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Optimizing Shop Floor Workflow Automation With Digital Twins: An AI-Enabled Framework

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Automation of shop floor tasks can deliver a level of operational efficiency impossible to achieve otherwise. However, it is often challenging to achieve workflow automation solutions compatibility with companies' existing IT architecture and to ensure automated workflows are efficient and robust. To solve these known problems, an AI-enabled framework consisting of three modules is proposed. The first module, Process Mining, observes existing manually performed workflows and discovers workflow graphs from them. The second module, Recommender System, utilizes the discovered workflow graphs to generate task execution recommendations for the end user to help integrate existing workflows into workflow automation software. The third module, Simulation, assists with identifying integration-related issues with the recommended tasks by enabling "what if" scenario evaluations.

While the mobile robot approach does not need to be adjusted for the implementation of the event simulation methodology, another challenge is to address semiconductor assembly factory service engineering aspects. Semiconductor assemblies consist of many chips and transistors that require signal processing services across different production processes. Therefore, the workshop floor has to depend on the proper service provisioning, routing and scheduling approaches that would affect service performance metrics such as workload balancing and service make-span. On the other hand, the routing and scheduling have to take ability-to-serve criteria in real-time into consideration, which adds onto the computational complexity exponentially with respect to the increase of the system size. Therefore, a heuristic approach based on resource agent-based analytical methods is applied to address such computationally complex problems, and a customized simulation modeling approach is developed to devise test cases in workshop floor settings for the validation of given problem instances.

Keywords: Digital Twin; Simulation Modeling; Work Environments; Shop Floor; Manufacturing Layouts; Selecting Factors; Factory Time Simulation; Workflow Automation; Digital Twin Development.

1. Introduction

Today's industrial world is teetering on the edge of the Fourth Industrial Revolution (Industry 4.0). The widely discussed connectivity of machines and cyber-physical systems is fundamentally changing the way factories develop, operate, plan, and optimize. The dissolution of boundaries on the shop floor introduces new obstacles such as data deluge; yet it also opens a plethora of opportunities to enhance productivity and flexibility beyond imaginations. It can enable truly new modes of production, characterized by a higher autonomy of individual manufacturing resources, self adaption to unforeseen disturbances, and even self-organization of autonomous production systems.

The wide availability of high-fidelity data sources enables a profound understanding of the complex dependencies and interrelations of the Ontological or Machine Level (i.e., industrial assets like CNCs, robots, and AGVs specifically designed to transform raw materials into finished products). New modelling paradigms from Data Science, Cyber-Physical Systems, Optimization, and Artificial Intelligence can facilitate the self-organization and adaptation of shop floor processes and infrastructures. At the same time, advanced analytics can cope with the increased complexity and dynamical properties of industrial processes. The deep knowledge of the system enables a profound understanding of the complex dependencies and interrelations at the design and planning levels, allowing for a more holistic evaluation of design alternatives.

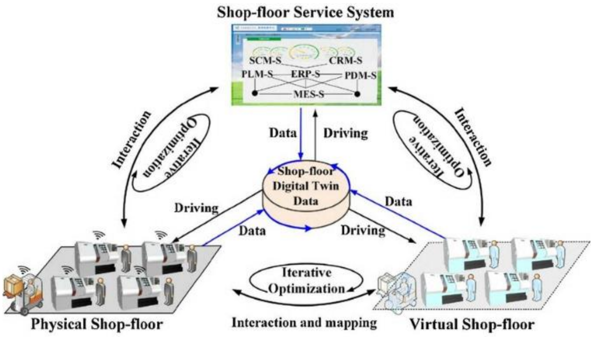

Fig 1: Shop Floor Workflow Automation

1.1. Background and Significance

The rapid increase in flexibility requirements for manufacturing systems comes with a significant increase in complexity. A reaction to this flexibility trend has been to use virtual simulations, where manufacturing systems can be simulated based on modeling instead of building physical prototype systems. Digital twins have emerged as a technology to predict the undesirables and ensure desired performance of complex systems, control actions, and production. A digital twin of a manufacturing system can be defined as a virtual factory with real-world interactions. Digital twins have got attention in the manufacturing research spectrum, as researchers have tried to explore the capabilities offered by this technology. However, their industrial application of it has seen only limited successes.

Simulations can emulate numerous possible scenarios regarding a manufacturing system, to select the most desirable one. Virtual simulations are thus becoming an integral part of a digital twin. However, the nature of a simulation model is such that creating simulation models that can be extended as a digital twin is a challenge. This necessitates a structured approach for creating the models, ensuring their accuracy and flexibility, enough to be updated along the life cycle of the factory. A collaboration between machine learning and discrete event simulation is called an AI simulation joint capability construction framework. This framework can coordinate and orchestrate EN-cooperation with AI-enabled simulation joint capabilities as versatile envisioned entities. Generation, and utilization life cycle of ENs can be an example of detailed conceptualizations for smart manufacturing that can be made for indicating AE capability development mechanisms. Monitoring and reporting structures, hinges capacity can be another example of conceptualization for advanced preventive maintenance.

