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# Leading-Edge Production Engineering Technologies

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**ABSTRACT**
*Production engineering technologies are ever advancing to tackle problems encountered in manufacturing of products and rendering of services. This paper presents a number of challenges encountered by producers, and the industrial revolutions that these producers have kickstarted to handle these production challenges, while also identifying leading-edge production engineering technologies that have enabled these technological revolutions. The methodology employed was the systematic literature review of scholarly articles published between 2010 and 2021. The result of the research was the identification of some leading-edge production engineering technologies that are helping producers improve productivity such as robotics, smart factories and Internet of Things (IoT); Artificial Intelligence and predictive maintenance; 3D printing and additive manufacturing.*

**KEYWORDS:** Additive Manufacturing, Internet of Things, Production Engineering, Robotics, Smart Factories.

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## 1. INTRODUCTION

Production Engineering is a specialisation of Mechanical Engineering, that deals with the planning, designing, development, implementation, operation, maintenance, and management of all processes involved in the manufacturing of products or rendering of services. Traditional production activities are saddled with numerous challenges which affect productivity. Some challenges are manual handling and safety, maintaining the right inventory levels, lack of efficient and profitable production of customised and small-lot products through monitoring and controlling automated and complex manufacturing, stand-alone and segregated manufacturing and weak integration of production systems, product life cycle and intercompany value chain (Shi *et al.*, 2020). Other challenges identified by Khan and Turowski (2016) include poor data integration and management, poor process flexibility as demanded by customisation and security of people, products and production facilities environment. With the advent of leading-edge technologies in production and manufacturing, organisations are additionally faced with challenges such as how best to implement and keep up with these technologies in order to achieve operational goals such as reduced costs, improved efficiency, increased safety and product innovation while staying relevant and competitive.

Various industrial and technological revolutions have been provoked to combat the challenges of traditional production and manufacturing, from Industry 1.0 to Industry 5.0. The First Industrial Revolution also known as Industry 1.0 occurred around the 1780s and involved an evolution from traditional manufacturing processes to manufacturing processes which used water and steam. Moreover, the use of fuel sources such as steam and coal made machine use more feasible and allowed for faster and easier production and the possibility of all kinds of innovations and technologies. The Second Industrial Revolution, Industry 2.0, also known as the Technological Revolution occurred around the 1870s and saw the introduction of newer technological systems, especially superior electrical technology at the time, which enabled manufacturers to use more sophisticated machines and carry out mass-production using assembly lines, thereby improving productivity. The Third Industrial Revolution occurred around the 1970s and began with the first computer era and involved the use of

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electronics and Information Technology to improve automated production with the aid of the Internet, connectivity and renewable energy. Even though the automated systems of Industry 3.0 were dependent on human input and intervention, the era saw the use of these systems within assembly lines to perform human tasks using Programmable Logic Controllers (PLC). Industry 3.5 which occurred around the 1980s saw the offshoring of production to low-cost economies in order to reduce the costs of production further.

The Fourth Industrial Revolution, Industry 4.0, which is the industrial revolution of today, is the period of smart machines, storage systems, and manufacturing facilities that could automatically share information, initiate operations, and control one another without the need for human interaction, all made possible with the aid of the Internet of Things (IoT). Rossi (2018) explained that Industry 4.0 brings robots, interconnected devices and fast networks of data within a factory environment together, to improve the productivity of the factory and execution of routine tasks that are best conducted by robots and not humans. The Fifth Industrial Revolution, Industry 5.0, which is the industrial revolution of the future, will see the return of human hands into the industrial framework and the reconciliation of humans and machines in order to work together to improve productivity. While the current Industry 4.0 era is concerned with the conversion of traditional factories into IoT-enabled smart facilities that use cognitive computing and interconnect through cloud servers, the Industry 5.0 era will have mass implementation of Cobotics where humans will be back in the industrial production process collaborating with the smart machines and systems. Therefore, workers will be upskilled to provide value-added tasks in production, leading to mass customisation and personalisation for customers (Rossi, 2018). This will create higher-value jobs and enable workers and humans to focus on the responsibility of product and service design, enabling the development of products and services that are considerably more bespoke and personal.

The main objective of this paper is to provide a description of the latest technologies that can help production companies improve productivity in the present day. The paper attempts to fill a research gap posed by the need for a study that aggregates the modern-day production engineering technologies.

## 2. MATERIALS AND METHODS

The methodology employed was the systematic literature review of scholarly articles published between 2010 and 2021, which were related to the topic of Leading-Edge Technologies in Production Engineering. The search engine utilised was Google Scholar and papers were sourced from various publishers. A five-phase process was followed in conducting the literature review. Phase 1 was a pilot search of articles in order to get an in-depth understanding of the literature, Phase 2 was the location of the studies by encompassing a large body of relevant articles, Phase 3 was the development and use of a selection and evaluation criteria or inclusion/exclusion criteria such as articles being published between 2010 to 2021 and being published in English, Phase 4 was the analysis and synthesis of the selected articles, Phase 5 was reporting of the results.

