**Material Design Process-Property Optimization Using Neural Network Modelling of Binder Jet Manufacturing**

Be sure to have the authors add the name of the software package used:

. The reason it is important is that different machine learning software packages make different assumptions for the doing the training trials (backward and forward with MANY different potential adjustment settings). Those assumptions are crucial if someone tries to replicate results. The authors don't state any parameters that they changed leading me to assume they left the software defaults in place.  Hence, we need to know the software.

Sairam Vangapally

Minnesota State University

 sairam.vangapally@mnsu.edu

Shaobiao Cai

Minnesota State University

shaobiao,cai@mnsu.edu

**Abstract**

Among additive manufacturing processes, such as binder jet 3D printing, manufacturing can fabricate complex geometrical parts with no support structures without employing heat during the part building process. It is of great interest to many engineering applications like biomedical, aerospace, automobile industries. However, the mechanical properties of printed materials vary dependent on process parameters and conditions, hence there is a need to tune the process parameters and conditions for optimal characteristics. In this study, feed forward back propagation artificial neural network model is developed to quantify the relationship between three parameters and compressive strength. The model is developed based on experimental data and it was validated with known data. It can be a useful tool for prediction and increase design and manufacturing efficiency.

**Introduction**

Binder jet additive manufacturing technology is originally developed at MIT in 1990 and commercialized in 2010 (Gibson, et al., 2010). This technology is capable of printing variety of materials including metals, sand, and ceramics. Binder jetting is an additive manufacturing process in which liquid binding agent is selectively deposited on powder particles. The print head strategically drops binder into powder and layers are then bonded together to form 3D product. The process involves binding, curing, de-powdering, sintering, and finishing. The main technique of manufacturing using binder jet additive manufacturing is as follows: (a) The CAD file is sliced into layers and STL file is generated; (b) Each layer begins with thin distribution of powder spread over the surface of a powder bed, (c) Using a technology similar to ink-jet printing, a binder material selectively joins particles where the object has to be formed, (d) A piston that supports the powder bed and part in progress lowers so that the next powder layer can be spread and selectively joined, (e) This layer by layer process repeats until the part is completed. (f) Following a heat treatment, unbound powder is removed, and the metal powder is sintered together.

In this study the output characteristics considered are compressive strength, radial, and longitudinal shrinkage rates. These are chosen from the binder jetting application perspective in bone scaffold engineering, as the complex bone structure produced should be dimensionally accurate with compressive strength. The process parameters which affect the output characteristics of samples of the binder jet additive manufacturing are represented in fish-bone diagram as shown in Figure 1. The parameters include powder size, layer thickness during binding, part orientation in the bed, drying time during binding, heater power, roller speed, curing temperature, curing time, sintering time, sintering temperature, and sintering atmosphere. Any variation in the above-mentioned parameter changes the output properties. These make the relationship between input process parameters and output properties very complicated. Hence there is a need to tune the process parameters to achieve controlled and stable process.



Figure 1. Fishbone diagram representing various parameters involved in the process.

Some experimental work in process parameters and property relationships have been presented in the literature. Torres et al. (2018) studied some of the building design parameters such as the effect of temperature to the tensile strength of PLA material for solid samples. To reflect the structure effects in material design, Vangapally et al. (2017) studies the effect of lattice arrangement and process parameters on dimensional and mechanical properties. Due to the complexity of the influence of large number of building factors to the final material properties, studies on different factors are available. For example, the studies on the binder setting saturation value, layer thickness, location of made-up parts were presented by various authors (Yao et al., 2002; Hsu et al., 2010; Suwanprateeb et al., 2012). It is noticed that practical parts can be made with different materials, in addition to polymer and plasters, metal and alloy are among the popular choices as well. Investigations on the effects of similar design parameters with metal alloy have been carried out as well. The study done by Tang et al. (2016) was focused on mechanical properties of SS316 samples made by binder jetting with default process parameters whereas Cai et al. (2019) studied the process parameters such as temperature and particle size to the product properties of SS316 recently for controlled operations. Research on other alloy such as bronze infiltrated stainless steel was presented by Doyle et al. (2015) on the studies of the effects of layer thickness and orientation of the parts using binder jetting.

