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Fuzzy Logic and Back-Propagation Neural Networks for Optimal Performance

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Abstract

Thus far, the Taguchi technique is found only efficient in obtaining the combination of optimal factor settings when a single product/process response is considered. In today’s dynamic environment, customers are interested in multiple quality responses. This research, therefore, utilizes fuzzy logic and backward-propagation neural networks (BPNNs) to optimize process performance for products of multiple quality responses. In this research, quality characteristics are transformed to signal to noise (S/N) ratios, which are then used as inputs to a fuzzy model to obtain a single common output measure (COM). Next, BPNNs are employed to obtain full-factorial experimental data. Finally, the combination of factor levels that maximizes the average COM value is chosen as the optimal combination. Three case studies are provided for illustration; in all of which the proposed approach provided the largest total anticipated improvement. This indicates that the proposed approach is more efficient than Taguchi-fuzzy, grey-Taguchi, and Taguchi-utility methods. In conclusion, the fuzzy-BPNN approach may greatly assist process/product engineers in optimizing performance with multiple responses in a wide range of business applications.

Keywords: fuzzy logic, backward-propagation, Taguchi technique, multiple response, optimization

1. Introduction

Traditionally, the Taguchi method was widely applied for optimizing a single quality response of a product or process (Al-Refaie, *et al*., 2017; Dasgupta *et al*., 2014; Al-Refaie, 2012). In today's competitive markets, customers are increasingly interested in multiple quality responses of products (Al-Refaie, 2013b,c; Çakıroğlu and Acır, 2013). Several methods have, therefore, been developed to optimize process performance for multiple responses of a product, including data envelopment analysis (Al-Refaie *et al*., 2009), fuzzy regression (Al-Refaie, 2013a), artificial neural networks (Al-Refaie, *et al*., 2016), fuzzy methods (Al-Refaie, 2015a; Bose *et al*., 2013), utility concepts (Sivasakthivel *et al*., 2014), and goal programming (Al-Refaie *et al*., 2014; Al-Refaie, 2015).

1.1 Fuzzy logic

The principles of fuzzy logic are applied to deal with vague and uncertain information (Al-Refaie, 2014a,b,c; Yang and Huang, 2012). A typical fuzzy system includes a fuzzifier which depends on membership functions (MFs); a rule evaluation engine; definitions of the MFs for the output; a fuzzy rule set; and a defuzzifier to transform the fuzzy output value into a comprehensive output measure. The centroid defuzzification method is utilized in this research. Several studies utilized this fuzzy logic approach for optimizing performance with multiple quality characteristics (AL-Refaie, 2010; AL-Refaie *et al*., 2012; Sun and Hsueh, 2011; Mandic *et al*., 2014).

1.2 Backward Propagation Neural Network

An artificial neural network (ANN) that has a finite number of layers with different neurons serving as the computing elements can emulate some aspects of human behavior. The capabilities of the ANNs are stored in the interunit connections, strengths, and weights, all of which are handled and tuned in the learning process (Moosavi and Soltani, 2013). The most popular type of ANN consists of input, hidden, and output layers. A common type of ANN is the backward propagation neural network (BPNN), in which the gradient descent method is applied to adjust the weights used in the approximation. With a BPNN, a fixed number of neurons must be set before data training, whereas a large range of inputs can be covered because sigmoid neurons are used in the hidden layer (Xia *et al*., 2010). Radial basis fuzzy neural networks (RBFNNs) have been widely used in many business applications

(Chen *et al*., 2013). Further, several studies have utilized ANN approaches for optimizing performance with multiple quality responses. For example, Furtuna *et al*. (2011) combined ANNs with genetic algorithms to optimize a synthesis process. Lin *et al*. (2012) optimized a continuous sputtering process by combining the Taguchi method, neural networks, desirability functions, and genetic algorithms for a solar energy selective absorption film continuous sputtering process.

This research extends ongoing research by integrating fuzzy logic and BPNN techniques for optimizing process performance with products of multiple quality responses. The remainder of this work is outlined in the following sequence. Section Two presents the optimization procedure. Section Three discusses illustrative case studies. Section Four provides research results. Finally, conclusions are summarized in Section Five.

