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► **To cite this version:**

Yicha Zhang, Zhiping Wang, Yancheng Zhang, Samuel Gomes, Alain Bernard. Bio-inspired generative design for support structure generation and optimization in Additive Manufacturing (AM). CIRP Annals - Manufacturing Technology, 2020, 69 (1), pp.117-120. 10.1016/j.cirp.2020.04.091 . hal-02942458

**HAL Id: hal-02942458**

**<https://hal.science/hal-02942458v1>**

Submitted on 23 Aug 2022

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# Bio-inspired Generative Design for Support Structure Generation and Optimization in Additive Manufacturing (AM)

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Additive Manufacturing (AM) is widely used to manufacture complex and personalized medical components. However, the generation and manually removing of support structures in the pre- and post-processing stages are still time-consuming and costly. To improve the automation of preparation while reducing support structure volume, post-processing time and cost, this paper proposes a bio-inspired generative design method, integrating parametric L systems, evolutionary optimization and an AM processing simulation model, to generate light-weight, easy-to-remove and heat-diffusion-friendly biomimetic support structures. Dental components are modelled and manufactured for validating the proposed method. The results obtained are compared with that of existing commercial software tools.

Design optimization, Additive manufacturing, Support structure

## 1. Introduction

Additive Manufacturing (AM) has become a competitive processing method in the manufacture of highly customized high-value components with complex geometries for its non-linear relationship between cost and complexity [1]. However, 'as-printed' is not the same as 'as-designed' since there are preparation tasks, e.g. building orientation determination and support structure design, along the digital chain to influence the feasibility, suitability and stability of AM [2, 3]. For the powder bed based metallic AM processes, such as Selective Laser Melting (SLM), the design of the support structure is critical since there is not only a need to sustain the overhanging areas and concave features in printing, but also a requirement of heat diffusion mediums to resist thermal distortion [4, 5]. In medical applications, components usually have thin-wall features with freeform shapes. Designing support structures for these components is challenging and removing these structures is often done manually because the components, e.g. dental parts, are fragile and it is hard to make specific fixtures for machining in the post-processing stage. In addition, the material use rate is very low, only about 30% as up to 50% of powders are wasted on support structures. Furthermore, the manual post-processing is more costly. Therefore, how to design an optimized support structure with reduced material use, easy-to-remove for post-processing and friendly heat-diffusion properties to reduce the cost and improve printing quality becomes the core research question. However, existing solutions for support structure design have limitations for complex components in metallic AM. Hence, this paper proposes a new bio-inspired generative design method to grow optimal natural tree shape structures to offer supporting and heat-diffusion function in printing.

## 2. Related work

To generate support structures for a component with a fixed build orientation, there are two main steps: 1. Identify the

support areas or points and 2. Generate a structure topology to connect the support points with the build base. Facet normal vectors or slice contours and AM manufacturing constraints, e.g. maximum lateral bridge length, maximum inclination angle, are used to identify support areas. To define the topology of support structures, direct projection-based methods, cellular structure filling and volumetric topology optimization methods are widely practiced. In projection generation methods, overhang areas are projected onto the building base and then linear thin walls with predefined cross-section profiles are generated along the projection rays. Many commercial AM preparation tools adopt this method because of easy manipulation. However, there is no optimization nor consideration of AM constraints. The printability of the support structure itself is not checked. For the cellular filling methods, predefined cellular lattice cells are used to replace solid walls in the projection-based method to form porous supports to reduce the volume of materials [6-8]. In addition, Dijkstra's Algorithm [9] is applied to search for the shortest connection path for filling cellular units. Similar approaches are reported in [10, 11], where different search algorithms are used. The main problem of these methods is that there is no validation for the generated sparse lattice or tree shape structures. In [11], the floating tree branches in the demonstration example show the problem of non-self-support of the modified lattice grid. To avoid the limits of lattice filling, three new types of filling cell shapes, 'Y' 'IY' and 'Pin' shapes were investigated in [12]. The aim is to predefine printable unit shapes for filling to ensure the support quality. However, the feasibility was only verified by a simple overhang plane example. Further validation is required for the case of complex components. To explore the potentials of tree shape, in [13, 14], supporting cone and modified local tree nodes generation rules were proposed to generate tree shape support structures. Searching algorithms are used to find for the minimum accumulative path length, and then variable strut diameters are assigned to different branch layers to guarantee sufficient support strength. However, these methods were only tested by a plastic AM process without considering

other metallic AM processing constraints. To further simplify the support generation, a bridge support structure design method was proposed in [15]. Manufacturability, e.g. lateral maximum bridge length is considered in the support design. But this method is still only used for the plastic AM process and the variation of strut diameters for different bridge layers has not been considered. To summarize, current methods have the following problems:

