Applying Neural Networks Approach to Achieve the Parameter Optimization for Censored Data

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Abstract: - This study proposes an approach based on neural networks to perform the analysis of the censored data. Two neural networks are constructed: the first neural network is designed to estimate the censored data by means of constructing the model derived from the uncensored data and, the second neural network is designed to obtain the optimum parameter settings of control factors by using the uncensored data and the estimated censored data. The proposed approach can not only be used for control factors with categorical level setting, but also for continuous setting. Furthermore, the approach proposed herein will be employed for Taguchi's dynamic experiment. One numerical example demonstrates the effectiveness of the proposed approach.

Key-Words: - censored data, neural network, parameter optimization

1 Introduction

To optimize a product or process, engineers usually perform designed experiments to determine the optimum settings of process parameters. However, for some uncontrollable causes such as equipment-related damage, experimental failure, or the limitation of the experimental time and cost, only part of the experiment can be completed. In this case, the experimental data consists of two parts: incomplete data and complete data. Incomplete data are referred to as the censored data, which usually arise in a situation where the response variable is time to failure, e.g. accelerated life testing. The complete data are viewed as uncensored data. The statistical analysis is more difficult to perform for an experiment with censored data.

In the conventional designed experiment, the type of censored data can be roughly divided into type I and type II censored sample. For type I censored sample, a criterion value of the quality response must be pre-determined, and the number of the censored data do not be pre-determined which will lead it to be a random variable. For type II, the number of the censored data must be pre-determined and the quality response does not be pre-determined which will lead it to be a random variable. In addition, the censored sample can be divided clearly into four types: left singly censored, right singly censored, doubly censored and multiple censored (progressively censored or hypercensored) samples.

The design of experiment and Taguchi's experiment are two methods frequently employed to study the optimum parameter settings of a product or an operational process. In the conventional experiments, most censored data analysis primarily focus on the type I censored data. Especially, the censored data may be frequently occurred on the entire factor's level combination for type I censored samples. The primary method to such type I censored data analysis is to initially fit a model by using the uncensored data, and the fitted model is then employed to predict the mean of the censored data of the factor/level combination. For instance, Hahn, Morgan and Schmee (1981) proposed the method of Iterative Least Square (ILS) to fit the model; Hamada and Wu (1991) also proposed a method of maximum likelihood estimation (MLE) to replace the ILS method to fit the model. However, the ILS method of Hahn et al. does not recommend how to determine the optimum parameter settings and, the MLE method of Hamada and Wu need complicated computations and the MLE value may not exist under some situation like as the main effect and two-factor intersection simultaneously involved in the initial model. There are not any particularly developed method to analyze type II censored data, transforming the type II censored data into type I censored data is a frequently employed technique. Hence, the model construction can be viewed as an important factor when we analyze the censored data. Taguchi method combines experimental technology with the quality loss to improve quality. Taguchi's parameter design can be divided into two classes: static and dynamic characteristic experiments. The two classes also markedly differ in that the dynamics class employs the signal factor and the static class does not. The various values of signal factor will influence significantly the quality response. Until now, the static problem has received more attention than a dynamic problem. In recent years, the dynamic problem has been addressed more than the static experiment. Dynamic experiments usually require more experimental runs than a static experiment. For experimental analysis involving censored data, Taguchi (1987) developed minute accumulation analysis (MAA) for the static problem. However, the MAA can not be directly employed for a dynamic problem.

Artificial neural networks (ANN) have been used in a wide variety of applications, ranging from classification and pattern recognition to optimization and control (NeuralWare, 1990). Furthermore, ANN has successfully employed to model the complexity structure of a system including linear or non-linear relationship (Funahashi, 1989; NeuralWare, 1990). Employing the neural networks to model the interrelation among input (or control factors) and output (or response) of a quality system by using the experimental data will be an easy approach than statistical approaches (Ko, Kim, Kim and Choi, 1998; Su and Miao, 1998). In lieu of above circumstances, this study proposes a generalized neural networks approach to perform the censored data analysis in both the conventional experiment and Taguchi's experiment while considering static/dynamic characteristics. The first neural network is constructed to identify the feature concealed in experiment and store this feature into the connected weights between layers of the network. Restated, the uncensored experimental data can be modeled to estimate the censored observations. The second neural network is employed to optimize the parameter settings by combining the uncensored data with the estimated censored data.

