ARTICLE TEMPLATE

The ASSISTANT project: AI for high level decisions in manufacturing.

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ABSTRACT
This paper outlines the main idea and approach of the H2020 ASSISTANT (LeArning and robuSt deciSIon SupporT systems for agile mANufacTuring environments) project. ASSISTANT is aimed at the investigation of AI-based tools for adaptive manufacturing environments, and focuses on the development of a set of digital twins for integration with, management of, and decision support for production planning and control. The ASSISTANT tools are based on the approach of extending generative design, an established methodology for product design, to a broader set of manufacturing decision making processes; and to make use of machine learning, optimization, and simulation techniques to produce executable models capable of ethical reasoning and data-driven decision making for manufacturing systems. Combining human control and accountable AI, the ASSISTANT toolsets span a wide range of manufacturing processes and time scales, including process planning, production planning, scheduling, and real-time control. They are designed to be adaptable and applicable in a both general and specific manufacturing environments.

KEYWORDS
Artificial intelligence, Data analytics, Digital twins, Decision aid, Reconfigurable manufacturing systems, Process and production planning, Scheduling and real-time control

1. Introduction

This paper presents the main scientific ideas of the European project ASSISTANT. With a multidisciplinary consortium combining key skills in AI, manufacturing, edge computing and robotics (*Assistant, project EU, ICT 38: AI for manufacturing*, n.d.), ASSISTANT is focused on the development of AI-based tools that capture and streamline the workflows of adaptive manufacturing environments. In particular, ASSISTANT will design and develop a set of digital twins: AI systems that incorporate manufacturing domain knowledge and utilize machine learning (ML), optimization,

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and simulation techniques to construct digital replicas of manufacturing environment elements and tools capable of producing, reasoning on, and evaluating production plans. To facilitate deep integration of systems and harness value from data, the digital twins will structure and expose information in the form of knowledge graphs (domain models) that allow data scientists and external end users to embed domain knowledge in, and use the twins without detailed understanding of the underlying systems. The ASSISTANT tools are aimed to facilitate integration of complex manufacturing systems with diverse data sets into singular logical systems for automation and operation of complex collaborative production systems that can be dynamically reconfigured on demand. The ASSISTANT project aims to make concrete contributions towards increased productivity, flexibility, and robustness in manufacturing systems; as well as making advances towards sustainable learning and knowledge transfer in complex systems through integration of human experience and machine intelligence.

AI technologies are extensively used today for automation and learning in the delivery of digital services in the cloud computing offerings of companies such as Google, Facebook, and Amazon. However, while these services are commercially successful, scalable, and widely applicable in conventional ICT environments, large parts of the underlying business models are based on harnessing the economy of scale effects of massive data centers which is not directly transferable to manufacturing. The reality and needs of manufacturing industries that make this approach challenging include the fact that manufacturing often targets production of dedicated products (instead of generalized services), using specialized tools (instead of generic ICT platforms), and addresses small markets (instead of broad ICT-based or integrated business segments). Certain AI-related technologies have since long been adapted and developed for manufacturing, e.g., automated machine tuning and predictive quality inspection, but manufacturing AI tends to be applied at fine-grained decision making levels which makes it hard to scale these efforts. To extend the capabilities of manufacturing AI systems and make them more applicable in broader scenarios, ASSISTANT employs a combination of predictive and prescriptive analytics techniques to embed AI technologies in higher-level manufacturing decision making such as process planning, production planning, and scheduling. To retain human control and system accountability, ASSISTANT develops a generative design framework for optimal interaction between human decision making and AI-based decision support. As defined in (Aameri, Cheong, & Beck, 2019), generative design is an approach to iterative design where users can specify goals expressed in terms of objectives and mathematical constraints, and software applications develop sets of feasible and/or optimal design solutions for human evaluation. While generative design was originally developed for iterative product design, the ASSISTANT project develops tools to extend the technique to other manufacturing decisions.

Application and use of AI technologies require extensive amounts of data. Use of AI for production planning and control also places requirements for timely delivery (real time) of high quality data. Manufacturing environments tend to be rich sources of data, albeit typically diverse and heterogeneous in nature. A well-developed use of such data would allow the extension or improvement of models and processes within the manufacturing domain. In so doing, applications like Design for Six Sigma and Design for Manufacturing, can use AI to extract the required knowledge from various phases of the product life cycle.

The path to extract that information and produce the required knowledge has been proposed following three possible links: (1) dynamically generate knowledge bases, (2) determine minimum information requirements, and (3) data-interoperability support.

The first two are strongly linked to AI. ASSISTANT can be linked to both processes by considering that: knowledge graphs, model constructions, and generative design are linked to (1), while an understanding of the minimum information needed to construct sound models, and therefore providing them to the system, is linked to (2). As expected, the linked behaviours to be constructed by AI should be provided with enough representability and curated to produce useful knowledge.

To meet the projects' data management and curation needs, ASSISTANT defines an architecture with a set of digital twins (to be embedded in manufacturing environments) that make data available through a shared data management platform: the ASSISTANT data fabric.

In summary, ASSISTANT employs a combination of generative design techniques and machine learning to develop tools for data-driven production management decisions. ASSISTANT goes beyond the current state of the art use of digital twins by:

(1) Incorporating machine learning to automate the development of digital twin data models from IoT/ERP/MES data, including estimation and management of model parameter uncertainties.
(2) Iteratively applying machine learning mechanisms to continuously retrain and improve digital twin data models.
(3) Basing on the synergy between machine learning and digital twins, extending the concept of generative design to cover a broader set of manufacturing processes, including process planning itself.

ASSISTANT provides products and services that are usable in a wide range of manufacturing processes leading to agile production processes and improved quality of products and processes. First, ASSISTANT will foster the adoption of predictive analytics in a wide range of manufacturing processes. Despite the short return on investment of prescriptive analytics tools, most manufacturers are not using such tools due to the high initial investment or lack of personalization. The implementation of prescriptive analytics tools requires high consulting costs to adapt software. ASSISTANT will provide model acquisition from data that will reduce these costs since the software will automatically adjust to the requirements of the shop floor. This will result in the large-scale adoption of prescriptive analytics in manufacturing. Second, ASSISTANT aims to transfer the recent development of adaptive stochastic/robust optimization to manufacturing companies. Such techniques provide decisions (process planning, production planning, scheduling) that are not only robust to various uncertainties but select the states (resource usage, inventory level) to react appropriately when unknown parameters unfold. The intelligent digital twin for process planning (resp. production planning and scheduling) will lead to production systems (resp. production plan and schedule) with the right level of agility. Finally, ASSISTANT will provide an intelligent twin for flexible process planning that accounts for quality. This tool assists the process engineer in selecting the resources and equipment of the manufacturing system, as well as the fine-tuning of the operation parameters, and deciding when and where to perform quality checks. Thanks to the availability of historical process plans and their resulting product/process quality, the user will be able to design a process plan that leads to high product/process quality and foresee alternative process plans in case of defects or machine breakdown. Also, the real-time controller will provide a real-time update in the production schedule and process plan in case of a defective operation or machine breakdown.

