Optimisation and Output Forecasting using Taguchi-Neural Network Approach

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This paper proposes an approach based on Taguchi's method to predict the optimum process parameters and forecasts the outputs at these parameters using Neural networks. The predicted data from Taguchi's Design of Experiments (DoE) are quite useful in obtaining optimised output parameters, using some regression models. In multiple input (MI) systems, with no cost function defined explicitly in terms of system variables, Taguchi's solution provides best accurate alternative. Neural networks on the other hand provide the output corresponding to the optimum process parameters obtained in Taguchi method. A case study demonstrates the approach. Results are presented in the form of graphs and tables.

Keywords: Taguchi design of experiments; Process parameters; Optimisation; Neural networks; Function approximation

INTRODUCTION

In many applications of engineering, it is necessary to find the best possible solution set from a table of experimental data. Especially, in situation where multiple input variables are involved, the optimum cannot be that easy to identify in between the data. One way to tackle this problem is to obtain an explicit mathematical relationship between the parameters and adopt the conventional methods of optimisation. But this approach is not always feasible. Alternative for such problems is to employ the method of Taguchi's experimental design[1]. The DoE is a powerful statistical technique for studying the effect on the outcome of multiple variables simultaneously. Usually every system is influenced by two sets of process variables, namely, (i) controllable, and (ii) uncontrollable. The objective of experiments is (i) to determine the most influential controllable variables on the output response, (ii) setting the controllable variables so as to minimise the output variations, when the output has reached the desired value, and (iii) to minimise the effects of uncontrollable variables.

Recently several applications of Taguchi's technique are found in engineering. Naidu and Gowda[2] employed Taguchi method of obtaining process parameters for optimum coating thickness of teflon in spray-painting application. Manna and Bhattacharyya[3] presented an experimental investigation to find the influence of cutting parameters of EDM. Here Taguchi's method is used to optimise wire EDM parameters for effective machining of aluminium reinforced metal matrix composite. Gandhi[4] implemented Taguchi technique on the gear sub-assembly of four-speed gearbox. The objective here is to achieve a low-end play. Tsai and Mort[5] presented the discrete and quantitative parametric scheduling problems of an integrated manufacturing system. Here the relationships between the operational parameters and the performance measures are established using Taguchi method.

In the multi-variables systems, usually it is a typical task to obtain the outputs without correlation. Based on the experimental points accurate fit that relates output to all the inputs can be found. This becomes a cumbersome task when number of inputs becomes large. Neural networks provide an alternative solution for this function approximation task. Many researchers[6-8] adopted Taguchi method for optimum design of Neural networks.

Finding of optimum process parameters using Taguchi's method is not uncommon. At the same time Neural networks for predicting optimum outputs is also well-known. Sometimes, it is quite advantageous to employ Taguchi's approach along with Neural networks. Mezgar, *et al*[9] designed a robust manufacturing system using DoE and neural networks. Benardos and Vosniakos[10] presented a neural network modelling approach for prediction of surface roughness in face milling.

In the present study, it is shown that Taguchi's methodology can be used as a prior step in predicting the optimum outputs from a neural network. Three-layer perceptron network with adaptive learning rate is employed to predict the outputs corresponding to the optimum parameters obtained from Taguchi method. A case study for prediction of optimum output from a blast furnace under the influence of seven independent parameters illustrates the methodology.

TAGUCHI METHOD

Taguchi's method of experimental design is an efficient way to determine the optimum factor level combinations to achieve a minimum standard deviation (variation) while keeping the mean on the target. It is a most efficient problem-solving tool that can update or improve the performance of the product or process design and system with a sufficient experimental data. Taguchi suggested the use of orthogonal arrays, which are the shortest possible matrix of permutations and combinations. The main aim of this method is

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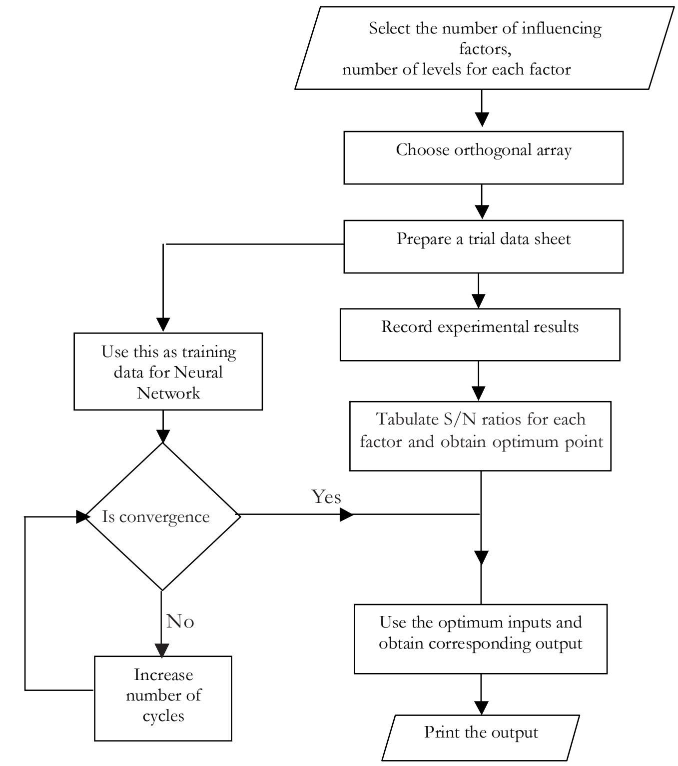

Figure 1 Flowchart of the present approach

that all parameters are varied at the same time the effect on the performance and in the interactions can be studied simultaneously. To select the orthogonal arrays, the following steps are to be employed.

