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ScienceDirect

Procedia Manufacturing 38 (2019) 117–124

Procedia MANUFACTURING

www.elsevier.com/locate/procedia

29th International Conference on Flexible Automation and Intelligent Manufacturing (FAIM2019), June 24-28, 2019, Limerick, Ireland.

Optimizing the hardness of SLA printed objects by using the neural network and genetic algorithm

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Abstract

In the developing field of manufacturing, 3D printing is rapidly increasing the horizon of what is possible. However, the possibility of implementing new 3D methods of production has brought new challenges for industries, particularly in the case of changing traditional mind-sets about methods of manufacturing. This is due to the traditional and fixed mind-sets of experienced designers and of course owing to the lack of knowledge on 3D printing. In this paper, 3D printing processes were optimized by using a new algorithm; this advanced algorithm is created by combining the characteristics of an artificial neural network (ANN) and a genetic algorithm (GA). Furthermore, the print efficiency and quality of final products can be improved by optimizing 3D printing experimental conditions.

In the current study, stereolithography (SLA) was employed as the 3D printing technique. This particular technique is commonly used to fabricate solid objects that are photochemically solidified. Based on previous research results, three main contents of process planning in 3D printing were defined and used as input to build the ANN model to predict the hardness. With orientation ranging from 0 to 90 degrees, ultraviolet post-curing (UV curing) time ranging from 20 to 60 minutes and annealing time from 0 to 4 hours, over 100 samples were tested to create a large sample set. It was observed that the orientation had the most significant impact while UV curing time had the lowest significant impact on the printed object's hardness. In addition, based on the hardness results, the predicted orientation of 0 degrees, UV curing time of 60 minutes and an annealing time of 2.88 hours were the optimum experimental conditions for the final printed object's hardness. From this study, it was concluded the new algorithm could be used to optimize the hardness of printed objects and to provide key information for the improvement of existing 3D printing technology.

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2351-9789
10.1016/j.promfg.2020.01.016

Keywords: 3D printing; Stereolithography; Artificial neural network; Genetic algorithm

1. Introduction

Three-dimensional printing (3D printing), or Additive Manufacturing (AM) can be defined as a layer upon layer fabrication technology using the consolidation of feedstock material to build up the desired geometrical shape of 3D components [1]. These components are fabricated by using a variety of AM techniques with precise topologies from three dimensional CAD data [2]. In the infancy of AM technology in the 1980s, the main applications were focused on the prototypes. However, during the following decades, the manufacturing technology and materials developed and currently, this adaptable technique is brought to a more mature stage of production and new fields of application typically include high-value manufacturing in industries [3-4]. Furthermore, wide-ranging applications are emerging due to the reduced costs, and lots of AM customer products (end-user applications) have begun to appear [2-3].

Stereolithography (SLA) is a type of 3D printing technology which utilizes photopolymerization to produce layered structures and is widely used in the field of tissue engineering. It is also known as solid free fabrication, optical fabrication, solid imaging, resin and photo-solidification printing [5]. SLA is superior to other 3D printing technologies, as SLA can create objects with high resolution (20 µm in comparison with 50–200 µm for other fabrication technology), which is limited only by the width of the concentrated ultraviolet (UV) laser. The advanced technique works by focusing a UV laser on to the surface of photopolymer resin to cure the molecule chains and solidify the resin forming the pre-programmed 3D object. Once the material is exposed to the concentrated UV light, it will be solidified immediately, one single layer at each time, until all layers in the model are finished [6]. In addition to a post-processing to remove excess resin, some other processes such as a UV curing and thermal annealing processes are usually adopted to improve the part's finish and property.

Although the AM technology is an industrially mature manufacturing process, it has also created new challenges for industries. The technology offers the opportunity to create individual parts with a high degree of design freedom, eliminating the need for designers to consider manufacturing designs and removing the need for companies to identify suitable parts for AM. Moreover, unlocking the design potential of AM is a challenge for designers, who are lack knowledge or unfamiliar with these AM technologies and persist in using traditional methods in manufacturing [2,4]. Several researchers have tried to analyze the influence of some important printing parameters and develop convenient methods for determining the optimum properties of the printed objects, for instance by Leutenecker-Twelsiek *et al*. They have measured the influence of part orientation in design for additive manufacturing. The study presented a framework for design guidelines to determine the part orientation in the early stage of the design [3]. Zguris analyzed the effect of UV curing on mechanical properties of SLA. In his study, it was concluded that it is most advantageous to use the increased temperature and a 405 nm wavelengths light source to maximize the post-cured mechanical properties of parts printed with Formlabs resins on Form 1+ and Form 2 printer [7]. Martinez *et al*., have studied the optimization of drug release rates by increasing water concentration (up to 30% w/w) in the initial resin formation in SLA printing. They found that the higher water content in hydrogels can release drug faster [8].