Further apart from studying the process property relationship, it is very important to establish quantitative relationship between process parameters and properties as it cuts down the cost of experiments. Physics-based modeling is almost impossible for 3D printing as it involves powder-binder reaction, curing and sintering. Numerical models can be effective in finding the appropriate parameters with respect to desired output characteristics. Artificial neural network is the well-known method to serve as a numerical model based on experimental data, hence a numerical model was developed for the 3D additive printing process using artificial neural network. Figure 2 shows the schematic representation of neural network generating output values based on fed input parameters. It is a system of mathematical equations working on data approximating the human brain. Neural network consists of neurons connecting each other with respective weights and passing the information.

Input Parameters

Output Characteristics

**Neural Network**

Figure 2. Neural Network Schematic representation.

The neural network method has been applied to study many relatively complicated systems such as the study done by Cundari et al. (1997), who compared neural network models to quantum mechanical models for predicting the mechanical properties of inorganic system and concluded that neural networks give more accurate predictions. In neural network method, feed forward back propagation network is a popular choice. For example, Asada et al. (1997) used a feed forward back propagation network to predict the superconducting transition temperature of material as a function of chemical composition. Vermeulen et al. (1996) used to predict the finishing temperature of rolling mill as a function of processing parameters. In addition to these studies, researchers have used it to study different materials as well. For example, the predicting of the fatigue life of unidirectional composite done by Al-Assaf et al. (2001) and the study of ceramic materials as a function of composition done by Scott et al. (2007).

Though there many studies used the neural network mothed in manufacturing processes, few used it for additive manufacturing process. Few was done on neural network modeling of additive manufacturing processes. The current work aims at developing a predictive model using feed forward back propagation artificial neural network for the jet binding manufacturing process. A predictive model is designed to define the relationship between process parameters and compressive strength using the experimental data. Feed forward back propagation neural network was used to develop predictive model which establishes the relationship between process parameters and desired output characteristics.

**Experimental Design**

In the experimental design, powder material Stainless steel 316 powder with particle size of 30 µm was used. The material is obtained from Ex-One and used with no further treatment. The chemical composition of stainless-steel powder is showed in the Table 1.

Table 1. Chemical composition of SS31 (wt%)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| C | Mn | P | S | Si | Cr |
| 0.08 max | 2.00 max | 0.045 max | 0.03 max | 0.75 max | 16.00-18.00 |

Full factorial design of experiments was used to test all the possible combinations in current research with three parameters and two levels each, 23 =8 experiments should be conducted. Table 2 represents the total experiments considered in the study.

Table 2. Full Factorial Experimental Plan, Low-level is represented as 0 and High level is represented as 1. A (low- 50 µm, high- 100 µm), B (low- 2hours, high- 4 hours), C (low- 1120 oC, high- 1180oC).

|  |  |  |  |
| --- | --- | --- | --- |
| **Experiment** | **Layer Thickness(A)** | **Sintering Time(B)** | **Sintering Temperature(C)** |
| 1 | 0 | 0 | 0 |
| 2 | 0 | 0 | 1 |
| 3 | 0 | 1 | 0 |
| 4 | 0 | 1 | 1 |
| 5 | 1 | 0 | 0 |
| 6 | 1 | 0 | 1 |
| 7 | 1 | 1 | 0 |
| 8 | 1 | 1 | 1 |

Samples were created following the design plan as shown in Figure 3. Three types of structures, namely solid (a) circular structure, (2) 1mm circular lattice structure and (3) 1mm cubical lattice structured (these are named in the Figure 3(a) below) are used in this study. All the eight experiments for each type of structure were conducted, and the setup is shown in Figure 3(b)The desired output characteristics compressive strength was recorded as input to the numerical neural network model (More details can be found in the previous work done by Cai et al. (2019).



Figure 3. (a) Binder jet additive manufactured samples with various structures, and (b) Sample testing MTS setup.

**Neural network model design**

Artificial neural networks (ANN) are preferable tools compared to other available data modeling tools, as it is capable of mapping complex non-linear relationship between input factors and output characteristics. With training the neural network with known data, it can provide approximate output results with unseen data which makes the technique useful for predictive applications. In the neural network method family, feed forward back propagation neural network is the simplest efficient ANN in use and found its applications in developing predictive experimental models. Feed forward back propagation neural network with sigmoid activation function was considered for designing the model.

