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Fog-Based Solution for Real-Time Monitoring and Data Processing in Manufacturing

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***Abstract*—Today's industry is facing an increased need for implementing intelligent manufacturing solutions, capable of integrating existing machinery with new technologies. Current solutions do not provide support for analyzing vast amounts of data. Also, implementation of cloud architectures proved inappropriate for real-time or near real-time processing and control because of the network latency. Under these considerations, the new paradigm of fog computing provides promising characteristics enabling greater scalability, fast reaction time and increasing security through a local private processing cloud structure. This paper evaluates the integration capabilities between existing technologies with new devices for seamless integration of the fog computing paradigm and provides an architecture solution for this upgrade.**

Keywords—fog computing; manufacturing; Internet of Things; Wireless Sensor Networks

I. INTRODUCTION

The manufacturing industry must keep up with the requirements of production speed and easy reconfiguration involved in today's processes. New opportunities arrive from state-of-the-art technological breakthroughs. While traditional asset management represents a time-consuming, costly and hard to deploy operation, continuous improvements in sensors, software analytics and data processing components are making it easier to handle by a wider circle of users with different process requirements.

The evolution of IoT (Internet of Things) and Cloud technologies, along with increased accessibility of internet connected devices, lead to a growing market and many implemented applications [1]. IoT is playing an important role in improving efficient data collection and enabling availability through applications in various domains like industry, healthcare, smart home, transportation, agriculture, retail etc. It allows monitoring and control of any existing device and facilitates access to new data. This high volume of data produced by IoT challenged researches and professionals to identify new architectures capable of minimizing the Cloud connectivity issues through new layers like Fog Computing and decentralized platforms [2]. Also, data analysis technologies evolved to support all the stages required to transform it into relevant information: data preparation, data mining and visualization [3].

By leveraging IoT, advanced data analytics and AI (Artificial Intelligence), manufacturing processes can change the way they handle maintenance operations and manage equipment faults, preventing costly downtime and conforming to the delivery time and product quality requirements. Through an integrated proactive maintenance approach plant owners can speed up the decision-making process, increasing productivity. Wider adoption of intelligent solutions at the plant level is restrained by the implementation challenges involved:

- Many older machines are not equipped with the required sensors or don't have implemented communication protocols.
- Monitoring and control systems existing at the plant level have don't have the processing capabilities required for building and running intelligent analytics strategies.
- Moving data to cloud is still seen as a violation of data privacy.
- The price for new intelligent devices is still high, or demanding increased integration effort in existing manufacturing systems.

This paper aims to provide an architecture design solution for a manufacturing system that will integrate Fog and Cloud computing to enable a production coordination and support new asset maintenance methods in this domain. Our approach is oriented to enabling asset monitoring during its entire lifecycle, allowing the implementation of performant analysis using risk maintenance and uncertainty management correlated with process control. The proposed system will gather data from WSN and IoT-based smart connected assets.

II. RELATED WORK

Cloud technologies were first proposed as a solution for improving manufacturing processes by Li in 2010 [4]. Cloud manufacturing exploits the existing service-based operations defined for manufacturing applications with cloud computing, IOT [5] and other advanced technologies to achieve new manufacturing resources, centralized management, and intelligent business models [6].

As presented in [6] the history of Cloud manufacturing begins in 1900s in USA, through the implementation of services provided by Cloud Computing for Cloud manufacturing and substantiation of the Cloud Manufacturing layers.

This paradigm was also approached for implementing advanced solution in process control applications, exploiting the different requirements between real-time operation and performance optimization [7].

Benefits of cloud adoption in the manufacturing domain are empathized in [8]. The authors also identify and define the main actors involved in such processes: Cloud Consumer, Cloud Provider (Cloud Service, Cloud Service Management, and Security), Cloud Broker and Cloud Carrier.

A solution for collaborative design based on the cloud paradigm is discussed in [9]. It provides an approach where all actors involved in different levels of the process, from idea to design, analysis, evaluation, prototype, and final product, cooperate during the entire lifecycle of the product manufacturing. A cloud architecture combining collaborative design, integrated manufacturing and supply chain management is presented by Wu et al. in [10], [11].

