Designing a System for a Process Parameter Determined through Modified PSO and Fuzzy Neural Network

Jui-Tsung Wong[1], Kuei-Hsien Chen[2,*], and Chwen-Tzeng Su[3]

[1] Department of International Business, Shih Chien University Kaohsiung Campus, Neimen Shiang, Kaohsiung, No. 200, University Rd, Neimen Shiang, Kaohsiung, Taiwan, 845
g9221802@yuntech.edu.tw

[2] Department of Industrial Engineering and Management, National Yunlin University of Science and Technology, 123 University Rd. Sec. 3 Douliou, Yunlin 640, Taiwan, R.O.C.,
Tel.: +886 5 5342601 x5194; Fax: +886 5 5312073
g9321803@yuntech.edu.tw

[3] Department of Industrial Engineering and Management, National Yunlin University of Science and Technology, 123 University Rd. Sec. 3 Douliou, Yunlin 640, Taiwan, R.O.C.
suct@yuntech.edu.tw

Abstract. In the manufacturing industry, the key to retaining a competitive advantage lies in increased yield and reduced a number of reworks. Determining the optimal parameters for the process so that the quality characteristics can meet the target is an important strategy. Traditional statistical techniques such as response surface methodology and analysis of variance, whose basic assumptions must be met, are generally used in this regard. In recent years, artificial intelligence has reached a sufficient level of maturity and is extensively being used in various domains. This paper proposes a system based on the modified particle swarm optimizer (PSO) and the adaptive network-based fuzzy inference system (ANFIS) to determine the process parameters. A perturbed strategy is incorporated into the modified PSO. The application of this system is then demonstrated with the determining of parameters in the wire bonding process in the IC packaging industry. Moreover, the performance of the modified PSO is evaluated with testing functions. The results show that the modified PSO yielded a superior performance to traditional PSO. In the optimization of the process parameter, the modified PSO is able to find the optimal solution in the ANFIS model.

Keyword: wire bonding process, determination of process parameters, modified particle swarm optimizer, adaptive network-based fuzzy inference system.

1 Introduction

Businesses in the high-tech industry are faced with increasing competition. Given the high cost of raw materials, the key to survival in this industry lies in increased yield. As far as optimizing the process parameters is concerned, the engineers' priority has become using efficient and convenient methods to adjust controllable parameters in

* Corresponding author.

T. Washio et al. (Eds.): PAKDD 2008, LNAI 5012, pp. 785–794, 2008.

order to bring quality characteristics close to the desired target. Traditional statistical techniques such as analysis of variance and response surface methodology are generally used to determine the process parameters ([1], [2], [3], [4], [5], [6], [7]). However, if such techniques are to be applicable, their basic assumptions must be met. This paper proposes an artificial intelligence-based system in determining the process parameters.

The particle swarm optimizer (PSO) was an evolutionary computation first proposed by [8]. Like bird flocking, fish schooling, and swarm theory, PSO was inspired by the social behavior of animals. In executing the PSO, every individual particle moves in accordance with a randomized velocity in the flying experience of itself and others in the same swarm. Unlike traditional genetic algorithms, PSO possesses memory, so the optimal solution for the swarm in execution will be memorized. Individual particles will also memorize the personal best solution. The velocity of every particle will be updated accordingly. PSO, when used in the optimization of process parameters, is deemed a very useful approach ([9], [10]). Trelea [11] analyzed how the selection of parameters in PSO affected convergence and the performance of finding the solution through dynamic system theory.

The adaptive network-based fuzzy inference system (ANFIS) is basically a fuzzy neural network. First proposed by [12], ANFIS systematically generate fuzzy rules from the training data of input and output. This is a supervised neural network based on fuzzy theory, which has been in extensive use in the prediction and control domain. Cai et al. [13] used ANFIS to predict the state-of-charge of high power in a rechargeable

