WORK ROLL GRINDING –MODELING AND OPTIMIZATION USING ARTIFICIAL NEURAL NETWORK AND GENETIC ALGORITHM

Dr.N.Alagumurthi

Department of Mechanical EngineeringPondicherry Engineering College, Pondicherry-605014, INDIA

ABSTRACT

Selection of optimum parameters in work roll grinding mainly relies on the experience and expertise of individuals working in grinding industries. Systematic knowledge accumulation regarding the manufacturing process is essential in order to obtain optimal process conditions. It is not safe a priori to presume that rules of thumb, which are widely used on the shop floor, always lead to fast production and to increased productivity. Thus, neural network Meta models are suggested in this work in order to generalize from examples connecting input process parameters, such as wheel speed work speed, in-feed, Traverse speed, dress depth and dress lead. These examples or knowledge are gathered from experiments from industrial practice, which are designed systematically using orthogonal arrays (DOE). Neural network model thus developed yields a more accurate process than the regression method. Furthermore, they can be employed in the fitness function of a genetic algorithm that can optimize the grinding conditions.

1. Introduction

Process Modeling and optimization are very important issues in manufacturing engineering. Machining process are usually too complicated to warrant appropriate analytical models and most of the time, analytical models developed based on many assumptions which contradict reality. Therefore, empric process models are often obtained, but strictly speaking, empric models are applicable only within the range for which the models were initially established. More importantly, it is sometimes difficult to adjust the parameters of the above-mentioned models on-line according to the actual situation of the machining process. The operations of machining process thus still rely heavily on human operators.

Matasushima and Sata (1) first suggested a hierarchical structure of intelligent machine tool controllers to emulate human operators. Recently, neural networks have become more and more important as an intelligence technique in pattern recognition areas (2, 3). Chryssolouris and Guillot (4) evaluated different process modeling techniques and concluded that a proper neural network model could best estimate state variables.Rangwala and Doenfield (5) started suing neural networks in order to learn and optimize turning processes. The aim of this paper is to show how work roll grinding processes can be modeled by using DoE and back propagation neural networks.

2. Objective

This study was made on grinding of the work rolls used in the cold rolling Sendzimir mills. Optimal setting of machining parameters is an essential issue in the roll grinding machine, because it permit to assure a correct precision and a good surface roughness of the work rolls which is made of D2 steel. Since the work rolls were used in pairs, all the work rolls should be ground to obtain a minimum surface roughness. To obtain a minimum surface roughness consistently the optimal settings of the factors should be identified. In this present study, an investigation has made to study the effect of various grinding parameters on surface finish on work rolls and grinding power required in roll grinding machine using Neural Network Model and Design of Experiment. Parameters such as wheel speed, work speed, traverse speed, in-feed, dress depth and dress lead were used in the respective models. These models were then used to find the optimum process parameters.

A brief description of this approach on roll grinding of work rolls made of D2 steel and its results is presented in this work.

3. Methodology Description

A lot of attempts have been made to describe more effectively and adequately the grinding process.

Corresponding Author E mail: alagu_pec@yahoo.co.in

Courtesy: Proceedings of 2nd international conference on Recent Advances in Material Processing Technology-National Engineering College & Society for Manufacturing engineers, K. R. Nagar, Kovilpatti – 628 503, Tamilnadu, India

Although the best parameter setup in the factorial design combinations can be successfully identified by applying the Taguchi method, the real optimal values in the completed explored region cannot be guaranteed by Pignatiello (6).To overcome this shortcoming, a new approach for planning a design of experiment, a neural network, was proposed. In terms of the training on the data set used in the Taguchi analyses, a neural network was constructed. Several extra experimental results which were not included in the orthogonal array were included and used to test the constructed network model. The strong functional mapping capability of the neural network model does provide a feature in which neural nets and traditional experimental design methods can be combined to make a new and more effective experimental design methodology. Experimental data based on the DoE provide training for constructing neural network Meta models and can be easily used in optimizing process parameter values through embedding into the fitness function of an appropriate genetic algorithm.

4. Design of Experiments (DoE)

Design of experiments is a procedure to systematically organize experiment runs in order to improve processes in the most effective way. DoE involves a fraction of the possible parameter combinations for a given experiment, which result in conducting a minimum number of experiments without loss of significant information. This combination fraction is chosen according to rules and statistic matrices called Taguchi's orthogonal array (OAs). The DoE procedure can be divided into three stages:

experiment design, experiment running and statistical analysis. Experimental design involves the choice of process parameters and parameter levels, determining parameter interactions as well as the choice of the appropriate OA according to desired resolution. The chosen OA defines the number of experiments to conduct and parameter level values, which are carried out in second stage of DoE. During the third stage, analysis of variance (ANOVA) determines which parameters are statistically important along with their influence in the process. Since a non-linear characteristic exists among the parameters in the grinding process, the L_{27} orthogonal array was utilized to provide a sufficient degree of freedom. There are six controllable factors were considered to study their effect on surface roughness.

