

Research on the Neural Networks Used for Shaping Tubes by the Liquid Extrusion Process

Le-Hua Qi, He-Jun Li, Jun-Jie Hou, and Pei-Ling Cui

(Submitted 2 September, 1999; in revised form 12 October 1999)

Liquid extrusion, as a new kind of metal forming process for shaping tube and bar products directly from liquid metal, can reduce the intermediate steps and production costs and make the materials doubly strengthened. But it has not been widely used since the process parameters are now selected by experience, which can easily result in a high reject rate. In order to analyze the contributing factors of the process, the artificial neural network method was used in this paper. The network architecture was determined by adopting 125 sets of experimental data of the shaping tubes of AlCuSiMg alloy as samples and, by contrast, one or two hidden layers and the numbers of nodes and other network parameters. The knowledge base for the process parameters of liquid extrusion has been established. The values predicted by the knowledge base are very consistent with the practical ones. The result shows that the introduced method is feasible and effective.

Keywords neural network, liquid extrusion, knowledge base

1. Introduction

The liquid extrusion process, as a method of forming tube, bar, and shape products from liquid metal in a single process, is a kind of new metal forming technology, which has been developed in recent years. The key characteristic of this process is that it combines solidification under pressure and large plastic deformation. By the process, the middle forming procedures are needless, and the production cost can be reduced greatly. Moreover, the extruded materials can get doubly strengthened.[1] Since this process has come into being, it has gained special attention from the experts in the field of plastic forming.[2] But the product is formed directly from liquid metal, so the control of all kinds of key technologic parameters must be very strict. If any of the parameters is not properly selected, the forming process will be terminated or the products will be ineligible. This is a multiobjective optimization problem. To solve the problem, the knowledge base of the technologic parameters should be established to ensure correspondence of the deforming velocity and solidification velocity, which is just the key subject that has cost extensive hard work of the researchers in this field. But, at the present stage, the application of the technology is still limited in that the determination of process parameters is based on the empirical data, and the reasonable resolution is yet to be found. In this paper, the neural network as a modeling technology to establish the knowledge base of technologic parameters for shaping tubes has been explored, by which the deforming pressure and the deferring period before applying pressure can be precisely predicted and the optimum control of the process can be realized.

Le-Hua Qi, He-Jun Li, Jun-Jie Hou, and **Pei-Ling Cui,** Department of Mechanical Engineering, Northwestern Polytechnical University, Xi'an, 710072, People's Republic of China.

2. Presentation of the Problems

The liquid extrusion process has been developed on the basis of research achievements in combining the characteristics of liquid metal forging and hot extrusion and continuous casting. The forming process can be described as follows. After the liquid metal is poured into the extruding container, the high pressure produced by a hydraulic press is directly applied to the solidifying or quasisolidified metal by the punch, which makes it flow, crystallize, and solidify under pressure, and then the quasisolidifying metal is extruded to the entrance of the forming die and undergoes large plastic deformation owing to the reduction of the section; after that, the tube, bar, or shape products are formed in the single process (Fig. 1). According to the experimental research and the simulation of solidification and temperature field of the product in the entire liquid extrusion process,[3] both liquid and solid metal exist in the beginning of the process, and two kinds of movements exist in the extrusion process: one is that the liquid and solid metal move down as a whole until they are extruded out; another is that the inner liquid metal tends to solidify and its volume reduces bit by bit ($V < V_t$), and that the thickness of the solidified metal increases ceaselessly ($U > U_t$) (Fig. 2). For the stability of the process and the acquisition of eligible products, the solidifying interface of the lower part of the liquid metal must be maintained above the exit of the forming die all the time (Fig. 2); the ideal state is that h remains invariable, that is, the moving up velocity of the solidifying interface at the bottom of the liquid metal, which is transmitted from the solidification velocity, must not be less than the extruding velocity of the punch. The correspondence of both can pledge the continuous existence of liquid metal in the container and keep the process as liquid extrusion, meanwhile making the products extrude out in a completely solidified state to maintain the continuity of the procedure. To realize this target, the necessary condition is that the extruding velocity of the punch and the temperature field of the die must be controlled effectively. In fact, it is by means of regulating all technologic parameters that the stability of the forming process and the forming quality can be pledged. But the liquid extrusion process involves a series of complex systems such as metallurgy, heat transfer, plastic deformation, and so on. There is great difficulty in building precious mathematical models. So establishing a knowledge base of technologic parameters is very important.

