Methods to arrange the production means and components

Deliverable 4.2



MULTI-METHOD WORKSPACE FOR HIGHLY SCALABLE PRODUCTION LINES



Project identifier	MUWO		
Project title	Multi-method workspace for highly scalable production lines		
Document version	1.0		
Planned delivery date	M18 (July 2022)		
Actual delivery date	M18		
Document title	Methods to arrange the production means and components		
Work Package	WP 4		
Abstract	This deliverable presents the communication systems that will be used for data and information transmission; the algorithms that will be developed, the process flow; and how the monitoring of the machines and equipment that provide data will be carried out, together with the indicators that will be used for this purpose.		
Keywords	Communication, algorithm, tool, production planning, scheduling, KPI		

Function	Name	Entity
Author	Irene Torrego	Accuro
Autioi	Alli Kafali	ACD
Editors	Irene Torrego	Accuro
Euliors		
	Ali Kafali	ACD
	Salvador Cobos	Accuro
	Ricardo Martins	
Contributors	Filipe Correia	Sistrade
Contributors	Fábio Coelho	
	Bruno Mota	
	Carlos Ramos	ISEP
	Pedro Faria	



Executive summary

Work Package 4 aims to perform simulations of production processes and different production means in order to verify whether it is possible to combine or reorganize in a way that will improve their efficiency. These simulations will take into account a number of use-case dependent factors that will determine whether one production means is suitable for a process, or whether it is possible to combine different working methods for the same process, creating a flexible multimethod workspace. The results of the simulations should be arranged in such a way that an optimal configuration can be obtained based on different criteria.

Therefore, this deliverable presents the communication systems between machines, sensors, devices, etc. that will be used for data and information transmission; the algorithms that will be developed in relation to production planning, distributing the work between the different machines available in the plant, regardless of their degree of automation, the monitoring of machines and equipment and the predictive maintenance of equipment; the process flow; and how the monitoring of the machines and equipment that provide data will be carried out, together with the indicators that will be used for this purpose.





Partner contributions record

#	Entity	Contributor on Phase 1	Date of Contribution1	Contributor on Phase 2	Date of Contribution2
1	Accuro	Х	14/07/2022		
2	ACD	Х	04/07/2022		
3	Alpata				
4	Evosoft				
5	Inovasyon				
6	ISEP	Х	26/07/2022		
7	Progim				
8	SisTrade	Х	20/07/2022		



Changes record

Version	Date	Entity	Description of Changes	
0.1	27/06/2022	ACCURO	Creation of document template and initial document structure	
0.2	04/07/2022	ACD	Update of document structure and added UC contributions	
0.3	14/07/2022	ACCURO	Added UC3 contributions	
0.4	20/07/2022	SISTRADE	Added information about use case description, communication, monitoring, KPIs and processes related to UC1	
0.4.1	22/06/2022	ACD	Added UC2 figures' captions	
0.5	26/07/2022	ISEP	Completed "Methods and Tools" information in UC1	
1.0	26/07/2022	ACCURO	Compilation of contributions from all partners, and final editing and formatting	





Contents

1.	Intro	duction	8
	1.1.	Document objectives and scope	8
	1.2.	Document structure	8
2.	State	e of the Art methods to arrange production means	9
:	2.1.	Standardization	9
:	2.2.	Standardization of Products and Processes	9
3.	Arra	nging production means	11
;	3.1.	UC1 – IDEPA's Use case (Portugal)	11
	3.1.1	1. Description	11
	3.1.2	2. Communication	12
	3.1.3	3. Method and Tools	13
	3.1.4	4. Monitoring	16
	3.1.5	5. KPI	17
	3.1.6	6. Process	19
;	3.2.	UC2 – GTF Rotor cell operation (Turkey)	19
	3.2.1	1. Description	19
	3.2.2	2. Communication	20
	3.2.3	3. Method and Tools	22
	3.2.4	4. Monitoring	29
	3.2.5	5. KPI	30
	3.2.6	6. Process	33
;	3.3.	UC3 – ALBERO's Use case (Spain)	34
	3.3.1	1. Description	34
	3.3.2	2. Communication	36
	3.3.3	3. Method and Tools	37
	3.3.4	4. Monitoring	39
	3.3.5	5. KPI	39
	3.3.6	6. Process	40
4.	Cond	clusions	43
5.	Refe	erences	44
Li	st of	figures	
Fig	jure 1.	Jacquard production process	11
Fig	jure 2.	Ratière production process	11
Fig	jure 3.	OPC UA Communications	12
Fig	jure 4.	Flowchart of the proposed machine learning model training process	14
Fig	jure 5.	Flowchart of the proposed scheduler	16





Figure 4 - EHMS process	19
Figure 1. GTF rotor cell production means	20
Figure 2. ROS Fundamental Structure	21
Figure 3. Sample robotic system generation	21
Figure 4. MTConnect Architecture	22
Figure 5. Machine priority for executing a work order	25
Figure 6. Maintenance plan	28
Figure 7. Testing related production data	28
Figure 8. Optimization phases of the algorithms	29
Figure 9. Monitoring of the machines' status	29
Figure 10. Detailed monitoring of the machines	30
Figure 11. KPI selection Interface	33
Figure 12. KPI Edit Screen	33
Figure 13. Robot operation process	34
Figure 14. Workflow in ALBERO	35
Figure 15. Software interfaces	37
Figure 16. Data collection from sensors	41
Figure 17 Process when an anomaly is detected	41
Figure 18 planning algorithm execution processes	42
Figure 19 planning process for parameter changes	42
List of tables	
Table 1. Sensors acquired for Loom 9	16
Table 2. Sensors acquired for Loom 10	17
Table 3. Sensors acquired for Loom 11	17
Table 4. Sensors acquired for Loom 12	17
Table 5. IDEPAs use case KPIs	18
Table 6. KPIs collected from factory production systems – UC2	30
Table 7 Key Performance Indicators – UC3	39





1. Introduction

1.1. Document objectives and scope

The objective of this deliverable is to establish a method to arrange the production means and components, creating flexible production processes and workspaces that enhance production efficiency.

This document compiles information on the production processes, means and components involved in each use case, indicating the priorities to be taken into account in order to establish a standard method

1.2. Document structure

This document is structured in two main sections that collect all the information needed to develop the methods to arrange the production means: Section 2 provides State of the Art information about methos to arrange the production means, particularly about scandalization of processes and products; in Section 3, the methods and tools to be developed and used in the project for arranging production means are described, as well as communication interfaces and protocols, how

Finally, Section 4 presents the conclusions of this deliverable, summarizing the information collected from all use cases.





2. State of the Art methods to arrange production means

There are methods for arranging of production means. These are standardization standards used in industry in order to provide benefits for mass production.

2.1. Standardization

Standardization is the process of setting and applying certain rules with the contribution and cooperation of all parties. In standardization applications, the basic document is the standards.

Standards are documents that have been created with the participation of all relevant parties, agreed upon, prepared for common and repeated uses, and approved by an authorized body. Non-governmental organizations such as the private sector, SMEs, universities, the public, associations and unions are among the relevant stakeholders. They are prepared for purposes such as establishing safety and quality requirements for products, services, processes and facilities, improving processes (manufacturing, management, etc.), expanding the use of technology, removing commercial barriers, opening up to new markets, protecting the environment, ensuring the safety of life and property.

Standards are documents that prioritize human health, life and property safety, foresee that products are produced as an example, high quality, suitable for use and especially economically, and whose accuracy is based on the finalized results of scientific, technical and experimental studies.

2.2. Standardization of Products and Processes

Product standardization refers to the process of ensuring uniformity and consistency between different iterations of a particular good or service available in different markets. If a product is replaced, it is replaced only superficially. Otherwise, the characteristics of the good or service remain the same. Product standardization is done using the same materials and processes, has the same packaging, and is marketed under the same name.

The strategy of product standardization requires compliance with certain rules to maintain the nature, appearance and quality consistency of a product. These guidelines are generally accepted rules that are followed when producing a good or performing a service. Guidelines may apply to an organization or an industry. Product standardization guidelines can be applied at national (TSE) or international (ISO, CE) level.

Products can be standardized or customized to a targeted consumer base. Standardized goods and services promote ease of use for the consumer and attract consumers on the basis of consistent quality. Product standardization is based on the use of the same basis in markets. It is a must for certain types of technology [1] and building materials. The characteristics of a product are kept as uniform as possible.