Equ 1: Objective Function: Optimize Workflow Efficiency

$$\min\left(C_{\max}\right) \quad \text{or} \quad \max\left(\frac{P}{T}\right)$$

Where:

- $C_{\max}$ = maximum completion time across all jobs
- P = total number of parts/products completed
- T = total time interval

2. Understanding Digital Twins

Although numerous academic articles on digital twins are available, the lack of common definitions remains a problem. A digital twin is generally concerned with the virtual representation of the physical world but varies in terms of levels of abstraction, fidelity, manifest variabilities, and interfaces. Generally, there are three primary types based on the components that constitute the digital twin: (1) the mass and energy discrete components; (2) the system components at different abstraction levels; (3) the components that constitute the twin. No matter what the components are, the data paths that link the twin with its real-world counterpart are one of the necessary parts for a digital twin. A digital twin includes a cloud model (digital twin cloud) to store the digital representation and links its physical counterpart through data paths.

The digital twin technology creates a virtual representation of a physical asset or process, enabling real-time monitoring, analysis, and optimization . Digital twins received attention in various industries, including machine tools, assembly shop floors, and smart agriculture, with the necessary focus on facility layouts and operations. In a digital twin-based shop floor, digital twin-based facility layouts and process plans are proposed to optimize resource usage and improve productivity. A digital twin-enabled acceleration structure modeling and usage assessment framework is developed to identify the critical limitations of the standardized accelerator structure. Facility planning in a digital twin-enabled framework is addressed to create a detailed grouping layout for a new shop layout. A customizable simulation framework for digital twins of machine tools is created to make them customizable and user-friendly for production planners. Hybrid digital twins are proposed to analyze the process planning and scheduling methods of neural architecture searches.

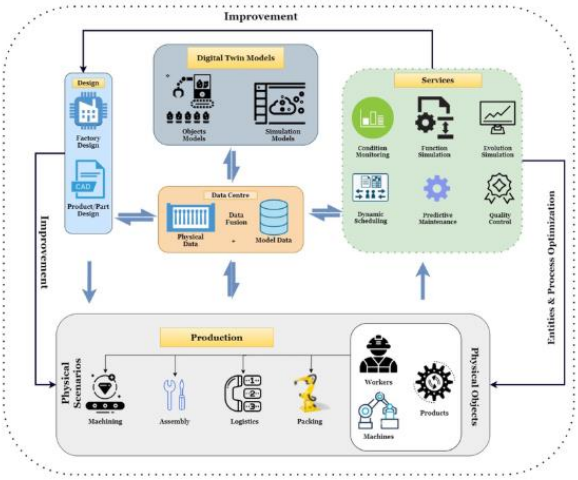

Fig 2: Conceptual framework of digital twin

2.1. Definition and Concept

A Digital Twin (DT) is a data-connected digital replica of physical factories, enabling simulation of shop floor operations through real-time data integration from IoT devices, such as sensors and controllers. Thus, it can track shop floor workflow/activity status and simulate future workflow. The extensive definitions of a DT sector highlight its multifaceted nature. In manufacturing, a DT is a data-connected 3D digital counterpart of the physical system, reflecting the past, present, and future behaviors of the physical twin, fully enabling hardware-software interaction [1]. It relies on a representation of the factory formed using 3D CAD models paired with an Industry 4.0-enabled Data Model. Digital data from Internet of Things (IoT) sensors is connected to the digital replica factory through the Model-Driven Development process. Digital twins can be regarded as one of the key elements of smart factories and Industry 4.0. The main aim of digital twins in the shop floor is to represent the current status of the shop floor and simulate/analyze future changes to improve the efficiency of the shop floor manufacturing process. Digital twins are data-connected, digital representations of the physical world formed using data, models, and algorithms. Current states of the physical twin are reflected into the digital twin using data from the sensors embedded in the physical systems. By combining digital data with models, the past and future states of the physical twin can be simulated through a digital twin. This enables the visibility of the shop floor to track the current status of each machine, product, and activity, and the analytical capability to analyze areas for process improvement.