Holland *et al*. developed the genetic algorithm (GA), the algorithm was treated as one of the most effective optimization tools in various scientific fields [9]. The adaptive heuristic search algorithm is based on the evolutionary concepts of natural selection and genetics. This algorithm characterizes the intelligent exploitation of a random search used to resolve optimization problems [10]. A combination of GA and neural network simulation was used to develop a non-iterative model to obtain the maximum cooling capacity of the adsorption heat pump by Krzywanski *et al* [11]. In this paper, we also used a combination of GA and Neural network to investigate the effect of three printing experimental conditions (orientation, UV curing time and annealing time) on the hardness of the printed samples.

1.1 Part Orientations

The part orientation indicates the rotation of the object in the building space around the axis of the printer coordinate system. However, it does not contain the part translation along the coordinate axis of the printer's coordinate system during part positioning [12]. Based on the working principle of SLA which is a layer by layer manufacturing process, the orientation has a significant influence on the final printed property and internal part geometry. Since there exists a difference between the part geometry in the printing direction (z-axis of the printer coordinate system) and the geometry orthogonal to the print direction, the print layer thickness at print direction will be consistent. However, the thickness in the plane of the orthogonal direction to printing direction is discontinuous and built-in discrete steps [3]. On the other hand, the part orientation of an object in Additive manufacturing has a complex effect on part's processing time and cost, because it affects the downstream preparation procedures, such as tool-path generation, slicing, support generation which co-determine the final print time and cost [13].

1.2 Neural network

The artificial neural network is an algorithm developed based on the human cognitive process; a highly connected system of elementary processors that mimic biological neurons [14]. ANNs has strong adaptability and learning ability, it can store experimental data and make it available for use [15]. It is commonly used to estimate the complex nonlinear relationship from mass data without prior knowledge about the structure of the mathematical model. Similarly to human reflection, the body responds to the stimulus. The ANNs also can train the network by continuously giving network input and corresponding output at very high speed, therefore, the ANNs can sometimes overcome the shortcoming of the programmed computing approach and the experimental procedures.

ANNs is treated as a black box model and has many engineering applications such as artificial intelligence, automatic control, pattern recognition, etc. In practical applications, most neural network models use the backpropagation (BP) neural network and its transformed form. The BP neural network is the core part of the forward network and embodies the essence of the artificial neural network. However, the BP network is not a perfect network. The main disadvantages are the slow convergence of the learning phase and the inability to guarantee a global minimum. Its network connections weights are usually determined by a local search algorithm that uses the gradient error descent method, so it is often difficult to find the optimal network structure and weights after repeated trials. The introduction of genetic algorithm provides a good alternative to backpropagation algorithms. The optimization of initial synaptic weights of the neural network is carried by a genetic algorithm.

1.3 Genetic algorithm

Genetic Algorithm (GA) is usually applied in optimizations [16]. It is an efficient search algorithm based on genetics and the natural evolution mechanism. It abandons the traditional search methods, simulates the natural biological evolution process, and randomizes the target space by means of artificial evolution. The aim of GA is to iteratively select the best set of individual solutions minimizing an objective function. Each individual in the total population is encoded as a chromosome. At each step, the GA algorithm selects several individuals randomly as the parents and uses them to create next generation by simulating Darwin's genetic selection and the natural evolution (selection, crossing and mutation operations). This process is completed until the population evolves to the best set of the individual solution, a sense that reaches the point where the synaptic weights are no longer modified.

2. Experimental

2.1 Materials

Commercially available photopolymer resins (GP Plus 14122) examined in the study were purchased from DSM's Somos (DSM, China). All 3D printed parts were manufactured on a $Viper\ Si^2$ (3D systems, USA) in stock configuration. Solid files of each sample were loaded into Buildstation 5.5.1 software, a model of a regular cuboidal bar drew by Solidworks with fixed dimensions 120mm (L) $\times$12mm (W) $\times$ 6mm (H). The layer height was 0.1mm and the beam diameter produced by laser was 0.25mm. Standard settings from software were used for the building density.