Product standardization reduces the variety of products available that serve a similar purpose. There are general standards that goods must meet. When it comes to industry-wide





standardization, consumers can choose from a range of goods and services, all of which are different, but offer the same overall benefits and are of the same overall quality. The uniformity and consistency of products are cost-effective and improve production efficiency.





3. Arranging production means

3.1. UC1 - IDEPA's Use case (Portugal)

3.1.1. Description

In the IDEPAs use case, there are four industrial legacy looms retrofitted with the latest digital sensors, edge processing technologies, and protocols. The company is now producing a great amount of bottom-up data, most of it acquired by Sistrade ERP and it will be providing the data as a testbed base for the MUWO technologies, although machine data is not collected. For better quality of products and to reduce machine downtimes, it is only logical to collect this data, analyze it and predict failures in quality and machines, so rescheduling can be made to diminish the cost and time lost.

IDEPA has two independent production processes:

- Manufacture by Jacquard-type looms
- Manufacture by Ratiere-type looms

Current IDEPA Production System > Jacquard

The flow of the Jacquard production process is summarized in the following diagram:

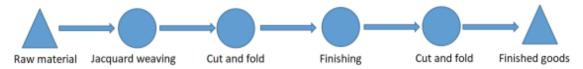


Figure 1. Jacquard production process

In this process, the yarns are acquired abroad and supply the production for long periods (typically 3 months). The reel is of the medium of heavy height and size. The orders and respective planning are not dynamically very high. In addition, the equipment is capable of providing a large number of variables about the production process.

Current IDEPA Production System > Ratière

The Ratière production process flow is summarized in the following diagram:

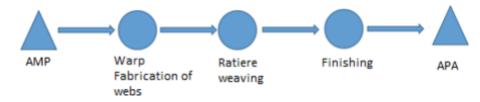


Figure 2. Ratière production process

In this process, the yarns are purchased abroad and supply the production for long periods (typically 3 months). The reel is of medium or heavy height and size.

- Three warping machines, two old-fashioned and one more recent
- The webs are of reduced size and weight. Each web can supply a loom for a relatively short period





- There are six distinct loom classes. Within each class, non-homogeneous functional group, the looms are distinguished by the maximum width that can work
- Each loom has several heads (six), and only one or all of them can be in operation at the same time
- The physical characteristics of the yarn greatly influence the permissible weaving speed, which can vary by a ratio of 1 to 10 times
- There are high dynamics in terms of orders, as well as marked seasonality

3.1.2. Communication

3.1.2.1. OPC UA Communication

Open Platform Connectivity (OPC) is a standard for interoperability and industrial communication, developed for securing data flows during their circulation between several parties in industrial automation. This standard exists in the form of a series of specifications defining the interface between servers and clients and is implemented by software developers, industrial parties, and end-users. It is now ubiquitous in modern industrial environments.

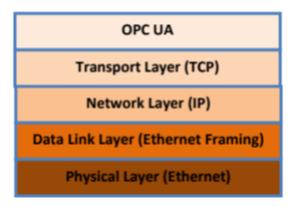


Figure 3. OPC UA Communications

This multi-layered approach meets the objectives of the original design specifications, namely the functional equivalence, platform independence, security, extensibility, and comprehensive information modeling. OPC-UA is a client-server architecture intended for the Industrial Internet of Things, allowing transparent communication from sensor-actuators to the developed system. OPC-UA was designed with security in mind and thus has security integration throughout the set of specifications. To become certified an application must support all basic security functionality. OPC-UA is designed to work in multiple environments and on multiple platforms, but as result, it is not tied to one platform and the security built into the platform. It is already the core communication standard for I4.0 compliant communications.

It is not difficult to predict that OPC-UA will be used to acquire the sensor data being sent by the loom machines. This data will be stored, presented to the user via the EHMS platform, and analysed by the ISEP algorithms.





3.1.2.2. MQTT Communication

MQTT is a lightweight protocol for sending simple data flows from sensors to applications and middleware. It includes three components: subscriber, publisher, and a broker. The publisher collects data and sends it to subscribers. The broker tests publishers and subscribers, checking their authorization and ensuring security. MQTT suits small, cheap, low memory, and low power devices.

MQTT will be mainly used to exchange data between the EHMS platform and the ISEP algorithms and vice versa, by creating direct and real-time channels between the two environments.

3.1.3. Method and Tools

In the IDEPAs use case, the predictive set is composed of a predictive maintenance algorithm, predictive quality algorithm, and scheduling algorithm. The next subsections describe these topics in detail, presenting the developments and intended results in each of them.

3.1.3.1. Predictive maintenance algorithm

For Predictive maintenance (PdM), four machine learning models are implemented, an Artificial Neural Network (ANN), Random Forest (RF), Gradient Boosting (GB), and a Support Vector Machine (SVM) model. It is up to the user to choose which model is used to make the predictions since each model has its own benefits and drawbacks.

The training process can be done in batches or mini-batches. In an initial phase, the batch approach is taken since it allows to have a model ready to be applied in the real world. Nevertheless, after the initial model is constructed the training process is carried out in real-time via data streaming or mini-batches, as represented in Figure 4.

For real-time training, the proposed solution starts by obtaining the newest machine data (i.e., air temperature, machines' process temperature, rotational speed, torque, tool wear, and machine failure information) from the machine data database employed in the facility. The database can describe either the culmination of all machine data from all the machines in the facility, or the data of a single machine. Then, before training starts, a data preprocessing phase begins in which: (1) aggregate all the data collected into a single data file, if the data is separated into different files (i.e., data aggregator); (2) normalize data scales and types, primarily between data from two different machines (i.e., data normalization); (3) fill missing values on the gathered data (i.e., data imputation); (4) remove and correct possible irrelevant and erroneous data (i.e., data filtering); (5) transform raw data into features that better represent the underlying problem (i.e., data engineering); and finally, (6) balance machine data failure and non-failure points (i.e., data balancing).





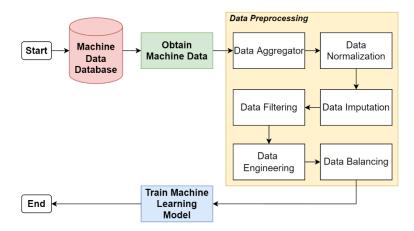


Figure 4. Flowchart of the proposed machine learning model training process

Then, the preprocessed data is used to train the machine learning models (i.e., ANN, RF, GB, or SVM), wherein the ANN neuron weights are adjusted due to the back-propagation feature, or, in the case of the RF, GB, and SVM models, they have to be reconstructed from the start using new and past data.

It is worth noting that the models are trained using an automatic hyperparameter optimizer, which focuses on finding the optimal hyperparameter values to obtain a high-performing model.

The methodology for real-time application of the implemented machine learning models in a machine can be divided into three phases:

- 1. Data acquisition-obtains the necessary machine data from the machine to be inspected;
- 2. Data preprocessing–applies data normalization, imputation, filtering, and engineering on the obtained machine data:
- 3. Machine failure status prediction—uses one of the models, designated by the user, to predict the machine failure status (0 for non-failure and 1 for failure).

3.1.3.2. Predictive quality algorithm

A Predictive Quality algorithm will be developed, and implemented in IDEPA, in order to assess possible associations between product quality and the machine features data.

The algorithm has, as its working ground, two distinct types of data as its input: time-series based data, containing information from the machine sensors (as described in section 3.1.4) and static/historical data retrieved from the productive environment, supplied by the production management systems installed in the IDEPA's shopfloor (in this case, SistradeERP).

Using the supplied data, together with the real results of finished product conformities and non-conformities records, it is intended to infer the causal relationships between the various input data and the quality of the final finished product.

In order to achieve this, algorithms based on Machine Learning and Artificial Intelligence supervised techniques will be applied, in order to also determine the most interesting and





meaningful features that allow a better inference, improving the final results. For model development and training, previous records of finished product conformities and non-conformities will be combined with production data history.

By applying the Predictive Quality approach, it is intended, as the final, goal to increase the end-product overall quality. This is an extremely sensitive and important subject in the demanding market that IDEPA is inserted on. Consequently, it is intended to tackle different areas, such as reducing the non-conformity product production (and therefore wasted raw materials), increase of production efficiency and effectiveness, and an improvement to the production sustainability. This system will be integrated with IDEPA's production management system in the context of improving interoperability and data integration, thus allowing a more efficient extraction of value in the context of production processes.

