Enhancing Cognition for Digital Twins

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Abstract— **In the era of Industry 4.0, Digital Twins (DTs) pave the way for the creation of the Cognitive Factory. By virtualizing and twinning information stemming from the real and the digital world, it is now possible to connect all parts of the production process by having virtual copies of physical elements interacting with each other in the digital and physical realms. However, this alone does not imply cognition. Cognition requires modelling not only the physical characteristics but also the behavior of production elements and processes. The latter can be founded upon data-driven models produced via Data Analytics and Machine Learning techniques, giving rise to the so-called Cognitive (Digital) Twin. To further enable the Cognitive Factory, a novel concept, dubbed as Enhanced Cognitive Twin (ECT), is proposed in this paper as a way to introduce advanced cognitive capabilities to the DT artefact that enable supporting decisions, with the end goal to enable DTs to react to inner or outer stimuli. The Enhanced Cognitive Twin can be deployed at different hierarchical levels of the production process, i.e., at sensor-, machine-, process-, employee- or even factory-level, aggregated to allow both horizontal and vertical interplay. The ECT notion is proposed in the context of process industries, where cognition is particularly important due to the continuous, non-linear, and varied nature of the respective production processes.**

Keywords — Industry 4.0, Digital Transformation, Cognitive Factory, Digital Twins, Enhanced Cognitive Twins

I. INTRODUCTION

In the era of digital transformation towards Industry 4.0, manufacturing and production processes are in the frontline [1]. In order to enable this digital transformation, the blending of the real and digital production world is required, with all parts being interconnected, including sensors, machines, products, systems, processes and people. In this regard, Cyber Physical Systems, digital infrastructures, IIoT connectivity and specialized software (among others) enable the continuous monitoring of physical assets and processes included in the production process. This facilitates effective event detection and enables simulation and optimization of production assets and processes, thus supporting informed decision making for the key stakeholders.

A prominent enabler of this digital transformation is provided by Digital Twins (DTs), which define a virtual transference of the physical world to the digital realm. DTs can offer a plethora of capabilities to contemporary production systems. On this account, DTs quickly captured the attention of the industry and the academy with the International Data Corporation (IDC) [2] predicting that by 2020, 30% of Global 2000 companies will utilise data stemming from digital twins in order to improve product innovation success rates and organisational productivity, achieving gains of up to 25%. The quick uptake of DTs has led to a market size valued at $2.26 bn in 2017 [3], rising to $3.8 bn in 2019 with a projected expansion at a Compound Annual Growth Rate (CAGR) of 45.4% and $35.8 bn until 2025 [4]. These projections are supported also by the estimated 20.8 bn connected sensors and endpoints by 2020 [5] in the IoT market, which is a key enabler of DTs. DTs are also identified in the report as a prominent way to enable savings of $bn's in maintenance repair and operation (MRO) and optimised IoT asset performance in the long run as well as asset management and overall operational efficiency.

This significant potential of DTs was initially utilized in improving the design of assets, using extensive simulations to evaluate various operational scenarios. However, with real-time data quickly becoming a commodity, the incorporation of data-driven models has become critical in effectively modelling physical assets and their behavior. As stated in the 2018 World Manufacturing Forum (WMF) Report [6]: "Built on the foundations of the IIoT and utilizing data analytics combined with cognitive technology, the emerging field of Cognitive Manufacturing is characterized by the vision and capacity to perceive changes in the production process and know how to respond to these dynamic variations with minimal human intervention. It does this by proposing improvements in processes and operations while suggesting alternatives to reduce cost and environmental impacts." This had led to the recent development of the concept of Cognitive (Digital) Twins (CTs), which incorporate data-driven models produced via Data Analytics and Machine Learning to the DT artefact.