2.2 Methods

2.2.1 Orientation in Stereolithography (SLA)

Liquid photopolymer resin was contained in a metal container which contained enough resin for the parts build. Once the print platform was in complete contact with the surface of the resin, ensuring there are no gaps or bubbles between the platform and the resin. Laser from the gun cured the resin under the exposed areas until the samples were printed. In order to investigate the effects of the orientation parameter, there are two main tasks [17], one is determining the desired alternative orientation from the infinite alternative print orientation in print space for the 3D objects, and the other one is selecting concrete orientations for each specimen. Hence, three different variables were defined as $0^0, 45^0, 90^0$ with a fixed around X axis. Once the process was finished, the cured parts surface were wiped with a steel tool to remove excess unreacted resin and then soaked in fresh isopropanol ($\geq$ 99%) to further remove uncured resins. All the cured samples were kept in UV resistant conditions after this process.

2.2.2 UV curing

UV-curing experiment was performed using a UV Light Box (Multistation, France). The curing apparatus is composed of a heat sink with a mounted UV fluorescent tube array (PHILIPS, TLDK 30W, Holland) around samples at a fixed distance in three walls. In order to investigate the effects of UV curing parameter, three variables of UV curing time (20, 40, and 60 minutes) were chosen for the samples. Even though the UV-cure process is simple, it is hard to accurately control the UV-curing conditions such as uneven exposed time of samples under UV light. This issue was solved by turning the body of samples every 20 minutes during the curing process.

2.3.3 Annealing process

The annealing process was carried out in an electric oven (Gallenkamp Hotbox Size 1). In this experiment, the temperature was set $45C^0$ and three variables of annealing time (0, 2, 4 hours) were selected for the sample. For each set, seven samples were tested. One set with 0 hours annealing was treated as control. All the pieces were checked before being tested for obvious defects to ensure the accuracy of the experiment. The pieces were placed on an aluminium foil to ensure the bottom was heated evenly. After the annealing time, the samples were taken out to cool down slowly to room temperature.

2.2.4 Mechanical testing – Hardness

The hardness tests were carried out on Shore Durometer Analog (Bowers Group Co., Ltd, Camberley). Based on the technical data sheet of fundamental material (GP Plus 14122) and an ASTM D2240 standard, the type D scale was selected to measure the hardness of printed samples. Before testing, the instrumented hardness tester was carefully calibrated for force and indenter displacement. The tested printed material was set in a vertical position below the indenter. The hand shank was pressed until the foot was in full contact with the tested material to ensure the indenter plugged in the surface of the material. Each test was tested at room condition and 10 determinations were performed, and the average was considered [18].

2.2.5 The proposed hybrid algorithm

The proposed hybrid algorithm in this paper combines the neural network potentials, predicting results from process data, and the GA qualities to find the optimal solution by means of the global parallel search. The basic idea of using genetic algorithms to optimize the weights of neural networks takes into account three main steps. During the first stage, the neural network structure linked the inputs (processing parameters) and outputs (final hardness) was determined. Later, an optimization process based on GA was performed to find the most optimal weights for the neural network training. The last stage constitutes in the use of the BP method to refine the previously established values improving the network response.

In the training phase, once the main set of variables was defined. In order to solve the network over-learning problems and make these experimental data distributing homogeneously to cover, a valid operation space the Central Composite Design (CCD) was performed. The CCD is the most commonly used Response Surface Design (RSD) which is a set of Advanced Design of Experiments (DOE) techniques helping better understanding and optimization of responses. In this paper, a model of a response variable with a bend was established by this method. The total 25 input couples were divided according to the percentage 80% for the network training, 20% for the validation test.

During the proper design of an ANN considers the number of neurons in the input and output layer that determine the architecture of an ANN because these neuron numbers are related to the input and output parameters, respectively. In this study, three input parameters (the orientation *O*, the UV curing time T_{uv}, the annealing time T_a) were selected to define the number of neurons on the input layer. The final printed object's hardness constituted the output parameter. To determine the number of neurons on the hidden layer several tests were operated that showed eleven neurons could obtain the best approximation during training. Therefore, the final structure of the network turned out to have [3-11-1] eleven neurons in the hidden layers using the sigmoid function as activation function for neuron. A flowchart of the GA-optimized ANN algorithm is also shown in Fig. 1, where the GA is performed to find the most optimal weights for the neural network training.