Our objective is not to have AI systems replacing humans, but humans working together with AI systems in optimal complementarity. In ASSISTANT, through the use of decision cockpits, wearable devices, and chatbots, humans will work in collaboration with the AI modules, intervene in the process without disrupting it and contribute seamlessly to the decision-making. The working environment will be human friendly, providing comfort and promoting cooperation to achieve higher efficiency levels in manufacturing. This goal will require an optimal distribution of workers and machines on the shop floor. More precisely, ASSISTANT will provide tools for supporting process engineers, the production managers, and the human operators. The process planning twin will assist the process engineers with the design of a reconfigurable manufacturing system, reducing the amount of expert work required to set up the system and account for quality issues and the workers' well-being. The production managers will be able to track the status of the process in real-time, also allowing them to validate recovery plans in case of unplanned events. In addition, the production planning and scheduling twins help to plan manufacturing operations. ASSISTANT's AI modules will automate these processes. However, the production managers can seamlessly interact, by entering targeted KPIs, and modifying solutions by hand based on the human experience that AI lacks and on information/knowledge absent from the computer system, resulting in efficient collaboration. Tools for support of human operators provide a clear view of the operation status and give the ability to interact with the process, allowing real-time decisions made by humans and better human-robot interaction. ASSISTANT's AI systems will reduce the strain on the human workers by balancing tasks between the humans and the other available resources. Particular focus will be given to allocating the strenuous and repetitive tasks to the robots, allowing humans to work on more delicate operations with confidence and comfort.

Our project's outcomes leverage AI to impact employment and quality of jobs positively and, at the same time, support the production of a legal and ethical framework for AI at the European level. Reconfigurable production systems are supposed to support humans in production but often lead to an increased required skill set, which can easily lead to stress and overstrain. ASSISTANT wants to solve these problems through AI-based methods by supporting and further including humans with individual skill sets. As a result, humans have a heightened awareness of critical and safety tasks in their job. This increases the on the job motivation due to an assistive system, and it results in better human working conditions and health. ASSISTANT aims to initiate the path of AI introduction into working environments and systems that enhance human capabilities and empower individuals and society while respecting human autonomy and self-determination. ASSISTANT will mobilize a research landscape far beyond direct project funding, involve and engage European industry, reach relevant social stakeholders, and create a unique reference point within the AI4EU ecosystem that provides a manifold return on investment for the European economy and society. ASSISTANT will contribute to building a unique framework in which industry, SMEs, and academics in the manufacturing arena can understand and apply the trustworthy AI guidelines requirements as an actionable plan from the company's workers to the business units.

The paper is an extension of Beldiceanu et al. (2021), and it successively presents the objective and the main vision of the project in section 2, a state of the art in section 3, the main scientific building blocks of the project (section 4, a discussion (section 5), and a conclusion (section 6).

2. Objective of the project

This section describes the current industrial challenges before providing the main concept of our project.

2.1. Challenge for industry

The manufacturing industry is undergoing a paradigm shift from mass production to mass customization and more recently mass individualization. As a result, companies tend to increase the size of their product assortments, launch new products more frequently, and constantly adjust their production processes (acquire new equipment). In this context, their survival depends on their reconfigurability, adaptability, and flexibility. This paradigm shift has led to technological advances (such as reconfigurable manufacturing systems and adaptable factories), where resources can be removed, added, and replaced quickly. To manage such agile production systems smoothly, manufacturing companies are increasingly adopting information technologies to have a complete and accurate view of their processes on the shop floor. Such technologies are often referred to as the "internet of things" (IOT), and they include: RFID, various automatic sensors on machines and products, and manufacturing execution systems, among others. In addition, simulation tools that accurately describe the configuration of the system are available for reliable offline testing without disturbing the online physical environment.

ASSISTANT aims to rely on recent advances on optimization, simulation, predictive analytics, prescriptive analytics, and machine learning to help manufacturing companies from various sectors to reduce costs, increase product and process quality, shorten unplanned downtime, and increase production throughput.

ASSISTANT aims to tackle the following manufacturing challenges:

(1) Complex production planning challenge: production planning is more and more complex because the number of end items and components increases, and accounting for the capacity of flexible resources is difficult. In addition, with the constant changes many parameters (e.g., demand, processing times, component arrival dates) vary significantly, and they are difficult to forecast accurately.

(2) Product and process quality challenge: the lack of regularity and consistency in the production process makes it difficult for manufacturers to ensure product/process quality. In addition, new tools and equipment are frequently acquired or modified, and their performance is difficult to predict.

(3) Hyper dynamic worker challenge: manufacturing systems are more and more robotized, and most systems will become hybrid with humans and machines. Typically, robots handle the regular flow, whereas operators bring flexibility. In such a system, workers become hyper-dynamic, and they are more exposed to injuries.

(4) Unsustainable industrial practices: the manufacturing industry must address environmental and social challenges. While industrial practices have focused on economic performance, more and more industries consider sustainability assessment methods and indicators to alter purely economic-based strategies.

2.2. The intelligent digital twin concept

ASSISTANT aims to provide a set of related AI-based, explainable intelligent digital twins that help process engineers and production planners to operate collaborative production systems based on the data collected from IoT devices and external data sources (see Fig 1).

As observed Fig 1, the data are perceived from sensors in the factory and external sources, creating a real-time digital image of the factory. Second, the reasoning step includes the three decision models (process planning/production planning/scheduling) built from the real-time image of the factory, as well as advanced prescriptive analytics techniques to create the plans that can be validated through simulation. Third, the plan is then executed through a real-time control module. The blue arrows in the above Figure represent this virtuous data circle, whereas the black arrows illustrate the feedback loops between the twins.

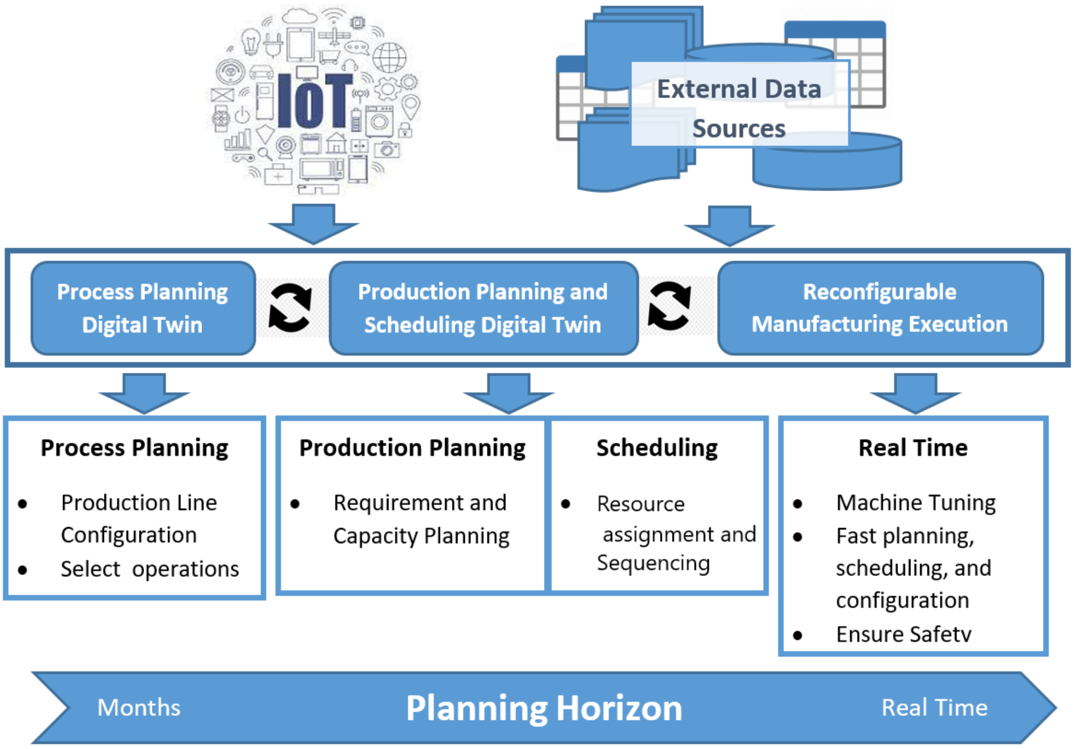

Figure 1. Set of interrelated twins for decision aid

- Such a tool will be based on the synergy between digital twins and machine learning to synthesize models for manufacturing
- In addition, the system monitors the production resources in real-time, ensuring that all required resources are available, and allowing fast re-planning when necessary.

