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Abstract

In the context of the future industry, companies have urged to innovate the manufactured products. Today, additive manufacturing makes it possible to respond to the needs of the market in terms of customized production. The recent advances in additive manufacturing technologies have caused a considerable increase in the number of products manufactured by additive processes in industries. In order to satisfy customers' demands and make the investment in additive machines profitable, it is necessary to deal with the production organization in additive manufacturing. This research focuses on the scheduling and nesting problem of production with technological constraints. The objective is to minimize the total delay of the parts to be produced and to maximize the use rate of the additive manufacturing machines. Two models are proposed for powder-based laser technologies and multi jet fusion technology, to estimate the production time in additive manufacturing based on real data. The nesting and scheduling problem is modelled by mixed linear programming. A small example is used to validate the proposed model using the Cplex solver. Due to the NP-hardness of the problem studied, this research develops a heuristic approach to solve large-sized instances. Computational experiments conducted on small and medium size instances indicate that the proposed heuristic is capable to give better solutions within a reasonable time. To evaluate the heuristic performances on large instances, a comparison of the heuristic results is performed with the lower bounds obtained by relaxing the model. The numerical results show that the solutions found by our heuristic are near to the lower bounds proposed.

Keywords: Additive manufacturing, production time, scheduling, planning, placement

1. Introduction

In recent years, the evolution of information technologies has forced companies to change their paradigm of product manufacturing. Indeed, customers are more and more exigent in terms of manufacturing costs, product quality and personalized production. In order to be competitive and to best meet the different needs, companies must innovate in the

products which they supply to their consumers. In this context, today's additive manufacturing processes make it possible to follow with the current challenges by the technological progress made in recent years (Zhang et al., 2014; Özceylan et al., 2018). They offer the possibility to manufacture parts, with simple or complex geometries, in small or large series, in time and at a reasonable cost (Zhang et al. 2014; Mellor et al., 2014). Due to their characteristics and specificities, additive manufacturing processes have become very popular technologies in several manufacturing contexts, especially in customized production (Yılmaz, 2020; Zhang et al., 2014). They consist on stacking layers one by one in order to produce a part from a numerical data model (Li et al., 2017). In contrast with traditional technologies, additive manufacturing, known as 3D printing, offers several advantages, such as production flexibility and efficient use of resources and building materials (Huang et al., 2012; Mellor et al., 2014; Kucukkoc et al., 2016). In fact, additive manufacturing technologies can be used to produce parts with extremely complex shapes which sometimes cannot be realized with conventional technologies (Zhang et al., 2014). In addition, the manufacturing layer by layer does not need tools, which helps to reduce the production costs and times. Initially, in 1980, additive manufacturing (3D printing), was limited to rapid prototyping, prototype and model making applications (Vayre et al., 2012). Today, with the evolution of materials and manufacturing technologies, additive manufacturing is used in direct parts production (Li et al., 2017). The importance of additive manufacturing technology has been recognized in several application domains (Tofail et al., 2018). In fact, many companies in various sectors such as medicine, automotive, aeronautics and aerospace currently use it (Zhang et al., 2014; Kucukkoc, 2019).

Additive manufacturing processes based on materials in powder form, such as Selective Laser Sintering (SLS), Fusion Laser Melting (SLM), Direct Metal Laser Sintering (DMLS) and Electron Beam Melting (EBM), have received significant attention in research and industrial sectors, due to their advantages in high precision metallic parts production (Li et al., 2019b). These technologies are based on the principle of melting material in the form of powder using an energy source (ASTM: F2792-12a). In fact, the principle of powder bed technologies is simple. Firstly, the powder is spread with a roller or a squeegee on the building plate. Secondly, an energy source sweeps the powder to be fused in order to create a layer. When a layer is built, the tray (also called the bed) descends and another layer of powder is distributed on the top and this process is repeated until all layers of the object in question are constructed. Finally, post-processing operations may be required in order to

improve the quality of the part (Chergui et al., 2018). Recently, new technology has been developed to be more adaptable to functional prototyping and serial parts manufacturing, namely Multi Jet Fusion (MJF) (Morales-Planas et al., 2018). This technology is similar to powder sintering technology; it is a powder bed technology that uses an infrared heating element instead of a laser. These technologies have become very interesting in many industrial applications, and even in the food sector (Özceylan et al., 2018). This study focuses on these powder bed additive technologies, specifically the MJF and laser technologies.

Over the past few years, additive manufacturing has experienced rapid growth in personalized parts manufacturing and it has been predicted that the additive manufacturing market will be multiplied nearly six-fold to reach $12 billion by 2025 (Vicari, 2015). As a result, this growth will cause several problems for the company's various processes. Indeed, most of additive manufacturing technologies still suffer from low production speeds due to its nature of the layer-by-layer process. Moreover, the operating costs of powder bed machines are generally very high (Li et al., 2017). Consequently, it is necessary to solve some problems related to the use of additive machines in order to improve their performance and reduce their costs, especially the planning problem in additive manufacturing. In the literature, the grouping of several identical or non-identical parts in a single job batch is considered as the main strategy to optimize additive machine use rates, manufacturing costs and time (Piili et al., 2015). In the grouping process, the optimization of parts placement considering capacity constraints and the various specifications of parts and additive machines represents a major problem in production planning, due to their impact on the job production time. In addition, as previously mentioned, the job production requires pre-processing and post-processing operations. These operations have a considerable impact on the production planning and they have to be considered in the production scheduling, especially when the parts have due dates and fixed delivery times. The issue that then arises is how to group the parts into jobs and order them on the available resources, considering the technological constraints, i.e. the processing operations, the deviation and non-overlap between the parts in the build platform, while optimizing one or more performance measures.

Due to the very limited research on production planning and scheduling problems in additive manufacturing, the current paper considers the two-dimensional placement and scheduling problems under technological constraints. This paper contributes to the literature by proposing two models to estimate the job production time for powder-based laser

technologies and multi jet fusion technology based on real data, and also by developing a mathematical model and heuristics to solve the placement and scheduling problem.

The paper is organized as follows. A literature review and the main contributions are presented in the second section. Based on real data collected from a company, two models to estimate production time for laser powder technologies and MJF technology are proposed in section 3. The problem of parts scheduling and placement in additive manufacturing is defined and mathematically modelled in Section 4. A small example is provided in the same section. To solve large instances, a heuristic is developed in section 5. Section 6 provides the numerical experiments. A conclusion is drawn in section 7 with some perspectives.

2. Literature review

The literature in the domain of production's organization in additive manufacturing is recent and emerging, the proof is that the majority of the papers on this subject have been published in the last four years. The existing studies on the production planning in additive manufacturing are summarized in Table 1.

In order to increase production and resource utilization rates in additive manufacturing, nesting and scheduling approaches are important for efficient production management. However, the majority of the literature treats these two problems separately (Zhang et al., 2020). For example, Zhang et al. (2017) studied the problem of the placement of parts in additive machines. They are interested in the process of optimizing the orientation of the construction for multi-part production and proposed a two-step approach as a resolution method. The objective of their study is to maximize the rate of use of additive machines. Similarly, Canellidis et al. (2016) proposed a Genetic Algorithm (GA) to solve the placement problem of parts in the building platforms.

The problem of scheduling production in additive manufacturing is first introduced into the literature by Kucukkoc et al. (2016). They proposed a mathematical model to maximize the use of manufacturing surface by respecting the delivery times of the parts. The objective of their study is to group parts into work packages and allocate them to resources in order to optimize production cost per volume of material. However, the model is not validated on data instances to determine its performance. Next, Li et al. (2017) introduced the problem of planning additive machines. They developed a mathematical model to determine the optimal allocation of several parts on a set of machines with different specifications. The

proposed model is solved by Mixed Integer Linear Programming (MILP) using Cplex solver and two heuristics (best fit and adapted best fit) have been developed to solve large instances. Experimental studies have been conducted to validate their work and assess the performance of heuristics. Their findings proved that the planning in additive manufacturing could significantly reduce costs. Kucukkoc (2019) discussed the scheduling problem in additive manufacturing in order to optimize a performance measure related to processing time. He proposed models based on MILP to assign parts in job batches and schedule them on one or more machines while minimizing the makespan. However, in the above-mentioned studies, they did not take into account the due dates in the scheduling problem. In this context, Kucukkoc et al. (2018) contributed to this question by proposing a GA (genetic algorithm) for production planning based on the output dates and due dates of the parts to be manufactured. Ransikarbum et al. (2017) proposed a decision support tool based on multi-objective optimization to address the assignment problem of parts to additive machines for Fused Deposition Modeling (FDM). They modelled the problem with MILP. The objectives are to reduce production costs, balance the load between machines and reduce the total delay and the total number of unprinted parts. Fera et al. (2018) studied the problem of production scheduling on a single machine. They have developed a genetic algorithm to minimize total advance/delay costs and production costs. Nevertheless, the studies reviewed above consider only the areas and volumes of the parts in the grouping process.

