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Procedia CIRP 88 (2020) 387–392

www.elsevier.com/locate/procedia

13th CIRP Conference on Intelligent Computation in Manufacturing Engineering, CIRP ICME '19

Smart cloud manufacturing platform for resource efficiency improvement of additive manufacturing services

Alessandro Simeone[a],*, Alessandra Caggiano[b,c], Yunfeng Zeng[a]

[a]*Intelligent Manufacturing Key Laboratory of Ministry of Education, Shantou University, China*
[b]*Department of Industrial Engineering, University of Naples Federico II, Italy*
[c]*Fraunhofer Joint Laboratory of Excellence on Advanced Production Technology (Fh-J_LEAPT UniNaples), Italy*

* Corresponding author. Tel.: +8613411903575; *E-mail address:* simeone@stu.edu.cn

Abstract

Recent advancements in Industry 4.0 key enabling technologies allow for the dynamic sharing of additive manufacturing services in a cloud manufacturing context, with great potential on resource efficiency improvement at network level.
This paper proposes the conceptualization and development of a modular-structured cloud platform to match users' instances generating feasible solutions according to various manufacturing scenarios.
The proposed cloud manufacturing platform includes a service modelling and dynamic matching module, an intelligent resource distribution optimization module and a decision-making support module to assist users in characterizing the generated solutions.
A simulated case study is reported to exemplify technical and economic advantages for industrial resource efficiency improvement.

Keywords: Cloud manufacturing; additive manufacturing; resource efficiency

1. Introduction

During the last years, due to progress in computation power and systems technology, laser based additive manufacturing (AM) has advanced to a technology with high potential for industrial application [1]. Laser based AM processes share the same manufacturing principle, although each process might have its own range of usable materials, procedures, and applicable situations. The principle behind laser based AM technologies lies in the use of a laser beam to provide thermal energy for the melting and consolidating of the additive materials, or to provide light quanta of a certain wavelength to initiate a chemical curing reaction in vat polymerization [1].

Additively produced parts exhibit innovative shapes, complex features and lightweight structures that are difficult or even impossible to produce with conventional processes. In this framework, ensuring the quality and repeatability of additively produced parts is a fundamental need to meet the stringent requirements and certification constraints imposed by leading sectors, like medical and aerospace [2].

Among AM processes, Laser Powder-Bed Fusion (LPBF) is receiving increasing interest in the industry since it offers a number of advantages in comparison with other freeform fabrication techniques [3]. The process is based on laser irradiation of a pre-laid bed of metal powder [4]: depending on the processing parameters, either sintering (Selective Laser Sintering - SLS) or complete melting (Selective Laser Melting - SLM) of the metal particles can be achieved.

The original field of application for this process is rapid prototyping, but it is expanding in areas such as the medical or aerospace industry, which take advantage of the high degree of freedom in design offered by AM processes [5]. Generally, AM is employed for manufacturing of small series or single parts. This could negatively affect the efficiency of the process, in terms of time, energy and material efficiency. To improve resource efficiency, the combination of several parts within the same building volume represents an interesting solution.

As regards the time efficiency, the laser scanning time depends on the area to be scanned, therefore it increases with the number of parts simultaneously built on the platform.

10.1016/j.procir.2020.05.067

However, the time for powder recoating, performed by the brush on each scanned layer, is the same independently from the number of parts present on the platform. Hence, the overall processing time for each AM part is reduced by increasing the number of parts simultaneously built.

Energy efficiency is strongly related to time efficiency: the reduction of the overall processing time for each AM part has a positive impact also on the machine power consumption.

As regards material efficiency, it is essentially related to the amount of waste metal powder, i.e. the powder which is laid on the bed but is not scanned by the laser. As a matter of fact, after each layer scan, only a portion of the powder bed is scanned and melt by the laser for part construction, while the rest remains unmelt. To reduce the waste of material, recycling can be performed on this portion of unmelt metal powder in order to be reused.

However, the powder material properties may change due to repeated recycling, affecting the mechanical behavior of parts [6]. Studies recently conducted on recycling and reuse of powder in SLM processes showed that, especially for lightweight alloys, a substantial change occurs in the particle size distribution, which considerably affects the flowability [7]. Due to the change of material properties, the metal powder is only reused for a given number of cycles, after which it is disposed. By producing more parts simultaneously on the same platform, the proportion between scanned and unmelt powder at each cycle increases, thus reducing the amount of powder to be recycled or disposed.

