

# Study of Deformation-Compensated Modeling for Flexible Material Path Processing Based on Fuzzy Neural Network and Fuzzy Clustering

Yaohua Deng<sup>1</sup>, Sicheng Chen, Jiayuan Chen, Hui Chen and Liming Wu  
Guangdong University of Technology, Guangzhou China

Email: dengyaohua@gdut.edu.cn

**Abstract.** In this paper, the Flexible Material Path Processing (FMPP) deformation compensation modeling method based on T-S fuzzy neural network is proposed. This method combined with T-S fuzzy reasoning and fuzzy neural network. Firstly, fuzzy clustering is introduced to extract fuzzy membership functions and the fitness of fuzzy rules of T-S fuzzy neural network antecedent from historical processing data; secondly, through back-propagation iteration to calculate connection weights of the network. Processing experiments shows that T-S fuzzy neural network modeling in this paper is superior to typical T-S model, the angle error and straightness error processing by NTS-FNN is decreased than these of STS-FNN.

## 1. Introduction

The flexible material processing (FMPP) discussed in this paper refers to the process that takes various complex graphical processing on flexible material (combined by multi-layer soft material), and uneven three-dimensional pattern strayed on the surface of flexible material [1, 2].

FMPP deformation caused by multiple factors, generally several relevant variables will be regulated to reduce processing errors. Essentially the compensation control of FMPP deformation is a multi-input and multi-output process, at present, intelligent modeling of FMPP is mainly based on method of regression analysis, fuzzy reasoning and neural network [3, 4]. Such as method of Neural Network PLSR refers in [5]; Kernel PLSR studied in [6] which suitable for real-time process modeling. Through analysis of literatures above, it's concludes that fuzzy, neural network modeling method has a strong non-linear expression, it's very suitable for dynamic and complex uncertainty process modeling. As FMPP deformation is not only influenced by primitive angle, interpolation rate, processing direction angle and flexible parts clamping way, etc., but also the actual machine process has a problem that requires deformation compensation prediction has high real-time. Single fuzzy neural network modeling approach is hard to build the complex and high real-time prediction model.

For this reason, this paper proposes FMPP deformation compensation modeling that effectively combines T-S fuzzy reasoning, fuzzy neural network, and introduces fuzzy clustering to achieve antecedent network model identification.

## 2. FMPP deformation compensation model constructed by T-S fuzzy neural network

In figure 1, the T-S fuzzy neural network structure of FMPP deformation compensation includes structuring membership function, rules fitness of antecedent network, and calculating the weight parameter of consequent network [4].