Recently, some papers have been focused on how to solve the planning problem in additive manufacturing by addressing both scheduling and nesting issues. Oh et al. (2018) investigated the batch placement problem based on a 2D nesting method in order to avoid surface damage. To do this, the authors proposed a decomposition method using a Binary Space Partitioning (BSP) method to cut a part into smaller pieces. Furthermore, they also developed a GA for placing and grouping the decomposed pieces into several batches. Wang et al. (2019) developed a cloud-based additive manufacturing production planning system that takes into account lead time, height and part shape. They proposed a computer vision-based approach in order to efficiently nest the irregular parts in the building platform. Chergui et al. (2018) addressed the problem of production planning and scheduling of additive machines. They proposed an approach that considers the due dates and specifications of the parts. Chergui et al. (2018) divided the problem into two sub-problems, grouping the parts and scheduling the work packages. Dvorak et al. (2018) investigated the problem of parts planning on several additive machines to optimize the number of overdue parts and to meet deadlines

and nesting constraints (two-dimensional bin packing). Li et al. (2019a, 2019b) introduced the problem of dynamic order acceptance and scheduling in on-demand production with powder bed fusion systems. Li et al. (2019b) developed an approach that allows manufacturers to take simultaneous decisions on the acceptance and scheduling of dynamic incoming orders to optimize the average profit-per-unit-time during the whole makespan. Zhang et al. (2020) studied the scheduling and the nesting problem for the production planning of multiple parts on several additive while minimizing the makespan. They developed an approach that combines heuristics and a genetic algorithm in order to consider the decisions of allocation and placement of parts simultaneously.

The literature on planning in additive manufacturing is in its early stages and mainly concerns two problems: the assignment of parts to additive machines and the nesting of parts in the building platforms. However, as mentioned in the previous section, most of the literature considers these two problems separately or simplifies the nesting process by grouping parts based on their volume and area (Li et al., 2017; Kucukkoc, 2019). Only some very recent contributions have attempted to combine the two problems for efficient production planning, see Table 1. Nevertheless, there are some limitations in their studies. In fact, most of them consider regular part shapes (Chergui et al., 2018) and a single additive manufacturing technology. Moreover, in the estimation of manufacturing times, no study has been conducted that integrates and estimates the time of the different pre-treatment and post-treatment operations. These operations are called in this study as technological constraints, since they are necessary and must be taken into account for more precise planning. The main research contributions of this work are summarized as follows:

- Two cycle time estimation models are proposed for powder-based laser technologies and multi jet fusion technology based on real data.
- Mixed Linear Programming (MLP) formulation is proposed for the combined scheduling and nesting problem considering additive manufacturing process requirements, technological constraints.
- An exact resolution is performed and a heuristic is developed to solve the planning problem in additive manufacturing.
- The nesting process is based on the projection of parts on the horizontal and vertical dimensions, as opposed to Chergui et al. (2018) which consider rectangular shapes.

Table 1. Related research papers classification

Reference	Objective	Bin packing	Batch processing	Due date	Technological constraints	Manufacturing technology	Solving approach
Zhang et al. (2017)	Max. utilization rate	√				SLA	GA
Canellidis et al. (2016)	Max. utilization rate	√				SLA	GA
Kucukkoc et al. (2016)	Min. production cost		√	√		SLM	Heuristic
Li et al. (2017)	Min. production cost		√			SLM / DMLS	Cplex/ Heuristic
Kucukkoc (2019)	Min. makespan		√			SLM	Exact
Kucukkoc et al. (2018)	Min. maximum lateness		√	√		SLM	GA
Ransikarbum et al. (2017)	Min. lateness and cost		√	√		FDM	Cplex
Fera et al. (2018)	Min. adv./late. & cost		√	√		DMLS	GA
Oh et al. (2018)	Min. cycle time	√	√			SLS/SLM	Heuristic
Wang et al. (2018)	Max. utilization rate	√	√	√		SLS	Computer vision
Chergui et al. (2018)	Min. lateness	√	√	√		SLM/SLS/DMLS	Heuristic
Dvorak et al. (2018)	Min. makespan	√	√	√		SLM	Heuristic
Li et al., (2019a)	Max. profit	√	√	√		EBM/SLM	Heuristic
Li et al. (2019b)	Max. profit	√	√	√		EBM/SLM	Heuristic
Zhang et al. (2020)	Min. makespan	√	√	√		SLA	GA
The current paper	Min. lateness	√	√	√	√	SLM/SLS/DMLS /MJF	Cplex /Heuristic

Mathematical notations and preliminaries

I	Set of parts indexed by i
K	Total number of jobs indexed by k
M	Set of machines indexed by m
MX_m, MY_m, MZ_m	Length, width and height of machine m
X_i, Y_i, h_i	Length, width and height of part i
d_i	Due date of part i
e_i	Desired deviation for part i
$\boldsymbol{v_i, s_i}$	Volume and area of part i
Vl_m	Laser scanning speed of machine m
Dl_m	Laser diameter of machine m
Ev_m	Vector deviation, the distance between two scans of machine m
Tc_m	Layering time of machine m
Ec_m	Layer thickness of machine m
$\boldsymbol{Tc_{k,m}}$	Layers construction time for job k on machine m
Ts_i	Sandblasting time of part i
Rp	Project review time
Tp	File preparation by reference
Tp_m	Preparation time of machine m
Th_m	Heating time of machine m
Td_m	Unpacking time of machine m
Tt	Sorting time
Te	Packaging, labelling time
Dt_m	Time required for temperature descent on machine m
$\boldsymbol{a_{i,k}^m}$	If part i is assigned to job k on machine m 1, otherwise 0
$\boldsymbol{z_{k,m}}$	If the job k on the machine m is used 1, otherwise 0
$\boldsymbol{l_{i,j}^{k,m}}$	If part i is placed before part j in job k on the x – axis 1, otherwise 0
$\boldsymbol{b_{i,j}^{k,m}}$	If part i is placed before part j in job k on the y – axis 1, otherwise 0
$\boldsymbol{x_i, y_i}$	Coordinates of part in the x and y–axis
$\boldsymbol{R_{i,k,m}}$	Delay of the i–th part assigned to job k on machine m
$\boldsymbol{T_{k,m}}$	Production time of job k on machine m
$\boldsymbol{C_{k,m}}$	Completion time of job k on machine m
$M1$	A big number

3. Models to estimate job production time

In order to ensure on-time production and to plan production in a more accurate and predictable way, it is necessary to consider the time of all operations that take place along the manufacturing process. Indeed, the estimation of the total job production time is essential for production scheduling, especially when decisions on the parts' grouping are taken during the planning process and also during the scheduling phase of all jobs on additive machines (Kucukkoc, 2019; Liu et al., 2019).

3.1. Job production time estimation for the MJF technology

MJF technology is the last innovation in the field of additive manufacturing on the powder bed. Currently, this technology is used to manufacture functional prototypes and parts for small and medium production series for various industrial applications. The MJF process is characterized by the capacity to produce parts with high precision. In fact, it enables to print objects layer by layer with a thickness varying between 0.07 and 0.12 mm, usually with a thickness of 80 microns. Moreover, the particularity of this technology is its rapidity compared to other processes, due to its construction process by an agent. The MJF process scans the surface at each pass at a constant speed, in other words, the number of parts in this layer has no influence on the construction time, which allows estimating the layer construction time with high precision. However, as mentioned in the introduction section, job completion requires other operations than layer construction, such as file and machine preparation and post-processing operations. In the following, we describe in detail all the operations required along the additive process.

3.1.1. Preparation of numerical files

The preparation of the files is made from a CAD file. Several operations can be realized during this phase. For example: files import, repertory creation, files' errors check and correction, files conversion into a standard format, files compression, parts placement on the virtual platform according to the production scheduling, file standard format slicing, transfer of the standard file to the printer, etc. The duration of this operation depends on the number of parts in the job and on the time needed to repair the errors in the files.

3.1.2. Machine preparation

In the machine preparation phase, two types of operations can be identified: human and machine operations. Human operations cover all the activities in which the printer

participates, for example, machine cleaning, powder loading, machine set-up, positioning the production platforms and adjusting the machine. Machine operations are all operations executed by the machine itself such as heating and preparation of the first layer. The total preparation time of the machine depends essentially on their characteristics and the reactivity of the printer.

3.1.3. Layer construction

The parts are built layer by layer. The duration of this operation is the sum of the times taken to build each layer. As the construction time of a layer is regular, then the construction time of all the parts depends only on the maximum height in the considered job. Consequently, doubling the height of the room is equivalent to doubling the construction time of the layers.

3.1.4. Post-processing

At the end of the manufacturing process, the parts must be removed from the platform and submitted for some last finishing operations, sorting and packaging. During the unpacking operation, cooling, generally natural, must be conducted. According to a printer of the MJF technology, the unpacking time takes three times the construction time of the layers, for a natural cooling.

Based on information and measurements collected from a constructor of the MJF technology, a summary of the various operations and an average time estimation for each are given in Table 2.

