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QUALITY AND PRODUCTIVITY IMPROVEMENTS IN ADDITIVE MANUFACTURING

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To the Graduate Council:

I am submitting herewith a dissertation written by Huseyin Kose entitled "QUALITY AND PRODUCTIVITY IMPROVEMENTS IN ADDITIVE MANUFACTURING." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Industrial Engineering.

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QUALITY AND PRODUCTIVITY IMPROVEMENTS

IN ADDITIVE MANUFACTURING

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ABSTRACT

Additive manufacturing (AM) is a relatively new manufacturing technology compared to the traditional manufacturing methods. Even though AM processes have many advantages, they also have a series of challenges that need to be addressed to adapt this technology for a wide range of applications and mass production.

AM faces a number of challenges, including the absence of methods/models for determining whether AM is the best manufacturing process for a given part. The first study of this thesis proposes a framework for choosing specific AM processes by considering complexity level of a part. It has been proven that the method works effectively through numerical experiments.

Optimization of process parameters through expensive and time-consuming experiments is another issue with AM. To address this issue, an empirical model is presented in the second study to optimize parameters for minimizing building costs through maximizing the trade-off between productivity and quality. The proposed model proves to be effective in reducing building costs at any quality level. The results indicate that process parameters can be optimized quickly and accurately, as compared to the time-consuming and expensive experimental methods.

Another limitation of AM is the lack of capability to use multiple materials, which is a concern when adapting this technology to mass production. To address this issue, a new scheduling model with considering multi-material types is introduced in the third study. Based on the numerical results, the proposed model can provide optimal sequence by maximizing the trade-off between tardiness and material switching cost.

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CHAPTER 1. INTRODUCTION

1.1. Additive Manufacturing

1.1.1. What is Additive Manufacturing

A definition of additive manufacturing (AM) refers to what was formerly known as rapid prototyping (RP) but is more commonly referred to by its current name, 3D Printing. RP is a term used widely in a variety of industries to describe a process for creating a system or component model before a commercialized product (Gibson et al., 2015). It is a manufacturing technology which is based on a layer-by-layer process that creates a part directly from the data provided by Computer-Aided Design (CAD) files (Fox et al., 2016). In contrast to subtractive manufacturing (SM) processes which subtract material to achieve desired geometry, AM adds material to the main piece to create the final parts. Therefore, AM processes are widely used in new product development. Figure 1.1 shows new product development involving AM. It shows that using AM enables users to save a lot of time and effort in new product development. Aside from that, it will also give users the chance to try more models. Recent interest in this technology has led to its constant evolution, reimagination, customization, and adaptation to a multitude of industries including automotive, aerospace, engineering, medicine, biological systems, and food supply chains (Gao et al., 2015).

Across manufacturing industries, AM technologies have the potential for expanding the capabilities of SM processes, manufacturing machinery, and supply chains. With AM, a more flexible manufacturing environment can be provided to corporations by reducing the number of production lines and dependence on thirty-party suppliers. By providing these, it can positively impact smaller firms and end-users by enabling them to become self-sufficient “designers and manufacturers” that can develop innovative products and production systems (Gao et al., 2015).

1.1.2. The Types of Additive Manufacturing Processes

AM processes can be used with three types of materials, namely polymer, ceramic, and metal (Additive manufacturing researh group, 2020). The polymer is a widely used material in AM applications. The most common types of polymers used in additive manufacturing systems are acrylic butadiene styrene (ABS), polylactide (PLA), polycarbonate (PC), polyamide (Nylon), epoxy resin, wax, and photopolymer resin (Petrie, 2019). The widely used ceramic-based powders are silica glass, porcelain, silicon carbide (Travitzky et al., 2014). The following metals are suitable for the manufacturing structural and integral component parts: Maraging steel, titanium alloy (Ti6AI4V), 15-5ph stainless steel, cobalt chrome alloy, aluminum (alsi10mg), gold, and silver (Seifi et al., 2016). Different AM processes require different material types. The following paragraph will discuss the variations of AM processes by mentioning the material they utilize.

Different types of AM processes are actively used around the world for various purposes. They are classified into three categories: liquid-based, solid-based, and powder-based. Liquid-based and powder-based systems dominate the industry today (Wong and Hernandez, 2012). The major and widely used AM processes are as follows: Stereolithography, fused deposition modeling, binder jetting, selective laser sintering (SLS), selective laser melting (SLM), and electron beam melting.

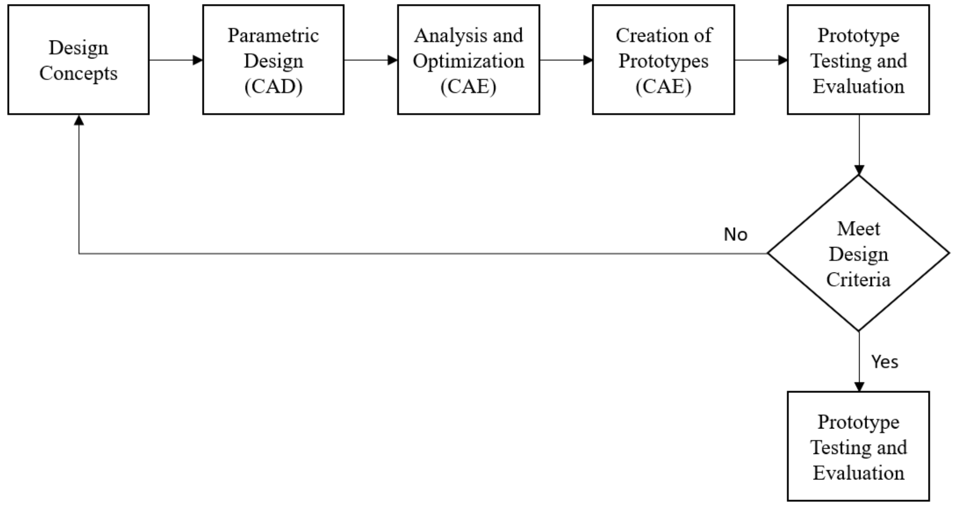

Figure 1.1 Product development cycles (Wong and Hernandez, 2012)

Stereolithography

One of the most widely used AM process is stereolithography which is a liquid-based process where an ultraviolet laser is used to cure or solidify a photosensitive resin (Wong and Hernandez, 2012). Figure 1.2 shows the schematic view of stereolithography.

The process is started with designing the 3D model of the object based on the utilized SL equipment and material. Then ultraviolet laser is applied to solidify a specific location based on the 3D model. Upon completion of the associated layer, the platform is lowered to allow for the next layer to solidify by the laser. The leveling blade is used to make sure that the next layer is coated with resin. Different resin types are available, including standard, castable, tough and durable, high temperature, and dental resin. (Varotsis, 2019). The material can be chosen according to the required material properties of the product. The resin must be refilled into a clean container and the parameters are default set by the manufacturer. In every production process, regardless of the material, the process is repeated from the beginning and the parameters can easily be altered based on the different material types.

Fused Deposition Modeling

Another widely used AM process type is solid-based fused deposition modeling in which thin filaments of plastic are fed into a printer where they are melted and extruded in a thickness of typically 0.25 mm (Wong and Hernandez, 2012). Figure 1.3 shows the schematic view of fused deposition modeling.

The platform is lowered after the associated layer is extruded to open room for the new layer.

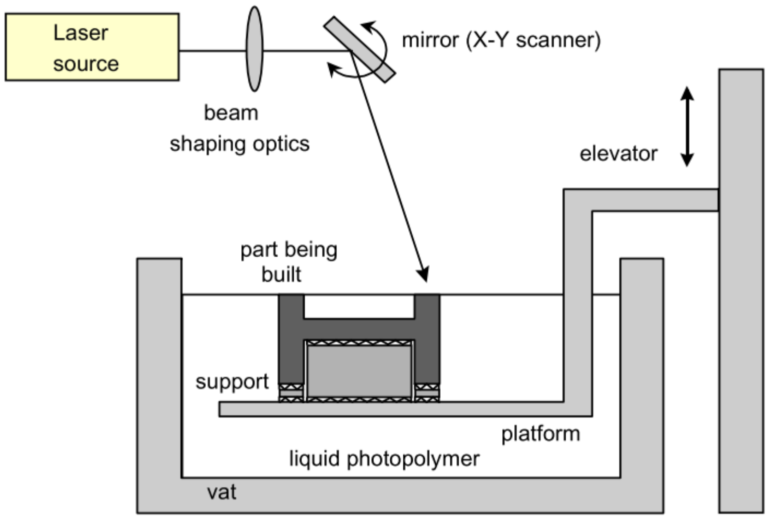

Figure 1.2 A schematic view of the stereolithography (Park et al., 1998)

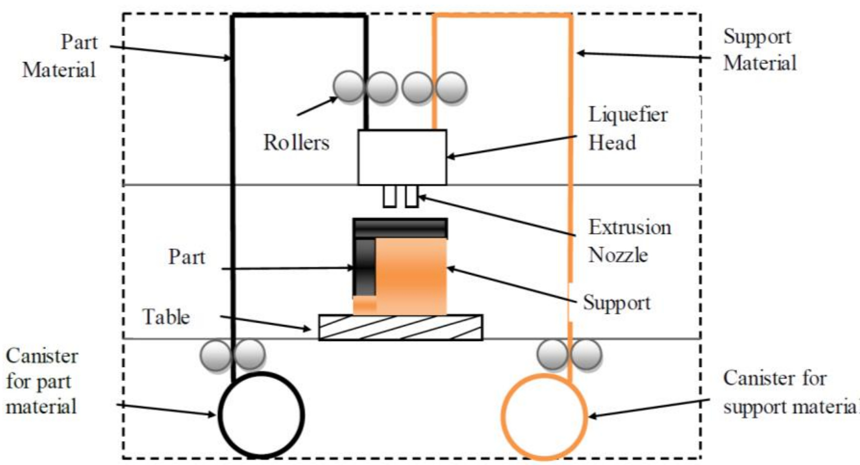

Figure 1.3 Schematic view of fused deposition modeling (Equbal et al., 2018)

Several types of material can be used in this AM process which can be divided into two categories: polymers and metals (Cooper, 2001; Mireles et al., 2012). In order to obtain better quality regardless of using metal or polymer, the machine must be cleaned, calibrated and parameters optimized very well based on the new material type.

SLS and SLM

SLS and SLM is a three-dimensional powder-based printing processes in which a powder is sintered or fused using a laser beam to create the objects. SLS and SLM are essentially the same AM processes except for several small differences. While SLM is specifically used for only metal alloy materials, SLS is used for a variety of materials such as plastic, glass, ceramic, and even metal alloys (Lawrence, 2014). Figure 1.4 shows the schematic view of SLS/SLM.

SLS uses a carbon dioxide laser beam to sinter powder material so that they can fuse together at the molecular level without fully melting. However, SLM uses a laser to fuse the powder to fully melt the material. In this way, the material is not fused together but rather melts to form a homogeneous part. The powder is stored in a special cartridge in the system and spread onto the platform after the current layer is fused. Regardless of material type, SLS and SLM machine must be cleaned, calibrated, and parameters must be optimized if the material type changes.

Binder Jetting

Binder jetting printing process is similar to any other powder-based printing process. The only difference is that in binder jetting, a part is built in multistep AM processes since the

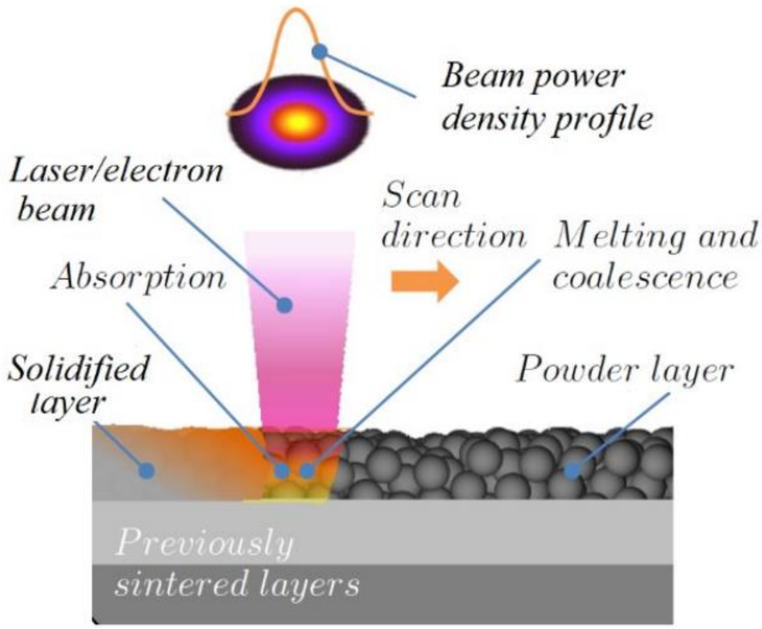

Figure 1.4 Schematic view of SLS/SLM (Lawrence, 2014).

binder material is involved in the production process. The powder material is usually joined together with a binder material, which is usually a form of liquid (Gokuldoss et al., 2017). Figure 1.5 shows the schematic view of the binder jetting AM process.

Binder jetting AM processes can use any material which is available in the form of powder. The powder material is spread over the build platform and then bound together with a layer of the binder. Since powder are joined together with an adhesive material, build quality is not usually enough for aerospace and automobile parts (Kim et al., 2019). The process requires multistep post-processing such as curing, de-powdering, sintering, infiltration, annealing, and finishing (Wong and Hernandez, 2012; Xu et al., 2015).

1.1.3. Impact of Additive Manufacturing on Manufacturing Industry

AM was used as a prototyping technique during its early stage of development. Today, however, AM technologies are not just used for prototyping purposes. With today's technology and materials, it is also used for the finished products. Therefore, the use of AM techniques for manufacturing applications is growing rapidly. Figure 1.6 shows the growth rate of AM based on the Wohler's report 2010.

Growth rate for 2010 was 24.1% based on the same report (Wohlers, 2010). Worldwide, additive manufactured goods collected $967 million in revenue, and the United States took in $367 million or 38 percent of global production in 2013 (Wohlers, 2014). Table 1.1 shows the types of products that were manufactured using AM techniques for the various industry subsectors. There are three variations of utilizing AM based on the research conducted by Thomas and Gilbert (2015). The first variation involves users purchasing their own AM machines and producing products themselves. The second scenario

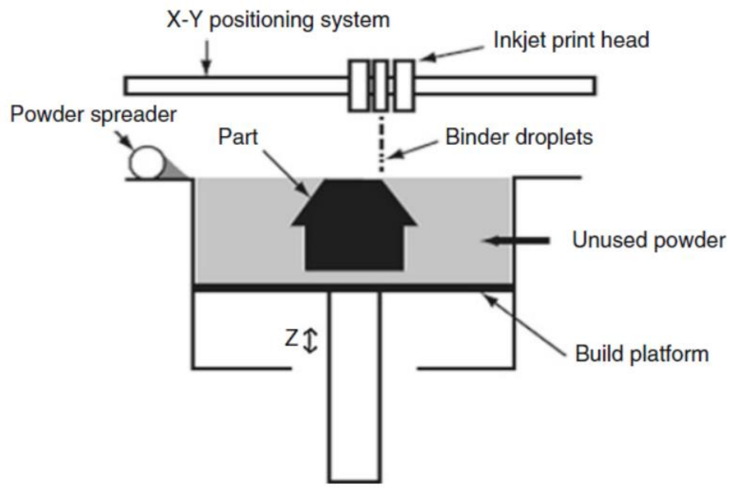

Figure 1.5 Schematic view of the binder jetting process (Kim et al., 2019)

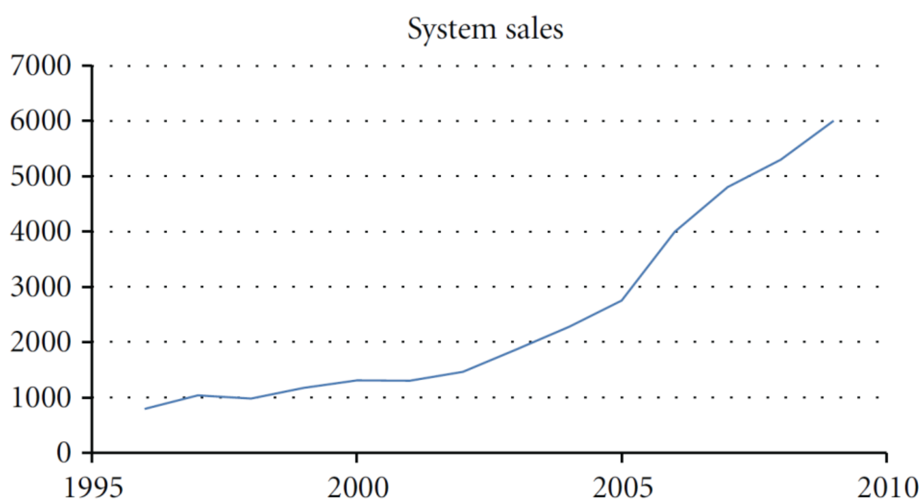

Figure 1.6 Growth of AM between 1995 and 2010 (Wohlers, 2010)

considers scenario involves copy shops where users submit their designs to a manufacturer to produce it. Another scenario is the adoption of additive manufacturing by commercial manufacturing, which will result in profound changes in design and production. These results can be seen in Table 1.1 for various industrial subsectors.

1.1.4. Advantages of AM over Subtractive Manufacturing

AM technology is growing rapidly with its unique features and great potential in cost, speed, quality, impact, and transformation/innovation (Attaran, 2017; Dimitrov et al., 2014). As explained in previous sections, it suffices to have an AM machine and 3D model in order to produce an object without requiring any special, sophisticated tools or production lines. This unique feature of AM reduces the need for logistics, time from production to sale, and environmental impact (Attaran, 2017; Paris et al., 2016). Because of this, AM has the potential to reduce the complexity of the supply chain (Cohen et al., 2014; Huang et al., 2013; Nyman and Sarlin, 2014). Although AM may not be able to replace traditional manufacturing in the near future, it is expected to drive major innovations in the manufacturing sectors.

Compared to SM, AM offers many advance and unique features. The number of AM applications is growing rapidly in a variety of manufacturing sectors thanks to these unique advantages, even though it also has several downsides as we will discuss in the next section. Based on the study conducted by Attaran (2017), eight major advantages of AM has shown in the Figure 1.7.

Industrial Efficiency

AM would enable consumers to customize and produce their own products to fit their own needs. With this flexibility and convenience, AM provides an opportunity that parts are continuously available for users with fixed production prices. Consumers can thus turn into micro-manufacturers thanks to this technology.

Mass Customization

AM processes are not set only one product type since it does not require production and assembly lines. AM systems are capable of processing a wide range of materials and can produce highly complex parts without requiring complex and costly set-up procedures. Therefore, mass customization can be achieved at a low cost with AM technology.

On-Demand Manufacturing

The large bulk inventory management and shipping are the significant expenses for the firms. These costs are critical restrictions for the manufacturers. AM systems can be facilitated easily, allowing parts to be produced near the area where they are needed. This can drastically reduce storage and shipping costs. With AM technology, the cost of inventory and shipping is not big concern for the manufacturers and consumers.

Decentralized Manufacturing

It is already mentioned that AM could reduce the complexity of the supply chain, logistical costs and environmental impacts by manufacturing items closer to the end destination. As a result, production can be decentralized, leading to a shorter time between production and sale.

Table 1.1 The goods produced by using AM for various industry subsectors (Thomas and Gilbert, 2015).

