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Test parameters optimization for constrained spray forming of aluminum alloy based on artificial neural network

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Abstract

Spray deposition with following continuous extrusion (SD-CE) forming technique is a novel technology that combines spray forming and continuous extrusion. Optimization of test parameters for spray deposition is an important part of SD-CE. In this study, Al-20Si alloy was produced by spray forming at different melt temperature and gas pressure, and obtained grain diameter of 8 group primary silicon phase. Based on the experimental results, an Artificial Neural Network (ANN) with single hidden layers composing of 10 neurons was employed to simulate optimizing of test parameters for spray deposition. The inputs of the model are melt temperature and gas pressure. The output of the model is grain diameter. Finally, the minimum relative error of grain diameter is 0.09%, the maximum relative error is 8.38%, and error majority concentrate within 3.80%, the average absolute relative error(AARE) is 1.04%, R is 0.097, the error is small. The optimal test parameters for spray deposition are melt temperature(829 °C) and gas pressure(0.2 MPa). The results indicate that the ANN model is an easy and practical method to optimize the test parameters for spray deposition of Al-20Si alloy. Thereby this model is a useful reference for optimizing the test parameters of SD-CE

1. Introduction

Spray forming is of interest as a manufacturing technique that combines near-net-shape capabilities with the structural control available through rapid solidification. As-spray formed preforms always contain some pores, in order to eliminate the pores, it is necessary to densify the preforms of spray forming by hot extrusion, forging and so on. However, the applicability of the spray forming process to the preparation of the near-net-shape preforms is limited by the secondary processing step [1].

A novel technique, namely spray deposition with following continuous extrusion forming technique (SD-CE/SC [2, 3]), has been recently developed in an effort to manufacture full density materials in one step. In SD-CE, inert gas atomized liquid metals into small droplets and deposited into the groove of the extrusion wheel, then, the deposited perform is directly extruded by continuous machine [2]. Results from experimental studies suggest that pore-free Al-20Si alloy with uniform distribution of Si particles can be fabricated by SD-CE without additional operations. However, optimization for SD-CE process parameters is difficult, because there are many parameters such as atomization gas pressure, melt temperature, extrusion ratio etc, and these parameters affect each other.

Machine learning (ML) [4] is an interdisciplinary subject between computer science and statistics. It is the core of artificial intelligence and data science. It promotes the availability of online data and low-cost computing through algorithm learning [5]. Artificial neural network (ANN) is the main machine learning method for material performance prediction, and has been widely used in materials science [6, 7], such as the prediction of high temperature flow stress for deformed alloys [8–10].

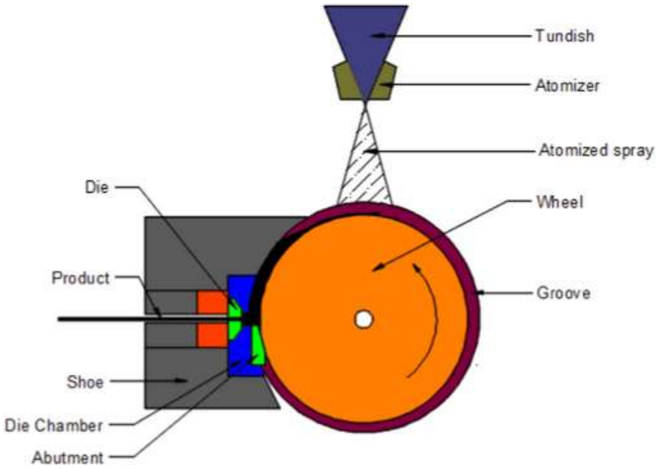

Figure 1. A schematic illustration of the SD-CE process [3].

