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EXECUTION OF NEWLY DEVELOPED ALGORITHMS FOR PROCESS PARAMETER OPTIMIZATION FOR MACHINING RESPONSE

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Abstract

Final products in manufacturing industry are gone through various machining operations. Achieving optimum machining responses is challenging task in industry. Due to severe competition among industry and increasing demand of quality, it becomes necessary to utilize optimization techniques. In the present study, demonstration of advanced algorithms was done to process parameter optimization for better machining responses. Utilization of Genetic Algorithm (GA) and newly developed algorithms: Teaching Learning based Optimization (TLBO) as well as "JAYA" (Sanskrit word means Victory) algorithms were done for optimization. A case study is discussed on development of objective function for machining response following actual experiments using response surface methodology (RSM). Results obtained from the optimization suggest that these advanced algorithms can be useful for machining parameters optimization.

Keywords: Teaching Learning based optimization, JAYA, Genetic Algorithms, Response Surface Methodology, and Optimization.

1. Introduction

Machining refers to exclusion of unnecessary material in the form chips in order to get desired shape. Machining processes are selected based on desired shape such as turning, milling, drilling, broaching. Machining process required single point as well as multi point cutting tool with different geometry [1]. Proper machining responses including force generated during machining, vibration of tool holder, irregularity of machined surface, material removal rate, wear of tool are difficult to achieve due to non-linearity of process. The performance of machining processes can be achieved by optimizing process parameters that provide ranges of cutting parameters which leads to target machining responses at economical cost[2]. Researchers are using population based non-conventional algorithms for example, GA (genetic algorithm) PSO (particle swarm optimization), ABC (artificial bee Colony) etc., from last twenty years in various engineering problems instead of the conventional techniques [3-10].

Modern manufacturing technology has developed over time with the involvement of many branches of engineering for targeting elevated machining process efficiency. Choosing best machining state is important step for achieving this condition[11]. Complex geometry products which produce after number of machining operations, machinist pursues with optimum process control variables for avoiding variability in machining outputs. In multi response optimization, Parameter optimization is done to compensate between quality and cost for reliability (fatigue strength) as well as productivity improvement. Process parameter optimizations are done after development of mathematic equation of variables-response and in process correlation [12,8]. Modelling is done after defining input factors for particular machining response. Later on sequentially designed experiments are performed to measure the response. Linking of cause-effect between input factor and output variables is done after statistical analysis (e.g. ANOVA, regression analysis). Developed model gives mathematical equation with estimated regression coefficients. Earlier developed models are not considered with dynamic effects of machining for example surface roughness may affect by tool vibration and chip thickness variation due to cutting forces. Therefore apart from basic input factor (for example feed rate and nose radius of cutting tool for calculating surface roughness), researcher have focused on mathematical modelling with additional process parameters to reach ideal or near-ideal cutting condition(s) for better machining response.

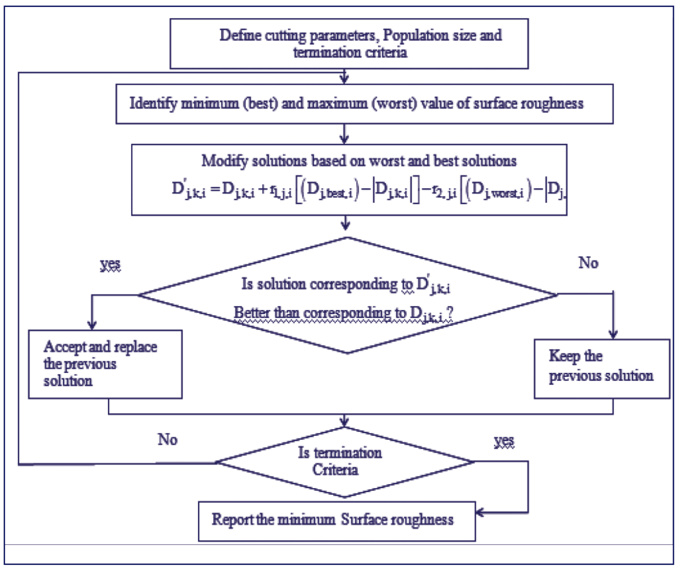
Researchers have implemented statistical regression [13], artificial neural network [14] and fuzzy set theory [15] for optimization. In some literatures, optimization methods also based on Taguchi method[16] , response surface design [17] Genetic algorithm [18], Tabu search[19], and simulated annealing [20] are utilized. In spite of many studies in field of machining parameters optimization, there is lack of generalized models for input (process parameters) and output (machining responses), which is appropriate to all varieties of metal cutting processes[21]. Luong, Spedding [22] stated after literature survey that there is need to develop universal mathematical model that can be applied for forecast cutting performance over a extensive range of cutting situations. Most of the advanced algorithms require certain algorithm control parameters, constraints some assumption for applying real engineering problems are discussed in the literature [23-25]. Incorrect selection of these parameters would lead to wrong results. For e.g. values of algorithm control parameters such as cross-over and mutation possibility with string length need to be set before optimization in the case of Genetic algorithm. Similarly, Particle swarm optimization involves inertia weight and a large constant for particle best and globally best.

