SESAME

Smart European Space Access through Modern Exploitation of data science

D1.2 State of the Art update

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Table of Contents

List of Figures

List of Tables

List of Acronyms

Acronym	Explanation
ABC	Artificial Bee Colony
AI	Artificial Intelligence
AIBCS	Artificial Intelligence-Based Control System
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Networks
ATAS	Attitudes Towards Automation Scale
BBP	Batch Back Propagation
BDA	Big Data Analytics
BFF	Big 5 Factors
BITU	Behavioural Intention to Use
BN	Bayesian networks
CED	Cause and Effect Diagram
CGD	Conjugate Gradient Descent
CLSC	Closed-Loop Supply Chain
CSE	Self-Efficacy
DOE	Design Of Experiments
DT	Decision Tree
DWD	Discrete Wavelet Decomposition
DWT	Discrete Wavelet Transform
EFI	Empirical Force Index
EICAS	Engine Instrumentation Crew Alerting System
ES	Expert System
FC	Facilitating Conditions
FKNN	Fuzzy K-Nearest Neighbours
FMECA	Failure Modes and Effects Analysis and Criticality
FFT	Fast Fourier Transform
FT	Fault tree
FTA	Fault Tree Analysis
FSW	Friction Stir Welding
GA	Genetic Algorithm
GONNS	Genetically Optimized Neural Network System
GP	Genetic Programming
HAZ	Heat Affected Zone
HAZOP	Hazard and operability study
HMM	Hidden Markov Models

KNN	K-Nearest Neighbours
KPI	Key Performance Indicator
LBM	Laser Beam Welding
LM	Logistics Management
L-M	Levenberg-Marquardt
LMQ-N	Limited Memory Quasi-Newton
LOF	Local Outlier Factor
LSA	Latent Semantic Analysis
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MLD	Mixed Logic Dynamical
MMC	Metal Matrix Composite
MPC	Model Predictive Control
NDT	Non-Destructive Testing
OBP	Online Back Propagation
OM	Operations Management
PCA	Principal Component Analysis
PEOU	Perceived Ease of Use
PR	Product Recovery
PU	Perceived Usefulness
Q-N	Quasi-Newton
QP	Quick Propagation
RCA	Root Cause Analysis
RFT	Random Forest Tree
RL	Reverse Logistics
RMSE	Root Mean Square error
RSM	Response Surface Methodology
SADT	Structured Analysis and Design Technique
SCM	Supply Chain Management
SN	Subjective Norms
STFT	Short Time Fourier Transform
SVD	Singular Value Decomposition
SVM	Support Vector Machine
TAM	Technology Acceptance Model
TRA	Theory of Reasonable Action
TRI	Technology Readiness Index
UTAUT	Unified Theory of Acceptance and Use of Technology
UTS	Ultimate Tensile Strength
WAP	Windsor Aluminium Plant

1 Executive Summary

A specific requirement of Space industry is very high quality. Non-quality conformance can lead to launch delays and launch failures, which can cost tens or even billions of Euros and loss of human lives. Until now, Europe has mastered the production of high quality launchers via complex labour-intensive inspection processes and heavily maintenance programs. A more efficient industrial organization and governance have been the base for the development of new launchers: Ariane 6 and Vega-C. With these new launchers, the aim is to reduce the launch cost by 50% and nearly double the production rate. The use of advanced manufacturing techniques, such as friction stir welding (FSW), have been introduced in the production floor in order to guarantee high quality welds.

This deliverable presents a deep analysis of the state of the art of the key data science technologies involved to master the production and logistics management of the new Ariane 6 launcher and Kourou's space port, including an overview of past EU projects related to SPACE industry and FSW process.

Regarding the key data exploitation technologies involved in SESAME project:

- Predictive & Proactive Maintenance: machinery maintenance in industry has evolved from Breakdown maintenance to Time Based Preventive maintenance and today's Predictive and Proactive maintenance philosophies are the most popular being more interesting due to its diagnosis and prognosis capabilities. An overview of the requirements, algorithms and benefits are described.
- Resource Management optimization: Supply chain and the optimization of resource usage is a key aspect for improving the performances of launch vehicle centres operations. A review of the most interesting works in this context is performed and the most promising approaches for the SESAME purposes are discussed in detail. In particular, much attention has been devoted to Model Predictive Control, Data Driven Expert Systems, and Digital Twin approaches.
- Predictive Quality: the creation of data-driven models based upon computational intelligence and machine learning algorithms is key for predicting the quality of the manufactured components. A comprehensive bibliography research is presented considering the different stages of the data driven models: data fusion, supervised and unsupervised algorithms, focusing in quality prediction and mechanical properties prediction of the FSW process.

Finally, technology acceptance aspects of SESAME proposed solutions is also considered and discussed, focusing on interaction between humans and the key technologies of SESAME project.

2 Introduction

2.1 Project Overview & research objectives

A specific requirement of Space industry is very high quality, namely zero defects. This is the case for human missions, but also for valuable satellites and robotic exploration: launch delays can cost tens of mil-lions and launch failures billions Euros and loss of human lives. Europe mastered this capability for the production and operation of Ariane and Vega launchers, via complex labour-intensive inspection processes (people checking the work of other people and machines in subsequent steps) and heavy maintenance programs.

Today's state of the art is delivering good results for high volume / average quality industries, such as automotive and consumer electronics. By addressing launch industry's low volume / high quality case, SESAME will push the frontier of Machine Learning (ML) further, with benefits for other similar industries. As importantly, SESAME will bring a concrete contribution to European competitiveness in space by developing and data driven solutions facing the complexity of the space industry, addressing the following objectives:

1. Develop a complete data management framework to proactively manage risks in new automated production and operations.
2. Develop new Predictive Maintenance and Quality components to implement new automated launcher production and operations maintaining quality and reliability.
3. Implement new logistic processes (adaptive operations) that allows an optimal management of resources in an environment where resources are shared among different organisations and products.
4. Evaluate the benefit of these new capabilities in realistic operational scenarios developed based on two very challenging Use Cases.
5. Accompany the consequent transformation of human competencies, create new job profiles.
6. Evaluate other possible sectors for which the proposed predictive framework could be applied to create a large eco-system with tools for Predictive Maintenance and Quality.

2.2 Survey of past European projects

A specific requirement of Space industry is very high quality. Non-quality conformance can lead to launch delays and launch failures, which can cost tens or even billions of Euros and loss of human lives. Until now, Europe has mastered the production of high quality launchers via complex labour-intensive inspection processes and continuous adaptation of maintenance programs to fit production constraints. However, it is foreseen that tomorrow's space launch market will be characterized by increasing cost-competition from disruptive new players (SpaceX, Rocket Lab, etc.) which will require higher production rate. The need to put satellites into orbits within a short preferred time window is going to grow significantly in the coming decades.

Several large collaborative projects have been launched in Europe to address these issues. On one side, there are the initiatives that focused on the development of cost-effective launcher systems for small satellites. The SMILE project[1] developed a cost-effective European launcher system for small satellites (target price below 50.000 Euro/kg) and a Europe-based ground facility for these launcher systems. This project started in 1st January 2016 and ended in 31st December 2018. The ARION project[2], which is due to finish in the 31st January 2020, is a two year initiative that proposes revolutionary reusable rockets to be used as micro-launchers and suborbital launch vehicles. The key objectives of this project are to finalise the design of ARION suborbital vehicle, to develop a launch infrastructure, to qualify the reusable launch vehicle in space, and to commercialise this technology in Europe.

On the other side, Europe has taken major steps to guarantee Europe’s independent access to space for the high-end satellite market. A more efficient industrial organization and governance have been the base for the development of new launchers: Ariane 6 and Vega-C. With these new launchers, the aim is to reduce the launch cost by 50% and nearly double the production rate. The use of advanced manufacturing techniques, such as friction stir welding, have been introduced in the production floor in order to guarantee high quality welds. Several large collaborative projects have been launched in Europe to assess the benefits of FSW, improve its technology readiness and competitiveness, and to industrialise/apply it in commercial production. The main European initiatives related to the maturity improvement of the FSW technology are explained below and summarised in Table 1.

The overall objective of the EuroStir project is to accelerate the use of friction stir welding in Europe[3]. The project involved 38 partners from different countries and aimed to achieve industrial implementation by 50% of the participants within 5 years.

The collaborative project QualiStir, which was jointly funded by an industrial consortium and the European Commission, developed a system that was able to control the FSW process by monitoring key weld parameters[4]. The QualiStir system was easily interfaced with either robots or FSW machines and provides automated in-process monitoring and non-destructive testing (NDT) suitable for welding complex three dimensional geometries. This means to be able to detect all defects associated with FSW.

The objective of the WAFS project was to advance the state of the art of FSW to enable the widespread adoption of the technology to primary structures in airframes[5]. Project outputs and areas of innovation were: (1) FSW tool designs and process parameters; (2) new techniques for improvement of properties of joints made with FSW; (3) repair procedures FSW; (4) design data and rules in airframe applications and (5) modelling tools for FSW.

The JOIN-DMC project further developed the FSW technology to join dissimilar materials and composites, focusing on three material combinations. The materials selected for evaluation were industrially relevant combinations. The knowledge gained was applied to the topic of weld repair using FSW techniques[6].

The TANGO project[7] aimed to achieve major reductions in the operating costs of civil transport aircraft, by validating new design, manufacturing and test technologies which improve the airframe structural efficiency. Within the project, four such test structures were constructed, specifically, a composite wing box and metal to composite joint, a composite joint, a composite centre wing box, a composite fuselage section and an advanced metallic fuselage section.

The objective of the MAGJOIN project[8] is to develop a suitable joining technology for magnesium components and for aluminium-magnesium joints to overcome problems of fragile failure of the joints due to metallurgical and technological aspects. The project aims to explore FSW, as well as a new welding process based on laser melting of special powders as filler material to solve metallurgical problems.

The LOSTIR project[9] developed a low cost torque/force monitoring device for retro fitting to milling machines to facilitate their application to FSW. The end user partners in the project were “Sapa technology” (Sweden) and “BAE systems” (UK) both evaluated the LOSTIR device at their respective sites and were able to establish an increased confidence in quality of welded joints.

European researchers developed a multi-physics modelling software tool for simulating the FSW process in the DEEPWELD project[10]. The tool integrated a novel material flow solver at the smallest scale with industrially available finite element modules to model all phases of the FSW process. The tool was applied to actual aeronautical components and it was validated in experiments of welded panels. The results showed that developed software was able to accurately predict the residual stress and deformation of welded panels.

The development of FSW systems for the automotive and marine sectors was investigated in the SPOTSTIR[11] and Mobi-Weld[12] European funded projects.

The OASIS project[13], which is due to finish in 2020, will establish and demonstrate the cost-effectiveness of manufacturing aluminium aircraft structures using the latest developments in Laser Beam Welding (LBW) and FSW. With developments in LBW and FSW, it is now possible to fabricate “rivetless” aluminium aerostructures using welding processes. These new processes produce a lighter weight, distributed load path with the potential for enhanced strength and structural stiffness, ‘no holes’ and a smoother (more aerodynamic) surface. In addition to being more structurally efficient, the new processes are cheaper and reduce inspection & maintenance requirements. The project is led by TWI, who are leaders in both LBW and FSW techniques. The OASIS researchers will design, demonstrate and evaluate the suitability of a range of process variants in creating optimised aluminium aircraft structures, including appropriateness for emerging alloys (e.g. 3rd generation Al-Li, 2nd gen Scalmalloy).

Acronym	Title	Project ID.	Start date	End Date	Value (€)
EuroStir[3]	European Industrialisation of Friction Stir Welding	2430	01/12/00	01/12/05	8.5M
QualiStir[4]	Development of Novel Non Destructive Testing Techniques and Integrated In-line Process Monitoring for Robotic and Flexible Friction Stir Welding Systems	G4ST-CT-2001-50117	01/11/01	31/10/03	2M
WAFS[5]	Welding of airframes by friction stir	G4RD-CT-2000-00191	01/03/00	28/02/03	5M
JOIN-DMC[6]	Joining dissimilar materials and composites by friction stir welding	G5RD-CT-1999-00090	01/01/99	30/07/03	2M
TANGO[7]	Technology application for the near term business goals of the aerospace industry	G4RD-CT-2000-00241	01/04/00	31/12/05	85M
MAGJOIN[8]	New joining techniques for light magnesium components	G5RD-CT-1999-00134	01/01/00	31/03/03	3M
LOSTIR[9]	Development of a low cost processing unit for friction stir welding	508587	01/11/04	31/10/06	1M
DEEPWELD	Detailed Multi-Physics Modelling of Friction Stir Welding	75787	04/05	04/08	2.7M
SPOTSTIR[11]	The development of a hand held friction stir spot welding gun for automotive vehicle body repair	33084	15/02/07	14/02/09	1M
Mobi-Weld[12]	Low force mobile friction stir welding system for on-site marine fabrication	315238	01/01/13	31/12/2015	1.5M
OASIS[13]	Optimisation of Friction Stir Welding (FSW) and Laser Beam Welding (LBW) for assembly of structural aircraft parts	785557	01/02/18	31/07/2020	1.4M

Table 1. International collaborative projects on Friction Stir Welding

3 Resource Management optimization

In this section we review concepts and methods of interest especially for the SESAME activities to be developed in Task 3.2: “Intelligent and adaptive models to optimize resource management”. We provide a concise review of key concepts and we extract from the review performed a selection of the key and recent contributions from the technical literature which could be of interest for the above-mentioned SESAME activities.

3.1 Introduction

- **Resource management** has covered a fundamental role in the industrial sector since after World War II. Its objective can be summarized as the ability of efficiently producing, storing and/or shipping goods from producers to consumers. Such brief description hides a number of complex activities which have to be addressed. Resource management is addressed in the following areas:

- **Operations Management** (OM), dealing with production activities and in charge of the transformation processes from raw materials/components to the final components/products. Typical problems in this area consist in planning, implementing and controlling the assembly, manufacturing and processing phases;

- **Logistics Management** (LM), dealing with storage and transportation activities and in charge of guaranteeing efficient and on-time shipping of goods. Typical problems in this area include the optimal placement of warehouses, storage strategies and, more in general, network design;

- **Supply Chain Management** (SCM), dealing with the products’ value chain in its entireness i.e. from the collection of raw materials, to the shipping and the distribution phases. SCM embeds OM and LM activities: SCM tackles resource management from a holistic perspective considering all the steps involved in the components’ lifecycle (Figure 1).

