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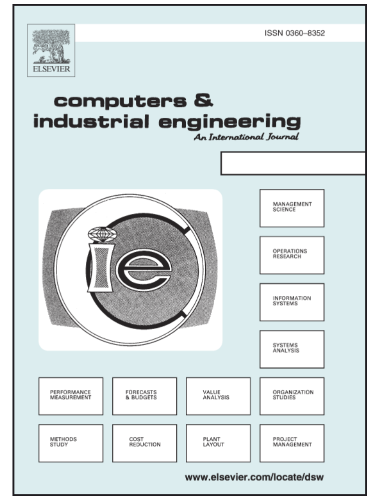

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Production scheduling and nesting in Additive Manufacturing

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Abstract

Additive manufacturing AM - 3D printing - is evolving and is currently experiencing its phase of industrialization. Applications are multiple and some are starting to have a real impact on the supply chain. With the use of layer-by-layer additive construction manner, AM changed the way of designing and manufacturing parts. AM technologies are planned to be the core of the next generation of production systems. Still, only few planning and scheduling approaches are proposed in the literature in order to operate AM systems efficiently.

In this work, the planning, nesting and scheduling problem in additive manufacturing is introduced. The aim is to satisfy the orders received from different distributed customers by due dates. The rising interest comes as AM's reaching a threshold level of maturity and the existing production planning and scheduling approaches have to be adapted and further developed in order to meet the technical and the organizational requirements of the additive manufacturing technologies. The mathematical formulation of the problem is presented, and a heuristic approach is proposed and developed in Python in order to solve it. The proposed heuristic solution is explained step by step, and illustrated using a numerical example. Experimental tests using the proposed heuristic are carried out, underlining the importance of planning/scheduling for an optimized production with AM.

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1. Introduction

Additive Manufacturing (AM) is the process of joining materials to make parts from 3D model data layer upon layer as opposed to subtractive manufacturing technologies. Additive manufacturing takes its roots from rapid prototyping developed for creating models and prototype parts. Rapid prototyping is known as the first form of creating layer-by-layer a 3D object using Computer-Aided Design (CAD) [1]. Additive Manufacturing, and despite its existence for more than three decades, did not gain popularity in industry until very recently. In fact, the recent fast growth rate of AM among industrials and researchers in several fields is proof that it has the potential to be an effective technology for manufacturing components and final products [2]. Based on its maturity in some extent, AM becomes today a main technology in some manufacturing contexts since it can be used in several application fields, especially in customized production [3].

Additive manufacturing has its specific features and characteristics that distinguish it from traditional technologies, the layer-by-layer method for instance, which enables AM to manufacture designed parts with complex geometries without using fixtures, tooling, or mold [3]. In addition and as shown in Figure 1, the inputs of AM machines are only raw materials and the 3D model of the part converted to an AM format which are loaded into the machine. Finally, post-processing operations may also be required in order to improve the quality of the part.

As a result, these characteristics impact the various processes within a company: product design [4], manufacturing process, production planning and scheduling, as well as supply chain and logistics [2]. In contrast, the existing methods seem to be insufficient to address the whole range of dynamics, and therefore, the need for a paradigm shift is necessary to achieve performances

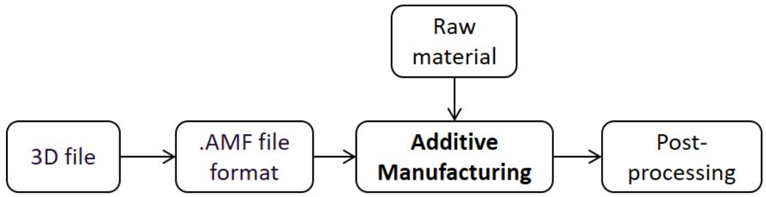

Figure 1: Additive Manufacturing process

that are realized through the implementation of AM [2].

Because very little research addresses the production planning and scheduling issues in additive manufacturing, to the best of our knowledge, this is the first work to address this research question, integrating additive manufacturing process characteristics such as build-time estimation and nesting problems with scheduling algorithms.

The following sections are organized as follows: An exhaustive literature review is presented in Section 2, summarizing the major findings and the most pertinent research works related to the topic. In Section 3, the production planning and scheduling problem in additive manufacturing is introduced, and the relevant mathematical model is presented in section 4. The proposed heuristic approach and build time estimation model are explained in Section 5. In section 6, a numerical example is provided in order to demonstrate the solution of the AM scheduling problem using the proposed heuristic. An experimental study is conducted in section 7, and a final conclusion is drawn in section 8.

2. Literature Review

Additive manufacturing methods and processes are increasing in terms of market share and industrial applications such as automotive, aerospace, and medical, and this growth is expected to continue over the next few years [5]. The AM processes are very numerous and can be classified according to different criteria: the material feed stock, energy source, build volume$\cdots$ [6]. In terms of materials processed, plastics are currently leading the AM market, with around

30,000 machines used in production in 2015 [5]. However, the metal AM market is also growing, with over 1500 machines. According to Bikas et al. [5], it is expected that the metal AM machines will see double-digit percentage growth in their sales over the next 5 years. In 2014, Frazier [6] reviewed the metal additive manufacturing technologies, and classified these processes into three main categories: (i) powder bed systems, (ii) powder feed systems, and (iii) wire feed systems. In terms of processes' energy source, particular focus is given to laser-based and electron-beam additive manufacturing processes in industrial applications [5].

Laser-based additive manufacturing (LAM) processes use a laser source of low to medium power in order to melt, solidify or cure the material [5]. Two sub-categories can be distinguished in LAM processes, highly depending on the material's phase change mechanism: laser melting and laser polymerization. The material used in this latter is usually a photosensitive resin, cured upon its exposure to UV radiation, provided by a low-power laser source. Laser melting processes are either powder-bed or powder-feed based systems. The laser beam is used in this case to melt the material (always in the form of fine powder), which then cools down and solidifies to form the final part [5]. According to Bikas et al. [5] classification, the laser melting based AM processes are selective laser sintering (SLS), selective laser melting (SLM), direct metal laser sintering (DMLS), laser engineered net shaping (LENS), direct metal deposition (DMD), laser powder deposition (LPD) and selective laser cladding (SLC). However, in this work, only powder-bed laser-based processes are considered. In fact, compared to the powder-feed laser-based systems, selective laser sintering (SLS), selective laser melting (SLM), and direct metal laser sintering (DMLS) are not just some of the most significant AM processes used in industries and research centers, but they also have a very similar operating processes with regards to machine preparation, powder layering, powder melting, and ending operations, allowing for the construction of a generic build time estimation model for these processes.