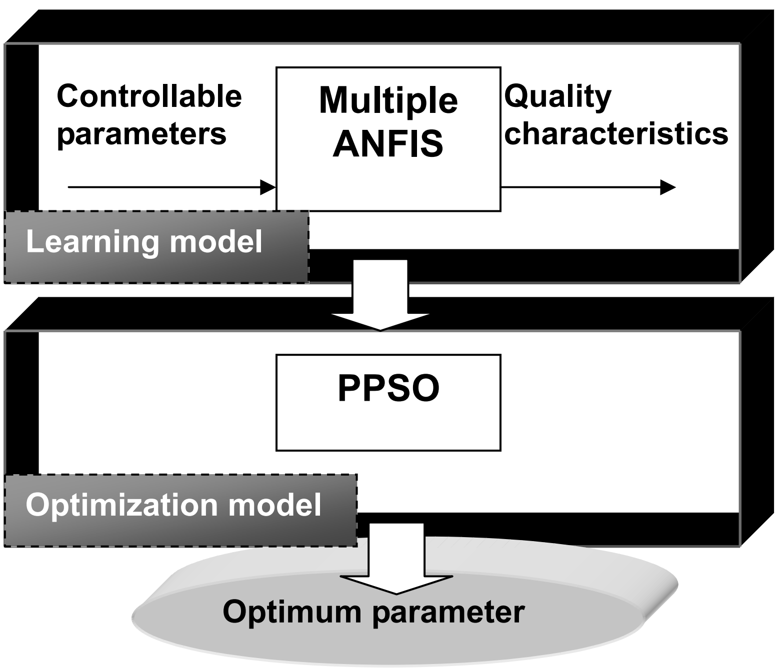


Fig. 1. The framework of the proposed method

battery, whose performance was then compared with the back-propagation artificial neural network (BPN). In this simple testing, it is found that ANFIS outperformed BPN. Mar and Lin [14] used ANFIS to formulate rules in controlling the speed of cars to avoid collisions. ANFIS were used in other areas by [15], [16], [17], [18].

This paper, therefore, proposes a system for determining the process parameters by using ANFIS as the simulation model. A modified PSO is then used to determine the optimal process parameters. A perturbed strategy is also incorporated into the modified PSO to better avoid caving into the local optimum. This method is therefore called PPSO. The application of the method is then demonstrated and tested with the finding of process parameters for the second bonding process, which is an important step in the IC packaging industry. Figure 1 is the framework of the proposed method.

2 The Architecture of the Proposed Approach

2.1 The Integrated System

Figure 1 shows that the learning process of the proposed method is multiple ANFIS, its trained input being the controllable parameters of the process, and the output being the quality characteristics. Once the input/output is established by multiple ANFIS, PPSO algorithm is then used to find the optimal process parameters.

2.2 PPSO Algorithm

The procedure for the algorithm is shown in figure 2. Since the quality characteristic of this example is the larger-the-better case, PPSO is basically a maximum problem. The PPSO algorithm, unlike traditional PSO algorithms, includes the perturbed strategy. Its implementation is as follows:

Step 1. (Initial solution): Randomly generate L initial solutions.

Step 2. (Update the velocity): The calculation of every particle in the PPSO algorithm is moved by two sets of information, which are the current optimal solution and the optimal solution for individual particles. PPSO algorithm moves the whole group of particles toward the optimal solution through the global optimum (*gbest*). Individual particles perform the calculation in accordance with their personal memory. The particles update their velocity as follows:

$$v_{ij}^{k+1} = wv_{ij}^{k} + c_1 rand_1 \left(pbest_{ij} - s_{ij}^{k} \right) + c_2 rand_2 \left(gbest_j - s_{ij}^{k} \right) \tag{1}$$

where v_{ij}^{k} is the velocity of particle i at controllable parameter j at iteration k. w is the inertia weight within the range [0, 1]. c_1 and c_2 are two constants; $rand_1$ and $rand_2$ represent the uniformly random value between 0 to 1. s_{ij}^{k} is the position (solution) of particle i at controllable parameter j at iteration k. $pbest_{ij}$ is the value of the optimal solution of particle i at controllable parameter j. $gbest_j$ is the value of the global optimum at controllable parameter j. The initial velocity is generated randomly.

Step 3. (Update position): The update of the solution for every particle is as follows:

$$s_{ij}^{k+1} = s_{ij}^{k} + v_{ij}^{k+1} \tag{2}$$

Step 4. (Obtain quality characteristic): The quality characteristics are obtained through a model learned by ANFIS.

