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ON THE ROLE OF DISCRETE EVENT SIMULATION IN THE INDUSTRIALISATION OF 3D-PRINTING MANUFACTURING SYSTEMS

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Abstract

The ability of additive manufacturing (AM) to release designers from the limitations of traditional production is unmatched. This adaptability makes it possible to design components that are strong and perform well while using the least amount of material. Because AM can create designs that are efficient and light, it has become widely used worldwide and has grown into a multibillion-dollar business with a wide range of materials and procedures. However, there are obstacles to overcome in the industrialisation of AM, including maintaining consistent quality, cutting costs, and maximising production efficiency. Discrete Event Simulation (DES) shows up as a vital instrument for conquering these obstacles. In order to improve process quality and encourage wider usage of 3D printing in manufacturing, this article focuses on using DES to simulate and optimise AM's industrialisation.

Keywords: Additive Manufacturing (AM); 3D-printing technology; Industrialisation; Discrete Event Simulation (DES) ; Optimisation

1. Introduction

Additive Manufacturing (AM) often called 3D printing (3DP) has a drastic effect of removing the use of traditional molding techniques. This enables people to design complex geometries where the number of components may be reduced. Using a digital 3D model as a basis, this approach develops components layer by layer and progressively. 3DP has evolved from an original concept to an essential component of modern production thanks to recent developments in materials and procedures [1]. Standards such as ISO/ASTM 52900:2015 are increasingly governing technology as it continues to industrialize [2]. AM has shown to be very valuable in the production of lightweight, integrated structures, especially in the aerospace, medical, and automotive industries. This has become a key area for researchers and engineers in both business and higher learning. These technologies have the enormous potential to change product designs, supply networks, and production methods, making it possible to create more complicated parts more cheaply and efficiently [3].

The need to maximise the utilization of AM facilities is expanding as AM materials and processes continue to advance, especially in terms of cutting the time and cost of 3D printing in industrial production [4]. Due to changing consumer needs and the requirement for quick modifications through flexible production layouts and processes, manufacturing organizations today confront significant hurdles in production planning and management. It may be particularly challenging to increase efficiency in complex production environments, especially when it comes to identifying and eliminating bottlenecks. The dedication of simulation tools, which are powerful and efficient, is essential to the intended end. Those tools are the main ones" that are used to speed up the manufacturing process from start to finish, which includes planning, implementation, and operational management [5].

In the context of 3D printing, the partnership between HP and Siemens at the DFactory in Barcelona is a significant step forward in 3D printing productivity and automation. The DFactory project aspires to streamline the HP Jet Fusion 3D printing production workflow by incorporating Siemens' advanced automation solutions which allow for high-volume and continuous manufacturing with human intervention being minimal. The objective is to accomplish "lights out manufacturing," in which processes are carried out automatically without the need for human oversight—even throughout the dark. In such a setup, all production-related tasks, including material handling, assembly, and quality assurance, are handled by machines, robots, and automated systems, enabling factories to run around the clock. In this way, the labour costs are reduced, the human error is minimised and it is the sustainable production that has more chances to be promoted [6]. Among DES is one of the most used simulation approaches for researching and improving manufacturing processes among other methodologies [7]. The modelling, simulation, optimisation, and visualization of logistics, manufacturing systems, and other operational elements are made easier by DES technologies. Because of its adaptability, DES is very useful for conducting in-depth analyses of system features, identifying possible weak points or bottlenecks in process flows, and enhancing important performance metrics including productivity, material handling costs, energy consumption, and resource usage [8].

For example, Omogbai and Salonitis [9] proposed using DES to simulate and assess lean manufacturing improvement initiatives before their use. Velumani and Tang [10] also demonstrated how to use DES to control production bottlenecks in batch processes and evaluate operational conditions. In addition, Prajapat et al.[11] created a DES model for a repair plant, giving decision-makers a tool to assess different facility layouts and configurations in order to maximise output.

This paper is divided into the following sections: Section 2 serves as an analysis of the existing research on DES. Section 3 looks at the evolution and significance of simulation in AM. Section 4 deals with the use of DES as a simulation tool within this provided context. Section 5 offers an overview of the simulation process that was done in the preceding work. Section 6 explores the role of digital twins, and finally, Section 7 recapitulates the most important findings of the study.

