CHEMICAL ENGINEERING TRANSACTIONS
VOL. 51, 2016

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Tichun Wang, Hongyang Zhang, Lei Tian

ISBN 978-88-95608-43-3; **ISSN** 2283-9216

DOI: 10.3303/CET1651217

Research on the Prediction Model for Abrasive Water Jet Cutting Based on GA-BP Neural Network

Songsheng Deng[a], Lianhuan Guo[a], Jinfa Guan[a], Guangdong Guo[b], Xin Yang*[c]

[a]Department of Military Oil Supply Engineering, Logistic Engineering University of PLA, Chongqing 401331, China
[b]Naval University of Engineering, PLA, Tianjin 300450, China
[c]Department of Industrial & Manufacturing Engineering, Florida State University, Tallahassee 32304, United States
xyang2@fsu.edu

In combination with genetic algorithm (GA), the prediction in abrasive water jet (AWJ) cutting depth and process parameters optimization are implemented aiming at the disadvantages of slow convergence rate and prone to trap in local optimal solution of BP neural network. Moreover, the prediction unit for AWJ cutting is developed to make the network model visible for convenience in guiding the operation during actual machining. The neural network, when combined with GA, makes full use of nonlinear mapping ability of neural network and global optimization capability of GA. Prior to further optimization of BP algorithm, this paper adopts GA to optimize the initial weight and threshold to the area near to global minimum point. The contrast between prediction and experimental results shows that the GA-BP neural network can implement the prediction of cutting depth and optimization of process parameters effectively.

1. Introduction

The AWJ cutting technology has such characteristics as high energy and cold state, generates no thermal stress, open fire and poisonous and harmful gas when compared with traditional machining techniques. Therefore, it is widely applied in cutting various materials difficult to process, e.g., fragile, thermo sensitive and composite material (Wang et al., 1999; Kovacevic et al., 1994). In actual machining process, cutting depth is often judged by the known process parameters, so the equipment operator shall summarize the experience in a long term, but it is lack of necessary theoretical and technical guidance method. It becomes quite necessary to establish a reliable prediction model to reduce equipment energy and abrasive consumption which will improve the AWJ machining efficiency.

(Hashish, 1984) applied theoretical analysis to establish the theoretical model for AWJ cutting. Empirical models were also deduced for AWJ cutting based on experimental data (Li et al., 2011; Wang, 2009). However, as a complex non-linear cutting process, AWJ is influenced by various process parameters in which the correlation exists, and the existing theoretical model and empirical model are established under various simplified or assumed conditions, which are greatly different to the actual conditions and adverse to guidance in actual machining. Artificial neural network (ANN) prediction models were established for its good nonlinear approximation performance (Parikh and Lam, 2009; Yang et al., 2005; Lei et al., 2005), but the single model fails to implement the global optimization. (Chakravarthy and Babu, 2000) improved the performance of AWJ prediction model by using a hybrid optimization method of fuzzy logic theory combined with GA.

In this paper, the GA-BP neural network prediction model for AWJ cutting is established, the prediction in cutting depth and process parameters optimization are implemented and the visual AWJ cutting prediction unit is developed. The neural network, when combined with GA, makes full use of nonlinear mapping ability of neural network and global optimization capability of GA. It resolves defect of slow convergence rate and prone to trap in local optimal solution of BP neural network. Firstly, the nonlinear mapping model established by BP neural network functions as prediction in AWJ cutting depth and process parameters; moreover, GA plays a role in optimization of neural network structure, i.e., obtain the individual of the maximum fitness value by means of global optimization idea, and the fitness value in GA shall be calculated through neural network.

Please cite this article as: Deng S.S., Guo L.H., Guan J.F., Guo G.D., Yang X., 2016, Research on the prediction model for abrasive water jet cutting based on ga-bp neural network, Chemical Engineering Transactions, 51, 1297-1302 DOI:10.3303/CET1651217

2. Implementation of Neural Network

2.1 Network input/output parameters

Many factors will affect AWJ cutting performance. The input parameter is impossible to cover all factors during neural network modeling, otherwise the modeling and training process will become quite complex. According to the existing experimental conditions, pump pressure, traverse rate, impact angle, standoff distance, mass flow rate, focus diameter and number of repetitive cutting are selected as input parameters and cutting depth is used as the only output parameter.

