http://ansinet.com/itj

ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 9 (5): 918-926, 2010
ISSN 1812-5638

Employing Artificial Neural Networks into Achieving Parameter Optimization of Multi-Response Problem with Different Importance Degree Consideration

Kun-Lin Hsieh
Department of Information Management,
National Taitung University, 684, Sec.1, Chung-Hua Rd., Taitung, Taiwan

Abstract: This study proposed a procedure based on Artificial Neural Networks (ANNs) technique with different importance degree consideration to address parameter optimization of a multiple responses problem. No matter what type of the experimental designs being employed, the proposed approach can be directly employed. Besides, the consistency and difference between those multiple responses can be also studied via the aggregation weight values in our proposed procedure. An illustrative example owing to the lead frame manufacturer in Taiwan is also employed to demonstrate the effectiveness and rationality of the proposed procedure.

Key words: Multi-response problem, parameter optimization, Back-Propagation Neural Network (BPNN), lead frame, aggregation weight

INTRODUCTION

Design of Experiment (DOE) can be viewed as a well known technique to be used to address the process improvement or parameter optimization. The philosophy is to study the relationship between the design parameter (or the noise parameters) and the response. Herein, the design parameters and noise parameters will affect the quality of products or operational processes. The design parameters are factors that can be controlled by the designers and the noise parameters, e.g., the environmental factors, are factors that can not be controlled by designers. As for the issue of parameter optimization, how to obtain the parameter setting to achieve the response optimization is the primary consideration. That is, setting status of the design parameters will be expected in such a way that the response can attain the desired target with the minimum variation.

After reviewing the related studies (Fowlkes and Creveling, 1995; Montgomery, 1991; Myers and Montgomery, 1995), many studies only address a single evaluation response of the manufactured product or process. The complexity and relationship among the multiple responses will let it be a difficult problem to be addressed. However, the customer or the process frequently considers more than one quality response in practice in the recent years. For a multi-response problem, the conventional MANOVA (Johnson and Wichern, 1992) and the Response Surface Method (RSM) (Myers and Montgomery, 1995) are two techniques frequently applied in the experimental designs domain. But, both theories were hard to be understood for most practitioners. Besides, Taguchi method (Fowlkes and Creveling, 1995; Peace, 1993; Phadke, 1989) is another approach which had frequently used to achieve robust experiment in quality engineering. However, most successful applications of Taguchi method still keep to addressing a single response problem. For addressing the multiple responses problem, Taguchi method need to separately optimize the single evaluation response and the optimum setting of parameter can be then determined via engineering judgment. Until now, several approaches (Ames *et al*., 1997; Castillo *et al*., 1996; Chapman, 1995; Leon, 1996; Phadke, 1989; Su and Tong, 1997; Tong *et al*., 1997; Su and Heish, 1998; Lan, 2009; Lan and Wang, 2009) were proposed to perform the optimization of multiple responses. However, most proposed approaches almost intend to make an integrated index under final decision-making for parameter optimization. However, the information inhibited behind the system might be lost under making the integration action.

Artificial Neural Networks (ANNs) had mentioned to be applied into process modeling problem (Rumelhart *et al*., 1986; Barletta *et al*., 2007; Hsieh and Lu, 2008; Krishnaiah *et al*., 2006; Ozel *et al*., 2007; Lan and Wang, 2009; Kun-Lin, 2009). Tong and Hsieh (2001) had proposed a novel means of applying artificial neural network to solve the multi-response optimization combining the quantitative and qualitative response. Although, the parameter optimization can be obtained, the different importance among those multiple responses still can not be included well into the process analysis. In lieu of above circumstances, we will propose a procedure based on ANNs to perform optimization of the multi-responses problem with different importance consideration in arbitrary experimental design. No matter that the control factors owing to the level form or the real value, this proposed procedure could be utilized.