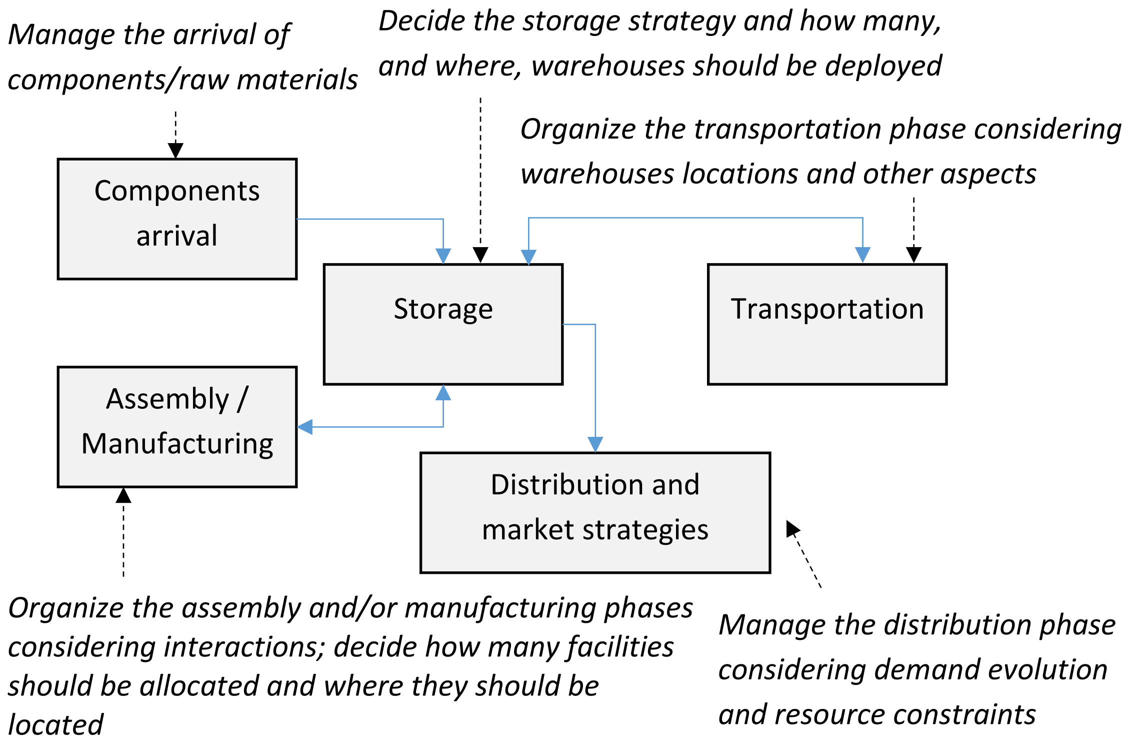

Figure 1. Problems addressed in Supply Chain Management (SCM)

3.2 Supply Chain Management

Supply Chain Management encompasses the following activities: *procurement*, i.e. the activities aimed at collecting raw materials and/or components to be transformed; *production*, i.e. the activities involved in the transformation of raw materials and/or components into the final goods; *distribution*, i.e. the activities related to the warehouses and inventory management and to the goods shipping; *sales*, i.e. the activities related to goods' pricing and selling. All these activities can be designed and implemented at different levels (Figure 2):

- at the *strategic* level it is defined the network over which the above-mentioned four activities are performed; typically, strategic decisions are taken considering medium- or long-time horizons;
- at the *tactical* level, the decisions are aimed at increasing the efficiency of the network defined accordingly to strategic decisions;
- at the *operational* level, the aim consists in efficiently scheduling the activities in order to deliver goods in time.

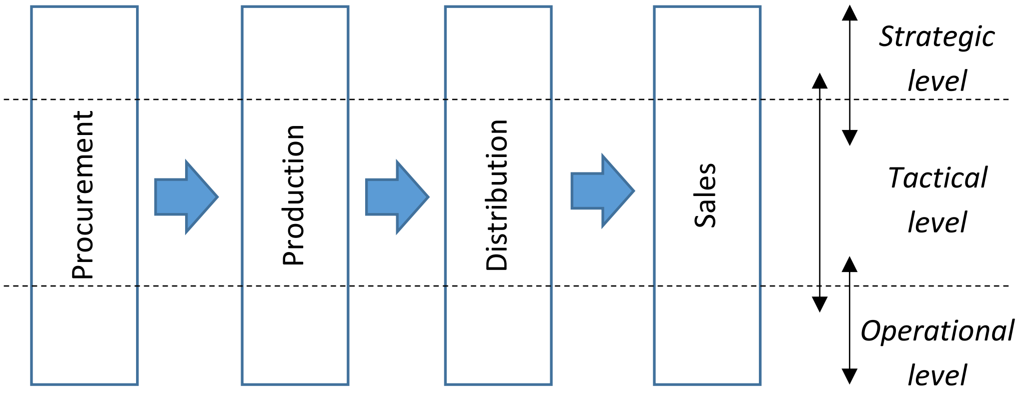

Figure 2. SCM activities

Literature can thus be reviewed accordingly to the level and/or the activities involved in the decision-making process. The focus will be mainly on the operational level.

An additional criterion for the analysis is represented by the technique adopted for decision-making: historically queueing theory, operations research and optimization theory have provided the foundations of SCM and are still widely adopted. Recently, many data driven approaches have been proposed, also empowered by the Big Data revolution and the concept of Industry 4.0. Such approaches currently represent one of the major trends in this research area and will be deeply investigated in the following.

Before proceeding such investigation, it is worth introducing the concept of reverse logistic and closed-loop supply chain, which has gained increased attention in the recent years, also in the space industry.

3.2.1 Reverse Logistics and Closed-loop Supply Chains

Recently, also due to environmental awareness, the concept of circular economy has gained attention and SCM models have been extended in order to take into account also flows of goods from consumers to producers[14]. In this context, two main aspects can be identified: Product Recovery (PR) and Reverse Logistics (RL). The former aspect represents the enabler for reversing the flow of goods and is peculiar of the specific product nature. The latter addresses the aspects related to storage and transportation. In other words, with RL it is meant the ability of efficiently carrying recovered products from consumers to producers (or in general to those players able to renew their value).

Closed-Loop Supply Chain (CLSC) refers to a more general scenario where reverse flows are envisaged along all the supply chain i.e. embeds the notion of RL (Figure 3). This concept can play a significant role in SESAME in order to increase the flexibility of the adaptive models to be designed. Kazemi et al.[15] presented an exhaustive review of this class of methodologies.

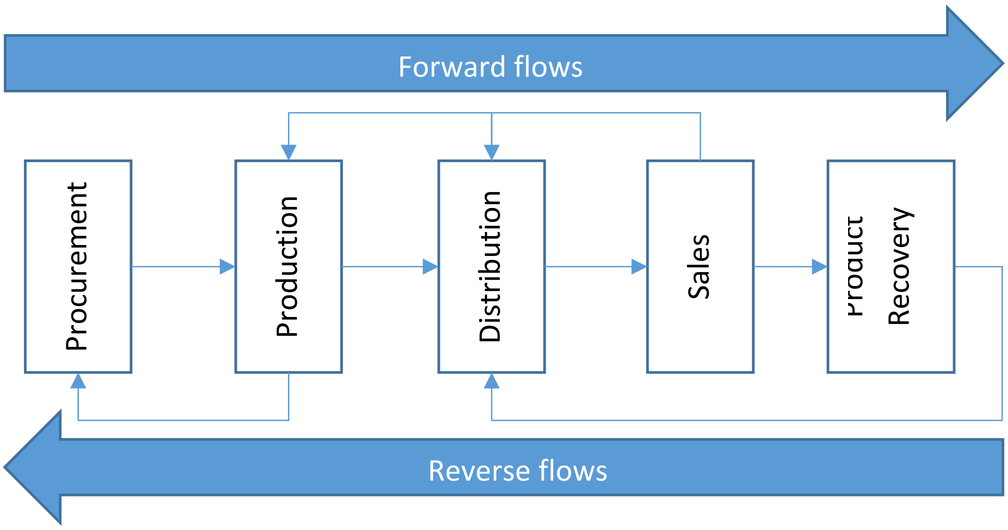

Figure 3. Closed Loop Supply Chain

CLSC models promises to provide useful inputs for launch centres operations and logistics management. As a matter of fact, costs reduction has been identified as the main barrier in the Satellite industry and re-usability of components has been considered a fundamental aspect. In this sense, embedding reverse flows for harmonizing post-launch operations with all the supply chain activities in launch centres models could provide significant benefits. Furthermore, the ability of embedding reverse flows, predictive maintenance and quality techniques will provide launch centres with high-quality efficient rescheduling abilities.

3.3 Introduction to Supply Chain Modelling and Management Tools

Techniques coming from various areas have been adopted to solve SCM problems and, in particular, queueing and optimization theories provided fundamental inputs to such field. Among the SCM areas which have benefitted from such inputs there are operations scheduling, warehouses placement, inventory and distribution strategies, network design.

Queueing theory allows to model the components arrival, processing and checkout phases. Typically, the starting point consists in modelling single queueing nodes for then building a queueing network modelling the interactions and mutual dependencies between different processes. A queueing node (Figure 4) can be characterized in terms of the components' arrival (λ) and checkout (μ) rates and of the node's processing capacity (k). Also, the arrival and checkout phases can be characterized in terms of probability distributions. Queueing networks are composed by two or more queueing nodes providing a snapshot on the process interdependencies which may involve bottlenecks. Typically, for queueing networks a relevant parameter to be considered is the total number of components currently in the processing phase (or, in other words, the network workload): such parameter allows to implement workload distribution strategies between nodes.

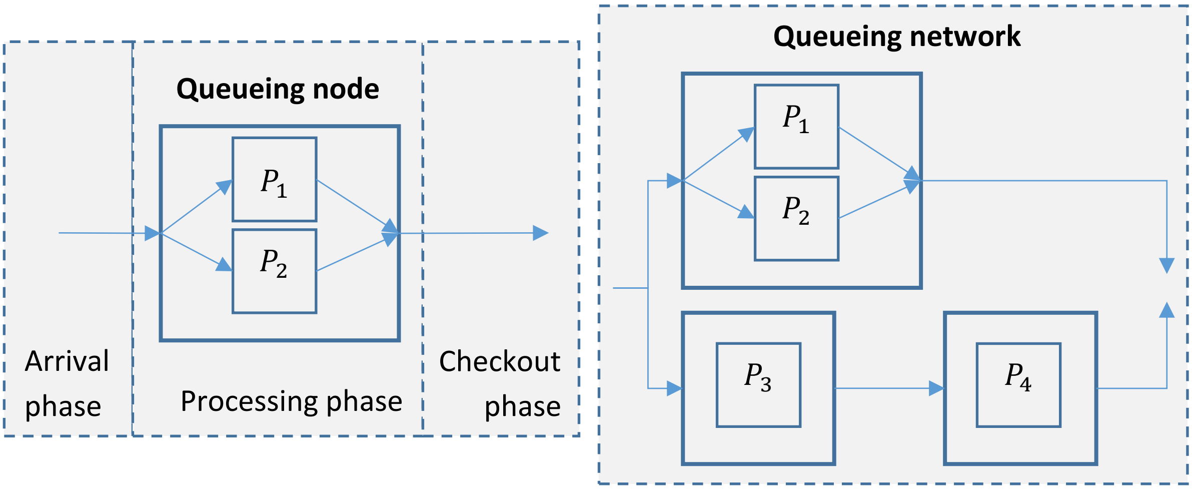

Figure 4. Example of Queueing nodes and networks

Optimization theory allows to define optimal strategies for improving quality, efficiency, cost and time savings at many levels of supply chains. Classic Operations Research optimization models, indeed, have been successfully used to solve many operations and logistics problem related, for example, to warehouses placement, inventory strategy and production levels definition. Optimization based models provide consistent and transparent means to determine optimal SCM strategies. In general terms, an optimization model can be described as:

$$\min_{x \in X} f(x) \quad s.t. \quad \begin{cases} g_i(x) \leq 0 \\ h_i(x) = 0 \end{cases} \tag{1}$$

where

- $f(\cdot)$ is the *objective function* and describes the criteria adopted to evaluate the solution
- $x \in X$ is the vector of *decision variables*, which belong to the *admissible set* X, modelling the decisions to determine (e.g. production levels, placement of a given warehouse in a given location, etc.)
- $g_i(\cdot)$ and $h(\cdot)$ are sets of *constraints* modelling the peculiar structure of the given SCM (e.g. resource limitations, network dynamics, …)

The structure and properties of the functions f, g and h have a direct impact on the optimization model properties which drive the choice of the adopted solution algorithm.

In the context of optimization-based models, (meta) **heuristics** have been successfully applied as well. Such techniques proved to be well suited to search for optimal solutions in multi-objective optimization problems.

Expert Systems (ESs) represent a powerful tool for decision support in the context of logistics and, more in general, supply chain management. With these systems, the decision-making problems can be solved directly considering significant amount of unstructured data.

Artificial Intelligence algorithms, such as machine learning or data mining algorithms, are used to process unstructured data in order to perform context-aware decisions. Feedback loops can be embedded in the decisional process in order to exploit data availability thus allowing to implement reactive decision strategies. ESs can be classified based on how the expert knowledge is imitated. Rule based ESs represent the expert knowledge with a set of rules following an *if-then* paradigm. Fuzzy ESs allows to model scenarios in which the expert knowledge has a certain degree of uncertainty or, better, in which the knowledge cannot be expressed by well-defined and non-ambiguous definitions. In neural networks ESs the knowledge is represented by the weights associated to each neuron. Hybrid ESs combines two or more of these (and other) approaches, depending on the application scenario, in order to exploit the benefits of each type of models.

Simulation-based approaches cover an important role in SCM and, more specifically, in operations management. Indeed, analytical models (such as queueing or optimization theory) strive to cope with large-scale scenarios for what concerns performances evaluation. In such context, the complexity of the scenario is reflected by high computational and modelling costs which may be impractical. On the other hand, simulation-based approaches constitute a powerful tool for evaluating performances of supply chains. As an example, Monte Carlo simulations proved to be very useful for organizations to evaluate risks of their supply chain thus allowing to increase their efficiency. In the same context, emulation-based approaches constitute a powerful tool for SCM. Emulation- and simulation-based approaches differ in the fact the former ones embed a part of the real systems i.e. of its real dynamics. In this context, Digital Twins have been broadly used.

Many criteria have been proposed to classify SCM models:

- Based on the level (strategic, tactical, operational) of the decision-making process (see Section 3.2)
- Based on the activities (procurement, production, distribution, sales) involved (see Section 3.2)
- Based on the nature of the adopted model (analytical, heuristic, statistical, simulation based, expert system, optimization based, hybrid)
- Based on the nature (centralized, decentralized) of the decision-making process

In the following, we first report selected survey papers available in the literature, dealing with supply chain management methods, and we then focus the analysis on those approaches which appear best candidates for the SESAME activities to be developed in Task 3.2: “Intelligent and adaptive models to optimize resource management”.

3.4 Existing Reviews Papers on Supply Chain Control

In the literature there are some technical papers reviewing control approaches to the problem of supply chain control. Among the most comprehensive survey papers we found, we cite the one written by Ivanov et al.,[16] which discusses frameworks and tools to model supply chains, from high level block diagram conceptualization of the supply chain to the low-level mathematical techniques to model the single phases of the supply chain. The survey has a focus on optimal control methods. Another interesting survey paper is Monostori et al.,[17] which is focused on decentralised, distributed and cooperative approaches to optimize logistics. The paper surveys different methods available in literature and present a case study on drinking water logistics optimization based on robust model predictive control. Such cooperative techniques could have interest in the scenario tackled in SESAME, which involve different interacting actors and supply chains. Another relevant contribution is the review presented by Sarimveis et al.,[18] which is focused on optimal control, dynamic programming techniques, model predictive control, also discussing stochastic and robust algorithms, as possible ways to consider uncertainty factors in the supply chains. The paper also presents a block diagram based high level modelling of the supply chain, identifying and modelling important key performance indicators. Finally, one last paper we mention is Wikelhaus et al.,[19] which has a more industrial and technological focus (rather than a methodological one, as the paper cited above), and surveys the vision, objectives and driving technologies (IoT, big data, cloud computing, etc.) behind the new logistics 4.0 paradigm.

3.5 Model Predictive Control (MPC)

Model Predictive Control (MPC) is an optimization-based control technique which gained significant attention in the last decades, starting from the field of chemical process control, and that is nowadays used in many industrial domains.

It has attracted so far great attention especially in the field of low-level process control, but it is now increasingly finding applications also in logistics and operations management.

We give in the following a quick introduction to the MPC concept, to better understand the literature survey presented in the following and also because MPC is a key candidate for the SESAME adaptive models to be developed in Task 3.2, possibly in combination with other techniques. For a more in-depth discussion, the reader is referred to the standard reference textbooks[20].

MPC is a particularly versatile and convenient control technique for several reason:

- It is an optimization-based technique, meaning that the control action is computed from the solution of a mathematical optimization problem. As such, the control designer specifies an objective function and a set of mathematical constraints. This provides great design flexibility in practice, since the objective function can be designed by the user to encode the aspects that he/she would like to be optimized (e.g. minimize costs, minimize time to complete a task, optimize quality parameters, etc.), while constraints are included to make sure that the control action complies with all the constraints present in the control problem (e.g. technical, economical, user-driven constraints, etc.);

- MPC can easily and naturally tackle multivariable control problems, meaning that it can include in the formulation multiple inputs and multiple output variables. This is not obvious for the other classical control techniques.

