ASSISTANT: Learning and Robust Decision Support System for Agile Manufacturing Environments

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Abstract: The European project ASSISTANT concept will provide a set of AI-based digital twins that helps process engineers and production planners to operate collaborative mixed-model assembly lines based on the data collected from IoT devices and external data sources. Such a tool will help planners to design the assembly line, plan the production, operate the line, and improve process tuning. In addition, the system monitors the line in real-time, ensures that all required resources are available, and allows fast re-planning when necessary. ASSISTANT aims to make cost-effective decisions while ensuring product quality, safety and wellbeing of the workers, and managing the various sources of uncertainties. The resulting digital twin systems will be data-driven, agile, autonomous, collaborative and explainable, safe but reactive.

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

1. INTRODUCTION

We present in this paper the main scientific ideas of our new European project ASSISTANT. With a multidisciplinary consortium combining key skills in AI, manufacturing, edge computing and robotics (Assistant, 2020), the project ASSISTANT aims to create intelligent digital twins through the joint use of machine learning (ML), optimization, simulation and domain models. The resulting tools will help to design and operate complex collaborative and reconfigurable production systems based on data collected from various sources such as IoT devices. ASSISTANT targets a significant increase in flexibility and reactivity, product/process quality, and in the robustness of manufacturing systems, by integrating human and machine intelligence in a sustainable learning relationship.

AI challenges in the context of manufacturing. While AI is already a reality for the GAFA (Google, Apple, Facebook, and Amazon), it is not yet enough present in manufacturing. The GAFAs are using AI to deliver services to a large public, but manufacturers' business models and needs are quite different: they address small markets with dedicated products, which require specialized tools. While AI is already used to make low-level manufacturing decisions such as automated machine tuning or predictive quality, the project relies on predictive and prescriptive analytics to extend the use of AI to higher-level manufacturing decisions such as process planning, production planning and scheduling. As a human must remain responsible for making such high-level decisions, ASSISTANT will rely on the generative design framework to help users find the best plans. Generative design (Aameri et al., 2019) is an iterative design process allowing, "a user to specify goals expressed as objectives and constraints to a software application and the application returns a set of feasible and/or optimal design solutions". While the generative design was proposed in the context of product design, ASSISTANT aims to extend the use of this technique to other manufacturing decisions.

The use of AI within generative design requires reliable and real-time data. In manufacturing, such data is nowadays available in digital twins. Within ASSISTANT, the classical definition of a digital twin is seen as a *data fabric*, used by generative design techniques through machine learning to yield data-driven decisions. ASSISTANT will go beyond the traditional trial-and-error use of digital twins and generative design by:

1. Using machine learning to automatically develop part of digital twins from data from IoT/ERP/MES, and to model parameter uncertainties in digital twins.
2. Systematically organizing the cooperation between digital twins and machine learning tools to improve models.
3. Extending the idea of generative design while taking into account the synergy between machine learning and digital twins.

2. CHALLENGES FOR INDUSTRY

Current situation in the manufacturing industry. The paradigm shift from mass production to mass customization and mass individualization drives companies to launch new products frequently: their survival depends on their reconfigurability, adaptability, and flexibility to face various uncertainties. This has led to technological advances (such as reconfigurable manufacturing systems and adaptable factories), where resources can be rearranged, and replaced quickly. These new production systems must be simple, inexpensive, easy to maintain and update, and robust to hazards. AI is timely for helping manufacturing companies from various sectors to bring down costs, increase quality by reducing product defects, shorten unplanned downtime and transition times, and increase production speed.

ASSISTANT has been designed to tackle the different levels of manufacturing challenges:

1) *Complex production process challenge*: The large number of end items and components makes production planning extremely difficult. The constant system changes and variability lead to many parameters (e.g. demand, processing times, component arrival dates) that vary significantly and are difficult to forecast accurately.

2) *Product and process quality challenge*: The lack of regularity in demand makes it difficult to ensure product-process quality. With frequent system reconfigurations, new tools and resources are frequently acquired or modified, and the performance of these tools and their impact on the production system is difficult to predict.

3) *Hyper dynamic worker challenge*: As manufacturing systems become more and more robotized, most systems will be a hybrid with humans and machines, where robots handle regular flow and operators bring flexibility. This leads to the development of cobots where humans help machines. In such a system, workers are more exposed to injuries, and it is crucial to account for safety and ergonomics.