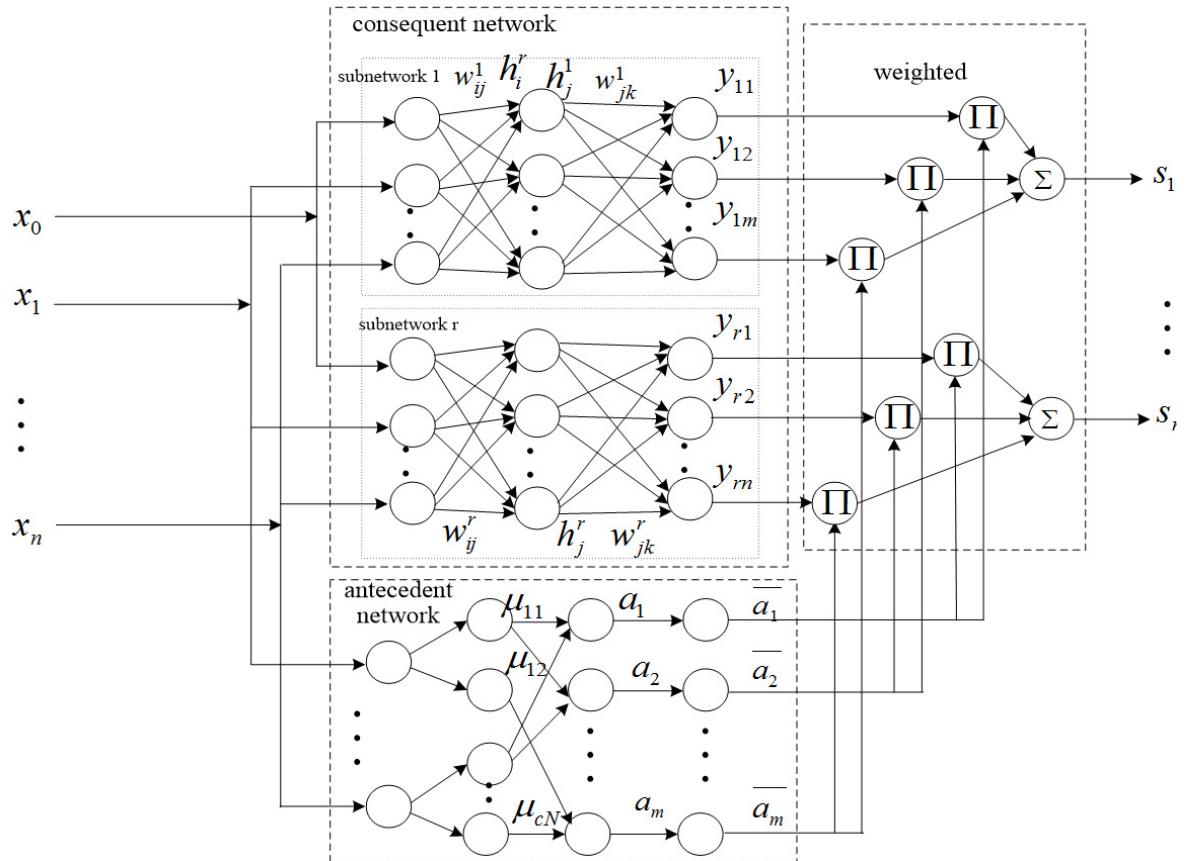
The purpose of division of FMPP input data (FMPP deformation influence factors) is to divide input data fuzzy level, to identify coordinates of center of each clustering and division district width, introducing T-S fuzzy neural network front part of antecedent to extract input membership functions and the fitness of the fuzzy rules. Fuzzy clustering of the input data is mainly for working out fuzzy partition matrix and clustering centers. Fuzzy clustering distance measure is shown by Mahalanobis distance, through calculating minimum objective function (equation 1) of  $c$  groups of fuzzy clustering

---

<sup>1</sup> Corresponding author

division to obtain data point  $x_k$ 's clustering centers and fuzzy partition matrix:

$$\text{Min}\{J(X;U,V)\} = \sum_{i=1}^c \sum_{k=1}^N (u_{ik})^\beta D_{ikM_i}^2 \quad (1)$$



**Figure 1.** Construction of T-S fuzzy neural network model after extension.

In equation 1:  $X = \{x_1, x_2, \dots, x_n\}$  is the  $n$ -dimensional input data set.  $U = [u_{ik}]$  is the fuzzy partition of  $X$  ( $u_{ik}$  is a  $k$ -th sample that about  $i$ -th class membership degree), and  $\sum_{i=1}^c u_{ik} = 1, k = 1, 2, \dots, N$ . Then equation 1 can use Lagrange multiplier method objective function and constrains, so Lagrange multiplier  $\lambda$  is introduced to form a new objective function.

$$\text{Min}\left\{\bar{L}(X;U,V,\lambda)\right\} = \sum_{i=1}^c \sum_{k=1}^N (u_{ik})^\beta D_{ikM_i}^2 + \sum_{k=1}^N \lambda_k \left(\sum_{i=1}^c u_{ik} - 1\right) \quad (2)$$