3.1.3.3. Scheduling algorithm

The proposed scheduler aims to achieve a cost-effective and preventive maintenance optimization by using a combination of artificial intelligence techniques, such as genetic algorithms, and deterministic-based optimizations. Accordingly, it addresses a joint optimization of product requests and maintenance activities, while considering a multi-objective optimization to minimize costs and machine occupation rates standard deviation (i.e., preventive maintenance). It considers available locally generated energy (e.g., photovoltaic generation), dynamic pricing, and multiple retailers to further reduce costs. Furthermore, it is capable of taking into account a wide variety of constraints, for example, machine priority, product deadlines, task setups, task order, task collision, time available for maintenance, etc.

It is worth noting that the scheduler not only allows energy cost optimization by scheduling tasks according to the availability of energy sources and the energy prices, but it also enables the consideration of demand response programs and maintenance activities, by shifting tasks away from the demand response event period and by making space for maintenance activities, respectively.

The proposed scheduler for production line optimization is divided into three main components: cell balancing, genetic algorithm, and deterministic optimizations, as shown in Figure 5. The first component, cell balancing, focuses on balancing the requests by the different cells available for manufacturing. Then, a genetic algorithm is used to obtain an optimized schedule, this component can be divided into four main phases: the creation of the initial population, the breeding of individuals (i.e., crossover), maintaining genetic diversity (i.e., mutation), and the selection of the individuals for the next generation. Finally, two deterministic optimizations are applied to the optimized schedule from the genetic algorithm to further reduce costs (cost optimization) and increase space for maintenance activities (shift optimization).



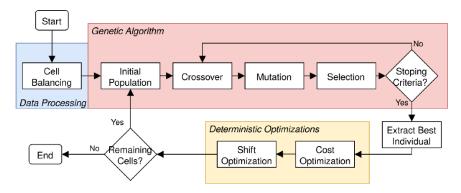


Figure 5. Flowchart of the proposed scheduler

The proposed algorithm also enables the use of flexibility in production lines for demand response participation, machine breakdowns (i.e., reactive maintenance), and the degradation of product quality, by rescheduling an already made schedule. It is worth noting that demand response events include sudden changes in energy prices and energy consumption restrictions, which, if they are respected, can award the user with monetary incentives.

3.1.4. Monitoring

Sistrade is currently acquiring the necessary data to elaborate an Al algorithm to infer the root causes of product quality non-conformities, a predictive maintenance algorithm, and a scheduling algorithm.

On a first level, structured data related to the production orders within the shopfloor is being extracted from the installed MES system and shared through a middleware database. The shared data contains information on human resources, operations, product type, maintenance orders, job orders, and productive resources.

Besides this, data related to the machine's sensorization, is being monitored and collected through the machine's industrial protocols (OPC UA). Tables Table 1 to Table 4 describe the list of sensors, by machine, that are being currently monitored.

Table 1. Sensors acquired for Loom 9

Equipment	Description Sensor name		
	Cutting Tool Temperature	Cutting_Tool_Temperature	
Loom 9	Inductive Sensor	Inductive	
	Kilowatt-hour Meter	Power_Meter	
		Green	
	Light Tower	Orange	
		Red	
	Power Cabinet Temperature	Cabinet_Temperature	





Table 2. Sensors acquired for Loom 10

Equipment	Description Sensor name	
	Ambient Temperature and	Humidity
	Humidity Sensor	Temperature
	Cutting Tool Temperature	Cutting_Tool_Temperature
Loom 10	Inductive Sensor	Inductive
	Kilowatt-hour Meter	Power_Meter
	Power Cabinet Temperature	Cabinet_Temperature

Table 3. Sensors acquired for Loom 11

Equipment	Description Sensor name	
	Cutting Tool Temperature	Cutting_Tool_Temperature
	Inductive Sensor	Inductive
	Kilowatt-hour Meter	Power_Meter
Loom 11	Light Tower Power Cabinet Temperature	Green
		Orange
		Red
		Cabinet_Temperature

Table 4. Sensors acquired for Loom 12

Equipment	Description Sensor name	
	Cutting Tool Temperature	Cutting_Tool_Temperature
	Inductive Sensor	Inductive
	Kilowatt-hour Meter	Power_Meter
Loom 12	Light Tower	Green
LOOM 12		Orange
		Red
	Power Cabinet Temperature	Cabinet_Temperature

3.1.5. KPI

The Key performance indicators collected by Sistrade and ISEP are of great importance since they will allow evaluating whether its expectations are being met, or whether it is necessary to make any readjustments.





Table 5. IDEPAs use case KPIs

Key Performance Indicator ID	Title	KPI Description	Improv.
KPI_UC1_SisTrade_pt_1	Quality control_1	Reduction in client complaints of the final product due to the application of quality prediction algorithms	50%
KPI_UC1_SisTrade_pt_2	Quality control_2	Reduction of non-conformities in products (scrap) in kg (before and after project)	40%
KPI_UC1_SisTrade_pt_3	Predictive maintenance_1	Failure prediction. This is the basis for the KPI PT_4 and PT_5. The introduction of predictive maintenance algorithms will allow to identify the flaws and fail modules of equipment	90%
KPI_UC1_SisTrade_pt_4	Predictive maintenance_2	Breakdown costs reduction. By employing predictive maintenance algorithms, it is intended to create an almost breakdown-free environment, allocating the costs to components that are presented as critical by the algorithm	70%
KPI_UC1_SisTrade_pt_5	Predictive maintenance_3	Downtime reductions. This indicator is associated with the reduction in breakdowns, maintaining the production line with minimal interruptions.	90%
KPI_UC1_SisTrade_pt_6	(Re)Scheduling_1	Reduction of delayed orders.	70%
KPI_UC1_SisTrade_pt_7 (Re)Scheduling_2		Improvement in algorithm execution time.	80%
KPI_UC1_ISEP_pt_1	Renewables_1	Local energy generation integration (avoiding sending it to the grid) [KWh]	15%
KPI_UC1_ISEP_pt_2	Flexibility_1	Amount of shifted load to other periods [KWh]	30%
KPI_UC1_ISEP_pt_3	Flexibility_2	Peak power consumption reduction [KW]	10%
KPI_UC1_ISEP_pt_4	Processing_1	Reduction in computation load by implementing heuristic approaches [GB]	30%
KPI_UC1_ISEP_pt_5	Forecastin_1	Improvement in load forecast accuracy [%]	5%
KPI_UC1_ISEP_pt_6	Bill_1	Energy bill reduction [%]	5%





3.1.6. Process

The IDEPAs use case has multiple components involved with a constant data flow. Most of the components to be developed, such as the EHMS, are highly data-dependent, making it critical to correctly establish the system architecture and type of data/format that will be exchanged.

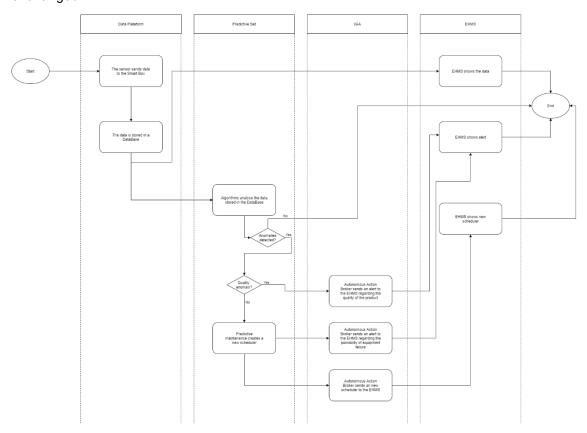


Figure 6 - EHMS process

The data acquired by the sensors, and provided by the SmartBox, will be stored in MongoDB. This data can be accessed by both the EHMS platform and the predictive algorithms, described in this document. These algorithms will analyze the data output anomalies (once they are detected), that are subsequently shown in the EHMS platform for manual analysis. Depending on the type of anomaly, and its severity, it can trigger different types of alarms.

