AM Feature and Knowledge Based Process Planning for Additive Manufacturing in Multiple Parts Production Context

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Abstract

Additive Manufacturing (AM) has played an important role in manufacturing, especially in customized production. It is an ideal 'Concurrent Manufacturing' which enables fabricating a group of same or even different multiple parts simultaneously within one build volume due to its unique layer by layer processing way. However, there is very few available methods or tools for users, e.g. the AM manufacturing service bureaus, to optimize the process and production plan in multiple parts production context. To deal with this problem, this paper introduces an AM feature and knowledge based systematic process planning strategy. The main contents and key issues of process planning for AM in multiple parts production context are analyzed. Then, a developing CAPP system based on a systematic process planning framework for AM in this multiple parts production context is presented. Finally, some test examples are applied to demonstrate the functions and effectiveness of some key modules of the developing system.

Introduction

Additive Manufacturing (AM) processes employ a layer by layer processing manner to deposit material layers progressively for building 3D parts according to sliced 3D CAD models. This special processing way allows AM machines to build multiple parts simultaneously by placing multiple part slices within each building layer. Significant savings in cost and time can be achieved in rapid prototyping (RP/AM) by manufacturing multiple parts in a single setup to achieve efficient machine volume utilization [1]. Hence, in real application, to improve the machine utilization, parts are usually built batch by batch in AM machines per run but not only one by one. This forms the multiple parts production context (Figure 1).

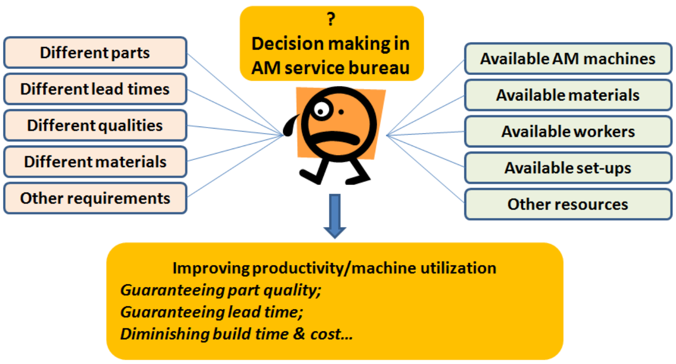


Figure 1, Difficulties of decision making in Multi-part production context.

To make a group of parts built, process technicians or planners have to do a set of optimizations and decision makings for preparation work, process planning. As defined by Marsan and Dutta [2], there are usually four main planning tasks, orientation optimization, support design, slicing and tool-path/scanning-path planning. To solve these tasks, researchers had proposed numerous solutions [3-9]. However, most of these solutions were designed for single part production context where only one part is built per machine run and they only focused on the operational level to help transfer a virtual CAD model to a physical model [3]. In addition, these solutions lack systematic. Systemic discussed here refers to two main aspects: the integrity of process planning content, including both of 'macro planning' (e.g. manufacturability analysis, etc) and 'micro planning' (specific planning tasks for processing, e.g. orientation optimization), the systematic analysis of the interdependence between different process planning tasks. Obviously, incomplete process planning cannot realize the full processing chain (Figure 2). The lack of interdependence analysis between the process planning tasks cannot guarantee optimal planning results. As stated by Kurkarni et al. [3], 'process planning problems are not individual problems alone, but they are related to each other'. Besides, in multiple parts production context, the planning tasks and their characteristics are different to those in single part production context. Hence, to realize a full processing chain and obtain better planning results for AM in multiple parts production context, this paper introduces a feature and knowledge based systematic process planning strategy. To reduce the complexity, the post processing in the processing chain is not included.

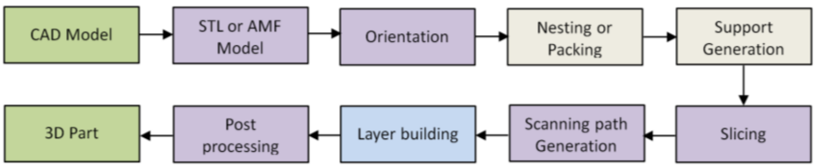


Figure 2, General processing chain of AM ('micro level'; 'one-way' information flow).

The left of this paper is arranged as follows: the second section will analyse the process planning problem in multiple parts production context; the third section will introduce the development of the proposed strategy; the fourth section will present the implementation of two key modules; the fifth section will present test examples for demonstration; the last section is the conclusion.

Problem description

In AM service bureaus (Figure 1), different orders may come from different clients with different production requirements, e.g. lead time, cost, quality, etc. Therefore, production technicians or planners have to make different decisions and optimizations so as to do the preparation work for production. The preparation work is mainly used to answer two types of key questions: 'Whether a part is suitable to be processed by AM processes?' and 'How to produce a part?' In this paper, all of the preparation work for AM production is defined as process planning and is proposed to be grouped into two levels: 'macro planning' and 'micro planning', which are used to deal with the two types of questions. In the 'macro Planning' level, the main planning tasks include: manufacturability analysis, selection of AM process or manufacturing scenario, prediction of build time, cost and general part quality, etc. These tasks are usually beyond the processing chain in AM. While in the 'micro planning' level, the planning tasks are composed by: orientation optimization, work space planning, support generation, slicing, tool path planning, etc. To conduct process planning in multiple parts production context, the foremost thing is to identify the planning tasks. In AM service bureaus, different AM machines already install different preprocessing software tools to help process planners to deal with the planning tasks, but only for the 'micro planning' level. For the planning tasks in the 'micro planning' level, they usually use different algorithms designed for specific processes. It is hard to develop compatible support generation, slicing and path-planning algorithm for all the AM processes. Therefore, it is better to use the available tools to deal with the above three planning tasks. However, these tools cannot provide enough support to the orientation optimization and work space planning in the multiple parts production context. For example, current software (e.g. 'Magics' software) can only orientate parts one by one, which cannot guarantee an optimal orientation results. In multiple parts production context, the total build time, cost and quality not only depend on the individual part's build orientations but also their combination. For space planning, current methods mainly use part's bounding box and apply BL-GA methods [10], which waste much building space and cannot obtain optimal solutions. Fortunately, current AM machines usually can accept CAD models with STL format. This enables the availability of developing generic orientation optimization and work space planning methods with uniform output, positioned multiple CAD models in STL format, for the later planning tasks, e.g. support generation, slicing, on different preprocessing platforms installed in different AM machines. Therefore, there is no need to develop planning methods for all the planning tasks in the 'micro planning' level except for the orientation optimization and work space planning tasks. Hence, the general planning tasks in multiple parts production context can be identified as shown in Figure 3. The tasks colored with green in the figure are executed on specific preprocessing platforms of specific AM machines.