2. Optimization Procedure

The three categories of quality responses that are typically discussed are the smaller-the-better (STB), larger-the-better (LTB), and nominal-the-best (NTB) type responses. The proposed procedure for optimizing a process performance for products of multiple quality responses involves the following steps:

Step 1: In an orthogonal array (OA), n experiments are conducted to examine L controllable factors to improve J quality characteristics as shown in Table 1, where y_{ijk} is the kth replicate of the jth response at the ith experiment; i=1,…,n; j=1,…,J; k=1,…,K. Compute the SNR (η_{ij}) for the jth response at experiment i using the proper formula from the following:

$$\eta_i = -10\log[(\sum_{k=1}^{K} y_{ik}^2)/K],\ \forall i \qquad \text{For STB} \tag{1}$$

$$\eta_i = -10\log[(\sum_{k=1}^{K} 1/y_{ik}^2/K)],\ \forall i \qquad \text{For LTB} \tag{2}$$

$$\eta_i = -10\log[\bar{y}^2{}_i/s_i{}^2]\ \ \forall i, \qquad \text{For NTB} \tag{3}$$

where $\bar{y}_i$ and s_i are the estimated average and standard deviation in experiment i for response j, respectively.

Step 2: Use fuzzy logic, or Mamdani-style calculations, to convert multiple quality responses into a single response. The η_{ij} values are set as the input variables, whereas the COM_i values are the outputs. The fuzzy inference process is conducted in four stages:

i) *Fuzzification* of the input variables, η_{ij}, as follows. Define the MFs for each quality response using the η_{ij} values that correspond to that quality response. Let the values of $Gi1$, $Gi2$,…, and GiJ denote fuzzy subsets defined by their corresponding MFs; *i.e*.,μG_{i1}, μG_{i2}, …, and μG_{iJ}. Use the minimum and maximum values of η_{ij} to generate the MF for each quality response, as shown in Fig.1.

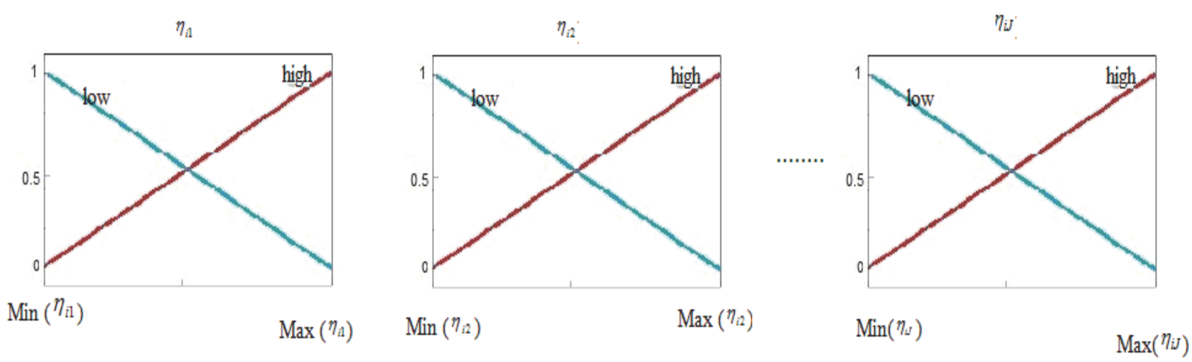


Figure 1. MFs for inputs.

ii) Rule evaluation. Generate the fuzzy rules that relate the inputs with the output. The fuzzy rules consists of a group of J inputs, one output measure F, and T rules. For example, the rules for the ith experiment can be formulated as:

Rule 1: if η_{i1} is G11 and η_{i2} is G12… and η_{iJ} is G1J then F_1 is M_1 else, Rule 2: if η_{i1} is G_{21} and η_{i2} is G_{22}….and η_{iJ} is G_{2J} then F_2 is M_2else,

. . . .

. . . .

. . . .

Rule T: if η_{i1} is G_{T1} and η_{i2} is G_{T2} …and η_{iJ} is G_{TJ} then F_T is M_T.

iii) Aggregation of the rule outputs. From the rules, the MFs of the output are calculated. For example, the value of Mt obtained from the fuzzy rules represents the fuzzy subset defined by MFs, μMt. To compute the Mt for each rule t, the $\eta_{ij}\eta_{ij}$ value for each quality response is used as an input variable of the rules. The fuzzy reasoning of the rules will yield the output using the max-min compositional operation. Fig. 2 depicts the fuzzy value for each quality response in experiment i. For illustration, when two quality responses are examined using the first rule (low in the first quality response and low in the second quality response), the output is set to low; or min (low Gi1 and low Gi2).