Therefore in present study, execution and comparison with the GA algorithm of two newly developed algorithms-TLBO and JAYA are done. Main advantage of these algorithms is that they don't need any specific algorithm control parameters. Hence it can also be extended for execution in material removal processes. These algorithms are listed in detail in section below.

JAYA Algorithm:

JAYA stands for win in Sanskrit (Indian). It is firstly conceptualize and implemented by Rao [26] . It is based on the concept that selects such variables which move response towards optimum results and avoid worst results. It does not require any algorithm control parameters, like GA, PSO etc. rather needs only input variable, number of points and value function. Algorithm's steps are shown in figure 1.

Fig.1. Flow diagram of JAYA algorithm [27]

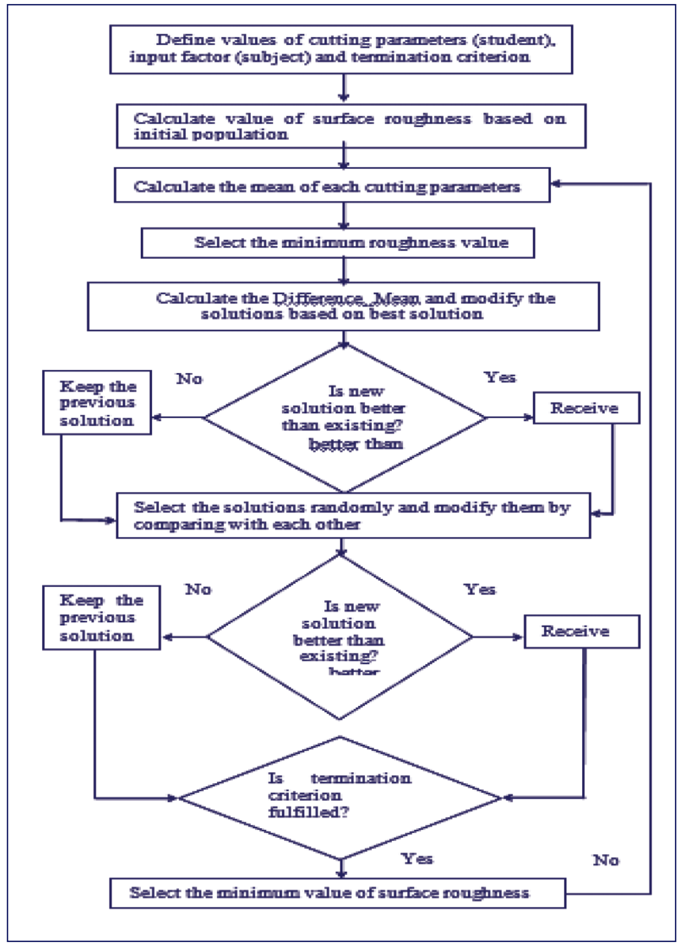


Sahu, Andhare [27] explains implementation of JAYA algorithms with practical example. One can also refer to https://sites.google.com/site/jayaalgorithm/ for further clarification of the algorithm. This algorithm is successfully demonstrated in the present research for minimization of roughness of machined exterior in turning of hard material (Ti alloys).

Teaching Learning Based Optimization (TLBO):

Rao et al. [28], introduced another advanced algorithms namely TLBO. It is based on the concept of teacher in class room and leaner. It consists of 2 phases- explicitly teacher phase and learner phase. Flow diagram of TLBO algorithm as shown in fig. 2 teacher tries to improve results of the students; later on the students seek to boost the results amongst themselves. Number of subjects mentioned here shows design variables; number of learners represents population size; and the final result is indicated as the objective function value. Teacher means best value of objective function which tries improving results of other students. Additionally in learning phase function tries to improve their results by interacting with each other. In TLBO algorithm, population size are identical to learners and number of input factors are identical to different subjects Value of objective function is similar to overall result of student. Sahu, Andhare [29] have defined algorithm steps. For more clarity please refer to https:/sites.google.com / site /tlborao/. To minimize roughness of component exterior, TLBO algorithm is executed in the present work.