In this paper, we introduce the notion of Enhanced Cognitive Twins (ECTs), taking the notion of cognition a step further by providing CTs with the tools to actually "suggest alternatives to reduce cost and environmental impacts" as the

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WMF report states. This is implemented by incorporating optimization algorithms built to work both with numerical and data-driven models of production assets, thus facilitating decision-making under different objectives. The end-goal is to enable the realization of the Cognitive Factory as an ensemble of independent but intertwined ECTs, that are (i) able to self-learn, and thus to effectively detect and react to anomalies and disruptions, but also to opportunities that may arise, (ii) enjoy a local or global view of operations and (iii) are capable for short-, mid- and long-term optimization and reasoning.

The notion of ECT is being developed within a recent project called FACTLOG (https://www.factlog.eu/) that envisages the design, implementation and evaluation of ECT to enable process industries to apply energy-aware factory-analytics and decision making. Hence the FACTLOG approach and impact on actual plant floors is strongly intertwined with the ECT concept. We mention this to emphasize that our work contributes to the ongoing discourse on how DTs may become more impactful and intelligent, particularly in manufacturing, anticipating affirmative and solidly evaluated answers through the FACTLOG implementation and evaluation.

The rest of the paper is as follows: Section 2 presents the current work on Digital Twins, Section 3 introduces the Enhanced Cognitive Twin (ECT) Concept, Section 4 presents the FACTLOG project and the instantiation of the ECTs within it and Section 5 presents the concluding remarks and sets the outlook for future research.

II. Previous Work

Starting from NASA in 2010, a Digital Twin is defined as "an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin. It is ultra-realistic and may consider one or more important and interdependent vehicle systems" [7]. From this definition it is evident that there is a need to have a virtual entity that reflects accurately a physical respective entity. The notion of DTs has evolved from different similar definitions given with respect to the academic lens, application context or integration level under which they are examined. Hence, similar definitions include those for Digital Models, Digital Shadows or Digital Avatars [8, 9] where there is a uni-directional transfer of data from a Physical Entity to a Virtual Entity in a manual or automatic way, creating a Virtual Copy that only receives input to update its state and current condition. However the aforementioned approaches in virtualization lack the bi-directional approach needed to close the loop and enable additional services, namely going from Physical Entity to Virtual Entity and from the Virtual Entity to the Physical entity. Although a uniformly accepted definition is yet to be produced (see [10] for a literature review on DT definitions) a DT is in its base a "virtual representation of a physical object or system across its unique lifecycle utilizing real-time data from multiple sources to intrinsically enable learning, reasoning and contributing for extracting actionable insights" [11]. In order to achieve this, a DT should have a number of key properties with most important being an ability to reflect the physical space onto the digital in real-time and with a self-evolving manner as a means to enable initially the interaction and subsequently the convergence of the two spaces, the Virtual and the Physical [12].

DTs have found their place in Industry 4.0 and smart manufacturing mainly with cases that provide information continuity [13], data management [14] along the product lifecycle, as well as monitoring of physical twin assets [15] to even optimization of system behaviour [16] predominately in product design [17], production line design [18], shop floors [19] and production process optimization [20] purposes. DTs are found predominately in the discrete manufacturing sector where items (and/or parts) are designed and produced in an individual manner or in lots. Here, the application of DTs has been utilized in different phases from the initial design of the end-product to its optimized production.

A prominent manufacturing sector is that of process industries which differs from discrete (batch) manufacturing in the sense that concentrations of ingredients and materials' composition can be changed in a continuous manner directed by complex chemical reactions, which are conducted under different working conditions in terms of time [21]. This naturlly leads to control problems that are "strongly nonlinear with mixed constraints, complex couplings, competing objectives and uncertainties on various levels" [22].

Nevertheless, it must be noted that the nonlinearity present in the process industries is not the only requirement making cognition so important. Cognition offers an abstraction layer that, regardless of the production techniques used underneath, enables reasoning and insights. Despite the varied nature of underlying industrial processes, higher management levels and business processes remain quite uniform, thus requiring appropriate abstractions that enable cognition capabilities. We consider congnition as arising from a real-time processing layer where observations (i.e. events), knowledge and experience interoperate to enable us to understand and control the behaviour of a plant floor.