This concept includes broad applications of production simulation, optimization, Artificial Intelligence (AI), etc. Digital twins can replicate the workflow, jobs, machines, orders, product properties, etc. of the physical shop floor using digital data obtained from the physical systems. Also, it can support the simulation of the shop floor workflows using a modified and improved representation of the current state. Digital twins can illustrate the reproduction/execution of workflow/agent-based simulation of the shop floor processes. This application can be used to evaluate effects of resource change on process performance indicators, AI techniques for scheduling processes, etc. The simulation model development process involves a selection of the modelling approach based on the evaluation objective, an analysis of data to extract meta-models, and the implementation of simulation models in any discrete event simulation or agent-based simulation software.

2.2. Types of Digital Twins

Digital Twin is a means of representing and monitoring a ‘physical’ entity or entity set in a digital domain. Representation is done through visualizing real objects into 3D CAD modelling or using digital renderers, animation techniques, and real-time high-speed computation engines. A DT is established by connecting digital models to data fed from the physical space and key attributes of the system. Such data interpretation includes breaking mean-centering and time-series analysis as the system elements expand the state space due to uncertainties in inner dynamics or external interaction. Monitoring involves data sampling, cleaning, and clean batch optimization effect modeling, which can incur expensive uses of change dust, clean water, pressure-drops, equipment-stresses, and lubricant use in the manufacturing domain in a context-specific area. Based on the cyber element and communication network, a Digital Twin guarantees real-time detailed object behavior and deep insights. To reconcile forecasting with meaningful, plan-enabling views and/or embedded intelligence on the manufacturing floor, the proposed DT approach introduces a specific assessment of susceptibility zones on cylindrical objects under disparate heating conditions with diverse roughness characteristics. Such fuzzy zones can be interpreted effectively using DT-PD modeling. The DT-enabled framework provides a list and priority of upcoming actions. Using graphical scenarios, it facilitates understanding and adjustability of the expected timeframe of a framework automation effect in manufacturing domains. A data-driven process-mining (PM) portfolio can be used to reconstruct as-is workflows and inference of models that aggregate individual, aligned processes. Conversely, the lack of metric-enabled verification raises challenges for the reconciliation of reality with regard to expectations by business process models (BPM). The advent of Digital Twins - a virtual replica of a physical object or process that leverages data to observe and analyze - holds great potential for augmenting these analyses and generating insights that merit potential further investigation. More specifically, the PM-DT convergence is exemplified for the manufacturing shop-floor transformation of a deployment scenario in a German automotive OEM. Current gaps and challenges are described, along with specific needs for methodological frameworks - including interactions in between domain- and physics-based simulations of DT with corresponding data-driven approaches from the PM spectrum - within a hybrid AI-enabled framework.

2.3. Applications in Manufacturing

The interplay between the physical and virtual worlds has evolved due to the massive deployment of the Internet of Things (IoT) technologies and accompanying developments, forming Cyber-Physical Systems (CPS). Several industries are striving to build their own digital representations of the physical worlds, commonly referred to as Digital Twins (DT). Digital twins, a virtual copy of a physical object, have been widely considered an integral part of Industry 4.0 technologies. Digital twins combine simulation models of the physical entities with operational data to analyze the physical entities' performances. Generally, using a comprehensive digital twin enables better understanding and optimization of the physical entity. However, Rich data recording from various sources and resolution levels in Smart Shops create a challenge in managing a scalable comprehensive digital twin. A comprehensive digital twin architecture to manage a digital twin at multiple abstraction levels is modeled. To demonstrate its effectiveness in a digital twin-enabled intelligent real-time decision-making use case and application, an AI-enabled framework is devised to automatically optimize the shop floor workflow domain.

Industry 4.0 technologies are changing the characteristics of production systems in terms of the complexity, heterogeneity, and resolution of the integrated components. The digitization of manufacturing has led to extensive deploying sensors, devices, and systems to record large amounts of data with different granularity and quality across various levels of the shop floor. Using these data, understanding, monitoring, simulations, and analyses are needed to improve the performances and resilience of the manufacturing systems. Digital Twin, a virtual copy of a physical entity, is a widely investigated tool to use the collected data of the physical entity to analyze and improve its performances. Using a digital twin, better understanding, and performance of the physical entity can be achieved through a simulation-based analysis of the physical entity's future status and performances.

3. The Role of AI in Workflow Automation

The emergence of artificial intelligence has impacted various industries while fostering the growth of intelligent manufacturing systems. Traditionally, shop floor equipment has been monitored by simple PLCs or indicators, generating data that provides limited insight into the operation's efficiency. Presently, advanced manufacturing entails automatic equipment inputs and outputs measured through data acquisition devices and control systems. However, the data generated is vast and highly dimensional, fostering the demand for advanced AI techniques to enhance the utilization of the data. AI has garnered attention worldwide via research funding and institutional alliances and by being consolidated and showcased by larger manufacturing companies. Nevertheless, the expertise needed to conduct AI-related production research remains nascent in small- and medium-sized manufacturers.