Most recent work literature focuses on improving the process planning for

AM. For example, a process planning algorithm was proposed by Zhu et al. [7], linking hybrid manufacturing technologies and process planning, based on a hybrid process. This process planning algorithm enables a part to be manufactured while taking into consideration process capabilities, production time and material consumption. Furthermore, another two resource/material requirements based algorithms were proposed by Habib et al. [8] in order to improve and optimize the AM process planning. The design stage, including product and process development for AM, has been a big focus in recent AM research. Zhang et al. [3] proposed an evaluation method to assess the design from a process planning perspective in order to help designers improving their designs and get more benefits from additive manufacturing technologies. It consists of a "two-level process planning framework for additive manufacturing" along with a "two-level evaluation framework for the design in AM" and a set of indicators in order to assess and help improving the design for AM. Within a case study, they showed the effectiveness of the proposed frameworks. The impacts that AM's implementation could have on the supply chain, production processes, operations management, and sustainability were hinted by Ashourpour et al. [2]. In their paper, the need of making strategic reconfigurations within production, distribution and logistics structures was expressed, and a set of recommendations for doing so were proposed. Also, Kopf et al. [9] proposed an approach of production planning system based on the process's maturity level, but their study focuses more on maturity assessment using only Selective Laser Melting (SLM) to demonstrate the method.

A successful implementation of AM technologies into a production environment also needs an accurate cost and build-time estimation model that allows the estimation of the real cost and the processing time of each part, even though it may be manufactured in the same build job along with other parts of different geometries and dimensions. Rickenbacher et al. [10] investigated the different cost models proposed in the literature, and showed that by simultaneously building up multiple parts, the total manufacturing time as well as the set-up time, and therefore the total cost per part can be significantly reduced.

This cost-model helps to optimize construct jobs and manufacture parts more economically using SLM technology. Furthermore, with some adjustments, the model can be used in the SLS process as well, thus covering most of powder-bed LAM processes. Zhang & Bernard [11] on the other hand, reviewed the former proposed methods for AM build time estimation, and found that most of these models are neither accurate nor practical for real use in application. In addition, they are also too complicated and difficult to build, taking into account the difficulty to get all parameters for most of the models. Thus, Zhang & Bernard [11] proposed an analytical time estimation method to compensate the lacks in previous models. The method is based on the analysis of processing procedure and the production context. Also, Piili et al. [12] found that by building parts simultaneously the costs can be reduced by 81% to 92% compared to building single parts separately, and showed that an optimal utilization of the build platform (optimal placement/nesting solution) can be seen as the main variable the user can affect under multiple parts manufacturing context. Indeed, this placement (nesting) optimization in AM is a major key factor for decision making and build job optimization in the production planning and scheduling in AM problem.

As the focus of AM becomes increasingly centred on manufacturing functional parts under a multi-parts production context, the planning and scheduling of parts to be processed on these AM machines becomes highly important in order to reduce time and cost. Therefore, the placement (nesting) of parts into the build platform becomes a sub-problem in the AM scheduling one, in order to optimize build jobs and machine utilization, but also to ensure the quality of each part in the job. However, little research has been conducted to address the planning and scheduling issues in additive manufacturing. Li et al. [13] clearly stated in their paper, that this topic has not yet been studied in literature: "However, to the best of the author's knowledge, no research has been conducted to address planning of production with AM technologies" [13]. Zhang et al. [14] also reported that "currently, due to the insufficient maturity of manufacturing functional parts and little research attention paid on the process planning or scheduling in AM, only a few solutions were proposed in literature to deal with the part placement problem" [13].

Li et al. [13] introduced the production planning in additive manufacturing problem for the first time in literature, and proposed a mathematical model to formulate it. The aim of their study was to find the optimum allocation of the different parts into a set of different machines with different specifications (processing speed, unit time cost$\cdots$), while minimizing the average production cost per volume of material. In their study, only one type of material was considered, no nesting problem was integrated, and no due dates were taken into account for fulfilling orders. Li et al. [13] also proposed two heuristic procedures called "best-fit" and "adapted best-fit" rules, along with a numerical example comparing the optimal and heuristic solutions. Li et al. [13] also carried out a computational study to evaluate the performance of the proposed heuristics and demonstrated the necessity of developing specific planning and scheduling techniques for additive manufacturing processes.

3. Problem description

Focus will be given to multi-parts production planning and scheduling with AM machines, considering orders delivery times in order to fulfil demands received from customers by due date. The AM processes considered in this study are laser AM processes (LAM), including selective laser sintering (SLS), selective laser melting (SLM), and direct metal laser sintering (DMLS).

The production with powder-bed based LAM machines is operated on a job by job basis [13], with the possibility of simultaneously building up multiple parts with similar or different geometries in the same job, in order to reduce the total manufacturing time and cost. Before starting each job, a set of machine preparation operations are needed, such as loading of the STL files, adjustments of the machine, filling of powder materials, laser generation, scanning head positioning, and filling-up the build chamber with a tightly controlled atmosphere of inert gas. These preparation operations may vary from one machine to another. After that, the job can be started. The laser selectively fuses or melts powdered material by scanning cross-sections generated from the sliced STL of SLC files. After each scanned cross-section, the powder bed (which is controlled by a piston) is lowered by one layer thickness and a new powder layer is applied using a rotating roller to spread the powder evenly. Powder layering and cross-section scanning operations are repeated alternately until all the parts are completed. Finally, parts are removed from the build chamber once the job is finished and all powder is removed from the parts. The machine is then cleaned and prepared to receive the next job. Some other post-processing operations may also be required in order to improve the quality of parts.

As illustrated in Figure 2, the problem considered in this study consists of a set of customers' orders with fixed delivery times. These are to be performed on a set of identical AM parallel machines, while minimizing violation of due dates and maximizing machine utilization.