Category	Percent of Total AM Made Products	Shipments of US Made AM Products ($millions 2011)	Total Shipments ($millions 2011)	AM Share of Industry Shipments
Motor Vehicles	19.5%	48.0	445 289.4	0.01%
Aerospace	12.1%	29.8	157 700.7	0.02%
Industrial/business machines	10.8%	26.6	365 734.8	0.01%
Medical/dental	15.1%	37.2	89 519.5	0.04%
Government/military	6.0%	14.8	32 784.4	0.05%
Architectural	3.0%	7.4	72 186.9	0.01%
Consumer products/electronics, academic institutions, and other	33.6%	82.7	895 709.8	0.01%
Total	100.0%	246.1	2 058 925.5	0.01%

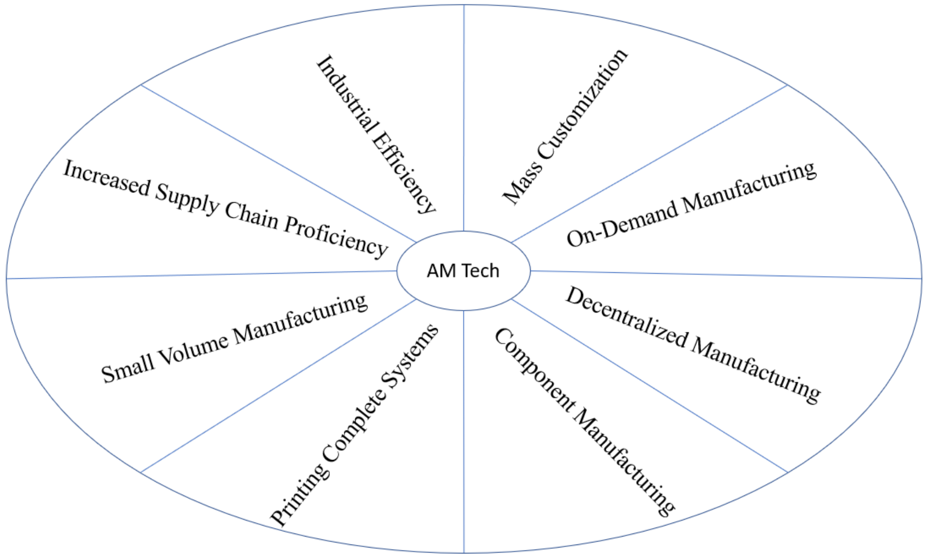

Figure 1.7 Advantages of AM

Component Manufacturing

AM processes are highly customizable and capable of producing complex parts. Therefore, another area where AM is successfully applicable is component applications. Variety of subsectors utilize this technology for component manufacturing such as automotive and aerospace. These industrial sectors mostly require producing very complex parts as monolithic as possible with minimum inventory because the mechanical properties of the parts can be negatively affected as the number of assembly sub-parts increases. With the distinctive features, AM is a practical solution for the big and small size companies' problems. The aerospace and automotive industries comprise almost a quarter of the AM market.

Printing Complete Systems

Creating an item with many parts through the assembly lines makes the manufacturing systems more complex and expensive. AM has the capability to produce a complete system without requiring an assembly line and complex procedures. AM has this flexibility, making it easy for users to utilize this technology efficiently and effectively. By reducing complex components of traditional manufacturing systems, it also helps firms save a great deal of money.

Increased Supply Chain Proficiency

As already mentioned in the previous sections, AM has the capability to produce parts near the consumers which could save a lot of time and reduce costs associated with shipping and inventory. This unique capability of AM makes this technology preferable especially for small businesses and manufacturers.

Small-Volume Manufacturing

Small volume manufacturing is a serious challenging for many subsectors such as automobile and aerospace. As part of their effort to increase efficiency and compete with other manufacturers, firms seek robust methods to reduce high inventory management costs for small volume parts. AM is a suitable technology for these companies to achieve their goal. Small volume manufacturing in AM industry is growing rapidly and expected to increase to $1.1 billion by 2025 (Attaran, 2017). While the AM applications increase for small volume manufacturing, the cost of material decrease 11% for new supplier into the market (Vicari and Kozarsky, 2013). This indicates that AM is more economically feasible to compare the other manufacturing methods for various applications.

1.1.5. Challenges in Additive Manufacturing

AM technology has so many advantages over SM systems. However, it also has some drawbacks besides these advantages. Based on the article published by Expert Roundap (2019), this section will provide a brief overview of the major challenges in AM systems shown in Figure 1.8.

Slow Production Speed

Production speed is a key factor in the manufacturing industry for mass or high-volume production. Manufacturing products and delivering them to consumers within a reasonable timeframe provides efficient and effective planning for sustainable manufacturing. Current industrial 3D printing technology has a problem with production speed, and it is still lagging behind traditional machine-based manufacturing. This problem is a serious obstacle to the adoption of AM to mass or high-volume production.

Figure 1.8 Major Challenges in AM

Quality Assurance

Quality, which is defined as the density level of the printed object, is considered as the most important factor in AM. AM has three main quality issues, namely porosity, keyholes, and dimension precision. If the powder is not sufficiently melted due to the low laser power or high scan speed, it causes unmelted powder particles in object's structure which is called as porosity. If the powder evaporates during the AM process due to the high laser power or low scan speed, it creates holes in object's structure which is called as keyholing. AM faces certain challenges with quality consistency, especially in producing fully dense metal parts because of porosity and keyhole formations. In addition to these, it is very important that the manufactured parts do not have any geometrical errors. There are concerns regarding the accuracy of dimensions in AM since it is a relatively new manufacturing technique (Al-Ahmari et al., 2019). The challenge of maintaining dimensional accuracy in AM has been addressed in several studies and new methods are being developed to solve this issue.

Lack of Industry-Wide Standards

One of the major barriers to the widespread adoption of AM is the absence of standards. So far, there is no widely accepted process for choosing AM over SM. Besides, different standards are needed for other critical factors such as the quality of printed parts. A more uniform, globally accepted set of industry standards would be extremely beneficial to all manufacturer and consumers.

High Initial Investment

Investing in AM might be expensive as AM machines can cost up to $1,000,000 (Brockmann et al., 2015). Consequently, small manufacturers tend to think twice when purchasing AM machines for their production processes. More cost-effective AM machines could help small manufacturers and overcome this issue.

Workforce Challenges

A lack of engineers, managers, and executives who fully understand the technology to be able to work in the field and develop strategies to increase the efficiency and effectiveness of AM is a significant challenge.

Software Challenges

Am industries still have major bottlenecks in design and data preparation. Hardware systems with high productivity are emphasized and the value of intelligent software solutions is currently ignored in AM processes.

1.2. Aim

The goal of this research is to provide users *a decision support tools to use the AM machine efficiently and effectively*. These decision support tools provide a method to measure the complexity level of a part to ensure if the part is appropriate for AM, better optimization of process parameters of the AM machine, and a production scheduling model to use two material types for a single AM machine to increase the efficiency. The goal will be achieved through three specific objectives: 1) Identifying the major decision factors for related AM processes; 2) Developing mathematical models or methods to provide an effective tool and 3) Providing useful managerial insights that can help users to improve the manufacturing process and identifying research gaps for the new studies.

1.3. Research Overview

This research consists of three studies that investigate the different issues of AM systems as shown in Figure 1.9.

The first study is discussing a framework to select the appropriate AM processes. An empirical model is developed to optimize process parameters in the second study and a scheduling model is developed for production planning and scheduling.

Study 1 focuses on developing an AM process selection framework by considering complexity and other important factors such as labor cost, manufacturability, etc. The most important part of this section is the method to estimate the complexity level of a part by using a pixel density ratio with image analysis. In the literature, there is no method or model to estimate the complexity level of a part, particularly for manufacturing process selection. The manual estimation of the complexity is challenging and takes a great amount time. The problem of the US defense agency could be a good example for this: The agency arbitrarily selected a dozen of parts that they believed appropriate for AM because they were considered "complicated" enough. When we asked for their definition of part "complexity", they could not give an answer. They also mentioned that there are so many manufacturing processes and procedures that any kind of manual or complicated methods are not applicable to evaluate their large list of parts. Thus, a new method is introduced in this study to estimate the complexity level of a part for manufacturing selection. The

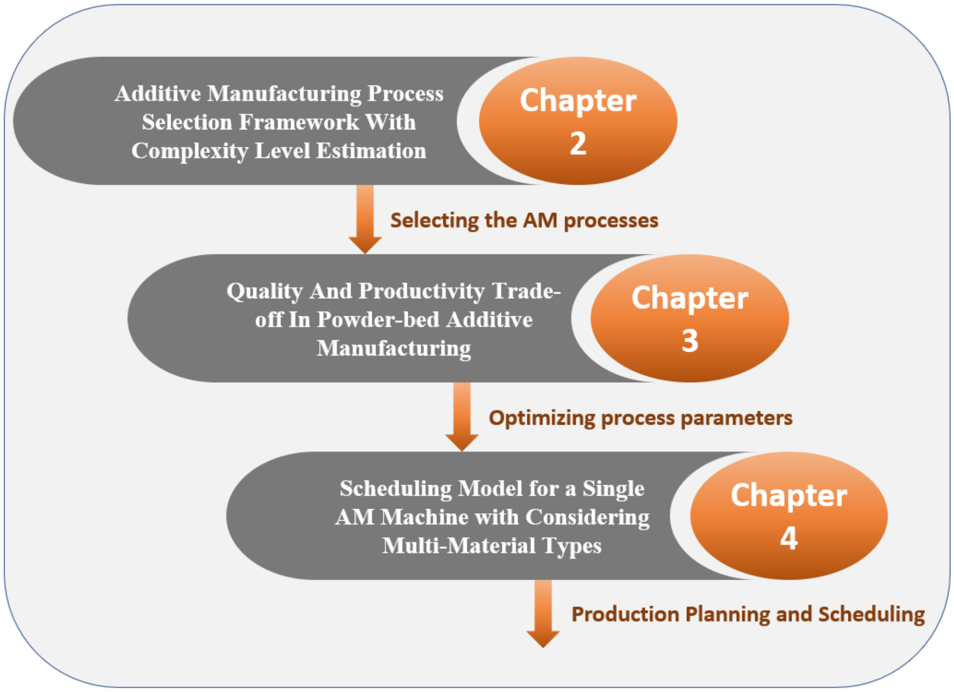

Figure 1.9 A diagram illustrating the research flow.

method is validated with numerical experiments. The sample parts, whose complexity levels have already been evaluated by the manufacturing experts, are used in the numerical experiments. The complexity levels of sample parts are estimated with high accuracy. The new method can quickly and consistently evaluate the complexity of a great number of parts without any involvement of experts with manufacturing experience.

Study 2 concentrates on two key factors in AM systems which are quality and productivity. Quality is considered a difficult factor to manage since there is no reliable way of measuring it. Achieving high quality for final parts is challenging in AM systems. Focusing only on acquiring a high-quality level for produced parts may cause significantly high operational costs in AM processes. Thus, a trade-off between these two concerns is vital for maintaining printing operations efficiently and effectively. A nonlinear model is developed to optimize process parameters to acquire the lowest operational cost while keeping the quality at the desired level. The process parameters that are considered in the optimization are laser power, scan speed, layer thickness, hatch distance, and laser spot size. The nonlinear model is solved by utilizing the enumeration method and the optimal results for each process parameter are obtained. To show the significance level of each process parameter, the combined and individual effects of all process parameters were analyzed in a numerical experiment. It is also showed that the proposed empirical model yielded lower building costs than those from similar studies in the literature and is effective in maximizing productivity at the desired quality level.

The last study proposes a scheduling model for a single AM machine with considering multi-material types. In this study, the key factors that can affect both quality and operational costs are identified. It is determined that waiting time and the time for the material changeover might have a great impact on both quality and operational cost. As mentioned before, taking quality into account is always difficult in AM processes. The parameter settings and the calibration of the AM machine must be reset when the AM machine is switched to a different material type and this process affects the quality of the printed part. Since the calibration and process parameters of the AM machine are very difficult to set optimally right after the material changeover, the quality levels of the produced parts might be relatively lower. The quality will be increased as more parts are made with the same material type due to the better calibration and parameter optimization. In this study, all these important factors are considered while developing the mathematical model. The study also provides useful and effective insights for industrial practitioners and identifying the research gaps for future studies.

CHAPTER 2. ADDITIVE MANUFACTURING PROCESS SELECTION FRAMEWORK WITH COMPLEXITY LEVEL ESTIMATION

Abstract

Decision-making between additive manufacturing (AM) and conventional manufacturing (CM) is a difficult process because of the lack of generally accepted guidance. A majority of studies in the literature focus on choosing a specific AM process when the AM is already presumed for producing a given part. However, the decision between AM and CM is more challenging. Many researchers and practitioners believe that AM has advantages for producing complex parts. Thus, complexity can be used as a decision-making criterion. However, there is no method or model to evaluate how complex a component is, particularly from the viewpoint of manufacturing. This study introduces a framework that uses a new method to estimate the complexity level of a given part and then make a selection between AM and CM. The framework also uses other important factors such as manufacturability, material type and cost models to select a specific AM process for the part. To validate the proposed method for estimating the complexity level, the sample parts whose complexity has already been evaluated by manufacturing experts in literature were gathered. The results show that the proposed method can successfully and consistently evaluate the complexity of a great number of parts without any involvement of experts with manufacturing experience.

2.1. Introduction

Additive manufacturing (AM) and conventional manufacturing (CM) are two manufacturing types commonly used for producing parts (Herzog et al., 2016). CM includes casting, forging, and machining (Shannon, 1948; Heisel and Meitzner, 2006; Watson and Taminger, 2018). Compared to CM, AM can produce complex and highly customized parts and may reduce material waste during the manufacturing process. However, AM may have a high initial investment cost and could be less efficient and more expensive for large quantities of parts (Newman et al., 2015).

There are several frameworks and models in the literature for selecting a specific AM process for a given part. However, the majority of them presume that AM has already been selected as a production technique. Manufacturability, material type, and cost can be used to select a specific AM process. Only a handful of studies have investigated the choice between AM and CM. So far, there is no widely accepted method or model for comparing AM and CM quickly for a large number of parts. Conceptually, AM is widely believed to be preferable for complex parts (Knofius et al., 2019; Mançanares et al., 2015; Romano et al., 2017). However, there is no effective method or model to estimate the complexity level of a part and use the level to facilitate the choice between AM and CM. This study introduces a new framework that uses a new method to estimate the level of complexity in a consistent way across all parts by using a simple pixel density ratio method that uses image analysis. Considering the other significant attributes such as manufacturability, material type, and total cost makes the proposed method a comprehensive AM process selection framework.

This study was motivated by our interaction with a large US defense agency. The agency was asked to evaluate AM for their millions of parts. The agency arbitrarily selected a dozen of parts that they believed appropriate for AM because they were considered "complicated" enough. When we asked for their definition of part "complexity", they could not give an answer. They also mentioned that there are no procedures that can evaluate their large list of parts for their suitability for AM.

2.2. Literature Review

This section has two parts. The first covers the existing studies on complexity in order to explain the distinguishing characteristics of the proposed method from existing methods for estimating the complexity level of a part. The second part will discuss the general framework/methods for selecting a specific AM process.

Despite significant academic research work on estimating the complexity of manufacturing or production systems, there is a lack of awareness in research on manufacturing process selection based on part complexity (Bermejo et al., 1997; Calinescu et al., 1998; Stoop and Wiers, 1996). To the best of our knowledge, there are very few previous studies that can be associated with this subject.

Chen and Sundaram (2005) developed an algorithm to estimate the complexity level of 2D shapes by using correlates of Kolmogorov complexity (entropy measures of global distance and local angle) and a measure of shape randomness. However, the algorithm particularly aimed at applications in computer vision rather than manufacturing. Additionally, the algorithm only considered the outer properties of a part in evaluating its complexity and ignored its inner structures. Similarly, Su et al. (2006) estimated the complexity of 2D shapes by using three properties: the complexity of boundary, the global structure, and the symmetry of the shape. They also did not consider inside structures. Valentan et al. (2011) developed a method to estimate the complexity level of 3D shapes by using basic features of the STL file, which is a type of file generated from CAD files. The process is simply based on the manual analysis of the STL file, and therefore, the method needs a great deal of time by experts to provide results for many parts. Like the methods mentioned earlier, the estimation is based only on the outer properties of 3D parts. Page et al. (2003) conducted a research to estimate the complexity of a discrete approximation of planar curves in 2D images and manifold surfaces for 3D triangle meshes based on the information theory created by Shannon (1948). Similar to other studies, the inner properties of parts were not considered in the evaluation process. Besides, the proposed methods were slow and inapplicable to evaluate thousands of parts because the methods were complex and involved manual effort. The third estimation approach proposed by Rigau et al. (2005) considers the inside structures of a part and used integral geometry and information theory tools to quantify the shape complexity from two different perspectives; inside structures and outer structures of a part. This approach follows complicated and time-consuming processes for collecting data for a part's inner and outer properties. They have developed the model based on Monte Carlo computation, and the concept of complex uniformly distributed global lines, and mutual information definition. Since they only focus on the theory of their model, they have not specified the computational time of their model with a numerical experiment. However, Monte Carlo computation is known to be complex and takes a considerable amount of time. Liang et al (2007) indicated that running an algorithm developed by using Monte Carlo computation costs 115 minutes for each run. It can be easily concluded that their method would take much longer than 115 minutes for a single part since they consider two conceptually complex tools aside from Monte Carlo computation. Since the proposed method can provide a result in seconds for a single part, the difference in computational efficiency would be more than 115 mins. If thousands or millions of parts are taken into consideration, then the computation difference would be massive. Therefore, similar to the previous methods, this estimation approach is not quite applicable for a large number of parts.

The last existing approach developed to estimate the complexity of a single part CAD model uses a mesh-based method (White et al., 2003). Mesh generation is performed first to capture details of the parts and sometimes detect representation of the problems of a solid model. However, mesh generation is difficult for particular formations of CAD model such as a filleted section colliding with the boundary of another face. Therefore, several new approaches have been introduced to simplify the CAD models for mesh generation (Armstrong et al., 1998; Blacker et al., 1997; Mobley et al., 1998; Sheffer et al., 2000; Tautges, 2001). The method with the proposed algorithms was successfully implemented and accurately estimated the complexity of a single CAD model. However, the run time to implement this method for thousands of parts would take an excessive amount of time because of the complexity of the meshing process. Thus, the mesh-based method would not be a solution to current industrial needs for manufacturing process selection when thousands or millions of parts are considered to evaluate.

In this study, however, the CAD file with image analysis will be used for collecting the required data which is easier and quicker compared to the existing four methods in literature. Our approach considers both the inner and outer edges by utilizing the standard orthographic orientation views. Since the method is quite straightforward and only aims to estimates complexity levels particularly for manufacturing process selection, it is suitable and reliable for large-scale industrial applications.