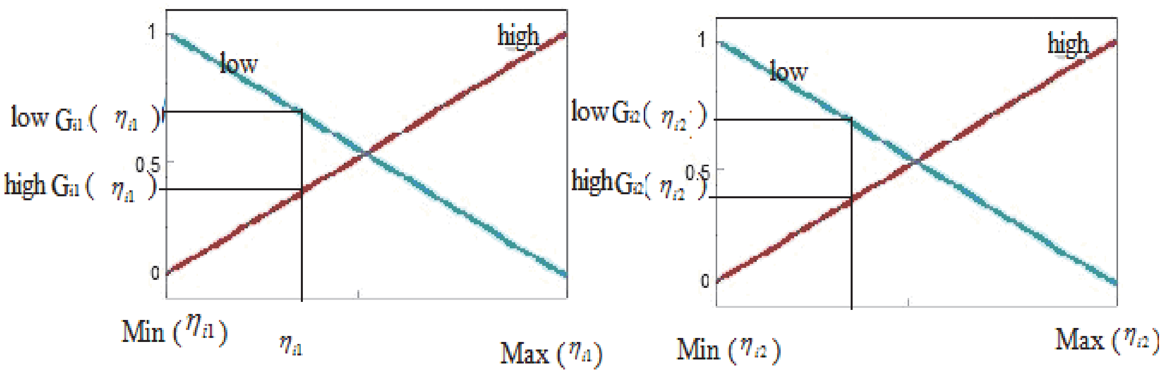


Figure 2. Fuzzy value for each quality characteristic in experiment *i*

iv) The fuzzy inference output μC_o is defuzzified by the COG method into a crisp value COM_i. The larger is the *COM* value is, the better the performance is. The COM_ivalue is calculated for each experiment and then it can be displayed as shown in Fig. 3.

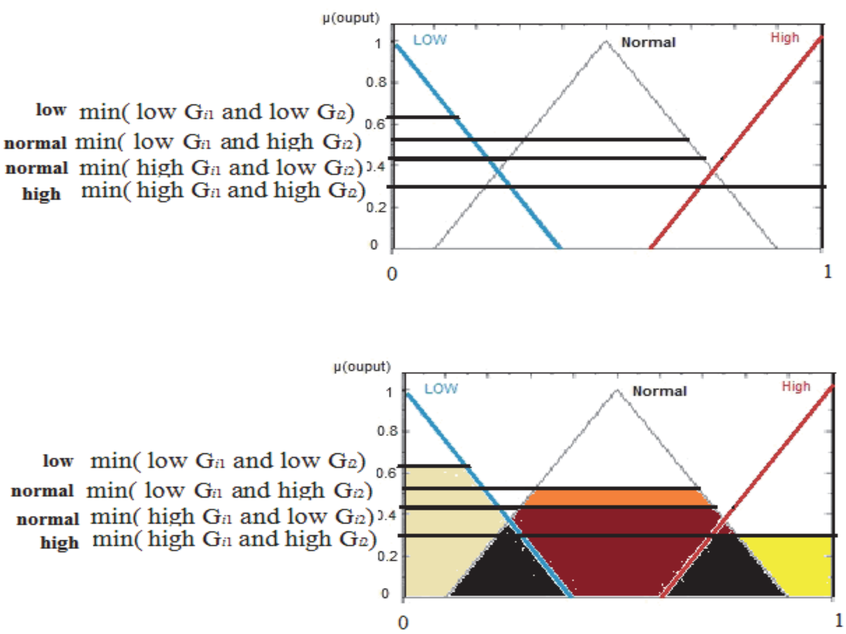


Figure 3. Defuzzification using COG method

Step 3: Generate the full data set of the *COM* using BPNN techniques with a multilayer perceptron model, in which the OA is employed as the input matrix, while the *COM* values are the output matrix. Calculate the averages of the *COM* values at each factor level. The level that has the largest average *COM* value is identified as the optimal level for this factor.

Step 4: Compare the total anticipated improvement in each quality response; which is calculated as the sum of S/N ratio averages at the combination of optimal factor levels minus that at the initial combination of factor levels, between the proposed approach and the previously used techniques.

3. Illustrations

The proposed procedure will be illustrated through three case-studied which were previously investigated using other approaches.