ASSISTANT aims to make sustainable effective decisions while ensuring product quality, the safety and well-being of workers, and managing the various sources of uncertainty. The resulting intelligent digital twin systems will be data-driven, agile, autonomous, collaborative and explainable, safe and reactive.

These intelligent digital twins enhance advanced planning systems with machine learning and data analytics not only to predict the values of uncertain parameters based on data available from the shop and external sources, but also to enhance the accuracy of the decision models by learning the behavior of a constantly changing shop floor, and to estimate conditions outside normality that could cause problems.

Following recent trends, we can undoubtedly predict that future manufacturing systems will be highly digitalized and reconfigurable with hyper-dynamic workers. Consequently, ASSISTANT focuses on factories with production processes, and assembly lines where multiple product variants are processed and where digital twins already partially exist. Such production systems are composed of multiple stations, where the resources (workers/robots/tools) can move from one station to another.

The following intelligent twins will be developed:

- The process planning twin helps the process engineer design a manufacturing system that can be re-configured while maintaining a high level of product/process quality and without escalating costs. This twin computes the possible process plans, and it selects the possible configuration of the shop floor. The goal is to design a factory with enough configurations to deal with the various scenarios of future demands. Machine learning approaches may automatically detect the resources and equipment able to perform a certain process. Besides the ability to perform a task, the tool may predict the speed and quality associated with a process plan. We will use AI methods to analyze the data and to evaluate the specific process plans. The goal is to develop AI techniques to predict the quality and efficiency of a process plan. The resulting prediction model will be included in the optimization algorithm to find a process plan that respects the takt time, quality requirements, and other KPIs.
- The production planning twin helps the production manager to operate an agile factory. This intelligent twin adjusts the production capacity to the demand (specifies the shop floor configuration, sets the worker requirement, subcontracts labor, sets number of functional assembly lines), and places the orders of components with the suppliers. In addition, this twin accounts for various sources of uncertainties such as demand, production defects, process durations, etc.
- The scheduling twin allocates the operations to the resource, and it assigns a precise moment to perform each operation.
- The real-time control twin executes the plans on the manufacturing systems in real-time. It incorporates a hierarchical modelling approach to represent the resources and their capabilities virtually, as well as the manufacturing tasks that need to be executed. During the manufacturing process execution, this model synthesizes real time sensor data coming from cameras, laser scanners, force sensors, creating an enhanced model with autonomous, CNN based, 3D semantic mapping. Based on this real time reconstruction of the environment and the process, the intelligent twin detects anomalies in the process and products, and it updates the parameters of the equipment when required. For instance, time series analysis can be extended to consider data streams from captors on the machines. As a result, this twin can detect correct machine cycles, and it can detect situations leading to product or process quality issues. In addition, the twin detects deviations from the plan and triggers feedback to other twins to update the plans when required. Finally, machine learning tools detect dangerous situations, modifying the settled actuation of automated resources when required.

These aspiring digital twins will have the following characteristics:

- Data-driven: The twins will ensure a continuous link from the data generated by IoT devices to the decision aid tools and decision-makers. Data availability is one of the main challenges for the use of AI in manufacturing, and we will develop a data fabric for automatic data cleaning and reconstruction to manage the full life cycle of the data. In addition, the data fabric uses domain knowledge to integrate data from heterogeneous sources: IoT devices, industrial data, and market data (e.g. demand, energy prices). The data allow a precise estimate (and continuous updating) of the model parameters and their variability.
- Self-adaptive: The intelligent digital twins will self-adapt based on feedback from the shop floor, past simulations, and user interactions. ASSISTANT will investigate the possibility of automatically enhancing the prescriptive analytics models by using AI adaptive representations. For example, decision-makers often modify solutions suggested by decision support systems manually. Algorithms will be developed to learn these modifications to adapt the models.
- Collaborative: The intelligent twins offer graphical interfaces to help process engineers and production directors make decisions through generative design, with tools to visualize the solution pace, tools to compare different solutions, and chatbots. In addition, the real-time digital twin helps workers input and visualize the tasks to perform by means of wearable devices (augmented reality glasses and smartwatches).
- Explainable: Human planners will remain responsible for all significant decisions. Thus, decision aid models need to be explainable. More precisely, despite the constant automated changes in the decision aid models, humans will continue to understand and visualize them. Finally, the user will be able to interact easily (e.g., add constraints, modify decisions) through the generative design approach.
- Ethical-by-design: Responsible AI considers the process in which AI is developed, incorporated, and its interactions with human operators. ASSISTANT will be ethical-by-design and ethical-in-design. These ethical design approaches ensure compliance, security, data protection, privacy by design, fairness - including gender, race and religious aspects of operators - and explicablity through formal analysis and representation of regulatory principles as well as incorporating the stakeholder's inputs in the solution. Furthermore, "ethical in design" aims at developing and using AI in proper and verifiable ways.
- Safe, reactive, and easily integrated: due to an adequate selection of computation resources (cloud/fog/edge), the tool will allow the user to have control over the resources used for computation in such a way that confidential data remains within the company's premise, or circulate in an encrypted fashion to fog or cloud computers.
- Autonomous: The intelligent digital twin network autonomously actuates the decision validated by the decision-makers. Moreover, a control loop may suggest to the user to: (1) replan the production when the current plan is not implementable; (2) reconfigure the production system when the production capacity is not adapted to the demand.

Fig. 2 illustrates the concept of ASSISTANT. The architecture of the intelligent digital twin networks follows the classical three-step framework (perception, reasoning, actuation). The figure is related to Fig 1 by considering that the perception (IOT and external sources) and the actuation (actions based on the process planning production planning, scheduling, and real time components) are linked to the digital twin components. The linkage between the digital twin and the actuation components (i.e. factory components) is through the reasoning performed by using the accumulated information and reality representation. Further explanations of the perception, reasoning, and actuation components are described next.