There are several recent studies that propose frameworks/methods to select an AM process for a given part from a variety of perspectives. Watson and Taminger (2018) developed a computational model to determine whether AM is more efficient than CM for a given metallic part by only considering the energy consumption. They ignored the part complexity, an important aspect for the choice between AM and CM. Besides, it was not specifically designed to select specific AM process. Baumers et al. (2015) developed a similar cost estimator model by considering the process energy consumption and build time. Their model presumes that the AM process is already selected as a manufacturing technique. The model only helps to choose a specific AM process based on the energy consumption and does not consider other significant attributes such as labor costs, machine costs, etc. Similarly, Yim and Rosen (2012) and Hällgren et al. (2016) developed their cost models to select the proper AM process for a given part. They also presumed that AM is already selected. As shown in Table 2.1, they considered more cost components than Baumers et al. (2015). On the other hand, Bikas et al. (2019) developed a framework to decide whether AM is an appropriate manufacturing solution for a given part. Three levels were included in their framework. Level 1 determines if AM is potentially beneficial by replying to a set of predetermined questions. Levels 2 and 3 investigate the technical feasibility and manufacturability of AM for that part, respectively. Since the framework relies on answers to predetermined questions, it is not a practical solution to automatically solve the AM process selection problem. As shown in Table 2.1, the proposed framework

Table 2.1 Comparison of AM process selection methods based on the attributes being considered.

Attributes being Considered	Watson and Taminger (2018)	Valentan et al. (2011)	Baumers et al. (2015)	Yim and Rose (2012)	Hällgren et al. (2016)	Bikas et al. (2019)	This study
Easy data collection	✓						✓
Complexity		✓					✓
Computational Burden							✓
Energy Consumption	✓		✓				✓
Cost			✓	✓	✓		✓
• Machine purchase cost				✓	✓		✓
• Machine operation cost				✓	✓		✓
• Material cost			✓	✓	✓		✓
• Labor cost				✓	✓		✓
• Energy cost			✓	✓	✓		✓
Material Type	✓		✓		✓	✓	✓
Manufacturability	✓					✓	✓

in this study considers more attributes than all other models, methods, or frameworks for AM process selection in the literature.

2.3. Methods

2.3.1. AM Process Selection Framework

This study proposes a framework in Figure 2.1 to select an AM process for a given part through two levels. At the first level, the part will be selected for AM or CM based on its complexity level. If AM is the choice, a specific AM process will be selected based on manufacturability, material type, and cost models at the second level.

The process starts with the calculation of the complexity, C_i, for a part i, which is detailed in subsection 3.2, and then compares the level against a threshold value C^*. Part i will be selected for AM if its complexity level C_i is higher than C^*. This constitutes the first and most important level of the AM process selection framework. Next, the parts that will be additively manufactured are classified according to their material types, including metal and non-metal. Non-metal materials include thermoplastic polyurethane, polyetherethekeytone, polyamide (Nylon) 11 and 12, ABS, polycarbonate, ABS blend, polylactic acid, polyetherimide and others. A metal part can be produced by powder-bed fusion, binder jetting, direct energy deposition, or fused deposition modeling; and the choice depends on cost models. Powder bed fusion, specifically selective laser sintering used for polyamide, thermoplastic, polyurethane, and polyetherethekeytone (Chatham et al., 2019). Fused deposition modeling AM processes can print ABS and other types of plastic including polycarbonate, polylactic acid, and polyetherimide (Ahn et al., 2002).

Similar to the metal printing, the choice depends on the cost models for several non-metal material types, as illustrated in Figure 2.1 The costs models used in this study to determine which AM process is more economic and efficient for a given part can be found in the studies conducted by Yim and Rosen (2012) and Baumers et al. (2015)

2.3.2. Estimating the Complexity Level of a Given Part

Computer-based modeling of a part is a similar process to drawing a picture. When an artist draws a picture, she usually uses paint or other similar tools to create a shape and often has to use more paint if she wants to depict more details when the picture gets more complicated. Figure 2.2-a shows an image of a cat without a lot of details and uses only a few lines. The more detailed and complicated picture of the same cat is depicted in Figure 2.2-b. In this case, the picture contains much more lines to depict all the details on the cat than the number of lines used in Figure 2.2-a. In other words, Figure 2.2-b uses a greater amount of paint than Figure 2.2-a to show all the details and elaborations.

This concept is similar to most cases of the computer-based modeling of a part. Pixels are used instead of paint in the design process of solid modeling. However, the outer and inner properties of an object must be considered in this process from the manufacturing viewpoint while only outer shapes are considered in the drawing. This major difference is a difficult factor to complexity estimation because capturing the inner properties of an object might be a complicated and time-consuming process if there is no effective tool to collect data. Since pixel density changes depending on the complexity level, it can be used to evaluate the object's complexity level. The only problem here is determining what kind

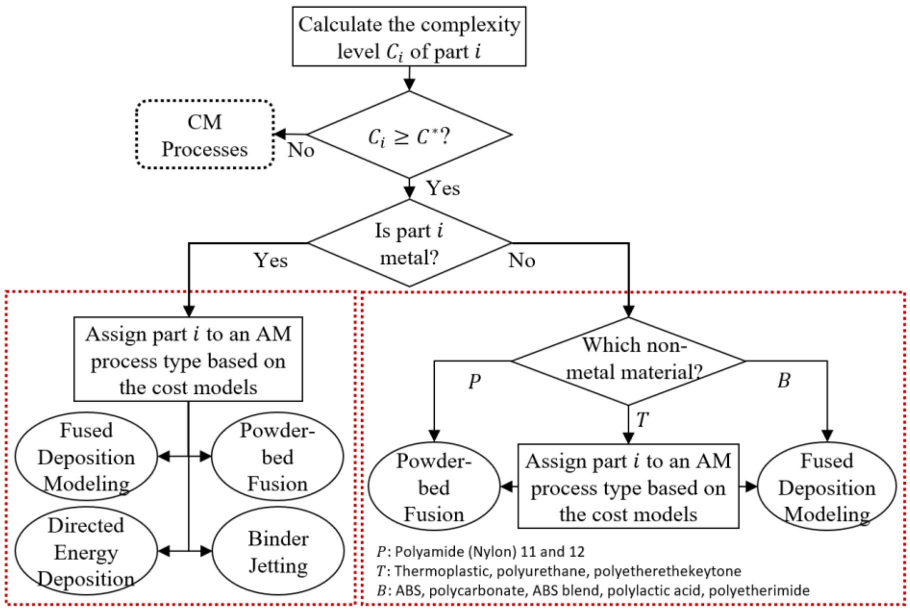

Figure 2.1 AM process selection framework.

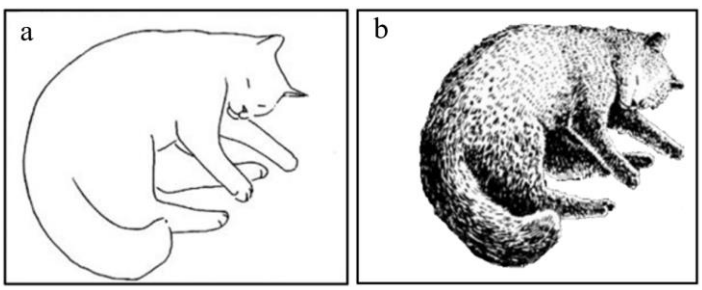

Figure 2.2 Example of simple and detailed/complex drawing (Sutterstock, 2019)

of tool or instrument could be used to acquire data in order to analyze pixel density for both the inner and outer properties of a given part. In the modern manufacturing systems, parts are designed with CAD software in a two-dimensional or three-dimensional model to create precision drawings or technical illustrations. Each CAD system has a different method of describing geometry, both mathematically and structurally, and this information is held in CAD files, which are a digital file format of a part generated by CAD software. The inner and outer properties of a part are represented in CAD files by projecting it in different perspective views for production purposes. Typically, each CAD file has four major drawing views to depict the structural properties of a part so that users can comprehend and reproduce every geometric and design detail with high precision. An example of these drawing views is shown in Figure 2.3. These four drawing views are called the standard orthographic orientation views, which include isometric, top, front, and side views. The advantage of the drawing views is that every single view contains all the characteristics of the entire part by representing them with specific lines or shapes.

The isometric view illustrates a part in three dimensions. As its name implies, the top view is a visual representation of an object from above. Although some properties of the object might not be visible in this view, they must be represented by lines or shapes. For example, a large hole on the part clearly visible in the front view but it cannot be seen from the top view directly. However, this hole is represented by lines in the top view as can be seen in Figure 2.3 in order to provide detailed information about the structural property of the part. Similarly, side and front views also contain all geometric and structural details of the given part. Since drawing views have so many advantages and contain all inner and outer

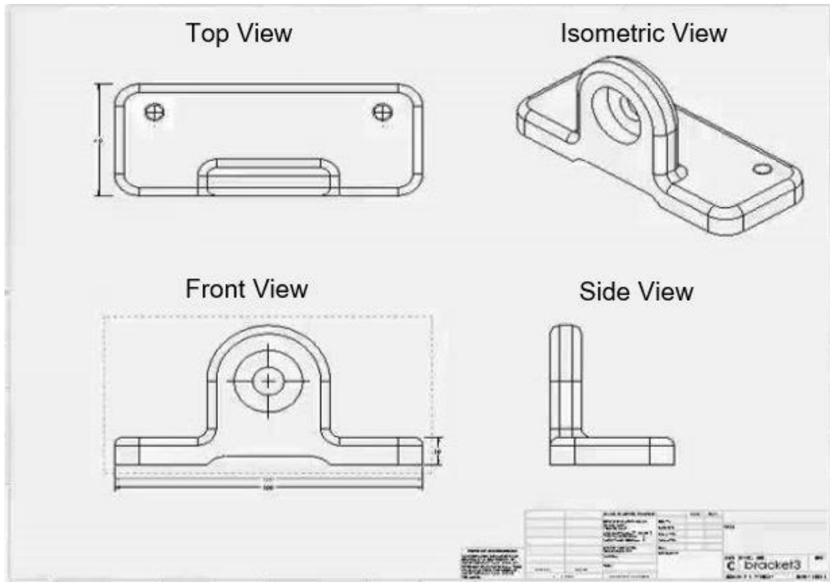

Figure 2.3 Drawing views of a part (Jamie, 2014).

properties of a part, the proposed method in this study uses these views to estimate the complexity level. The standard orthographic orientation views are analyzed to obtain the pixel density ratio considering lines and shapes in each view by using the image analysis tool in Python. In other words, the pixel amount used for the lines will be obtained and this value will be divided by the total pixel amount of the whole part based on each orthographic orientation view by using the developed image processing method. Please note that the line thickness needs to be normalized across drawings. The obtained final value between 0 and 1 by using equation (1) is considered an estimated complexity level for the part for each view. The complexity of each drawing view is estimated based on the pixel density ratio C values, which can be obtained with the following equation.

$$C = \frac{Total\ pixel\ density\ of\ edges}{Total\ pixel\ density\ of\ the\ part} \tag{1}$$

All four views are considered in the analysis and averaged in order to increase accuracy and reliability.

The sample parts shown in Figure 2.4, which were specifically designed for complexity analysis, were collected from the literature in order to show that the proposed method works effectively. The complexity levels of the selected sample parts have already been estimated by the experts in the experimental work conducted by Valentan et al. (2011). The sample parts have various inner and outer properties. It starts with a simple cube and continues with different geometrical shapes to test the proposed method.

Figure 2.5 shows the complexity level of these parts evaluated by the experts' opinions. Based on this, sample part 1, which is a simple cube, has the lowest complexity compared to the other parts. The most complex one is sample part 6, which is a free form part. These complexity levels make sense because we can see that the cube's inner and outer properties are simple compared to the other parts, based on the analysis. Part 6 is clearly more complex than the other sample parts because it has more inner and outer properties arising from the free form characteristic of this part. This will be further discussed in detail.

We redrew all sample parts by using SolidWorks, a CAD software package, to test the proposed complexity estimation method. All drawing views were created with the same settings.

2.4. Results and Discussions

The estimated complexity levels are shown in Figure 2.6 for all sample parts. The results show that obtained complexity levels almost identical to the complexity level evaluated by manufacturing experts. Part 1 still has the lowest complexity level. The estimated complexity levels for other sample parts are also quite similar to those in Figure 2.5, except part number 2. This will be discussed further in this section after explaining some important distinctive points about the sample parts.

Figure 2.7 shows two sample parts remodeled in CAD software. As mentioned earlier, the lowest complexity level was obtained for part 1 based on both implemented method in this study and the experts' opinions. The reason for this can be seen clearly in the drawing views in Figure 2.7-a. The pixel density formed by the lines that represent the inner and

Figure 2.4 Selected sample parts for complexity evaluation (Valentan et al., 2011)

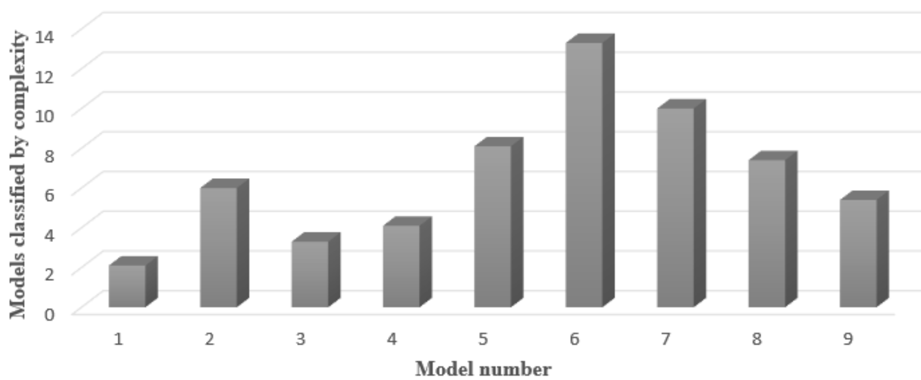

Figure 2.5 Complexity level of the sample parts evaluated by manufacturing experts (Valentan et al., 2011)

outer properties of part 1 is significantly low. Thus, the cube has a low pixel ratio value. On the other hand, the pixel density ratio of the drawing views of part 2 in Figure 2.7-b is higher as the lines and shapes take up more space than the lines and shapes take up in Figure 2.7-a. This increases the pixel density ratio for part 2. Therefore, the complexity level of this part was estimated higher than part 1.

The most complex part among all the sample parts is shown in Figure 2.8. Since part 6 has more inner properties and irregular shapes than the other parts, the density level of the pixels that form the edges in the total sectional area of the associated view is much greater than the other parts. This can be clearly seen in the isometric view and standard orthographic orientation views in Figure 2.8. In direct proportion to this increase, the obtained complexity level ($C = 0.437$) of this part is higher than other parts.

As mentioned earlier, almost all the complexity levels obtained for sample parts are equivalent to the complexity level evaluated by the experts in Valentan et al. (2011), except part 2. There could be a few reasons for this error. The first could be correlated with the complexity level evaluation analogy used by the experts. Because the experts might have different opinions on the same sample part, the complexity level of part 2, which is a sphere-shaped part, may vary according to different experts. For example, the experts in Valentan et al. (2011)'s study considered that the sphere parts were quite complex for manufacturing because of the surface quality concern. Others might consider that the sphere-shaped parts are not complex parts (Rigau et al., 2005). To avoid this, more expert's opinions could be collected to increase the reliability of the method. Another potential reason could be related to the insufficiency of features and properties considered in the

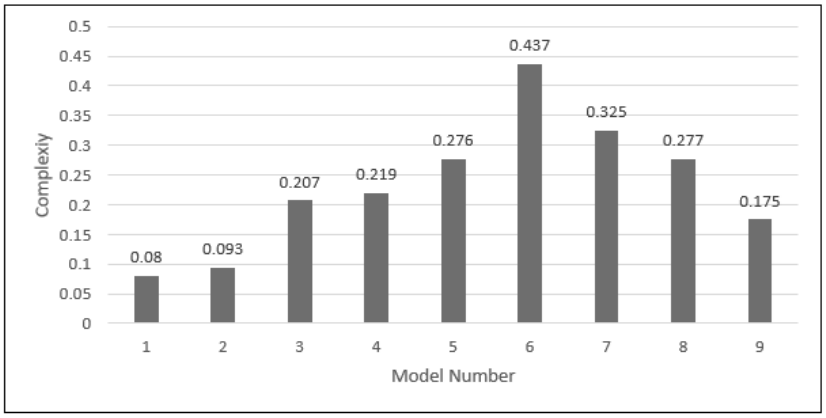

Figure 2.6 The complexity values obtained for the sample parts.

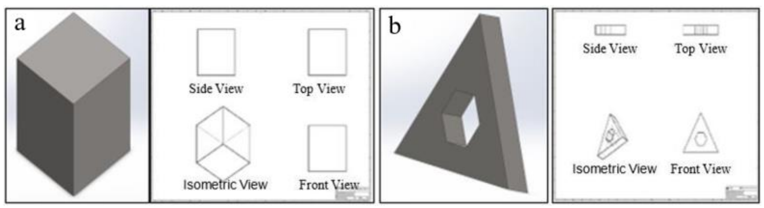

Figure 2.7 Sample parts with drawing views, where (a) $\boldsymbol{C} = \mathbf{0.08}$*, (b)* $\boldsymbol{C} = \mathbf{0.207}$

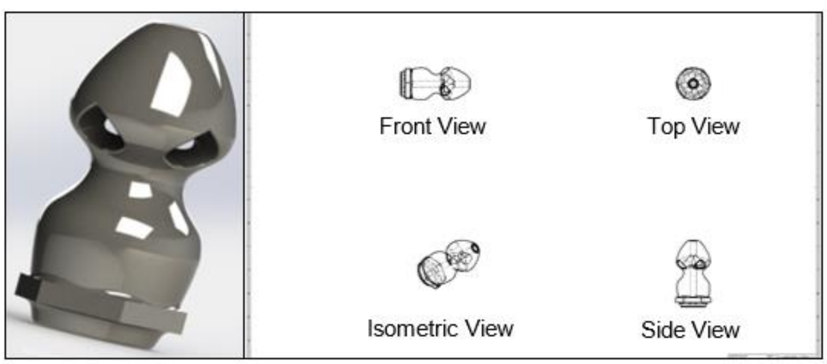

Figure 2.8 Drawing views of the most complex part ($\boldsymbol{C} = \mathbf{0.437}$*)*

complexity estimation process. It is possible that considering only the inner and outer properties might not be enough to evaluate the complexity level of some specific parts such as spheres where additional concerns might exist. To avoid this, additional properties or features could be added to the proposed method to increase the accuracy level for some specific parts. However, it must be noted that considering more properties or features will lead to a more complicated and time-consuming method or model, which may not be applicable for estimating a large number of parts automatically. A manufacturer may have thousands or millions of parts to consider when they evaluate AM against CM.

After being selected for AM, a part is classified into a specific AM process based on the material type and manufacturability, as shown in Figure 2.1. The cost models are then used to determine a specific AM process. The overall cost, $C_{overall}$ consists of different cost components that can be found with the following equation.

$$C_{overall} = C_p + C_o + C_m + C_l + C_e \tag{2}$$

Here, C_p is machine cost, C_o is operation costs, C_m is material costs, and C_l is labor costs. The cost model developed by considering these components can be found in the study conducted by Yim and Rosen (2012). The only component that was not considered in the mentioned model is energy cost C_e. The cost model that considered energy consumption can be found in the study conducted by Baumers et al. (2015). The part will be assigned to a specific AM process based on the lowest cost obtained by using cost models.

2.5. Conclusions

In this study, a new framework is proposed for selecting an AM process. A new method is introduced to estimate the complexity level, which is one of the most important attributes that should be considered in comparison between AM and CM. This method is simpler and faster than current models, methods, or frameworks in the literature and can be applied to a large number of candidate parts for AM.

The proposed method for estimating the complexity level of a part was validated by conducting numerical experiments with sample parts specifically designed for complexity evaluation. The complexity levels of these selected sample parts have already been evaluated by experts in the literature. The results show that the complexity level obtained with the proposed method in this study, which does not involve manual efforts, is almost equivalent to the complexity level evaluated by the experts.

