Modeling and Simulation of Manufacturing Processes and Systems: Overview of Tools, Challenges, and Future Opportunities

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Received: 26 September 2022 | Revised: 13 October 2022 | Accepted: 21 October 2022

Abstract-Manufacturing is an important part of the modern economy. It is characterized by complexity in terms of systems, approaches, and interactions with intrinsic and extrinsic factors. Numerous efforts have been developed to use modeling and simulation tools to improve manufacturing efficiency and productivity and to achieve maximum quality, especially with the different mutations in the factories of today. This paper reviews the conventional and modern tools used in manufacturing system design and production improvement. Challenges that need to be addressed by the simulation community are discussed in depth. Finally, the evolution, advances, current practices, and future opportunities are discussed in the context of the contemporary manufacturing industry.

Keywords-production processes; systems; tools; simulation; modeling; mutation; Industry 4.0; Indystry 5.0

I. INTRODUCTION

The majority of factories today face many challenges when trying to define how to acquire and maintain their position in the competitive business environment. A major challenge is to ensure that production, supply, and customer processes are correctly implemented and stabilized. These processes transform the input material and increase its value [1-3]. The main goal of the factories and enterprises today and in the future is to increase the value of the product effectively and to produce the smallest possible amounts of waste [4-6]. Therefore, production processes have attracted a strong interest in the modern factory design [7-9]. Consisting of various devices which have a set of tasks, trigged by specifics commands, a manufacturing system is traditionally evaluated and analyzed by simulation [10-11], which is a powerful and widely recognized technique [12].

While most previous works were focused in the simulations and modeling of manufacturing systems as a tool of analysis and development, the orientation of our research into new manufacturing approaches is directed towards the area of modern manufacturing systems, using reconfigurable manufacturing systems, adaptive logistics, and the concept of Industry 4.0. New simulation systems which must be adapted to this new requirement are therefore discussed.

The article deals with the description of the simulation tools and modeling of conventional and modern manufacturing concepts that are potentially highly applicable for use in future factories and the core descriptions of these tools in the process control for the Industry 4.0 and the emerging Industry 5.0. Therefore, after considering factory mutations, the paper investigates the evaluation, advances, current practices and future trends of simulation methods and approaches. Digital twins, suitable performance, lean in manufacturing system, IoT-enabled forms, and Virtual Reality (VR) in process design, planning, and verification are examined.

II. MUTATION OF FACTORIES

During the last decade, an increase on the demand of individualized products and natural resources has been noticed [13]. Besides, the huge evolution in technology and the smart concepts stimulate the user demand [14-17]. As a consequence, strong mutations in the society behavior, lifestyle, and consumption are noticed and are considered as new indicators of globalization [18-21]. The manufacturing systems represent a significant growing share to the global trade and become more and more challenging [22-24].

Authors in [25] are among the first who introduced the virtual manufacturing concept by integrating different factory models, whereas authors in [26] proposed virtual facilities for different ways in a smart manufacturing system, including simulation, virtual organization, and emulation facility. Actually, the most important point in the factory mutation is the appearing of the Factory of Things (FoT) [27]. FoT is based on technology characterized by the embedment of physical devices and many electronic compounds, with a wireless internet connection, known as the Internet of Things (IoT) [28-30]. It is fueling the industry 4.0 and space, health, and nanotechnology factories [30-32]. New challenges are raised by the Industry 4.0 which drives smart factories by: i) data

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volumes and connectivity, ii) business intelligence capabilities, iii) human machine interaction, iv) emergence of modern transferring digital instructions to the physical world [33-37]. As a consequence, IoT is considered to be a key technology, required to support the propagation of successful Smart Manufacturing as the extension of the IoT concept to manufacturing systems [38-41]. Besides, as information is the most required input for a smart factory, advanced technologies like wireless sensor networks and cyber physical systems are needed to provide the parameters used in the analysis platform for seamless, automated simulation, optimization of shapes and geometry, and management of data and outputs [42-44]. These elements create a smart environment, and make communication between machine process compounds with central processing or various other possibilities [45]. This new concept is resumed as [26]: evolution of a system of data in terms of time, process, and manipulation: i) calculation of the time between a stop and the next start event in a manufacturing operation, ii) calculation of the number of produced parts between two steps as a second service [46].