Literature provides a variety of nesting procedures based on different algorithms to combine several parts within the building volume. Ma et al. proposed a heuristic method for efficiently packing irregular objects by combining continuous optimization and combinatorial optimization. Starting from an initial placement of an appropriate number of objects, the positions and orientations of the objects are optimized using continuous optimization. In combinatorial optimization, the gaps between objects are further reduced by swapping and replacing the deployed objects and inserting new objects [8]. Lutters et al. [9] developed a 3D nesting of complex shaped objects. The algorithm starts with the determination of the preferred orientation of a part, and uses a non-deterministic approach, closely related to the "Brazil Nut Effect" to do the actual nesting. Chen et al. [10] presented Dapper, a global optimization algorithm for the DAP problem which can be applied to both powder and Fused Deposition Modeling FDM-based 3D printing. The solution search is top-down and iterative. Starting with a coarse decomposition of the input shape into few initial parts, a pile is progressively packed in the printing volume, by iteratively docking parts, possibly while introducing cuts, onto the pile.

In this framework, the objective of this paper is to propose the conceptualization and development of a Smart cloud manufacturing platform for resource efficiency improvement of AM services. Recent advances in Industry 4.0 key enabling technologies allow for the dynamic sharing of AM services in a cloud manufacturing context, with great potential on resource efficiency improvement at network level [11, 12].

In this research work, a modular-structured cloud platform is proposed to match multiple users instances generating feasible solutions according to various manufacturing scenarios. The proposed cloud manufacturing platform includes a service modelling and dynamic matching module, an intelligent resource distribution optimization module and a decision-making support module to assist users in characterizing the generated solutions.

A simulated case study is reported to exemplify technical and economic advantages for industrial resource efficiency improvement.

2. Framework

A cloud manufacturing framework is developed in this research work aimed at enabling the sharing of distributed AM resources for efficiency improvement at industrial network level. A schematic flowchart is reported in Fig. 1.

2.1. Users instances

Cloud manufacturers users, i.e. suppliers and customers access to the cloud manufacturing platform through a specifically designed graphic user interface (GUI) [11].

Through such GUI, users input their instances, including company and job data. A generic customer instance, C_i is defined as:

$$C_i = \{ID_{ci}, m_{ci}, T_{ci}, Q_{ci}, DL_{ci}, L_{ci}, STL_{ci}, AR_{ci}\} \quad (1)$$

Where

- ID_{ci}: progressive instance identification number generated by the system
- m_{ci}: material
- Powder size

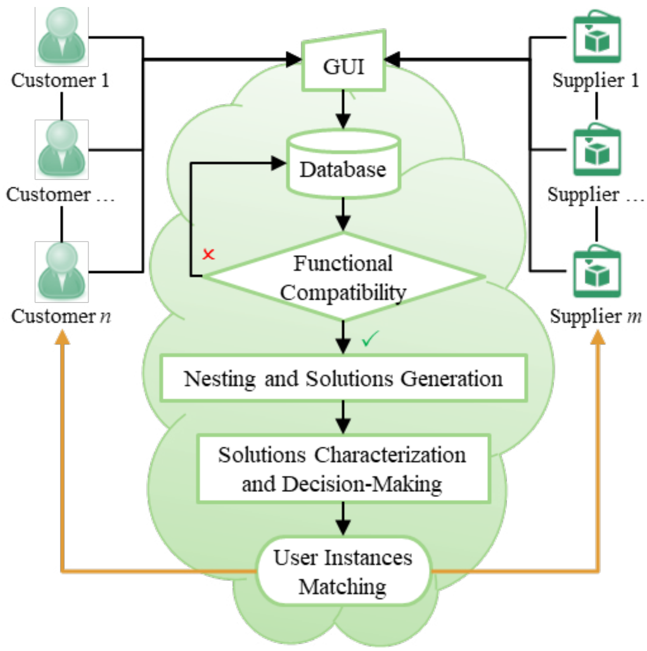


Fig. 1. Framework Flowchart

- T_{ci}: technology, here the customer can specify the required technology from a range of compatible ones, e.g. FDM, SLS, SLA, DLP, DMLS, SLM etc.
- Q_{ci}: batch quantity (units)
- DL_{ci}: customer deadline
- L_{ci}: customer location
- STL_{ci} : the 3D model of customer part, including geometrical information and tolerances

Additionally, a customer can specify a number of additional requirements, i.e. AR_{ci} , such as postprocessing operations, painting, assembling etc. (see Rudolph et al. [13]).