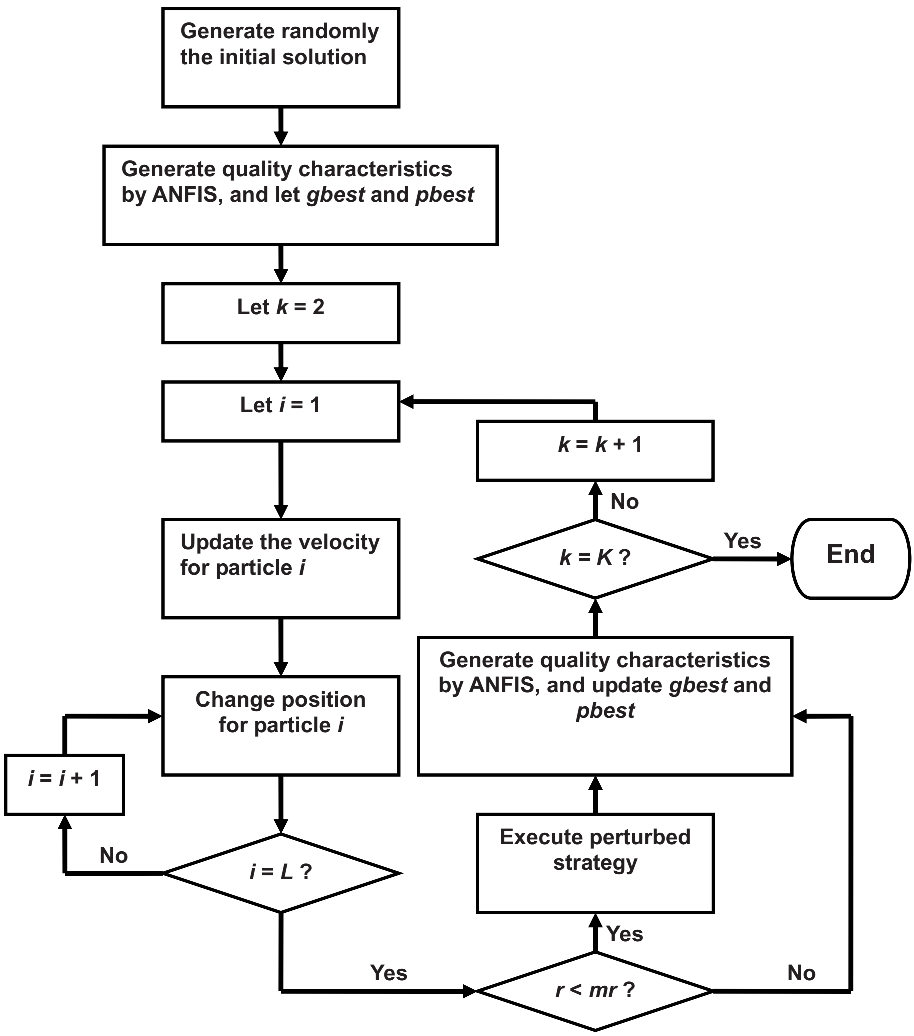


Fig. 2. Flow chart of the PPSO

Step 5. (Perturbed strategy): This is the key step in the modified PSO. When a random value between [0, 1] $r <$ the perturbed rate pr, the perturbed strategy is executed. Its procedure is as follows:

begin
  if $r < pr$
    for $i = 1$ to L
      $\left\{ v_{ij}^k \mid j \in E_i^k \right\} \leftarrow$ a random value between $[a, b]$;
    end for
  end if
end

where a and b are adjustable parameters. A controllable parameter of particle i, E_i^k, is chosen randomly at iteration k.

3 Proposed Algorithm Test

This section compares the performance of the PPSO proposed by this paper and the PSO through the testing functions, the objective being maximum equations (3)-(6). The algorithm is run on every function 100 times; the initial solution is generated with the uniform random number between [–5, 5]. The parameter of the algorithm is $w = 0.7$, the number of particles = 200, and the number of iterations = 7000. Moreover, parameters $c_1 = 1.2$ and $c_2 = 1.2$ are used in equations (3)-(5). Parameters $c_1 = 1.2$ and $c_2 = 0.7$ are used in equation (6).