2. State-of-the-Art on DES

For the analysis and optimisation of business processes, simulation modelling presents a large potential. A case in point is the said models can dynamically simulate different parameter values, for instance, by varying arrival rates or service intervals, to help identify the bottlenecks and evaluate the alternatives [12]. Furthermore, graphical representations of processes that may be interactively updated and manipulated to visualize process dynamics are another feature of simulation models. This strategy has shown to be quite successful in resolving issues and enhancing manufacturing system design. Law and McComas [13], have pointed out that modelling and simulation are very helpful in industrial settings. However, multiple objective analyses and optimisation inside these simulations are uncommon. DES technology is developing quickly; many academic articles and new software features are being released every year. Numerous industries, including healthcare patient flows, military tactics, logistics, contact centers, and restaurants, have used DES software and languages. Profit optimisation, which entails determining which options provide the maximum profits over time, is a common goal in DES [14]. Though traditionally the main priority has been income, environmental concerns are becoming more significant. There is an increasing need to address these issues in more detail as long as natural resources are used.

The industrialisation of 3D printing has been greatly affected by the development of DES technology. 3D printing processes have been something manufacturers can see with the aid of advanced DES technology, able to model such aspects as material handling, machine operations, post-processing, and quality control. With this detailed simulation, it is feasible to discover and fix potential problems before the physical production phase, thereby the transition from prototyping to full-scale manufacturing is simpler. Thus, DES is a valuable tool for advancing the development and improvement of 3D printing technology, promoting innovation, and raising industrial productivity.

3. The Evolution and Impact of Simulation in Additive Manufacturing

Since its debut in the late 1980s, AM has seen substantial change. It was first mostly used for fast prototyping, which made it possible for designers to produce physical versions of their designs rapidly and affordably. However as materials, technology, and manufacturing methods continue to progress, AM has evolved into a full manufacturing method that can produce end-use parts for a variety of sectors [15]. Consequently, the fact that AM now boosts industrial productivity through the use of digital systems and automation. Its usage goes beyond rapid prototyping, including both direct production of parts, as well as manufacturing tools for industrial use.

AM possesses distinct benefits which include its ability to produce intricate and lightweight designs with minimal use of materials, making it a desirable option for the production of advanced manufacturing solutions. For instance, AM is commonly used in the aerospace sector for making parts that are lighter as well as stronger than the traditional way of making parts. In addition, in the sector of medicine, AM facilitates the process of a production of bespoke implants and prostheses that are detailedly designed to fit the specific needs of the individual patients [16].

One important aspect of AM is that it produces material properties that can vary from one point to another within the same part. This variation makes it necessary to employ predictive simulation tools for accurate part design, especially for mission-critical applications. Because simulation can simulate and forecast the real behaviour of the manufacturing system, it saves time and money by eliminating the need for expensive trial-and-error trials. This is why simulation is essential to AM industrialisation [17]. With simulation software, models that are dynamic and interactive may be created to mimic the functioning of real production processes. Technology has advanced significantly in the industrial sector recently, making it possible to create intricate and affordable AM components. Enhancing the design of parts for mechanical performance and weight efficiency and modelling the AM process for these components are the two key aims driving this development, which is mostly driven by advancements in equipment and software [18].

It is essential to comprehend and optimise the processes involved in the design and development of 3D-printed parts in order to manufacture high-quality parts. Specific qualities like temperature control and form precision may be attained with the use of efficient simulation approaches [19]. The optimal input values are sought in simulation optimisation in order to minimise resources and improve insights. All aspects of 3D printing, from the melting of raw materials to the final tool path required to make a product, are covered by AM simulation. Throughout the whole printing process, accurate numerical simulations are critical to the success of AM. In order to generate lattice structures, optimise manufacturing processes, create practical designs, ensure performance during usage, and precisely calibrate materials, simulation is essential in several key areas of 3D printing.