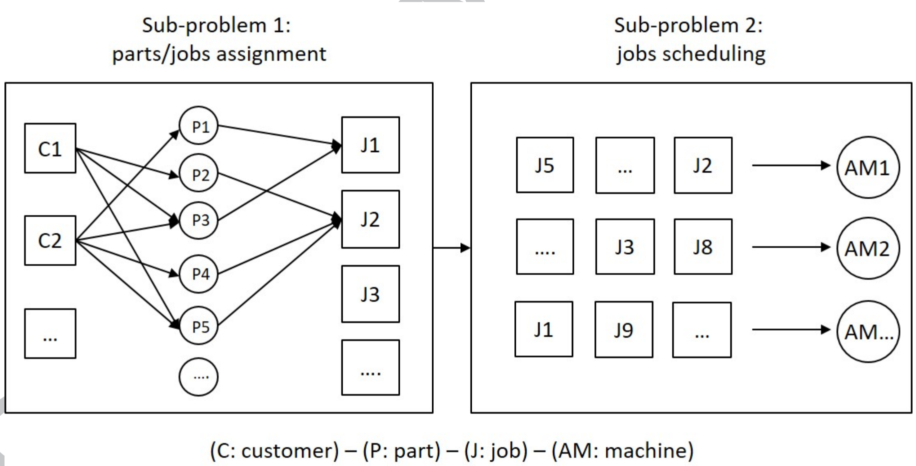

Figure 2: Problem description

The customers' orders will be dispersed on a part by part basis using due date, height, production area, and volume. A first sub-problem is how to cluster the set of n parts ($i = 1, \ldots, n$) with different due dates d_i, heights h_i, production area a_i, and volume $(a_i \times h_i)$, from customers, and to allocate them to a set of l jobs $(j = 1, \ldots, l)$. Each job j consists of one single operation and has a deterministic processing time p_j and a due date d_j. Next, the sub-problem is how to optimally place these parts into the specified build space (maximum production area and maximum supported height), taking into consideration the processing time of each job and its due date.

Once the jobs are formed, the objective of the second sub-problem is to schedule the l jobs on a set of m $(k = 1, \ldots, m)$ identical parallel additive manufacturing machines. These AM machines have the same dimensions of the build envelope (maximum production area A) and the same layer thickness and build speed. It is also assumed that all jobs are available at time zero and ready to be processed on these machines. Each AM machine can process only one job at a time, and one job cannot be processed on different machines at the same time. The scheduling problem considered here is about finding an assignment of all jobs to the AM machines, and the schedule (sequencing) of all jobs on all machines that minimizes the total tardiness. The tardiness T_j of a job j is defined by $T_j = \max\left\{0, c_j - d_j\right\}, \forall j = 1, \ldots, l$, where c_j is the completion time of the job j.

A different combination of parts in the same job will lead to different processing times, due dates, and machine utilization indicators (Figure 3). This would also affect the scheduling of the l jobs later in the second step of the problem solving. The processing time of a job is mainly influenced by the maximum height of parts assigned to the job, as well as by the total parts production area and volume. Also, the due date of each job is defined as the minimum due date of parts assigned to the job. Machine utilization is defined by two main indicators, namely the minimum compactness C defined as the minimum coverage of the build area, and the build height difference of parts assigned to the job (difference of Z-heights) [11], [14].

The following example provides an illustration of how different combinations of parts would affect the job-related parameters and schedule: let's consider eight (8) different parts with different heights, production areas, volumes, and

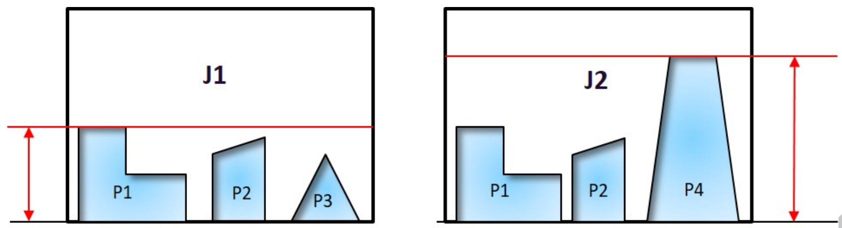

Figure 3: Parts clustering in jobs

due dates, as presented in Table 1. These parts are to be scheduled on one AM machine, and therefore, parts are clustered into two jobs of four parts.

Table 1: Example of 8 parts with their specifications

Part Pi	$P1$	$P2$	$P3$	$P4$	$P5$	$P6$	$P7$	$P8$
Height (mm)	64	77	145	155	75	65	165	175
Prod. area (mm^2)	2475	2700	2750	2700	8000	7500	8550	6500
Volume (cm^3)	158.4	207.9	398.75	418.5	600	487.5	1410.75	1137.5
Due date (h)	10	10	30	30	10	10	30	30

Two cases are generated:

- in the first case, parts are clustered into 2 jobs : $Job_1 = \{P1, P2, P5, P6\}$ and $Job_2 = \{P3, P4, P7, P8\}$. The results presented in Table 2 show that both Job_1 and Job_2 can be successfully scheduled on a single AM machine with respect to their due dates, with a processing time of 7.9 $hours$ and 18.09 $hours$ for the two jobs respectively.
- in the second case, and by simply swapping part $P7$ and part $P2$ between the two previous jobs, all the parameters including the processing time, the machine occupation indicators, and the jobs' due dates change as shown in Table 3, and both jobs are tardy, with a total tardiness of 25.76 $hours$.

Table 2: Results of case 1

Job	Parts	Processing time (h)	Area coverage %	Z-height difference	Due date (h)	Completion time (h)	Tardy/ nontardy
Job_1	$P1, P2, P5, P6$	7.9	51.69	4.33	10	7.9	nontardy
Job_2	$P3, P4, P7, P8$	18.09	51.25	10.00	30	26.99	nontardy

Table 3: Results of case 2

Job	Parts	Processing time (h)	Area coverage %	Z-height difference	Due date (h)	Completion time (h)	Tardy/ nontardy
Job_1	$P1, P5, P6, P7$	15.35	66.31	33.67	10	15.35	tardy
Job_2	$P2, P3, P4, P8$	14.06	36.63	32.67	10	30.41	tardy

To solve this problem, the following assumptions are made. Only one type of material is considered for all parts. The parts' geometry and material volume considered are not the real geometries and material volumes. In order to reduce the complexity of the nesting problem, parts are represented by their hull boxes, and the material volumes considered are the boxes' volumes. Thus, the considered production area of each part is the projection of its hull box onto the build platform. The parts' build orientations are predefined and fixed according to each part's optimal build orientation that ensures its quality. Hence, parts can only pivot on their build axis or move horizontally on the build platform.