4.1. Experiment Details

The experiment includes six controllable process parameters with three levels were used as shown in Table-1.Grinding experiments were conducted on an SHIBAURA semi-automatic roll grinding machine. The diameter of the work rolls is between 68-56mm and length of 1.53 meter made of D2 forged steel with hardness of R_c 60.Grinding wheel is made of green silicon carbide with grit size of 120 microns. The diameter of grinding wheel was 610mm and the width 76mm.The Diamond point tool tip was used for dressing the grinding wheel for each trial of Experiment.

The surface roughness measurement was carried by using Taylor-Hobson surface roughness measuring instrument with cut off length of 0.8mm .The measurement was taken at four different locations of work roll and considered the average roughness value to find out Signal to noise(S/N) ratio. A digital clamp power meter (DCPM) is used to take the measurement of power requirement at grinding wheel spindle.

Table 1: Factors and their levels.

Sl.No.	**Factors**	**Levels**		
		Low (-1)	**Middle (0)**	**High (+)**
01	Wheel Speed in rpm	400	450	500
02	Work Speed in rpm	100	110	120
03	Traverse Speed in m/min	0.5	1.0	1.5
04	Infeed in micron	10	15	20
05	Dress Depth in Microns	10	15	20
06	Dress lead in m/min	0.1	0.15	0.2

5. Utilizing Taguchi Experimental design

The Taguchi L_{27} orthogonal array was used as the inner array to design the data collection plan as shown in Table.2.The signal to noise ratio is used as the response of interest. There is a signal response, calculated on three observations, at each of the 27 inner array experimental design points. This response (R_a) is calculated over the four points in the inner array. Since the surface roughness values are a "Smaller- is – best" variable type. In order to find out the most important influencing factors on mean response for the "Smaller– is – best " type, the surface roughness needs to be calculated as follows,

$$S/N_s = -10 \log \left[1/n \sum_{i=1}^{n} Y_i^2 \right] \qquad \text{--- (1)}$$

Where

Y_i = Average Surface roughness of the trails.

Table-2 shows the details of L27 Orthogonal array experiments and its responses.

Table 2: L_{27} Orthogonal Array Experimental Trails and its responses

S. No.	**W_s rpm**	**J_s rpm**	**T_s m/min**	**d µm**	**D_p µm**	**D_s m/min**	**Ra µm**	**S/N**	**P** kw	**S/N**
01	400	100	0.5	10	10	0.10	0.0756	22.421	3.10	-9.827
02	400	100	0.5	10	15	0.15	0.0730	22.733	3.20	-10.103
03	400	100	0.5	10	20	0.20	0.0723	22.813	2.95	-9.396
04	400	110	1.0	15	10	0.10	0.0740	22.613	2.80	-8.943
05	400	110	1.0	15	15	0.15	0.0780	22.156	2.72	-8.691
06	400	110	1.0	15	20	0.20	0.0763	22.345	2.68	-8.562
07	400	120	1.5	20	10	0.10	0.0826	21.653	2.74	-8.755
08	400	120	1.5	20	15	0.15	0.0820	21.722	2.80	-8.943
09	400	120	1.5	20	20	0.20	0.0780	22.156	2.86	-9.127
10	450	100	1.0	20	10	0.15	0.0743	22.576	2.94	-9.366
11	450	100	1.0	20	15	0.20	0.0750	22.498	3.02	-9.600
12	450	100	1.0	20	20	0.10	0.0690	23.222	2.56	-8.164
13	450	110	1.5	10	10	0.15	0.0746	22.537	2.68	-8.562
14	450	110	1.5	10	15	0.20	0.0690	23.222	2.73	-8.723
15	450	110	1.5	10	20	0.10	0.0710	22.974	2.84	-9.066
16	450	120	0.5	15	10	0.15	0.07100	22.974	2.70	-8.627
17	450	120	0.5	15	15	0.20	.0696	23.138	2.69	-8.599
18	450	120	0.5	15	20	0.10	0.0670	23.477	2.78	-8.569
19	500	100	1.5	15	10	0.20	0.0703	23.056	3.08	-9.771
20	500	100	1.5	15	15	0.10	0.0660	23.608	3.10	-9.827
21	500	100	1.5	15	20	0.15	0.0676	23.392	3.12	-9.883
22	500	110	0.5	20	10	0.20	0.0620	24.151	3.20	-10.103
23	500	110	0.5	20	15	0.10	0.0610	24.292	3.35	-10.500
24	500	110	0.5	20	20	0.15	0.0626	24.059	3.40	-10.629
25	500	120	1.0	10	10	0.20	0.0616	24.198	3.18	-10.048
26	500	120	1.0	10	15	0.10	0.0630	24.012	3.15	-9.966
27	500	120	1.0	10	20	0.15	0.0593	24.533	3.12	-9.883

