Introducing Building Blocks for Industry 4.0, an Analytics Application for the Federated EFPF Platform

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Abstract

The increment of data generated through the implementation of Industry4.0 standards has allowed the development and implementation of industrial analytical and predictive maintenance tools. However, the solutions are tailor-made for each use case, and the availability of generic tools to use in a large spectrum of applications is limited. This situation can change with the disruption of industrial cloud federated platforms allowing the connection of Internet-of-Things (IoT) devices to cloud-native applications that can enhance the data-driven decisions taken from analytical tools working with manufacturing data. In this paper, we propose an application with three analytic modules addressed for the manufacturing industry and developed to work as part of the EFPF ecosystem which will allow the use of data analytics and predictive maintenance methodologies for SMEs.

Keywords

Federated platforms, predictive maintenance, cloud manufacturing

1. Introduction

With the implementation of the Industry4.0 standards and the general availability of IoT devices, the quantity of data has increased considerably. This increment is particularly important for the SMEs manufacturing industries which traditionally had a disadvantage position compared to large companies with massive productions that can develop tailor-made solutions for their production lines. To democratize the generation and exploitation of industrial data, different connected platforms have been developed to allow interoperability between IoT components and smart factory tools.

For this purpose, the European Factory Platform Foundation (EFPF) [1] is a federated system that connects industrial platforms to integrate their services in a single platform enabling the use and development of Industry 4.0, IoT, Artificial Intelligence, Analytics and Digital Manufacturing solutions through a single ecosystem. The connection is performed through its main component, the EFPF Data Spine [2] which provides the basic components for a secure data exchange, registration and integration of API services.

Within the EFPF ecosystem, we propose the Building Blocks for Industry 4.0 solution (BBI4.0) that will implement novel data-driven predictive maintenance (PdM) solutions tailored for industrial applications. The solution will extend the EFPF capabilities by offering new cloud-native signal

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processing, acceleration analysis and anomaly detection tools (ADT) by implementing machine learning and deep learning techniques that can be operated and interpreted by shopfloor technicians. The solution is intended to be as generic as possible and allow its use for any data formatted as time-series.

2. Proposed solution

In order to respond to the aforementioned issues, the proposed solution aims to provide analytics insights for manufacturing industries based on predictive maintenance.

The design is divided into its two main application fields:

- *Analytics modules* cover the different aspects related to the models and methods implemented to manipulate and extract information from the data.
- *System architecture* covers all the aspects related to the integration with the EFPF platform, the management of the analytics modules and the interaction with the stakeholders.

The system will be developed to be used with data uploaded from a file (batch data) and data streamed from IoT sensors publishing through the EFPF data spine. All three modules defined in the following subsections will accept both types of data except for the training phase of the predictive maintenance module, which will be required to be uploaded from a file with a selected dataset.

2.1. Analytics modules

The BBI4.0 modules work as building blocks for predictive maintenance solutions, incrementing the EFPF platform capabilities. They cover the data analytics cycle from the raw data to the report of the data analysis results.

2.1.1. Signal processing and feature engineering module

The data pre-processing module is aimed at transforming raw sensor time-series data into enhanced time series that will include time and frequency domain metrics. From the time-domain will be possible to extract extreme values, mean values, deviation values and higher moments of the statistical distribution. Instead, from the frequency domain, band amplitude and max peaks will be available. The new data representation extracted by this module can be then visualized or ingested by different machine learning algorithms to construct a complex data analysis pipeline.

This is intended to be an extremely reusable module, capable of analyzing multi-variate time-series without a predefined structure. The module is equally designed to cover the necessities of the following modules and as a pre-processing module for data scientists requiring time-series algorithms.

2.1.2. Acceleration analysis module

One of the most important sources of industrial data is generated from vibration sensors useful in any process involving moving or rotating components. This module will help the data visualization process by providing and showing indirect measures that can be extracted from the measured data. It will use the vibration from the 3-axis data to show displacement values and track its time evolution.

The module will use acceleration data to compute derived measures and increment the information available to analyze the vibration behavior of the measured components. It will provide two key outcomes: The first will be the vibration axis for a defined period. This axis will be compared with historical data and thus, it will be possible to identify misalignments produced after a given period. As a second analysis, it will show the displacement of the sensor over time.

2.1.3. Predictive maintenance module

The last analytical module is the core of the application, it will contain different anomaly detection algorithms. In this module, the user will be able to either provide a numeric time-series data or connect the module to the signal processing module to use parameters extracted from the data. The output will consist in the detected anomalous or novel patterns that may be considered as an alarm.

For the identification of anomalous data, it will be possible to choose from different machine learning algorithms. The current list includes state of the art unsupervised machine learning algorithms such as Isolation Forest [3], Local Outlier Factor [4] and Robust Covariance and anomaly detection pipelines based in Long Short-Term Memory (LSTM) recurrent neural networks [5].

The use of the module is designed to have an initial training step that will generate a trained model with the selected parameters which will be stored for testing future data. This first step will require representative data in which it is known to have a controlled number of defective data and will be uploaded from a csv file. For testing purposes, it will be possible to select between the different trained algorithms and the data will be either streamed or uploaded depending on the user requirements and possibilities. The module will return the number of anomalies for the given data, and it will be possible to compare how the frequency of the anomalies varies with time.

This module is designed to be reusable in a wide range of production cases, capable of analyzing multi-variate time-series only requiring that the data is formatted in a table or received through the EFPF data spine as an MQTT message. This will give the possibility to train, manage and deploy machine learning in manufacturing environments without extensive knowledge of the algorithms.