We consider here the MPC formulation in discrete time, with sampling interval T.

MPC is based on a radical paradigm shift. Most of the classical control techniques are based on the concept of feedback. This means that the output of the controlled process is compared to a reference, desired value, and the control action is computed based on the error between the current output and the desired one. The measure of the current output of the process is the feedback, which allows to compute the error, and then the control action.

In MPC instead, the current and the future best control action are computed by solving an optimization problem which takes into account the predicted evolution of the system in a time window of the future and tries to optimize it against the desired evolution of the system over the same time window (i.e. the reference). Thus, MPC is somehow based on the predicted error of the system over a future time window, while classical control techniques are based on the current value of the error. Therefore, it is called a “predictive” technique. It is further called “*model* predictive”, because in order to predicted evolution of the system in the time window in the future over which the optimization problem is defined, it needs to include a model of the system, i.e., an equation (in the typical case), able to mathematically describe the process under control (basically, able to tell how the outputs of the process change in function of the controlled inputs, so that the optimization process can automatically best select the control inputs so that the process outputs best matches the reference over the future time window).

Some terminology and notation. We usually denote with k the generic current time interval when the MPC problem is solved in order to compute the optimal control (we recall that we are in a discrete time setting, where time is sampled with period T). The MPC problem is defined from k to a time N time steps in the future. This time span is called the “prediction horizon” or “control horizon” in literature. The prediction horizon is therefore given by the interval $[k, k + N - 1]$, in intervals notation, or $[kT, (k + N - 1)T]$ in absolute time notation.

Figure below is a classical representation of the MPC overall control concept.

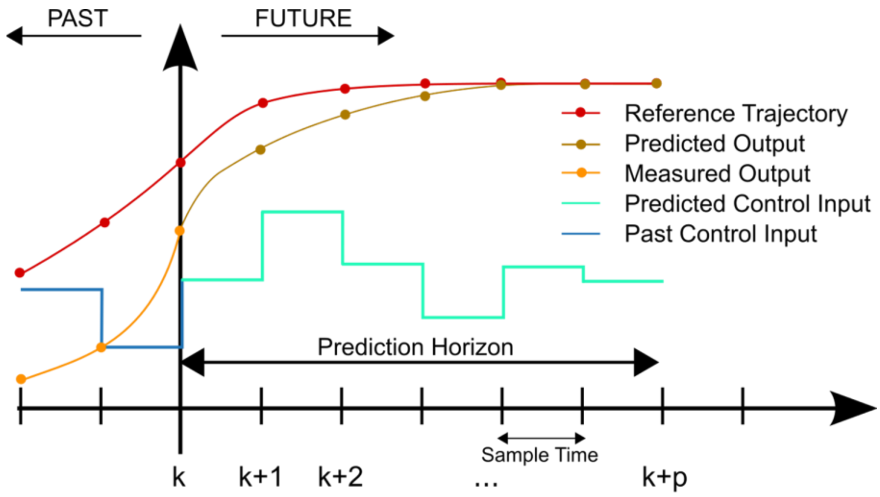

Figure 5. MPC overall concept (Source: [Wikimedia Commons](), [GNU Free Documentation License](), Version 1.2)

Summarizing, and looking at Figure 5, MPC computes the control action by solving an optimization problem defined over the prediction horizon $[k, k+N-1]$. The optimization problem is built based on the knowledge of:

1. A (mathematical) model of the system under control (needed to predict the evolution of the system);
2. The current (i.e., at time k) state of the system, obtained from measurements;
3. The knowledge of a reference trajectory to track (it enters the objective function).

MPC follows then a *receding horizon approach*, meaning that, after the control sequence over the entire control horizon is computed by solving the optimization problem, only the sample at time k is applied to the system and the whole process is reiterated at the next time $k+1$.

So, the sequence of steps of the basic MPC control are:

1. At the generic time k, measure the state of the system;
2. Build and solve the optimization problem over the control horizon;
3. Extract the first sample of the derived optimal control sequence and apply it to the system;
4. Wait for the next time $k+1$ and reiterate the procedure from step 1.

It is clear then from the above also that the optimization process must be compatible with the time step T. Time complexity is indeed one of the main challenges for MPC, but the progress in computing hardware and in solving methods make it applicable nowadays in wide practical areas.

In literature emerged two main branches of MPC:

1. *Classical MPC, also called stabilizing or tracking MPC*. In this case, the objective function contains tracking terms of the kind $(y - y^{ref})^2$, which force the process output y to follow the reference y^{ref}, which explains the nomenclature given;
2. *Economic MPC*, in which the objective function terms usually do not have a tracking meaning, but rather an economical meaning. This mean that the designer directly encodes into the objective function the optimization of some performance criteria for the system, rather than pushing the system to follow a predefined trajectory (computed in turn to optimize performance of the system), as in standard MPC.

A final remark. Each time the problem is solved, a feedback on the current state of the system is taken from the process. Similarly, every input signal into the optimization problem which might be time varying can be updated. This is for example applicable to forecasts (e.g., of demand or resources, needed inputs, physical variables), predictions (e.g., on the health status, on the predicted quality). This gives to the MPC a kind of proactive behaviour of great interest in practical applications.

We next discuss the review of relevant papers applying MPC in the context of operations optimization.

Esten et al.,[21] applies MPC to the optimization of the operations of a supply chain network (customers, retailers, distributors, warehouses, production facilities, and suppliers), modelled using the Mixed Logic Dynamical (MLD) methodology, which integrates dynamical models (e.g. to model actual systems/phenomena, like the piling up of inventory) and logic constraints (to capture inherent logic constraints, operational modes, etc.). Customers' demand is included as a disturbance and the maximization of the overall profit is sought via proposed centralised, decentralised and semi-decentralised models. This approach is potentially very interesting for the launch systems optimization, as launch systems can be seen indeed as integrated supply chains. Mixed Logic Dynamical modelling seem to us useful in SESAME since it allows to capture both the physical processes ongoing in the operations, as well as the many logical constraints present. A key reference discussing Mixed Logic Dynamical modelling is the one written by Bemporad et al.[22]. Wang et al.[23] apply MPC to the optimization of semiconductor manufacturing. MPC is here applied to ensure that the targets decided at strategic and tactic levels (e.g. inventory targets) are optimally tracked and ensured by the operations. An interesting case study analysed is the optimization of the operations of multi-product manufacturing, which is of interest for the launch systems operating multiple launch vectors. The paper shows how important KPIs can be modelled into the mathematical formulation, in order to optimize the operations. These include: the inventories, the work-in-progress, the throughput, etc.

Several other references investigate MPC in the context of operations management and inventory control. Among the recent ones, we mention Maestre et al.,[24] which explicitly introduces economic MPC, the variant of MPC discussed above, in which the MPC objective function directly includes economic performance indicators, so that the control will result in the optimization of the economic performance of the controlled system. The proposed mathematical formulation is a mixed one, in the sense that it includes both continuous variables (typically, stock levels) and discrete ones. For example, Boolean variables are introduced to model the on-off decisions suggested by the algorithm (e.g., to do or not a specific action). The objective function terms aim to: minimize the stock levels, minimize expenses and purchase orders. Constraints are added to consider the maximum storage capacity, minimum safety stock level and operational constraints (maximum number of constraints that can be placed in a day).

Although from a completely different application field, Lin et al.[25] present an interesting application of MPC to logistics because it explicitly integrates quality considerations into the problem formulation. The aim is to best decide the harvesting, storage and processing decisions in the potatoes industry in order to maximise the quality of the product and minimize waste. Farms and factories are modelled as a logistic network (mathematically, via a graph) and the decision variables correspond to the number of product units to move from one node to the other in the logistic network. Real time product quality measurements, as well as quality prediction models are integrated into the formulation, in order to make control quality aware. In addition, weather forecasts are included, since weather conditions impacts the deterioration process of the product.

Given the above and similar papers found in the literature, we can conceptualize the following tasks for the application of MPC in the case of SESAME, in the scope of adaptive model design (Task 3.2):

1. Derive a model of the systems and the operations under control:
    a. Set of equations capturing the evolution of relevant and controlled variables and KPIs, such as, the inventory levels, the waiting times, the quality of the products, the throughput, etc.
    b. Model of the logistic network (graph) constituted by the different locations, factories and systems composing the launch centre. When relevant, also the specific dynamics of the different systems need to be included;
    c. Mathematical constraints to model the physical and the operational limitations present, as well as the manufacturing logics and rules to be respected. For example: maximum stocking capacity of sites, minimum quality requirements, sequence of manufacturing and assembly of parts, etc.
2. Integrate the model with external SESAME modules, providing e.g. forecasts of relevant variables impacting the adaptive models of operations developed in point 1. For example, the predicted quality of the worked parts and the predictive health status of machinery, the predicted weather at launch site can have an impact on the decision of the operations;

3. Analyse the resulting mathematical model and decide for a solver to be used to solve the resulting mathematical problem. Evaluate problem complexity and its compatibility with the application domain.

3.6 Expert Systems and Data-driven methods

Expert Systems proved to be particularly suited for optimizing supply chains especially at the operational level (see Section 3.2). The advancements in Big Data Analytics (BDA), in this context, allows to build ESs with prediction and cognitive capabilities. In Chapters 4 and 5, BDA is discussed with respect to the maintenance and quality assurance problems. In this section it will be discussed the integration of BDA techniques in the supply chain with the aim of building proactive ESs. Such systems are of great interest in the context of Task 3.2 (adaptive model design) since they allow to solve the decision-making problems in an automatized way eventually taking in consideration inputs coming predictive maintenance and quality algorithms.

In the context of the SESAME project, these features will be of extreme interest given complex and heterogeneous nature of data and operations in a launch centre. The integration of BDA techniques and the adoption of ESs for SCM have already been successfully applied in many sectors. As an example, the impact of BDA in OM has been discussed in Choi et al.,[26] where the authors also describe how the adoption of soft sensors for collecting data increases the reliability and efficiency of industrial environments. More specifically, it discussed the integration of predictive analytics techniques in the context of SCM (i.e. not limited to maintenance and quality assurance). The disruptive effect, in terms of increased efficiency in the supply chain, of BDA is also discussed in Wang et al.[27] In this work the authors focus on the adoption of BDA techniques in the more general context of SCM with the aim of address the decision-making problem in a holistic way. This aspect has been dealt with in Lee et al.,[28] where the authors propose an architecture for a decision support system in an industrial environment. More specifically, the authors take in consideration hybrid systems and show how BDA techniques can be exploited to gather and process data, in a centralized and automatized way.

An exhaustive review of BDA techniques applied to SCM has been performed in Nguyena et al.[29]. An interesting aspect covered in this work is the relation between BDA and CLSC (see Section 3.2.1). The authors underline the fact that in this context the literature is not sufficiently developed. In addition, they point out that predictive analytics has received less attention with respect to prescriptive analytics despite its potential impact on SCM.

For the SESAME purposes, an interesting work is Kaur et al.,[30] where the authors discussed the effect of integrating Big Data in the supply chain modelling. It is showed the positive impact on the supply chain performances and more specifically that real-time fluctuations of the operating conditions can be well addressed. The authors also discuss the computational costs of such solution. Given the increased complexity, a heuristic is proposed.

The above-mentioned works (as well as the others reviewed) underline the potential impact of the adoption of data-driven expert systems for the optimization of launch centres operations. Big Data can be exploited to induce predictive capabilities (and more in general to create expert knowledge based on which activities can be planned in a cognitive way) in the decision-making process. Following these considerations, the work presented in Chapters 4 and 5 can be extended to the resource optimization problem. Particularly interesting is the integration of Big Data directly in the modelling phase.

3.7 Simulation based approaches

In simulations-based approaches, operations optimization is carried out by simulating operations under many different scenarios, each considering a different configuration of the decision variables in the admissible set, and/or a specific realization of the stochastic processing impacting the operations (e.g., demand levels, prices, etc.). This approach is often used when the operations scenario is very complex, involving many processes and variables, and uncertain factors. In these cases, the simulation approach often replaces or coexist with other exact, e.g. optimization-based methods.

Liu et al.[31] present a review of the main simulation-based approaches used in the optimization of manufacturing systems. The paper discusses both discrete and continue decision space settings, and surveys different optimization approaches available and tested in literature. In the discrete setting, the space of operations decision variables is discrete, and the methods thus proceed to the enumeration of the available decision options and to the selection of the ones optimizing a given performance criterion. More refined methods are discussed for the complex cases when exhaustive search is prohibitive. In case of continuous decision space, the paper presents a good survey of both local and global optimization methods, such as response surface methodology, gradient-based methods, stochastic approximations and others (local methods, i.e., working through incremental improvements of local solutions), and global methods, such as evolutionary algorithms, taboo search, simulated annealing, particle swarm optimization and other heuristics. Concerning these methods, Lee[32] presents an excellent review of several recent genetic optimization-based algorithms applied to operations management, across all the fields of the discipline, including notably for the interest of SESAME: (demand) forecasting, operations planning and control, scheduling and maintenance. Kefalas et al.[33] present a taboo search approach for the optimization for the scheduling of the operations. Similarly, Balaji et al.[34] introduce particle swarm optimization and simulated annealing to minimise the makespan in a manufacturing system.

A last, very interesting paper using a simulation-based approach is Patrap et al.,[35], which present a decision support system for improving the operations of a coal port terminal, which is a case study that presents similarities with the one tackled in SESAME, sharing similar classes of logistic constraints and optimization goals. The decision support tool developed by the authors is a port modelling tool with embedded various operational rules that capture the coal handling operations.

3.7.1 Digital Twin

A key aspect for the implementation of optimized and adaptive logistic and operations models is the derivation of a digital model, a representation of the processes to be optimised. A relevant concept in this sense is that of the "Digital Twin". The digital twin is a digital replica of the controlled system (including from single components to complete processes), which captures all the relevant aspects of the system and which is dynamically kept aligned with the evolution of the actual system, being fed with the measurements coming from the field. The digital twins established in a given supply chain or a given industrial process thus concur to create a virtual space representing to the operator an accurate and easily accessible replica of reality. This is useful in different ways: it increases the awareness of the real status of the system, and it provides the needed ground to test optimised procedures on the virtual system and then deploy them in the real one. As already mentioned, the digital twins are linked with the real system via a sensor and information layer/cloud which keeps the real and the virtual words aligned. Among the key references we found in this sector, we report Bao et al.,[36] which discuss modelling and operations of digital twins in manufacturing, also elaborating on a real case study from the aerospace manufacturing industry. The paper clearly demonstrates how the use of digital twins can e.g. reduce defects and reworking (by performing quality tests on digital twins during production, and triggering proactive condition-based corrective actions on the real parts being manufactures) and production times and inventory accumulation (by optimizing logistics and operations in the digital replica of the system first and then implementing them on the real system). It is therefore expected that the use of the digital twin concept can improve the system flexibility and contribute to the reduction of operational and capital costs, as well as to the increase of the efficiency in using resources. Another interesting and useful reference on the use of digital twin concept in production management is Zhuang et al.,[37] which discuss the use of digital twin technology in the context of the control of a product assembly shop-floor. The paper illustrates also the transition from the classical shop floor production management and control strategies (which are passive and reactive) to the real-time approach, the predictive one and, finally, the proactive one, in which the system can not only predict the future status (e.g. health status) of components (like in the predictive stage) but also uses all the available information to best control and adapt the operations of the process. This paper is very interesting in the context of the SESAME projects, since it treats a real case study given by the modelling and optimization of a satellite assembly shop-floor, and it shows how the concept of the digital twin expand the real process into a cyber-physical dimension, in which advanced control tools and methods can be deployed to improve quality, cost, reliability and other key performance indicators for the system.

