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Optimization of multiple quality responses involving qualitative and quantitative characteristics in IC manufacturing using neural networks

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Abstract

The optimization of product or process quality profoundly influences a manufacturer. Most studies have focused primarily on optimizing a quantitative (or qualitative) quality response, while others have concentrated on optimizing multiple quantitative quality responses. However, optimizing multiple responses involving both qualitative and quantitative characteristics have scarcely been mentioned, largely owing to the inability to directly apply conventional optimization techniques. In this study, we present a novel approach based on artificial neural networks (ANNs) to simultaneously optimize multiple responses including both qualitative and quantitative quality characteristics. Two neural networks are constructed: one for determining the ideal parameter settings and the other for estimating the values of the multiple quality characteristics. In addition, a numerical example from an ion implantation process employed by a Taiwan IC fabrication manufacturer demonstrates the proposed approach's effectiveness. © 2001 Published by Elsevier Science B.V.

Keywords: Multiple responses; Qualitative characteristic; Quantitative characteristic; Optimization; Back-propagation neural network (BPNN); Semiconductor

1. Introduction

Stringent market competitiveness has driven manufacturers to enhance product quality. Off-line quality control is a cost-effective means of optimizing the product and process design in support of on-line quality control. Under this approach, design parameters and noise parameters heavily influence the responses of a product or operational process. Design parameters are factors which the designer can control. Noise parameters are factors which a designer can generally not control. A robust design is desired to obtain the optimum design parameter settings for a product or an operational process in such a manner that the product response attains its desired target with minimum variation. Most investigations involving robust designs have focused primarily on optimizing the single response of a manufactured product or process. However, many manufactured products are diversified, causing more than one response to be considered. For instance, the defect count on the sensitive area and the amount of ion implanted may require simultaneously consideration for an ion implantation process in a semiconductor manufacturing process.

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In most products, the quality response with a quantitative feature is frequently considered owing to the inherent nature of the quality response. Conventional experimental design [13] techniques can be employed to investigate the relationship between quality response and design parameters (or noise parameters). In addition, while combining experimental design techniques with quality loss considerations, Taguchi's method [5,17,18,22] is an efficient approach for off-line quality control when the single quality response is involved. In some cases, the interested quality response may be a qualitative (or categorical) quality response. Optimization of a qualitative quality characteristic has seldom been mentioned [6,15]. To optimize the qualitative quality characteristic problem, the qualitative response is generally represented by the percentage form or it is classified into several categories. In addition, discriminant analysis [7] can be performed to identify the relevant factors when analyzing a qualitative response problem. The accumulation analysis (AA) [22] developed by Taguchi can also be performed to optimize the ordered categorical quality response.

In practice, multivariate analysis of variance (MANOVA) [7] and the response surface method (RSM) [14] are two methods frequently employed to optimize a multi-response problem. Other multi-response optimization techniques developed until now can be found in [1,2,4,8–10,12,19,21,24,25]. However, these optimization procedures are only designed for a quantitative multi-response problem. As the product and process become increasingly complicated, multiple quality responses may involve qualitative and quantitative characteristics. For instance, the defect count of the sensitive area and the amount of ion implanted in a wafer may require simultaneously consideration for an ion implantation process in a semiconductor manufacturing process. However, the fact that optimization of such a multi-response problem has rarely been studied reflects the necessity for an appropriate method.

In light of above developments, this study presents an artificial neural network (ANN) approach to optimize the multiple quality responses involving qualitative and quantitative responses. Two neural networks are constructed to resolve the above multi-response problem: one of the neural networks determines the ideal parameter settings while the other estimates the optimum values of the multiple quality characteristics. The rest of this paper is organized as follows. Section 2 reviews literature related to the optimization of both a single qualitative responses and the multiple qualitative responses. Section 3 reviews the theory of artificial neural networks. Section 4 presents the proposed approach. Section 5 provides an illustrative example to demonstrate the proposed approach's effectiveness. Finally, concluding remarks are made in Section 6.

2. Literature review

2.1. Optimization of the multiple quality characteristics

Khuri and Conlon [8] proposed a procedure, based on a polynomial regression model, to simultaneously optimize several quantitative responses. In their procedure, a distance function is initially employed to measure the deviations from the ideal optimum. By doing so, the multiple responses can then be optimized by minimizing the distance function under appropriate operating conditions.