Generally, the knowledge acquisition for traditional expert systems relies on artificial transplant. The expert knowledge, which is obtained from the correlative fields indirectly, is stored via computer as regular form. However, since it is very difficult to describe with certainty the knowledge for many fields, moreover, the traditional expert systems cannot directly learn the knowledge from the situation of the field, it is not easy to establish the feasible expert system.

An artificial neural network has been employed with notable success in a wide range of areas such as the modeling of systems with unclear process, material designing and optimum controlling, and so on.[4,5] It provides a feasible method for systems with several variables that cannot be described by mathematical model. In a network, the knowledge is represented by means of many interconnected neurons and their connection weights. The acquisition of knowledge involves learning the sample library obtained from the practical process by experts according to a special learning algorithm. The connection weights are modified during the learning, until the network satisfies the error value of the system. Then, the knowledge and the experience are captured and stored in the interconnected neurons and their connection weights. That is to say, the interrelationship among the variables is acquired by means of a direct learning of the practical data. When presenting the new technological parameters, the network can give an output that is the result of the generation and synthesis of what has been learned and stored in its connection weights, by which the prediction values of the technological parameters can be obtained and then the knowledge base of technological parameters can be established. Hence, the above problems can be solved by establishing the knowledge base of technological parameters on the neural network.

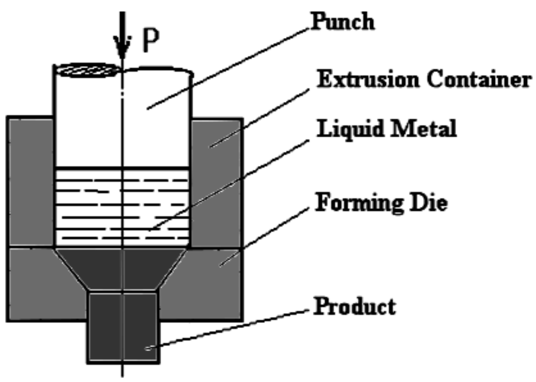


Fig. 1 Schematic diagram of the liquid extrusion process

3. The forming of a technologic parameters knowledge base

3.1 Neural Network Model

In this paper, an error back-propagation neural network with three layers, including input, hidden, and output layers, is used as a network structure for acquiring knowledge (Fig. 3). Each node represents a neuron, which can only send its output to the units on the upper layer and receive its input from the lower layer. The process that takes place in the neural network to acquire knowledge with the back-propagation learning algorithm involves forward and backward transmission. The forward transmission occurs when input information is presented and every processor is fed with the weighted sum of the output of the processor in the previous layer and produces an output through an activation function, and the output signal is subsequently transmitted to the next layer. The backward phase occurs when the estimated output is not sufficiently close to the desired output, that is, the error signal is propagated back along the primary path. The connection weights are adjusted by using a gradient decent method until the optimum value is achieved.