2 Literature Review

Hahn and Nelson (1974) reviewed graphical, maximum likelihood and linear estimation methods for analyzing censored life data. However, results obtained from graphical methods vary according to different individuals since they employ a subjective judgment procedure. Although statisticians generally recommend the maximum likelihood method, practitioners having limited statistical training usually find it difficult to comprehend. Moreover, the maximum likelihood method requires an enormous amount of computational time. Hahn, Morgan and Schmee (1981) also suggested the method of iterative least square (ILS) to analyze censored data. An initial least square fit is obtained, herein, the censored data are treated as failure. The initial fit is then used to estimate the expected failure time for each censored observation. Next, using these estimates to obtain a revised least square fit. This procedure is iterated until estimate of two iteration is small than a pre-determined value.

Taguchi (1987) developed the minute accumulating analysis (MAA) method for interval-censored reliability data. The data are represented by 0 and 1. In each cycle, if the individual test piece is alive, it is expressed as 1; however, if it is dead, it is expressed as 0. This generated binary data can be treated as if they came from a split-plot experiment. The main-plot factors are control factors studied in the experiment; the sub-plot factor is the time factor created in the binary data. However, by treating censoring times as the actual failure times, the unobserved failure and censoring times may significantly differ, and, consequently, the MAA method may causes serious deficiencies.

Hamada and Wu (1991) proposed an iterative procedure for analyzing the censored data for the fractionated experiments. This procedure combines the maximum likelihood estimation and iterative least square. The data are initially transformed to achieve near normality. The maximum likelihood estimation is then used to select a tentative model which is combined uncensored and censored data. Next, the censored data are estimated by employing the iterative least square. This cycle continues until the selected model stops changing. Several models may be identified and diagnostic checking can be performed to assess their adequacy. Finally, the optimal factor/level combination can be determined. Torres (1993) proposed a method depends on the rank transformation of the quality response to analyze the unreplicated factorial experiments with possible abnormalities. The normal plot of the effects of the ranked observations is used to determine the significant factors. However, this method only can be used to analyze an unreplicated experiment. Tong and Su (1997) proposed a nonparametric method to analyze the censored data. In their method, the rank transformation of the response is used. In addition, those factors which significantly influence response average and standard deviation are identified according to the normal plots of the fitted regression's coefficients for the ranked values. In a later work, Su and Miao (1998) proposed an artificial neural network approach to analyze the censored data. However, their approach can not determine the optimum setting values of control factors with the continuous form.

3 Dynamic characteristics

Taguchi's dynamic experiment can be viewed as a modification of his static experiment. In Taguchi's dynamic experiment, the experimental factors are grouped into three classes: control factors, signal factors and noise factors (Phadle, 1989; Peace, 1993). In general, a control factor is a factor whose value can be set or adjusted by the experimenters. The control factor provides an opportunity to enhance the process's performance. In addition, a signal factor is a factor whose inputting value can significantly influence the value of the quality response, that is, a signal factor will significantly influence the average of the quality response as well (Fowlkes and Creveling, 1995). A noise factor is a factor whose value cannot be set or, if it can be controlled, the cost is too high or the inconvenience is too great. In addition, the noise factor causes a process to vary, i.e. the noise factor may adversely influence the quality of the experiments. Figure 1 depicts graphically Taguchi's dynamic system. Taguchi's parameter design concentrates primarily on determining a robust setting of the design parameters to minimize the impact of the noise factors. A dynamic system can be viewed as composed of a signal and subsequent responses that can be affected by noise. Therefore, Taguchi's parameter design for a dynamic system focuses primarily on determining a robust setting of the design parameters to maximize the strength of the signal in relation to minimizing the impact of the noise factor (Phadke, 1989; Fowlkes and Creveling, 1995).

The relationship between the signal factor and the quality characteristics is assumed to be linear in Taguchi's philosophy, i.e. $Y = \beta M + \varepsilon$, where β denotes the system's sensitivity and ε represents the error term. By considering the different level's combinations of control factors, the equation can be rewritten as $Y = \beta(d)M + \varepsilon(d)$, where d denotes the control factor level's combination, $\beta(d)$ represents the system's sensitivity under d, and $\varepsilon(d)$ is the random error term under d. To evaluate a dynamic system's robustness, Taguchi proposed the following formula:

$$\eta = 10\log\frac{\beta^2}{MSE} \qquad (1)$$

for evaluating the SN ratio in decibels (dB). Herein, the mean square of error (MSE) represents the mean square of the distance between the measured response and the optimally fitted line. The related principle for a dynamic SN ratio is thoroughly described in Peace (1993) and Phadke (1989).