Logothetis and Haigh [12] simultaneously applied multiple regression and linear programming to optimize the multi-responses problem. Derringer and Suich [4] used the desirability function to optimize multi-response problems. They initially transformed several responses into a single response and, then, obtained a complete desirability value by taking the geometric average of the multiple desirability values. Castillo et al. [2] modified the desirability function to avert a situation in which the non-differentiable points appear in the original desirability function. In a related work, Layne [10] presented a novel procedure to determine the optimum factor/level combination. He employed the criterion of minimizing the loss function, maximizing the desirability function and minimizing the distance function. Notably, the controversies of Layne's method can be generated by simultaneously comparing the three results to determine the optimum parameter setting.

Pignatiello [19] utilized a variance component and a squared deviation-from-target to form an expected loss function to optimize a multi-response problem. He initially constructed a regression model and, then, minimized the expected loss function. However, when implementing this method in practice, the necessary cost matrix may be difficult to obtain. Chapman [3] proposed a co-optimization approach, which combines all responses using a composite response, to place constraints on some or all responses and then minimize or maximize one of the responses.

Leon [11] presented a method based on a standardized loss function with the specification limits to optimize a multi-response problem. However, only the nominal-the-best (NTB) response is appropriate for this method. Tai et al. [23] claimed that quadratic modeling is invalid for non-symmetric loss functions. They also recommended developing an empirical loss function for a multi-response problem. Ames et al. [1] also presented a quality loss function approach in the response surface models to resolve a multi-response problem.

In addition, several other techniques have been developed to optimize the multi-response problem. Lai and Chang [9] proposed a fuzzy multi-response optimization procedure to derive an appropriate combination or process parameter settings. Tong et al. [25] developed a multi-response signal to noise (MRSN) ratio, capable of integrating the quality loss for all responses, to optimize the multi-response problem. In a later study, Su and Tong [21] proposed a principle component analysis (PCA) approach to optimize the multi-response problem. Initially, the quality loss of each response was standardized. Next, the principle component analysis was then applied to transform the primary P quality characteristics into k summary quality characteristics, where $k < P$. Finally, the optimum factor/level combination can be obtained by minimizing the sum of standardized quality loss. Tong and Su [24] also proposed a procedure, capable of applying fuzzy set theory to multiple attribute decision making (MADM), to optimize a multi-response problem. That investigation also applied a similar technique for ordering preference by the similarity to an ideal solution index to determine the optimum parameter setting.

2.2. Optimization techniques for a qualitative characteristic

Taguchi [22] developed accumulation analysis (AA) to effectively resolve the qualitative (categorical) response problems. Taguchi's AA primarily consists of four steps: (1) define the corresponding cumulative categories; (2) determine the effects of the factor's levels; (3) plot the cumulative probabilities; and (4) predict the accumulated probabilities of each category under optimum conditions. Taguchi also recommended using the Omega (Ω) transformation to transfer the accumulated probability of the factor level to a corresponding Ω value, thereby yielding the predicted accumulated probability of the qualitative response. The optimum factor/level combination can be determined by screening the factor effect diagram. However, Taguchi's AA might lead to an erroneous result under a subjective assessment while attempting to determine the optimum level combination from the factor effect diagram.

Nair [15] presented two scoring schemes (SS) to identify the dispersion and location effects. That investigation recommended using the mean square to identify a prominent effect. The optimal condition of dispersion and location effects can be obtained according to the contribution of both effects of each control factor. The final optimal control factor/level combination is obtained by adjusting between the dispersion effect and location effect.

Jean and Guo [6] proposed a weighted probability scoring scheme (WPSS) to reduce the drawbacks of Nair's SS. Their approach is simpler and more straightforward than Nair's, in that they incorporate the dispersion and location effects into a single mean square deviation (MSD). In addition, the expected mean square deviation for each category can be obtained according to the definition of the categories. The optimal control factor/level combination is obtained by selecting the minimum mean squared deviation.

All methods mentioned above only focus on either the optimization of the multi-response with the quantitative forms or that of a single response with qualitative form. However, for the multi-response simultaneously involving the qualitative and quantitative forms, they still cannot be directly employed.

3. Neural networks

A neural network is a parallel computing system consisting of many processing elements (PEs) connected

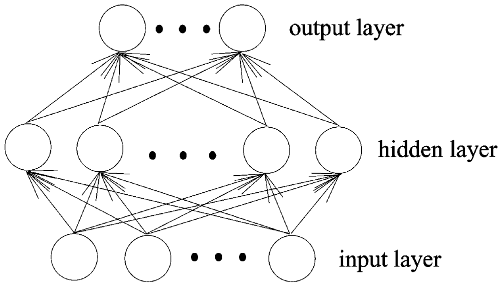

Fig. 1. Topology of a typical neural network.

from layer to layer. Each PE can receive several effective input signals, which subsequently pass through a weight set (i.e. the strength of the connection between PEs), to sum up all arrived signals. An activation function determines the activation value. The output signals of the PEs may be sent to other PEs on the next layer or return to itself through interconnections. Depending on the interconnection architecture among the neurons, the activation function transforms inputs into outputs, and the learning rules lead to several different architectures. The characteristic architecture of a neural networks can be defined as the number of PEs in each layer. Fig. 1 depicts the topology of a typical neural network.