5.1 ANOVA

Table.3 and 4 represents the Analysis of Variance (ANOVA) table for responses Surface roughness and Power required for grinding. From the ANOVA Tables, Wheel Speed contribute more on influencing the surface roughness and grinding power required followed by Traverse Speed, In-feed and Work Speed

Table 3: ANOVA Table for Surface Finis

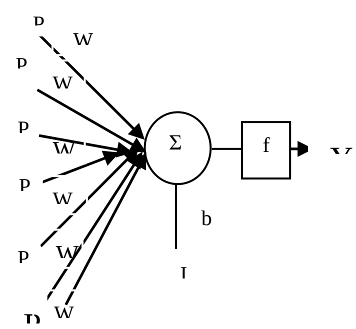
Factors	DF	SS	MS	F-value	P.S.
Wheel Speed	2	0.000785	0.0003912	106.12	0.0001
Work Speed	2	0.0000122	0.0000061	1.65	0.228
Traverse Speed	2	0.0001265	0.0000633	17.16	0.0001
Infeed	2	0.0000440	0.0000220	5.96	0.010
Dress Depth	2	0.0000296	0.0000148	4.02	0.042
Dress Lead	2	0.0000101	0.0000051	1.37	0.287
Error	14	0.0000516	0.0000037	-	-
Total	26	0.0010565			

Table 4: ANOVA Table for Grinding Power Required

Factors	DF	SS	MS	F-Value	P.S
W_s	2	0.188	0.094	70.21	0.183
J_s	2	0.015	0.0076	8.08	0.013
T_s	2	0.010	0.005	5.03	0.005
I	2	0.057	0.028	21.38	0.052
D_p	2	0.006	0.0030	1.219	0.001
D_l	2	0.0084	0.0042	1.70	0.003
Error	14	0.0345	0.00246		
Total	26	0.319			

6. Neural network Model

Neural Networks have been found to be a good alternative to traditional analytical techniques, for modeling of complex manufacturing process. This is because of the number of process variables involved and the non-linear nature of the problems. If a process can be realistically modeled, the model may be experimented upon to explore the process behaviour. A Neural network consists of a number of simple, highly interconnected processing elements or nodes and is a computational algorithm that processes information by dynamic response of its processing elements and their connections to external inputs. Back propagation neural network consists of three or more layers including an input, one or more hidden layers, and an output layer. The network investigated in this paper is illustrated in Figure.1.To develop a back propagation neural network model for surface roughness in work rolls, training and testing data are collected. The data sets consist of both the input parameters and the resulting output parameter. The back propagation learning algorithm employs a gradient or steepest-descent heuristic that enables a network to self-organization in ways that improves its performance over time. The network first uses the input data set to produce its own output. This forward pass through the back



Y= f (W.p+b)

Fig 1 Mathematical model of a typical model

6.1 Training and Testing of the neural network model

To train the developed networks, encoded values for the selected parameters and the means of three performance measures listed in the Table-1 served as inputs and outputs values for neural model. In this work, training function selected based on the Lavenberg-Marquardt Algorithm to update the weights and bias. In this study, the ‘tansigmoid ‘transfer function is used for hidden layers and the ‘pureline’ transfer function is used for the output layer. Ten additional experiments, each with a different controllable factor levels setup based on the significant factor found in the ANOVA table were used for model testing. Table .5 summarizes these complete values.

The training and testing MSEs of the neural network model for varying combinations of the number hidden nodes and learning rates are performed using MATLAB environment are summarized in the

Table.6.The convergence criteria employed in network training was a mean square error less than or equal to10^{-6} or a maximum of 10000 iterations. It is observed that the 6-6-1 network with a learning rate of 0.07 provides the most precise forecasting results with lowest MSEs. It is noted that the built neural network model provides high

precision forecasting. The results show that the network performed good generalization ability and presented more opportunities for identifying the real optimal parameter setup. The excellent generalization ability of the network model is clearly apparent.

