Enabling Digital Warehousing by an Additive Manufacturing Ecosystem

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Abstract

A digital twin or digital replica is a virtual model of a physical asset such as a product, process, system, or facility. It utilizes data from an actual physical asset to understand better and augment its performance, powered by artificial intelligence (A.I.), machine learning, and data analytics. Digital twins can mirror a physical twin and reveal issues before they occur. They rely on sensors embedded in the physical world to transfer real-time data about the operative process and environment. The data collected from the connected sensors is then analyzed on the cloud and is accessible via a dashboard. Digital twins are powerful masterminds to drive innovation and performance. Unsynchronized production can easily cause problems such as the backlog of intermediate warehouses, unsmooth production, and long production cycles. Synchronized production helps to improve overall efficiency and reduce waste. The material handling, production logistics path, movement pattern, suspension, and caching mode of the WIP (Work-In-Process) need to be planned based on the equipment's action and behavior mode. Unloading, distributing, and delivering raw materials to the manufacturing unit and warehouse are all part of material handling. The digital twin technology provides a highly efficient runtime environment for simulating complex systems and searching for robust computational optimization models. Digital twin technology has a wide range of economic value depending on the monetization model. This study explored costly industrial or business equipment, services, or processes that can be optimized by reducing asset downtime and lowering overall maintenance costs. These capabilities are essential, making internal software competencies crucial to driving value.

Keywords
Industry 4.0, Digital Twin, Digital Warehousing, Additive Manufacturing, and e-Manufacturing.

1. Introduction
At the dawn of the 21st century, the world is witnessing the fourth industrial revolution and the digital transformation of the business world, which is commonly referred to as Industry 4.0. (Ardito et al. 2018), (Bauer 2018), (Shadravan et al. 2021) and (Rad et al. 2015). Since the term "Industrie 4.0" was first publicized in 2011, the digital transformation created by Industry 4.0 has immediately grabbed the attention of industrialists and governments worldwide (Nascimento et al. 2018) and (Mirabi et al. 2018). During the first industrial revolution in the 18th century, the world was challenged to meet the ever-growing demand for goods from limited and diminishing resources, while limiting their impact on the environment and society (Beier et al. 2018), (Zakertabrizi et al. 2021), (Hosseini et al. 2021), and (Müller et al. 2018). It is increasingly recognized that Industry 4.0 can contribute to sustainable economic, environmental, and social development (Talaeikhozani et al. 2020), (Taheri et al. 2018) and (Gabris et al. 2022). The industry 4.0 environment places computers, smart materials, and intelligent machines in constant communication, interacting with the environment, and making decisions without the need for human intervention (Shokrolahzade et al. 2017) (Gilchrist 2016) and (Shokuhi et al. 2017). The digitalization of manufacturing and business processes and the deployment of smarter machines and devices may offer numerous advantages such as increased productivity, increased resource efficiency, and reduced waste (Shadravan et al. 2019) and (Tortorella et al. 2018). The present study seeks to address this issue by examining how the Digital Industrial Revolution - a set of underlying digital technologies and design principles - can help achieve economic, environmental, and social sustainability. Therefore, this study presents a concise analysis of the concept of the industry 4.0 phenomenon and its functionality.

This technological framework presents a background for smart manufacturing scheduling (SMS), which is designed to optimize production processes in an interoperable context by combining digital twin (DT) technology for automated and self-adaptive scheduling in real-time with zero-defect manufacturing (ZDM) management model to guide systems and processes toward a scenario without interruptions (Farrokhzadeh et al. 2013), (Serrano-Ruiz et al. 2021) and (Hadi et al. 2021).

1.1 Objectives

- A novel multi-dimensional categorization system has been developed for the digital twin.
- Identifies existing digital twin technology limits in industrial management.
- Investigates the financial impacts of OEE optimization by using digital twin

2. Literature Review

2.1 Industrial Revolution

2.1.1 First industrial revolution (Industry 1.0)

In the early nineteenth century, steam power and mechanization of production led to the First Industrial Revolution starting around 1760 and lasting until about 1840 (Khajeh et al. 2020), (Wrigley, 2018) and (Ebrahimi et al. 2015). Due to the mechanized version, the production is eight times greater than conventional methods. The mechanized version of what was previously done on basic spinning wheels produced eight times the volume in the same amount of time. The power of steam was already known. The greatest breakthrough in enhancing human productivity was the harnessing of it for industrial purposes. Steam and waterpower played a crucial part in the first transition from manual to machine production growth during the industrial revolution. To begin with, the industrial revolution gave birth to industries such as textiles, iron, steam power, machine tools, chemicals, cement, gaslighting, glassmaking, agriculture, papermaking, transportation, mining (canals and improved waterways (Shadravan et al. 2018), roads, and railways), and other advancements (Kanboh et al. 2021), (Dastoorian et al 2018), and (Vinitha et al. 2020).