## 3. RESULTS AND DISCUSSION

The result of the literature review carried out was the identification of leading-edge production engineering technologies which provide advanced manufacturers with an advantage in manufacturing and production engineering. These technologies include robotics, smart factories and Internet of Things (IoT); Artificial Intelligence and predictive maintenance; 3D printing and additive manufacturing.

### 3.1 Robotics, Smart Factories and Internet of Things

Robotics refers to an interdisciplinary field that involves design, construction, operation and use of robots within production processes. In order to improve production rates, many organisations are implementing the use of advanced robots to improve production. Nowadays, robotics is also offered as a service to allow organisations which cannot normally afford the cost of acquiring and implementing advanced robotics within their production processes to rent robots and use them as part of their workforce.

A smart factory is a highly computerized production floor that continuously collects and shares data through connected machines, devices and production systems. The four intelligent features of smart factories as listed by Shi *et al.* (2020) include the ability to self-organize, learn, and maintain environmental as well as their own information for analysing their behaviours and abilities; interoperability and real-time control of the internet; high integration using robot vision systems and artificial intelligence technologies; and the use of virtual reality technology such as signal processing, animation technology, intelligent reasoning, prediction, simulation and multimedia technologies to virtualize manufacturing processes and products and facilitate the human-machine integration of smart factory. With the use of smart factories, companies will no longer need to set up unique production runs to fabricate identical products or parts, enabling customised production to be as affordable as mass production. These will aid the factories in becoming more efficient, with a decrease in raw material waste. Pech *et al.* (2021) enumerated some of the devices utilised in smart factories grouping them into motion, position, proximity and speed sensors which monitor the machine or product position on the production lines (Cottone *et al.*, 2013; Luo *et al.*, 2019; Shoaib *et al.*, 2014); vibration and torque sensors which utilise Fourier transform signal processing to detect failures in machine components (Kiangala & Wang, 2018; Kozlowski *et al.*, Uhlmann *et al.*, 2017); acoustical, sound and ultrasonic sensors which utilise microphone devices together with machine learning to estimate relevant information such as the character of an object and its location (Kaptan *et al.*, 2018; Ryu & Kim, 2020); pressure, force, touch and tension sensors which identify the pressure deviations in the object of interest or environment based on barometric, piezoelectric, capacitive, optical or resonant sensing principles (Musselman & Djurdjanovic, 2012); optical, light and machine vision sensors which capture visual data and conduct a digitisation process using machine learning algorithms (Mennel *et al.*, 2020; Sergiyenko *et al.*, 2018); temperature sensors which obtain temperature information directly using resistive temperature detectors, thermistors and thermocouples or indirectly using infrared sensors (Sadiki *et al.*, 2019; Salvatore, *et al.*, 2017; Villalobos *et al.*, 2020); liquid, flow, gas and chemical sensors which are useful for monitoring the current intensity in pipelines using magnetic, ultrasonic or thermal detectors (Chien & Chen, 2020; Farahani *et al.*, 2014); electronic current, energy and magnetic sensors which measure the current draw of machines (Alberto *et al.*, 2018; Jureschi, 2016; Zhang *et al.*, 2019); virtual sensors which are embedded in the software layer of machines to enhance the knowledge of the machines (Al-Jlibawi *et al.*, 2019; Indri *et al.*, 2019); and nuclear, chemical, microparticles and nanoparticles sensors which enable monitoring directly within the monitored object (Jia *et al.*, 2021; Thakkar *et al.*, 2021; Singh *et al.*, 2021).

Gillis (2021) described the Internet of Things (IoT) as a network of integrated computing devices, mechanical and digital machinery, objects, animals, or people with distinct identifiers and possessing the ability to transfer data without the need for human-to-human or human-to-computer interaction. With the use of IoT's cheap, connected and increasingly abundant sensors, organisations can now monitor various aspects of manufacturing than ever before, including machinery, deliveries, and even employees.

Figure 1 shows the principal benefits of manufacturing operations automation.

