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ORIGINAL ARTICLE

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Simultaneous optimisation of the broadband tap coupler optical performance based on neural networks and exponential desirability functions

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Abstract This study presents an integrated procedure using neural networks and exponential desirability functions to resolve multi-response parameter design problems. The proposed procedure is illustrated through optimising the parameter settings in the fused bi-conic taper process to improve the performance and reliability of the 1% (1/99) single-window broadband tap coupler. The proposed solution procedure was implemented on a Taiwanese manufacturer of fibre optic passive components and the implementation results demonstrated its practicability and effectiveness. A pilot run of the fused process revealed that the average defect rate was reduced to just 2.5%, from a previous level of more than 35%. Annual savings from implementing the proposed procedure are expected to exceed 0.5–1.0 million US dollars. This investigation has been extensively and successfully applied to develop optimal fuse parameters for other coupling ratio tap couplers.

Keywords Parameter design · Multi-response problem · Neural network · Exponential desirability function · Single-window broadband tap coupler

1 Introduction

Optical performance in a coupler manufacturing process is usually influenced by more than one variable. These variables include machine parameters, raw materials, the process followed, environmental conditions and so on. From the perspective of cost or feasibility, some variables cannot be precisely controlled. Furthermore, even when these variables are controllable, the optimal combination of parameter levels that maximises product quality may be unknown. The Taguchi method is a conventional approach to resolving this problem. This method allows engineers to determine a feasible combination of design parameter levels such that the variability of a product's response is reduced and the mean is close to the target. However, optimising a multi-response problem using the standard Taguchi method is difficult. The usual recommendation for the optimisation of a process/product with multiple responses is left to engineering judgment and is verified by experiments [1]. However, the introduction of human judgment increases uncertainty in the decision-making process. Logothetis and Haigh [2] applied the multiple regression technique and linear programming approach to optimise a five-response process by the Taguchi method. Their method was limited when the t-values of the regression coefficients were insignificant or when the coefficient of determination was low. Pignatiello [3] presented a quadratic loss function for multi-response problems and established a predictive regression model using controllable variables. Following the descent direction and repeatedly establishing a new local experimentation region, this method minimised the expected loss. However, it was difficult to determine the cost matrix and additional experimental observations were required. Tong et al. [4] proposed a procedure to determine the multi-response signal-to-noise (MRSN) ratio through integrating the quality loss of each response. However, determining the weight ratios for responses was difficult, and the optimal combination of factor levels was likely to be dominated by the "maximum quality loss" in the total of the trials. Antony [5] proposed an approach using the Taguchi loss function and principal component analysis to optimise a submerged arc-welding process. In this study, it was difficult to determine the optimal parameter settings if two or more eigenvalues

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greater than one were obtained according to Kaiser's criterion [6]. Superimposing the response contour plots and finding an optimal solution by visual inspection is a simple and intuitive approach to resolving multi-response problems [7]. However, such a method is severely limited by the number of input variables and/or responses [8]. The use of a dimensionality reduction strategy has thus become a popular means of simultaneously optimising (compromising) multiple responses. This method converts a multi-response problem into a single-response problem with an aggregated measure, which has often been defined as a desirability function [9, 10] or as an estimated distance from the ideal design point [11]. Kim and Lin [8] developed a modelling approach based on maximising exponential desirability functions for optimising a multi-response system. Their approach aimed to identify the settings of the input variables to maximise the degree of overall minimal level of satisfaction with respect to all the responses. Furthermore, the method required no assumptions regarding the form or degree of the estimated response models and was sufficiently robust to handle the potential dependences between response variables.

In this study, an integrated procedure based on neural networks and exponential desirability functions was proposed to optimise the parameter settings in the fused bi-conic taper (FBT) process that fabricates 1% (1/99) single-window broadband tap couplers. The proposed optimisation procedure can help manufacturers of fibre-optic passive components by greatly improving the performance and reliability of 1% (1/99) single-window broadband tap couplers at minimum cost.