2.1.2 Second industrial revolution (Industry 2.0)

Industrialization, which lasted from the late nineteenth century to the early twentieth century, is the second phase of the industrial revolution. Manufacturing mass production with the use of machine tools is the major emphasis of the revolution. New technologies like electricity, telephones, internal combustion engines, train networks, gas, telegraph, sewerage, and water supply are adopted during the second revolution. Iron, electrification, steel, rail, machine tools, paper making, chemical, petroleum, rubber, maritime technology, bicycles, automobiles, applied science, fertilizer, telecommunications, engines, turbines, telecommunications, and modern business management are some of the industries and technologies that have been developed (Yin et al. 2018) and (Baumers and Holweg 2019).

2.1.3 Third industrial revolution (Industry 3.0)

The third industrial revolution began in the 1970s with computerized partial automation and automation industries. In this transformation, the manufacturing industry is entering the automation business. The profession of engineering has seen an incredible expansion in the production sector. Without human intervention, industries are automating the entire production process. Electronics and computer-controlled gadgets drive automation. Automation improves the industrial system's dependability and efficiency (Shrivastava et al. 2021) and (Rajaei et al. 2021). Manufacturing, transportation, facility operations, and utilities are some industries where they can be used. However, automation supplants human labor. It produces huge increases in unemployment rates as a result of new technology. An industrial robot is a new technology that will help the industry shift. The industrial robot will work in many axes with extreme precision. It manufactures similar products that are more effective. The programmable integrated circuits design industrial robots. Welding, painting, assembling, labeling, and testing are examples of industrial robot applications. The International Federation of Robotics estimates that there are 1.64 million industrial robots globally (Franzen et al. 2020), (Dastoorian et al. 2022) and (Bina et al. 2019).

2.1.4 Fourth industrial revolution (Industry 4.0)

Industry 4.0 began in the twenty-first century. Through machine learning and cloud computing technology, Industry 4.0 generates cyber-physical systems in which all systems are connected, communicated, and processed. Industry 4.0 is linked to the Internet of Things (IoT), which aids manufacturing and service delivery. Artificial intelligence, high-end robots, and augmented reality are examples of modern technologies (Ghobakhloo, 2020). Figures 1, 2, and 3 show the evolution of industrial modernization.