PARAMETER OPTIMIZATION DURING MULTI-RESPONSE PROBLEM

Derringer and Suich (1980) applied the desirability function to optimize the multi-responses problems in a static experiment. Castillo *et al*. (1996) demonstrated the modified desirability functions for optimizing the multi-response. However, their method may lead to an inaccurate result for some inexperienced users and may increase the uncertainty in determining the optimal parameter setting and is difficult for the practitioners who have only limited statistical training. Layne (1995) presented a procedure, which considers simultaneously three methods: weighted loss function, desirability function and a distance function, to determine the optimum parameter combination. The controversies may be generated by simultaneously comparing three methods to determine the optimum setting. Khuri and Conlon (1981) proposed a procedure, based on a polynomial regression model, to simultaneously optimize several responses. Logothetis and Haigh (1988) also optimized a five-response process by utilizing the multiple regression technique and the linear programming approach. These two methods are also computationally complex and, therefore, are difficult to be utilized on the shop floor. Pignatiello (1993) utilized a variance component and a squared deviation-from-target to form an expected loss function to optimize a multiple response problem. This method is hard to implement for that a cost matrix must be obtained, in addition, the amount of the experimental observations are required. Chapman (1995) proposed a co-optimization approach, which composites all response by using a composite response. This approach might confuse some inexperienced practitioners in determining which ranges of the constraint's can be safely expanded. Leon (1996) presented a method, which is based on the notions of a standardized loss function with the specification limits, to optimize a multi-response problem. However, only the Nominal-The-Best (NTB) characteristic is suitable to employ this approach, which may limit the capability for this approach. Ames *et al*. (1997) presented a quality loss function approach in the response surface models to deal with a multi-response problem. The basic strategy is to describe the response surfaces with experimentally derived polynomials, which can be combined into a single loss function by using known or desired targets. Next, minimizing the loss function with respect to process inputs locates the best operating conditions. Lai and Chang (1994) proposed a fuzzy multi-response optimization procedure to search for an appropriate combination or process parameter settings. A strategy of optimizing the most possible response values and minimizing the deviation from the most possible values is used which considers not only the most possible value, but also the imprecision of the predicted responses. Tong and Su (1997) developed a Multi-Response Signal to Noise (MRSN) ratio, which integrates the quality loss for all responses, to solve the multi-response problem. Conventional Taguchi method can be applied based on MSRN. The optimum factor/level combination can be obtained. Su and Tong (1997) also proposed a principle component analysis approach to perform the optimization of the multi-response problem. Initially, standardizing the quality loss of each response; the principle component analysis is then applied to transform the primary quality responses into fewer quality responses. Finally, the optimum parameter combination can be obtained by maximizing the summation standardized quality loss. Hsieh (2006) had proposed an AI technique, i.e., the Backpropoagation Neural Network (BPNN), to address the multi-response problem. The non-linear relationship between the process parameter and process response can be modeled well by using BPNN. Besides, the continuous parameter settings can be obtained by their proposed approach. However, the different importance among multi-responses can not be included in Hsieh's approach and it will limit his real application.

WEIGHT VALUE CONSIDERATION DURING MULTI-RESPONSE PROBLEM

The choice and the summation for the weight values of several criterions and the difference comparison among several performances with weighted consideration will be the problem for the issue of Multiple Criterions Decision-Making (MDCM) (Zeleny, 1982, 1992). As for the choice of weight value, it will be more difficult to be determined during the multiple criterions consideration for those practitioners. Hence, AHP (Saaty, 1994, 1996, 2001; Lai *et al*., 1999; Rammanathan and Ganesh, 1995; Ngai, 2003) was developed to overcome such issue by dividing those criterions into the primary and secondary criterions with hierarchy. However, the test of consistency frequently limited its real applications (Nishizawa, 1995). As for the summation of the weight value, the practitioners will face the problem of how to summarize the weight effect of each criterion with the case of several experts. The average concept was the method frequently been used to compute the weight value of each criterion. However, the variation between different experts will be omitted by using the average concept to compute the weight value. Restated, it can be viewed as meeting the problem of common consensus during those experts. Generally, the larger degree of importance of criterion will denote the corresponding weight value to be set a larger value. Tong and Su (1997) proposed a procedure, which applied fuzzy set theory to Multiple Attribute Decision Making (MADM) for optimizing a multi-responses problem. Although, their method can reduce the uncertainty in determining each response's weight, it is still computational complicated to be practically used. Shen and Hsieh (2006) had proposed a fuzzy weight aggregator to address the decision-making about the weight values with different experts. The consistency and difference between several experts can be included in their proposed approach. Hence, it will be included into this study.

