suitable maintenance actions before serious problems occurred. A dynamic predictive maintenance framework was presented in [21] that deals with the decision making and optimization in multicomponent systems.

Predictive analytics can be conceived as an extension of data mining technology. Enabled by historical data and high computing power they can reveal underlying information through sophisticated functions and machine learning models.The scale of such functionalities require a cloud infrastructure. However, pushing as much as possible functionality to the edge can reduce communication costs and reduce the response time for actions to be taken. Therefore new approaches are needed. Data mining [8] and management [20] techniques are one of the key enablers in the design of a condition-based maintenance capability. In general, all systems like manufacturing, automotive, oil and gas, and others dump large amounts of data periodically from different sources. Artificial intelligence involves the development of powerful reasoning algorithms and prediction techniques [16]. Advantages of cloud computing include the virtualization of the resources, parallel processing, security of the data and service integration, thus minimizing the cost and restriction for automation and maintenance infrastructure [13]. An integrated predictive maintenance platform was proposed in [5], consisting of three main pillars. The first pillar was related with data acquisition responsible for data extraction and analysis, while the second pillar was responsible for maintenance modelling knowledge modelling and representation. The final pillar has advisory capabilities on maintenance planning with emphasis given to environmental and energy performance indicators. A semantic framework for predictive maintenance in a cloud environment was introduced in [17].

In the context of smart manufacturing, fog computing can provide advanced services [14]. Fog computing [3] can be perceived as the extension of cloud computing to edge nodes of a network. Its purpose is to preserve the advantages of cloud computing, improving an integrated systems efficiency [15], security [1], sustainability [7], while reducing the amount of data transported to the cloud for processing [9]. The distributed architecture of a fog network and for computing reduces the bandwidth needed and the back-and forth communication between field devices and the cloud-based central management and orchestration node(s) [11].

3 Approach

The envisioned SERENA platform, enabling the predictive maintenance concept, will be based upon the following key technologies: a) remote condition monitoring and control, b) AI condition-based maintenance and planning techniques, c) AR-based tools for remote assistance and human operator support, controlled under d) a cloud-based platform for versatile remote diagnostics.In this paper and as part of the current platform implementation the supported functionalities that have been integrated as services include a visualization, a predictive analytics and a scheduling service.In Fig. 1 the main components of the SERENA system are presented.

In order to facilitate the predictive analytics deployment on a factory floor, the SERENA project proposes a distributed, lightweight and scalable architecture which through the collective use of its integrated services will provide predictive maintenance solutions to the shop floor personnel. The architecture is implemented following a micro-services architecture pattern. On top of it,

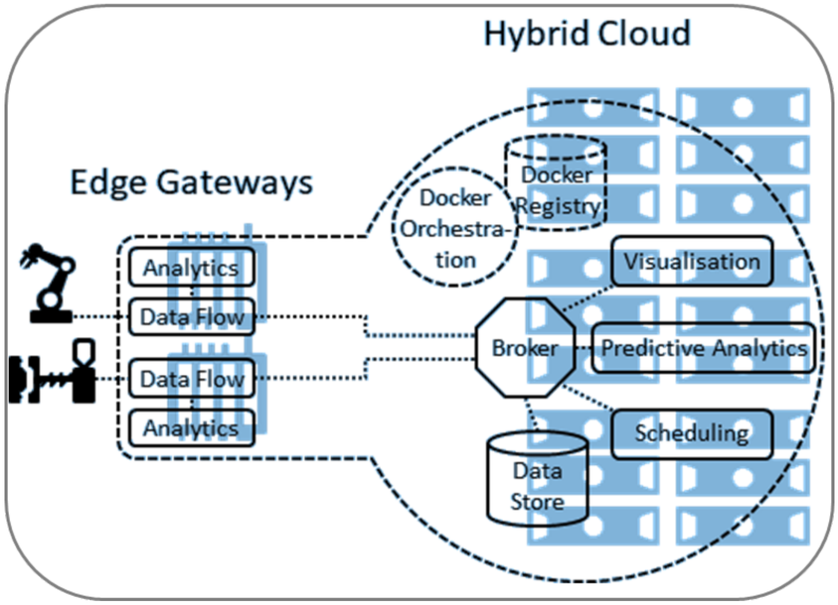

Fig. 1: SERENA system architecture.