4) *Unsustainable industrial practices*: in the past, industrial practices have focused on economic perspectives. But the manufacturing industry now has to also consider policies, regulations and process restrictions to address environmental and social challenges. Sustainability assessment methods and indicators can be added at different levels of strategic decision-making, altering purely economic-based strategies.

3. STATE OF THE ART

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 2019), predictive maintenance (Yam 2001), online scheduling (Hammami 2017). Key challenges include the general complexity of aggregating and analyzing data in general yet meaningful ways.

The development of AI requires accurate and real-time data. This data can be taken from Digital twins. The digital twin has been introduced as a virtual representation of real objects (Glaessgen 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 2016).

The state-of-the-art/baseline tools for high-level decision-making in manufacturing (production planning, scheduling) 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 better represent the possible values that can take uncertain data (Thevenin et al., 2021). Techniques to include data analytics into the linear program classically used in APS have been developed (Thevenin 2020, Bertsimas 2018), but their application in manufacturing remains scarce (Zhao 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 APS receive accurate data, and to analyze the output of the plan.

Similarly, many approaches have been developed to design conventional manufacturing line, they can be adapted or replaced to meet the new challenges posed by reconfigurable manufacturing systems (Koren 2018; Hashemi-Petroodi 2020; Yelles-Chaouche 2020). While different approaches have been developed to use the flexibility of RMS efficiently by automatizing process planning (Battaïa 2020), the issues of designing reconfigurable lines are not yet sufficiently studied.

The human factor plays a crucial part in manufacturing systems (Hashemi-Petroodi 2020b). As such, robotic support of humans for a collaborative assembly greatly enhances those systems (Michalos 2014).

4. PROJECT OBJECTIVES

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).

⧫ 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.

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 from 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 reconfigurable with hyper-dynamic workers, and highly digitalized. Consequently, ASSISTANT focuses on factories with production processes, and assembly lines where multiple variants of a product 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.

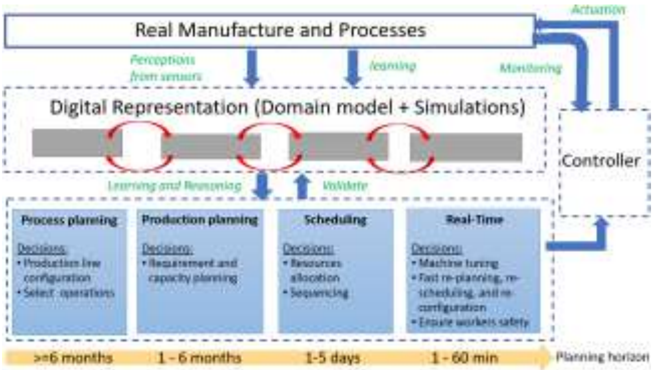

Fig. 1. Set of interrelated twins for decision aid

The following four intelligent twins will be developed:

- The process planning twin helps the process engineer to 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.
- The production planning twin helps the production manager to operate an agile factory. This intelligent twin adjusts the production capacity to the demand (specify the shop floor configuration, set the worker requirement, subcontract labor, set number of functional assembly lines), and place the orders of components to the suppliers. 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. This intelligent twin detects anomalies in the process and products, and it updates the parameters of the equipment when required. 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 situations that are dangerous for humans and modify the behavior of automated resources when required.

The twins will be data driven, self-adaptive, autonomous, collaborative, explainable, safe, and reactive.

Fig. 2 illustrates the concept of ASSISTANT. The architecture of the intelligent digital twin networks follows the classical three-step framework (perception, reasoning, actuation).

1) *Perception*: data are sensed from various sources: IoT devices, ERP data, external data, data generated by the developed intelligent digital twins themselves. This data is automatically cleaned, classified, and stored. Finally, these heterogeneous data are integrated into ontologies to create a real-time image of the factory and its environment. This replicate of the factory is enriched with simulation (discrete event simulation, multi-body simulations, ...) models that model the dynamics of the processes.