Furthermore, the 2018 WMF Report [6] mentions four lines of work to materialise Cognitive Manufacturing, two of which are captured by CTs: 'Hyper-Connected Intelligent Machines' and 'AI-Driven Cognitive Operations'. The third one, named 'Smart Optimisation of Resources', is not, at least not explicitly. In that regard, in an effort to also place focus on this aspect of cognition, we envisage the progress of the Cognitive Digital Twin by empowering it with optimization algorithms facilitating decision-making at a narrow or a broad scope, thus giving rise to the Enhanced Cognitive Twin, elaborated on the next chapters.

III. Enhanced Cognitive Twin

A. *The ECT Concept*

The Digital Twin concept enables the mirroring of the physical counterpart to the virtual space including the interchange of data between the two. Still, virtualization alone is no longer a static design-time process that requires using numerical methods to model the physical element; it has evolved in a dynamic, run-time process that continuously needs to adapt the behavioural model of the digital counterpart to mirror the behaviour of the physical element, giving rise to the Cognitive Digital Twin. The Enhanced Cognitive Twin is a Digital Twin coupled not only by Cognitive (i.e., self-awareness) abilities like anomaly detection and behavioral learning but also with the ability to decide on actions of the physical twin that will improve the metrics characterizing its state or role. In that regard, an ECT relies not only upon data coming from the physical twin and then processed through analytics or Machine Learning (ML) but also upon optimization methods supporting decision making. This conceptually constitutes the ECT not only as a valuable tool for monitoring and control but also as an indispensable part of the decision-making process that aids in the optimization of the overall system. The introduction of optimization methods within the core of the Cognitive twin and the effect brought forth by it is the main key differentiating point when compared with currently available Digital Twin solutions.

Fig. 1 depicts the conceptual view of the Enhanced Cognitive Twin. In the heart of the ECT exist the Knowledge Core, a novel type of knowledge-base with semantics-driven detection, learning, prediction, inference and decision capabilities. It comprises of a set of predictive analytics and machine learning models created and updated by monitoring, cleansing and utilizing the flow of incoming data from multiple sources (e.g. the physical counterparts, Sensors etc.) across all areas of the industrial system's operating conditions. It also integrates historical data and production chain operations alongside with domain knowledge from human experts. Hence, the ECT can learn and update itself to represent its real-time status and operating conditions in parallel to and reflecting the physical asset. Moreover, the ECT can detect, assess, infer and predict the physical (twinned) system's current and potential behavior, make decisions and interact with machines and humans both in the digital and physical realms.

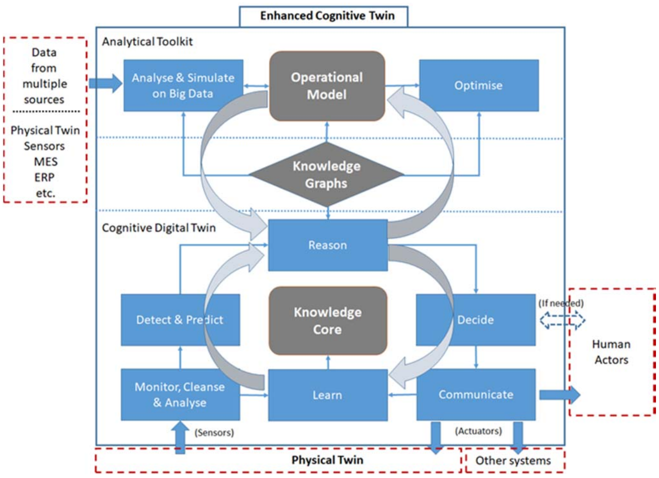

Fig. 1 Conceptual View of the Enhanced Cognitive Twin

The Knowledge Core is augmented by the Operational Model of the twinned system [23] and further enhanced through continuous analysis of big data incoming from multiple and diverse sources (sensors, ERP, MES, legacy systems, etc.), simulation of the system and the way it responds to various (potential or real) events, management actions and operational strategies. The continuously updated Operational Model (incorporating both numerical, static models as well as analytical, data-driven ones) may be used to optimize the real system's operation and production processes in an energy-aware manner, to drive recovery actions in case of emergencies as well as to assess and optimize predictive maintenance efforts.