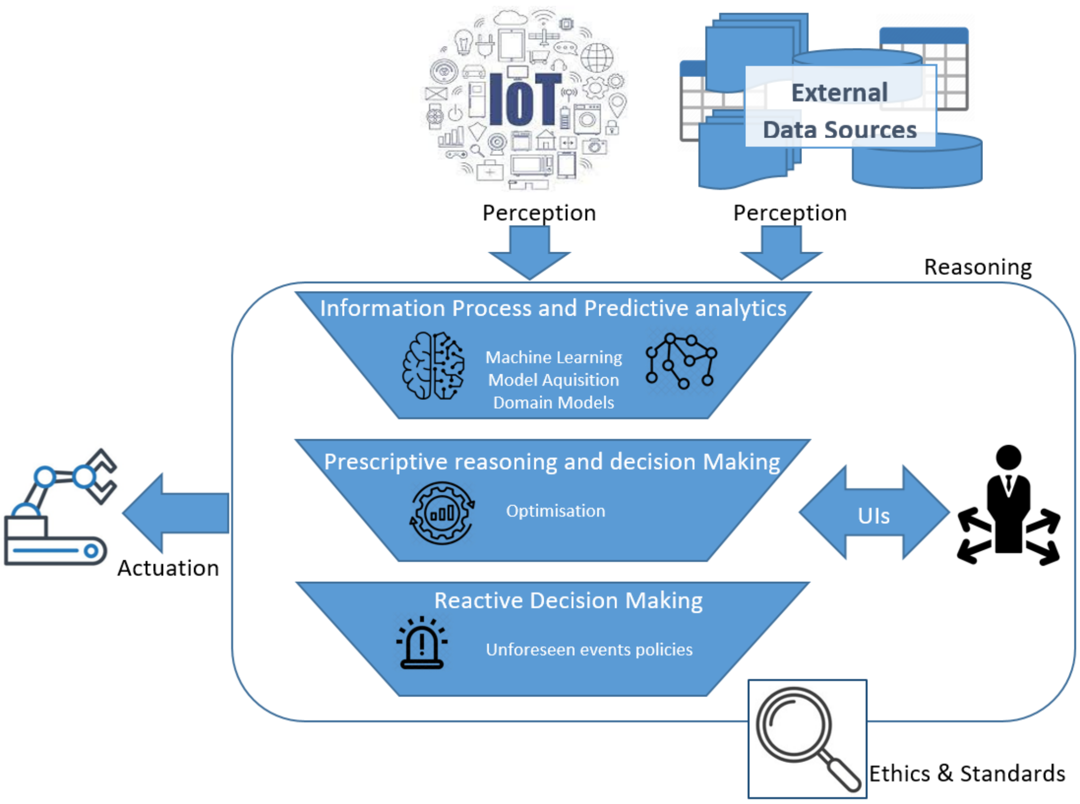

Figure 2. Concepts of ASSISTANT

(1) Perception: The real time perception of the factory is achieved through data capturing by various sensors. The source of data varies from Internet of Things (IoT) devices and Enterprise Resource Planning (ERP) data to the data captured from the intelligent digital twins. Once captured, those data are cleaned, structured and stored. Then, the useful data are integrated in ontologies reconstructing the real time scene of the shop floor. Finally, a set of simulation tools, such as discrete event and multi-body simulation, are used to enhance the factory perception by modelling the manufacturing system behavior.

(2) Reasoning: This component incorporates the following three steps:
   (a) During the first step, the goal is twofold: a) to provide valuable predictions for the future state of the manufacturing system in factory, production line and resource level, and b) to assess the feasibility of a production plan in terms of operating parameters and safety. To achieve that, information processing and predictive analytics are implemented to learn the future process parameters such as duration, resource availability, etc. On top of that, user experience, related to stochastic parameters (e.g., the varying demand profile), is captured and methods such as probability distribution is used to model the uncertainty of such parameters.
   (b) The second step facilitates the decision-making process utilizing prescrip-

tive analytics based on an optimization data-driven model. Techniques such as constraint programming are used in this step. The data-driven nature of the model relies on the usage of the data available in the real time factory digital twins that are automatically updated based on the changes in the shop floor. The explicability of the decision-making tool is achieved through the deployment of a visualization interface. Thanks to this interface, inexperienced users can assess the model and modify it based on their experience, if needed. AI methods such as search based heuristics and meta heuristics and optimization methods are used to generate optimal decisions considering the factory uncertainty. Through the visualization interface the user can study the suggested plan and filter the solutions by tightening the targeted KPI values. Then, the selected solutions are validated through the virtual factory simulation. While the simulation is negative, the models are iteratively enriched through model acquisition techniques to learn to represent the reality of shop floors better.

   (c) The final step focuses on reactive decision-making in terms of generating strategies to react in a fast and efficient way to unforeseen events. These strategies vary from simple decision rules easily understandable by the production manager, to fast re-optimization techniques based on the model designed in step (b), or black box neural network policies.

(3) Actuation: After the validation of the generated plan, the real-time-control module dispatches the scheduled tasks to the resources involved, including robots, machines and human operators. Dedicated interfaces to each resource are deployed to enable communication with the machine and robots, while wearable devices are used to include the human operators in the loop. The execution of the schedule is continuously monitored to track the progress and detect unexpected events that may occur. In the latter case, the actuation attempts to re-schedule the remaining work. An automatic alert is triggered if the schedule cannot be modified autonomously, and human intervention is needed. The data captured by the real-time-control module are used to update the real time digital reconstruction of the factory.

3. State of the art

As ASSISTANT is a multi-disciplinary project, we provide below a short state of the art in the main fields of the project, and we explain how this state of the art must be extended to realize the vision of our project.

3.1. AI for high level manufacturing decisions

The adoption of data-driven modeling and the underpinning use of IoT and machine learning technologies are widely considered to have revolutionized the manufacturing industry. However, adoption and market penetration are slow and often incremental. For example, ML techniques for smart manufacturing processes have been demonstrated in shop floor control (Wang & Jiang, 2019), predictive maintenance (Yam, Tse, Li, & Tu, 2001), and online scheduling (Hammami, Mouelhi, & Said, 2017), among other tasks.

In general, the incorporation of Machine Learning or Artificial Intelligence (AI) components in manufacturing can be characterized by autonomous intelligent sensing, interconnection, collaboration, learning, analysis, decision-making, and execution of human, machine, material, environment, and information processes in the whole system and its life cycle

Even though a direct adaptation of AI components could be made in the industrial sector, several technical, ethical, legal, and security challenges need to be overcome.

At a higher level, these challenges include: (1) the need of processing data at speed, (2) the need for skilled human resources who are able to operate and understand AI techniques for supporting the acceleration of executions on heterogeneous systems, (3) the ethical dimension of using AI in manufacturing environments, and (4) the legal requirements that define a framework in which AI components can operate and construct a dimensional landscape where the manufacturing sector can provision or use techniques to fulfil internal and external needs.

At a lower level, challenges are different depending on the domain of application and functionalities involved.

Key challenges include the complexity of aggregating and analyzing data in general, yet meaningful, ways. In the bigger picture, ML and data analytics have not been sufficiently explored for manufacturing system design, production planning, nor scheduling, Shang and You (2019). Recently, to address such challenges, programming abstractions based on regular expressions and quantitative aggregation iterators were formalized to synthesize a safe code with performance guarantee: Abbas, Alur, Mamouras, Mangharam, and Rodionova (2018); and optimization components (Beldiceanu, Carlsson, Douence, & Simonis, 2016).
ASSISTANT contributes to the use of AI methods for high-level manufacturing decisions such as process and production planning. The resulting approaches will provide the right level of reconfigurability since they hedge against uncertainties well characterized through machine learning. Unlike most existing black-box AI methods, ASSISTANT relies on the acquisition of explicable models. To overcome the challenge of data acquisition, data cleaning, and data confidentiality (which are related to the higher-level challenge of processing data at speed) , ASSISTANT provides a standardized data fabric, building on technology-neutral and highly efficient communication patterns, it supports instrumentation and integration of diverse legacy systems, as well as the use of distributed (edge/fog/cloud) computing resources for analysis and training on data. Building on the data fabric and the interconnected digital twins, we will adapt the framework to the manufacturing context, and improve the design and operation of production systems.

To overcome the challenges related to the ethical dimensions, as we will describe later on, specific approaches built into responsible AI considerations are included.

3.2. Acquire robust optimization parameterized models

Discrete optimization relies on models that are typically executed by solvers, e.g. Mixed Integer Programming, Constraint Programming solvers. Technology independent modeling languages like MiniZinc (Nethercote et al., 2007) incorporate global constraints as building blocks (Beldiceanu, Carlsson, & Rampon, 2012) to come up with concise models. While usually built by experts, a recent new line of research tends to acquire models from data Bessiere, Koriche, Lazaar, and O'Sullivan (2017); Kumar, Teso, and De Raedt (2019), where global constraints are used as a learning bias to acquire models from a limited amount of data (Beldiceanu et al., 2016).

ASSISTANT intends to advance the state of the art of model acquisition in two ways. First, we will address the question of learning parameterized models that can be transposed to several situations, i.e. a model should not become invalid if we add/remove a machine: in the context of manufacturing, typical parameters are numbers/type/capacity/speed of machines, task characteristics, cost matrices and dependency graphs. Second, we will initiate a line of research where model acquisition interacts smoothly with digital twins to converge to more realistic models. It has been shown that discrete optimization models have a strong structure which allows one to acquire models from a restricted set of samples, Beldiceanu et al. (2016). To get more realistic models we aim to integrate digital twins into the learning process in a smart way: rather than considering the huge amount of simulated data generated by a digital twin, we plan to use active learning, Bessiere et al. (2017), to query digital twins in a focused way in order to converge to more robust models.