2 Characteristics and construction of couplers

Branching components (sometimes given the synonyms couplers and splitters) are passive components with more than two ports that distribute optical power among fibres in a predetermined fashion. Wavelength insensitive couplers are branching components in which power is routed independently of the wavelength composition of the optical signal. Each component may combine and divide optical signals simultaneously, as in bi-directional (duplex) transmission over a single fibre. However, the wavelength-division multiplexers/de-multiplexers (WDMs) are branching components in which power is routed based on the wavelength composition of the optical signal. Passive optical branching components are being used in numerous commercial applications, such as optical fibre communications, optical fibre amplifiers and lasers and so on. The FBT technology is used to produce both WDMs and couplers. This technology relies on bringing bare fibre into contact, then melting and drawing the cross-section to produce a tapered region, as illustrated in Fig. 1a [12]. This procedure produces a very thin tapered region, which must be processed extremely carefully, and must be packaged to protect the components during shipping, handling and installation. In a typical package, as illustrated in Fig. 1b [13], the fused section of the fibres is suspended above the quartz substrate, and positioned between two epoxy supports for mechanical stability. This assembly is then enclosed in a metal tube and sealed. The FBT process has been used for over a decade to fabricate most of the coupler components used in various fibre optic telecommunication, instrumentation, and sensor systems. The FBT process is used extensively not only because of its ready availability and relatively low cost, but also because of its inherent environmental stability and versatility.

3 Optimisation methodologies

The optimisation methodologies, neural networks and desirability functions needed for developing the proposed solution procedure are briefly introduced in this section.

3.1 Back-propagation neural networks

Neural networks mimic the way by which biological brain neurons generate intelligent decisions. Numerous neural network models exist that simulate various aspects of intelligence. To resolve parameter design problems with multiple responses, the back-propagation (BP) neural networks are applied to construct the functional relationship between control factors and output responses in an experiment. A standard BP neural model consists of three or more layers, including an input layer, one or more hidden layers and an output layer. The theoretical results revealed that a single hidden layer is sufficient to allow a BP neural model to approximate any continuous mapping from the input patterns to the output patterns to an arbitrary degree of freedom [14]. The training of a BP neural network involves three

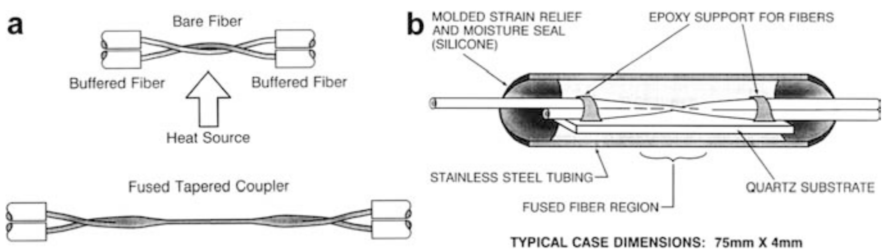

Fig. 1 a Fabrication of a FBT device. **b** Metal tube package for a FBT device stages: (1) feed-forward the input training pattern, (2) associated error calculation and back-propagation, and (3) weight and bias adjustments. Once network performance is satisfactory, the relationships between input and output patterns are determined and then the weights are used to recognise new input patterns. The two parameters with the greatest effect on the training performance of a BP neural network are the learning rate and momentum. The learning rate controls the degree of weight change during training. The momentum avoids significantly disrupting learning direction when some training data differ markedly from the majority from most of the data (and may even be incorrect). A smaller learning rate and larger momentum reduce the likelihood of the network finding weights that are only a local minimum, but not a global one [14]. The detailed algorithm of the BP neural network and the guidelines for selecting appropriate training parameters can be found in Fausett [14] and Hagan et al. [15].

