Quality prediction of steel pipe extrusion based on RBF neural network

Ziyang Zheng [1], Mingzhe Jiang [2, *]

[1] College of Materials Science and Engineering, Fuzhou University, Fuzhou, China, 350108

[2] College of Chemical Engineering, Qingdao University of Science and Technology, Qingdao, China, 266042

* Corresponding Author Email: jiangmingzhe2005@163.com

Abstract. Predicting and optimizing extrusion molding process parameters is a significant and challenging research topic in the field of manufacturing, but machine learning-based approaches remain relatively scarce. In this study, orthogonal experiments were designed to simulate the extrusion process using Simu fact Forming software. The thinning rate, stamping speed, and friction coefficient were used as independent variables. Subsequently, prediction models for extrusion force and equivalent force were established based on a Radial Basis Function (RBF) neural network. The data obtained from the simulation software were used as the training set, and additional experiments outside the training set were designed for validation. The model achieved a relative error below 6%, demonstrating its reliability. This study not only proposes a novel method for predicting process parameters in steel pipe extrusion but also holds significant value for optimizing these parameters and improving product quality. The application of this model can benefit various manufacturing sectors, including automotive, aerospace, and construction, where precise control of extrusion parameters is critical for enhancing product performance and reducing material waste.

Keywords: RBF neural network, Steel pipe extrusion, Quality prediction, Orthogonal experiments.

1. Introduction

Extrusion molding is a plasticity process primarily used for metal forming. It offers several advantages, including high productivity, precise dimensional control, and flexibility, allowing the production of parts with complex cross-sections while improving the mechanical properties and surface quality of materials. Due to these benefits, extrusion molding is widely used in fields such as biomedical materials [1], automotive manufacturing [2-3], construction, aerospace, and aviation.

The quality of extruded products is strongly correlated with the process parameters used during the forming process. Traditional methods of parameter determination require numerous experiments, often leading to low accuracy and making process control challenging. Surrogate models, which are based on design of experiments (DOE) and statistical analysis, provide an alternative method for addressing these challenges. Common surrogate models include Radial Basis Function (RBF) networks, Kriging, response surface methodology, and Artificial Neural Networks (ANN) [4]. For example, Kallakunta et al. [5] used response surface methodology in hot-melt extrusion (HME) technology to optimize the formulation and processing of a solid self-emulsifying drug delivery system. Mamidi et al. [6] applied differential scanning calorimetry and response surface methodology to optimize the HME process with a focus on material savings. Additionally, Angshuman et al. [7] utilized Artificial Neural Networks (ANN) to predict systematic experimental design data, aiding in the development of response surface models. These studies offer new methods for optimizing extrusion process parameters, reducing costs and resource consumption.

To address the limitations of traditional process parameter formulation, this paper utilizes experimental design and simulations conducted with Simu fact Forming software. A prediction model for extrusion stress and equivalent force, based on an RBF neural network, is proposed. The model achieves a relative error of below 6% between the predicted and simulated values, enabling fast and accurate prediction of extrusion molding process parameters.

1.1. Workpiece processability analysis

C15_c steel pipe was selected as the subject of this study. The pipe has an outer diameter of 58.26 mm, an inner diameter of 47.24 mm, and a height of 54.6 mm, with inner bottom corners rounded to a radius of 2 mm. For the model, the Ring Mash grid generator was used to generate a hexahedral mesh, with the maximum refinement degree set to 5. The 3D geometry and mesh division are shown in Figure 1. During processing, the extrusion pressure and equivalent force significantly affect the quality of the final products. Therefore, it is essential to determine appropriate extrusion pressure and equivalent force to ensure product quality. The extrusion process was carried out using hydraulic press equipment under a uniform speed extrusion mode.