3.1 Optimization of High-Speed CNC Machining

This case aimed at the optimization of high-speed computer numerical controlled (CNC) machining with four quality responses: surface roughness (SR, μm), tool life (TL, minute), cutting force (CF, N), and power consumption (PC, W) using the Taguchi-fuzzy approach (Gupta, et al., 2011). The controllable process factors with their corresponding level values are summarized in Table 1. The four quality responses were LTB type quality responses. The L_{27} array was used for the experimental layout.

Table 1. Machining parameters and their levels in case study (1).

Factor/process parameter		Level 1	Level 2	Level 3
x_1	Cutting speed (m/min)	120	160	200
x_2	Feed rate (mm/rev)	0.10	0.12	0.14
x_3	Depth of cut (mm)	0.20	0.35	0.50
x_4	Nose radius (mm)	0.40	0.80	1.20
x_5	Environment	Dry	Wet	Cryo

Step1: The η_{ij} values of each quality response were computed for the 27 experiments using Eq. (2); the obtained values are listed in Table 2.

Step 2: The fuzzification of the η_{ij} values of SR, TL, CF, and SR was performed. The two fuzzy subsets (low and high) were assigned to the η_{ij} values of SR and TL and three fuzzy subsets (low, normal, and high) were assigned to the η_{ij} values of PC and CF. Table 3 displays the high and low representations for the η_{i1} values of SR response. Fig. 4 displays the MFs for SR, TL, PC, and CF. The rules that relate the MFs of the responses to the output are shown in Table 4. The aggregation of the rule outputswas performed. The nine fuzzy subsets were assigned to the output COM value, as shown in Fig. 5. Defuzzification was carried out to convert the fuzzy value of the output to a crisp *COM* value for each experiment using the COG method. Table 5 shows the calculated COM_i value for each experiment. The nine fuzzy subsets were assigned to the output and then the COG method was used to convert the fuzzy output value to a crisp output value.

Table 2. Experimental results for CNC machining

	SR		TL		CF		PC	
Exp. *i*.	μm	η_{i1}	Min	η_{i2}	N	η_{i3}	W	η_{i4}
1	1.410	-2.985	29.000	38.489	171.300	-40.731	1066.000	-58.759
2	0.710	2.894	34.000	40.175	147.500	-43.379	1560.000	-63.862
3	0.600	4.485	54.670	44.297	111.740	-44.677	866.000	-60.562
4	0.470	6.554	34.670	40.341	120.300	-41.611	1493.000	-63.484
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
24	0.180	14.886	37.660	41.062	168.700	-44.546	1613.000	-64.155
25	0.640	3.831	18.000	34.657	162.000	-44.196	1573.000	-63.937
26	0.310	10.170	34.330	40.258	162.500	-44.217	1453.000	-63.248
27	0.480	6.374	16.660	30.111	276.160	-48.827	1667.000	-64.438

Table 3. Values of the η_{i1} for the SR in fuzzy logic

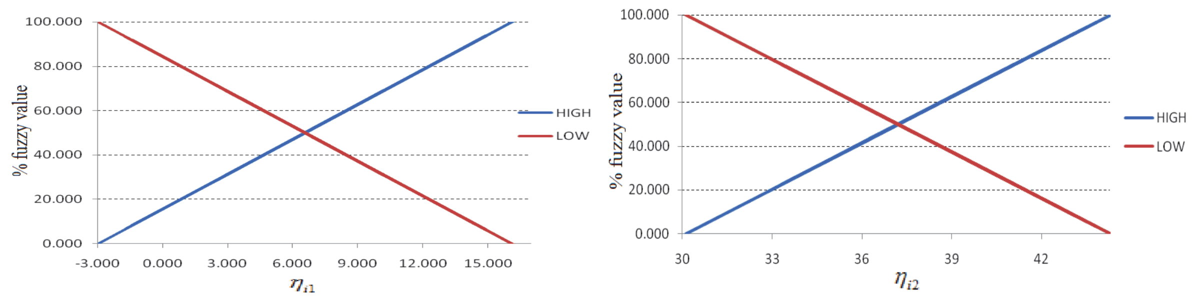
η_{i1}	HIGH (%)	LOW (%)	η_{i1}	HIGH (%)	LOW (%)
-2.985	**0.000**	**100.000**	10.170	68.939	31.061
2.894	30.809	69.191	3.609	34.556	65.444
4.485	39.147	60.853	3.831	35.720	64.280
6.554	49.990	50.010	2.460	28.535	71.465
14.256	90.352	9.648	16.097	**100.000**	**0.000**
-1.414	8.233	91.767	12.862	83.047	16.953
3.522	34.100	65.900	3.434	33.639	66.361
-1.264	9.019	90.981	7.953	57.321	42.679
0.724	19.437	80.563	6.016	47.170	52.830
14.895	93.701	6.299	14.886	93.654	6.346
6.871	51.651	48.349	3.831	35.720	64.280
7.195	53.349	46.651	10.170	68.939	31.061
4.731	40.436	59.564	6.374	49.046	50.954
2.885	30.762	69.238			