The requirement for getting the extremum of  $\bar{L}(X;U,V,\lambda)$  is:

$$\left\{ \begin{aligned} \frac{\partial \bar{L}}{\partial \mu_{ik}} &= [\beta(\mu_{ik})^{\beta-1} (D_{ikM_i})^2 + \lambda] = 0 \\ \frac{\partial \bar{L}}{\partial v_i} &= \sum_{k=1}^N (\mu_{ik})^\beta \frac{\partial}{\partial v_i} [(x_k - v_i)^T M_i (x_k - v_i)] = 0 \\ \frac{\partial \bar{L}}{\partial \lambda} &= (\sum_{i=1}^c u_{ik} - 1) = 0, 1 \leq i \leq c, 1 \leq k \leq N \end{aligned} \right. \quad (3)$$

Therefore, if values of data set  $X$ , the categories number of clustering  $c$ , and the fuzzy weighting exponent  $\beta$  are known, through equation 3 data partitioning, optimal fuzzy classification matrix and cluster center all can be worked out [1, 7].

Suppose the fuzzy partition matrix of input data is  $U = [u_{ik}]$  after fuzzy clustering division, fuzzy category of  $c$  set is  $G_i (1 \leq i \leq c)$ , then categories center of  $G_i$ ,  $v_{iq}$ , and corresponding variance  $\sigma_{iq}^2$  is:

$$v_{iq} = \frac{\sum_{k=1}^N (u_{ik})^\beta q_k}{\sum_{k=1}^N (u_{ik})^\beta}, \quad \sigma_{iq}^2 = \frac{\sum_{k=1}^N (u_{ik})^\beta (q_k - v_{iq})^2}{\sum_{k=1}^N (u_{ik})^\beta} \quad (4)$$

If the input data space division requires a high fuzzy clustering, in each  $G_i$  category data  $q_k$  is very close to the category component of  $v_{i,n+1} (i=1,2,\dots,c)$  of the clustering center  $V_i = [v_{i,1}, v_{i,2}, \dots, v_{i,n+1}]^T$  (variance is  $\sigma_{iq}^2 \approx 0$ ), clustering center is correspond to  $G_i$ , then category value  $q_k$  which is the shortest distance from categories center  $v_{iq}$  can use as the decision function  $D(G_i)$ . Corresponding, relative to  $G_i$  membership function of  $x_k$  is shown as equation 5.

$$Z_{ji}(x_{kj}) = \text{Exp}\left(-\frac{|x_{kj} - v_{iq}|}{|v_{iq} - v'_{iq}|} \times \gamma\right) \quad (5)$$

Corresponding, rule fitness of  $x_k$ , is expressed by equation 6:

$$\nu_i = \prod_{j=1}^n Z_{ji}(x_{kj}), i=1,2,\dots,c \quad (6)$$

Equation 5 and 6 are the calculation formula of membership function and rule fitness when constructing the T-S fuzzy neural network model.

The value of consequent network parameters  $w_{ij}^r$  and  $w_{jk}^r$  are calculated based on steepest descent learning algorithm. Supposed  $S_r = [s_1, s_2, \dots, s_r]^T$ ,  $S_r' = [s_1', s_2', \dots, s_r']^T$  represent consequent neural network's actual output and expecting output. Then the network output minimum variance of error cost function is  $E_{mse} = \frac{1}{2} \sum_{r=1}^p (s_r' - s_r)^2$ .

### 3. Processing test experiments

Here real measure data of FMPP are taken to test the performance of the new deformation compensation model T-S fuzzy neural network (below it called NTS-FNN) discussed above [1].

Taking the primitive angle  $x_1$  ( $^\circ$ ), feed depth  $x_2$  (mm), primitive types (circle or line)  $x_3$  (circle: 1, line: 2) and processing step  $L_{step}$  (mm)  $x_4$  as deformation influence factors, they also are the input parameter  $s$  of NTS-FNN,  $s_1, s_2$  are the feed compensation parameters of the  $X, Y$  direction, they are the output of NTS-FNN. To construct NTS-FNN model, it mainly includes: (1) construct antecedent network membership function  $Z_{ji}(x_{kj})$ , fuzzy rule fitness  $\nu_i$  (2) calculate  $w_{jk}^1, w_{ij}^1, w_{jk}^2, w_{ij}^2$  of consequent network parameter.