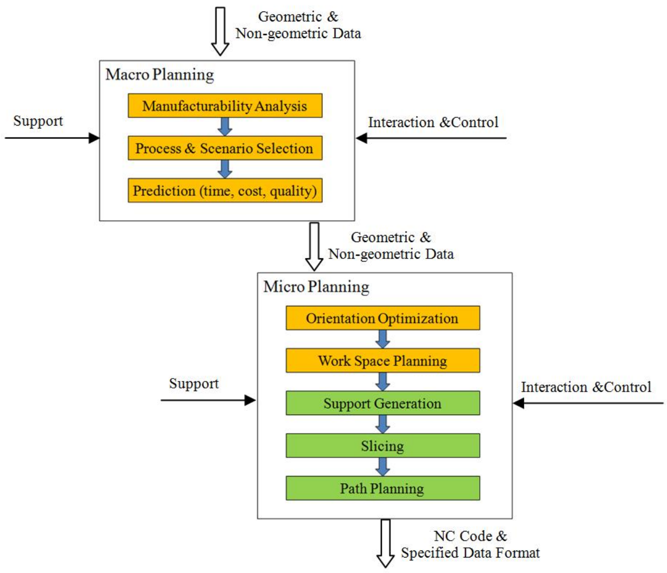


Figure 3, Main planning tasks of process planning in Multi-part production context.

To solve these process planning tasks in multiple parts production context, the key issues should be identified. Dutta et al. [11] regarded process planning in AM as computation problems since the planning models, algorithms, optimization and decision making models require much computation as well as the reuse of production knowledge. In this paper, feature and knowledge are used to design solutions to deal with the key issue for each of the identified planning task. And an additional task, 'Grouping/Clustering parts', is proposed to reduce the computation for some planning tasks with a combinatorial characteristic. The next section will introduce the development of a feature and knowledge based systematic process planning strategy.

Development of the proposed strategy

- **Manufacturability analysis**

Manufacturability analysis is the first planning step either in multiple parts production context or single part production context. The output of this task is the feedback on the availability of processing a given part by using AM processes. The main content of the analysis contains geometric analysis and non-geometric analysis. Geometric analysis refers to analyze the size of a part and key geometric features of a part. Current AM machines have limitations on the processing size. Some parts with sizes that exceed the build volume and cannot be decomposed to build would not be processed by AM processes. Some parts may be filled into a build volume, but they may collide with the boundaries of the build volume when they are rotated in the build volume. This cannot guarantee the parts to be built in good orientations with acceptable production quality. Another type of geometric analysis, analysis of surface features, is more difficult. Although AM processes can build any geometric shape theoretically, they also have limitations. The limited layer thickness may have difficulty to build some shape features with very small sizes. The slicing procedure may cause some problem to build facing features (two parallel plane faces with a very small distance). The complicated distortion of AM processes cannot guarantee the shape accuracy of some features like long tiny holes or cylinders or large planes, shells, etc. Therefore, to conduct the geometric analysis, data base of processing characteristics of AM processes or benchmarking results of AM processes should be provided. Apart from this, a key or problematic feature base should be constructed to help identify the possible problematic areas on a given part model. Hence, feature recognition algorithm is also required. The non-geometric analysis is mainly focusing on the analyzing of the production requirements, e.g. part quality, build time, cost etc. For executing this analysis, benchmarking results of AM processes should be provided. Besides of the information or knowledge data base, decision tool is also needed to act as reasoning or searching during the decision making. Many former methods adopting 'Screen' method which eliminates alternatives according to the checking of decision attributes, e.g. size, time, cost, tensile strength, etc, one by one. This method is efficient for the geometric analysis. However, when conducting non-geometric analysis, it would miss some potential alternatives which are very close to meet the production requirements. Therefore, to prevent the missing of some potential alternatives, an integrated decision making model (MADM) [12] is adopted for the non-geometric analysis by providing the deviation extent of each decision attribute. In real application, when some designs can be modified, the deviation extent evaluation result may help to dig or attract more potential production possibilities. Therefore, a functional module for this planning task is depicted in Figure 4. The interaction and control is used to modify and control the input and output as well as set the decision attributes.

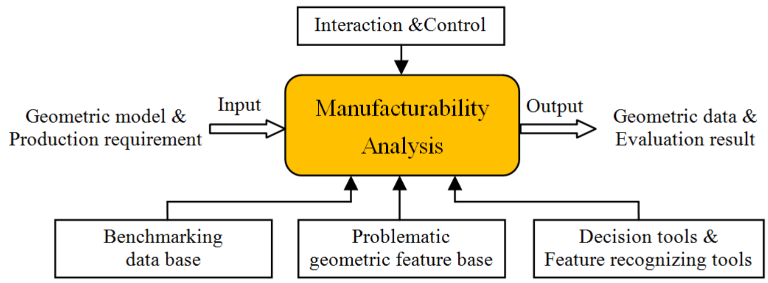


Figure 4, Functional module for 'Manufacturability Analysis'.

- **Process and manufacturing scenario selection**

When the manufacturability analysis is finished, an evaluation result will be obtained. If a part can be processed by AM processes, then there usually a set of finite alternative manufacturing scenarios (machine, setup, material, etc.) to produce a prototype according to production requirements. Hence, the second planning task is to evaluate those alternatives and identify the optimal one according to the production requirements and preference. The input of this task is the alternatives generated by the manufacturability analysis. The output of this task is the rank of alternative, either AM process or manufacturing scenario. To conduct the evaluation, benchmarking results of AM processes and related manufacturing scenarios should be provided as information or knowledge base. Then a decision making model is necessary to generate evaluation index for the decision support. Besides, the user preference and setting of attributes are required during the evaluation. Hence, human interaction and control are inevitable. Therefore, a full solution for this task can be depicted by a function module as described in Figure 5.

