Dimensional Accuracy Prediction for Shape Memory Polymer Using Artificial Neural Networks

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Abstract

Shape memory polymers (SMPs) and its fabrication process has recently attracted much attention because of their potential application as soft active materials. In this work, a dimension accuracy approach using artificial neural networks (ANN) is presented for overcoming the dimensional challenge in shape memory polymer/graphene oxide (SMP/GO) composites using projection-type Stereolithography (SL) 3D printing. Experimental trials were conducted to achieve proper SMP photo-resin mixing (monomer, cross-linker, photo-initiator) and suitable GO dispersion in SMP/GO composite. An artificial neural network (ANN) was designed based on back propagation theory for modelling dimensional error on specimens. ANN training and testing phases used Stereolithography (SL) historical data and results were compared using two different ANN architecture. Using the ANN approach, this paper reports a maximum Pearson correlation of 77.7 % during testing. It could be used as a reference for fabrication, and dimensional error modelling of SMP/GO composites fabricated via SL 3D printing technique.

Keywords
4D printing, material extrusion, artificial neural network, polymer nanocomposites, shape memory polymer

1. Introduction
3D printing technique has been demonstrated to be an innovative manufacturing method for industrial, medical, automotive and aerospace sectors (Santo et al. 2014). 3D printing technique with a high finishing resolution and fast curing speed is stereolithography (SL). This process is divided in two main classes of processes: scanning type (SLA) process, and projection type process. The former uses a UV laser beam to cure sections of photo-resin in a layer-by-layer fashion up to the completion of the part. The projection type uses a digital light projector (DLP) to cure resin by projecting the cross section of sliced layers of the CAD file up to the completion of the part (Choong et al. 2017a, Choong et al. 2017b, Choong et al. 2016). Recently 3D printing concept has evolved into 4D printing by incorporating smart materials (Marquez and Bolborici 2017, Marquez 2016, Renteria-Marquez, Renteria-Marquez and T. L. Tseng , Chavez et al.) in 3D printing technologies (Tibbits 2014). A strategy to promote the utilization of 4D printing in design and manufacturing stages is to increase the list of materials available. This increment of material availability implies adapting new polymer composites to commercial or customized 3D printers (Monkman 2000, Kim et al.

2017e, Kim et al. 2017a, Xu et al. 2017, Kim et al. 2017b, Kim et al. 2017c, Kim et al. 2018a, Rosales et al. 2018, Rosales, Huang and Lin 2017, Kim et al. 2018b). Shape memory polymers (SMPs) are capable to memorize a primary shape, subjected to a strain change, maintain a secondary shape, and recovered to the primary shape after external stimuli is applied. SMP functionality has two stages: fixing or programing and recovery. The former step fixes the SMP parts into a secondary shape while the second step consists in applying a stimulus to recover the part to its original shape, which is known as shape memory effect (SME) (Lendlein and Kelch 2002, Schmidt et al. 2011, Liu, Qin and Mather 2007). Moreover, SMP part fabrication using 3D printing has been attempted yielding successful demonstration of SMP functionalities and material-machine integration (Yang et al. 2016a, Kim et al. 2017a, Kim et al. 2017f, Li, Gao and Luo 2016, Rosales et al. 2017, Zarek et al. 2016, Yu et al. 2015, Garcia Rosales et al. 2018b, Rosales et al. 2018).

3D printing of photo-responsive SMP/GO nanocomposites using projection stereolithography (SL) could be a feasible manufacturing alternative. This implies to customize photo-curable resin material ratios and fabricate photo-thermal polymer composites from resin/ graphene-oxide (GO) mixture. Moreover, a photo-thermal stimulus could be better controlled when the photo-thermal material (i.e., GO) is distributed non-uniformly in SMP matrix. Another challenge on 3D printing of SMPs is part dimensional accuracy evaluation that involves the study of all the critical parameters, which can lead in complex optimization problem (Yang et al. 2016b, Choong et al. 2017b, Rahman et al. 2021). Dimensional accuracy is drawback on the final SL parts due to material shrinkage caused by photo-resin properties and fabrication settings. Not only SMPs produced by SL has led in dimensional accuracy errors, in general, it has been a challenge to overcome in 3D printing. An alternative is to evaluate artificial neural network (ANN) methodology performance as a modelling tool on SL for dimensional accuracy prediction on SMP parts. By using ANN, it is possible to predict dimensional accuracy error on SMP parts and obtain an insight of the dimensional error on final parts by evaluating the process parameter without actual fabrication of the parts.