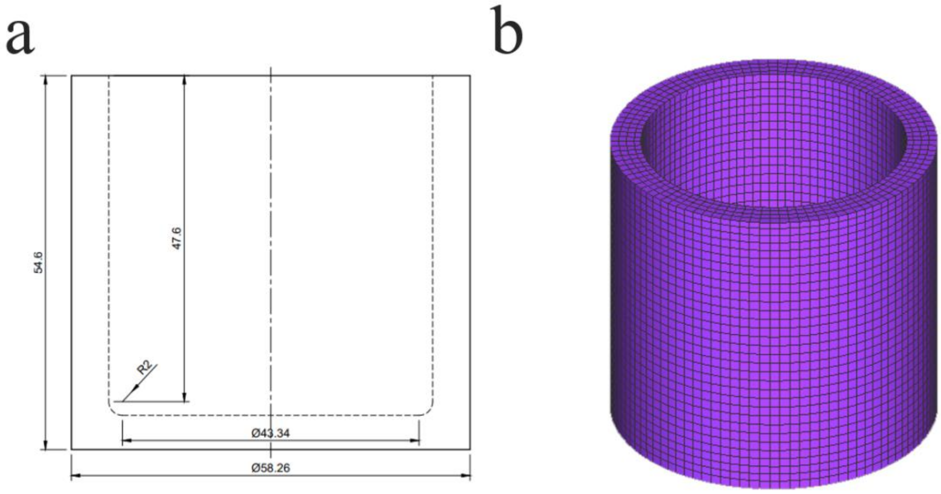


Figure 1. (a) Gross three-dimensional drawing, (b) Rough grid diagram.

1.2. Orthogonal experiment

Orthogonal experimental design is a method used to study multi-factor, multi-level experiments. The key is to determine the experimental factors and levels based on the process and the characteristics of the workpiece being processed. In this study, based on the characteristics of Simufact Forming software and practical experience, thinning rate, stamping speed, and friction coefficient were selected as the three factors for the orthogonal experiments. Extrusion pressure and equivalent force are known to be important indices for evaluating the quality of the extrusion molding process.

Based on practical experience, the workpiece temperature and ambient temperature were both set to 25°C (room temperature). The extrusion equipment used was a hydraulic press, and the material of the workpiece was set to C15_c, with other parameters set to their default values. Three levels were selected for each process parameter, and a single-factor test scheme was employed for the experiment. The experimental results are shown in Table 1.

Table 1. Single factor test scheme and results

Experiment No.	Thinning rate /%	Punching speed /mm•s^{-1}	Coefficient of friction /N•m^{-2}	Equivalent force /MPa	Extrusion Forcee /KN
1	0.2	5	0.2	685.12	145.032
2	0.3	5	0.2	804.11	205.81
3	0.4	5	0.2	831.97	256.347
4	0.3	3	0.2	768.48	206.579
5	0.3	8	0.2	793.1	210.775
6	0.3	5	0.1	766.2	195.059
7	0.3	5	0.3	792.13	223.62

In this paper, data is predicted using an RBF neural network model. First, the data is normalized using the following formula:

$$X_i = \frac{X_i - min(\mathrm{X})}{max(\mathrm{X}) - {}_{\min}(\mathrm{X})} \tag{1}$$

Where *X* is the matrix containing all elements,

The experimental data was collected from orthogonal experiments, where each variable was tested at specific levels. The values in the table were normalized using equation (1):

Table 2. Normalized Dataset

Experiment No.	Thinning rate /%	Punching speed /mm•s^{-1}	Coefficient of friction /N•m^{-2}	Equivalent force /MPa	Extrusion Force /KN
1	0.0	0.4	0.5	685.12	145.032
2	0.5	0.4	0.5	804.11	205.81
3	1.0	0.4	0.5	831.97	256.347
4	0.5	0.0	0.5	768.48	206.579
5	0.5	1.0	0.5	793.10	210.775
6	0.5	0.4	0.0	766.20	195.059
7	0.5	0.4	1.0	792.13	223.62

This transformation scales the data to a range of [0, 1], allowing for better convergence and performance of the RBF neural network.