Table 2. Average time estimation of each operation for the MJF technology

Operation	Average estimated time	Fixed[1] or Variable[2]
Project review (R_p)	30 min	Fixed
File preparation by reference (Tp)	1 min/ref	Variable
Machine preparation (Human Op) (Tp_m)	30 min	Fixed
Machine Heating (Th_m)	60 min	Fixed
Layers construction ($Tc_{k,m}$)	9 to 13 s/layer	Variable
Unpacking (Td_m)	3 * $Tc_{k,m}$	Fixed
Sandblasting (Ts_i)	Ts_i	Variable

[1] Time does not depend on the content of the job.

[2] The time varies according to the content of the job and the characteristics of each part.

Sorting of parts (*Tt*)	1 min/ref	Variable
Packaging, labelling (*Te*)	1 to 2 min/box	Variable

For a given job *k* and machine *m*, we can then estimate the completion time $T_{k,m}$ using the following formula Eq. (1).

$$T_{k,m} = \left(R_p + Tp_m + Th_m\right) + \sum_{i \in I} (Tp + Tt + Te)\, a_{i,k}^m + \frac{max_{i \in I}\left\{h_i\, a_{i,k}^m\right\}}{Ec_m}\, Tc_m + \sum_{i \in I} a_{i,k}^m\, Ts_i + 3\, Tc_{k,m} \quad (1)$$

3.2. Job production time estimation for the laser process

Based on a simple model for estimating the layer construction time for laser fusion processes issued from an engineering techniques notice (Pillot, 2016) and the model proposed by (Zhang and Bernard, 2013), we can estimate the layers' construction time for a given job *k* on machine *m* by the Eq. (2).

$$Tc_{k,m} = \sum_{i \in I} \frac{v_i\, a_{i,k}^m}{Vl_m Ec_m (Dl_m + Ev_m)} + \sum_{i \in I} \frac{s_i\, a_{i,k}^m}{Vl_m Ec_m} + \frac{max_{i \in I}\left\{h_i\, a_{i,k}^m\right\}}{Ec_m}\, Tc_m \quad (2)$$

In order to estimate the total time needed to execute a job in a precise manner, it is necessary to take into consideration the times related to preparation and post-processing operations. In Table 3., we present the main common operations of the powder bed technologies and we give an estimate of the average duration of each operation. We note that the measurements are conducted for the SLS technology. The time required to complete a job using the powder bed process can be estimated by the Eq. (3).

Table 3. The main operations necessary to realize a job with powder bed processes

Operation	Average estimated time	Fixed[3] or Variable[4]
Temperature descent (Dt_m)	120 min	Fixed
Layer construction ($Tc_{k,m}$)	$Tc_{k,m}$	Variable
Unpacking (Td_m)	3 to 8 hours	Variable

[3] Time does not depend on the content of the job.

[4] The time varies according to the content of the job and the characteristics of each part.

$$T_{k,m} = \left(R_p + Tp_m + Th_m + Dt_m\right) + \sum_{i \in I} (Tp + Tt + T_e) a_{i,k}^m + \sum_{i \in I} a_{i,k}^m Ts_i + Tc_{k,m} + Td_m \quad (3)$$

Independently from the process used, it is difficult to estimate the blasting time for a given part since it depends on several parameters. In the following section, we propose a predictive approach to estimating blasting time.

3.3. Empirical model to predict the blasting time

3.3.1. Approach and assumption tests

In this section, we seek to establish an empirical model for predicting blasting time and to identify the most significant parameters in the blasting time estimation. The objective of this study is to statistically illustrate the relationship between surface (s_i), volume (v_i), surface-to- volume ratio (s_i/v_i), complexity (C_i) of the part and blasting time (Ts_i). We propose to use multiple stepwise regression to analyze the independent variables and study their effects on a dependent variable (blast time). In this technique, the proposed model is constructed from a set of parameters by removing independent variables from the statistics estimated at each step. The result of this procedure includes the values of the coefficient, standard error, *T*-Stat value and *P*-value of each independent variable. In order to analyze the results and to be able to identify the most influential variables, we use a statistical test to make a choice between two statistical hypotheses ($H0$ and $H1$). The assumptions used are as follows:

$H0$ (Null assumption): Parameter = 0
$H1$ (Alternative assumption): Parameter ≠ 0

The null assumption will be rejected if the *P*-value is less than or equal to the significant level α, in other words, parameters whose *P*-value is less than or equal the significant level α will be considered as influential variables. At each step, if the *P*-value is higher than the significant level then we accept the null hypothesis and we reject the alternative hypothesis. In addition, the variable with the highest *P*-value will be removed from the predictive model. The process stops when all existing variables have a *P*-value lower than α. The model for estimating blasting time with four factors is given by the Eq. (4).

$$Ts_i = a_0 + a_1 v_i + a_2 s_i + a_3 \left(\frac{s_i}{v_i}\right) + a_4 C_i \quad (4)$$

With:

Ts_i : Represents the dependent variable (the blasting time)

v_i, s_i, C_i : Represent the independent variables

a_0, a_1, a_2, a_3, a_4 : Unknowns coefficients, to be estimated

3.3.2. Results analysis

In order to study and analyze the effects of independent variables on blasting time, we established an experimental study to measure blasting time. Table 4. shows the parts selected, the values of the different parameters and the blasting time measured for each part. To determine the values of the different parameters (volume and surface), we used *Netfabb* software. However, it is difficult to determine the complexity value for each part. Thus, we assume that this value is determined by the printer according to the geometry of each part. The value assigned to C_i is between 1 and 5: the complexity is 1 if the part is not complex and is 5 if the part is very complex.

As mentioned previously, the first step is to identify the variables that have the most impact on the blasting time. Tables 5, 6 and 7 present the regression results obtained by *Minitab* software, based on the values of the independent variables for the 13 selected parts and the measured blast time. The significant level α is fixed at 5%, giving a 95% confidence level.

As shown in Table 5., parameter v_i (volume) has the highest *P*-value, that is also more than significant level (5%). Therefore, the null hypothesis is accepted, that is, the volume has no significant impact on the blasting time and should be removed from the table (the volume coefficient is null). The second regression must be run with the same data by removing the volume v_i.

Since the variable $\left(\frac{s_i}{v_i}\right)$ has a *P*-value > 5%, then the assumption *H*0 is accepted, that is, the coefficient of this variable is zero. We then remove this variable from the data and run the regression model again. The results of the model excluding the variable $\left(\frac{s_i}{v_i}\right)$ are given in Table 7.

All *P*-values are less than 5%, then reject the null hypothesis and accept the *H*1 hypothesis; The regression analysis stops at this step. According to this result, the surface and

complexity of the part are the most significant parameters for the estimation of the blasting time. Therefore, the blasting time can be estimated by the following equation with a correlation coefficient of 96%, which allows us to conclude that the established regression model given by the Eq. (5) is exhaustive:

$$Ts_i = -0{,}3069 + 0{,}0007229 * s_i + 0{,}87248 * C_i \quad (5)$$

Table 4. Data on the parts and their measured blasting time

Part	v_i (cm^3)	s_i (cm^2)	s_i/v_i (cm^{-1})	C_i	Ts_i (min)
Sphere dia 10 F0.1	0,04908	3,0417	61,9743276	1	0,5
Sphere dia 10 F0.01	0,05202	3,1313	60,1941561	1	0,5
Sphere dia 20 F0.01	4,1747	12,5453	3,00507821	1	0,5
Sphere dia 100	520,1641	313,1281	0,60197945	1	1
Sphere dia 200	4174,7129	1254,5283	0,30050649	1	1,5
Sphere dia 150	1759,1925	705,2662	0,40090337	1	1,2
Cube 10	1	6	6	1	0,5
Cube 50	125	150	1,2	1	0,8
Cube 100	1000	600	0,6	1	1
Cube 50 25 holes	99,6146	301,9812	3,03149538	3	2
Cube 100 25 holes	796,9292	1207,925	1,51572436	3	3
Cube lattice 50 25x25 holes	48,2365	303,0979	6,28357986	4	4
Lattice sphere 24 15x15 holes	2,8365	50,734	17,8861273	5	4

Table 5. Results of the first regression

	Coefficient	Standard Error	*T*-value	*P*-value
Constant ($\boldsymbol{a_0}$)	-0,3372	0,2204	-1,53	0,170
v_i	-0,0000071	0,0001705	-0,04	0,968
s_i	0,0006677	0,0004221	1,58	0,158
s_i/v_i	-0,004110	0,005522	-0,74	0,481
C_i	0,86274	0,07694	11,21	0,000

Table 6. Results of the second regression

	Coefficient	Standard Error	*T*-value	*P*-value
Constant ($\boldsymbol{a_0}$)	-0,3364	0,2053	-1,64	0,140
s_i	0,0006532	0,0002186	2,99	0, 017
s_i/v_i	-0,004049	0,004981	-0,81	0,440
C_i	0,86444	0,06090	14,20	0,000

Table 7. Result of the third regression

	Coefficient	Standard Error	*T*-value	*P*-value
Constant (a_0)	-0,3069	0,1479	-2,08	0,065
s_i	0,0007229	0,0001819	3,97	0,003
C_i	0,87248	0,05717	15,26	0,000

3.3.3. Empirical model validation of the blasting time model

To check the error in the Eq. (5), we take five different new parts and we compare the times estimated by the regression model with the times measured. Figure 1. shows the selected parts, the values of the different parameters, the measured blasting time and the estimated time.