The growing increase of IoT devices and the uncertain latency in cloud data transmission required a new architecture solution that will enable fast near real-time reaction in applications like emergency or failure management [12]. Fog virtualization level allows computing, fast situation analysis and reaction to occur at a local level, closer to IoT devices and only pushes relevant data to the cloud. Cisco defined "fog computing"as a new abstraction level "earlier to the things that produce and act on IoT data" [13]. The equipment deployed at this level act as fog nodes and ensure small scale cloud functionality that can acquire and process data from any device with computing, storage, and network connectivity can be a fog node. Existing factory processing devices like industrial controllers, switches, routers, embedded servers are primitive representations of fog nodes, supporting easy adoption of this paradigm [13]

One of the important benefits that fog computing offers is implementation of real-time or near real-time solutions of that require very low and predictable latency. Other characteristics of the fog are: mobility, wireless access, heterogeneity, geographical distribution, location awareness [13]. These benefits were integrated with the IoT domain in applications like smart cities or ambient assisted living [14]. Adoption of fog architectures in manufacturing domain is at its early stage and most papers focus on identification of implementation architectures and application domains. First perspectives of benefits from adopting for architecture in manufacturing was presented in [12]. They include domains requiring fast decisions, like failure management, geo-distributed applications and efficient production planning. In [15] the authors provide a fog computing-based framework for online process monitoring, detailing the components on the workflow, communication protocols and predictive analytics levels. The paper also highlights the benefits of implementation of a fog computing-based framework: connectivity between physical devices and the cloud, low and predictable network latency, remote access to high volumes of factory data in secure manner, high performance computing and real time data analytics. A different perspective oriented to cyber-physical systems that embed PMML-encoded machine learning models is presented in [15].

III. System Architecture

This section presents a fog-based architecture for the manufacturing domain, allowing integration of new IoT devices with existing plant equipment. It can enable better exploitation of existing manufacturing ICT systems through acquisition and analysis of large volumes of real-time data. The platform works on top of existing networking infrastructure, integrating wired and wireless industrial communication with new IoT-based sensors and devices. Its role is to merge and create various sensing data from multiple edge nodes, being able to deliver smart and customized services to users and businesses. Such a system has two main advantages: leveraging implementation of advanced processing algorithms, like implementation of predictive maintenance and fault diagnosis models, and providing a scalable network, more easily adapted to decentralized or geographical distributed manufacturing processes.

The overall system architecture for integration of IoT and plant floor devices in a Fog architecture for manufacturing processes is presented in Fig.1.

The first level is represented by process legacy machinery and sensors, along with new devices like IoT and WSN (Wireless Sensor Networks). Plant Floor sensing area is divided into the following:

a) Smart Sensors and Control for monitoring and controlling the process motors, pumps and conveyors (including voltage, current and power supplied, vibration level etc.).

b) Video monitoring cameras for intelligent assistance in applications like quality control, robot assistance in components assembly, safety and security operations.

c) Process sensors for monitoring the operational and environmental parameters (like temperature, humidity, gases, air pollutants etc.).

d) Mobile robots for manipulating products and components, pieces assembly, material cutting or glueing, etc.

Towards monitoring these devices, with different roles, communication protocols and heterogenous data sources, there is a need for adding **Fog gateways**. This layer works as a bridge between WSN, plant floor devices and the Fog node, so as to form a seamless management platform across all available data sources and cloud. They act both as protocol adapters from typical plant floor communication towards cloud integration and as data aggregators, allowing different data formats and sampling periods.

To facilitate further integration in architectures aligned to the fog computing paradigm, smart devices and gateways that are to be installed in a factory shall use 6LoWPAN standard. This is an IP based communication built upon the IEEE 802.15.4, which ensures that every smart device gets an individual IP address. This way a group of smart devices will be engaged in a Neighborhood Area Network based on

6LoWPAN. These collect data from plant floor and are capable to send it to Fog nodes.