1.3. Predictive modelling

The RBF neural network is a type of feed-forward neural network with local approximation capabilities, known for its excellent nonlinear fitting and generalization abilities. Proposed by Moody and Darken [8], it offers superior learning speed and approximation capabilities compared to other neural networks and has been successfully applied in areas such as recognition and evaluation [9].

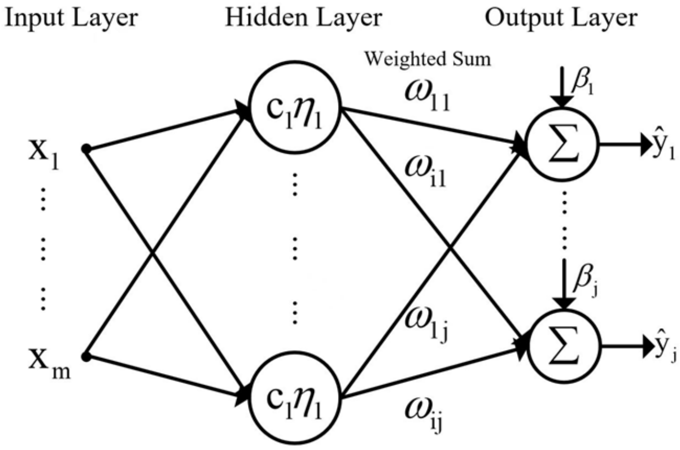


Figure 2. Diagram of the structure of the RBF neural network

As shown in Fig. 2, the structure of the RBF neural network is composed of the input, hidden, and output layers [10]. The input layer receives the preprocessed data and passes it to the hidden layer. The hidden layer performs nonlinear mapping from the input data space to the hidden layer space, transforming the nonlinear inseparable problem in the low-dimensional space into a nearly linearly separable problem in a higher-dimensional space. Finally, the output layer calculates the network's output by weighting the hidden layer's outputs.

The radial basis function is defined as the distance from a point x in the coordinate space to the center ccc. Let the input data vector be $\boldsymbol{x} = [x_1, x_2, \cdots, x_m]^T$, , where m is the dimension of the input data, I is the number of neurons in the hidden layer, and J is the number of network outputs. In this paper, a Gaussian function is used as the kernel function for the RBF neurons, and the network output can be expressed as:

$$\hat{\boldsymbol{Y}}=(\hat{y}_1,\hat{y}_2,\cdots,\hat{y}_J)^T=\begin{bmatrix}\omega_{11} & \omega_{21} & \cdots & \omega_{I1}\\ \omega_{12} & \omega_{22} & \cdots & \omega_{I2}\\ \vdots & \vdots & \cdots & \vdots\\ \omega_{1J} & \omega_{2J} & \cdots & \omega_{IJ}\end{bmatrix}\begin{bmatrix}\varphi(\|\boldsymbol{x}-\boldsymbol{c}_1\|)\\ \varphi(\|\boldsymbol{x}-\boldsymbol{c}_2\|)\\ \vdots\\ \varphi(\|\boldsymbol{x}-\boldsymbol{c}_I\|)\end{bmatrix}+\begin{bmatrix}\beta_1\\ \beta_2\\ \vdots\\ \beta_J\end{bmatrix} \tag{2}$$

Where: y_j is the j-th output value of the output layer, where $j=1, 2, 3,...,J$, ω_{ij} is the connection weight of the i-th hidden layer neuron corresponding to the j-th output, $i=1,2,...,I$; β is the bias value; φ() is the Gaussian function operator of the form.

$$\varphi(\|\boldsymbol{x}-\boldsymbol{c}_i\|)=\exp\left(-\frac{\|\boldsymbol{x}-\boldsymbol{c}_i\|^2}{2\delta_i^2}\right) \tag{3}$$

Where i_c,i_δ are the centre vector and width of the ith neuron, respectively.