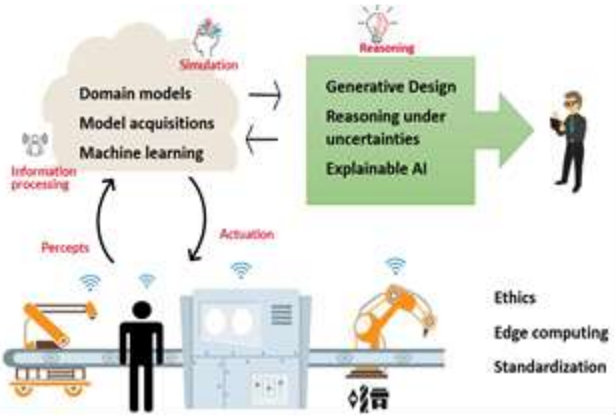

Fig 2. Concepts of ASSISTANT

(2) *Reasoning*: The reasoning step has three sub-steps:

(a) The information processing and predictive analytics step learn the values of future parameters (e.g., process durations) using machine learning techniques (e.g., random forest, neural networks). In addition, the user might want to hedge against the uncertainty of some parameters (e.g., demand), and machine learning is used to describe (e.g., as a probability distribution) the uncertainty of these stochastic parameters. Once learned, the values (or the uncertainty description) of these parameters are updated in the domain models. Finally, this step produces useful predictions on the state of the factory (or production line or machine), such as the feasibility and safety (e.g., no robot collisions) of an assembly plan.

(b) The prescriptive reasoning/decision-making is based on an optimization model (e.g., constraint programming) tailored for the decision to be made. The models are automatically built from the data available in the real-time image of the factory, and they automatically adapt to changes in the factory. Consequently, the model is data-driven. To produce explainable decision proposals, the tool will generate a visualization of the prescriptive analytics model. The visualization also allows a non-expert to modify the models. From this model, AI Approaches (genetic algorithms, learning variable neighborhood search, ...), stochastic and robust optimization suggest appropriate decisions in an uncertain environment. The user analyzes the solutions thanks to a graphical representation of the search spaces, and they can filter solutions by tightening the targeted KPI values. The decisions are validated through simulation on the virtual replicate of the shop floor. While the simulation is negative, the models are iteratively enriched through model acquisition techniques to learn to better represent the reality of the shop floor.

(c) The reactive decision-making step designs the policies to implement to react to unforeseen events in a timely manner. These policies can be simple decision rules easily understandable by the human planner, fast re-optimization techniques based on the model designed in step (b), or black box neural network policies.

(3) *Actuation*: Once the plan is validated by the decision-maker, the real-time-control module runs the operations of the production schedule and tunes the machines to make sure all parameters stay within predefined intervals. Thanks to continuous monitoring, in case of unexpected events, the actuation modifies the schedule in real-time, and it triggers alerts when the situation cannot be adjusted automatically. During actuation, the real-time digital twin communicates with workers thanks to wearable devices. Finally, the actuation monitors some data that are inputs to production planning and production system reconfiguration, and it updates their values in the digital image of the factory.

5. METHODOLOGY

Our methodology is divided into three pillars: research, development, validation.

At the *research level* (pilar 1) we aim to:

(a) Engage the optimization, machine learning, and manufacturing scientific communities in a dialogue to address key issues of robust, adaptable, and reconfigurable manufacturing systems.

(b) Exploit both statistical and symbolic machine learning approaches. While learning neural networks are critical for finding correlations in data and come up with predictions (finding trends in a stream, doing predictive maintenance), combining machine learning and discrete optimization is crucial to acquire optimization models (from various data sources) that can be directly executed by solvers (e.g. CP solver, MIP solver) to generate production plans.

(c) Go from ad hoc optimization software to synthesized optimization software. Currently, most production scheduling models are developed manually for each type of production environment under some fixed assumptions. Such an approach is not feasible in a reconfigurable environment, and we aim to synthesize the production of models and software components directly from the acquired data.

(d) Use the digital twins as intelligible oracles for machine learning. Digital twins give engineers the ability to check the feasibility of their decisions. A key idea of the ASSISTANT project is to enable the communication between digital twins and machine learning to speed up the convergence of learning algorithms toward operational executable models.

(e) Provide explanation-based interaction with humans. Both digital twins and machine learning should be able to put humans in the loop by providing human interpretable concise explanations.

At the *development level* (pilar 2), we aim to design a multilevel distributed architecture that goes from the specification of the manufacturing/assembly system down to the execution of a production plan, which organizes the circulation of data to allow machine learning and to provide a feedback loop where humans can interfere.

The *validation and application* level pilar aims (a) to demonstrate the feasibility and relevance of the approach in relation to three concrete industrial case; (b) Provide a toolbox of components for possible use cases outside of the project.