Figure 4 represents the architecture of neural network used in the study. In the model as shown in the figure, A is layer thickness, B is sintering time, C is Sintering temperature, O is compressive Strength, Σ represents summation and F(x) is activation function, b1 and b2 are bias. There are three different layers in neural network. The left most layer is the input layer. Input parameters are fed into neural network through this layer. The middle is the hidden layer. This layer connects the input and output layer. It is called hidden as its values are not observed in the training set. The rightmost layer is the output layer. In the layer all the hidden neurons produce output. In feed forward, neurons in input layer are connected to neurons in hidden layer, whereas neurons in hidden layer are connected to output layer. Back propagation is a training method in which neurons adjust their weight to achieve the target output. The network contains three layers with a total of 8 nodes, 4 being hidden nodes, 3 input nodes and 1 output node. Other symbols/parameters defined in the model are listed below.

* + Xi, input values fed to neural network through input node i
	+ W1ij, weights connecting input-hidden nodes where i represents input node and j represents hidden node
	+ W2jk, weights connecting hidden-output nodes where j represents hidden node and k represents output node
	+ b1, bias at hidden node
	+ b2, bias at output node
	+ F(x), activation function
	+ δk, error information at output node
	+ δj, error information at hidden node
	+ ΔW1, delta weights at input-hidden layer
	+ ΔW2, delta weights at hidden-output layer
	+ Zj, hidden node,
	+ Yk, output node
	+ Sigmoid function is used as activation function for this model: F(x) =1/(1+ⅇ^(-x))



Figure 4. Neural Network Schematic representation

The training, feed forward and back propagation processes are used. In feed forward process, first the random numbered weights for input-hidden layer and hidden-output layer are initialized. Then the inputs are transferred to nodes in hidden layer where the summation of input values with respective node weights take place and then transferred to next layer applying the activation function shown below.

Zin (1)

Yin = F (Zin) (2)

The value at hidden nodes gets transferred to output nodes where it gets multiplies with respective weights before applying activation function to produce output

Yout=+ (3)

*Output=F(Yout)* (4)

In feed forward process, errors and weights at different notes are calculated and updated. The error or margin is calculated by comparing target value with output value of the developed model by using Equation (5).

 e = (Target-Output) 2 (5)

The error information at output is found using Equation (6).

 (6)

The error information at hidden unit is calculated using Equation (7).

 (7)

The weights updating at input-hidden layer are calculated using Equations (8) and (9).

 = (8)

 + (9)

The weights updating at hidden-output layer are found using Equation. (10) and (11).

 = (10)

 + (11)

The compressive strength value is normalized so all the values are in the range of 0 to 1 using the Equation (12).

 *Oi* = (12)

Where *Yi* represents compressive strengths of each experimental run *i* (1 to 8)

The training process and parameters involved at each step are shown in Figure 5. The neural network is trained such that error between desired output and actual output is less than 0.05.

Figure 5. Flow chart showing the entire training process and the parameters involved.

After successful training, the network is tested with new data sets for its performance. Then the value obtained using the network is denormalized to find the predicted value as shown in Equation (13). With it, the difference between the predicted value and the actual value can be analyzed.

 (13)

**Results and Discussion**

Experimental analysis was performed to determine the effect and significance of layer thickness, sintering time, and sintering temperature on compressive strength. The collected experimental data was used to the developed neural network model predicting compressive strength given the inputs of layer thickness, sintering time, and sintering temperature. Three cases are conducted. In the first case, the data used for the neural network is from compression testing of solid structure. In the second case, the data used is from compression testing of 1mm circular lattice structure. In the third case, the data used is from compression testing of the 1mm cubical lattice structure. In the neural network, it uses back propagation algorithm as training algorithm, sigmoid function as activation function, and the network has one hidden layer.

***Solid Circular Structure***

Data for solid circular structure is presented in Table 3. The compressive strength of the samples fabricated using the eight experimental settings were normalized as shown in Table 3. The feed forward back propagation network was trained with seven datasets leaving behind the one data set of experiment 7 for testing the network performance.