2.2.6 ANN training process (learning)

The first step to the network training consists of obtaining recognizable data in the vectors form. Hence, a set of random weights were finally coded in the form of an individual's chromosomes by obeying the coding principle [19]. The total length of the chromosome is 56 (11+33+1+11). The task of the training is to minimize the gap between the predicted output by the ANN and the desired output. In that sense, the Lecenberg-Marquardt-Backpropagation (LM-BP) [20] learning algorithm was used to minimize an objective least mean squared (LMS) error function, *f(u)*, which was introduced, according to:

$$f(u) = \frac{1}{2}\sum_i (D_i - P_i)^2 \tag{1}$$

$i = 1,2...N$, where N represents the numbers of neurons in the output layer. D indicates the desired output of the final experimental hardness and P shows the predicted hardness via the developed model. For our system, the equation (1) reduces to:

$$f(u) = \frac{1}{2}\sum(D - P)^2 \tag{2}$$

A Matlab program was designed for optimizing the weights by using a genetic algorithm. The initial assumptions were selected as 20 units of population, 100 is the number of generations, the rate of crossover and mutation was 0.7 and 0.01, respectively. During this procedure, the weights were consecutively updated by the local gradients of $f(u)$ relative to the coupled weight. This process would be stopped until the initial weight was determined in the direction of the decreasing error gradient.

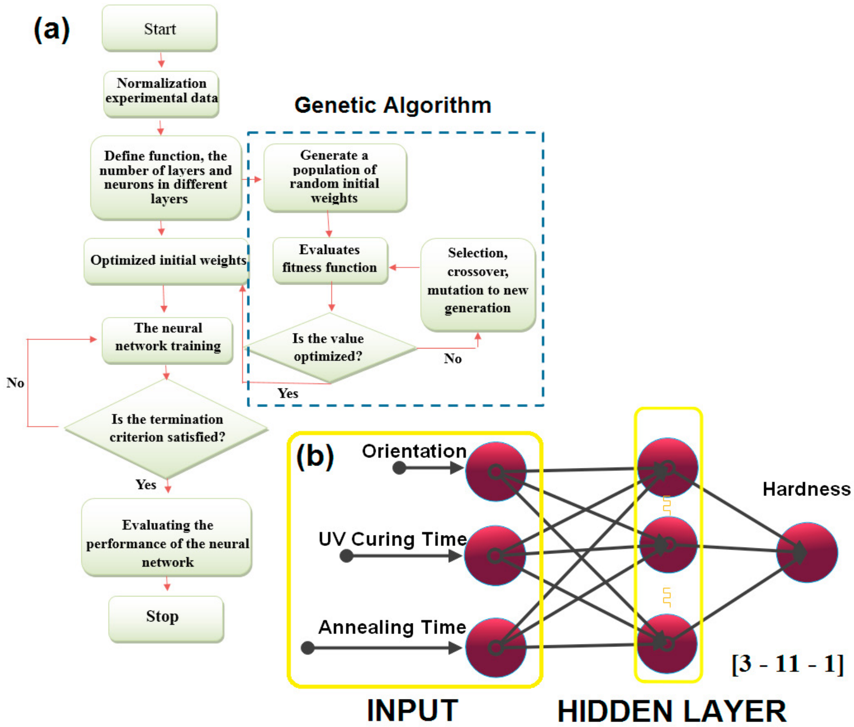

Fig. 1. (a) Computational flowchart of the hybrid algorithm model; (b) Multilayer Perceptron (MLP) neural network architecture.

3. Results and discussion

3.1 Experiment verification base on GA-ANN

The accuracy verification of the predicted output is a significant process for all the modelling approaches. To avoid the trouble to unjustifiability and overfitting for predicted results, a model can be appropriate only if it forecasts experimented samples and out-of-samples with low error estimates. Hence, in the current study, predicted values were used to print components to verify the predicted results. The experimental data are shown in Fig. 2a. And the accuracy in prediction of hardness by the model was also noted for other nine couples of new, previously unseen by the ANN independent data set (Fig. 2b).

As given in Fig. 2a, it indicated the predicted results had substantial compatibility with experimental results: the predicted results were located within the range of ±1% of relative error, whereas the maximum error was R=0.18%, the experimented hardness 81.30, predicated hardness 81.15 respectively. In Fig. 2b, a good coherence also was evident between model prediction and experimental measurement of hardness. Table 1a shows detailed data and illustrates that the relative errors for most of the forecasted hardness were lower than ±1%. These data proved that an accurate hardness can be obtained, even under the different value of processing variable, according to the proposed adaptive filling model based on GA-ANN, which provides key information for the adaptive filling control of existing 3D printing technology.

