Use of Response Surface Methodology and Exponential Desirability Functions to Paper Feeder Design

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Abstract: - Applying parameter design to a system that has a binary-type performance, an efficient metric is to employ the operating window (OW) which is the range between two performance limit thresholds. Paper feeder design is a typical problem of the OW method. The wider OW, the higher performance of the system is. This study uses an approach based on artificial neural networks (ANN) and desirability functions to optimizing the OW design of a paper feeder. The approach employs an ANN to construct the response function model (RFM) of the OW system. A novel performance measure (PM) is developed to evaluate the OW responses. Through evaluating the PM of the predicted OW responses, the best control factor combination can be obtained from the full control factor combinations. A simulated example of a paper feeder design is analyzed. Performing the approach to parameter design problems, engineers do not require much background in statistics but instead rely on their knowledge of engineering.

Key-Words: - Artificial Neural Networks, Exponential Desirability Functions, Operating Windows, Response Surface Methodology, Response Function Model, Paper Feeder Design

1 Introduction

While performing parameter design, engineers often encounter the situation that a system has a binary-type performance (i.e. good or bad, 0 or 1). A common way to quantify the system's performance is to compute the ratio of bad results to total results (i.e., a percentage of defective results) then transfer the percentage into Taguchi's SN ratio of STB [10, 16]. This method may need a large number of experiments when the rate of failure is low; besides, the information of experiments data cannot be exploited to the analysis. A more efficient metric is to employ the operating window (OW) which is the range between two performance limit thresholds. The wider OW, the higher performance of the system is [3].

The concept of the OW was developed by Clausing [2]. He used an OW response for the design of a friction-retard paper feeder in a copier machine. The function of a paper-feeding mechanism in a copier machine to feed exactly one sheet of paper each time the mechanism receives an input signal. When the mechanism does not feed any paper, it is called "misfeed." When two or more sheets of paper are fed into the copier machine at the same time, it is called "multifeed." As shown in Figure 1, this mechanism applies friction between the feeder roller and the paper, and the torque of the feed roller feeds the paper into the printer [3, 8].

The friction force between the feed roller and the paper is determined by the spring force applied below the paper tray. When the spring force is too small, no paper will be sent out of the paper tray (misfeed). When the spring force is properly set, one sheet of paper will be sent out. When the spring force is set too large, two or more sheets might be sent out of the tray (mulitfeed). The objective the paper feeder design is to minimize the rate of both failure modes, i.e., misfeed and mulitfeed. Herein, spring force is a critical parameter of the paper feeder and is easy to measure. Let the threshold value of the spring force for sending one sheet of paper be *x* (gram-force). Let the threshold value of the spring force for multifeeding two or more sheets be *y* (gram-force). We can find two threshold values of the force at which the misfeed stops (*x*) and at which the multifeed starts (*y*). Then, (*x*, *y*) forms the OW [16].

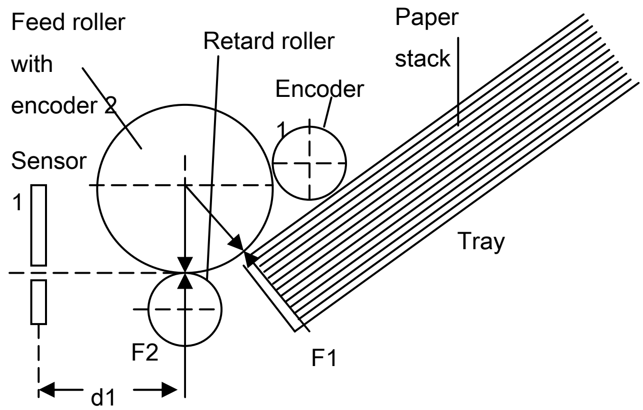

Fig.1 Paper feeder mechanism

Thus, the objective of the paper feeder design becomes to minimize *x* to decrease number of misfeeds, and to maximize *y* to decrease number of multifeeds. Figure 2 shows two situations of an operating window. The operating window of situation B is wider and has a greater robustness than the window for situation A [17].

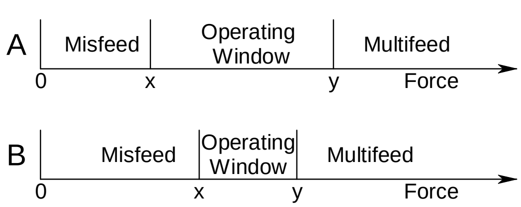

Fig.2 Operating window.

