UNICO I+D Project
6G-DATADRIVEN-05

6G-DATADRIVEN-05-E9

Distributed orchestration for AI/ML (initial release)

Abstract

Distributed orchestration for AI/ML is a rising methodology to distribute the resource allocation in large networks. In this deliverable we do a comprehensive review of the state of the art of distributed orchestration, and also proposed an initial design of distributed orchestration framework enabling agile placement of AI/ML at the continuum edge. Namely, we propose an initial framework that embraces all data sources and Edge facilities within Industry 4.0 premises.

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List of Acronyms

ADMM: Alternative Direction Method of Multipliers

AI/ML: Artificial Intelligence / Machine Learning

DNN: Deep Neural Network

DRL: Deep Reinforcement Learning

DT: Digital Twin

IoT: Internet of Things

MIMO: Multiple Input Multiple Output

NFV: Network Function Virtualization

NOMA: Non-Orthogonal Multiple Access

NPN: Non Private Network

ROS: Robot Operating System

SDN: Software Defined Networks

SFC: Service Function Chain

USRP: Universal Software Software Radio Peripheral

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Resumen Ejecutivo

Este documento proporciona una revisión del estado del arte en orquestación distribuida para el proyecto 6G-DATADRIVEN-05. Además, el documento proporciona un diseño inicial de un marco de trabajo (*framework*) que permite el despliegue ágil de algoritmos de inteligencia artificial y aprendizaje máquina en el Edge.

Los principales resultados descritos en este entregable son:

- un análisis detallado del estado del arte en orquestación distribuida;
- una clasificación de las distintas técnicas de orquestación distribuida identificadas en el estado del arte;
- la definición de un marco de procesado de datos en entornos de industria 4.0 con equipamiento Edge; y
- la definición de una entidad analítica que permite el procesado in situ de los datos de una fábrica, y el procesado de datos distribuidos de otras fábricas.

En línea con la arquitectura propuesta en el presente documento, se ha llevado a cabo investigación relacionada con la industria conectada usando inteligencia artificial. En concreto, se ha publicado:

- una solución que permite usar inteligencia artificial para mitigar la interferencia inalámbrica en el control remoto de un brazo robótico (Groshev, Martín-Pérez, Guimarães, Oliva, & Bernardos, FoReCo: A Forecast-Based Recovery Mechanism for Real-Time Remote Control of Robotic Manipulators, 2022); y
- la formulación del problema de despliegue de servicios de robots para entornos de industria conectada (Khasa Gillani, 2022).

El resto del documento está redactado en inglés, de cara a maximizar el impacto del trabajo realizado en este proyecto.

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Executive Summary

This document reviews the state of the art on distributed orchestration for the 6G-DATADRIVEN-05 project. It also exposes an initial design of a framework enabling agile deployment of AI/ML algorithms on the Edge.

The main contributions of this deliverable are:

- a detailed analysis of the state of the art on distributed orchestration;
- a classification of the different orchestration techniques in the state of the art;
- the definition of a framework for processing data in Industry 4.0 environments equipped with Edge premises; and
- the definition of an analytics entity that alows the processing of data within the Edge premises of a factory floor, so as the processing of data distributed in other factory floors.

Inline with the proposed framework, the following research has been carried out in the context of Industry 4.0 using artificial intelligence. In particular, these are the produced scientific publications:

- a solution to mitigate the Wireless interference of remotely controlled robotic arms (Groshev, Martín-Pérez, Guimarães, Oliva, & Bernardos, FoReCo: A Forecast-Based Recovery Mechanism for Real-Time Remote Control of Robotic Manipulators, 2022); and
- the formulation of the problem related to the deployment of robotic services in connected industry (Khasa Gillani, 2022).

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1. Introduction

The trend in recent network deployments is to move the computational power closer to the user, i.e., the Edge. Such trend is mainly motivated by either the latency reduction due to a closer deployment to the end user, or due to the dedicated resources in environments as factory floors.