2.2 Network topological design

1. Number of network layer and nodes

As the most widely applied forward neural network structure, single hidden layer BP neural network approximation is available for the continuous function in any closed interval, i.e., three-layer BP network can complete n to m dimensional mapping (Chen et al., 2015). Therefore, a three-layer BP network are adopted in this paper with 1 hidden layer, 7 nodes of input layer and 1 node of output layer.

The range of node number of hidden layer is determined as 4-14 according to the empirical formula (1) and then trial method is adopted to confirm the node number of hidden layer. The error value obtained through forward calculation is the immediate basis for judgment of the network performance quality. When node number of hidden layer is 10, the error will be minimum.

$$n_1 = \sqrt{n+m} + a \tag{1}$$

Where n is the number of input neuron; m is the number of output neuron and a is a constant between 1-10.

2. Excitation function selection

Considering that the problem to be solved is a high nonlinear mapping problem with multiple inputs and single output, the nonlinear S function (tansig function) is selected from input layer to hidden layer of network model to implement the nonlinear mapping and the linear function (purelin function) is selected from hidden layer to output layer, to implement the arbitrary output in the real number field. According to the analysis above, the neural network model established for predictive output is shown in Figure 1.

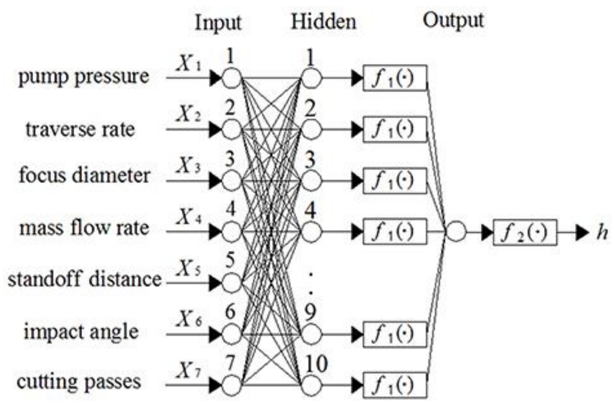

Figure 1: Neural network model

2.3 Network model training

The gradient descent is generally adopted for correction of various weights and thresholds of common BP neural network, i.e., expanded δ. The method will have "saw-tooth phenomenon" and even trap into the local minimum in the process of optimization searching (minimal point). In this paper, L-M (Levenberg-Marquardt) BP algorithm based on numerical optimization is adopted for adjustment of weight and threshold during back-propagation of network error, until to the pre-set error requirement. The network training sample adopts the data obtained from the experimental contents mentioned above and the optimal initial weight and threshold are selected by the GA.

3. Flow for Optimization of BP Neural Network Algorithm by GA

3.1 Chromosome coding

Spatial data processing can't be processed by the GA before encoded to genotype series structure data of genetic space (Chambers, 1995). The chromosome coding in this paper adopts the real number encoding for weight and threshold in each layer. The multi-dimensional matrix W_1, B, W_2 and S for representing the BP network weight and threshold is expressed by one-dimensional matrix. Each gene of the chromosome represents a weight or threshold in the network. Taking three-layer network structure in Figure 10 as an example, the coding form is shown as follows: (w_{111}, …, w_{1lm}, b_1, …b_m, w_{211}, …, w_{2mn}, s_n), where *l* is [1,7], *m* is [1,10] and *n* is 1.

3.2 Initial population generation

The initial chromosome pool is generated by means of initial population function and its expression is *initPpp*= *Initalizega*(*popu, aa, 'gabpEval'*), where *popu* is initial population size, *aa* is the value range of each gene and *gabpEval* is fitness function. The length of the chromosome in population $L=W_1+B+W_2+S+1$ and the last bit of each chromosome is the fitness value of the chromosome.

3.3 Fitness function

As for BP neural network, the smaller training error has a higher chromosome priority, so the reciprocal of sum of squared errors of all object samples is adopted as the fitness value in this paper. The specific function is shown as follows: [*fitness*]= gabpEval(*T*), where *fitness* is the fitness value of chromosomes. If the output value of three-layer neural network is calculated, each chromosome shall be decoded, to obtain the weight W_1 and W_2 and threshold B and S of the corresponding nerve cell and calculate the corresponding network output value matrix Y of each sample according to formula (2).

$$Y = f_2\left(W_2 \cdot f_1(W_1 \cdot X, B), S\right) \tag{2}$$

The sum of squared errors of each sample group can be calculated by formula (3).

$$E = \sum_{k=1}^{N} (T_k - Y_k)^2 \tag{3}$$

Where N is sample size and chromosome fitness value fitness=1/E.