Table 3. Inputs A (Layer thickness), B (Sintering time), C (Sintering temperature) along with normalized predicted output of compressive strength in the range of 0 to 1 for solid circular structure.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **A (Layer thickness)** | **B (Sintering time)** | **C (Sintering temperature)** | **Y (Compressive Strength, MPa)** | **Expected****Output(O)** |
| **1** | 0 | 0 | 0 | 745.5 | 0.351 |
| **2** | 0 | 0 | 1 | 1780.5 | 0.899 |
| **3** | 0 | 1 | 0 | 1811.0 | 0.915 |
| **4** | 0 | 1 | 1 | 1972.0 | 1.000 |
| **5** | 1 | 0 | 0 | 82.9 | 0.000 |
| **6** | 1 | 0 | 1 | 879.5 | 0.422 |
| **7** | 1 | 1 | 0 | 978.5 | 0.474 |
| **8** | 1 | 1 | 1 | 1083.5 | 0.530 |
| Maximum value in Y column | 1972.0 |  |
| Minimum value in Y column | 82.9 |  |

The error graph and the different learning rates for the neural network model during the training are plotted in Figure 6. The error graph using the error value obtained in each iteration is shown in Figure 6(a), where the necessary iterations to reach the goal was approximately 7500 iterations, high iterations signify the acuteness of carried calculations. From 15 to 7500 iterations, the error was changing in decimal places. The method is developed such that the neural network stops training once the error between network output and actual output is less than absolute value of 0.05. Different learning rates were presented to network from 0.1 to 2 and the training error is plotted against learning rate as shown in the Figure 6(b). The maximum error in training allowed was 0.05 absolute value. The optimum learning rate for minimum error was found to be 0.6 in the training phase for the network. The network is tested for a target value of 0.470 and the value obtained from the network is 0.488, and it indicates a good performance for prediction.



Figure 6. (a) Training error vs number of iterations and (b) Performance of network architecture for different learning rates of the *solid circular structure* for the neural network model

***Circular Lattice Structure***

The same feed forward back propagation network used for predicting the compressive strength of solid was used for training and testing the compressive strength of 1 mm circular lattice structure. The compressive strength of the samples fabricated using the eight experimental settings were normalized as shown in the Table 4. Data obtained from experiment two was used for the network testing while other remaining data was used to train the network.

Table 4. Inputs A (Layer thickness), B (Sintering time), C (Sintering temperature) along with normalized predicted output of compressive strength in the range of 0 to 1 for circular 1mm lattice structure.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **#** | **A (Layer thickness)** | **B (Sintering time)** | **C (Sintering temperature)** | **Y (Compressive Strength, MPa)** | **Expected Output(O)** |
| **1** | 0 | 0 | 0 | 160.3 | 0.150 |
| **2** | 0 | 0 | 1 | 654.3 | 0.651 |
| **3** | 0 | 1 | 0 | 739.9 | 0.738 |
| **4** | 0 | 1 | 1 | 998.6 | 1.000 |
| **5** | 1 | 0 | 0 | 12.8 | 0.000 |
| **6** | 1 | 0 | 1 | 303.3 | 0.295 |
| **7** | 1 | 1 | 0 | 229.3 | 0.220 |
| **8** | 1 | 1 | 1 | 545.5 | 0.540 |
| **Maximum value in Y column** | 998.6 |  |
| **Minimum value in Y column** | 12.8 |  |

The error graph and the different learning rates for the model during the training are plotted in Figure 7. The error graph is plotted using the error value obtained in each iteration, as shown in Figure 7(a), where necessary iterations to reach the goal was approximately 200000 iterations. From 100 to 199000 iterations, the error was changing in decimal places hence the straight line. Different learning rates were presented to network from 0.1 to 2 and the training error is plotted against learning rate as shown in the Figure 7(b). The maximum error in training allowed was 0.05 absolute value. The optimum learning rate for minimum error was found to be 2 in the training phase for the network. The network is tested for a target value of 0.650 and the value obtained from the network is 0.678.



Figure 7. (a) Training error vs number of iterations and (b) Performance of network architecture for different learning rates of the *1 mm circular lattice structure* for the neural network model.

***Cubical Lattice Structure***

The compressive strength of the 1mm cubical lattice structured samples fabricated using the eight experimental settings were normalized along with inputs, shown in the Table 5. Data obtained from experiment six was used for testing the network while remaining data was used to train the network the same as before.