Neural networks can model the non-linear relationship between the system's input and system's discrete or continuous output. The hidden structure of the non-linear relationship can be learned by passing the training pairs through the network. Several conventional supervised learning neural models include perceptron, back-propagation neural network (BPNN), learning vector quantization (LVQ), and counter propagation network (CPN). The BPNN model is frequently used and, therefore, selected herein. A gradient-descent algorithm [16,20] is employed to minimize the error function for a BPNN model. The training process introduces the training set to the network, and then adjust the connected weight according to the difference between the produced and target outputs. The error at the output layer propagates backward through the network and, in doing so, the error can be minimized by network training. The adjustment of connection weights is repeated until the training count arrives at a defined level or the error converges toward an acceptable level. The back-propagation learning algorithm is thoroughly described in [16,20].

4. Proposed approach

A particular relationship must exist between the input and output of a system. However, most modularization approaches can only modularize a system by employing forward direction. Restated, a system's output can be viewed as a function of a system's input. However, from a logical perspective, the reverse direction can also be employed to modularize a system. The system's ideal output is generally known and the system's input can be found for this ideal output. For instance, the target value of the response of a product is known and the ideal parameter settings for attaining the target value can be determined through a designed experiment. The system's feature hidden in the experiment can be directly used to modularize a system by employing the neural network. In this study, we apply this logical concept of reverse direction to determine the optimum parameter settings of a multi-response problem. That is, the response/parameter's combination is applied to the input/output of the first neural network (reverse direction). The relationship between responses and parameter's combination will be learned since the neural network being trained well. Inputting the desired responses into the trained neural network, the ideal parameter's combination can be obtained. Hence, the first neural network can be required as a procedure of parameter searching. Then, the parameter's combination/responses is applied to the input/output of the second neural network (forward direction). The relationship between parameter's combination and responses will be also learned since the neural network being trained well. Inputting the ideal parameter combination we found into the trained neural network, the estimated results of responses can be obtained. Hence, the second neural network can be required as a procedure of response estimating. If these two neural networks are only separately employed, it will give rise to two situations: (1) several confirmation activities may be required when the single neural network's performance is under trained or over trained since neural network with reverse direction being separately utilized; (2) all possible parameter's combinations are sent into the single