3.4 Selection, crossover and mutation operation

Select or copy operation is intended for selecting excellent individuals from the current individuals, so that they can be used for subsequent genetic manipulation as a parent. The higher fitness value an individual has, the higher chance of selection it has, and the selection operator selected in this paper is geometric programming sorting selection (normGeomSelect).

The crossover operation is the characteristic operation of the GA: the individuals in the group are matched at random; some chromosomes of each individual are exchanged according to crossover probability to obtain the new generation individual. The new individual has the feature inheritance of its parent individual. In this paper, the crossover operator adopted is arithmetic crossover, with the design crossover probability of 0.6.

As for the mutation operation, an individual is selected from the population at random, to change the value of a bit in series structure data at a certain probability. GA has a low probability of mutation, with the common value range of 0.01-0.1. The common mutation operator adopted in this paper is non-uniform mutation (nonUnifMutation).

4. Visual Development of Network Model

The corresponding prediction unit is developed and the visual operation for network model is implemented for convenience in prediction and optimization of relevant contents concerning AWJ cutting. The unit consists mainly of network modeling module, preferred initial weight and threshold module, BP neural network training module, cutting depth prediction module and cutting process parameters optimization module.

4.1 Network modeling module

Ticking the seven parameters of pump pressure, traverse rate, impact angle, standoff distance, abrasive mass flow rate, focus diameter and number of passes in “Parameter Input” column and tick the cutting depth in “Predictive Output” column, as shown in Figure 2; click “Model”; and then the system will automatically call MATLAB procedure written and build the neural network model required according to the mode in Figure 1. The modeling procedure is show as follows: net=newff(minmax(p), [S1,1], {'tansig','purelin'},'trainlm'), where S1 is the number of nerve cell in hidden layer.

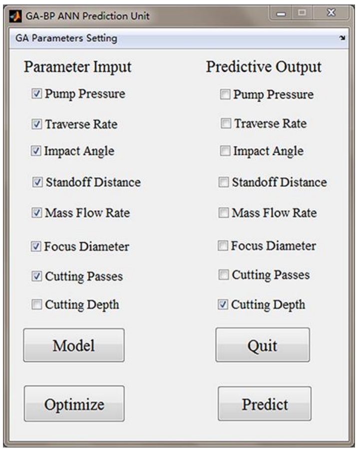

Figure 2: BP neural network modeling

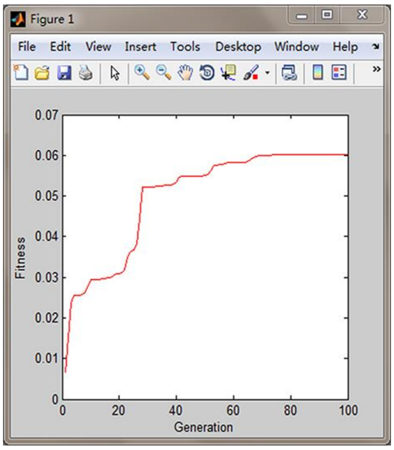

Figure 3: Optimal individual fitness value

4.2 Preferred initial weight and threshold module

After the experimental sample data is subjected to normalization processing, the individual encoding length can be determined and a local optimum chromosome can be selected from the initial population according to the quantity of network nerve cell established. Then, the GA toolbox (GAOT) can be called to conduct the selection, crossover and mutation operation for chromosome, so as to obtain the new population after each genetic manipulation, save the optimal chromosome in new population and calculate its fitness value, and if it reaches the pre-set genetic algebra, the genetic manipulation will terminate. Therefore, an optimal individual can be obtained in the process of each GA operation, and its fitness value shall be recorded. The corresponding weight and threshold of the individual having the maximum fitness value can be assigned to the neural network, by means of comparison of fitness values of the optimal individuals in the initial population and the new population. Figure 3 is the change curve of fitness value of optimal individual recorded by MATLAB procedure in the calculation process.