1.4. Training algorithms for neural networks

The training task of the RBF neural network mainly includes two aspects: the first aspect is determining the number of neurons I i in the hidden layer, and the second aspect is determining the center vector i_c, width i_δ, connection weights ω_{ij} and bias β. This study employs a grid search algorithm to identify the optimal parameters. The optimal parameters obtained are as follows:

Table 3. Optimal parameters of the neural network algorithm

Norm	Expansion speed	Maximum number	Display Interval	Target performance
Squeeze /N	1.825	10	1	200
Equivalent force /KPa	0.980	10	1	200

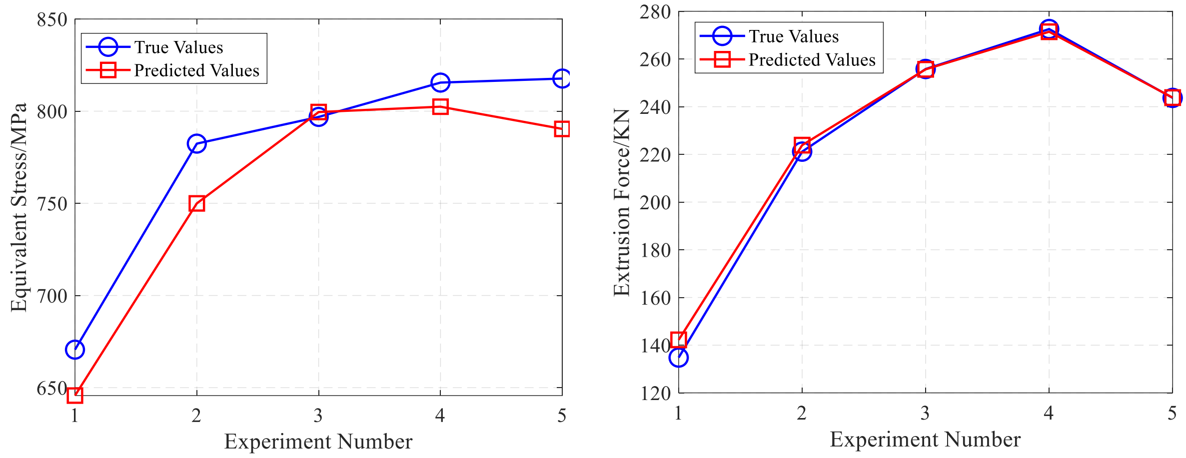
The RBF neural network excels at handling nonlinear relationships, and there are often complex nonlinear connections between extrusion force, equivalent force, and process parameters. With an appropriate number of nodes (10 hidden layer nodes), spread rate (10), and norms (1.825 and 0.980), the RBF network can effectively learn these nonlinear relationships, thereby enhancing the model's predictive capabilities,by setting the target performance to 200, overfitting was effectively prevented.

2. Results and discussion

In summary, based on the experimental results from orthogonal experiments, the thinning rate, stamping speed, and friction factor are selected as the sequence of factors related to the system. The equivalent force of the processed workpiece and the squeezing force are considered as the system outputs and incorporated into the RBF neural network. Five sets of experimental data outside the training set are used as the validation set. The results obtained after training are as follows:

