# The Choice of Welding Parameters and Prediction of Weld Seam Dimensions for Welding Rapid Prototyping

XU Jian-ning, ZHANG Hua, ZHANG Guang-yun, LI Yu-long, HU Rong-hua Key Laboratory for Robot and Weld Automatization of Jiangxi province Nanchang University Nanchang,China Niatxu76@hotmail.com

Abstract—The data of welding seam width and height were obtained by TIG welding experiments. Two models were established using BP neural networks: One can predict the weld seam dimensions by inputting the welding parameters, and the other model can perform oppositely. Originally by inputting given welding seam dimensions to the model one, the welding parameters can be predicted. Then change the parameters a little properly and input them to model two, the welding seam dimensions which would reflect the weld parameters whether were needed can be acquired. So appropriate weld parameters can be chosen to control the weld seam dimensions by the two models, and good experiment results were acquired.

### *Keywords*—welding rapid prototyping, welding seam dimensions, welding parameters, BP neural networks

#### I. INTRODUCTION

Welding rapid prototyping can prototype dense microstructure metal parts. The principium is: CAD modeling  $\rightarrow$  approximate process  $\rightarrow$ slice process  $\rightarrow$ welding deposition  $\rightarrow$  3D parts[1]. The deposited metal parts are made up of several layers of weld seams, and each layer contains several strips of weld seams, which is constant after the former slice process. We should know the welding parameters according to the given dimensions of weld seam before slice. So it is necessary to establish the model between weld parameters and weld seam dimensions.

## II. ACQUIRING OF DATA OF WELD WIDTH AND WELD HEIGHT IN SINGLE-TRACK AND SINGLE-LAYER WELDING

There are many effective factors of welding prototyping. While keeping other effect factors unchanged, we only study the weld height and weld width under different welding parameters such as welding current, welding speed and wire feed rate, which are easily regulated.

In single-track and single-layer welding, experiment and research results show that if the current is too low and the welding speed and wire feed rate are too high, it will be difficult to melt the welding wires and to prototype continuously. On the contrary, if the current is too high and the welding speed and wire feed rate are too low, the low welding height will be obtained, the steel plate would be fully penetrated and tungsten electrode will be burned soon. So we choose proper range welding parameters to do our experiments after consideration to all aspects.

#### A. Test Conditions

We use TIG welding technology, DCSP, water cooling under the steel plate to improve the heat dissipation conditions to reduce Hot Deformation. The arc length is about 5mm. The material of steel plate is A3, with  $400 \times 70 \times 3$ mm dimension. Wire material is H08Mn2SiA,  $\phi$  0.8mm. The diameter of Cerium Tungsten Electrode is 2.4mm. Shielding gas is Ar 99.99%, flow of gas is 12L/min. Welding seam length is 70mm.

#### B. Welding experiments

Weld a single-track and single-layer seam with current ranging from 110A to 130A, welding speed ranging from 100mm/min to 180mm/min and wire feed rate from 70cm/min to 150cm/min.

Ignore some bad parameter combinations such as the 130A, 110mm/min, 80cm/min. As this group welding parameters will cause little welding height and penetration. First, we keep the other two parameters unchanged and only alter the other one, in order to get the different welding seam dimensions basing on different parameter groups. To reduce the error of measurement, we measure a point every 7mm along the welding seam direction to get its height and width value, and then average them respectively. The average will be the height and width value of the welding seam. There are 87 groups welding seam dimensions we have got in all.

#### III. THE BP NEURAL NETWORK STRUCTURE BETWEEN SINGLE-TRACK AND SINGLE-LAYER WELDING SEAM'S PARAMETERS AND ITS DIMENSIONS

It is difficult to establish the mathematic model of welding seam dimensions and welding parameters because of the complexity of welding thermal process. Well, artificial neural network has the properties of strong robustness, fault tolerance, self-learning, self-organizing and self-adapting, and can process complicated nonlinear and uncertain objects. Thus, 3 layers BP neural network which can approach arbitrary function is used to establish the model between welding parameters and welding seam dimensions. The principle of BP neural network is mentioned in many literatures and reference books[2]. So it won't be discussed in detail in this paper. In this paper, two neural network models were established: Model one can predict the welding seam dimensions from welding parameters, with the input nodes of the welding current, welding speed and wire feed rate, and the output nodes of height and width of welding seam. Well, Model two works oppositely, with the input nodes of welding dimensions, as showed in fig 1:

