A NEW ROBUST DESIGN MODELING METHOD BASED ON GENERALIZED REGRESSION NEURAL NETWORK

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Abstract- Over the recent two decades, robust design has been popularly utilized as a powerful method to improve the quality of products in the offline stage of manufacturing processes. Most estimation methods to define the functional relationships between the input factors and output responses are based on the response surface methodology (RSM) which requires several assumptions. Unfortunately, these assumptions are not always hold in the practical industrial problems. Based on the nature of artificial neural networks (ANNs), these relationships can be conducted without any assumption. Therefore, the primarymotivation of this paper is to propose the ANNs as an alternative modeling method in robust design. First of all, an ANN framework-based robust design modeling method is proposed. Secondly, the generalized regression neural network-based modeling method is proposed to estimatethefunctions between the input and output variables.Finally, a comparative study between the proposed neural network-based estimation method and the conventional least squares method based on RSM is conducted in the numerical example. The final results show the efficiency of the proposed neural network-based modeling method in robust design.

Keywords- Robust Design, Response Surface Methodology, Generalized Regressionneural Network, Estimation.

I. INTRODUCTION

Robust parameter design (RPD) or robust design (RD) first proposed by Taguchi [1] has been identified as one of the most powerful methods to improve the quality of product/process in the quality engineering. The primary purpose of RD is to identify the optimal factor settings by minimizing the process variance and process bias (i.e., the deviation between the process mean and the desirable target value) as small as possible. Taguchi [1] introduced RD consisting of two basic steps based on the experimental design and two steps model. However, the technique proposed by Taguchi to find the optimalsolutions to the RD problems was criticized about the assumptions, experimental design, and statistical analysis [2]-[5]. Based on RSM, Vining and Myers [6] proposed the dual response model approach where the process mean and process variance are estimated as two separate functions of input factors by using LSM. This proposal also introduced an RD optimization model in which the process mean is kept as the target value while the process variance is minimized. Based on this proposal, the principle of RD is generated and used up to now with three sequential steps, such as design of experiments, estimation, and optimization. The dual response optimization model is further extended in order to obtain the better solutions by using standard nonlinear programming techniques, such as the generalized reduced gradient method and the Nelder-Mead simplex method [7], [8]. In order to minimize the process bias and process variance simultaneously, the mean squares error (MSE) model is proposed where the process bias and the process variance are minimized with the same weight values [9]. However, in order to estimate the input-output functional relationship in RSM by using LSM, several assumptions are often made, such as the error terms must be independent and normally distributed with constant variance and zero expectation. The Gauss Markov theorem is not guaranteed as one or more of these assumptions are violated. In that case, other methods such as transformation, weighted least squares, and maximum likelihood estimation can be utilized to perform valid estimation.However, the weighted least squares method is usually used to estimate the functions for the unbalanced data while the MLE method is often used to conduct the functions for the non-normal distribution data.

In the last years, artificial neural networks (ANNs) or neural networks (NNs) have grown in popularity in solving a variety of problems in different fields of science and engineering. ANNs are computational models inspired to the human brain functionality and structure and are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown. ANNs are generally the systems consisting of interconnected neurons which can compute values from inputs, transform, and transfer the transformedinformation into the outputs. A number of recent studies showed that the functional relationship between the inputs and outputs in NN can be conducted without any assumption because of the nature of ANN. In addition, the complex relationship can be effectively modeled with any desired accuracy. Therefore, the NN-based estimation method would be more economical and more flexible in practical

applications. In the early attempt to integrate NN into RD, the NN is applied into the design of experiments step in order to explore the information between the inputs and outputs variables and then the input-output functions are estimated based on RSM [10], [11].

Therefore, the primary purpose of this paper is to propose an alternative RD modeling method based on NN. Firstly, the NN-based modeling method is integrated into the RD framework. Secondly, the generalized regression NN-based modeling methodis proposed to conduct the desirable functions between the input factors and output responses. Finally, a numerical example is performed to investigate the effectiveness of the proposed NN-based modeling method. The better solutions can be obtained from the proposed method compared to the conventional LSM based on RSM in terms of EQL. The ANN framework-based robust design modeling method is illustrated in Fig. 1.