PROPOSED APPROACH

Generally, a particular relationship may exist between input and output for a system. From mathematical viewpoint, the logical relationship can be modeled by constructing the model for system. System's output can be viewed as a function of system's input. Due to the logical analysis, the reverse inference can also be employed to model a system, that is, the input can be also viewed as a function of the output. It can be clearly interpreted from the mathematical definition: a direct mathematical concept is $O = f(I)$ and a reverse mathematical concept is $O = f^{-1}(I)$, where, the O denotes the system's output, I denotes the system's input and f will be mathematical relationship between O and I. The neural networks can be used to model this logical analysis to achieve quality optimization (Barletta *et al*.., 2007; Heish, 2006; Hsieh and Lu, 2008; Krishnaiah *et al*., 2006; Ozel *et al*., 2007). In this study, we also apply the logical analysis mentioned to construct the procedure and make modification. The proposed procedure can be utilized for the conventionally experimental design and the Taguchi's experiment. The concept of the procedure will be given as follows.

Phase I. Determine the weight values of those multiple responses according to the experts:

- **Step 1:** Compute the membership degree μ_{ij} according to X_{ij} for the evaluation table which is made by several experts

Assuming that there are n responses, m experts, evaluation value X_{ij} of ith response for jth expert, we can construct such evaluation table. Then, the ideal point of each criterion can be obtained by finding the maximum X_{ij} value among each response. Next, the membership degree μ_{ij} for each evaluation value with respect to the ideal point can be computed via the Eq. 1:

$$\mu_{ij} = \frac{X_{ij}}{\max_i \{X_{ij}\}} \tag{1}$$

- **Step 2:** Compute the harmonizing mean of each criterion by using Eq. 2

Where α will denote the degree of importance and the larger α will represent the enlarger effect of importance. Generally, we can take α to be 1 for simplifying the analysis.

$$h_i = \frac{1}{m}\sum_{j=1}^{m}\frac{1}{(\mu_{ij})^{\alpha}} \tag{2}$$

- **Step 3:** The average weight of ith response (w_i) can be computed as Eq. 4 by using e_i. The value (e_i) of ith response can be computed as Eq. 3 by using the Eq. 2:

$$e_i = \frac{1}{h_i} \tag{3}$$

$$w_i = \frac{e_i}{\sum_{j=1}^{n} e_i} \tag{4}$$

Phase II. Parameter optimization

Case I: For discrete parameter combination (i.e., level combination of control factors):

Step 1: Randomly select the data from the designed experiment to form the training and the testing data set of the neural network. The ratio of the testing/training set is about 1/4 (NeuralWare, 1990)

Step 2: Determine the optimal level settings for process parameters

- Firstly, compute the desirability value (Derringer and Suich, 1980) of each response according to the following formulas

The-Nominal-The Best (NTB): The value of y is expected to the target T. When the y equals to T (target), the desirability value equals to 1; if the departure of y excesses a particular range from the target, the desirability value equals to 0 and, such situation represents the worst case. The desirability function of the-nominal-the-best can be written as the Eq. 5:

$$d = \begin{cases} \left(\dfrac{y - y_{min}}{T - y_{min}}\right)^s, y_{min} \le y \le T, s > 0 \\ \left(\dfrac{y - y_{max}}{T - y_{max}}\right)^t, T \le y \le y_{max}, t < 0 \\ 0, \text{ otherwise} \end{cases} \quad (5)$$

where, the y_{max} and y_{min} represent the upper/lower tolerance limits of y, s and t represent the weight value of response and the weight value can be obtained from phase I.

The-Larger-The Best (LTB): The value of y is expected to the larger the better. When, they excess a particular criteria value, which can be viewed as the requirement, the desirability value equals to 1; if the y is less than a particular criteria value, which is unacceptable, the desirability value equals to 0. The desirability function of the-larger-the-best can be written as the Eq. 6:

$$d = \begin{cases} 0, y \le y_{min} \\ \left(\dfrac{y - y_{min}}{y_{max} - y_{min}}\right)^r, y_{min} \le y \le y_{max}, r > 0 \\ 1, y \ge y_{max} \end{cases} \quad (6)$$

where, the y_{min} presents the lower tolerance limit of y, the y_{max} presents the upper tolerance limit of y, r represents the weight of response and the weight value can be obtained from phase I.

The-Smaller-The Best (STB): The value of y is expected to be the smaller the better. When the y is less than a particular criteria value, the desirability value equals to 1; if the y excess a particular criteria value, the desirability value equals to 0. The desirability function of the-smaller-the-best can be written as the Eq. 7:

$$d = \begin{cases} 1, y \le y_{min} \\ \left(\dfrac{y - y_{min}}{y_{max} - y_{min}}\right)^r, y_{min} \le y \le y_{max}, r > 0 \\ 0, y \ge y_{max} \end{cases} \quad (7)$$

where, the y_{min} presents the lower tolerance limit of y, the y_{max} presents the upper tolerance limit of y, r represents the weight of response and the weight value can be obtained from Phase I.