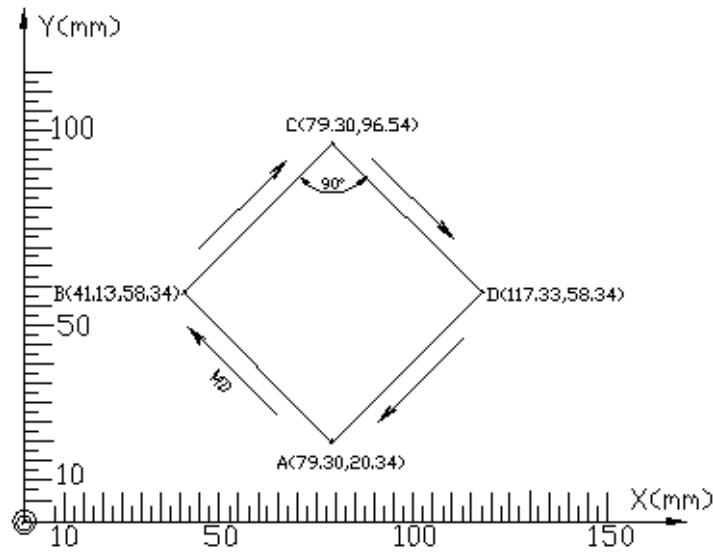


Figure 2. Processing track geometry.

Choose processing track angle error  $f_\alpha$ , straightness error  $f_l$ , primitive minimum processing time  $t_p$  as machining performance test indicators, to be more, performance indicators compares with standard-based fuzzy neural network prediction model STS-FNN (antecedent network of 4-20-40-40, consequent network structure of 5-7-2, error back-propagation EBPA algorithm) [4].

Taken the pattern in figure 2 as the processing track, polyurethane sponge as flexible material (modulus of elasticity  $E=0.3652\text{Mpa}$ , Poisson's ratio is 0.25), length, width and height of the flexible material is  $150\text{mm}\times 100\text{mm}\times 15\text{mm}$ . Processing experiments that without precompensation (NC), feedback compensation control based on STS-FNN or NTS-FNN is conducted separately.

Start with point A, clockwise continuous processing 14 times, and respectively gained processing track sample of without precompensation, feedback compensation control based on STS-FNN, NTS-FNN, after data treatment, to remove 3 groups of sample that starting point and end point is not closed in these sample without precompensation (NC) processing. Each selected 11 groups of samples to measure processing track angle errors, straightness errors.

Figure 3 shows comparative graph of processing errors of processing track angle error  $f_\alpha$ , straightness error  $f_l$  that without precompensation (NC), compensation by STS-FNN, NTS-FNN. Processing track angle error:  $f_{a-NC}, f_{a-STSFNN}, f_{a-NTSFNN}$ ; straightness error:  $f_{l-NC}, f_{l-STSFNN}, f_{l-NTSFNN}$ . Further can be calculated the processing track angle error of the average without precompensation (NC), compensation by STS-FNN, NTS FNN are  $f'_{a-NC} = 5.09^\circ$ ,  $f'_{a-STSFNN} = 4.06^\circ$ ,  $f'_{a-NTSFNN} = 2.42^\circ$  average straightness errors are  $f'_{l-NC} = 0.44\text{mm}$ ,  $f'_{l-STSFNN} = 0.34\text{mm}$ ,  $f'_{l-NTSFNN} = 0.25\text{mm}$ .