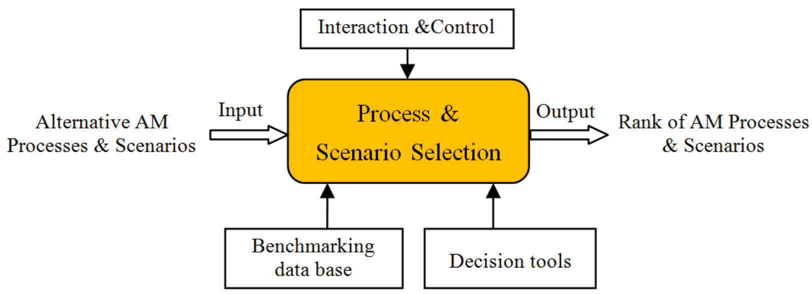


Figure 5, Functional module for 'Process & Scenario Selection'.

- **Prediction (time, cost and quality)**

Prediction is very important in AM process planning. For upstream departments, it is used to give quotation/pricing and support the communication with clients or even help the redesign; for downstream sectors, it is useful for the optimization and decision making during the 'micro planning' stage. The main contents include the estimation of build time, cost and production quality. However, this task is also very difficult to accomplish. Fast, simple analogical or empirical estimation models are usually efficient for the build time and cost estimation but they suffer from the low accuracy problem. Analytical models can give more accurate estimation results but they lose efficiency since they need detailed process planning results. In this multiple parts production context, another big challenge of build time and cost estimation is how to determine the build time and cost for individual parts which are built simultaneously. For the production quality estimation, it is more complicated. Currently, there are two types of methods. One is to use mathematical/numerical methods to compute on the geometric models or simulate the processing procedure. This type of methods needs many mathematical/numerical or geometric assumptions due to the unknown complexity of phenomenon from physical or chemical or multiple coupled fields. Hence, the accuracy cannot be guaranteed. In addition, the efficiency of this model is relatively low due to the large computation. Another type of methods is to use experimental results for constructing empirical models. These models have a better accuracy and higher efficiency. However, they need large quantity of experiment results and production knowledge. Another difficulty of this task is that there is usually no generic prediction model for all the AM processes and manufacturing scenarios. Specific models should be constructed for specific processes and scenarios. Hence, this task is a knowledge-intensive and computation-intensive problem.

To solve this task, two types of prediction methods from literature are used. To give fast prediction of build time and cost for the quotation/pricing, analogical or empirical estimation models [13, 14] are adopted. To construct different estimation models for different AM manufacturing scenarios, different production record data bases and processing specifications of these scenarios, usually stored in benchmarking result base or machine resource base, should be provided. To give accurate estimation of built time and cost for individual parts in multiple parts production context, the analytical generic build time modeling method proposed in [15] is chosen. To use this method, processing specifications of each AM manufacturing scenario should be provided. To predict the production quality, knowledge based method is used to give fast prediction. To support the optimization and decision making in the 'micro planning' stage, parametric models are chosen, e.g. the surface roughness prediction model used in KARMA platform (*http://www.femeval.es/proyectos/karma*). Therefore, a full solution for this task can be obtained and described in Figure 6.

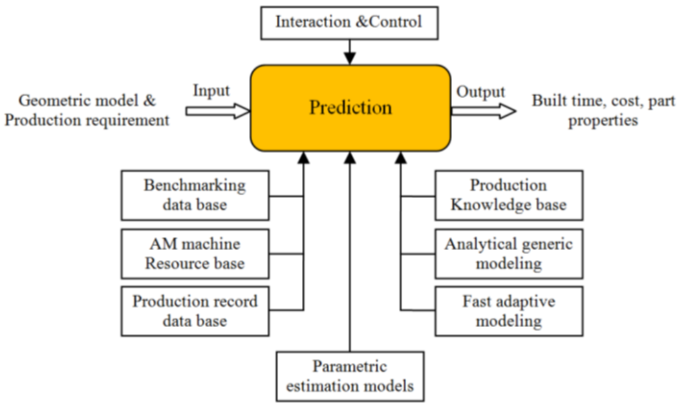
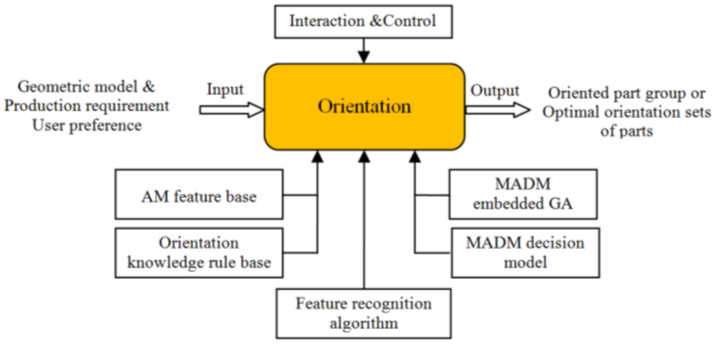


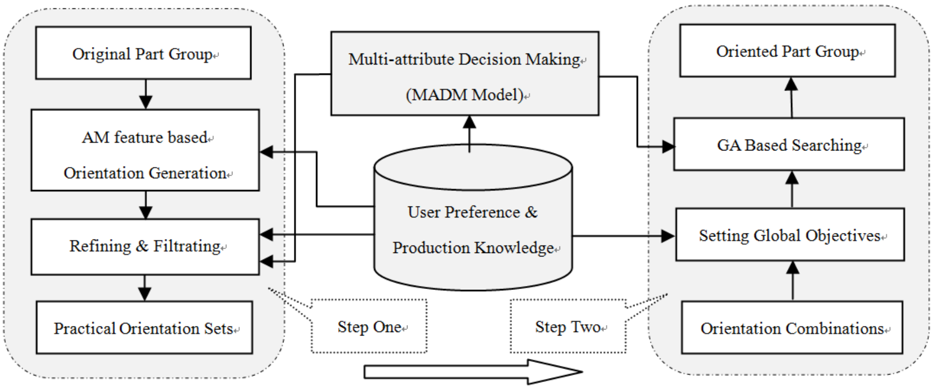
Figure 6, Functional module for 'Prediction'.