For the project use cases, the entire ASSISTANT chain will be implemented, starting with data collection, followed by the enrichment of digital twin and leads to the different AI-based decision support tools for process design, production planning/scheduling, and real-time control in manufacturing systems. These decision-support tools (demonstrators) will be tested based on (anonymized) data from "real" business environments within the ASSISTANT framework as stand-alone prototypes. After successful validation of demonstrators, the use cases, system/process specifications, system architecture, concepts, methods, techniques, algorithms, and software code will be available for ASSISTANT consortium partners. They may be incorporated into the studied manufacturing systems for application in daily operations by the consortium partners at their own cost. Most of the results of the project will be disseminated as large as possible in the industry to increase the number of their users. This novel methodology will be validated on a significant panel of use cases selected for their relevance in the current context of the digital transformation of production in major manufacturing sectors undergoing rapid transformations like energy (Siemens), industrial equipment (Atlas Copco), and automotive sectors (Stellantis) which already make extensive use of digital twins. 11 academic and industrial partners are involved, see Fig. 3.

Fig. 3 Project consortium

6. DISCUSSION

The expected progress beyond state of the art and innovation potential is as follows:

Recent AI innovations were mostly developed by the GAFA to provide on-line customized software services for the masses. Such early adopters of AI have large business models focusing on fast growth. As AI is their core activity, they have acquired a digital maturity. Moreover, the GAFAs have natural and direct access to a huge amount of data through online services. Manufacturing is focused on the core business with dedicated optimization software to address key problems they face (safety, quality, costs, service level), which must have a rapid return on investment, even if operating at smaller scales. Transferring the GAFA AI approach to manufacturing is a real challenge.

The conception of ASSISTANT's intelligent digital twin network requires the following several breakthroughs:

- The use of machine learning for high level manufacturing decisions.
- Acquire robust optimization parameterized models by combining machine learning and digital twins
- Machine learning to learn digital twin's parameters, and inclusion of uncertainties in domain models.
- The extension of generative design to all manufacturing decisions.
- Data driven optimization to design reconfigurable production systems.
- Optimization under uncertainties for production planning.
- Develop tools for human interaction with AI systems and safe human-robot collaboration.

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 explainable models. The main line of researches in ASSISTANT are summarized below.

A real-time picture of the production system thanks to the data-fabric. To overcome the challenge of data acquisition, data cleaning, data confidentiality, it is provided a standardized data fabric, building on technology-neutral and highly efficient communication patterns, 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 contribute to improving the design and operation of production systems.

Acquire robust optimization parameterized models by combining machine learning and digital twins. The innovation potential of ASSISTANT intends to advance the state-of-the-art of model acquisition. First, we will provide methods to learn 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 production scheduling, typical parameters are the 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. Discrete optimization models have a strong structure that allows one to acquire models from a restricted set of samples (Beldiceanu 2016). To get more realistic models we aim to integrate digital twins in 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 (Bessière 2017) to query in a focused way digital twins to converge to more robust models.

Machine learning to learn digital twin's parameters and inclusion of uncertainties in domain models. Contrarily, to existing digital twins who use ML mostly 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. We will use human-understandable AI, by incorporating white-box modeling techniques in domain modeling, including behavioral models of schedules, machine behavior. Another aspect is that these domain models and AI algorithms need to explicitly take into consideration uncertainties. We will extend domain modeling languages to support the modeling of uncertainties. In addition, we will use digital twins to produce more realistic explainable decision aid models based on reinforcement learning (e.g. learn physical restrictions) that optimize the full process globally.

The extension of generative design to all manufacturing decisions. 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.

Data-driven optimization to design reconfigurable production systems. 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.

Optimization under uncertainties for production planning. 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 one to get predictions about the values of various unknown parameters. 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.

Develop tools for human interaction with AI systems and safe human-robot collaboration. 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.

7. CONCLUSION

This paper presents the main object and the concept of the research project ASSISTANT. The project started in November 2020, and it will last three years. The innovative ideas of ASSISTANT aim to provide decision-makers with *generative design-based software* for the entire cycle of manufacturing decisions from process selection, production system design to planning, scheduling, and real-time control. Rather than writing ad hoc code, it provides a set of intelligent digital twins that *self-adapt to the manufacturing environment*. ASSISTANT promotes a methodology that enhances the generative design with learning aspects of AI from the data available in manufacturing. The project aims to synthesize predictive/prescriptive models adjusted to the shop floor for each decision level. Digital twins will be used as oracles by ML to converge towards models in phase with reality. In this context, ML is used to predict parameter values, characterize parameter uncertainty, and acquire physical constraints.

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