4.3 BP neural network training module

In the learning process of BP neural network, the computation process for error back propagation is more complex than that for error forward propagation. Levenberg-Marquardt BP algorithm is adopted for error back propagation. The neural network can display the dynamic training process. The training termination conditions are set as the maximum training steps of 2,000, training mean square error MSE of 1e-28 or error curve gradient of 1e-5, and the training will terminate in case of any of the three conditions above is met. In this training, the error curve gradient firstly reached the termination condition of below 1e-5.

Figure 4 shows the fitting coefficient of network model R=0.99953 for the sample data, indicating that the fitting sample of GA-BP neural network has a high precision to implement the effective nonlinear mapping.

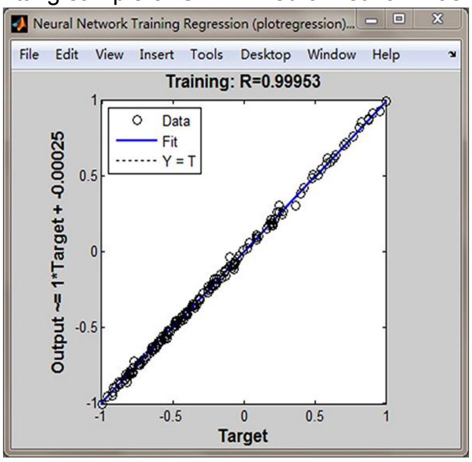

Figure 4: Sample fitting curve

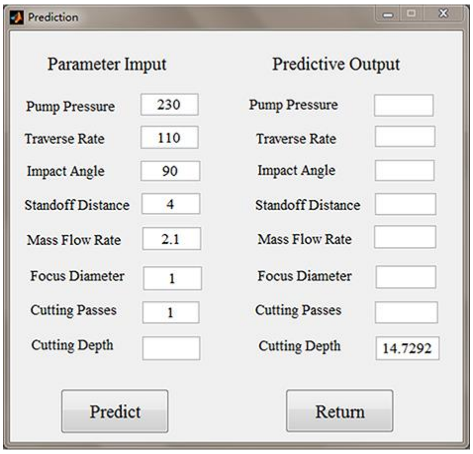

Figure 5: Predictive output of cutting depth

4.4 Cutting depth prediction module

The subsequent prediction can be conducted after the neural network training is completed. Click “Predict” in Figure 2, input various values in “Parameter Input” column on popped-up interface and click “Predict” to obtain the corresponding “Predictive Output”, as shown in Figure 5.

4.5 Process parameters optimization module

Process parameters optimization module: its function is to select a group of process parameters to achieve maximum cutting depth. Click “Optimize” and then MATLAB procedure will read parameter data from Excel document of data1, select the group having maximum cutting depth and show its corresponding cutting depth.

4.6 Experimental Verification for Network Model Performance

After the network training is completed, AWJ cutting model will have the prediction and optimization functions. In this paper, cutting depth prediction is applied for experimental verification of model performance and testing its generalization ability. Five groups of non-modeling sample data are applied for inspection on the performance of prediction and comparison between predictive and experimental results, as shown in Table 1.

Table 1: Comparison between predictive and experimental results

Parameter	1	2	3	4	5
Pump pressure (MPa)	150	230	190	270	190
Traverse rate (mm/min)	110	140	110	110	80
Impact angle (°)	115	90	90	90	90
Standoff distance (mm)	4	7	4	4	7
Mass flow rate (kg/min)	2.1	2.1	5.2	2.1	2.1
Focus diameter (mm)	1	1.2	1	1.5	1
Number of cutting passes	1	1	1	1	2
Experimental depth (mm)	6.93	10.18	18.64	11.52	20.78
Predictive depth (mm)	7.50	10.62	17.70	12.06	19.53
Relative error (%)	7.6%	4.1%	5.3%	4.5%	6.4%

Table 1 shows that the predictive results of cutting depth based on GA-BP neural network model established coincide well with experimental results, with relative error range of 4.1%-7.6%, so the established network has a good prediction performance and therefore can be used for prediction in AWJ cutting depth.
Meanwhile, replace the data in data1.xlsx by five groups of experimental data and then the interface shown in Figure 6 will automatically pop up after clicking "Optimize". Cutting depth under the shown combination is the largest one among the five groups, indicating the conformity with actual results listed in Table 1 and reliability of parameters optimization function.