3.2. UC2 – GTF Rotor cell operation (Turkey)

3.2.1. Description

In GTF Rotor Cell Operation use case, there are smart industrial resources to be planned in production cell. The production cell, which consists of components such as CNC, robot arm and conveyor described in the previous sections in the factory environment, has been designed to be naturally positioned in the middle of the factory. After the robot model was added to the factory environment, models of other production components began to be added. Conveyor belts, which will enable the transport of the parts to be processed in the system,





were also drawn through the Blender program and added to the Unity environment. Models for CNC machine and robots are designed with according to real life systems. In Production Cell scenario:

- A production cell that creates the digital twin environment; It consists of two robot arms, conveyor belts that carry the products to be sent and to come, a CNC machine, a transport robot and a human operator inspecting the incoming products.
- 2. The robot arms in the production cells that make up the digital twin environment (simulation environment for short) must meet the requirements specified in UC2_SR_1.
- 3. The production processes to be carried out in the simulation environment should be determined by the inputs to be sent from outside.
- 4. The operations performed at that moment in the simulation environment should be displayed on an information panel in the simulation environment.

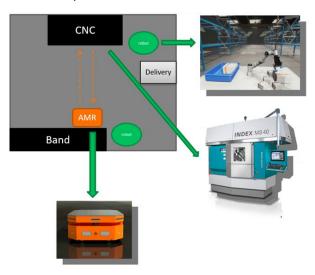


Figure 7. GTF rotor cell production means

3.2.2. Communication

3.2.2.1. ROS Communication

Unity is a physics engine that provides the environment to design digital twins in simulation environments for robots to perform increasingly complex tasks with full autonomy to sense, respond to the environment and execute actions within it. Unity, which has started to support in this field due to the increasing importance of simulation software in the robotics industry, which has been gradually increasing in recent years, aims to position itself as an ideal simulation environment tool due to its ease of use and the abundance of educational resources and materials.

ROS can perform abstraction from hardware expected from an operating system, low level device control, realize commonly used functionality, messaging between processes, and package management. The communication topology of ROS is based on the network structure from terminal to terminal. Thus, data losses caused by slowness in communication of computers connected with a heterogeneous network are prevented. For the table in which peer-to-peer





communication needs spouses and relationships with each other, the structure containing XML-RPC and named as master is used in ROS. ROS consists of four main concepts: node, message, subject and service. The node is where processes are performed. Communication between these nodes takes place via messages. The messages flow over the topics. Topics communicate in the publisher / subscriber structure. Therefore, the subjects provide asynchronous communication. Services are used instead of subjects for synchronous communication.

Communication between processes running in the ROS environment takes place in the terminal-to-terminal structure. Communication between processes can be performed in two types, asynchronous and synchronous. Instant messages between transactions can be displayed and external intervention can be made. In order to benefit from these advantages provided by ROS, it is necessary to have detailed information about the ROS architecture examined in two groups as the file and functional structure of ROS.

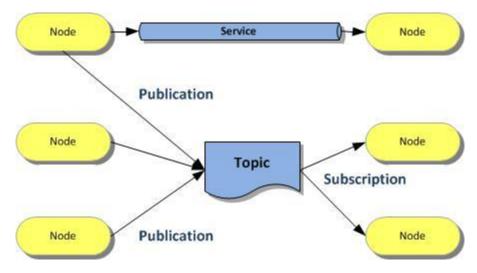


Figure 8. ROS Fundamental Structure

The factory environment digital twin work within the scope of MUWO continues. Unity supports the asset package that contains the models of many robots (Figure 9).

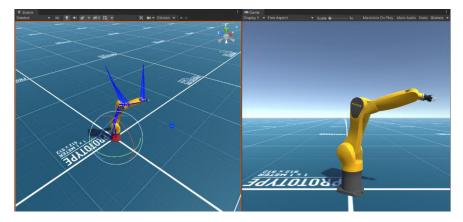


Figure 9. Sample robotic system generation

Thanks to the robotic integration packages included in Unity, it has made the transfer of robot packages designed in the ROS environment very simple to the simulation environment. Two software packages, ROS-TCP Connector and URDF Importer, developed by Unity, are used for





this integration. ROS-TCP Connector, one of these packages, provides a connection between ROS and Unity, enabling the robot running in ROS to be easily controlled and viewed on Unity, while URDF Importer enables a ROS robot to be modelled on Unity using a urdf file.

3.2.2.2. MTConnect

MTConnect is a universal factory floor communications protocol. It is designed specifically for the shopfloor environment. While there are numerous communication solutions available for the shop floor, MTConnect offers one very distinct difference. MTConnect is the first standard to define a "dictionary" for manufacturing data. This means that data from multiple machines will have a common definition —name, units, values, and context. With MTConnect, the data is defined only once at the MTConnect compliant interface to the device or machine tool. Once the data is defined based on the MTConnect standard protocol, it can then easily be used by all MTConnect compliant software applications. Thiseliminates the need to redefine the data within each application. This fundamental difference significantly reduces start up time, overall project costs, and long-term maintenance of software system interfaces. MTConnect compliant devices process information locally and then provide that data in a consistent format to any application - ERP, MES, Production Management Systems, Maintenance Systems, browsers, spreadsheets, and countless other applications. This approach leads to a plug-and-play atmosphere that mimics the PC computer arena.

MTConnect Most Basic Architecture

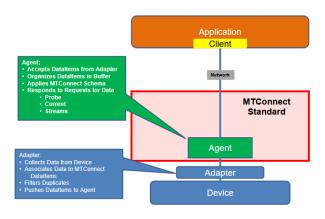


Figure 10. MTConnect Architecture

3.2.3. Method and Tools

3.2.3.1. Planning algorithms

3.2.3.1.1. Scheduling and Planning Algorithms

Making the data (preparation time, processing time, transportation time between machines, energy consumed, etc.) available in planning/scheduling algorithms with the help of a model based on the product/part collected as big data, estimation of parameters in similar operations for personalized products, Development of real-time scheduling process taking into account production dynamics.





Operation and machine data and other data are used through class structures. The main functions that create the initial solutions and other sub-functions that help the calculations are defined. As functions can be used jointly by algorithms, special functions of each algorithm are also defined.

The purpose of the component is to read the data through excel and interface and calculate which job will be done on which machine and in which order. Component; generates an initial solution, compatibility is calculated over this solution and choices are made. It runs the objective function and evaluates the solutions by crossing and mutating the selected genes. When the stopping criterion is reached, the solution with the best gene available becomes the final solution.

The component first imports the jobs, the operations of the job, machine information, suitable machines for the operations and the processing times of the operations on the machines from the excel format, by reading the population size, mutation rate, crossover probability and number of iterations from the interface. In addition, the initial solution generation method and the neighborhood structure generation technique are also selected through the interface. The component fills the read data into appropriate class structures and uses them from there. The initial solution is generated. Population is created over this solution. Compatibility is calculated over this solution and choices are made. It runs the objective function and evaluates the solutions by crossing and mutating the selected genes. When the stopping criterion is reached, the solution with the best gene available becomes the final solution.

3.2.3.1.2. Hybrid Simulated Annealing Algorithm

Firstly, the component reads the jobs, operations of the job, machine information, suitable machines for the operations and the processing times of the operations on the machines from the excel format. Reads the starting temperature, cooling coefficient, number of neighborhoods and iteration information from the interface to the system. In addition, the initial solution generation method and the neighborhood structure generation technique are also selected through the interface. The component fills the read data into machine and operation lists and uses them.

The machine list consists of machine objects derived from the machine class. Machine objects contain the name of the machine and the information of the operations that can be processed on that machine.

The operation list consists of operation objects derived from the operation class. Operation objects are objects that contain information such as the name of the operation, its group, sequence, the information of the machine to which the operation is assigned, the earliest start and completion times of the operation, the latest start and completion times, and lists of its predecessors and successors.

• Creation of Initial Solution

The initial solution is randomly generated, a random value is generated for each operation. By sorting these values, the operations are also sorted. Operations are assigned to machines randomly by following the steps below:





- Random Initial Solution: Operations are randomly assigned to alternative machines.
- <u>Shifting Bottleneck Heuristic:</u> An algorithm that aims to minimize production time by optimizing machine operation plans.
- <u>Shifting Bottleneck Heuristic Considering Parallel Machines</u>: Operations are assigned to balance the workload on parallel machines.

Thus, it becomes an input to metaheuristic algorithms. The initial solution is ready.

