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ARTIFICIAL NEURAL NETWORK WITH HYBRID TAGUCHI-GENETIC ALGORITHM FOR NONLINEAR MIMO MODEL OF MACHINING PROCESSES

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Abstract. *This paper developed an artificial neural network (ANN) model with hybrid Taguchi-genetic algorithm (HTGA) for the nonlinear multiple-input multiple-output (MIMO) model of machining processes. The HTGA in the MIMO ANN model finds the optimal parameters (i.e., weights of links and biases govern the input-output relationship of an ANN) by directly minimizing root-mean-squared error (RMSE), which is a key performance criterion. Experimental results show that the proposed MIMO HTGA-based ANN model outperforms the MIMO ANN methods with backpropagation (BP) algorithm given in the Matlab toolbox in terms of prediction accuracy for the nonlinear model of machining processes.*
Keywords: Machining processes, Artificial neural network (ANN), Hybrid Taguchi-genetic algorithm (HTGA), Multiple-input multiple-output (MIMO)

1. Introduction.

Modeling methods can be used in several fields of production engineering, e.g., planning, optimization or controls. Difficulties in modeling the manufacturing processes are manifold. To name a few, the great number of different machining operations, multidimensional, nonlinear, stochastic nature of machining, partially understood relations between parameters, lack of reliable data are some stages, which one can overcome through modeling. One of the ways to overcome such difficulty is to implement fundamental models based on the principles of machining science. However, in spite of progress made in fundamental process modeling, accurate models are not yet available for manufacturing processes. Heuristic models are usually based on the thumb rules gained from experience, and used for qualitative evaluation of decisions. Empirical models derived from experimental data still play a major role in manufacturing process modeling [1,2].

On the other hand, it is known that the artificial neural network (ANN) is a successful approach for dealing with the nonlinear mapping [3-5]. Because they can handle high-level nonlinearities, numerous parameters and missing information, the ANNs can be used as operation models. Their inherent learning capabilities also enable them to adapt to changes in the production environment, and they can be used when the exact relationships among various manufacturing parameters are unknown [1]. Genetic algorithms, another class of search algorithms modeled on natural evolutionary processes, are highly effective for function optimization, for efficiently searching large and complex (multimodal, discontinuous, etc.) spaces, and for finding the near-global optima. Therefore, Venkatesan et al. [1] proposed a genetic algorithm-based ANN model for turning processes used in various manufacturing industries, in which large and complex neural network weight-selection problems are solved by genetic algorithms. Although the genetic algorithm-based ANN model proposed by Venkatesan et al. [1] has demonstrated good prediction accuracy, it is worthwhile to investigate whether an improved genetic algorithm can further enhance the ANN model in terms of prediction accuracy for turning processes in manufacturing industries.

This study applied the hybrid Taguchi-genetic algorithm (HTGA) because Ho (the fourth author of this paper) and his associates have shown that this improved genetic algorithm performs the best of those reported in the literature [6-10]. Thus, by using a hybrid HTGA which combines the genetic algorithm [11] and the Taguchi method [12-14] to find the optimal parameters (i.e., weights of links and biases govern the input-output relationship of an ANN), the ANN can properly construct an input-output mapping based on both human knowledge and the stipulated input-output data pairs by directly minimizing the root-mean-squared-error (RMSE) performance criterion [15-17]. Experimental results of Ho et al. [15] and Ho and Chang [16] have shown that the prediction accuracy of the HTGA-based ANN model outperforms the prediction accuracy obtained by the ANN model with backpropagation (BP) algorithm given by the Matlab toolbox. However, in the work of Ho et al. [15] and Ho and Chang [16] it is shown that the HTGA-based ANN model is only multiple-input single-output (MISO) nonlinear relationship. To the authors' best knowledge, the multiple-input multiple-output (MIMO) nonlinear relationship with HTGA-based ANN model is not discussed in the literature. Therefore, the purpose of this paper is, by using the HTGA in the MIMO ANN model to find the optimal parameters (i.e., weights of links and biases govern the input-output relationship of an ANN), to investigate the promoted effectiveness of predicting the outputs in the machining processes, where the RMSE criterion is directly minimized. In this paper, some experimental results are also given to make the comparison of effectiveness with those obtained by the Matlab toolbox in terms of prediction accuracy.

2. **Problem Statement.** In practical implementation sensors, machine controllers and computers would provide a part of parameters of an ANN operation model. For simulating the machining process in the investigations to be reported here, all information is generated via theoretical models, which are functions of several input variables. It should be stressed that in a practical implementation theoretical models are not necessary. They are used in the present case only to provide simulated samples for training and testing purposes. The validity of the equations is determined by the minimum and maximum boundaries of the parameters. Four nonlinear equations are used in the following equation to create data vectors [1,2]:

$$F_a = 1560 f^{0.76} a^{0.98} \left[\sin(x)\right]^{-0.22}, \tag{1a}$$

$$P = 0.039 f^{0.76} a v, \tag{1b}$$

$$T = \left(1.85 \times 10^{10}\right) f^{-0.7} a^{-0.42} v^{-3.85}, \tag{1c}$$

and

$$R_a = 8.5 f^{1.8} a^{0.08} v^{-0.9} r_c^{-0.5}, \tag{1d}$$

where a, f, v, x, r_c, T, F_a, P and R_a denote the depth of cut, the feed, the speed, the cutting edge angle, the corner radius, the tool life, the force (main force component), the power, and the required roughness, respectively. The ranges of the variables in (1) are as follows:

$$
\begin{aligned}
&f : 0.1 - 0.4 \text{ (mm/rev)},\\
&a : 1 - 4 \text{ (mm)},\\
&v : 75 - 200 \text{ (m/min)},\\
&x : 1.3 - 1.66 \text{ (rad)},\\
&r_c : 0.4 - 1.2 \text{ (mm)},\\
&T : 5 - 60 \text{ (min)},\\
&F_a : 800 - 3,000 \text{ (N)},\\
&P : 3.8 - 13.5 \text{ (kw)},
\end{aligned}
$$

and

$$R_a : 0.0015 - 0.023 \text{ (mm)}.$$

According to the ranges of the variables, 100 data sets were obtained from (1). Of these, the current study selected 80 training data sets (Tables 1-4) to train the proposed MIMO ANN; after training, the remaining 20 testing data sets (Tables 5-8) were then used to verify the accuracy of the predicted outputs. Five input variables $X = [f, a, v, x, r_c] = [x_1, x_2, x_3, x_4, x_5]$ have a major impact on the four output variables $Y = [F_a, P, T, R_a] = [y_1, y_2, y_3, y_4]$. The architecture of the MIMO ANN used in this paper is shown in Figure 1, which is a three-layer feedforward MIMO ANN with four nodes chosen in the hidden layer being good enough for the learning performance. Referring to Figure 1, the input-output relationship of the three-layer feedforward ANN with sigmoid activation function

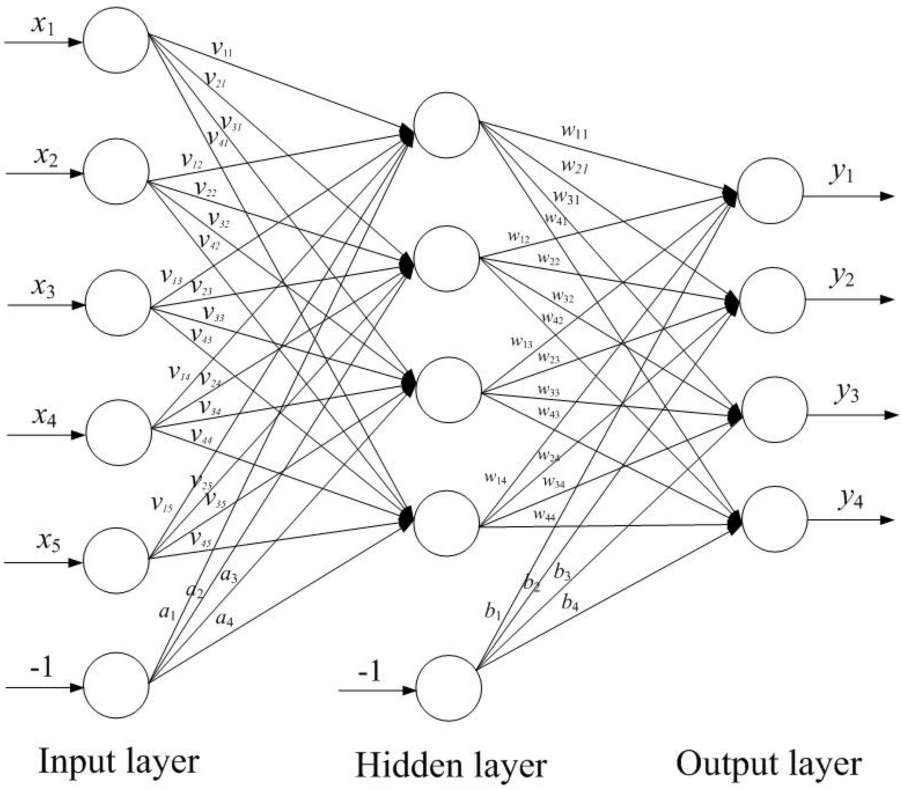

FIGURE 1. Three-layer feedforward MIMO ANN for the machining process

TABLE 1. Comparison of results in training data set (output variable F_a)