4 Predictive & Proactive Maintenance

4.1 Introduction

Maintenance philosophies can be divided in four categories:

- **Corrective / Run to Failure maintenance**, basic philosophy of repairing or replacing damaged components just before or when the equipment comes to a complete stop. Maintenance people perpetually operates in an unplanned crisis management mode. This approach can work well if equipment shutdowns do not affect production and if labour and material costs do not matter.
- **Preventive / Time based maintenance**, activities are scheduled at predetermined time intervals, based on calendar days or runtime hours of machines. In this approach, maintenance can be performed too early or too late. Equipment would be taken out for overhaul at a certain number of running hours. It is possible that, without any evidence of functional failure, components are replaced when there is still some residual life left in them.
- **Predictive / Condition based maintenance** consists of scheduling maintenance activities only when a functional failure is predicted or detected. Mechanical and operational conditions are continuously or periodically monitored, and when unhealthy trends are detected, the troublesome parts in the machine are identified and scheduled for maintenance. The machine would then be shutdown at a time when it is most convenient, and the damaged components would be replaced.
- **Proactive / Prevention maintenance**, this philosophy lays primary emphasis on tracing all failures to their root cause. Each failure is analysed and proactive measures are taken to ensure that they are not repeated. It utilises all of the predictive / preventive maintenance techniques discussed above in conjunction with Root Cause Analysis (RCA). RCA detects and pinpoints the problems that cause defects. It ensures that appropriate installation and repair techniques are adopted and implemented. It may also highlight the need for redesign or modification of equipment to avoid recurrence of such problems.

Machinery maintenance in industry has evolved from Breakdown maintenance to Time Based Preventive maintenance. Presently, the Predictive and Proactive maintenance philosophies are the most popular. Due to the high maintenance costs when using Preventive maintenance, an approach to rather schedule the maintenance or overhaul of equipment based on the condition of the equipment was needed. This led to the evolution of Predictive maintenance and its underlying techniques. Proactive maintenance requires continuous monitoring of equipment to prognose and diagnose faults.

Diagnostics and prognostics are two key concepts, respectively, for Proactive and Predictive maintenance. As depicted in Figure 6**Erreur ! Source du renvoi introuvable.**, the diagnostics process is posterior to an early detection on the system while prognostics process is anterior.

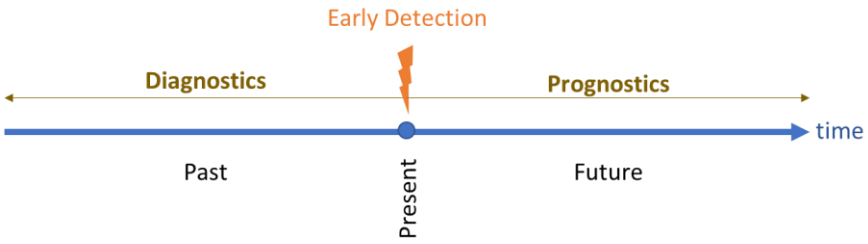

Figure 6. Diagnostics vs Prognostics

To achieve Predictive or Proactive maintenance goals, early detection is, the third key concepts, and also the first and necessary step. Indeed, early detection means that algorithms are able to see weak signals of system behaviour change. Only after this detection, a prognostic can be computed and not before because no signature of an incipient fault is present in the monitored, observed data. When no weak signal is detected, it means system health is good. Reviews of early detection, prognostics and diagnostics methods are presented in the next sections.

4.2 Early detection

Classical approach of system monitoring applying threshold over a given measurement is still widely used. As the alarm is triggered the equipment must be partially if not totally disabled. At this point some parts might be already deteriorated and corrective maintenance to be performed before the system is restarted.

The automatisation of process and raise of data acquisition and storage over the last decades have set the stage for smarter and more cost-efficient approach. Knowledge of performances, condition monitoring and multivariate analysis using a set of sensors and measurement allow to build models to characterize the equipment behaviour described as "the set of actions and operations made by the equipment sub-systems in conjunction with themselves and the system environment"[38]. The definition of the expected behaviour through statistical and mathematical models is then used for an early detection purpose to detect slight on changes on equipment and anticipate failure before it happens.

There exist several methods in literature to build early detection models. Most of them rely firstly on system knowledge to build an on-line operational condition computing using an appropriately chosen set of external sensor[39] and filter the signals regarding the said conditions. Conditioned signals are then to be used by algorithms to characterize a specific state of the system. Finally, statistical learning and artificial intelligence methods are used to build robust models considering the system evolutions. The methods used depends on the data in input and rely either on univariate or multivariate approach. Most used approaches in early detection methods are:

- **Univariate approaches**
  - Slight change detection to be performed using methods based on detection window (e.g. confidence interval, Cumulative SUM)[40]. The alert is not triggered over a single value detection but the tendency to be over or under a threshold closer from the "normal behaviour value". Although this kind of methods demands control over the signals characteristics as the system evolves, its simplicity and reliability are a big advantage for early detection.
  - Trend analysis is performed using the same principle as slight change detection applied on first derivative.
- **Multivariate approaches**
  - Values correlation: Exploiting values correlation and knowledge of the said correlation. For a given operational condition and a given set of explicative variables "x_1, x_2,… x_n", the algorithm estimates an output "y" for each instant "t" : $y(t) = f\{x_1(t), x_2(t), \dots, x_n(t)\}$. The model is learnt using a data set of supervised data defined as normal behaviour.
  - Principal Component Analysis: "reduces the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation of the variation present in the dataset "[41]. Fault detection is then accomplished by applying change detection methods to transformed collection data and comparing it to the characteristics recorded from normal behaviour.
  - Pattern recognition[42] and model-based methods[43]: there exist a large panel of methods based on neural network using supervised training output/input and analytical redundancy using the comparison of actual outputs of monitored system with outputs created using a mathematical model. Despite being very efficient, the main issues of this kind of approach is to keep control over the mathematical knowledge and the physical correlation with the system. The input data used for the system evolutions have to be supervised for a better control over the model's lifecycles.

4.3 Predictive maintenance

Prediction of the future behaviour of an equipment is affected by different types of uncertainty that come from different sources that are: input uncertainty from system, measurement uncertainty from sensors, operational environment uncertainty from usage conditions, and modelling uncertainty from degradation model. Four tasks are essential to integrate different sources of uncertainty during prognostics algorithm development[44]: Represent uncertainty, Quantify uncertainty, Propagate uncertainty and Manage uncertainty. An accurate prognostic enables safe operation of an equipment as long as it is healthy. Due to importance of such aspects, study on PHM has grown quickly in recent years, where several review papers on classifications of prognostics approaches have been published[45,46,47]. Prognostics approaches are generally classified as follows: physics based, data-driven and hybrid.

4.3.1 Physics based prognostics

The physics, also called model, based prognostics approaches use explicit mathematical representation for formalizing physical understanding of degradation. RUL estimates with such approaches are achieved on the basis of acquired knowledge of the process that affects normal operation of the equipment and mechanisms that cause failure. They are based on the principle that failure occurs from fundamental processes: electrical, chemical, mechanical, thermal, radiation[48]. As an example, common approaches of physics/model based approaches are spall progression models, crack-growth models or gas path models for turbine engines[49].To identify possible failure mechanisms, such approaches use knowledge like loading conditions, geometry, and material properties of a system[50].

Behaviour physics based model depends on parameters of the model, which are obtained from laboratory test or estimated real time using measured. In context to that, In literature, different works categorize physics based prognostics as physics of failure or system modelling approach[51,52]. Physics based prognostics is application specific. Such methods are based on assumptions that system behaviour can be described analytically and accurately. Physics based models are usually applied at component or material level[53]. However, physics based methods might not be a good choice for most industrial applications, as fault types can change from one component to another and are hard to identify without interrupting equipment operation[54].

4.3.2 Data-driven prognostics

Data-driven prognostics approaches are black box models that learn equipment behavior directly from condition monitoring data to fit changing observations. They are low cost approaches and have the advantage of better applicability. They require data to gain knowledge internally, instead of detailed external knowledge from experts. Several studies are performed to classify data-driven approaches. Ref. Commonly, data-driven approaches are classified in machine learning/artificial intelligence and statistical approaches[55].

4.3.2.1 Machine learning approaches

The branch of Artificial Intelligence that attempt to learn by examples and are capable to capture complex relationships among collected data that are hard to describe. They have the advantage of low implementation cost and can be deployed so quickly. Depending on the type of data, learning with such data-driven methods can be performed in different ways. (1) Supervised learning can be applied to labeled data, i.e., inputs and the desired output is known. (2) Unsupervised learning is applied to unlabeled data, (3) Semi-supervised learning that involves both labeled and unlabeled data Machine learning approaches can be categorized as follows:

- Connectionist methods[56,57]: Artificial neural networks (ANN), Neuro-Fuzzy systems.
- Bayesian methods[58,59,60,61]: Markov Models and variants, e.g., Hidden Markov Models (HMM), State estimation methods, e.g., Kalman Filter, particle filter & variants
- Instance Based Learning methods[62]: K-nearest neighbor algorithm, Case-based reasoning.
- Combination methods[63]: Connectionist & state estimation techniques, Connectionist & clustering methods, Ensemble to quantify uncertainty/robust models.

4.3.2.2 Statistical learning approaches

RUL is achieved by fitting the empirical model, a function, as close as possible to the collected data and extrapolating the fitted curve to failure criteria. Such models can be regression methods for trend extrapolation for e.g. linear, exponential and logarithmic functions. Like machine learning approaches they are simple to conduct. Also they require sufficient data to learn degradation behavior. Si et al.[64] presented a review of statistical methods From this systematic review paper, some commonly known prognostics approaches are: stochastic filtering (or state estimation) methods like Kalman filters, particle filters and variants, hidden Markov models and variants etc.

Data-driven approaches encounter a common criticism that they need more data as compared to physics based modeling. Obviously sufficient run-to-failure data are necessary to train data-driven models and to capture complex relations among data. Sufficient quantity means that data have been observed for all fault modes of interest[65]. The machine learning prognostics could be performed with an ANN to recursively predict the continuous state of degradation, until it reaches the defined failure threshold. Bayesian techniques can be applied to manage prognostics uncertainty. In contrast, instance based learning does not require failure threshold and can estimate RUL directly by matching similarity among saved examples and new test instances[66]. They are also known as experience based approaches[67]. A combination of different machine learning methods can be an appropriate choice to overcome the drawbacks of an individual method. Whatever approach is considered for prognostics modeling, it is necessary to integrate operating conditions and actual usage environment.

4.3.2.3 Hybrid approaches

A hybrid approach is a combination of physics based and data-driven prognostics approaches that attempts to leverage the strengths from both categories. According to literature, hybrid prognostics is performed in two ways[68]:

Series approach also known as system modeling that combines physics based model having prior knowledge about the process, and a data-driven model which serves as a state estimator of unmeasured process parameters that are hard to model by first principles[69]. In other words, for series hybrid, a physics based model is combined with online parameter estimation technique to update model parameters when new data are available. An et al.,[70] presented a Matlab based tutorial that combines physics based model for crack growth and particle filter that uses the observed data to identify model parameters.

Parallel approach can benefit from advantages of physics based model and data-driven model, such that the output of resulting hybrid model is more accurate. According to literature, with parallel modeling, the data-driven models are trained to predict the residuals not explained by the first principle model[71]. In PHM discipline different terminologies are being used for parallel modeling. Baraldi et al.[72] called it as parallel hybrid, for an application of choke valve. A hybrid model to fuse outputs from physics based and data-driven model was proposed by Hansen et al.[73]

4.4 Proactive maintenance

Proactive maintenance gathers predictive maintenance that aims at evaluate the future behaviour of a system and diagnostics which objective is the knowledge of its past state. Proactive maintenance relies in the need to understand the main causes of failure on which Management or Operations may have some control, so that they can avoid the chronic failure and returning to a specified plan of action.

Main causes of failures, or root causes, can be defined as the basics causes identifiable and on which management has control[74]. Causes can be classified according to their nature. Physical when Equipment failure is caused by physical reasons; Human when caused by human intervention or Latent when caused by organizational-level decisions. Failure analysis, or Root Cause Analysis, can be performed through variety of methodologies[75],[76] that could be qualitative: performed for brainstorming or quantitative : complex mathematical methods. The most common used in Reliability Engineering being:

- Failure Modes and Effects Analysis and Criticality (FMECA)[77]
- Fault Tree Analysis (FTA).
- Cause and Effect Diagram (CED)[78]
- Hazard and operability study HAZOP[79]
- Bayesian Inference.

Implementation of such methodology eliminates or minimizes those root causes that can generate recurrent failures, not focusing on the actual consequences of failure Depending on the type and depth of analysis to be performed, it is necessary to use properly methods that best suits the needs addressed.

Cause and Effect Analysis	High	✓	✓		✓					✓	
	Low			✓		✓	✓	✓	✓		✓
HAZOP	High	✓		✓	✓	✓	✓		✓		
	Low		✓					✓		✓	✓
Bayesian Networks	High	✓		✓		✓	✓	✓	✓		✓
	Low		✓		✓					✓	
FMEA	High	✓	✓		✓	✓		✓			
	Low			✓			✓		✓	✓	✓
Fault Tree Analysis	High	✓	✓	✓			✓	✓	✓		
	Low				✓	✓				✓	✓
RCA Methodology / Characteristics		Ability to define problems	Easy to use	Information requiremts	Experience dependence	Time and Resources consumption	Definition of all causal relationships	Provide paths to root causes	Explain how solutions prevent recurrence	Ability to include human errors	Ability to predict future events

Table 2. Comparison of Root Cause Analysis methodologies

Erreur ! Source du renvoi introuvable. Table 2 gives a comparison of the main methodologies according to some characteristics such as their ability to define problems or their ability to predict future events for instance.

Completing a full RCA analysis and obtaining optimal performances may require the use of a combination of methods especially when dealing with complex systems[80]. Such RCA combined approach requires a knowledge formalisation and modelling of system functional and dysfunctional behaviour.

Functional modelling can be supported Structured Analysis and Design Technique (SADT) methodologies which consists in defining the qualitative causal relationships between the functions performed by the overall components of the system and the quantitative interactions related to the morphologic, spatial or temporal properties, i.e. flows, of these components. A dysfunctional model can then be based on the functional analysis by identifying degraded modes and failure states of the components and deviations in the flows behaviour.

Degradation and deviations can be spread to the rest of the system through the various components interactions according to the causality principle: Potential cause of a degraded mode is either a deviation of an input flow or a deterioration of the supporting component; its potential effect being a deviation in the output flows of this same component.

A relationship definition[81] leads to a causality chain of flows within a process and allows to perform RCA in order to identify the physical causes that produce an event. For this aspect, there are used the following dependability methods:

- FMECA: to model failure modes of the functions, failure modes of the components, failure consequences (impact on the flow and other functions) and the criticality of the failure.

- HAZOP: to model flow deviation, cause of flow deviation and failure consequences (impact on the flow).

Moreover, dependability methods such as Fault tree (FT), or Bayesian networks (BN) to identify groups of elementary events or combination of events that lead to a failure event, as well as, the identification of the logical links between essential components are complementary to the dysfunctional modelling. Such combined approach based on the system analysis (SADT, FMECA, HAZOP analysis, FT) are support to an automatic generation of a causality chain to identify the main causes that produce performance deviations.

The addition of probabilistic methodology such Bayesian Networks[82] can be applied to use the graphical structure of the system causality network and use inference algorithms to compute probabilistic states of the components based on expert knowledge and/or experience return fed from historian of the use of the component or other similar components.

Bayesian Networks may ensure a complete maintenance diagnostic and decision making tool, enabling:

- Automatic root cause identification and isolation,
- Experience Feedback integration and update,
- Automatic causal graph update.

5 Predictive Quality (EUT, all)

Decision Support Systems for manufacturing optimization and process control monitoring have been widely investigated, offering customized and tailor made solutions for specific sectors. With the introduction of Industry 4.0 and the consequent newly available process data, new research works have been carried out developing novel approaches based on the process data exploitation for quality prediction by means of Artificial Intelligence solutions.

5.1 Existing methodologies for manufacturing quality prediction

Due to the large number of variables and the complexity of the process, it is very difficult to establish cause-effect correlations between the variables of the manufacturing process or to establish analytical expressions governing a highly non-linear system. For this purpose, the creation of data-driven models based upon computational intelligence and machine learning algorithms is key for predicting the desired outcomes, such as the quality of the manufactured component or the alloy mechanical properties, without knowing the physical behaviour of the system. A comprehensive bibliography research is presented below to summarize the state of the art methods used for production quality.