3.2 Desirability functions

Suppose that there are r output responses $y=(y_1, y_2, ..., y_r)$, determined by a set of input variables $x=(x_1, x_2, ..., x_p)$. The general multi-response problem can be defined as

$$y_j = f_j(x_1, x_2, ..., x_p) + \varepsilon_j \text{ for } j = 1, 2, ..., r \tag{1}$$

where f_j denotes the response function between the jth response and the input variables; and ϵ_j represents the error term. Usually, the exact form of f_j cannot be known, but can be estimated over a limited experimental region by using model-building techniques, such as regression and neural networks. Integrating all the different responses simplifies such a complicated multi-response problem as a single objective optimisation problem. The desirability function approach transforms an estimated response (e.g. the jth estimated response $\hat{y}_j$) to a scale-free value d_j $(0 \le d_j \le 1)$, called desirability. The larger value of d_j increases as the desirability of the corresponding response increases. Hence, the multi-response problem can be stated as [8]:

$$\underset{x}{\text{maximize}}\ \lambda \tag{2}$$

subject to

$$d_j\{\hat{y}_j(\mathbf{x})\} \geqslant \lambda \text{ for } j = 1, 2, ..., r \tag{3}$$

$$\mathbf{x} \in \Omega \tag{4}$$

where Ω denotes the experimental region.

The exponential desirability function is suggested as follows [8]:

$$d(z) = \begin{cases} \frac{\exp(t) - \exp(t|z|)}{\exp(t) - 1}, & \text{if } t \neq 0 \\ 1 - |z|, & \text{if } t = 0 \end{cases} \tag{5}$$

where t is a constant $(-\infty < t < \infty)$, called exponential constant, and z denotes a standardised parameter representing the distance between the estimated response and its target in units of the maximum allowable deviation. For example, for the nominal-the-best (NTB), smaller-the-better (STB), and larger-the-better (LTB) type responses [16], the parameter z can be defined, respectively, as [8]:

$$z = \frac{\hat{y}_j(\mathbf{x}) - T_j}{y_j^{\max} - T_j} = \frac{\hat{y}_j(\mathbf{x}) - T_j}{T_j - y_j^{\min}}, \text{ for } y_j^{\min} \leqslant \hat{y}_j(\mathbf{x}) \leqslant y_j^{\max} \tag{6}$$

$$z = \frac{\hat{y}_j(\mathbf{x}) - y_j^{\min}}{y_j^{\max} - y_j^{\min}}, \text{ for } y_j^{\min} \leqslant \hat{y}_j(\mathbf{x}) \leqslant y_j^{\max} \tag{7}$$

$$z = \frac{y_j^{\max} - \hat{y}_j(\mathbf{x})}{y_j^{\max} - y_j^{\min}}, \text{ for } y_j^{\min} \leqslant \hat{y}_j(\mathbf{x}) \leqslant y_j^{\max} \tag{8}$$

where the bounds on a response ($y^{\min}{}_j$ and $y^{\max}{}_j$) should be specified in advance. The bounds may be determined according to the specification limits of the product or process, the regulations or standards of the organisation, the physical range of the response or the subjective judgments of the decision makers. z ranges between -1 and 1 for an NTB type response, and otherwise ranges between 0 and 1. In either case, the desirability function value $d(z)$ achieves its maximum value of 1 when $z=0$. The function $d(z)$ given in Eq. 5 has been proven to provide a reasonable and flexible representation of human perception [17, 18] and is convenient to handle analytically [8].

3.3 Proposed optimisation procedure

The proposed procedure for resolving a multi-response parameter design problem comprises seven steps and is summarised as below:

Step 1 Identify the quality characteristics (responses), major control factors, noise factors and exponential constant for each response.

Step 2 Assign control and noise factors to the orthogonal arrays; conduct the experiment and collect the experimental data.

Step 3 Design a BP neural network to represent the relationship between input control factors and output responses.

Step 4 Present all possible factor level combinations to the developed network (in step 3) and compute the estimated responses.