B. *Introducing ECTs in the Cognitive Factory*

The ECT can be utilized to reflect any given physical unit at any level of production operations. To name but a few, an ECT can be used to virtualize machine(s), process step(s), overall process(es) and eventually even a whole factory. We can elicit the ECT at those different hierarchical levels and in turn have ECTs interacting with each other both horizontally and vertically, thus giving rise to an aggregated structure. In this regard, the Cognitive Factory can be built by integrating ECTs which are not isolated but share meaningful information between them: coordination information is passed along horizontally, while only relevant information for decision making and context is passed along vertically, towards the higher levels. An indicative example would be to have an ECT of a mission-critical machine (monitoring and controlling its state and actions) providing information to an ECT of a specific process step that feeds the ECT of a production process. These ECTs can exist, act and react independently while also exchanging information through the different datasets shared and their respective semantics. In such a case, the interaction of the respective ECTs needs to be orchestrated by a higher level of supervisory control (giving rise to the Cognitive Factory), being directed by the business needs, time horizon and scope of the different events that need processing at any given time.

Overall, the ECT concept can be extended to apply with different configurations within industrial environments and interacting with other systems in a peer-to-peer or aggregation mode. For example, individual twins can be aggregated for twinning an industrial complex with multiple production lines or an industrial park that follows symbiotic practices or share common transportation hubs, environmental regulations and socio-economic environments. In such settings, lower level ECT systems will only share meaningful data to their counterparts on a need-to-know basis and only delegate functions that outgrow the scope of their responsibilities in a subsidiary manner. This way, each ECT will encapsulate data and behavior of its own and collaborate with other ECTs from different levels based on natural interactions that are observed in the physical world and also mirrored in the digital domain.

IV. FACTLOG AND THE ENHANCED COGNITIVE TWIN

A. *The FACTLOG project*

The FACTLOG (Energy Aware Factory Analytics for Process Industries) project envisages the introduction of the Enhanced Cognitive Twins in the process industries, in order to facilitate cognition towards improving the behaviour of the complex process systems inherent in production and operations. In particular, by incorporating different pipelines of machine learning and analytical tools at different levels (from machines to process steps and from processes to the whole production plant), FACTLOG enables the Deployment and Assessment of coherent Enhanced Cognitive Twins in specific sectors in process industries which are represented in the project.

B. *ECT realization within FACTLOG*

The conceptual architecture of FACTLOG is structured upon service pipelines through which the available data flows as depicted in Fig. 2. One pipeline implements the cognitive core of the ECT by offering learning, event detection and prediction as well as reasoning capabilities using data streams from the physical counterparts. For each ECT, this pipeline interacts with a second one offering analytics and reasoning on big 'raw' data incoming from multiple sources. These two pipelines interact through Knowledge Graphs and as a result the ECT is enhanced by a meta-structure that enables data

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interoperability among the multi-source data flows and a stronger level of reasoning and cognition at pipeline level.

Note that the interaction between these two different types of data-driven modelling approaches is semantically-enriched and guided by Knowledge Graphs (KGs). The combined approach of using ML algorithms and data analytics as well as KGs set the basis of a solid cognitive computing system allowing for fine-tuning results and increasing processing and reasoning capabilities. The semantic models add features to a given data set that makes the development of cognitive processes much more agile. The combination of quantitative-driven (ML+data analytics) and qualitative-driven (KGs) approaches brings together the computing capacity of machines and the human knowledge and insights that are needed to address different use cases in Industry 4.0.