When feeding forward, the output of node i is defined as follows:

$$O_i = f_1(X_i) \quad \text{(Eq 1)}$$

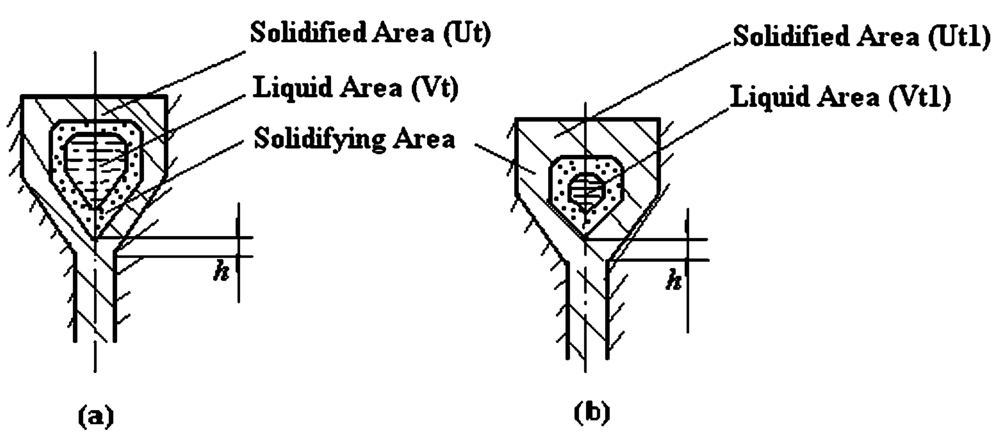


Fig. 2 Varying pattern of liquid and solid areas during the liquid extrusion process. **(a)** The deferring period is t. **(b)** The deferring period is $t_1 = t +$.

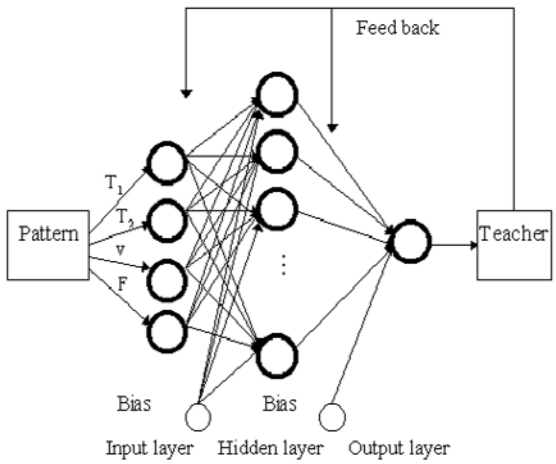


Fig. 3 Illustration of a three-layer back-propagation neural network

Table 1 The chemical composition of the experimental alloy, Wt.%

Cu	Si	Mg	Al
4.0–5.0	0.11	0.07	Bal.

$$X_i = \sum_k \omega_{i,k} O_k - \theta_i \quad \text{(Eq 2)}$$

In both equations, $\omega_{i,k}$ is the connection weight between the current node and node k in the preceding layer; O_k is the output of node k; θ_i is the threshold value of node i in the current layer; and $f(\cdot)$ is the activation function in this research, which is defined as follows:

$$f_i(X_i) = \frac{1}{1+e^{-X_i}} \quad \text{(Eq 3)}$$

The objective function of the training network is defined as follows:

$$E = \sqrt{\frac{\sum_{p=1}^{M}\sum_{j=1}^{Q}(d_j^p - O_j^p)^2}{M \bullet Q}} \quad \text{(Eq 4)}$$

Here, M is the number of training samples; Q is the number of output layer nodes; and d_j is the desired output.

By modifying the learning parameters $\omega_{i,k}$ and θ_i,E tends to the minimum value; then, the error-correction formula is

$$\Delta\omega_{i,k}(m) = -\eta\frac{\partial E(m-1)}{\partial \omega_{i,k}(m-1)} + \alpha\Delta\omega_{i,k}(m-1) \quad \text{(Eq 5)}$$

In this equation, $\Delta\omega_{i,k}(m) = \omega_{i,k}(m) - \omega_{i,k}(m-1)$; $\eta \in (0,1)$ is a learning rate, $\alpha \in (0, 1)$ is a momentum factor, and m is the current number of iterations.