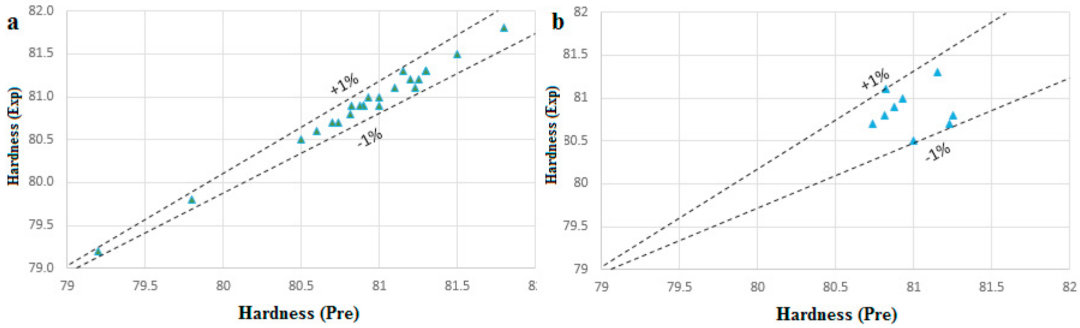

Fig. 2. (a) comparison of the hardness predicated and experimented by the model; (b) comparison of the hardness experimented and predicted by the model for new, previously unseen by the ANN independent data set.

3.2 Optimization (GA-ANN) results

The goal of GA-ANN model optimization was to determine the maximum hardness of an SLA 3D printed samples. Constraints were based on the data error in the field test. The issue was solved by using a mean value method to ensure the accuracy of the experimental database. Every individual represents the combination of the three observed variables. The random initial population was evaluated under constantly selection operation, crossover operation and mutation operation until the best combination for the experimental process was estimated through the fitness function (MLP model, Best mean fitness value = 0.999458).

Table 1. (a) The detail data about the comparison between hardness experimented and predicted by the model; (b) comparison between optimized and real experimental hardness results under optimised settings.

(a)	Experimented hardness	Predicated hardness	R (%)
Data used for testing network	80.90	80.99	0.12
	80.90	80.82	-0.10
	81.20	81.25	0.06
	81.10	81.23	0.16
Data used for Validation	81.30	81.15	-0.18
	81.00	80.93	-0.09
	80.70	80.74	0.05
	80.80	80.81	0.02
	80.90	80.87	-0.03

(b) Input variables	Optimized values
Orientation	0^0
UV curing time (min)	60
Annealing time (h)	2.88
Output	
Best predicated hardness	81.67
Real experimented hardenss	81.35

Fig. 3a shows the best individual of three investigated variables in this study. All data were normalized by using the Regularization method and the range is [-1, 1]. The results showed that when the orientation was 0 degree, the UV curing time selected 60 minutes and annealing time was 2.88 hours respectively, and the optimal predicted hardness would be obtained, that was 81.67. The optimal combination of experimental conditions, best-predicted hardness and real experimental hardness are shown in Table 1b. In addition, we also performed a single factor analysis, then analysed which factor has the greatest impact on the final mechanical property by the extremum method. The extreme range in annealing time, orientation and UV curing time were respectively: 0.53, 0.68, 0.48. It demonstrated that the orientation had the most significant impact whereas UV curing time had the lowest significant impact on the printed object's hardness. Fig. 3b illustrates the mean squared error variation in the weight optimization process by GA. As can be seen from the line graph, during this period from 0 to around 50 generations, there was a dramatic decrease in MSE, felling from the original 0.1 to the final 0.01. This implies that the GA plays a significant role in the entire optimized model that is it can search a global minimum rapidly. The desired error of the model was reached after the 100^{th} iteration number. In other words, the best initial weight was obtained after 100 generations of the population evaluation.

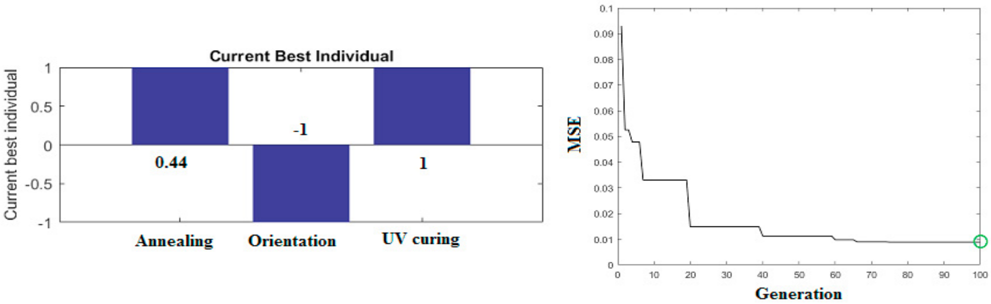

Fig. 3. (a) Current best individual of three variables for optimal hardness; (b) initial weights optimization results by GA.