To meet the goal of moving resources closer to the end user, it is necessary to perform an adequate allocation of resources. This is, to decide where applications should run (in the Cloud or Edge), and how the traffic should be prioritized or steered to reach such servers. Both problems are tackled in the literature and is within the umbrella or resource orchestration.

Due to the large network infrastructures, it becomes challenging to solve the resource orchestration problem. Typically, such problem is modelled using optimization formulations, and solved using off-the-shelf mathematical solvers. However, this becomes intractable in large networks. Hence, distributed resource orchestration is a powerful tool to split the allocation problem in multiple subproblem easier to solve.

In this deliverable we overview the distributed orchestration state of the art, and do a classification of the existing techniques. We detail how the research community has tackles the resource allocation problem since 2018 in the Edge continuum stratum, and detail the techniques they propose to tackle the problem. The state of the art ranges from classical ADMM methods, to more recent techniques as federated learning and multi-agent AI/ML.

This deliverable also proposes a framework to collect and process the data in industry 4.0 environments, exploiting the benefits of the Edge continuum, e.g., central edge, on-site edge, or regional edge. We propose the architectural blocks necessary to collect the heterogeneous data of factory floors, and an Analytics entity in charge of analyzing the industrial data for multiple tasks such as industry 4.0 maintenance, and distributed resource allocation over the Edge continuum and IoT devices within the factory floor.

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2. State of the Art on Distributed Orchestration

Distributed Orchestration tackles the problem of allocating resources to deploy network services as video streaming platforms, assisted vehicle driving, or remote control of robots in a factory floor. All these services use the network substrate – i.e., the network links' bandwidth and servers' computational resources – to provide a functionality. Their proper behaviour depends on whether they have access to the network resources. For example, a robot remote control service does not deliver commands in time if it traverses congested links, hence, it will suffer from high jitter or latencies.

Hence, it is of paramount importance to adequately allocate network resources to services in order to guarantee that all of them work as expected. In Distributed Orchestration, the idea is to find algorithms working in a distributed manner to find solutions about how to allocate network resources. The distributed approach is especially useful for large network substrates in which solving an orchestration problem results in a large search space towards the optimal solution, for the distributed approach splits the problem so each distributed agent solves a local problem, and later all agents interact to exchange their partial solutions and converge to a global optimum.

In the following we go over the recent state of the art on Distributed orchestration in recent network deployments considering wireless, Edge and even the fog stratum. We overview the problem tackled by each work, and conclude the section with a Table that clasifies all the works based on the used techniques.

(Castellano, Esposito, & Risso, 2019) presents a distributed orchestration algorithm that partitions the resources to be orchestrated across an Edge infrastructure. The algorithm is an (1-1/e)-approximation solution that relies on **voting process** to solve in a distributed fashion the resource orchestration.

(Wen, 2020) proposes using a **genetic algorithm** that works on top of Hadoop to assess the resource orchestration in a geo-distributed cloud environment. The work focuses on meeting the security requirements using a metric that checks the disparity between the security requirements of the services, and the security features of the servers.

In (Xinchen Lyu, 2018), authors propose a distributed approach to decentralize the flow orchestration. Namely, authors formulate a model to minimize the average cost of attending the network demand at multiple SDN controllers. The optimization problem is broken down into **subgradient descends** that are solved in a distributed manner to decide the traffic attended by each SDN controller, so as the state exchange between them in case the solution decides to switch off a controller. Thanks to Lyapunov optimization, authors provide a bound for the optimality gap in their distributed approach.

In (Chen, et al.), authors tackle the SFC orchestration problem over IoT devices. The proposed solution breaks the SFC orchestration into two different steps: i) selecting which SFC to orchestrate; and ii) doing the SFC resource assignment over the stratum. The latter step is tackled in a distributed manner that uses **Q-learning**.

