A New Perspective for Production Process Analysis using Additive Manufacturing – Complexity vs Production Volume

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Abstract:

Since the early days of industrial manufacturing, decisions like the analysis of economic or financial break even, the determination of optimal production level and similar problems were taken using the number of parts as the main decision driver. While in the last years the manufacturing community was simply observing the evolutions of the additive manufacturing (AM) technology, nowadays it is changing its perspective to be a player of this revolution. Since AM has become feasible and applicable to the industrial manufacturing, as reported in (Fera, et al., 2016) and (Costabile, et al., 2017), the industrial world is now calling for innovative methods for the integration of this new technology operations management in traditional production systems. The aim of this paper is to present a novel approach to classify and analyse the production of specific products using AM or subtractive manufacturing (SM), using complexity as a decision driver and not the number of products to manufacture. The effectiveness of the method is tested on a data set built for this scope.

Key-words: Additive Manufacturing, Productions Systems Operations Management, Technology Selection

1. Introduction

The industrial world is paying an increasing attention to additive manufacturing (AM), one of the key enabling technologies which could help in pushing industrial manufacturing systems in the revolutionary direction of mass customization (Liu, et al., 2015) (Mourtzis, et al., 2015). AM was discussed and analysed in the international literature since the mid-1990s (Sachs, et al., 1993) using a study by a research group of the Massachusetts Institute of Technology (MIT). After its birth, AM has been investigated as a new technology capable of producing goods directly and autonomously. The first AM productions used polymer powders; this was mainly due to the machines' technology (Kruth, et al., 1998) (Kim & Shahinpoor, 2002) (Levy, et al., 2003). In the last years this new technology deserved a great attention in the bio-manufacturing sector while the possibility to use it in other industry sectors was considered worthy of further feasibility analysis and investigations (Feldman & Ronzio, 2001) (Yan, et al., 2003) (Lysaght & Hazlehurst, 2004) (Sun, et al., 2005). More recently, 3D printing (also known as AM) was introduced into the world of metal products. The increasing application of AM both in real cases and in technological laboratories has pointed out opportunities and criticalities. In recent years, AM has been employed in some first pilot production systems for the aerospace and aeronautic sector in application laboratories in collaboration with MIT (La Monica, 2013) (Duerden, 2011). Typical productions in these fields focus on items characterised by small production volumes. Industries, often with the support of universities and research centers, are trying to understand the applicability of this new technology to replace, or at least integrate, their traditional production systems, since they perceive an opportunity with AM to optimize and integrate their design, engineering, production and logistic processes.

This paper aims to present a new method for the evaluation and selection of the best technology, i.e., AM or SM, for the production of a specific item. Such method, instead of using production volume as the key driver to determine production cost, focuses on the complexity of the item to manufacture. This idea is supported from the very well known sentence: "with AM, complexity is for free"; its meaning implies a paradigm change also in the production cost determination process, i.e., to switch from the production volumes driver to the complexity driver.

To achieve this goal the first part of this paper discusses the complexity issues and possible metrics to measure complexity itself, as present in scientific literature; after that, a new complexity index is presented and it is associated with the manufacturing cost; such association is introduced to present a new analysis framework used to prove the possibility to use complexity as a cost driver for production decisions. Finally, a validation of the results is executed using neural networks.

2. Literature review

In conventional manufacturing systems (subtractive, formative and joining processes) engineers and designers make use of Design For Manufacturing and Assembly (DFMA) methods. In this context, complexity is a problem since shape or any other type of complexity imply an increase of machining steps, more tool paths and/or expensive custom tooling (Conner, et al., 2014), thus designers aim to avoid it. Also (Gibson, et al., 2014) discussed about AM and its capabilities in comparison with other traditional manufacturing processes. As stated by Edmonds, 1995, complexity covers a multitude of aspects (Edmonds, 1995). Several authors recognize that in conventional manufacturing there's a direct link between production costs and shape complexity (Hague, et al., 2003); such link is not generally described mathematically but is usually modelled as a black-box. On the other hand, AM is recognized to allow the production of parts of any complexity with no need for additional tooling (Hague, et al., 2004) and with no production costs increase (Lindemann, et al., 2012). (Merkt, et al., 2012) suggested that the formula 'complexity-for-free' could also improve product performance at the same cost. So, since the introduction of AM technology, it appeared quite clear that this technology could represent a disruptive innovation for the production of any kind of item with any kind of complexity especially when shape, geometric and feature complexity are concerned. Accordingly to Rosen (Rosen, 2007), to this extent it's possible to define two main capabilities of AM:

- Shape complexity: any kind of shape is producible, only one part production is feasible (no cost adding) and the customization is an easy task which enables shape optimization.
- Material complexity: the material can be differentiated in any part of the item, point by point, layer by layer and so on, enabling the production of parts with different complex material compositions.

Several works about the measurement of complexity were published over the last years. As clear from the literature analysed so far, complexity is one of the key factor for AM, therefore it is useful to report some relevant contributions in this topic.