- Train the neural network by assigning the (level setting of parameters)/(desirability value of response) as the (inputs/outputs) of the neural network. The RMSE (Root of the Mean Square Error) value of the training and testing phase will be taken as an evaluation index since comparing the different network's architecture, i.e. the number of PEs in input layer - the number of PEs in hidden layer- the number of PEs in output layer, the learning rate, the possible momentum, the transfer function. The architecture with the minimum training RMSE and testing RMSE values is selected to be the optimum architecture

For example, an experiment has three design parameters (A, B, C) with two levels and three responses Y_1, Y_2 and Y_3. And then, those three responses will have different importance and it will be described with respect to different weight value. And then, the desirability value of response can be computed according to Eq. 5-7. The structure of the training and testing data set can be represented as follows (where $Factor_{(Level)}$ denotes the level label of Factor, D_{IJ} denotes the desirability value for the Ith response for the Jth trail):

	Network's input	Network's output
No.	Parameter's combination	Responses
1	$[A_{(Level)}, B_{(Level)}, C_{(Level)}]$	D_{11}, D_{21}, D_{31}
	•	•
	•	•
8	$[A_{(Level)}, B_{(Level)}, C_{(Level)}]$	D_{18}, D_{28}, D_{38}

- Retrain the selected neural network to arrive at the steady state (i.e., the RMSE value will not make any change or less than the pre-designed criterion) by combining the above training and testing set in Step 1 into a training set
- Input the all possible parameters' level settings (according to the combination of different level) to the trained neural network, the estimated desirability values can be obtained

Step 3: If the users can not accept the estimated response values, re-choose the parameter factors or go back Step 2 to re-train the neural network architecture. Otherwise, the analysis procedure can stop.

Case II: For control factor with mixed type (including the level label and continuous value or all the continuous type):

Step 1: Randomly select the data from the designed experiment to form the training and the testing data set for the neural network. The ratio of the testing/training set is about 1/4

Step 2: Determine the optimal parameter combination

- Firstly, compute the desirability value of each response according to Eq. 5-7.
- Train the neural network by assigning (response value and the desirability value of each response/ level setting of parameters) as the (inputs/outputs) of the neural network. If the factor is discrete type, the output of corresponding PE will be represented as the level number. The RMSE values of the training and testing phase will be the evaluation index when different network's architectures are compared. The architecture with the minimum training and testing RMSE values is selected to be the optimum architecture

For example, a static experiment has three design parameters (A, B, C) with two levels and three responses Y_1, Y_2 and Y_3. And, those three responses will have different importance and it can be represented by using the different weight values. And then, the desirability value can be computed according to Eq. 5-7. Herein, factor A is discrete type and factor B and C are the continuous type. The structure of the training and testing data set can be represented as follows (where $Factor_{(Level)}$ denotes the level label of Factor, $Factor_{(value)}$ denotes the continuous value of Factor, Y_{IJ} denotes the response value of Ith response for the Jth trail, D_{IJ} denotes desirability of the Ith response for the Jth trail, D_{IJ} denotes the desirability value for the Ith response for the Jth trail):

No	Network's input	Network's output
1	$Y_{11}Y_{21}Y_{31}\ D_{11}D_{21}D_{31}$	$[A_{(Level)},\ B_{(value)},\ C_{(value)}]_1$
	•	•
	•	•
8	$Y_{18}Y_{28}Y_{38}\ D_{18}D_{28}D_{38}$	$[A_{(Level)},\ B_{(value)},\ C_{(value)}]_8$

- Retrain the selected neural network's architecture to approach the steady-state (i.e., the RMSE value will not make any change or less than the pre-designed criterion) by combining the above training and testing set in Step 1 into a training set
- The optimum parameter combination can be obtained by inputting the ideal values or the targets, i.e., the multiple responses' ideal condition, the desirability value (1) and the expected weighted response to the trained neural network

Step 3: Estimate the responses' values and determine the effect of the control factor on responses.