3.2 Establishing the Knowledge Base of the Technological Parameters

By adopting the AlCuSiMg alloy as the experimental material (Table 1), experiments for forming tubes by the liquid extrusion process were undertaken by a 3150 KN hydraulic press. By varying the process parameters, such as the pouring temperature of liquid metal (T_1), the die temperature (T_2), the deforming velocity (ν), and the deferring period before applying pressure (t), and so on, 125 sets of experimental data were collected as the sample library.

During the liquid extrusion process, the technological parameters are conditioned to each other. Among them, the deforming pressure and the deferring period before applying pressure have significant influence on forming quality. Considering all of the factors, the deforming pressure is defined as follows:

$$F = f[T_1(\zeta), T_2(\zeta), \nu(\zeta), t(\zeta)] \quad \text{(Eq 6)}$$

The deferring period before applying pressure is defined as follows:

$$t = f[T_1(\zeta), T_2(\zeta), \nu(\zeta), F(\zeta)] \quad \text{(Eq 7)}$$

where

F is deforming pressure of liquid extrusion,
t is deferring period before applying pressure,
T_1 is pouring temperature of liquid metal,
T_2 is temperature of the die before pouting liquid metal,
ν is deforming velocity, and
ζ is parameter relevant to the material.

For improvement of the convergent speed of the network and the prediction precision of the knowledge base, this paper presents an attempt at simulating the deforming pressure and the deferring period before applying pressure separately by making use of two networks, the BPF and BPT. The steps of acquiring knowledge can be described in the following discussion.

Step 1 was to construct the training sample library. The 105 sets of data were selected from 125 sets of experimental data of liquid extruding tubes, which were used for training the network, and the remaining 20 sets of data were used as the testing sample library.

Step 2 was to initialize the neural network. There were four nodes in the input layer, which denote the four parameters T_1, T_2, ν, and t or F, respectively. There was one node in the output layer, which denoted the deforming pressure F or the deferring period before applying pressure t (Fig. 3). The number of hidden layer nodes can be randomly selected according to the practical requirement, which is ten for the BPF network and eight for the BPT network in this paper. The initial weights of the network were selected between −0.5 and 0.5 at random.

Step 3 was to train the BPF and BPT networks separately by using the BP learning algorithm introduced before. By modifying the connection weights and threshold values in an iterative process, the expected accuracy could be achieved at last.

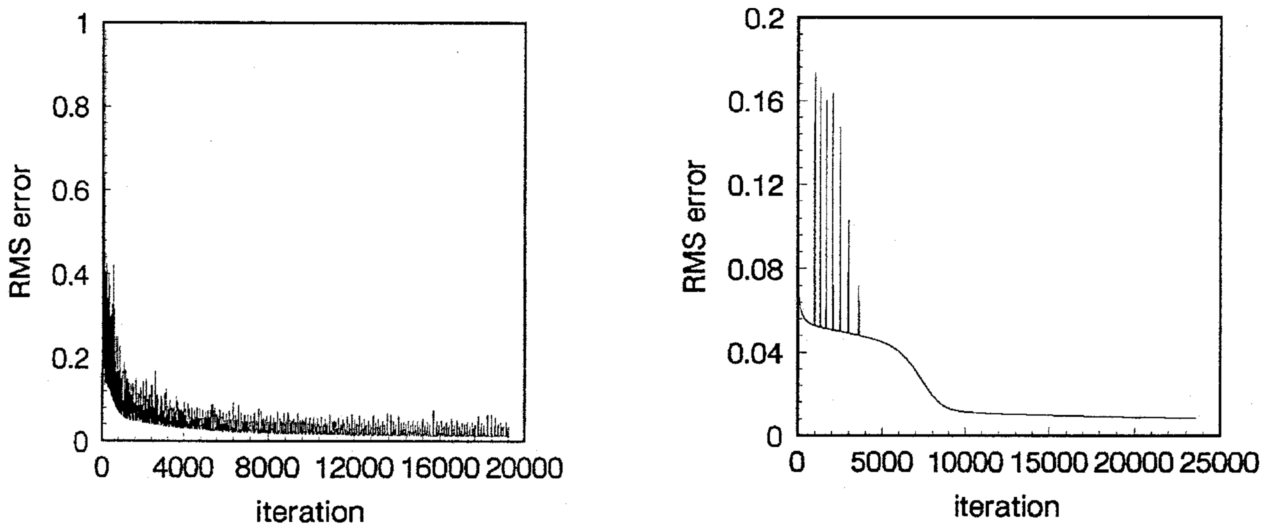
Step 4 was to input the testing sample library (20 sets) to verify the reliability of the network.