Table 4. Generated fuzzy rules when three MFs are studied in case study (1).

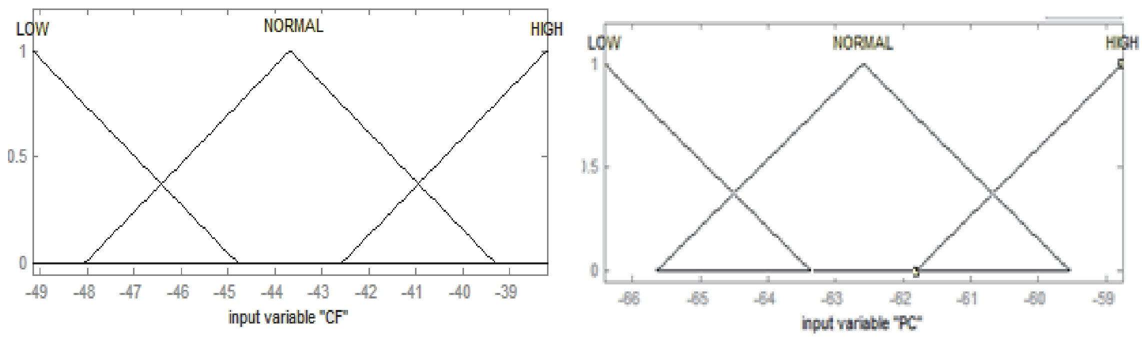
η_{ij}				***COM***	η_{ij}				***COM***
SR	TL	CF	PC		SR	TL	CF	PC	
LOW	LOW	LOW	LOW	Lowest	HIGH	LOW	LOW	LOW	Low
			NORMAL	NLow				NORMAL	Nmid
			HIGH	Low				HIGH	Mid
		NORMAL	LOW	NLow			NORMAL	LOW	Nmid
			NORMAL	Low				NORMAL	Mid
			HIGH	Nmid				HIGH	Nhigh
		HIGH	LOW	Low			HIGH	LOW	Mid
			NORMAL	Nmid				NORMAL	Nhigh
			HIGH	Mid				HIGH	High
	HIGH	LOW	LOW	Low		HIGH	LOW	LOW	Mid
			NORMAL	Nmid				NORMAL	Nhigh
			HIGH	Mid				HIGH	High
		NORMAL	LOW	Nmid			NORMAL	LOW	Nhigh
			NORMAL	Mid				NORMAL	High
			HIGH	Nhigh				HIGH	Nhighest
		HIGH	LOW	Mid			HIGH	LOW	High
			NORMAL	Nhigh				NORMAL	Nhighest
			HIGH	High				HIGH	Highest

Table 5. COM_i for case study (1).

Exp. *i*	*COMi*	**Exp. *i***	*COMi*	**Exp. *i***	*COMi*
1	0.572	**10**	0.608	19	0.801
2	0.469	**11**	0.678	20	0.459
3	0.691	**12**	0.463	21	0.353
4	0.562	**13**	0.692	22	0.404
5	0.732	**14**	0.459	23	0.373
6	0.358	**15**	0.454	24	0.568
7	0.686	**16**	0.541	25	0.433
8	0.391	**17**	0.442	26	0.554
9	0.3	**18**	0.531	27	0.238



a) SRb) TL



a) MFs for the CF b) MFs for the PC

Figure 4. MFs for η_{ij} values.