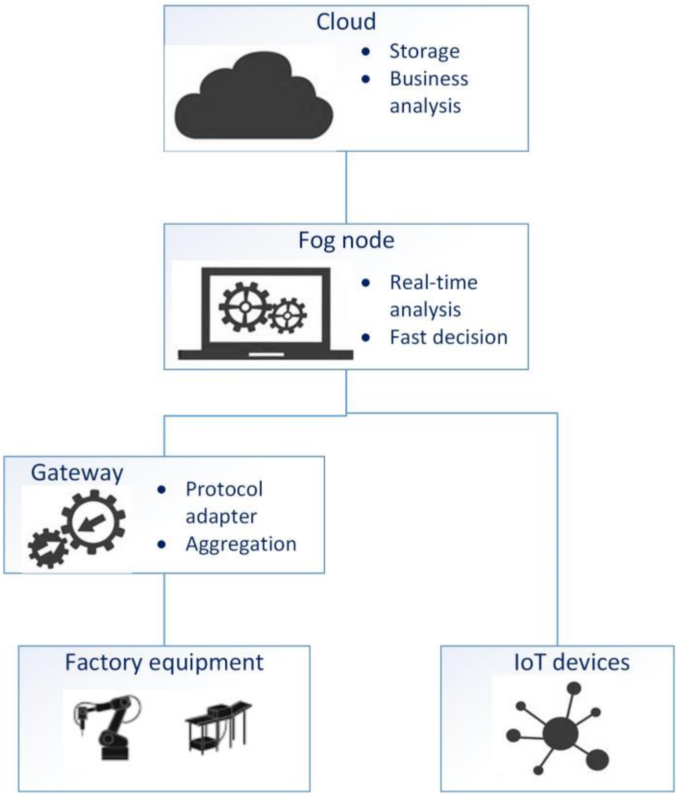

Fig. 1. System architecture for a Fog based manufacturing process

At the **Fog node** data is collected in real time for analytics and fast decision-making, and a Backbone network like 3G/4G is used for communicating to Cloud. Beyond the basic management services like data acquisition, data storage, visualization, processing and failure handling, the real-time data analysis is a key requirement that can be implemented at this layer. Because of the limited resources available at the sensor devices, typical cloud architectures require all data to be uploaded to a virtualized site to facilitate further processing. Such data collected from independent IoT sources often have implicit but disparate assumptions of interpretation. Such implicit assumptions of data interpretation must be addressed before the services can be dynamically composed and delivered. These Fog nodes support heterogeneity, cloud integration and distributed data analytics as we take the advantage of the low latency with a wide and dense geographical distribution. This also reduces the network traffic, latency and provides scalability. This helps in improving reliability of the manufacturing process, in improving the efficiency of the operation and extending the asset life.

The role of the **cloud level** in such architectures is focused in analytics that don't require real-time processing, like development of the prediction and fault identification models, business analytics, production planning etc. This layer uses JAVA RESTful web services for the communication with different virtualized sites and with centralized servers. This technology provides the managed interfaces, consisting of development environment and APIs, to support customized IoT applications and services. After the operation of the related web services, the cloud will present the results to the user in the form of REST-style data through HTTP.

IV. Platform For Virtualisation of a Manufacturing Process

Our aim in investigating a fog-based architecture is the development of a hybrid platform for design, simulation analysis and reconfiguration of flexible manufacturing lines. It will include both real models of existing equipment as well as virtual models. These can be used in scenarios developed in a Virtual Development Environment to evaluate production line performance. The development environment represents a proof-of-concept for Hybrid Process Simulation (HPS) applications.

A. Manufacturing process description

The structure of the physical application is illustrated in Fig. 1. It is a laboratory assembly from ASTI Automation [16] consisting of a flexible assembly line built from several individual stations, acting as interoperable and reconfigurable line modules. The first station uses a robotized pallet supply/retrieval unit with pallet buffer to store pallets for the product pieces and to place them on a conveyor belt. A second station aligns the pallet to fit a certain position, places the first piece of the product on it and forwards it to the next station. A mobile robotic arm continues the assembly with several small pieces. The assembly is performed based on a video inspection of the positioning of the product on the line. The following station is responsible for mounting and pressing the last piece, resulting in a compact product. The final station is responsible for product griping and stacking.

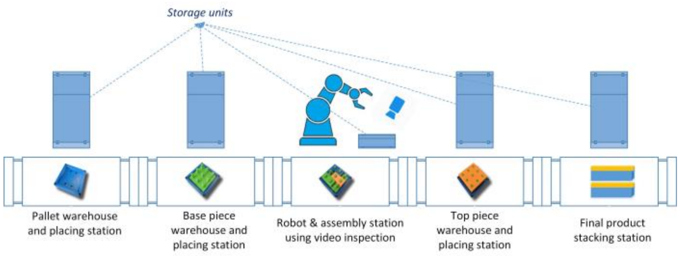

Fig. 2. Structure of the manufacturing line application

B. Fog integration of the manufacturing process

Smart sensors will be deployed for controlling a product to enter the next processing station, for detecting the buffer stack state (with or without pieces) or for video analysis to support piece recognition and assisted assembly. Each station has its own industrial controller, acting as a fog node for real-time monitoring and data processing. This way the plant can be designed to allow line automatic reconfiguration and better production planning. The cloud level can adapt the control parameters or strategy of a fog node to support this functionality. This way, the fog node reduces network latency associated with cloud communication and allows fast access to real time data without spatial constraints. Even if in our laboratory set-up each node processes a limited amount of data, they can be scaled for hundreds of data sources. Fog nodes can be connected through the communication link both to the cloud and to other factory nodes.