Table 5. Inputs A (Layer thickness), B (Sintering time), C (Sintering temperature) along with normalized expected output of compressive strength in the range of 0 to 1 for cubical 1mm lattice structure.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **#** | **A (Layer thickness)** | **B (Sintering time)** | **C (Sintering temperature)** | **Y (Compressive Strength, MPa)** | **Expected Output(O)** |
| **1** | 0 | 0 | 0 | 154.5 | 0.151 |
| **2** | 0 | 0 | 1 | 545.2 | 0.564 |
| **3** | 0 | 1 | 0 | 612.3 | 0.635 |
| **4** | 0 | 1 | 1 | 958.3 | 1.000 |
| **5** | 1 | 0 | 0 | 11.6 | 0.000 |
| **6** | 1 | 0 | 1 | 250.9 | 0.253 |
| **7** | 1 | 1 | 0 | 253.2 | 0.255 |
| **8** | 1 | 1 | 1 | 326.4 | 0.333 |
| **Maximum value in Y column** | 958.3 |  |
| **Minimum value in Y column** | 11.6 |  |

Similar error graph and the different learning rates for the model using the cubical structure during the training are plotted in Figure 8. The error graph plotted using the error value obtained in each iteration is shown in Figure 8(a), where it can be observed that the necessary iterations to reach the goal was approximately 7500 iterations. From 75 to 7500 iterations, the error was changing in decimal places hence the straight line. Different learning rates were presented to network from 0.1 to 2 and the training error is plotted against learning rate as shown in the Figure 8(b). The maximum error in training allowed was 0.05 absolute value. The optimum learning rate for minimum error was found to be 2 in the training phase for the network. The network is tested for a target value of 0.250 and the value obtained from the network is 0.276.



Figure 8. (a) Training error vs number of iterations and (b) Performance of network architecture for different learning rates of the *1 mm cubical lattice structure* for the neural network model

*- Model Validation*

 The current model was compared for predicting the values with the work done in the literature and the results are presented below. In the validation, the study used is the neural network model for predicting the hardness of shielded metal arc welded joints given the input of current, voltage, welding speed, magnetic field (Singh et al., 2013). The data for neural network training is tabulated in Table 6. The comparison analysis of predictive resultant data to the experimental results as well as the literature work is presented in Table 7. The difference between the experimentally tested HRC hardness and predicted hardness using the current model is also represented in Table 7. It is observed that the currently developed neural network model agreed with the literature work, and the experimental data very well. The minimum difference between the experimental value and the value predicted using current model is 0.04 % and the maximum difference is 8.9%. The simple average among all the 7 data sets is 3.82% which shows some improvement to the referenced 4.95%. The small difference is believed to be the different architecture used by the reference model and the current neural network model.

Table 6. Neural network training data for comparison study (Singh et al., 2013).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Exp #** | **Current(A)** | **Voltage(V)** | **Welding speed(mm/min)** | **Magnetic field (Gauss)** | **Hardness** |
| 1 | 90 | 24 | 40 | 0 | 90 |
| 2 | 90 | 24 | 40 | 20 | 90 |
| 3 | 90 | 24 | 40 | 40 | 90 |
| 4 | 90 | 24 | 40 | 60 | 92 |
| 5 | 90 | 24 | 40 | 80 | 94 |
| 6 | 95 | 20 | 60 | 60 | 91 |
| 7 | 95 | 21 | 60 | 60 | 88 |
| 8 | 95 | 22 | 60 | 60 | 86 |
| 9 | 95 | 23 | 60 | 60 | 84 |
| 10 | 95 | 24 | 60 | 60 | 82 |
| 11 | 100 | 22 | 40 | 40 | 88 |
| 12 | 100 | 22 | 60 | 40 | 90 |
| 13 | 100 | 22 | 80 | 40 | 93 |
| 14 | 90 | 20 | 80 | 20 | 89 |
| 15 | 95 | 20 | 80 | 20 | 86 |
| 16 | 100 | 20 | 80 | 20 | 84 |
| 17 | 105 | 20 | 80 | 20 | 83 |
| 18 | 110 | 20 | 80 | 20 | 80 |

Table 7. Comparison and validation of the current neural network model.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Experiment Hardness (HRC)** | **Prediction value from the literature [22]** | **Prediction value using current model** | **Difference %** |
| 1 | 91 | 85.6 | 90.96 | 0.04 |
| 2 | 86 | 85.1 | 93.7 | 8.9 |
| 3 | 89 | 85.4 | 93.84 | 5.4 |
| 4 | 89 | 85.2 | 87.6 | 1.54 |
| 5 | 81 | 84.8 | 82.64 | 2.02 |
| 6 | 78 | 84.6 | 82.8 | 6.1 |
| 7 | 79 | 83.9 | 81.04 | 2.58 |
| Average Difference | **4.95** | **3.82** |

