A modified Genetic Algorithm for Time and Cost Optimization of an Additive Manufacturing single machine scheduling

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ABSTRACT

Additive Manufacturing (AM) is a process of joining materials to make objects from 3D model data, usually layer – by – layer, as opposed to subtractive manufacturing methodologies. Selective Laser Melting, commercially known as Direct Metal Laser Sintering (DMLS®) is the most diffused additive process in nowadays manufacturing industry. Introduction of DMLS® machine in a production department has remarkable effects on industrial design but on production planning too, for example on machine scheduling. Scheduling for a traditional single machine can employ consolidated models. Scheduling of an Additive Manufacturing machine presents new issues because must consider the capability to produce different geometries simultaneously. The aim of this paper is to provide a mathematical model for an AM/SLM machine scheduling; this model has a computational complexity NP – HARD, so possible solutions must be found by metaheuristic algorithms. Accounted technique is Genetic Algorithms; this algorithm solves sequential optimization problems by handling vectors; in the present paper, we must modify them to hand a matrix. Effectiveness of proposed algorithms will be tested on a test case formed by 30 Part Number production plan with a highly variability in complexity, distinct due dates and low production volumes.

Keywords: Additive Manufacturing, Scheduling, Time, Cost, Metaheuristics, Production Planning

1 INTRODUCTION

Additive Manufacturing (AM) is a topic that is experiencing a continuous enlargement, in fact it collects an increasing number of researches year by year and covers several research areas, from the design of the products and materials investigations to the manufacturing issues.

This paper aims to analyze how to schedule production orders for a single AM (DMLS®) machine considering a time and costs optimization framework. The purpose is to find out a mathematical model that is a useful tool for Production Planners who must schedule AM production, to respect due dates without exceeds cost and earliness, perfectly in line with Lean Manufacturing principles.

In section 2 it is presented a formalization of the problem that will be studied in this paper; in Section 3 this paper presents a brief literature review about AM in actual specified research field: production planning. The literature is systematically reviewed but not much suggestions seems to be aligned with the actual needs of the industrial sector for a single machine AM machine Scheduling Problem (AMSP). In Section 4 there is the model formulation for AMSP, with multi - objective function (OF) that is subject to constraints about geometrical volume of the parts to be produced and about other production variables. In this section the OF combinatorial Optimization Problem (MOP) is divided in a time and cost part and each one is represented in details and the computational complexity for AMSP is demonstrated to be NP – HARD. In the following section 5 it is provided a way to solve AMSP by a traditional metaheuristic algorithm like Genetic Algorithms (GA), even if since this stage of presentation it is worth to note that this algorithm *as – is* cannot provide a solution to AMSP. The GA needs some changes to operate over the proposed mathematical model. A GA based on a 2 – D Crossover will be presented in detail. In section 6, there is a test case to check the effectiveness of proposed algorithm, with special regards to time and costs reduction, but also to running time. In Section 7 new purposes will be proposed for future improvements and researches.

2 OPEN ISSUE / SCHEDULING PROBLEMS ANALYSIS

A traditional scheduling problem is defined as follows:

“Given a set of jobs $J = \{J_1, J_2, J_{3,} \dots\}$ and a set of machines $M = \{M_1, M_2, M_{3,} \dots\}$, assign job to resources to optimize (minimize/maximize) an objective (certain goal)”.

The production systems that satisfy demands for orders or for the stocks, generally produces the parts dividing the demand in smaller parts, that are defined as batches of a specific part number (PN); when it is needed to pass from a PN to another it is needed a change over. The batch quantity is accurately chosen to minimize setup number during production, since they are activity without added value.

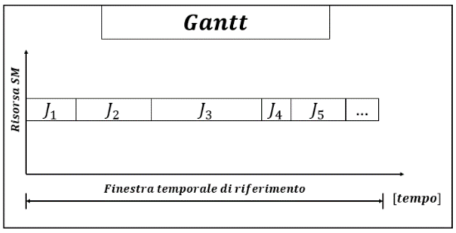


Figure 1: Traditional schedule shape

The scheduling problems are commonly represented using a Gantt diagram (figure 1), that shows how single machine scheduling problem is a sequential optimization problem, where sequence is a vector of jobs. In fact, the goal is to find the best combination of jobs on the machine to optimize a certain objective: lateness, tardiness, flow time, number of late job, make span, etc.

Process sequence in computational terms is a vector resumed as follows:

$$S_{SM} = [J_1, J_{2,} J_{3,} \dots] \rightarrow S_{SM} = [1, 2, 3 \dots]$$

The aim of traditional single machine scheduling is to find the best combination of the quantities to be produced in advance, i.e. jobs.

Scheduling principles change in case of AM machine. A generic *j – th* job can be constituted by several geometries. The job is now heterogeneous in AM, i.e. the single production run can involve several PNs and not only one like in the traditional machines. This news can be summarized as follows. Let us to call "build" a set of several traditional jobs, that can be identified as the couple constituted by *G* and *n*, where *G* identifies the geometry type to be produced and *n* the number of parts to be produced for the *j-th* production run called build.

$$build_j \leftrightarrow \{(G_1, n_1), (G_2, n_2), (G_3, n_3), \dots, (G_i, n_i)\}$$

Job is a heterogeneous concept in AM, corresponding with build chamber composition, usually known synthetically as *build*. To point out this latter concept we can propose a figure by Baumers.