Step 5 Apply the exponential desirability functions to transform the multiple responses into an aggregated performance measure.

Step 6 Optimise the parameter settings by selecting the combination that maximizes the overall satisfaction (λ).

Step 7 Conduct the confirmation experiment, and if the result is unsatisfactory, return to step 1 and repeat the proposed procedure.

Table 1 The specifications of 1% (1/99) single-window broadband tap couplers, the exponential constants and values of $y^{\min}{}_j$ and $y^{\max}{}_j$

		CR (%)	EL (dB)	IL-A (dB)	IL-B (dB)	PDL-A (dB)	PDL-B (dB)
Grade	Premium	99 ± 0.2	≤ 0.20	≤ 21.50	≤ 0.20	≤ 0.30	≤ 0.30
	A	99 ± 0.2	≤ 0.40	≤ 22.00	≤ 0.30	≤ 0.35	≤ 0.35
	B	99 ± 0.2	≤ 0.60	≤ 23.00	≤ 0.60	≤ 0.40	≤ 0.40
Exponential constant		2.5	2	−1	1.5	1	3
$y^{\min}{}_j$		98.8	0.00	18.00	0.00	0.00	0.00
$y^{\max}{}_j$		99.2	0.60	23.00	0.60	0.40	0.40

4 Case study

This section demonstrates the effectiveness of the proposed procedure using a case study, which was undertaken to optimise the fused process parameters and hence improve the performance and reliability of the 1% (1/99) single-window broadband tap coupler.

4.1 Problem encountered

The problems encountered in a factory's mass-production of versatile couplers are machine instability, environmental influences (such as temperature, humidity, and airflow) and product diversity. In addition, each machine must be sufficiently stable to copy the optimal parameter and mass production is ineffective without the optimal parameter. To apply the proposed procedure to optimise the parameter settings in the FBT process, the quality characteristics of interest must be identified first. Discussion with the personnel managing quality and reliability engineering identified six crucial quality characteristics (responses), and these characteristics were selected herein to enhance quality performance, as follows:

1. *CR (%)* Coupling ratio (NTB)
2. *EL (dB)* Excess loss (STB)
3. *IL-A (dB)* Insertion loss at 1% tap port (STB)
4. *IL-B (dB)* Insertion loss at 99% through port (STB)
5. *PDL-A (dB)* Polarization dependent loss (at 1% tap port) (STB)
6. *PDL-B (dB)* Polarization dependent loss (at 99% through port) (STB)

The engineering management agreed that convex exponential desirability functions should be employed for the responses IL-A, while concave exponential desirability functions should be employed for the responses, *CR*, *EL*, *IL-B*, *PDL-A* and *PDL-B*. Table 1 lists the specifications of different grades of 1% (1/99) single-window broadband tap couplers. The table also lists the exponential constants, and values of $y^{\min}{}_j$ and $y^{\max}{}_j$ in Eqs. 6, 7, and 8.

Several variables influence the performance of the tap coupler. Discussion with the product engineer revealed that tap coupler optical performance in the fused process may depend on the following process-related control factors:

1. *DS* Drawing speed
2. *PRL* Pre-drawing length
3. *HMF* Hydrogen (H_2) mass flow
4. *TH* Torch height
5. *PHT* Pre-heating time
6. *HP* Hydrogen (H_2) pressure

Table 2 lists the experimental levels of the critical process control factors mentioned above.

4.2 Experiments and data collection

Six control factors at three levels require $3^6 = 729$ trials for a full factorial experiment, a lengthy process. The main effects of control factors could be accurately estimated by conducting 18 experimental trials arranged according to a Taguchi $L_{18}(2^1 \times 3^7)$ orthogonal array [19]. Hence, the six control factors were assigned to columns 3 to 8 in the Taguchi L_{18} orthogonal array and Table 3 lists the collected experimental data. Notably, the four responses, *CR*, *EL*, *IL-A* and *IL-B*, were collected at three wavelength levels, namely 1510 nm, 1550 nm, and 1590 nm. Table 3 lists the data for the worst case in the three wavelength conditions for further analysis.