Fig. 2. Flow Diagram of TLBO algorithm [29]



2. Mathematic Modelling of machining response

Initially, before parameter optimization, important step in any metal cutting operation is to find out control variables (for example cutting speed, feed rate, depth of cut) which influence the machining response. This is done by developing mathematical model which again classified as: mechanistic and empirical[30]. The mechanistic model is defined as in process parameters relation with the response for cutting process. Nevertheless, there is still scope of developing mechanistic models in metal cutting process [22]. The necessary first step for development of mathematical model is to conduct design of experiments. Sahu, Andhare [31] have explained in details regarding various methods of design of experiments, their implementation and calculation of regression coefficients.

Analysis of Variance (ANOVA):

Prediction models developed for response after performing experiments using design of experiment are need to be verified through statistical test. Ronald Fisher (1918) developed a statistical tool called analysis of variance (ANOVA) which demonstrates variation between variables and response. In machining process experiments, ANOVA is applied to see the significant and insignificant cutting parameters of the predicted model. It is done through varying the parameters individually over the response[31] . It works on two hypotheses namely: G_0 which means there is not a significant variable in other words all regression coefficients are zero and G_1 which means there is at least one significant variable over response in other words at least one non zero regression coefficient. For the experiments to become conclusive, the hypotheses G_0 must be false (Bartlett, M. S. 1946). To verify hypotheses, regression and errors are calculated. Later on, two parameters namely F value and p value is calculated for the model. Whereas, p value (less than 0.05) is called the probability of the predicted models to become significance. Further, R^2 (correlation coefficient), which mathematically defined as ratio of sum of square of regression to the total sum of square is calculated. R^2 gives the knowledge about model equations in terms of difference between experimental and theoretical values. Higher value of R^2 suggests goodness of fit of the model. Adding variables (effective or non effective) in quadratic model will increase the R^2 value however, this does not mean model is improved. Therefore it will be better to evaluate sometimes adjusted correlation coefficient (R^2_{adj}) which is defined as (1- sum of square (error)/sum of square (total)). Large difference between R^2 and R^2_{adj} suggests that there are non-effective terms in the model. After evaluating all the values experimenter can remove insignificant terms from the prediction model. Backward elimination approach is one method to modify the prediction model. In this method, insignificant terms are removed based on F value and p value.

Following study shows implementation of response surface methodology for analyze response and cutting parameters as input variables.

3. Execution Of Advanced Algorithms For Minimizing Roughness of workpiece (Ti Alloys)

In this case study an attempt was made to execute advanced algorithms for optimum process parameters for minimizing of roughness of work piece. Genetic algorithm (GA) and newly developed algorithms namely Teaching learning based optimization (TLBO) and "JAYA" (Sanskrit word means Victory) algorithms are used for optimization. Initially turning operations were performed on hard material (Ti Alloys) based on design of experiment. Objective function for minimizing roughness of work is developed using response surface methodology (RSM) based on actual experimental results. Developed model was used as an objective function after statistical validation and confirmation with additional milling trials. Roughness of machined Surface is extensively used to indicate the quality of machined part [32,33]. Roughness of machined Surface is affected by numerous factors such as - cutting speed, feed, depth of cut, tool geometry, tool wear, etc.[34,35,8,33]. Hence Roughness of machined Surface is an important response. Central composite design under RSM was used for design of experiments. Input factors and their rates, are shown in table 1. Table 2 shows the list of experiments in terms of implied as well as normal levels. Eq. 1 shows conversion of natural level into coded value.

Table I Ranges Of Machining Parameters Used For Central Composite Design

Level ->	Lower most	small	Mid point	elevated	Upper most
implied value (c)	-1.682	-1	0	1	1.682
Work Speed (Z) (m/min)	59.9	80.4	110	140	161.4
Tool Feed (G) (mm/min)	62	86	96	120	126.6
Tool Depth (U) (mm)	0.83	1.0	1.5	2	2.37

$$c_1 = \frac{Z-(Z_{max}+Z_{min})/2}{(V_{c\,max}-V_{c\,min})/2}; c_2 = \frac{G-(G_{max}+G_{min})/2}{(G_{max}-G_{min})/2}; c_3 = \frac{U-(U_{max}+U_{min})/2}{(U_{max}-U_{min})/2} \quad (1)$$

Table II List Of Experiments After Central Composite Design

Run Order	*Z*	*G*	*U*
1	-1	-1	1
2	1	-1	1
3	1	1	-1
4	0	0	1.682
5	-1	-1	-1
6	1	-1	-1
7	0	0	0
8	0	0	0
9	-1	1	1
10	-1	1	-1
11	-1.682	0	0
12	1.682	0	0
13	1	1	1
14	0	0	0
15	0	-1.682	0
16	0	0	0
17	0	0	0
18	0	0	0
19	0	0	-1.682
20	0	1.682	0

This study shows, statically determination of cutting parameters to get minimum roughness of work piece. Experiments are performed on hard material (Ti alloys) work piece and roughness of work piece is measured. For repeatability, roughness is measured at number of location on machined work piece. Table 3 shows the value of machining response against the cutting parameters used in machining.