Several developments show the benefits of using AI and other predictive modelling techniques in, for example, metal casting problems: casting design[83], mould selection[84], casting defect diagnosis and prevention[85,86], design of mould filling and feeding systems, process monitoring, and prediction of casting characteristics[87].

5.1.1 Data fusion techniques for industrial applications

Data fusion is the process of combining data from different sources with the aim of maximizing the useful information content, for improved reliability or discriminant capability, whilst minimizing the quantity of data ultimately retained[88]. Information fusion strategies can improve the reliability and robustness of a decision system[89]. There are three different fusion levels according to the representation of data: data level, feature level, and decision level.

The multi-sensor fusion method has been widely used in the literature to improve the robustness of the monitoring system[90]. Denkena et al.[91] introduced the concept of sensor fusion, where an algorithm for optimal multi-sensor configuration was developed. Niu et al.[88] proposed a condition monitoring and prognostics system based on data fusion strategy to monitor the health degradation of a methane compressor. Aliustaoglu et al.[92] proposed a sensor fusion method for cutting tool health condition monitoring based on fuzzy logic. Liu et al.[93] proposed a machining condition recognition approach based on multi-sensor fusion and support vector machine, with the aim to monitor the cutting tool wear and the work-piece deformation.

5.1.2 Supervised algorithms

A number of approaches and methods have been under research, focusing in different Artificial Intelligence methods, such as Support Vector Machine (SVM), Random Forest Tree (RFT), Artificial Neural Networks, etc. Some of the main supervised algorithms used in manufacturing process monitoring are described below.

The **Support Vector Machine (SVM)**[94] algorithm focuses on finding a hyperplane that divides the n-dimensional space defined by input data into two regions, maximizing its distance or margin (see Figure 7). Depending on the chosen kernel, the method allows both linear and non-linear classification, thanks to the mapping of entries to a larger space, where the separation hyperplane can be found in a simpler way.

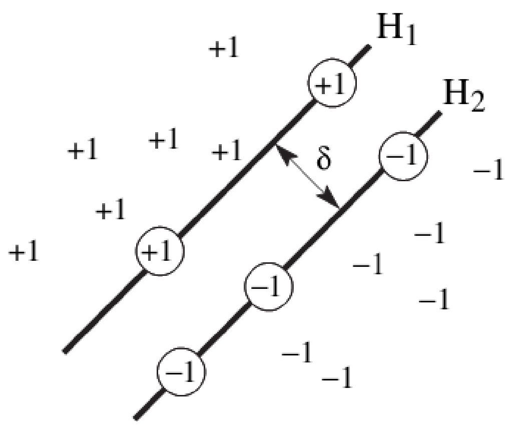

Figure 7. Rationale behind the Support Vector Machine

The **K-Nearest Neighbours (KNN)**[95] is based on the premise that the prediction or classification of an unknown instance can be accomplished through the relationship with known instances, weighted by a metric or distance. Typically, the Euclidean distance is used as a measure of similarity, but other distances can be implemented and used to better adjust the operation of the algorithm and the type of data. Figure 8 illustrates the rationale of the KNN algorithm: it finds the k neighbours closer to the new sample to determine its class.

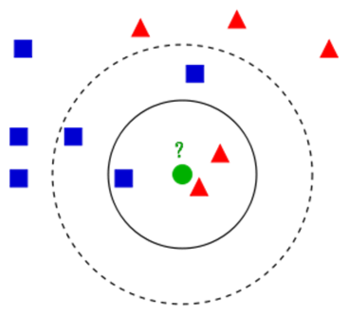

Figure 8. Rationale behind the K-Nearest Neighbours

The **Decision Tree (DT)**[96] is a popular tool in machine learning that that makes divisions in the data set ensuring the maximum number of data in the same category or tag within each division. In the example of Figure 9, during the training of the decision tree 4 divisions, also called “leaves”, have been created. Against new data from x1 and x2, the DT would be able to determine the class following the reasoning shown in Figure 10.

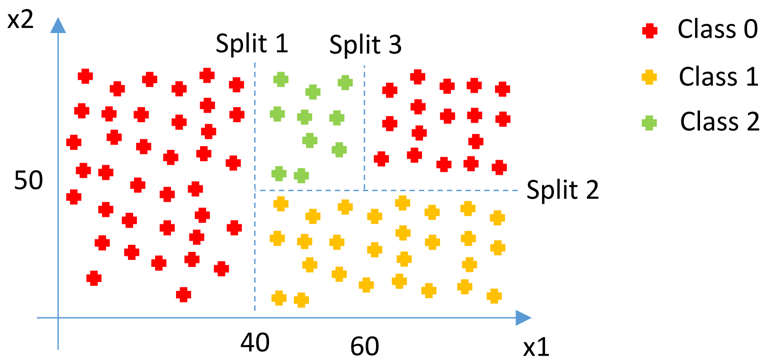

Figure 9. Divisions (leaves) created by the Decision Tree

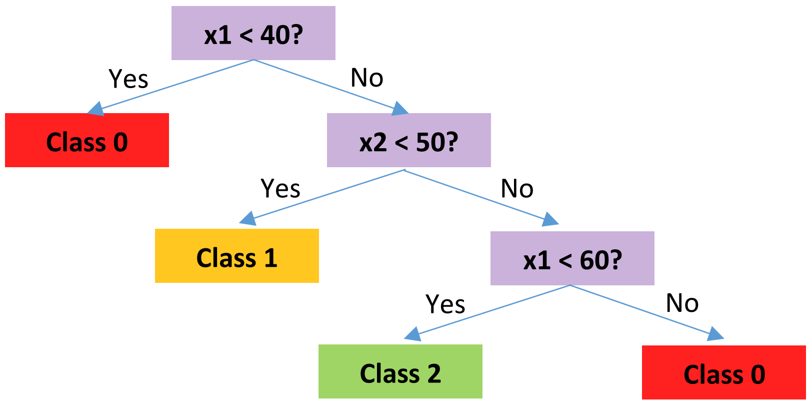

Figure 10. Decision Tree created for the example shown in Figure 9

The **Random Forest Tree (RFT)**[97] is an ensemble algorithm which is built on a multitude of decision trees during the training of the model (see Figure 11). The principle in which the "ensembles" are based is the following: a set of "bad" predictors can together become a good predictor. In the case of the Random Forest Tree, "bad predictors" are in fact decision trees, while the good predictor is the set of random trees. Each tree of the set makes a prediction and the most voted by the set of trees is the winning prediction. The RFT can also provide additional information, such as the identification of the most relevant variables in the process.

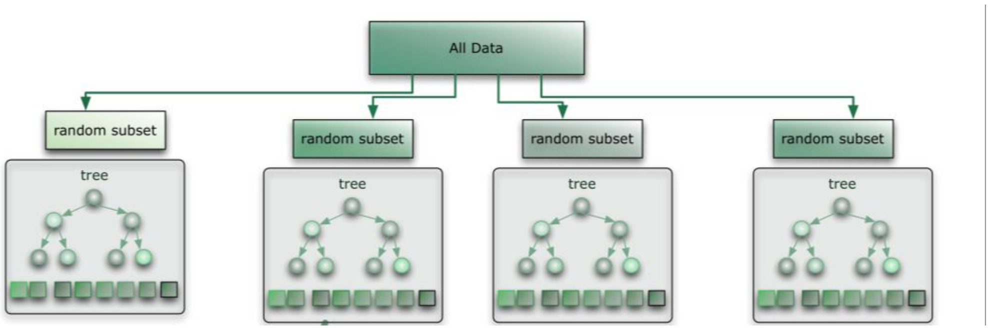

Figure 11. Rationale behind the Random Forest Tree

The **Artificial Neural Network (ANN)**[98] is one of the main tools used in machine learning, which intends to replicate the human brain learning process. Neural networks consist of input and output layers, as well as hidden layers that transform the inputs into something that the output layer can use. They are excellent tools for finding patterns which are far too complex or numerous for a human programmer to extract and teach the machine to recognize. During the training of the ANN, the backpropagation technique allows the ANN to adjust its parameters in order to improve the predictive performance of the model.

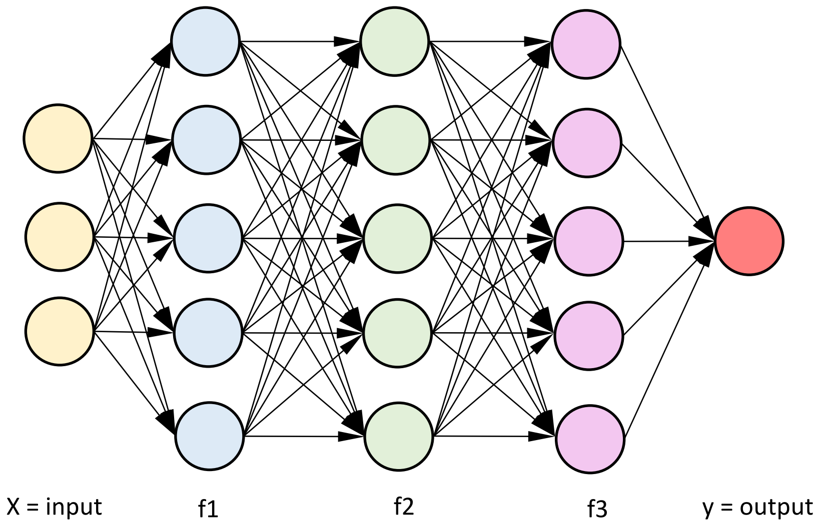

Figure 12. Artificial Neural Network example

The SVM algorithm was used to effectively monitor the machining process of thin-walled parts, where machine tool wear and work-piece deformation always coexist[99]. Diez-Olivan et al.[100] demonstrates the benefits of using a kernel-based SVM approach to monitor the health condition of a marine diesel engine over time.

Tadeusiewicz[101] described the applicability and the usefulness of **ANN** in foundry process. Mares et al.[102] proposed an Artificial Intelligence-Based Control System (AIBCS) based on

Case Based Reasoning for the analysis of metal casting properties in an integrated solution, with data acquisition, statistical control and properties prediction. The AIBCS was designed to support aluminium casting processes and it was successfully deployed and used at the Ford/Nemak Windsor Aluminium Plant (WAP) to analyse the casting properties. Carvajal et al.[103] successfully used **ANN** to recognise flaws in the radioscopic inspection of cast aluminium pieces. Di Lorenzo et al.[104] used **ANN** to prevent ductile fracture in cold forming operations, showing that neural networks represent a powerful tool to improve the production quality in industry. Świłło et al.[105] proposed a vision based approach using neural network techniques for surface defect inspection and categorization of machined aluminium die castings. The presented approach detects and classifies three groups of defects: blowholes, shrinkage porosity and shrinkage cavity.

Penya et al.[106] investigated the use of Bayesian networks for forecasting the presence of micro-shrinkages in ductile iron castings in two different foundries. A similar study was performed by Santos et al.[107], where the **KNN**, **Bayesian networks** and **ANN** were tested and benchmarked. The results show that the Bayesian networks trained with Tree Augmented Naïve seems to be the best option to foresee micro-shrinkages in the iron casting. Similar studies were performed[108,109] to predict the Ultimate Tensile Strength of the iron casting different machine learning classifiers. Most researchers[107-110] select the best classifier for each defect or data set. Nieves et al.[111] proposed to foresee the defects of the casting via a meta-classifier that combines different classifiers and hence does not need to select the best algorithm for each defect or available data. The results show that by combining methods it is possible to increase the accuracy of the prediction of microshrinkages. However, it was not possible to improve the behaviour of the combined classifier beyond the single classifier for the prediction of the ultimate tensile strength.

Few works have been done until now using AI to predict the quality of mechanization processes such as milling, lathe and grinding. The main works on mechanization prediction are developed on Chatter prediction, which are based on the generation of stability diagrams[112,113] being these analytical works. And few works have explored the possibility to add mobile solutions in order to monitor the milling process via external platforms[114] or using the sensors of the machines[115]. On roughness prediction, there are also few works on AI mainly using Fuzzy Models[116] or **ANN**[117] to predict lineal roughness parameters using the configuration of the system. Prediction of surface roughness in CNC end milling is achieved in[118] by installing a multi sensor system to record the sound and the electrical power on the grinding cycle and then using Machine Vision and **ANN**. Surface roughness of the mechanized surface has also been predicted using ANN[119]. Also, **ANN, SVR and Genetic Programming** (GP) have been implemented to model the roughness in Single point incremental forming process[120].

5.1.3 Unsupervised algorithms

Unsupervised algorithms are mainly used in the context of outlier and novelty detection. Those anomalies that deviate sufficiently from most observations are called outliers and their number is significantly smaller than the proportion of nominal cases (typically lower than 5%). The anomalies are called novelties, instead of outliers, when the model has been trained on a dataset free of anomalies.

Excluding outliers from a dataset is a task from which most data mining algorithms can benefit. For example, a heavily imbalance class distribution in the dataset can affect the efficiency and robustness of supervised algorithms. Therefore, an outlier-free dataset allows for accurate modelling tasks, making outlier detection methods are extremely valuable for data cleaning[121].

A comparative evaluation of outlier detection algorithms was presented by Domingues et al.[122] the selected methods are benchmarked on publicly available datasets and novel industrial datasets, in terms of extensive scalability, memory consumption and robustness tests. Some of the main outlier detection methods are described below.

One-class SVM[123] is a domain-based method which relies on the construction of a boundary separating the nominal data from the rest of the input space by applying the support vector machine algorithm to one-class problems. The method computes a separating hyperplane by maximizing the margin between the input data and the origin in the high-dimensional space. The algorithm allows a percentage of data points to fall outside the boundary in order to prevent over-fitting from happening. This percentage acts as a regularization parameter.

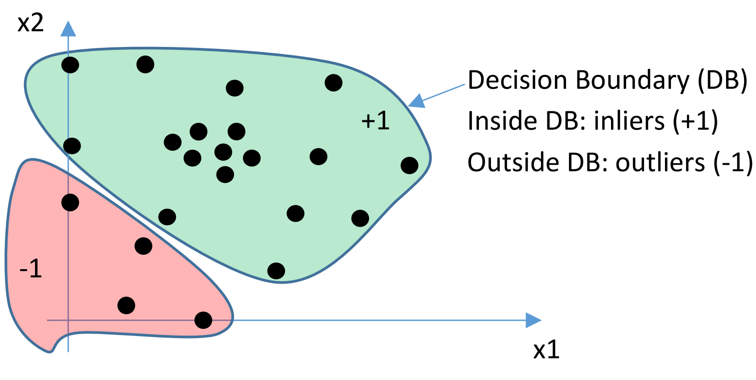

Figure 13. One-class SVM classifier

Local outlier factor (LOF)[124] is a well-known distance based approach that studies the neighbourhood of each data point to identify outliers. For a given data point, this algorithm computes its degree of being an outlier based on the Euclidean distance between the data point and its closest neighbour. A recent study[125] shows that LOF outperforms Angle-Based

Outlier Detection[126] and One-class SVM when applied on real-world datasets for outlier detection.

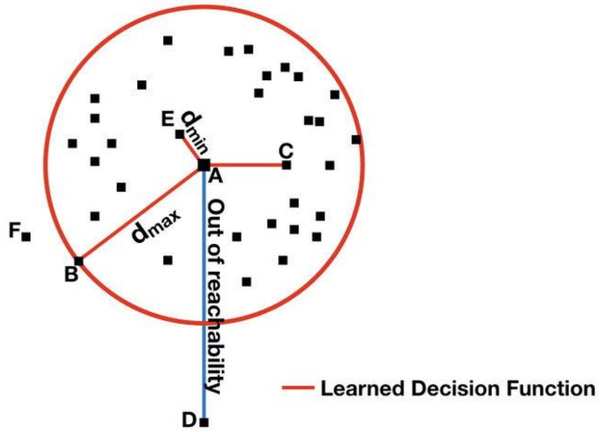

Figure 14. Local Outlier Factor: each point is compared with its local neighbours instead of the global [127]

Isolation forest[128] is a method that focuses on isolating anomalies instead of profiling normal points (see Figure 15). It uses random forests to compute an isolation score for each data point. Recursive random splits are performed on attribute values, hence generating trees able to isolate any data point from the rest of the data. Domingues et al.[129] showed that this was the most performing outlier detection method for the real-world datasets of their study.