Creating_Neighborhood

The objective function is calculated by considering the initial solution. This value is assigned as a starting point for the current solution and the best solution. As better solutions are obtained in each iteration, the best solution will be updated and improved. The following operations are performed for the number of iterations specified at the beginning.

Neighborhoods are generated as much as the number of neighbors that need to be looked at from the solution at hand. 2 operations are selected randomly and their indexes are returned.

The locations of these operations are interchanged. All operations are then assigned to randomly selected alternative machines. In this way, a new neighborhood is created. Operation sequences and machine operation sequences are corrected. The objective function of this neighborhood is calculated.

- Random Selection: Neighborhood structure is obtained by swapping 2 randomly selected operations.
- <u>Swapping 2 operations on the same machine</u>: Swapped 2 operations on the same machine. Sometimes there is the problem of getting stuck with the local best.
- Replacing 2 operations on the same machine, 2 random operations in 25 iterations: Created to fix the problem of getting stuck in local bests in the previous solution.
- <u>Workload</u>: Alternative machines to which operations will be assigned are selected considering the workload. Machines with a low workload are assigned priority.





1	Α	В	С	D	Ε	F	G	Н	1
1	Orders	Operation Order	Operations	M1	M2	M3	M4	M5	M6
2	1	1	011	5		4			
3	1	2	012		1	5		3	
4	1	3	013			4			2
5	1	4	014	1	6				5
6	1	5	015			1			
7	1	6	016			6	3		6
8	2	1	021		6				
9	2	2	022			1			
10	2	3	O23	2					
11	2	4	024		6		6		
12	2	5	025	1	6				5
13	3	1	031		6				
14	3	2	032			4			2
15	3	3	O33	1	6				5
16	3	4	O34		6	4			6
17	3	5	O35	1				5	
18	4	1	041	1	6				5
19	4	2	042		6				
20	4	3	O43			1			
21	4	4	044		1	5		3	
22	4	5	045			4			2
23	5	1	051		1	5		3	
24	5	2	052	1	6				5
25	5	3	O53		6				
26	5	4	054	5		4			
27	5	5	O55		6		6		
28	5	6	O56		6	4			6

Figure 11. Machine priority for executing a work order

Evaluation of Neighborhood Solutions

If the value of the neighboring solution is better or equal to the current solution -It will be greater or less than the objective function, this will be expressed as better- it is accepted as the current solution and the current solution is updated. If this value is better than the best solution, the best solution is also updated.

If the value of the neighboring solution is worse than the current solution, the acceptance probability is calculated. It is accepted or rejected according to the probability of acceptance. The temperature value is used to calculate the acceptance probability.

$$P(Acceptance) = e^{-(\frac{\Delta}{T})}$$
, $\Delta = NEIGHBORING SOLUTION – CURRENT SOLUTION$

If the probability of acceptance is greater than the random number produced, the solution is accepted and the opportunity is given to bad solutions. Other iterations continue over the accepted neighborhood. If this neighborhood is rejected, the iteration continues by calculating new neighborhoods over the previously accepted neighborhood. After the determined number of neighborhoods are calculated, the temperature value is updated again at the rate of the cooling coefficient before starting a new iteration. When the





specified number of iterations are completed, the algorithm stops. The best solution is the result. This solution is printed on the screen as a table and as a Gantt chart.

3.2.3.1.3. Hybrid Genetic Algorithm

The component first reads the jobs, operations of the job, machine information, suitable machines for the operations and the processing times of the operations on the machines from the excel format, and reads the starting temperature, cooling coefficient, number of neighborhoods and iteration information from the interface to the system. In addition, the initial solution generation method and the neighborhood structure generation technique are also selected through the interface. The component fills the read data into machine and operation lists and uses them from there.

The machine list consists of machine objects derived from the machine class. Machine objects are objects that contain the name of the machine and the information of the operations that can be processed on that machine.

The operation list consists of operation objects derived from the operation class. Operation objects are objects that contain information such as the name of the operation, its group, sequence, the information of the machine to which the operation is assigned, the earliest start and completion times of the operation, the latest start and completion times, and lists of its predecessors and successors.

Initial Solution Creation

The initial solution is randomly generated. A random value is generated for each operation. By sorting these values, the operations are also sorted. Operations are assigned to machines randomly. All elements of the population are created in this way. Thus, it becomes an input to metaheuristic algorithms. The initial population is ready. After the population is formed, the objective functions of all the elements are calculated and the best solution is assigned to the current solution and the best solution as a starting point. As better solutions are obtained in each iteration, the best solution will be updated and improved.

The following operations are performed for the number of iterations specified at the beginning.

Selection process

The selection can be done following two different methods:

- Roulette: A population is created with children selected according to the probability of being selected, and iterations continue with this population.
- <u>Tournament</u>: Population is created by taking the best of the binary selections and iterations continue with this population. Children with good genes are protected.

In this case, the selection is done by roulette method. In this method, the cumulative probability is calculated. The ratio of the objective function value of each element in the population to the total objective function value becomes the probability of being selected. The cumulative probability of the first element is assumed to be 0 and the cumulative





probability of that element is calculated when we add the probability of choosing each element with the probability of choosing the previous element. A random number is derived for each element in the population. Elements of random numbers falling into cumulative probability intervals are selected. In this way, the population is rebuilt.

• Crossover Process

The crossover ratio is calculated by multiplying the population number by the crossover probability. Two paired children are selected randomly from the population at the rate of crossover. The crossover points of each 2 children to be crossed are selected. Pairs are crossed at the crossover points; that is, the genes of the first child up to the crossover point are put into the genes of the second child after the crossover point. The genes of the second child after the crossover point are put into the genes of the first child up to the crossover point.

The New Population consists of the offspring of the cross. If the number of populations cannot reach the required value due to the crossover ratio, the number of populations is kept constant by adding the children with the best value according to the objective function to the population.

After the crossover, the locations of the repetitive genes and the missing genes are determined in children. Excess genes are replaced by missing genes. Then, the operation order is corrected and the objective function values are calculated.

Mutation Process

Mutations are made in each iteration. There are two mutation methods:

- Mutate continuously: Mutation operation is used in each iteration.
- <u>Make a mutation in 25 iterations</u>: Mutation is made in certain iterations. This way good genes are not lost.

The mutation rate is calculated by multiplying the mutation rate by the population number and the number of genes. The genes to be mutated are determined. Operations in these genes are assigned to randomly selected alternative machines. After the mutation, the objective function is recalculated.

Evaluating Solutions

The current solution is updated with the best objective function value in the population. If current solution is better than the best solution, the best solution is also updated. The iteration continues. The algorithm stops when the specified number of iterations is reached. The best solution is the result. This solution is printed on the screen as a table and as a Gantt chart.

3.2.3.2. Maintenance data integrated into scheduling algorithms

Scheduling algorithms must also take into account when the equipment is unavailable due to maintenance Therefore, planning algorithms must integrate maintenance data. For this purpose, the following aspects are considered:





- Predictive Maintenance: Predictive maintenance should be done before the specified date.
 - Different planned and predictive maintenance can be done for that machine at the same time, same part maintenance is either scheduled maintenance or predictive maintenance. The operation is indivisible for predictive maintenance.
 - If the operation is split for planned maintenance, predictive maintenance can also be done there.
- Appropriate Spaces: If there is a suitable space in the machine so that no translation is
 made on the operation date, predictive maintenance is performed in that space. If there
 is no suitable space, predictive maintenance is performed before the operation and the
 operation is postponed.
- **Planned Maintenance:** If the operation can be divided into parts, the operation can be divided for planned maintenance, but if not, the operation is postponed.