The remainder of this paper is organized as follows: Section 2 discusses the conventional LSM estimation method based on RSM. Section 3 introduces the proposed generalized regression NN-based modeling method. The case study as well as the comparative study are conducted and discussed in Section 4. Finally, conclusions are drawn in Section 5.

II. THE CONVENTIONAL LSM BASED ON RSM

RSM is a collection of mathematical and statistical tools commonly used in modeling and analyzing RD problems. The main idea of RSM is to use a sequence of designed experiments to obtain optimal responses by estimating input-response functional forms when the exact functional relationships are not known or very complicated [12]-[14].Based on RSM, the functional relationship between the response of interest and the control factors can be represented as:

$$y = X\beta + \varepsilon \tag{1}$$

where$X$ is a matrix of control factors, β is a column vector of model parameters, and ε is the random errors. Normally, this function is illustrated in the second-order model in practical industrial problems. The estimated process mean and standard deviation functions can be respectively illustrated as:

$$\hat{m}(x) = \hat{a}_0 + \sum_{i=1}^{p} \hat{a}_i x_i + \sum_{i=1}^{p} \hat{a}_i x_i^2 + \sum_{i=1,i<j}^{p} \sum_{j=1}^{p} \hat{a}_{ij} x_i x_j \tag{2}$$

and

$$\hat{n}(x) = \hat{b}_0 + \sum_{i=1}^{p} \hat{b}_i x_i + \sum_{i=1}^{p} \hat{b}_i x_i^2 + \sum_{i=1,i<j}^{p} \sum_{j=1}^{p} \hat{b}_{ij} x_i x_j \tag{3}$$

The unknown coefficients of the mean and standard deviation functions can be estimated by the LSM as follows:

$$\hat{a} = (X^T X)^{-1} X^T \bar{y} \tag{4}$$

and

$$\hat{b} = (X^T X)^{-1} X^T s \tag{5}$$

where $\bar{y}$ and$s$ are the observation average and standard deviation of replicated responses, respectively.

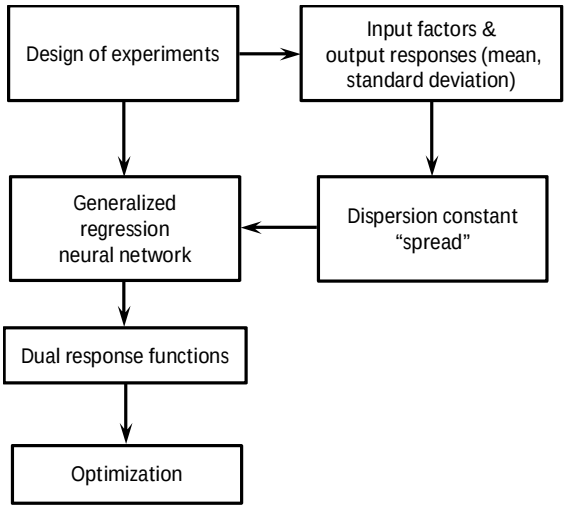


Fig.1. The ANN framework-based RD modeling method

III. THE PROPOSED GENERALIZED REGRESSION NEURAL NETWORK-BASEDMODELING APPROACH

A. On overview of neural network

An artificial neuron is a mathematical function received as a model of biological neurons. The artificial neuron receives one or more inputs, sums them with the associated weights, and then the summed information is transformed by an activation function (or transfer function) to produce an output. ANN is a network consisting of thousands or millions artificial neurons with a highly interconnected biological structure. Generally, the neural network consists of one input layer, one or more hidden layers, and one output layer. The overall structure of neural network is demonstrated in Fig. 2.