The cost components are provided to select a specific AM process. In this way, a user can determine if AM is suitable for a given part by using complexity and then select a specific AM process based on the manufacturability, material type, and cost models. Therefore, the proposed framework is the first comprehensive framework in the literature that includes complexity, manufacturability, material type, and cost components. With the high computational efficiency, it is a promising framework that can help solving the current AM selection problems in the manufacturing industry.

CHAPTER 3. QULITY AND PRODUCTIVITY TRADE-OFF IN POWDER-BED ADDITIVE MANUFACTURING

Abstract

Additive manufacturing (AM) is a technology that creates parts directly from 3D CAD files based on a layer-by-layer manufacturing process. Quality and productivity are the two key concerns in powder-bed AM processes, which are one of the most-widely used AM in the industry. Because of the keyholes and porosity formation occurring in the object's structure during printing process, quality is considered a difficult factor to manage. On the other side, focusing only improving quality could result in higher building cost and inefficient printing operations. Thus, a trade-off between these two concerns is vital for maintaining printing operations. To the best of our knowledge, there is no study in the literature that has yet considered this trade-off in a systematic way and can provide optimal results for productivity based on a desired quality level. This study combined equations from previous studies in a systematic way to create an empirical model to optimize major process parameters, laser power, scan speed, layer thickness, hatch distance, and laser spot size for a trade-off between quality and productivity in powder-bed AM processes. The combined and individual effects of all process parameters were analyzed in a numerical experiment to show their significance for the printing process. The case study also showed that the proposed empirical optimization model yielded lower building costs than those from similar studies in the literature and is effective on maximizing productivity at the desired quality level.

3.1. Introduction

AM technology promises many advantages, such as enhancing geometrical freedom, reducing material waste, and shortening product development cycles (Tian et al., 2017).

AM processes for metal printing are classified into three categories: powder-bed, powder-feed, and wire-feed (Galati and Iuliano, 2018). Among these, powder-bed AM processes are one of the most widely used AM for manufacturing metal parts (Kruth et al., 2007). In this process, powder particles are melted in each layer where laser beams or electron beams are used in order to build a part. Laser Powder Bed Fusion (LPBF), Direct Metal Laser Sintering (DMLS) and Electron Beam Melting (EBM) are the most well-known powder-bed metal AM processes (King et al., 2015).

Productivity and quality are the two key concerns in powder-bed AM. Quality is defined as the density level of the printed object in this study, which implies that higher density means better quality (Galati and Iuliano, 2018). Especially for high-value components, high quality and reliable control of mechanical properties require careful process control and tracking (Haden et al., 2015). Besides quality of the printed part, productivity, which is defined as time used per unit of production, is also an important concern (Gusarov et al., 2018). A slow building rate is a big concern and limitation for powder-bed AM processes (Sun et al., 2016). Gutowski et al. (2017) reported that the process rate of powder-bed AM can be up to three times slower than the conventional manufacturing and energy consumption can be also up to two times higher than the conventional manufacturing. Because of these, a trade-off between quality and productivity is vital for minimizing the building cost while keeping the quality at desired level.

Productivity and quality are affected by many factors such as process parameter settings, powder morphology, environmental gases, and the thermal conductivity of a material. Among all these factors, the variation of process parameters has a great impact on final quality of printed parts and efficiency of the printing process (Sun et al., 2016). Therefore, this study particularly investigated the effect of the major process parameters; laser power, scan speed, layer thickness, laser spot size, and hatch distance, and their interactions on the quality and productivity (Sun et al., 2013). Among all the major process parameters, laser power and scan speed are relatively more significant because they have higher impacts on final quality and productivity of the printing process (Read et al., 2015). It was reported that using optimal laser power and scan speed could improve the quality and production rate by as much as four times (Buchbinder et al., 2011). Research on high layer thickness fabricated of 316L by using selective laser melting conducted by Wang et al. (2017) demonstrated how mechanical properties and surface roughness change with different thickness values. In addition to this research, several studies also indicate that layer thickness is a significant process parameter for increasing relative density and efficiency (Delgado et al., 2012; Matilainen et al., 2014). Hirvimäki et al. (2013) reported that they obtained the highest and lowest energy density by applying hatch distance 0.03 mm and 0.07 mm respectively. In this way, they highlighted the significance of hatch distance in AM processes. Like hatch distance, laser spot size also influences energy density and may cause keyholing in the printed object. Reducing spot size could slow the printing process down if it is not selected optimally depending upon the other process parameters (Wayne et al., 2014). Therefore, the objective of this study is to combine outcomes from the previous studies to create an empirical model to optimize all major process parameters in powder-bed AM in a systematic way to minimize the total building cost through a trade-off between productivity and quality.

The existing research about the optimization of process parameters in powder-bed AM are merged into two approaches. In the first approach, up to three process parameters are usually optimized rather than considering all major process parameters because experiments for all parameter combinations for different cases are expensive and time-consuming with current methods. In the second approach, studies mainly focus on improving either quality or productivity individually. Only a handful of studies consider improving both, but not in a systematic way. Instead, they applied new technologies or strategies to improve the printing process. Optimizing all major process parameters and improving productivity while maintaining a desired quality level are our major contribution.

The first differentiation of this study from the previous studies is the systematic consideration of the effect of all major process parameters and their interactions on productivity and quality through the empirical model. As already mentioned earlier, the existing studies mostly focus on up to three process parameters because experiments for all parameter combinations for different cases are expensive and time-consuming. Wang et al. (2017) investigated the possibility of using greater layer thickness to improve the efficiency of SLM. They reported that building rate could be increased up to 12 mm^3/s by optimizing layer thickness, 3-10 time higher than the previous studies. Besides, Fotovvati and Asadi (2019) has also verified the important effect of layer thickness, orientation, distance from free edges on the material microstructure by reporting results and statistical analysis of 300 mechanical tensile testing for the layer thickness ranging from 0.5 mm to 1.6 mm. Gu et al. (2013) reported energy density is a critical factor on porosity and microstructure of SLM 14-4PH stainless steel part by varying the scan speed while keeping the laser power at a constant level. Kamath et al. (2014)investigated laser power and scan speed by using a simple model of laser melting and single-track experiments to show relative density could remain >99% at high laser power values. Since laser power and scan speed are considered critical parameters in the powder-bed AM processes, many studies in literature focused on these two parameter settings to improve quality and productivity (Laohaprapanon et al., 2012; Spierings and Levy, 2009; Sun et al., 2016). Read et al. (2015) considered three process parameters, laser power, scan speed, and hatch distance, and showed that laser power, scan speed and the interaction between scan speed and hatch distance have the major influence on porosity formation. On the other side, Aboulkhair et al. (2014) analyzed how morphology and size distribution of the metal powders governs the formation of gas powers and controls the followability. All research mentioned above add significant values to literature, but the important point here is that other major process parameters apart from the focused ones were kept constant in these studies and therefore, the effect of many parameters and their interactions were sort of ignored due to expensive and time-consuming methods. However, in this study, all major process parameters were considered without cost and time limitations tanks to the high computational ability of the empirical model.

Improving both quality and productivity together by optimizing process parameters is the second contribution that differentiates this study from the previous studies. These two objectives are generally investigated separately in the literature. Since quality is considered a more critical concern for AM, most studies concentrated on improving quality rather than productivity. Irrinki et al. (2016) reported that powder attributes have important effects on the densification and mechanical properties by conducting experiments on four types of powder. Verlee et al. (2012) have also investigated how particle size, particle shape, printing temperature, and printing time affect the final properties of printed objects. Ahmed et al. (2016) analyzed the effect of laser power, scan speed and hatch distance on relative density with one factor at a time by keeping other parameters constant and illustrated the effect of each of these parameters on the quality. Hiren et al. (2019) has reported that the laser power, scan speed, layer thickness and hatch distance have important effects on dimensional accuracy of printed objects in powder-bed fusion by presenting the experimental results with various input parameters while processing CL50WS. Since these process parameters are very important for relative density, many similar studies can be found in the literature (Carter et al., 2014; Kempen et al., 2011; Read et al., 2015; Tian et al., 2017). On the other side, Gusarov et al. (2018) have reported that productivity can be increased by using alternative laser density distributions. They suggested 1 kW for laser power and 300 mm/s for laser scan speed, which are much higher than the recommended parameters for production (less than 100 w for laser power and less than 30 mm/s for scan speed) (Gusarov et al., 2018). Besides, some studies focus on the effect of layer thickness and laser spot size. Sun et al. (2013) investigated the effect of layer thickness and reported that increasing in layer thickness causes rising nodulizing tendency and uneven melt. As mentioned before, layer thickness is also an important factor for productivity (Wang et al., 2017). Deng et al. (1992) have analyzed the effect of the beam profile on SLS product quality and showed that 95% relative density could be obtained with 3 mm of output beam size. The above studies analyzed various process parameters but some focused on the quality while others focused on the productivity. Focusing only on quality could result in lower productivity and ultimately higher building cost. Similarly, concentrating only on productivity may result in lower quality. In this study, productivity can be improved at a given quality level by optimizing process parameters in a systematic way via an empirical model, whose effectiveness will be demonstrated in the numerical experiments.

Improving both quality and productivity in a systematic way is the third differentiator of this study. In the literature, only handful of studies considered improving quality and productivity together, but not in a systematic way. Researchers often studied effect of new materials or methods on quality of final products and productivity of printing process. However, even if new materials or methods are available to test and evaluate their effect on the quality and productivity, the full potential of these materials and methods may not be observed if all parameters are not optimized based on the characteristics of the material type or methods. Khan and Dickens (2012) conducted research about processing of precious metals and alloys using the SLM process. They tested the 24-carat gold (Au) powder for apparent density, tap density, particle shape and size distribution by processing material with the SLM machine and explained the effects of material on major process parameters such as scan speed, laser power and the porosity formation. Although material properties are crucial for quality and efficiency of the printing process, the full potential of tested material can be observed much better if the process parameters are optimized based on tested materials. Fotovvati et al. (2019) reported that the scanning strategy has an important effect on surface roughness and thus on dimensional accuracy. Aboulkhair et al.

(2014) conducted a research about new scanning strategies to improve relative density of printed objects and process efficiency by examining Aluminum alloy AlSi19Mg. However, they did not consider the effect of combined parameters along with the scanning strategy to obtain maximum output. The optimum scanning strategy might be different if any of major parameters are changed for different printing operations.

3.2. Mathematical Model

In this section, the mathematical and empirical background of the optimization model will be explained. Since the objective of this study is to minimize the building costs of printed part by improving productivity of running 3D printing machine through varying laser power, scan speed, layer thickness, laser spot size, and hatch distance, they will be used as decision variables in the empirical model.

As mentioned earlier, minimizing keyhole and porosity formation in the object's structure is significant to obtain high quality for a printed part. To do that, specific ranges for laser power and scan speed with allowable layer thickness and hatch distance were created for the optimization model. For each laser power range, there will be a corresponding range of scan speed with allowable layer thickness and hatch distance. Binary variables are used to determine which range will be selected with associated laser power. According to these values, a trade-off between process parameters will be performed to optimally maintain the printing operations. The formation of ranges is demonstrated in Table 3.1. The most important advantage of the empirical model is that the ranges could be formed based on any quality level.

Table 3.1 Ranges for laser power and scan speed along with allowable hatch distance and layer thickness for minimizing the porosity.

	Range *J*				
	1	**2**	**3**	**…**	$\boldsymbol{n}$
$\left(P_j^L, \quad P_j^U\right)$	$(P_1^L, \quad P_1^U)$,	$(P_2^L, \quad P_2^U)$,	$(P_3^L, \quad P_3^U)$	$\dots$	$(P_n^L, \quad P_n^U)$
$\left(V_j^L, \quad V_j^U\right)$	$(V_1^L, \quad V_1^U)$,	$(V_2^L, \quad V_2^U)$,	$(V_3^L, \quad V_3^U)$,	$\dots$	$(V_n^L, \quad V_n^U)$
$\left(h_j^L, \quad h_j^U\right)$	$(h_1^L, \quad h_1^U)$,	$(h_2^L, \quad h_2^U)$,	$(h_3^L, \quad h_3^U)$	$\dots$	$(h_n^L, \quad h_n^U)$
$\left(\delta_j^L, \quad \delta_j^U\right)$	$(\delta_1^L, \quad \delta_1^U)$,	$(\delta_2^L, \quad \delta_2^U)$,	$(\delta_3^L, \quad \delta_3^U)$,	$\dots$	$(\delta_n^L, \quad \delta_n^U)$

Here, P_j^L , V_j^L, h_j^L, δ_j^L define lower bounds for the ranges. The values for the corresponding process parameters cannot be less than the defined lower bound values for the selected range. Similarly, P_j^U, V_j^U, h^U, δ_j^U define lower bounds for the selected range. The values for the corresponding process parameters cannot exceed the defined upper bound values for the selected range. The ranges can be created based on the data that can be aggregated from the experimental research. In this way, relative density could be kept at a desired level and guaranteed that it cannot be less than the density level set by the ranges. If parameter/parameters are selected out of these ranges, the desired quality level is unlikely to achieve and porosity or keyholing may occur in the object structure. If the selected laser power is lower than the lower bound and scan speed is higher than the upper bound, porosity formation is likely to occur in the object's structure. If laser power is higher than upper bound and scan speed is lower than the lower bound, then keyholing is likely to occur in the object's structure.

The parameters and decision variables in the mathematical model are explained below.

Decision Variables

V	Scan speed (mm/s)
$\boldsymbol{P}$	Laser power (W)
$\boldsymbol{h}$	Hatch distance (mm)
$\boldsymbol{\delta}$	Layer thickness (mm)

σ Laser spot size (mm)

x_j Binary variable

Parameters

V^t Threshold scan speed (mm/s)

V^p Volume of the printed part (mm^3)

P_j^L Lower bound of laser power (W) for range *j*

P_j^U Upper bound for laser power (W) for range *j*

V_j^L Lower bound for scan speed (mm/s) for range *j*

V_j^U Upper bound for scan speed (mm/s) for range *j*

δ_j^L Lower bound for layer thickness (mm) for range *j*

δ_j^U Upper bound for layer thickness (mm) for range *j*

h_j^L Lower bound for hatch distance (mm) for range *j*

h_j^U Upper bound for hatch distance (mm) for range *j*

D Thermal diffusivity of the molten material

K Thermal conductivity of the molten material

A Absorptivity of the molten material

T^b Boiling temperature of the material (K)

T^m Melting temperature of the material (K)

T^p Peak temperature for the material (K)

t_p Required total time for building a part (s)

E^c Cost of energy consumption $(\$/Unit)$

O^i Total hourly operational cost rate $(\$/h)$

C^e Unit-cost of electricity $(\$/kWh)$

h^s Enthalpy at melting (J/kg)

There are three significant costs in 3D printing operations: material cost, operational cost and the cost of energy consumption (Deng et al., 1992). Material cost is not a subject of this study because it is not a cost generated by the running 3D printing machine. Thus, the objective of this study is the building costs, including operational cost and cost of energy consumption.

Tang et al. (2017) conducted a research on the prediction of lack of fusion porosity for powder bed fusion. In that study, the build rate was defined as $h\delta V$. Based on this, the required total time for building a part with a volume of V^p can be found as in equation (1).

$$t_p = \frac{V^p}{h\delta V} \tag{1}$$

As mentioned earlier, the objective function consists of two components. The first component is an operational cost. O^i is the total hourly operational cost rate of labor, machine, facility, software, spare, and maintenance in the printing process.

The second component of the objective function is the cost of energy consumption E^c which can be found with the equation (2).

$$E^c = \frac{C^e E V^p}{\delta} \tag{2}$$

Here, E is energy density per millimeter square and equals to $\frac{P}{Vh}$. The objective function could be written as below.

$$\text{Minimize} \qquad \frac{V^p}{\delta V h}\left(O^i + C^e P\right) \tag{3}$$

Two types of failure formation; keyhole and porosity must be minimized while minimizing the building cost. King et al. (2014) calculated the threshold scan speed (V^t) associated with laser power (P) and laser spot size (σ) as below.

$$V^t = \frac{D}{\sigma^3\pi^3}\left[\frac{A\,P}{K\,T^b}\right]^2 \tag{4}$$

From this, the threshold for scan speed could be generated as in (5),

$$\frac{D}{\sigma^3\pi^3}\left[\frac{A\ P}{K\ T^b}\right]^2 \leq V \tag{5}$$

As stated earlier, exceeding the peak temperature will cause keyhole formation in the object`s structure. Thus, the constraint for the peak temperature is also very important for the quality of the printed part. According to King et al. (2014), the constraint for the peak temperature can be set as below.

$$\frac{\sqrt{2}AP}{K\sigma^{1/2}\pi^{3/2}} tan^{-1}\sqrt{\frac{2D}{V\sigma}} \leq\ T^p \tag{6}$$

Keyhole formation is also related to the normalized enthalpy. King et al. (2014) also defined the normalized enthalpy as in equation (7).

$$\frac{\Delta H}{h^s} = \ \frac{AP}{\pi h^s\sqrt{DV\sigma^3}} \tag{7}$$

Where ΔH is the specific enthalpy. They also defined threshold normalized enthalpy to minimize keyhole presence in molten material.

$$\frac{\Delta H}{h^s} \geq\ \frac{\pi T^m}{T^b} \tag{8}$$

From equations (7) and (8), the constraint for minimizing the keyhole presence in the printed part could be written as in (9).

$$\frac{AP}{\pi h^s\sqrt{DV\sigma^3}} \geq \frac{\pi T^m}{T^b} \tag{9}$$

Here, h^s is the enthalpy at melting and it can be calculated with the following function.

$$h^s = \frac{K\,T^m}{D} = \rho c\,T^m \tag{10}$$

Besides, the printed part must be protected from the porosity (Čapek et al., 2016). To do that, scan speed and laser power settings must be adjusted properly in allowable layer thickness and hatch distance values. Therefore, as mentioned earlier, the ranges for laser power and scan speed have been set to manage the quality level for the printed part. In this concept, the following constraints are created to minimize porosity formation. J is the set of ranges and variable $x_j = 1$ if range j is selected. Here, M is a big number.

$$\begin{aligned} P &\geq P_j^L - M\left(1 - x_j\right) \\ P &\leq P_j^U + M\left(1 - x_j\right) \end{aligned} \qquad j \in J \tag{11}$$

$$\begin{aligned} V &\geq V_j^L - M\left(1 - x_j\right) \\ V &\leq V_j^U + M\left(1 - x_j\right) \end{aligned} \qquad j \in J \tag{12}$$

$$\begin{aligned} \delta &\geq \delta_j^L - M\left(1 - x_j\right) \\ \delta &\leq \delta_j^U + M\left(1 - x_j\right) \end{aligned} \qquad j \in J \tag{13}$$

$$\begin{aligned} h &\geq h_j^L - M\left(1 - x_j\right) \\ h &\leq h_j^U + M\left(1 - x_j\right) \end{aligned} \qquad j \in J \tag{14}$$

$$\sum_j x_j = 1 \tag{15}$$

Overall, the complete model is shown below with objective function and all constraints.