The Predictive Maintenance module used as the baseline for the Analytics implementation is the EFPF Anomaly Detection Solution (ADS) [6]. Anomaly detection refers to the problem of finding patterns in data – often referred as anomalies - that do not conform to the expected behavior. ADS enables the creation of building blocks and the execution of machine learning-based analytic algorithms on data retrieved from sensors, including a preset of machine learning algorithms supporting supervised and unsupervised scenarios. This is designed to operate on real-time data as well as historic data.

2.2. Proposed system architecture

To allow BBI4.0 interoperability, the architecture is designed to be integrated with different components from the EFPF Data Spine. This section describes the how the proposed architecture enables interoperability by using EFPF Data Spine components that can be seen in Figure 1.

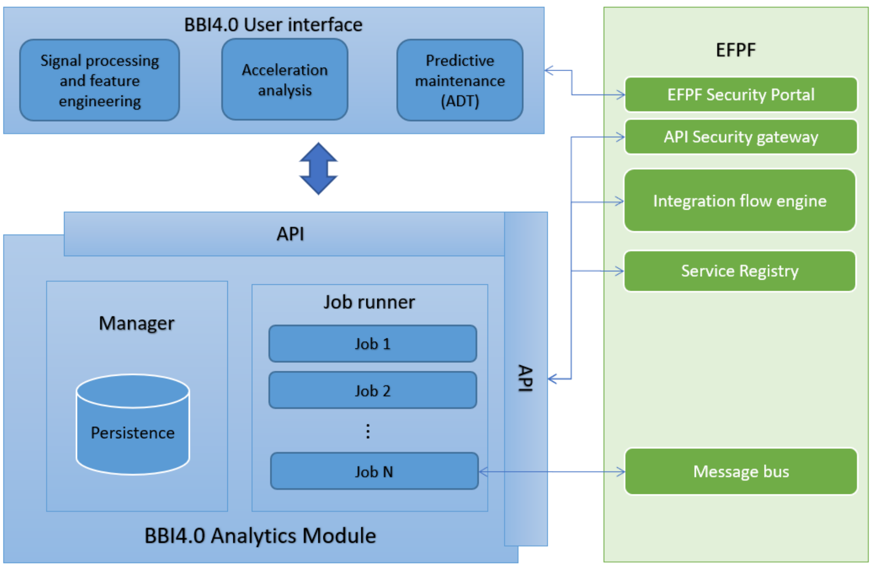

Figure 1: BBi4.0 architecture

As shown in Figure 1, the integration, interoperability, and management of the BBI4.0 application is managed from the “BBI4.0 Analytics module”. This module is responsible for managing the lifecycle of jobs: from the creation to the end of its execution. In the context of the application, a job can be of two types: a model training job or an analysis job. A model training job is responsible for training the specific ML algorithms required by the predictive maintenance module. An analysis job is responsible to execute an analysis process, either ML based or not, from all the defined modules over a defined source of data.

Through the Analytics module, different modules can interact with each other. This also provides a dedicated user interface for each module with similar functionalities and capable to analyze batch data and streaming data provided from the EFPF Data Spine. Interoperability is guaranteed by the Security Portal, Service Registry and API Security Gateway (ASG) services from EFPF.

The EFPF Security Portal means the main entrance to the EFPF ecosystem for service providers and users, offering credentials and connecting to different federated platforms through a single sign-on (SSO) implementation. Furthermore, the Data Spine Service Registry offers the discovery, integration and orchestration of services among platforms. This is enabled through an API that presents the catalog of registered services. This catalog contains the connectors for IoT components that supply data to BBI4.0, which needs to be also registered as a service. Finally, the ASG component ensures the secured connection between the application, the EFPF components and the platform users.

3. Conclusions and future work

The work presents a cloud-based predictive maintenance application that has the potential to increment the quantity of data-driven decisions in manufacturing SMEs. The designed solution simplifies the methodology used to implement predictive maintenance solutions, enhancing manufacturing industries, which currently have sensors installed in their equipment, but no analysis is performed, are able to gain knowledge about their processes.

Table 1
Individual innovations from the BBI4.0 application and target stakeholders.

Individual Innovation	Target Stakeholders	Description
Signal Processing Module	Data Scientists developing data-based solutions	The solution is intended to be the first step to extract information from time-series data-focused, but not exclusive, on industrial environments.
Acceleration Analysis Module	Involves from manufacturing companies their innovation managers, quality control departments and operators. Also serves for data scientists developing new data algorithms focused on industrial processes.	The solution is related to the generation of data during manufacturing processes, and has a different impact on each stakeholder. First, manufacturing companies will have more information available, incrementing the knowledge of their processes. In the case of data scientists, the virtual sensor will be a base to develop new data-based solutions.
Predictive Maintenance Module	Manufacturing companies, their innovation managers and quality control departments	The solution will impact the stakeholders by notifying them of possible anomalies in production that without the module might not be identified until they severely impact the production. These anomalies include the early identification of defective components and other

	anomalies produced by tooling or machinery that without an early intervention might not be identified until they force to stop the production.

The modular design of the application allows each component to be individually used and exploited. Thus, the exploitable results are related with the different individual innovations given by each module defined in Table 1.

For testing purposes, the application will be tested with EFPF open datasets [7] and other vibration datasets [8]. The use of EFPF datasets will allow comparison with available results on these pilots, including the ADT.

4. Acknowledgements

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