With the advancement of AI-enabled hardware and processing capabilities, human intelligence can be offloaded on industrial Internet devices, which are essential for tracking, monitoring, inferring, and supervising equipment and workflow in manufacturing operations. Subsequently, these AI-embedded systems generate insightful outputs instead of data streams. With low implementation costs, the AI systems can be integrated into existing manufacturing equipment and enable insight into states, operations, efficiency, and resource utilizations. The inability to derive efficiency, reliability, and cost insights would render automated solutions ineffectual. This indicates the need for intelligent automation for manufacturing, especially with a significantly higher rate of automation compared to other industries.

Common AI-enabled Industrial Internet applications for AI-embedded workflow monitoring and equipment supervision are classified into the following dimensions: how to recognize targets, how to track the trajectory of targets, how to infer the state of targets, and how to respond to the outputs of inference. An industrial Internet solution portfolio provides hardware and software for small- to medium-sized manufacturers for equipment supervision on a service subscription basis. Based on developed AI models, descriptors are proposed specifically for either workflow monitoring or equipment supervision.

A systemic approach for workflow monitoring and equipment supervision across manufacturing levels is proposed. The systemic AI-embedded workflow monitoring and equipment supervision solutions provide a low-latency and integrable platform for optimizing the shop floor's workflow automation. Using production-related codes or system-level identifiers, the manufacturing flow can be acquired and customized. Responses from manufacturing workflow and equipment status can be used to calibrate models or adapt to environment changes. The information extracted using AI can mitigate the sharp decline in pre-trained model performance or infer states of observably unnoticed scenarios.

Fig 3: AI Workflow Automation

3.1. AI Technologies Overview

The performance of intelligent manufacturing (IM) systems relies on data-manipulating technologies, such as machine learning (ML) methods, that aim to optimize their functioning through various models. Digital twins (DTs) represent an efficient way of merging physics-based and data-driven models, enabling a more precise disruption in im data manipulation taking advantage of ICPs. The growing interest in combining these technologies requires a clear understanding of their functionalities and interactions. Their duties, dealings, and major international standards will be summarized as expected.

AI is defined as the capability of a system to mimic human cognitive functions, such as learning and problem-solving. The vision for AI can be traced back to the ancient times when mystics were dreaming of creating something as capable as the human mind. The term AI was coined in 1956 at the Dartmouth conference, where it was recognized as an interdisciplinary field not restricted to one technology. The 1997 victory of IBM's Deep Blue over reigning chess champion Garry Kasparov attracted big companies and investments. Although proposing different definitions, all agree on AI being a technological and scientific discipline intended to develop computerized procedures that carry out normally-abstracted, no-formalizable, and semantic tasks. AI has evolved towards a more human-centered paradigm. A graphical representation of the timeline with some relevant events in AI's history is provided.

AI technologies are classified into those requiring large amounts of numerical data labeled according to some clear criteria (supervised), ML methods, and those relying on an extensive understanding of the system's physics (white-box). DT can be defined as a particularly sophisticated model based on engineering and scientific knowledge that captures a real-world object's features and performance. AI methods may drive complex process systems (algorithm-selected inputs and process-algorithm interaction) but are ineffective in modeling high-order interactions. AI approaches can be classified based on whether inputs are continuous (cont. AI) or discrete (dis. AI). Regardless of the input form, AI is gaining relevance in manufacturing. AI solutions have proved their disruption power in predictive maintenance applications, "in the loop" toolbox for wide-ranging modeling and optimization tasks, process parameter optimization for energy-saving targets, and semi-supervised ML applications for replacing computationally heavy solvers.

3.2. Machine Learning in Manufacturing

Machine learning (ML) is a field of computer science that deals with the analysis of data and the development of algorithms capable of learning and improving from that data . ML applies to statistics, data mining, pattern recognition, and artificial intelligence. In manufacturing, ML enables machines to create rules or heuristics to accomplish a specific task or produce a predetermined output based on a set of indicators. With experience, machines gradually make better decisions on the tasks in question.

AutoML is specifically designed to automate ML processes. It essentially consists of recommending specific algorithms for specific datasets or optimizing feature selection/configuration and hyperparameters for a given algorithm on a specific dataset. With great benefit for small and medium-sized companies or industries with technical staff limited in knowledge of ML and data science, this kind of software, tools, or libraries is in great need. Automated data processing pipelines capable of implementation without the wide deployment of a data science team could significantly speed up the integration of results of the data-driven revolution in manufacturing. In addition to a set of data and a server, any industry could efficiently and effectively control and tag production and quality in real time.