Minimize $\dfrac{V^p}{\delta V h}\left(O^i + C^e P\right)$

Subject to $\dfrac{D}{\sigma^3 \pi^3}\left[\dfrac{A\ P}{K\ T^b}\right]^2 \leq V$

$$\frac{\sqrt{2}AP}{K\sigma^{1/2}\pi^{3/2}} tan^{-1} \sqrt{\frac{2D}{V\sigma}} \leq \ T^p$$

$$\frac{\pi^2 h^s T^m \sqrt{D}}{T^b A} \leq \frac{P}{\sqrt{V\sigma^3}}$$

$$P \geq P_j^L - M\left(1 - x_j\right) \qquad j \in J$$

$$P \leq P_j^U + M\left(1 - x_j\right)$$

$$V \geq V_j^L - M\left(1 - x_j\right) \qquad j \in J$$

$$V \leq V_j^U + M\left(1 - x_j\right)$$

$$\delta \geq \delta_j^L - M\left(1 - x_j\right) \qquad j \in J$$

$$\delta \leq \delta_j^U + M\left(1 - x_j\right)$$

$$h \geq h_j^L - M\left(1 - x_j\right) \qquad j \in J$$

$$h \leq h_j^U + M\left(1 - x_j\right)$$

$$\sum_j x_j = 1$$

$$V, P, \delta, h, \sigma \geq 0; \; x_j \in \{0,1\}$$

3.3. Numerical Experiments and Discussions

As already mentioned earlier, there are several studies investigated the optimization of process parameters for improving quality or productivity in powder-bed additive manufacturing. These studies were conducted using the experimental methods in order to optimize process parameters for specific cases. A limited number of process parameter could be analyzed together with these methods. As explained in the literature review, optimizing only a few process parameters while fixing the others might not give satisfactory results. In order to illustrate this important point, data about process parameter settings are collected from selected studies in the literature. The building costs are calculated based on parameter settings from collected data and determined sample size. Then the building cost results are compared to the result of this study in this section. The aim of the comparison is to show how the empirical model effective in decreasing building cost by taking all major process parameters into account and removing limitations on the number of analyzed parameter combinations while keeping the quality at a desired level.

Different from the previous studies that were aimed at obtaining either the best quality or the highest building rate, these numerical experiments targeted at the lowest cost while maintaining an acceptable quality level. The relative density is used as an indicator of quality based on the literature. The AM process is assumed to use a Concept laser powder-bed fusion machine and 316L stainless steel which is one of the most widely used AM materials (Kamath et al., 2014). Part dimensions are assumed as $40\,mm\ x\ 40\,mm\ x\ 40\,mm$ to calculate the building cost (Saunders et al., 2017). The results for optimal parameter settings are obtained for scan speed up to 1200 mm/s.

The machine cost is considered as an operational cost in the total building cost. Wohler and Caffrey assumed the fixed cost of an AM machine to be $780,000 and the annual maintenance cost is $20,000 with a 7-year lifespan (Wohler, 2015). Considering the improvement possibilities, they provided that the price of the machine can go down to $546,000 with $2,000 annual maintenance costs over 11 years of lifespan. Therefore, we estimate the average annual purchasing and maintenance cost as $119,772. If the average working hours for a 3D printing machine is assumed 90 hours per week and the 3D printing machine is assumed to run with 90% utilization in this working period (Brockmann et al., 2015), the hourly cost rate of the 3D printing machine can be found as $28.435 /h. The average hourly labor cost for AM is taken as $45 /h and the other costs (facility, software, spares, and utilities for maintaining the printing operation) are assumed as 20 $/h (Indeed, 2018). $0.12 per kilowatt-hour is taken for a unit cost of energy consumption (U.S Energy Information Administration, 2018).

The ranges for laser power and scan speed along with allowable layer thickness and hatch distance are created for minimizing porosity and keyhole formation as explained before. It should be noted that the ranges can be set based on any quality level. They can be narrowed down if a specific quality level is desired to be obtained. The ranges created for the numerical experiments are just an example to show how the empirical model works. Kruth et al. (2010) investigated the porosity level on 316L parts with using $100\ W$ laser power and scan speed up to $380\ mm/s$. They investigated the different variations of hatch distance up to $0.12\ mm$ and layer thickness up to $0.06\ mm$. They have reported that 97.57% is the lowest density level obtained in that study with a normal curling angle. Exceeding these values might end up with a dramatic decrease in density level for the corresponding laser power level. Kamath et al. (2014) conducted research that shows the density level can go down 96% when the laser power is in between $200 - 250\ W$ with scan speed ranging in $350 - 900\ mm/s$ and layer thickness up to $0.065\ mm$. They reported that the relative density level is above 99% for all combinations given in range 2 for laser power values more than $250\ W$. When the laser power increases, low porosity can be obtained even with high scan speed, layer thickness, and hatch distance values. Wang et al. (2017) used high laser power ($380\ W$) to investigate the porosity level on a part using high layer thickness up to $0.15\ mm$ and hatch distance up to 0.36. They reported that the lowest relative density level is 99%. Similarly, Sun et al. have conducted research on investigating stainless steel 316L with low porosity and high building rate by using high laser power ($380\ W$) and fixed layer thickness ($0.05\ mm$). They reported that the density values $\geq$ 99% were recorded for all fabricated sample parts for scan speed up to $1250\ mm/s$. However, the high laser power range is not a preferable range in AM processes due to the instability of the melt pool (Turichin et al., 2016). The ranges for the numerical experiment have been created as in Table 3.2 based on these results.

The results showed in Table 3.3 are the results for building cost of each study with the relative density range based on selected parameter settings.

Table 3.2 Set values for laser power, scan speed, layer thickness, and hatch distance.

	Range *j*		
	1	**2**	**3**
Power Range $\left(P_j^L, \quad P_j^U\right)$	(100, 200)	(200, 300)	(300, 400)
Scan speed range $\left(V_j^L, \quad V_j^U\right)$	(100, 380)	(380, 900)	(900, 1200)
Allowable layer thickness δ_j	(0.03, 0.06)	(0.06, 0.065)	(0.065, 0.1)
Allowable hatch distance h_j	(0.075, 0.12)	(0.12, 0.24)	(0.24, 0.36)
Relative Density	(97.5%-99.9%)	(96%-99.9%)	(99%-99.9%)

As shown in Table 3.3, the obtained building cost is lower in this study to compare to all other studies except study 9. However, the lowest density level for that study is quite low to compare to the density level in this study. Above 98% density level is expected to obtain in this study since the obtained scan speed level is quite lower than the defined upper bound for the corresponding range. Building cost depends on the effect of each individual process parameter and their combined interactions in powder-bed AM processes. Therefore, all significant process parameters must be optimized together to obtain the low building cost with acceptable quality. Increasing or decreasing in value of one or several parameters might increase the building cost or decrease the quality due to their negative influence on the other process parameters. Table 3.3 illustrates this logic by showing building cost results based on optimized process parameter settings. In this table, the values in bold indicate the focused parameters considered in optimization for the corresponding study. All studies considered only two process parameters for optimization and keep the rest of them as a fixed value. Therefore, building costs of the printed part in these studies are quite high except for study 9. Although the lowest building cost obtained in study 9, the quality level for this study is lowest due to the parameter selection. The parameter values in Table 3.3 clearly show that non-optimal process parameter combinations could cause a slow building rate or low quality.

Building costs and process parameter settings are analyzed in this section to show the individual and combined effect of these parameter settings on productivity and quality. Figure 3.1 shows how building cost changes depending on scan speed. Recall that, the scan speed is one of the most important process parameters which have a great impact on

Table 3.3 Building costs based on optimized process parameter settings.

	P (W)	**V (mm/s)**	**σ (mm)**	**h (mm)**	**δ (mm)**	**Relative Density**	**Building Cost** ($\$/$ $Unit$)	**Study**
1	100	**100**	0.2	0.08	**0.05**	99.4%-99.7%	$ 4,688.89	(B. Zhang et al., 2013)
2	100	**100**	**0.055**	0.075	0.075	99% - 99.9%	$ 3,334.32	(Scipioni Bertoli et al., 2017)
3	100	**200**	0.2	0.08	**0.05**	99.2%-99.4%	$ 2,344.44	(B. Zhang et al., 2013)
4	100	**300**	0.18	**0.126**	0.03	98.4-98.9%	$ 1,653.93	(E. Yasa et al., 2011; Evren Yasa et al., 2010)
5	104	**350**	0.2	0.13	0.03	99%-99.5%	$ 1,380.28	(Spierings and Levy, 2009)
6	104	**400**	0.2	0.13	0.03	99%-99.5%	$ 1,207.75	(Spierings and Levy, 2009)
7	100	**300**	0.2	0.08	**0.075**	99%	$ 1,041.98	(B. Zhang et al., 2013)
8	100	**300**	0.2	**0.125**	0.06	98.8%-99.2%	$ 833.58	(E. Yasa et al., 2009)
9	100	**380**	0.18	0.126	**0.06**	95.8-98.9%	$ 652.87	(Kamath et al., 2014)
10	100	**332**	**0.2**	**0.12**	**0.06**	98%-99.3%	$ 784.62	This Study

building rate and quality. Parallel to this fact, the significant effect of scan speed on building cost could be clearly observed in Figure 3.1. Building cost increases with decreasing in scan speed because operational costs increase due to longer building time. As shown in Figure 3.1, the scan speed in this study is obtained lower than several studies. The reason for this is that the empirical model obtains optimal value for all process parameters which also have a significant effect on both productivity and quality. Thus, instead of improving one parameter solely, obtaining the optimal results for all process parameters is significant for better productivity. This is also very important to obtain an acceptable quality level since all parameters are critical for the quality. Therefore, although building cost in this study is slightly higher than the study 9, the quality level is much better. Study 2 aimed to keep relative density %99 or above in order to achieve the best quality and they optimized process parameters based on this purpose (Bertoli et al., 2017). They kept scan speed level as low as possible to get the highest relative density in that study, but it caused the highest building cost eventually. It is expected to have a high building cost if high quality is desired in AM. However, hatch space and layer thickness are not well-optimized based on the other process parameters, and they used fixed values for these parameters. Therefore, scan speed was decreased to maintain the desired quality level. The important point here is that they could have obtained lower building costs at the same quality level if they could have optimized all fixed process parameters based on the other settings. Similarly, in other studies, they mostly used fixed parameters and optimized one process parameter along with scan speed. In this study, however, low building cost was obtained by considering all major process parameters in optimization based on the desired

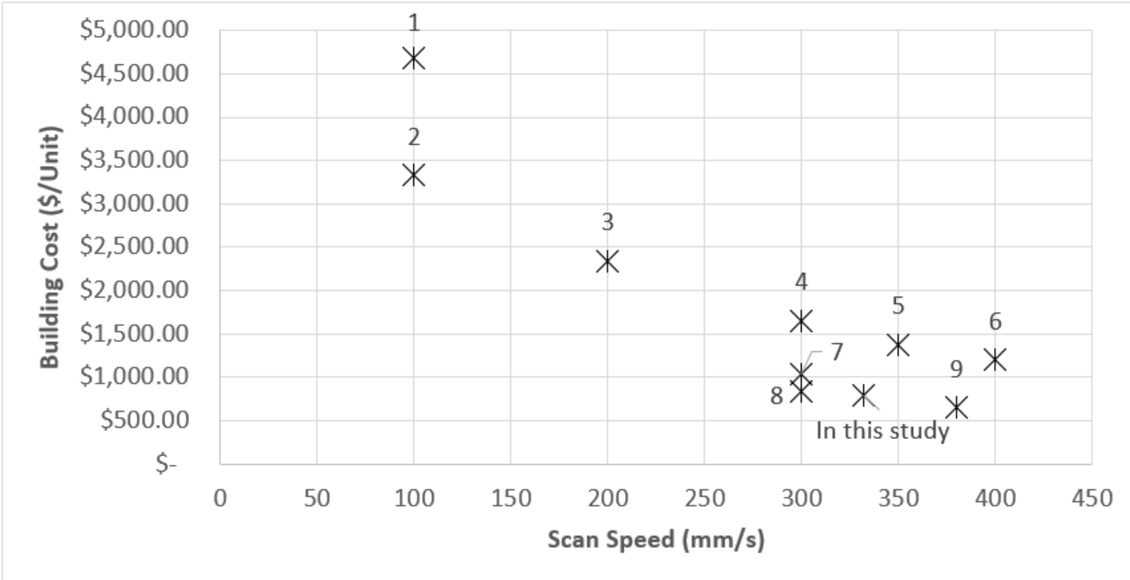

Figure 3.1 Changing in building cost depending on laser scan speed settings.

quality level. Even if a high quality was desired, relatively low building cost could be obtained by systematically optimizing major parameters.

As stated earlier, the combined effects of major process parameters are also important for building cost and quality. To show how laser power, layer thickness, and hatch distance are effective on productivity, the combined effect of each process parameter with scan speed are shown in Figure 3.2. In Figure 3.2-b, it can be seen that the combined effect of layer thickness and scan speed have a significant impact on the building cost. The reason for this is that the layer thickness is one of the most important parameters that highly influence the building time. Similarly, the significant effect of hatch distance on the building cost can be seen in Figure 3.2-c. Like layer thickness, hatch distance also affects the building time directly and thus, it is an important parameter for the building cost. In Figure 3.2-a shows that laser power is not as effective as the hatch distance and layer thickness on building cost. However, laser power is a very important process parameter for quality. Wang et al. (2017) show that with high laser power, high density can be obtained with high scan speed, layer thickness and hatch distance values. However, high laser power ranges are not a preferred range in AM because the melt pool might become unstable and very hard to control.

Figure 3.3 illustrates the importance of layer thickness by showing the change in building cost by altering the values of layer thicknesses. Except few studies, fixed layer thickness was used in the optimization. In this study, however, layer thickness was also optimized through the empirical model considering its interactions with other process parameters and thus, the low building cost was obtained.

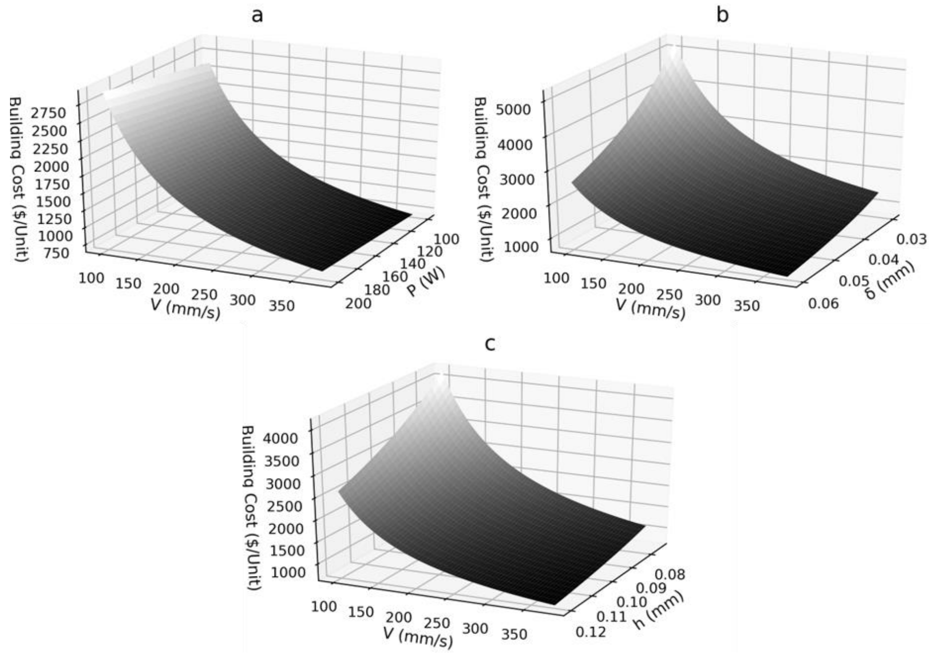

Figure 3.2 Changing in building cost depending on combination of scan speed and laser power (a), scan speed and layer thickness (b), scan speed and hatch distance (c)

The interesting point in Figure 3.3 is that although studies 2 and 7 used thicker layer values to compare to other studies, the building costs are still high (Zhang et al., 2013). The reason for this is that quality level was maintained by compromising with other process parameters which eventually causes the higher building cost. Similarly, studies 4, 5 and 6 used smaller values for layer thickness and obtained the high building cost. They could have optimized layer thickness by considering the interactions between other process parameters to improve scan speed and hatch distance values which also have a significant effect on building rate. In this way, they could have decreased the building cost significantly at the same quality level. It can be stated that using thicker or thinner layers without considering the interaction of this parameter with other process parameters might result in high building cost or low quality.

Hatch distance is also an important process parameter setting that must be considered in the optimization. Figure 3.4 shows how hatch distance affects the building cost. It is effective on productivity because it is a major process parameter for building rate and thus, it affects the building time. It is also significant for the quality because it is a major factor for an overlap of single scan paths of the moving heat source which causes multiple exposes on some points. As shown in Figure 3.4, while several studies used lower hatch distance values, several of them used higher values for this parameter. For most of the studies, these parameters are considered as fixed values. For example, studies 1, 2, 3 and 7 used fixed low hatch distance values and thus, the building costs for these studies are quite high. On the other hand, study 9 used high hatch distance value with a high scan speed and therefore, the density level is quite low to compared to other studies. Therefore, the process parameter

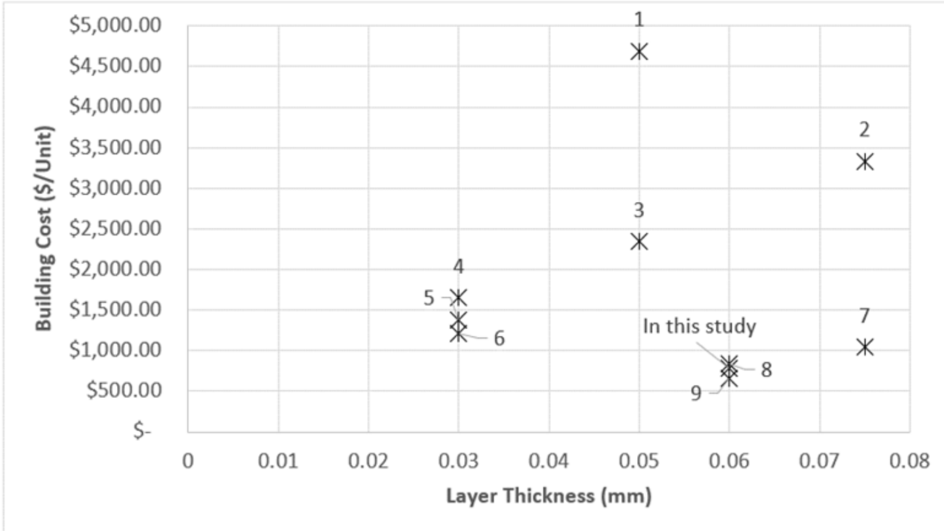

Figure 3.3 Changing in building cost depending on layer thickness settings.