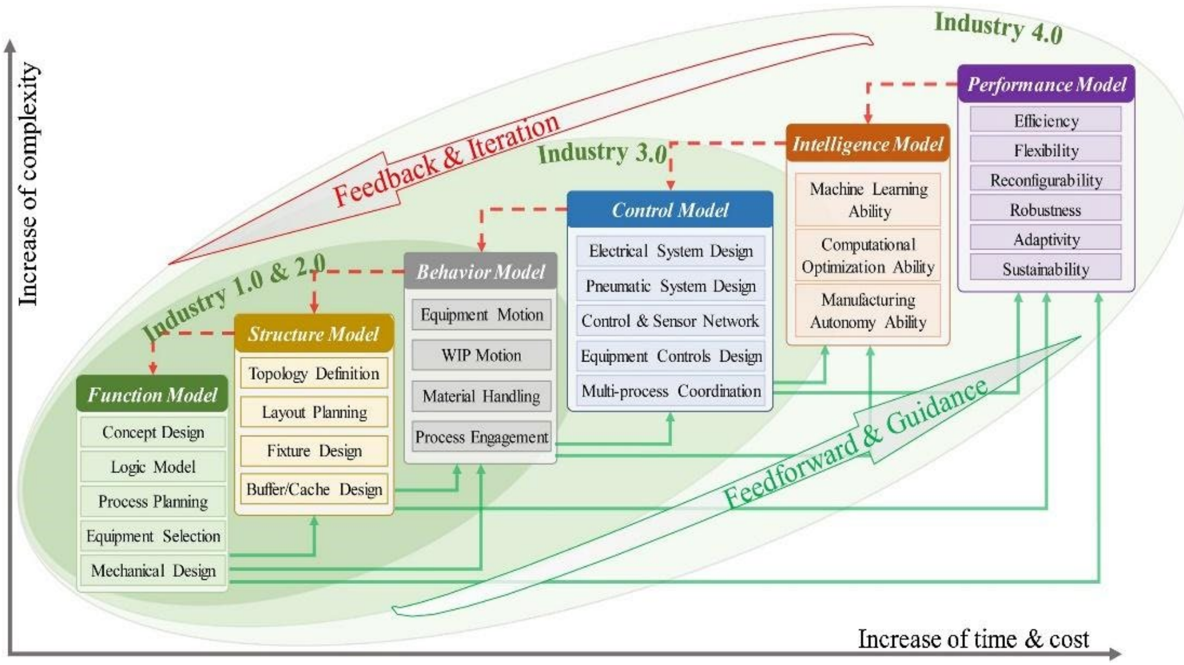

Figure 1. A framework for the design of smart manufacturing systems (Leng et al. 2021).

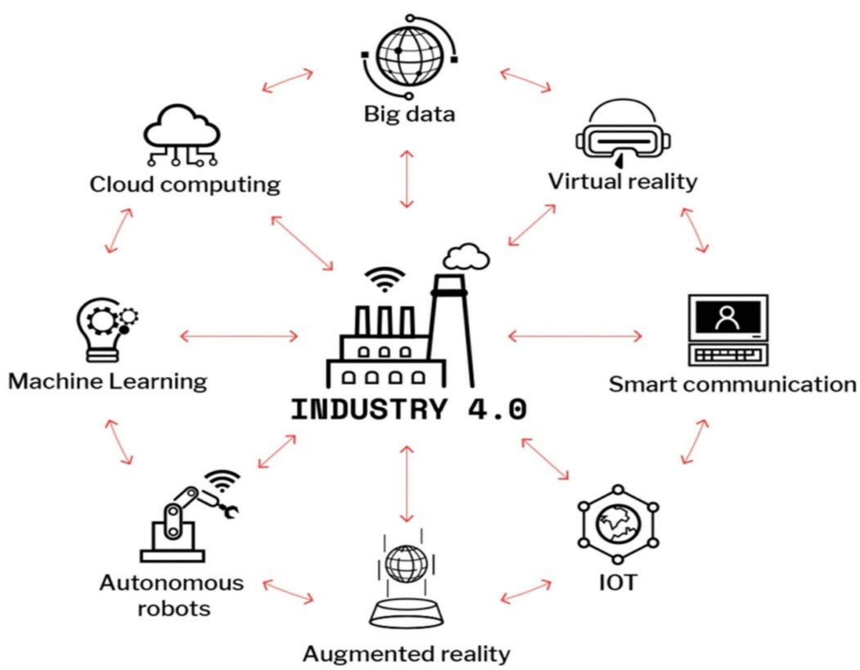

Figure 2. Industry 4.0 Architecture (Shrivastava et al. 2021).