Moreover, three levels of optimization may be utilized depending on the scope and the time horizon examined, offering ECTs the ability to solve well-defined production optimization problems including (a) short-term (i.e., real-time) re-scheduling and re-configuration of machines or entire processes, (b) mid-term scheduling and lot-sizing for specific processes or for the entire plant and (c) long-term capacity planning.

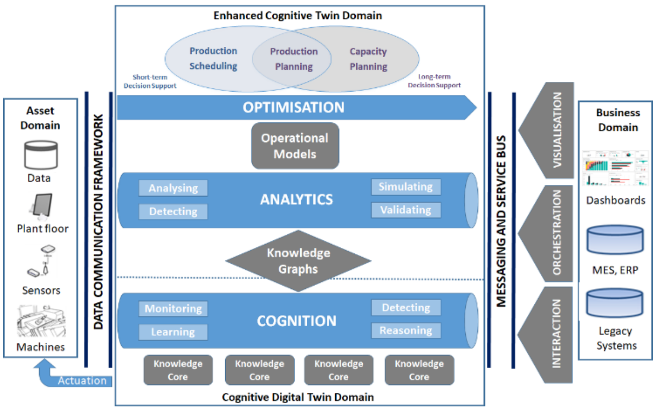

Fig. 2: FACTLOG Conceptual Architecture

Moving from the FACTLOG Conceptual Architecture to the Technical Architecture a data communication framework is in place to handle the collection, processing, integration and management of multisource, multiscale and multivariant data from the production assets. Moreover, a messaging and service bus can facilitate module interaction within the ECT as well as an API-based communication with the business domain. The latter facilitates real-time visualization of the production processes and status and interaction with the users, while also incorporating a higher level of orchestration, thus enabling high-level supervisory control. Lastly actuators may be incorporated to enable the implementation of real-time decisions automatically, communicating them from ECTs straight to the physical twin in production. To illustrate the above, we need to deploy different enablers that characterize the concept of ECT: a) a profile that characterizes the identify along with descriptive information and models of the asset that is twinned; b) the relationships of the ECT with other ECTs thus constructing a factory or process or other hierarchy as a network of connected ECTs; c) the cognition aspects (with regards reasoning, simulating, predicting and optimization); d) trustworthiness aspects to ensure proper transmission of information; e) visualizations to end users about the status and potential alerts/ notifications; f) the computation needs and deployment aspects (could/fog/edge) and finally, g) define the lifecycle of the ECT. Those enablers are used in different phases of a cognitive factory operation model. As Fig. 3 illustrates, the first thing is to model the factory or other production context (workstation, process, machine, etc.) as a network of interconnected ECTs. Initially, data is introduced from various sources (e.g. ERP, MES, EMIS, Physical Twins, Human Operators). In the Cognitive Core functionality, Detection services (CEP) coupled with Simulation and Prediction Services as well as Optimization Services, utilize data driven and model driven approaches over Process models to enable the ECTs to collaboratively (a) predict/identify an anomaly of any given nature (e.g. an upcoming machine breakdown), (b) identify potential mitigation (or response) measures with optimal outcomes, (c) simulate the optimized outcomes' results and cascading effect in the future and lastly (d) return with an informed outcome on the proposed course of action to be either presented to the involved stakeholders for approval and/or rejection or directly to actuation on the physical counterparts (also informing all other coupled ECTs).