ANN is massively parallel-distributed processors based on data, which have a tendency to store experiential knowledge and making it available to use [11]. ANN theory learns from a previously obtained data, which is called as training sets, then to check the system accuracy using test data [12]. ANN is very powerful about the solution of non-linear problems [13]. ANN are being widely used in material fields [14, 15], this may be due to ANN attempts to model the causes of human brains [16]. For example, At present, ANN has become a very popular tool of Al-Si alloy performance prediction [17–19]. ANN has been developed to predict porosity percent of Al-Si casting alloys, and is used to correlate chemical composition and cooling rate with porosity [20, 21]. ANN accurately predicted the corrosion resistance of Al-Si-Mg-based metal matrix composites reinforced with SiC particles, average square of the Pearson product-moment correlation coefficient (R2), maximum mean square error(MSE), and minimum root mean squared deviation(RMSD) were calculated as 0.9904, 0.00002476, and 0.00157480,respectively, it can be seen that the experimental results are highly consistent with the ANN results [22]. ANN predicted the mechanical properties of A356 including yield stress, ultimate tensile strength, maximum force and elongation percentage, the prediction of ANN model was found to be in good agreement with experimental data [23, 24].

In light of the aforementioned discussion, ANN algorithm was introduced to optimize some SD-CE parameters. In the present paper, the experiment results obtained with as-deposited Al-20Si alloy are presented. Moreover, the effects of parameters on the size of Si particle are discussed.

2. Experimental

Hypereutectic binary Al-20Si alloy was selected as the experimental material.Al-20Si alloy was prepared using Al-50Si alloy and pure aluminum(99.5%) in appropriate proportions. The alloys were melted in a resistance type furnace 200 °C above their respective melting points. In SD-CE process, as shown in figure 1 [3].

It has been found that the low atomization pressure increases the liquid fraction of the deposited material, causing some of the liquid phase to escape from the gap between the wheel and the tool. However, when the atomization pressure is higher than 0.3 MPa, the droplets will stick to the flow controller, resulting in much material waste. For Al-20Si alloy, the appropriate gas pressure is 0.1–0.25 MPa.

The experimental parameters and process of the spray deposition experiments were as follows. Atomization gas was N_2, and atomization pressure was 0.1 MPa,0.15 MPa,0.2 MPa, and 0.25 MPa respectively. Nozzle diameter was 4 mm,deposition distance was 350 mm, speed of the disk was 1600rpm, angle between two disks was 7°. The liquidus temperature of Al-20Si alloy is 689 °C, therefore melt temperature chooses 829 °C and 859 °C respectively. A high velocity inert gas atomized molten metal, two rotating disk limited flying droplets, then droplets spray deposits onto deposition substrate [2]. The width of the spray-formed billets was in the range of 22–60 mm, the height of the billets was in the range of 19–55 mm.

Spray-formed billets were prepared for metallographic observations. In each case, the whole section was observed ,but the quantitative analyses were achieved in the center of the section.

Microstructures of Al-20Si deposition billets were shown in figure 2-figure 3 [25].

It can be seen from figures 2 and 3 that the size of the primary silicon continues to decrease, and the roundness becomes better with the pressure increases. At the same time, it can also be seen that the size of primary silicon increases with the increase of melt temperature.