Table 4. Validation Set Data Table

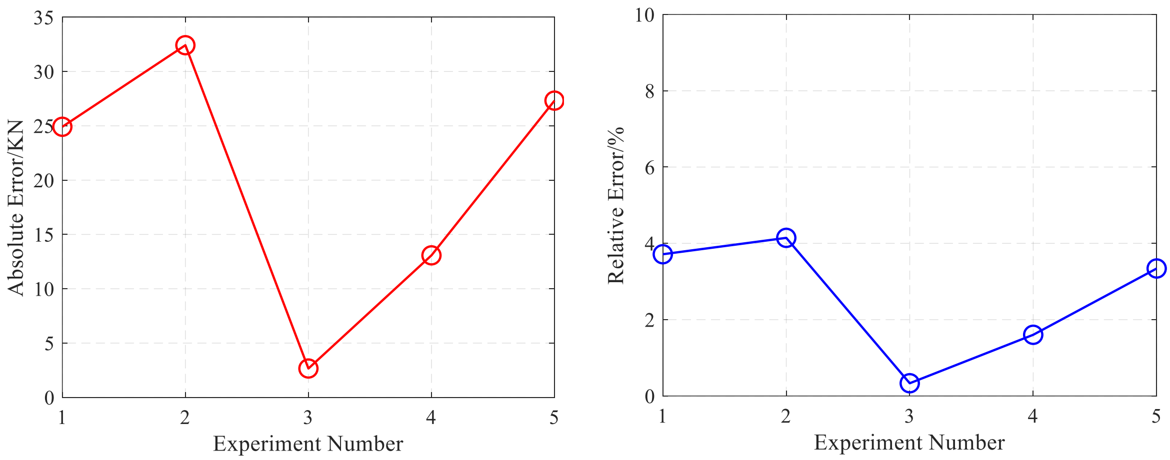
Experiment No.	Thinning rate /%	Punching speed /mm•s^{-1}	Coefficient of friction /N•m^{-2}	Equivalent force /MPa	Extrusion Force /KN
1	0.0	0.0	0.0	670.61	134.801
2	0.5	0.0	1.0	782.38	221.157
3	1.0	0.0	0.5	796.86	255.797
4	1.0	0.5	1.0	815.49	272.555
5	1.0	1.0	0.0	817.68	243.683



(a) Extrusion Force (b) Equivalent force

Figure 3. Comparison of model predictions with true values

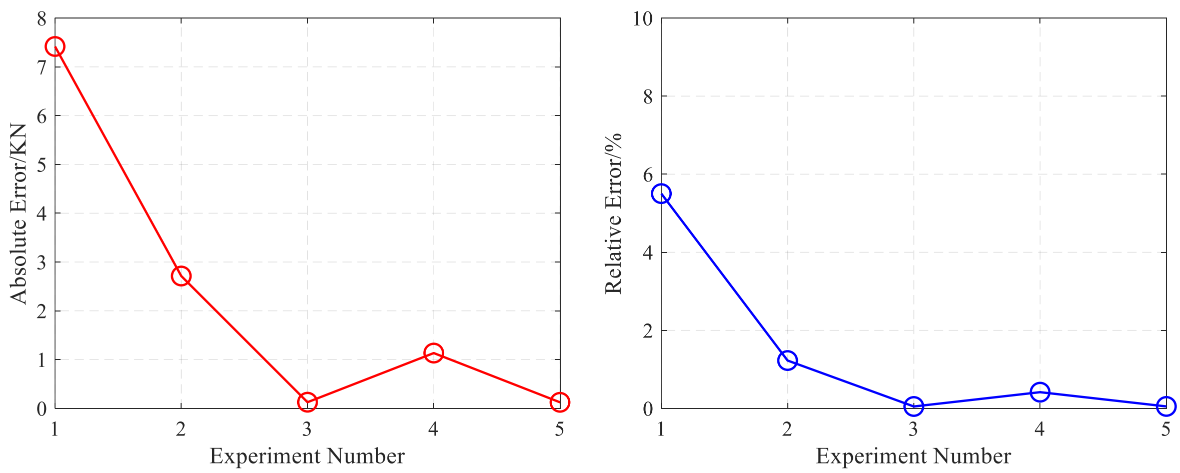
The trends of the predicted and actual values of the equivalent force are similar, and the squeezing force matches well with the predicted and actual values. The predicted residuals for the fourth and fifth groups of equivalent force gradually increase, while the predicted values for the third group are more accurate. The visualized images of the predicted residuals and relative errors are then presented:



(a) Absolute error (b) Relative error

Figure 4. Prediction results of equivalent stress

For the predictions of equivalent forces, the third group has the highest relative residuals, but the relative errors are all less than 5%, indicating that the model performs well on unseen data.



(a) Absolute error (b) Relative error

Figure 5. Predicted results of extrusion force

For the prediction results of extrusion force, the relative errors for the first group are larger and exhibit an overall downward trend, with all relative errors being less than 6%, indicating that the model performs well on unseen data.