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To achieve an optimal orchestration policy for cellular Edge computing, (Liu, 2019) proposes DIRECT, an algorithm funded on **ADMM methods** to decide the resource allocation on **cellular Edge** nodes. The algorithm aims at minimizing the cost of a orchestrating resources for slices with heterogeneous latency requirements. The associated optimization problem is split into subproblems with auxiliary variables that then derive the updates for the corresponding decision variables in the dual problem. As a result, DIRECT uses ADMM to update the decisions an is proved to achieve local minimums. DIRECT was tried on real USRPs and managed to orchestrate the resources from different network slices to meet the latency demand of each of them.

This magazine (Alam, et al., 2018) explains the problematic of orchestrating resources in a cloud-to-fog substrate composed of heterogeneous devices. Authors propose using a **Docker based solution** that deploys containers for each task of the service, and deploys such services over the distributed resource stratum depending on the latency and resources constraints. The results show that using a docker based solution achieves fault-tolerant and flexible deployments that adapts to the resource needs, and envisions the whole resource pool as a unique pool that becomes available for the service deployment.

To accommodate trusted SFCs in the Edge and Cloud continuum, authors of (Guo, Dai, Xu, Qiu, & Qi, 2020) propose an architecture that combines block chain with DRL. First, service providers must authenticate the provided services in the trusted chain to ensure that the service is secure. Then, the corresponding SFC is orchestrated within the pool of different Edge cloud facilities using a DRL-based solution. Each **Edge facility has a dedicated DRL**, hence, being capable of telling whether it is possible to deploy the SFC or not. In the case the Edge DRL cannot find a possible deployment for the SFC, it sends the request up to a DRL agent at the cloud to find a solution. Therefore, the proposed orchestration solution is a hierarchical approach over a distributed pool of Edge cloud facilities.

In (Chen & Xu, 2021) authors exploit the usage of **multi-agent DRL** to achieve an optimal resource allocation in a distributed manner. Each Edge server runs a local DRL that learns the peculiarities of both resources and computing capabilities as the Edge runs local services. The distributed learning achieves a convergence towards an optimal solution, yet considering the local peculiarities. As the Edge server foresees local changes, the authors propose what they call N2O, a neural network orchestrator that sends information back to a global actor that enhances the service deployment. The work proofs the stability and convergence of the proposed solution proving the Lipschitz conditions.

The V-Edge solution (Falko Dressler, 2021) envisions a fully distributed pool of computing resources that goes beyond the Edge. In particular, it considers that the mobile users may also exchange the data processing and computing capabilities they hold. Consequently, the authors propose a whole resource stratum comprising Cloud, Edge, and end-users' resources. Regardless of the device, **V-Edge is an architecture that deploys micro-services** as containers within the devices. In case there is a fault in the network, it is capable of migrating or instructing the microservice deployment to an

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end-user nearby the consumers. Also, V-Edge envisions the possibility of training a distributed AutoML solution that updates its parameters to achieve a fully distributed training, update, and orchestration of the resources.

Authors of (Malandrino, Chiasserini, Molner, & Oliva, 2022) study the performance of **distributed machine learning over a network** infrastructure for, e.g., orchestration related tasks. The work models the distributed machine learning as a set of learning nodes as servers running tasks to minimize an objective function. To **optimize the process**, the learning nodes depend on the data provided by information nodes in the networks, as a server with a database. Authors propose a DoubleClimb algorithm that tells the number of training iterations to do achieve the target performance decreasing as much as possible the exchanged data over the network. With the proposed approach it is possible to perform distributed orchestration, while minimizing the network overhead.

In the spirit of the prior work, authors of (Malandrino, Chiasserini, & Giacomo, Efficient Distributed DNNs in the Mobile-Edge-Cloud Continuum, 2022) also study the effect of distributed machine learning in a Cloud to Mobile continuum. This time authors study the **split/distribution of a DNN into its different layers**, and how to deploy each of them in different servers over the network. The paper proposes an algorithm called RightTrain that selects the best nodes/servers to run each layer and achieve an optimal training. The solution uses an expanded graph with all the possible deployments, and have optimality guarantees regarding the training performance of the AI/ML models.