***Current neural network prediction and potentials***

The data obtained for the above three experimental structure cases was used as input to the developed neural network to predict the compressive strength. The feed forward back propagation network was trained with seven datasets and one data set of experiment result was used for prediction comparison analysis for testing the network performance. Upon reach the normalized prediction meeting the defined computational accuracy, the normalized compressive strength was denormalized for each of the three cases. The prediction was further compared with the experimental measured results. Table 8 shows the experimental compressive strength of the three different structures obtained from physical experimentation and the predicted value output from the numerical neural network model.

Table 8. Neural network results for different structures.

|  |  |  |  |
| --- | --- | --- | --- |
| Structure | Experimental Compressive Strength (MPa) | Predicted CompressiveStrength (MPa) | Difference (%) |
| Solid | 978.5 | 1005.5 | 2.75 |
| 1mm Circular | 654.3 | 681.5 | 4.15 |
| 1mm Cubical | 250.9 | 273.9 | 9.16 |

The predicted values were found to be in good agreement with that of experimental resultant data with the maximum difference being 2.75%. The values obtained using neural network are slightly greater than the values obtained using experimentation. It should also be noted that the performance of network can be more or much more robust with more sets of experimental training input data. The percentage difference between a target value and its prediction can be even closer as the network gets more data for training. Also, the performance of the model may be improved further either by changing the number of hidden nodes used in the study or by using a different architecture in future studies. The current neural network model is expected to be helpful in identifying the set of parameters to achieve desired compressive strength to eliminate the great amount of efforts and time required in experimentation.

The model may be used to develop feed forward artificial neural network using back propagation training algorithm if needed. Data normalization prior to training process is crucial to obtain good results as well as to the fast calculations (Nguyen et al., 2009). Network architecture has significant effect on prediction results. It would be a good practice to rely on the number of input and output parameters to decide the architecture of feed forward neural network, the number of hidden layers and hidden nodes in the structure. Once the architecture is decided, training algorithm and activation function need to be chosen which is like the current study which used back propagation algorithm with sigmoid activation function. With the normalized input values, target values, network architecture and activation function, the model can be developed according to the training algorithm.

**Conclusions**

Experimental design techniques were used to design and create the three structures: solid circular, circular with 1mm lattice, and circular with 1mm cubical structures. MTS material testing was performed, and experimentation data was corrected. A feed forward back propagation neural network with sigmoid activation function was developed. The neural network uses back propagation algorithm as training algorithm, sigmoid function as activation function and the network has one hidden layer. The model was validated using the published data in literature. Furthermore, experimental data of the three different structures were used as input to the model. Performance analysis of the developed neural network model using the experimental data was performed. It was found that the model prediction agrees with the experimental results. The developed model predicts the compressive strength given over the range of layer thickness, sintering time and sintering temperature parameters and it can serve as framework to setup the process design parameters to achieve desired output characteristics. The model was developed for the purpose of material structure design optimization. Due to the complexity of multi-parameter multi-level effects to material properties, the conducting of a huge number of lab experimentations to get meaningful results is great challenge. The study shows the capability of feed forward back propagation neural network as a good technique for determining the compressive strength of binder jetting samples. The analysis reveals the applications of neural network in material science and engineering particularly in additive manufacturing. It is noticed that the benefit and applications go beyond. It can be very efficient if many factors are involved in a complex process and each factor plays roles at different level. Broad applications (other than material structure design) of the model may be found, especially for the those involving multi-parameter multi-level complex studies in areas like medical, engineering or even business areas. In those studies, a large number of trial-and-error data are typically needed to get meaningful results. However, neural network would help with better design solutions, providing directions and possible results in the front. Thus, large amount of efforts, time and cost needed for conducting large array of experiments may be saved.

