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Optimal design of a 3D-printed scaffold using intelligent evolutionary algorithms

Mitra Asadi-Eydivand[a,*], Mehran Solati-Hashjin[b], Alireza Fathi[c], Mobin Padashi[c], Noor Azuan Abu Osman[a,**]

[a] Department of Biomedical Engineering, Faculty of Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia
[b] Department of Biomedical Engineering, Amirkabir University of Technology, 15914 Tehran, Iran
[c] Department of Mechanical Engineering, Babol University of Technology, Iran

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ABSTRACT

Fabrication of three-dimensional structures has gained increasing importance in the bone tissue engineering (BTE) field. Mechanical properties and permeability are two important requirement for BTE scaffolds. The mechanical properties of the scaffolds are highly dependent on the processing parameters. Layer thickness, delay time between spreading each powder layer, and printing orientation are the major factors that determine the porosity and compression strength of the 3D printed scaffold.

In this study, the aggregated artificial neural network (AANN) was used to investigate the simultaneous effects of layer thickness, delay time between spreading each layer, and print orientation of porous structures on the compressive strength and porosity of scaffolds. Two optimization methods were applied to obtain the optimal 3D parameter settings for printing tiny porous structures as a real BTE problem. First, particle swarm optimization algorithm was implemented to obtain the optimum topology of the AANN. Then, Pareto front optimization was used to determine the optimal setting parameters for the fabrication of the scaffolds with required compressive strength and porosity. The results indicate the acceptable potential of the evolutionary strategies for the controlling and optimization of the 3DP process as a complicated engineering problem.

1. Introduction

Additive manufacturing (AM) is a layer-over-layer manufacturing technique. In most cases, enables complex components to be manufactured that are difficult to fabricate or cannot be made using conventional methods. Among AM practices, powder-based three-dimensional printing (3DP) is the most capable technique for bone tissue engineering (BTE) applications [1–6].

Seeding and cultivating scaffolds with bone cells is the standard method in BTE. Scaffolds are highly porous 3D structures that aim to imitate the natural extracellular matrix (ECM) of bone on a temporary basis. From a technical point of view, scaffold engineering sets high demands on design and materials. In addition to chemistry, interconnected porosity, permeability, and mechanical strength are critical parameters that define the performance of a scaffold. These factors cannot be controlled precisely through conventional fabrication processes [7–9].

The immense potential for fabrication of scaffolds due to its maximum control over porosity and its ability to reproduce the customized anatomical design with great fidelity to the 3D medical pictures are the main advantages of the powder-based 3DP [10–12].

Fig. 1 shows a schematic illustration of the 3DP process. First, the chosen physical object is modeled on a computer-aided design (CAD) system. Then, the CAD model is converted to the stereolithography (STL) file format. A software program analyzes the STL file and mathematically slices the model into cross sections based on the selected layer thickness. The cross sections are recreated using the reaction of the powder and the binder. This process is repeated layer by layer until a 3D object similar to the design is formed. During the fabrication process, the printer head jets a liquid into thin layers of powder according to the object profile created by the software. Subsequently, a build chamber (build-bed) containing the powder bed is lowered to enable the spreading of the next powder layer. Following the consecutive application of layers, the unbound powder is removed, and the 3D part is produced

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* Corresponding author. Tel.: +60 1123288084; fax: +60 3 7956 1378.
** Corresponding author.
E-mail addresses: mitra@um.edu.my (M. Asadi-Eydivand), azuan@um.edu.my (N.A. Abu Osman).

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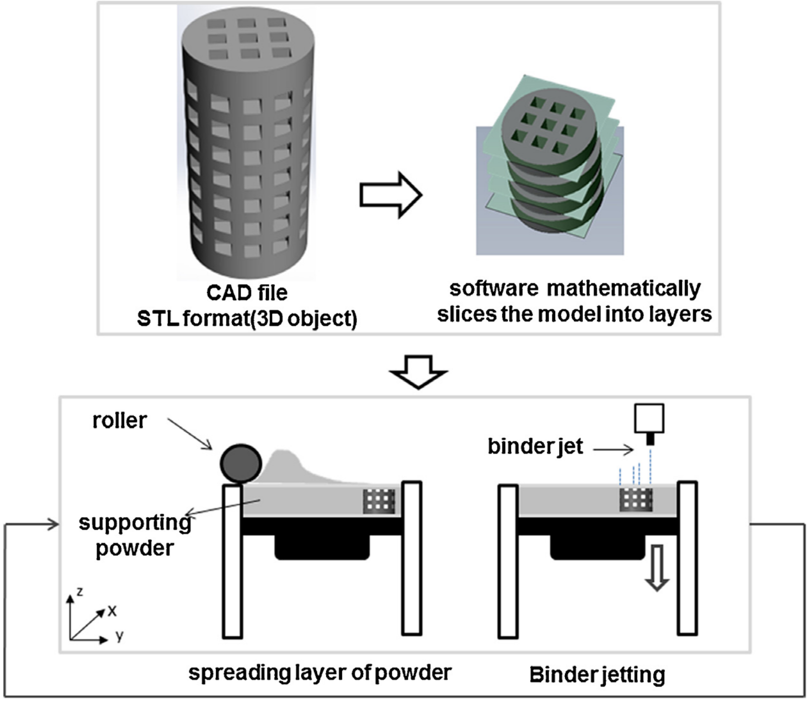