Traditionally, ML has been applied statically in manufacturing and similar industries. This means that by characterizing, often by hand, how the data acquisition systems and tools used to store, preprocess, and analyze data work and how they are interconnected at the system architecture level data, static ML methods can assess and name information flows, specifications, and even final performance measures. Unfortunately, this has two key drawbacks. First, large, complex models may be hardly interpretable. Second, pre-trained models, even if large and randomized, lack flexibility, which limits their ability to adapt to rapid system evolution.

3.3. Predictive Analytics and Decision Making

The proposed SFFA-DT framework leverages the advantages of the advanced Digital Twin (DT) architecture. Most production systems are digitized, and as a result, a data explosion has occurred on the manufacturing floor. DTs allow for time representations and history knowledge and generalize Data-Driven Decision Making (D3M) based on the ability to predict future states [4]. As the data floods, and complex structure increases, the identification of the problem and its solutions requires a more dynamic functionality.

At the manufacturing scene, intelligent equipment including sensors, cameras, and Machine Learning (ML) models can be placed on or near areas of interest to reduce the volume and dimension of data. Instead of processing the images at the control center, a DT can complete the pre-process and train processes. The input layer of the DNN can be changed to adapt to the images or audio datasets with other dimensions. The result output can be represented in basic performances of the entities instead of the individual level. The processed images or audio can be sent to the uploaded system, L1, for an online service. The structure of the SFFA-DT is a hierarchical manner similar to the Automation Pyramid.

First, the management level of DT models the integrated processes and monitors the global performance. The data preparation includes the extraction of relevant data from various historical/System Databases (SDB) and Real-Time Databases (RTDB) via SQL with timestamps to ensure unique data. Such data is usually large and inconsistent, with redundancy and outliers, which have to be cleaned before analysis. Raw data is cleaned through SQL and Python with efforts to increase the repeatability of the data preparation and cleaning progress. Based on the cleaned data, ML algorithms are selected according to characteristics in the application of product-type prediction.

Equ 2: Task Scheduling Constraints

$$\min \sum_i \sum_j x_{ij} t_{ij}$$

Subject to:

- $\sum_i x_{ij} = 1 \quad \forall j$ (each task assigned once)
- Machine capacity/time constraints
- Precedence constraints: $C_j \geq C_k + t_k$ if task k precedes j

4. Integration of Digital Twins and AI

The integration of AI and digital twins (DTs) increases automation royalty in discovering, understanding, and simulating aspects of real systems which can augment respectability, accuracy, and comprehensibility of 3D/4D models of systems using observational data extracted from systems with or without causing interferences.

Analysis of time series data is a type of model analysis. It analyzes aggregated data collected from systems as histograms or time series of quantities. The simplest form of understanding mass and capacity of systems is the histogram of the number of masses and the remaining capacity of machines collected over time. Analysis of time series data can also be carried out from a higher-level perspective by using probabilistic models such as Hidden Markov Models

(HMMs) or comparatively sophisticated models, e.g., simulations and neural networks, to overcome the latent transition problem. The predictive accuracy of these methods has also been improved by searching unobserved states and by applying unsupervised and supervised machine learning (ML) methods. the 3D aspect is usually prescribed with models while the temporality/4D aspect is generated and updated. Essence means not the real system but a visually and interactively reconstructed version of the real system for conceptualization or understanding which reflects fundamental aspects or dynamics of the real system by various abstraction, omission, and aggregation.

Potentially, countless models themselves without energy may be represented. Even the holy grails of the models, Mahalanobis–Taguchi Systems (MTS), and pre-defined environment pre-supposed for Simba can be violated. Digital twins work as E-Transition based on CCS and T-S Systems in both sending aspects to digital worlds and in receiving aspects to understand or analyze aspects of systems in the interactive way mentioned above. Even different types of state or aspect spaces of digital twins work jointly and in harmony with expected fusion/symbiosis merits and their efficiency/sophistication can be improved by having more models. However, this fusion virtual space is disentangled on the modeling side in computational implementation. Computationally, DT works independently as a graphical e-world or model world and as the model specification and operation is confined in this e-world. Therefore, development across spaces is not directly and instantaneously compatible. This can be bridged with homomorphic learning and reasoning.