A build is made – up by various PNs/Geometries to produce each one with its independent number $n_{i,j}$, as it is possible to see from a representation of a generic build for an AM machine.

$$build_j = \left[n_1, n_{2,} \dots, n_{n_g}\right]$$

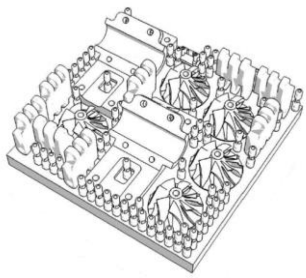


Figure 2: Build concept

It is worth to note that there is the possibility that a single build could not satisfy the overall demand, so the planner must divide production in several builds. Index j for the builds goes from 1 to n_b, i.e. the required number of build needed to complete production. Therefore, AM machine schedule form is a set of builds, i.e. a matrix, as shown in Table 1.

At the end of this paragraph, so it is possible to summarize the AM scheduling problem in the following research questions:

1. What is the number of each geometry/PN for each build?
2. How many build are necessary to complete production?

As it is possible to see the research questions for the Am are different from the ones for the SM. After this paragraph to introduce the research questions on the AM scheduling, let us to pass to the literature review paragraph in which it will be investigated the presence of papers in the international literature about the single machine scheduling, AM or SM, with similarities to the research questions previously introduced.

S		Geometries				
		1	2	3	…	n_g
Build	1	$n_{1,1}$	$n_{2,1}$	$n_{3,1}$	…	$n_{g,1}$
	2	$n_{1,2}$	$n_{2,2}$	$n_{3,2}$	…	$n_{g,2}$
	3	$n_{1,3}$	$n_{2,3}$	$n_{3,3}$	…	$n_{g,3}$
	…	…	…	…	…	…
	n_b	$n_{nb,1}$	$n_{nb,1}$	$n_{nb,3}$	…	$n_{nb,ng}$

Table1: AM schedule model shape

3 LITERATURE REVIEW

In the last 20 years, papers about Additive Manufacturing (AM) have been increased systematically. According to (Witherell et al., 2017) (Costabile et al., 2017) (Fera et al., 2016) (Fera et al., 2017) this is a multi – disciplinary topic, because it links together design, material science, energy consumptions, life cycle management, laser technology, computer science, supply chain management and production planning too. The importance of the AM research field of management is witnessed also by some research papers appeared recently last year (Pour et al., 2016) the paper, in its conclusions, presents a set of proposals to reconfigure the production system and supply chain to enable AM as a reliable and functional system.

All the above research field present several papers over the years, but very few seems to consider an AM machine in the production department context, maybe because the first studies were devoted more to understand the capability of this new technology, especially using metals instead of plastic powders. This paper aims to analyse how to schedule production orders for an AM (DMLS®) machine to achieve a time and cost optimization.

A systematic literature review has made to discover possible source for the proposed paper goal, i.e. Additive Manufacturing scheduling problem.

The chosen databases were the most important in the technical field and they are namely: ScienceDirect®, IEEE Xplore®, International Journal of Operational Research®, Scopus®, Web of Sicence® and so on.

Unfortunately, the sources are not so many, but few of them are however present in the cited database, following these sources are reported.

A first source is (Li et al., 2017), a work about production planning of distributed AM machines to fulfil demands received from individual customers in low quantities. The aim of the paper is to understand how to group the given parts from different customers and how to allocate them to various machine to minimize average production cost per volume of raw material. The authors recognized that the problem is not resolvable in acceptable time by a normal CPU, so preferred to create two different heuristics. The heuristics take in account the fact that AM machines are different, located in several part of the globe and two main information for the products to be realised are available, i.e. maximum part height and production area of machine. It is worth to note that this is a good way to optimize the problem, but it neglects the important fact that sometimes with supports structures the machine chamber allows a part on top of each other production. Moreover, aim of this paper is to investigate the scheduling of a single machine in a specific production system and not in a geographically distributed environment, so the paper can give some advice on the problem, such as the complexity and the mathematical model, but it is a different problem from the one it is faced in this paper.

In (Ransikarbum et al., 2017) authors propose a decision support model based on a multi – objective optimization for orientation of batch of parts and multiple printers, given fixed, un-rotated orientation of parts. A model that considers operating cost, load balance among printers, total tardiness and total number of unprinted parts as objectives in fused deposition modelling (FDM) process is provided. Even if this model is close to the answer to our research question, for the fact that it refers to a multi printer distributed environment, it does not fulfil the objective of the present research.