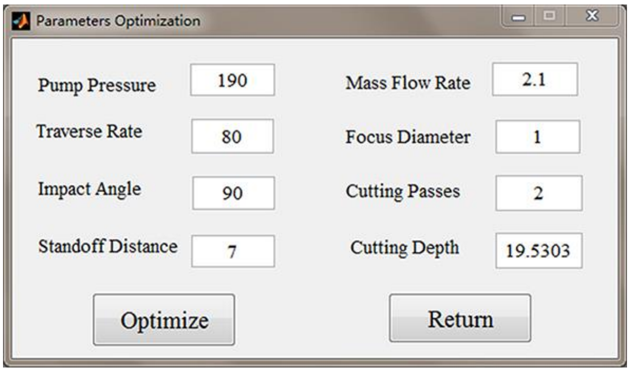

Figure 6: Parameters optimization result

5. Conclusions

After topological structure and training algorithm are designed by organic combination of GA-BP neural network and AWJ technology, the global optimization is implemented for network initial weight and threshold by means of GA, to prevent the neural network being trapped in the local optimal solution. The experimental results show that the model established can achieve the effective prediction in cutting depth and process parameters optimization. Supported by GA-BP network modeling technology, MATLAB programming calculation and GUI interface development technology, the visual cutting depth prediction and parameters optimization unit is beneficial to guide the AWJ's application in actual industrial machining.

Acknowledgements

The research team acknowledges the financial support by the project from General Logistics Department of PLA (No. YX213C208).

References

Chakravarthy S. P., Babu N. R., 2000, A hybrid approach for selection of optimal process parameters in abrasive water jet cutting, Proceedings of the Institution of mechanical Engineers, Part B: Journal of Engineering Manufacture, 214, 781-791, DOI: 10.1243/0954405001517847.

Chambers L., 1995, Practical Handbook of GAs: Applications, CRC press, Florida.

Chen X., Xu L. S., Xu M., 2015, Application of an improved BP neural network model in enterprise Network Security Forecasting, Chemical Engineering Transactions, 46, 1261-1266, DOI: 10.3303/CET1546211.

Hashish M., 1984, A modeling study of metal cutting with abrasive waterjets, ASME Journal of Engineering Materials and Technology, 106, 88-100, DOI: 10.1115/1.3225682.

Kovacevic R., Fang M., 1994, Modeling the influence of the abrasive waterjet cutting parameters on the depth of cut based on fuzzy rules, International Journal of Machine Tools and Manufacture, 34, 55–72, DOI: 10.1016/0890-6955(94)90040-X.

Lei Y. Y., Jia Q., Yang G. L., Qiu G., Ma C., Song Q. J., 2005, Abrasive waterjet precise machining based on artificial neural network, Journal of Sichuan University: Engineering Science Edition, 37, 155-159, DOI: 10.15961/j.jsuese.2005.06.031.

Li H., Wang R., Yang D., Zhou W., Li L., 2011, Determination of rotary cutting depth on steel pipes with the abrasive water jet technique, Proc. IMechE, Part C: Journal of Mechanical Engineering Science, 225, 1626–1637, DOI: 10.1177/0954406211400670.

Pratik P. J., Lam S. S., 2009, Parameter estimation for abrasive water jet machining process using neural networks, International Journal of Machine Tools and Manufacture, 40, 497-502, DOI: 10.1007/s00170-007-1363-7.

Wang J., Wong W. C., 1999, A study of abrasive waterjet cutting of metallic coated sheet steels, International Journal of Machine Tools and Manufacture, 39, 855-870, DOI: 10.1016/S0890-6955(98)00078-9.

Wang J., 2009, A new model for predicting the depth of cut in abrasive waterjet contouring of alumina ceramics, Journal of Materials Processing Technology, 209, 2314-2320, DOI: 10.1016/j.jmatprotec.2008.05.021.

Yang L., Peng Z. B., Tang C. L., Zhang F. H., 2005, Numerical model of AWJ cutting speed based on artificial neural network, Transactions of the Chinese Society for Agriculture Machinery, 36, 117-120, DOI: 10.3969/j.issn.1000-1298.2005.05.030.