Therefore, the main goal of the present study is to fabricate 3D print photo-responsive SMP/GO nanocomposites using projection SL and observe their dimensional accuracy. In addition, it is intended to evaluate artificial neural network (ANN) methodology performance as a modelling tool on SL (3D printing technique) for dimensional accuracy prediction on SMP parts.

2. Experimental Detail

SMP photo-resin results from mixing of tert-butyl acrylate (tBA) as monomer solvent, di (ethylene glycol) diacrylate (DEGDA) as crosslinker, and Phenylbis (2,4,6-trimethyl-benzoyl) phosphine oxide (BAPO) as photo-initiator, all obtained from Fishier Scientific (USA). The SMP photo-resin has a T_g of 69.5 ºC (Choong et al. 2017b). This SMP resin was selected because it is suitable for DLP process (Choong et al. 2017b). Graphene Oxide (GO) nanoflakes (Graphene Oxide, flakes, 15-20 sheets by Aldrich, USA) were chosen as photo-thermal nanofiller due to their high photo-thermal properties over other materials, and its performance shown in previous polymer nanocomposite studies (Zedan et al. 2012, Yu and Yu 2015, Yoonessi et al. 2012). SMP resin (tBA/ DEGDA/ BAPO) was fabricated by using DEGDA content of 20 wt.%, BAPO content constant (2 wt.%), and mixing (Vortex Mixer) for 30 min as shown in Table 1.

Uniform and continuous SMP/GO nanocomposites with GO content (2wt.%) were obtained by blending with SMP resin. SMP resin and GO were mixed (Vortex Mixer) for 30 min. Homogeneous pure SMP and SMP/GO were poured onto a DLP bath for 3D part fabrication. The DLP printer (Wanhao duplicator 7) was selected because of its accessible cost and simple operational procedure. SMP specimens were printed according to ASTM D790 (three point bending test specimen) (International 2017). Figure 1 shows the actual fabricated specimens. Prior trial and error fabrication attempts on DLP leaded to process parameters selection. Table 2 presents the parameters settings used for specimen fabrication (reference). The specimens were removed from the platform upon completion.

Table 1. Material content on SMP resin

Material	Type 1	Type 2	Type 3
Di(ethylene glycol) diacrylate (DEGDA) / wt.%	10	20	30

Figure 1. Fabricated specimen. SMP/GO specimen

Table 2. DLP parameter settings

Parameter	Value
Slice thickness (mm)	0.020
Exposure Time (ms)	30000
Bottom Exposure (ms)	40000
# of Bottom Layers	2

3. Proposed Methodology for Dimensional Accuracy Prediction

Clearly, in Figure 2, the dimensional variations are observed on the produced samples which is one of the main challenges in producing SMPs. Therefore, ANN modelling designs were implemented using stereolithography (SL) historical data (Lee et al. 2001) with 140 data points (111 data samples for training, 29 samples for testing) and evaluated based on cost convergence and Pearson correlation (R) coefficient for dimensional error response. We designed two neural networks for experiment. The first network was designed with 3 inputs, 3 hidden layers/4 neurons each, 1 output) shown in Figure 3(a). Whereas the 2nd network had 3 inputs, 2n+1 neurons, 1 output as shown in Figure 3(b). The ANN used 3 process inputs namely the layer thickness (displacement of platform on Z axis), curing depth (light penetration during curing), and hatch spacing (distance between projected curing light beams). The final output of this network is dimensional error. For ANN training, three different number of epochs (1000, 3000, 5000), and two learning rate (alpha) values (0.01 and 0.001) were selected. In addition, we used Mean Squared Error (MSE) for cost evaluation. The ANN code was written on Phyton language based on back propagation theory (Hecht-Nielsen 1992).