3.3 Effect of three experimental conditions on the hardness

Based on the determined number of neurons and output of the proposed model, the effect of variables on the final parameter is a complex three-dimensional structure. As showed in Fig. 4, it indicated the cross-effect of two variables on hardness. It effectively verified the above conclusion. For instance, Fig. 4a demonstrated that the UV curing time was proportional to the hardness, however, the orientation was correlated negatively with hardness; Similarly, with the increase of the UV curing and annealing time (Fig. 4b), the final hardness increased overall but it had a little decrease meanwhile the annealing time raised from 3 to 4 hours; Fig. 4c showed the cross effect within orientation and annealing time on hardness was unstable. It reached a peak when the annealing time was selected between 3 and 4 hours and the orientation closed to 0 degrees. All the analysis presented that within the range of determined variables, the orientation and UV curing time had a significant impact on hardness that was positive and negative effect respectively. There were no marked differences in hardness between annealing time (from 0 to 4 hours), however, the best solution appeared to around 3 hours annealing period.

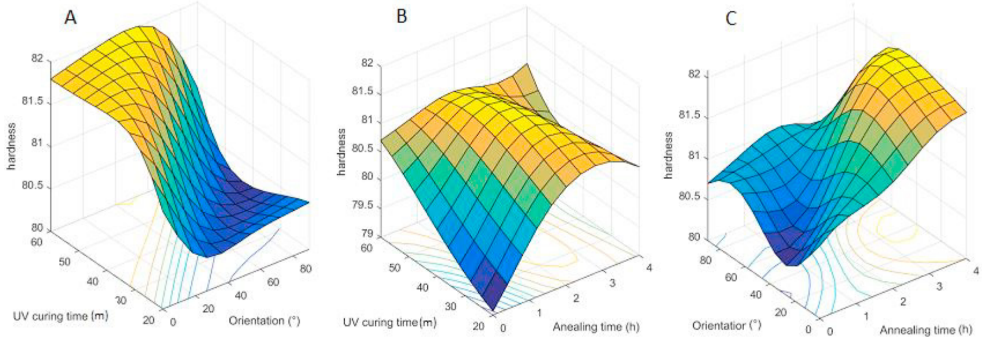

Fig. 4. A set of surface plots shows the cross-effects on hardness: (a) UV and orientation on; (b) UV and annealing; (c) orientation and annealing.

4. Conclusion

This paper constitutes the first attempt to optimize 3D printing experimental conditions for the final hardness determination by using a hybrid performance of neural networks and genetic algorithms. The proposed hybrid model was used to predict hardness from a combination of three processing parameters. The genetic algorithm is incorporated into optimizing neural network initial weights. The optimization allowed improving the network performance such as mean squared errors and iteration numbers compared to the standard neural network.

By referring to study results, UV curing time and orientation have a strong relation with hardness. A rise of UV curing time and a drop of orientation will increase the predicted value of final hardness. The highest value of the hardness which can be obtained for the considered range of lab parameters is equal to 81.67. It can be achieved for orientation $O = 0^o$, UV curing time $T_{uv} = 60$ minutes and annealing time $T_a = 2.88$ h. By comparing the experimental value with the results of the present model, the evaluated hardness gives a good agreement with the experimental measurement. The relative error for predicted values with deviations is less than 1%. This work has proven that the experimental conditions caused comparative influence on the printed object. Hence, it is feasible to use a combination of GA-ANN to model and identify the main parameters to optimize the hardness of the printed object which has provided key information for the improvement of existing 3D printing technology. However, each of the methods can be further developed before drawing final conclusions. For instance, using softplus unit instead of a sigmoid unit for the activation function and adding more hidden layers and neurons will gain more improvements in the accuracy and representation of the network. Additionally, the GA might be helped by using a form of Clusterine to the initial random weights. If these lab parameters can be optimized using a more precise model than that from GA-ANN model simulation, this may offset the relative accurate parts results.

Acknowledgements
This work was supported in part by financial support from Athlone Institute of Technology under the Presidents Seed Fund, Enterprise Ireland funding under the Technology Gateway program, grant number TG-2017-0114 and Science Foundation Ireland (SFI) under Grant Number 16/RC/3918, co-funded by the European Regional Development Fund.

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