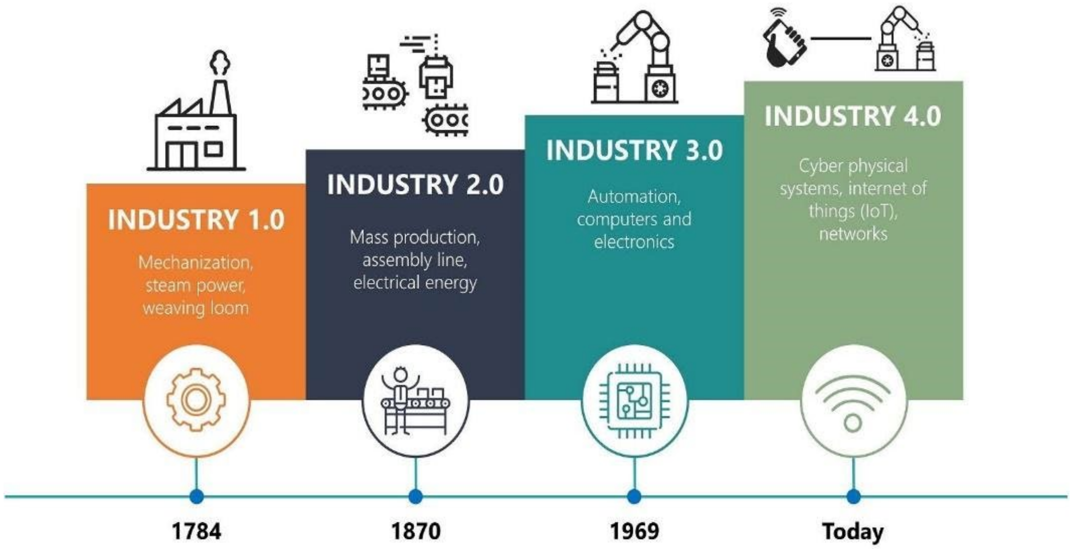

Figure 3. Evolution of Industry Modernization (Shrivastava et al. 2021).

2.2 Digital Twin Technology:

Digital twin is a digital (or virtual) representation that appears like, performs like, and connects to a physical element or system with the objective of improving or optimizing decision making over any time horizon, according to a broad definition. The DT paradigm shift is defined by the integration of these three features, which distinguishes DTs from standard representations that capture either the likeness or the behavior of a physical part or system but do not have a close relationship to the physical system. Although all three properties are required for the greatest results, the fidelity of each varies according to the DT's goal and application (Yu et al. 2022).

SMS has been described as very adaptable, intelligent, adaptive, and autonomous in several blueprints. To deal with more unforeseen changes and demands, these SMS performance targets should be assessed and optimized during the design phase. Scholars are using digital twin technology to increase system performance (such as quality, adaptability, and reconfigurability). Product quality is a critical factor for assessing the effectiveness of a freshly designed SMS. On the one hand, from the standpoint of the product, mathematical modeling of tolerance standards is crucial for total tolerance analysis, which might be aided by digital twin technology (Perno et al. 2022).

Manufacturing process planning is a technique used by engineers in the early stages of MSD to assess manufacturability, cost, and efficiency based on product design manufacturing features. It includes selecting and sequencing production operations. In the process plan process, few studies have been undertaken on how to deal with random disturbances and complex loadings. Obtaining enough process information and seeking optimal decisions consumes 74% of the planning time in current simulation-based process planning systems. Process planning is the first phase in SMSD that digital twin technology can help with (Farahani et al. 2022) and (Sleiti et al. 2022).

Table 1. Evolution of simulation modeling paradigm (Blaž, 2022)

Individual application:	**Simulation tools:**	**Simulation-based System Design:**	**Digital Twin Concept:**
Simulation is limited to very specific topics by experts, e.g. mechanics. **1960+**	Simulation is a standard tool to answer specific design and engineering questions, e.g. fluid dynamics. **1985+**	Simulation allows a systemic approach to multi-level and multi-disciplinary systems with an enhanced range of applications, e.g. model-based systems engineering. **2000+**	Simulation is a core functionality of systems by means of seamless assistance along the entire life cycle, e.g. supporting operation and service with a direct linkage to operation data. **2015+**

Table 1 shows the evolution of the simulation modeling paradigm. Figure 4 shows the traditional MSD to a digital twin based SMSD strategy shift.