4. Mathematical model

The problem is composed of two sub-problems:

The first sub-problem. is about how to cluster the set of n parts ($i = 1, \ldots, n$) with different due dates, heights, and production areas, and then allocate them to a set of l jobs ($j = 1, \ldots, l$), while considering nesting and placement issues.

The second sub-problem. is about how to schedule the set of l ($j = 1, \ldots, l$) previously formed jobs on a set of m ($k = 1, \ldots, m$) identical parallel AM machines.

4.1. Sub-problem 1: part/job assignment

We introduce the variable x_{ij} as the binary variable that takes the value 1 if the part i ($i = 1, \ldots, n$) is assigned to job j ($j = 1, \ldots, l$), and 0 otherwise. The set I_j defines the sub-set of parts assigned to job j. The problem of clustering the parts into a set of jobs is a binary integer quadratic programming problem (BIQP), and is formulated as follows:

$$\min \sum_{i=2}^{n} \sum_{i'=1}^{i-1} (d_i - d_{i'}) x_{ij} x_{i'j}, \forall j = 1, \ldots, l \tag{1}$$

subject to

$$\sum_{j=1}^{l} x_{ij} = 1, \forall i = 1, \ldots, n \tag{2}$$

$$\sum_{i=1}^{n} a_i x_{ij} \leq A, \forall j = 1, \ldots, l \tag{3}$$

$$p_j \leq \min_{i \in I_j}(d_i), \forall j = 1, \ldots, l \tag{4}$$

$$d_j = \min_{i \in I_j}(d_i), \forall j = 1, \ldots, l \tag{5}$$

$$\sum_{i=2}^{n} \sum_{i'=1}^{i-1} \texttt{overlap}(x_{ij}, x_{i'j}) = 0, \forall j = 1, \ldots, l \tag{6}$$

$$\sum_{i=1}^{n} a_i x_{ij} / A \geq C, \forall j = 1, \ldots, l \tag{7}$$

$$x_{ij} \in \{0, 1\}, \forall i = 1, \ldots, n, j = 1, \ldots, l \tag{8}$$

In the above formulation, equation 1 represents the minimization of the total differences of due dates between parts belonging to the same job. Constraint 2 ensures that each part must be assigned to one and only one job. Constraint 3 is needed to ensure that the total area of parts assigned to the same job must be smaller than the maximum available production area of the AM machine. Constraint 4 guarantees that the processing time of each job must be smaller than the minimum due date of parts assigned to the job. Constraint 5 ensures that the due date of each job must be equal to the minimum due date of parts assigned to the job. Constraint 6 prevents the overlapping of the bounding boxes of parts' projection areas, where `overlap()` is an external function using the Axis Aligned Bounding Box (AABB) method [15]. Constraint 7 ensures that the build platform area coverage must be greater than the minimum compactness required for the machine. Finally, constraint 8 defines the boundary values for all variables.

4.2. Sub-problem 2: job scheduling

Once the jobs are formed, a second part of the problem consists of finding the optimal assignment and schedule of the l jobs on the m machines. We introduce the following binary variables: y_{jk} takes the value 1 if the job j $(j = 1, \ldots, l)$ is processed in machine k $(k = 1, \ldots, m)$; $z_{jj'}$ takes the value 1 if the job j is scheduled directly before the job j' on the same machine ; z_{0j} and $z_{j,l+1}$ take the value 1 if the job j is respectively the first and the last job on the same machine. The proposed mixed integer linear programming (MILP) model of the second sub-problem adapted from Biskup et al. [16] can be described as follows:

$$\min \sum_{k=1}^{m} \sum_{j=1}^{l} T_j y_{jk} \tag{9}$$

where $T_j = \max\left\{0, c_j - d_j\right\}$ is the tardiness of the job j.

subject to

$$\min \sum_{k=1}^{m} y_{jk} - W_j = 0, \forall j = 1, \ldots, l \tag{10}$$

where W_j takes the value 1 if $\sum_{j=1}^{l} x_{ij} \geq 1, \forall i = 1, \ldots, n$, and 0 otherwise.

$$\sum_{j'=0, j' \neq j}^{l} z_{j'j} = 1, \forall j = 1, \ldots, l \tag{11}$$

$$\sum_{j'=1, j' \neq j}^{l+1} z_{jj'} = 1, \forall j = 1, \ldots, l \tag{12}$$

$$\sum_{j=1}^{l} z_{0j} = m, \forall j = 1, \ldots, l \tag{13}$$

$$c_{j'} \geq c_j + p_{j'} - M(1 - z_{jj'}), \forall j, j' = 1, \ldots, l \text{ and } j \neq j' \tag{14}$$

In this formulation, equation 9 represents the objective of the minimization of the total tardiness. Constraint 10 states that if any part is assigned to job j, j must be assigned to one and only one machine. Constraint 11 ensures that each job is preceded directly by another job or by the fictive job 0 if it is the first job scheduled on a machine. Constraint 12 guarantees that each job is directly followed by another job or by the fictive job $l + 1$ if it is the last job scheduled on a machine. Constraint 13 ensures that at most m machines are used. Constraint 14 ensures that a machine can process at most one job at a time, where M is the big M.

5. Proposed heuristic

In this section, we propose a new heuristic approach for the production planning and scheduling problem in AM. The proposed heuristic is implemented in Python, and the pseudo-code of the main loops in the proposed heuristic is presented in Algorithm 1. The pseudo-code of the main function used in the heuristic for the selection of parts to be assigned to the different jobs is presented in Algorithm 2.

As described in the previous section, the main objective is to fulfil demands received from distributed customers by due date, under a multi-part production context using additive manufacturing machines. For this main reason, the earliest due date scheduling rule (EDD) is integrated in the heuristic. In the earliest due date (EDD) rule, the job which has the nearest due date enters service first, in other words, EDD-order is an order based on due date, and the sequence of remaining jobs is sorted based on a non-decreasing due date order. Furthermore, EDD rule is simple, fast, and optimal if the objective is to minimize the maximum tardiness, and it performs very well with regards to due dates, which perfectly matches the scheduling objective.

In order to clearly explain the proposed heuristic, a set of terms need to be defined. A part is called an assigned part once it has been assigned to a temporary job, a scheduled part is a part that has already been assigned to a scheduled job, and an unscheduled part, is a part which has not been assigned yet to a scheduled job. A temporary job is a job used to regroup the distributed parts of each machine's available part list and form the final scheduled jobs. The machine's list of available parts is a list of candidate parts that are susceptible to be scheduled on machine k. And the machine's list of scheduled jobs is a list of jobs, where a position in the schedule is assigned to each job.