This magazine (Miloud Bagaa, 2021) identifies the architectural need of integrating AI in a cross system network architecture, i.e., an holistic architecture embracing both the core network, servers, and end devices. The envisioned architecture proposes to plug **across system Network Intelligence Function (NIF)** that collects data from all sources in a distributed manner to automate the network management, i.e., scaling the computational and networking resources devoted to running the services.

In Network virtualization, the resources have to be distributed over the cloud and edge facilities to deploy the services. Also, the requirements of each slice should be met by the substrate selected to run the resources. In (Halabian, 2019), the authors model the assignment of slices to resources using an optimization problem, as followed in the state of the art. The proposed solution formulates a distributed approach that aims at resource fairness in the slices deployment, i.e., the resources substrate must equally assume the service demand. Authors propose a game-theory approach that finds a **Nash equilibrium** through a distributed server-to-slice **auction** mechanism.

The NFV resource allocation becomes a challenging problem in large network architectures due to the vast volume of decision variables. To mitigate the problem, authors of (Yu, Bu, Yang, Nguyen, & Han, 2020) propose to simplify the problem in two stages: i) perform a **Bender decomposition** that converts integer variables into continuous ones; and ii) finding solution of the associated dual

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problem. To tackle the latter problem, the authors resort to ADMM to solve the problem in a distributed manner with each node of the network substrate solving a subproblem that later updates the decision variables.

In the context of IoT devices, energy harvesting is a trend. The device collects energy from the radio transmission received from the antenna, and then decides the data and service to run. In the paper, authors formulate an optimization problem to achieve energy efficiency deciding when to transmit data, and when to collect energy from MIMO-NOMA transmissions. The proposed solution in (Wang, Lin, Lv, & Ni, 2021) is funded in non-linear fraction programming to make the problem convex, and then resorts to an ADMM approach to perform a distributed approach that decides when each IoT device should collect energy, and when to transmit data.

When performing distributed approaches to perform resource allocation, there are sensitive exchanges of data that may disclose information regarding the network infrastructure. (Jason Hughes, 2022) tackles precisely this concern in distributed resource allocation by introducing slight randomizations in the exchanges of data in the distributed approach. The authors use **optimal transport theory** to decide the resource allocation. Using such theoretical framework, they solve the associated optimal transport problem using the **ADMM** technique to achieve a distributed solution that iteratively converges to an optimal allocation.

In (Wang, Tao, Zhang, Zhang, & Hou, 2019) the authors decide how to offload tasks at a device, cloud and edge continuum. The paper models that each task asks for a number of CPU cycles to complete its execution. Based on where the task is offloading, and the computing power of the devices, the tasks will take less or more time to be completed. Overall, the authors formulate the associated optimization problem and simplify it so it can be assessed with the **ADMM** method in a distributed fashion, i.e., with parallel executions that iteratively refine the decision variables of the associated dual problem. The goal of the work is to minimize the time it takes to complete all the offloaded tasks.

Similar to other federated learning approaches, the authors of (JIANJI REN, 2019) suggest to perform task offloading between the Edge and a set of IoT devices. Specifically, they advocate to a **federated learning** approach where each agent knows about the local resource usage to converge to a common policy that decides the offloading of resources.

Due to the channel varying channel conditions, it is a tight challenge to distribute information between wireless-connected entities that collaborate in a **federated/distributed learning** procedure. Despite the task to be solved – whether it is orchestration or other AI/ML task – bad channel conditions may limit the amount of data to exchange. Therefore, authors in (Amiri, Gündüz, Kulkarni, & Poor, 2021) study how to **schedule the parameters' updates over wireless** connections to converge to an optimal solution in federated learning. The paper presents a novel scheduling approach where each distributed agent decides when to transmit, and how much data to transmit

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throughout the learning process. Results proof convergence rules depending on the distribution of the data diversity and distribution over the nodes holding each agent training.