- Train the neural network by assigning the (level setting of parameters)/(desirability value of response) as the (inputs/outputs) of the neural network. The RMSE values of the training and testing phase will be the evaluation index when different network's architectures are compared. The architecture with the minimum training RMSE and testing RMSE values is selected to be the optimum architecture

For example, an experiment has three design parameters (A, B, C) with two real values and three responses Y_1, Y_2 and Y_3 And, those three responses will have different importance and it can be represented by using the different weight values. And then, the desirability value can be computed according to Eq. 5-7. Factor A is discrete type and factors B and C are the continuous type. The structure of the training and testing data set can be represented as follows (where $Factor_{(Level)}$ denotes the level label of Factor, $Factor_{(value)}$ denotes the continuous value of Factor, D_{IJ} denotes the desirability value for the Ith response for the Jth trail):

No.	Network's input	Network's output
1	$[A_{(level)},\ B_{(value)},\ C_{(value)}]_1$	D_{11}, D_{21}, D_{31}
	•	•
	•	•
8	$[A_{(level)},\ B_{(value)},\ C_{(value)}]_8$	D_{18}, D_{28}, D_{38}

- Retrain the selected neural network's architecture to arrive at the steady-state (i.e., the RMSE value will not make any change or less than the pre-designed criterion) by combining the above training and testing set in Step 1 into a training set
- Input the optimum parameter condition obtained in step 2, the estimated response values can be obtained

Step 4: If the users can not accept the estimated response values, re-choose the parameter factors or go back step 2 to re-train the neural network

ILLUSTRATIVE EXAMPLE

In this study, we apply an example owing to lead frame manufacturing improvement introduced by Hsieh (2006) to demonstrate the proposed procedure. Lead frame is a necessary material to the conventional Integrated Circuit (IC) packaging. Taping process is an important operation for lead frame manufacturing. Figure 1 graphically depicts the concept diagram of the lead frame

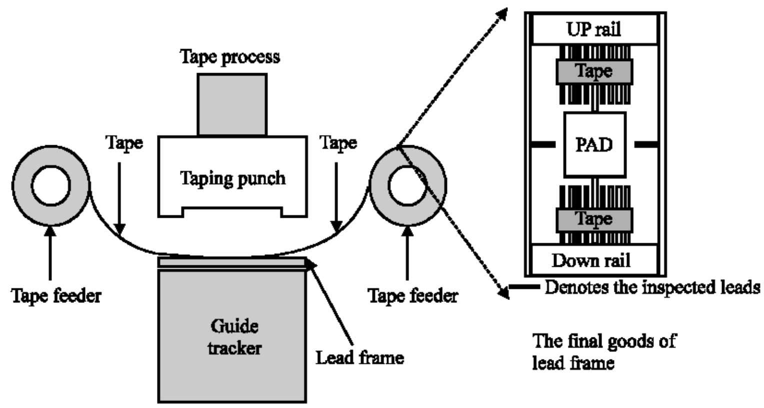

Fig. 1: The concept diagram of the taping process in taping station

and the taping process. The purpose of the taping process is to maintain the co-planarity of the leads and make it to be efficiency utilized during the wire bonding.

To avoid the broken in wire bonding during the subsequent packaging, the taping strength must be monitored by the lead frame manufacturer. The height of the adhesive bleeding is another important consideration except the taping strength. During the current setting values of related process parameters for SO product series, the average taping strength is about 145 g and the variance of the taping strength is about 36 g; the average height of adhesive bleeding is 7.4 mil and the variance adhesive bleeding is 1.32 mil. The quality of taping process can not be accepted by the lead frame manufacturer. The manufacturer would like to perform the parameter optimization for simultaneously optimizing two responses: maintaining the taping strength (Y1) as 180 g and the height of adhesive bleeding (Y2) as 5 mil.

After performing a brainstorming, four control factors as pressure strength (A), spacing (B), curing temperature (C) and dwell time (D) are chosen. For experienced judgment, each control factors have three level settings for designed experiments. Table 1 shows the level settings of control factors. The current settings are denoted by underline. To reduce the experimental time and cost, an Orthogonal Array (OA) L_9 is selected (Taguchi, 1996). Each parameter combination will repeat five trails, hence, 45 data are observed.