The two failure modes can be eliminated if *x* is reduces to zero and *y* is increase to infinity. Therefore, *x* is a small-the-better (STB) characteristic and *y* is a larger-the-better (LTB) characteristic. The optimization of the OW can be treated as to optimize simultaneously the responses of both STB and LTB in a system.

The response function methodology (RSM) is an efficient approach to for the modeling and analysis of problems in which one or more response of interest are influenced by several control factors. Using the RSM, one can find the relationship between the responses and control factors, and then to optimize the responses [11]. Accordingly, this study uses the RSM to model the paper feeder's OW responses. The response function model (RFM) is built by training an artificial neural network (ANN). The well-trained ANN can be applied to predict all possible OW responses by inputting full control factor combinations. To optimize simultaneously the responses of *x* and *y*, exponential desirability functions are used to integrated the two response into a single measure. Finally, the best control factor combination can be obtained by maximize the single measure.

The rest of this paper is organized as follows. Section 2 introduces the ANN approach. Section 3 applies the exponential desirability functions to measure the STB and LTB response. Section 4 proposes the resolving approach for paper feeder design. Section 5 implements the approach to a paper feeder design. Conclusions are provided in Section 6.

2 ANN

ANN has been successfully applied to determine the optimal parameter design of a process [6, 7]. Applying the method, the ANN is trained by the results of a fractional factorial design, and is then used to estimate the response values for the full factorial design. Among the successful implementations of an ANN, the backpropagation (BP) training method is most reliable. The most used non-linearity for the BP algorithm is a sigmoid logistic function [12, 15].

The best structure of an ANN is identified through comparing the root of mean-square-error (RMSE) of each structure. This error-calculation method is used to determine the amount of variance between the expected and actual outputs of an ANN. The lower the RMSE, the better the ANN predicts. Several structures of neural networks with different numbers of hidden layers and neurons in each hidden layer are tested to find the best structure with the lowest RMSE. The processes of training a well network are as follows:

Step 1. Determine the artificial neural networks structure, initial connection weights, and offsets.

Step 2. Present inputs and desired outputs.

Step 3. Calculate the actual output.

Step 4. Calculate the RMSE.

Step 5. Adjust the weights of the networks.

Step 6. Repeat steps 2—5 for each training pair until the RMSE of the entire set is acceptably low.

Several structures of neural networks with different numbers of hidden layers and neurons in each hidden layer are selected and are tested to find the best structure with the lowest RMSE. Then the weights of all the links of the networks are decided.

3 Exponential Desirability Functions

The exponential desirability function approach was introduced by Harrington [5] and further modified by Kim and Lin [9] and Chang [1]. The exponential desirability function transforms an estimated response (e.g. the $\hat{r}_j$ estimated response) to a scale-free value d_j, called desirability. It is a value between 0 and 1, and increases as the desirability of the corresponding response increases. Goik et al. [4] firstly applied desirability functions to operating windows design. To evaluate different types of quality characteristics, the desirability functions are employed here and are slightly modified.

For the LTB type with lower specification limit (LSL), the desirability function of the d value (denoted by d^{LTB}) is formulated as Equations (1) and (2).

$$d^{LTB} = \exp(-(\exp(-Z^{LTB}))) \tag{1}$$

where

$$Z^{LTB} = \frac{\hat{r} - r_{\min}}{r_{\min}}, \tag{2}$$

$r_{\min}$ represents the LSL of response r.

For the STB type with upper specification limit (USL), the desirability function of the d value (denoted by d^{STB}) is formulated as Equations (3) and (4).

$$d^{STB} = \exp(-(1 + Z^{STB})) \tag{3}$$

where

$$Z^{STB} = \frac{\hat{r} - r_{\max}}{r_{\max}}, \tag{4}$$

$r_{\max}$ represents the USL of response r.

4 The Approach

The proposed approach for analyzing the OW response problem comprises three phases. The first phase involves collecting experimental data for training an ANN to represent the RFM of the system, which is capable of predicting the corresponding OW responses by giving a specific factor combination. In the second phase, two novel performance measures derived from exponential desirability functions are developed for evaluating the OW responses. The third and final phase provides the integration of performance measures and the optimization processes which maximize the OW responses by using the RFM and the measures. Figure 3 shows the flowchart of the approach. The details of the three phases are described in Sections 4.1–4.3.