All the aforementioned works study the use of distributed approaches to perform orchestration over the network substrate. The recent state of the art typically considers the whole Cloud to Edge to device continuum to schedule and allocate the resource usage. It is thus a tendency to foresee the network as a whole continuum that does not only focus on the switching and servers and end devices that connect to the network, i.e., the tendency is to also embrace the mobile phones and IoT devices to perform service tasks.

Table 2-1 classifies the existing works on distributed orchestration based on the technique they use. Overall, works either use multi agent ML, federated learning, traditional decomposition of the associated optimization problem using ADMM, or game theory.

TABLE 2-1: CLASSIFICATION OF DISTRIBUTED ORCHESTRATION TECHNIQUES IN THE STATE OF THE ART

Orchestration technique	Works	Technique Description
Optimal Transport Theory	(Jason Hughes, 2022)	It uses the theoretical framework of Gaspard Monge to determine how to transport/allocate services to a destination/server.
Federated Learning	(Malandrino, Chiasserini, Molner, & Oliva, 2022);	All the learning nodes perform gradient descends based on local information, and their parameter updates are averaged and exchanged among all to find a global optimum, yet distributing the computation locally at each node.
ADMM	(Liu, 2019); (Wang, Lin, Lv, & Ni, 2021); (Jason Hughes, 2022)	The alternating direction method of multipliers distributes the computation of solutions for convex optimization problems.
Game Theory	(Castellano, Esposito, & Risso, 2019); (Halabian, 2019); (Yu, Bu, Yang, Nguyen, & Han, 2020)	In game theory the different distributed nodes participate in a game (the resource allocation) to get incentives. The goal is that all nodes maximize their incentives (e.g., resource usage) to meet a global equilibrium (e.g., global optimum of the resource allocation).
Architecture based	(Alam, et al., 2018); (Falko Dressler, 2021); (Miloud Bagaa, 2021);	These works present architectural solutions that rely on containers and micro-services, so the network requests for distributed deployments using the proposed orchestration architectures.
Multi Agent	(Chen, et al.); (Guo, Dai, Xu, Qiu, & Qi, 2020); (Chen & Xu, 2021);	In multi-agent solutions each node runs an agent to dispatch the service deployment within the corresponding server. Then, they coordinate to exchange the attained orchestration solution.
Genetic Algorithms	(Wen, 2020);	Genetic algorithms try possible resource allocations following a certain

		strategy/genome that is iteratively modified until the yield solution becomes the optimal.
Optimize the distributed learning	(Malandrino, Chiasserini, & Giacomo, Efficient Distributed DNNs in the Mobile-Edge-Cloud Continuum, 2022)	The work optimizes how to distribute the different layers of an AI/ML model to achieve convergence given the computational and network constraints of the underlying network stratum.
Lyapunov optimization	(Xinchen Lyu, 2018);	This technique grounds on the theoretical framework of Lyapunov control to give convergence and optimality guarantees on metrics to be optimized such as the average experienced latency of the orchestrated services.

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3. Distributed Orchestration framework for agile placement of AI/ML at the continuum edge

In this section we propose a framework for agile placement of AI/ML in an edge continuum for industry 4.0. The idea is to embrace all the data sources and processing locations to have a distributed orchestration and management of both AI/ML, and data. To that aim we envision a framework that comprises the collection, storage, and distribution of heterogeneous data sources in the factory floor; so as Edge premises at different stages.

The proposed framework addresses the converge of two technological trends: the mobile network and the industry evolution. On the former, 5G introduces several changes that help to create a more flexible and de-centralized network, which can be adapted to the requirements of the end-user. This is particularly true for the 5G User Plane, where features like the Control/User Plane Split (CUPS) allow to decentralize the management of the end-user data and enable the creation of new applications environments that can be located close to the end-user. These features, along other ones like network slicing, are the basis for moving end-user application to edge or even on-premises locations. On the latter, the evolution in the last years is towards a fully connected industry, where the industrial processes are not manual and isolated anymore. New technology enablers like wireless access and DT have been adopted by the industry and are the root for its further evolution towards smart manufacturing.