4.3 Data analysis

The experimental results presented in Table 3 were analysed using the proposed procedure. Randomly

Table 2 Critical process control factors and their experimental levels

Control factor	Code	Level 1	2	3
Drawing speed	A	DS_1	DS_2	DS_3
Pre-drawing length	B	PRL_1	PRL_2	PRL_3
Hydrogen (H_2) mass flow	C	HMF_1	HMF_2	HMF_3
Torch height	D	TH_1	TH_2	TH_3
Pre-heating time	E	PHT_1	PHT_2	PHT_3
Hydrogen (H_2) pressure	F	HP_1	HP_2	HP_3

Level 2 is the existing level

Table 3 Collected experimental data

Trial	Factor						Response											
	A	B	C	D	E	F	CR		EL		IL-A		IL-B		PDL-A		PDL-B	
							Rep. 1	Rep. 2	Rep. 1	Rep. 2	Rep. 1	Rep. 2	Rep. 1	Rep. 2	Rep. 1	Rep. 2	Rep. 1	Rep. 2
1	1	1	1	1	1	1	98.644	98.775	0.053	0.047	19.715	20.239	0.104	0.090	0.180	0.170	0.010	0.010
2	2	2	2	2	2	2	98.733	98.791	0.011	0.021	20.464	20.271	0.050	0.061	0.240	0.230	0.030	0.020
3	3	3	3	3	3	3	98.798	98.728	0.060	0.084	20.287	20.201	0.103	0.139	0.310	0.280	0.020	0.020
4	1	1	2	2	3	3	98.689	98.830	0.049	0.034	20.005	20.379	0.097	0.085	0.180	0.190	0.020	0.010
5	2	2	3	3	1	1	98.748	98.783	0.025	0.097	20.367	20.458	0.079	0.151	0.200	0.270	0.020	0.010
6	3	3	1	1	2	2	98.747	98.817	0.059	0.017	20.211	20.584	0.101	0.054	0.490	0.410	0.030	0.020
7	1	2	1	3	2	3	98.797	98.831	0.025	0.160	20.326	20.440	0.066	0.211	0.200	0.220	0.030	0.020
8	2	3	2	1	3	1	98.617	98.709	0.134	0.024	19.960	20.208	0.194	0.067	0.340	0.280	0.020	0.010
9	3	1	3	2	1	2	98.738	98.783	0.045	0.056	20.135	19.964	0.100	0.109	0.270	0.250	0.020	0.010
10	1	3	3	2	2	1	98.612	98.720	0.039	0.109	19.951	20.515	0.100	0.158	0.170	0.170	0.100	0.020
11	2	1	1	3	3	2	98.954	98.768	0.075	0.100	20.302	20.205	0.145	0.146	0.210	0.240	0.010	0.010
12	3	2	2	1	1	3	98.779	98.759	0.038	0.022	20.227	20.173	0.091	0.071	0.360	0.390	0.030	0.020
13	1	2	3	1	3	2	98.720	98.632	0.068	0.075	20.350	19.735	0.117	0.056	0.210	0.220	0.020	0.010
14	2	3	1	2	1	3	98.791	98.811	0.070	0.086	20.048	20.389	0.130	0.138	0.320	0.290	0.020	0.030
15	3	1	2	3	2	1	98.662	98.793	0.190	0.083	19.772	20.094	0.248	0.136	0.290	0.280	0.030	0.030
16	1	3	2	3	1	2	99.105	98.731	0.051	0.058	20.410	20.060	0.095	0.113	0.170	0.180	0.020	0.030
17	2	1	3	1	2	3	98.682	98.758	0.060	0.059	19.687	20.245	0.114	0.101	0.210	0.240	0.010	0.020
18	3	2	1	2	3	1	98.775	98.613	0.061	0.390	20.314	20.128	0.106	0.443	0.300	0.280	0.030	0.020