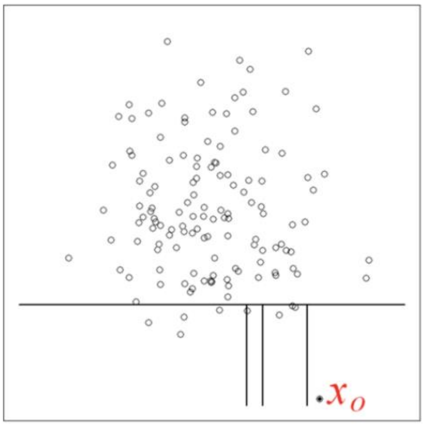

Figure 15. Identifying outliers with Isolation Forest

Unsupervised methods have been successfully applied to fault detection and component failure prediction on critical systems[130]. Manco et al.[131] showed the benefits of using unsupervised methods to detect early train door failures. The results showed that high-degree outliers are effective indicators of incipient failures.

5.1.4 Knowledge Discovery for manufacturing

Designing and developing a data analytics system that can extract knowledge driven by the quality prediction can provide high value insights of the process. To this end, input parameters and extracted features can be used to identify which are the most relevant for the quality prediction. When labels are available, the use of some supervised techniques, such as the Random Forest Tree, can be effective to identify the most relevant features or inputs of the process. Also, Principal Component Analysis (PCA), Singular Value Decomposition (SVD), Latent Semantic Analysis (LSA), clustering, and other unsupervised techniques are some of the methods that can be used to identify patterns and extract useful information. Finding patterns within monitored data allows to deepen the knowledge of the problem and the underlying physics of the process.

The absence of a visible recurrent pattern can also be a very useful information if, for example, failures are deviations from normal behaviour[131]. The latter can indicate the transient and/or the abnormal device values under which the machine is operating. Manco et al.[131] used an unsupervised technique for early detection of faults from diagnostic data and for characterizing door failures on metro trains. Diez-Olivan et al.[132] used a kernel density-based pattern classification approach to identify behavioural patterns in blind fasteners installation. Fastener features, such as diameter and height of the formed heads, and torque-rotation signal data were used for the analysis. The behavioural patterns were identified from resulting high density regions in the reduced feature space.

5.2 Friction stir Welding quality prediction

Fiction stir welding is a relatively new solid-state joining technique, which is versatile, environment friendly and energy and time efficient. Typically, there are three primary control parameters: rotational speed, weld speed and vertical position. However, many other variables can be measured or used as control parameters, such as motor power, tool temperature, and forces (X-force, Y-force and plunge force). It is often desired to understand the effects of process conditions on the performance metrics of the joints, such as Ultimate Tensile Strength (UTS), yield strength, micro-hardness and average grain size. Because of the high complexity of the material flow generated by the thermomechanical stirring process and the micro-structural evolution within the weld, it is often difficult to derive accurate and yet transparent enough mathematical models that characterize the welded material behaviours and the process parameters. The non-linear behaviour as well as uncertainties in process parameters and performance metrics of the welded joints makes it difficult to establish correlation between them. For this purpose, the creation of predictive models is based on the use of statistical learning modelling.

5.2.1 Mechanical properties prediction

Few researchers have investigated the relationship between such process variables and output variables such as the quality of the weld, tool temperature, etc. Martel et al.[133] proposes to use a 16-run Design Of Experiments (DOE) to analyse the effects of nine process variables on selected outputs of the FSW process. By identifying which variables have a large effect on the response, the study reveals that rotational speed, welding speed, and plunge depth are the three most significant factors of the FSW process.

Dewan et al.[134] consider that the rotational speed, welding speed and plunge force are key critical parameters in the determination of ultimate tensile strength of welded aluminium alloys. Utilizing experimental data containing the tensile properties of 73 samples, an optimized Adaptive Neuro-Fuzzy Inference System (ANFIS) and ANN models were developed to predict the UTS of FSW joints[134]. An Empirical Force Index parameter (EFI) was defined and used as input variable also, as it helped to reduce the Root Mean Square error (RMSE) and Mean Absolute Percentage Error (MAPE) significantly. The best predictive model yielded a RMSE and MAPE of 29.70 MPa and 7.75% respectively, based on leave-one-out cross validation. A recent study[135] investigates the use of K-nearest neighbour and Fuzzy KNN (FKNN) based classification models for weld quality prediction using weld process parameters, a pin speed ratio, an empirical relation, and features extracted from weld signal data using the Discrete Wavelet Decomposition (DWD) technique. To this end, the weld signals of X-force, Y-force, plunge force, rotational speed, welding speed were used. The models that only use the welding process parameters as inputs obtain moderate classification accuracies of approximately 92-93% (i.e. the classification error of 8-7% is computed as the ratio of number of errors and the number of data points tested over all K-fold tests). When including the wavelet of the weld signal features in the classification algorithms, the classification accuracy increased to 100%. Therefore, in order to build the best model with highest classification accuracy, weld signal features should be employed together with process parameters. The results also show that using the Artificial Bee Colony (ABC), which is a population based optimization algorithm, is a successful approach to provide the feature selection ability to enhance the classification techniques.

The FSW behaviour related to AA5083 aluminium alloy, consisting of mechanical properties, average grain size and overall weld quality, is characterised by Zhang et al.[136] using a genetic multi-objective data-driven fuzzy modelling approach. The proposed fuzzy modelling methodology allows to generate fuzzy models to predict yield strength, overall weld quality index, and average grain size. Fuzzy models are convenient to generate smooth input-output response surfaces due to the good generalization ability of the elicited fuzzy model. This ability allows them to be combined with optimization techniques to identify the input parameters that will provide a desirable behaviour. The methodology presented improves the predictive capability of fuzzy systems via applying two learning techniques: (1) the multi-objective optimization algorithm NSGA-II to optimize the model's structure; (2) the gradient descent method to improve the model's parameters. Also, it allows to consider not only accuracy (precision) but also transparency (interpretability) of fuzzy systems.

De Filippis et al.[137] uses two separate Artificial Neural Networks to predict the ultimate tensile strength and the Vickers micro hardness of AA5754 H111 FSW butt joint. Some of the experimental data was obtained via qualitative analysis (macrographic test and visual inspection) or quantitative analysis (microhardness and ultimate tensile strength). The thermal parameters, such as the maximum temperature and the slope of the heating curve, were obtained through thermographic technique. The first ANN predicts the Vickers micro hardness of the Heat Affected Zone (HAZ) and has five different input parameters. The second ANN, which predicts the UTS, uses the same five inputs plus the Vickers micro hardness estimated by the first ANN. Different learning algorithms were tested to train the ANN models: Quick Propagation (QP), Conjugate Gradient Descent (CGD), Quasi-Newton (Q-N), Limited Memory Quasi-Newton (LMQ-N), Levenberg-Marquardt (L-M), Online Back Propagation (OBP), and Batch Back Propagation (BBP). The results show that the best training algorithm was the BBP, therefore both ANNs were trained based on a recursive procedure that estimates the weights according to the response of each layer errors. The MAPE computed for micro hardness (first ANN) and UTS (second ANN) were 0.29% and 9.57% respectively, showing that the neural networks were able to predict with significant accuracy, the mechanical properties of FSW joints, under a given set of welding conditions.

Bozkurt et al.[138] applies the decision tree technique to predict the tensile properties of the friction stir welded AA2124/SiC/25p Metal Matrix Composite (MMC) plates. The model developed can be used as an effective tool for predicting the tensile strength of MMC plates. However, more involved algorithms such as the Random Forest Tree technique may lead to a better solution than just using one decision tree.

Tansel et al.[139] use the Genetically Optimized Neural Network System (GONNS) tool for modelling and optimization of FSW process parameters. Five separate ANNs are used for the estimation of each of the following outputs of the FSW process: UTS, yield strength, elongation, hardness of weld metal and hardness of heat-affected zone. The assignment of each output to separate ANN improves the accuracy of the model, which allows for using less number of hidden nodes. The estimation errors of the ANNs were better than average 0.5%. After the ANNs are trained, Genetic Algorithm (GA) is used to find the optimal tool rotational speed and welding speed which maximizes UTS, while the other outputs are kept at the desired ranges.

Palanivel et al.[140] developed a mathematical model based on the Response Surface Methodology (RSM) to predict the ultimate tensile strength of friction stir welded dissimilar aluminium alloy AA6351-AA5083 joints. The polynomial equation incorporates the tool pin profile, tool rotational speed, welding speed, axial force, and the interaction effects of parameters. The adequacy of the model is tested using the analysis of variance technique

(ANOVA). The response surface graphs are studied to show the effect of FSW parameters on UTS, and the optimum process parameters are reported. Other studies[141,142] also use the RSM in the optimization of the FSW process for aluminium matrix composites.

A recent investigation[143] proposes to predict the mechanical properties of the FSW joints by using wavelet analysis of the current signals of the spindle and feed motors. The reason for using the current signals is that: (1) current sensors are inexpensive compared to force and acoustic emission sensors, (2) the chances of getting noisy signal are less. Out of the 65 experiments performed, two experiments are carried out under the same setting of process parameter (rotational speed and welding speed), although a difference in magnitude of the current signals confirm the process variability under the same operating condition. Moreover, UTS and yield strength of the joints from these two experiments also have a considerable difference. Thus, this suggests that any prediction mechanism based only on FSW process parameters may not yield satisfactory results. The change in the signals is a clear indication that signals are carrying some valuable information regarding the FSW process. In this study, a wavelet packet analysis is performed on the current signals and a new method is presented to select the best wavelet function, based on the ratio between energy and entropy of the signal. Using wavelet packet analysis, 192 features are computed and it is reduced to 9 most effective features using principal component analysis. The selected features along with tool rotational speed, welding speed, and shoulder diameter are fed to two neural network models: multi-layer feed-forward neural network and a radial basis function neural network for the prediction of UTS and yield strength.

Tool rotational speed signal and main spindle motor current signals are acquired in real time during the FSW process and analysed in time domain in a recent study[144], implementing fractal theory for feature extraction in terms of fractal dimension. The fractal dimension of current signal fails to capture prominently dynamic variations of the process, because there is little variation in the current signals against different process parameters. On the other hand, rotational speed signal captures the dynamicity of the process well. The fractal dimensions estimated from rotational speed signal using Higuchi and Katz method reveal that high fractal dimensions are associated to high UTS. The fractal dimension of rotational speed signal is proposed, together with rotational speed and welding speed, as indicators for efficient monitoring of FSW process. A regression analysis using these indicators delivers R^2 and adjusted-R^2 values of 0.97 and 0.93 respectively.

5.2.2 Non-quality prediction

The acoustic emissions produced during the FSW process are used by Soundararajan et. al.[145] to monitor the transient welding state and to identify the process changes related to the appearance of defects. The study showed the effect of variation of different parameters (amplitude, power spectrum density, coefficients of the discrete wavelet transform) on acoustic signals. The acoustic emissions produced were time variant only during plunge phase but they were steady during welding. The Fast Fourier Transform (FFT), Short Time

Fourier Transform (STFT), and discrete wavelet transforms (DWT) were applied on signals but the researchers found it difficult to correlate the frequency of the signal directly to various interactions and variations that occur during the process. Only the frequency corresponding to loss of contact between the tool and work piece was observed. The exact positions of defects were not localized.

Kumar et al.[146] focus on the identification of defects using discrete wavelet transform of force signals and statistical tools to exactly localize those defects. To extract better features from a signal, visualization of the signal in frequency domain is necessary. The force signals are, in general, non-stationary signals (i.e. frequency components present in signal varies with time). This means that Fourier Transforms cannot help to localize the different frequency components present in signal with time, because the signal is non-stationary. The STFT method allows to localize the frequency components with respect to time by windowing technique but the frequency-time resolution is fixed. Thus the application of DWT is necessary to study the occurrence of defects during welding. The study shows that the defects present due to accumulation of material, voids, etc., cause the force signal to undergo a sudden change or discontinuity and it is possible to detect these changes using wavelet transform. Both torque and force signals show abrupt behaviour (i.e. peaks) in the presence of defects. In the case of defect free welds, the force and/or the spindle torque signal are smooth and there are no abrupt changes in the signal.

A real time quality FSW monitoring system for DH36 steel plates is proposed by Baraka et al.[147]. The prediction model relies on frequency-based analysis of two key process parameters: the traverse force and the downward force (or plunge force). The fast Fourier transform algorithm is used to calculate the discrete Fourier Transform for finite length signals. The dynamic behaviour of a frequency domain quality marker (named as FFT threshold) is modelled in order to assess the resulting weld quality. An Interval type2 radial basis function neural fuzzy model (IT2-RBF-NN) is trained and tested with 20 and 5 weld samples respectively. The results show that the achieved predictive performance is more than 80% in forecasting the weld quality thresholds on different levels of inputs.

A recent investigation[148] shows that fractal dimensions can be used to detect the appearance of defects during the FSW process on real time. Most widely used signal processing techniques in defect identification are Fourier transform, short time Fourier transform and wavelet transform. However, these signal processing techniques present the following limitations: the inability to analyse non-stationary signal (Fourier transform), fixed window size (short Fourier transform), the need to select suitable mother wavelet function and optimum level for efficient signal decomposition (wavelet). Realizing the drawback with the available and widely used methods, fractal theory is implemented in this study for the analysis of signals. The rotational speed is measured by a laser tachometer and is later characterized by fractal dimension using the Higuchi’s method. In fractal analysis, no pre-processing on the signal is required (such as filtering the noise) and no a priori knowledge is required for interpretation of results. Fractal analysis can be applied directly to the signal in the time domain, hence fewer computational steps in the fractal dimension estimation algorithms help to deliver results faster[149]. It is a data driven approach and more importantly, fractal theory results in finding a single indicator termed as fractal dimension, sufficient to describe behaviour of the signal in time domain. The methodology proposed discretizes the speed signal during the welding period in segments and then computes the fractal dimensions for each segment. In this way, it is possible to monitor the evolution of the fractal dimensions during the welding period. The results show that the fractal dimensions decrease significantly when a defect is initiated. Once the FSW process becomes stable with the defect inside the weld, an increase in the fractal dimension is observed. This analysis helps to find a boundary beyond which defects are formed in the welded samples. However, present methodology cannot describe the shape, position and size of the defect.

The aforementioned survey of available research work conveyed the message that process parameters are not sufficient for monitoring FSW process and force signals and rotational speed signals were mostly used, followed by current signals and acoustic emissions.