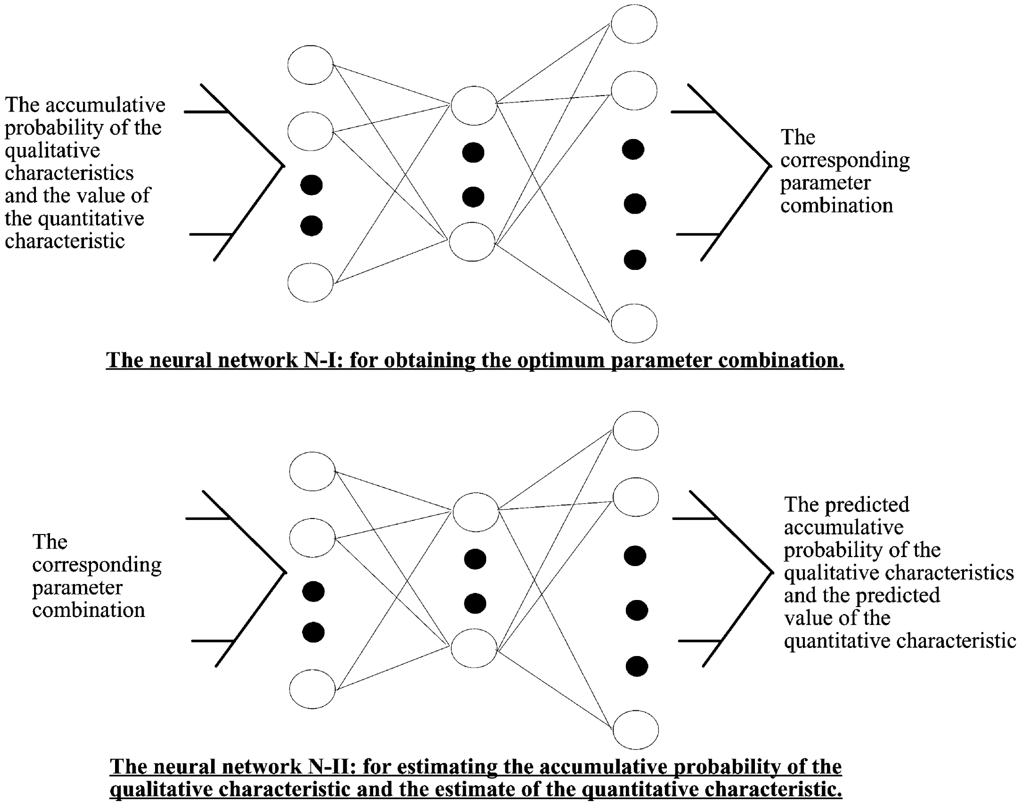

Fig. 2. The topology of the proposed approach.

neural network to search for the optimum parameter's combination since neural network with forward direction being separately utilized. It is a time-consuming task. Obviously, employing the two neural networks approach can work better and it is more flexible and efficient. Fig. 2 depicts the topology of the proposed neural network approach.

The proposed optimization approach for the multiple quality responses problem involving qualitative and quantitative characteristics is given in the following steps:

1. *Form the training set and the testing set of back-propagation neural network.* Randomly take around one-third of the experimental data [16] from the designed experiments to form the testing set of the back-propagation neural network. The remaining parts of the experimental data forms the training set of the back-propagation neural network.

2. *Construct the architecture of the back-propagation neural network N-I and determine the optimum parameter settings.*

   2.1. Compute the accumulated probability of the kth ordered category of a qualitative response with m ordered categories by using the following formula: $p_k = \sum_{i=1}^{k} n_i/(n_1 + n_2 + \cdots + n_m)$, where n_i denotes the count owing to the ith $(i = 1, 2, \ldots, m)$ ordered category. Accumulated probability is used herein for the following reasons: (i) the qualitative response is attributed to the ordered category, in that using the accumulated probability is more meaningful than using the probability; (ii) if the probability of the ordered category is used, the structure of the category may contain several zero input; and (iii) the process engineers usually estimate the accumulated probability directly and not the probability.

2.2. Assign the accumulated probability of each category of the qualitative response and the value of the quantitative response as the input signal of neural network N-I; the corresponding factor/level combination is assigned as the output signal of neural network N-I. Therefore, the structure of the training set and testing set can be represented as follows:

$$\begin{pmatrix} (p_1, p_2, p_3, \ldots, \text{response, factor-A, factor-B, factor-C}, \ldots) \\ | \longleftarrow \text{input signal} \longrightarrow | \longleftarrow \text{output signal} \longrightarrow | \end{pmatrix}$$

where p_i $(i = 1, 2, \ldots, m)$ are the accumulated probability obtained in Step 2.1; response denotes the value of the quantitative response, and factor-A, factor-B, factor-C, ... denote the setting values of factors A, B, C, ..., respectively. Assume that a designed experiment includes a factors, one qualitative response with m ordered categories, and n quantitative characteristics, then the size of the input signal of N-I and the size of the output signal of N-I are $(m + n)$ and a, respectively.

2.3. Test several different architectures (i.e. the number of PEs in the hidden layer) of neural network N-I by using the training set and testing set chosen in Step 1. The root mean square error (RMSE) [16] of each architecture can be utilized as the criterion in determining the optimum neural network. After approaching 10,000 epochs (where an epoch is one training data set presented to the network). The RMSE value of training can be obtained. Next, inputting the testing set into the trained architectures, the RMSE value of testing can be also obtained. The optimum architecture is the one which can simultaneously minimize the RMSEs from both of the training set and testing set in Step 1.

2.4. Incorporate the training set and testing set chosen in Step 1 into a final training set. Restated, assign all experimental data as the training set. Retrain the optimum neural network N-I chosen from Step 2.3 until the optimum neural network N-Is architecture reaches a steady-state.

2.5. Input the target value to the neural network N-I found in Step 2.4. Restated, input the ideal accumulated probability of each ordered category of the qualitative response and the ideal value of the quantitative response to neural network N-I. The ideal parameter settings can then be obtained by computing neural network N-II.