Another interesting work about the assignment of a specific job to a build is presented in (Zhang et al., 2016), this work focuses on how to optimally place multi – parts onto the machine build platform or in build space with respect to user defined objective. Authors present this problem as a NP – HARD 3D space problem, being a variant of nesting or packaging problem in 2D. The method is based on a two-step algorithm, the first step is to choose the parts orientation and later the second step defines the assignment of the part with an orientation to a specific build.

As anticipated no more valuable sources are available on this research theme, so summarizing all reviewed models try to consider AM machines in production planning context, but no one seems to detail about single machine scheduling. Specifically, there are not answer to our two research questions in the end of Section 2. So, it is possible to conclude that the research questions before introduced are open issues in the research field introduced so far.

4 MODEL FORMULATION

As introduced so far the AM scheduling is a problem to be solved since this technology started to be a permanent part of the production environment of several companies especially in the field of Defence and Aerospace. The question to which the paper wants to answer is always the same of all the scheduling problem, i.e.:

"What's the schedule that allows to respect due dates with the least production cost?"

The question is the same but the context as explained in the introduction is very different from the traditional one for the motivations illustrated in the previous paragraphs. So, let us to introduce a multi-objective model for the AM scheduling that is able to consider also the new constraints given by the new context.

This type of model in literature is known as Multi – objective Optimization Problem (MOP), because it presents double objectives: time and cost.

In our vision (Figure 3) Production Orders are the inputs of AM machine scheduling problem; the attributes of an order are:

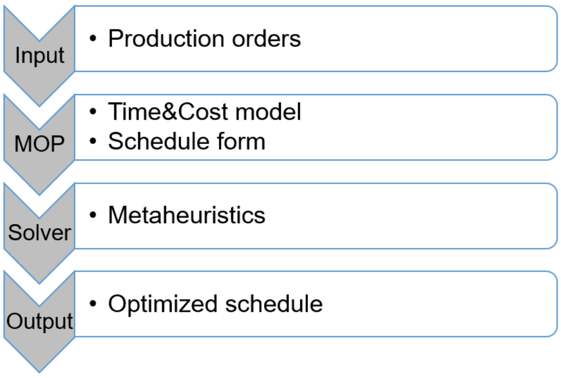


Figure 3: Mathematical Model Frame

d_i:	demand of $G_i - th$ geometry or PN	$[part]$
dd_i:	due date of $G_i - th$ geometry or PN	$[day]$
V_i:	volume of $G_i - th$ geometry or PN	$[cm^3]$

After that the attributes for the production orders are listed, it is worth to note that in this paper a Time & Cost model will be applied, in particular they will be considered the Completion Time (CT) and the Total Part Cost (TPC). CT is the time to produce a single unit of $G_i - th$ geometry, while TPC is the costs to be covered to produce a single part and it is possible to compute itself using the method illustrated in (Fera et al., 2017).

Once the main description elements of our model are described let us to introduce the mathematical formulation of the optimization problem here analysed. The basic model is taken from a research paper, that used earliness and tardiness as objective function (Nearchou, 2010); to these objectives in this proposal it is added the cost.

$$\boldsymbol{F_S = F_{ET} + F_{CP}} \qquad \boldsymbol{Min}!$$

where

$$F_{ET} = \sum_{i}^{n_g} [\alpha_S E_i + \beta_S T_i]$$

$$F_{CP} = \sum_{i}^{n_g} \gamma_S TOC_i$$

Subjected to:

$$\sum_{i}^{ng} n_{i,j} * V_i \leq V_{available} \;\; \forall\, j \in [1, n_b]$$

$$\sum_{j}^{nb} n_{i,j} = d_i , \qquad \forall i \in [1, n_g]$$

$$\alpha_S, \beta_S, \gamma_S, TOC_i, V_i, V_{available} \in \mathbb{R}^+$$

$$E_i, T_i, i, j, n_g, n_b, dd_i \qquad \in \mathbb{Z}^+$$

The proposed scheduling model has some hypothesis that are listed below:

- The scheduling problem faced here is a Single – machine scheduling problem, where the machine is an AM machine: DMLS® or SLM process based.
- The part orientation is given and it is present the required space for manual part removal.
- The build chamber allows construction of parts on top of each other by support structures or other solutions.
- Stock costs are neglected.

4.1 The objective function

Let start to explain the completion time part of the objective function. The due dates respect is the first goal to gain. Production planning must balance earliness and tardiness, two concepts summed up by term lateness.

$$E_j = max(0, dd_j - C_j), \;\; T_j = max(C_j - dd_j, 0)$$

In the previous equations, C_j is the completion time while dd_j is the due date of $j - th$ order.

Earliness must be compressed to reduce inventory costs as state JIT and Lean Manufacturing theory. Tardiness must be minimized to avoid monetary or strategic penalties. Starting from these well-known facets, it is possible to estimate the tardiness damages as a monetary penalty proportional for each day of delay, while a strategic damage will be neglected in this study, since the usual difficulty to evaluate and estimate it.