The ways to calculate and evaluate complexity are many; in the following the most interesting ones for our purpose will be briefly discussed. Valentan et al. used the number of triangles contained in 3D drawing (STL file) as the shape complexity index of a part (Valentan, et al., 2008). However "the utility of such measure is limited, given that the mesh density can be varied by processing software or user input" (Conner, et al., 2014). Joshi and Ravi in 2010 have defined a shape complexity factor using geometric information of the part; they defined five criteria based on number of cores, volume ratio, area ratio, thickness ratio and depth ratio, weighting these five criteria using a regression analysis on 40 industrial parts (Joshi & Ravi, 2010). Psarra and Grajewski in 2001 have defined, for 2D shapes, the degree of convexity of the perimeter as the index of complexity of a shape; they defined an index named Mean Connectivity Value (MCV) as the "percentage of locations that are connected to without crossing a boundary or falling outside the area of the shape"; this index was used to measure the complexity of floor plans of buildings (Psarra & Grajewski, 2001). In more recent years, Baumers et al. have noted that, for layer-by-layer processes, it's possible to transfer the Psarra and

Grajewski approach to 3D solid object geometry because, in AM processes, "a continuous 3D solid is split in a sequence of 2D layers" (Baumers, et al., 2016). They calculated the MCV for each layer and studied the correlation between its shape complexity and energy consumption for Electron Beam Melting. The finding is that for the AM such a correlation is not significant, thus confirming that for AM the complexity is for free, while there is a direct link between the layer area and the overall energy consumption.

As noted before, measuring complexity relates not only to product design issues, thus giving indications about an item's producibility, but also to production decisions. For example, Conner et al., 2014 have defined a decision support system based on complexity, customization and production volume to facilitate product development decisions (Conner, et al., 2014). They suggested that the complexity of an item depends on the number of features it contains, and by their location and geometry. Their approach replicated the one used by Joshi and Ravi, in 2010, but they reduced the number of criteria used.

From what discussed so far, AM plays a fundamental role in the industrial context in terms of development and realization of items with any grade of complexity, giving the possibility to overcome limitations of traditional manufacturing systems. In fact, the existence of such limitations was outlined by many authors trying to figure out methods to determine the right level of complexity in the design of the new parts.

Normally, for typical items already in production and thus, with standard complexities, the fixed costs of AM manufacturing systems are higher than the ones of traditional systems, and, given the standard production volumes, the AM unit variable costs are not able to make AM affordable or more convenient than traditional SM systems (Costabile, et al., 2017) (Fera, et al., 2016) (Lindemann, et al., 2012) (Piller, et al., 2015) (Baumers, et al., 2016) (Piili, et al., 2015). A choice between AM and SM implies a deep analysis of the production cost of an item having no limits in complexity (Fera, et al., 2017). Having dropped the complexity constraints which are usually present in SM systems, in fact, allows for a complete re-design of items for AM and, thus, the possibility to achieve considerably reduced variable unit costs.

So, the main goal of this paper is to demonstrate that it's possible to use the complexity of a part instead of its production volume as a decision driver for manufacturing technology selection.

3. The Research Method

To achieve the goal mentioned so far, i.e., using the complexity of the part as a decision driver for manufacturing technology selection instead of its production volume, the following tasks need to be developed:

- create a new method to measure complexity;
- calculate all the costs to manufacture a part using AM and SM;
- for the geometries considered, analyse data obtained from the complexity index and the manufacturing costs to find a correlation useful for the identification of an economical convenience frontier between traditional and advanced production methods.

All these steps are reported in the following figure.

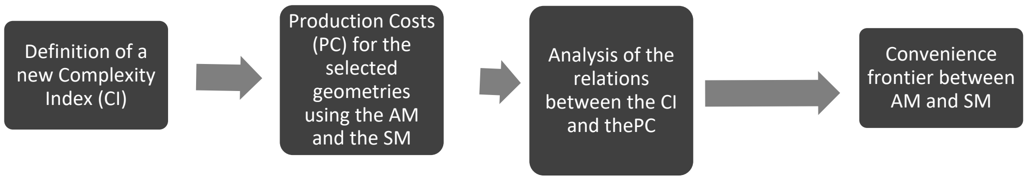

Figure 1: Research method proposed

3.1 The Complexity Index

As already mentioned, in this paper the complexity concept is used to define a new production management paradigm, useful to analyse Additive Manufacturing production technology. As often said, for AM complexity is for free. But what does this actually mean for production engineers? Is there any scientific evidence of a direct increasing relation between the complexity and the manufacturing cost using SM? How does this "free cost" become a decision key for the choice between these two different manufacturing technologies (i.e., AM and SM) ? Nowadays, all these questions are open and far from a solution. One aim of this paper is also to present a first attempt to give answers to them.

Thus, before starting to present a framework useful to demonstrate the possibility to evaluate production costs differently, let’s introduce a new index able to consider the several aspects of industrial items complexity; as it is well known, in manufacturing systems it’s possible to say that complexity can be referred to three elements:

1. Shape Complexity;
2. Variety and Entropy of information;

3. Operational Complexity.

In the following parts of this section the methods for the evaluation of these three components of complexity, as reported in the literature, are discussed in more detail than what done in the previous literature review section that, thus, finds here an extension. The reason is simply that the detailed and critical analysis of the methods in the literature allows us to immediately describe a new method for the measurement of complexity that we are proposing in this paper.

3.1.1 Shape Complexity

In the international literature, as already seen before, many sources are available to measure complexity in its different meanings, so it is important to bound the problem through some initial assumptions:

1. only aspects related to the difficulty to produce a particular object will be taken into account;
2. only metal objects manufacturing will be considered;
3. aspects related to the organization, production environment and supply chain will be not taken into account.

The first method studied and used to model the shape complexity is the one by Psarra and Grajewski (Psarra & Grajewski, 2001) that is a 2D complexity analysis model.

They discussed the measurement of complexity limiting their investigations to two-dimensional geometric shapes defined in terms of edges, corners and solid lines perimeter. They define the degree of convexity of the perimeter shape as being inversely proportional to the shape complexity. The complete convexity is the property by which a line connecting any two point of the perimeter respects two simple rules:

1. the line connecting any two points doesn't cross the perimeter;
2. the line connecting any two points doesn't pass outside the area enclosed by the perimeter.

The concept of "visibility" of a point can be inferred starting from this definition: in a convex shape all points on the perimeter can be seen from any position without crossing the perimeter itself.