Objective	Technique	Input parameter	Output parameter	Feature extraction	Samples in the data set
Prediction of ultimate tensile strength of AA-2219-T87 aluminium alloy joints[134]	ANFIS, ANN	N, V, F_z, EFI	UTS	None	73
Prediction of FSW quality of AA-2219-T87 aluminium alloy joints[135]	KNN, FKNN	WF for F_x, F_y, F_z, V & N. PSR, EFI	WQ	DWT	66
Development of acoustic emission defect formation monitoring scheme[145]	None	AE	f	FFT, STFT, DWT	3
Development of defect formation using force and spindle torque signal monitoring scheme for AA1100 aluminium alloy joints[146]	None	WF for F_z and T	x-position of defects	DWT	2
Use of mechanical properties, weld quality and average grain size of AA5093 aluminium alloy joints for training and prediction of fuzzy models[136]	FHMO-FM	N, V	YS, WQ, AGS	None	25 for each output
Prediction of ultimate tensile strength and Vickers microhardness of AA5754 H111 butt joints[137]	ANN	N, V, p, MSHC	UTS, HV	None	16
Prediction of the tensile properties of the friction stir welded AA2124/SiC/25p metal matrix composite (MMC) plates[138]	DT	N, V	UTS	None	20
Prediction of mechanical properties of A11080 aluminium alloy joints[139]	ANN	N, V	UTS, YS, E, HV, HV_{HAZ}	None	20
Optimization of process parameters to maximize UTS of dissimilar aluminium alloy AA6351-AA5083 joints[140]	RSM	TPP, N, V, F_z	UTS	None	31
Prediction of surface weld quality [147]	ANN	N, V	Surface quality	FFT	25
Development of defect formation monitoring scheme[148]	None	N	Defects appearance	Fract. T	5
Prediction of UTS and YS[143]	ANN	WF for I_N, I_V	UTS, YS	WPT	65
Prediction of UTS[144]	Regression	I_N, N	UTS	Fract. T	10

Table 3. Data-driven modelling studies related to the quality prediction of Friction Stir Welding joints. Techniques: adaptive neuro-fuzzy inference system (ANFIS), artificial neural network (ANN), K-nearest neighbour (KNN), fuzzy K-nearest neighbour (FKNN), fast hierarchical multi-objective fuzzy modelling (FHMO-FM), decision tree (DT), response surface methodology (RSM). Input parameters: tool rotational speed (N), welding speed (V), x-force (F_x), y-force (F_y), plunge force (F_z), torque (T), empirical force index parameter (EFI), pin speed ratio (PSR), wavelet features (WF), acoustic emission signal (AE), position of the samples extracted from the weld bead (p), tool pin profile (TPP), Main spindle motor current signal (I_N), feed motor current signal (I_V). Output parameters: ultimate tensile strength (UTS), yield strength (YS), weld quality index (WQ), frequencies (f), average grain size (AGS), Vickers microhardness (HV), Vickers microhardness of heat affected zone (HV_{HAZ}), elongation (E). Feature extraction: discrete wavelet transform (DWT), Fast Fourier Transform (FFT), Short Time Fourier Transform (STFT), Discrete wavelet transforms (DWT), Fractal theory (Fract. T), Wavelet package transformation (WPT).

6 Technology acceptance (NUPSPA)

As indicated by Davis[150], technology offers the potential for substantially improving employees performance[151,152,153]. But sometimes, performance gains are often obstructed by users' unwillingness to accept and use available or new systems[154].

It has been well established that the interaction between humans and technology is influenced by a number of social and psychological factors and characteristics[155]. Scholars developed several theoretical models to explain the acceptance behaviour of end users. One of the most cited and well-known models is the so-called Technology Acceptance Model (TAM)[156,157]. TAM is considered the most influential and commonly employed theory for describing an individual's acceptance of information systems[158]. Chuttur[159] argues that the wide acceptance of TAM is based on the fact that the model has a sound theoretical assumption and practical effectiveness.

During the last decade, the TAM model and its revised forms has gained considerable prominence, particularly due to its transferability to various contexts and samples, its potential to explain variance in the intention to use or the use of technology, and its simplicity of specification within structural equation modelling frameworks[160,161].

Fred Davis first developed this model in his doctoral studies at Massachusetts Institute of Technology in 1986, starting from an adaptation of the more generalised Theory of Reasonable Action (TRA[162]). In this model, Fishbien and Ajzen stated that individual behaviour is driven by behavioural intentions. Behavioural intentions are a function of an individual's attitude toward the behaviour and subjective norms surrounding the performance of the behaviour.

They have defined "attitude" as the individual's evaluation of an object, the individual's positive or negative feelings about performing a specific behaviour. Attitudes are formed by a series of beliefs and result in a value being placed on the outcome of the behaviour[163]. If the outcome or result of a behaviour is seen as being positive, valuable, beneficial, desirable, advantageous, or a good thing, then a person's attitude will be favourable with a greater likelihood of the person engaging in the behaviour.

In addition to attitude, intention is influenced by subjective norms. A subjective norm is the perceived social pressure to engage or not to engage in a certain behaviour. Subjective norm is defined as an individual's perception of whether people important to the individual, so called relevant others, think the behaviour should be performed.

Later on, Ajzen[164] developed Theory of Planned Behaviour (Figure 16), which aim at explaining behavioural decision-making processes of human beings in order to better understand and predict their behaviour. The first two factors are the same as Theory of Reasonable Action[162] . The third factor, the perceived behavioural control, is the degree of control that users perceive that may limit their behaviour. It refers to the controllable degree that individuals feel when taking particular acts, which depends on three factors of capabilities, resources and opportunities[165]. The more capacities, resources and opportunities individual think they own in taking particular acts, the less expected obstacles and the stronger the perceived behaviour control individuals have[166].

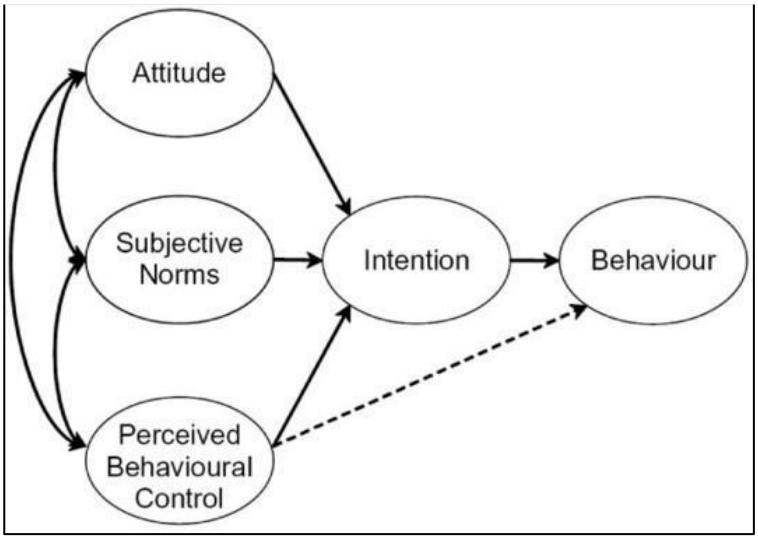

Figure 16. The earliest The Theory of Planned Behavior[164]

Starting from those earliest theories, Davis[156] developed this new version in order to better explain technology usage behaviour and to identify the factors that lead to user's acceptance or rejection of specific technology by combining technological aspects with organisational behaviour[167,157]. This model (Figure 17) assumes that an individual's technology acceptance is determined by two major variables: perceived usefulness and perceived ease of use[160].

As Davis[156] mentioned, employees tend to use or not use a new technology or a new IT application to the extent they believe it will help them perform their job better. Moreover, even if potential users believe that a given technology is useful, they may, at the same time, believe that the systems is too hard to use and that the performance benefits of usage are outweighed by the effort of using that specific technology. It refers to the effort a person estimates it would take to use technology and is closely related to competence beliefs[168].

The importance of perceived ease of use is supported by Bandura's[169] extensive research on self-efficacy, defined as "judgments of how well one can execute courses of action required to deal with prospective situations" (p. 122). Therefore, in this context, self-efficacy is similar to perceived ease of use as defined above.

Hence, perceived usefulness and perceived ease of use are indicated as fundamental and distinct constructs that are influential in decisions to use new technology. Although certainly not the only variables of interest in explaining user behaviour[170,167,171], they do appear likely to play a central role.

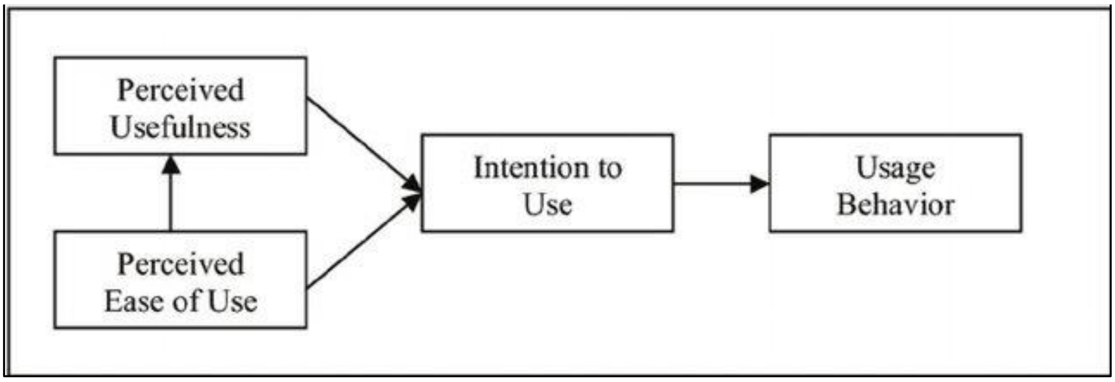

Figure 17. The earliest technology acceptance model[156]

Shroff et al.[172] described that by manipulating these two variables, technology systems developers can have better control over users' beliefs about a specific system and so can better predict their behavioural intention and actual usage of the system. Attitude towards using a new technology or system has been classified as a determinant that guides future behaviour or as a cause of intention that eventually leads to certain behaviour[173]. In TAM, attitude towards using a system refers to the evaluative effect of positive or negative feelings of individuals in performing certain behaviours[172].

Although researches and practitioners very well received it, some argue that the TAM does not take into consideration possible obstacles that would prevent the individual from adopting a particular technology[174]. Bogozzi[175] has stated that the TAM is too simple and leaves out important variables.

Thus, Mugo et al.[176] stated that both perceived ease of use and perceived usefulness are influenced by two categories of variables: internal and external variables. Internal variables consist of factors such as the attitude of the user, their pedagogical beliefs towards, and level of competency, whereas external variables include those external barriers faced by users during utilization. Such factors include organizational barriers, technological barriers, and social barriers.

Other authors[177,178] pointed that those two important variables (perceived usefulness and perceived ease of use) are often accompanied by external variables explaining variation in perceived usefulness and ease of use: subjective norms (SN), self-efficacy (CSE), and facilitating conditions (FC).

The final version of Technology Acceptance Model was formed by David et al.[179] as shown in Figure 18 both perceived usefulness and perceived ease of use were found to have a direct influence on behaviour intention[180].

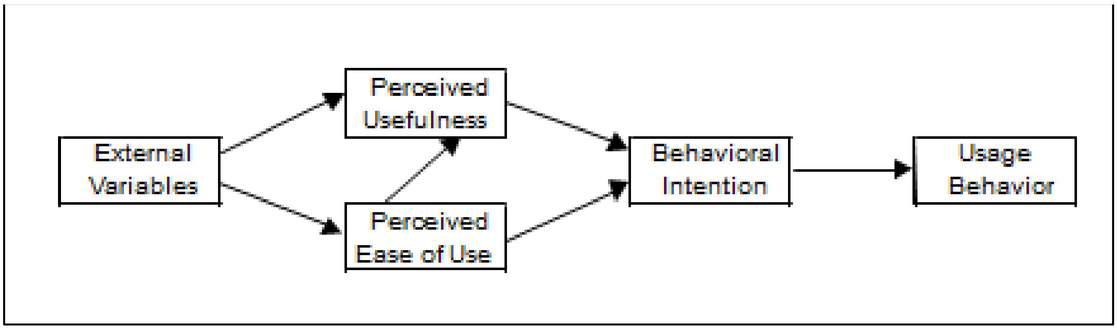

Figure 18. Final version of Technology Acceptance Model (TAM)[179]

However, despite those critics, it has also been recognized by others as a powerful, valid and highly reliable predictive model that can be used in several contexts[181,182]. Moreover, it constitutes an important theoretical contribution towards understanding technology usage and acceptance behaviours[183]. Other scholars[184,185] considered TAM a parsimonious and powerful theory which help researchers and practitioners to distinguish why a particular technology or system may be acceptable or unacceptable and take up suitable measures by explanation besides providing prediction[158].

Even though TAM has been tested widely with different samples in different situations and proved to be valid and reliable model explaining information system acceptance and use[186,179], many extensions to the TAM have been proposed and tested[185,187,188,189,190] .

Hornbæk et al.[191] have mentioned that a variety of moderators of the adoption and use of technology were identified in addition to the perceived usefulness and perceived ease of use. One of these constructs is perceived enjoyment[192,193], which adds experiential and hedonic aspects to TAM.

Other external variables that were introduced into TAM as suggested by Davis[157] are: system quality[194], training[195], compatibility, computer anxiety, self-efficacy, enjoyment, computing support, and experience[196].

Venkatesh, et al.[197] studied from the previous models/theories and formed Unified Theory of Acceptance and Use of Technology (UTAUT) shown in Figure 19. The UTAUT has four predictors of users' behavioural intention: performance expectancy, effort expectancy, social influence and facilitating conditions.

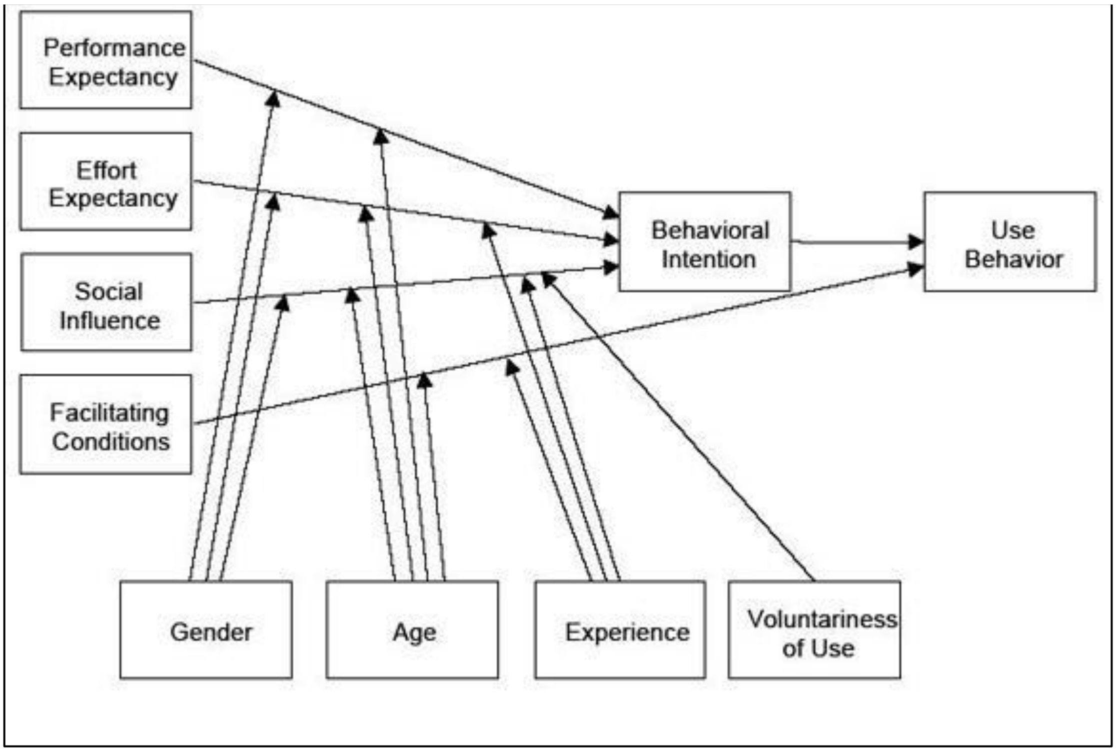

Figure 19. Unified Theory of Acceptance and Use of Technology (UTAUT)[197]

The technology acceptance theories and models were designed to predict the individuals' behaviours and measure the degree of acceptance and satisfaction for these individuals against any technology or information system.

With few exceptions such as Venkatesh[198], technology acceptance models make use of predictors that are exclusively cognitive, relating the adoption and actual behaviour of a new technology to attitudes, beliefs and perceptions[164,199]. Some of the previous models focus on internal antecedents of behaviour like attitudes, values and intentions while others focus more on external issues such as norms, incentives and institutional constraints.

6.1 Tools for measuring technology acceptance and the impact on work performance

The Technology Acceptance Model[156,157] with its newest developments stems from the challenges posed for HR practitioners by research studies on the effects of automation and AI[200]. Thus new roles for HR professionals are to support the employees in the whole process of introducing them to new technologies, training, performance evaluation and feedback. Should the situation arise, the HR departments should consider both re-skilling or up-skilling in order to replace those skills which may be obsolete[201].