docker containers are used to wrap individual services and deploy them across the network to edge gateways and through the SERENA cloud. The use of docker technologies and their distribution through the a docker orchestration manager allows software packages with its dependencies to run smoothly regardless of the underlying host. Virtual machines offer similar set of capabilities. However, while containers provide an abstraction layer at the application level, virtual machines (VM) abstract the physical hardware level, resulting in the size of containers being smaller than VMs. The adoption of same docker solutions in SERENA results in the creation of a unified architecture that can be operated and managed as a single unit. In addition, the common network interface decouples the system from its dependency on a specific technology offering technology transparency. The SERENA system and through its service oriented architecture can support its extention with additional functionalities. In this context and as at a first stage, the following functionalities were implemented and integrated to the platform.

1. Communication broker: The broker facilitates the communication between the edge gateway and the SERENA services, through multiple communication protocols such as REST and/or MQTT. Moreover, the broker can support integration with legacy systems such as enterprise resource planning (ERP) and manufacturing execution systems (MES).
2. Edge Gateway: The gateways are collecting data from the shopfloor sensors and other systems and transfer them to the cloud through the communi-

cations broker. The gateway may also host predictive models along with additional docker containers wrapping other functionalities.
3. Orchestration and Registry: The orchestration manager or orchestrator is responsible for managing the deployment, communication and execution status of the containers. The orchestration manager deploys containers from images residing into the SERENA docker registry, ensuring availability and trustworthiness of the images.
4. Data Store: The SERENA system data required by its services are stored in this component. The Data Store is also implemented as a container. Multiple data stores can be supported by the SERENA system.
5. Predictive analytics service: This service aims to build a predictive model based on historical data through multiple machine learning techniques and apply the models in near-real time to newly arrived data streams. Through the docker containers the trained model can be pushed down at an edge "smart" gateway to support short response times of the analytics' result.
6. Visualization: A real time HTML5 Unity 3D based visualization application integrated to the SERENA system. This application is connected to the SERENA platform in order to provide real time information to the maintenance operator, as a result of the predictive analytics.
7. Scheduling:A java based scheduling service for assigning predictive maintenance activities to maintenance personnel based on a set of criteria, such as experience level, skills, availability.

The aforementioned SERENA system with its integrated functionalities has been tested in a use case coming from the robotics industry and is presented in the following section along with some first results.

4 Use case

In order to test and validate the proposed approach, a test-bed has been built by COMAU and related to the predictive maintenance requirements of a robotic manipulator, and more specifically the incorrect belt tentioning and backlash phenomenon. This "RobotBox" consists of a motor from a COMAU medium size robot, with its associated controller. Then it is constituted by an adapter, a belt and a 5 kilos weight in place of the robot end-effector. At this point it should be mentioned that in a complete robot there are many factors affecting its physical condition, like temperature, humidity, vibrations. Hence, it is difficult to isolate single effects, especially considering that an industrial robot provides only limited monitored datasets through its controller For a COMAU robot this includes the axis position and the current required for the motor to perform the required action. With respect to the aforementioned, this initial experiment takes into account position and current of the RobotBox in order to study the belt tensioning phenomenon through the SERENA system. Raw data are transmitted in a JSON format to the edge gateway, where they are pre-processed locally to generate meaningful information named "smart" data. In this experiment, smart data include a set of 12 statistical values such as max, min, average, root mean square.

In this context, the predictive analytics service has been tailored to the belt tensionsing problem and the acquired data set. Six levels of belt tentioning have been defined by the domain expert. Then, these information along with the raw data acquired by the controller as imported to a neural network classifier to recognize the level of belt tensioning, along with an additional classifier providing qualitative status information about the backlash effect and an estimation of the remaining useful life, expressed in days.

As part of the experimental setup, presented in Fig. 2, all integrated functionalities were tested and evaluated.