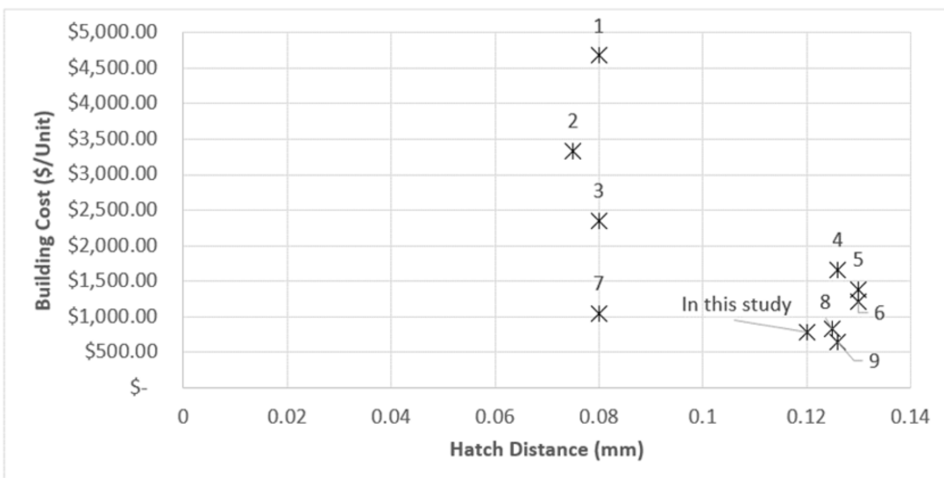

Figure 3.4 Changing in building cost depending on hatch distance settings.

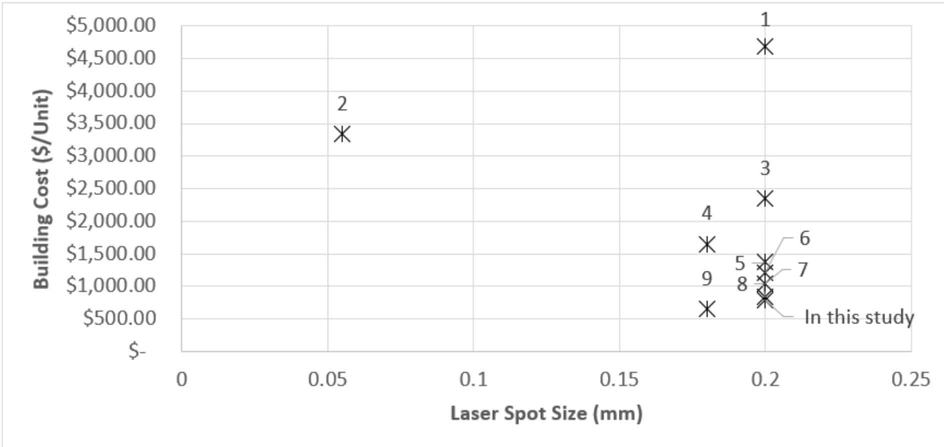

Figure 3.5 Changing building cost depending on laser spot size settings.

such as hatch distance and layer thickness significantly affect both productivity and quality. Optimizing these parameters with created allowable ranges is important for controlling the quality level while minimizing the building cost.

Figure 3.5 shows how building cost changes depending on the laser spot size. Since laser spot size does not affect the building rate directly, it is not as effective as layer thickness and hatch distance. However, it still affects the important parameters that have a significant impact on the building cost. Therefore, instead of using a fixed value for the laser spot size, optimizing this process parameter with other parameters will provide a better combination of parameter settings for both quality and productivity. As demonstrated in this section, the empirical model can provide better results for productivity due to its advantages of optimally adjusting parameter settings by considering the individual effect of all process parameters and the interactions between them.

3.4. Conclusions

It can be observed that the values for many process parameters were kept constant or not optimized effectively in numerous printing operations. Only several process parameters could be investigated together due to the limitation of the experimental methods. As explained in the figures shown in previous sections, there is no doubt that each process parameter has a significant impact on building cost in powder-bed AM processes. Thus, keeping some of them constant or not optimizing them well would make the process slower and expensive. The layer thickness in Bertoli et al. (2017) study can be given as an example for that. They kept the layer thickness much ticker to compare to other studies even if they desire high quality. Rather than fixing these parameters, adjusting them optimally based on the required quality level will help user to obtain optimal parameter settings for better productivity.

On the other hand, optimizing process parameters with experimental methods are expensive and time consuming if all major process parameters are desired to optimize. However, thanks to the empirical model created in this study, all process parameters could be optimized together with considering their individual and combined effects without these limitations and restrictions. And the most advantageous part of the empirical model is that it gives a great opportunity to decrease the building cost to a certain extend in any quality level in a cheaper and faster way.

CHAPTER 4. SCHEDULING MODEL FOR A SINGLE AM MACHINE WITH CONSIDERING MULTI-MATERIAL TYPES

Abstract

There are numerous studies about scheduling problems in traditional manufacturing. However, additive manufacturing processes have different dynamics that must be considered in the modeling process. For example, the printing process is considerably slow in AM, and therefore, it is expected to have a long waiting time in the production process. Besides, the quality factor, which can be affected by the material changeover, has not been considered in the planning and scheduling models. The trade-off between quality and costs of the material switching process is important. Having the ability to optimize material switching time by considering the quality and incorporating it into the scheduling process can help users make better decisions. The purpose of this study is to propose a scheduling model that takes quality into account to optimize the production process for a single AM machine using multi-materials.

Since the complexity of the optimization model is NP-Hard, it could not provide results for a large number of parts. Thus, two sophisticated constructive heuristic algorithms are developed to accelerate the solution process. The results show that second algorithm can provide better results in terms of CPU time and solution quality. Furthermore, the results demonstrate that trade-off between switching, and lateness cost is effective on scheduling for single AM machine.

4.1. Introduction

AM technology was not fully adapted to the manufacturing industry because of several problems including quality and productivity and thus scientists, medical doctors, students, professors, and artists use AM methods to rapidly build and analyze their models in the early stages of AM (Chua et al., 1998; Flowers, 2002). AM applications are growing rapidly in the manufacturing industries as already explained in the chapter one. The Wohlers (2020) presented in the first section indicates that nowadays, AM has been used not only for prototyping but for the final part as well. In this context, mentioning some real-world examples in which additive manufacturing has been used by major companies to produce the final products will help us understand the place of AM in the manufacturing industry. The following examples listed by Zahnd (2018).

- Adidas announced in April 2017 that they will produce 3D printed shoes, called Futurecraft 4D.
- Chanel, a giant French fashion company, announced that it will start producing entirely 3D printed mascara brushes in June 2018.
- In 2016, the New Mexico mobile phone company Optomec announced that they will start applying additive manufacturing for mass production.

The number of examples can be increased. Although it is too early to conclude that additive manufacturing is ready for mass production globally, it is clear that AM is rapidly growing and promising technology for manufacturing final parts and mass production in the near future. However, the research conducted in this area mainly focused on the quality and productivity for prototyping or low-volume production. Although these issues are important to improve AM processes, more research is needed to improve and optimize AM processes for high-volume or mass production. One of the major obstacles to the adaption of AM to mass or high-volume production is mostly considering only one material type in

AM production processes. This is also quite an important problem for low-volume production in AM. It is because devoting an expensive AM machine to only one material type is not an efficient way to use limited resources. This also has a serious impact on the environment. Therefore, there is a need for a scheduling model that consider multi-material type for production planning and scheduling.

This study proposes a scheduling model for a single AM machine with considering the multi-material type. It will be the first systematic analysis of a single AM machine considering multi-material types with taking the parts' quality into account. The proposed model could help solving the current AM industries' problems and filling the existing research gaps.

It is important the investigate the key factors that could affect both quality and operational costs of AM when multi-materials are considered for production planning. when AM machine changes the material type, it requires a certain amount of time to set up and calibrate the machine for the new material. It can be concluded that the waiting time and the machine switching time might have a serious impact on both quality of the parts and operation costs. These factors will be discussed in numerical experiments and discussions section of this chapter to see the effect of these factors.

Taking quality into account is always difficult for AM processes since there is no reliable way of measuring quality. In the AM processes, the quality of the part may depend on the specific period of the production. The parameter settings and the calibration of the AM machine must be reset when the AM machine is switched to a different material type. Since the calibration and process parameters are very difficult to set optimally right after the material changeover, the quality levels of the produced parts might be relatively lower at the beginning of the production. The quality will be increased as more parts are made with the same material type due to the better calibration and parameter optimization. Thus, material changeover plays a critical role for the quality level. Besides, it is also important for the operational costs because machine switching process add additional costs into the systems. Considering this while developing the scheduling and planning model could be an effective trade-off between quality and costs. This factor must be well optimized to have an efficient production planning and effective production process that could fulfill customers' needs in AM systems. The schematic view of the scheduling process is shown in Figure 4.1.

Computational Complexity of the Model

The scheduling problems of earliness and tardiness, which is considered the most common scheduling problems, have been extensively studied in the past decade. As in AM, these types of problems are also motivated by Just-In-Time production (Kootanaee et al., 2013). In Just-In-Time production, parts must be delivered in a specific time window that is called the due date for each part. The lateness penalty can be issued if the part is delivered later than its due date. Therefore, minimizing the job completion times around their due dates is one of the most common measures of performance (Wan and Yuan, 2013). Du and Leung (1990) conducted research on optimizing production schedule by considering minimizing total tardiness on one machine. In this study, they consider a set $\{J_1, J_2, \dots, J_N\}$ of N jobs on one machine. Processing time associated each job and a due date is denoted by $p(J_t)$ and $d(J_t)$ respectively. The tardiness of a schedule (S) for N job denoted by $T(J_t, S)$ is defined

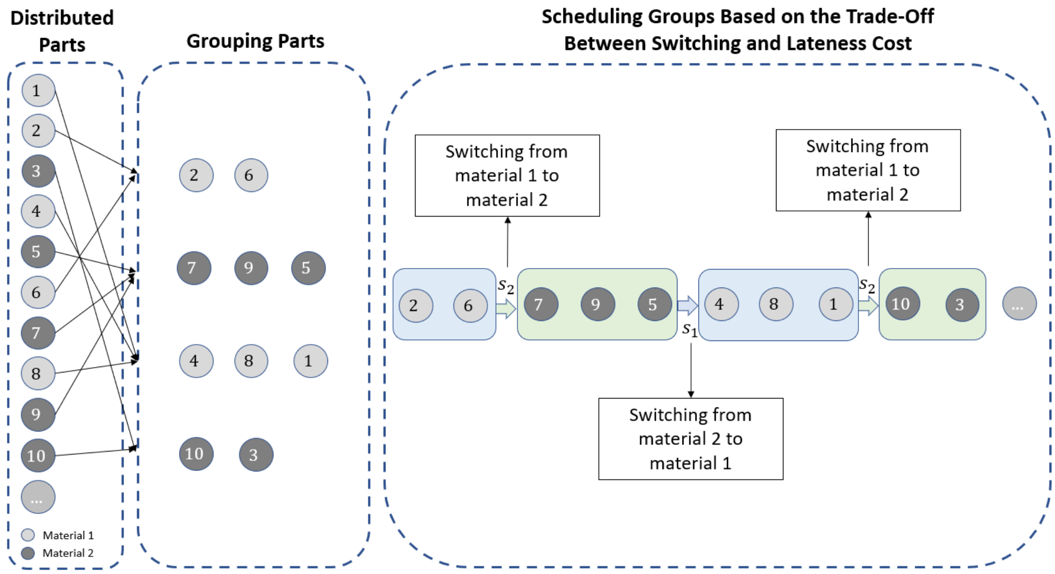

Figure 4.1 Demonstration of the proposed scheduling model

to be $T(J_t, S) = \max\{0, C(J_t, S) - d(J_t)\}$, where $C(J_t, S)$ is the completion time of each job. The aim is to minimize total tardiness cost which is denoted by $TT(S)$ and defined to be $TT(S) = \sum_{t=1}^{N} T(J_t, S)$. They proved that minimizing total tardiness cost in scheduling problems is NP-Hard. Lawler (1977) proved that even if all jobs have the same fixed production times, the total tardiness problem is still *NP*-Hard, if precedence constraints are introduced. Furthermore, Koulamas (2010) showed that the single machine total tardiness scheduling problems are *NP*-Hard problems. The proposed model is more complex than these problems because the switching process and quality reward are also considered in the systems in addition to total tardiness cost. Hence, the problem of scheduling problem for a single AM machine considering multi-material types is also *NP*-hard as contextualized above.

4.2. Literature Review

The current studies will be discussed in two categories: AM-related scheduling research papers and SM-related scheduling research papers. The important points about the current studies and the key factors that make the proposed study unique will be indicated in the following paragraphs.

The number of researches related to production scheduling in AM is considerably less than the number of research about SM because it is a relatively new field. Several papers have been published on this topic in the literature (Canellidis et al., 2016; Wang et al., 2016; Zhang et al., 2017; Ransikarbum et al., 2017; Chergui et al., 2018; Dvorak et al., 2018; Kucukkoc et al., 2018; Fera et al., 2018; Kucukkoc, 2019; Li et al., 2019; Zhang et al., 2020; Oh et al., 2020; Aloui and Hadj-Hamou, 2021). They have used different solution types based on the characteristic of their models. Kucukkoc (2019) used a CPLEX solver to obtain optimal solutions without using a heuristic model. Canellidis et al. (2016), Fera et al. (2018), Zhang et al. (2019), and Zhang et al. (2017) utilized a genetic algorithm to find the best feasible solution for their MILP model. On the other hand, Chergui et al. (2018), Dvorak et al. (2018), Li et al. (2019), and Oh et al. (2020) applied the heuristic model to solve the MILP problem. We only discussed the most related studies to our model to give details about their MILP. Next, the factors that make the proposed model unique will be explained.

The most similar study in the AM field is published by Kucukkoc (2019). He developed a MILP model to minimize makespan in additive manufacturing machine scheduling problems. He first considers a single AM machine and then extends his model to parallel machine scheduling with a single material type. Setup time is a key factor for AM scheduling problems that differentiate it from SM production scheduling problems. Because setup process significantly affects the production process since quality depends on the calibration and process parameters of the AM machine. Although the setup process of AM machine is considered in Kucukkoc's (2019) study, it only incorporated into the model as a parameter. They just wanted to obtain the time spending for setup time to minimize it. However, the setup time for AM machine is considered as a variable in our model that influences the quality reward of the produced part as explained in the methodology of the third chapter. In this way, the setup process can be optimized in order to obtain an efficient production schedule. Aloui and Hadj-Hamou (2021) developed a

MILP model for scheduling problems in AM under the technological constraint with considering a single material type. Similar to Kucukkoc (2019), they focus on setup time to minimize makespan; thus, setup time is considered as preparation time of machines and heating time of machines, which are also considered as parameters.

There are several key factors that make our study unique among the papers published in the AM literature. First, multi-material types considered in the proposed study. To the best of our knowledge, there is no study yet considered multi-material type scheduling model for AM processes. Considering multi material-type is very challenging for the scheduling model because the concept of the setup process is different. First changing material type in AM takes much longer. Second, setup time is relatively simple for a single material type production process because the calibration and process parameters will be optimized for the same material type. However, calibration and process parameter optimization are challenging if multi-material is considered in the system because different material requires different calibration and process parameter optimization. Thus, the quality of the produced part may dramatically decrease after each material changeover. This key factor must be considered in the model development process.

In recent years, the number of articles discussing the scheduling and planning in SM has increased in number as energy consumption, efficiency and effectiveness have become more important in sustainable manufacturing (Ji et al., 2013). There are several papers subjecting the single machine configuration in their model (Gong et al., 2015; Liu, 2016; Wang et al., 2016; Zheng and Wang, 2015). Several other studies examined the multiple machines with same property (Artigues et al., 2013; Ding et al., 2016). Besides these, some studies subjected mass production with the flowshop configuration or high variance with the jobshop configuration (Cuesta et al., 2014; Liu et al., 2015).

Among the mentioned studies, we will review most relevant to our proposed study, specifically, single machine scheduling models. Gong et al. (2015) created a mix integer scheduling problem in order to minimize energy cost for sustainable manufacturing. In this study, machine states, namely “off, startup, ready, production, shutdown, others”, defined with integer index. Energy cost is intended to minimize based on the determined objective function and constraints that are formed according to machine states. Similar to the proposed model, only one job can be scheduled at a time, so the whole batch can be scheduled. The defined constraint(s) allows only one state at a time for the machine, and it allows a constant power value to be assigned with the state in each case. Scheduling models and algorithms are widely used in the semiconductor industry because manufacturing large-scale integrated circuits is considered a complex process (Uzsoy, 1995). Several articles focus on minimizing the makespan on a single batch processing machine with the fixed batch processing time, all of which are considered deterministic cases (Ahmadi et al., 1992; Ikura and Gimple, 1986; Uzsoy, 1995). The makespan intended to minimize effectively with processing multiple jobs simultaneously by combining the jobs together in a batch form. Batch processing machines can be configured to operate in only two states: running and idle. Sung et al. (2002) approached the semiconductor scheduling problem with the dynamic programming algorithm since the release times of all jobs are different from one another, and the set of all jobs can be divided into a number of subsets.

The manufacturing process in AM is quite different from SM. Therefore, different factors must be considered while modeling the scheduling problem in AM. For example, an individual part in the AM requires a longer production time than it requires in SM and thus, queues would be expected in the system. Furthermore, most of the studies mentioned above do not consider the material type in scheduling models. The reason is that most SM processes do not require special procedures for changing material types or properties. SM systems can easily be adapted to different material types and properties at the initial stage. However, AM machine requires complex procedures each time the machine is switching to a different type of material. Moreover, the most important factor is that the quality of the final part is not affected by the process switching or set-up procedure in SM processes. However, quality is one of the most challenging factors in AM processes and can be easily affected by switching and setup operations. To sum up everything that has been stated so far, it can be concluded that the scheduling models for SM systems are not applicable to the industrial needs of AM systems without major modification.

4.3. Methods

4.3.1. Assumptions

1. Single AM machine with multi-material types.
2. At most one part can be produced at a single job.
3. Quality of parts will be improved as more parts are made with the same material type due to the better calibration and parameter optimization of the 3D machine. ($v_{ik} \geq v_{i,k-1}$)

3.1. Quality level will be improved based on the number of productions given in Figure 4.2.

4.3.2. Model Formulation

Parameters:

N Number of parts ($i = 1, 2, 3 \dots n$);

L Number of material types indexed by l;

a_{il} $= \begin{cases} 1, & \text{if part } i \text{ requires material } l \\ 0, & \text{otherwise} \end{cases}, \quad i = 1, \dots, n;$

K The maximum number of parts using the same materials and $K = \max_l \sum_{i=1}^{n} a_{il}$;

w_i Unit delay penalty of part i ($\$/hrs$);

d_i Due date of part i (hrs);

p_i Processing time of part i (hrs);

v_{ik} Value of part i if it is produced at the k^{th} position with the same material (we assume $v_{ik} \geq v_{i,k-1}$ due to the quality improvement over time if the same material is used);

s_l Setup time when the AM machine switches to material l; and

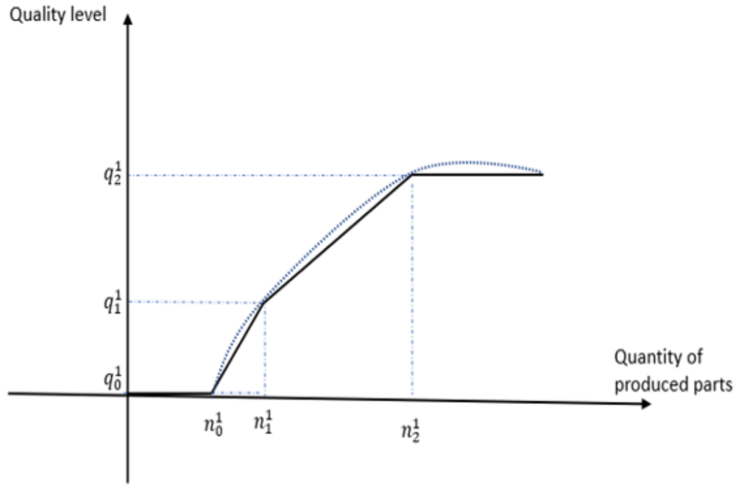

Figure 4.2 Example illustration of quantity of parts and quality reward relationship

c_l Cost for the machine switching to material l, including the cost of scrapped parts, $l \in L$.