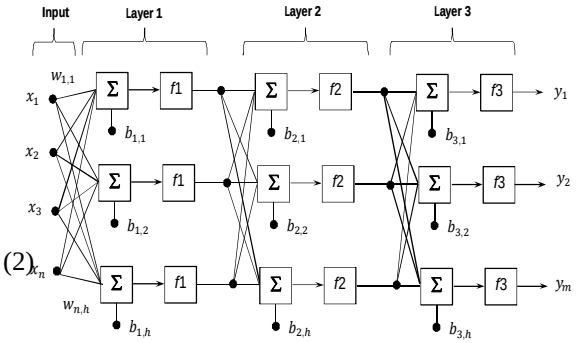


Fig. 2. The overall structure of NN

B. Generalized regression neural network

Generalized regression neural network (GRFN) is a feed-forward NN with a single hidden layer that uses radial basis activation functions (i.e. Gaussian functions) for hidden neurons. The GRNN was

proposed by [15] and reinvented by [16]. The number of the hidden neurons (or radial basic neurons) in the hidden layers usually equals to the number of the input vectors.The radial basis function (or kernel function) is centered at the point specified by the weight vector associated with the unit. Both the positions and the widths (or radius or spread) of these kernels must be learned from training patterns. The basic learning algorithm for GRNN employs a two-step learning strategy. First, it estimates kernel positions and kernels widths using an unsupervised least mean square algorithm to determine the connection weights between the hidden layer and the output layer. Then, after this initial solution is obtained, a supervised gradient-based algorithm can be used to refine the network parameters. Dispersion constant "spread"σhas a great relationship with the output of network. When the spread is wide, the covered input region is large. On the contrary, if the spread is narrow, the curve of radial basis function is relatively steep, and the neuron output relative to the weight approach the input vector is much bigger than others, network output is closer to the expectation [17]. In the output layer, there is no bias added to the input of the neuron. The output of output layer is calculated by the weight function which returns the dot product normalized by the sum of the input vector elements of the output of the hidden neurons and the associated weights.Normally, there are two output responses of characteristics of interest in RD, namely mean and standard deviation. Based on the dual response model principle, each of output response can be estimated separately in one neural network structure. The proposed modeling methodbased on the GRNN structure is shown in Fig. 3.

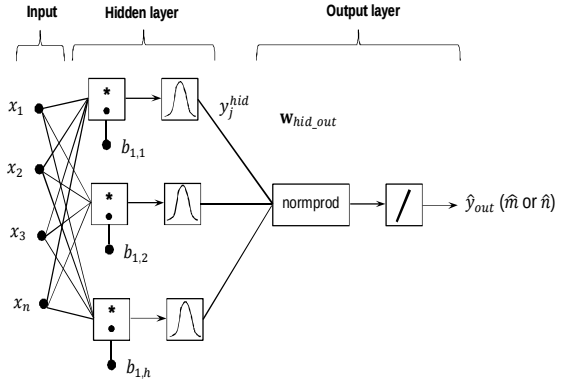


Fig. 3. The proposed GRNN-based RD modeling method

In the mathematic form, the output of the GRNN can be expressed respectively as follows:

$$\hat{y}_{out}(x) = \frac{\sum_{j=1}^{h} w_j \left[\exp-\left(\frac{\left\|\sum_{i=1}^{k}(w_{ji}-x_i)\right\| b_j^{hid}}{2\sigma^2}\right)^2\right]}{\sum_{j=1}^{h}\left[\exp-\left(\frac{\left\|\sum_{i=1}^{k}(w_{ji}-x_i)\right\| b_j^{hid}}{2\sigma^2}\right)^2\right]}. \quad (6)$$

Therefore, the estimated mean and standard deviation functions in this case can be illustrated respectively as

$$\hat{m}_{GRNN}(x) = \frac{\sum_{j=1}^{h_mean} w_j \left[\exp-\left(\frac{\left\|\sum_{i=1}^{k}(w_{ji}-x_i)\right\| b_j^{hid_mean}}{2\sigma^2}\right)^2\right]}{\sum_{j=1}^{h_mean}\left[\exp-\left(\frac{\left\|\sum_{i=1}^{k}(w_{ji}-x_i)\right\| b_j^{hid_mean}}{2\sigma^2}\right)^2\right]} \quad (7)$$

and

$$\hat{n}_{GRNN}(x) = \frac{\sum_{j=1}^{h_std} w_j \left[exp-\left(\frac{\left\|\sum_{i=1}^{k}(w_{ji}-x_i)\right\| b_j^{hid_std}}{2\sigma^2}\right)^2\right]}{\sum_{j=1}^{h_std}\left[exp-\left(\frac{\left\|\sum_{i=1}^{k}(w_{ji}-x_i)\right\| b_j^{hid_std}}{2\sigma^2}\right)^2\right]}. \quad (8)$$

IV. NUMERICAL EXAMPLE

The well-known printing study example usually used in RD, such as [6], [9], and [12], is employed in this paper. The printing experiment is conducted to investigate the effects of input setting: the speed (x_1), the pressure (x_2), and the distance (x_3) on the ability of a printing machine to apply colored inks to package levels (y). Each input factor has three levels, and hence the number of runs is 27. Three replications are performed at eachdata combination. The experimental data are displayed in Table I.