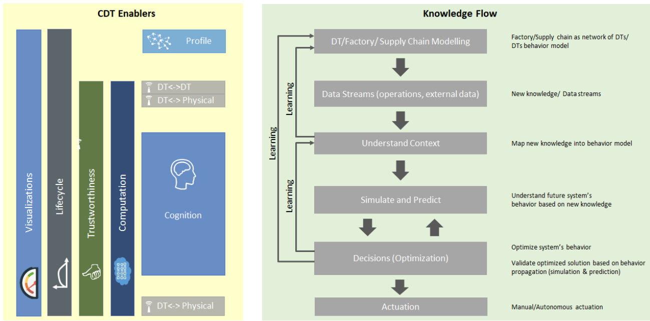

Fig. 3: FACTLOG Technical Architecture

C. ECT and Cognition

At the core of the ECT concept exists the need for cognition, as data-driven manufacturing (Industry 4.0) requires more "cognitive augmentation" of assets, for enabling data-driven continuous process improvement. In order to incorporate cognition into the digital twins, FACTLOG utilises D2Lab, a new generation industrial data analytics framework, which will serve as a meta-platform for supporting the development and deployment of various industrial application types, e.g., quality control, predictive maintenance, etc. The FACTLOG approach is based on the D2Twin [24] innovative data analytics approach where the model of a system is represented through a novel metaphor of data-driven CTs. This enhances the base DTs and respectively the system of interconnected ECTs with the ability to understand and resolve situations which can neither be modelled by design, e.g. encapsulated in numerical models, nor experienced in reality, i.e., behaviour in past data. This incorporated solution will have the capability to "reason" about the problem (e.g., level of the tool degradation for each particular machine and the type of product/material) based on real-time data from the current process. This cognition capability will be supported by the so-called "just-in-time simulation" of the process status in some suspicious/unusual situations in order to calculate the confidence that an unusual situation leads to an anomaly that should be resolved. Moreover, this data-driven simulation will also be able to show when an unusual situation will cause an anomaly, indicating for how long the current process settings can stay

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unchanged. The novelty of the approach is to define simulation models from the data-driven twins, using new techniques of predictive clustering and advanced rule induction from data, based on inductive data mining.

D. ECT and Data

The analytical models introduced in FACTLOG require ample sources of data to be fed into. However, one of the main challenges in designing holistic analytical models is processing different data with different modalities and modelling different types/modalities of data in real-time is not a trivial issue [25]. In order to design a universal analytical framework for real-time stream data processing in Intelligent Factories, a complex architecture is required that is able to adapt to the different modalities. Not only that, but also data synchronization and optimization issues occur before having data ready to be fed into the analytical models [26]. FACTLOG aims to provide a beyond the state-of-the-art holistic model of uncertainty and causal relations on several layers of an organization that integrates the following submodels: material flow patterns models, capacity statistical models, technological process models, deviation models between ideal technological simulation (PLM) and observed realizations, as well as logistic demand forecasting models. Material flow pattern models will take into account lead times for input materials and build uncertainty models in order to understand material shipping/logistics and various technological processes that need to be applied. Capacity statistical models will consider machine availability and breakdown models as well as human workforce uncertainty models. Technological process models will integrate domain knowledge. In order to handle the data requirements to enable an ECT, FACTLOG will employ the QMiner [27] framework as an analytical platform for large-scale real-time data streams as it contains a stack of state-of-the-art online data driven algorithms for online processing. QMiner aims to tackle issues relevant to multimodal data merging, data pre-processing and optimization, and the analytical design of the complex factory processes as an organism of endogenous interdependent process variables, yielding a common analytical model of the factory in real-time. Upon realization QMiner will enable the ECTs to utilize a plethora of multimodal data types in a seamless manner.

E. ECT and Knowledge Graphs

Extending the data manipulations towards enabling their consumption in a meaningful way, within FACTLOG, KGs will provide the core mechanism that will allow for the smooth orchestration of data as well as ML flows. The exploitation of KGs and ML techniques, will facilitate the direct interaction of data and knowledge extraction tools, since they offer the needed abstraction layer to properly define, in a machine understandable way (a) the meaning of each operation and (b) define the complex interactions that characterize machine learning algorithms and data.