4. Examples

In this paper, the software of the corresponding knowledge base is written by the C programming language according to the BP learning algorithm. Here, the BPT network for simulating the deferring period before applying pressure is taken as an example to illustrate the establishment of the knowledge base for technological parameters.

4.1 Selection of Network Structure and Parameters

Based on the input and output characteristics of the BPT network, two BP networks that have four input nodes and one output node, but one or two hidden layers, respectively, were constructed. Then, the structure parameters of two networks were determined by separate iterative training. The comparison of training results of the two networks is shown in Fig. 4. The abscissa represents the number of iterative trainings and the ordinate is the root-mean-square error of the system during the training process. It can be seen that the single hidden layer network is better. For the single hidden layer network, the error is less than 0.01 after 10,000 time trainings, and there is no vibration. But the error is still 0.08 after 18,000 time iterative trainings, and the vibration is very serious for the double hidden layer. Figure 5 shows the comparison of the system error and training cycles in a single hidden layer network by varying the learning rate η (Fig. 5(a)) and the number of hidden nodes (Fig. 5(b)) when the momentum factor was fixed as 0.9. It can be deduced that the system error and training cycles are comparatively small when the parameters are η: 0.07, α: 0.9, and hidden nodes: 8. Considering many factors, including system error and training cycles synthetically, the structure of the BPT network was determined as a three-layer network, that is, $4 \times 8 \times 1$.



(a) **(b)**

Fig. 4 Comparison of training results of two kinds of BPT networks η: 0.3, α: 0.6. **(a)** double hidden layers,**(b)** single hidden layer

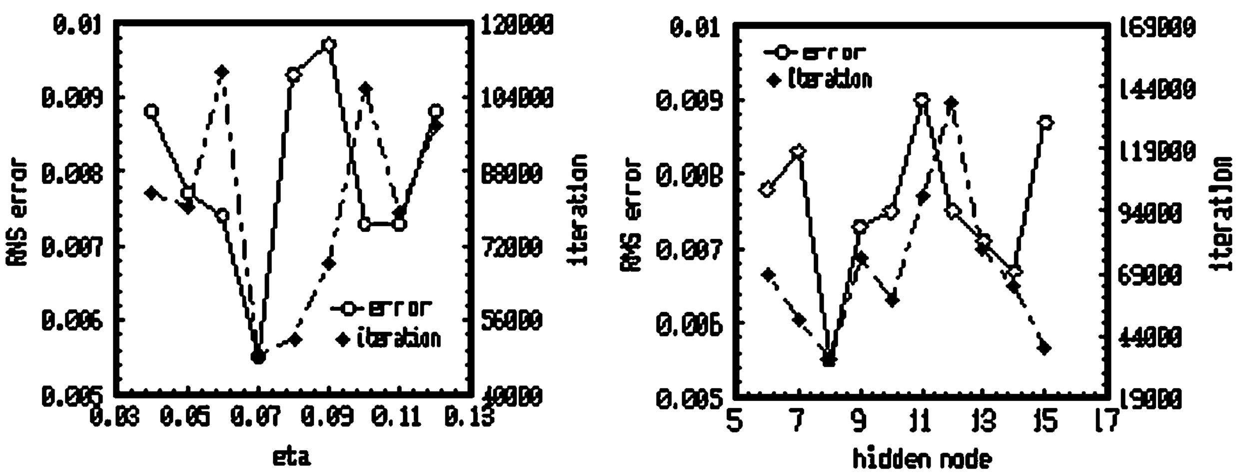


Fig. 5 The system error and training cycles vs variable parameters in the single layer network