III. DIGITAL TWINS

To create production process models, a digital twin of a physical process is needed, one that will enable process monitoring, real-time decision making, and control [47]. A digital twin represents a virtual model of a physical object which can simulate the object's behavior [48]. In that way it is possible to simulate production steps and to predict the impact on the product [49]. These simulations are highly utilized in Industry 4.0 to simulate products, robots, and humans in order to reduce failures and optimize resource consumption [50]. Numerical models are used for different manufacturing domains, beside the expansion of available data sources. They are particularly used for proving simulations of various parameters difficult to measure [51]. Therefore, hybrid digital twins are used to model the usual behavior of the underlying manufacturing process or system [52]. This hybrid concept offers new services like detecting data-driven anomalies on simulations for new protective data, virtual prototyping, or a virtual instance of a physical system (twin) [53]. The objective is to lead high precision models showing not only physical parameters, but also a representation of their behavior, for monitoring, simulation, optimization, and developing of new products [54].

IV. MANUFACTURING PROCESSES AND SYSTEMS: MODELING AND SIMULATION FOR SUITABLE PERFORMANCE

A manufacturing process is a system characterized by a continuous evolution, interaction, and mutation, as it is a complex dynamic system, composed of several elements: management approaches, production facilities, control and monitoring equipment, and machining tools and operators [55]. With the variation in user demand, the search for better performance, environmental constraints, stability of production systems, and increased competition, the manufacturing processes are becoming more and more complex [56]. Decomposition of a production system into subsystems of various depths is a necessity for the suitable analysis and effective study at the different levels of its specification [57]. Optimization of production and manufacturing processes is established through data processing tools [58]. This approach allows dissecting and deriving, the relations between elements of technology, transport, storing, and layout subsystems. However, it is not an evident or easy engineering task [59]. Therefore, models and simulations are used to achieve effective and efficient production, by improving existing processes, or innovating a required system, to reduce time cost, improve productivity, achieve competitively, and ensure quality [60]. It can be accomplished through a simulation of varied schemes of production on relation to different intrinsic and extrinsic factors (for example, parallel, sequential, or mixed schemes of production, different types of plant layout (process layout, product layout, combination layout, fixed position layout), design of manufacturing value chain, etc.) [61-69]. It is planned as consequent data usage, transformation, integration, and aggregation driving real innovation [70].

V. SIMULATION-BASED MULTI-OBJECTIVE OPTIMIZATION AND LEAN MANUFACTURING

A. Conventional Tools

To develop and improve manufacturing processes and different related systems, we use different simulation models. A good formulation of a model which describes the function, evolution, and interaction with different related elements is based on data analysis and study [70]. Different techniques for process improvement are exploited. Linear programming, Discrete-Event Simulation (DES), System Dynamic (SD), Markov Chain Analysis, and Monte Carlo Simulation are considered the most popular conventional simulation tools [71-74]. Various modeling formalisms have been established to describe the manufacturing processes and systems for varied fields and engineering applications (e.g. model of a machine, cell, line, site, etc.) [75, 76].

1) Discrete Event Simulation Parameters

The manufacturing systems are described with much formalism. The Discreet Event System (DEVS) specification is the most popular tool for modeling deterministic systems [77-79]. The elements are interchangeable in many cases and are related by graphs, diagrams, and Petri-net formalism [80-82]. As it is a rigorous and able tool to describe discrete event models in hierarchical and modular manner, DEVS is considered an efficient way to describe production processes mathematically when they are divided into different stages within a sequence of production steps [83, 84]. Complex and stochastic flows in production lines and logistics systems are also described by this simulation tool [85-87] with relatively minor investment. As indicated in [88], DEVS can provide several scenarios despite the need of a large amount of modeling time in order to analyze system performance and to converge to an optimum solution. However, as the simulation is not an optimization tool by itself, in some cases, the improved scenario cannot give an optimized solution [89, 90]. Unavoidable parameters in this stimulation tool are illustrated in Table I.