Workstation	Start Date	End Date	Maintenance Type
M3	1.11.2020 04:00	1.11.2020 05:00	Planned Maintenance
M3	1.11.2020 06:00	1.11.2020 08:00	Predictive Maintenance
M4	1.11.2020 04:00	1.11.2020 07:00	Planned Maintenance
M4	1.11.2020 09:00	1.11.2020 12:20	Predictive Maintenance

Figure 12. Maintenance plan

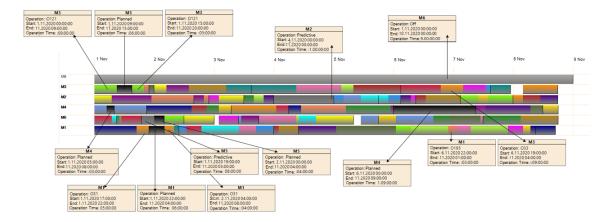


Figure 13. Testing related production data





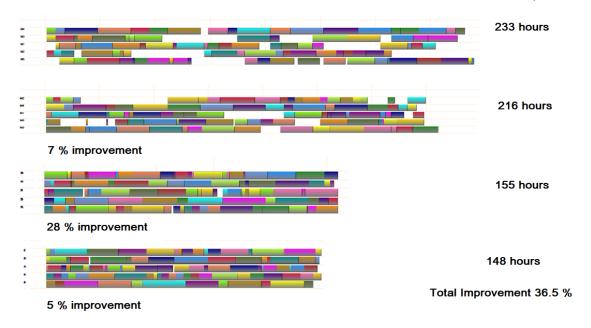


Figure 14. Optimization phases of the algorithms

3.2.4. Monitoring

First, the product tree of the products depending on the orders is created. There is information such as standard times, grams, pieces, etc. of products. Using it work order is created, which assigns the semi-finished products in these trees to the machine.

Work order starts production on the planned machines. While the machine has this job order, the status of the machine is monitored.

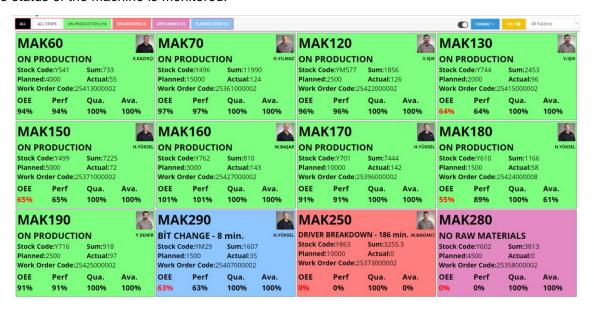


Figure 15. Monitoring of the machines' status

The work of the operators on the machine is followed. Intervention and follow-up of the operator, maintainer and quality worker to the machine is done more accurately.

Instant stops of the machine are followed. Posture types are followed by coloring. instant faults are easier to follow. Downtime is tracked.





The stock code used in the machine is followed. It can be seen how many products are produced in the machine in the current shift and how many products are produced in total. The planned quantity and the remaining quantity are followed. The amount of waste that occurs in production is monitored.

The operability, performance, OEE and quality ratios of the production are monitored instantly. The monitoring of these values is used to make improvements such as breakdown, maintenance and logistics.

It is also possible to monitor the machines in detail.

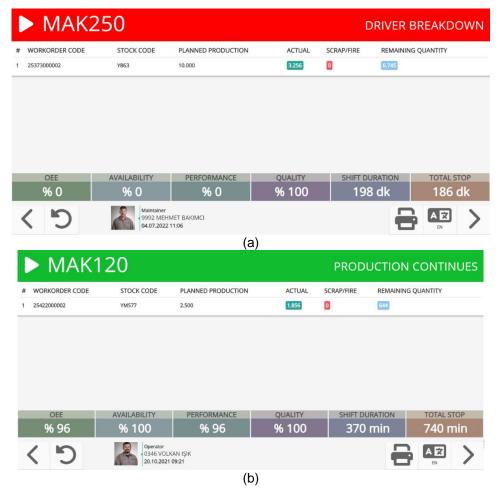


Figure 16. Detailed monitoring of the machines

3.2.5. KPI

In this section, the key performance indicators collected from factory production systems are given in Table 6. The table provides KPIs and descriptions of the KPIs. These KPIs provide valuable information on production means and planned components to be used in demonstrations.

Table 6. KPIs collected from factory production systems - UC2

No	KPI NAME	NOTES
1	TotalStopQuantity	Number of Postures





No	KPI NAME	NOTES
2	TotalStopTime	Downtime
3	OEERate	Ratio of Fully Productive Time to Planned Production Time
4	PerformanceRate	Ratio of Net Shift Time to Working Time
5	QualityRate	Ratio of Fully Productive Time to Net Working Time
6	AvailabilityRate	Ratio of Working Time to Planned Production Time
7	StandartTime	Elapsed Time - Planned Downtime - Ratio of Unplanned Downtime to Actual Production Number + Scrap
8	Total Product Qty	Actual Number of Production
9	Asset utilization	Asset usage
10	Capacity utilization	Capacity utilization
11	Mean time between failure (MTBF)	Mean time between failures
12	Mean time to repair (MTTR)	Average time between repairs
13	Percentage reduction in defect rates	Error rates
14	Number of production assignments completed in time ratio	Number of jobs completed on time
15	Stop Time to Work Time Ratio	Ratio of stops to working time
16	PPM	Parts per million
17	Cycle time	cycle time
18	First time through	It is the proportional value of the amount of product completed in a production process in accordance with quality standards for the first time. It is measured per shift or daily.
19	Increase in plant uptime	Operation time
20	Decrease in plant downtime	downtime
21	Overtime as a percentage of total hours	Percentage of overtime in total time
22	Planned work to total work ratio	Planned work rate in total work rate
23	Production Rate	The ratio of the time taken for production to the effective time in the period in which a process is actively operating.





No	KPI NAME	NOTES
24	Man power utilization	The ratio of the time that the maintenance personnel is on the job to the total time.
25	Manpower efficiency	Realization rate of planned working time
26	Preventive Maintenance Work Ratio	Ratio of preventive maintenance activities to total maintenance activity time
27	Emergency Maintenance Work Ratio	Ratio of emergency maintenance activities to total maintenance activity time.
28	Planned maintenance work ratio	The ratio of planned and predictive maintenance activities to total maintenance activity time.
29	Utilization about maintenance	Place of maintenance posture in total working time
30	Utilization in target time	Working time reached at target time
31	Harmful effect per year	Number of failures that cause environmental damage in a given time
32	Utilization about failure	The place of the stop related to the fault in the total run time
33	Utilization about planned maintenance	The place of the planned maintenance stance in the total working time
34	Harmful effect ratio	Rate of failures causing environmental damage
35	Possible Harmful effect ratio	Rate of failures with potential to cause environmental damage
36	Mean time between maintenance work orders	Number of maintenance work orders in total working time
37	Maintenance personnel ratio	Ratio of total number of maintenance personnel
38	Percentage maintenance personnel on shift	Ratio of maintenance personnel per shift
39	Schedule Compliance Ratio	Realization rate of scheduled jobs
40	Work-in-process (WIP)	Number of products in the workshop in a certain period
41	Machine preparation Time	Preparation times
42	Correctness of material	Raw material pending situations
43	Rework Ratio	Rework rate
44	Mean time between maintenance work orders causing downtime	Number of maintenance work orders causing downtime in total uptime

The KPIs given in Table 6 are can be used and configured according to production need. For the various type of productions and production variants, These KPIs can be altered or can be





redefined to meet production need. The interface for KPI selection in UC-2 is shown in Figure 17.



Figure 17. KPI selection Interface



Figure 18. KPI Edit Screen

3.2.6. Process

Reading the production data from the factory production plan, transferring the parts to be produced by making machine capacity planning to the virtual cell, finding the optimum production result according to different variations in the virtual cell and transferring it to the real production cell are the steps of the project.

In production area, cutting tools will transfer by automatic guided vehicle (AGV).

For Each CNC machines, the cutting tools will load into the machine by a robotic hand.

The purpose of the pre-production parameter is based on the product code of the products. it is necessary to determine how many weeks it can be produced in advance. When defining the production parameter from the front, identification will be made on the basis of the product





code. The strategic product priority parameter will be defined. Parameter identification will be made on the basis of the product code.

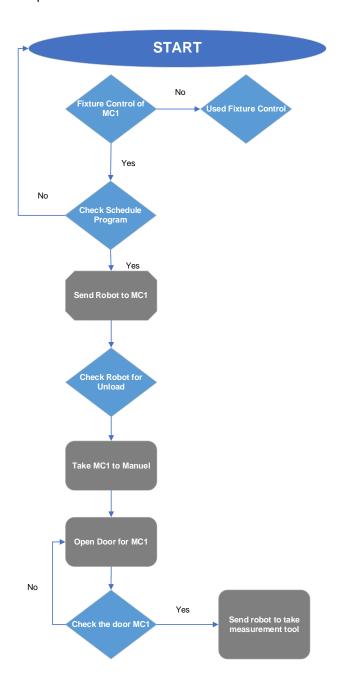


Figure 19. Robot operation process

3.3. UC3 - ALBERO's Use case (Spain)

3.3.1. Description

Construcciones Metálicas Albero is an SME from Madrid with more than 50 years of experience in the manufacture of metal structures and all their derivatives, linking production to the sector of elevator equipment, especially elevator components for passengers and loads. as well as pedestrian and sliding doors for forklifts and garages.