selecting the training and testing data sets from the experimental results, a BP neural network model was constructed to model the functional relationship between input control factors and output responses. A smaller learning rate and larger momentum are recommended for finding global minimum weights [14], and thus the learning rate and momentum were set at 0.25 and 0.8, respectively. The candidate neural models were obtained using the NeuralWorks Professional II/Plus [20] software, as shown in Table 4. The 6-7-6 neural network model with minimal training and testing RMSEs was selected based on the table. Through the well-trained BP neural model, the output responses under all possible control factor parameter combinations can be accurately predicted. Meanwhile, by applying the exponential desirability functions with pre-specified exponential constants in Table 1, multiple responses are transformed into a single response. Table 5 summarises five combinations of control factor parameter settings that produce larger values for the objective function (λ) and the corresponding desirability function ($d(z)$). Following consultations with engineers, the optimal levels of control factors were set as $A=DS_2$, $B=PRL_3$, $C=HMF_2$, $D=TH_2$, $E=PHT_1$ and $F=HP_3$.

Table 4 The candidate BP neural models

Structure	Training RMSE[a]	Testing RMSE[a]
6-4-6	0.0732	0.1208
6-5-6	0.0732	0.0647
6-6-6	0.0687	0.0573
6-7-6	0.0642	0.0494
6-8-6	0.0706	0.0795
6-9-6	0.0565	0.0625
6-10-6	0.0621	0.0828
6-11-6	0.0652	0.0832
6-12-6	0.0660	0.0687

[a]RMSE: root mean squared error [20]

4.4 Confirmation experiment

A confirmation was carried out by processing thirty (30) pieces of 1% (1/99) single-window broadband tap couplers at the optimal parameter levels of control factors. Table 6 lists the confirmatory results, and indicates that all of the thirty trials conform to the specification of 1% (1/99) single-window broadband tap couplers.

Table 5 Five combinations of control factor parameter settings that produce larger values for the objective function (λ)

No.	Control factor						$d(z)$						λ
	A	B	C	D	E	F	*CR*	*EL*	*IL-A*	*IL-B*	*PDL-A*	*PDL-B*	
1	DS_2	PRL_3	HMF_2	TH_2	PHT_1	HP_3	0.5636	0.9860	0.4535	0.9411	0.4658	0.9951	0.4535
2	DS_2	PRL_3	HMF_3	TH_3	PHT_1	HP_3	0.4596	0.9965	0.4440	0.9571	0.5361	0.9951	0.4440
3	DS_3	PRL_3	HMF_3	TH_3	PHT_1	HP_3	0.4972	0.9961	0.4407	0.9555	0.6191	0.9947	0.4407
4	DS_2	PRL_3	HMF_2	TH_3	PHT_1	HP_3	0.6118	0.9787	0.4396	0.9294	0.5741	0.9940	0.4396
5	DS_2	PRL_3	HMF_1	TH_2	PHT_1	HP_2	0.5027	0.9754	0.4392	0.9238	0.4731	0.9945	0.4392