A common way to model E&T problem is:

$$1|| \sum_{j=1}^{n} \alpha E_j + \beta T_j$$

Where:

E_j:	Earliness of $j - th$ job	$[day]$
T_j:	Tardiness of $j - th$ job	$[day]$
n	number of job	[#]
α:	constant weigh for E	$[1/day]$
β:	constant weigh for T	$[1/day]$

α, β are constant weight computed as follows:

$$\alpha = \frac{1}{\max(E_j) - \min(E_j)} , \qquad \beta = \frac{1}{\max(T_j) - \min(T_j)}$$

An important concept to underline is that in AM E&T of the completion time of an order is not related only to processing time on the same order (geometry). In fact, a single order can be divided in a certain number of build, each of them with an own geometrical mix; this means that with AM different jobs can be performed simultaneously achieving the number of parts due to the client in parallel with others. The classical problem of set-up is represented in a very different way, since it would be needed to have the raw material ready for all the geometries to be built or for the preparation of the building program on the machine, but all the times to change production related for example to the tools change are no more present.

The completion time of an order binds itself to the processing time of each build in which it is divided, to clarify this concept it is possible to see example in the following Table 2.

S		Geometries				C_j
		1	2	3	4	
Build	1	*7*	*3*	*2*	0	*18*
	2	*1*	*0*	*1*	*1*	*26*
	3	*0*	*4*	*0*	*0*	*34*
	4	*0*	*0*	*0*	*1*	*39*
DDi [day]		*25*	*30*	*26*	*11*	

Table 2: Example of jobs division between different buildings

In the above figure, order #2 is clustered in $build_1$ and $build_3$ and it will have a completion time of 34 days, with 4 days of Tardiness. Therefore, we propose a new version of E&T equation adapted to the AM context:

$$E_i = max(dd_i - C_j^{i,end}, 0)$$
$$T_i = max(C_j^{i,end} - dd_i, 0)$$

Where:

E_i:	Earliness of $i - th$ order
T_i:	Tardiness of $i - th$ order
dd_i:	due date of $i - th$ order
$C_j^{i,end}$:	completion time of $j - th$ build, the last in which $i - th$ order has been divided.

It is worth to note that the difference between the clustering of the production order in different builds is very different from the one proposed in the past, when the order was clustered focusing on the number of set-ups minimization. So, in the past the clustering was focused to minimize the completion time, but maximizing the number of objects processed in the single job on the machine, while now the objective is always the same but the number of objects for single build does not have to be the maximum possible respecting the delivery dates, but the maximum that can be hosted in the build camera volume, to optimize the volume saturation of the camera, that it is recognized as a key factor for the AM machines optimization (Fera et al., 2017).

The E&T objective function in the case of AM machine scheduling problem is modified as follows:

$$F(S)_{ET} = \sum_{i=1}^{n_g} (\alpha_S E_i + \beta_S T_i)$$

Where:

α_S:	Earliness constant weight	$[1/day]$
β_S:	Tardiness constant weight	$[1/day]$
E_i:	Earliness of $i - th$ order	$[day]$
T_i:	Tardiness of $i - th$ order	$[day]$
n_g:	number of order/geometries	$[-]$
F_{ET}:	Time part of proposed MOP	$[-]$

α, β are constant weights related to $s - th$ schedule and they are computed as follows:

$$\alpha_S = \frac{1}{max(E_s) - min(E_s)}, \qquad \beta_S = \frac{1}{\max(T_S) - \min(T_S)}$$

The first part of MOP focuses on the balanced reduction of E&T, so we expect a schedule where order completion dates are in a restricted neighbourhood of established due dates.

As before introduced the MOP is also composed by a cost part. (the $\boldsymbol{F_{CP}}$ part). For this cost part we will refer to a cost model specifically developed for the AM, recently appeared in the international literature (Fera et al., 2017).

The information needed to implement the costing model are:

- Unitary Completion time (CT);
- Unitary Part Cost (TPC);
- Schedule configuration as one reported in fig. 6.

TPC model allows computing $i - th$ PN unit cost in whatever build it is located, in the following table they are represented in their typical form.

TPC		Geometries			
		1	2	3	4
Build	1	€ *554,2*	€ -	€ *953,4*	€ 635,1
	2	€ -	€ *1.231,4*	€ -	€ *658,8*
	3	€ -	€ -	€ *1.156,6*	€ -
	4	€ -	€ *1.395,4*	€ -	€ *563,7*

Table 3: Total Production cost per part

Element by element multiplication between the Schedule matrix of the Table 2 and TPC computed following the model in (Fera et al, 2017) and represented in Table 3, provides a third matrix (Table 4), a sort of cost distribution along the schedule.