The numerical approach to the problem involves the implementation of the following different phases:

1. The area delimited by the perimeter is divided in elementary cells named voxels;
2. For each voxel its relative value of connectivity is calculated as the ratio between the number of cells connected to the voxel examined and the total number of the voxels;
3. Mean Connectivity Value (MCV) is calculated as the average of all connectivity values of voxels.

This method, developed for the architectural study of buildings' complexity, was also used by Baumers who tried to apply it also to the additive technologies for the production of items layer-by-layer (Baumers, 2012) (Baumers, et al., 2016).

Baumers initially assumed, similarly to what happens for subtractive technologies, the existence of a relationship between energy consumption and item complexity. This relationship was investigated calculating the Pearson correlation indexes between energy consumption and three main shape complexity parameters, i.e. the area of maximum section, the perimeter of the maximum section and the MCV (Mean Complexity Value). The results revealed a strong correlation of energy consumption with the area of the section, a moderate correlation with the perimeter and a weak correlation with the MCV. Thus, his results demonstrated that energy consumption is not related to shape complexity and that it's possible to state, once again, that for the AM cost is not a function of complexity.

The convexity index proposed by Psarra and Grajewski and applied by Baumers to AM was however, unfortunately, defined in 2D. An extension of this definition to the 3D case can be found in a paper published in 2012 by Lian et al. that proposed a new way to measure complexity of 3D meshes (Lian, et al., 2012). In this paper it's possible to find two different definitions of convexity indexes used to measure complexity; the first is connected to a probabilistic concept and the second to a ratio between volumes, i.e., the part volume (Volume (M)) and the envelope convex volume (Volume (CH(M)); for the purpose of this paper the second approach will be used. The equation of this index is reported in the following (1).

$$C(M) = \frac{Volume\ (M)}{Volume\ (CH(M))} \qquad (1)$$

3.1.2 Variety and Entropy of information

As far as entropy and information variety are concerned, these two complexity elements will be analyzed using the method proposed by El Maraghy and Urbanic (El Maraghi & Urbanic, 2003). The hypotheses of the authors are two and are connected to the variation of complexity:

- complexity varies with the number and diversity of features that must be manufactured, assembled and tested;
- complexity varies with the number, type, and effort needed for the realization of an activity to produce the feature.

The model proposed by the authors to compute and measure complexity is based on the combination of the three elements reported in the following figure.

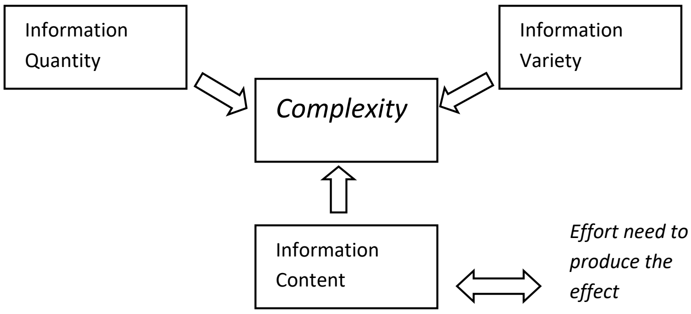

Figure 2: the El Maraghi & Urbanic model

Starting from this theoretical framework, the authors defined a new complexity index based on the elements represented in figure 2. The index is reported in equation (2).

$$CI_{product} = \left(D_{R,product} + c_{j,product}\right) \cdot H_{product} \qquad (2)$$

where:

- $CI_{product}$ is the complexity index;
- $D_{R,product}$ is the diversity index calculated as the ratio between the number of types of information and their total number;
- $c_{j,product}$ is the complexity coefficient of fabrication for the specific product, calculated as the mean of the efforts needed to realize all the specific features present in the product, once that a subjective effort scale has been defined;
- $H_{product}$ is the entropy of information, defined as the base-2 logarithm of the total number of information plus 1.

It is clear from equation (2) that the complexity coefficient is affected by the subjectivity of the experts called to assess the needed effort.

A different perspective from the one by El Maraghi & Urbanic is given by the theory of Cimatti that propose a modification of the previous formulation to reduce subjectivity

(Cimatti, 2009). This is discussed in the next paragraph as it relates, more strictly, to operational complexity.

3.1.3 Operational Complexity

The modification proposed in (Cimatti, 2009) consists of the introduction of 9 quantitative factors related to the specific firm's process and technology. However, this kind of solution still suffers from the fact that it makes reference to a specific firm and thus it’s not able to give a general complexity judgement on a specific product that would be equal for any firm. Moreover it’s worth to note that the model will violate the third initial assumption of the complexity analysis introduced in this paper, i.e., the one related to the organization issues.

3.1.4 Proposal of a new complexity index

As it is quite clear from the previous models presentation, no one covers all the possible issues related to the definition of complexity, so hereafter we present a new complexity index obtained merging the previous models with the aim to overcome their limitations. Equation (3) reports its formulation that takes into account:

(i) the convexity index defined by Psarra & Grajewski as modified for 3D shapes by Lian,

(ii) the information variety and the information entropy proposed by El Maraghi & Urbanic and

(iii) a new operational complexity index that overcomes the subjectivity of $c_{j,product}$ as defined in El Maraghi & Urbanic and its reference to specific firm characteristics as occurring in the Cimatti model.

$$PC = \frac{1}{30} \cdot [IV + (1 - CI) + OC] \cdot H \qquad (3)$$

where:

- IV is the information variety as defined by El Maraghi & Urbanic, calculated as $\frac{n}{N'}$, where *n* is the number of types of information and *N'* is the total number of information present;
- CI is the convexity index as defined in (1);
- H is the information entropy of the product analysed, calculated as $\log_2(N+1)$, where N is the total number of information and is limited to 1000 to limit the value of H between 0 and 10;