Table 2 The connection weights and threshold values of BPT networks

Hidden node		1	2	3	4	5	6	7	8
Input layer	1	−2.2622	−0.1511	−0.4185	5.2297	1.5976	1.8941	7.2771	−1.2575
	2	0.1901	−0.4703	−0.7020	1.8867	−1.5194	1.3923	−3.9804	−2.4602
	3	−0.1649	0.8051	1.4047	−2.2835	−0.7045	0.3588	−1.8824	−1.0130
	4	0.3028	−9.3919	−5.2928	0.7301	−3.2593	1.9019	−8.8934	−3.8406
	θ_i	−0.0840	−4.9216	−2.6576	−2.0709	−1.8764	3.4380	−11.8882	0.4328
Output layer	1	−1.5432	3.4086	−5.0954	5.4361	2.8697	6.9991	−7.2976	−3.7941
	θ_k				−2.1418				

The network parameters η:0.07, α:0.9

Table 3 The prediction results of BPT networks

T_1 °C	T_2 °C	v (mm/s)	F (MPa)	t (s) Practical	t (s) Predicted	t (s) Relative error
680	160	4	114	45	44.8574	0.00316977
690	180	3	105	50	50.6771	0.0135425
700	150	3	117	55	55.0884	0.00160739
710	200	5	100	64	64.3220	0.00503121
720	180	4	105	64	64.5377	0.00840231
720	170	4	100	55	55.0828	0.00150573

4.2 Verification of the Prediction Capacity of the Network

After the learning process, the connection weights and threshold values of the BPT network were determined (Table 2). It can be concluded that the absolute values of the weights in lines 1 and 4 are comparatively larger than those in lines 2 and 3, that is to say, the pouring temperature and the deforming pressure have larger influence on the deferring period before applying pressure among the four parameters, and the deforming pressure can be adjusted by the pouring temperature and the deferring period before applying pressure. The prediction results are shown in Table 3. According to Table 3, the relative error is all under 1.35%, that is the discrepancy between the expected value and the values from the neural network is within 0.01 to 0.7 seconds, which can satisfy the practical needs. The above analysis shows that the key parameters of liquid extrusion can be predicted by establishing the knowledge base on the neural network, by which the forming quality can be controlled stably. According to the prediction data, the experiments can be smoothly performed, and the results are good.

5. Conclusions

From the present investigation, the following conclusions can be obtained.

- In this paper, the knowledge base of liquid extrusion for shaping tubes has been established on the basis of the artificial neural network, by which the key process parameters of this technology can be predicted successfully. The discrepancies between the predicted value and expected value of the deferring period before applying pressure are all under 0.7 s. The prediction results are encouraging.
- The establishment of a knowledge base shows good learning precision and generalization and lays a foundation for the optimum controlling of the liquid extrusion process. Meanwhile, it is very useful for guiding the practical application of the process.

References

1. Qi Lehua: *Mater. Manufacturing Processes*, 1998, vol. 13 (3), pp. 405-13.
2. Zhou Dajun and Song Yuquan: *Forging Stamping Technol.*, 1993 vol. 5, pp. 18-23.
3. Li Hejun, Qi Lehua, Ren Xiangqian, Luo Shoujin, and Huo Wencan: *Chin. J. Mater. Res.*, 1994, vol. 8 (6), pp. 507-13.
4. T.A. Spedding, and Z.Q. Wang: *J. Mater. Processing Technol.* 1997, vol. 69, pp. 18-28.
5. J. Larkiola, P. Myllykoski, J. Bnylander, and A.S. Korhonen: *J. Mater. Processing Technol.*, 1996, vol. 60, pp. 381-86.