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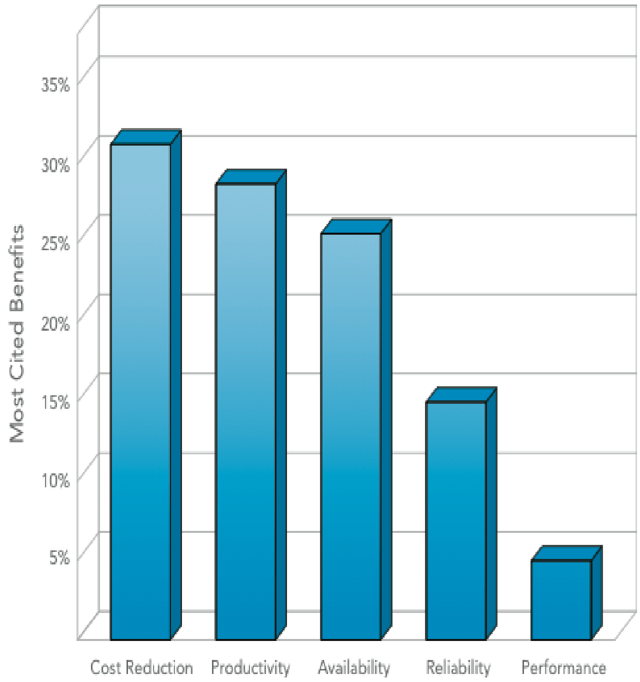


**Figure 1: Benefits of Manufacturing Operations Automation (Christiansen, 2020).**

From Figure 1, the benefits of manufacturing operations automation include cost reduction, increased productivity, availability, reliability and performance. With cost reduction being the highest benefit of automating manufacturing operations (Christiansen, 2020).

### 3.2 Artificial Intelligence and Predictive Maintenance

Product supply chains are complex, stochastic systems that present logistics analysts with issues such as increasingly diverse and difficult to predict variable customer demand (Kantasa-ard *et al.*, 2020). Machine learning, a subset of Artificial intelligence, enables these analysts to predict the amount of products/services that will be purchased during a definite future period. This information is crucial for producers to optimize their inventory levels and conduct replenishment decisions. Truly, machine learning methods have been shown to provide significantly less biased and more accurate forecasts than well-established, statistical methods (Kantasa-ard *et al.*, 2020; Spiliotis & Makridakis, 2020).

Machine breakdowns in the middle of a production run can have a negative impact on the schedule, cause delivery delays, or force employees to work overtime to make up for lost time (Pech *et al.*, 2021). Predictive maintenance anticipates system breakdowns in order to save maintenance costs (Selcuk, 2016; Tortorella, 2018). Therefore, predictive maintenance provides a set of tools based on continuous monitoring of the machine or process, to determine when a particular maintenance operation is necessary (Bukhsh *et al.*, 2019; Carvalho *et al.*, 2019). Predictive maintenance is also related to production robotization and Internet of Things, as a result of the fact that it involves the use of intelligent sensors which aid in collecting large amounts of data, which are efficiently analysed to support intricate decision-making and management of complex systems (Pech *et al.*, 2021). This allows for early detection of faults through tools based on historical data such as machine learning, thereby minimising maintenance costs, enabling implementation of zero-waste production, and reduction of the number of major failures. However, a challenge of predictive maintenance is the potential risk of Distributed Denial-of-Service (DDoS) attacks, which is a malicious attempt to interrupt a targeted server, service, or network's routine traffic by flooding the target or its surrounding infrastructure with internet traffic. Figure 2 shows the most common applications and use cases of Artificial Intelligence in manufacturing.

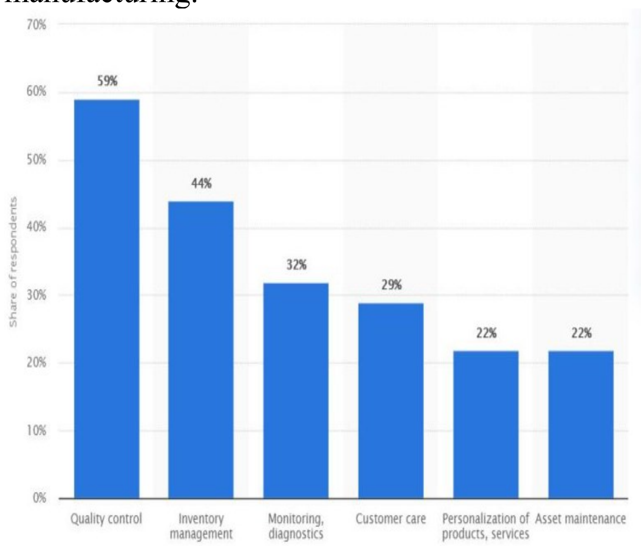


**Figure 2: Applications of Artificial Intelligence in Manufacturing (Dilmegani, 2020).**

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From Figure 2, the common use cases of Artificial Intelligence in manufacturing include quality control, inventory management, monitoring diagnostics, customer care, personalization of products/services and asset maintenance. With quality control being the area of highest application of Artificial Intelligence in manufacturing, and personalization of products/services and asset maintenance being areas of lowest applications of Artificial Intelligence in manufacturing (Dilmegani, 2020).