The average percentage error between the measured blasting times and the estimated blasting times for the five selected parts is negligible (less than 5%), therefore the blasting time estimation model provides satisfactory results.

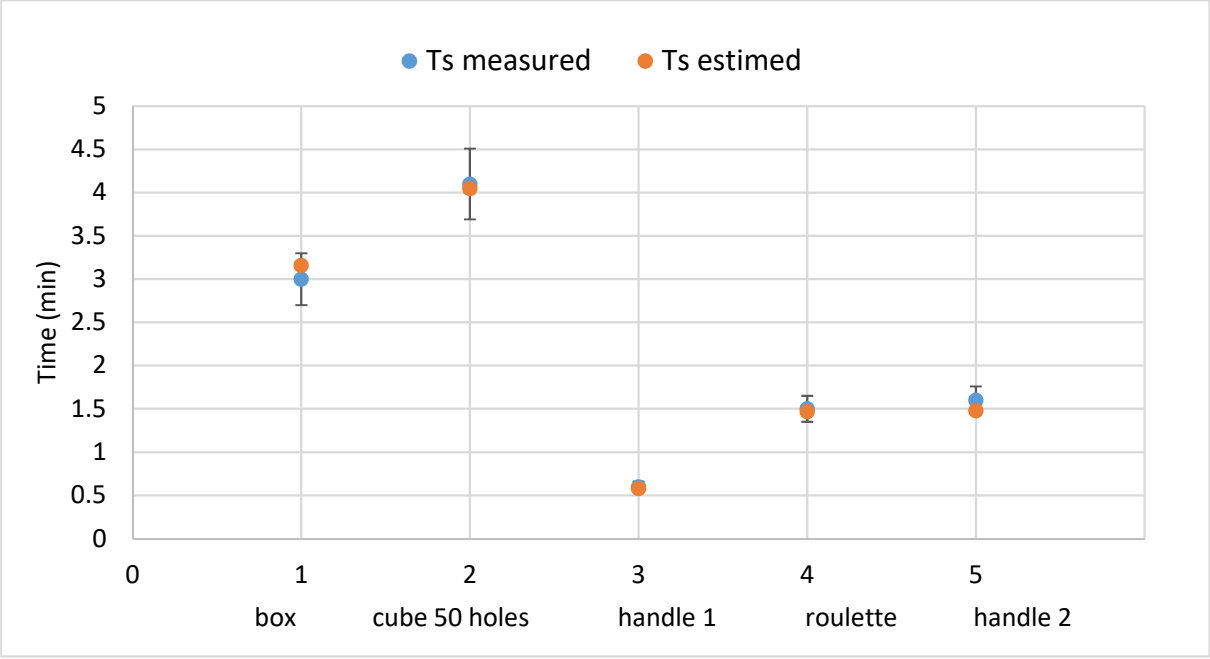

Figure 1. Measured time *VS* estimated time

4. Problem description and model formulation

4.1. Problem statement

As mentioned in section 3, this research focuses on production planning and scheduling in additive manufacturing, taking into account delivery times, two-dimensional

placement and relative time to different technological constraints. The production with powder-bed additive machines is realized on a job by job basis, with the possibility of producing several parts in the same job, in order to minimize the manufacturing time and cost (Li et al., 2017; Chergui et al., 2018). To start and finish a job, a set of operations are necessary, such as machine heating, powder filling, file preparation, sanding and parts packaging. Some of these operations are independent of the number of parts in the job, while others are dependent on the job content and the shape of the parts, such as, the blasting time that depends on several characteristics. The related literature dealing with production planning in additive manufacturing assumed that the time for technological operations are fixed. However, in cases where the production planning is based on the optimization of a performance measure related to production time or manufacturing delay, the consideration of the technological constraints became a crucial and important in the scheduling of parts on additive machines. The problem is how to regroup the parts in the jobs and schedule the jobs on [illegible] and technological constraints, while minimizing violation of due dates and maximizing machine utilization. Figure 2. presents the overall concept of the planning and scheduling problem studied in this paper.

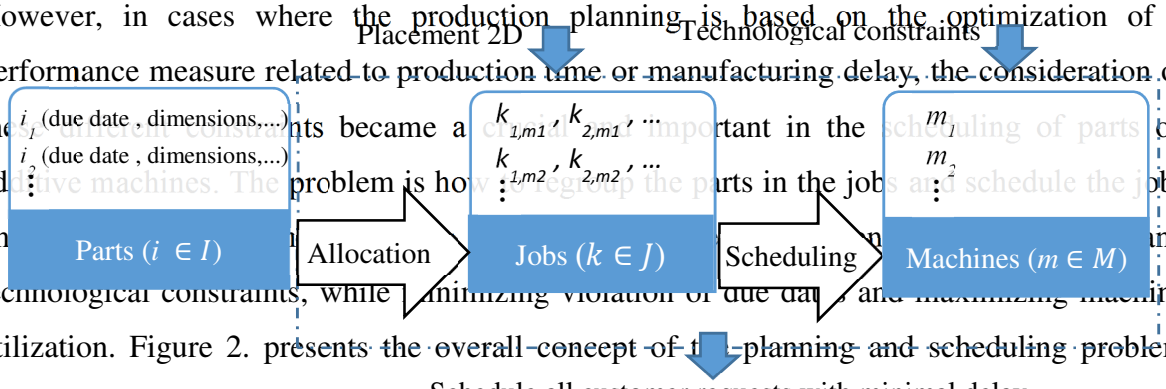

Figure 2. Production planning and scheduling in additive manufacturing

In this study, we consider a printer that receives a set of orders/parts I, $i = 1, ..., I$. Each part is characterized by design specifications and a deadline established by their customer. The design specifications of the part include geometric dimensioning information, volume v_i, height h_i, area s_i, vertical dimension Y_i and horizontal dimension X_i. These specifications form the basic parameters for the placement problem of the parts in the building platforms.

As shown in Figure 2., the problem consists of grouping the parts into production batches ($j = 1, ..., J$) and assigning these to the additive machines ($m = 1, ..., M$), where each

machine has specific characteristics, such as width, length of the production area, layer thickness and laser scanning speed, etc. In the scheduling process, each job must be performed on a single machine and each machine can only execute one job at a time. If two jobs are assigned to the same machine, the second planned job can only be started after the end of the first job, of course taking into account the time for operations preparation. When grouping the parts, we consider the problem of bin- packing in two dimensions to avoid overlapping between the parts and to ensure that the parts are well placed inside the construction plate, as opposed to the problem of placement per unit area. In addition, to prevent damage to the surfaces of the parts grouped together in the production batch, a spacing e_i must be considered when we combine part i with other parts. Moreover, as mentioned previously, the job production time varies depending on the content of the job, the characteristics of the parts and the characteristics of the machines. Therefore, the determination of the best combination of parts in a job under these constraints becomes a key question for the production planning in additive manufacturing.

The objective of this study is to combine the placement and scheduling problem in order to determine the set of jobs J planned at the machines M in such a way that all parts are produced, while minimizing the total tardiness time.

4.2. Model formulation

4.2.1. Problem Complexity

With the progress of additive processes, the placement or nesting problem of parts in construction platforms has become a very hot topic with a long discussion (Zhang et al., 2017). This problem is classified in the literature as NP-hard problems (Bansal et al., 2006; Christensen et al., 2017; Zhang et al., 2017). In addition, it is well-known that the problem of batch scheduling, especially in additive manufacturing, is proven to be NP-hard (Li and Zhang, 2018; Kucukkoc, 2019). Hence, the combination of these two problems studied in this paper is also strongly NP-difficult.

4.2.2. Assumptions

To ease the development of the model, assumptions made for the scheduling and placement problem are presented as follows:

- The geometry of each part is projected on the XY plane in order to determine the minimum rectangle limits that will be used to place the part in the building platform,
- All parts considered have the same manufacturing material,

- Parts orientations are decided before production planning. In other words, no orientation is possible during the allocation and placement of parts.