Similarly, a generic supplier instance S_j is defined as:

$$S_j = \{ID_{sj}, M_{sj}, m_{sj}, Q_{sj}, DL_{sj}, L_{sj}, STL_{sj}, AR_{sj}\} \quad (2)$$

Where:

- ID_{sj}: progressive instance identification number generated by the system
- M_{sj} : Machine information, including Technology T_{sj} Power consumption P_{sj} , Box size, S_{sj} and Tolerances, Tol_{sj}
- m_{sj}: material
- Q_{sj}: batch quantity (units)
- DL_{sj}: deadline
- L_{sj}: the supplier location
- STL_{sj}: the 3D model of supplier part including geometrical information and tolerances
- AR_{sj}: additional requirements availability.

All the submitted users instances will be stored in a dedicated database [11] for further processing.

2.2. Functional compatibility

Customer and supplier instances created via cloud user interface are subject to a first matching procedure to evaluate their compatibility. The Functional Compatibility (FC) indicator FC_{ij} between a single Customer Instance C_i and a single Supplier Instance S_i is a Boolean variable defined as:

$$FC_{ij} = \begin{cases} 0 & \text{Non compatible} \\ 1 & \text{Compatible} \end{cases} \quad (3)$$

The Functional Compatibility occurs when a number of conditions are satisfied simultaneously, specifically:

- Material: $m_{sj} \equiv m_{ci}$, including powder size
- Technology: $T_{sj} \equiv T_{ci}$
- Tolerance: $Tol_{sj} < T_{ci}$
- Additional requirements, if any: $PR_{sj} \equiv PR_{ci}$

Further FC assessment is carried out considering the minimum wall size, structural and mechanical characteristics etc.

2.3. Nesting

Since the product volume is determined by the product-design, the total production time can be minimized by optimizing the product orientation or nesting efficiency for batches with multiple products in order to reduce the batch height [14, 15].

The functionally compatible user instances pairs are inputted into a nesting module to obtain an optimized configuration

At this stage of research, in this paper, the instances nesting is carried out using a third party software, namely Magics Software developed by Materialise ® [16] which performs an optimized nesting process based on heuristic approach.

Depending on the user instances characteristics, the nesting algorithm can converge to a solution either as soon as all parts are processed and packed inside the build envelope or until a predefined nesting density is reached. Moreover, the software ensures that none of the parts collides with either another part or with the container.

2.4. Decision Making modules

Solutions are generated according to the nesting algorithm and each solution is consists in a number of nesting configurations each of which is characterized by the following factors:

- Number of units: SU_k is the number of supplier instance units per configuration, CU_k is the number of customer(s) units per configuration
- *PVU*, the platform volume utilization (%) defined as:

$$PVU = \frac{Volume\ of\ all\ parts}{build\ volume} * 100\% \quad (4)$$

- *ND*, the nesting density [9] defined as:

$$ND = \frac{Volume\ of\ all\ parts}{p_a * BH} * 100\% \quad (5)$$

where p_a represents the build platform area, BH is the build height (mm)

- *PT*, processing time required for the realization of the instances pairing, estimated according to the model proposed by Rickenbacher et al. [17] as follows:

$$T = T_p + k * T_{bja} + k * T_S + \sum_k T_{Bk} + k * T_R + T_{MC} \quad (6)$$

Where T_p is the time required to prepare the CAD data, T_{bja} is the time required to build the job assembly, T_S is the time required for machine setup, T_{Bk} is the build time of the configuration k build job, computed according to the linear regression model in [17], T_R is the time required for removing parts from the machine and T_{MC} is the time required to change material.