**References**

|  |
| --- |
| Al-Assaf, Y. & Kadi, H. (2001). Fatigue life prediction of unidirectional glass fiber/epoxy composite laminae using neural networks, *Composite Structures, 53*(1), 65-71.  |
| Asada, Y., Nakada, E., Matsumoto, S. & Uesaka, H. (1997). Prediction of t-c for yba2cu3oz doped with ca using neural network, *Journal of Superconductivity, 10*(1), 23-26.  |
| Cai, S., Vangapally S. & Zhao, Y. (2019). Experimental Design Analysis of 3D Printing Processes to the Optimization of Strength of Material, Journal of Modern Engineering, *20*(1), 5-11. |
| Cundari, T. & Moody, E. (1997). A comparison of neural networks versus quantum mechanics for inorganic systems, *Journal of Chemical Information and Computer Sciences, 37*(5), 871-875.  |
| Doyle, M., Agarwal, K., Sealy, K. & Schull, K. (2015). Effect of layer thickness and orientation on mechanical behavior of binder jet stainless steel 420+ bronze parts, *Procedia Manufacturing, 1*, 251-262.  |
| Gibson, D. R., & Stucker, B. (2010). *Additive manufacturing technologies*, Springer, 2010.  |
| Hsu, T. & Lai, W.(2010). Manufacturing parts optimization in the three‐dimensional printing process by the Taguchi method, *Journal of Chinese institute of Engineers,* 121-130. https://doi.org/10.1080/02533839.2010.9671604. |
| Nguyen, T., Yang, Y., Bae, K. & Choi, S. (2009). Prediction of deformation of steel plate by artificial neural network in forming process with induction heating," *Journal of Mechanical Science and Technology, 23,* 1211-1221.  |
| Scott, D., Coveney, P., Kilner, J., Rossiny, J. & Alford, N. (2007). Prediction of the functional properties of ceramic materials from composition using artificial neural networks, *Journal of the European Ceramic Society, 27*(16), DOI:10.1016/j.jeurceramsoc.2007.02.212. |
| Singh, R., Gupta R. & Sarkar, S. (2013). Application of artificial neural network for prediction of hardness of shielded metal arc welded joints under the influence of external magnetic field, *International Journal of Engineering Research and Development.* *5*(7), 84-88. |
| Suwanprateeb, J., Thammarakcharoen, F., Wasoontararat, K. & Suvannapruk, W. (2012). Influence of printing parameters on the transformation efficiency of 3D-printed plaster of paris to hydroxyapatite and its properties, *Rapid Prototyping Journal,* vol. 18, 4.  |
| Tang, Y., Zhou, Y., Hoff, T., Garon, M. & Zhao, Y. (2016). Elastic modulus of 316 stainless steel lattice structure fabricated via binder jetting process, *Material Science Technology, 32*, 648-656.  |
| Torres, P., Sandback, T. & Cai, S. (2018). Parametric Analysis of Building Parameters to Maximize Strength of Material Using Additive Manufacturing, *International Refereed Journal of Engineering and Science (IRJES)*, *7*(1)*,* 25-34. |
| Vangapally, S., Agarwal, K., Sheldon, A. & Cai, S. (2017). Effect of lattice design and process parameters on dimensional and mechanical properties of binder jet additively manufactured stainless steel 316 for bone scaffolds,” *Procedia Manufacturing*, *10*, 750-759.  |
| Vermeulen, W., Morris, P., deWeijer, A. & VanderZwaag, S. (1996). Prediction of martensite start temperature using artificial neural networks, *Ironmaking Steelmaking, 23*(5), 433-437.  |
| Yao, A. & Tseng, Y. (2002). A robust process optimization for a powder type rapid prototype, *Rapid Prototyping Journal, 8*, 180-189.  |

**Biographies**

**SAIRAM VANGAPALLY** is a graduate student in the Department of Mechanical and Civil Engineering at Minnesota State University, Mankato. Mr. Vangapally may be reached at sairam.vangapally@mnsu.edu

**SHAOBIAO CAI** is an associate professor in the Department of Mechanical and Civil Engineering at Minnesota State University, Mankato. His areas of expertise and research interests include interfacial contact mechanics and tribology, mechanical failure of materials, layered medium design, and the application of DFMA principles in the development of robust design solutions. He is a registered professional engineer in the state of Minnesota. He is a member of the American Society of Mechanical Engineers, the Society of Tribologists and Lubrication Engineers, and American Society for Engineering Education. Dr. Cai may be reached at shaobiao.cai@mnsu.edu