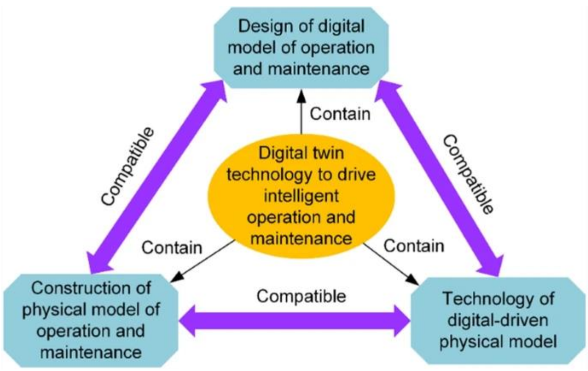

Fig 4: Digital Twin for Integration

4.1. Framework for Integration

Digital Twin is a technology that has found applications in many industrial areas, e.g., power systems, autonomous cars, and smart grids. In fundamental assessment, it is a mirroring of elements and their interactions in the physical world in the digital world. Digital Twin also has the ability to connect the models, computation, and data of a system throughout its lifecycle – from conceptual design, through realization, operation, decision support, to evolution and obsolescence. This has pushed the Digital Twin research frontier in both modelling and computation techniques, and in the technology areas of big data, 3D visualization, IoT, and system science applications. This technology has opened a plethora of possibilities to mitigate the complexities and unwanted events related to systems characterization, modeling, analysis, prediction, design performance study, operation optimization, and on-demand service specification.

Although the concept of Digital Twin has blossomed, the adoption and implementation of Digital Twin methods in manufacturing is still largely in its infancy. Especially, existing methods of creating virtual models for production systems using simulation and optimization need to be tailored to prepare for Digital Twin technologies that allow an interaction among virtual models and data feedback. Virtual simulations (or models) are considered to be an integral part of a Digital Twin that yield a foretelling of the future and thus support the Digital Twin's purpose, either to avoid possible undesired states of a system or to enhance desired states. However, methods or approaches to create simulation models that can be extended to be Digital Twins have not been structured as far as the author is aware. On the other hand, the virtual models need to be accurate enough so that the properties or behavior resulting from simulation can be believed.

4.2. Challenges and Solutions

Various studies have examined the adoption of digital twins in manufacturing processes, including factories and smart factories. Some examples of the digital twin's deployment in manufacturing include a digital twin for the modelling of virtual factories. On the other hand, various studies have focused on the development of digital twin technologies. The enabling technologies and tools for augmenting digital twins have been discussed. A system architecture to conceptualise the digital twins in different domains is delineated, with several case studies discussed, including virtual human factory and intelligent service robotics. Additionally, some other studies focused on the development of digital twins for a specific use case, such as the modelling of a factory workflow with a cell level digital twin and the digital twin's deployment in condition monitoring and control. Digital twins can encompass various domains, including systems, plants, processes, and parts, and their integrations are made possible by the representation of the digital twins in various model abstractions as the enhancement of roles in the digital twins. Therefore, one of the challenges in the research of digital twin is the design of a multi-application interoperable digital twin that can best leverage various digital twin models simultaneously while being extendable to support new applications.

Digital twins have numerous applications, and possible research directions can be listed. Management based digital twins: Involving a joint model comprising the overall information of a production line, such as a fuzzy digital twin of a flexible manufacturing system. These digital twins are also multi-purpose, as they can benefit planning, scheduling, and control applications. There are various mathematical models for such digital twins, including Petri nets and based approaches, machine learning/mathematical programming approaches, and min-max expressions, not including their numerous combinatorial counterparts.

5. Workflow Optimization Techniques

An important optimization area is the evaluation of the balance of production allocations when new production orders are being introduced. In this case, a weighted boolean sum function with dynamic weights can be considered concerning the workload, setup changeover times, production schedule, delivery dates, and deadlines of completion. The weights of the production behavioral characteristic factors can be assigned ordinal precedence, or heuristically estimated, through expert judgments or heuristics upon initial production allocation generation. The production resource agents can then ensure the awareness and observance of the prioritization goals or constraints regarding the refinement of the initial target behavior on dedicated neighboring computational nodes. The fittest schedules can then be replicated and dispatched to neighboring production agents while detouring through the evaluator agents and following their intrinsic AI-based competitive or synthetic-based heuristics. A configurable genetic algorithm can also choose tagged candidate schedules and let them evolve over generations to finally converge towards optimization near the best schedules. Inputs may flow according to each found schedule estimate, and the corresponding agent's production scheduler can execute the acquired input feeds by initializing, changing or abridging the actively scheduled production resources' states.

The targeted estimated outcomes can be periodically released to specified production resource agents, which can then undertake relevant adjustments on their production resources for ensuring alignment with the desired scheduled behavior. The same initial conditions can also be evaluated in another phase with other agent configurations on other computational nodes for balancing diversification in search and demand evolvement scenarios. Dynamic production workflow perturbation can be autonomously regarded as a newly incepted disruption event. Initially, whether or not to accommodate input flows of unfolded tasks is to be considered. If positively regarding the occasional incidence of excessive workload, a bi-level optimization scenario wide in workload distribution equilibrium and production schedule adaptation can be undertaken. The new load task can then be forwarded to relevant adaptive production resource agents if the input tasks are relegated to existing rush items, and no related condition will be proceeded accordingly. An optimization layer constructed atop the agents can perform high-level estimations.