3.3. Machine learning to learn digital twin's parameters and uncertainties

The digital twin has been introduced as a virtual representation of real objects (Glaessgen & Stargel, 2012). In a manufacturing context, the digital twin is composed of interconnected physical and functional models of resources, products and systems. The purpose is to improve production by carrying out autonomous decision-making in planning and operation (Boschert & Rosen, 2016). Feedback of the information and decisions to the previous planning phases are part of the concept Kahlen, Flumerfelt, and Alves (2017). The concept envisages a production-phase-spanning use of the resulting models and information in different software tools for increased flexibility and closed-loop operations. Digital twins were first introduced for product design by using CAD models and simulations. Later, the concept was extended to planning, operation and maintenance (Funk & Reinhart, 2017; Ivanov, Dolgui, Das, & Sokolov, 2019). Digital twins consist of multiple models from various domains. These domain models focus on conceptual modeling of a complex problem domain in order to gain better understanding. Languages such as UML and SysML permit automatic translation to executable/analyzable models. To tackle a specific domain idiom, domain-specific languages (DSL) were created, (Kelly & Tolvanen, 2008) . Major industry software providers such as IBM, ORACLE and SIEMENS already offer digital twins (e.g., Watson Internet of Things), that incorporate a machine learning aspect, especially in the context of IoT. Similarly, domain modeling is useful for many AI tools, e.g. TensorFlow (Abadi et al., 2016).

As ASSISTANT needs to deal with the complex, heterogeneous domains (i.e., several aspects of production lines), we will start from the above-described approaches combining AI and domain modeling. Contrary, to existing twins who use ML primarily for specific prediction tasks, we will enhance digital twins with machine learning for prescriptive analytics in manufacturing to make decisions leading to flexible and robust manufacturing decisions in the design, operation, and real-time stages. Furthermore, we will use human-understandable AI, by incorporating white-box modelling techniques in domain modeling, including behavioral models of schedules, machine behavior. Another aspect is that these domain models and AI algorithms explicitly need to take into consideration uncertainties. Therefore, we will extend domain modeling languages to support the modeling of uncertainties. In addition, we will use digital twins to produce more realistic explicable decision aid models based on reinforcement learning (e.g., learning physical restrictions) that optimize the entire process globally.

3.4. The extension of generative design to all manufacturing decisions

We would like to be able to generate suitable/optimal process plans, production plans, schedules, etc. In order to explore the possibilities in an automated way, we need to be able to model the "design space", i.e., the possible production plans, schedules, etc. This is a research challenge, given the multitude of domains that are joined in a manufacturing system. We tackle this challenge by creating a domain model that covers this design space (see also the citations). This domain model serves as input for both coarse grained learning (structure of the model, i.e., execution order of schedule), as well as fine-grained learning (i.e., learning exact parameter values).

Coarse grained "learning and inference" (in fact not an ML approach) will be done by optimization algorithms. For examples:

- determining an optimal process plan or schedule based on cost, throughput etc. This uses optimization algorithms based on a decision problem in combination with cost/throughput/... simulation
- determining an optimal schedule. This uses an optimization that heavily relies on uncertainties (availability of an operator, chance of breakdown, etc.).

Fine grained learning and inference will be done to determine model parameters. For examples:

- statistical analysis of historical data to determine distributions representing uncertainty.
- estimation of parameter distributions. This is achieved based on statistical analysis of the historical data. Parameters can be predicted using e.g., Bayesian networks.

The process of developing such AI solutions will be supported by a knowledge graph that contains a domain model and links it to data, models and other existing artefacts within a manufacturing context. This knowledge graph can be explored and queried for data, information, models. Examples are:

- scattered data can be easily queried to perform statistical analysis. The results can be stored as parameters with uncertainty in the knowledge graph (e.g., likelihood of a machine breaking down as a probability distribution).
- a Bayesian network can be extracted from the parameters in the knowledge graph that are modelled with uncertainty.
- a process plan outline (what resources, skills, tasks, etc. exist) can be extracted to serve as input for finding an optimal process plan.

Generative design is automated by a technique called computational design synthesis (CDS), (Chakrabarti et al., 2011). CDS aims at assisting designers through rapid exploration of the space of possible designs. The use of CDS in the early conceptual design phase requires the use of abstractions and formal models, and builds on domain modeling (Helms, Shea, & Hoisl, 2009) and DSL, in particular for the design of manufacturing/assembly lines, (Herzig, Berx, Gadeyne, Witters, & Paredis, 2016). The methods return optimal solution with regard to cost and throughput, outputted as formal architectural models. To the best of our knowledge, generative design has only been used to design products and production systems. We will extend the use of generative design to production planning and scheduling, allowing the user to specify targeted KPI, while the software returns solutions within a specified range.

3.5. Data driven optimization in manufacturing

Automatic decision support in tactical and operational manufacturing decisions relies on optimization/operation research techniques. With the development of computing technologies, software providers started to propose Advanced Planning Systems (APS) (Stadtler, 2005) to model the production process. The future of APS lies in the incorporation of data analytics techniques, to represent the possible values that uncertain data can take better, (Thevenin, Adulyasak, & Cordeau, 2021). Techniques to include data analytics into the linear program classically used in APS have been developed (Bertsimas, Gupta, & Kallus, 2018; Thevenin, Adulyasak, & Cordeau, 2022), but their application in manufacturing remains scarce (Zhao, Ning, & You, 2019). While APSs have a large added value for companies, they remain largely under-utilized because of their costs, and because it requires qualified planners to ensure the APS receive accurate data, and to analyze the output of the plan.
Similarly, many approaches have been developed to design conventional manufacturing lines, they can be adapted or replaced to meet the new challenges posed by reconfigurable manufacturing systems (Hashemi-Petroodi, Dolgui, Kovalev, Kovalyov, & Thevenin, 2020; Koren, Gu, & Guo, 2018; Yelles-Chaouche, Gurevsky, Brahimi, & Dolgui, 2020). While different approaches have been developed to use the flexibility of RMS efficiently by automatizing process planning (Battaïa, Dolgui, & Guschinsky, 2020), the issues of designing reconfigurable lines have not yet been sufficiently studied.

On the one hand, the discrepancy between the data used by the system and what is happening in the company leads to poor decisions from APS. In ASSISTANT, the intelligent digital twins make decisions based on real-time data. On the other hand, historical data analyzed with machine learning techniques allow predictions about the values of various unknown parameters to be obtained. We aim to integrate the resulting characterization of the uncertainties of such parameters to create plans that are robust to the uncertainties. Finally, to be aligned with the requirements and changes of the shop floor ASSISTANT aims to develop a tool to automatically build the scheduling models based on data. ASSISTANT will provide a method to design reconfigurable production lines with the right level of reconfigurability, while maintaining the required product/process quality. This will be achieved by using data analytics techniques to build the uncertainty sets, and by using machine learning to learn the implication of a process plan on the quality of the products and process.

3.6. Human interaction and safe human-robot collaboration

There are more and more robots in the manufacturing industry, and they take over regular the regular flow of operations, whereas human workers handle the production peaks Thevenin, Mebarki, and Chatellier (2021). In this context, the human factor plays a crucial part in manufacturing systems (Hashemi-Petroodi, Thevenin, Kovalev, & Dolgui, 2020). As such, robotic support of humans for a collaborative assembly greatly enhances those systems (Michalos et al., 2014). There are several industrial applications regarding humans in manufacturing systems, e.g. BMW and Audi AG introduced cooperative robots to work near human operators in Spartanburg and Ingolstadt plants. Indirect Human Robot Collaboration (HRC) is achieved by various human detection applications Liu and Wang (2017); Lv, Feng, Ran, and Zhao (2014), while direct HRC can be achieved through the use of wearable devices that provide real-time data Michalos, Karagiannis, Makris, Tokçalar, and Chryssolouris (2016). Apart from some small-scale experimental installations where humans have a more active role, most of the above applications have not reached the production site.