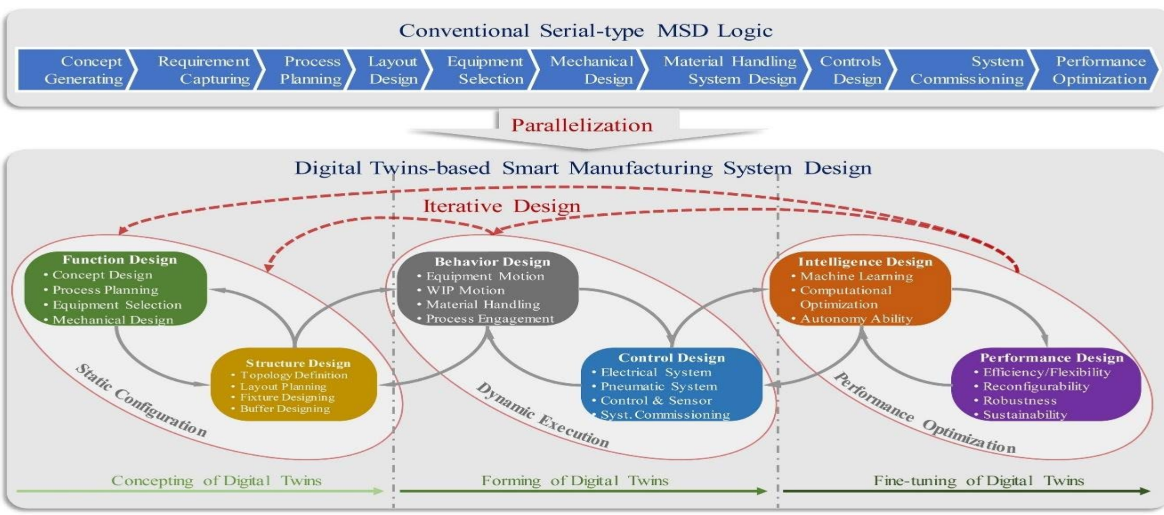

Figure 4. The shift from traditional MSD to a digital twin-based SMSD strategy (Leng et al. 2021)

3. Methods

3.1 Lifetime Costing Cycle (LCC)

The goal of lifetime costing (LCC) is to estimate the overall cost of design, development, operation, and retirement of a product across its entire existence. Designers can use the LCC analysis and methodology to define the projected total incremental cost of events for a specific item over its lifecycle. Furthermore, the LCC model encourages reliability-based design early in the product lifecycle. Cost estimating is the process of predicting LCC based on past data and eliciting expert knowledge. A classification for cost estimation methodologies was proposed by Niazi et al. (2006). These methods are divided into qualitative and quantitative techniques at the highest level. Parametric and analytical approaches are used in quantitative methodologies. One of the analytical approaches is activity-based costing (ABC), which is defined as a cost estimating approach that assesses the cost of completing distinct activities during a product lifecycle. ABC is a bottom-up strategy that can give a fairly accurate estimate (Farsi et al. 2021).

More reliable lifecycle cost assessment methodologies, such as ABC, require thorough and through-life cost information, according to the literature. To enable the retention and management of lifecycle cost model elements, a knowledge-based method is required. As a result, the creation of a Knowledge-Based System (KBS) allows for the gathering, management, interpretation, and application of relevant knowledge. The KBS is expected to help with LCC prediction during the design phase, as well as stochastic modeling to capture potential changes and uncertainties during the product lifecycle. Such a KBS must also be adaptive in order to automatically update LCC. Engineers and designers might benefit from using an automated bottom-up cost estimation tool to respond quickly and efficiently to changes in design, customer requirements, and market demands. Nonetheless, the biggest ongoing difficulty for enterprises is to examine LCC for significant equipment to discover the link to design-related decisions.

A Digital Twin (DT) is a set of technologies that can be used to help support the KBS by automating data retrieval and management. DT is a "digital representation of an observable manufacturing element with a technique to permit convergence between the element and its digital representation at an appropriate rate of synchronization" in the manufacturing environment (BS EN ISO 23247-1). The "thing that has an observable physical presence or operation" is also defined as an observable manufacturing element.

Accurate and dependable LCC at the product design stage is critical in high-value manufacturing sectors. However, LCC calculation is complicated by a lack of accurate historical data, a high level of uncertainty in cost data, and the difficulties of maintenance, repair, and overhaul. Early in the product lifecycle, the digital twinning process assists designers and engineers in exploring, evaluating, and making confident decisions with the potential to improve performance and quality, reduce cost, and shorten the processing time. Integrating DT with cost models for lifecycle cost assessment helps improve total lifecycle cost data capture. DT-based cost estimation can help uncover chances for performance improvement during the life of a piece of equipment.