- OC is the operational complexity defined as the average of the following five measurable indexes, defined on the product characteristics:
    1. $D = \frac{number\ of\ operations}{maximum\ number\ of\ operations\ executable}$
    2. $E = \left(1 - \frac{1}{number\ of\ tools\ needed}\right)$
    3. $F = \left(1 - \frac{1}{number\ of\ axis\ needed}\right)$
    4. $G = \frac{number\ of\ controls\ needed}{maximum\ number\ of\ controls\ executable}$
    5. $H = \frac{machining\ time\ needed}{maximum\ machining\ time\ for\ the\ products\ in\ portfolio}$

In (3) the elements in the square brackets can give a maximum value of 3, H can give a maximum value of 10. So, dividing H by 30, it is possible to have an index PC included between 0 and 1 and capable to measure complexity as a function of the number of information to be managed, the difficulty of realization and the convexity of the product. Moreover, as it is possible to see from the previous definitions, the index components are independent from the specific firm: to this aim also the first, the fourth and fifth elements of OC have to be calculated with reference to firms which have comparable SM manufacturing technologies.

To test the effectiveness of the equation (3), 20 products were selected, 10 belonging to a "simple" product family and 10 belonging to a "complex" product family, as it could be widely recognized by any practitioner. Equation (3) was applied to understand if it’s possible to calculate all elements of the equation. The model was applied to all geometries analysed and the results confirmed the general feeling about their complexity, in that what was thought as simple was confirmed as such and what was thought as complex resulted in a higher value of the PC index and was thus categorized as complex.

3.2 Production costs for AM and SM

In this section we will introduce the method used to calculate production costs using AM and SM.

For both production technologies an activity based costing method was selected to determine fabrication costs. Thus, following the structure of costs accounting for AM and SM are shown. Figure 3 reports main activities related to the fabrication of an item in both technologies.

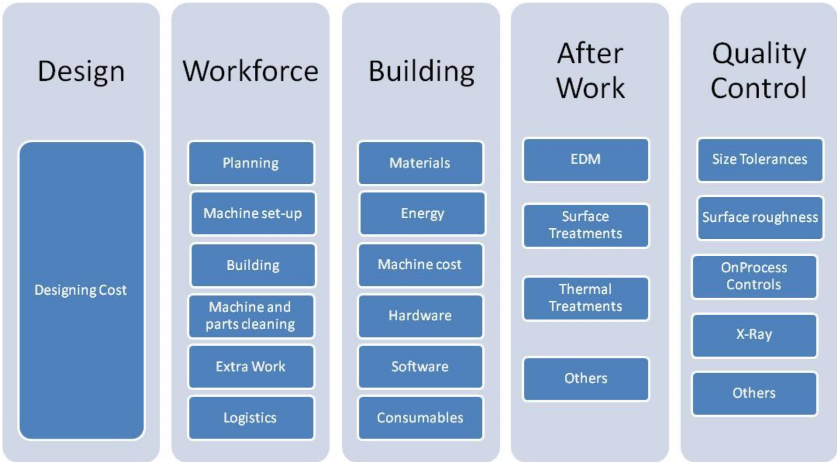

Figure 3: AM activity based costing framework

The formulation of the cost functions for each item included in Figure 3 is a traditional one, for both technologies, in that it can be always expressed as a function of the quantity, as reported in (4).

$$C_{item} = c_u \cdot Q \qquad (4)$$

So, reporting the complete formulation here would add no important information to this discussion. Details, however, of a cost model can be found in (Fera, et al., 2017).

The important aspect to underline is that AM and SM technologies, for all the reasons introduced so far, are different in terms of kind of products/items that can be manufactured in a production run (or, a "build"), i.e., for the SM in a single production run only one product is manufactured at the time, while for AM several items can be produced at the same time because the machine building space can be loaded with several items and/or types of item (see Figure 4).

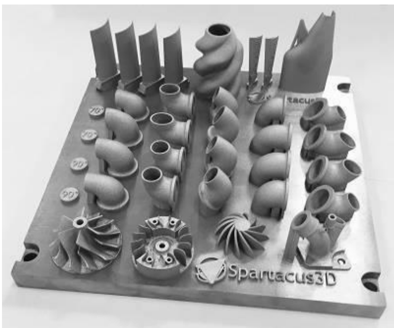

Figure 4: example of build loading for AM machine

This leads to understand that the difference between the two technologies is not in costs formulation but rather in their allocation. For instance, using (4) the energy cost can be simply determined as the product of the energy consumption in a run by the energy unit cost. But, in SM such energy cost would be a direct cost simply related to the amount of energy needed to manufacture that item, while in AM, if different products can be produced in a "build", it's an indirect cost and the energy cost of each item is determined starting from the total energy cost of that "build" divided among all items produced in the "build", using in example a cost driver related to the items volume.

3.3 The analysis framework

As clear from previous paragraphs, this paper is focused on the complexity index as the prime parameter to measure the effectiveness of the decision to adopt AM technology instead of SM to produce a certain item; as already stated, this cost driven decision model, based on complexity, reverses the approach of the traditional ones in which the break-even point is based on production volume.

In other words, if production volume is the main decision driver in traditional SM cost analysis, using the same paradigm to analyse AM could be misleading, because its main characteristics is to break the constraints related to item complexity, whose increase doesn't affect the total product cost.

So, this paper aims to find an empirical evidence of the existence of a separation frontier between AM and SM, when the costs of these two technologies are parameterized to complexity instead of production volumes.

The framework of the method, used to empirically see a graphical proof of the existence of the frontier, is reported in the following figure 5. This approach recognizes that it's not possible so far to find an analytical form of the function between complexity and production cost while the corresponding relation is determined simply empirically.