Simulation tools are vital for cost-effective AM because they assist in the optimisation of different processes of the technology. By developing and improving lattice structures often utilized in AM, employing optimisation techniques to refine designs, and keeping an eye on phase changes to calibrate materials, they aid in functional design [20]. AM simulation brings several benefits. It increases the likelihood of successful printing, helps in making part design and quality improvements, as well as in preventing print failures. Imparting a full AM process insight allows for production optimisation thus reducing shape changes and increasing reproducibility. In addition, AM simulation is one of the methods used in cost reduction and elimination of the material waste problem, while at the same time, it facilitates the optimisation of designs, thus lowering the production and development costs. Additionally, the simulation also helps to locate the most critical elements of the printing, thus, avoiding the misprint that is very costly [21].

4. The Role of Discrete Event Simulation in AM

Discrete event modelling is best for the development of systems consisting of components that switch states at particular times due to either their own operations or interactions with others. This strategy is particularly applicable when the action of a system can be viewed as a succession of cross-nonoverlapping time intervals, mostly under the influence of some stochastic nature. DES is a system that is mainly composed of entities that are doing some tasks and interacting through activities and events. A system is seen as a collection of linked, attribute-rich entities that carry out tasks and interact with one another through actions and events in a DES model.

Simulation has been proven to be a very useful tool to improve the breakdowns of the manufacturing system and to find solutions for operational challenges. The application of DES in production has been widespread for energy consumption analyses, bottleneck reduction, and line balancing [22]. Although DES has existed since the 1950s, recent advancements in technology have made it possible to, for example, combine DES with virtual reality or to use automatic data generation as input for DES simulations [23]. Research has shown that IoT systems may monitor assembly lines and provide real-time data into DES for analysis and improvement. For instance, Ingemansson et al.[24] investigated how DES might use auto-generated data. The creation of DES systems, which can update their simulations continually using data stored remotely, is one significant accomplishment. Real-time data can be generated by machines equipped with sensors in a smart factory or Industry 4.0 environment, as exemplified in Figure 1. In this setup, the digital manufacturing execution system (DES) is a component of the cyber-physical system (CPS) that creates a real-time digital twin (DT) of the physical objects in the factory. In order to obtain the most recent parameters and produce updated findings, DES has networking capabilities and the ability to make scheduled Internet queries.

A locally run DES can the parameters like standard deviation and averages gotten by the application that is at the cloud service through remote requests. This web application can be the user's interface of a smart production center whereas it is also possible to connect with the intelligent production paradigm. In this case, the data stored in the cloud can be from real-world processes, which are monitored through the Internet of Things (IoT); the cloud-stored data is then analysed to make simulations, so a digital twin is created. In order to facilitate subsequent usage, DES can also transmit its results to the cloud. The purpose of the AR app was to project the digital simulation of things and their operations, which got the input data from the cloud to display the DES processes and results. The behaviour of physical systems, such as interacting entities whose states change, is often studied and simulated using DES [25]. It is frequently used as an auxiliary instrument in production to enable "what-if" encounters in order to check different settings and suggest alternative plans.

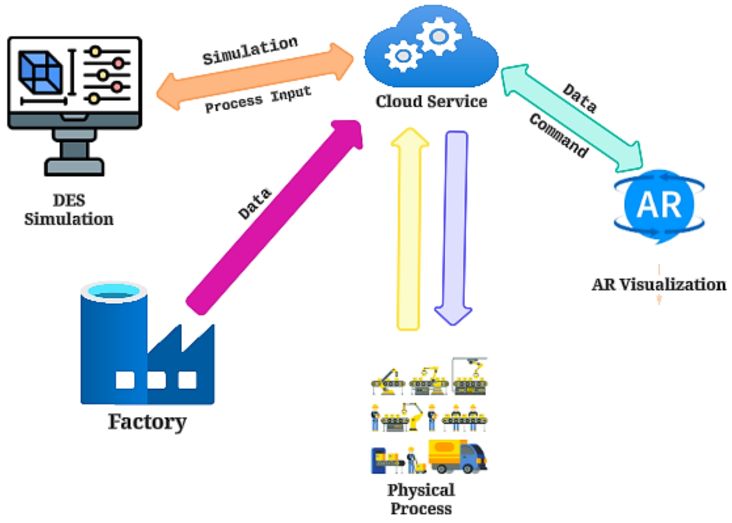

Fig. 1. DES simulation concept from a smart factory.