3. Conclusion

In this study, we developed a quality prediction model for steel pipe extrusion based on a Radial Basis Function (RBF) neural network, focusing on two critical process parameters: extrusion force and equivalent force. Through simulation experiments and orthogonal tests, we successfully trained the model and demonstrated its ability to predict process outcomes with high accuracy. The model achieved relative errors below 6% when tested on unseen data, validating its reliability and generalization capacity.

This RBF neural network model provides a novel and effective method for predicting extrusion molding process parameters, which is crucial for optimizing production processes. Its application can significantly improve the quality control of steel pipe extrusion, reduce the need for extensive experimental trials, and enhance overall production efficiency. Moreover, the model's approach can be extended to other manufacturing sectors where precise control of extrusion parameters is essential, such as in the automotive, aerospace, and construction industries.

Future work will focus on expanding the model's applicability to more complex extrusion processes and exploring its potential integration with real-time production monitoring systems.

References

[1] Ding Y, Lin J, Wen C, Zhang D, Li Y. Mechanical properties, corrosion, and biocompatibility of Mg-Zr-Sr-Dy alloys for biodegradable implant applications. J Biomed Mater Res B Appl Biomater. 2018; 106 (6): 2425. https: //doi.org/10.1002/jbm.b.34051.

[2] Zhao, X., Gao, P., Zhang, Z., Wang, Q., & Yan, F. Fatigue characteristics of the extruded AZ80 automotive wheel. International Journal of Fatigue.132 (2020): 105393.https: //doi.org/10.1016/j.ijfatigue.2019.105393.

[3] Vazdirvanidis A, Pressas I, Papadopoulou S, Toulfatzis A, Rikos A, Katsivarda M, Symeonidis G, Pantazopoulos G. Examination of Formability Properties of 6063 Alloy Extruded Profiles for the Automotive Industry. Metals. 2019; 9 (10): 1080. https: //doi.org/10.3390/met9101080.

[4] Yang, Jiangen and Shengrui Yu. "Prediction of process parameters of water-assisted injection molding based on inverse radial basis function neural network." Polymer Engineering and Science 60 (2020): 3159 - 3169.

[5] Venkata Raman Kallakunta, Narendar Dudhipala, Dinesh Nyavanandi, et al. Formulation and processing of solid self-emulsifying drug delivery systems (HME S-SEDDS): A single-step manufacturing process via hot-melt extrusion technology through response surface metho-dology [J]. International Journal of Pharmaceutics, 2023, Volume 641: 123055. DOI: 10.1016/j.ijpharm.2023.123055.

[6] Hemanth K. Mamidi, Bhagwan D. Rohera. Material-Sparing Approach using Differential Scanning Calorimeter and Response Surface Methodology for Process Optimization of Hot-Melt Extrusion [J]. Journal of Pharmaceutical Sciences, 2021, Volume 110, Issue 12: 3838 - 3850. DOI: 10.1016/j.xphs.2021.08.031.

[7] Deka, A., Hall, J.F. A framework for optimizing process parameters in fused deposition modeling using predictive modeling coupled response surface methodology. Int J Adv Manuf Technol 131, 447 – 466 (2024). https: //doi.org/10.1007/s00170 - 024 - 13078 - w.

[8] J. Moody, C. Darken, Learning with localized receptive fields. In: Proceedings of the 1988 Connectionist Models Summer School, Morgan-Kaufmann, Publishers, 1988.

[9] Hanmei Wu, Xiaoqing Cai, Man Feng. The evaluation of course teaching effect based on improved RBF neural network [J]. Systems and Soft Computing, 2024, Volume 6: 200085. DOI: 10.1016/j.sasc.2024.200085.

[10] Ismayilova, A., Ismayilov, M. On the universal approximation property of radial basis function neural networks. Ann Math Artif Intell 92, 691 – 701(2024). https: //doi.org/10.1007/s10 472 - 023 - 09901 - x.