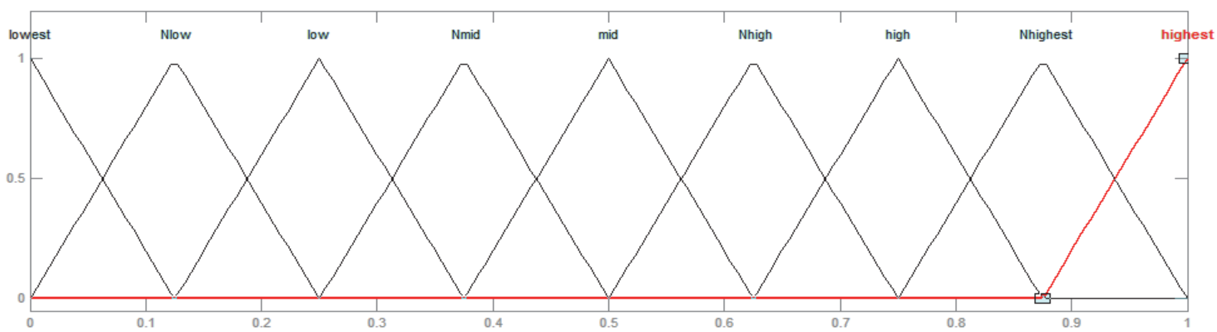


Figure 5. MFs of *COM* for case study (1)

Step 3: The BPNN technique was used to generate the full data set for the *COM* values. Table 6 displays the full dataset.

Step 4: The average *COM* values were calculated at each factor level, as shown in Table 7. The proposed method identified $x_{1(1)}x_{2(2)}x_{3(1)}\ x_{4(2)}\ x_{5(3)}$as the optimal combination of factor levels, whereas the fuzzy-Taguchi approach identified $x_{1(1)}x_{2(1)}x_{3(1)}\ x_{4(2)}\ x_{5(3)}$ as optimal.

Table 6. Predicted *COM* values for case study (1).

	Factors					
Run No.	x_1	x_2	x_3	x_4	x_5	*COMi*
1	1	1	1	1	1	0.5469
2	1	1	1	1	2	0.5881
3	1	1	1	1	3	0.6262
4	1	1	1	2	1	0.5014
5	1	1	1	2	2	0.5836

6	1	1	1	2	3	0.6326
⋮	⋮	⋮	⋮	⋮	⋮	⋮
241	3	3	3	3	1	0.7595
242	3	3	3	3	2	0.6642
243	3	3	3	3	3	0.5603

Table 7. *COM* averages of the full factorial design for case study (1).

Factor	Levels		
	1	2	3
x_1	**0.5770**	0.5377	0.5107
x_2	0.5594	**0.5887**	0.5073
x_3	**0.5680**	0.5227	0.5147
x_4	0.4808	**0.5928**	0.5818
x_5	0.4391	0.5153	**0.6510**

3.2 Optimization of Ground Source Heat Pump System for Space Heating and Cooling

Sivasakthivel, *et al*. (2014) proposed a methodology that used the concept of utility to optimize the space cooling (SC) coefficient of performance, and the space heating (SH) coefficient of performance for aground source heat pump. In their study, the parameters optimized were the condenser inlet temperature, condenser outlet temperature, dryness at evaporator inlet, and evaporator outlet temperature, as shown in Table 8. The parameters affecting the heat pump were optimized using Taguchi and utility methods. The SH and SC coefficients of performance were classified as LTB. An L_9 array was utilized for providing experimental layout. The η_{ij} values were calculated and are displayed in Table 9.

Table 8. Control factors and their levels in case study (2).

parameters	Condenser inlet temp. (C˚)	Condenser outlet temp. (C˚)	Dryness fraction at evaporator inlet	Evaporator outlet temp (C˚)
Labels	x_1	x_2	x_3	x_4
Level 1	70	40	0.24	6
Level 2	75	42	0.27	10
Level 3	80	44	0.30	14

Table 9. Values of $\eta_{ij}$for SH and SC.

Exp. *i*	SH	η_{i1}	SC	η_{i2}
1	4.056	12.161	3.66	11.269
2	3.978	11.993	3.589	11.099
3	3.942	11.914	3.513	10.913
4	4.149	12.358	3.648	11.241
5	4.093	12.240	3.396	10.619
6	4.036	12.119	3.725	11.422
7	4.242	12.551	3.454	10.766
8	4.185	12.433	3.783	11.556
9	4.128	12.314	3.531	10.957

Mamdani-style steps were conducted in whichthree fuzzy subsets (low, normal, and high) were assigned to the four η_{ij} values for each of SH and SC. The MFs for the output are displayed in Fig. 6.