No.	Observed value	HTGA-based ANN		BP-based ANN	
		Predicted value	Error (%)	Predicted value	Error (%)
1	2674.7452	2240.4491	16.24	2240.4491	16.24
2	1805.5933	1966.0509	8.89	1818.9042	0.74
3	2037.3119	2097.8330	2.97	2238.4792	9.87
4	1961.4636	1961.5203	0.00	1647.9224	15.99
5	2046.1743	2105.9093	2.92	2132.3051	4.21
6	2126.0097	2123.8348	0.10	2114.7735	0.53
7	2499.1225	2200.4614	11.95	2421.0831	3.12
8	1652.9779	1538.2025	6.94	1465.9095	11.32
9	1488.7703	1295.9127	12.95	1251.9853	15.90
10	886.2652	1100.5049	24.17	1044.9556	17.91
11	948.2078	1057.9565	11.57	1318.3688	39.04
12	1927.1691	2010.1752	4.31	2005.2507	4.05
13	1863.9958	2027.1158	8.75	1745.8232	6.34
14	1221.7432	1337.4762	9.47	1221.2559	0.04
15	2528.8121	2523.3175	0.22	2371.2462	6.23
16	1440.9512	1344.9616	6.66	1830.9202	27.06
17	1185.8215	1125.3249	5.10	1142.2655	3.67
18	1258.5142	1183.6320	5.95	1148.3720	8.75
19	1331.5104	1588.2364	19.28	1679.0458	26.10
20	2688.8551	2510.5136	6.63	2363.5638	12.10
21	1641.8445	1705.8356	3.90	1489.1536	9.30
22	1192.9917	1174.7678	1.53	1402.4808	17.56
23	874.7617	1059.1384	21.08	1111.7330	27.09
24	1800.7825	2019.2365	12.13	1945.1707	8.02
25	2814.0376	2578.4730	8.37	2493.5730	11.39
26	2047.5595	2152.7914	5.14	2265.6630	10.65
27	2256.9739	2236.3124	0.92	2335.7892	3.49
28	1301.0031	1275.4264	1.97	1248.4396	4.04
29	2044.3693	2070.8462	1.30	2228.6301	9.01
30	1621.2023	1484.8200	8.41	1489.9415	8.10
31	894.2542	1140.4926	27.54	1025.8481	14.72
32	1778.2101	1748.1870	1.69	1684.7583	5.26
33	2731.8912	2351.3509	13.93	2315.4998	15.24
34	1897.5679	1963.8841	3.49	1735.3831	8.55
35	2029.1024	1954.2319	3.69	2187.6575	7.81
36	1119.5002	1185.4049	5.89	1093.8075	2.30
37	1535.7503	1370.9634	10.73	1956.2017	27.38
38	1527.7405	1360.7203	10.93	1382.9794	9.48
39	1225.3303	1073.9121	12.36	1198.7998	2.17
40	1497.1190	1406.4205	6.06	1454.4845	2.85

Table 1. (Continued)

41	1917.5454	1853.3763	3.35	1737.1560	9.41
42	1646.8892	1561.2496	5.20	1537.6116	6.64
43	1637.3618	1588.0394	3.01	1401.1019	14.43
44	1797.9188	1686.9251	6.17	1595.1308	11.28
45	2043.5025	2151.0185	5.26	2188.2484	7.08
46	1977.7143	2146.0939	8.51	1746.8082	11.68
47	1541.5908	1435.9680	6.85	1427.1038	7.43
48	1635.5673	1893.7579	15.79	1892.3790	15.70
49	1799.0582	1808.4640	0.52	1543.5211	14.20
50	1770.1205	1867.5591	5.50	1952.4590	10.30
51	2016.0302	2210.3106	9.64	1817.7223	9.84
52	1052.3085	1139.3107	8.27	1084.1553	3.03
53	2256.1123	2403.5515	6.54	1811.0248	19.73
54	1618.2028	1518.7011	6.15	1508.2610	6.79
55	2844.5978	2613.9300	8.11	2447.2819	13.97
56	1100.8073	1175.9497	6.83	1178.7074	7.08
57	2407.2648	2530.0150	5.10	2120.0921	11.93
58	1283.6530	1184.2230	7.75	1576.6143	22.82
59	1813.3746	1849.6336	2.00	2022.9792	11.56
60	1858.5573	1868.1501	0.52	2265.0720	21.87
61	2387.3417	2433.8870	1.95	2014.5089	15.62
62	1559.8975	1357.9625	12.95	1346.3405	13.69
63	1267.6545	1191.1174	6.04	1168.2673	7.84
64	1338.7491	1269.5169	5.17	1299.0644	2.96
65	1614.6531	1428.6796	11.52	1559.6737	3.41
66	2266.2594	2474.0716	9.17	2132.6991	5.89
67	955.7991	1129.8555	18.21	1077.8518	12.77
68	1032.1747	1060.7142	2.76	1421.3912	37.71
69	2255.5301	2410.2490	6.86	2199.6735	2.48
70	1112.9738	1134.3861	1.92	1285.4725	15.50
71	1160.6831	1200.7696	3.45	1135.5680	2.16
72	1626.0760	1496.4420	7.97	1419.8154	12.68
73	2148.9339	2159.8828	0.51	1866.5742	13.14
74	2308.9505	2227.2512	3.54	1945.9586	15.72
75	1501.4554	1276.6083	14.98	1257.6979	16.23
76	1790.4489	1746.8082	2.44	1677.2729	6.32
77	2544.6527	2337.5620	8.14	2280.4368	10.38
78	1906.5372	2051.3448	7.60	1936.7004	1.58
79	2371.3444	2464.0255	3.91	2425.6137	2.29
80	1204.4529	1330.7788	10.49	1453.8935	20.71
Average error			7.33		11.12

Table 2. Comparison of results in training data set (output variable P)

No.	Observed value	HTGA-based ANN		BP-based ANN	
		Predicted value	Error (%)	Predicted value	Error (%)
1	13.2611	10.3096	22.26	10.7594	18.87
2	8.7267	8.9750	2.85	8.9295	2.32
3	9.7191	9.6223	1.00	10.5609	8.66
4	9.3041	9.3119	0.08	8.4179	9.53
5	9.7540	9.6360	1.21	10.1722	4.29
6	9.9965	9.6924	3.04	10.0884	0.92
7	12.0931	10.0393	16.98	11.3229	6.37
8	7.8147	7.2708	6.96	7.3600	5.82
9	6.9086	5.9835	13.39	6.0618	12.26
10	4.2365	5.1469	21.49	4.8974	15.60
11	4.3462	5.0385	15.93	5.9781	37.55
12	8.7985	9.1180	3.63	9.4603	7.52
13	8.9359	9.2928	3.99	8.6810	2.85
14	5.9006	6.5115	10.35	6.0400	2.36
15	10.8209	11.0507	2.12	10.8905	0.64
16	6.6311	6.4715	2.41	8.3496	25.92
17	5.4730	5.2671	3.76	5.3235	2.73
18	5.7226	5.4710	4.40	5.3681	6.19
19	6.4357	7.3227	13.78	8.0474	25.04
20	12.0843	11.1408	7.81	11.0671	8.42
21	7.8490	8.1566	3.92	7.5758	3.48
22	5.4548	5.5356	1.48	6.4132	17.57
23	4.1573	5.0030	20.34	5.1778	24.55
24	8.8622	9.2764	4.67	9.4712	6.87
25	11.6407	11.3366	2.61	11.4057	2.02
26	9.3414	9.7352	4.22	10.5363	12.79
27	10.3435	10.0529	2.81	10.8723	5.11
28	6.2378	5.8743	5.83	6.0117	3.62
29	9.5531	9.4712	0.86	10.4498	9.39
30	7.4252	6.7774	8.72	7.1169	4.15
31	4.2864	5.2898	23.41	4.8210	12.47
32	8.0797	7.9509	1.59	7.9663	1.40
33	12.6405	10.5627	16.44	10.9460	13.41
34	8.9252	8.9787	0.60	8.5053	4.70
35	9.5343	9.0196	5.40	10.2905	7.93
36	5.3576	5.4728	2.15	5.1888	3.15
37	6.9063	6.5389	5.32	8.7857	27.21
38	7.3923	6.2557	15.38	6.8957	6.72
39	5.6019	5.1023	8.92	5.5693	0.58
40	6.8944	6.4633	6.25	6.8657	0.42