ASSISTANT aims to improve the support of the human operator both in the context of indirect and direct interaction with robots: i) we aim at more reliable human recognition than previous applications, extracting the human's status and intentions in order to adapt to their behavior, entering a ii) direct interaction state when required: wearable devices, such as AR glasses or smart watches will provide a set of sensors giving input data for deep learning methods to extract models of humans' status and intentions. ASSISTANT will comply fully with ethics requirements concerning human safety in collaborative manufacturing systems.

3.7. Sustainable metrics in manufacturing companies.

Manufacturing companies measure managing metrics (KPIs) related to each sustainable pillar, namely economic, environmental, and social components. The optimization at the different levels (e.g. strategic, tactical, or operational plan generation) will account for these sustainability pillars, and the company's stakeholders will fix the levels of participation of each pillar.

Manufacturing companies have broad know-how in expressing their interest on economic representative KPIs. These KPIs will be evaluated based on the net benefits associated with the decisions, which are linked directly or indirectly to objective functions variables established in the optimization processes,

The social perspective KPIs will be evaluated based on, but not limited to, the ethical frameworks. These KPIs are fundamentally based on Organizational values-based KPIs, Ethical requirements based KPIs (i.e., derived from the European Trustworthy guidelines), Risk-based AI considerations linked to the social pillar and other socially based considerations and constraints that do not violate regulatory considerations specified by the previously defined instruments.

Finally, the environmental perspectives will be evaluated based on standardized tools or KPIs correlated to environmental concerns. Different approaches and metrics are currently used in the manufacturing sector (e.g. Life Cycle Assessment) that enforce the use of energy sustainable features, such as carbon emission and energy consumption. Therefore, our approach seeks to include such metrics during the reasoning processes.

4. Main scientific building blocks of the project

This section describes the tools requires to realize our vision. As shown in Figure 3, the framework requires the following components: (1) definition of an ethical-by-design architecture; (2) design of a data fabric leading to a real-time digital picture of the manufacturing system; (3) creation of a data orchestration ensuring data safety and short-latency; (4) creation of a human-centric framework; (5) development of predictive analytics tools to estimate uncertain parameters; (6) creation of self-adaptive data driven mechanisms and architecture in each intelligent twin; (7) development of decision aid algorithms for robust and agile planning; (8) development of an AI-based controller for actuation and reactive decision for real time control.

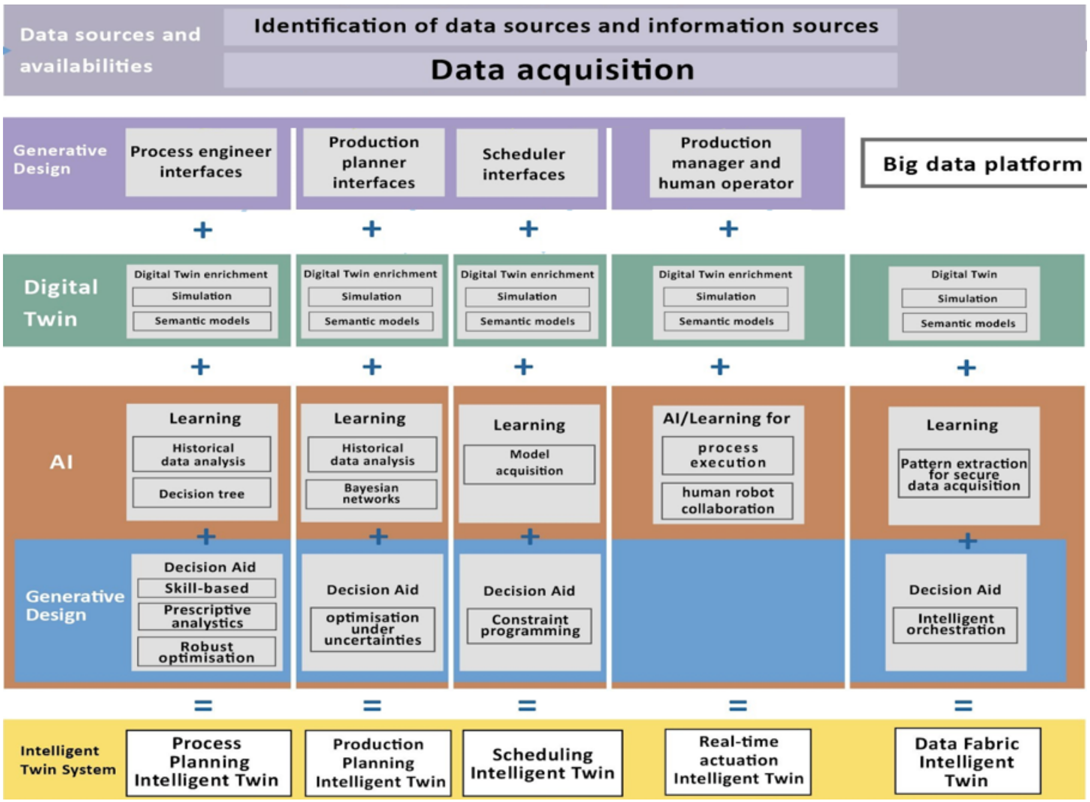

Figure 3. The set of tools required to build the ASSISTANT concept.

4.1. An ethical-by-design architecture

AI components can be developed and deployed under different criteria which have diverse impacts on the functionalities and legal concerns involved. These criteria lead to diverse opportunities to incorporate responsible considerations on AI components under different scopes. One scope involves components that can be built, deployed, and integrated under some pre-specified concepts or approaches (e.g. ethics) to embed, indirectly, the element with the specified concepts or methods (i.e. in-design). Another alternative implies that the component will be built with intrinsic capabilities or strategies that are part of the concepts or approaches of interest (i.e. by-design). Finally, the concepts can be specified as part of codes, standards, and regulations that ensure the integrity of the different components and stakeholders under the umbrella of selected considerations (i.e., for-design).

The ethics by-design approach includes best practices that include ethical or responsible deliberations already in the design process. These practices include organizational aspects (e.g., establishing an ethics board) and suggestions for the actual process. Therefore, what is to be achieved, at a design level, is supported by ethically driven decision routines that are integrated into the AI systems. By integrating these routines (by-design), the incorporation of ethical considerations (as those defined by ongoing requirements or strategies – e.g. trustworthy requirements) and values (that include those derived from manufacturing goals and considerations) within a technical architecture design process can be performed.

To operationalize this process, specific strategies and considerations should be defined at the beginning of the development process. In our case, these considerations are driven by the use of human-centric considerations, the ART principles, and those derived from EU requirements and regulations (e.g., AI act and Trustworthy requirements). In ASSISTANT, the main strategy used to define the scope of the integration of responsible AI considerations implies the fulfilment of a human-centric approach within the architectural definition. To do this, first, a technical definition of what is proposed to be built must be defined. This technical definition is constructed by a set of requirements established by each digital twin component within ASSISTANT. Then, the integration of responsible AI considerations is performed in a recursive process, allowing modification of the defined technical architecture.

To gather the requirements within the project, an integrated-requirements engineering methodology is proposed. The foundations of the methodology are formed by the stakeholder's current processes and practices. To secure the acceptance of ASSISTANT by its end-users, all stakeholders are involved in the design of the ASSISTANT architecture and, therefore, in the definition of the current processes and practices. The current practices reflect an image of current processes and contain several challenges. These challenges constitute the major drivers for the project and, ultimately, the foundation for the requirements. Two main types of requirements are distinguished, the end-user requirements and the IT requirements.