The presenting settings are denoted as underline. In this illustrative example, the control factors nearly have a continuous form, thereby accounting for why the optimal control values can be studied. Hence, the case II of the proposed approach will be performed. To simplify the proposed approach, the neural network package software, i.e., Neural Professional Plus/II [15], is used to develop the required networks. It is a C based simulator that provides

Table 1: The level settings of the control factors

	1	2	3
Factor	(Level)		
Pressure strength (kg cm^{-2})	P-1	P	P+1
Spacing (mil)	S-1	S	S+1
Curing temperature (mil)	C-15	C	C+15
Dwell time (sec)	t	t+1	t+2

Table 2: The evaluation result of five experts

Expert	Taping strength (Y1)	Height of adhesive bleeding (Y2)
1	5	2
2	4	2
3	5	3
4	5	2
5	4	4

a system for developing various neural network models. Before, we perform the parameter optimization, we discussed with the senior engineers to determine the importance degree of those two responses. And then, five senior engineers and managers were grouped to determine the related importance about those two responses by using the scale five. And, the evaluation result of those five experts will be given in Table 2. For each response, Likert's 5 scales was applied into achieving evaluation. Restated, score 5 will denote the most importance and score 1 will denote the less importance with the respect response. Next, the phase I of our proposed procedure will be taken to compute the suitable weight values as 0.6024 (for taping strength) and 0.3976 (for the height of adhesive bleeding).

Next, ten trials (this example includes forty-five trials) are randomly chosen from the forty-five trails to form the testing set and the remainder are used to form the training set. This makes the proportion of testing/training to be about 1/4. Herein, all factors will have the continuous type, we will choose the procedure of mixed type. In such procedure, the number of PEs in the input layer for neural network is five (including two responses, two desirability

Table 3: The RMSE of the training and testing for step2

Structure	Training RMSE	Testing RMSE
5-3-4	0.512	0.584
5-5-4	0.428	0.499
5-7-4	0.253	0.397
5-9-4*	0.196	0.263
5-11-4	0.185	0.291
5-13-4	0.194	0.327

*Denotes the optimum neural network's structure

Table 4: The RMSE of the training and testing for step3

Structure	Training RMSE	Testing RMSE
4-3-2	0.318	0.415
4-4-2	0.264	0.362
4-5-2	0.185	0.208
4-6-2*	0.124	0.195
4-7-2	0.116	0.269
4-8-2	0.112	0.325

*Denotes the optimum neural network's structure

value of those two responses and the weighted response value). The number of output PEs for neural network will be set as four (including four control factors with the continuous type). These two responses in this case are NTB type, hence, the Eq. 5 will be used to derive the additional information. Due to that the weight values of those two responses were obtained as 0.6024 and 0.3976, the parameter of s (or t) in Eq. 5 will be set as 0.6024 (for addressing Y_1) and 0.3976 (for addressing Y_2). Table 3 shows the options for determining the network's architecture and the structure 5-9-4 is chosen for having the better performance (training's RSME ≅ 0.196 and testing RMSE ≅ 0.263) with the learning rate being 0.125, the momentum value being 0.8, transfer function being sigmoid function, learning rule being delta-bar-delta rule and learning epochs being 5000. Re-train the chosen network's structure by combining the training and testing set to arrive at 5000 epochs. Then, inputting the ideal values (180, 5, 1, 1) to the trained network, the optimum parameter combination derived from neural network can be obtained: [pressure strength, spacing, curing temperature, dwell time] = [(P-0.51) kg cm^{-2}, (S-0.46) mil, (C-3.6) min, (t+1.5) sec].

Next, for obtaining the estimates of those two responses and determining the effect of the four control factors in step 3, the second neural network is constructed by assigning the (parameter combination/desirability value) to be the (inputs/outputs) of the network. The training and testing set are randomly selected to arrive at the (testing/training) proportion of 1/4. Table 4 shows the options of the network and the structure 4-6-2 is chosen for having the better performance (training's RSME ≅ 0.124 and testing RMSE ≅ 0.195). Re-train the second network chosen by combining the training and testing set to arrive at the situation of the weighted value having no any change. The estimated desirability values can be obtained by

Table 5: The result of the confirmation experiment

No.	Taping strength	Height of adhesive bleeding
1	185.00	4.900
2	183.00	4.500
⋮	⋮	⋮
9	183.00	4.900
10	182.00	4.800
Statistical analysis		
Mean	185.30	4.8200
Variance	2.79	0.1930

inputting the optimum parameter combination obtained in step 2 to the second network. The estimated responses of the taping strength and the height of adhesive bleeding can be transferred by using Eq. 5 to be 179.25 g and 4.95 mil. The estimated response values significant achieve the desired quality, the engineers can accept it and permit to perform the confirmation experiment.