- **Orientation optimization**

Orientation optimization is one of the key planning tasks to guarantee the production quality of parts. When a group of parts to be produced in one build, the orientation problem becomes more complicated. To guarantee each part's production quality, each part should be built in its optimal or near optimal orientation. To diminish the total build time and cost of one build, an optimal combination of parts' orientations should be found to diminish the total cross section area, total support volume or maximum build height, etc. However, for one given part, theoretically, there are possible infinite alternative build orientations. Therefore, for a group of parts in one build, there would be more possible infinite alternative orientation combinations. Even for a group of parts with finite alternative orientation sets, the number of alternative combinations will have a near exponential growth as the number of parts and parts' alternative orientations increase. As a result, a combinatorial NP-complete problem forms. Furthermore, when more objectives (attributes or criteria), such as minimizing the overall part surface roughness, overall volumetric error, total build time, total build cost, maximizing the overall part accuracy, etc., are taken into consideration during optimization or decision making, the NP-complete problem becomes multi-objective NP-complete problem with more complexity. Although the orientation optimization problem in multiple parts production context is more complicated and difficult than that in single part production context, the main sub tasks are similar. The first one is to generate alternative orientations for individual parts within a part group. However, the methods for single part orientation optimization proposed in literature cannot be directly used for multiple parts orientation problem. Because, on the one hand, the computation would be huge if too many alternative orientations are generated for each part, especially for those searching in an infinite solution space; on the other hand, not all the alternative orientations of each part can guarantee an acceptable production result for the related part. As discussed above, the general objective of the multiple parts orientation is to guarantee each part's production quality and at the same time to diminish the total build time, cost, overall accuracy error etc. Therefore, the first sub task for the multiple parts orientation problem is to efficiently generate a set of practical finite alternative orientations guaranteeing the production quality for each individual part within a group, but is not to rotate the parts freely respectively by doing an exhaustive searching, which would generate invalid alternative orientations. When the first sub task is finished, the second one is aimed to search out an optimal combination of parts' build orientations to minimize the total build time, cost and other user concerned objectives (called global objectives). For solving the first sub task efficiently, an AM feature based orientation generation method [16] is adopted. When using this method, a set of finite alternative orientations can be obtained for each part. However, there is a need to refine the alternative orientations for each part since not all of the alternative orientations are acceptable ones to guarantee the part's production quality. Impractical alternative orientations may cause invalid build orientation combinations, which cannot guarantee individual part's production quality, for the second sub task. Hence, to ensure all the alternative combinations are valid, a filtering process is added. The integrated MADM model proposed in [12] is adopted for the filtering. To identify the optimal orientation combination from the alternative ones, the second sub task applies a modified evolutionary algorithm. Therefore, a functional module and the detailed method are depicted in Figure 7 (a) and 7 (b).



(a), Functional module of 'Orientation'.



(b). Orientation optimization method for Multi-part production.

Figure 7, Functional module for 'Orientation' and detailed method.

- **Work space planning**

In multiple parts production context, work space planning is inevitable. Maximizing the compactness of parts is usually set as an optimizing objective when nesting or packing parts into a machine build volume. Theoretically, parts can be placed or rotated freely when nesting or packing. However, apart from the compactness, the production quality of each part should be guaranteed. Therefore, the work space planning task is coupled with orientation optimization task. Actually, orientation optimization and nesting or packing can be dealt with simultaneously. However, this is too complicated due to the combinatorial characteristic which causes expensive computation. Hence, orientation optimization and work space planning are processed sequentially in this paper. The output of orientation optimization is the input of the work space planning. For some AM processes that need support structure, parts can only be nested in one layer, which is a two-dimensional nesting problem. However, the two-dimensional nesting problem is different to other classical nesting problems since the parts can be rotated around three dimensions though they can only be placed in one layer. For those AM processes that do not need support structure, parts can be packed upon each other. Hence, this is a three-dimensional packing problem. To solve the two-dimensional nesting or three-dimensional packing problem, nesting algorithms should be used. These algorithms are serial ones, which place part one by one in sequence, or parallel ones, which nest or pack a group of parts simultaneously. When design or select nesting or packing algorithms, the efficiency should be considered since work space planning is a type of NP-complete or NP-hard problem. The output of this task is a group of positioned parts that can be sent to downstream planning tasks, support generation, slicing and scanning-path planning. Hence, a functional module, shown in Figure 8, can be designed for this task.

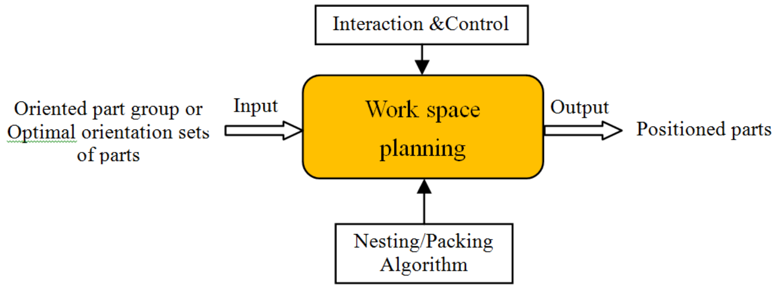


Figure 8, Functional module for ‘Work space planning’.

- **Grouping/clustering parts**

As discussed above, the orientation and work space planning tasks are combinatorial problems. The computation of optimization is usually expensive due to the large alternative combinations. To reduce the number of combinations, a modified group technology proposed in [17] is used to form part groups or clusters or sequences. Therefore, another planning task, grouping/clustering parts, is proposed for the multiple parts production context. However, this task is coupled with the orientation and work space planning tasks since the part group may be changed during orientation optimization or work space planning. To simplify the process planning problem in this multiple parts production context, this research set the grouping/clustering task before the orientation optimization task. When doing the latter two tasks, the part group or cluster can be changed according to the generated part sequence. This task is to generate a part sequence according to their ‘similarity’ which is not only limited to the geometric aspect. Part sequence is used to form part groups or part clusters. To form part sequence, production knowledge is required to identify attributes for ‘similarity’ measuring and a ‘similarity’ measuring model is needed. Therefore, a functional module can be proposed to solve this task as shown in Figure 9.

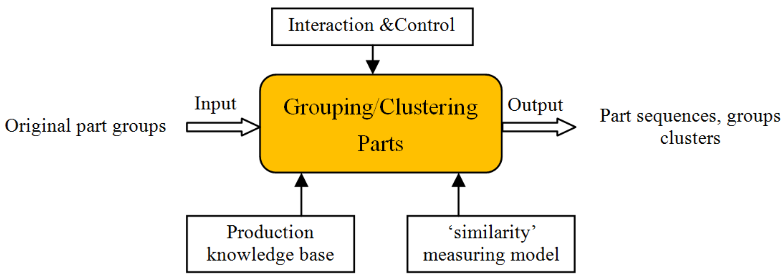


Figure 9, Functional module for ‘Grouping/Clustering parts’.

When all the modules for the main planning tasks in the multiple parts production context are built, then a full systematic process planning strategy forms. The proposed strategy can be fixed in a systematic process planning framework as described in Figure 10.