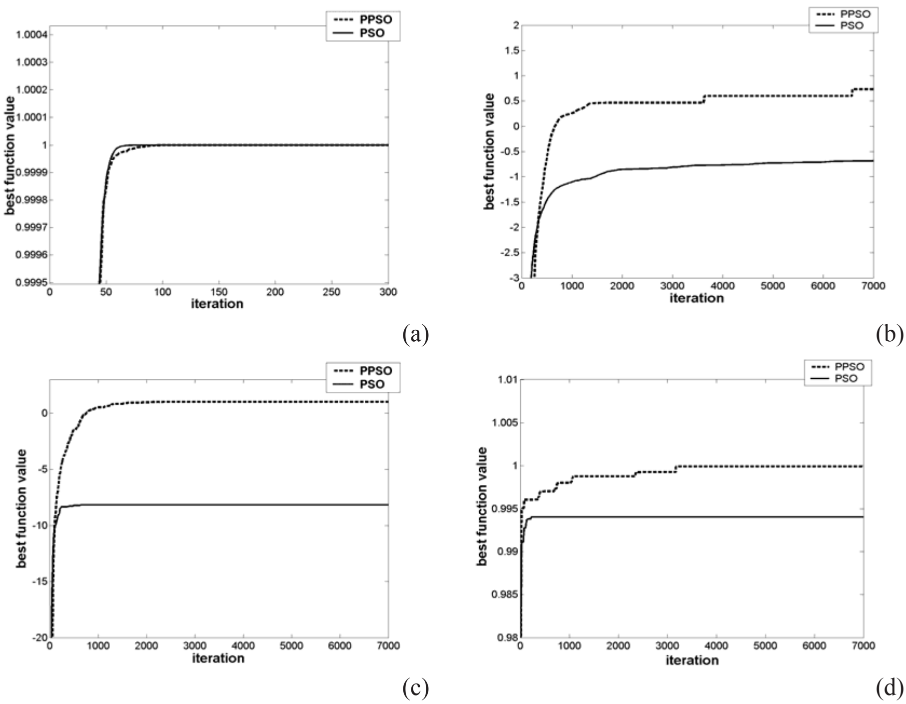


Fig. 3. Convergence process of PPSO and PSO in the (a) f_1, (b) f_2, (c) f_3, and (d) f_4

$$f_1 = 1 - \sum_{i=1}^{N} z_i^2 \tag{3}$$

$$f_2 = 1 - \sum_{i=1}^{N-1} \left[100 \times \left(z_i^2 - z_{i+1} \right)^2 + \left(1 - z_i \right)^2 \right] \tag{4}$$

$$f_3 = 1 - 10 \times N + \sum_{i=1}^{N} \left[z_i^2 - 10\mathrm{COS}\left(2\pi z_i \right) \right] \tag{5}$$