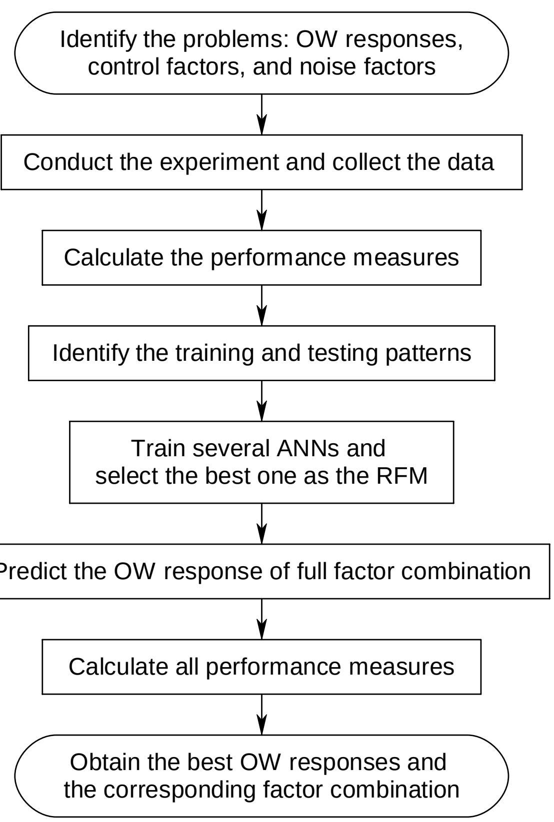

Fig. 3 The flowchart of the approach

Response Function Model

This phase uses an ANN to model the response function. The input and output data are assigned as the level values for the control factor and the OW responses, respectively. A well-trained ANN represents the system's RFM. For detailed discussion on how an ANN applied to parameter design, readers can refer to Rowlands et al. [13]. The process of the response function modeling consists of four steps, which are as follows:

Step 1. Randomly select the training and testing patterns from the experimental data.

Step 2. Select several ANN structures including input nodes, hidden layers, hidden nodes and output nodes.

Step 3. Set learning rate, momentum coefficient and executions iterations for each ANN structure.

Step 4. Train and choose a well-trained ANN as the RFM, which establishes the relationship function between control factors and OW responses of the system.

Performance Measures

For the paper feeder design, two OW responses (i.e., x and y) are simultaneously determined by of the system's control factor combinations. To measure the performance of the response x and y, the exponential desirability functions are employed here. For the response x, the desirability can be formulated as Equation (5).

$$d^x = \exp\left(-\left(1+\frac{\hat{x}-x_{\max}}{x_{\max}}\right)\right), \quad (5)$$

where $x_{\max}$ represents the USL of the OW response x, which is determined by the designer.

For the response y, the desirability can be formulated as Equation (6).

$$d^y = \exp\left(-\left(\exp\left(-\frac{\hat{y}-y_{\min}}{y_{\min}}\right)\right)\right), \quad (6)$$

where $y_{\min}$ represents the LSL of the OW response y, which is determined by the designer.

Optimum obtaining

To measure the overall performance of the paper feeder system, two OW responses need to be integrated into a single performance measure (denoted by PM). To enhance the overall performance PM, the optimizing of the OW response problem can be stated as:

$$\text{Maxminize} \quad PM = \sqrt{d^x \cdot d^y} \quad (7)$$

The optimization processes for obtaining optimal control factor combination are as follows:

Step 1. Predict all possible OW responses of the system by presenting full control factor combinations to the RFM.

Step 2. Calculate the overall performance (i.e., *PM* value) of each response at each combination.

Step 3. Compare the overall performance and obtain the best one and the corresponding control factor combination.

5 Implementation

A simulated example of paper feeder design is executed for obtaining the experimental data. Six control factors, A, B, C, D, E and F, are selected and are allocated in the L_{18} orthogonal array (OA) for the experiments [13]. Table 1 lists the control factor levels and their allocations. The simulated experimental data including misfeed threshold (x) and multifeed threshold (y) are listed in Table 2. The USL and LSL for the thresholds x and y are set as 500 and 400 grams, respectively.

Table 1 The control factors and their allocations

Label	Factors	Column in L_{18}	Levels 1	2	3
A	Pad coefficient of friction	1	Low	High	-
B	Retard pad force	4	Low	Nominal	High
C	Retard angle (degree)	5	19	21	23
D	Feed roll to pad lateral offset	6	-2mm	Centered	+2mm
E	Width of feed belt (mm)	7	10	20	30
F	Roll velocity	8	Low	Nominal	high

The RFM can be built through training an ANN model. The ANN is trained by assigning the levels of control factors and the values of thresholds (i.e., *x* and *y*) as the inputs and outputs of the network. Eight patterns are randomly selected for testing and 64 patterns are selected for training. The learning rate is set as auto-adjusting between 0.01 and 0.3. The momentum coefficient is set as 0.80. The number of iterations is set as 15,000. Table 3 lists several options of the network architecture; furthermore, the structure 6-8-2 with the lowest testing RMSE, 0.1468, is chosen to obtain a better performance.