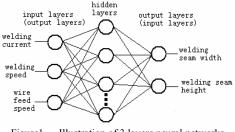


Figure 1. Illustration of 3 layers neural networks

The number of hidden layer nodes is determined by the following formula:

$$n_{hid} = (n_{in} + n_{out})^{\frac{1}{2}} + a$$

 $n_{hid}$  is the number of hidden layer nodes,  $n_{in}$  is the number of input nodes, and  $n_{out}$  number of output nodes.  $1 \le a \le 10$ .

We choose a hidden layer node number to establish the neural network respectively when it ranges from 9 to 12. The function of hidden neurons is "tansig" and output layer neurons transfer function is "purelin", using "trainlm" as the training function. The learning rate is 0.03 and the max training times is 2000.

#### IV. TRAINING OF BP NEURAL NETWORK

In order to ensure the safety and stabilization of BP neural network and to avoid of MSE increasing with the iteration times, we pretreated the data unitary by simply limit the data in closed interval: [0.1 0.9][3], using the following formula[4]:

$$y = 0.1 + \frac{0.8 \times (X - a)}{b - a}$$

b is the max value and a is the min value among the data.

The output of the network can be obtained by renormalization as the following formula:

$$X = a + \frac{(Y - 0.1) \times (b - a)}{0.8}$$

After normalization, two of the 87 data groups will be used for validation, the other 85 data groups will be used as inputs of the network. Then the 85 groups of data sample are inputted into the model 1 and model 2, and trained by matlab6.5 when the number of hidden layer nodes varies from 9 to 12. The training results are showed in fig 2, fig 3,fig4 table 1, and tab2 respectively.

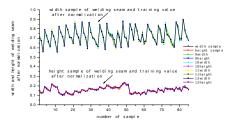


Figure2. Training results of different hidden Layer nodes for model one

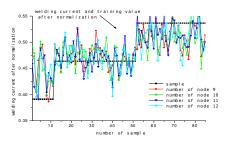


Figure4. (a)Training results of welding current

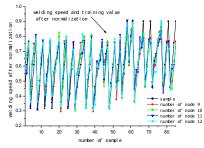


Figure6. (b). Training results of welding speed

TABLE I. TRAINING MSE OF MODEL ONE

Hidden layer	Training	MSE
number	times	
9	2000	1.3025e-004
10	2000	1.2009e-004
11	2000	1.0455e-004
12	2000	9.5651e-005

TABLE II. TRAINING MSE OF MODEL TWO

Hidden layer number	Training times	MSE
9	2000	0.0035993
10	2000	0.0036488
11	2000	0.00298
12	2000	0.0033337

From the training results in above figs and tables, we choose the model 1 which has 12 hidden layer nodes and model 2 which has 11 hidden layer nodes to predict the welding seam dimensions and welding parameters respectively. Inputting the data sample into the two models, the prediction results and experimental results are showed in table 3 and table 4 as follows:

		Expe	rimental welding parameters		Network predicted welding parameters			Relative error		
Width (mm)	Height (mm)	Current(A)	Welding speed (mm/min)	Wire feeding speed (cm/min)	Current(A)	Welding speed (mm/min)	Wire feeding speed (cm/min )	Current	Welding speed	Wire feeding speed
5.49	1.36	130	130	130	117.1889	117.7951	122.7749	8.91%	9.66%	6.37%
4.686	1.104	130	170	110	118.4966	148.4167	101.7729	6.77%	12.7%	4.84%
			TABLE IV.	PREDICTED	RESULTS AND AC	TUAL RESULTS FOR	MODEL TWO			
Wel		Velding speed	Wire feeding	Experiment	Experimental dimensions Network predicted dimensions		Ital dimensions Network predicted dimensions Relative er		elative erro	or
Curren	t(A)	(mm/min)	speed (cm/min)	Width(mm)	Height(mm)	Width(mm)	Height(mm)	Width(m)	n) He	ight(mm)
130		130	130	5.49	1.36	5.4475	1.3545	0.77%		0.1%
130		170	110	4.686	1.104	4.5636	1.0723	2.61%		0.68%

TABLE III. PREDICTED RESULTS AND ACTUAL RESULTS FOR MODEL ONE

From the above four tables, we know the MSE of model 1 is much little. It is suitable for use. However, the MSE of model 2 is too high to predict the welding parameters from the welding dimensions.