F. ECT and Optimization

A key enabler and key differentiating factor in the transformation of a DT to an ECT is the introduced Optimization toolkit which enables the ECT to perform optimization tasks. In regard with the optimization problems that relate to Industry 4.0, the vast majority of batch production and plant floor planning and scheduling optimization problems are NP-hard with combinatorial structure, and therefore it is computationally intractable to find an exact solution to such real-life problem using conventional algorithmic and mathematical programming approaches. More interestingly, due to lack of knowledge or the varying nature in real industrial plants, it is not always possible to provide the exact values of the optimization parameters [28] (e.g., raw material availability, processing times, prices, machine reliability, and market requirements) or to be aware of potential changes in product orders or order priority, equipment failures, resource changes, etc. Hence, a solution which is optimal with respect to estimated parameters may be poor after true realization of the parameters occurs. This uncertainty is ever existing especially with regard to specific process industries, where the content of a specific substance within the produce cannot be established with certainty until the product is actually produced (e.g., in oil refining processes, the Sulphur content of the produced LPG, which must be below certain specifications). Thus, finding ways to deal with uncertainty is as important as having the model itself, and can be applied to validate the use of mathematical models and preserve production feasibility during operations.

To deal with decision situations under uncertainty, our approach is to consider a set of all possible realizations of parameters to be a part of the input. This set is called scenario set and each particular realization of the parameters is called a scenario. Hence, a scenario represents a state of the world, which may occur. The cost of a solution depends on a scenario, so its value is also uncertain. In fact, a solution obtained is often evaluated ex post and compared with an optimal solution that could have been obtained if the true realization of the parameters had been available. In practice, the risk-averse decision makers are more interested in hedging against the worst possible scenarios. An interesting modelling approach, proposed to meet the above requirements, is the robust optimization framework under discrete or interval uncertainty representation and max-min or min-max regret criteria [28, 29, 30].

Another important issue, mostly in short-term decision support level where real-time (and/or reactive) optimization is concerned, is that the performance of a manufacturing process or control system depends mostly on its ability to rapidly adapt schedules to current circumstances. These dynamic (re-) optimization problems, where the optimization process is performed gradually in specific time intervals and evolves dynamically in an effort to incorporate the occurrence of new information or the update of old ones, can be approached by reactive and proactive frameworks. Such approaches can efficiently deal with solutions of dynamic optimization problems, with incomplete, uncertain or unknown input parameters and/or variables, which are made known or updated concurrently with the generation of the solution process in real-time. More specifically, a framework proposed to this direction leverages different robust optimization models which (i) build on well-known concepts such as obliviousness (where specific input parameters are unknown) with the goal to find a universal solution that performs well for all realizations of the hidden parameters (optimizing the worst-case ratio of solution and optimum over all realizations), or (ii) apply a multi-stage adjustable robust optimization approach (where decision rules optimized with respect to uncertain parameters and recourse actions depends on the realisation of uncertainty) for production scheduling.

FACTLOG aims to offer a complete optimization toolkit to the ECT based on hybrid local search, evolutionary computation [31] and data-driven optimization techniques [32, 33, 34] towards flexible resource-aware plant floor scheduling and optimization algorithms. These approaches can be used for solving complex scheduling problems with various side constraints, such as utility (renewable resources) and machine maintenance constraints, and they offer the capability of treating multiple scheduling objectives in a hierarchical fashion, including combined temporal and energy-aware objectives [35]. They also provide high level of accuracy by enhancing their planning capability through: (i) multiple (parallel) machine configurations (as decision variables) to better control the operating conditions (such as the speed and the temperature), while affecting multiple scheduling parameters (completion times, energy consumption, operating cost), and (ii) multiple execution modes, including among others, alternative routings and combinations of resource requirements for each production order or operation. The previous algorithmic framework introduced in the Optimization toolkit that support the ECT, will be enhanced with state-of-the-art algorithms for online robust scheduling problems, mainly focused on MILP [36] or meta-heuristics [37] techniques that can efficiently apply on multi-criteria optimization variants, extending them to deal also with resource-aware objective functions.