The end-user requirements are points of improvement and are valid for the whole project. They represent the main business drivers of the project, and need to be satisfied by the project outcomes. The IT requirements are based on the use cases desired scenario, and target the development by specifying software and hardware functionalities. The requirements are obtained by performing a deep analysis of the users' needs (production managers, process engineers, but also workers), based on interviews, questionnaires, and on-site workshops. The information about current processes, main problems and their underlying causes, KPIs for decisions, as well as ethical concerns on the use of AI in manufacturing is collected. The current situation of process and production planning, scheduling, and real-time control is analyzed. Then the requirements for the intelligent digital twins are established.

Based on these requirements, the global architecture is designed. The role of the overall architecture of ASSISTANT is to provide a framework for individual sub-architectures to collaborate in a common cause. The key for this approach is to introduce interoperability (i.e., information, technical, and visualisation interoperability) on the different sub-architectures.

Once the technical architecture is defined, the recursive process for integrating modifications that secure the human-centric considerations is implemented. In addition, ASSISTANT considers aspects that are preconditions for ethical conduct on accountability and effective, meaningful transparency. Therefore, we will carefully select the programming language level, foreseeable system behavior, API design, and interfaces. The architecture should also ensure stakeholders transparency, accountability, and foreseeability. Moreover, ASSISTANT incorporates requirements imposed by positive laws on fundamental rights protections such as the General Data Protection Regulation, non-discrimination legislation, labor law, among others. ASSISTANT then observes legal obligations that are democratically legitimated and enforceable under the Rule of Law.

4.2. The data fabric

To provide a unified platform for data management and storage, ASSISTANT realizes an intelligent data fabric that provides data structures, domain models, and communication subsystems to abstract underlying technical heterogeneities and connecting manufacturing, IoT, and AI systems in a shared communication system. Conceptually, the ASSISTANT data fabric can be seen to be composed of three parts: a live data streaming architecture, a storage architecture, and a domain-model based integration architecture. The live data streaming architecture (which is based on the Streamhandler platform developed by INTRASOFT) is responsible for integration with external equipment, data acquisition, and live data streaming. For the data fabric, Streamhandler acts as an intermediary and data acquisition front-end that provides stream processing capabilities and integrates the storage architecture part of the data fabric through data stream connectors. The storage architecture defines a service-oriented architecture for data storage, management, and composition where data of different types (e.g., structure, unstructured, and time series based) are efficiently stored and tagged with metadata for classification, search, and processing.

As part of the data analysis tasks, ASSISTANT will develop pattern recognition tools based on constraints to detect and clean missing or unreliable data, and the storage architecture provides light-weight data processing capabilities through a flexible plug-in system where plug-in tools can be triggered explicitly or reactively (e.g., based on the presence of metadata tags in new data sets). In the integration layer, which serves to provide a context-oriented interface to data and data storage systems, an ontology architecture for integration of data from various internal sources (captors that monitor product and process quality, RFID, MES, ERP systems, etc.) and external sources (data from customers, equipment supplier, energy supplier, raw material supplier, outsourcer data, etc.), tailored for prescriptive analytics, will be developed. Such an ontology will differentiate decisions to be make, parameters of the system, and KPIs. Besides data, the digital representation will include simulation models (e.g., discrete event system, multi-body simulations) to incorporate the process operation rules. Combined, these three subsystems provide a flexible data storage management platform tailored to the type of data and context of the project - adaptive manufacturing systems.

4.3. Data orchestration intelligence

To facilitate the seamless integration and scalability required to process and manage the type and amount of data produced in agile manufacturing environments, highly capable communication platforms are needed. The ASSISTANT data fabric's storage architecture is designed as a flexible service-oriented architecture that can be dynamically managed through use of modern cloud native orchestration systems. Towards this end, ASSISTANT will develop a management system for the storage architecture composed of two parts: a simulation platform for evaluation of resource management strategies, and a set of AI based tools for autonomous orchestration of the storage architecture services.

Based on simulation and AI, the orchestration system can be conceptually seen as a digital twin dedicated to the management of computational resources (similar to the way the ASSISTANT digital twins manage manufacturing resources). The data fabric simulation engine models the data flows both the manufacturing systems and the digital twins, and the orchestration system incorporates statistical and machine learning tools to characterize and predict the workloads of the systems. Combined, these tools constitute a foundation for an autonomous resource management system capable of intelligent load balancing and decision support for storage management, e.g., through recommendations of how to make best use of the diverse resources of cloud edge computing landscapes. The system is also intended to incorporate scheduling and planning algorithms, as well as tools that allow predictive evaluation management strategy decisions.

The overall design of the orchestration system will be human-centric, and allow users to visualize where the data is sent and keep complete control on data flows and placement decisions. The platform will be based on established technology-neutral mechanisms such as JSON-based REST services, Google protocol buffers, and OpenSSL for secure messaging, and built on state of the art Python, R, and Matlab libraries for time-series and deep learning techniques, as well as providing interfaces that allow integration with modern resource management tools such as Kubernetes, docker, and Istio service meshes. Overlap and integration of the data fabric into existing management frameworks such as the I4.0 Asset Administration Shell and the Reference Architectural Model RAMI 4.0 will be studied in the project.

4.4. Human centric decision cockpits

In our intelligent twins, users will create process plans, production plans, and schedules through generative design approaches. Consequently, the cockpits provide chatbots, tools for plans visualization (including precedence graphs, process plans, Gantt charts, and production tables), tools to highlight the differences between various solutions, and interfaces to add filtering constraints describing the desired solutions. In addition, we will investigate the use of wearable devices to help inexperienced workers perform manufacturing operations or maintenance.

4.5. Predictive analytics tools

Ignoring manufacturing uncertainties leads to suboptimal decisions. Nevertheless, the inclusion of uncertainty increases the model complexity, and consequently computation time and memory consumption. Thus, the decision-makers must be able to select carefully the types of uncertainties to include in the prescriptive analytics. We distinguish the unknown and the stochastic parameters. The former might vary significantly, but their variance does not have a critical impact on the decisions (e.g., the diameter precision of a drilled hole). They are replaced by their estimates. ASSISTANT provides machine learning tools to estimate them as accurately as possible. The latter are included in the decision models because manufacturers want to hedge against them. ASSISTANT provides prescriptive analytics to learn the representation of uncertainty from measurements or domain knowledge which can be a probability distribution represented by its type (e.g., Normal) and parameters (e.g., mean, variance), a non-parametric Bayesian network, a convex uncertainty set convenient for robust optimization, fuzzy variables, etc.

4.6. Self-adaptive decision aid system

The state-of-the-art decision aid systems in manufacturing rely on mathematical optimization techniques to suggest decisions to the user. Such models are efficient and easy to explain, but not flexible. ASSISTANT will render them self-adaptive. Besides using accurate and up to date estimated parameters (including the various costs) from the domain models, ASSISTANT will automatically learn the business logic (the constraints). The automatic generation of models mostly concerns the process planning and scheduling twins, since the production planning models are generic enough to be implemented in most factories without modifications. In process planning, the required operations along with the necessary resource skills, are inferred from the CAD model. First, we extend the assembly by a disassembly method to manufactured parts. Then, a resource-skill comparison automatically infers the resources (internal or to be bought) able to perform a task. In addition, we provide tools (e.g., random forest) to learn the impact of a process plan on the quality of products and processes and on long-term costs and worker satisfaction. The resulting decision tree will be translated into mathematical optimization models to find the process plan with the required quality, cost, and worker conditions and satisfaction. For scheduling, ASSISTANT will provide a model acquisition tool that enriches basic scheduling models with learned constraints. As a reinforcement learning approach, model acquisition evaluates the feasibility of a proposed schedule with simulations. Based on the set of proposed schedules and their feasibility, model acquisition generates the tightest set of constraints that excludes all infeasible plans (schedules). Finally, for all digital twins, based on the set of proposed plans and final plans validated by the users, the model acquisition tools automatically learn additional constraints leading to the plans the user wants.