Figure 2. Dimensional variation on produced samples using different process parameters

(a) (b)

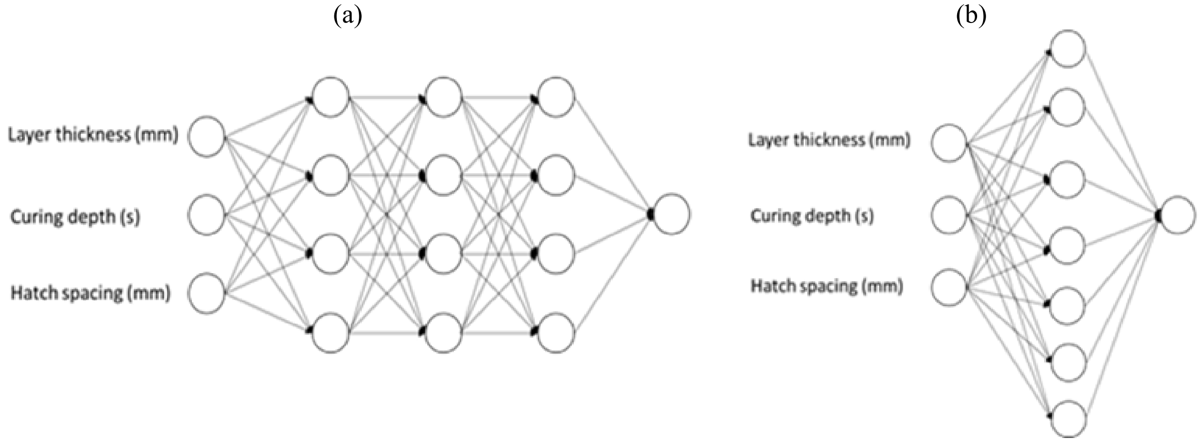

Figure 3. a) ANN with 3 inputs, 3 hidden layers/ 4 neurons each, 1 output. b) ANN with 3 inputs, 2n+1 neurons, 1 output

4. ANN Results

Figure 4 presents the cost results of the learning process at different epochs (1000, 3000, and 5000) using two different learning rate (α) values (0.01 and 0.001). To train the ANN, we used 111 data samples for training, and 29 samples for testing. The Mean Squared Error (MSE) was used to evaluate the model cost. It is observed that the ANN with 2n+1 neuron architecture and the learning rate of 0.001resulted the lower cost (0.00049334) and the higher R (0.77635969) value at 5000 epochs. See Figure 4(a) for comparisons on cost, and Figure 4(b) for R-value comparisons among the training variants. It is clearly observed that ANN (2n+1) neuron architecture at 5000 epochs and .001 learning rate obtained the best results. In Figure 5(a), it is noticed that cost converged to a minimum after 5000 epochs (iterations). This is an indication that after 5000 epochs the model is stable. Moreover, Figure 5(b) presents the correlation dispersion of the target values and predicted values, where it is possible to observe a correlation tendency. In addition, Figure 6 presents a comparison of target and predicted values of dimensional error under the fabrication parameters (layer thickness, curing depth, hatch spacing). Future work pertains to validate the results using actual data from SL process.

a) b)

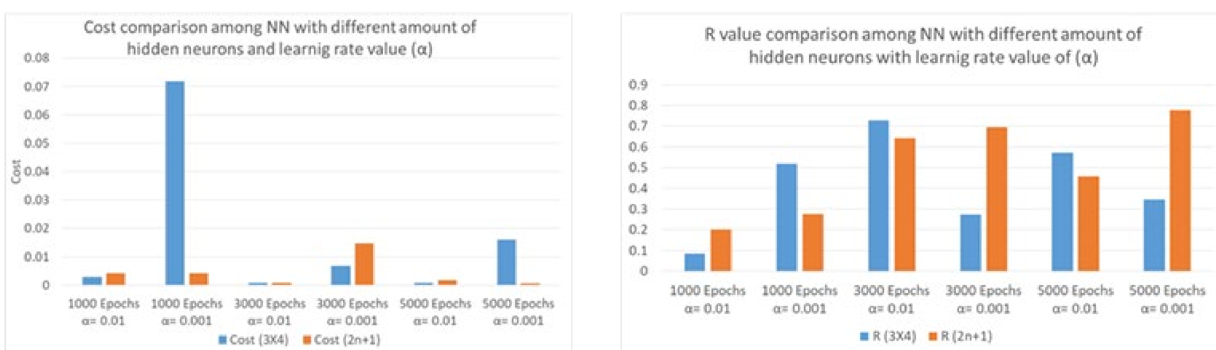

Figure 4. a) Cost results for various epoch amount and learning rates. b) R (correlation value) results for various epoch amount and learning rates.