3. *Construct the architecture of neural network N-II and estimate the ideal responses.*

3.1. Assign the factor/level combination as the input signal of neural network N-II. The corresponding accumulated probability of each category of the qualitative response and the value of the quantitative response are assigned as the output signal of neural network N-II. The structure of the training set and testing set can be represented as follows:

$$\begin{pmatrix} (\text{factor-A, factor-B, factor-C}, \ldots, p_1, p_2, p_3, \ldots, \text{response}) \\ | \longleftarrow \text{input signal} \longrightarrow | \longleftarrow \text{output signal} \longrightarrow | \end{pmatrix}$$

3.2. Test several different architectures (i.e. the number of PEs in the hidden layer) of neural network N-IIs by using the training set and testing set chosen in Step 2.4. The principle for determining the optimum neural network N-IIs architecture is the same as that in Step 2.3.

3.3. Incorporate the training set and testing set chosen in Step 2.4 into a final training set. Retrain the optimum neural network N-IIs architecture chosen from Step 3.2 until it reaches a steady-state.

3.4. Input the ideal parameter settings found in Step 2.5 to the optimum neural network N-II found in Step 3.3. By doing so, the estimated accumulated probability of each ordered category of the qualitative response and the estimated response values of the quantitative response can be obtained.

4. *Compare the estimated result with the target* (*i.e. the ideal accumulated probability of each ordered category of the qualitative response and the ideal value of the quantitative response*). If the estimated results in Step 3.4 do not significantly depart from the target, the analysis is completed. Otherwise, go back to Step 1 to reform the training set and testing set and repeat Steps 2–4 until the deviation between the estimated results and target can be accepted by users. For increasing the flexibility of application, the acceptable deviation will depend on the corresponding problem and the engineering experience.

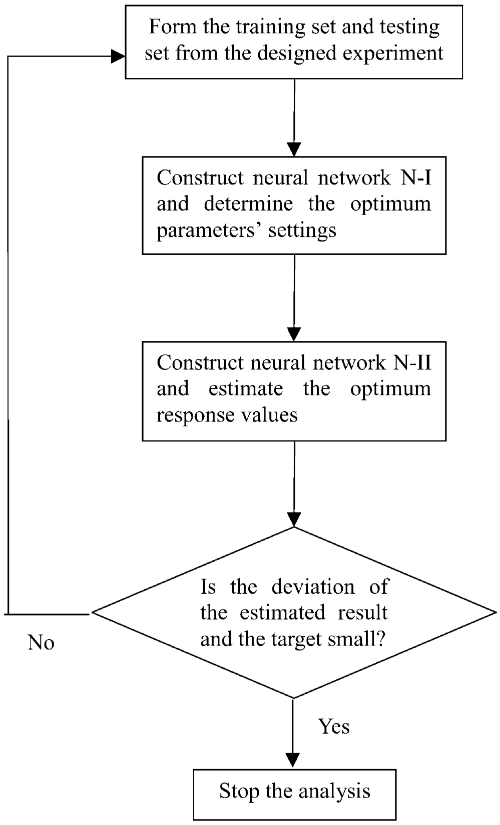

Fig. 3. The flow-chart of the proposed approach.

Fig. 3 schematically depicts the above procedure of the proposed approach.

5. Illustrative example

The following numerical example involves an ion implantation process from a Taiwanese IC fabrication manufacturer. Two quality responses are considered: one is owing to the qualitative response (i.e. the total defect counts of 36 sensitive areas in a wafer) and the other is owing to the quantitative response (i.e. the measurement of the ion amount). Furthermore, an equal importance of these responses is considered in the ion implantation process. Six control factors are studied and are denoted as A–F. Among them, five of them (B–F) are continuous and one (A) is discrete. Table 1 lists these control factors and their levels. The qualitative response includes five categories of the defect situation: very good, good, not good and not bad, bad and very bad. They are denoted by grade I, II, III, IV and V. Table 2 lists these responses. The quantitative response is the NTB with the target value of 1000 (after the data transformation). There are two repetitions. Table 3 summarizes the experimental data in a L_{18} orthogonal array. In addition, the accumulated

Table 1
Control factors and their levels[a]

Factor	Level 1	Level 2	Level 3
A	Type 1	Type 2	
B	6	12	18
C	50	100	150
D	5	10	15
E	4	8	12
F	25	50	75

[a] Starting levels are identified by underline.