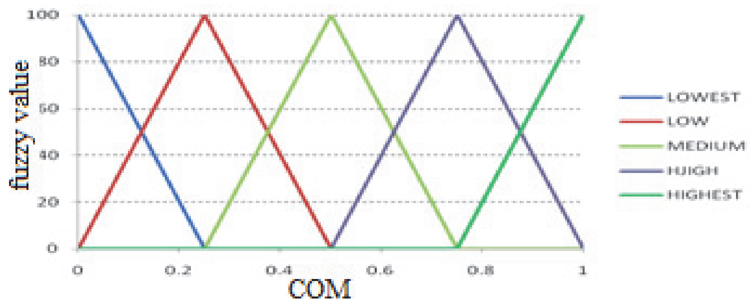


Figure 6. MFs for the output in case study (2).

The fuzzy value of the output was converted to a crisp value (the *COM* value) using the COG defuzzification method. The BPNN was used to complete the full data set for the *COM* value. The average *COM* value at each factor level was calculated; these values are displayed in Table 10. The proposed method identified the optimal combination of factor levels as$x_{1(3)}x_{2(3)}x_{3(1)}x_{4(3)}$; for each factor, the proposed method selected the level that had the maximum *COM* value.

Table 10. Averages for *COM* values in case study (2)

Factors	Levels		
	1	2	3
x_1	0.3225	0.5046	**0.5541**
x_2	0.4562	0.4548	**0.4702**
x_3	**0.5371**	0.4653	0.3789
x_4	0.4326	0.4625	**0.4861**

3.3 Optimization of Carbon Coatings

Yang and Huang (2012) optimized the wear resistance of zirconium-enriched diamond-like carbon coatings. They developed a multi-objective optimization method that combined the grey fuzzy and Taguchi approaches. The controllable factors were the bias voltage, zirconium target current, pulse frequency, methane gas flow rate, and the work distance, with three levels for each factor, as shown in Table 11. The responses selected were the coefficient of friction (Cof, μ), the wear rate (WR, $10^{-5}mm^3N^{-1}m^{-1}$), the deposition rate (DR, μmh^{-1}), and the water contact angle (WCA, ^{o}). An L_{18} array was used for conducting experimental work. The η_{ij} values were calculated for each quality characteristic. The two fuzzy subsets (low and high) were assigned to Cof, WR, DR and WCA, using the η_{ij} values. Then, nine fuzzy subsets were assigned to the output. The COG method was used to convert the fuzzy value to a crisp value (COM value). The BPNN technique was used to generate the full factorial data. The COM averages were calculated for each factor level, as shown in Table 12. The proposed method identified the optimal combination of factor levels as $x_{1(3)}x_{2(2)}x_{3\,(2)}x_{4\,(2)}\,x_{5(1)}$.

Table 11. Process factor settings in case study (3).

Factor	Symbol	Level 1	Level 2	Level 3
Bias voltage (-V)	x_1	40	55	70
Target current (A)	x_2	Zr:0.3	Zr:0.6	Zr:0.9
Pulse frequency (kHz)	x_3	70	90	110
Methane gas flow rate (sccm)	x_4	3	6	9
Work distance (cm)	x_5	9	12	15

Table 12. Calculated *COM* averages for case study (3).

	Level		
Factor	1	2	3
x_1	0.6999	0.7243	**0.7290**
x_2	0.7261	**0.7393**	0.7078
x_3	0.7045	**0.7420**	0.7367
x_4	0.6840	**0.7601**	0.7492
x_5	**0.7891**	0.7130	0.7612

4. Research Results

The optimal combinations of factor settings that were obtained using the proposed Fuzzy-BPNN can be anticipated to produce improvements. These anticipated improvements were calculated and the results are presented in the following subsections.

4.1 Optimization Results for CNC Turning Parameters

Table 13 summarizes the calculated improvement in each quality characteristic from the fuzzy-BPNN approach with the fuzzy-Taguchi concept. At the combination of initial settings ($x_{1(1)}x_{2(1)}x_{3(1)}\,x_{4(1)}\,x_{5(1)}$), the sum of η_{ij} averages of SR, TL, CF, and PC were calculated as 23.07, 192.37, -220.44, and -308.87 dB, respectively. The corresponding anticipated improvements using the Fuzzy-Taguchi (Fuzzy-BPNN) were -9.51 (10.99), 7.26 (8.28), 2.75 (2.19), and -0.08 (0.25) dB, respectively. It is clear that the Fuzzy-BPNN provided larger anticipated improvements than the Fuzzy-Taguchi by1.48, 1.02, 0.44, and 0.33 dB, respectively. Moreover, the Fuzzy-BPNN provided a total anticipated improvement that exceeded that of the Fuzzy-Taguchi method by 3.27 dB. The Fuzzy-BPNN notably enhanced process performance by 22.71 dB over the process performance at the combination of initial factor settings.