(a) (b)

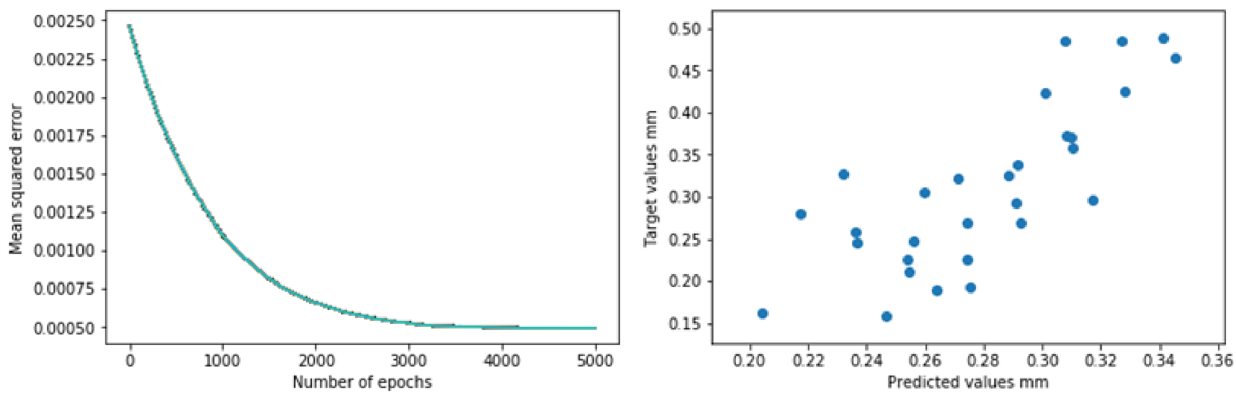

Figure 5. (a) Cost behavior during training of ANN with 2n+1 and (b) predicted vs target values during ANN model testing

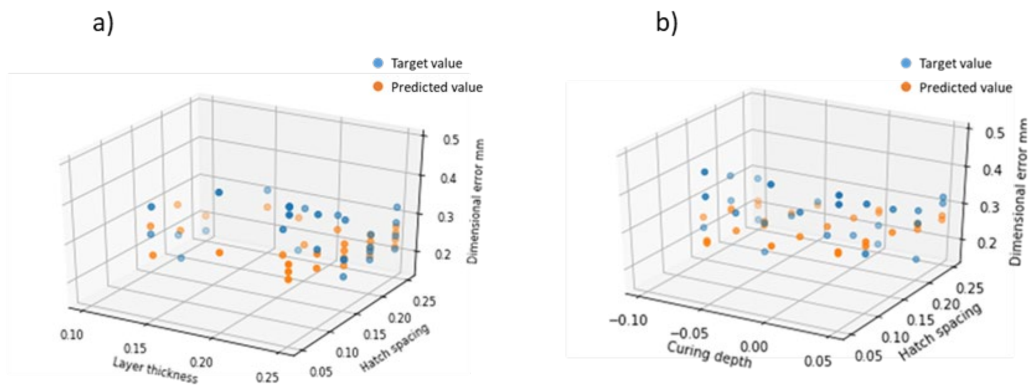

Figure 6. Target and predicted values of dimensional error. A) Layer thickness and hatch spacing. B) Curing depth and hatch spacing

5. Conclusion

This paper demonstrated the capability of producing SMP part on SL technology. A photo-polymer resin was developed using a monomer, crosslinker, and photo initiator. Later, SMP type 2 was selected based on recovery properties. Then, SMP resin type 2 was successfully combined with GO in order to produce SMP/GO. The programing capacities of SMP/GO where tested on a three-point bending test that resulted in cero failures and bending consistency among samples. The secondary shape was held, indicating good fixity capabilities. Moreover, dimensional variation was detected on SMP/GO due to fabrication settings, during trial-and-error attempts. Therefore, an ANN modelling technique was suggested in order to predict dimensional error output, a critical characteristic in SL process. Historical data with 140 data points was used for training and testing the ANN under different epochs and learning rates. The highest correlation value R was 0.776 at 5000 epochs with 0.001 learning rates. The findings on this paper could be used as a reference for SMP and GO/SMP fabrication using SL technology. Moreover, SMP/GO could be used in photo-responsive shape memory systems. Finally, the ANN could be used in future SL systems to predict the dimensional error based on fabrication settings.

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