First, the list of unscheduled parts is sorted based on a non-decreasing due date, and an empty temporary job is created on each of the m AM parallel machines. A list of available parts is determined for the first machine from those in list of unscheduled parts. The main criterion used for selection in this first step is the available area (remaining area) in the machine's build platform. After that, parts are selected one by one and assigned to the temporary job.

There are two possible cases for part selection. The first one is when the temporary job is empty: in this case, the first part in the list of available parts is selected, as it is the part with the earliest due date (list of unscheduled parts already sorted). The second case is when at least one part is already assigned to the temporary job. In this case, the selected part would be the one with the earliest due date, and which if added to the job, the processing time of the temporary job would not exceed the job's due date (the minimum due date of parts assigned to the temporary job).

Algorithm 1 Main heuristic algorithm

repeat
  Sort unscheduled part list according with earliest due date rule
  for k=1 to m **do**
    Ensure a temporary job on machine k
  end for
  k=1
  repeat
    for i=1 to n **do**
      if Available area in machine k is greater than the production area a_i of part i **then**
        Add part i to the list of available parts for machine k
      end if
    end for
    repeat
      Call: `part_selection`(machine k) (Algorithm 2)
      Update available area in machine k
      Update list of available parts for machine k
    until List of available parts for machine k is not empty
    Remove assigned parts from list of unscheduled parts
    Add a new additive manufacturing machine $k = k + 1$
  until $k \leq m$
  for k=1 to m **do**
    Move temporary job of machine k to the list of scheduled jobs of machine k
    Clear all temporary jobs
  end for
until List of unscheduled parts is not empty

Algorithm 2 Function `part_selection`(machine k) algorithm

if temporary job on machine k is empty **then**
    add part i to temporary job of machine k
    remove part i from list of available parts for machine k
else
    for i in list of available parts for machine k **do**
        add part i to temporary job of machine k
        calculate the processing time p_j of temporary job of machine k
        for i in temporary job of machine k **do**
            $EDD =$ minimum due date of parts in temporary job of machine k
        end for
        if $p_j \leq EDD$ **then**
            remove part i from list of available parts for machine k
        else
            remove part i from temporary job of machine k
        end if
    end for
end if

The available area on machine k is updated every time a part is added to the machine's temporary job, and therefore, parts assigned to temporary job and those who do not satisfy the processing time condition are removed from list of available parts for machine k. The list of available parts is also updated after each assignment according to the updated build platform's available area, and the assigned parts are removed from list of unscheduled parts to ensure that each part is assigned to exactly one machine. This cycle continues until there is no part available for this machine's temporary job. In the next step, parts are assigned to each subsequent machine's temporary job in the same way.

Once all the m machine's temporary jobs are constructed, these latter are to be added to the first position in the list of scheduled jobs of each relevant AM machine, and all machines' temporary jobs are cleared. The position of each job in the list of scheduled jobs represents its position in the schedule of the relevant AM machine. The whole cycle continues, and other iterations are made until all parts are scheduled, and all scheduled jobs are ordered by iteration on the list of scheduled jobs of each AM machine.

5.1. Calculation of processing time: build time estimation

As seen in section 2, an accurate estimation of the build time in AM is a key factor for an optimized production with additive manufacturing. Indeed, in our AM scheduling problem, the estimation of the processing time for all parts in the job is important to optimize the job's construction with respect to due dates. In the following, the proposed build time estimation model used for jobs' processing time estimation is described.

$$p_j = C_{z_{max}} \max_{i \in I_j}\{z_i\} + C_a \sum_{i \in I_j} a_i + C_v \sum_{i \in I_j} v_i, \forall j = 1, \ldots, l \tag{15}$$

where p_j is the processing time of job j, I_j is the set of parts assigned to job j, z_i is the height of part i, a_i is the production area of part i, v_i is the material volume of part i, $C_{z_{max}}$ is the maximum height constant, C_a is the production area constant and C_v is the material volume constant.

In our AM scheduling problem, only powder layering and cross-section scanning operations are considered for the estimation of the job's processing time. Time spent on machine preparation and post processing operations is integrated directly in the time spent on setting up a new job, as it does not vary too much from a job to another.

The processing time of a job j will be highly depending on the maximum height z_{max} of parts in the job. In fact, the more the parts in the job will be of an important height, the more the time spent on generating powder layers will be significant, especially when the layer thickness is smaller. The time spent on powder scanning is expressed in terms of parts' total production area and material volume ($C_a \sum_{i \in I_j} a_i + C_v \sum_{i \in I_j} v_i$). The constants $C_{z_{max}}$, C_a and C_v will depend more on the AM machine specifications (the layer thickness, laser diameter, laser scanning speed, hatching space...).

6. Numerical example

In this section, a numerical example is provided in order to demonstrate the solution of the AM production planning and scheduling problem using the proposed heuristic. The example problem consists of a set of twenty (20) parts with different dimensions, heights, production areas, material volumes, and due dates. These parts are to be scheduled on a set of m LAM machines. The parts' dimensions were generated randomly with respect to the machine's build envelope dimensions ($250 \times 250 \times 250$ mm), while the part's due dates were generated randomly within the range of 8 to 72 $hours$. The LAM machine parameters and the parts' specifications are presented in Table 4 and Table 5, respectively.

The numerical example problem is solved using the proposed heuristic under three cases: with a single machine ($m = 1$), two machines ($m = 2$), and three machines ($m = 3$). Also, it is assumed that all jobs are ready at time zero, and the time spent on setting up each new job (including machine preparation and post processing operations) is fixed to 1 $hour$.