A same geometry presents different specific cost, depending by production mix of build where it is located. The total order cost (OC) is the cost to produce an order with the clustering in a possible schedule in different builds. This OC is formally defined as follows:

$$OC = [OC_1, OC_2, \dots, OC_{n_g}]$$

S*TPC [€]		Geometries 1	2	3	4
Build	1	€ 3.879,3	€ -	€ 3.813,5	€ 635,1
	2	€ -	€ 8.619,7	€ -	€ 658,8
	3	€ -	€ -	€ 1.156,6	€ -
	4	€ -	€ 1.395,4	€ -	€ 2.254,5
OC(G_i) [€]		€ 3.879,3	€ 10.015,1	€ 4.970,1	€ 3.548,4

Table 4: Production cost per build

OC has n_g elements, as the number of orders. OC_i, instead, is the cost related to manufacture the $i-th$ order with the proposed clustering in a certain number of builds j, the number of the parts realized for each build is represented by the S_{ij}.

$$OC_i = \sum_{j}^{n_b} TPC_{ij}\, S_{ij} \;\; \forall i = 1, n_g$$

In the previous parts of this paragraph the penalties for a delay in delivery were presented; the mathematical formulation of this cost is reported following.

$$C_{Tard,i} = p_i * OC_i * T_i$$

Where:

$C_{Tard,i}$:	Tardiness cost of $i-th$ order	[€]
p_i:	Penalty related to $i-th$ order	$[\%/day]$
OC_i:	Order Cost of $i-th$ geometry	[€]
T_i:	Tardiness $i-th$ order	$[day]$

As it is possible to recognize in the industrial sector the cost of tardiness is proportional to the number of tardiness days. OC_i increases of a quote (p_i) for each day of tardiness.

The sum of OC and tardiness cost for $i-th$ Geometry lead to a value, defined as Total Order Cost (TOC_i), following reported.

$$TOC_i = OC_i + C_{Tard,i}$$

As it is possible to understand from the problem structure, the TOC mathematical formulation is a vector as the one below reported.

$$TOC = [TOC_1, TOC_2, \dots, TOC_{ng}]$$

The TOC is a vector where each element represents the amount of money needed to satisfy overall demand, with the proposed order clustering. It is worth to note that it is possible to compute also a scalar value to represent the economic effort to produce some geometries when a specific scheduling (S) is applied. This unique value is the sum of all the TOCs. This value is obtained summing all the TOCs for all the order/geometries to produce in the specific time frame.

$$C_P\, AM = \sum_{i}^{ng} TOC_i = 39054.18\ [€]$$

To make the cost part able to be summed to the time part it is introduced the C_P factor, this element must be a-dimensional and comparable to the time part. To allow to achieve this objective of summability and comparability, it is proposed an algorithm to find a proper weight for the AM cost. The wished weight must make a-dimensional C_P but also of the same order of magnitude than F_{ET}.

$$F_{ET}(S) \sim o(10)^1 \quad C_P(S) \sim o(10)^4 \; or\; further$$

To gain either goals, as before anticipated, it is presented a small algorithm that will be inside the general optimization procedure. Following the algorithm:

a. Find F_{ET} order of magnitude, indicated as k_1.
b. Compute C_P as sum: $\sum TOC_i$.
c. Find C_P order of magnitude, indicated as k_2.
d. Compute order of magnitude k_x by following equation:

$$10^{k_1} = \frac{10^{k_2}}{10^{k_x}} \rightarrow \ k_x = k_2 - k_1$$

Now can compute weight γ_S:

$$\gamma_S = \frac{1}{10^{(k_2 - k_1)}}$$

Finally, MOP Cost Part has the following weighted formulation:

$$F_{CP} = \sum_{i}^{n_g} \gamma_S TOC_i$$

4.2 The model constraints

Once the objective function was presented let us to present and explain the model constraints.

The first constraint presented in the model in the previous paragraph is the one related to the build chamber volume. When the planner must schedule a DMLS®, one of the first issues to be considered as practical constraint is the chamber volume of the machine. The maximum value available is computed as follows:

$$V_{chamber} = \ L_x * L_y * L_z$$

Where:

L_x	X – axis plate dimension	$[mm]$
L_y	Y – axis plate dimension	$[mm]$
L_z	build chamber height	$[mm]$
$V_{chamber}$	Build chamber volume	$[mm^3]$

Each PN has a proper geometrical volume, evaluable from CAD data; nevertheless, to assembly a build we must increase the PN volume to match some production needs, such as the following two:

- Part orientation: to confer precise mechanical characteristics to a product, the PN has to be built in selected growth directions. To ensure this growth direction, the designer considers support structures that needs for extra – volume.
- Removal space: the planner must consider the necessary space to manual part removal, so the geometries in a build can't be too close one to each other, so this produces another extra – volume.

The planner gets extra – volume required for part orientation and manual removal directly from Designer and add it to PN geometrical volumes. This "global" volume info is simply referred as "volume" for planning operations and saved in the form of a vector such the following one.

$$V = [V_1, V_2, \dots, V_{n_g}]$$

Once the elements of this constraint are presented, let us to present the mathematical formula for the volume constraint.

$$\sum_{i}^{n_g} n_{i,j} * V_i \leq V_{chamber} \ \ \forall \, j \in [1, n_b]$$

Where:

$n_{i,j}$	Number item $i - th$ in $j - th$ build	$[part]$
V_i	Volume of $i - th$ geometry	$[cm^3]$
$V_{chamber}$	Build chamber volume	$[cm^3]$
n_g	Number of order in the build	$[-]$
n_b	Number of build in the schedule	$[-]$

This constraint must to be valid for a single build, but also for each $j - th$ build in the schedule.