Table 2
Categorical definition of the qualitative characteristic

Category	Definition
I	Very Good
II	Good
III	Not good and not bad
IV	Bad
V	Very bad

Table 3
Experimental data

Number	Responses						
	Qualitative (categories) response					Quantitative response[a]	
	I	II	III	IV	V	N_1	N_2
1	33	3	0	0	0	745.2	741.4
2	24	5	6	1	0	968.3	972.1
3	6	2	20	8	0	800.2	796.1
4	0	14	4	4	0	795.9	797.8
5	2	12	4	12	16	791.4	796.6
6	4	12	20	4	8	800.4	802.1
7	0	2	6	14	14	912.2	908.2
8	10	2	8	4	12	650.0	645.7
9	0	0	0	24	12	651.2	650.3
10	34	0	2	0	0	1075.1	1072.5
11	30	2	4	0	0	1314.0	1316.1
12	10	10	12	0	4	884.4	890.5
13	14	8	10	4	0	884.3	886.6
14	8	16	12	0	0	817.4	826.5
15	0	8	6	4	18	796.0	800.1
16	18	12	6	0	0	819.8	816.1
17	10	6	0	4	16	821.8	824.2
18	0	4	2	6	24	732.4	735.6

[a] The value of the quantitative response are the form after transforming.

probability of each category of the qualitative response and the value of the quantitative response for the initial settings $A_1B_1C_3D_3E_1F_2$ are (I, II, III, IV, V, R) = (0.30, 0.48, 0.82, 0.94, 1.0, 1085.2), where I, ..., V denote the accumulated probabilities of the categories I, ..., V of the qualitative response and R represents the average value of the quantitative response.

To simplify the computation of the proposed approach, a neural network software package — Neural Professional II/Plus [16] is used to develop the required networks. This example contains 36 pairs of experimental data. Among these pairs, 12 pairs of experimental data are randomly selected to form the testing set of the back-propagation neural network. The remaining 24 pairs of experimental data are assigned as the training set of the back-propagation neural network. The accumulated probability of each category of the qualitative response is computed. Table 4 summarizes those results. Next, the accumulated probability of each ordered category of the qualitative response and the value of the quantitative response are assigned as the input signals of neural network N-I, the parameter settings are severed as output signals of neural network N-I. Factor A is a qualitative type herein and the coding for factor A is that 1 denotes the type 1, and 2 denotes the type 2. The PEs counts of the input and output layer of neural network N-I are 6 and 6, respectively, and the number of PEs in the hidden layer of the neural network N-I can be determined by trial-and-error. Table 5 lists several options of the neural network N-Is architecture; the structure 6-8-6 is selected to obtain the ideal continuous value of the parameters (for comparison of the training set's and the testing set's RMSE values). All experimental data are used as the final training set to retrain the chosen optimum neural network's architecture 6-8-6. This architecture of the neural network will reach a steady-state after 10,000 epochs training. By inputting the ideal targets (the ideal accumulated probability of each category of the qualitative characteristic (1.0, 1.0, 1.0, 1.0, 1.0) and the desired value of the quantitative characteristic (1000)) to the steady-weight set, the ideal parameter settings can be found as (A, B, C, D, E, F) = (type 1, 6.06, 46.32, 12.91, 11.63, 52.03).

Next, the neural network N-II is used to estimate the accumulated probability of each category of the

Table 4
The accumulated count (probability) of the qualitative characteristic

Number	Accumulated count (probability)				
	I	II	III	IV	V
1	33 (0.917)	36 (1.000)	36 (1.000)	36 (1.000)	36 (1.000)
2	24 (0.667)	29 (0.806)	35 (0.972)	36 (1.000)	36 (1.000)
3	6 (0.167)	8 (0.222)	28 (0.778)	36 (1.000)	36 (1.000)
4	0 (0.000)	28 (0.778)	32 (0.889)	36 (1.000)	36 (1.000)
5	2 (0.056)	4 (0.111)	8 (0.222)	20 (0.556)	36 (1.000)
6	4 (0.111)	4 (0.111)	24 (0.667)	8 (0.222)	36 (1.000)
7	0 (0.000)	2 (0.056)	8 (0.222)	22 (0.611)	36 (1.000)
8	10 (0.278)	12 (0.333)	20 (0.556)	24 (0.667)	36 (1.000)
9	0 (0.000)	0 (0.000)	0 (0.000)	24 (0.667)	36 (1.000)
10	34 (0.944)	34 (0.944)	36 (1.000)	36 (1.000)	36 (1.000)
11	30 (0.833)	32 (0.889)	36 (1.000)	36 (1.000)	36 (1.000)
12	10 (0.278)	20 (0.556)	32 (0.889)	32 (0.889)	36 (1.000)
13	14 (0.389)	22 (0.917)	32 (0.889)	36 (1.000)	36 (1.000)
14	8 (0.222)	24 (0.667)	36 (1.000)	36 (1.000)	36 (1.000)
15	0 (0.000)	8 (0.222)	14 (0.389)	18 (0.500)	36 (1.000)
16	18 (0.500)	30 (0.833)	36 (1.000)	36 (1.000)	36 (1.000)
17	10 (0.278)	16 (0.444)	16 (0.444)	20 (0.556)	36 (1.000)
18	0 (0.000)	4 (0.111)	6 (0.167)	12 (0.333)	36 (1.000)