4.2.3. Mathematical model

Using the Mathematical notations and based on the available formulations of the two-dimensional bin-packing problem (Li and Zhang, 2018; Onodera et al., 1991), we model the combined scheduling and placement problem in additive manufacturing as follows:

$$min \sum_{i \in I, k \in J, m \in M} R_{i,k,m} \tag{6}$$

Subject to the constraints:

$$R_{i,k,m} = max(0, C_{k,m} - d_i\, a_{i,k}^m - M1(1 - a_{i,k}^m)) \quad \forall\, i \in I, \forall\, k \in J, \forall\, m \in M \tag{7}$$

$$\sum_{m \in M} \sum_{k \in K} a_{i,k}^m = 1 \quad \forall\, i \in I \tag{8}$$

$$l_{i,j}^{k,m} + l_{j,i}^{k,m} + b_{i,j}^{k,m} + b_{j,i}^{k,m} \geq 3 - \left(a_{i,k}^m + a_{j,k}^m\right) - 2\left(1 - a_{i,k}^m\right) - 2\left(1 - a_{j,k}^m\right) \quad \forall\, i,j \in I: i \neq j, \forall\, k \in J, \forall\, m \in M \tag{9}$$

$$x_i + X_i + e_i \leq MX_m\, a_{i,k}^m + M1\left(1 - a_{i,k}^m\right) \quad \forall\, i \in I, \forall\, k \in J, \forall\, m \in M \tag{10}$$

$$y_i + Y_i + e_i \leq MY_m\, a_{i,k}^m + M1\left(1 - a_{i,k}^m\right) \quad \forall\, i \in I, \forall\, k \in J, \forall\, m \in M \tag{11}$$

$$x_i + X_i + max\left(e_i, e_j\right) l_{i,j}^{k,m} \leq x_j + M1\left(1 - l_{i,j}^{k,m}\right) \quad \forall\, i,j \in I: i \neq j, \forall\, k \in J, \forall\, m \in M \tag{12}$$

$$y_i + Y_i + max\left(e_i, e_j\right) b_{i,j}^{k,m} \leq y_j + M1\left(1 - b_{i,j}^{k,m}\right) \quad \forall\, i,j \in I: i \neq j, \forall\, k \in J, \forall\, m \in M \tag{13}$$

$$\sum_{i \in I} a_{i,k}^m \leq M1\, z_{k,m} \quad \forall\, k \in J, \forall\, m \in M \tag{14}$$

$$C_{k,m} \geq C_{k-1,m} + T_{k,m} + M1\left(1 - z_{k,m}\right)$$
$$C_{1,m} = T_{1,m} \quad \forall\, k \in \{2, .., J\}, \forall\, m \in M \tag{15}$$

$$\sum_{i \in I} a_{i,k+1}^m \leq\ M1 \sum_{i \in I} a_{i,k}^m \quad \forall\, k \in \{1, .., J-1\}, \forall\, m \in M \tag{16}$$

$$h_i a_{i,k}^m \leq M Z_m \qquad \forall\, i \in I\, \forall\, k \in J, \forall\, m \in M \qquad (17)$$

$$z_{k,m}, a_{i,k}^m, l_{i,j}^{k,m}, b_{i,j}^{k,m} \in \{0,1\}$$
$$C_{k,m}, T_{k,m}, x_i, y_i, R_{i,k,m} \in \mathbb{R}_+ \qquad \forall\, i,j \in I, \forall\, k \in J, \forall\, m \in M \qquad (18)$$

The objective function (6) aims to minimize the total lateness of all parts to be manufactured. Constraints (7) calculate the tardiness of each part with regard to the due date. Constraints (8) ensure that each part must be allocated exactly to one job on a single machine. Constraints (9) guarantee that if two parts are placed in the same job, they must necessarily be placed one after other (on the *x* or/and *y* axis). For example, if parts *i* and *j* are placed in the same job, then part *i* (respectively *j*) can be placed before *j* (respectively *i*) on *x* (respectively y) or part *i* (respectively *j*) is placed before *j* (respectively *i*) in the two axes. Constraints (10) and (11) ensure that the dimensions of the building platforms are not exceeded. In other words, by taking into account the desired deviation for each one, the coordinates of the parts cannot exceed the sizes of the building envelope. Constraints (12) and (13) guarantee that parts assigned to the same job do not overlap. Moreover, they make it possible to determine the coordinates of each part in the job to which it is assigned, according to the positions of the other parts in this job. In other words, if both parts *i* and *j* are assigned in the same job and part *i* is placed before *j* on the *x*- axis (respectively *y*- axis), then the coordinates of part *j* must be larger or equal to that of part *i* plus its length and the maximum desired distance between the two parts. Constraints (14) force that $z_{k,m}$ is equal to 1 if there is at least one part in the job *k* on machine *m* (the job is utilized). The constraints (15) calculate the completion time for each job used based on the job production time $T_{k,m}$. The job production time calculation is calculated using the machine specific parameters, the characteristics of used technology and the different technological operations. For the MJF technology and the laser-based technologies, the job production time estimation is performed using Eq. (1) and Eq. (3), respectively. Note that the blasting time in the considered technologies is estimated using Eq. (5). Constraints (16) ensure that the completion time of each job is greater than or equal to the sum of the completion time of the previous job and the production time. They are used to ensure the sequence of jobs. Constraints (17) ensure that the height of each machine must be respected in the assignment of parts. Constraints (18) define the nature of each decision variable. Note that *M1* is a large positive number.

4.2.4. Model validation: Exact resolution

To guarantee the validity of the proposed model, a small test problem is generated and solved by the exact methods using MLP. The model was coded on IBM Ilog Cplex Optimization Studio (V12.9). The code was run on an Intel® Core ™ i5- 4210U CPU @ 1.7 GHz with 6 GB of RAM. To simplify the scheduling and placement problem and to conduct simple tests, we consider in this study a single additive machine of the type SLS. Note that the only difference between an MGF machine and an SLM/SLS/DMLS machine is the job production time, which means that the scheduling and placement problem with MGF technology can be solved by simply configuring the program according to the characteristics of the machines. The parts' dimensions are generated randomly with respect to the machine's build envelope dimensions (250*250*250 mm). The machine parameters and the parts' specifications are shown in Table 8. and Table 9., respectively.

Table 8. Machine parameters

Build envelope	Layer thickness	Laser diameter	Vector deviation	Scan speed	Build time per layer
250*250*250 mm	0,3 mm	0,5 mm	0,1 mm	1400 mm/s	12 s/layer

Table 9. Data related to the parts generated

Part	X (mm)	Y (mm)	H (mm)	S (cm^2)	V (cm^3)	d (h)	e (mm)	C
P1	18	70	65	70	414	12	4	3
P2	29	80	20	51	388	14	2	2
P3	50	80	92	271	663	15	1	2
P4	18	23	100	467	900	18	1	2
P5	13	27	51	98	612	14	3	5
P6	26	81	31	712	874	19	3	1
P7	55	13	37	247	885	15	3	2
P8	24	88	16	360	625	13	2	3
P9	23	30	35	96	250	10	4	5
P10	25	20	44	72	246	18	2	5

The optimal solution is obtained by the Cplex solver in 395 seconds with an objective value of zero, that is, all parts are planned to be produced before their due date. Table 10. presents the optimal allocation of parts to the jobs used. The upper bound of the job number used $|k|$, in other words, it is possible that each part will be executed in a single job, but this is

not preferable because our goal is to increase the machine use rate by grouping several parts in a single job.

As shown in Table 10, a total of two jobs are used to regroup the 10 parts and produce them according to their due dates. For example, job 1 is used to produce parts P1, P2, P3, P5, P7, P8 and P9 with a maximum height of 92 mm. The completion time for this job is estimated to be 9,8023 hours. Note that the times of the different intermediate operations are included in the total time estimation. The parts of this job have been completed according to their due dates and their characteristics. As can be seen in Table 10, the parts affected to job 1 have due dates that exceed the job completion time.

Table 10. The optimal allocation of parts and the details of the jobs used

Job (k)	Allocated parts	*M*ax height (mm)	Job production time (h)	completion time (h)
1	P1, P2, P3, P5, P7, P8, P9	92	9,8023	9, 8023
2	P4, P6, P10	100	7,6224	17,425

Figure 3. shows the placement of the parts in the jobs to which they are assigned. It illustrates the allocation of the parts' bounding boxes projection areas onto the build platform.