4 Propose Approach

The motivation behind employing the neural network is that the feature hidden in the experiment for uncensored data can be directly used to model the corresponding system and, then, the censored data can be estimated from the model. Furthermore, Taguchi's SN ratio is an efficient index to evaluate quality (Phadke, 1989). It can be applied into all experimental design involving fractional factorial experiment and full factorial experiment. Two neural networks are developed: one for estimating the censored data and the other for determining the optimum condition. Figure 1 depicts the topology of the neural network approach proposed herein. The generalized neural network approach proposed herein is given as follows:

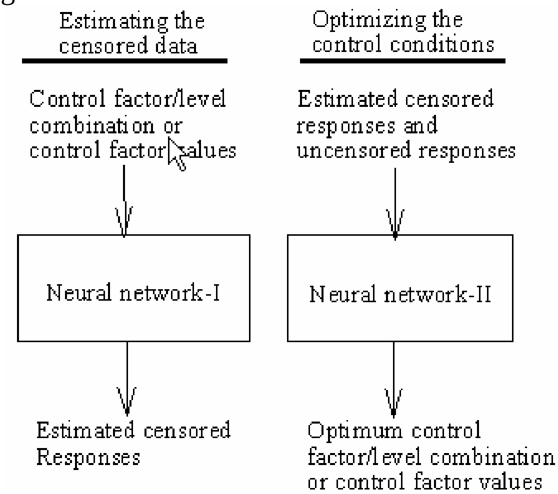

Figure 1. Topology of the proposed neural network.

Experimental design involving static (dynamic) characteristic {where the sign "+" in parenthesis represents the dynamic characteristic consideration.}

A. Control factors are qualitative:

<u>Phase I. Estimating the censored data (model construction)</u>

Step 1. Form the training and testing patterns by randomly selecting the data from the experimental trials.

Step 2. Construct the training architectures for neural network-I by assigning the level combination of control factor (+signal factor) and the location code/response of the uncensored data as the inputs/output of this network.

Step 3. Retrain the selected architecture of neural network-I to arrive at a pre-determined training epochs by combining the above training and testing sets in Step 1 into a training set, that is, combining the uncensored and censored data.

Step 4. Obtain the estimated censored data by inputting the corresponding level combination of control factors (+signal factor) and location code to neural network-I.

Phase II. Optimizing the control conditions (parameter optimization)

Step 1. Compute the SN ratio (+β) for each level combination of control factor according to quality characteristic. Commonly, quality characteristic can divide into three types: smaller-the-better (STB), nominal-the-better (NTB) and larger-the-better (LTB). The detailed formula of each SN ratio can refer to Phadke (1989), Peace (1993) or Flowkes and Creveling (1995). Then, form the training and testing patterns by randomly selecting the data from the experimental trials, which includes the estimated censored data from Phase I.

Step 2. Construct the training architectures for neural network-II by assigning level combination of control factor /SN ratio (+β) as the inputs/output of this network.

Step 3. Retrain the selected architecture of neural network-II to arrive at a pre-determined training epoch by combining the above training and testing sets in step 1 into a training set.

Step 4. According to the criterion for SN ratio value being maximum (+ β being close to 1), determine the optimal level combination of control factor by inputting all possible level combinations of control factor into the chosen network.

B. Control factors are a mixture of qualitative and continuous factors:

Phase I. Estimating the censored data (model construction)

This phase is the same as Phase I of the above control factors being qualitative except that Step 2 is modified to assign the qualitative control factor's level, continuous control factor's values (+signal factor) and corresponding location code/response of uncensored data as the inputs/output of the network.

Phase II. Optimizing the control conditions (parameter optimization)

Step 1.Form the training and testing patterns by randomly selecting the data from the experimental trials. The estimated censoring data from Phase I will be included in the training set.

Step 2. Construct the training architectures for neural network-II by assigning responses and location code/control factor levels on control values as the inputs/outputs of this network.

Step 3. Retrain the selected architecture of neural network-II to arrive at a pre-determined training epoch by combining the above training with testing sets in step 1 into a training set.

Step 4. Determine the optimal setting values of control factors by inputting the ideal response value and location code into the neural network-II.

When the fractional factorial experiment or full factorial experiment is employed, the analysis procedure is the same as Taguchi's experiment involving static characteristic.