Table 4: Machine specifications

Layer thickness	Laser diameter	Hatching distance	Laser head	Speed (contour/edge)	Build envelope ($L \times W \times H$)	Build time per layer
0.1 mm	0.6 mm	0.3 mm	single	900 mm/s	$250 \times 250 \times 250$ mm	12 s/layer

The part/job assignment was the same under the three cases, and as shown in Table 6, a total of six jobs were generated in order to regroup the twenty given parts. For example Job 1 was formed to produce $P1$, $P3$, $P4$, $P5$, $P6$ and $P17$, where a total of 15250 mm^2 were utilized from a 62500 mm^2 of the total available production area, with a maximum height of parts of 140 mm. The due date of the job is 8 $hours$ and its processing time is estimated at 7.93 $hours$. The jobs were ordered according to their due dates, and as it can be seen from

Table 5: Parts related data

Part i	X (mm)	Y (mm)	Height (mm)	Area (mm^2)	Vol. (cm^3)	Due date (hours)
$P1$	50	100	140	5000	700.0	24
$P2$	190	190	80	36100	2888.0	16
$P3$	15	70	50	1050	52.5	8
$P4$	20	100	90	2000	180.0	16
$P5$	100	25	20	2500	50.0	8
$P6$	30	33	88	990	87.1	48
$P7$	50	100	100	5000	500.0	24
$P8$	30	60	150	1800	270.0	24
$P9$	190	190	54	36100	1949.4	30
$P10$	20	100	147	2000	294.0	16
$P11$	100	10	111	1000	111.0	32
$P12$	47	30	120	1410	169.2	80
$P13$	80	60	50	4800	240.0	40
$P14$	45	28	190	1260	239.4	48
$P15$	35	115	90	4025	362.3	88
$P16$	90	95	90	8550	769.5	48
$P17$	35	150	45	5250	236.3	72
$P18$	69	45	120	3105	372.6	24
$P19$	112	80	180	8960	1612.8	18
$P20$	55	75	95	4125	391.9	72

Table 6, no job's processing time exceeds its own due date, which means that so far, the proposed heuristic fills the gap in the EDD rule. This latter performs well with regards to due dates, but if not, it is because the rule does not consider the job processing time.

The results of the three cases are presented respectively in Table 7, Table 8,

Table 6: Obtained jobs with their assigned parts and parameters

Job j	Scheduled parts	Max height (mm)	Total production area (mm^2)	Due date ($hours$)	Processing time ($hours$)
$J1$	$P1, P3, P4, P5, P6, P17$	140	15250	8	7.93
$J2$	$P2, P10$	147	36500	16	15.65
$J3$	$P7, P15, P18, P19$	180	21030	18	17.70
$J4$	$P8, P9, P12, P13, P16$	150	53709	24	17.33
$J5$	$P11, P14$	190	12025	32	12.41
$J6$	$P20$	95	3025	72	4.66

and Table 9. The tables contain the assignment of each job to the relevant AM machine, and its position in the schedule. The release date and the completion time of all jobs are also provided, along with the tardiness of each tardy job.

Case 1: $m = 1$

As it can be seen from Table 7, in the one single machine case, only $Job\ 1 = \{P1, P3, P4, P5, P6, P17\}$ is scheduled successfully, and as it is scheduled in the first position of $M1$ schedule, it starts at time 0, and will be delivered after 7.93 hours, that is 5 $minutes$ before its due date. The rest of the five jobs ($J2$, $J3$, $J4$, $J5$, and $J6$) are late, which leave us with 83% of late jobs, with a total tardiness of 123 $hours$, and only 8 parts from 20 (40%) are delivered in time.

Case 2: $m = 2$

As can be seen from Table 8, when using two machines, the set of six jobs is divided into two groups of three jobs for each machine as follows: $M1 = \{J1, J3, J5\}$, and $M2 = \{J2, J4, J6\}$. The late jobs are $J3$, $J5$, and $J4$, with a total tardiness of 27 $hours$.

Case 3: $m = 3$

By adding a third machine ($M3$), the obtained job/machine assignment will be as follows: $M1 = \{J1, J4\}$, $M2 = \{J2, J5\}$, and $M3 = \{J3, J6\}$ (Table 9). In this case, only one job ($J4$) is late, with a tardiness of 2.26 $hours$. Which means that the total tardiness has been minimized by 98% comparing to the single machine case. Furthermore, it is to be noticed that even though Job 4 is late comparing to its due date, only $Part$ 8 is considered late once the job has finished, as parts belonging to the same job don't necessarily share the same job's due date (see Table 5). In the end, 19 from 20 parts (95%) are delivered at time.

Table 7: Scheduling with one machine ($M1$)

Position	$Job\ j$	Machine	Release date (hours)	Completion time (hours)	Due date (hours)	Tardy / Nontardy	Tardiness (hours)
1	$J1$	$M1$	0.00	7.93	8.00	Nontardy	0.00
2	$J2$	$M1$	8.93	24.58	16.00	Tardy	8.58
3	$J3$	$M1$	25.58	43.28	18.00	Tardy	25.28
4	$J4$	$M1$	44.28	61.60	24.00	Tardy	37.6
5	$J5$	$M1$	62.60	75.01	32.00	Tardy	43.01
6	$J6$	$M1$	76.01	80.67	72.00	Tardy	8.67

Figure 4 shows the total production area utilized by each of the six jobs compared to the machines' total available area. As it can be seen from the figure, no job's production area exceeds the available area on the machine. The job with the highest area coverage is Job 4 with about 86% of utilized area, and the job with the lowest area coverage is Job 6, with 5% of build area coverage. Figure 5, shows the configuration of each of the six jobs obtained previously. It illustrates the allocation of the parts' bounding boxes projection areas onto the build platform.

Table 8: Scheduling with two machines ($M1$ and $M2$)

Position	$Job\ j$	Machine	Release date (hours)	Completion time (hours)	Due date (hours)	Tardy / Nontardy	Tardiness (hours)
1	$J1$	$M1$	0.00	7.93	8.00	Nontardy	0.00
2	$J3$	$M1$	8.93	26.63	18.00	Tardy	8.63
3	$J5$	$M1$	27.63	40.03	32.00	Tardy	8.03
1	$J2$	$M2$	0.00	15.65	16.00	Nontardy	0.00
2	$J4$	$M2$	16.65	33.98	24.00	Tardy	9.98
3	$J6$	$M2$	34.98	39.64	72.00	Nontardy	0.00

Table 9: Scheduling with three machines ($M1$, $M2$ and $M3$)

Position	$Job\ j$	Machine	Release date (hours)	Completion time (hours)	Due date (hours)	Tardy / Nontardy	Tardiness (hours)
1	$J1$	$M1$	0	7.93	8	Nontardy	0
2	$J4$	$M1$	8.93	26.26	24	Tardy	2.26
1	$J2$	$M2$	0	15.65	16	Nontardy	0
2	$J5$	$M2$	16.65	29.06	32	Nontardy	0
1	$J3$	$M3$	0	17.,7	18	Nontardy	0
2	$J6$	$M3$	18.7	23.36	72	Nontardy	0