The framework detailed in this section proposes to combine both worlds in order to provide and validate, in TRL7 environments, a reference architecture that addresses the challenge of integrating manufacturing industries using the 5G technology in order to propose solutions to different aspects: massive DTs, integration of 5G network in on-premises communications, offload of manufacturing applications to the cloud, with specific analysis on how this impacts in the industry security standards, and in general, to integrate the manufacturing data management in a standard IT ecosystem.

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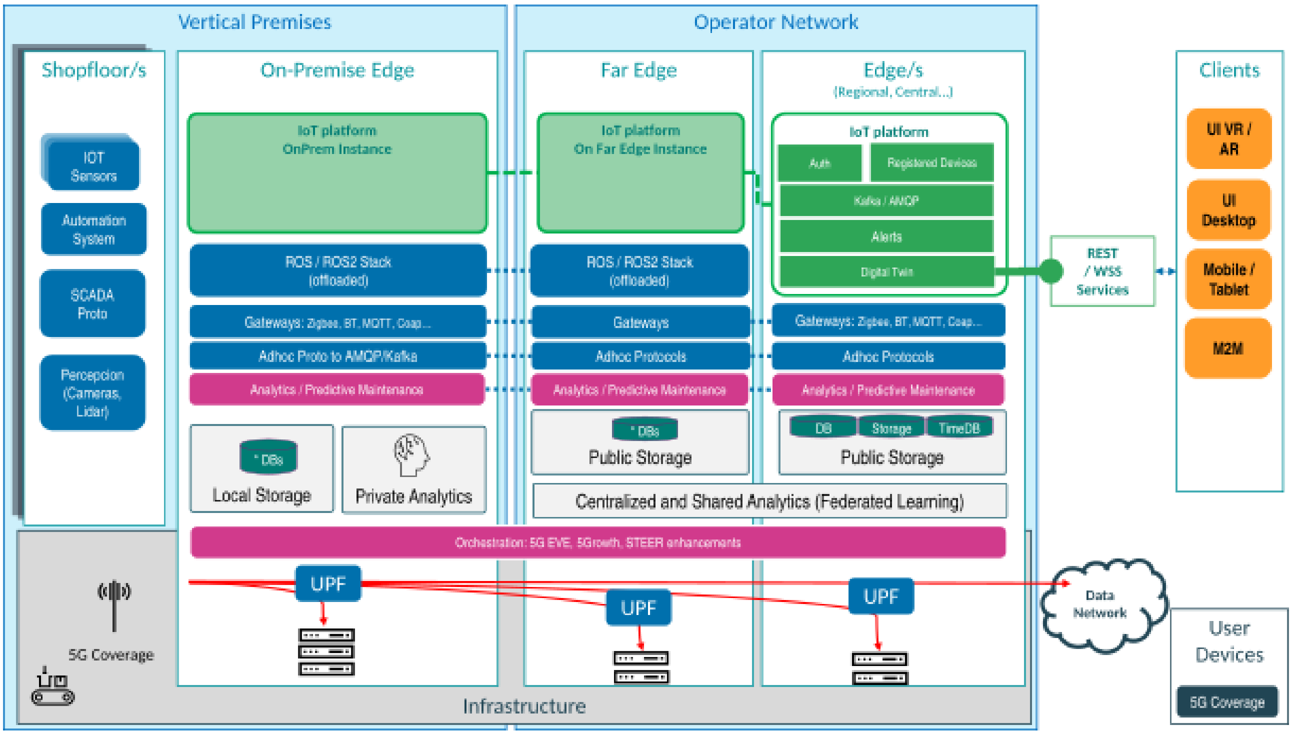

FIGURE 1: PROPOSED FRAMEWORK FOR DISTRIBUTED ORCHESTRATION FOR AI/ML

Figure 1 illustrates the proposed framework. We envisage a distributed environment, that combines infrastructure at the vertical (factory) premises ("On Premise Edge"), with infrastructure at the operator's premises, which can expand the so-called Far Edge (close to the factory) and other type of edges (local, regional, etc.).