2) Simulation Based Optimization

Simulations of processes, machines, lines, or entire factories are built for a variety of reasons including virtual experimentation, prediction, and optimization [91]. In order to be confident in any result of such a model, it must be validated against the real system [92]. The opposite also happens, when we wish to know whether the machines are operating as expected. This is done by comparing the data gathered from the simulation to the data gathered from the smart factory [93]. It is possible to perform this validation using summary statistical information, but it can hide the dependencies present in the underlying data [94]. Stimulation Based Optimization (SBO) combined with incline devices has a tremendous potential for the framework and handle advancement in fabricating. While SBO can be utilized to analyze complex energetic frameworks with high inconstancy and an expansive sum of conceivable arrangements, incline devices can make up a base for persistent change in individual processes [95]. Be that as it may, there is frequently a need of information in order to begin working with incline devices and reenactment approaches, particularly in production lines with a long history and tradition [22].

TABLE I. PARAMETERS OF DIFFERENT SIMULATION MODELS

Failures	Amounts of different kinds
	Distribution of durations
	Distribution of intervals
Cycle times	Of processes
	Of assemblies
	Of manual task (distribution)
Steps	Times (distribution)
	Dependencies between articles
Batches	Container sizes
	Delivery quantity
	Frequencies

B. Modern Tools

VR, 3D Discrete Event Simulation (DES), data analytics, and real-life data from the products, processes, and production systems are considered the most popular modern tools for simulation and optimization [96-98].

1) Virtual Reality (VR)

Integration of training in an immersive VR environment, with simulation, modeling, and data analytics, is planned to make harmonization and dissemination of knowledge more accessible [99, 100]. Demonstrating the 3D VR recreation based on genuine production line and item information envelops the as-is show of the fabricating plant, counting the consistent connections. In this stage, the substances within the VR can be considered computerized models of their physical partners [101]. The virtual tests of a computerized exhibition are based on the standards of simulation-type modeling [102]. Tests are utilized to survey the robustness and the ability of the physical equipment to comply with the prerequisites of the Terms of Reference (ToR) described within the virtual machine by the specialized computer program (SW) components [103].

2) Data Analytics and Real-Life Data from Products, Processes, and Production Systems

A virtual representation of fabrication frameworks utilizing the information from genuine industrial facilities can offer arrangements for item advancement and bolster item presentation forms, from design-to-manufacturing to simulation-based information analytics. It can allow shrewd generation frameworks [104-108]. Appropriately, the virtual plant is a coordinated, high-fidelity recreation demonstration of a fabricating plant, which offers a progressed choice bolster capability and can back the assessment and reconfiguration of unused or existing fabricating frameworks [109, 110]. Therefore, real-time information integration between VR-enabled VF recreations is considered to be superior with higher exactness, precision, and unwavering quality [111-113].

3) 3D Discrete Event Simulation (DES) Using FlexSim Simulation Tool

FlexSim simulation tool was utilized to create a VR recreation in [114]. It is a 3D DES computer program which contains common and health-care-focused items [115-116]. Its user-friendly drag and drop interface and comprehensive visual capabilities were considered important for quick experimentation. FlexSim's inserted VR capability permits clients to show, run, and control the recreations and collect the factual information in 3D graphical VR environment [117-119]. This capability brought significant preferences in diminishing the time for approval after each reconfiguration/redesign of the VR. The interesting sentence structure of the instrument makes it challenging to create customized models [25].