7. Simulation results

This section reports the experimental tests results of the proposed heuristic. In these tests, a number of instances were generated. An instance is a combination of a given number of parts $P\#$, and a number of machines $M\#$. In other words, $P10M2$ for example, refers to the case were 10 different parts are to be scheduled on 2 additive manufacturing machines. For each instance,

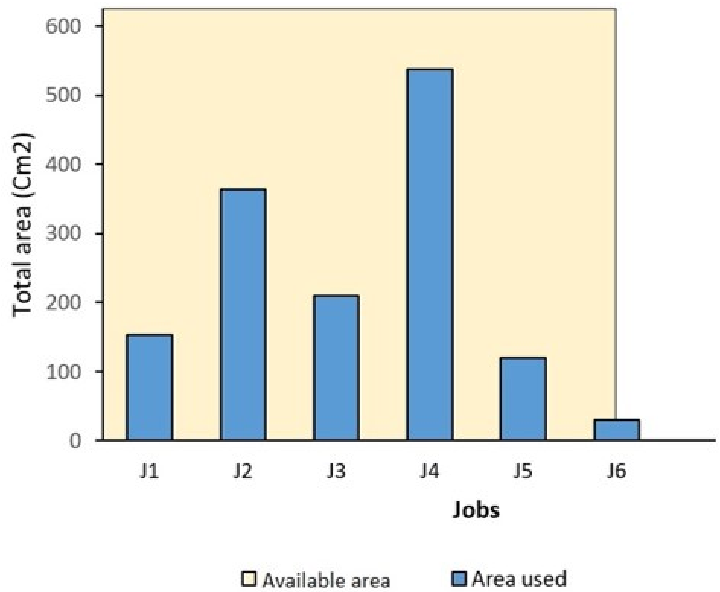

Figure 4: Total production areas of the utilized jobs

a different combination of parts, with different heights, production areas, and material volumes were generated randomly with respect to the build envelop dimensions ($250 \times 250 \times 250\ mm$). The due dates were also generated randomly within the range of 8 to 160 $hours$.

Each instance is generated 20 times, and as shown in Table 10, three cases are considered: (i) when the percentage of jobs scheduled successfully is at around 50%, (ii) more than 75%, and (iii) 100%. In the same table, the total number of formed jobs, the average number of assigned parts per job, the average number of assigned jobs per machine, and the number of tardy jobs is reported for each instance. For example, in the case of scheduling 20 parts on m AM machines, the parts are clustered into 7 different jobs, and as shown in Table 10, 4 jobs from 7 (57.14%) are delivered at time when using 2 AM machines ($P20M2$), while 6 jobs from 7 (85.71%) are delivered at time by adding a third machine ($P20M3$), and in order to achieve all the 7 jobs at time, 4 AM machines are needed ($P20M4$).

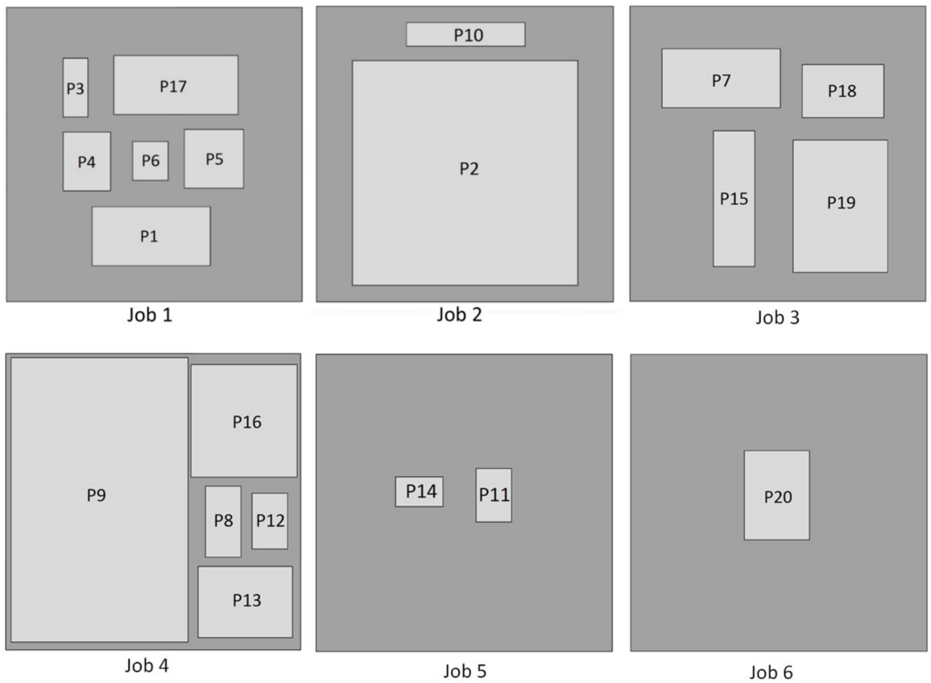

Figure 5: Jobs' configuration

Figure 6 shows the number of machines required to produce different quantities of parts with respect to due dates. This corresponds to the cases where 100% of jobs are scheduled successfully with regards to their due dates (Table 10). The average number of jobs required to regroup the different sets of parts for each case is also illustrated in Figure 6.

As it can be seen from Figure 6, only 2 to 4 machines are needed in order to produce small quantities of parts (from 10 to 30) within the fixed range of due dates (one week), about 4 to 5 machines for batches of 50 parts, while 9 to 10 AM machines are needed to achieve the 100 parts in one week. On the other hand, the number of machines will increase very considerably beyond the 100 parts, up to 25 machines in order to produce 200 parts in a period of one week. Taking into consideration the high cost in AM, mainly driven by the investment cost of the AM machines, it is a matter of a trade-off between this latter on one hand, and the production objectives (a high production rate and a high customer satisfaction rate) on the other hand. In order to illustrate this, the 200 parts case is detailed in Table 11, and Figure 7. The instances from $P200M10$ to $P200M26$ are presented in the table, along with the corresponding number and percentage of tardy jobs.