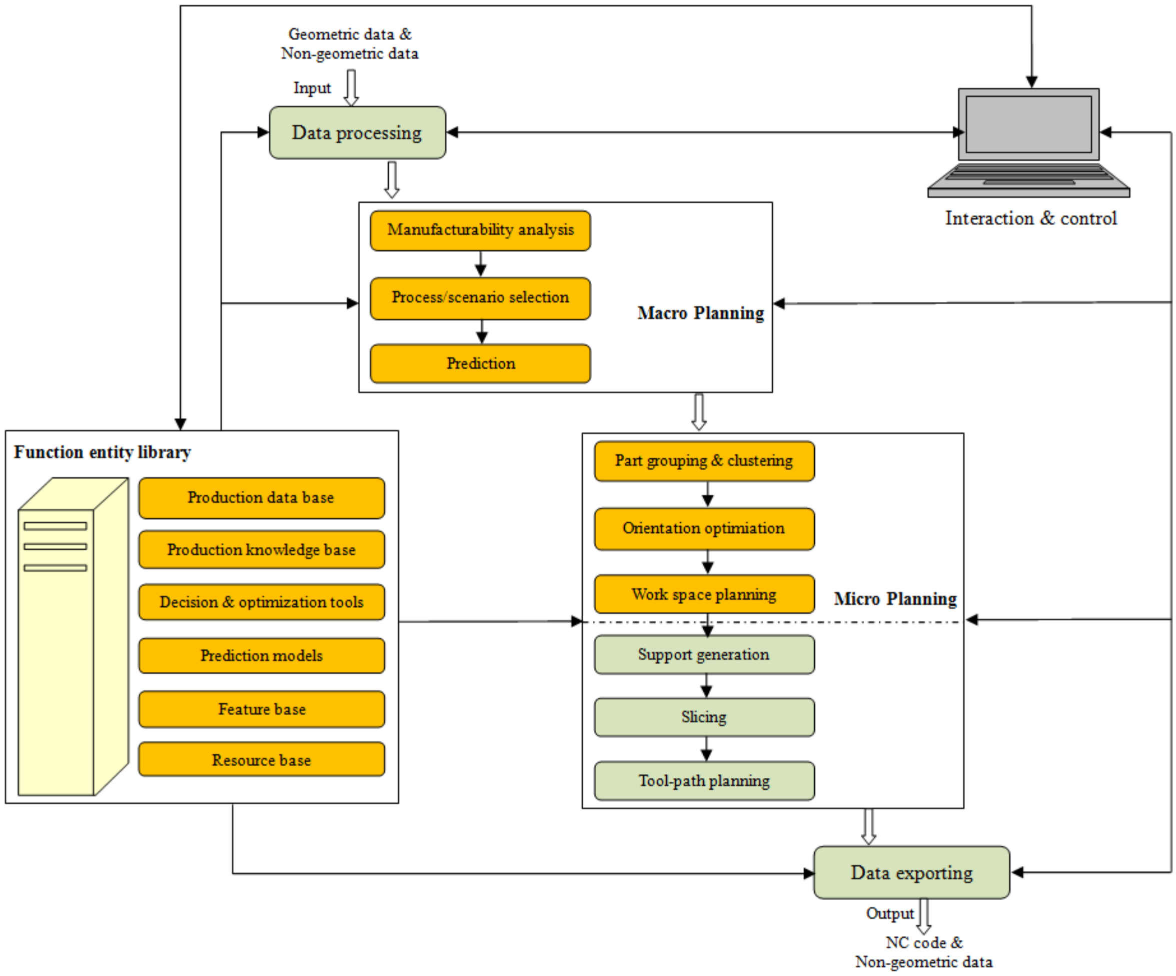


Figure 10, AM feature and knowledge based systematic process planning framework for AM in Multi-part production context.

Implementation of the proposed strategy

With the constructed process planning framework for the strategy as proposed above, CAPP systems with functional modules can be implemented. In real application context, for the planning tasks in the 'macro planning' level and the part grouping/clustering task in the 'micro planning' level, the implementation of the related functional modules depends on specific production needs and available resources. Different feature base, knowledge base, production data base, prediction model base, etc. can be used. There is no common standard or solution for all of these tasks. The authors had proposed some methods to solve the planning tasks in the 'macro level' [12] and a modified 'Group Technology' [17] for the grouping/clustering task. In this paper, for the limited space, only the implementation of other two planning tasks (orientation optimization and work space planning) in the 'micro planning' level is presented.

- **Implementation of the orientation optimization module**

The general method is already shown in Figure 7. There are two main steps: a. generating practical alternative orientation sets for each part to guarantee each part's production quality; b. searching out an optimal build orientation combination to optimize pre-set global objectives.

For the first step, an AM feature based orientation generation method [16] is adopted. Then, a refining/filtrating process is applied to select those alternative orientations which can guarantee the part's production quality. When a finite practical orientation set is generated for each part in a part group, a practical orientation space forms. The forming of the practical orientation space can be depicted by Figure 11 below.

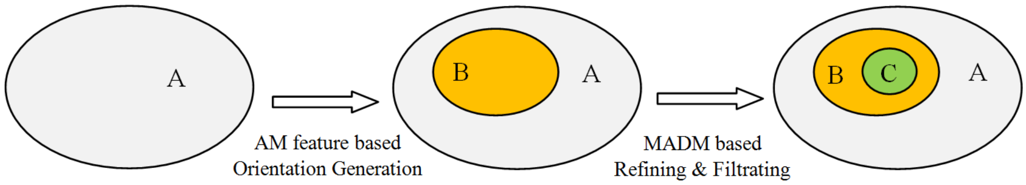


Figure 11, Identifying practical orientation space from original infinite orientation space in Step one.
(Note: A: infinite orientation space; B raw alternative orientation space; C: practical alternative orientation space)

When the practical orientation space is identified, the next step is to search out an optimal orientation combination to optimize related global objectives. In this paper, a modified genetic algorithm is designed for the optimization. The implementation of this module is realized on the Matlab platform (Version R2012b).

- **Implementation of the work space planning module**

For work space planning module, the input is a group of oriented parts, the output of orientation optimization module, which can only be rotated around the build direction and translated on the build platform. Hence, by using the parts' projections onto the build platform as nesting stencils, this problem can be transferred into a classical 2-Dimensional nesting problem. In this paper, a parallel 2-Dimensional method is developed. It can be depicted by Figure 12.