4.2 Results for the Optimization for Ground Source Heat Pump System

The anticipated improvements in SH and SC were computed and are displayed in Table 14, where the sums of the η_{ij} averages at the initial (optimal) factor settings result were 48.8553 (51.021) and 44.5497 (45.8437) for SH and SC, respectively. The anticipated improvements in SH and SC were 2.1657 and 1.2930 dB, respectively. The total anticipated improvement was 3.4587 dB. This indicates that because the system factors were set at the optimal combination of factor settings ($x_{1(3)}x_{2(3)}x_{3(1)}x_{4(3)}$), both quality responses improved concurrently.

4.3 Results for Carbon Coatings

Table 15 summarizes the improvements to the carbon coatings. Because the factor levels were set to the optimal combination of factor settings ($x_{1\,(3)}\,x_{2\,(2)}\,x_{3\,(2)}\,x_{4\,(2)}\,x_{5(1)}$), the quality responses Cof, WR, DR, and WCA were improved by 7.92, 5.02, 3.46, and 0.64 dB, respectively. The total anticipated improvement was 17.04 dB. For this case study, it is clear that the all four quality responses are improved significantly, which indicates the effectiveness of the proposed optimization approach.

Table 13. Improvement analysis of case study (1)

	Response	Sum of η_{ij} averages (dB)	Improvement (dB)
	SR	23.07	
Initial settings	TL	192.37	
$x_{1(1)}x_{2(1)}x_{3(1)}\,x_{4(1)}x_{5(1)}$	CF	-220.44	
	PC	-308.87	
	SR	32.58	9.51
Taguchi -Fuzzy	TL	199.64	7.26
$x_{1(1)}x_{2(1)}x_{3(1)}\,x_{4(2)}x_{5(3)}$	CF	-217.69	2.75
	PC	-308.95	-0.08
			19.44
	Total		

Fuzzy-BPNN approach $x_{1(1)}x_{2(2)}x_{3(1)}x_{4(2)}x_{5(3)}$	SR	34.06	10.99
	TL	200.65	8.28
	CF	-217.25	3.19
	PC	-308.62	0.25
		Total	**22.71**

Table 14. Improvement analysis of case study (2).

Approach	Response	Sum of η_{ij} averages (dB)	Improvement (dB)
Initial setting	SH	48.8553	
	SC	44.5497	
Fuzzy-BPNN	SH	51.021	2.1657
$x_{1(3)}x_{2(3)}x_{3(1)}x_{4(3)}$	SC	45.8437	1.2930
		Total	**3.4587**

Table 15. Improvement analysis for case study (3)

Approach	The quality characteristic (dB)	The sum of η_{ij} averages (dB)	Individual improvement (dB)
Initial setting	Cof	72.79	
	WR	462.64	
	DR	84.08	
	WCA	240.33	
Neural fuzzy $x_{1(3)}\,x_{2(2)}\,x_{3(2)}\,x_{4(2)}\,x_{5(1)}$	Cof	80.71	7.92
	WR	467.66	5.02
	DR	87.53	3.46
	WCA	240.97	0.64
		Total	**17.04**

5. Conclusions

This study proposed an effective fuzzy-BPNN technique to optimize process performance with several responses. Using fuzzy logic, signal-to-noise values were used inputs of a fuzzy model to generate a *COM* value. ANN techniques were then employed to generate the full experimental *COM* values. The average values for the *COM* were calculated at each factor level and were then used to determine the optimal combination of factor levels. Three case studies from previous literature were provided for illustration. The results showed that the proposed fuzzy-BPNN approach significantly improved process performance when compared to the results of the combined Taguchi methods with fuzzy and utility concepts. Among the advantages of the proposed approach are significant process performance improvement and determination of global optimality. In conclusion, the fuzzy-BPNN approach proposed in this research may support practitioners in optimizing process performance with multiple quality responses. Future research will consider the use of quality losses instead of signal-to-noise ratios.

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