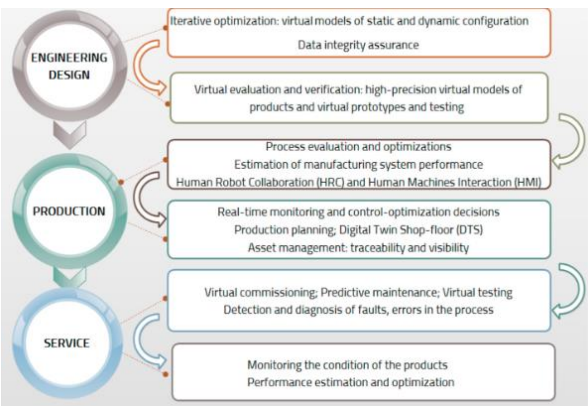

Fig 5: Workflow Optimization Techniques

5.1. Process Mapping and Analysis

The AI-enabled framework was developed in three subsections. In the first subsection, a framework for process mapping and evaluating automated workflow processes is introduced. The as-is process mapping flow was reformatted in the DSL. Further, the automated workflow was also notated using the modified process mapping flow. The matching of the two notations leads to the analysis of the gaps in the automated workflow process. Process mapping and analysis provides the foundations for model generation and re-engineering and evaluates the current status of the automated workflow process to suggest possible changes based on the factory and goal preferences. This study developed a framework for process mapping and analysis based on the DSL that includes methods for as-is and to-be process mapping and comparing the two mapping notations. Based on this framework, the as-is and to-be process mapping flows were produced, and initial matching was conducted. The initial matching led to the redesigning process of the automated workflow process, which has been discussed in detail in the next section.

Digital twin offers simulation capabilities to enable robust evaluation of the correct and efficient operation of the object under consideration. A generic definition of computational simulations is "virtual models that exploit mathematical principles and algorithms to simulate physical phenomena." In a digital twin context, the virtual model should mimic the physical system at least in the context of output fidelity, i.e., a measure of the "exactitude" of predicted behaviour based on the models being practically feasible. Considering the twin nature of the method, the former forms the foundation of the latter. Thus, the virtual models need to be accurate and flexible enough to be updated along the lifecycle of the object as desired in a digital twin. Otherwise, it cannot be a proper digital twin. Based on this perspective, the study at hand proposes the process of developing and maintaining the digital twins of manufacturing systems via discrete event simulation models, considering the best practices of conventional modelling efforts.

5.2. Lean Manufacturing Principles

An ideal shop floor in an automated factory should be consistent with shop floor kinematics and shop floor current state. To get an appropriate workflow plan, a model is trained that connects DTs with shop floor control software. This AI-enabled Workflow Automation model has been successively applied to the assembly line of engine brackets. This model can be customized and generalized to any kind of factory by considering their specific automata parameters. DT is used to build real-time visual states of the assembly line, and automation intervals are predicted with LSTM-based networks. Concurrently, the collaboration among robots and materials is simulated by DTs pre-manufacturing and on-site period. By utilizing generative and deep learning technologies, shop floor localized optimization has been conducted successfully. In this proposal, the smart factory design-to-automation pipeline is significantly enhanced by this DT-driven automatic design task. This DT-enabled assembly shop floor DT is an integrated hybrid digital world that visualizes the real aspect of thousands of interactive parts from a supply-facing view and a detailed virtual representation of on-site tracks and motions. A factory space is coupled with the simulation of every manufacturing logic. Synchronizations are introduced to eliminate day-to-day conflicts. A blueprint is generated and auto-piloted to off-the-shelf hardware, followed by repair provisioning. Finally, the shop floor is automatically cleaned and ready for production. As the requested showcase, a series of new automated processes for adding water in a hydrant is designed by DTs. Pipe lifts are systematically integrated with robotic arms and flexible conveyors for consecutive parts retrieval and water transfer.

5.3. Continuous Improvement Strategies

Continuous improvement is a structured approach that is applied systematically over long periods of time. The premise is that any activity that an organization engages in can be analyzed, redesigned, and/or improved. Expected benefits from continuously improving operations include increased productivity, enhanced quality and customer satisfaction, improved safety, and reduced costs. The case for continuous improvement requires ongoing attention, commitment, and education because of the risks associated with the implementation of a new way of doing business. Continuous improvement makes good sense intuitively.