Table 2. (Continued)

41	8.7478	8.3951	4.03	8.3678	4.34
42	7.5786	7.1743	5.33	7.2954	3.74
43	7.5788	7.2945	3.75	6.8775	9.25
44	8.5847	7.6796	10.54	7.9736	7.12
45	9.2360	9.6733	4.73	10.1749	10.17
46	9.5820	10.0502	4.89	8.8849	7.28
47	7.0924	6.5853	7.15	6.7919	4.24
48	7.9623	8.7238	9.56	9.1325	14.70
49	8.3988	8.4643	0.78	7.7697	7.49
50	7.8631	8.4006	6.84	8.9131	13.35
51	8.7784	9.6496	9.92	8.4725	3.48
52	5.0446	5.3007	5.08	5.1105	1.31
53	9.7288	10.5682	8.63	8.7147	10.42
54	7.4305	6.9877	5.96	7.1297	4.05
55	12.0458	11.5687	3.96	11.3111	6.10
56	5.2963	5.4546	2.99	5.5793	5.34
57	10.1511	11.0807	9.16	9.8545	2.92
58	5.6544	5.5966	1.02	6.9576	23.05
59	8.2341	8.4698	2.86	9.3446	13.49
60	8.7961	8.6983	1.11	10.5436	19.87
61	10.5178	10.7576	2.28	9.6369	8.38
62	7.3635	6.2111	15.65	6.5725	10.74
63	5.9548	5.5302	7.13	5.5229	7.25
64	6.2977	5.8688	6.81	6.1583	2.21
65	7.1022	6.5653	7.56	7.1142	0.17
66	9.5953	10.7657	12.20	9.7616	1.73
67	4.5972	5.2616	14.45	5.0677	10.23
68	4.9270	5.1350	4.22	6.5917	33.79
69	9.8925	10.5937	7.09	10.1977	3.08
70	5.1814	5.3417	3.09	5.9535	14.90
71	5.5738	5.5447	0.52	5.4109	2.92
72	7.7363	7.0441	8.95	7.1752	7.25
73	10.1212	10.0138	1.06	9.2937	8.18
74	10.7616	10.2896	4.39	9.6159	10.65
75	7.0528	5.8816	16.61	6.1346	13.02
76	8.1983	7.9509	3.02	8.0100	2.30
77	11.5866	10.4935	9.43	10.7685	7.06
78	9.2740	9.4029	1.39	9.4493	1.89
79	10.0474	10.7339	6.83	11.0079	9.56
80	5.7466	6.1447	6.93	6.9103	20.25
Average error			6.83		8.98

TABLE 3. Comparison of results in training data set (output variable T)

No.	Observed value	HTGA-based ANN		BP-based ANN	
		Predicted value	Error (%)	Predicted value	Error (%)
1	30.3132	38.6285	27.43	43.0458	42.00
2	39.4762	41.5291	5.20	46.2179	17.08
3	37.5481	39.6199	5.52	45.1408	20.22
4	46.3643	46.8257	1.00	44.9195	3.12
5	38.4069	39.6199	3.16	45.2707	17.87
6	40.3908	40.1452	0.61	45.4772	12.59
7	33.0348	39.2954	18.95	44.0845	33.45
8	48.9389	52.3200	6.91	48.1388	1.63
9	55.5842	53.8603	3.10	52.5473	5.46
10	57.3826	55.6456	3.03	56.7491	1.10
11	57.6888	55.1911	4.33	55.4980	3.80
12	45.7473	42.8363	6.36	47.7021	4.27
13	43.2588	41.3314	4.46	45.9582	6.24
14	59.6820	56.3980	5.50	51.4053	13.87
15	53.8030	55.3593	2.89	47.2506	12.18
16	48.9481	48.2568	1.41	51.6974	5.62
17	57.1785	55.0525	3.72	55.8787	2.27
18	58.4804	54.7987	6.30	55.6338	4.87
19	41.9926	46.5897	10.95	49.4135	17.67
20	44.3873	50.6381	14.08	44.6746	0.65
21	51.0015	50.9951	0.01	46.9408	7.96
22	54.2551	53.4089	1.56	54.4416	0.34
23	55.4806	55.8226	0.62	56.2564	1.40
24	36.5198	40.0389	9.64	45.5067	24.61
25	59.1915	55.6603	5.97	46.9467	20.69
26	43.8384	42.7389	2.51	46.6428	6.40
27	42.3027	44.0579	4.15	45.8106	8.29
28	49.9985	53.3646	6.73	52.8777	5.76
29	41.1107	41.2871	0.43	46.0467	12.01
30	50.7603	49.9830	1.53	51.3138	1.09
31	58.4704	55.3888	5.27	56.8524	2.77
32	50.1401	46.4451	7.37	50.3342	0.39
33	39.1111	43.2317	10.54	43.9871	12.47
34	44.9651	41.7858	7.07	47.3362	5.27
35	40.5584	41.7799	3.01	46.2385	14.00
36	55.0637	54.9669	0.18	55.4065	0.62
37	52.0808	51.5056	1.10	52.1371	0.11
38	46.1372	52.6328	14.08	49.4047	7.08
39	57.8037	55.1056	4.67	55.7016	3.64
40	50.7357	50.6706	0.13	52.3259	3.13

Table 3. (Continued)

41	48.2557	44.9254	6.90	48.5519	0.61
42	49.6463	47.8998	3.52	51.3463	3.42
43	55.4174	49.2778	11.08	50.3696	9.11
44	43.4104	46.6516	7.47	47.1828	8.69
45	46.3538	45.0139	2.89	47.3893	2.23
46	42.2701	42.1487	0.29	44.0874	4.30
47	51.4733	50.4670	1.96	52.0574	1.13
48	38.4402	41.5556	8.10	46.8641	21.91
49	51.9383	47.7995	7.97	47.1828	9.16
50	52.1533	49.2247	5.62	50.7591	2.67
51	57.1974	52.7833	7.72	50.2870	12.08
52	54.4140	55.1734	1.40	55.9259	2.78
53	59.8209	53.5240	10.53	47.9323	19.87
54	50.7678	48.6404	4.19	51.8214	2.08
55	53.1556	55.0111	3.49	45.6425	14.13
56	49.6001	54.5538	9.99	54.6334	10.15
57	58.7686	55.2413	6.00	48.0237	18.28
58	59.4433	54.4889	8.33	54.8725	7.69
59	48.1785	46.0880	4.34	49.3958	2.53
60	39.8683	41.7386	4.69	46.5483	16.76
61	52.2725	50.4020	3.58	46.3447	11.34
62	48.6368	52.0574	7.03	51.1840	5.24
63	54.3669	54.2233	0.26	54.8636	0.91
64	50.2234	52.8217	5.17	53.4148	6.35
65	58.5776	54.5125	6.94	53.9135	7.96
66	58.7499	55.5806	5.39	49.3516	16.00
67	54.3757	55.3210	1.74	56.1265	3.22
68	48.8378	53.3823	9.31	53.7954	10.15
69	51.1133	51.8804	1.50	47.5929	6.89
70	52.8927	54.2882	2.64	54.7869	3.58
71	53.1300	54.6836	2.92	54.6689	2.90
72	51.5070	52.5856	2.09	48.1093	6.60
73	42.8600	41.2252	3.81	44.4356	3.68
74	43.5011	40.9330	5.90	44.1140	1.41
75	52.9149	53.9695	1.99	52.0250	1.68
76	48.3124	45.8136	5.17	49.7175	2.91
77	42.1504	43.4854	3.17	44.6067	5.83
78	37.5131	39.8678	6.28	45.4093	21.05
79	55.8532	55.9583	0.19	48.4752	13.21
80	46.1067	51.5676	11.84	51.9128	12.59
Average error			5.31		8.46