### 3.3 3D Printing and Additive Manufacturing

One of the main enablers of customised manufacturing at scale is 3D printing and additive manufacturing. As its name implies additive manufacturing adds material to create an object and differs from traditional creation of objects by milling, machining, carving, shaping which involve material removal. According to Tumbleston *et al.* (2015), additive manufacturing processes such as 3D printing utilise time-consuming, stepwise layer-by-layer approaches for fabricating objects. In essence, 3D printing employs the use of computer-aided design (CAD) software or 3D object scanners which slice the object into ultra-thin layers and direct the path of a nozzle or print head for precisely depositing material in accurate geometric shapes, layer by layer, with each successive layer bonding to the preceding layer of melted or partially melted material to create the object. Therefore, 3D printers are used for giving physical form to digital designs ranging from personalised medical and dental products to adapted airplane and automobile parts.

A variety of different additive manufacturing processes exists such as powder bed fusion technology which melts or partially melts ultra-fine layers of material in a three-dimensional space using lasers, electron beams, or thermal print heads, blasting away superfluous powder from the item as the process completes; binder jetting where alternate layers of powdered material and a liquid binder are laid down by the print head; directed energy deposition where either a wire of filament feed stock or powder is melted by an electron beam gun or laser installed on a four-axis or five-axis arm; material extrusion where extruded polymers are drawn through a heated nozzle mounted on a movable arm, with the nozzle moving horizontally and the bed moving vertically, allowing the melted material to be built layer after layer with proper adhesion between layers achieved through temperature control or the use of chemical bonding agents; material jetting where a print head swings back and forth, similar to a 2D inkjet printer's head, but this time on the x, y, and z axes to build 3D objects, with layers hardening as they cool or curing with UV light; laminated object manufacturing and ultrasonic additive manufacturing which are two sheet lamination methods: laminated object manufacturing uses alternate layers of paper and glue, and ultrasonic additive manufacturing uses thin metal sheets connected by ultrasonic welding; and vat photopolymerization where in a vat of liquid resin photopolymer, an object is formed, with the photopolymerization process curing each microfine resin layer using ultraviolet light carefully directed by mirrors.

Figure 3 shows the various ways 3D printing has been implemented.

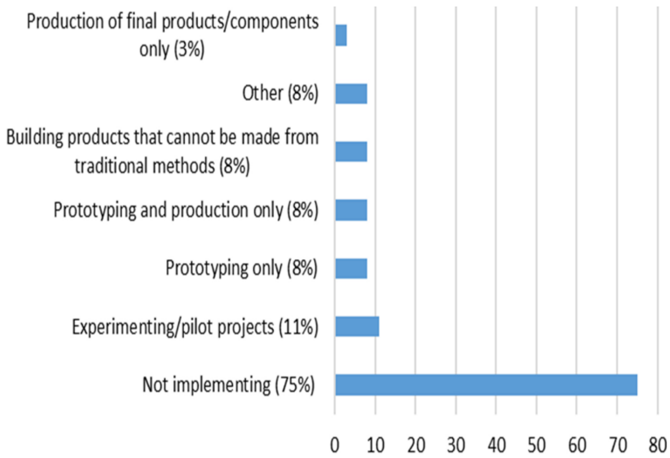


**Figure 3: Implementations of 3D Printing (Olsson *et al.*, 2019).**

From Figure 3, there is a low implementation of 3D printing, with the technology being implemented mostly in experimenting and development of pilot projects. Though 3D

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printing is predominantly used to generate prototypes and mock-ups as a result of the high cost of production, the impact of 3D printing is both disruptive and revolutionary (Garret, 2014). However, 3D printing in manufacturing is expected to mature in the coming years, changing from use in experimentations and prototype productions to production of low volume, bespoke and high-value products (Gebler *et al.*, 2014; Tumbleston *et al.*, 2015). The advantages of 3D printing for industry are ability to print many geometric structures, simplification of the product design process, relative environmental friendliness, increased flexibility, reduced warehousing costs and enabling adoption of mass customisation business strategy (Economist, 2011; Yin *et al.*, 2017). However, the disadvantages of 3D printing are that the 3D printing process takes time, 3D printed parts may not be as sturdy and might not meet tolerances (Yin *et al.*, 2017).

## 4. CONCLUSION

This research contributes to knowledge by providing a description of the latest technologies that are helping production companies improve productivity in the present day. The research has stated various challenges of traditional production systems and expounded on the various industrial revolutions and their technologies, concentrating on the technologies of the current Industry 4.0 and those of the future Industry 5.0 which together constitute the leading-edge technologies of production and manufacturing engineering. These leading-edge production engineering technologies are robotics, smart factories and Internet of Things (IoT); Artificial Intelligence and predictive maintenance; 3D printing and additive manufacturing. It is obvious that with the advent of these leading-edge technologies, organisations implementing them are experiencing increased productivity with a reduction in production times and cost of getting products to market. Therefore, by the use of robots and smart facilities which are more agile, versatile and clever, various production processes are getting faster, cheaper and more precise.

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