qualitative response and the value of the quantitative response under the ideal parameter settings found in neural network N-I. The 24 pairs and 12 pairs of experimental data selected for constructing the neural network N-I are used to train the neural network N-II. Herein, the parameter settings are assigned as the input signal of neural network N-II, and the accumulated probability of each ordered category of the qualitative response and the response value of the quantitative response are assigned as the output signal of neural network N-II. Hence, the PEs count of N-IIs input and output layer are equal to 6 and 6, respectively. Table 6 lists several options of neural network N-IIs architecture with different PEs count in the hidden layer; the structure 6-12-6 is selected to obtain the best performance (for compromising the training set's and the testing set's RMSE values). Next, all experimental data are utilized to form the final training set of the chosen optimum neural network's architecture 6-12-6 and retrain the neural network N-II. This architecture of the neural network reaches a steady-state after 10,000 epochs of training. By inputting the ideal parameter settings obtained from neural network N-I to the chosen neural network N-II, the estimated accumulated probability of each category of the qualitative response and the estimated value of the quantitative response can be found as $(\text{I, II, III, IV, V}, R) = (0.88, 0.96, 0.99, 1.0, 1.0, 1056.8)$. Comparing the estimated responses with the target (1.0, 1.0, 1.0, 1.0, 1.0, 1000) reveals that the deviation is

Table 5
The RMSE of neural network N-I

Architecture	RMSE (training)	RMSE (testing)
6-5-6	0.158	0.211
6-8-6[a]	0.126	0.182
6-11-6	0.103	0.191
6-14-6	0.087	0.223
6-18-6	0.072	0.224

[a] Denotes the optimal option after trade-off.

Table 6
The RMSE of neural network N-II

Architecture	RMSE (training)	RMSE (testing)
6-6-6	0.146	0.169
6-8-6	0.111	0.158
6-10-6	0.094	0.123
6-12-6[a]	0.085	0.102
6-15-6	0.076	0.114

[a] Denotes the optimal option after trade-off.

considerably small and the analysis is terminated. In addition, inputting the initial parameter combination into the neural network N-II allows us to obtain the estimated accumulated probability of each category of the qualitative response and the estimated value of the quantitative response as (I, II, III, IV, V, R) = (0.24, 0.45, 0.86, 0.98, 1.0, 1106.5). In addition, comparing the estimated responses from the proposed approach with the result (0.30, 0.48, 0.82, 0.94, 1.0, 1085.2) of the initial settings reveals that both results are quite close. Correspondingly, this example confirms the validity of the proposed approach.

Taguchi method is the popular method that most manufactures are employed it to analyze the parameter optimization. Herein, we also employ the Taguchi method to make comparison with our proposed approach. Assuming not only that Taguchi's AA and the conventional Taguchi method are employed separately to optimize the qualitative and quantitative responses of the same problem, but also that the results from both methods are compromised to obtain the optimum settings of the parameters for the above example. By applying Taguchi's AA to the qualitative response, the optimum parameter combination for the qualitative characteristic is $A_2B_1C_1D_3E_2F_1$ and the predicted accumulated probabilities of each category of the qualitative response are (I, II, III, IV, V) = (0.862, 0.926, 0.98, 0.995, 1.0). Fig. 4 summarizes the results of the predicted accumulated probability of each category for the initial parameter settings, Taguchi's AA and the proposed approach, respectively. According to this figure, the proposed approach has a higher predicted accumulated probability for each category than that of the initial settings and Taguchi's AA. Moreover, when Taguchi's method is applied to the quantitative response, the optimum parameter setting for the quantitative response is $A_1B_2C_1D_1E_3F_2$. To compromise the final parameters' settings for the results from qualitative and quantitative responses by Taguchi's method, our results indicate that a significant conflict arises in setting the optimum levels for factors A, B, D, E, and F, especially for factors A and D. However, following discussion with the process engineers, the final compromising parameters' settings is obtained as $A_1B_2C_1D_3E_2F_1$. To estimate the response values, by inputting the final compromising settings $A_1B_2C_1D_3E_2F_1$ into the neural network N-II, the estimated response values are (0.76, 0.85, 0.94, 0.99, 1.0, 1072.6). Table 7 compares the proposed approach and Taguchi's method with respect to the estimated results of the initial settings. According to this table, the estimated results for the proposed approach performed better than Taguchi's method and the initial settings.