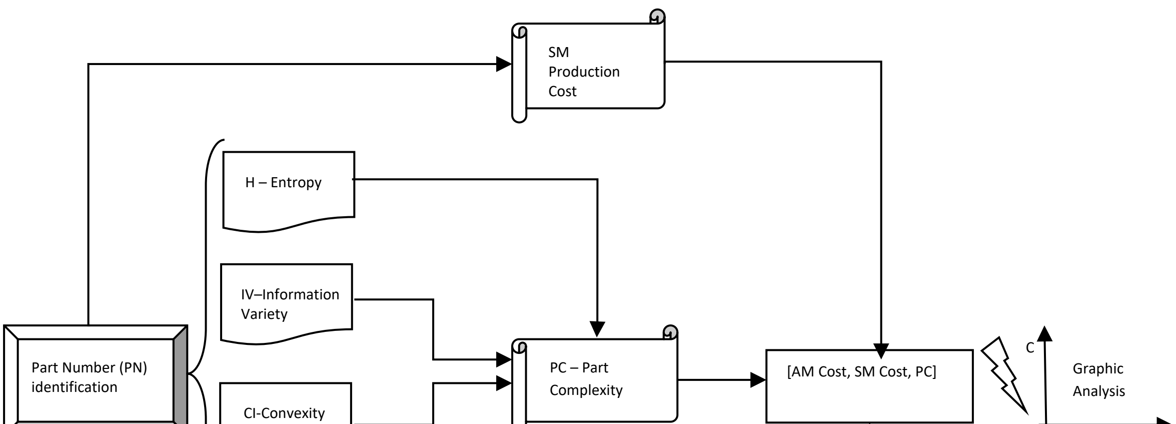

Figure 5: decision model framework

Some hypotheses have to be made:

- General hypotheses:
  - for all parts considered it's possible to compute the complexity index elements;
  - all the information needed to build (in case of AM) or to produce (in case of SM) a part are available.
- AM hypotheses:
  - the assignment of items to a build is random;
  - production cost is not influenced by the different heights of parts in a build;
  - the main factors influencing AM production cost are the volume (geometric volume) of the parts to be built and the build volume printing rate.
- SM hypotheses:
  - the main factors influencing SM production cost are the volume (geometric volume) of raw material and the material removal rate.

As clear from figure 5, once an item is identified, it is possible to calculate the complexity sub-indexes and, through the application of equation (3), the part complexity itself; in parallel, using the general cost framework reported in figure 3, production costs for the production of the identified part with AM and SM are computed; once these three elements are calculated for all the items a matrix [3xn] is built, where for each item the complexity index, the production cost using AM and using SM are reported. Finally, parts are increasingly ordered on the base of the complexity index, and then they are plotted on a graphic, where on the x-axis there are the items (previously ordered in terms of complexity) and on the y-axis there are the production costs for both technologies. So, to better understand the way in which the relation between the complexity and the costs will be represented, Figure 6 reports its expected results.

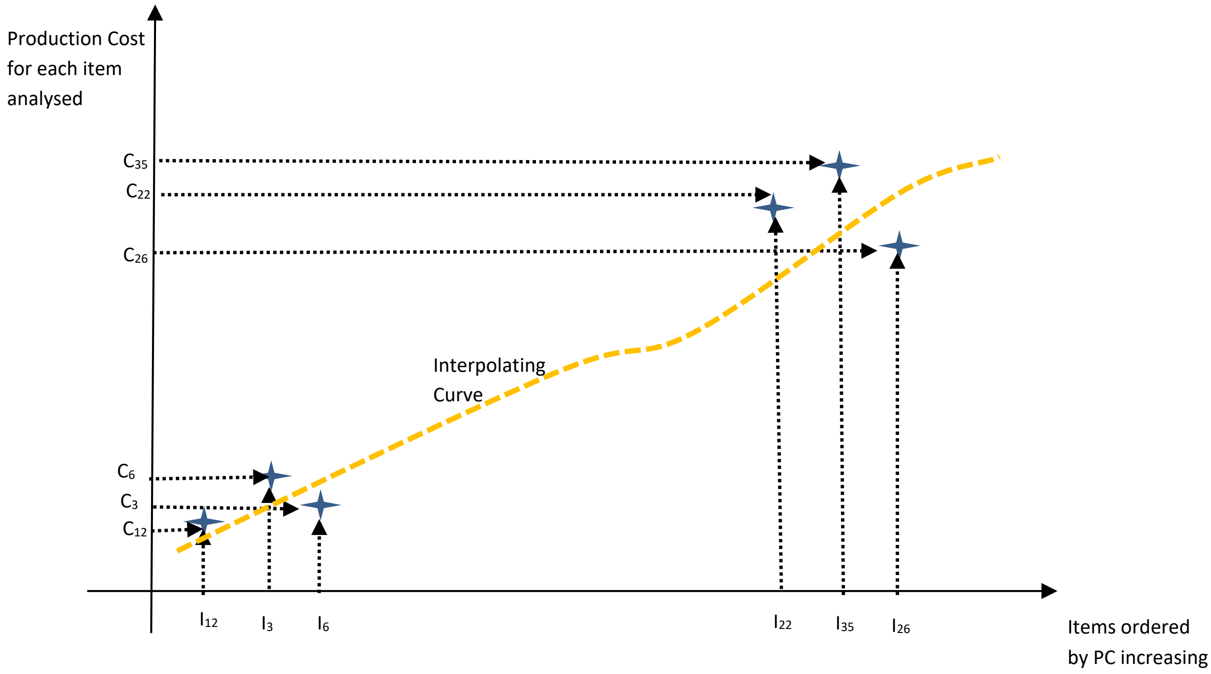

Figure 6: The expected result of the investigation

4 The application of the analysis model

To demonstrate the effectiveness and applicability of the complexity index and to apply the framework reported in figure 5 to obtain a diagram where production costs are related to complexity, a data set built as follows was created:

- the complexity sub-indexes variables and the production costs (AM and SM) were calculated for 40 items, divided in two sub-sets, the first constituted by parts easily producible using SM and a second one constituted by parts producible only with AM;
- the existence of additional 60 items was assumed, with an complexity intermediate between the two sets defined so far;
- the data about their complexity sub-indexes were interpolated at the best, using different interpolation functions; thanks to the interpolation it was possible to create a 100 parts data set, for which it was also possible to interpolate the costs of production.