Once new automated machines are in place, understanding the needed skills is one challenge, as well as making sure that the workforce has a skill variety, autonomy, and interdependence, as well as increased cognitive, creative, technical and social skills[202,203], to complement machines[204]. They also need to acquire and / or perform the remaining tasks that are not automated[205].

As explained above, TAM comprises two complementary dimensions as regards the activities performed: Perceived Usefulness – PU (employees' perception on the extent to which a machine would increase their performance) and Perceived Ease of Use – PEOU (the perception on the extent to which a machine would free an individual from effort) and they both impact the Behavioural Intention to Use – BITU of an individual to accept and use a technology[157].

However, these are not the only psychological constructs that have been taken into account when discussing the way in which we can measure the impact automation and AI have on work performance. The range of constructs which researchers have taken into account are varied and they refer to personality traits[206], social constructed traits - from computer anxiety[207] to optimism and mood[208]. Other identified factors that influence human-automation relationship are outside the individual and are in relation to the company's operations and work specifics, i.e. operator workload and trust toward automation[209,210] or organizational tenure, level of education and prior experience[211].

The first scale we have analysed for our current research is Parasuraman's[212] Technology Readiness Index (TRI). The starting point for this construct is mainly concerning the extent to which customers are willing to adopt and use a certain product or service, where new technology is embedded. However, the author mentions that the construct may be useful for the internal customer within an organization because „it can be viewed as an overall state of mind, resulting from a gestalt of mental enablers and inhibitors that collectively determine a person's predisposition to use new technologies"[212].
There are four dimensions of this scale[212,212]:

1. Optimism - it refers to the innate (or culturally built) view of technology and the belief that it offers people increased control, flexibility and efficiency (in connection with the perceived usefulness described by Davis[167]);
2. Innovativeness - defined as the tendency to be an early adopter, a pioneer and a thought leader;
3. Discomfort - the feeling that one is being overwhelmed by the technology and has no control over it;
4. Insecurity - where one would have complete lack of trust in technology and its ability to work properly (such attitude has been associated with a high score on neuroticism - one of the Big 5 factors model (BFF) of personality, based on the research of Groth-Marnat, et al.[213]).

If optimism and innovativeness are predictors of technology readiness, discomfort and insecurity are inhibitors. Based on two empirical studies, Parasuraman[212] concludes that the scale has sound psychometric properties and can be used to evaluate in depth the readiness of internal and external customers to embrace technology. It can be both used as a screening device but also for tech-support positions.

Prior to moving further, it would be useful to mention that the Big Five personality model, or the canonical model has been identified by McCrae et al.[214] and it defines the personality in terms of five main factors:

1. Neuroticism: which is defined as the general tendency to feel negative effects, like fear, sadness, guilt and is in opposition to emotional stability;
2. Extraversion: which is defined as the preference of people to be within large crowds, large groups, with self-confidence, energy and optimism. The opposite of being extravert is being reserved, independence and a quiet.
3. Openness: which is defined by active imagination, aesthetic sensitivity, intellectual curiosity in opposition to conservatism, and emotional inhibition.
4. Agreeableness: which is connected to interpersonal skills, altruism and sympathy and in opposition to hostility, egocentric tendencies, competitiveness rather than cooperation.
5. Conscientiousness: which is defined as an active process of planning, organizing and execution of tasks and in opposition to the inability to resist to one's impulses and temptations.

Personality has been thus put in connection early on in the research studies to technology acceptance. Keeton[215] argues that a high score in extraversion, openness and agreeableness correlates with a high attitude on technology acceptance, Devaraj et al.[216] state that neuroticism influences negatively the perceived utility of technology, while agreeableness influences it positively. Svendsen[217] found a positive relationship between conscientiousness and the behavioural intention to use technology and a positive influence of extraversion on all 3 components of TAM. When all factors of the personality have been measured in order to understand their influence on the technology acceptance of young Turkish users of mobile phones, Özbek et al.[218] conclude that „individuals with a high level of agreeableness, have a higher propensity to perceive smart phone technology as more useful, while those who have a higher level of neuroticism perceive smart phone technology as less useful. Furthermore, people with a higher level of openness perceive smart phone technology as more easy to use". In a similar research, Behrenbruch et al.,[219] have looked not only at personality traits but also at external factors influencing potential technology acceptance, like computer self-efficacy[220] and computer anxiety[207]. The results have shown that high extraversion supports an elevated level of technology acceptance and a significant relation between computer anxiety and trust[219].

Trust in IT and its artifacts has been a concept developed by Parasuraman et al.,[209] and developed in a subsequent article by Lee et al,[210] with a specific focus on automation. Lee et al,[210] define human-automation trust as an attitude „that an agent will help achieve an individual's goal in a situation characterized by uncertainty and vulnerability". This is important, because both over-trust in automation and lack of it have an impact on the degree to which employees rely on it. For instance, in an experiment performed by Bailey et al.[221] they asked the participants to perform a mock flight task and a system monitoring task consisting of three separate information displays (simulated engine instrumentation crew alerting system, or EICAS, display). *The system monitoring task was assisted by imperfect automated systems with high or low reliability conditions. Participants rated their trust levels higher and detected system failure more poorly under the high than the low reliability condition, and critically, this effect was more pronounced when the monitoring task required greater attentional resources.* Similarly, multitasking environments led to even poorer detection of automation malfunction than single-task environment[222], suggesting that attentional demand of multitasking and trust both influence operators' monitoring of automation. In a series of experiments performed by Karpinsky et al.[223] they showed that operators become more likely to distrust the automated signalling system under high workload. This, in turn, affects exclusively their performance. However: „Expert operators with substantial experiences interacting with automated systems may be less prone to exhibit these findings of the effect of task load on trust than novice operators, because their knowledge of the systems may allow them to override trust development based on bottom-up processing of the system's behaviour (e.g., performance dimension of trust)“[223].

We could conclude that one of the highest impacts technology has on human labour is, in fact, related to workload. But, as automated systems perform all sorts of calculations and processes, the chances for some mistakes to happen have reduced. However, this does not mean that the same effect has been transmitted to the overall human performance. Technology advances leads to human increased performance but, at the same time, raises several personal factors and attitudes that need to be understood and mitigated so we see a proportional level of human performance enhancement.

The concept of trust has been better operationalized by Parasuraman[212] , and a new layer has been added: the level of control from the human factor. They define a 10 level scale to refine automation, where between 1 to 5 there is overall human control of a task and from 6 to 10, through automation, the tasks are performed independently, with each level up the scale operators are provided with less feedback.

Apart from the increased efficiency which automation brings, we need to stress also the automation related accidents which can happen due to causes like: poor system design, organizational factors, software and hardware failures as well as causes related to the operator's misuse or disuse[209]. Particularly the last two situations - the misuse and disuse of automation are of importance for this project, because they impact the extent to which the employees rely or not in decision-making on automation.

The first meta-analysis on trust in automation has been published in 2014 by Hoff et al.[224] and started from the premise that „much of the existing research on factors that guide human-automation interaction is centred around trust“ in fact, a result of the extent to which humans are willing to rely on automation in everyday life and at work.

Hoff et al.[224] look at a plethora of types of trust and the dimensions one needs to consider when understanding the interaction between humans and automation. For this task, they have reviewed 127 research studies, where trust has been measured. There are 3 main facets of trust the authors have used, citing Marsh et al.[225] namely: dispositional trust, situational trust and learned trust. They are defined as follows:

1. Dispositional trust is an individual's enduring tendency to trust automation.
2. Situational trust depends on context and interaction and some of the factors influencing it are for instance the operator's state of mind, her attention capacity during a certain work load etc.
3. The learned trust is guided by past experience and it is dynamic, based on the previous interaction with similar or different type of automation.

We will detail each of these dimensions of trust in automation, as they shed some light on the types of variables we will need to take into account when doing our own evaluation. The dispositional trust may be influenced first by culture (tough it could be a matter of familiarity with the technology or a matter of economical development). Age is also a variable Ho et al.[226] showed that older adults trust technology more, but they don't follow a changed behaviour based on automation errors, while Johnson et al.[227] found, to the contrary, that older adults were better adjusting their behaviour based on errors reported by systems. Gender is also a factor as regards trust in technology, with women more inclined to trust certain communication's style and appearance[228]. Personality too is included among the variables which define the dispositional trust.

As regards the situational trust, Hoff et al,[224] include here several external variables, most importantly workload, meaning that while performing high workloads, operators must use automation more often to maintain pace with task demands, regardless of their level of trust[229]. Another factor to be taken into account is perceived risk, namely, in certain situations of high risk participants have not relied on automation[230,231] while in others they did, when perceived risks were lower[232]. Other constructs are included in the situational trust, though, they, in our opinion should have been included in the personality factors. For instance self-confidence - when self-confidence and trust are about equal, operators may prefer manual control[233]. The same applies for the concept: computer self-efficacy which is positively correlated with trust in automation[234]. Another facet of situational trust is subject matter expertise[224]. Research shows that if employees have extensive expertise in an area, they are less likely to depend on automation compared to beginners[235]. In conclusion, Hoff et al.,[224] state that: „Decisional freedom represents the extent to which operators are able to make thoughtful decisions about how to best utilize automation. It can be influenced by a variety of situational factors such as task difficulty, workload, organizational setting, subject matter expertise, mood, and attentional capacity. In general, trust likely has a weaker effect on reliance in the presence of situational factors that inhibit decisional freedom."

Learned trust is based on the lessons learned by humans from their previous experience based on which they decide the extent to which an automated system is to be trusted or not. Hoff et al,[224] include here: pre-existing knowledge (with people tending to trust more automation when it is portrayed as „expert"[236] but with the trust decreasing when the system generates errors[237]. Design features are important too, considering that the interfaces are providing the first visual component of the system. Thus increasing the

humanness of systems may help reduce automation disuse with certain types of automation. However, designers must consider the expected characteristics of potential users (e.g., age, gender, culture), as anthropomorphizing an interface can impact the trust formation process differently for diverse individuals[238]. An equally important aspect is the relationship between errors resulted from automated systems and trust: „In particular, research has shown that false alarms (when systems incorrectly alert operators to the presence of a signal) and misses (when automation fails to detect a true signal) generally have different effects on trust-dependent behaviours[239]. Importantly, false alarms call for compliance (operators must assume that a signal is present), while misses require reliance (operators must assume that a signal is absent). This distinction is significant because numerous studies have found that false-alarm-prone automation reduces operator compliance more than reliance, while miss-prone automation reduces reliance more than compliance[240,241,242,243] (quoted by Hoff et al.[224])".
Based on our literature review we would like to propose at least two tools that we feel should be added, based on our research in the research methodology we are proposing for the current project:

1. Attitudes Towards Automation Scale (ATAS) created by Humphrey[244]. The scale takes into account two dimensions, a vision for our future and the impact the automation has on humans in terms of its utility. It draws from the initial theory of technology acceptance[156,157], where a new, ideological feature is added, namely, the author builds on a pre-existing condition of humans' views about their future on Earth - which can be a Dystopic or an Utopic one. In the Dystopic future, AI and automation take over and work against humans, while in the Utopic future AI and automation work for the benefit of human kind. There are thus 4 factors loaded by the 34 items, namely: Utopic, Dystopic, Social Utility and Social Impact. The scale does not include items to measure attitude towards AI, and this is a recommendation which should be considered, should we want to use this scale in such organizational environment.

A sample of the items related to this scale include: Wherever automation can perform a task more efficiently than human labour, it should be utilized. / Work is only meaningful if it is paid. / The average standard of living will increase with automation. / Automation will decrease the average cost of living. / Increased automation will enable Universal Basic Income. / Replacing workers with automation is never acceptable. / Automation has no place in medicine.

2. Technology Readiness Index (TRI)[212] which is assessing the state of mind related to the adoption of technology, with its 4 dimensions: optimism, innovativeness, discomfort and insecurity. Distinct to ATAS (34), the items of this scale refer specifically to work situations, and thus can be more easily be put in connection to situational trust in technology.

A sample of items from this scale include: You like the idea of doing business via computers because you are not limited to regular business hours. / Learning about technology can be as rewarding as the technology itself. / You feel confident that machines will follow through with what you instructed them to do./ Other people come to you with advice on new technologies. / You enjoy the challenge of figuring out high-tech gadgets. / If you buy a high tech product or service, you prefer to have the basic model over one with a lot of extra features. / You do not consider it safe giving out a credit card number over a computer. / You worry that information you send over the internet will be seen by other people.

These two tools should be used in our view at different moments in the project evaluation. Namely the ATAS 34[244] should be used prior to employees performing in the new automated plant. The attitudes could be put in connection with personality traits from the Big Five model and with other scales like, for instance Multidimensional Work Ethic Profile[245]. These would provide valuable information on expectations people have and how the automation work should be introduced to them in the induction process.
Then, while the work is progressing a new assessment may be done, where we can measure TRI[212] in relation to work engagement[246] or work performance[247].
These will allow us to build a comprehensive image related to expectations, implementation and impact of automatization on the work processes and will create the right datasets to be able to extrapolate valuable lessons on the human-automation relation for other enterprises.

7 Conclusions (ALL)

Focusing on the specific and challenging requirements of the space industry, meaning zero defect manufacturing and high equipment availability, this document presents a survey of the key technologies and state of the art approaches for Predictive Maintenance, Resource Management Optimization and Predictive Quality.

Chapter 3 "Resource Management optimization" has presented and discussed a selection of interesting contributions found in the technical literature dealing with resource management optimization for advanced operations management and supply chain control. Several interesting techniques have been discussed, with a focus on the most recent works. The concepts, techniques and approaches presented are meant to provide useful inputs for the design of the algorithms to be developed by SESAME in task 3.2: "Intelligent and adaptive models to optimize resource management". The surveyed optimization-based approaches and, particularly, the model predictive control concept, appear very promising, because they allow for the explicit optimization of performance criteria, and they appear easy to integrate with other approaches, for example the data-driven ones, and with the algorithms on predictive quality and predictive maintenance, which will provide important inputs to improve the performance of the resource management algorithms of task 3.2.

Predictive and Proactive maintenance have been introduced in chapter 4. Start point of both activities is early detection, meaning that something has changed in the system behavior. Literature review shows that several approaches can be applied for smart maintenance and that it does not exist methods that work better than others. The choice of approaches for a specific system is driven by expert knowledge we have and also by available data. For a complex system, system of system, various approaches must be used to build a predictive or proactive maintenance application. This review will be an input for task 4.1 "Development of predictive maintenance digital technologies" which consists in the development and implementation activities for both industrial uses cases of Vitrociset and ArianeGroup.

Predictive Quality for manufacturing application has also been analysed, considering the two main Machine Learning solutions: supervised and unsupervised algorithms. Each family can provide a set of benefits and advantages. Supervised algorithms can provide and edge in quality prediction accuracy thanks to the training phase that allow for a better modelling of the process, while unsupervised can help to discover unwanted deviations that can lead to identify non-quality production. The application of ML solutions into the Friction Stir Welding process monitoring has also be addressed, focusing on mechanical properties prediction and non-quality prediction based on process data. Moreover a survey of relevant papers and the algorithms used for each application has been created (see Table 3). This review will be a basic input for Task 3.1 "Data Modelling and Fusion for predictive tools" and Task 3.3 "Quality Hybrid Expert System Design and Algorithms" which will focus on obtaining the proper data representation as well as developing the ML predictive quality models for the FSW process. State of the art algorithms show very promising capabilities that can enable the achievement of the challenging Predictive Quality objectives of the SESAME project.

Finally, Chapter 6 “Technology acceptance” has presented the main theories in the area of technology, automation, human resources and their performance, i.e. Technology Acceptance Model and its subsequent developments. Also, we looked at personal and organizational variables which are influencing human behaviour when automation takes place within an organization. The main concepts which will be measured in our research for this project - as variables they impact the behaviours of employees and their expected performance, are: technology readiness index, attitudes towards automation, work engagement and work performance. These in connection with personality variables, but also with job related factors, like work load, prior knowledge and gender or culture will allow us to develop a series of measures in order to minimize the errors due to the human factors in the process of production.

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