Continuous improvement is the incremental improvement of the efficiency and effectiveness of products, processes, and services over time, which is of special importance in manufacturing companies. The need of modern manufacturing companies is to improve products and processes more quickly and effectively and to deliver improved services. Also, they have to invest more money in more capable technologies, which in turn is needed to develop increased value.

The goal of work presented was to help manufacturers to improve shop floor operations by a systematic process with help of TOC and CI techniques. It is common in manufacturing factories that once new machines or processes that will increase throughput are implemented, those machines or changes are not analyzed further and are considered to be just maintained. On the contrary, improvements should be assessed and measured periodically against KPIs. The SHOP analysis tool was built and is intended to help Agile, Lean, and Mistake-proofing teams to analyze improvements in many dimensions. The application together with methodology is considered to be an asset that can widen the range of means for measurements and analyses by CI practitioners and researchers. For this work in manufacturing practice, the introduction of new technologies and machines focuses on obstacles that are inherent in production improvement projects.

Equ 3: KPI-Driven Feedback Loop for the Digital Twin

$$\theta_{t+1} = \theta_t + \alpha \cdot \nabla_\theta L(\theta_t)$$

Where:

- θ are parameters of the simulation model
- L is a loss function between simulated and real

6. Conclusion

This paper proposes AI-enabled intelligent frameworks to optimize Workflow Automation regarding digital twins of shop floor processes. Automation workflows continuously receive input data and produce output data. To automate with AI, the ability to understand the output data, gain predictive insights and maintain the output-dependent workflow are required. The output data of shop floor processes require object-specific understanding. For shop floor automation, the approaches based on a conventional data-centric method fail to grasp the required specific understanding. They lack the ability to “understand” the output data object-specifically. This paper proposes to use an object-centric representation for automated understanding, predicting insights, explaining insights, maintaining the automation pipelines, and safeguarding the production process.

The object-centric understanding enables an indication-aware and system-agnostic predictive analysis and explanation to mitigate the sophistication, prevent model errors for varied instances, and customize user requirements. Furthermore, by virtue of the model reuse, monitoring automation can be developed and sustained efficiently. For optimal parameter tuning on complex systems while ensuring system constraint satisfaction, a model-free optimization method is proposed. It ensures convergence to optimal settings regardless of the initial condition and enables the propagation of dynamic constraints during the operation based on the control approach. Other model-free process plans are realized regarding conservation and production line design. They can work for other tools beyond shop floor automation.

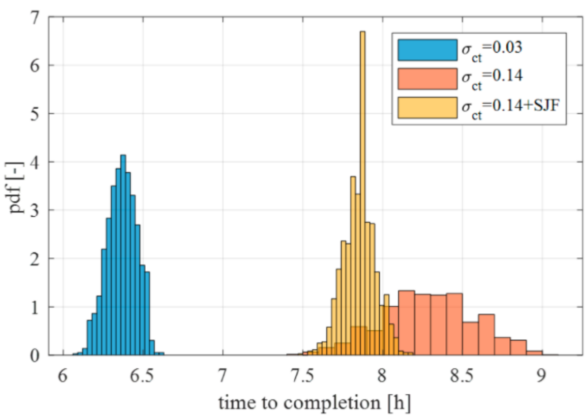

Fig : Digital Twin Based Optimization of a Manufacturing Execution System to Handle High Degrees of Customer Specifications

6.1. Future Trends

In recent years, the rapid integration of AI into various facets of society has spurred the need to clarify how best to develop, deploy, and govern AI systems. However, as AI reveals its potential to augment and change how work is organised and performed, there is a pressing need to revisit shop floor workflow automation. This data-driven AI-enabled Framework for Optimizing Shop Floor Workflow Automation provides a new foundation for analysing, designing, and optimising shop floor workflow automation across industries. This research makes advances in extending a full stack framework, methodologies, tools, and workflows for building both assessable and controllable implementations of smart workflow automation.

These newly introduced capabilities are validated using industrial-grade case studies involving the application of legacy industrial bots and current, state-of-the-art digital twins. Future research will explore integrating emerging AI techniques to provide an ever-richer toolbox for analysing, designing, and optimising complex smart workflow automation. Additionally, the applied domains will be expanded to include other aspects of smart workflow automation at different scales, and real implementations proposals will be developed in collaboration with responsible industrial partners. The digital twin models and technologies are well suited to examine and improve these complicated production processes where material handling robotics systems are already used to automate these complicated processes. In this regard, for an interface between the digital twins and the web-based environment, they have designed the architecture of a digital twin web-based comparative learning simulation platform with both localised and cloud computing embedded, which can create the authorable digital twin based on highly parametric digital twin model.

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