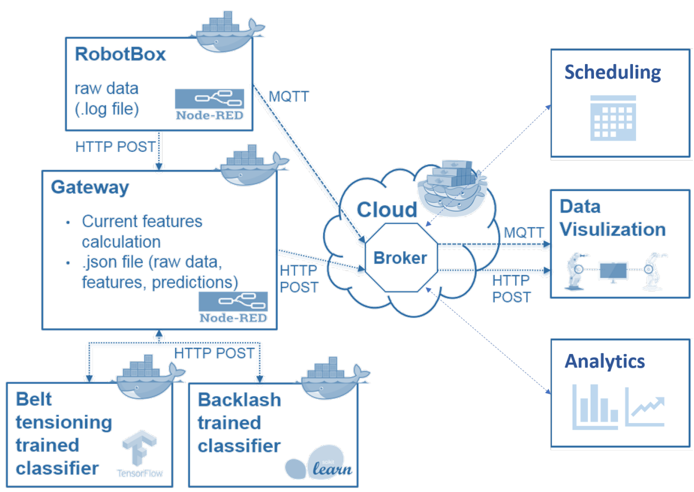

Fig. 2: SERENA system architecture

The predictive analytics model was implemented using the python tensorflow library with a training data set of 300 samples and with a hold-out validation approach. The confusion matrix of the final model is presented in Fig. 3.

The accuracy of the model was estimated at approximately 90%.Furthermore, it was noticed that the higher the environment temperature, the lower the current consumption of the motor. This can be supported by a lower friction between the components of the motor at a higher temperature.

Moreover, the analytics provide input to the visualization service that displays in real-time information about the RobotBox status as described by the input data and analytics (Fig. 4). As result the service itself provides an intuitive interface to the maintenance personnel towards enabling remote monitoring and condition evaluation of industrial equipment.

In addition, the scheduling service was tested assigning maintenance related tasks to the maintenance personnel.In the current experiment, the schedule was

Actual \ Predicted	0	1	2	3	4	5
0	**1373**	0	0	0	0	0
1	0	**2145**	0	5	0	0
2	0	0	**6673**	97	67	32
3	0	0	36	**3718**	40	219
4	0	0	51	230	**3302**	293
5	0	0	0	119	30	**3530**

Fig. 3: Final predictive analytics model confusion Matrix

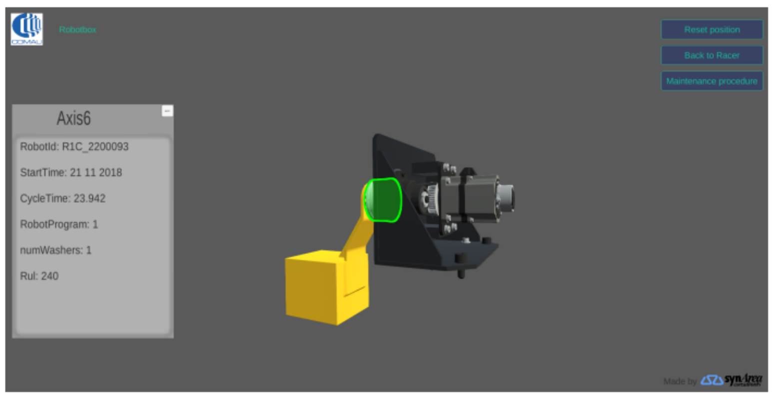

Fig. 4: Visualization app showing axis6 information updated in real-time.

generated in approximately 11 ms, and included the execution of two tasks (Fig. 5).

Fig. 5: Scheduling application interface displaying measurement time series.

5 Conclusions

As discussed in the paper the SERENA project proposes a lightweight fog computing architecture to enable predictive analytics and push functionalities from the cloud to the edge. Moreover, the proposed architecture has been tested with its first batch of integrated services to an industrial test-bed.

The platform itself has been designed and implemented to be scalable and support the integration of a different set of technologies. In the following period this will be tested extensive through the integration to the SERENA system of the four other industrial use cases within the project.

Finally, the analytics part is a critical aspect for enabling predictive maintenance solutions. As such, particular focus will be given on testing and improving the approaches assessed in the aforementioned testbed in the context of other demonstrators.

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