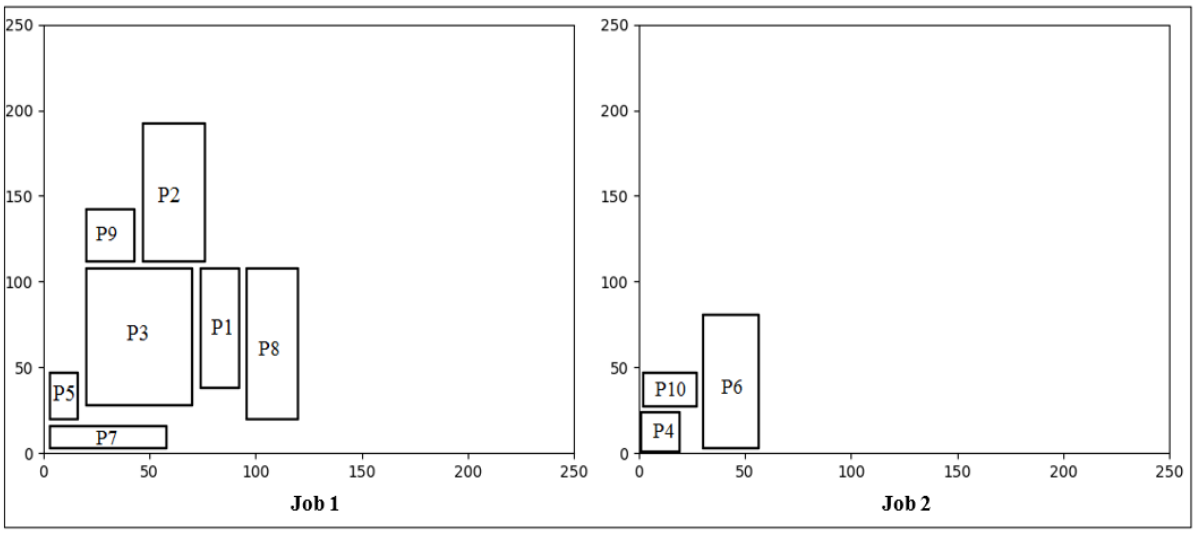

Figure 3. Assignment and placement of parts in the jobs used

Based on the optimal job configuration presented above, the Gantt diagram of the optimal solution can be constructed as shown in Figure 4. The numbers in the rectangles represent the part numbers assigned to each job, and the length of the bars corresponds to the manufacturing time. The parts assigned to each job start and finish their processing at the

same time, including the post processing operations, that is, we cannot start another job until after all the previous job operations have been completed.

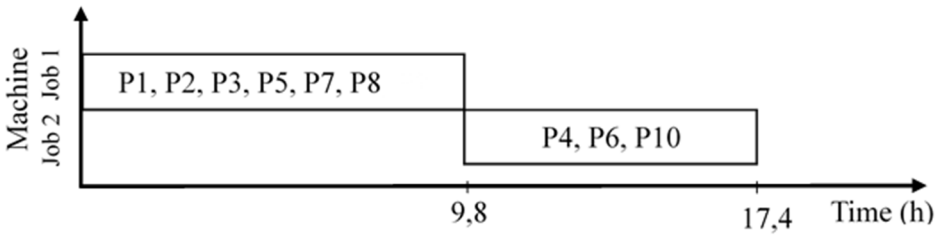

Figure 4. Gantt chart for the optimal solution

5. Heuristic method

Our model aims to solve simultaneously the parts placement in the building platforms and the job scheduling on the additive machines, in contrast to the study by Chergui et al. (2018) which divides the problem studied into two sub-problems. As mentioned previously, this problem is known in the literature as an NP-hard problem. Therefore, because of its computational complexity, large scale instances cannot be solved to optimality in a reasonable computation time by exact methods (as will be shown in Section 7). So, we develop a new heuristic approach to solve the combined placement and scheduling problem in large scales. The proposed heuristic is coded on python, and the pseudo-code of the heuristic is given in Algorithm 1.

As described in the previous section, the objective is to respond to requests received from distributed customers by due date. Since production resources are limited, therefore, the main goal is to efficiently plan production while minimizing the total lateness of parts to be manufactured. For this, sorting rules are used before the selection process and assignment of parts to available jobs. The algorithm starts by estimating the layer construction time for each part. In this step, the specificities of the technology used are considered. For example, for laser-based powder bed technologies, the construction time can be estimated based on the height, the surface and the volume of part, in contrast to MJF technology where the construction time is estimated by considering only the height of each part. Then, sorting rules are used to select the parts. In fact, parts are sorted according to the Earliest Due Date rule (EDD), according to the shortest construction time when the due dates are equal and according to height in the case where the times are equal. Thereafter, we start to select the first part according to the sorting rules used and we simulate each time the total delay

generated on all jobs when we decide to allocate this part in each of these jobs. Next, the selected part is assigned to the job which generates a minimum lateness. At this step, the part placement in the selected job will be tested by the Algorithm 2. If the selected part is well placed in the selected job at the start of this loop, we assign it and update the completion time. Otherwise, the second job is chosen which minimizes the lateness generated to affect the selected part. These last two steps are repeated until the selected part is placed. The steps of this algorithm are repeated until the assignment of all parts in the jobs.

Algorithm 1. Heuristic scheduling algorithm

Begin

For i =1 to $|I|$ **do**
  Estimate construction time t_i for part i
End for
Sort the parts in ascending order of their due date
If $i, j \forall \in I\ (d_i = d_j)$ **then**
  Sort the parts in increasing order of their estimated construction time
  If $i, j \forall \in I\ (t_i = t_j)$ **then**
    Sort the parts in ascending order of their height
  End if
End if
for $i = 1$ to $|I|$ **do**
  for $K = 1$ to $|J|$ **do**
    Calculate total delay RT_k when we assign part i to work k
  End for
  NbTest ← 0
  Add ← False
  While (Add = False et nbTest < m) **do**
    IndiceDelayMin ← work index which has the smallest total delay time to which part i is assigned
    if placement (i in le job indexDelayMin) = True **then**
      Update work completion time
    Else
      nbTest ← nbTest + 1
      $RT_{IndexDelayMin}$ ← Infinite
    End if
  End while
End for

End

To realize the placement of the parts in the jobs used, we have defined a function that allows to create a table of the remaining areas in each job, sub-areas. In each iteration of Algorithm 2, we test if a given part can be assigned to an area or not. If yes, then we assign the part and we delete the used area, and we update the initial array of areas, otherwise we repeat the loop until the part is assigned or all the areas of the array are checked. The main steps to make the placement are presented in Algorithm 2.

Algorithm 2. Two-dimensional placement

```
Begin
1 :  Z = Table of available rectangular areas (contains an area the size of the job at the start)
2 :  Function placement (i):
3 :      j ← 0
4 :      While (j < size (Z)) do
5 :          if i can be placed in Z [j] do
6 :              Place i dans Z[j]
7 :              Delete Z[j]
8 :              Add the two sub-areas created by adding i to Z
9 :              Sort Z in order of minimum length of rectangles
10 :             Return True
11 :         else
12 :             j ← j + 1
13 :         End if
14 :     End while
15 :     Return false
     End
End
```

6. Computational results

This study is a first research introducing the problem of production planning in additive manufacturing with technological constraints, so there are no reference instances available in the literature to compare the effectiveness of the proposed approach. In this section, we evaluate the performance of the heuristic with randomly generated instances. Accordingly, two experiments are conducted. In the first experiment, the results of the proposed approach are compared with the results obtained by the exact method for small instances to get the

average gap. In the second experiment, we conduct experiments on large instances and we evaluate the quality of the approached solutions using lower bounds obtained by the relaxation of the MLP model. For each instance type, we generate 15 test problems, as shown in Table 11. The parts and jobs numbers in small instances are generated in the range [5-15], while for large instances these numbers are comprised between 20 et 150. The coordinates (Xi, Yi) and the height h_i for part $i \in I$ are randomly generated in a rectangle of size 20×120. Since the shapes of parts considered in this study are irregular, the surface and the volume of each part are generated in the interval [50,1000]. The due dates and the complexity of the parts are generated in the ranges [12-100] and [1-5], respectively.

Table 11. Data structures for computational tests

Instance size	Instance ID	Number of parts	Number of jobs
Small and Medium	P5J2	5	2
	P5J3	5	3
	P5J5	6	4
	P6J4	6	4
	P7J1	7	1
	P7J2	7	2
	P9J2	9	2
	P9J3	9	3
	P10J2	10	2
	P10J3	10	3
	P12J3	12	3
	P12J5	12	5
	P14J2	14	2
	P17J5	17	5
	P20J4	20	4
Large	P25J4	25	4
	P30J4	30	4
	P30J5	30	6
	P35J5	35	5
	P38J5	38	5
	P40J4	40	4
	P43J5	43	5
	P45J4	45	4

P52J5	52	5
P50J12	50	12
P55J10	55	10
P59J10	59	10
P60J6	60	6
P65J12	65	12
P70J15	70	15

6.1. Comparison of optimal and heuristic solution methods

In this section, a comparative analysis between the proposed heuristic and the exact method is provided by solving, in an optimal and approximate manner, the small and medium sized instances. The mathematical model is coded on IBM Cplex Optimization Studio v12.9. The proposed heuristic is coded in Python 3.7 and all numerical tests are performed in a PC running Windows 7 Home 64-bit with an Intel Core i7-4210U @ 1.7 GHz and 6 GB RAM. The maximum computation time for the MLP model is fixed to two hours.

Table 12 presents the comparison between the results obtained by the two resolution methods. More specifically, in The first column indicates the name of the instance is given. The second, third and fourth columns report the total lateness, the job number and the computation time obtained by the Cplex solver, respectively. The fifth, sixth and seventh columns represent the results obtained by the proposed heuristic and the last column shows the solution quality deviation of the proposed heuristic with the Cplex solver.