Decision Variables:

x_{ij} $= \begin{cases} 1, & \text{if part } i \text{ is produced as job } j \\ 0, & \text{otherwise} \end{cases}, i, j = 1, \ldots, n;$

z_j^k $= \begin{cases} 1, & \text{if the } j\text{th job is at the } k\text{th position with the same material} \\ 0, & \text{otherwise} \end{cases};$

t_j Time of completion of job j; and

S_j Switching cost of the j^{th} job;

T_i Tardiness of part i;

R_i Reward of part i, which depends on quality level

In the proposed model, we considered N number of parts and jobs which is indexed by i and j respectively. L material types are considered which is indexed by l. K indicates the maximum number of parts using the same materials.

Constraints:

Based on the second assumption, it is required to ensure that all parts are manufactured and only one part is produced in a single job. The following two constraints are formulated to satisfy these requirements.

$$\sum_{j} x_{ij} = 1, \quad i, j = 1, \dots, n \tag{1}$$

$$\sum_{i} x_{ij} = 1, \quad i, j = 1, \dots, n \tag{2}$$

Here x_{ij} is a binary variable denotes if part i is produced at the job j. Based on this, the constraint (1) ensures that each part must be produced. The constraint (2) indicates that only one part is produced per job.

Delivering parts to the customers before the due date is important in AM industries. If a part is not delivered before the due date (d_i), the tardiness cost (w_i) will be applied as a penalty costs to the total costs. Therefore, the completion of each job (t_j) must be determined to calculate tardiness costs.

$$t_j \geq t_{j-1} + p_i x_{ij} + \sum_{l \in L} s_l a_{il} z_j^1 - M\left(1 - x_{ij}\right), \quad i, j = 1, \dots, n \tag{3}$$

Constraint (3) gives the completion time of the job j. t_{j-1} in constraint (3) is the completion time of the preceding job. p_i is the processing time of part i. s_l is setup time when the AM machine switches to material l and a_{il} indicates the material type required for part i. The binary variable z_j^1 is 1 if the machine switches to the material l, 0 otherwise.

Now the tardiness cost due to the late delivery of parts must be calculated. Since the competition time of job j is found in (3), then the tardiness cost can be calculated with the following constraint.

$$T_i \geq \max(0, t_j - d_i), \quad i = 1, \dots, n \qquad 4$$

Constraint (4) can be written as the following set of constraints.

$$T_i \geq 0, \qquad i = 1, \dots, n \qquad \text{4-a}$$

$$T_i \geq t_j - d_i - M(1 - x_{ij}), \quad i, j = 1, \dots, n \qquad \text{4-b}$$

Here, M is a sufficiently big number. t_j is the completion time of the job j and d_i is the due date for part i.

One of the most important contributions of the proposed model is considering quality reward of part i based on its quality level. Among all other factors, it is very difficult to consider the quality factor in the modeling process. Because quantifying the quality is not possible since there is no reliable way to measure it. Each organization might have their own quality definition depending on their requirements. However, it is known that the quality level of finished parts is improved as more parts are made with the same material type because of the better calibration and parameter optimization of the AM machine. Thus, rewards for higher quality parts can be defined based on the number of parts consecutively produced with the same material type.

The best way to consider the quality in the modeling process is to define a reward value v_{ik} for part i after the AM machine switched the material l. v_{ik} is a reward value for part i that will be increased as more parts are produced with the same material type because of the better calibration and process parameter optimization as mentioned earlier. Thus, it is assumed that $v_{ik} \geq v_{i,k-1}$ in the proposed model. The quality reward can be defined as follows based on v_{ik} and k^{th} position of the production process which is defined by z_j^k after material changeover.

$$R_i \leq \sum_{k=1}^{K} v_{ik} z_j^k + M(1 - x_{ij}), \quad i, j = 1, \dots, n \qquad 5$$

Here, M is a sufficiently big number. After each material changeover, there will be certain number of parts produced with the same material type. Thus, the position must be determined to capture the quality level of the produced part. z_j^k defines the position after each material changeover to define the quality reward. The quality reward is represented by R_i in (5).

z_j^k must indicate only one position after material changeover. Therefore, the following constraint is created to show that there is only one k^{th} position.

$$\sum_{k=1}^{K} z_j^k = 1, \quad j = 1, \dots, n \qquad 6$$

Another important contribution of the proposed model is considering multi materials for a single AM machine. Material changeover is a costly process in AM systems. Therefore, it is very important to optimize it if multi-materials are considered in the production process. There are three significant operation costs during the material changeover. The first one is the material cost because some materials are wasted when cleaning the AM machine and setting it up for the next material type. The second one is the cost of scrapped parts. After switching the AM machine to material l, some parts are scrapped to calibrate systems and optimize process parameters. And the last one is the labor costs. Extra labor hours must be spent for cleaning the machine and setting it up again. This process is costly and time-consuming. Cost for the machine switching to material l, including the cost of scrapped parts is considered in c_l and minimized in the objective function.

Optimizing machine switching time is a critical factor in the AM manufacturing planning because of the reasons mentioned above. The tradeoff between operation costs and fulfilling demand must be considered very carefully when determining the switching time. The following constraint is created to find the switching position if the machine is switched to material l.

$$z_j^1 \geq \sum_{i=1}^{n} a_{il} x_{ij} - \sum_{i=1}^{n} a_{il} x_{i,j-1}, \quad j = 1, \dots, n; l \in L \qquad 7$$

Constraint (7) captures if the AM machine is switched to material l. As mentioned earlier, a_{il} is a binary variable that defines the material type required to produce part i.

Then the switching cost can be calculated with the following constraint.

$$S_j \geq \sum_{i=1}^{n} \sum_{l \in L} c_l a_{il} x_{ij} - M\left(1 - z_j^1\right), \quad j = 1, \dots, n \qquad 8$$

Here, M is a sufficiently big number. c_l is the cost of switching, if the switching occurs, including the cost of scrapped parts.

As mentioned earlier, v_{ik} depends on the k^{th} position of the parts produced with the same material type after the material changeover. As z_j^1 defined in (7), the position that defines number of parts produced with the same material type must be captured as well. The following constraint is created to capture the k^{th} position.

$$z_j^k \geq z_{j-1}^{k-1} - z_j^1, \quad j = 1, \dots, n \tag{9}$$

Here, z_{j-1}^{k-1} is the position of the previous job j and z_j^1 is the position when the machine is switched to material l. It is assumed that there is no reward for the first part after switching, and therefore the initial position $z_0^k = 0$, for $i, k = 1, \dots, n$.

Finally, we have binary and sign restrictions on the variables.

$$x_{ij}, z_j^k \in \{0,1\};\ t_j, S_j, T_i, R_i \geq 0 \tag{10}$$

<u>*Objective Function:*</u>

The objective function is to minimize total cost which includes lateness cost and cost of switching to material l and scrapped parts minus total reward. The first component of the objective function is the tardiness costs. The following equation yields the total tardiness costs.

$$\text{Tardiness cost} = \sum_{i=1}^{n} w_i T_i \tag{11}$$

w_i in (10) is the unit delay penalty cost of part i. The second component of the objective function is the total cost of machine switching to material l, including the cost of scrapped parts.

$$\text{Total switching cost} = \sum_{j=1}^{n} S_j \tag{12}$$

The last component of the objective function is the quality reward considered based on the quality level. And the following equation will give us the quality reward for higher quality parts.

$$\text{Quality reward} = \sum_{i=1}^{n} R_i \qquad 13$$

Then the objective function for the proposed model is as follows.

$$\text{Min} \quad \sum_{i=1}^{n} w_i T_i + \sum_{j=1}^{n} S_j - \sum_{i=1}^{n} R_i \qquad 14$$

As will be discussed in the numerical experiments and results section, the model is not very efficient to solve a large number of parts. Therefore, two constructive heuristic models are developed to accelerate the solution process.

The first constructive heuristic model is developed based on Moore's (1968) rule. The model was developed by using the processing times and due dates. The rule applied to the first part of the model and then the constructive heuristic algorithm is developed by combining the second part.

The First Constructive Heuristic Algorithm Based on Moore’s Rule.

First Part: Finding the optimal sequence for each material group based on Moore’s (1968) rule.

Let us consider sequencing n jobs, $J_1 \ldots J_n$ based on the given processing times, $p_1 \ldots p_n$ and due dates, $d_1 \ldots d_n$. For parts in two separate groups of material, perform the following steps.

Step 1: Scheduling parts based on shortest processing time. ($J_{i_1} \ldots J_{i_n}$ where $p_{i_1} \leq \cdots \leq p_{i_n}$)

Step 2: Find the first late job. If there is no late job then the algorithm terminates, and the optimal sequence is found.

Step 3: If there is a late job J_{i_q}, reorder jobs based on the due dates until the late job ($J_{i_1} \ldots J_{i_q}, J_{i_{q+1}} \ldots J_{i_n}$ where $d_{i_1} \leq \cdots \leq d_{i_q}$)

There are two cases:

1. If all parts are early in $J_{i_1} \ldots J_{i_q}$, then accept it as the current sequence and go to step 2.
2. Otherwise, reject the late job J_{i_q} and remove it from the sequence. Go to step 2 and accept the resulting sequence as the current sequence (rejected jobs will be added at the end of the queue)

Second Part: Inserting each part from one material group to another material group one by one with comparing the objective function to find the best sequence.

Step 4: Insert each part from one material group to another one in order. Perform this step until all parts are inserted.

Step 5: Terminate the algorithm after all parts are inserted and accept the current sequence as the final sequence.

Second Constructive Heuristic Algorithm Based on Jackson's Rule.

Step 1: Schedule parts based on due dates ($J_{i_1} \ldots J_{i_n}$ where $d_{i_1} \leq \cdots \leq d_{i_n}$) (Jackson's rule (Hall and Shmoys, 1992))

Step 2: Obtain the initial result $(j_{i_1} \dots J_{i_n})$.

Step 3: Identify the batches for different material groups.

Step 4: Improve batching by swapping the batches.

Step 5: Compare the objective values and find the best sequence with the minimum cost.

4.4. Numerical Experiments and Discussions

As already mentioned earlier, several studies are reported in the literature that investigate scheduling models with considering tardiness in the AM and SM. It has already been explained why the scheduling models developed for SM cannot be adapted to AM. Meanwhile, the scheduling models developed for the AM are based on one material type. Consequently, the new scheduling model considering multi-material types was developed in the previous section. A series of numerical experiments will be presented to demonstrate the efficiency of the proposed scheduling model by considering multi-material types in this section.

The data used in numerical experiments generated based on the ranges collected from the literature (Aloui and Hadj-Hamou, 2021; Canellidis et al., 2016; Chergui et al., 2018; Dvorak et al., 2018; Fera et al., 2018; Kucukkoc et al., 2018; Kucukkoc, 2019; Li et al., 2019; Oh et al., 2020). Example data for parameters is shown in Table 4.1.

As already shown in parameters, l represents the material type, p_i and d_i denote processing time and due date for part i respectively. Table 4.2 shows solution time for different number of parts. Since the model is *NP*-Hard, it cannot provide solutions in an acceptable time as the number of parts increases. The mathematical model provides solutions to experiments with less than 12 parts quickly, as indicated in Table 4.2. When the number of parts increases to 13 and more, then the model could not provide an optimal solution and the gap is around 48.1.

It is clear from Table 4.2 that the complexity of the problem is high since the model could not provide a solution for only 13 parts. The lower bound which is caused by fractional solution and big M needs to be lifted by cut constraints. The cuts in (15) and (16) are added to accelerate the solution process. After adding cuts, the solution time accelerated as shown in Table 4.3. The optimal solution can be found up to 25 parts in an acceptable solution time.

$$t_i \geq t_{j-1} + \min_{i=1,\dots,n} p_i, \qquad j = 1, \dots, n \tag{15}$$

$$\min_k v_{ik} \leq R_i \leq \max_k v_{ik} \qquad i = 1, \dots n \tag{16}$$

Table 4.3 indicates that the optimal solution could not be achieved if the number of parts was more than 30. Therefore, sophisticated heuristic models are developed to solve model as explained in the previous section.

The First Constructive Heuristic Algorithm Based on Moore's Rule.

Moore (1968) has developed an algorithm based on the shortest processing time and due dates of the parts. The first algorithm is developed based on these rules in this study. The steps of the algorithm are explained below with a numerical example.

Table 4.1 Demonstration of generated data

Parts	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
$\boldsymbol{p}$	20	3	4	7	18	10	8	9	5	13	9	14	6	8	19	15
$\boldsymbol{d}$	35	25	15	10	36	19	13	16	24	18	32	28	16	8	44	22
$\boldsymbol{l}$	2	2	1	1	1	2	2	1	1	2	2	1	1	1	2	2

Table 4.2 Preliminary results for different number of parts

Number of parts	**Number of materials**	**Gap %**	**Optimal solution is obtained**	**CPU Time (s)**
5	2	0	Y	0
6	2	0	Y	0
7	2	0	Y	0
8	2	0	Y	1
9	2	0	Y	5
10	2	0	Y	10
11	2	0	Y	174
12	2	0	Y	574
13	2	48.1	N	339409

Table 4.3 The results after adding cuts.

		Initial Model			With Cuts		
Number of parts	**Number of materials**	**Gap %**	**Optimal solution is obtained?**	**CPU time (s)**	**Gap %**	**Optimal solution is obtained?**	**CPU time (s)**
5	2	0	Y	0	0	Y	0
6	2	0	Y	0	0	Y	0
7	2	0	Y	0	0	Y	0
8	2	0	Y	1	0	Y	0
9	2	0	Y	5	0	Y	0
10	2	0	Y	10	0	Y	0
11	2	0	Y	174	0	Y	0
12	2	0	Y	514	0	Y	0
13	2	48.1	N	339409	0	Y	0
20	2	-	-	-	0	Y	42.25
25	2	-	-	-	0	Y	1415.29
30	2	-	-	-	0.04	N	275214

Step 1: Scheduling parts based on the shortest processing time. ($J_{i_1} \ldots J_{i_n}$ where $p_{i_1} \leq \cdots \leq p_{i_n}$).

Step 2: Find the first late job. If there is no late job then the algorithm terminates, and the optimal sequence is found. The first late parts are highlighted according to the completion time of each job as shown in Figure 4.3.

Step 3: If there is a late job J_{i_q}, reorder jobs based on the due dates until the late job ($J_{i_1} \ldots J_{i_q}, J_{i_{q+1}} \ldots J_{i_n}$ where $d_{i_1} \leq \cdots \leq d_{i_q}$). Since there is a late job, the parts are re-scheduled based on the due date until the late jobs. It is shown in Figure 4.4.

There are two cases: if there is a late part after the parts are re-sequenced based on the due dates, reject the late job J_{i_q} and remove it from the sequence. Go to step 2 and accept the resulting sequence as the current sequence (rejected jobs will be added at the end of the queue). If all parts are early in $J_{i_1} \ldots J_{i_q}$, then accept it as the current sequence and go to step 2. There is no late job in the first list and thus, part 6 is not rejected and the sequence is accepted as the current sequence. However, there is a late job in the second list and therefore, part 4 is rejected and added to the end of the queue as shown in Figure 4.5. The best sequence with minimum cost can be found after applying this rule to each material group separately. Then, the second part of the algorithm can proceed.

Step 4: Insert parts from one material group to another one in order. Perform this step until all parts are inserted. As shown in Figure 4.6, there will be several options of sequences, $Se_1 \ldots Se_9$. The best sequence with the minimum cost will be selected, Se_9.

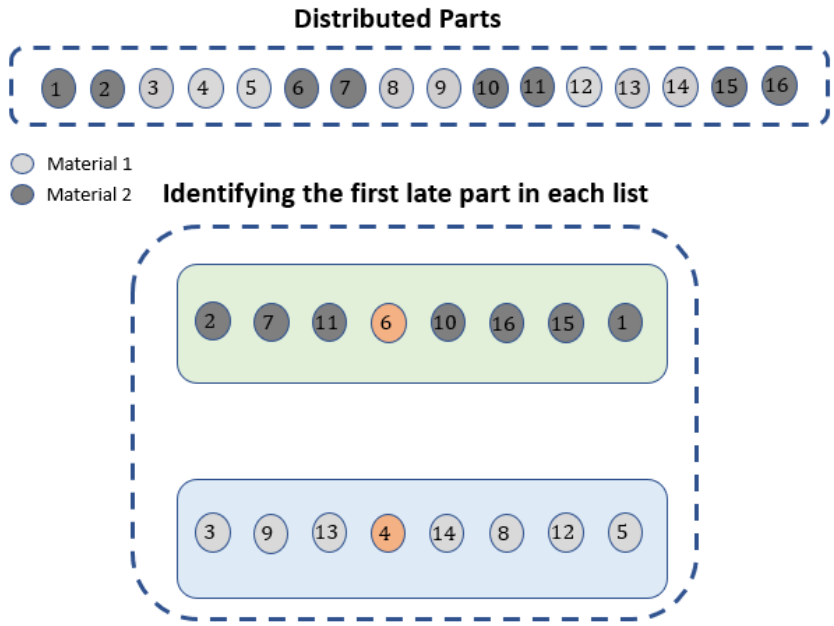

Figure 4.3 Scheduling parts based on the shortest processing time and identifying the first late parts in the list.

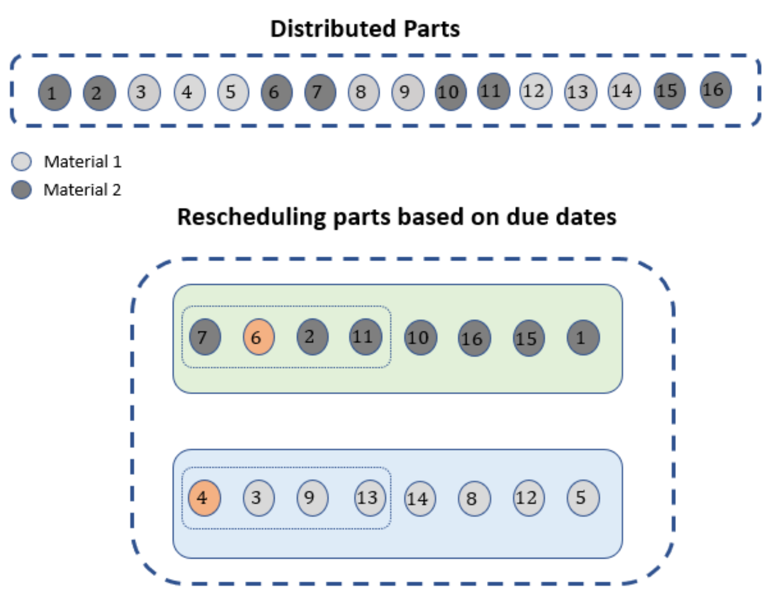

Figure 4.4 Rescheduling parts based on the due dates until the late parts.