After the geometrical volume constraint, it will be presented the production constraint. This constraint requires that the sum of all clustered orders for the $i - th$ PN provides the corresponded $i - th$ demand value in the analysed period. This condition is represented mathematically as follows:

$$\sum_{j=1}^{nb} n_{i,j} == d_i \,, \qquad \forall i = 1, n_g$$

It is worth to note that the values of the variable $n_{i,j}$ can be included in the interval following reported.

$$n_{i,j} \in [0, n_{max}]$$

This set of value has a lower limit always equal to 0 and an upper limit n_{max}, that is continuously updated because it is connected to $i - th$ unit present in build $(j-1) - th$. This condition can be summarized as follows:

$$n_{max} = \begin{cases} \overline{d_i}, & j = 1 \\ \overline{d_i} - \sum_{j=1}^{j-1} n_{i,j} \,, & j > 1 \end{cases}$$

The $\overline{d_i}$ value seems to recall the demand vector values for the $i - th$ order but in this vector there is another element to take in account, that is directly connected to the volume constraint. In fact, it is important to remember that the machine chamber could not accomplish necessarily the total quantity d_i, because the volume constraint is present, so the value of demand assigned to the $j - th$ build will be practice computed using the following formula, that is the product of the two model constraints in practice.

$$\overline{d_i} = \min(d_i, \left\lfloor \frac{V_{chamber}}{V_i} \right\rfloor)$$

Even if the last mathematical representation is the result of the two constraints mixed, it is decided to use the representation of the previous paragraphs with the two separate constraints. This solution can be easier in the implementation of the present method in a real case.

4.3 Computational Complexity

The proposed multi – objective model has two fundamental parts: one for the optimization of the E&T, derived from literature, and another, proposed by the authors for the cost optimization.

E&T weighted form is similar to following formulation:

$$\sum_{j=1}^{n} \alpha E_j + \beta T_j \rightarrow \sum_{j=1}^{n} E_j + T_j$$

In fact, α and β are constant weights and they do not influenced the problem complexity.

The formulation on the right is NP – HARD, as presented in (Wan & Yuan, 2013). So, adding the cost part to E&T formulation, produces an increase of complexity, so it is possible to say that our problem is a NP – HARD computational problem and for this reason a heuristics approach will be developed.

5 SOLVER DESIGN

Since the last part of the previous paragraph stated the NP-HARD complexity, as before said in this paper it will be presented a heuristics method to solve the problem. In particular, because the theme is very new in the scheduling sector, we preferred to apply two very well-known heuristics, i.e. the Genetic Algorithm (GA). Nevertheless, we must do some considerations about GA original configuration, because the AM scheduling presents differences from the traditional single machine scheduling problem. In fact, as we will present, these techniques are good to manipulate schedule as vector shape; in AMSP there is a matrix, so it is needed to update the cited algorithms to work with them on our proposed structure.

Starting from this traditional approach in this paper it is proposed a modified version of the Genetic Algorithm (PGA). Starting from an initial population where N_p is the number of random schedules. Index k goes from 1 to N_p, number of members in the initial configuration. The proposed GA mixes initial population order to favourite diversification; later, parents k - th and $k + 1 - th$ (P_1, P_2) intersect and produce two children (C1, C2). Now, there is a set of 4 schedules represented by $PC = \{P_1, P_2, C_1, C_2\}$ where PGA selects two schedules with the best OF value and replaces P_1 and P_2.

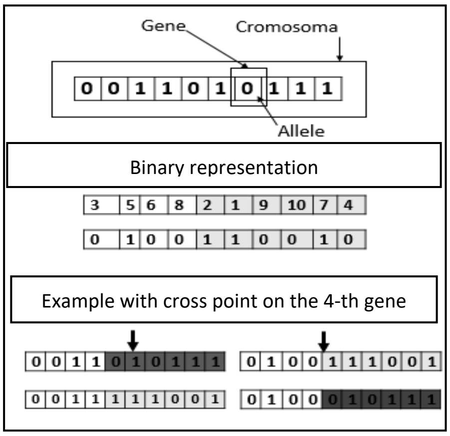
In the above set PC, better schedules could be anyone of the possible choices available in the set. For instance, the typical elements of the GA are represented in figure 4.

Generally to mix the parents genes, it is applied a crossover operator, go on until the counter k respects the relation $k < N_p$, i.e. when a new generation is fully completed. The overall termination criterion for all algorithm is generally the standard deviation $\sigma(F_s)$ of the OF over entire population. When the $\sigma(F_s)$ is less than an imposed tolerance (10^{-6}) the algorithm terminates, because all members are the same (similar).

Nevertheless, there is an emergency termination criterion about maximum no – improvement iteration number, because sometimes convergence condition requires too much time to be gained.