- List the number of factors and interactions of interest
- Decide the number of levels for the factors
- Calculate the degree of freedom (DoF) for the factors

The Degree of Freedom (DoF) is associated with each piece of information that is estimated from the data. A simple way to find the DoF of each parameter is to subtract one from the total number of levels for each. Taguchi tabulated 18 basic orthogonal arrays, which are known as standard orthogonal arrays. An arrays name indicates the number of rows and columns it has and also the number of levels in each of the columns. For example the array L4(23) has 4-rows and 3-two level columns. Generally an array is simply referred only by the number of rows. After orthogonal array selection, a trail data sheet is prepared by merely assigning the factors and their interactions with the array-columns. Experiments are conducted using the trail data sheet and the data are recorded as experimental results. Once this is done, the results are then analysed using analysis of variance (ANOVA). According to Taguchi method, the S/N ratio is the ratio of signal (desirable value, which is the mean for output characteristic) and the noise (undesirable value which is square deviation for output characteristic). The units of signal and noise are in decibel (dB). The S/N ratio is used to measure the quality characteristics. Mathematically it is computed using the following relationship

$$S/N = -10 \log_{10}\left[\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right] \quad (1)$$

where n is the number of variables and y_i is the value of each variable. From the tabulated S/N ratios for each level in each parameter linear graphs are drawn. Based on the highest S/N ratio, the optimum level for each parameter is obtained.

NEURAL NETWORKS

The Neural Networks are found to be good function approximators in many applications. They are the data processors. The data may be optimum data set or experimental parameters. At present there is a necessity of online optimum input information for training a neural network so as to obtain the process outputs very quickly. Since a three layer neural network is universal in the sense that essentially any function can be implemented to any desired degree of accuracy with sufficient number of hidden neurons, the neural network in this study is limited to feed forward networks. Back propagation algorithm is well known for training neural networks[11]. In the present paper, C^{++} program is employed for training experimental data through the three layer perceptron model. The predicted optimum parameters from Taguchi's experimental design can be trained in a neural network to predict the process output. The proposed methodology of combined Taguchi and Neural Network is shown in the Figure 1.

CASE STUDY

The approach is shown with an application of evaluating productivity from a blast furnace unit in steel plant. Usually steel plant's productivity depends upon several factors. In the present study based on the interactions eight control factors are found to influence the amount of pig iron production. Based on the experimental information, the following three levels are identified for each process parameter (Table 1).

Minimum number of experiments to be conducted is equal to 17. Since all the factors are considered at three levels, a three level orthogonal array design was chosen which could accommodate 17 experiments needed to be conducted. The linear graph of configuration L_{27} (that is, 27 experiments) is found suitable for the purpose of experimentation. Physical layout given in Table 2 illustrates the orthogonal array for the purpose of experimentation.

Result and analysis of experiments indicate the parameters adopted for carrying out the operation. The details of S/N ratio is given in Table 3. Response curve to find optimum levels can also be drawn from this table for each parameter. Table 4 gives the optimum control parameters obtained from S/N ratio in each level. A three

Table 1 Table of control factors

Code	Factor/Parameter	Level 1	Level 2	Level 3
A	Coke rate, kg/t	503	515	526
B	Coke ash, %	13.19	13.22	13.32
C	HBT, °C	1000	995	1015
D	Blast volume, m^3/min	5125	5095	5100
E	Steam flow, t/h	6.9	8	7.3
F	Blast moisture, gm/m^3	45.4	46	42.03
G	Blast pressure, kg/cm^2	3.35	3.30	3.25
H	Top pressure, kg/cm^2	2.00	1.97	1.99

Table 2 Orthogonal array layout for experimentation

Experimental Number	A 1	B 2	C 3	D 4	E 5	F 6	G 7	H 8	9e	10e	11e	12e
1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2	2	2	2	2
3	1	1	1	1	3	3	3	3	3	3	3	3
4	1	2	2	2	1	1	1	2	2	2	3	3
5	1	2	2	2	2	2	2	3	3	3	1	1
6	1	2	2	2	3	3	3	1	1	1	2	2
7	1	3	3	3	1	1	1	3	3	3	2	2
8	1	3	3	3	2	2	2	1	1	1	3	3
9	1	3	3	3	3	3	3	2	2	2	1	1
10	2	1	2	3	1	2	3	1	2	3	1	2
11	2	1	2	3	2	3	1	2	3	1	2	3
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15	2	2	3	1	3	1	2	1	2	3	2	3
16	3	3	1	2	1	2	3	3	1	2	2	3
17	3	3	1	2	2	3	1	1	2	3	3	1
18	3	3	1	1	3	1	2	2	3	1	1	2
19	3	1	3	2	1	3	2	1	3	2	1	3
20	3	1	3	2	2	1	3	2	1	3	2	1
21	3	1	3	2	3	2	1	3	2	1	3	2
22	3	2	1	3	1	3	2	2	1	3	3	2
23	3	2	1	3	2	1	3	3	2	1	1	3
24	3	2	1	3	3	2	1	1	3	2	2	1
25	3	3	2	1	1	3	2	3	2	1	2	1
26	3	3	2	1	2	1	3	1	3	2	3	2
27	3	3	2	1	3	2	1	2	1	3	1	3