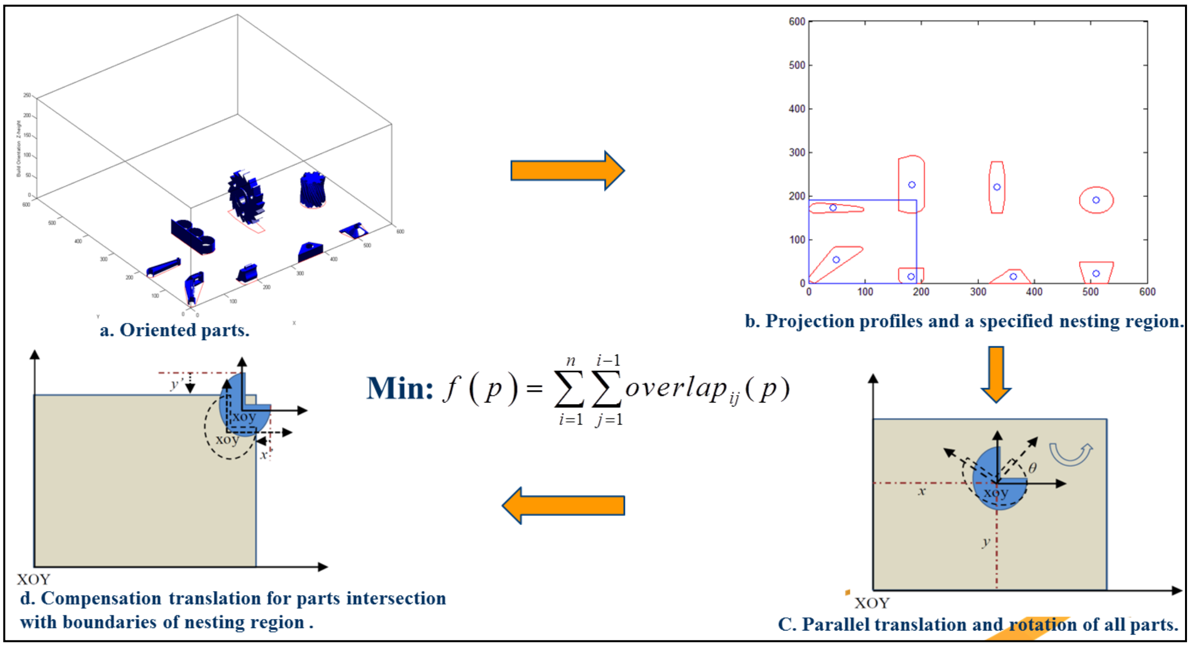


Figure 12, A proposed parallel 2-D nesting method.

The first step is to project all the parts onto the build platform. Then, use polygons to represent these profiles. To avoid the contact or collision of parts after being nested, a minimum distance is set to expand the polygons. The third step is to apply a special genetic algorithm using polyploidy chromosome to represent the position of a polygon (three parameters) for searching an optimal nesting solution with minimum total overlap area. Based on the obtained minimum overlap area, nesting decision can be done. When a minimum overlap with the value of 0 can be found, it means that the part group can be placed into a specified region without collision, and vice versa. The main reason to use the parts' projections for nesting is that some overhangs of parts may need support structures even their base areas are smaller than the projection areas. This will avoid the placement of parts under other parts' overhangs. Hence, the up and down surfaces of parts will not be damaged by the support structures. However, this would cause some waste of work space when the overhangs have an angle to the build direction with less than 45 or 30 degrees where support structures may not be needed and other part could be possibly placed under the overhangs. But, the main objective of this research in the current stage is to testify the feasibility of the proposed method in the prototype level. Hence, this situation is not considered at present. Another reason to use the projection profiles as nesting stencils is to reduce computation cost since using voxel-based method to compute the interference between 3D models will cause more computation time. To ensure all the polygons are within the specified region during movement, a compensation translation is used to move those polygons that intersect with the region boundaries. The last step is to place the related 3D parts into the related specified 3D region by using the obtained optimal solution's position data.

In the current stage of this research, the main focus of nesting is 'Decision problem' (judging whether a group of parts can be nested into a specified region), which is the base of other nesting or packing problems since solutions for bin/knapsack/strip packing can easily be devised when given a (heuristic) solution method for the 'Decision problem' [18]. Modified algorithms can be developed to meet the real nesting needs according to this basic problem. The work space planning module is also implemented on the Matlab platform. To testify the feasibility of the developed algorithms, two illustrative examples are presented respectively in the following section.

Test examples for two main modules

- **Test example for orientation optimization module**

To demonstrate the implementation of the proposed two-step solution for the orientation optimization module, an orientation optimization for a part group composed by sixteen parts to be manufactured by a SLA machine is presented as an example. An assumption is made that no clear user preference is given for the optimization except a general objective on minimizing the build time & cost and guaranteeing the production quality at the same time. The part group is shown in an experimental building envelope as depicted in Figure 13.

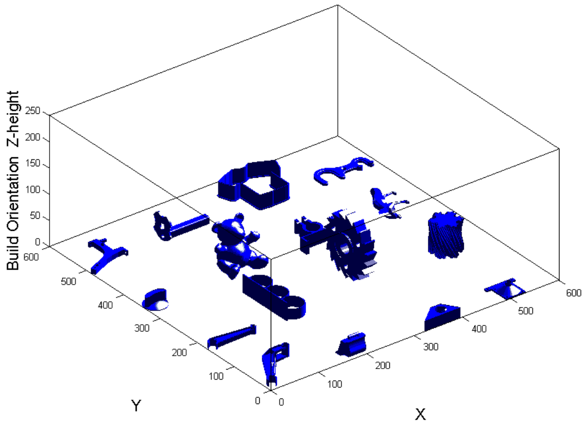


Figure 13, A group of parts to be oriented.

The first step is to generate practical alternative orientation sets for the parts. surface roughness (*R-μm*), support volume (*V-mm*^{3}), build height (*Z-mm*), build time (*T-min*), cost (*C-euro*) and the projection area onto the XOY platform (build platform) (*A-cm*^{2}) are identified as decision attributes and are taken into consideration simultaneously and equally to evaluate all the raw alternative orientations. After refining/filtrating, 16 sets of practical alternative orientations are generated for the part group. One set of practical orientations for a part is presented in Figure 14. Then, the next step is to search out an optimal orientation combination to optimize the global objectives. In this example, to reduce the build time & cost and improve the average production quality, five objectives, *Z-max* (Z_{max}*-mm)*, the maximum build height of the parts; *Difference of build heights* (*std(Z)*) ; *Average projection area onto the vat bottom* (A_a*-cm*^{2}*)* ; *Average support volume* (V_a*-mm*^{3}*)* and *Average surface roughness* (R_a*- μm)*, are set as global objectives with equal weights assigned.