- Limited to non-metallic AM processes where the main constraints are geometry related. For metallic AM processes, very little research has been done.
- Not enough attention is paid to the manufacturability and stability of the support structure itself. In metallic AM, the support structure strength, heat diffusion performance and the deformation of the support structure caused by thermal stress should be considered.
- How to select the most suitable support points on the overhang areas is neither explained nor studied.
- Method validation is only based on relatively simple cases and very little numerical simulation is available. Complex demonstration examples at industrial level are missing.

To solve these problems and meet the requirements of dental fabrication, this paper attempts to give a practical solution. The next section presents the proposed method.

### 3. Bio-inspired generative design method

In the preparation stage of AM, the determination of build orientation couples with the support structure design since it directly defines the solution space of the support structure design problem. For complex components, the coupled relationship makes the problem more complicated. To limit the scope of research, the proposed method starts from a Stereolithographic (STL) model with a predefined build orientation. Regarding the build orientation optimization for complex medical components, readers can find further details about an AI based solution in [16]. Figure 1 below describes the method workflow.

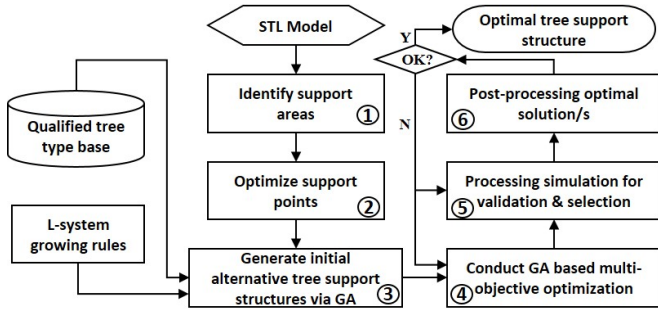


Figure 1. Workflow of the bio-inspired design & optimization method.

#### 3.1. Step 1: Identify support areas

After importing an STL model with a predefined build orientation, overhang areas can be identified by using the angles between the facets of the normal vectors and the build direction, or calculated by using information from slicing contours. In this paper, information regarding normal vectors of facets is applied and the maximum inclination angle of printing is set at 45°.

#### 3.2. Step 2: Optimize support points

As reviewed above, there is no investigation about how to identify the most suitable support points on the overhang areas. Actually, it is a key factor influencing the support structure design space and printing quality. Here, a re-projection optimization strategy is developed. At first, all the overhang areas are projected onto the build base, XOY plane. Then, the projected 2D area is decomposed into a set of squares/bounding boxes, whose

sizes are calculated by the use of projection height, the density and distribution of the facet vertices, etc. Within each square, a set of finite evenly distributed 2D points are generated. After that, an optimization algorithm is applied to translate and rotate the 2D point grid to minimize the total number of grid points within the 2D projection area. Finally, these points within the area are re-projected onto the 3D overhang surfaces to form support points. It should be noted that the maximum distance between 2 points in the grid should respect the maximum bridge printing length of AM capability in order to avoid any surface collapse in printing. In this example, the value is 1mm (it is possible to set different values in practice to meet the shape accuracy requirement and respect the AM process capability). Figure 2 shows the optimization procedure via a mandible implant part.

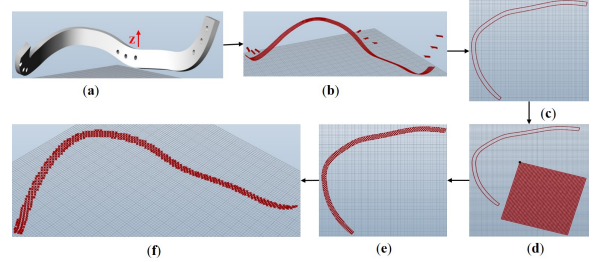


Figure 2. Workflow of the support point optimization: (a). oriented component; (b). identified overhang areas; (c). 2D projection of overhangs; (d). 2D point grid rotation searching; (e). minimum grid points within the 2D projection; (f). optimal support points (re-projected grid points onto the overhang areas).

#### 3.3. Step 3: Genetic algorithm for populating alternative solutions

The core of generative design is to apply an evolutionary algorithm to populate alternative solutions in the design space. To build a single solution, the mathematical theory of L systems [17], which simulate the growing of plants, is adopted as the growing rule for tree structure development.