Table I. Printing experimental data

Runs	x_1	x_2	x_3	$\bar{y}$	s	s^2
1	-1	-1	-1	24.000	12.490	156.000
2	0	-1	-1	120.333	8.386	70.333
3	1	-1	-1	213.667	42.829	1834.333
4	-1	0	-1	86.000	3.464	12.000
5	0	0	-1	136.667	80.407	6465.333
6	1	0	-1	340.667	16.166	261.333
7	-1	1	-1	112.333	27.574	760.333
8	0	1	-1	256.333	4.619	21.333
9	1	1	-1	271.667	23.629	558.333
10	-1	-1	0	81.000	0.000	0.000
11	0	-1	0	101.667	17.673	312.333
12	1	-1	0	357.000	32.909	1083.000
13	-1	0	0	171.333	15.011	225.333
14	0	0	0	372.000	0.000	0.000
15	1	0	0	501.667	92.500	8556.333
16	-1	1	0	264.000	63.498	4032.000
17	0	1	0	427.000	88.606	7851.000
18	1	1	0	730.667	21.079	444.333
19	-1	-1	1	220.667	133.822	17908.330
20	0	-1	1	239.667	23.459	550.333
21	1	-1	1	422.000	18.520	343.000
22	-1	0	1	199.000	29.445	867.000
23	0	0	1	485.333	44.636	1992.333
24	1	0	1	673.667	158.210	25030.330
25	-1	1	1	176.667	55.510	3081.333
26	0	1	1	501.000	138.935	19303.000
27	1	1	1	1010.000	142.454	20293.000

A variety of criteria are used in robust design solutions to perform a comparative study. Among these criteria, the expected quality loss (EQL) is widely used as a

critical optimization criterion. The expectation of the loss function can be given as

$$EQL = \theta[(\hat{m}(x) - T)^2 + \hat{n}^2(x)] \quad (9)$$

where θ denotes a positive loss coefficient, usually $\theta = 1$; and $\hat{m}(x)$, T, and $\hat{n}(x)$ are the estimated mean function, the desirable target value, and the estimated standard deviation function, respectively. In this example, the target value is $T = 500$. Using EQL, the optimal solutions of each approach can be conducted and compared.

The estimated mean and standard deviation functions usingthe conventional LSM estimation methodbased on RSM can be represented in the second-order model as follows:

$$\hat{m}(x) = 327.630 + 177.000x_1 + 109.426x_2 + 131.463x_3 + 32.000x_1^2 - 22.389x_2^2 - 29.056x_3^2 + 66.028x_1x_2 + 75.472x_1x_3 + 43.583x_2x_3$$

and

$$\hat{n}(x) = 34.883 + 11.527x_1 + 15.323x_2 + 29.190x_3 + 4.204x_1^2 - 1.316x_2^2 + 16.778x_3^2 + 7.719x_1x_2 + 5.109x_1x_3 + 14.082x_2x_3.$$

By using MATLAB software package, the proposed GRNN structures information after training used to estimate the process mean and standard deviation functions is provided in Table II.

Table II. Generalized regression neural network after training information summary

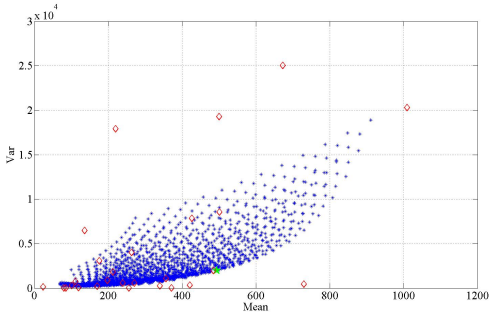
Model	Transfer function	Hidden neurons	Spread
Mean	Radbas -Purelin	27	0.5
Std	Radbas -Purelin	27	0.5

Based on the RD optimization model as illustrated in equation (9), the optimal control settings as well as the associated process mean, process variance (i.e., the process standard deviation squared),process bias, and EQL values of the proposed GRNN-based modeling method with the conventional LSM estimation method based on RSM are shown in Table III.