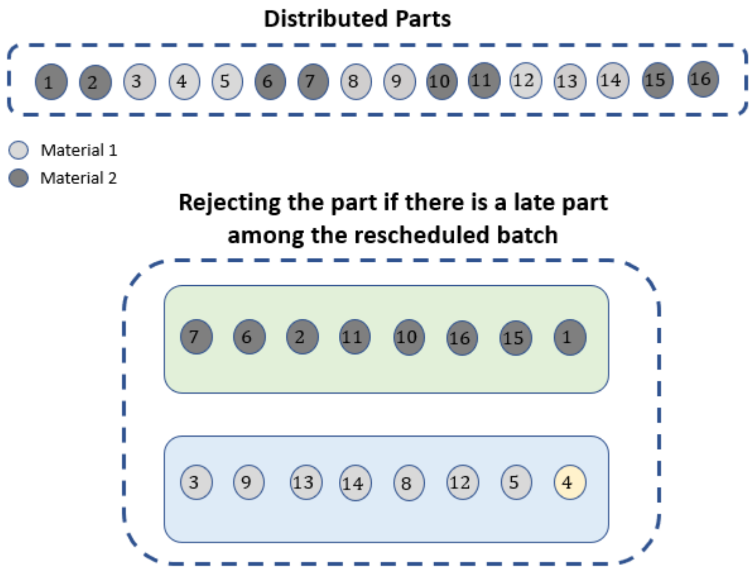

Figure 4.5 Rejecting parts if there is a late part after re-sequencing parts based on the due dates.

Step 5: Terminate the algorithm after all parts are inserted and accept the current sequence as the final sequence as shown in Figure 4.7.

Second Constructive Heuristic Algorithm Based on Jackson's Rule.

Following are the steps to apply the second algorithm to the same data presented in Table 4.1.

Step 1: Schedule parts based on due dates (J_{i_1} ...J_{i_n} where $d_{i_1} \leq \cdots \leq d_{i_n}$) (Jackson's rule (Hall and Shmoys, 1992)). Figure 4.8 shows the parts scheduled based on the due dates.

Step 2: Based on the rule in step 1, an initial result will be obtained (j_{i_1} ...J_{i_n}).

Step 3: Batches for different material groups will be created according to the material type. Figure 4.8 also shows the identified batches for two material groups.

Step 4: The batching process will be improved by swapping them to increase the quality of the solution. For example, Figure 4.9 shows the improved batching process after first iteration.

Step 5: The total cost will be calculated at each iteration as new batches are created. In this way, the best sequence with the lowest costs will be obtained. Figure 4.10 shows the final sequence found by using the second algorithm.

Table 4.4 and 4.5 shows results obtained by using the heuristic models. Gaps are calculated by taking the average of 20 runs since the parameters may affect the results significantly. Table 4.4 shows CPU time and solution quality for each method. The CPU time is limited with 1 hr for all instances. The gaps indicate the difference between optimal results and the results obtained by using the indicated method. Table 4.5 shows relatively large list of parts

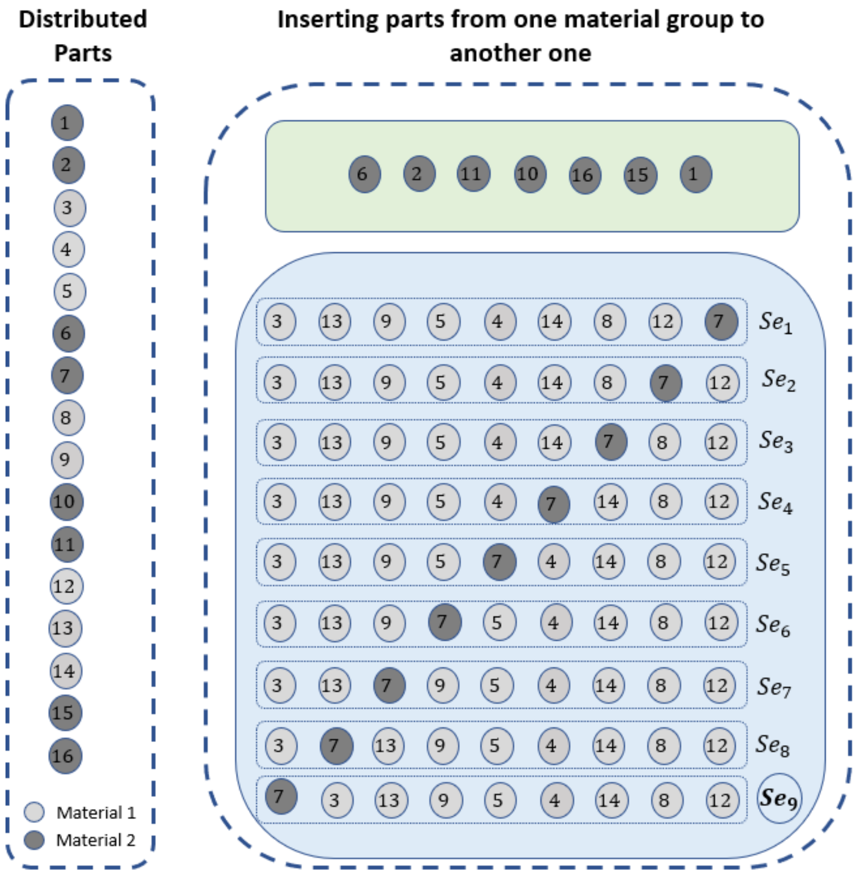

Figure 4.6 Inserting parts from one material group to another one.

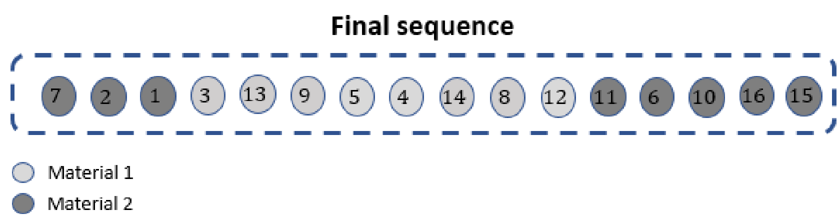

Figure 4.7 Final sequence found by using first algorithm.

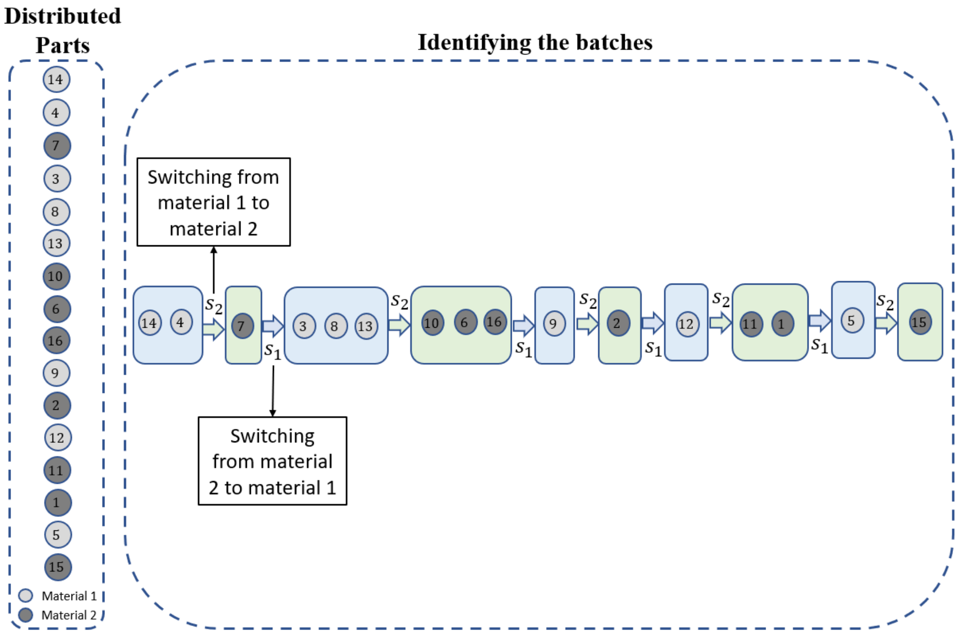

Figure 4.8 Identifying batches for two material groups after scheduling them based on their due dates.

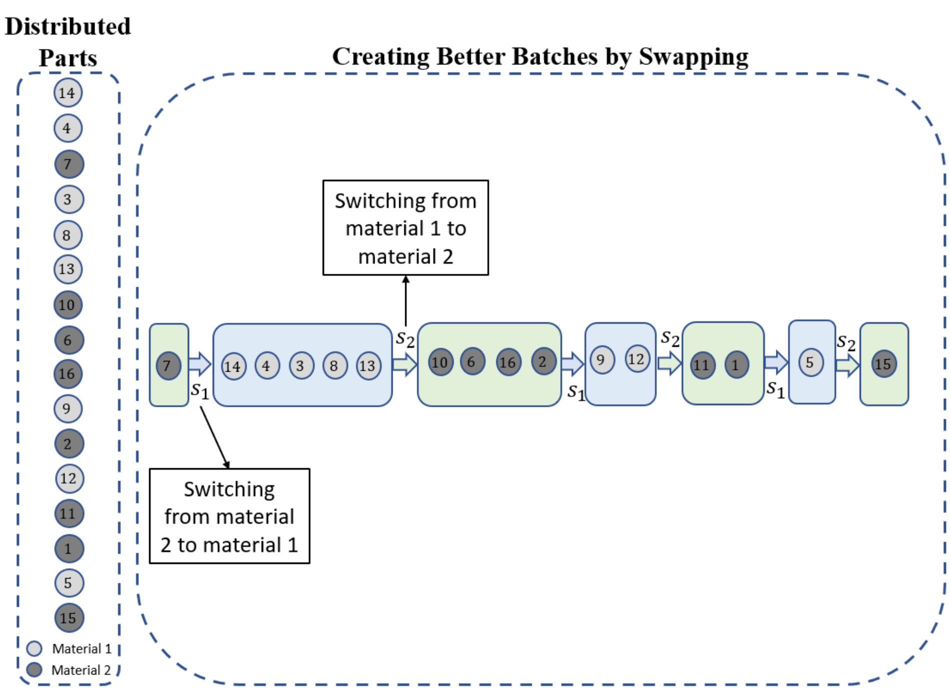

Figure 4.9 Creating better batches by swapping.

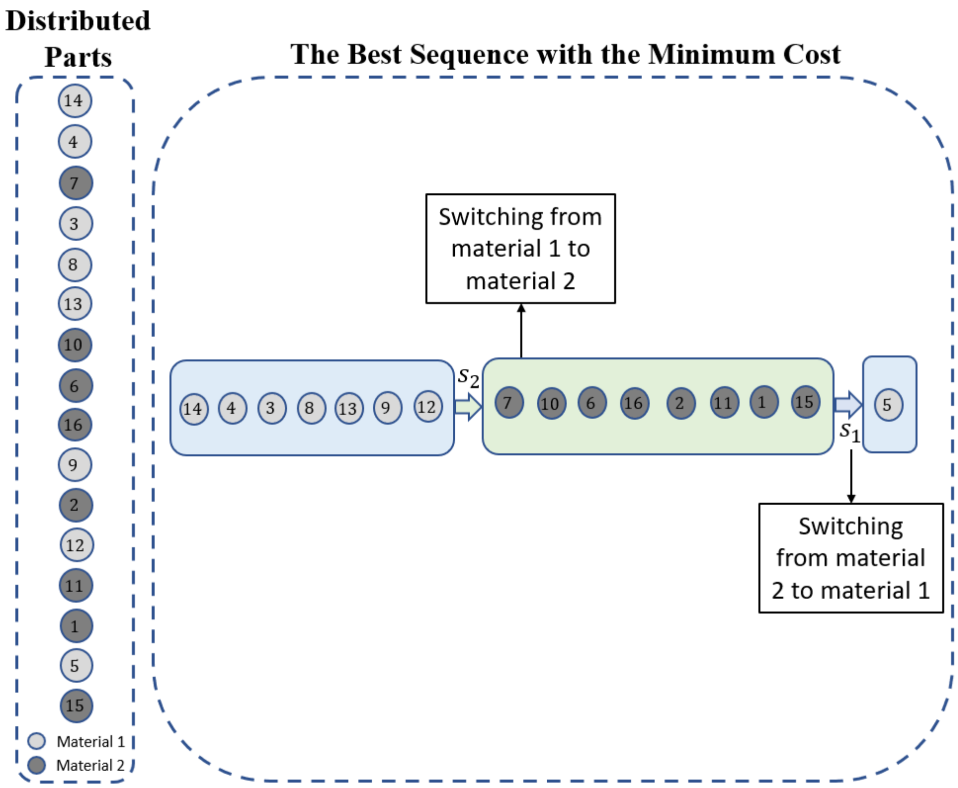

Figure 4.10 Final sequence obtained by using the second algorithm.

to compare to Table 4.4. In this case, initial model cannot provide the best results. The best results are obtained by using the second algorithm. The columns "Gap" shows the difference between results from second algorithm and results from the indicated method. The optimization model cannot provide a solution for 500 and 1000 parts in an hour, and thus, the gap cannot be calculated for these instances in Table 4.5. As shown in these tables, the second algorithm is performing better than the first algorithm in terms of solution quality and CPU time. Moore's rule is developed to minimize the total number of late parts in the system. Since the first algorithm developed based on Moore's (1968) rule, the quality of the results is poor compared to the second algorithm. On the other hand, second algorithm is developed based on the Jackson's rule which minimizes the total lateness cost. In this case, the quality of the results is much better as shown in Table 4.4 and 4.5.

The Factors that Influence the Switching Process

Materials changeover is a very significant factor in a scheduling problem involving multi-material types.

The identification of the factors that affect the switching process in AM production is critical. Table 4.6 shows the optimal sequence along with the number of switches for the parts with the given parameters.

Here, column j indicates the job that part i scheduled at. s_1 and s_2 denote the required switching time for material 1 and material 2 respectively. c_1 and c_2 represent switching costs for material 1 and material 2 respectively. This experiment has only one switching where the AM machine switches from material 2 to material 1. Table 4.7 shows the analysis

Table 4.4 Results obtained by using different methods.

	Initial Model		With Cuts		First Algorithm		Second Algorithm	
Number of parts	**Gap %**	**CPU time (s)**	**Gap %**	**CPU time (s)**	**Gap %**	**CPU time (s)**	**Gap %**	**CPU time (s)**
5	0	0	0	0	12.8	0	1.56	0
6	0	0	0	0	11.62	0	1.54	0
7	0	0	0	0	10.23	0	1.68	0
8	0	1	0	0	13.54	0	3.74	0
9	0	5	0	0	16.42	0	3.82	0
10	0	10	0	0	18.56	0	5.78	0
11	0	174	0	0	16.12	0	4.64	0
12	0	514	0	0	14.23	0	4.48	0
13	49.5	3600	0	0	14.52	0	4.36	0
20	54.8	3600	0	42.25	12.64	0	4.24	0
25	56.5	3600	0	3600	12.48	0	3.98	0
30	58.4	3600	0.045	3600	11.84	0	3.72	0

Table 4.5 Obtained results for large number of parts.

	Initial Model		First Algorithm		Second Algorithm
Number of parts	**Gap %**	**CPU time (s)**	**Gap %**	**CPU Time (s)**	**CPU Time (s)**
50	65.6	3600	9.35	0.0156	0.0156
100	69.4	3600	9.14	0.1455	0.0156
500	-	3600	6.82	17.172	0.0625
1000	-	3600	6.28	135.90	0.1406

of the factors affecting material changeover by altering several parameters. An important observation from Table 4.7 is that it is expected to have fewer switching in the systems as the switching time and costs increase in the system. Despite increase in these values, the number of switches increases as the due dates are shortened for several parts. Increase in the number of material changeover indicates a trade-off between tardiness and switching costs is critical. It is clear from the trade-off that the proposed model is significant to operate AM production process efficiently when multi-material types are considered.

4.5. Conclusions and Future Works

A scheduling model considering multi-material types is developed in this study. The model is tested with a different number of parts. It is presented that the initial model is not quick enough to provide results for more than thirteen parts. Therefore, the cuts are added to lift to lower bounds caused by fractional solutions and big M.

The model with cuts has provided optimal solution up to 25 parts. However, it is not quick enough for more than 30 parts. An optimal sequence for a number of thousands or even tens of thousands of parts must be found in the majority of the instances in the AM industry. For such cases, the formulated model with cuts may not be sufficient to provide a solution within an acceptable timeframe. A sophisticated heuristic algorithm is therefore required to find the optimal sequence for a large number of parts.

Two sophisticated heuristic algorithms are developed to accelerate the solution process. Constructive first heuristic algorithm is developed based on Moore's (1968) rule. Although

Table 4.6 Optimal sequence for a specific instance

$s_1 = 2\ hr, s_2 = 4\ hr,\ c_1 = \$4,\ c_2 = \$6$						
Parts	$\boldsymbol{l}$	$\boldsymbol{p_i}$	$\boldsymbol{d_i}$	$\boldsymbol{w_i}$	$\boldsymbol{j}$	**Switching**
1	1	2	6	7	J_1	0
2	1	7	13	7	J_2	0
3	1	11	19	7	j_3	0
4	2	16	25	7	j_5	1
5	2	20	38	7	j_7	0
6	1	8	20	7	j_4	0
7	2	13	37	7	j_6	0

Table 4.7 Optimal Sequence after altering several parameters.

For $s_1 = 6\ hr, s_2 = 8\ hr,\ c_1 = \$8,\ c_2 = \$10$						
Parts	$\boldsymbol{l}$	$\boldsymbol{p_i}$	$\boldsymbol{d_i}$	$\boldsymbol{w_i}$	$\boldsymbol{j}$	**Switching**
1	1	2	13	7	J_3	1
2	1	7	20	7	J_4	0
3	1	11	33	7	j_6	0
4	2	16	17	7	j_2	0
5	2	20	21	7	j_7	1
6	1	8	20	7	j_5	0
7	2	13	14	7	j_1	0

the solution time is fast for large number of parts, the quality of the solution is not satisfying. Therefore, the second heuristic algorithm is developed based on Jackson’s rule (Hall and Shmoys, 1992). This algorithm can provide better results in terms of both solution quality and CPU time.

Finally, the factors that influence the material changeover has identified with a numerical experiment. Based on this experiment, it is shown that the model is very critical increasing the efficiency of the system by making a trade-off between tardiness and switching costs.

CHAPTER 5. CONCLUSION

Three important issues of additive manufacturing have been addressed in this thesis dissertation. A framework to select specific AM process by considering the complexity level of a part, quality, and productivity trade-off in powder-bed AM and developing a scheduling model for multi-material AM applications.

In the first study, a method to select a specific AM process is developed to provide a guidance for users to select AM over SM techniques based on the complexity level of a part. The complexity level-based method has been validated through numerical experiments. Following the decision that AM is the most appropriate manufacturing technique for a given part, a framework is developed for selecting AM processes based on machine, operation, labor, material, and energy costs.

In the second study, an empirical model has developed to optimize process parameter of powder-bed AM processes to make a trade-off between quality and productivity. The effectiveness of the model has been verified with a numerical experiment. According to the results, low building costs can be achieved with the proposed model based on desired quality levels. By using the model, users can optimize process parameters quickly and accurately without requiring costly and time-consuming experimental methods.

The third study introduced a new scheduling model for AM with considering multi-material types. Numerical experiments demonstrate that the proposed model provides an optimal schedule for AM production process by maximizing the trade-off between tardiness and switching costs. Since the initial model could not provide a solution for more than thirteen parts, cuts were added to accelerate the solution time. Although the cutting process sped up the process significantly, it became clear that they were not enough to solve a large number of parts. The heuristic models are developed to speed up the solution process. And it is showed that the second algorithm performs better results than the first algorithm for the small and large number of parts in terms of solution quality and CPU time.

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