Many changes are happening in the simulation field nowadays, e.g., the transformation of DES applications from design to operation, and thus, the advantages of simulation in production processes are throughout the whole. A prominent trend is the adoption of hybrid modelling practices and optimisation tools and algorithms [26], along with the improvement of the capabilities of DES and the provision of new value for producers. Although DES does not physically interact with the system, it offers data to change a process based on factors added to the system, such as processes, time, and labour. The combination of DES with other Industry 4.0 technologies such as AR, IoT, and digital twins tore down this barrier by enhancing the application of DES to this zone [27]. Despite its simplicity, DES is a robust and sometimes expensive tool, offering three primary worldviews: activity-oriented, event-oriented, and process-oriented simulations. Although these viewpoints highlight distinct facets of the model, they are all interpretable from one another since they all adhere to basic modelling concepts.

5. Overview of the Simulation Process

A summary of the Selective Laser Sintering (SLS) based AM simulation process was presented in our earlier work (Figure 2 shows the production plan). In order to optimise production, key elements including setup and processing times, cost control, and bottleneck identification were all represented in the simulation. FlexSim software which follows the core principles of Discrete Event Simulation (DES) was used to record the dynamic behaviour of the AM manufacturing setting.

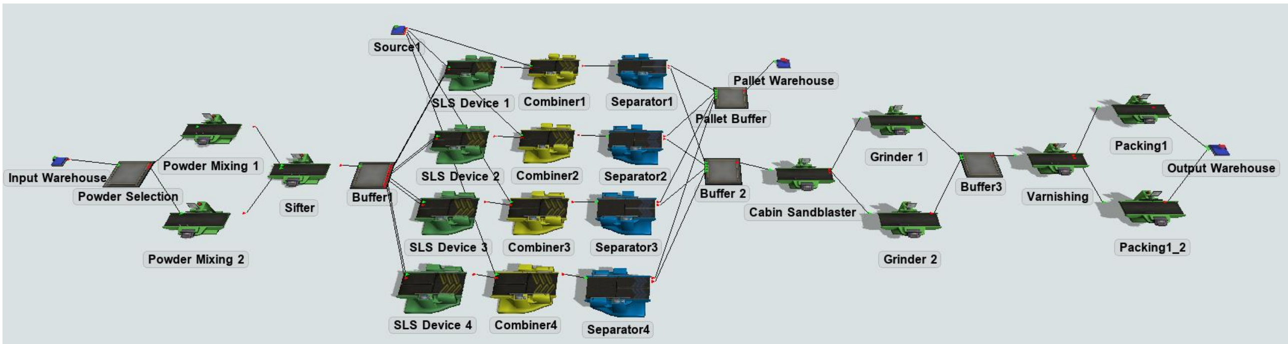

Fig. 2. Simulation model of SLS production line in FlexSim [28]

Important variables were incorporated into the model. For instance, a given number of parts were planned to be prepared concurrently on an SLS machine by taking into account the processing time and setup duration. The investigation also assessed how well machines were being used in terms of strategic configurations to boost productivity, reduce idle time, and enhance performance. The approach comprised simulating the AM process using three main stages—preprocessing, processing, and post-processing—with hypothetical data. A reference model was considered to simulate SLS machine configurations producing the desired number of parts annually, based on operational conditions like the shifts per day and number of working days per year. In order to maximise throughput, our simulation sought to locate idle periods and bottlenecks in the system.

Materials are fed into the system from an input warehouse and mixed in a powder selection buffer before being transported to a sifter to separate grain sizes. Following processing, the parts are arranged so that they depart the machines simultaneously. Due to software restrictions, the plan comprises separator machines for unpacking and combiners to expedite packing, allowing a seamless transition between phases. Buffers are included in the model to gather completed parts and pallets before they are returned to the warehouse for further usage. Parts are given various operations such as sandblasting and grinding to components to enhance their finish and correct any dimensional errors. Every stage is intended to maintain high standards of quality before varnishing and final examinations. Eventually, after being coated for protection and going through the quality control tests, such parts are boxed following rules and sent to the final warehouse for distribution. This methodical technique shows how to integrate efficiency and effectiveness in the AM simulation process in a balanced way while simultaneously improving production efficiency and guaranteeing excellent quality at every stage.