Examples of the parts belonging to the first and second sub-set are reported in figure 7 and 8.

Figure 7: SM part producible

Figure 8: AM part producible

In the following figure 9 the values and the interpolating functions of the four sub-indexes for the 40 parts used for this experiment are reported.

So, as it is possible to see from the previous figure 9, the parts chosen for the experiment are various and consistent to create good interpolation curves, that were individuated using MATLAB© to maximize the R^2 index with 95% of confidence bounds. For each index, in the following parts of this section, the interpolation curves are reported.

$$IV_{fit} = 3.077 \cdot 10^{-10} x^5 - 7.62 \cdot 10^{-8} \cdot x^4 + 6.699 \cdot 10^{-6} \cdot x^3 - 0.000203 \cdot x^2 + 0.002336 \cdot x + 0.3484 \quad (5)$$

$$CI_{fit} = 0.338 \cdot e^{-0.1223 \cdot x} + 0.3508 \cdot e^{-0.001736 \cdot x} \quad (6)$$

$$OC_{fit} = -1.09 \cdot 10^{-8} \cdot x^4 + 1.329 \cdot 10^{-6} \cdot x^3 + 3.844 \cdot 10^{-7} \cdot x^2 + 0.002873 \cdot x + 0.3207 \quad (7)$$

$$H_{fit} = 5.31 \cdot 10^{-9} \cdot x^4 - 1.623 \cdot 10^{-6} \cdot x^3 + 0.0001357 \cdot x^2 + 0.001641 \cdot x + 0.4173 \quad (8)$$

From these equations (from (5) to (8)) it could be possible for anyone to replicate the experiment.

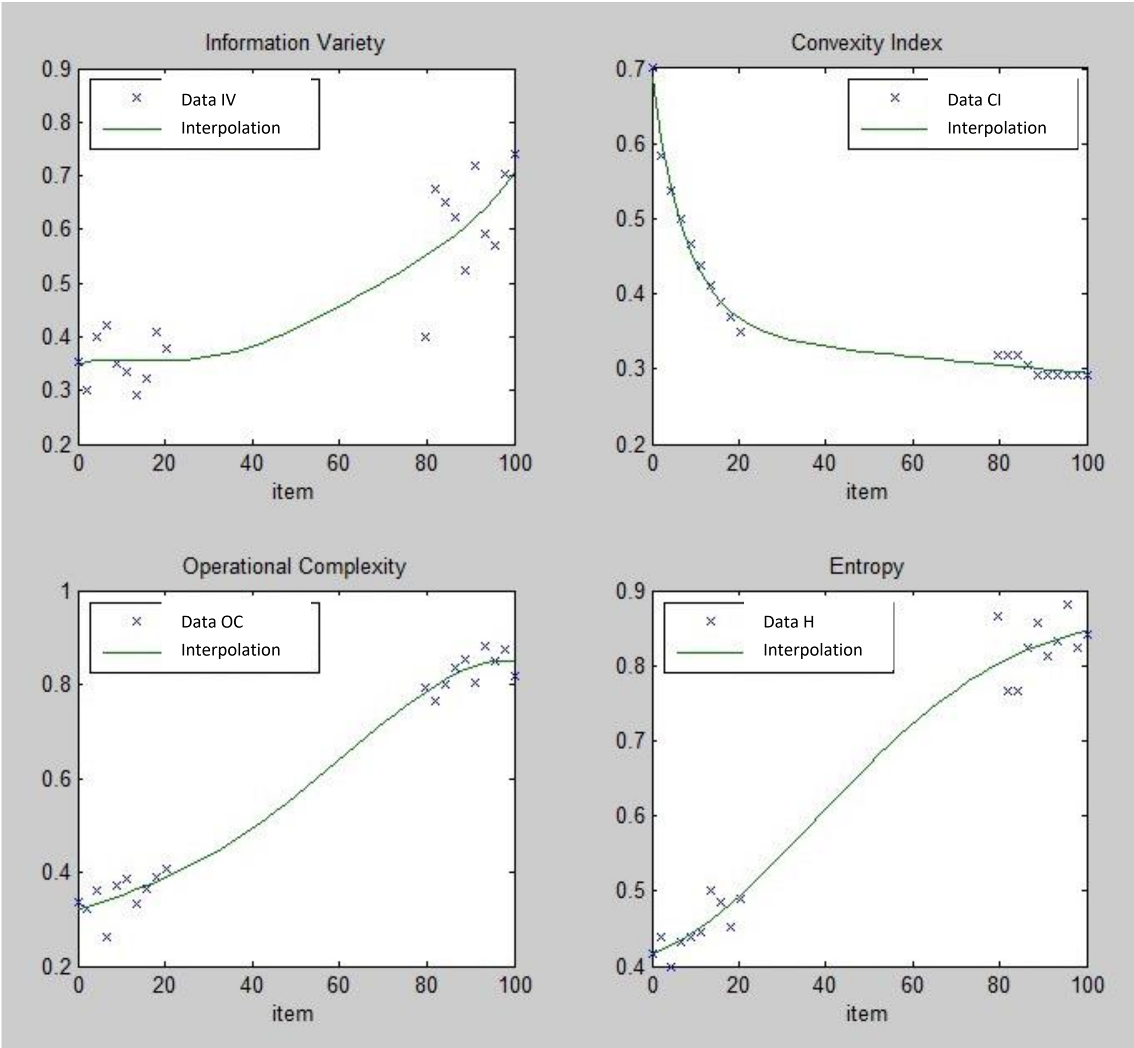

Figure 9: Values of the four sub-indexes of the Part Complexity Index and their interpolating curves