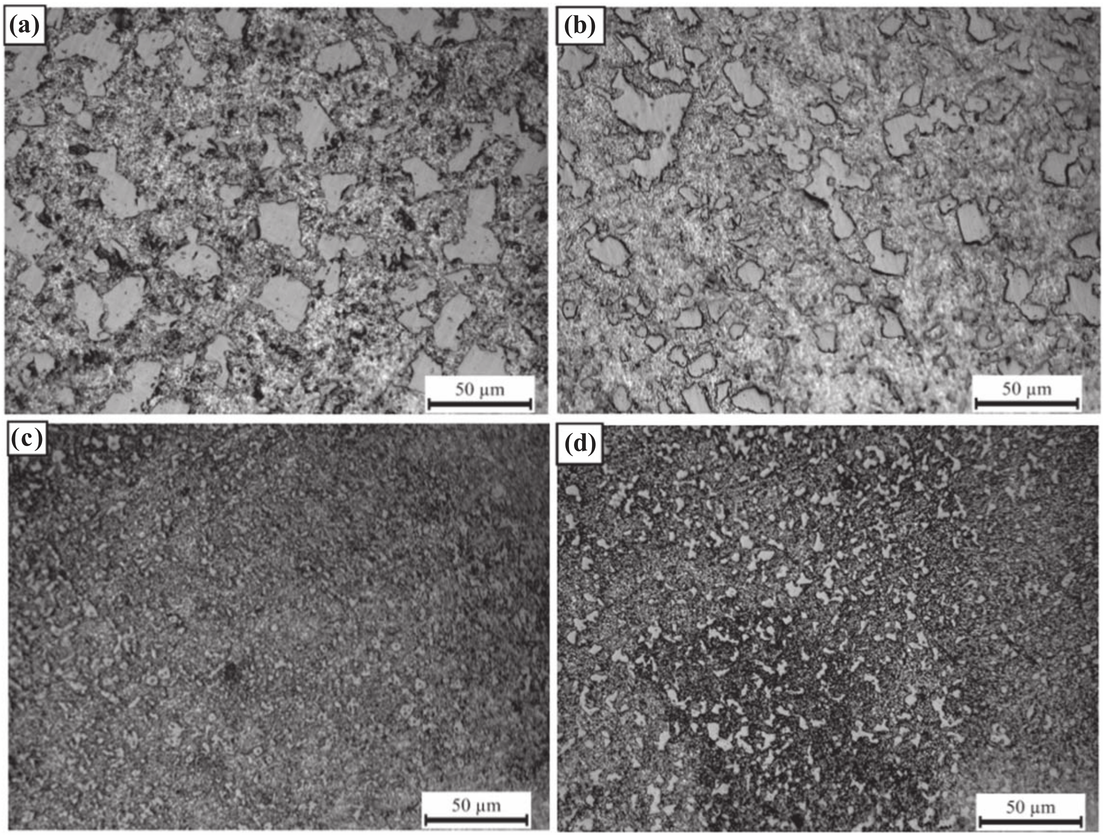

Figure 2. Microstructures of spray-formed Al-20Si alloy(829 °C) (a)0.10 MPa; (b) 0.15 MPa; (c) 0.2 MPa; (d) 0.25 MPa [25].