To let the reader to better understand what will be proposed in this paper, it is reported briefly what are the traditional crossover operators applied to the GA (Figure 4). The core of GA is the so-called crossover mechanism that turns two parents in the same number of child. In a single machine traditional scheduling problem there is a sequence of job that represents a chromosome; instead, each job is a gene. Two feasible solutions are two chromosomes that must be intersected, by different crossover; some of them are:

- Fixed cross – point;
- Random cross – point;
- Double cross – point;



The above cross – points are well suited to operate on a job sequence as a vector form, i.e. a 1 – dimensional structure. In single machine AM scheduling problem there is a matrix so we must propose some changes.

As before anticipated an AM problem present a 2 – D structure and this suggests a 2 – D Crossover (2DC) mechanism. The proposed 2DC provides a double intersection and operates as follows. At first, it considers orders as the genes and generate a random number called $i \, \epsilon [1, n_g - 1]$. Random number i is the column where cut schedule; this lead to two group of chromosomes. In the following example of Table 5, $i = 2$. The first intersection is an exchange of the same colour (green and blue) columns.

Once realized first intersection, there is the generation of a second random number $j \, \epsilon [1, n_b - 1]$. Random number j represents the row where cut schedule; this lead to two group of chromosomes. In the following example of Table 6, $j = 3$. Thus, the second intersection is an exchange of the same colour rows (green, red, blue orange).

As it is possible to see, the bi – dimensional form of the problem has also connections and consequences on the resolution techniques too.

7	0	4	1	1
0	7	0	1	1
0	0	1	0	2
0	1	0	4	1

7	8	1	5	4
0	0	1	1	0
0	0	0	0	1
0	0	3	0	0

7	8	4	1	1
0	0	0	1	1
0	0	1	0	2
0	0	0	4	1

F_S=7,64

7	0	1	5	4
0	7	1	1	0
0	0	0	0	1
0	1	3	0	0

F_S=7,41

Table 5: Horizontal Intersection of 2D - Crossover

7	8	4	1	1
0	0	0	1	1
0	0	1	0	2
0	0	0	4	1

7	0	1	5	4
0	7	1	1	0
0	0	0	0	1
0	1	3	0	0

0	1	3	0	0
7	0	1	5	4
0	7	1	1	0
0	0	0	0	1

F_S=6,72

0	0	0	4	1
7	8	4	1	1
0	0	0	1	1
0	0	1	0	2

F_S=7,80

Table 6: Vertical Intersection of 2D - Crossover

6 Test Case

In this section, the model proposed is tested through a test case. This experiment is useful to stress the model and the proposed solving algorithms performances. The test case proposed covers the situation usually most critic for the conventional manufacturing production systems, i.e. a production composed by different orders with the following characteristics: low volume, high geometrical variability, so enormous difficulty to gain EPQ.

First, from this experiment it is expected that starting from one or a family of feasible solutions, PGA is able to optimize them, reducing OF value. This experimental result will ensure, at least, the computational effectiveness of proposed techniques.

In a second step of the experiment, it will be discussed the algorithms efficiency, looking in particular to:

- due dates respect that will be measured from the traditional service level index;
- costs reduction that will be measured in percentage of the basic value;
- running time that will be measured in seconds.

6.1 Test case Data Set

Test case data are shown in table 7. There are 30 PNs, highly different in form and dimension, but with low production volume, between 5 and 10 units. Production Orders for AM department covers six months, so the due dates go from 60th to 180th day. AM machine is a DMLS® and presents a build chamber volume of: $V_{max} = 13437.50\ cm^3$.

The experiments have been performed with a laptop equipped with *Intel Core i7® - 4700MQ*, *CPU* of $2.40GHz$, 16 GB of *RAM*. All algorithms are coded in *Matlab® 7 R2015a.*

PN [#]	DD [*day*]	D [*pieces*]	V [cm^3]	h [*mm*]	ρ [g/cm^3]	T_{prep} [*hours*]	Penalty [*%/day*]	s_{max} [cm^2]
1	120	7	146	50,55	8	1	1	82,1
2	60	5	52,87	85	8	1	2	120
3	180	10	108,9	62,5	8	1	2	344,22
4	120	7	64,17	37,73	8	1	1,5	21
5	120	5	200,8	183,4	8	0,5	3	208,08
6	90	5	66,94	56,02	8	1	1,5	178,72
7	120	5	90,15	95	8	0,5	2	57,04
8	120	8	188,2	162,5	8	1	2	104,56
9	150	9	33,65	32,29	8	1	1,5	97,12
10	180	9	290,2	186,6	8	1	1,5	112,28
11	60	5	62	150	8	0,5	1	176,715
12	180	10	6	73	8	1	2	41,8539
13	180	10	9	65	8	0,4	1	33,1831
14	90	8	56	115	8	0,6	2	103,869
15	120	5	17	100	8	0,4	1	213,825
16	150	8	44	165	8	0,4	3	78,5389
17	120	7	4,87	100	8	0,1	1	3,14159
18	60	5	2,9	22	8	0,2	1	38,4845
19	180	10	112	70	8	0,4	1	116,899
20	90	5	150	122	8	0,4	2	201,062
21	150	8	375	160	8	0,7	1	4,90874
22	60	5	17,5	25	8	0,1	1	28,2743
23	90	6	36	60	8	0,2	1	12,5664
24	120	7	13,4	40	8	0,2	1	10,1788
25	90	5	22,6	36	8	0,3	2	9,62113
26	120	7	7	35	8	0,4	2	12,5664
27	60	4	11	40	8	0,4	1	10,1786
28	90	5	4	45	8	0,4	2	9,62113
29	120	7	15	50	8	0,4	2	19,635
30	180	10	0,569	20	8	0,4	2	3,14159