Table 4. Comparison of results in training data set (output variable R_a)

No.	Observed value	HTGA-based ANN		BP-based ANN	
		Predicted value	Error (%)	Predicted value	Error (%)
1	0.0140	0.0124	11.72	0.01572	12.30
2	0.0118	0.0130	10.53	0.01213	2.78
3	0.0180	0.0156	13.57	0.01670	7.24
4	0.0054	0.0041	23.65	0.00919	70.20
5	0.0155	0.0150	3.24	0.01551	0.09
6	0.0154	0.0150	2.45	0.01541	0.06
7	0.0200	0.0150	25.16	0.01833	8.34
8	0.0052	0.0037	29.68	0.00859	65.27
9	0.0054	0.0052	3.40	0.00797	47.67
10	0.0073	0.0076	4.34	0.00697	4.50
11	0.0132	0.0139	4.98	0.01184	10.30
12	0.0137	0.0140	1.83	0.01529	11.61
13	0.0109	0.0120	9.85	0.01103	1.21
14	0.0022	0.0025	11.97	0.00679	208.56
15	0.0180	0.0173	3.93	0.01886	4.76
16	0.0190	0.0196	3.33	0.01567	17.53
17	0.0093	0.0087	6.37	0.00857	7.80
18	0.0078	0.0065	16.24	0.00844	8.18
19	0.0130	0.0127	2.00	0.01227	5.63
20	0.0157	0.0148	5.86	0.01792	14.11
21	0.0044	0.0033	24.61	0.00826	87.83
22	0.0129	0.0126	1.97	0.01216	5.73
23	0.0099	0.0101	1.76	0.00825	16.72
24	0.0163	0.0151	7.08	0.01333	18.24
25	0.0180	0.0168	6.93	0.01979	9.94
26	0.0160	0.0155	2.97	0.01763	10.21
27	0.0177	0.0161	9.14	0.01804	1.91
28	0.0072	0.0067	6.39	0.00813	12.97
29	0.0187	0.0164	12.50	0.01700	9.10
30	0.0096	0.0090	6.64	0.01092	13.77
31	0.0056	0.0063	13.18	0.00649	15.96
32	0.0123	0.0129	4.51	0.01295	5.32
33	0.0152	0.0145	4.51	0.01709	12.45
34	0.0134	0.0139	3.69	0.01175	12.31
35	0.0217	0.0177	18.57	0.01665	23.26
36	0.0053	0.0058	8.69	0.00693	30.77
37	0.0217	0.0206	5.03	0.01727	20.43
38	0.0056	0.0059	4.65	0.00814	45.35
39	0.0124	0.0134	7.80	0.00988	20.35

Table 4. (Continued)

40	0.0108	0.0098	9.16	0.01114	3.14
41	0.0109	0.0118	7.84	0.01249	14.55
42	0.0122	0.0124	1.60	0.01165	4.53
43	0.0072	0.0074	3.25	0.00898	24.78
44	0.0080	0.0094	17.18	0.00978	22.25
45	0.0163	0.0161	1.27	0.01715	5.22
46	0.0071	0.0067	5.10	0.00996	40.24
47	0.0097	0.0092	4.91	0.01051	8.34
48	0.0153	0.0152	0.76	0.01345	12.11
49	0.0057	0.0052	8.31	0.00910	59.67
50	0.0157	0.0165	5.24	0.01637	4.28
51	0.0131	0.0147	12.57	0.01461	11.51
52	0.0073	0.0071	2.09	0.00718	1.59
53	0.0093	0.0114	22.96	0.01306	40.38
54	0.0121	0.0123	1.55	0.01157	4.37
55	0.0146	0.0149	1.78	0.01907	30.64
56	0.0087	0.0074	15.09	0.00816	6.22
57	0.0124	0.0143	14.93	0.01672	34.87
58	0.0153	0.0171	11.98	0.01511	1.27
59	0.0176	0.0177	0.85	0.01639	6.87
60	0.0214	0.0182	14.89	0.01760	17.77
61	0.0121	0.0143	18.37	0.01466	21.16
62	0.0073	0.0072	1.45	0.00864	18.37
63	0.0085	0.0079	7.54	0.00817	3.87
64	0.0098	0.0086	12.11	0.00944	3.63
65	0.0168	0.0184	9.36	0.01428	15.02
66	0.0146	0.0161	10.12	0.01745	19.55
67	0.0073	0.0071	2.47	0.00721	1.24
68	0.0177	0.0189	6.82	0.01197	32.38
69	0.0152	0.0159	4.48	0.01735	14.17
70	0.0120	0.0112	6.79	0.01044	12.96
71	0.0059	0.0060	1.08	0.00727	23.25
72	0.0042	0.0038	9.27	0.00796	89.48
73	0.0086	0.0089	3.85	0.01168	35.85
74	0.0092	0.0096	4.58	0.01251	36.02
75	0.0052	0.0054	3.51	0.00774	48.77
76	0.0118	0.0121	2.84	0.01245	5.49
77	0.0136	0.0143	4.84	0.01695	24.65
78	0.0151	0.0148	2.21	0.01316	12.84
79	0.0189	0.0182	3.58	0.01962	3.82
80	0.0111	0.0095	14.60	0.01082	2.57
Average error			7.97		20.76

Table 5. Comparison of results in testing data set (output variable F_a)

No.	Observed value	HTGA-based ANN		BP-based ANN	
		Predicted value	Error (%)	Predicted value	Error (%)
1	1128.6560	1141.8715	1.17	1465.7125	29.86
2	1536.6373	1514.1705	1.46	1405.6325	8.53
3	2511.6301	2553.2591	1.66	2165.0044	13.80
4	2092.6299	2269.4057	8.45	1850.6185	11.56
5	1086.2307	1026.4391	5.50	1178.3135	8.48
6	1897.9920	2081.8773	9.69	1691.6527	10.87
7	2659.0043	2444.3271	8.07	2467.7682	7.19
8	2417.1944	2471.1169	2.23	2220.5537	8.14
9	2379.5764	2425.4167	1.93	2316.6817	2.64
10	2208.0205	2358.2453	6.80	2383.0652	7.93
11	877.7381	1058.1535	20.55	1183.0411	34.78
12	2168.3549	2113.0007	2.55	1860.8617	14.18
13	1936.2864	2107.4851	8.84	1922.1236	0.73
14	1634.3030	1509.4429	7.64	1450.3478	11.26
15	1124.9851	1044.7586	7.13	1222.6348	8.68
16	2298.5530	2402.1726	4.51	2318.6516	0.87
17	2530.5206	2290.4829	9.49	2152.9884	14.92
18	1586.2017	1475.7587	6.96	1516.1404	4.42
19	2500.6317	2304.6657	7.84	2379.5195	4.84
20	1388.1744	1464.1367	5.47	1477.5316	6.44
Average error			6.40		10.51

Table 6. Comparison of results in testing data set (output variable P)

No.	Observed value	HTGA-based ANN		BP-based ANN	
		Predicted value	Error (%)	Predicted value	Error (%)
1	5.2296	5.4482	4.18	6.6900	27.93
2	7.4123	6.9321	6.48	6.9859	5.75
3	10.5833	11.1918	5.75	10.0648	4.90
4	9.1241	9.9018	8.52	8.6537	5.16
5	5.0827	4.9056	3.48	5.4937	8.09
6	9.2225	9.6869	5.04	8.6364	6.36
7	12.1540	10.8659	10.60	11.4540	5.76
8	10.5961	10.8522	2.42	10.3506	2.32
9	10.5846	10.7321	1.39	10.7721	1.77
10	9.3457	10.2204	9.36	10.7357	14.87
11	4.2497	5.0194	18.11	5.5311	30.15
12	10.3093	9.6587	6.31	9.2673	10.11
13	8.4503	9.2272	9.19	8.8103	4.26
14	7.7833	6.8894	11.49	7.1752	7.81
15	5.2834	4.9994	5.38	5.7186	8.24
16	10.0518	10.4945	4.40	10.6538	5.99
17	11.6472	10.4954	9.89	10.3716	10.95
18	7.2776	6.7373	7.42	7.2271	0.69
19	11.6252	10.3688	10.81	11.1308	4.25
20	6.7318	6.7036	0.42	7.2016	6.98
Average error			7.03		8.62