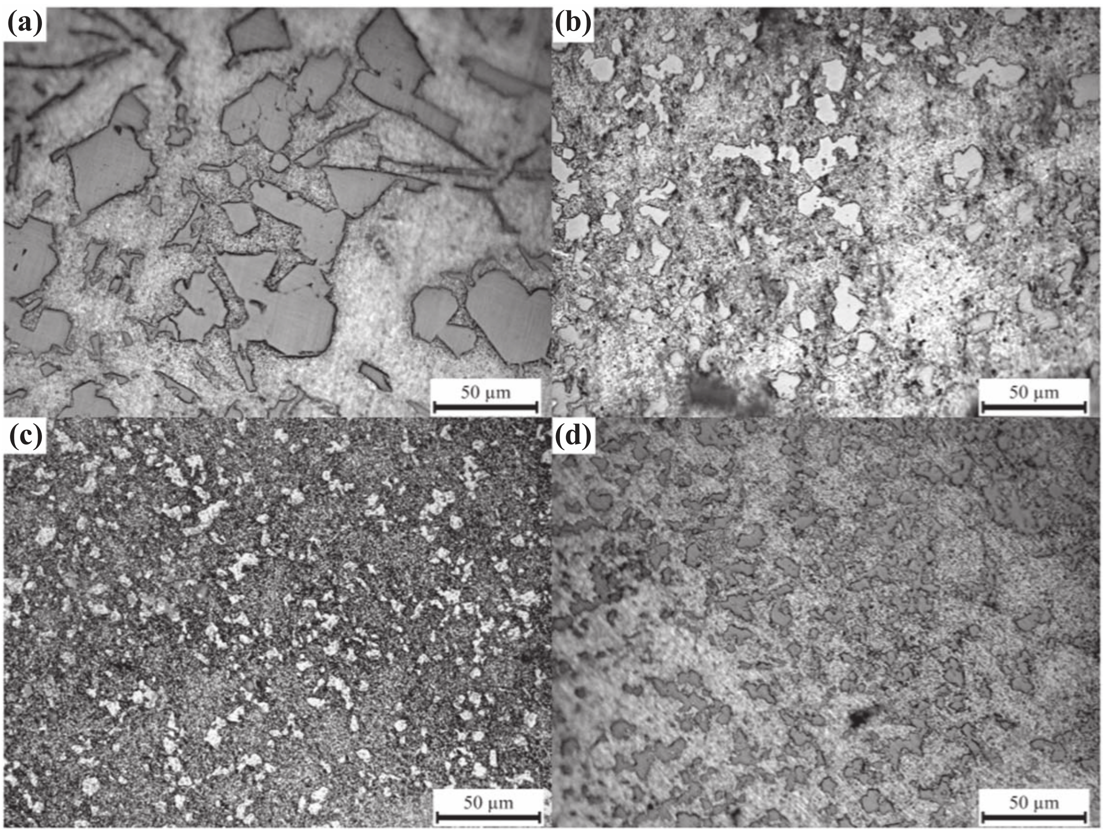

Figure 3. Microstructures of spray-formed Al-20Si alloy(859 °C) (a)0.1 MPa; (b)0.15 MPa; (c) 0.2 MPa; (d) 0.25 MPa [25].

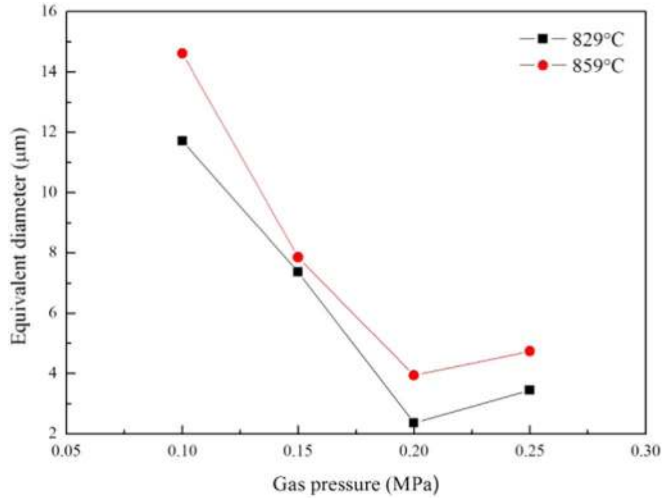

Figure 4. The values of primary silicon phase in spray deposition Al-Si alloys [25].

The formula of the mean grain diameter is defined as (1) [26].

$$D = \frac{1}{n}\sum_{k=1}^{n} 2\sqrt{S_k/\pi} \tag{1}$$

Where D represents the mean grain diameter, S_k represents the area of the k-th primary silicon.$S_k$was obtained from figure 2-figure 3 by the image analysis software Image-Pro plus. The values of grain diameter of primary silicon phase in spray deposition Al-20Si alloy are shown in figure 4 [25]. Figure 4 shows the minimum grain diameter is 2.37 μm when gas pressure is 0.2 MPa and temperature is 829 °C.

The quantity of experimental data in figure 4 is too little, which is not enough to the training and testing demand of ANN. Therefore, select the GetData Graph Digitier tool to take data from the two polylines of figure 4 and extract the data. Finally, 308 data were extracted from figure 4.

In this section, experimental processes have been explained with the details. The aim of this process is to produce some experimental data to use in the training and testing set of the neural network.

The following is a flow chart showing the construction of a neural network model and the determination of optimal test parameters for spray forming of aluminum alloy, as shown in figure 5. The flow chart will be elaborated in the next two sections.

3. The developed ANN model

3.1. Structure of ANN

A typical ANN model contains an input layer, an output layer,and a hidden layer, which are connected by the processing units called neurons. The input layer is used to receive data from outside, while the output layer sends the information out. The hidden layer is a layer that contains a systematically determined number of processing elements, is to provide the complexity for non-linear problems. In addition, hidden layer can be multilayer. During training, ANN updates weights and biases by using input-output pairs [27].The output of neural network model is as follows.

$$y = f\left(\sum_{i=1}^{n} w_i x_i - \theta\right) \tag{2}$$

Here, f is the transfer function,w_i is the weight, and θ is the threshold value.

sigmoid function is a strictly increasing function, it can better balance behavior between linear and nonlinear. And an advantage of the function is that the output range is limited, so the data in the transfer process does not easily dissipate. So, sigmoid function is used in the present model:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