C. Cloud computing for process virtualization

The cloud level uses data-driven methods for possible fault diagnosis and predictive maintenance. It includes process interfaces to connect to the fog level and a development environment that allows the definition of function blocks and networks to model the manufacturing process. A model-based representation of the plant allows virtualization of the manufacturing process for better production planning, machinery upgrades or plant reconfiguration. The platform will use condition monitoring to predict the "health" state of the manufacturing equipment. For example, by measuring the time interval of a production piece on the conveyor line we can predict motor maintenance requirements.

The platform allows access to process data integrated with process simulations, such as the user can sustain a real-time control of production, including product machining process, assembly process, production system planning and reconfiguration for improved manufacturing system efficiency and reliability. Both the models for data acquisition (distributed sensor configurations for visual servoing systems) as well as the ones for the dynamic behavior will be encapsulated as function blocks. These function blocks will be used as software resources stored in an online cloud-based library.

D. Function block library

The cloud library is available as a components-based function blocks application. The function blocks encapsulate variables, parameters, modelling and computing algorithms that are required for the analysis and simulation of the real manufacturing process. The design takes under consideration the possibility of implementation as a distributed application, through the use of several Docker containers connected through a network using REST services. The library uses three types of function blocks:

- **Interface model blocks** represent a specific process attached to an equipment; the functionality includes data acquisition, processing and transmitting commands to and from the fog level;
- **Operational function blocks** that are application specific and implement communication and signal processing functions;
- **Algorithm function blocks** that execute mathematical functions, modelling algorithms, algorithms for specific analysis like fault diagnosis etc.

The management of the library and function block execution take place from a web application with the structure illustrated in Fig. 3. A user can see available function blocks, can add or use single block functions, for which he must configure the communication parameters (IP, port, tag address) for the data input and output. These blocks can be automatically executed on the cloud server with a direct connection with the manufacturing process, through the fog level. The user can see in the web interface the input values and the result of the execution, with a refresh rate of 500 ms. The values can be linked to the fog node for a near-real-time execution, where the refresh rate depends on the network latency and server load. A user disconnection does not stop the function block execution, as it continues to run as a service in the cloud.

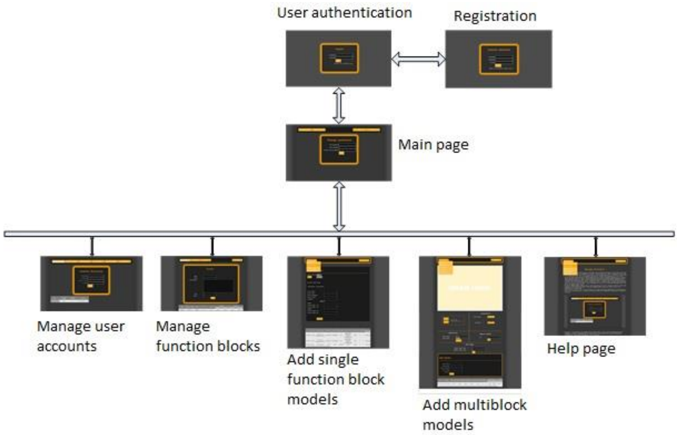

Fig. 3. Function block library interface structure

Multiblock models represent function blocks networks implemented by linking several single block inputs and outputs to obtain an algorithm with increased complexity (Fig. 4). After a multi block model is created, its architecture is saved in a descriptor file using YAML language, to be available for loading and launching in future applications. This approach is used in existing control logic and mathematical modelling tools to achieve better control and easier maintenance of implemented functions. The page for multiblock model development allows a user to select existing function blocks, to add constant values as inputs or to graphical link inputs and outputs using a drawing area.

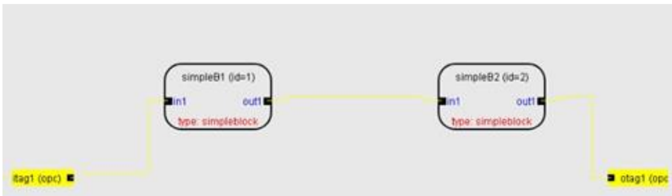

Fig. 4. Drawing interface for the multiblock model

Through the use of function blocks the library allows the execution of process models, algorithms and analysis of process state. The execution results can be forwarded to the fog node as data stream or can be generated in XML files to be processed and presented graphically in the cloud node.

V. Monitoring and Control of a Visual Servoing System

In the presented manufacturing line application, the visual servoing system is used to control the robotic manipulator in the correct selection and positioning of the pieces needed for the assembly. The real time operation was implemented with a simple control law that compares current and expected features of the image plane to compute the error (Fig. 5).