Table 7. Comparison of results in testing data set (output variable T)

No.	Observed value	HTGA-based ANN		BP-based ANN	
		Predicted value	Error (%)	Predicted value	Error (%)
1	52.3575	52.9692	1.17	54.0639	3.26
2	47.9001	49.7116	3.78	49.4401	3.22
3	58.3212	55.2413	5.28	47.6195	18.35
4	56.4366	52.8364	6.38	49.7942	11.77
5	54.5976	55.6161	1.87	55.7400	2.09
6	43.2696	42.3671	2.09	44.4533	2.74
7	40.4807	48.4811	19.76	44.7277	10.49
8	50.9368	53.3764	4.79	46.8552	8.01
9	46.9152	49.6230	5.77	46.1411	1.65
10	56.8179	56.3596	0.81	49.5611	12.77
11	50.9528	55.4774	8.88	55.2915	8.52
12	40.7054	40.1098	1.46	44.4887	9.29
13	55.0746	52.2994	5.04	50.6735	7.99
14	46.8027	49.6260	6.03	49.3398	5.42
15	53.0403	55.0348	3.76	55.2413	4.15
16	51.5758	54.7780	6.21	47.7227	7.47
17	41.3301	41.3461	0.04	43.9281	6.29
18	49.8545	50.0096	0.31	51.2106	2.72
19	39.2462	43.2051	10.09	44.6008	13.64
20	43.3073	49.7470	14.87	50.0863	15.65
Average error			5.42		7.77

Table 8. Comparison of results in testing data set (output variable R_a)

No.	Observed value	HTGA-based ANN		BP-based ANN	
		Predicted value	Error (%)	Predicted value	Error (%)
1	0.0145	0.0159	9.44	0.0128	11.72
2	0.0070	0.0077	10.21	0.0085	21.27
3	0.0131	0.0150	14.55	0.0170	29.83
4	0.0134	0.0152	13.54	0.0147	9.64
5	0.0132	0.0148	11.83	0.0094	28.45
6	0.0069	0.0078	13.11	0.0095	37.35
7	0.0190	0.0154	19.12	0.0190	0.08
8	0.0170	0.0167	1.87	0.0173	1.57
9	0.0156	0.0155	0.45	0.0180	15.14
10	0.0196	0.0191	2.48	0.0196	0.06
11	0.0116	0.0119	2.68	0.0089	23.39
12	0.0096	0.0126	31.32	0.0116	21.25
13	0.0144	0.0155	7.79	0.0160	11.17
14	0.0074	0.0081	9.02	0.0091	22.43
15	0.0143	0.0155	8.36	0.0099	30.70
16	0.0204	0.0183	10.44	0.0186	9.01
17	0.0110	0.0109	0.81	0.0151	36.98
18	0.0099	0.0090	9.45	0.0112	13.42
19	0.0183	0.0152	17.14	0.0181	1.30
20	0.0097	0.0091	5.69	0.0099	2.13
Average error			9.97		16.35

is as follows:

$$\hat{y}_k = \frac{1}{1 + \exp\left(-\left(\sum_{j=1}^{4} w_{kj}\left(\frac{1}{1+\exp\left(-\left(\sum_{i=1}^{5} v_{ji}x_i - a_j\right)\right)} - b_k\right)\right)\right)}, \tag{2}$$

where $\hat{y}_k$ $(k = 1, 2, 3, 4)$ denote the predicted output variables (i.e., the predicted the tool life, the force (main force component), the power, and the required roughness) of the ANN; x_i $(i = 1, 2, 3, 4, 5)$ denote the input variables (i.e., the depth of cut, the feed, the speed, the cutting edge angle, and the corner radius); v_{ji} $(i = 1, 2, 3, 4, 5$, and $j = 1, 2, 3, 4)$ denotes the weight of the link between the jth node of hidden layer and the ith node of input layer; w_{kj} $(j = 1, 2, 3, 4$ and $k = 1, 2, 3, 4)$ denotes the weight of the link between the kth node of output layer and the ith node of hidden; a_j and b_k $(j = 1, 2, 3, 4$ and $k = 1, 2, 3, 4)$ denote the biases for the nodes of hidden layer and the node of output layer, respectively.

It can be seen that the weights of links and biases govern the input-output relationship of the proposed MIMO ANN. Therefore, the proposed MIMO ANN can be employed to learn the input-output relationship by using the HTGA. After training, the values of weights of links (w_{kj} and v_{ji}) and biases (a_j and b_k) can be obtained by directly maximizing the following RMSE performance criterion with 80 training data sets (Tables 1-4):

$$J = \sqrt{\frac{\sum_{k=1}^{4} (\hat{y}_k - y_k)^2}{80 \times 4}}. \tag{3}$$

Equation (3) shows that the value of the performance criterion J actually depends on the set $\{v_{ji}, a_j, w_{kj}, b_k\}$ $(i = 1, 2, 3, 4, 5,\ j = 1, 2, 3, 4$, and $k = 1, 2, 3, 4)$. Therefore,

$$\begin{aligned} J &= f(v_{ji}, a_j, w_{kj}, b_k) \\ &\equiv f(h_1, h_2, \ldots, h_{44}). \end{aligned} \tag{4}$$

where $h_1,\ h_2, \ldots, h_{44} \in [-10,\ 10]$. This optimization problem is equivalent to the following:

$$\text{minimize } J = f(h_1, h_2, \ldots, h_{44}). \tag{5}$$

The HTGA, which is described in detail below, can be used to search for the optimal solution for the optimization problem in (5), where (5) is a nonlinear function with continuous variables. The HTGA combines the genetic algorithm [11] with the Taguchi method [12-14]. In the HTGA, the Taguchi method is performed between the crossover and mutation operations of a TGA. The genetic algorithms are enhanced by using two major Taguchi tools (signal-to-noise ratio and orthogonal arrays) to optimize gene selection in crossover operations by incorporating the systematic reasoning capability of the Taguchi method (for a detailed description of the Taguchi method, see Taguchi et al. [12] and Wu [13]; for a detailed discussion of HTGA see Tsai et al. [3,6]; Ho et al. [15] and Ho and Chang [16]). The detailed steps of the HTGA are as follows:

Detailed Steps: HTGA

Step 1: Set parameters.
Input: population size M, crossover rate p_c, mutation rate p_m, and number of generations.
Output: the set of $V = \{h_1, h_2, \ldots, h_{44}\}$ and the value of J in (4).

Step 2: Initialize by using J in (4), which is the fitness function defined for the HTGA. Calculate the fitness values of the initial population, where randomly generated chromosomes in the initial population are given in the form $V = \{h_1, h_2, \ldots, h_{44}\}$ for the problem in (4).

Step 3: Perform selection operation by roulette wheel approach.

Step 4: Perform crossover operation. The probability of the crossover is determined by the crossover rate p_c.

Step 5: Select a suitable two-level orthogonal array $L_\gamma\,(2^{\gamma-1})$ for the matrix experiments, where γ denotes the number of experimental runs, and $\gamma - 1$ is the number of columns in the orthogonal array. The orthogonal array $L_{64}\,(2^{63})$ is used in the illustrative results given in the next section.

Step 6: Execute the matrix experiments using randomly selected chromosome pairs.

Step 7: Calculate the fitness values of the γ experiments in the orthogonal array L_γ $(2^{\gamma-1})$ by using (4).

Step 8: Calculate the effects of the various factors.

Step 9: Generate one optimal chromosome based on the results from Step 8.

Step 10: Repeat Steps 6 through 9 until the expected number $M \times p_c$ is met.

Step 11: Perform Taguchi method to generate the population.

Step 12: Perform mutation operation. The probability of the mutation is determined by the mutation rate p_m.

Step 13: Generate the offspring population.

Step 14: Sort the fitness values in increasing order among the parents and offspring populations.

Step 15: Compare feasible M chromosomes and select the best chromosomes for the constraint for use as the parents of the next generation.