Table 1. Result of the algorithm test

1.	Tested function Equation (3)				Optimal solution $z_i=0$ $f_1(z_i)=1$			
	PSO				PPSO			
	Min.	Avg.	Max.	∇ [a]	Min.	Avg.	Max.	∇
$N=3$	1.000	1.000	1.000	100	1.000	1.000	1.000	100
$N=6$	1.000	1.000	1.000	100	1.000	1.000	1.000	100
$N=9$	1.000	1.000	1.000	100	1.000	1.000	1.000	100
$N=12$	1.000	1.000	1.000	100	1.000	1.000	1.000	100
2.	Tested function Equation (4)				Optimal solution $z_i=1$ $f_2(z_i)=1$			
	PSO				PPSO			
	Min.	Avg.	Max.	∇	Min.	Avg.	Max.	∇
$N=3$	1.000	1.000	1.000	100	1.000	1.000	1.000	100
$N=6$	1.000	1.000	1.000	100	1.000	1.000	1.000	100
$N=9$	–2.986	0.798	1.000	92	1.000	1.000	1.000	100
$N=12$	–3.320	–0.589	1.000	16	–2.987	0.920	1.000	98
3.	Tested function Equation (5)				Optimal solution $z_i=0$ $f_3(z_i)=1$			
	PSO				PPSO			
	Min.	Avg.	Max.	∇	Min.	Avg.	Max.	∇
$N=3$	0.005	0.970	1.000	97	1.000	1.000	1.000	100
$N=6$	–4.970	–0.264	1.000	28	1.000	1.000	1.000	100
$N=9$	–10.940	–3.447	1.000	3	1.000	1.000	1.000	100
$N=1 2$	–17.904	–9.029	–0.990	0	1.000	1.000	1.000	100
4.	Tested function Equation (6)				Optimal solution $z_i=0$ $f_4(z_i)=1$			
	PSO				PPSO			
	Min.	Avg.	Max.	∇	Min.	Avg.	Max.	∇
$N=3$	1.000	1.000	1.000	100	1.000	1.000	1.000	100
$N=6$	0.988	0.999	1.000	85	1.000	1.000	1.000	100
$N=9$	0.988	0.998	1.000	73	1.000	1.000	1.000	100
$N=12$	0.975	0.994	1.000	48	0.993	1.000	1.000	99

a: ∇ is the number of optimal solutions obtained

$$f_4 = 1 - \sum_{i=1}^{N}\left(\frac{z_i^2}{4000}\right) - \prod_{i=1}^{N}\cos\left(\frac{z_i}{\sqrt{i}}\right) \quad (6)$$

Table 1 shows that in all 100 runs, except for when N = 12, PPSO is able to find the global optimum for every testing functions, and yielded superior performance to the PSO. Figure 3 shows the improvement of the average best solution for equations (3)-(6). The results indicate that the perturbed strategy can effectively prevent this algorithm from caving into the local optimum.

4 Example Application of the Approach

This section demonstrates the applicability of the proposed method through the optimization of parameters for the second bonding process.

4.1 The Wire Bonding Process

In semi-conductor manufacturing, the wire bonding process is the key technology in the packaging industry. The goal is to connect the chip with the inner lead in the lead frame with a fine gold wire so that the electronic signals of the IC chips can be transmitted. The bonding point should be firmly secured, or the IC chip will not function. Therefore, the wire bonding process plays a pivotal role in the whole IC packaging industry, the key point being the finding of the optimal parameter for the wire bonding process. During the bonding process, the tip of the gold wire is first molten into a small ball, and then pressed onto the first bonding point. The gold wire is then placed in the designated path, and pressed onto the second bonding point, as shown in figure 4.

The data used in this paper is the actual process output [19]. The main controllable parameters in the second bonding process include: bonding force, bonding time, the intensity of ultrasonic power. Its quality characteristic is wire pull.