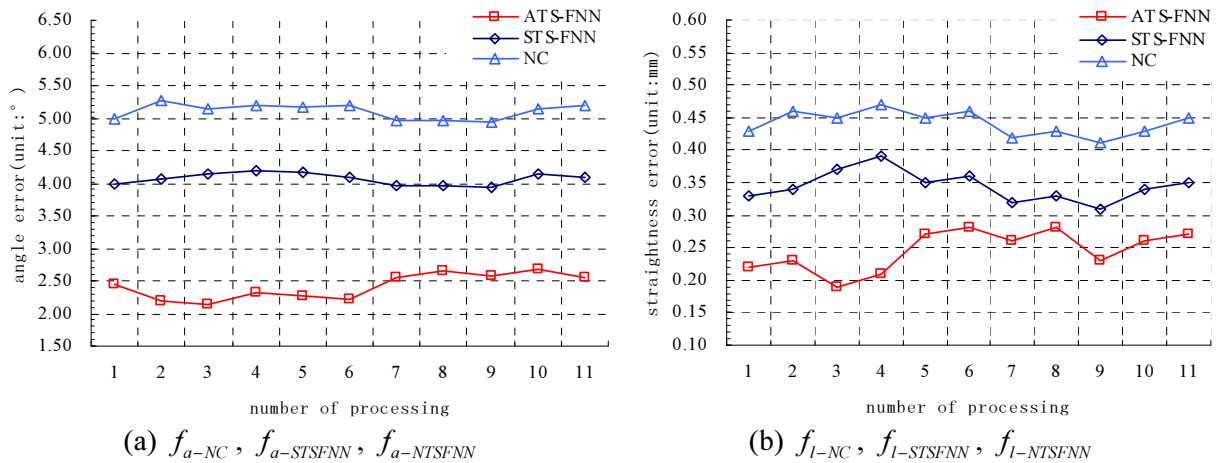


Figure 3. Comparative graph of processing errors.

#### 4. Conclusion

In the T-S fuzzy neural network modeling process, pre-optimized input space through fuzzy clustering method, ensure antecedent network membership function, simplify fuzzy rule number, help saving fuzzy reasoning time, improving model training speed. FMPP deformation compensation modeling method includes the advantage of fuzzy clustering and T-S fuzzy neural network method. Through compensated by NTS FNN, angle error, straightness error is 40.44%, 28.76% decreased than these of STS FNN.

#### Acknowledgements

This work is partially supported by National Natural Science Foundation of China (No. 51205069) and The Production Study Research Combination Project of Huizhou City No. 2011C010002008. Thanks for the help.

#### References

- [1] Yaohua Deng, Guixiong Liu and Qiaofu Liao 2011 Research of FWP Process Deformation Compensation Forecasting on the Basis of TS-FNN *Advanced Materials Research* **295–297** 2430–2437
- [2] Deng Yaohua and Han Wei 2011 Regression Calculation Model of Flexible Material Processing Deformation based on Distributed Sensors Measurement *Advances in Information Sciences and Service Sciences* **3(3)** 208–212
- [3] Sun Zengqi and Xu Hongbin 1997 Fuzzy-neural network based on T-S model *Journal of Tsinghua University (Sci &Tech)* **37(3)** 76–80
- [4] Deng Yaohua and Liu Guixiong 2012 ATS-FNN-Based Modeling and Simulation for Compensation Prediction of FWP Machining Deformation *Journal of South China University of Technology (Natural Science Edition)* **40(3)** 146–151
- [5] J M Karthikeya, Udayagiri V R, Taleb Moazzeni, et al. 2008 Detection algorithms for the Nano Nose *19th International Conference on Systems Engineering* 399–404
- [6] Kyungpil Kim, Jong-Min Lee and In-Beum Lee 2005 A novel multivariate regression approach based on kernel partial least squares with orthogonal signal correction *Chemometrics and Intelligent Laboratory System* **79** 22–30
- [7] Zhang Dong-B, Wang Yao-Nan and Huang Hui-Xian 2008 Fuzzy Rough Model Based Rough Neural Network Modeling *Acta Automatica Sinica* **34(8)** 1016–1023