As reported by the framework reported in figure 5, in parallel with the complexity index calculation it was possible to compute production costs for the parts analysed. Also for costs the same scheme was applied, i.e., the cost of production was calculated for all the 40 parts analysed and the costs for the additional 60 items was obtained with an interpolation (see (9) for the SM); the results show that the AM production cost is constant, being invariant to the complexity and having fixed a geometric volume of the parts to be produced. Instead the production cost calculated for each of the 40 parts using SM is a increasing function of complexity (fig. 10).

$$SM\_Cost_{fit} = 1.678 \cdot 10^{-7} \cdot x^6 - 4.547 \cdot 10^{-5} \cdot x^5 + 0.004575 \cdot x^4 - 0.1969 \cdot x^3 + 2.73 \cdot x^2 + 42.64 \cdot x + 1529 \quad (9)$$

When all these elements were defined it was possible to achieve a graphical representation of the costs as a function of part complexity. In figure 10 the cost diagram is reported, with the items ordered in increasing complexity (the curve with the "x" dot).

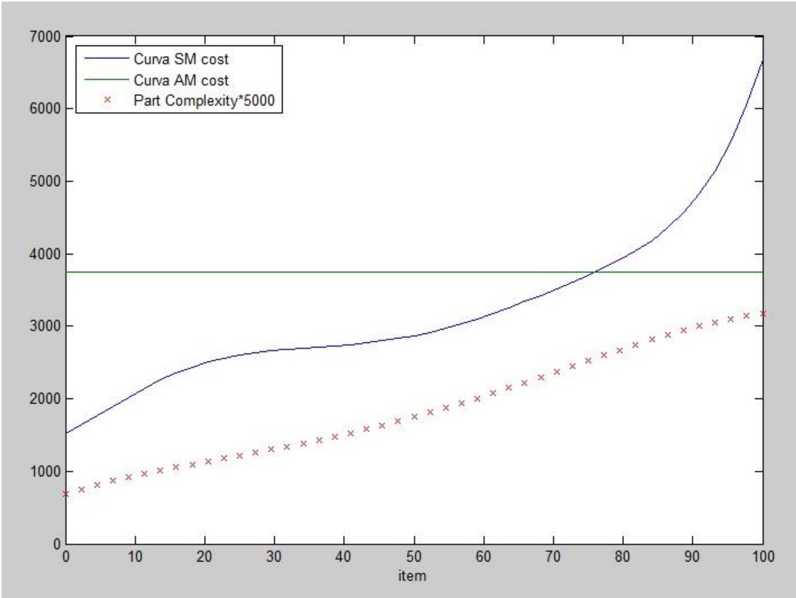

Figure 10: costs functions and part complexity index curve

As it is possible to understand from the equation (9) and figure 10, the SM cost respects what is commonly felt about the production cost of the complex items, i.e., the cost grows with the item complexity. Moreover, it is possible to see that for the parts with greater complexity the costs have an exponential growth and that is actually a good representation of the fact that some very complex objects could be impossible to be produced using standard SM technologies.

But a very interesting result of this study concerns the identification of a break-even point between SM and AM costs when they are connected to complexity. From this evidence it is possible to understand that a convenience frontier between AM and SM exists when they are evaluated in terms of complexity instead of production volumes.

As it is clear from the figure 11, there are two regions in the diagram of figure 10, one in which the SM is more convenient than the AM and one in which the convenience is inverted.