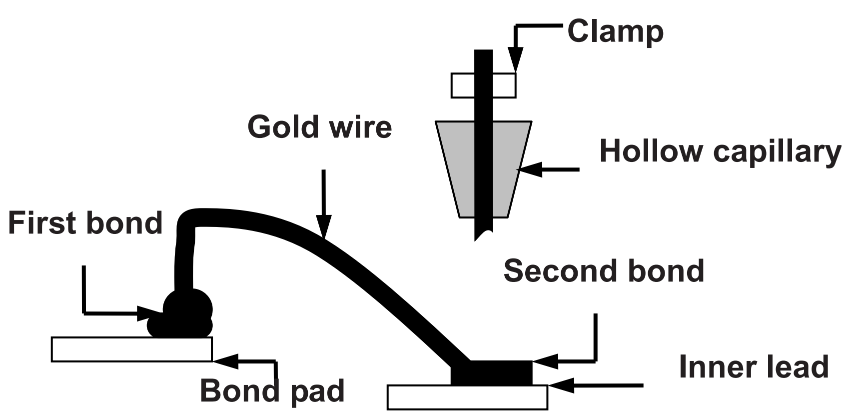


Fig. 4. A typical wire bonding process

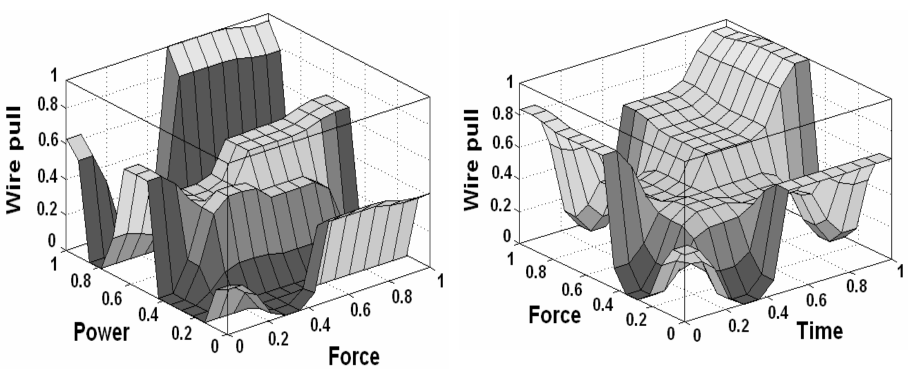
4.2 The Learning Result of ANFIS

In order to enhance the learning of ANFIS, the controllable parameters and quality characteristics are first pre-processed. This means normalizing the original data so as to avoid overlooking the importance of variables of a smaller range if the range of the variables in the trained data became wider. This will prevent the entire network learning being dominated by variables with a greater range, and also affect the entire learning result of ANFIS. Therefore, this experiment normalized the quality characteristics and the parameters between [0, 1].

Table 2. The learning result of ANFIS

Number of membership	Membership function					
	Triangle		Trapezoid		Bell-shaped	
	Training error	Testing error	Training error	Testing error	Training error	Testing error
3-3-3	0.083153	0.15436	0.083241	0.16392	0.083241	0.12689
4-6-4	0.038244	0.21061	0.061158	0.09495	0.049367	0.11436
6-4-6	0.037719	0.34165	0.061158	0.44553	0.049267	0.42281

The parameters of ANFIS learning include: membership function and the number of memberships among the variables. In terms of membership function, triangle, trapezoid and bell-shape are chosen for testing. There are also three sets of numbers chosen as the number of membership among the variables. Table 2 shows that when the membership function is a trapezoid and the numbers of memberships are [4-6-4], the root mean square error (RMSE) is the smallest. Therefore, this paper adopts this model. Figure 5 shows the response output for quality characteristic in ANFIS.



(a) (b)

Fig. 5. The response surface showing the effect of (a) bonding force and the intensity of ultrasonic power, (b) bonding force and bonding time on the wire pull

4.3 The Proposed Algorithm Implementation

In the packaging industry, the larger the quality characteristic of the second bonding process, the better. This paper uses the PPSO algorithm to find the largest wire pull for the gold wire.

Table 3 shows the result of PSO and PPSO algorithm in 30 runs at the second bonding process. The result indicates that the PPSO algorithm is able to generate the near-optimal parameters for the manufacturing process under the ANFIS-trained model in all 30 runs.

Table 3. Result of the optimization algorithm for the example

Algorithm	Max.	Min.	Avg.	Standard deviation
PSO	1.0000	0.9583	0.9917	0.0167
PPSO	1.0000	1.0000	1.0000	0.0000

5 Conclusion

Manufacturing in the high-tech industry is a complex undertaking. Designing an efficient and easy decision-making system to determine the parameters for processing is, therefore, of paramount importance. Traditional statistical techniques may be restrained by basic assumptions. Therefore, this paper proposes a system for determining the optimal parameters for the process based on artificial intelligence.

This paper uses an adaptive network-based fuzzy inference system to construct the simulation model for the process. A modified particle swarm optimizer algorithm is then used to determine the optimal parameter for the process. This paper then tested the performance of the PPSO algorithm with testing functions, the result of which shows that the perturbed strategy used by PPSO is effective at avoiding caving into the local optimum. This paper further demonstrated the application of the proposed approach with the second bonding process in the IC packaging industry. As far as the optimal parameter in this example is concerned, figure 5 shows that a local optimum exists in the relationship model of controllable parameters and quality characteristics. The result of the testing also shows that this PPSO algorithm is able to find the global optimum under the ANFIS model.