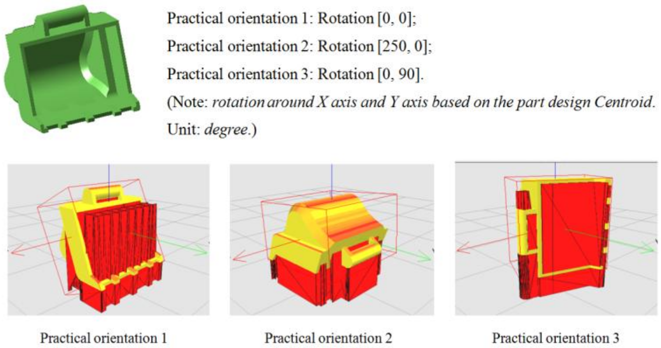


Figure 14, Practical alternative orientation set for a part.

The aspired goal used for global optimization is obtained by conducting five single optimizations for the five global objectives. It is similar to TOPSIS method. The aspired goal is composed of the five obtained optimal values of the five objectives and it is given as

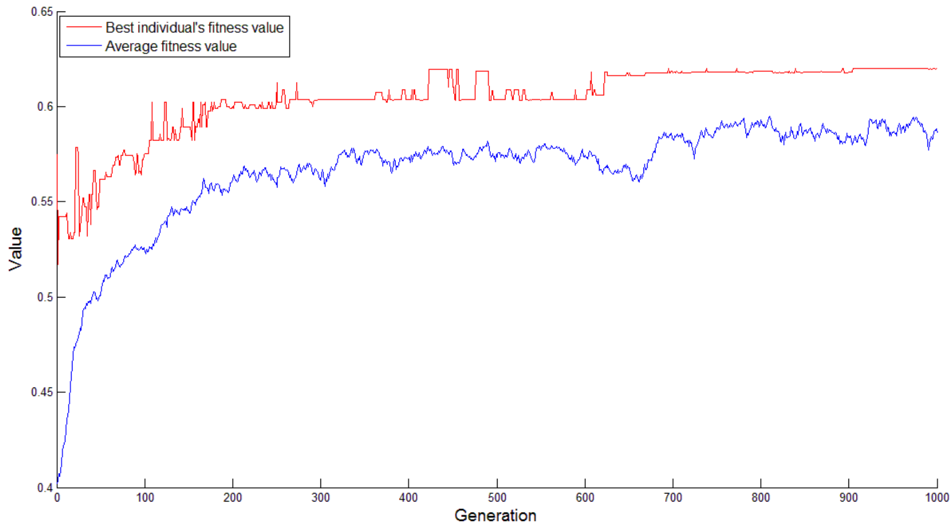
Aspired Goal = [80.4300, 16.1420, 2.4712, 376.4075, 4.1769]. (6)

With the obtained aspired goal and the design genetic algorithm, the global optimization can be conducted. The parameters for the designed GA are set as:

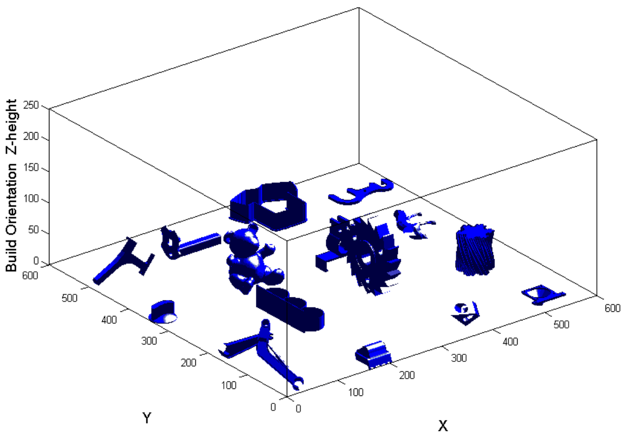
Chromosome length: *16, the number of the parts;*

Population size: *400;*
Crossover Probability: *0.7;*
Mutation probability: *0.1;*
Generation: *1000.*

The optimization result is presented in Figure 15 below.



(a), Optimization procedure.



Five-objective optimization

Optimal solution: C = [1 3 1 3 1 1 2 1 4 1 1 1 1 2 1 2]

Best value: [80.4300, 16.7977, 4.8181, 393.5944, 5.5069]

Aspired goal: [80.4300, 16.1420, 2.4712, 376.4075, 4.1769]

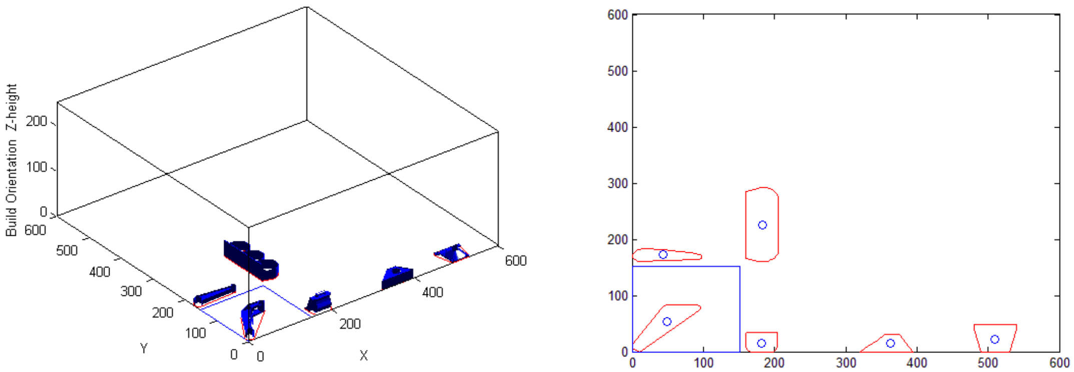
(b), obtained optimal solution

Figure 15, Orientation optimization result for the 16 parts.