G. Evaluating the ECTs

In order to design, develop and evaluate the Enhanced Cognitive Twins for their capability to support Smart Factories in the Industry 4.0 era, a series of pilot applications have been envisaged. The selected pilots offer indicative business cases in the process industries under which the ECT concept will be validated in the course of the pilots and include:

Waste-to-Fuel tr ansformer plants that are transforming any hydrocarbon-based waste into a high-quality synthetic diesel by using a chemical-catalytical de-polymerization process that runs on low temperature and low-pressure. These plants are already using the latest available software and hardware technology allowing remote control and maintenance of each part of the plant and the process itself. However, they do not include any analytics, anomaly detection, prediction or optimization features. The ECT is expected to facilitate the provision of the aforementioned services in order to enable a better understanding, optimization and decision making given the available data and this will be the focus of its evaluation. **Oil refineries**, which handle crude oil in a 24/7 continuous production of many petroleum products such as LPG, naphtha, gasoline, diesel and fuel oil, with high levels of energy consumption. In this case, there is the need to create an energy- and production quality–aware decision support system towards intelligent decision-making for the refinery, especially with regard to early detection/prediction of out-of-specs production, and subsequent support for recovering to on-specs production in them most energy-efficient manner. The ECTs will enable the real time monitoring, projection and adjustment on potential off-specs production leading to its evaluation in a fuzzy and complex environment. **Textile industry**, where fine woolen fabrics are produced with the highest of standards. In the weaving process, set-up times may differ substantially depending on the characteristics of two consecutive fabrics being produced on the same loom, affecting heavily the production efficiency of the weaving process as well as the production schedule of the multi-step energy-consuming fabric finishing process. The ECTs in this pilot will be evaluated for their ability to model and optimize subsequent processes in the fabric production process. **Steel manufacturing** industry, where there is a need to reduce the environmental impact of the operating processes. In order to do so, ECTs will enable an optimization of the machinery operational capacity and maintenance processes. The focus of the ECTs in this pilot is to maximize throughput from raw material to finished products per machine utilized. Last but not least ECTs will also be implemented and evaluated in the **Automotive industry**, where reduction of downtime caused by breakdown and improvement of overall equipment efficiency is sought after and as such the ECTs will simulate and optimize the entire set of involved machines and processes in order to optimize production taking under consideration breakdowns and pre-emptive maintenance. The aforementioned distinct business cases will lay the ground for the examination of the potential benefits the Enhanced Cognitive Twin concept can bring to the Cognitive Factory and Industry 4.0

V. CONCLUSIONS

This paper discusses the novel concept of Enhanced Cognitive Twin, designed to incorporate cognition and optimization capabilities in the process industries. Main advantage of using cognition is the possibility to resolve previously unknown situations in an efficient way. Building on top of cognition the ECT introduces the optimization toolkit which now enables the ECT to conduct optimization tasks and return highly valuable results to be consumed by other ECTs or human actors involved in the process. During the FACTLOG project instantiation, the ECT will be applied and evaluated in different business cases in various process industries (waste-to-fuel, Oil refineries, Textile production, Steel manufacturing and Automotive industry) and with different goals (e.g. production scheduling, pre-emptive maintenance) and taking full advantage of the additional capabilities of the ECT over the standard Digital Twin context. The benefits derived from the introduction of the ECT concept in the process industries are envisaged to be improved efficiency and transparency of operations and production, through the introduction of the optimization toolkit within the ECT and the ability to derive to better decisions in real or near real time through the interplay of the optimization and simulation. Lastly, alongside this implementation and evaluation, the formalities of ECT definition and conceptualization will further evolve in the process of tailoring to each application scenario and relevant to the enabling technologies, the capabilities and the KPIs, illustrating this ECT impact.

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