References

1. Kalil, S.J., Mauger, F., Rodrigues, M.I.: Response surface analysis and simulation as a tool for bioprocess design and optimization. Process Biochem 35(6), 539–550 (2000)
2. Kincl, M., Turk, S., Vrecer, F.: Application of experimental design methodology in development and optimization of drug release method. Int. J. Pharm. 291(1-2), 39–49 (2005)

3. Pech-Canul, M.I., Katz, R.N., Makhlouf, M.M.: Optimum conditions for pressureless infiltration of SiCp performs by aluminum alloys. J. Mater. Process. Tech. 108(1), 68–77 (2000)
4. Kwak, J.S.: Application of Taguchi and response surface methodologies for geometric error in surface grinding process. Int. J. Mach. Tool. Manu. 45(3), 327–334 (2005)
5. Hewidy, M.S., El-Taweel, T.A., El-Safty, M.F.: Modelling the machining parameters of wire electrical discharge machining of lnconel 601 using RSM. J. Mater. Process. Tech. 169(2), 328–336 (2005)
6. Gao, Y.L., Jiang, H.H.: Optimization of process conditions to inactivate Bacillus subtilis by high hydrostatic pressure and mild heat using response surface methodology. Biochem. Eng. J. 24(1), 43–48 (2005)
7. Kansal, H.K., Singh, S., Kumar, P.: Parametric optimization of powder mixed electrical discharge machining by response surface methodology. J. Mater. Process. Tech. 169(3), 427–436 (2005)
8. Kennedy, J., Eberhart, R.: Particle swarm optimization. In: IEEE International Conference on Neural Networks, vol. 4, pp. 1942–1948. IEEE Press, New York (1995)
9. Costa Jr., E.F., Lage, P.L.C., Biscaia Jr., E.C.: On the numerical solution and optimization of styrene polymerization in tubular reactors. Comput. Chem. Eng. 27(11), 1591–1604 (2003)
10. Ourique, C.O., Biscaia Jr., E.C., Pinto, J.C.: The use of particle swarm optimization for dynamical analysis in chemical processes. Comput. Chem. Eng. 26(12), 1783–1793 (2002)
11. Trelea, I.C.: The particle swarm optimization algorithm: convergence analysis and parameter selection. Inform. Process. Lett. 85(6), 317–325 (2003)
12. Jang, J.-S.R.: ANFIS: adaptive-network-based fuzzy inference system. IEEE T. Syst. Man. Cy. 23(3), 665–685 (1993)
13. Cai, C.H., Du, D., Liu, Z.Y.: Battery State-of-Charge (SOC) estimation using adaptive neuro-fuzzy inference system (ANFIS). In: The IEEE International Conference on Fuzzy Systems, vol. 2, pp. 1068–1073. IEEE Press, New York (2003)
14. Mar, J., Lin, F.J.: An ANFIS controller for the car-following collision prevention system. IEEE T. Veh. Technol. 50(4), 1106–1113 (2001)
15. Ho, S.Y., Lee, K.C., Chen, S.S., Ho, S.J.: Accurate modeling and prediction of surface roughness by computer vision in turning operations using an adaptive neuro-fuzzy inference system. Int. J. Mach. Tool. Manu. 42(13), 1441–1446 (2002)
16. Lo, S.P.: An adaptive-network based fuzzy inference system for prediction of workpiece surface roughness in end milling. J. Mater. Process. Tech. 142(3), 665–675 (2003)
17. Yeh, F.H., Tsay, H.S., Liang, S.H.: Applied CAD and ANFIS to the Chinese Braille display optimization. Displays 24(4-5), 213–222 (2003)
18. Ryoo, J., Dragojlovic, Z., Kaminski, D.A.: Control of convergence in a computational fluid dynamics simulation using ANFIS. IEEE T. Fuzzy Syst. 13(1), 42–47 (2005)
19. Huang, K.M.: Applying Taguchi's method to study the optimum parameter for the 50mm fine pitch on the pad in the wire bonding process of the IC assembly. Master Thesis of Engineering, Yunlin University of Science & Technology (2002)