- Energy consumption: a basic economic estimation of the energy consumption was obtained as follows:

$$E = E_{uc} * \sum_k (P * T_{Bk}) \quad (7)$$

Where E_{uc} is the unitary energy cost for the supplier (CNY) which depends on the supplier location, and P is the maximum nominal machine power (kW). T_{Bk} takes into account the time required for the preheating, the creation of inert atmosphere, the laser scanning, the powder spreading, the cooling down and machine cleaning [18].

- Distance cost, to be calculated for each instance pair based on the customer and supplier locations adopting a distance cost coefficient taking into account batch volume and weight.
- Supplier Rating: a score ranging from 1 to 5 based on the historical feedback

Decision-making modules are developed within a solution management system described in the next section.

2.5. Solutions Management System

Following a generic supply entry S_j, the supplier allowance time is computed as the difference between the planned production start and the S_j entry date. During this time, the customers instances are considered for matching as follows: when a customer instance C_i is submitted, the system will evaluate the FC and the nesting as per sections 2.3 and 2.4.

When a solution is generated, the customer is allowed to pre-select one of the available solutions from various suppliers, subsequently the instance is queued to allow for the supplier to wait for new customer instances submissions to evaluate which customer instance(s) to accept or reject.

If a new customer instance, e.g. C_{i+1}, is submitted during the C_i queueing time, then the system will compute and generate a new solution including C_i and/or C_{i+1} to incorporate one or both customers. Once the solutions are updated a deadline evaluation is carried out to verify the solutions feasibility. At this point the procedure is repeated: the new customer pre-selects a solution and join the queue.

Once the supplier allowance time is expired, eventually the supplier will select the customer(s) instances to be incorporated and those to be rejected. The timeline flowchart for the scheduling management procedure is reported in Fig. 2.

3. Case study

With the aim of exemplifying the proposed framework, a simulated case study was setup with 3 Suppliers and 3 Customers. The case study data are reported in Tables 1 and 2.

To reduce the case study complexity, the following assumptions were taken into account:

- All the processes mentioned in the case study are Direct Metal Laser Sintering (DMLS)
- Both customers and supplier instances are submitted simultaneously to avoid complex scheduling management
- No support needed for the realization of any of the suppliers and customers instances
- All the instances are submitted in the same day, i.e. 24 June 2019
- Both customers and supplier instances have the same powder size