At the service level, we consider the following components:

- *Factory devices*: these devices have connectivity with the proposed framework. Examples of them are machines with SCADA protocols (Modbus, Ethercap, etc ...), AGV and Robotic Arms with Robot Operating System (ROS), IP Cameras, various Sensors using different access technologies (BT, Zigbee, LoRa, 833MHz, etc ...).
- *Gateways*: devices in charge of preforming the required protocol translations to enable them interconnect with the platform. They acquire data from factory devices, so they must be implemented according to their requirements. These gateways can work on all edges (On Premise, Far, Region, Central ...), and are selected depending on the latency and bandwidth requirements.
- *Edge Stack*: distributed, edge implementation of computing processes that used to run locally in the devices, but that can be moved to the network under some circumstances, to benefit from the edge computing power and centralized data processing. For example, the primary ROS node can be implemented at the edge (container) and leave the robot as a simple data sender and command receiver.

- *Analytics and predictive maintenance*: this logical component provides the platform with AI capabilities, so processes that make use of sensor data can be deployed. Different types of data can be stored both in the On-Premise Edge, thus keeping the data always in the client network, as well as in the central servers. In the latter case, Federated Learning techniques can be used so the data remains in the client network. This logical component is also in charge of using the prior section distributed orchestration techniques to orchestrate the resources of both the On-Premise Edge, and other Edge premises for federated learning orchestration purposes.
- *IoT platform*: In order to provide the entire environment with a coordinated system, an IoT platform is used as a baseline to facilitate the integration with other components. This platform will run on the edge (regional, central) and will have the following modules: (i) DT: describes the factory ontology and structuring all the components and granting a single entry point for consulting the status of the factory; (ii) Alerts Module: launches alerts according to data criteria; (iii) Messaging Bus: central bus that distributes the data among the components; (iv) Device Registry: stores, identifies and controls the factory devices in a unitary way; and, (v) Authentication: authentication module, both for Clients and for M2M.

All this infrastructure is supported by a 5G network, integrated in the on-premises communications using a NPN approach, where the network deployed on the premises of the manufacturing industry is integrated with the public telco operator network, as an evolution of current private networks. For that, we propose to deploy in the industry premises only the nodes required for providing communications, i.e., the Radio Access Network and the User Plane Function. With that, we can provide Device-to-Device communication as well as access to on-premises, far edge or cloud applications.

Finally, the services associated with industrial use cases on the end user side, which will interact with the platform, will be heterogeneous. The access to the platform shall go through open protocols (REST, WSS...) and will be able to both access the data and act on the DT. The means of exploitation of data and visualization will vary depending on the use case, allowing scalability to different industries and incorporation of multiple industrial applications.

It is worth mentioning that the proposed framework considers both distributed and On-site AI/ML through the Private and Centralized/shared analytics, respectively. Also within the analytics entity we plan to study incorporating the distributed orchestration techniques proposed in Section 3.

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4. Summary and Conclusions

This document presents a state of the art on distributed orchestration solutions. The document revisits the recent research on the topic and provides a clasification of existing techniques ranging from classic distributed optimization tools as ADMM, to late AI/ML techniques as federated learning, or multi-agent solutions. The existing solutions analysed through the second section of the document have proved a high performance regarding resource allocation in Cloud to Edge continuum pool of resources.

The document also provides a framework that embraces distributed pools of resources in Industry 4.0 scenarios. In particular, it envisions a continuum of Edge premises collecting local data that may, or not, be shared among other premises. The framework devises a Private Analytics entity that runs algorithms for Industry 4.0 tasks as maintenance, and also executes orchestration algorithms that may work in a distributed manner with other Edge premises through the centralized and shared analytics, so federated learning orchestration is possible.

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