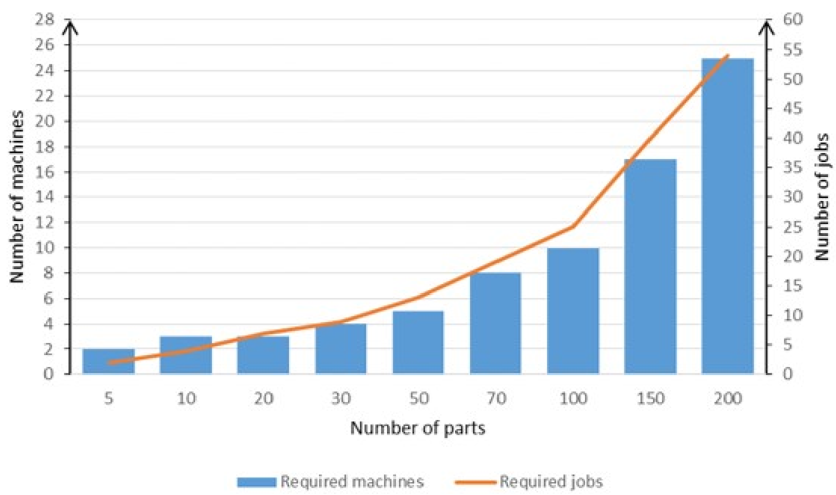

Figure 6: Required number of machines per number of parts

As it can be seen from Figure 7, 45% of jobs are tardy when using 10 machines for the 200 parts production in one week, and the number of tardy jobs can be reduced to 30% when using 14 to 15 AM machines. While more than 10 other machines are needed in order to achieve the 0% of tardy jobs. This means that the number of machines should be doubled in order to compensate the remaining 30% of tardy jobs. Which is the equivalent of an investment of more than 2.5 million euros.

8. Conclusion

In this work, the production planning and scheduling of identical parallel AM machines was considered. Manufacturing orders received from distributed

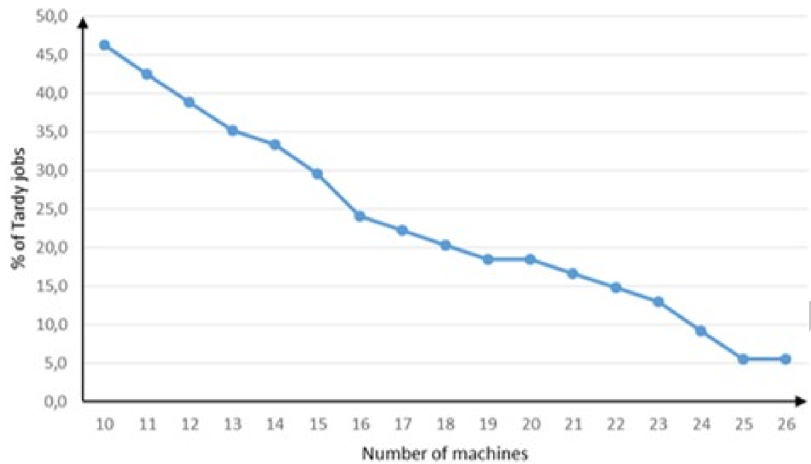

Figure 7: Percentage of tardy jobs per number of machines ($\#P200$)

customers were dispersed on a part by part basis using specific due date, height, production area, and volume, then regrouped in a job by job basis in order to be scheduled on the set of given AM machines. The objective was to fulfil the different orders by due dates and to minimize the total tardiness, while maximizing machine utilization. To do so, we first reviewed the existing literature related to the topic and found that little research attention is paid to address this research question. However, all pertinent information was gathered and integrated in the solution building mechanism, including the AM processes specifications, existing cost and build time estimation models, nesting methods, and existing scheduling methods and heuristics approaches. After that, we defined and explained the problem characteristics, which differentiates it from the classical machines scheduling problems. Then, we presented the mathematical formulation of the problem and proposed a heuristic procedure in order to solve it. The heuristic approach was build based on the earliest due date (EDD) rule, developed in Python and explained step by step through some numerical demonstrative cases. In the end, we conducted some experimental tests, showing the need of developing proper additive manufacturing planning and scheduling methods, in order to meet the technical and the organizational requirements of AM.

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Table 10: Data and results of the experimental tests

Instance	Number of parts	Number of machines	Number of jobs	Average Parts/job	Av. Jobs/ machines	Tardy jobs	Succeeded jobs	% of success
$P05M1$	5	1	2	3	2	1	1	50.00
$P05M2$	5	2	2	3	1	0	2	100.00
$P05M3$	5	3	2	3	1	0	2	100.00
$P10M1$	10	1	4	3	4	2	2	50.00
$P10M2$	10	2	4	3	2	1	3	75.00
$P10M3$	10	3	4	3	1	0	4	100.00
$P20M2$	20	2	7	3	4	3	4	57.14
$P20M3$	20	3	7	3	2	1	6	85.71
$P20M4$	20	4	7	3	2	0	7	100.00
$P30M2$	30	2	9	3	5	4	5	55.56
$P30M3$	30	3	9	3	3	3	8	88.89
$P30M4$	30	4	9	3	2	0	9	100.,00
$P50M3$	50	3	13	4	4	5	8	61.54
$P50M4$	50	4	13	4	3	2	11	84.62
$P50M5$	50	5	13	4	3	0	13	100.00
$P70M4$	70	4	19	4	5	9	10	52.63
$P70M6$	70	6	19	4	3	4	15	78.95
$P70M8$	70	8	19	4	2	1	18	94.74
$P100M5$	100	5	25	4	5	12	13	52.00
$P100M6$	100	6	25	4	4	6	19	76.,00
$P100M10$	100	10	25	4	3	1	24	96.00
$P150M8$	150	8	40	4	5	17	23	57.50
$P150M10$	150	10	40	4	4	9	31	77.,50
$P150M17$	150	17	40	4	2	1	39	97.50
$P200M12$	200	12	54	4	5	25	29	53.,70
$P200M16$	200	16	54	4	3	13	43	79.63
$P200M25$	200	25	54	4	2	3	51	94.44

Table 11: 200 parts case data and results

# of machines	10	11	12	13	14	15	16	17	18
# of tardy jobs	25	23	21	19	18	16	13	12	11
% of tardy jobs	46.3	42.6	38.9	35.2	33.3	29.6	24.1	22.2	20.4
# of machines	19	20	21	22	23	24	25	26	
# of tardy jobs	10	10	9	8	7	7	5	3	
% of tardy jobs	18.5	18.5	16.7	14.8	13.0	13.0	5.6	5.6	

Highlights

- We investigate the problem of production planning and scheduling using Additive Manufacturing
- We propose a two-phase approach based on MILP.
- We develop a heuristic approach to solve the problem.
- The experiments confirm the importance of planning and scheduling for an optimized production with additive manufacturing.