4) Simulation for Learning Factories: The Example of Fischertechnik Manufacturing Plant Models

Manufacturing businesses are transitioning towards more independent and smart generation lines within the Industry 4.0. Learning production lines as small-scale physical models of shop floors is done in order to conduct inquiries about the shrewd fabricating zone without depending on costly genuine generation lines or totally mimicked information. Learning factories are used for conducting investigations within the setting of commerce administration and IoT [120]. The physical Fischertechnik manufacturing plant model mimics complex generation lines. Three case studies of combined BPM and IoT were considered in [121-125], i.e. the execution of a BPM deliberation stack on behalf of a learning manufacturing plant, the experience-based adjustment and optimization of fabricating forms, and the stream processing-based conformance checking of IoT-enabled forms. By utilizing physical manufacturing plant models as test beds for assessment, investigation is more realistic–but more challenging–than utilizing artificial information in this kind of profoundly energetic CPPS. Physical plant models empower the approval and exhibition of inquiries about artifacts in an ensured environment [125]. At the same time, this close-to-reality recreation of a genuine generation line encourages the exchange of created concepts into hone.

C. Model-Based System Engineering (MBSE)

MBSE could be a key enabler for building complex frameworks as can be seen by the expanded number of related distributions [125-127]. For effectively building Industry 4.0 frameworks, the MBSE community plays a pivotal part by empowering the previously mentioned plan standards. Model-based framework designs have appeared to encourage the improvement of such frameworks, but their application to

Industry 4.0 has not been efficiently explored [128]. To comprehend the commitment of MBSE to Industry 4.0, precise mapping has been conducted in [30, 129-130], which uncovered that computerized representation of robotized frameworks, i.e. their interfacing and information models, as well as their integration and (re)configuration are the prime Industry 4.0 concerns tended to by MBSE. Most published papers contribute strategies and ideas to illuminate specific challenges of Industry 4.0.

VI. FUTURE OPPORTUNITIES AND CHALLENGES

Investigation on the evolution and recent developments of industrial simulation technology and describing the gaps and future trends in this field are important in order to explore future opportunities for more effective manufacturing processes and system implementations. In the complex item digital twin arrangement, the items display and reenact procedures that create and expand tremendous sums of (generally organized) information. The arrangement of models along the complete lifecycle of a complex item (e.g. as outlined, as fabricated, as kept up) requires advanced modeling-simulation techniques. Looking at the mechanization within the machine fabricating field and mechanical autonomy, the larger challenge is signified by the working program, particularly planning program frameworks. Another distinctive challenge is the actual execution. In this way, projection and enhancement of the computerization and mechanical autonomy program frameworks ended up critical and with issues. In this manner, the information analytics capability was not most centered on advancement. The DA capability of the recreation device was utilized to produce standard diagnostics for the shop-floor operations [131].

Nowadays, the concept of the shrewd plant is rising with the joining of the virtual and physical universes. As indicated above, the shrewd manufacturing plant could be a fabricating environment that can handle turbulences amid utilizing decentralized data and communication structures for ideal administration of generation forms. Within the case of a conventional plant, it is not fundamental to consider turbulences since the planning and execution tasks are consecutively performed. In other words, a conventional production line does not begin execution before the ultimate affirmation of the generation planning. A shrewd manufacturing plant, in any case, permits the concurrent advance of the planning and execution errands, since it has the means to handle turbulences in real-time generation [132].

This issue lead us to talk about the next generation of simulation systems, especially the need of more human-centered technology approaches, nascent in Industry 4.0, and now central to the emerging Industry 5.0, which is a value-driven concept based on three principle cores: human-centricity, sustainability, and resilience [133-135]. Simulation tools and modeling must adapt to the requirements of the new concepts of Industry 5.0: changes do not happen overnight in the systems that will use these new trends. The challenges are to find suitable modeling and simulation tools to introduce the concepts of the new paradigm in each essential segment of the manufacturing and to draw a connection matrix between key enablers for Industry 4.0 and 5.0, particularly people, companies, and technology [136, 137].

VII. CONCLUSION

This paper at first highlighted the conventional and modern simulation and modeling tools used in manufacturing system design and production improvement. Challenges needed to be addressed by the simulation community were discussed in depth. Finally, evolution, advances, current practices and future opportunities were discussed in the context of the contemporary manufacturing industry, particularly the challenges of the Industry 4.0 and the opportunities of Industry 5.0.

This paper can be applicated mainly in the field of the development of smart manufacturing systems, where the control system and the manufacturing process use simulations in order to predict efficiently the processes of future factories.

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