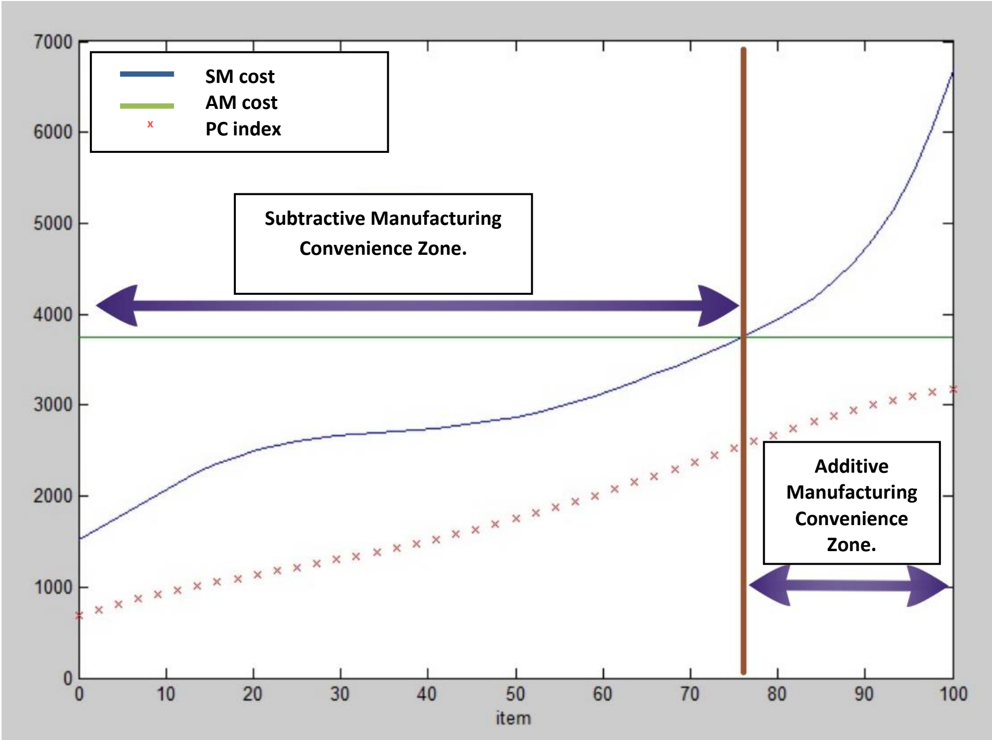

Figure 11: Convenience zones for AM and SM

Once obtained this result, we also studied a method to validate it, i.e., to confirm that the complexity index application can lead to recognize an economic convenience frontier.

This validation was developed using a neural network with not-monitored learning (or self-organizing maps). This method was applied using the special add-on of MATLAB©. What we wanted to obtain was to understand if there is an organization of the production items, characterised using the part complexity sub-index. To do this a data set of 1000 items was created, with different levels of complexity measured through equation (3). The neural network was trained with this data set to obtain cluster of items with similar complexity. Moreover, a cost calculated with the model reported in figure 3 was associated to each item. The elements of the data-set were created starting from the 100 items analysed before and interpolating the remaining ones in a similar way of what was done before. After that the network has learned about the association of complexity and cost, it could be possible to upload additional data to extend the results obtained so far. The output of the add-on of MATLAB© using the 1.000 items used to train the network is reported in figure 12.

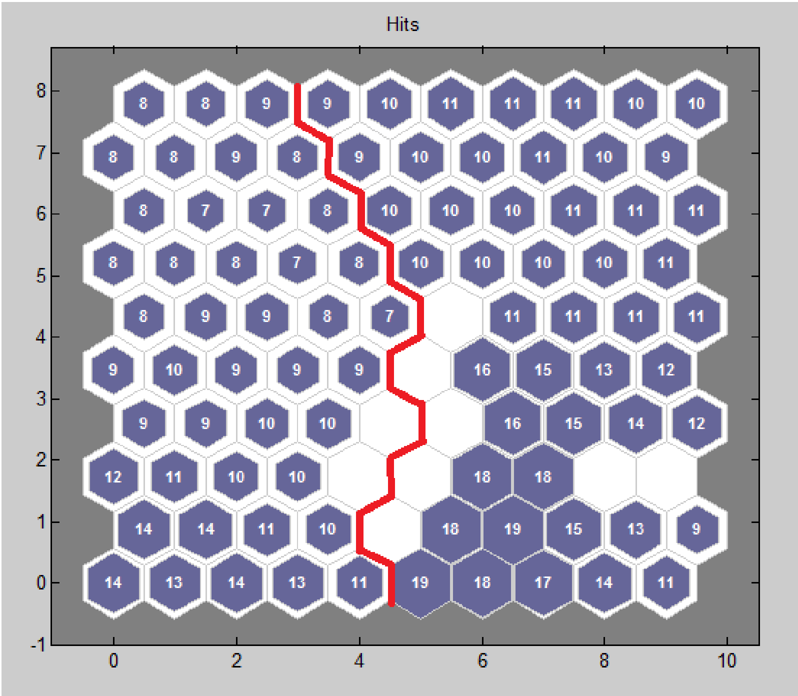

Figure 12: self-organised map for 100 items with different complexity

Each honeycomb element in the map represents a cluster of items with similar complexity (the number shown in each honeycomb is the number of items included by the neural network inside that element). The outcome, analysing how each honeycomb element is composed, is that what was considered to be more convenient in SM on the convenience diagram in figure 11 was always put on the right of the red edge of the map in Figure 12, while what was considered to be more convenient in AM on figure 11 was always on left of the red edge of figure 12.

Thus, this result indirectly confirms that using the new part complexity index defined in this paper it's possible to recognize a convenience frontier between AM and SM.

Conclusions

In this paper the theme of AM is described differently from traditional production economic point of views. In fact, traditionally AM is measured and compared with traditional manufacturing methods such as the subtractive ones using production volume as the driver to decide what technology is better to apply. This approach to the problem seems weak: using that driver to comparatively analyze AM and SM could be misleading because the analysis through production volume doesn't highlight the great advantages that AM offers in terms of complexity.

The aim of this paper was to present a new part complexity index able to measure the multi-level aspects of complexity, using convexity, operational complexity and information entropy. A traditional activity based cost model was used to determine manufacturing costs of items produced using AM or SM. The use of a traditional cost formulation implies that the evaluation approach is conservative in favour of the SM. After that, costs and complexity measured for each item of a defined experimental set were plotted on a convenience diagram which has clearly two convenience areas, one representing the item set to be more conveniently manufactured in SM, the other in AM.

The existence of a frontier between the parts was confirmed also by the application of a neural network self-trained with a data-set of 1000 items that, after having clustered all items by similarity in terms of complexity, confirmed the existence of an area in which all items are more conveniently producible with AM and one instead in which all parts are more conveniently producible with SM.

So, as result of the present research it is possible to state that:

- to better assess the convenience of using AM it's possible to refer to complexity instead of production volume;
- complexity is composed of many facets while up to date in the literature it was measured only referring to a part of the problem;
- a convenience frontier between AM and SM exists if complexity is used as a decision driver and this offers a new way to look to technology selection decisions;
- the cost related to the production with SM is a growing function of the complexity.

These results are very useful for the next researches on the implementation and integration of AM in traditional production environments. Next steps include, for example, the analysis of the economic impact of decisions related to AM machine loading, lot sizing and scheduling.

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