Note : e-represents dummy factors

Table 3 Variations of S/N ratio with different parameters

	Levels		
Parameters	1	2	3
Coke rate	–3.07	–5.500	–5.50
Coke ash	–3.07	–6.430	–0.35
H B T	–5.50	–1.047	–3.07
Blast volume	2.99	–6.400	–7.60
Steam flow	–4.80	–3.070	–1.76
Blast moisture	–3.70	–3.070	–2.31
Blast pressure	2.99	–6.400	–8.00
Top pressure	0.87	–4.800	–6.40

Table 4 Optimum parameters details

Parameters	Optimum Level	Value
Coke rate	1	503
Coke ash	3	13.32
H B T	2	995
Blast volume	1	5125
Steam flow	3	7.3
Blast moisture	3	42.03
Blast pressure	1	3.35
Top pressure	1	2.00

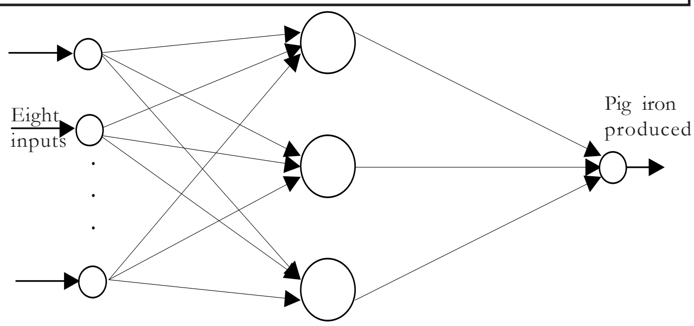

Figure 2 Neural Network in the present case study

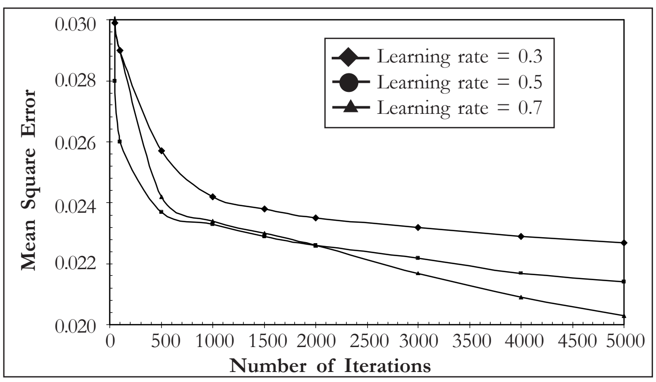

Figure 3 Training trends of the neural network

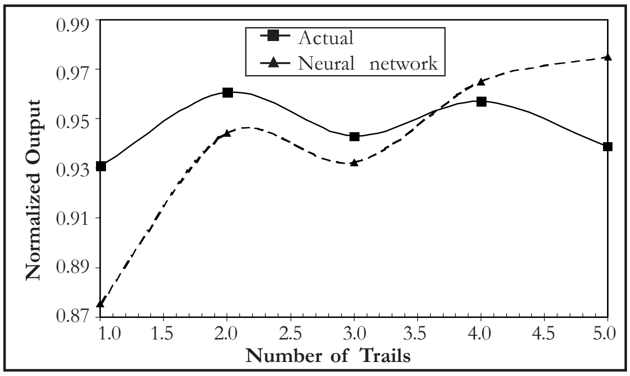

Figure 4 Comparison of neural network predictions

layer neural network is trained with data for the physical layout of orthogonal array depicted in Table 2. This designs a functional relationship between eight process parameters and productivity of pig iron. The considered neural network is shown in Figure 2 with input-output parameters.

Training trend with following network parameters is considered, and is shown as a function of number of cycles in Figure 3 for different values of learning rates.

Learning rate (η) : 0.5

Error tolerance : 0.001

Number of hidden units : 3

The parameters identified from Taguchi method (Table 4) are provided as inputs to the neural network. A value of 5717 kg/heat of pig iron is obtained as output from the neural network, whereas the actual output at the optimum process parameter is found to be 5720 kg/heat. Likewise some series of trails are conducted over one month information. Figure 4 shows the neural network and actual plant outputs as a comparison. It shows that neural network predictions are excellent.

CONCLUSION

The present article illustrates the concept of Taguchi optimum process-design together with Neural Network forecaster. A steel-plant case study that computes pig iron productivity has been considered as an example to show the methodology. The accuracy of the approach is within 5% which is accepted for industries like steel plants.

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