6. The Digital Twins

Modern manufacturing system design is directly impacted by the growing complexity and unpredictability of the present manufacturing and economic environment. More automation, reduced lot sizes, shorter product life cycles, and more product variability are some of the major developments that are being facilitated by intelligent control systems. As a result, suppliers and manufacturers in the discrete manufacturing space are putting more of an emphasis on automation, simulation, and digitization—all of which are critical at the production line and equipment levels. These developments are forcing businesses to incorporate cutting-edge technical solutions and redefine manufacturing methods [29].

Digital Twins (DTs) have become a key element of the changing landscape of digital technology. A virtual model that replicates its physical counterpart in real-time and is used for continuous monitoring, optimisation, and decision-making is called a digital twin [30]. DTs are essential to modern industrial processes because they allow smooth transitions between virtual and physical systems through real-time communication. The use of DTs has been further hastened by the emergence of Industry 4.0, which brings with it technologies such as IoT, Big Data, and predictive maintenance. These tools presently serve as the digital equivalents of Cyber-Physical Systems (CPS), establishing a constant data connection between the digital and real worlds [31].

Digital twins are particularly useful in AM. Industry 4.0 requires the ability to create complex, non-standard structures, which AM makes possible. While AM can speed up production and minimise material waste, improving mechanical characteristics is still difficult and frequently necessitates expensive, time-consuming trial-and-error procedures. Manufacturers may significantly reduce the requirement for physical trials and increase the accuracy of parameter selection by simulating various manufacturing situations using DTs. This integration expedites cuts down on the time needed for product qualification, boosts quality, and optimizes the use of resources [32].

A crucial element of the Digital Twin structure is simulation. Production planning is enhanced, processes are streamlined, and production concepts are validated with the use of techniques like DES [33]. Near-optimal solutions for operational efficiency can be obtained by combining simulation with optimisation methods like genetic algorithms. Nonetheless, there are still issues with gathering high-quality input data and the time needed for comprehensive simulations. A linked data strategy can assist in dealing with these difficulties by automatically extracting data and thus enhancing the connection between the physical and digital systems [34].

Building a Digital Twin for AM is a systemic, collaborative approach. The process is typically divided into three stages: defining the scope of the digital twin, developing the digital master, and creating the digital shadow [35]. This includes defining the elements to be modeled, simulating production systems using DES, and gathering real-time data for traceability and continuous monitoring. From process and design to automation, every step needs teamwork to guarantee that the digital twin can precisely optimise output and decision-making. Even with continuous progress, more work has to be done in areas like data representation, simulation detail, and fortifying the bond between digital and physical systems [36].

7. Conclusion

The industrialisation of 3D printing technology offers a lot of chances for manufacturing innovation and advancement. This study's main finding is that the inefficiencies and bottlenecks in the current AM procedures prevent them from being as effective and scalable as they could be. But it also presents difficulties that need to be resolved to guarantee AM on a large-scale adoption. In order to tackle these obstacles, we utilized Discrete Event Simulation (DES) as a tactical instrument to simulate and evaluate the production process, enabling the pinpointing of significant inefficiencies. DES offers a powerful tool for overcoming these challenges by providing manufacturers with the ability to simulate, analyse, and optimise production processes.

This study has depicted how DES can increase AM production efficiency, decrease expenses and guarantee better quality via relevant case studies and feasible applications as compared to other similar examples. The outcomes show considerable increases in resource allocation, decreased idle periods, and increased production efficiency. Future developments in technology are anticipated to make DES increasingly crucial to AM's industrialization and widespread application in a variety of industries.

Amplitude of AM's capabilities is more likely when DES is combined with cutting-edge technologies like digital twins, AI, and the Internet of Things. To further improve AM operations, future research will concentrate on incorporating real-time data collecting and investigating the possibilities of cutting-edge technologies inside the DES framework. By implementing this technology, manufacturers may find ways to build cheaper, eco-friendly, and more efficient production processes which might lead to the wider use of AM in various industries.

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