#### V. THE CHOICE OF WELDING PARAMETERS AND CONTROL OF WELDING SEAM DIMENSIONS.

#### A. The choice of welding parameters

Though the MSE of model 2 is high and it is difficult to predict the welding parameters we needed by model 2

directly, we can primary predict them by model 2 first. Then input them into model 1 to predict the welding seam dimensions, if the welding seam dimensions are what we want, the welding parameters predicted by model 2 are OK! Else we should rectify those parameters according to the influence them have on the welding rapid prototyping (For example: heightening the wire feeding speed can increase the height of the seam and reducing the welding current can decrease the width.) Then we input the rectified parameters into the model 1 to predict the welding seam dimensions again. Repeat it till the model 1 outputs the correct welding seam dimensions. And the welding parameters inputted into model 1 will be what we demand.

#### B. examples of control of welding seam dimensions.

If the anticipant size of a welding seam is 4.5mm height and 1.0mm width, we input the data into model 2, the forecasting results will be acquired as showed in table 5. Then we input the forecasting results into model 1 to obtain the forecasting welding parameters in table 6.

TABLE V. PREDICTED RESULTS OF MODEL TWO

		predicted welding parameters			
Width (mm)	Height (mm)	Current (A)	Welding speed (mm/min)	Wire feeding speed (cm/min)	
4.5	1.0	123.65	169.98	98.62	

TABLE VI.	PREDICTED RESULTS OF MODEL ONE

Welding current(A)	Welding speed	Wire feeding	predicted welding seam dimensions	
	(mm/min)	speed (cm/min)	Width(mm)	Height(mm)
123.65	169.98	98.62	4.3034	1.0391
120	154	97	4.5152	1.0874

From table 6, we know the width is much less than value that we demand, so the welding speed is slowed down, and the other two parameters are adjusted properly, to increase the width. The final selected parameters are bold-faced listed in table 6. Their forecasting seam dimensions are exported by model 1 and listed in table 6, which satisfy us and prove that with the selected welding parameters in table 6 we can prototype the welding seam whose size will be what we need.

#### VI. CONCLUSION

Two BP neural network models which can predict the welding parameters from welding seam dimensions and forecast welding seam dimensions from welding parameters respectively are established. They are helpful for us to choose the welding parameters that we demand correctly, and to exactly predict the welding seam dimensions, which can be used as a basis to estimate whether the parameters are suitable for welding or not. That is very significant for appropriate choice of welding parameters, slice of prototyping parts and design of deposit trajectory for welding rapid prototyping.

#### ACKNOWLEDGMENT

This work is supported by the Special Program for Key Basic Research of the Ministry of Science and Technology, China(Grant No. 2005CCA04300) and the Natural Science Foundation of Jiangxi Province, China (Grant No. 0650092).

#### REFERENCES

- [1] [1]Yu Ming Zhang; Li, P.; Chen, Y.; Male, A.T. Automated system for welding-based rapid prototyping. Mechatronics, 2002, 12(1): 37-53
- [2] [2] Dilthey, Ulrich; Hichri, Haitem. Structure of a monitoring and control system for the on-line checking of GMA welding processes on

the basis of a neuro-fuzzy architecture. Welding and Cutting,  $2003,\!55(6)\!:316\!-\!321$ 

- [3] [3] Lin Yong; Wang Wei; Yang Yongbo Rizhao Vocational Techical collegeXu Qing,Establishment of artificial neural networks for optimizing welding parameters by matlab, Welding & Joining, 2001(5):14-16
- [4] [4] Di, Li; Srikanthan, T.; Chandel, R.S.; Katsunori, Inoue. Neuralnetwork-based self-organized fuzzy logic control for arc welding. 2001, 14(2):115~124