Table 12. Comparison of optimal and heuristic solution methods

Instance ID	The MLP model (Cplex)			Proposed heuristic			*Optimal Gap (%)
	Objective value (h)	# of jobs used	CPU time (s)	Objective value (h)	# of jobs used	CPU time (s)	Objective value
P5J2	0.00	1	0,28	0,00	1	0,14	0,00
P5J3	0.00	1	2,28	0,00	1	0,15	0,00
P5J5	1.40	1	5,76	1,40	1	0,15	0,00
P6J4	0,13	1	7,33	0,13	1	0,16	0,00
P7J1	0,00	1	12,23	0,00	1	0,16	0,00
P7J2	0,54	2	20,84	0,54	2	0,16	0,00

P9J2	0,00	2	199,34	0,00	2	0,17	0,00
P9J3	0,43	3	318,21	0,75	3	0,17	74,41
P10J2	0,00	2	356,75	0,00	2	0,16	0,00
P10J3	1,44	2	390,02	1,76	2	0,17	22,22
P12J3	3,79	2	4123,1	6,56	2	0,17	73,08
P12J5	1,09	3	4275,4	1,54	3	0,18	41,28
P14J2	NA	NA	NA	1,70	2	0,18	NA
P17J5	NA	NA	NA	2,43	2	0,18	NA
P20J4	NA	NA	NA	1,90	2	0,29	NA
Average	**0,74**	**2**	**809,3**	**1,77**	**2**	**0,17**	**17,58**

*Optimal Gap= 100 × (heuristic solution value - Cplex solution value) / Cplex solution value

As shown in Table 12., the proposed heuristic allows to find a solution near to the optimal solution with an average gap of 17,48%. In fact, in some test problems, the heuristic returns the same objective function found by the Cplex solver. For example, in the case of scheduling of 10 parts, all parts are optimally planned without lateness within 356,75 seconds, while the proposed heuristic returns the same objective function within 0.16 seconds. Moreover, the proposed algorithm returns the same number of jobs obtained by the exact resolution in the first 12 tests (P5J2- P12J5). In addition, by increasing the size of the problem, the execution time of the solver has increased considerably, while the proposed heuristic has a constant execution time compared to the Cplex solver, see Figure 5. Indeed, for a total of 15 test problems, the Cplex solver was able to provide a solution only for the first 12 instances. For the instances P14J2, P17J5 and P20J4, the solver cannot find any feasible solution within the time limit. Consequently, it is clearly more difficult for Cplex to solve the large sized instances due to the NP-difficult nature of the studied problem.

In the tested problems, it is important to note that deadlines and the number of jobs have a significant impact on the objective function. In fact, when the dates of the parts deadlines are very short and close, the parts are planned with an important lateness. For example, in the test problem P12J3, the parts are planned in an optimal and approximate way with a total lateness of 3,79 h and 6,56 h, respectively. On the other hand, when the due dates are very relaxed and more remote, the production planning can be scheduled within the desired deadlines, for example the test problem P10J2. With respect to the job number, the increase of this number can improve the production planning since there may exist better combinations of the parts in

the different jobs that will minimize the total delay. The impact of the number of jobs in production planning are discussed in Section 6.3.

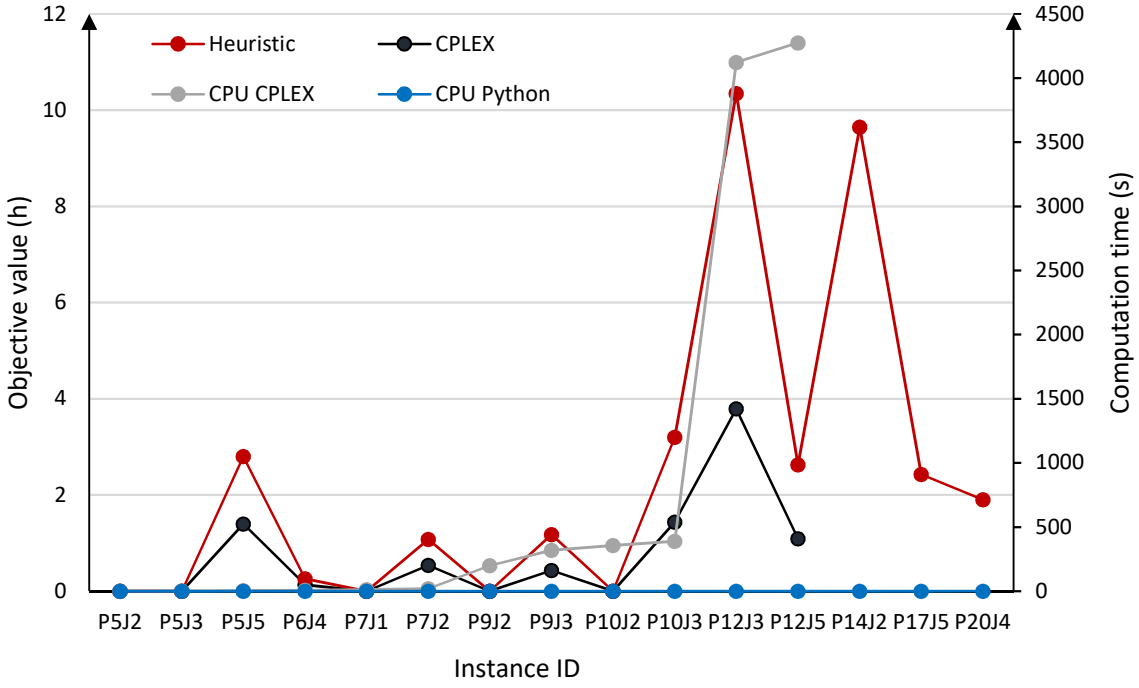

Figure 5. Performance of the heuristic and the MLP for small and medium-sized instances

6.2. Computational results on randomly generated large-sized instances

In order to evaluate the performance of the proposed heuristic on large-sized instances, we attempted to compare the results obtained by our heuristic and the exact method. . however, an out of memory error is occurred due to the complexity of the studied planning problem. Therefore, we evaluated the performance of our heuristic approach using lower bounds. Here, to find a lower bound, we are inspired to the study made by Ahmadi Javid and Azad (2010). Indeed, the lower bound is obtained by relaxing the MLP model presented in section 4.2.3, in other words, we relaxed the placement constraints in two dimensions. We solved various instances and we calculated the deviation from the lower bound found by the relaxed MLP. It is important to note that the lower bound found by the solver is not necessarily the maximum value in the considered tests but it remains a lower bound for the considered problem. The computational test results for large instances are presented in Table 13.

As shown in Table 13., the average difference between the heuristic solution and the lower bound is 56,41%. This indicates that the solution found by our heuristic approach is

near to the lower bound obtained by the relaxed MLP with a mean error bound of 56,41%. In some cases, the lower bounds are found by the proposed heuristic, as shown in the instances P43J5 and P60J6 in which the parts have very relaxed due dates and the number of jobs is very sufficient to schedule the production. However, in the cases where the number of parts is important and the number of jobs is limited, the developed heuristic solves the placement and scheduling problem of the parts with an error bound. For example, the heuristic resolution of the instance P30J5 provides an approximate solution with a total delay of 7,23h and an error bound of 23,38% based on the proposed lower bound. The job configuration of the heuristic resolution of the instance P30J5 is shown in Figure 6. Overall, the proposed approach allows obtaining better solutions for large instances in an almost instantaneous computation time, as opposed to exact methods that require a high memory to find the optimal solutions. Consequently, the proposed heuristics are efficient to solve large-scaled problems.

Table 13. Assessment of the quality of the solution obtained by the heuristic method using a lower bound

Instance ID	The relaxed MLP		Proposed heuristic		Gap** (%)
	Lower bound (h)	CPU time (s)	Objective value (h)	CPU time (s)	
P25J4	0,21	0,74	0,31	0,18	47,62
P30J4	5,49	0,16	9,50	0,17	73,04
P30J5	5,86	0,44	7,23	0,18	23,38
P35J5	5,61	0,17	8,75	0,18	55,86
P38J5	1,45	0,14	3,01	0,19	107,59
P40J4	2,75	0,22	4,29	0,19	56,33
P43J5	0	0,18	0	0,22	0
P45J4	1,26	0,34	1,86	0,18	47,62
P52J5	0	2,12	0	0,26	0
P50J12	40,02	3,40	48,49	0,32	21,16
P55J10	7,25	3,53	13,90	0,27	91,72
P59J10	29,40	3,20	70,18	0,28	138,71
P60J6	0	3,90	0	0,25	0
P65J12	139,47	6,80	257,04	0,47	84,29
P70J15	0,21	0,74	0,31	0,18	47,62
Average	--	--	--	--	**56,41**

[**]Gap = 100 × (heuristic solution value - lower bound value) / lower bound value