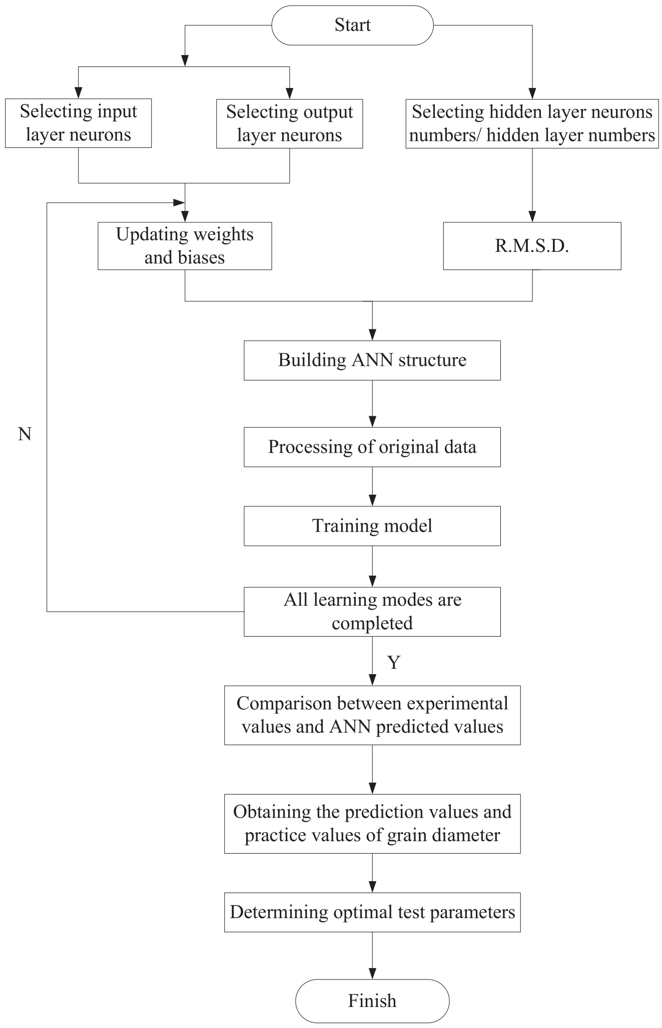

Figure 5. The flow chart for constructing artificial neural networks and determining optimal test parameters.

3.2. Hidden layer of ANN

According to experience, the main process parameters of spray deposition are melt temperature and gas pressure, so the inputs of the model choose melt temperature and gas pressure, the output parameter is the grain diameter. The Root Mean Square Deviation (R.M.S.D.) was used to determine the numbers of hidden layers or the node numbers of each hidden layer. R.M.S.D. The formula is (4) [28].

$$R.M.S.D. = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\sigma_{pred} - \sigma_{\exp})^2} \tag{4}$$

Where σ_{pred} is predicted value, $\sigma_{\exp}$ is experimental value. Under different neuron number of single hidden layers, the lower R.M.S.D. values indicate that the neuron number of single hidden layer is more suitable for the model. Temperature is 829 °C, gas pressure is 0.15 MPa, output is grain diameter, the set data applies the formula (4), when the neuron number of a single hidden layer is from 3 to 12, the values of R.M.S.D. are shown in table 1.

As can be seen from table 2, when the neuron number of the single hidden layer is 10, R.M.S.D. value is the minimum. In addition, at this time R.M.S.D. value is relatively low, so the model selects a single hidden layer is enough, do not increase the number of hidden layers. A three-layer feed forward back propagation ANN (as shown in figure 6) was employed to optimize the test parameters for spray deposition of Al-20Si alloy. In other words,the 3 layers ANN model of the test parameters for spray deposition of Al-20Si alloy is more appropriate.

3.3. Processing of original data

The inputs of the network are melt temperature (°C) and gas pressure (MPa), respectively. The output is grain diameter (μm).

Table 1. R.M.S.D. of different neuron number of single hidden layer.

The neuron number of single hidden layer	R.M. S.D.	The neuron number of single hidden layer	R.M. S.D.
3	0.33	8	0.15
4	0.31	9	0.16
5	0.19	10	0.11
6	0.14	11	0.13
7	0.17	12	0.20

Table 2. Prediction values and practice values of grain diameter.