Fig. 1. Schematic illustration of the 3DP process.

[13–17]. Setting the 3DP process parameters is a complex and time-consuming task, as there are many variables that influence the printed part quality for particular applications. In many cases, these variables conflict with each other. In recent years, many reports have been made on the 3DP fabrication of BTE scaffolds, and its critical process factors and parameters [18–22]. Many studies have focused on improving the dimensional accuracy (DA) and mechanical properties of 3D-printed objects and have shown sensitive process parameters that can be tuned to improve the desired attributes. These characteristics are related to the process parameters and can be improved with proper adjustment [4,19,20,23–25].

Although a number of successful production experiments have been conducted, the quality assessment of fabricated parts remains to be one of the main challenges. Factors influencing quality have been studied through diverse indicators. However, a significant amount of work has not focused on mechanical properties and porosity together for the fabrication of tiny pores on scaffolds in the application of BTE. The cost of the end products of the process is high. Therefore, from a technological and economic point of view, selecting the process parameters for the optimization of manufactured parts is highly essential. In the context of the 3DP process optimization for improving the performance of the prototype, the soft computing method is a promising approach to monitor and model the process based on physical understanding and experimental data [26].

Achieving the optimal process parameters for fabricating 3D parts using the experimental tests is a time-consuming and costly approach. Numerical models of the process can be effective tools in finding the appropriate process parameters according to the demanded characteristics. From the physical modeling point of view, the 3DP process is complex. Many physical phenomena (e.g., powder and binder reaction and removing unbound powder) affect product quality. Based on the author's experiments and analysis, it has been observed that the relation between the porosity and compression strength of the porous structures and the influential parameters are nonlinear and uncertain. On the other hand, it is a very formidable task to provide an authentic and exact physics-based mathematical formulation, which can effectively represent the effect of layer thickness, delay time between spreading of each powder layer and printing orientation on the porosity and compression strength of the porous structures. Solving all the related governing equations using the analytical or numerical methods to obtain a mathematical model of the 3DP process is not only difficult but may also be impossible. To overcome this problem, the best way is to use a soft method to obtain a data-driven mapping system to approximately analyze the destined properties of the porous structures. Many researchers prefer to use semi-experimental models instead of numerical models to model the physical process, such as the 3DP process. Artificial neural network (ANN) [27–30], fuzzy system [31,32], Hammerstein–Wiener [33,34], time series [34], and Kalman filter are some of the well-known methods for establishing an experimental model of a system based on the available experimental data. To select a soft method which can be reliably used for this case study, the authors considered several techniques and conducted a primitive study such as neural networks, polynomials, splines, and etc. Published papers on ANNs suggest that this modeling methodology is a promising alternative tool for process modeling [35–40]. This method can overcome conventional modeling difficulties as it has the advantages of ease of implementation and capability of constructing a complex nonlinear map between inputs and outputs of a system. A few studies have been conducted on ANN modeling of the 3DP process. This research aims at developing an experimental based predictive model for the 3D printing process using the aggregated artificial neural network (AANN) method. The AANN algorithm is one of the well-known variants of the neural networks models which has been used in many engineering applications [41–45]. Aggregating multiple neural for improving the generalization of neural networks, is its main contribution. Many researchers have shown that a more accurate predictive model can be obtained in comparison with a single neural network with the same number of neurons by aggregating several neural networks [46,47]. Finding a single neural network that can model a highly uncertain complex engineering phenomenon is often difficult. The major drawbacks of these artificial machines often result from over fitting and high computational complexity. Combining a set of independent