Table 5: Testing Experimental Data

W_s rpm	J_s rpm	T_s m/min	d micron	D_p micron	D_s m/min	Ra micron	P Kw
400	100	0.5	10	10	0.1	0.080	2.30
430	110	1.0	10	10	0.15	0.076	2.65
450	120	1.5	15	15	0.2	0.077	2.70
470	100	1.0	15	20	0.1	0.063	3.10
500	110	1.5	20	20	0.15	0.081	3.25
400	120	0.5	20	15	0.2	0.078	2.50
430	100	1.0	10	10	0.1	0.073	2.40
450	110	1.0	10	15	0.2	0.061	2.60
470	120	0.5	15	20	0.15	0.063	2.80
500	100	1.5	20	15	0.1	0.070	3.15

7. Optimization of work rolls grinding using Genetic Algorithm

GA form a class of adaptive heuristics based on principles

Table 6: Forecasting results for the performance Measures

No. of nodes at Hidden Layer	Learning rate	MSE-Training data	MSE – Testing data
04	0.05 0.06 0.07 0.08 0.09 1.00	$9.87x10^{-07}$ $8.55x10^{-07}$ $9.91x10^{-07}$ $9.99x10^{-07}$ $9.87x10^{-07}$ $1.75x10^{-06}$	$7.58x10^{-07}$ $9.87x10^{-07}$ $9.99x10^{-07}$ $6.53x10^{-07}$ $8.54x10^{-07}$ $9.45x10^{-07}$
05	0.05 0.06 0.07 0.08 0.09 1.00	$9.63x10^{-07}$ $9.73x10^{-07}$ $1.02x10^{-06}$ $9.93x10^{-07}$ $9.44x10^{-07}$ $9.95x10^{-07}$	$5.72x10^{-07}$ $9.00x10^{-07}$ $1.89x10^{-06}$ $5.67x10^{-07}$ $5.05x10^{-07}$ $9.87x10^{-07}$
06	0.05 0.06 0.07 0.08 0.09 1.00	$9.75x10^{-07}$ $8.075x10^{-07}$ $5.64x10^{-07}$ $9.96x10^{-07}$ $9.87x10^{-07}$ $7.92x10^{-07}$	$2.83x10^{-07}$ $3.86x10^{-07}$ $9.45x10^{-09}$ $8.52x10^{-07}$ $6.15x10^{-07}$ 8.8x10-07
07	0.05 0.06 0.07 0.08 0.09 1.00	$9.75x10^{-07}$ $8.67x10^{-07}$ $9.98x10^{-07}$ $5.73x10^{-07}$ $8.97x10^{-07}$ $9.53x10^{-07}$	$7.65x10^{-07}$ $9.75x10^{-07}$ $1.45x10^{-07}$ $4.42x10^{-07}$ $9.55x10^{-07}$ $9.80x10^{-07}$

derived from the dynamics of natural population genetics. The searching process simulates the natural evolution of biological creatures and turns out to be an intelligent exploitation of a random search. The mechanics of GA is simple, involving copying of the binary strings. GA comprises of three basic operators, i.e., the reproduction operator selects good strings, crossover operator recombines good sub strings from good strings together to form s better sub string and the mutation operator further alters the string locally to create a string which is found to be better. [D.E.Goldberg, 1989].A simple Genetic Algorithm adopted here is illustrated as,

Begin
Initialize population;
Evaluate population;
Repeat
Reproduction;
Crossover;
Mutation;
Evaluate population;
Until (termination criteria);
End.

7.1 Defining Optimization Criteria

One of the main steps in GA optimization methodology involves setting appropriate criteria for the optimization, i.e., the objective function. Usually, an objective function is presented in analytical form as a function of input parameters. In the approach followed in the present work, trained ANNs play the role of this function, aiming at finding grinding parameter values that offer minimum surface finish with less grinding power required. These two requirements lead to increased productivity and improved quality. Ten-bit strings were used for variable coding according to their minimum and maximum values. Coding from real numbers to binary strings as well as manipulation of values in either form is carried out with regard to the variable limits. Moreover, each variable participates in the chromosome with the same number of bits. The population was chosen to have 50 chromosomes and the maximum number of generations was 200. The generation gap, which determines the number of new chromosomes to be inserted in the new generations, was set to 80% of the population size.