The optimization result shows that the optimal solution is very close to the unattainable aspired goal. Four sub-objectives have attained a good approaching to their individual optimal solutions respectively except for the fourth sub-objective, minimizing the average support volume. If more preference weight can be given to the fourth sub-objective during the Many-objective optimization procedure, the evolutionary search would provide a solution with a better value for the fourth sub-objective. However, the values for other objectives may be affected. This is normal for multi-objective optimization problems where compromise among the investigated objectives should be often made. The example has testified the availability of the proposed two-step solution for the multiple parts orientation optimization problem. Infinite orientation combination space can be greatly reduced by the AM feature based alternative orientation generation method and an optimal orientation combination is obtained by applying an improved genetic algorithm.

- **Test example for work space planning module**

An assumption is made that a group of parts are already oriented and exported from the orientation module. They are displayed in Figure 16 (a). As introduced above, the first step of nesting is to get the projection profiles and set the nesting region. In this example, a square region is selected as nesting region. The left corner of the nesting region is the origin point of the global coordinate system. And the compactness is set as 0.7. Therefore, after projection operation, the obtained polygons and nesting region are depicted in Figure 16 (b).



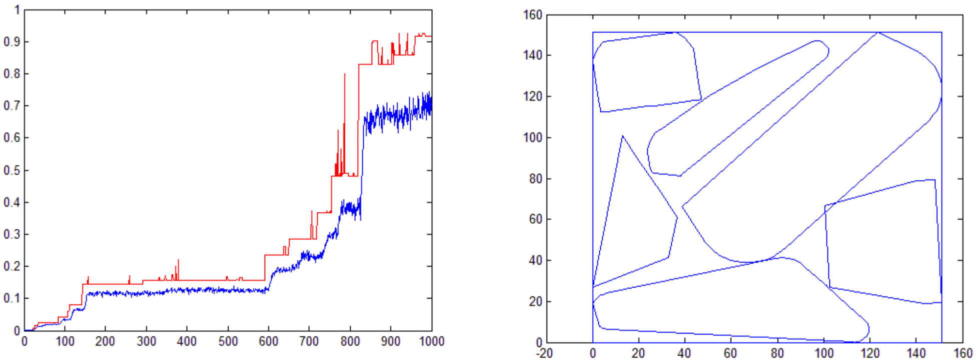
(a) (b)

Figure 16, (a), Six parts to be nested and a specified nesting region; (b), Convex approximate polygons.

The following step is to apply the designed genetic algorithm to conduct the evolutionary searching. In the genetic algorithm, a running condition is set as: if the best fitness value is more than 0.95, then jump out the iteration and check the current obtained best solution. Because the polygon used for nesting is just an approximation and expended loop to represent a part's projection boundary. Hence, when the fitness value is big enough and even it does not equal 1 (total overlap area is 0), the obtained related solution may meet the nesting requirement that is no collision between parts exists. Certainly, more rigorous running conditions can be set, e.g. the fitness value arriving at 1, which requires no overlap exists. The operating parameters of the genetic algorithm are set as:

Chromosome length: *6, the number of the parts;*
Population size: *200;*
Crossover Probability: *0.9;*
Mutation probability: *0.2;*
Generation: *1500.*
Step length of translation*: 1mm;*
Step length of rotation*: 1 degree.*

After computation, an optimization result can be obtained. The current best fitness value is found as 0.9525 at the 1000th generation (Figure 17 (a)). The total computation time is 3162.1578 seconds. The figures presented below show the nesting result. As depicted in Figure 17 (b), the nested polygons have a small overlap. However, there is no collision between the parts (Figure 18) due to the expanded polygons and their approximation.



(a) (b)

Figure 17, a, Optimization procedure; b, Nested polygons with tiny overlap.

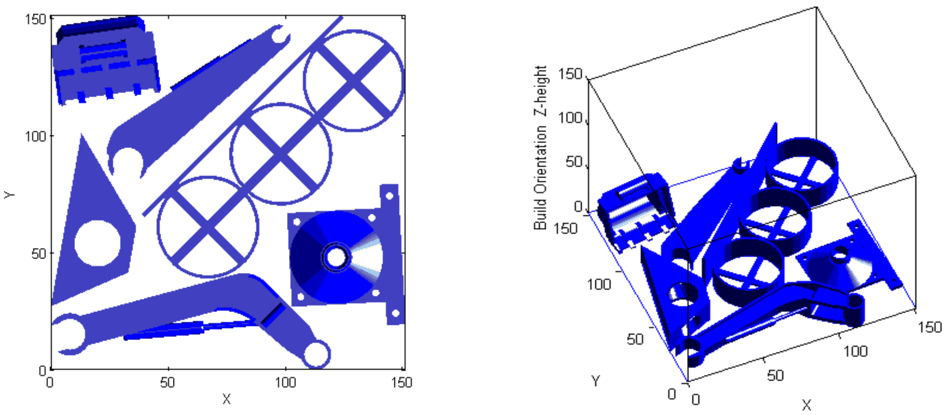


Figure 18, Nesting result for the six oriented parts.

The result shows that the proposed nesting algorithm is feasible to solve the 2D nesting problem of the work space planning module. However, the computation time is a little long. The behind reasons may include: large compactness; small translation step length and rotation degree; poor setting of parameters or operations for the genetic algorithm, etc. As stated before, this research focuses on testifying the parallel nesting method at the prototype level. Hence, more research should be done to improve the computation performance. However, it has the potential to compete with other nesting methods for AM proposed in literature since the parts can be rotated at any degree and small parts can be packed into the inner open holes of other bigger parts to further improve the compactness if concave polygons with multiple loops are used to represent projections with holes. This cannot be realized by current nesting methods proposed for AM in literature since many of them are 'legal placement' method that does not allow the occurrence of overlap during the nesting. Therefore, more advanced computation technical methods, faster computer languages, advanced graphics algorithms etc., can be applied to improve the nesting performance and computation performance of the proposed nesting strategy. Therefore, further research should be done to improve the performance of the proposed method when applies it in real engineering context since computation time is very important.

Conclusion

This paper presents a study on process planning for AM in multiple parts production context. A feature and knowledge based systematic process planning strategy is proposed. A process planning framework is constructed and some of the main modules of a developing process planning system are implemented on the Matlab platform. However, this is just the initial result of the current study. Due to the complexity of process planning problem, further research should be carried out. Future work will be conducted to investigate the construction of AM feature base, AM production knowledge base, AM process benchmarking base, prediction model base, the improvement of decision models, optimization algorithms, program codes, the systematic analysis for the interrelations between different process planning tasks, etc.

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