Table 2 The allocations of the control factors and the experimental data

Experiment No.	Control factor array						*x* value (gram)				*y* value (gram)			
	A	B	C	D	E	F								
1	1	1	1	1	1	1	335	340	298	326	633	680	816	720
2	1	2	2	2	2	2	309	321	282	279	635	595	735	637
3	1	3	3	3	3	3	335	286	373	228	664	677	774	756
4	1	1	2	2	3	3	286	429	414	300	660	682	594	729
5	1	2	3	3	1	1	463	309	352	314	586	788	613	604
6	1	3	1	1	2	2	267	323	339	259	754	745	702	678
7	1	2	1	3	2	3	331	290	335	249	586	709	685	533
8	1	3	2	1	3	1	302	272	395	269	798	691	712	778
9	1	1	3	2	1	2	250	337	335	368	613	669	591	665
10	2	3	3	2	2	1	390	370	384	202	531	508	805	758
11	2	1	1	3	3	2	255	282	277	326	702	666	704	654
12	2	2	2	1	1	3	245	381	329	325	631	698	592	609
13	2	2	3	1	3	2	323	247	326	321	680	655	605	727
14	2	3	1	2	1	3	273	247	340	354	698	755	691	724
15	2	1	2	3	2	1	360	153	282	292	648	700	782	696
16	2	3	2	3	1	2	231	226	335	221	529	698	640	539
17	2	1	3	1	2	3	173	273	377	223	560	587	797	714
18	2	2	1	2	3	1	199	307	323	285	613	621	806	753

Table 3 The candidate ANN models

Architecture	RMSE	
	Training	Testing
6-4-2	0.1329	0.1478
6-5-2	0.1325	0.1474
6-6-2	0.1316	0.1476
6-7-2	0.1319	0.1477
6-8-2	**0.1313**	**0.1468**
6-9-2	0.1324	0.1473
6-10-2	0.1315	0.1469
6-11-2	0.1314	0.1473
6-12-2	0.1317	0.1471
6-13-2	0.1315	0.1475

Through the RFM, the responses x and y under any possible combinations of control factors can be accurately predicted. Then, the PM value of the responses x and y can be calculated easily by applying Equations (5) — (7). Table 4 lists six factor combinations that have larger PM values. Paper feeder designers can freely choose appropriate control factor combinations from Table 5 under the considerations of cost, time, and material. Moreover, the control factor combinations (A_2, B_3, C_1, D_3, E_3, F_2) is the best one in terms of PM value.

6 Conclusion

In this study, an ANN-based approach is proposed to resolving the operating window design of a paper feeder. The approach consists of three phases. First, an ANN is trained to represent the RFM of the system. Second, the *PMs* of the predicted OW responses are evaluated by presenting full combinations of control factors into the RFM. Finally, the best control factor combination can be obtained by maximizing the *PM* value. The implementation of the paper feeder design reveals the approach's effectiveness. Performing the approach, engineers do not require much background in statistics but instead rely on their knowledge of engineering. Besides, no costly statistical software package is needed when engineers employ the approach. Engineers can gain a software package of ANN at a relatively low cost, thereby increasing their desire to adopt the approach. The proposed approach can be also applied to other industrial systems that have binary-type performance such as wave soldering and resistance welding. Furthermore, in future research, some meta-heuristics techniques such genetic algorithm and simulated annealing can be considered introducing to the optimization process for improving the effectiveness of the approach.

Table 4 Six factor combinations that have larger *PM* values

No.	Control factor settings						$\hat{x}$	$\hat{y}$	d^x	d^y	*PM* value
1	A_2	B_3	C_1	D_3	E_3	F_2	216	691	0.6498	0.6166	0.6330
2	A_2	B_3	C_1	D_3	E_2	F_3	215	687	0.6502	0.6136	0.6316
3	A_2	B_3	C_1	D_3	E_3	F_1	230	709	0.6317	0.6302	0.6309
4	A_2	B_3	C_1	D_3	E_2	F_2	219	689	0.6459	0.6154	0.6305
5	A_2	B_3	C_1	D_3	E_3	F_3	217	683	0.6478	0.6106	0.6289
6	A_2	B_1	C_1	D_3	E_1	F_2	235	704	0.625	0.6264	0.6258

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