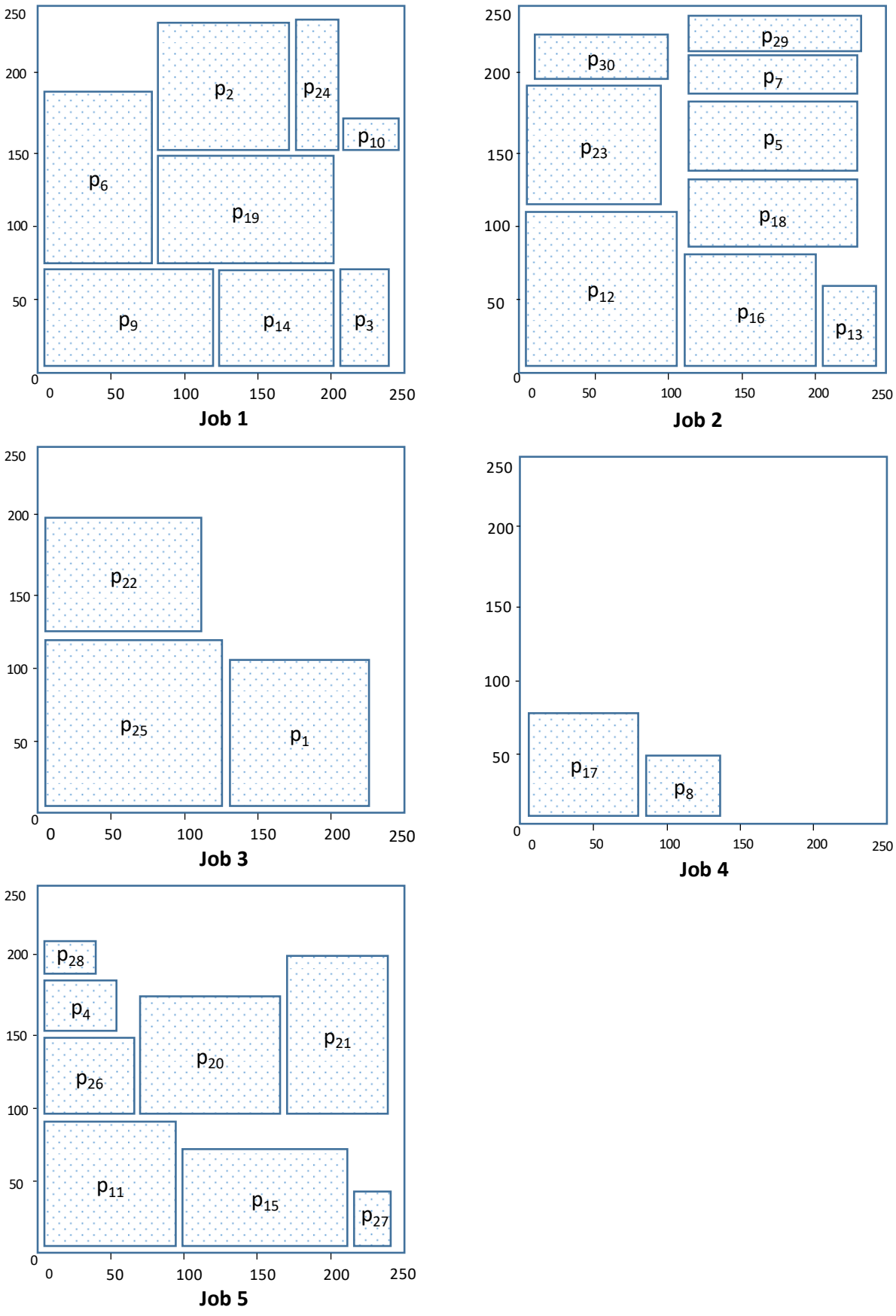

Figure 6. Jobs Configuration for Instance P30J5- Heuristic resolution

6.3. The effect of the number of jobs on the total lateness

By increasing the number of jobs, the total tardiness can be reduced. This is clear in figure 7 for the instance of 59 parts. As the number of jobs increases, the possibility to obtain better combinations of the parts with minimal delay becomes greater. As can be seen in figure 7, the parts are planned with a total delay of 572,74 h with 7 jobs, while with the addition of one job, the total delay decreases approximately 36%. When the number of jobs exceeds 11, the total tardiness of all parts converges to 69,9 h which represents a reduction of 87,79% compared to the case with 7 jobs. However, the increase of the number of jobs can reduce the machines' utilization rate, because the objective is to minimize the total lateness. This observation is consistent with the finding reported by Chergui et al. (2018). Therefore, it is crucial to find a trade-off between production objectives, namely the planning with the minimum of tardiness, and the number of jobs to be used in order to increase the utilization rate of the building platforms. Here, a good compromise between these two objectives can be achieved with 10 jobs.

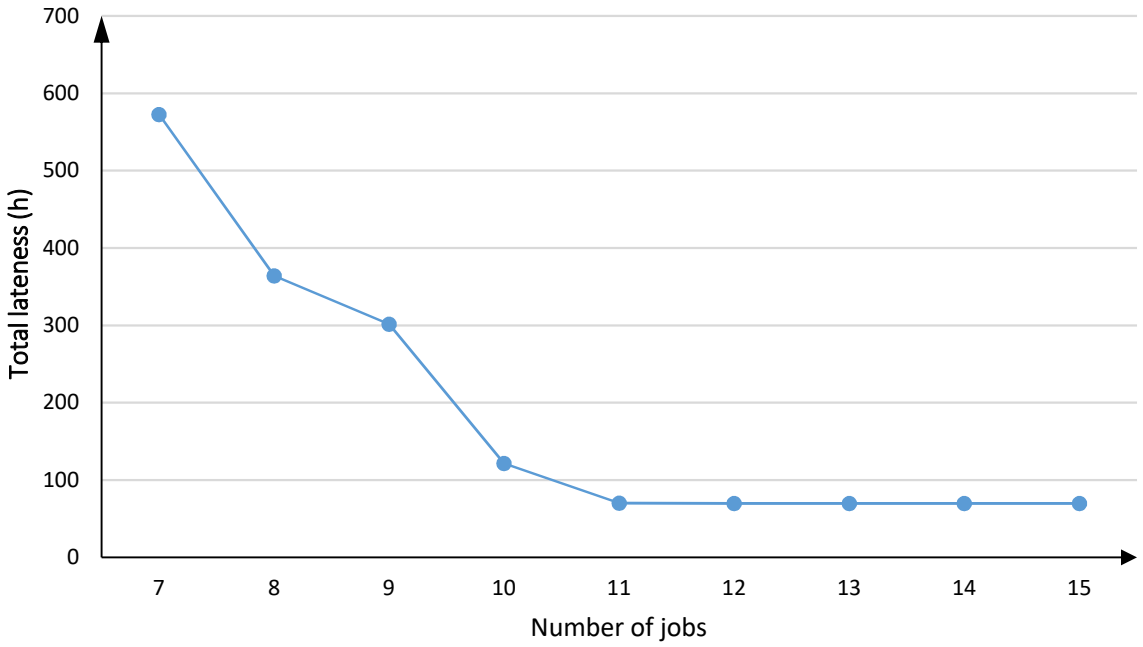

Figure 7. Total lateness with the increase of the number of jobs (Instance of 59 parts)

7. Conclusions and future research

In this study, we are interested in the problem of planning and scheduling of production in additive manufacturing, taking into account the different technological constraints. The goal

is to minimize the total tardiness of all parts to be produced while maximizing the rate of use of additive machines, thanks to the possibility of making several parts in the same job. In order to plan more precisely the production, we have proposed two models for estimating the time required to achieve a given job, according to their content, for laser-based powder and MJF technologies. Next, we established a predictive approach to estimate the sanding time, based on real data. After that, we mathematically modelled the placement and scheduling problem in additive manufacturing. We started by solving the problem with the exact method using mixed linear programming on the Cplex solver. A numerical example of a small instance is used to validate the proposed model. Due to the complexity of the planning problem studied, a new heuristic approach based on the rule of the earliest due date and the shortest estimated manufacturing time is developed to solve large-scale problems. To evaluate the performance of the proposed heuristics, numerical tests were conducted based on the thirty different instances which were randomly generated. Firstly, a comparative study of exact (Cplex) and heuristic solutions on small and medium-sized instances was performed. The results showed that the proposed heuristic is capable to find better solutions with an optimality gap of 17,58% within a very reasonable computation time. Secondly, due to the NP-hard nature of the problem studied, a comparative study of the heuristic results with respect to the lower bounds founded by the relaxed MLP is realized in order to evaluate the heuristic performance on large instances. The findings indicated that the solutions founded by our heuristic are near to the lower bounds proposed, with an average gap of 56,41%. Finally, the impact of the number of jobs on the total lateness is analysed. The results revealed that by increasing the number of jobs, the total delay in the planning of all parts is reduced.

For future research, it is interesting to develop more effective and elegant heuristic methods to solve the model. Furthermore, future studies can focus on the investigation of a systematic method to obtain the maximum lower bounds for large-scaled problem instances. Another research direction consists to integrate the stacking of the parts in the building platforms, in other words, to combine the three-dimensional placement with the scheduling problem under technological constraints. In addition, the placement problem with real shapes can be considered in future research in order to improve the utilization rate of the additive machines. Moreover, in recent years, Machine Learning (ML) methods have seen a considerable expansion in prediction problems. These methods could be used to build prediction models of job production time.

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