Step 16: If the specified stopping criterion is met, go to Step 17. Otherwise, repeat Steps 3-16.

Step 17: Compare RMSE performance criteria J to determine if the stopping condition has been met. If so, go to Step 18. Otherwise, repeat Steps 2-17.

Step 18: Display the optimal chromosome and the optimal fitness value.

3. **Results and Discussion.** The proposed MIMO HTGA-based ANN model was directly compared with the MIMO BP-based ANN approach given by the Matlab toolbox. In the evolution environment for the HTGA-based ANN, population size was 200, crossover rate was 0.8, mutation rate was 0.1, and generation number was 200. The training parameters for the MIMO HTGA-based ANN were $-10 \le h_m \le 10$ $(m = 1, 2, \ldots, 44)$. We can obtain that the optimal parameters (i.e., weights of links and biases govern the input-output relationship of an ANN) are those shown in Table 9, and the performance criterion $J = 0.0820$. Figure 2 shows the convergence results for training RMSE performance criterion J in (5) with HTGA. Figures 3-6 show comparison of predictive performance

Table 9. Optimal parameters of MIMO HTGA-based ANN

Optimal parameters h_m $(m = 1, 2, 3, \ldots, 44)$					
$h_1 = -3.8267$	$h_2 = 5.7374$	$h_3 = -1.5312$	$h_4 = 1.3269$	$h_5 = 1.1685$	$h_6 = 4.4156$
$h_7 = 3.4009$	$h_8 = -0.3736$	$h_9 = -8.9911$	$h_{10} = -1.5033$	$h_{11} = 1.4382$	$h_{12} = -4.5588$
$h_{13} = 0.2042$	$h_{14} = -2.9777$	$h_{15} = -2.2730$	$h_{16} = -8.4179$	$h_{17} = -7.0140$	$h_{18} = 0.2800$
$h_{19} = -1.9681$	$h_{20} = 1.3598$	$h_{21} = 6.8839$	$h_{22} = 1.6071$	$h_{23} = -1.7853$	$h_{24} = -9.3360$
$h_{25} = 1.1782$	$h_{26} = 1.3932$	$h_{27} = -3.1145$	$h_{28} = -2.4746$	$h_{29} = 1.7955$	$h_{30} = 0.9170$
$h_{31} = -2.6107$	$h_{32} = -2.4849$	$h_{33} = 1.6636$	$h_{34} = 2.7168$	$h_{35} = 1.5011$	$h_{36} = 2.7367$
$h_{37} = -8.9434$	$h_{38} = 0.2765$	$h_{39} = 4.6988$	$h_{40} = -2.0905$	$h_{41} = -0.7678$	$h_{42} = -0.6527$
$h_{43} = 1.0609$	$h_{44} = -0.4860$				

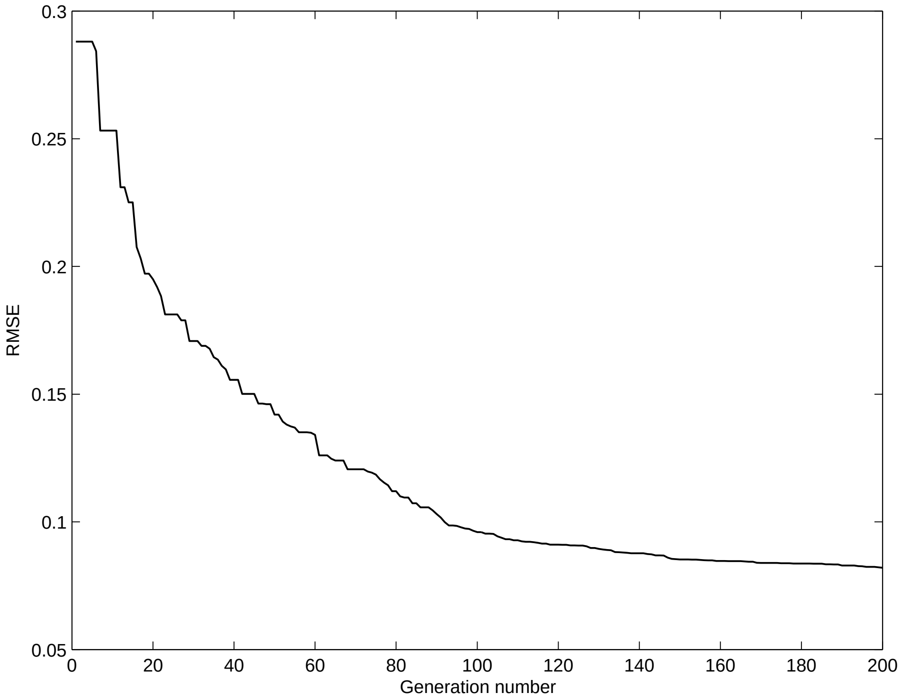

FIGURE 2. Convergence results for training RMSE performance criterion J when using HTGA

TABLE 10. Comparison of prediction results

Output variable	HTGA-based ANN		BP-based ANN	
	Average error of training data set (%)	Average error of testing data set (%)	Average error of training data set (%)	Average error of testing data set (%)
F_a	7.33	6.40	11.12	10.51
P	6.83	7.03	8.98	8.62
T	5.31	5.42	8.46	7.77
R_a	7.97	9.97	20.76	16.35

when using the proposed HTGA-based ANN model and the BP-based ANN approach given by the Matlab toolbox with training data sets. Figures 7-10 show comparison of predictive performance when using the proposed HTGA-based ANN model and the BP-based ANN approach given by the Matlab toolbox with testing data sets. It can be see that the proposed MIMO HTGA-based ANN model obtains a better model fit. Tables 1-4 show the predicted values, the errors and the average error of the predictions of output variables obtained, respectively, from the proposed HTGA-based ANN model, and the BP-based ANN approach given in the Matlab toolbox with training data sets. Tables 5-9 show the predicted values, the errors and the average error of the predictions of output variables obtained, respectively, from the proposed HTGA-based ANN model, and the BP-based ANN approach given in the Matlab toolbox with testing data sets. Table 10 concludes the comparison of prediction results. The average errors of training and testing data sets of the proposed HTGA-based ANN approach are 7.33 and 6.40 for output variable F_a, 6.83 and 7.03 for output variable P, 5.31 and 5.42 for output variable T, and 7.97 and 9.77 for output variable R_a. However, the average errors of training and testing data sets of the proposed BP-based ANN approach given in the Matlab toolbox are 11.12 and

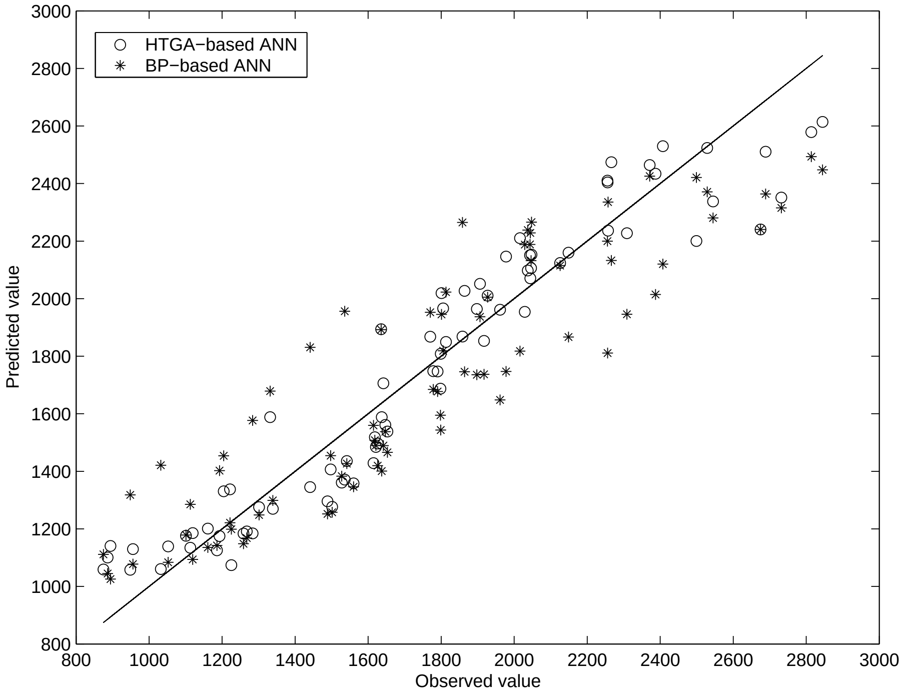

FIGURE 3. Comparison of predicted values versus observed values when using HTGA-based ANN in training data set (output variable F_a)