Melt Temperature/ °C	Gas Pressure MPa^{-1}	Experimental values μm^{-1}	ANN prediction μm^{-1}	Absolute error μm^{-1}	Relative error/%
829	0.10	11.71	11.72	0.01	0.09
829	0.15	7.37	7.40	0.03	0.41
829	0.20	2.37	2.43	0.06	2.53
829	0.25	3.45	3.47	0.02	0.58
859	0.10	14.62	14.16	0.46	3.15
859	0.15	7.85	7.82	0.03	0.38
859	0.20	3.94	4.27	0.33	8.38
859	0.25	4.74	4.92	0.18	3.80

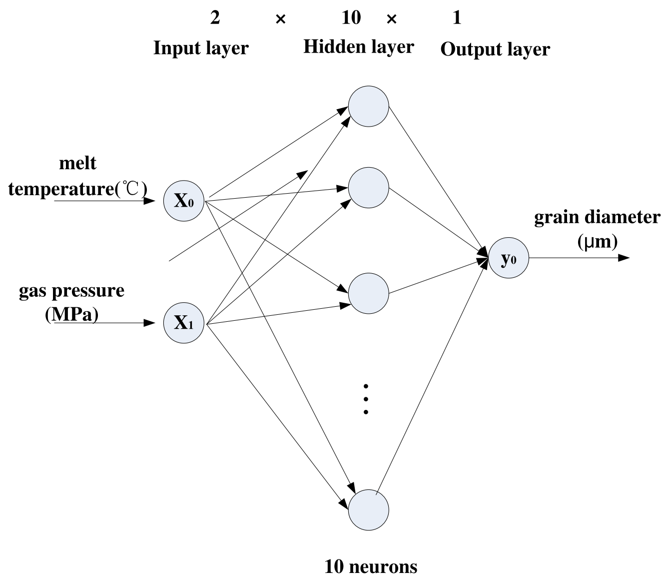

Figure 6. The optimum structure of ANN architecture found for the present study.

In neural networks, input variables should be normalized within the range from 0 to 1. The following formula is widely used to normalize the data in the neural network modeling [29].

$$X' = 0.1 + 0.8 \times \left(\frac{X - X_{\min}}{X_{\max} - X_{\min}}\right) \tag{5}$$

Here, X represents the original data, $X_{\max}$ and $X_{\min}$ represent the maximum and minimum values of X, and X' represents the unified data corresponding to X.

In the ANN model, there are 308 data sets. In brief, the data sets were divided into two parts containing four-fifths of the data sets(called the training dataset) to create the ANN model and one-fifth of the data sets(called the testing dataset) to evaluate the ANN model. That is to say, 484 data sets were used to validate the network and to stop training before overfitting, and the remaining121 data sets were used to test the predictive accuracy of the trained and verified model.

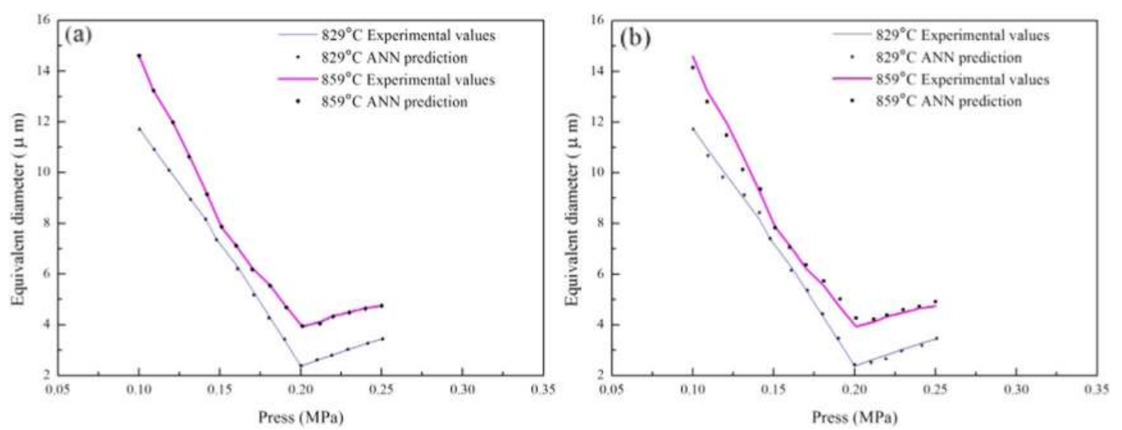

Figure 7. Comparison between experimental values and ANN predicted values of Al-20Si alloy: (a) training samples (b) testing samples.