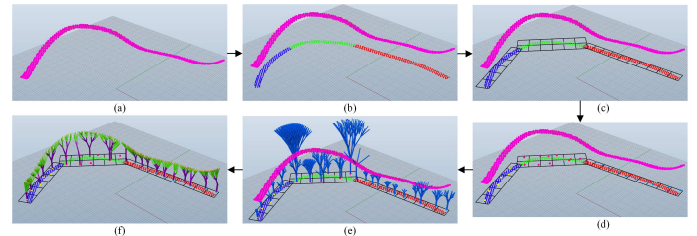
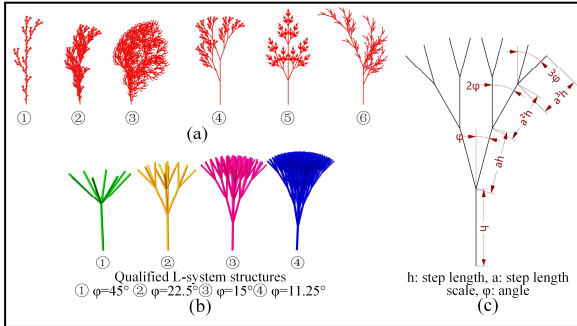


Figure 3. (a). support points; (b). projection of support points; (c). decomposition of projection areas; (d). randomly generated tree roots; (e). randomly selected tree types for growing; (f). pruned trees.

Figure 3 shows the main steps of a tree structure generation: 1. Determine the underneath space of the support area; 2. Randomly select tree type shapes in a data base and plant tree roots randomly within the decomposed 2D projection areas with random rotation angles around the build orientation, and then grow the trees with L-system rules to intersect with the 3D overhang areas; 3. Connect support points with tree branch nodes and find the shortest path of each; 4. Finally, select the shortest connections and remove the invalid L-system edges (not in the connection path) to obtain pruned trees. The branch shape and size are controlled by section profile and size level ratio. Different layers of branches can have different diameters or even diverse section profiles. These values are calculated according to the requirements of support strength and thermal distortion control. To generate valid trees to satisfy the printability and ensure self-support, a set of predefined qualified basic tree shapes, validated (by both numerical and physical experiments) for self-support and shape accuracy, are stored in a database as inputs of the tree population algorithm. This is to ensure that each of the populated

alternative solutions is valid. Figure 4 shows the L-system theory and some predefined tree types. By adding extra operating parameters, translation and rotation, to 2D L-systems, 3D tree structures can be generated. To populate alternative tree structures, a genetic algorithm (GA) is developed to operate these parameters.



**Figure 4.** (a). L-system for growing simulation of natural trees; (b). predefined valid basic tree shapes; (c). L-system parameters.

### 3.4. Step 4: GA-based multi-objective optimization

Theoretically, the solution space of this design problem is infinite since the space under the overhang areas is continuous and infinite topology shapes can be defined as support structures. Hence, to search for the optimal solution with multi-objective consideration, an evolutionary algorithm is a practical tool. This method adopts NSGA-II for searching. Two objective functions are defined to minimize the support volume and support collisions, and five variables, among which the initial position and initial orientation represent the tree root position and the tree rotation angle around the build direction on the XOY plane respectively, are set for populating the alternatives. Figure 5 presents the GA parameters and its encoding. The final output of this step is a Pareto front with a set of finite non-dominated solutions for further decision making.

Objectives	Chromosome
<ul style="list-style-type: none"> <li><b>Volume of support structures:</b> <math>F_1(x) = V = \sum_{i=1}^n v_i</math> where <math>v_i</math> is the volume of <math>i</math>-th L-system, <math>V</math> is sum of volumes.</li> <li><b>Number of collisions:</b> <math>F_2(x) = C = \sum_{j=1}^n c_j</math> where <math>c_j</math> is the number of collisions between <math>j</math>-th L-system and the part, <math>C</math> is sum of collisions.</li> </ul>	<ul style="list-style-type: none"> <li><math>L_1 L_2 \dots L_k \dots L_n \rightarrow L_k</math> is the <math>k</math>-th L-system structure</li> <li><math>s_1 s_2 \dots s_k \dots s_n \rightarrow s_i</math> is one of 4 kinds of L-system</li> <li><math>h_1 h_2 \dots h_k \dots h_n \rightarrow h_i</math> is step length</li> <li><math>a_1 a_2 \dots a_k \dots a_n \rightarrow a_i</math> is step length scale</li> <li><math>p_1 p_2 \dots p_k \dots p_n \rightarrow p_i</math> is initial position</li> <li><math>\alpha_1 \alpha_2 \dots \alpha_k \dots \alpha_n \rightarrow \alpha_i</math> is initial orientation</li> </ul>