4.7. Decision aid for robust and adaptable manufacturing

ASSISTANT provides prescriptive analytics considering the uncertainty contained in the digital twin. This uncertainty can be represented by scenario samples or uncertainty sets. Then, a mathematical representation of the manufacturing system which includes decisions that are taken in a robust way to perform well on all scenarios. In addition, wait-and-see recourse actions for each scenario which allow reaction to foreseen probabilistic events are designed and optimized. Process planning will account for demand uncertainties, possible machine failures, etc. and consider recourse actions such as resource (human/robot) movements and modular equipment replacements. Production planning is mostly impacted by demand, lead time, capacity, and yield uncertainties. Recourse actions include express deliveries of components from local suppliers; subcontracting part of production; adjusting production capacity with temporary labor; reallocation of components that were reserved to end-items that can no longer be manufactured.

4.8. AI based controller for actuation and reactive decisions

ASSISTANT will provide an AI-based controller for safe actuation on the shop floor. Once the user validates the plan in intelligent process planning, production planning, and scheduling intelligent digital twin, the controller communicates these plans to the right resources (machine, robot, etc.). ASSISTANT will provide pattern recognition, deep learning, or statistical learning to detect situations leading to bad product quality, machine breakdowns, and deviations from the plan. If such a situation is detected, the controller reacts instantly. When simple adjustments are not possible, the plan is updated. To ensure the safety of the worker during process plan reconfiguration, robots we will use deep learning to detect obstacles as well as human presence and behavior.

5. Discussion

ASSISTANT encompasses research, development, and validation. With respect to research, the goal of the project is to:

(1) Provide a platform for different scientific communities (optimization, machine learning, and manufacturing) that allows them to address key challenges in a holistic way, such as robustness of systems, adaptability, and reconfigurability.
(2) Build on scientific advances in both statistical and symbolic machine learning. The goal is to cover the range of descriptive, predictive and prescriptive analysis using the most appropriate techniques. Finding correlations in data can be done using statistics (e.g., to find trends in a data stream). Based on such correlations, predictions can be achieved using a neural network (e.g., for predictive maintenance). Machine learning and discrete optimizations, implemented by e.g., constraint programming or mixed-integer programming, can be used for optimizing manufacturing systems (e.g., generating optimal production plans, optimal settings, etc.).
(3) Automate optimization analyses. In the current state, optimization software is used in a per-case manner (e.g., manual creation of production scheduling models) with some given assumptions. This is not adequate in a reconfigurable environment. We intend to generate models and software components from the available data.
(4) Employ digital twins as validation components for what-if analysis using AI. Digital twins offer a way to simulate scenarios correctly, hence supporting engineers in their decision process. In order to support this, ASSISTANT will design the communication between a digital twin and AI models, so that they can be more easily converted into operational and executable AI solutions.
(5) Create human-centric interaction with the AI system, where the reasons behind decisions or suggestions provided by the AI system are easily explained. Operations and engineers need to be kept in the loop of the output of digital twins and AI solutions by means of interpretable explanations.

With respect to development, the full life cycle of production systems is addressed going from the specification of a manufacturing or assembly line up to the execution of tasks in machines/workstations. The architecture manages the data throughout the all life cycle of system, and supports human-centric interfaces at several decision points.

ASSISTANT validates and applies its research by means of three concrete industrial cases, by Stellantis, Atlas Copco and Siemens Energy, as well as a demonstrator case by Flanders Make. A complete solution will be implemented for each case considered. This starts with data collection, creation of digital twins and usage of AI tools for decision support for process planning, production planning, production scheduling and real-time control.

All developed material including tools, demonstrations, use cases, architectures, algorithms, code, etc. will be made public after the project is completed.

The ASSISTANT research project fosters collaboration between researchers working in the fields of AI and experts in manufacturing. The ASSISTANT consortium is composed of Academics on AI ethics (UCC, EUV), AI and Edge Computing (UCC, BITI), AI and Optimization (IMT, UCC), Production Industry (LMS, FLM, TUM), as well as technology providers (INTRASOFT, FLM, SIEMENS AG), and manufacturers (SIEMENS Energy, ATLAS COPCO, PSA).

ASSISTANT aims to improve decision-making in manufacturing from the design of the manufacturing system, its operation management, and the control of its execution. To enhance these decision aid tools, we will use the massive amount of data generated on the shop floor to automatically acquire elements (constraints, objectives) of mathematical models and constraints programming models. These decision models will also account for uncertainties for the parameters that cannot be predicted accurately. As a result, the decision aid modules will automatically adapt to changes of configuration of the shop floor. In addition, the modules associated with each type of decision will communicate through a feedback process. Thus, the decision validated by the decision-maker will automatically be actuated on the shop floor. This set of modules yields an intelligent digital twin network, and its creation requires several breakthroughs:

- Developing tools to acquire optimization models by combining the recent in machine learning and digital twins;
- Investigating the use of machine learning to learn the parameters of the digital twin's model (simulation model, optimization models, etc.);
- Enhancing forecasting methods to predict a probability distribution of an uncertainty set rather than a single value;
- Extending the generative design approach to production system design, production planning, and scheduling;
- Investigating data-driven optimization to design assembly lines;
- Investigating stochastic programming for practical production planning problems;
- Developing AI system for safe, fence-less, human-robot collaboration.

The recent breakthroughs related to AI were provided by the GAFA, and they mostly aim to provide online customized services. Transferring these breakthroughs to the manufacturing industry is a challenge. The GAFA are early AI adopters who have large business models, AI is their core activity, and they acquired maturity in these technologies. In addition, these companies have access to a massive amount of data via their online services. On the contrary, the core business of the manufacturing industry is production. Manufacturers need dedicated software to address pressing issues on the shop floor, such as reducing production costs, increasing service levels, improving quality, detecting defects, improving safety.

While ASSISTANT focuses on improving manufacturing decisions on the shop floor, the idea of the project may be extended to other applications. This includes application to logistics where decisions include network design, warehousing, distribution, routings, and last-mile deliveries. Indeed, these types of applications are often solved with operation research models, and more and more devices such as GPS trackers and RFID tags, are used to track information. The ideas may also apply to services such as health care management, where decisions include the location of health care facilities and their capacity, the staffing, the assignment of patients to rooms and staff, nurse scheduling.

The ASSISTANT concept would also be valuable in a remanufacturing context. First, the process planning tool may be extended to deal with the design of a disassembly line in the remanufacturing context. The design of a disassembly line follows the same steps as in assembly, but there is a need for more flexibility to deal with the unknown quality of the disassembled parts. This quality issue may lead to random process duration, or even different operations depending on the state of the item. In this context, the digital twin for real-time execution could help select the right operation depending on the quality of the part discovered during disassembly. Finally, the intelligent digital twin for production planning can improve operations management in remanufacturing facilities. In particular, this tool may alleviate the issues associated with the uncertainty about the number of end-of-life items collected.

6. Conclusion

This paper outlines the objectives and the main approach of the European research project ASSISTANT (November 2020 - October 2023). Building on a generative design approach, ASSISTANT aims to produce a set of AI-based tools that support operators and actors of adaptive manufacturing environments and increase the flexibility, efficiency, and robustness of manufacturing environments. The ASSISTANT tools cover the entire cycle of manufacturing decisions, ranging from process selection to production system design, and include tools applicable at multiple time scales for detailed planning, scheduling, and real-time control of manufacturing. ASSISTANT produces a set of digital twins that are capable of adapting to manufacturing environments and promotes a generative design-based methodology where tools continuously retrain and learn from manufacturing data, and synthesize predictive and prescriptive models that adjust to the reality of the shop floor at multiple decision levels. The ASSISTANT digital twins are used in conjunction with ML to train models, predict parameters and characterize parameters, as well as inferring constraints for planning processes.

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