3.4. Model training

The model training was accomplished by using NN toolbox available with Matlab2016b software. The training function is 'trainbr', the training goal is 0.001, the learning rate is 0.05, after 2425 iterations, the system converges, the system error achieves training objectives.

Genetic algorithm (GA) solves optimization problems that depend on multiple variables. The combination of ANN and GA can solve modeling and optimization problems [30]. Using GA can create a new generation with better individuals, stopping the simulation when the goal is reached or after a certain number of iterations.

By optimizing the ANN structure and parameters, preventing the overfitting of artificial neural network, and finally keeping the training and testing losses at the same level [31].

4. Results and discussion

The contrast of experiment sample values and network predicted values about the optimizing test parameters for spray deposition of Al-20Si alloy is shown in figure 7, respectively. The contrast of training sample values and network predicted values is shown in figure 7(a), the contrast of testing sample values and network predicted values is shown is figure 7(b).

As is observed in figures 7(a) and 7(b), the ability of ANN in predicting the optimizing test parameters for spray deposition of Al-20Si alloy is greater. As shown in table 3, the grain diameter is the minimum value when temperature is 829 °C and gas press is 0.2 MPa, the experimental results show that the optimizing test parameters for spray deposition of Al-20Si alloy is 829 °C and 0.2 MPa.

Meanwhile, prediction values and practice values of grain diameter also can be seen from table2 that the minimum relative error is 0.09%, the maximum relative error is 8.38%, and the error majority concentrate within 3.80%, error is very small.

The capability of ANN is in terms of the average absolute relative error(AARE) and standard statistical parameters of relative error (R), which are defined below [29]:

$$AARE(\%) = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{E_i - P_i}{E_i}\right| \times 100 \tag{6}$$

$$R = \frac{\sum_{i=1}^{N}(E_i - \bar{E})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{N}(E_i - \bar{E})^2\sum_{i=1}^{N}(P_i - \bar{P})^2}} \tag{7}$$

In which, E_i and P_i are the experimental value and the predicted value of grain diameter, respectively; $\bar{E}$ and $\bar{P}$ are the mean values of E_i and P_i, respectively; N is the total sample number of model.

After calculated, ANN AARE and R of Al-20Si alloy grain diameter are 1.04% and 0.997 respectively, which shows the established ANN model of Al-20Si alloy about the optimizing test parameters for spray deposition has high predictability.

The SD-CE experiment was carried out at a temperature of 829 °C and an atomization pressure of 0.2Mpa, and then the sample was subjected to a tensile test. The room temperature strength of the Al-20Si alloy was 210 MPa, the elongation was 9.2%, it had good mechanical properties.

5. Conclusions

In the present work, a set of spray deposition tests were carried out on an Al-20Si alloy within the temperature range of 829 °C–859 °C under the gas pressure of 0.1,0.15,0.2 and0.25 MPa. On the basis of experimental grain diameter values under different temperature and gas pressure conditions, an artificial neural network model has been developed to predict the optimizing test parameters for spray deposition of Al-20Si alloy.

Based on the present study, the following conclusions can be drawn:

(1) The experimental results show that the optimizing test parameters for spray deposition of Al-20Si alloy are 829 °C and 0.2 MPa.

(2) The number of hidden layers and the node numbers of each hidden layer use the Root Mean Square Deviation (R.M.S.D.).It was founded that a network with a single hidden layer consisting of 10 neurons gives the best trade of error and cost.

(3) A comparative evaluation of train values,test values and ANN predicted values were carried out. It is obtained that the minimum relative error is 0.09%, the maximum relative error is 8.38%, and error majority concentrate within 3.80%, MAPE is 1.04%, the error is small.

(4) The obtained results show that the ANN model is statistically accurate and is a robust tool to describe and predict the optimizing test parameters for spray deposition of Al-20Si alloy.

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