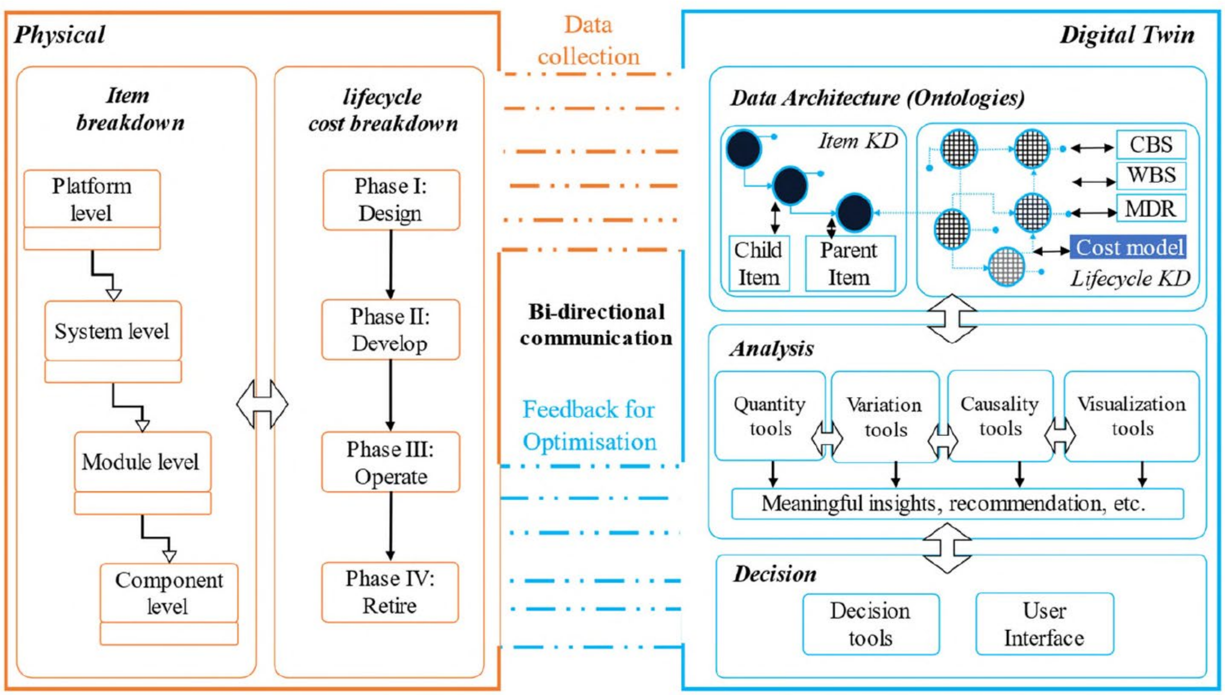

Figure 5. Digital twin architecture for an effective LCC estimation (Farsi et al. 2021)

3.2 Life Cycle Assessment (LCA) and Life Cycle Costing (LCC)

The circular model's environmental and economic performance is assessed using Life Cycle Assessment (LCA) and Life Cycle Costing (LCC) (figure 5). The LCA and LCC results show the suggested technologies' principal environmental and economic hot spots. Although they are meant to address different problems, the LCA and LCC techniques can be combined because they use the same life cycle thinking methodology. LCA analyzes a product system's environmental performance, whereas LCC evaluates a technology's cost-effectiveness and economic viability from the standpoint of economic decision-makers. When the scope and system boundaries of the LCA and LCC are the same, the environmental and economic studies can complement each other in the decision-making process.

The economic impact assessment aims to determine all expenses associated with the proposed technology within the system boundaries, highlighting cost drivers and profitability. The inputs are expressed in terms of purchasing cash flows, while the outputs are expressed in terms of sales cash flows. Different economic measures were calculated to define outcomes that could aid in cost-conscious decision-making. The present value PV_T, which indicates the value generated by the technology during its lifespan, related to the present value of money, is the earliest and perhaps most basic calculated economic indicator (Hajibabaee et al. 2021) and (Di Maria et al. 2022).

The PVT is calculated according to the following equation, representing the sum of the net yearly economic cash flows $(Revenues)_T - (OPEX)_T$, discounted by the future value of money $1/(1 + x)^T$:

$$PV_T = \Sigma_{t=1}^{T} \frac{(Revenues)_T - (OPEX)_T}{(1+x)^T}$$

Where x is the discount rate and T is the infrastructure's estimated lifetime, which is set at 25 years. The discount factor (1 + x)T represents the present value of future cash flows or the present value of one euro found in year t (Di Maria et al. 2022). The value of x is difficult to calculate because it varies from instance to case, but it should represent the rate of financial assets with relative risk (Arnaboldi et al. 2014).