Although, the estimated optimal parameter setting is denoted as [(P-0.51) kg cm^{-2}, (S-0.46) mil, (C-3.6)°C, (t+1.5)sec], the actual parameter setting is determined as [(P-0.5) g cm^{-2}, (S-0.5) mil, (T-4) mil, (t+1.5)sec] due to that it is hard to directly set the operating parameter by using the predicted recommendation. Finally, the confirmed experiments for the proposed procedure are performed. Table 5 shows those results. The average value of the taping strength is 185.3g and the average height of adhesive bleeding is 4.82 mil. They are close to the target value (180 g, 5 mil) than the current result. The result obtained from the confirmed experiments for the proposed procedure indicate that using the proposed approach can efficiently enhance the product quality, thereby confirming the proposed approach's effectiveness. The process engineers can accept the results from the optimal parameter setting as [(P-0.4) g cm^{-2}, S mil, (T-3)°C, (t+1.5)sec]. Moreover, the variances of the two responses (taping strength's variance is about 2.79 g and the height's variance is about 0.193 mil) for the confirmation experiment are significantly less than that of the current settings. Although, only one experiment is employed in this study, the validity of the proposed approach can still be verified.

CONCLUSION

In this study, an optimization procedure based on ANNs modeling technique with the different importance degrees for multiple responses is proposed. The proposed approach can not only be employed in conventional experimental design, but Taguhci's experimental design is also can be performed. The proposed approach can provide several metrics: (1) The continue parameter's optimum condition can be obtained since the control factor being quantitative form; (2) The importance degrees (or the weight values) of those multiple responses can be included into the parameter optimization. And, the consistency and difference among those multiple responses can be considered well in this proposed procedure and (3) The ANNs operation can be viewed as a black-box processing, hence, the practitioners can rapidly and easily applied it via any ANNs software, especial for those engineers having the limited statistical training. In addition, we will suggest collect more experimental data to train neural networks, the higher neural network's modeling capability may be achieved. The engineers can efficiently optimize the multi-response problem in the field of the quality improvement by employing the proposed optimization procedure.

REFERENCES

Ames, A.E., N. Mattucci, S. Macdonald, G. Szonyi and D.M. Hawkins, 1997. Quality loss functions for optimization across multiple responses surface. J. Qual. Technol., 29: 339-346.

Barletta, M., A. Gisario and S. Guarino, 2007. Modeling of electrostatic fluidized bed (EFB) coating process using artificial neural networks. Eng. Appl. Artific. Intell., 20: 721-733.

Castillo, E.D., D.C. Montgomery and D.R. McCarville, 1996. Modified desirability functions for multiple response optimization. J. Qual. Technol., 28: 337-345.

Chapman, R.E., 1995. Photochemistry multiple response co-optimization. Qual. Eng., 8: 31-45.

Derringer, G. and R. Suich, 1980. Simultaneous optimization of several response variables. J. Qual. Technol., 12: 214-219.

Fowlkes, W.Y. and C.M. Creveling, 1995. Engineering Methods for Robust Product Design. 1st Edn., 1st Printing, Massachusetts: Addison-Wesley Publishing Company.

Hsieh, K.L., 2006. Parameter optimization of a multi-response process for lead frame manufacturing by employing artificial neural networks. Int. J. Adv. Manuf. Technol., 28: 584-591.

Hsieh, K.L. and Y.S. Lu, 2008. Model construction and parameter effect for TFT-LCD process based on yield analysis by using ANNs and stepwise regression. Exp. Syst. Appl., 34: 717-724.

Johnson, N. and D. Wichern, 1992. Applied Multivariate Statistical Analysis. Prentice-Hall, Englewood Cliffs, N.J. USA.

Khuri, A.I. and M. Conlon, 1981. Simultaneous optimization of multiple responses represented by polynomial regression functions. Technometrics, 23: 363-375.

Krishnaiah, J., C.S. Kumar and M.A. Faruqi, 2006. Modelling and control of chaotic processes through their bifurcation diagrams generated with the help of recurrent neural network models Part 2: An industrial study. J. Process Control, 16: 67-79.

Kun-Lin, H., 2009. The application of value analysis based on Kano's two dimensions model and value expansion model. Inform. Technol. J., 8: 1020-1026.

Lai, Y.J. and T.H. Chang, 1994. A fuzzy approach for multiresponse optimization: An off-line quality engineering problem. Fuzzy Set Syst., 63: 117-129.

Lai, V.S., R.P. Trueblood and B.K. Wong, 1999. Software selection: A case study of the application of the analytical hierarchical process to the selection of a multimedia authoring system. Inform. Manage., 36: 221-232.

Lan, T.S., 2009. Taguchi optimization of multi-objective CNC machining using TOPSIS. Inform. Technol. J., 8: 917-922.