7.2 Objective Function

The objective function was formulated according to the optimization criteria such as minimum surface roughness and grinding power required.

$$\mathbf{f}(X) = W_1 * net1(X) + W_2 * net2(X) \qquad (2)$$

Where X is a 6 x 1 array holding grinding parameter values,

net1(X) is the output value of the ANN model for surface finish

net2(X) is the output value of the ANN model for grinding power required

7.3 Genetic Operators

Stochastic universal sampling was implemented for chromosome selection in the GA, with a 70% single point crossover rate and 2.5% population mutation rate. These choices were made after a necessary number of GA runs and proven to lead to the best GA performance for the present case. The best chromosome per generation is depicted in Figure.2 for the case giving equal weight age to both surface finish and grinding power required. It is obvious that convergence is achieved approximately in the 225the generation. The objective function value for the optimal chromosome is f(x) =2.74, which is very near the lower boundary of the objective function value field. After decoding the binary chromosomes back to real parameter values, the optimal process parameter values for work roll grinding are obtained is presented in the Table.8.Confirmation trails were carried out and its results are almost matched with optimized results obtained using GA.

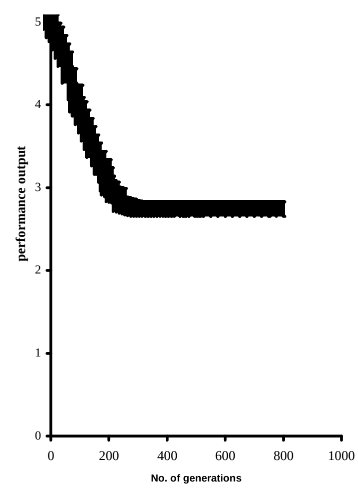


Fig 2: Objective function for the best chromosome in each generation

Table 8: Optimum grinding parameters and its simulated result

W_s rpm	J_s rpm	T_s m/ min	d µm	D_p µm	D_s m/ min	Ra µm		P kw	
						Using ANN and GA	Exp. results	Using ANN and GA	Exp. results
440	110	1.5	15	15	0.2	0.070	0.070	2.71	2.72

8. Discussions and Conclusion

Despite the fact that the developed methodology involves many stages and different tolls, its basic idea and goal is that how grinding parameters of work roll grinding can be determined in optimum way. As for the methodology of optimization of grinding conditions, current practice involve the empirical selection of those parameters, general rules of thumb and the specific know-how of each company. DoE methodology radically reduces the number of necessary execution runs. If ANN accuracy is deemed unsatisfactory, the number of levels in each parameter may be increased as a first measure – additional measures being consideration of sensitivity analysis in order to distribute sample points more correctly in the parameter space, etc.,

As far as optimization criteria concerned, the responses given considered both the surface finish and grinding power required. The GA used a weighted objective function incorporating the ANN models and succeeded in finding the optimum values with little tuning of its parameters, referring mainly to the genetic operators and less the coding of the variables. In this paper, we have shown that ANN can be a better machining process modeling tool. When integrated with Genetic algorithm, ANN can also be very effective in optimizing the grinding processes.

9. References

1. *K.Matsushima and T. Sata, 'Development of intelligent machine tool', Jnl. of Faculty Eng., University, Tokyo, No.35, pp: 299-314 (1980).*
2. *L.Monostori and D. Barschddorff, 'Artificial neural networks in Intelligent Manufacturing ', Robotics computer Integrated Manufacturing No.9, pp: 412-436 (1992).*
3. *R.P. Lippmann, 'An introduction in computing with neural network', IEEE ASSP Magazine, pp: 4-22, (1982).*
4. *G. Chryssolouris and M.Guillot, 'A comparison of statistical and AI approaches to the selection of process parameters in intelligent machining, Jnl. Engg. Industry. No.112, pp: 122-131 (1990).*
5. *S.Ranagwala and David A. Dornfield, 'Learning and optimization of machining operation using computing abilities of neural network', IEEE Trans. Sys. MangementNo.19, pp: 299-314,(1989).*
6. *Pignatiello J.J., 'An overview of the strategy and tactics of Taguchi', Inst. Ind. Engg. Transactions Vol.20; pp.247-254 (1988).*
7. *Ross J., 'Taguchi technique for quality Engineering', McGraw-Hill, Singapore, (1999).*
8. *McGraw-Hill, Singapore, (1999).*
9. *Godlberg.D.E. 'Genetic algorithms in search, optimization and machine learning', Addison Wesley, Reading, MA. (1989).*
10. *Benardos P.G. and Vosniakas G.C. (2003), 'Predicting surface roughness in machining: a review', Int. J. Machine Tools Manufacture, Vol.43.No.8.pp.833-844. (2003).*
11. *Deb K. (1995), 'Optimization in Engineering Design: Algorithms and examples', Prentice-Hall, New Delhi.*