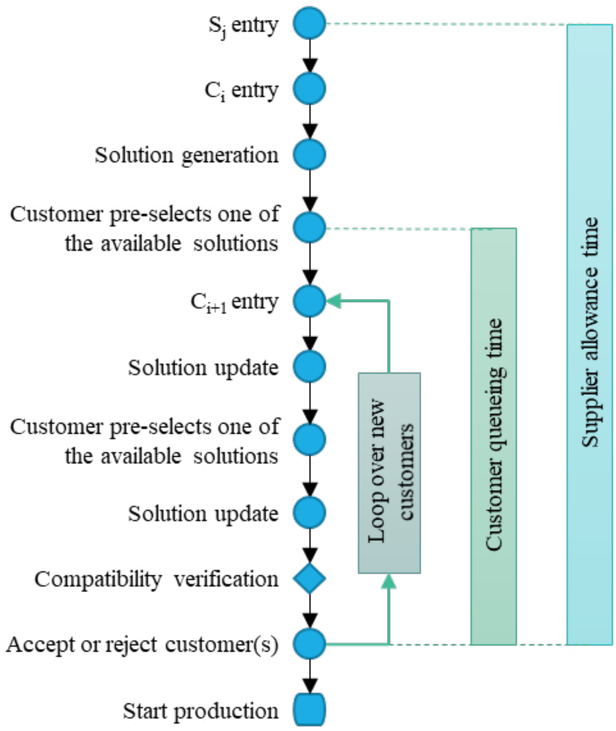


Fig. 2. Solutions management system timeline

Table 1. Suppliers instances data

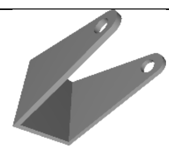
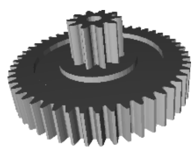
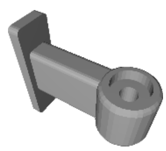
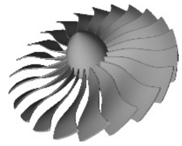
Supplier ID	*M*	*m*	*P*	*Q*	*DL*	*L*	*STL [max size, mm]*
S_1	EOS M290	EOS MaragingSteel MS1	8.5	80	10 December 2019	Guangzhou	 [40 50 75]
S_2	M2 Cusing	CL 31AL Aluminium alloy (AlSi10Mg)	10	50	11 November 2019	Wuhan	 [123 123 50]
S_3	EOS M400	EOS MaragingSteel MS1	20.2	80	1 January 2020	Hangzhou	 [53 118 135]

Table 2. Customers instances data.

Customer ID	*m*	*Q*	*DL*	*L*	*STL [max size, mm]*
C_1	CL 31AL Aluminium alloy (AlSi10Mg)	120	10 October 2019	Shanghai	 [64 24 20]
C_2	EOS MaragingSteel MS1	50	15 November 2019	Shenzhen	 [100 100 25]
C_3	EOS MaragingSteel MS1	100	1 December 2019	Shantou	 [168 26 27]

4. Results and discussion

With reference to the case study data reported in Tables 1 and 2 and according to the FC criteria described in Section 2.2, the FC matrix for this case study, evaluated by the cloud platform, is reported in Table 3. Nesting results are summarized in Table 4, for all the compatible instances pairings. Based on the results shown in Table 4 and comparing the deadline requirements reported in Tables 1 and 2, the supplier will select their most suitable pairings according to the processing time and a resource utilization criterion, i.e. $\widetilde{PVU}$ defined as the weighted sum of the PVU_k over the BH_k:

$$\widetilde{PVU} = \frac{\sum_k (PVU_k * BH_k)}{\sum_k BH_k} \tag{8}$$

Table 3. Functional Compatibility Matrix.

	C_1	C_2	C_3
S_1	0	1	1
S_2	1	0	0
S_3	0	1	1

Table 4. Nesting results for all the compatible pairings

Instances pairing	Conf.	SU_k	CU_k	PVU (%)	ND (%)	BH (mm)	PT (h)
$S_1 + C_2$	K1	27	50	7.23	7.46	314.92	99.90
	K2	53	0	4.74	9.55	161.20	113.87
$S_1 + C_3$	K1	69	48	8.69	9.58	294.75	226.32
	K2	11	52	3.71	9.59	125.91	106.83
$S_1 + C_2 + C_3$	K1	14	50+29	7.59	7.84	314.92	117.26
	K2	66	0+52	8.63	9.36	299.80	227.08
	K3	0	0+19	1.00	8.59	37.73	29.93
$S_2 + C_1$	K1	20	116	28.22	29.15	333.85	973.90
	K2	22	4	23.5	28.75	286.14	818.80
	K3	8	0	8.46	26.21	112.94	294.84
$S_3 + C_2$	K1	43	38	18.65	19.28	348.35	1647.01
	K2	37	12	15.35	22.8	242.30	1405.12
$S_3 + C_3$	K1	43	100	19.21	20.15	343.30	1776.10
	K2	37	0	14.94	23.95	224.6	1399.64
$S_3 + C_2 + C_3$	K1	43	12+100	19.62	20.28	348.35	1780.44
	K2	37	38+0	16.23	19.46	300.35	1418.78

Table 5. Supplier Decision-Making indicators.

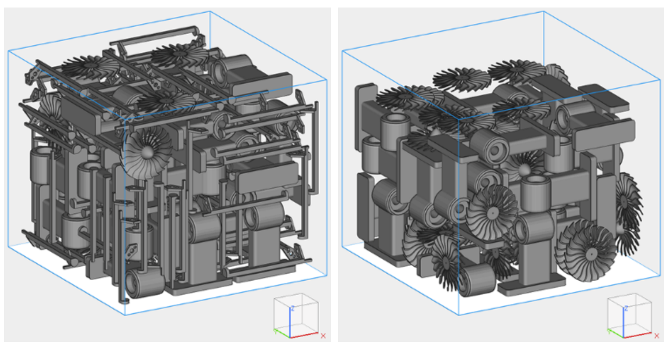
Supplier	Instances pairing	$\widetilde{PVU}$	Deadline Conflict
S_1	$S_1 + C_2$	6.3870	None
	$S_1 + C_3$	7.1994	None
	$\boldsymbol{S_1 + C_2 + C_3}$	**7.6868**	**None**
S_2	$\boldsymbol{S_2 + C_1}$	**23.3324**	**None**
S_3	$S_3 + C_2$	17.2963	None
	$S_3 + C_3$	17.5213	None
	$\boldsymbol{S_3 + C_2 + C_3}$	**18.0504**	**None**