Table 6 Confirmatory results

Tube no.	Response						Quality grade
	CR (%)	*EL* (dB)	*IL-A* (dB)	*IL-B* (dB)	*PDL-A* (dB)	*PDL-B* (dB)	
1	99.1454	0.0750	20.7492	0.1170	0.1821	0.1186	Premium
2	99.1467	0.0693	20.7476	0.1189	0.1389	0.0070	Premium
3	98.8475	0.0397	20.2982	0.0850	0.1533	0.0105	Premium
4	98.8470	0.0483	20.3336	0.0986	0.1176	0.0101	Premium
5	99.1564	0.1351	20.8581	0.1779	0.1809	0.0075	Premium
6	98.8429	0.0931	20.2487	0.1396	0.1023	0.0074	Premium
7	99.1583	0.0590	20.8036	0.0998	0.0725	0.0100	Premium
8	99.1608	0.0338	20.7816	0.0800	0.1762	0.0110	Premium
9	98.8367	0.0917	20.3342	0.1378	0.0977	0.0114	Premium
10	99.1639	0.0340	20.8063	0.0800	0.1918	0.0106	Premium
11	99.1640	0.0500	20.8259	0.0899	0.1060	0.0110	Premium
12	98.8763	0.1817	20.6937	0.2308	0.1483	0.0094	A
13	99.1655	0.1420	20.9280	0.1783	0.1057	0.0222	Premium
14	98.8343	0.1174	20.6461	0.1561	0.1513	0.0147	Premium
15	99.1657	0.0499	20.8220	0.0912	0.1174	0.0038	Premium
16	99.1669	0.0410	20.8273	0.0843	0.1037	0.0116	Premium
17	99.1681	0.0872	20.8694	0.1339	0.1275	0.0211	Premium
18	98.8297	0.0925	20.2815	0.1343	0.1266	0.0104	Premium
19	99.1703	0.0591	20.8585	0.1067	0.1426	0.0134	Premium
20	99.1731	0.0421	20.8661	0.0855	0.1929	0.0146	Premium
21	98.8259	0.0592	20.3308	0.1002	0.1553	0.0090	Premium
22	98.8165	0.0588	20.2778	0.1015	0.1320	0.0090	Premium
23	98.8144	0.0941	20.3265	0.1407	0.1142	0.0062	Premium
24	98.8123	0.0245	20.3064	0.0764	0.1239	0.0153	Premium
25	98.8116	0.0842	20.4651	0.1361	0.1737	0.0170	Premium
26	98.8089	0.0468	20.1464	0.0988	0.1211	0.0055	Premium
27	98.8084	0.0325	20.3034	0.0789	0.1616	0.0116	Premium
28	99.1930	0.1654	21.0803	0.2062	0.0778	0.0112	A
29	98.8059	0.0859	20.3388	0.1335	0.1348	0.0189	Premium
30	98.8053	0.0521	20.2461	0.1019	0.0889	0.0076	Premium

Moreover, 28 of the 30 couplers are graded as "Premium" and the others are graded as "A". The authors are confident that the obtained optimal combination of process control factor parameters can be directly applied to mass producing fused optical couplers.

4.5 Implementation

The optimal levels of process control factors were implemented in a pilot run of the fused process in a phase over 20 days. Evaluation of 200 couplers revealed that the average defect rate was reduced to 2.5%, from over 35% previously. Meanwhile, the monthly device output from the factory is approximately 10,000 pieces this year. The demand is expected to grow rapidly in the coming months, with annual growth of over 50% being assumed. Consequently, this valuable investigation to optimise the fused process parameters can not only increase throughput by 30% through increasing the yield ratio, but can also increase the price by 25% through producing more reliable high performance couplers. Given these achievements, annual savings are expected to reach USD 500,000–1,000,000, well above the cost of the experiment, at only around USD 3,000.

5 Conclusions

This investigation proposed an integrated procedure based on neural networks and exponential desirability functions to resolve the parameter design problem with multiple responses. Effectiveness of the proposed procedure was demonstrated using a case study which was undertaken to optimize the fused process parameters that have been made in the development of FBT couplers to enhance the performance and reliability of the 1% (1/99) single-window broadband tap coupler. A pilot run of the fused process over 20 days was implemented and evaluation of 200 pieces of couplers revealed that the average defect rate reduced to just 2.5%, from over 35% previously. Annual savings from implementing the proposed procedure are expected to exceed 0.5–1.0 million US dollars, whereas the expenditure for the experiment was below USD 3,000. This investigation has been extensively and successfully applied to develop the optimal fuse parameters for other coupling ratio tap couplers, such as 2/98, 3/97, 4/96, ..., 50/50.

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