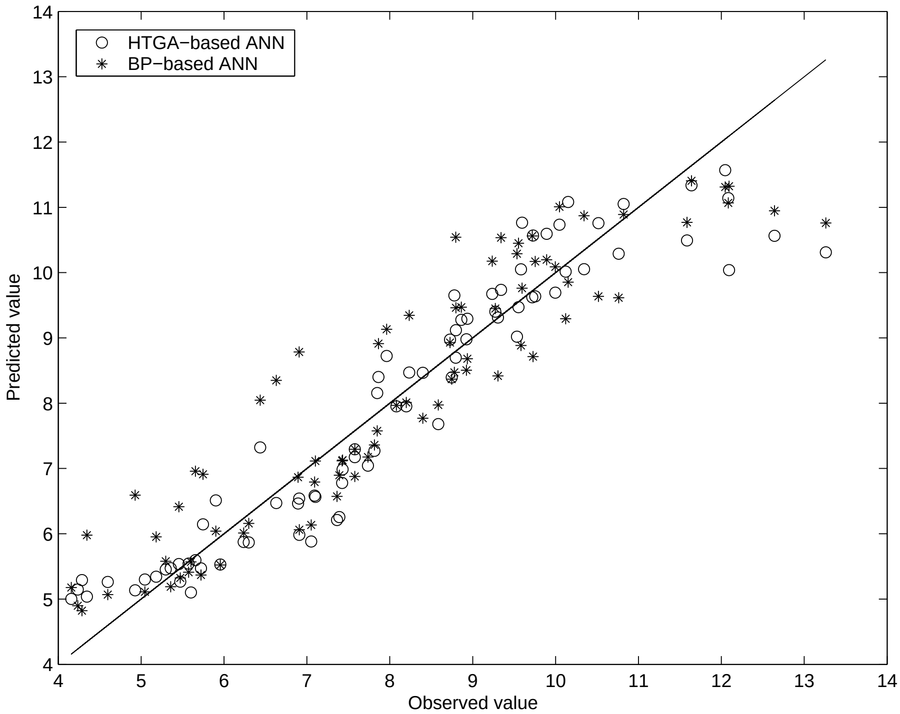

FIGURE 4. Comparison of predicted values versus observed values when using HTGA-based ANN in training data set (output variable P)

10.51 for output variable F_a, 8.98 and 8.62 for output variable P, 8.46 and 7.77 for output variable T, and 20.76 and 16.35 for output variable R_a. It can be concluded the proposed MIMO HTGA-based ANN model outperforms the BP-based ANN approach given in the Matlab toolbox in terms of prediction accuracy.

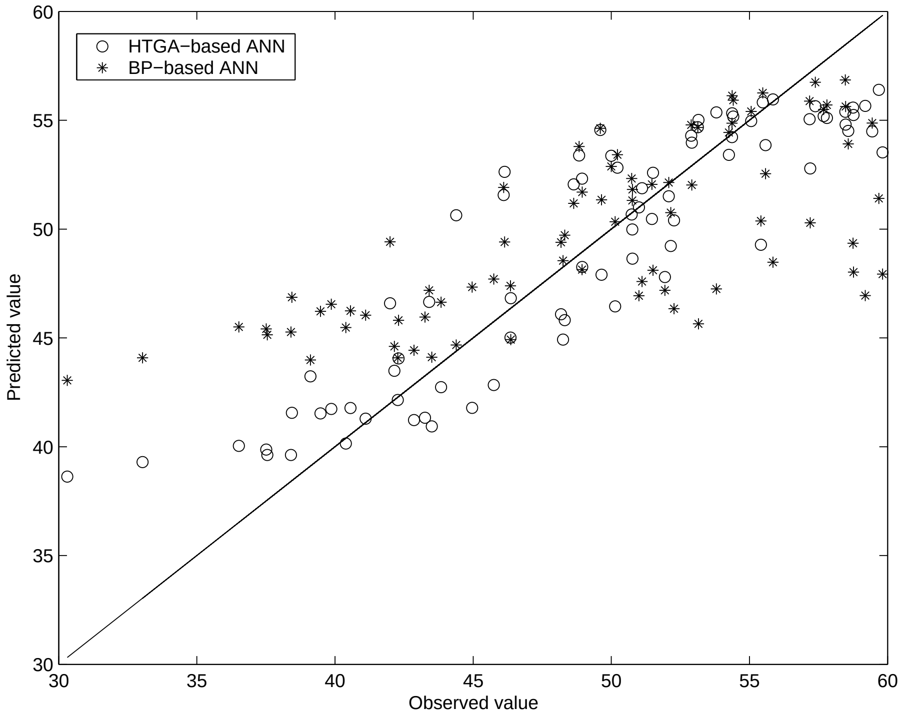

FIGURE 5. Comparison of predicted values versus observed values when using HTGA-based ANN in training data set (output variable T)

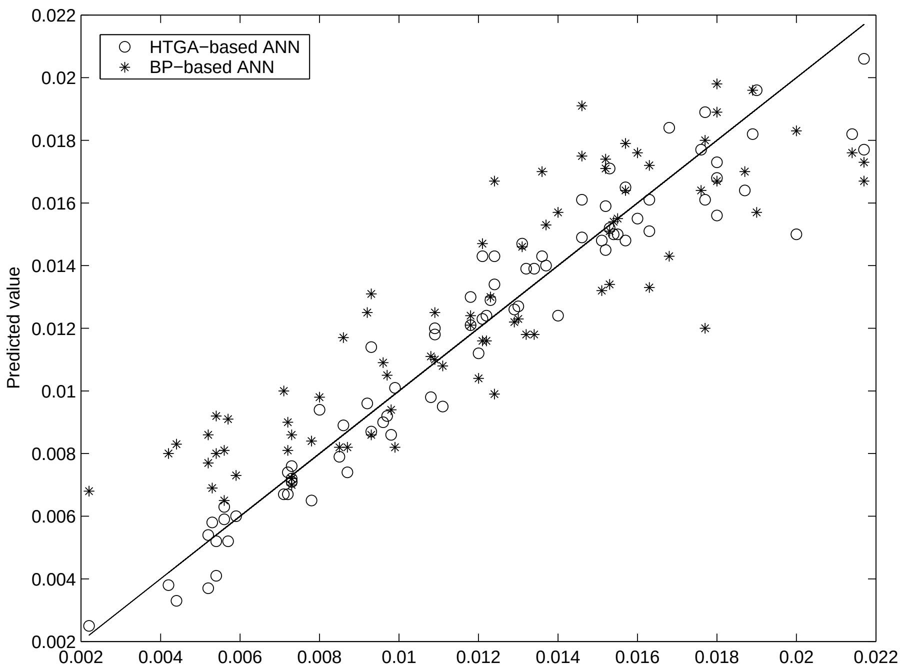

FIGURE 6. Comparison of predicted values versus observed values when using HTGA-based ANN in training data set (output variable R_a)

4. **Conclusions.** An MIMO HTGA-based ANN model has been proposed in this paper to effectively predict the four output variables (the tool life T, the force F_a, the power P, and the required roughness R_a) of the machining processes by using five input variables (the depth of cut a, the feed f, the speed v, the cutting edge angle x, and the corner