**Figure 5.** Optimization problem description and GA encoding.

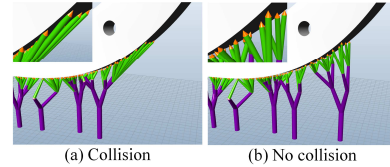
### 3.5. Step 5: Processing simulation for validation and selection

Even though the trees are generated by using validated basic tree types with self-support capability, it is still necessary to predict temperature evolution and deformation of support structures themselves since they are pruned and will directly influence shape accuracy, when catching floating volumes during printing, and the final distortion caused by residual stress. Hence, to further evaluate the Pareto solutions, a processing simulation model is applied to simulate the printing procedure of support structures by using a super-layer strategy. Heat transfer simulation is the focus for evaluation. In this simulation model, the non-exposed powder is considered for heat diffusion throughout the support branches. To distinguish the different material domains, two interfaces between support and non-exposed powder and between powder bed and gas are tracked by the level-set method, in which the interface for the deposited layer (between powder bed and gas,  $\psi^f$ ) is updated by the deposited thickness  $\Delta z_i$  through  $\psi^{(t+\Delta t)} = \psi^t - \Delta z_i$ . The linear diffusion equation is used to improve computation efficiency for heat transfer analysis. Finally, the best heat transfer support structure in the Pareto solution with the minimum deformation, especially with the minimum branch tip translations, is identified as the best

solution. More detailed information of this numerical model is referred to [18].

### 3.6. Step 6: Post-Processing the optimal solution

Once a final solution or a subset of Pareto solutions is selected, it is still necessary to do some post-processing. At first, there is a need to check the collision places (Figure 6a) when the minimum value of the second objective function is not zero. To avoid surface repair after printing, the branches intersecting with convex features of overhang areas can be further broken into sub-branches or move slightly to avoid contact. Then, to enable easy removing, the tips of the branches are modified as cone shapes to connect with the support points (Figure 6b).

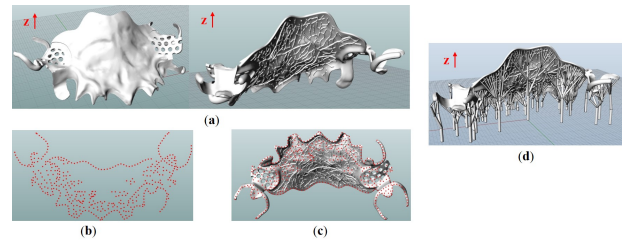


**Figure 6.** Collision cases and cone tips.

As shown in the workflow (Figure 1), two design iteration loops are set for searching and tuning to optimize the support structure. The six steps are designed specifically to reply to the open questions at the end of Section 2.

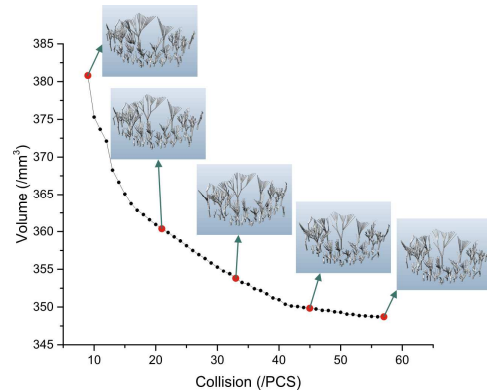
## 4. Case study

In this section, a real dental component (Figure 7a) of a patient is selected for method validation. The component is also tested by three other popular industrial support generation tools for comparison.



**Figure 7.** (a). STL model of the dental component; (b). grid points within 2D projection area; (c). support points on the overhang areas; (d). an alternative tree support structure for the dental component.