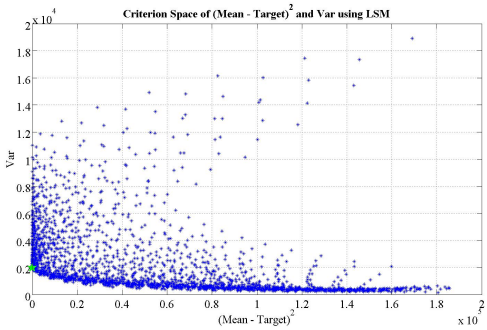
Table III. Comparative results

Method	Optimal factor settings	Mean	Bias	Variance	EQL
LSM	0.999, 0.071, -0.250	494.670	5.320	1997.530	2005.910
GRNN	0.999, 0.999, -0.480	499.523	0.476	674.304	674.530

The comparative results showed that the generalized regression neural network-based estimation approach may provide remarkably small EQL criterion values. The process bias and the process variance valuesin the proposed GRNN-estimation method are remarkablysmaller than that in the conventional LSMestimation method based on RSM. Consequently, the associated EQL value obtained from proposed GRNN-based modeling method is significantly smaller than from the conventional LSM based on RSM. Therefore, the results showed that the better solutions can be obtained from the proposed GRNN-based modeling method. Theprocess mean vs. the variance and the squared bias vs. the variance of the conventional LSM estimation method based on RSM and the proposed GRNN-based modeling methodarerespectively illustrated in Fig.4a, 4b, 5a, and 5b to demonstrate the optimization results in terms of criterion spaces.The red stars show the criterion space obtained from the experimental data. The optimal settings are marked as green circles in each figure.

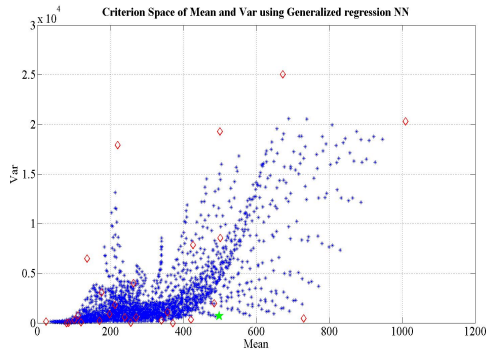


(a)

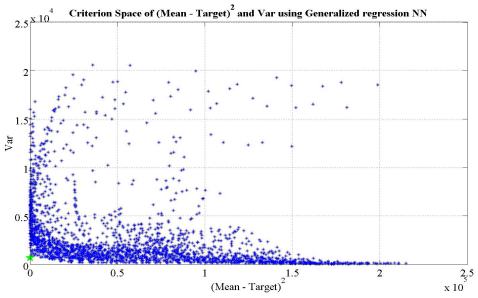


(b)

Fig. 4. Criterion space of estimated functions using the LSM based on RSM, (a) the process mean vs. the variance, (b)thesquared bias vs. the variance



(a)



(b)

Fig. 5. Criterion space of estimated functions using the proposed GRNN-based modeling method, (a) the process mean vs. the variance, (b) the squared bias vs. the variance

CONCLUSIONS

In this paper, the basic assumptions of the LSM based on RSM can be avoided by using the proposed neural network-based RD modeling method. The proposed generalized regression neural network-based modeling method can be used as an alternative modeling method in RD. By using MATLAB software package, the proposed GRNN-based modeling method can be conducted quickly and efficiently. The final optimal results proved that the better solutions can be received by using the proposed modeling method compared to the conventional LSM based on RSM. For further study, the proposed generalized regression artificial neural network-based RD modeling method can be conducted for time oriented responses and for multiple responses optimization problems in RD.

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