The estimated optimal parameter setting is (type 1, 6.06, 46.32, 12.91, 11.63, 52.03). After discussing the results with the engineer, the actual parameter setting is determined as (type 1, 6, 45, 12.5, 12, 50) since some difficulties arise in setting the parameters as the estimated optimal parameter setting. Finally, the confirmed experiments for the proposed procedure are performed. Table 8 summarizes those results. This table reveals not only that the average accumulated probability of each category of the qualitative response are (0.88, 0.96, 0.99, 1.0, 1.0), but also that they are close to the target value (1.0, 1.0, 1.0, 1.0,

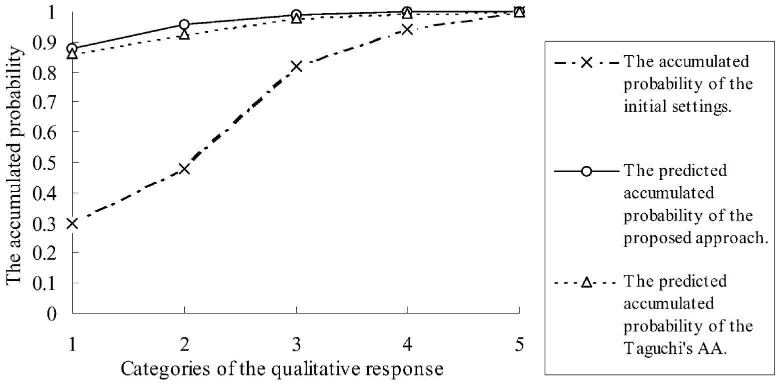

Fig. 4. The accumulated probability of the qualitative response.

Table 7
Comparison of the optimum settings from Taguchi method and the proposed approach[a]

Method	Optimum conditions						Qualitative response (accumulated probability)					Quantitative response (estimated value)
	A	B	C	D	E	F	I	II	II	IV	V	
The settings of Taguchi's method	Type 1	12	50	15	8	25	0.76	0.85	0.94	0.99	1.0	1072.6
The settings of the proposed approach	Type 1	6.06	46.32	12.91	11.63	52.03	0.88	0.96	0.99	1.0	1.0	1056.8
The initial settings	Type 1	6	150	15	4	50	0.24	0.45	0.86	0.98	1.0	1106.5

[a] The estimated results of the initial settings is also included in this table.

Table 8
Results of the confirmed experiments for the proposed approach

Confirm experiment number	Qualitative response					Quantitative response	
	I	II	III	IV	V	N_1	N_2
1	29	34	35	36	36	1045.5	1044.3
2	30	33	36	36	36	1045.8	1047.1
Average accumulated probability	0.819	0.931	0.986	1.000	1.000		

1.0). The average value of the quantitative response (1045.7) is also close to the target value (1000). Results 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 estimated results of setting (type 1, 6.06, 46.32, 12.91, 11.63, 52.03) are (0.88, 0.96, 0.99, 1.0, 1.0, 1056.8) and the confirmed results of the actual settings (type 1, 6, 45, 12.5, 12, 50) are (0.82, 0.93, 0.99, 1.0, 1.0, 1046.5). These two results are close and, therefore, the process engineer can accept the parameter setting as (type 1, 6, 45, 12.5, 12, 50). Although only one experiment is employed in this study, the validity of the proposed approach can still be verified.

6. Concluding remarks

With an increasing complexity of manufactured products, assessing a product may not merely be a single quality response. Optimizing the multiple quality responses is an increasingly task for many manufacturers. Furthermore, multiple responses may simultaneously involve qualitative and quantitative quality characteristics. Taguchi method cannot be directly applied to optimize such multi-response problems involving qualitative quality and quantitative quality characteristics. In light of such situations this study presents a novel approach based on artificial neural network technique to effectively optimize the multiple quality responses involving both qualitative (categorical) and quantitative characteristics. An illustrative example demonstrates the proposed approach's effectiveness. Results presented herein confirm that the proposed approach has several merits: (1) the proposed approach does not require a complicated computation. In addition, an analyst with limited statistical training would find it relatively easy to comprehend the proposed approach. Engineers can directly apply the neural network software to develop the required model or to design an appropriate neural model by themselves; (2) applying the proposed approach allows us to obtain the ideal settings of the continuous parameters; and (3) the uncertainty when making a decision regarding the optimum parameter settings in Taguchi method can be efficiently averted.

In addition, the neural network approach proposed herein can also be applied to the multi-response problem with all quantitative or all qualitative characteristics. When responses are all qualitative or all quantitative characteristics, we merely need to slightly alter the structure of the neural networks to obtain the ideal parameter settings.

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