5 Illustrative Example

5.1 Dynamic characteristics

A dynamic characteristic optimization design of circuit for AF-200M camera's signal measuring system can be found in Chinese Society for Quality Control (1995). This numerical example contains seven control factors with three levels and two replications for four signal factors. The L_{18} orthogonal array is employed herein. According to this table, Y_{ijk} represents the observation of the j-th noise under k-th control condition for i-th signal factor, where i=1~4, j=1~2, and k=1~18. In this study, we transfer the complete data into a right-censoring data by assuming that any measuring value which exceeds 2 is regarded as the censored data. The censored data are represented with bold faces in Table 1. This example contains forty censored data, which leads to a situation in which the proportion of the censored data to the complete data (censored data + uncensored data) is about 1/3.

The proposed approach is applied to analyze the above case. The censored data must initially be estimated. The setting values of control factors, setting value of signal factor, location code and β (represents the sensitivity of a dynamic system)/response are severed as the inputs/output of the neural network-I, then the predicted censored data are obtained. For this numerical example, there are two replications. Restated, they are identified as inputting location codes for providing more information to the neural network. The additional location code herein is decoded as 1 and 2. Figure 2 displays several options of network architecture; the structure 9-6-1 is selected to obtain a better performance (RMSE ≅ 0.086). Notably, the estimated censored data can be obtained by inputting the corresponding control factor values, signal factor value and location code to the trained network. Table 2 displays all the estimates of the censored data. The study also compute SN ratio and β value for each trial by combining the estimated censored data with the uncensored data. To obtain the optimal condition, the SN ratio and β value/control factor values are severed as inputs/outputs for neural network-II. Figure 3 displays several options of neural network architecture; the structure 2-6-7 is selected to obtain a better performance (RMSE ≅ 0.121). The network generates a steady state of the connected weight after 10,000 training epochs. The optimum control factor values can then be obtained by inputting ideal response and β value (the ideal β value equals 1) to the pre-determined 10,000 training epochs. The optimum control factor values of this example are (A, B, C, D, E, F, G) = (112.4, 0.376, 46.33, 12.05, 1.68, 1.74, 0.62). To compare the proposed approach with the Taguchi's dynamic method, we input the optimum condition, signal factor value and location code to neural network-I; eight predicted responses are derived as well. Table 3 displays these predicted responses.

Table 1. The experimental data (see ref. 15).

No	M_1		M_2		M_3		M_4	
	N_1	N_2	N_1	N_2	N_1	N_2	N_1	N_2
1	0	0	1	1	**2.8**	**3**	**3**	**3**
2	0	0	1	1	2	2	2	**2.7**
3	0	0	1	1	2	2	2	2
4	0	0	2	1.9	**3**	**3**	**3**	**3**
5	0	0	1	1	2	2	**2.1**	2
6	0	0	1	0	2	0	2	0
7	0	0	2	2	**3**	**3**	**3**	**3**
8	0	0	2	2	**3**	**3**	**3**	**3**
9	0	0	2	2	**2.9**	**3**	**3**	**3**
10	0	0	1.8	1.3	**2.9**	**2**	**3**	**3**
11	0	0	1	1	1.7	2	2	**2.3**
12	0	0	1	1	2	0	2	0
13	0	0	2	2	**2.6**	**2.8**	**3**	**3**
14	0	0	1	1	2	0.7	**2.3**	0
15	0	0	1	1	2	2	1	2
16	0	0	2	2	**3**	**3**	**3**	**3**
17	0	0	2	0	**2.8**	0	**2.9**	0
18	0	0	1	1	2	**2.6**	2	**3**

Table 2. The estimated censored data and the assumed censored data.

	Result									
	Y_{311}	Y_{321}	Y_{411}	Y_{421}	Y_{422}	Y_{314}	Y_{324}	Y_{414}	Y_{424}	Y_{415}
Assumed censored data	2.8	3	3	3	2.7	3	3	3	3	2.1
Estimated censored data	2.83	2.95	3.04	3.06	2.64	2.92	2.98	3.02	3.04	2.07
	Result									
	Y_{317}	Y_{327}	Y_{417}	Y_{427}	Y_{318}	Y_{328}	Y_{418}	Y_{428}	Y_{319}	Y_{329}
Assumed censored data	3	3	3	3	3	3	3	3	2.9	3
Estimated censored data	3.05	2.93	2.97	2.95	3.04	3.05	3.01	2.98	2.84	2.96
	Result									
	Y_{419}	Y_{429}	Y_{3110}	Y_{3210}	Y_{4110}	Y_{4210}	Y_{4211}	Y_{3113}	Y_{3213}	Y_{4113}
Assumed censored data	3	3	2.9	2	3	3	2.3	2.6	2.8	3
Estimated censored data	3.02	2.94	2.93	1.94	2.92	3.05	2.37	2.64	2.91	3.06
	Result									
	Y_{4213}	Y_{4114}	Y_{3116}	Y_{3216}	Y_{4116}	Y_{4216}	Y_{3117}	Y_{4117}	Y_{3218}	Y_{4218}
Assumed censored data	3	2.3	3	3	3	3	2.8	2.9	2.6	3
Estimated censored data	2.82	2.21	2.92	3.04	3.01	3.04	2.86	2.88	2.63	2.98