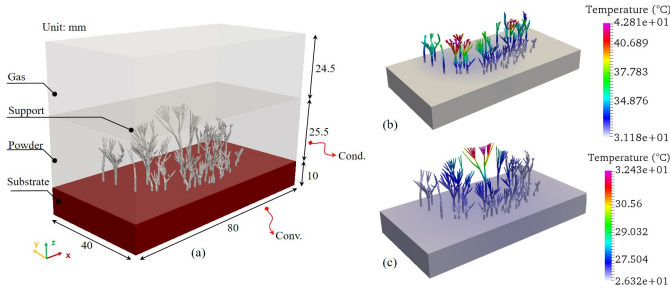
According to the method workflow, the first step is to calculate the overhangs and then optimize the support points for the component. Figure 7b and 7c show the results. Once the support points are obtained, L-system rules can be embedded into the GA algorithm for growing trees. GA operations on the five variables can populate a large number of alternative trees. In this case, the 4 basic tree types in Figure 4b are used. After that, the two objective functions drive the GA to search for non-dominated solutions. The output of this step is a Pareto front (Figure 8).





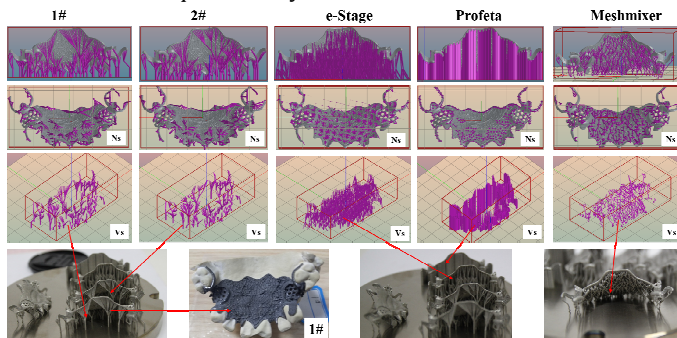
**Figure 8.** 5 non-dominated solutions on the Pareto front.

A processing simulation is then applied to further evaluate the Pareto solutions in order to locate the optimal one with minimum thermal distortion. A simulation example is presented in Figure 9, where, after the dwell time, the temperature values of the entire tree are close to room temperature (20°C), and a very small temperature gradient is found in the tree structure. This implies a very small distortion could happen to this tree.



**Figure 9.** (a). tree structure growing simulation model; (b). temperature distribution in printing after dwell time (growing height of 12.6mm); (c). temperature distribution at the end of printing after dwell time (growing height of 25.5mm).

After the post-processing of the support structures, two of them are selected for physical experiment validation and comparison. A Ti-6Al-4V material and a Profeta SLM medical fabrication machine with existing working parameter setting are used for a comparison experiment. Figure 10 and Table 1 show the printing results with that of three other tools for comparison. Since support volume and the number of support/contact points directly determine the post-processing time and cost, Table 1 only gives a quantitative comparison of support volume while others are done qualitatively.



**Figure 10.** Comparison of preparation and printing results.

**Table 1** Printing result and comparison of four methods

Solution	1#	2#	E-stage	Profeta	Meshmixer
$V_s(g)$	2.06	1.99	3.29	6.93	2.16
$N_s$	Less	Less	Most	Medium	Most
$R_a$	Best	Best	Worse	Worse	Worst
$P_t$	less	less	more	more	most

$V_s$ : support volume;  $N_s$ : number of support/contact points;  $R_a$ : surface roughness;  $P_t$ : post-processing time. **Note:** component volume is 3.34 g.

In the comparison, observations are found such as: **a.** the tree structures can well support the complex overhang areas without any collapse; **b.** Shape accuracy is very good since the printed part can be directly inserted into the assembly model without any adaptation; **c.** Support points are greatly reduced as compared with others, which means the post-processing time spent on removing support and repairing the contact surface areas on the components can be greatly reduced; **d.** The support volume has been greatly reduced too. Even though the solution of Meshmixer

can also reduce many support materials, it has a very bad surface roughness and an extra difficulty for repairing the contact areas due to too many support points. In addition, its shape accuracy is not acceptable since it is hard to assemble. Generally, the proposed approach performs the best out of the four methods.

## 5. Conclusion

The proposed method can save more than 40% of support material and reduce much post-processing time. It has the potential to replace current support design tools for dental AM and can also be adopted for other industrial applications using SLM. In addition, the designed support structures are parametric and easy to control and adapt. However, the main challenge of the method is the computation cost of the numerical simulation. That is why it is only used to evaluate the limited Pareto solutions but not directly embedded into the GA iteration loop to evaluate large number of intermediate alternative solutions. Cost-effective AM processing simulation models and tools are still in urgent need.

## Acknowledgement

The authors would like to express their sincere appreciation to Mr. Tan Shujie, PhD candidate, from Nanjing University of Aeronautics and Astronautics and Nanjing Profeta Intelligent Tech. Co. for their support on providing SLM processing and material parameters for simulations and case study experiments.

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