Table 5 reports the $\widetilde{PVU}$ computed for each solution, and considering that no deadline conflicts are reported, a likely scenario for supplier decision-making in terms of solution selection is:

- $S_1 \rightarrow [S_1 + C_2 + C_3]$
- $S_2 \rightarrow [S_2 + C_1]$
- $S_3 \rightarrow [S_3 + C_2 + C_3]$

An example of nesting configuration in reported in Fig. 3 with reference to the solution $[S_3 + C_2 + C_3]$ selected by S_3.

To allow for the selection of the most suitable solution by the customer, the Customer Decision-Making Support Module provides a detailed visual report of the solutions to identify an appropriate match for the realization of the desired manufacturing tasks. The spider web chart shown in Fig. 4 shows the solution characterization criteria for the supplier. With reference to C_3, the two alternatives are represented by $[S_1 + C_2 + C_3]$ and $[S_3 + C_2 + C_3]$.



(a) (b)

Fig. 3. Nesting configurations for $[S_3 + C_2 + C_3]$

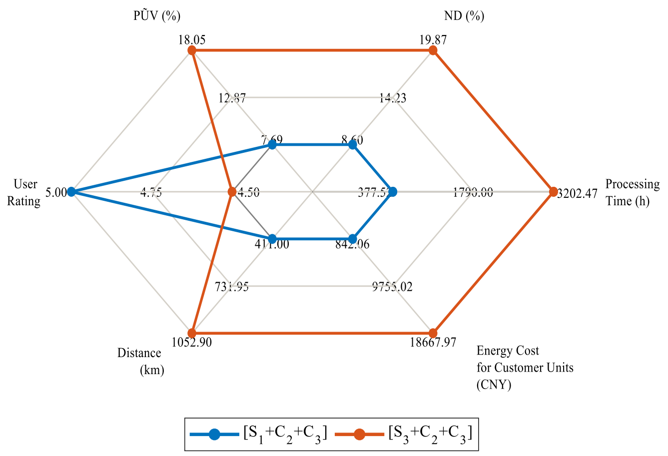


Fig. 4. Customer Decision-Making spider web for C_3

The first solution shows more favorable conditions in terms of user rating, distance-related cost, energy cost per customer unit, and processing time, while the second solution shows favorable conditions in terms of volume utilization and nesting density. The final choice is let to the customer who is enabled to select the most suitable manufacturing solution.

5. Conclusions

This paper reported the conceptualization and the development of an intelligent cloud platform to allow for a dynamic sharing of AM services.

The platform is built with a modular structure for an effective handling and management.

A database module is dedicated to the acquisition and the storage of users instances. An intelligent computation module firstly assesses the functional compatibility amongst users instances, then performs a nesting operation to generate geometrical configurations finally computes a number of attributes to generate and characterize solutions.

A decision-support module is then developed to assist both suppliers and customers in the choice of the best solutions, based on specific solution characterization factors such as processing time, energy consumption, volume utilization, distance cost and user rating.

Further work will be focused on the management of conflicting solutions as well as on a more accurate energy and processing time modelling possibly by using real-time sensor data.

Acknowledgements

The research results presented in this paper are based on the activities carried out in the framework of the following projects:

- CLOUD MODE "CLOUD Manufacturing for On-Demand manufacturing sErvices" (000011-ALTRI _DR_3450_2016_RICERCA_ATENEO-CAGGIANO) funded by the University of Naples Federico II, Italy, within the "Programma per il finanziamento della ricerca di Ateneo" (2016-2019).
- Research Start-up Fund Subsidized Project of Shantou University, China (No. NFT17004).

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