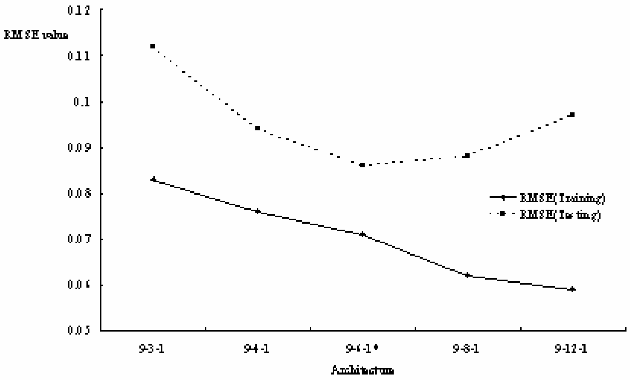

Figure 2. The training RMSE values of BPNN-II

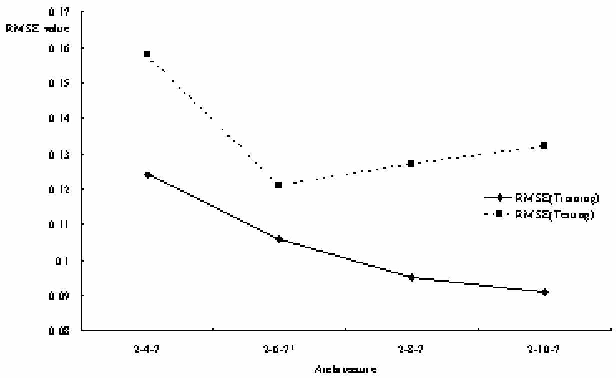

Figure 3. The testing RMSE values of BPNN-II

The fact that Taguchi's MAA can not be employed to analyze a dynamic problem accounts for why this example is analyzed only by employing Taguchi's dynamic method for the original data; in addition, the optimum condition is A1B1C2D3E3F3G1. The predicted SN value of the proposed approach exceeds Taguchi's dynamic SN value by about 2.27dB. Notably, the obtained optimal condition is close to the optimal level combination from Taguchi ' s dynamic method. This finding indicates that the proposed approach is also effective in terms of analyzing Taguchi's dynamic problem with censored data. Table 4 compares Taguchi's dynamic method with the proposed neural network approach.

Table 3. The predicted response values

	Signal factor			
	M_1	M_2	M_3	M_4
N_1	0	1.02	2.09	3.11
N_2	0	1.05	2.07	3.08

Table 4. The comparison results (example 2)

	A	B	C	D	E	F	G	Gain
Taguchi's dynamic method	100	0.[illegible]3	51	11.8	1.8	2	1	11.28dB
The proposed approach	112.4	0.376	46.33	12.05	1.68	1.74	0.62	13.45dB

6 Concluding Remarks

This study presents a novel neural network approach to analyze the censored data from Taguchi's dynamic experiment. The numerical example demonstrates the proposed approach's effectiveness. According to those results, the proposed neural network approach has several merits: (1) the proposed approach uses new model construction concept to learn the inherent feature in designed experiments by using the censored data; (2) the approach is more reasonable in terms of identifying the continuous parameter settings in Taguchi's dynamic experiments with censored data analysis; (3) the approach can efficiently reduce the time and cost for performing experiment by employing suitable censored data analysis in Taguchi's dynamic experiments; and (4) any analyst with limited statistical training have relative ease in comprehending the proposed approach. In addition, engineers can directly use the neural network software to develop the required model or to design the suitable neural model by themselves. Although the approach does not restrict the amount of censored data, an appropriate proportion of incomplete/complete would appear to be 1/3 (Tong and Su, 1997). Generally speaking, regardless of what approach is applied to an experiment involving too many censored data, the analysis result may possibly lead to an incorrect suggestion of parameter settings.

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