The processes carried out at Albero cover different metal transformation processes, from cutting metal parts of different materials and thicknesses, to the assembly of components for different industrial sectors, through welding, punching or bending of the material. They stand out among them:

- Laser cutting with different materials and thicknesses.
- Punching of iron, stainless maple, galvanized, aluminium, brass, and copper with punched machining with numerical control.
- Bending with tools adapted to the needs of the component.
- Welding: manual welding with specialized operators from MIT in welding, TIG and spot welding as well as with robotic MIG welding cells.
- Deburring, polishing, rounding off edges, removal of scale, satin, brushing and grinding of metal surfaces.
- Baked EPOXY powder paint.
- Assembly of components for distinctive industrial sectors.

The manufacturing process of the parts begins with the cutting and punching of the metal plates, as illustrated in Figure 20 processes that are carried out in parallel according to the specifications of the parts to be produced.

They then go on to the bending phase, which accounts for 80% of the average production time, becoming one of the main bottlenecks in the production of elevator components.

The parts then go into welding, where they are welded together to form larger components.

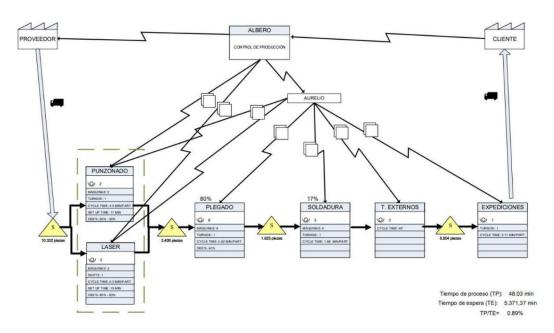


Figure 20. Workflow in ALBERO

Finally, the pieces go through deburring and painting, if necessary, before reaching the assembly area, where the assembly of elevator doors, freight elevators or garages is carried out.





Most of the machines require an operator who knows how they work and uses them to continue manufacturing, since they are not very automated. They have different types of machines: analogue and digital, so that, within the same process, one or the other must be used depending on the characteristics of the process.

All the processes start from phases of laser cutting and punching. Later they can go through cutting, sanding, folding, external/internal painting, internal coatings, assembly, etc., but the first phase is always the same, so it has a greater workload. Therefore, optimizing the work in these phases is of vital importance so that production does not deteriorate at this point and can continue smoothly.

Some of the machines currently used in Albero are old and repairing faults can be very expensive, not only because the production of the components but also it is difficult to find replaced parts. Therefore, the installation of sensors that can monitor specific variables is the vital importance for increasing the level of digitalization in a low level of communication.

Once these sensors are installed, the data collected can be used to analyze the performance of the operator throughout the day, average production times, rest times, etc., which allows identifying aspects in which the performance could be improve the production.

To face these challenges, Accuro proposes the development of an Integrated Manufacturing Platform that will offer intelligent planning of supplies and production thanks to artificial intelligence algorithms capable of integrating data on suppliers, delivery times, stock in warehouses, lists of orders, product sales, average production times for each component and in each phase, availability of machines and employees, etc., analyze them and propose a flexible production plan that allows increasing the efficiency of the processes.

Regarding sensitization, the bending line has been chosen to collect and analyze information related to process efficiency. A Q-learning algorithm will be developed for the identification of patterns and anomalies in the data coming from the machines and tracking beacons available in the factory, alerts will be generated when it is observed that the machine operation is not normal and, in case the machine is not available for repair, a notification will be sent so that the planning algorithm will take into account that the machine is out of service and reorganize the production. Similarly, the data will be used to perform an analysis of the performance and efficiency of the work performed.

3.3.2. Communication

The communication can be done with the interaction of IoT devices and a gateway that can support different protocols of communication such as MQTT, http, CoAP, etc. These protocols will be end-to-end encrypted to improve network security, thus preventing any attacker listening to the network traffic from reading the messages in clear and understandable text. One of the most commonly used protocols for communication between components, excluding IoT devices, is the http protocol, which by itself is not encrypted. However, TLS/SSL will be used to encrypt





communications between network devices for the same purpose as the encryption of the previous protocols.

A cloud computing service will be implemented using servers for storage and thus generate environments accessible from any smart device, focusing on remote hosting to make IT processes more efficient. In addition, it will facilitate Big Data analysis and data processing, which will be too complex for these factories starting from an analogue system.

3.3.2.1. Design of APIS

Two APIS are going to be developed, as a communication interface between applications to communicate data from the databases to the different systems. The information, or representation, will be delivered via HTTP in one of these formats: JSON (JavaScript Object Notation), HTML, XLT, Python, PHP or plain text. The description of the two APIS is:

- API to communicate the knowledge database information. This API will be of the REST type, this type is generated due to a series of limits in the architecture.
- API to enable communication and sending information between systems and add ERP data. This API will be of SOAP type, standard protocol to enable communication between different languages and platforms.

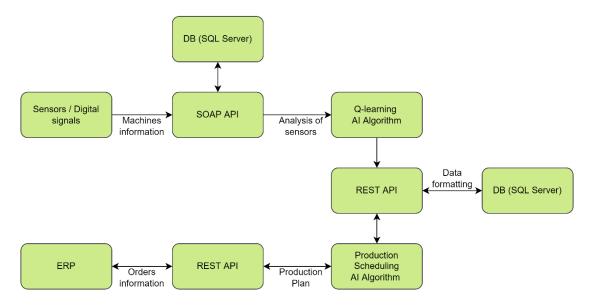


Figure 21. Software interfaces

SOAP requires more bandwidth for its usage. Since SOAP messages contain a lot of information inside of it, the amount of data transfer using SOAP is generally a lot. This particularity is due that SOAP can only work with XML format. As seen from SOAP messages, all data passed is in XML format. However, REST does not need much bandwidth when requests are sent to the server and, REST permits different data format such as Plain text, HTML, XML, JSON, etc. But the most preferred format for transferring data is JSON.

3.3.3. Method and Tools

Two algorithms of AI will be implemented:





3.3.3.1. Q-learning algorithm.

With this algorithm we will obtain as a result different anomalies that can occur in the factory once the information from the sensors is analyzed. In case of not detecting anomalies, it will send the results obtained after applying the Q-learning algorithm.

This artificial intelligence algorithm performs the following tasks:

- Data collection. It will collect data from the API that it is generated from the sensors.
- Storage in the DB through the API. The results obtained will be stored in the database once the execution of the Q-learning algorithm is finished.
- Detect anomalies and analyze the information from the sensors.

3.3.3.2. Planning algorithm.

To obtain as a result different metrics and warnings about the optimization of manufacturing processes, which allow learning a set of rules to decide what actions to take and under what circumstances to do it, in the field of planning industrial systems of changing batches (at the level of analysis of the machines).

This artificial intelligence algorithm performs the following tasks:

- Data collection. It will collect data from the ERP system relating work orders to available
 workers and materials. It will also collect data from the API that has the results obtained
 by the Q-learning algorithm.
- Storage in the DB through the API. The results obtained will be stored in the database once the assigned manufacturing process is finished when the machine is turned off.
- Balance of results. To finally place the order, this information will generate a balance of results of the workers involved in the process.

Moreover, security in the cloud is a shared responsibility between the cloud provider and the customer. The responsibilities ACCURO takes care of are on the client side, making sure that the information sent to the cloud is encrypted, does not contain malicious code, and will not be manipulated by unauthorized third parties.

This is going to be done with various security measures implemented on different devices that make up the network and this network itself, such as those outlined below. Protect the management console in the cloud, controlling and monitoring access to it using privileged access, such as:

- Protect virtual infrastructure as containers, data stores and other resources; establishing robust security systems and practices to prevent unauthorized access to automation scripts and cloud provisioning tools.
- Protect API ssh keys by avoiding embedding them in application source code.
- Protect consoles and management tools from unauthorized access.
- Protect process code by removing unneeded sensitive information from processes.
- Protect administration accounts for applications by controlling and monitoring access privileges to the administration console.