3.3 Overall Equipment Effectiveness (OEE)

A classic measurement metric in manufacturing is the Overall Equipment Effectiveness (OEE), which is used as a comprehensive indicator for effective capacity utilization (Jonsson and Lesshammar 1999). Continuous improvement initiatives often track availability, performance, and quality over time as part of continuous improvement initiatives (Kang et al. 2016). Operations managers can also use it to identify sources of production losses and hidden capacity within the system (Muchiri et al. 2008). OEE is widely used in industry but is especially effective in cases where lost capacity costs are high (Dal et al. 2000), which is relevant in additive manufacturing as indicated by cost models (Baumers et al. 2016). The use of OEE in AM has been shown to be useful for cost appraisal by appropriately adjusting production time and related time-dependent cost model elements (Dirks and Schleifenbaum 2019) and (Fera et al. 2017). While Fera et al. (2017) acknowledge several differences between AM and the traditional, repetitive manufacturing setting in which OEE was conceived, neither study explains how OEE for AM operations should be assessed. Reid (2019) creates the Overall Additive Manufacturing Effectiveness (OAME) measure in an attempt to close this disparity. This study sheds light on the importance of in-situ defect mitigation as a production cost, as it reduces the amount of time available for efficient manufacturing. However, the author makes the unrealistic assumption that all flaws can be detected and fixed in situ. As a result, the OAME measure is incomplete because other quality issues are overlooked, such as non-correctable production faults, one of Baumers and Holweg's four defect categories (Baumers and Holweg 2019). The figure 6 below summarizes the structure of OEE:

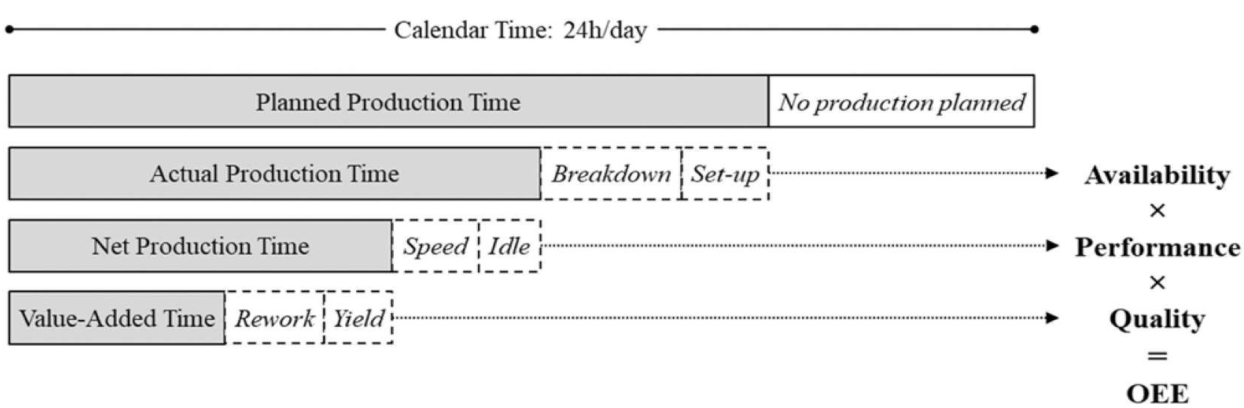

Figure 6. Schematic of OEE calculating the fraction of planned production time and summary of the "six big losses" (dashed boxes) (Basak et al. 2022)

OEE is calculated as the ratio of Fully Productive Time to Planned Production Time. In practice, it is calculated as:

OEE = Availability × Performance × Quality

in which:

Availability = Run Time / Planned Production Time

Performance = (Ideal Cycle Time × Total Count) / Run Time

Quality = Good Count / Total Count

4. Conclusion

As a general principle, AM users should strive to maximize process efficiency by operating in a way that produces the highest OEE, which corresponds to low levels of the six production losses. As a function of utilization (availability) and build rate (performance), the production cost of AM decreases. As the constituent metrics strongly suggest that performance is important, future empirical studies should examine the effects of technological advancements in AM processes.

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