Lan, T.S. and M.Y. Wang, 2009. Quality prediction model of injection-molded rib design using back propagation network. Inform. Technol. J., 8: 847-854.

Layne, K.L., 1995. Methods to determine optimum factor levels for multiple response in designed experimentation. Qual. Eng., 7: 649-656.

Leon, N.A., 1996. A pragmatic approach to multiple-response problem using loss function. Qual. Eng., 9: 213-220.

Logothetis, N. and A. Haigh, 1988. Characterizing and optimizing multi-response processes by the taguchi method. Qual. Reliability Eng. Int., 4: 159-169.

Montgomery, D.C., 1991. Design and Analysis of Experiments. 1st Edn., Grupo Editorial Iberoamerica, DF., Mexico, pp: 589.

Myers, R.H. and D.C. Montgomery, 1995. Response Surface Methodology. John Wiley and Sons, Inc., New York.

NeuralWare, Inc., 1990. NeuralWorks Professional II/Plus and NeuralWorks Exporer. NeuralWare, Inc., Penn Center West.

Ngai, E.W.T, 2003. Selection of web sites for online advertising using the AHP. Inform. Manage., 40: 233-242.

Nishizawa, K., 1995. A consistency improving method in binary AHP. J. Operat. Res. Soc. Jap., 38: 21-33.

Ozel, T., Y. Karpat, L. Figueira and J.P. Davim, 2007. Modelling of surface finish and tool flank wear in turning of AISI D2 steel with ceramic wiper inserts. J. Mater. Process. Technol., 189: 192-198.

Peace, G.S., 1993. Taguchi Methods: A Hands-on Approach. Addison-Wesley Longman, Reading, MA, USA.

Phadke, M.S., 1989. Quality Engineering Using Robust Design. Prentice Hall, Englewood Cliff, New Jersey.

Pignatiello, J.J., 1993. Strategies for robust multi-response quality engineering. IIE Trans., 25: 5-15.

Rammanathan, R. and L.S. Ganesh, 1995. Using AHP for resource allocation problem. Eur. J. Oper. Res., 80: 410-417.

Rumelhart, D.E., G.E. Hinton and R.J. Williams, 1986. Learning Internal Representations by Error Propagation. In: Parallel Distributed Processing: Explorations in the Microstructures of Cognition, Rumelhart, D.E. and J.L. McClelland (Eds.). MIT Press, Cambrige, UK., pp: 318-362.

Saaty, T.L., 1994. Fundamentals of Decision Making and Priority Theory with the Analytic Hierarchy Process. RWS Publications, Pittsburgh.

Saaty, T.L., 1996. Decision Making with Dependence and Feedback: The Analytic Hierarchy Process. RWS Publications, Pittsburgh.

Saaty, T.L., 2001. Decision Making for Leaders: The Analytic Hierarchy Process for Decisions in a Complex World. RWS Publications, Pittsburgh.

Shen, C.C. and K.L. Hsieh, 2006. Incorporating fuzzy aggregation operator and grey relationship analysis into constructing a MCDM model. WSEAS Trans. Inform. Sci. Appl., 3: 2100-2106.

Su, C.T. and K.L. Heish, 1998. Applying neural networks approach to achieve robust designn for dynamic quality characteristics. Int. J. Qual. Reliabil. Manage., 15: 509-519.

Su, C.T. and L.I. Tong, 1997. Multi-response robust design by principal component analysis. Total Qual. Manage., 8: 409-441.

Taguchi, G., 1996. Statistical Analysis (in Japanese). Maruzen, Tokyo.

Tong, L.I. and C.T. Su, 1997. Optimizing multi-response problems in the Taguchi method by fuzzy multiple attribute decision making. Qual. Reliab. Eng. Int., 13: 25-34.

Tong, L.I. and K.L. Hsieh, 2001. Optimization of multiple quality responses involving qualitative and quantitative characteristics in IC manufacturing using artificial neural networks. Comput. Ind., 46: 1-12.

Tong, L.I., C.T. Su and C.H. Wang, 1997. The optimization of multi-response problems in Taguchi method. Int. J. Qual. Reliabil. Manage., 14: 367-380.

Zeleny, M., 1982. Multiple Criteria Decision Making. 1st Edn. McGraw Hill, New York, USA.

Zeleny, M., 1992. An essay into a philosophy of MCDM: A way of thinking or another algorithm?. Comput. Operat. Res., 19: 563-566.