Table 7: Test case data

6.2 Initial Solution Algorithm (ISA)

As it is cited in Section 4 the production orders are the only information required for the implementation of the model. AM schedule to satisfy the demand is a matrix with a fixed columns number, but a variable number of rows (builds).

This is due to order clustering principle. A first feasible solution is needed and this solution is developed by a third algorithm, named ISA, to gain an Initial Random Schedule, as shown in table 8.

ISA algorithm can produce one or a family of N feasible solutions.

S [#]	F_{ET} [-]	F_{COST} [-]	F_S [-]	N BUILD [#]	C_P [k€]	L_S [%]	$C_{tardiness}$ [k€]
1	11,44	17,52	28,96	9	175,20	43,33	36,31
2	12,62	17,20	29,82	7	172,00	43,33	33,12
3	14,30	17,64	31,94	10	176,39	40,00	35,04
4	13,78	17,69	31,47	7	176,92	30,00	39,89
5	11,41	16,10	27,50	10	160,98	46,67	19,36
6	12,36	16,68	29,04	9	166,79	50,00	27,61
7	11,75	17,02	28,77	9	170,18	43,33	28,84
8	15,25	16,36	31,61	8	163,59	40,00	24,51
9	10,63	16,53	27,16	8	165,30	46,67	26,82
10	14,66	17,80	32,45	8	177,96	30,00	39,51

Table 8: set of 10 possible Initial feasible solutions

Moreover, as input there is a parameter $0 < k \leq 1$ capable to modify maximum chamber volume:

$$V_{available} = k * V_{max}$$

This parameter alters the volume filling, contributing to expand feasible solution region and so metaheuristics searching domain. This simple algorithm generates a first random vector of integers, by *randi() Matlab®* function; after the algorithm verifies production and volume constraints. If the build is feasible and partially empty, an *Optimization Module* starts to fill it with the PNs with sooner due date. The random build generation, as well as k parameter, contribute to diversification of solutions. The initial feasible population is shown in table 8.

6.3 The PGA implementation and results

The PGA works with a random point 2-D Crossover (as before described), so it is normal to observe different results after different trials, as reported by Table 9.

		Run [#]				
		1	2	3	4	5
OF	[-]	6.60	6.05	7.92	7.60	7.42
CP	[k€]	153.12	149.02	157.73	155.24	156.71
LS	[%]	56.67	60.00	56.67	66.67	71.43
It	[#]	1126	1119	524	1122	1122

Table 9 Proposed Genetic Algorithm Results

Generally, PGA gives good solutions, with sensible reduction of OF. Iteration number are superior than 1000 in all cases, less than in #3 ($it = 524$) that presents also the worst result among trials. Table 1 explains the details of case #2, the best result among the five trials performed.

As it is possible to see from table 4, the OF improvement is far than 77% while the cost of production decreases of 9.85% and the LS increases of 28.57%.

		Initial	**Final**	**Δ [%]**
OF	**[-]**	27.16	6.05	-77.72
CP	**[k€]**	165.30	149.02	-9.85
LS	**[%]**	46.67	60.00	28.57

Table 1: Results of Genetic Algorithm

7 Conclusions and discussion of the results

In this paper it was faced a new research theme related to the operations management optimization using a single machine with the AM technology. In particular, it was stated the mathematical problem as a multi-objective function based on the balancing of the optimization of earliness/tardiness and production costs (considering in these also the penalties for delayed orders). This multi-objective function was constrained with two main constraints, one for the geometrical volume of the printing chamber and one for the respect of the due dates.

Built the mathematical model (that is a NP-HARD problem) in this work it was presented a traditional heuristic, modified to respect the AM technological characteristics, i.e. the genetic algorithms.

This algorithm was applied to a test case built for the occasion, which simulates the case in which a traditional manufacturing production system receive orders that generally make difficulties in the respect of the demand, i.e. orders characterized by low volumes and high geometrical variability between the PNs to be realized.

The heuristics was applied and the optimized results from the first initial solution that was produced using a simple algorithm illustrated before and named ISA.

At the end of this paper so it is possible to say that the single machine problem using the AM technology can be faced using a heuristic such as the PGA, that was modified for the occasion having very good results in terms of operations and in a very good calculation running time.

In fact, as it is possible to see that PGA has good performances on all the three evaluation parameters, i.e. the value of the objective function, the value of production costs and the service level percentage and also about the calculation time. Next steps of the present work will be to compare the heuristics here presented with others such as the tabu search or the particle swarm optimization.

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