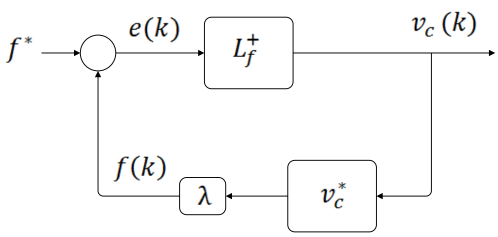

Fig. 5. Control law of the robotic arm based on the visual servoing system

Considering a servoing application, the tracer vector $f_m = [x_n, y_n, a_n, \tau, \xi, \alpha]^T$ can be used to characterize the object in the image [17]. The first three components of the vector f_m are used to control the components of the linear speed corresponding to the robot. Considering a project of the object in the image plane, its position relative to the coordinate system is given by:

$$x_n = a_n x_g \tag{1}$$

$$y_n = a_n y_g \tag{2}$$

$$a_n = Z^* \sqrt{\frac{a^*}{a}} \tag{3}$$

where:

n is the number of points describing the image object

Z^* represents the desired depth between the camera and the object in the reference image,

a^* represents the area of the object in the reference image

a represents the area of the current analyzed object and

(x_g, y_g) represents the center of gravity attached to the object.

As presented in [18], the interaction matrix L_f for the moments of the image defined by *n* points is given by equation (4).

$$L_f = \begin{bmatrix} -1 & 0 & 0 & a_n e_{11} & -a_n(1+e_{12}) & y_n \\ 0 & -1 & 0 & a_n(1+e_{21}) & -a_n e_{11} & -x_n \\ 0 & 0 & -1 & -e_{31} & e_{32} & 0 \\ 0 & 0 & 0 & \tau_{w_x} & \tau_{w_y} & 0 \\ 0 & 0 & 0 & \xi_{w_x} & \xi_{w_y} & 0 \\ 0 & 0 & 0 & \alpha_{w_x} & \alpha_{w_y} & -1 \end{bmatrix} \tag{4}$$

The difference between the target features and the current features represents the error function:

$$e = f - f^* \tag{5}$$

This allows a representation of a simplified control law for the camera velocity as:

$$v_c^* = -\tfrac{1}{2}\lambda L_f^* e \tag{6}$$

where:

L_f^* - is the Moore-Penrose pseudoinverse of L_f

λ – represents the proportionality factor,

The camera velocity can be represented as:

$$v_c^* = [v^* \ \ \omega^*]^T \tag{7}$$

where:

$v^* = [v_x^* \ v_y^* \ v_z^*]^T$ - the linear component of the velocity

$\omega^* = [\omega_x^* \ \omega_y^* \ \omega_z^*]^T$ - the angular component of the velocity

The fog node ensures real time processing of the visual information and control of the mechanic grip. The cloud level allows model improvement, predictive maintenance and machine learning by correlating images with robot actions (the fog node reacts in a certain way for specific results of the image, these actions can be learned to allow faster decisions).

The model of this servoing system was encapsulated as a function block in the virtualized platform. We used it in a single function block with a matrix representation of the interaction matrix. Function block inputs are represented by vectors of the image definition $f = [x_n, y_n, a_n, \tau, \xi, \alpha]^T$. The output is the camera velocity.

After creating the function block, the execution can be started by selecting it in the launch model page. This loads the YAML architecture description file and sends it to a REST interface on a dedicated server that assigns the required resources in the cloud. Each function block is stored as an executable file. When allocating required resources, each such executable file from the architecture is encapsulated in a docker container and these containers are then sent to cloud. To be able to execute the model, the user is asked to load a file with input data. The file is sent to a REST interface that stores it in the cloud. The first block of the model takes its input data from this file. This function block is an interface between the file and the rest of the model, with no other role that to forward data to the operational and algorithms function blocks. Data generated from the execution in saved in an output file that can be downloaded from a specific link provided by the web application.

VI. CONCLUSIONS

This paper evaluates the integration capabilities between existing technologies with new devices for seamless integration of the fog computing paradigm in manufacturing domain and provides an architecture solution for this upgrade. The fog node can be seen as a private local cloud, enabling real-time processing and control. As the communication uses IoT protocols, these is an easy adoption of this architecture in current cloud-connected manufacturing processes. The virtualization of the presented process allows access to advanced computing resources that can be exploited in near-real-time or offline execution. The scalable architecture can be easily adapted to integrate existing machinery and new devices, through the use of fog gateways and docker container at the cloud level.

Future work will include development of a prototype for a fog computing manufacturing system in the predictive maintenance area, using machinery from the presented educational application. This prototype will include the direct connection between the visual servoing system and its model in the cloud to evaluate and improve the manipulation arm control strategy.

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