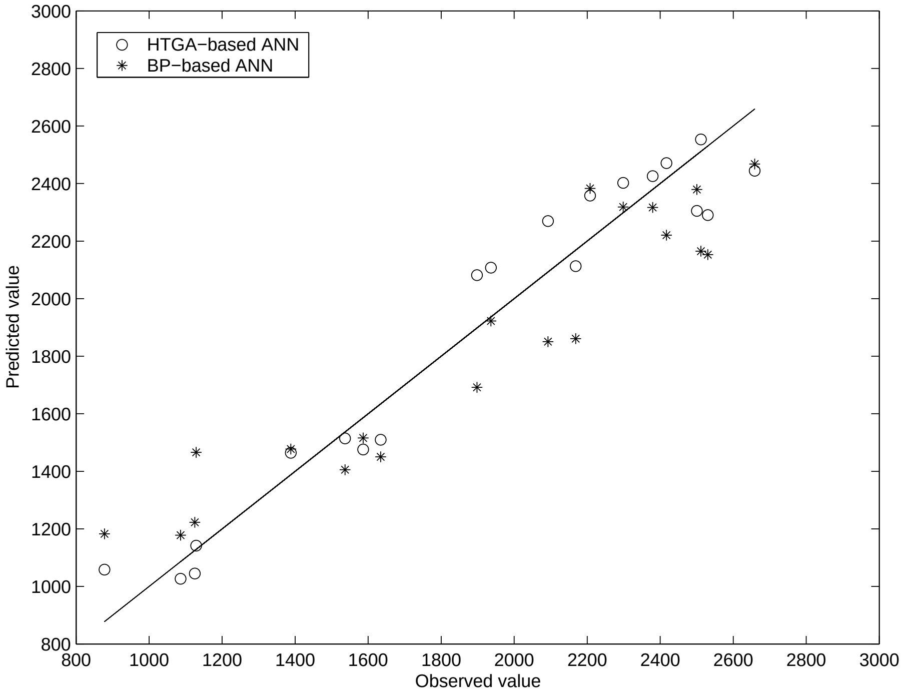

FIGURE 7. Comparison of predicted values versus observed values when using HTGA-based ANN in testing data set (output variable F_a)

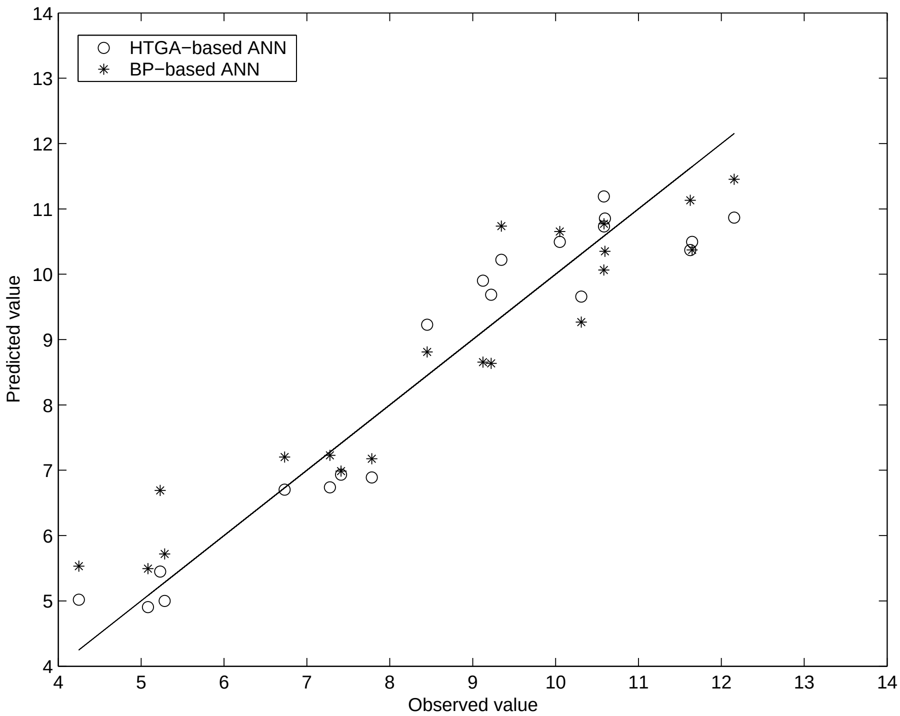

FIGURE 8. Comparison of predicted values versus observed values when using HTGA-based ANN in testing data set (output variable P)

radius r_c). The HTGA is applied in the MIMO ANN to find the optimal parameters (i.e., weights of links and biases govern the input-output relationship of an ANN) by directly minimizing the RMSE performance criterion. Experimental results have shown that the

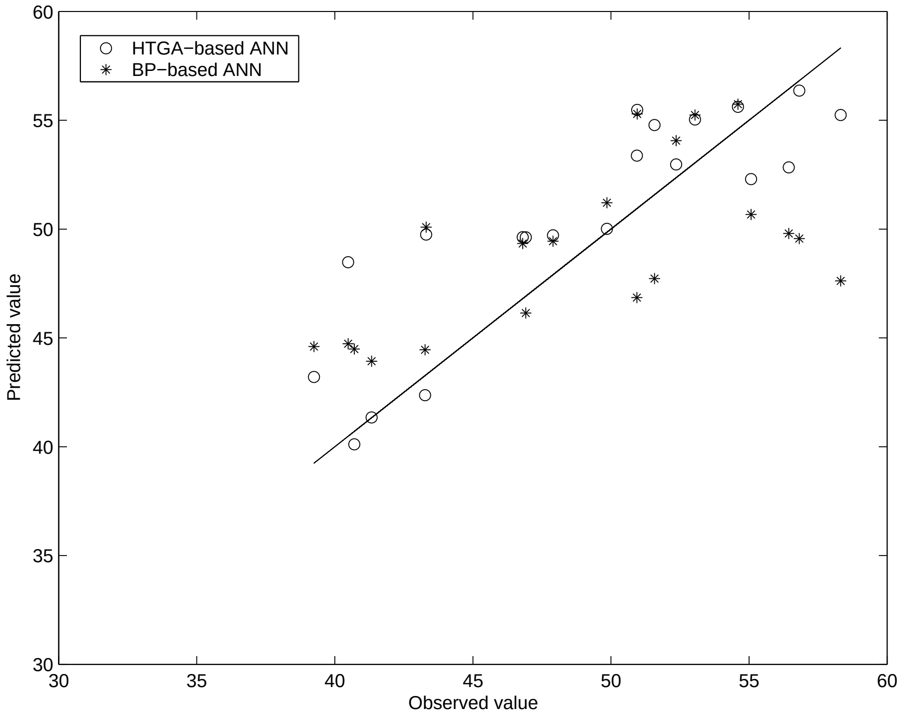

Figure 9. Comparison of predicted values versus observed values when using HTGA-based ANN in testing data set (output variable T)

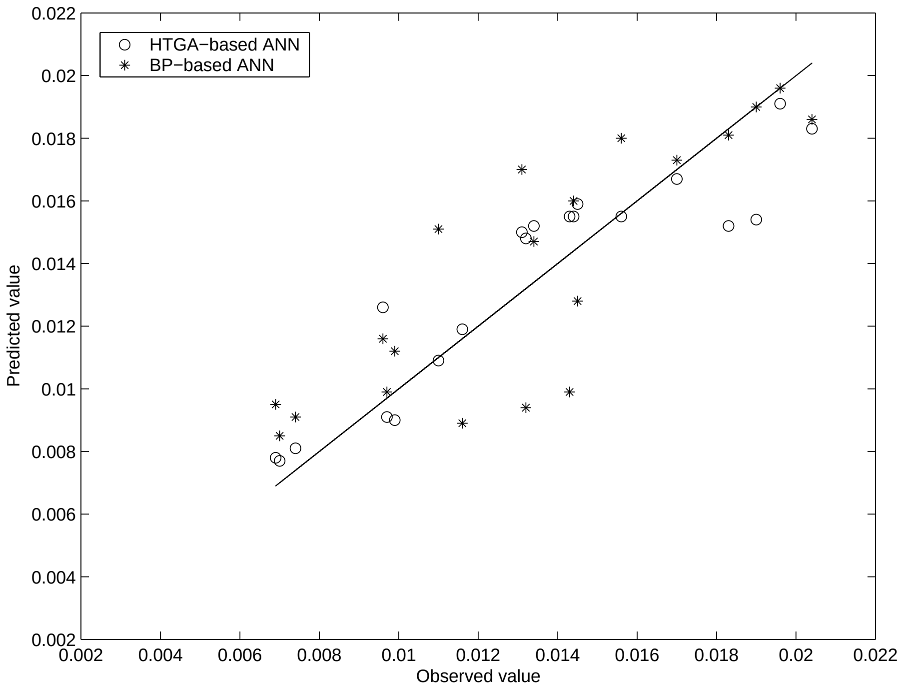

Figure 10. Comparison of predicted values versus observed values when using HTGA-based ANN in testing data set (output variable R_a)

prediction errors of the MIMO HTGA-based ANN model outperforms the prediction errors obtained from the BP-based ANN approach given in the Matlab toolbox.

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