3.3.4. Monitoring

A system will be developed that will incorporate the business logic, which will be based on Al algorithms or software robots that will be achieved through algorithms to optimize or make processes more flexible, in this way artificial intelligence will be distributed throughout the company's processes.

The knowledge generated in this business logic process will feed back to the rest of the systems and will connect the platform with information received from third party applications.

Moreover, modular dashboards will be developed to visualize and monitories the information collected and that can be interpreted by managers to make decisions regarding personnel planning and order planning. They will be able to visualize different KPIs and graphs that will allow factory operators to make decisions in real time, as well as simulate actions for future decision making. In the same way, it will allow monitoring the state of the warehouses, stock of materials from suppliers.

This point is important, since the design of appropriate dashboards will help managers to understand what is happening in the factory in real time by visualizing the information.

3.3.5. KPI

In this section, the Key Performance Indicators calculated from the data collected from the production systems and sensors and estimated from the algorithms are presented in Table 7.

Table 7. Key Performance Indicators – UC3

ID	Description
KPI1	Efficiency of Interoperability (EI) can measure the difference of times between prediction of interoperability and time of production. This indicator should measure the time for processing a product using all the constrains in the simulation for producing a product. This variable can be expressed as prediction time of interoperability (PTI) and the variable time of production (TP). Therefore, the formula to calculate this KPI is:
	$EI = \frac{PTI}{TP} \cdot 100$
	The Improvement of learning phase is another important indicator because the algorithm is based on a reinforcement methodology. Thus, the system must help to optimize the process.
KPI2	A way to know this aspect is through the discount factor (DF) that is a variable that can vary between 0 and 1 to scale down the rewards (R) more and more after each step so that, the total sum remains bounded. The discounted sum of rewards can be obtained as:
	$DF = R_t + \gamma R_{t+1} + \gamma^2 R_{t+2} + \gamma^3 R_{t+3} + \cdots$
KPI3	Efficiency of scheduling planning (ESP).
	The scheduling planning will consider all the constrains when an order is produced in the ERP and this information is processed in the algorithm. Using this information,





ID	Description	
	a predicted time for scheduling is defined (PTS). This time must be compared with the real time of production (TP) using the following equation: $ESP = \frac{PTS}{TP} \cdot 100$	
	Measure the productivity of the workers (MPW).	
KPI4	The productivity of the workers can be measured using sensors as beacons. With these sensors, the system can measure elapsed times in areas of work (ETW) and in areas out of the area of work (ETNW) such as a cafeteria. The MPW can be defined using the normal time of working (NTW) that include official rests. The MPW can be obtained as:	
	MPW = (ETW - ETNW) - NTW	
	Comparison between automated and manual operations.	
KPI5	There are products that are manufacturing in an automated way when the code is sent to a CNC machine. The problem is that some products cannot pass the quality test and it needs to remanufacture again in a manual operation. This process can lead in increasing the time of production and it is necessary to evaluate this time for calculating the final time of production (TP) for each product: $TP = TA + TM$	
	Where TA is the time in an automated way and TM is the time for a manual remanufacture.	
	Overall efficiency in terms of parts produced.	
KPI6	In order to guarantee that the delivery orders are completed in time, this KPI can compare the delivery time (DT) that is required by a client and the time obtained using for producing the product using all the algorithms of AI (DT with AI). This KPI can be expressed as:	
	$OF = \frac{\text{DT with AI}}{\text{DT}} \cdot 100$	

3.3.6. Process

Four processes will be described below.

The first process consists of sending data from the sensors such as a beacon sensor. This information is sending to the Gateway. The Gateway uses an API to communicate with the database and store the data in it. When the information is stored, the database sends a confirmation message to notify that it has received and stored the data correctly.

Figure 24 shows a sequence diagram representing the process of sending the data and store the data. This process can be used by any IoT sensor installed in a machine or used in an operator such as a beacon.





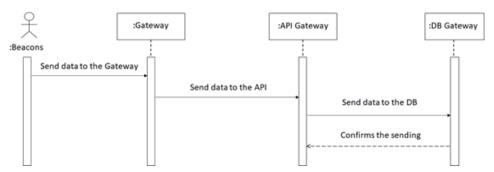


Figure 22. Data collection from sensors

The second process is when the Q-learning algorithm is executed when an anomaly is detected.

This algorithm first collects the information needed using the Gateway API which obtains the data from the Gateway database.

After receiving the data, the algorithm is executed, and the results are sent to the knowledge database using its API and obtaining a confirmation message from it (see Figure 23).

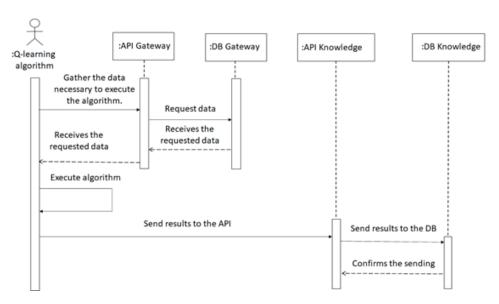


Figure 23 Process when an anomaly is detected

The third process is the scheduling algorithm that collects all the data necessary for its execution from the knowledge base using its API and fetches this data. After, the algorithm interchange data from the ERP that can be used in the scheduling planning. Finally, it saves the data in the knowledge database using its API and receives a confirmation message from it (see Figure 24).





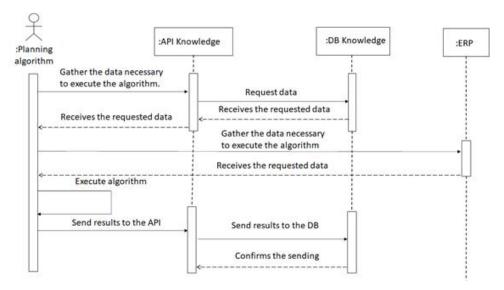


Figure 24 planning algorithm execution processes

Finally, the four process us the planning manager that sends the planning changes to a web client. When these changes are received, the web client send the data to the Knowledge database using the API designed to interface the knowledge database and it gets a confirmation message (see Figure 25).

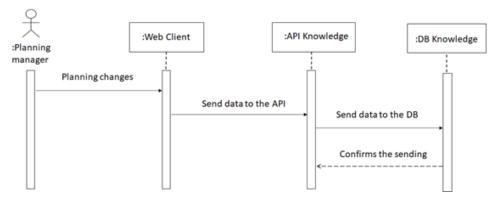


Figure 25 planning process for parameter changes





4. Conclusions

The different application scenarios of the use cases lead to a wide variety of equipment to be used in the project, thus the way in which they communicate is also different. Depending on the sensors and equipment to be used, communication standards and protocols such as OPC-UA, MQTT, ROS communication or MTConnect will be followed, even REST and SOAP APIs will be developed for communicating the different systems.

A common element in all three use cases is the scheduling algorithm that endows flexibility to the production lines, but following different types of algorithms and procedures. These algorithms will allow reconfiguring the production means to optimize production in terms of production times and usability of machines and equipment, but also in terms of energy consumption and costs. In general, these algorithms will be based on genetic algorithms.

In addition to the scheduling algorithms, algorithms will be developed for the predictive maintenance of equipment, the results of which will also be taken into account in the planning algorithms, algorithms for product quality prediction and algorithms for the analysis of data collected by sensors allowing the monitoring of both machines and personnel.

With regard to monitoring and KPIs, monitoring is based on the measurement and visualization of the data collected from the machinery and the sensors installed on them, and the defined indicators. A series of KPIs have been defined, mostly oriented towards the variables measured by the sensors and machines, but also KPIs derived for the aforementioned ones that allow the efficiency of equipment, workers and overall production to be measured, which also allows to measure the degree to which the objectives of the use case are met.

In should be noted that, due to the issues occurred with the Spanish use case (change of use case at the end of 2021), its definition is not as detailed as the others, a really important task for the correct execution of the use case. Therefore, the Spanish consortium will try to further elaborate on the communication protocols and standards between devices / machines / equipment, and the algorithms to be developed as the project progresses, considering the submission of a document to provide further information on the matters superficially explained in this deliverable in relation to UC3.





References

[1] G. Tassey, «Standardization in technology-based markets,» *Research Policy*, vol. 29, nº 4-5, pp. 587-602, 2000.