Table III Machining Variables And Respected Roughness Of Machined Surface

Z(m/min)	*G(mm/ min)*	*U(mm)*	*S_w(μm)*
110.6	86	1.5	0.531
120.6	86	1.5	0.549
59.9	86	1.5	0.809
140.8	62	1	0.447
110.6	96	2.34	0.618
80.4	120	1	0.756
140.8	120	1	0.473
110.6	86	1.5	0.582
110.6	86	1.5	0.582
140.8	62	1	0.414
140.8	110	2	0.464
110.6	126.4	1.5	0.612
110.6	86	1.5	0.573
110.6	86	0.66	0.523
80.4	62	2	0.737
80.4	110	2	0.834
110.6	86	1.5	0.572
110.6	5.6	1.5	0.544
161.4	96	1.5	0.376
80.4	72	1	0.737

Model for prediction of roughness of machined surface is developed by the procedure explained by [27]. Model adequacy is confirmed through ANOVA analysis which finds out significant and insignificant variables mentioned in table 4. Using backward elimination technique, unimportant words are detected and removed.

Table IV Anova Analysis For Roughness Of Machined Surface Roughness

Source	*SS*	*DF*	*MS*	*F*	*p*
Model	0.29	8	0.03	31.46	< 0.001
Z	0.22	1	0.24	236.16	< 0.001
G	5.6e-3	1	5.3e-3	7.36	0.05
U	4.5e-3	1	3.5e-3	5.39	0.0786
Z x G	3.9e-5	1	3.6e-5	0.10	0.94
Z x U	1.0e-4	1	0.7e-4	0.51	0.73
Ux G	2.0e-5	1	1.9e-5	0.05	0.97
Z^2	3.0e-3	1	2.9e-3	2.40	0.1
F^2	8.3e-4	1	6.5e-4	0.85	0.52
U^2	3.6e-4	1	1.6e-4	0.45	0.619
Residual	0.05	9	0.7e-3		
Lack of fit	9.6e-3	4	0.9e-3	3.85	0.592
Pure error	1.2e-3	4	3.3e-4		
Core Total	0.25	19			

Table 4 presented ANOVA for the model which suggests significant value. Correlation coefficient (R^2) was found as 94.13 % shows that model is 94% close to experimental. Moreover, F value and P values are observed for the significance of each coefficient in the full model. Higher values of "F" and lesser values of p ($p < 0.1$) specify that the conforming variable is decidedly significant. Hence, after removing all non-significant terms from the model, the reduced model is shown in eq. 2.

$$S_w = 1.2 - 0.002 \times Z + 0.001 \times G + 0.05 \times U + 1.6e - 7 \times Z^2 \quad (2)$$

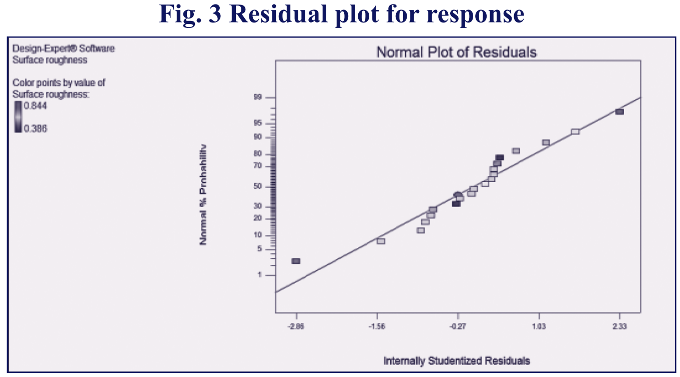
Confirmation Experiments for Prediction Model for Workpiec Roughness:

Five additional experiments are performed for the verification of developed as described in table 5. Cutting parameters considered for the validation are under the previously defined ranges but are at different level than used for actual experiments. Experimental values are compared with the values getting from prediction model. Those values were compared after performing experiment at same values of cutting parameters. Each of those values are shown in Table 5, shows the % error and expected value between real experiments. Figure 3 shows a residual plot versus expected response. Every single points in residual plots are lies along the straight line which means that normality assumption is satisfied.

Table V Validation Experiments For Model Confirmation

Parameters	*Plan 1*	*Plan 2*	*Plan 3*	*Plan 4*	*Plan 5*
Z	75	95.0	110.0	132.0	165.0
G	84	90	100	115	70
U	0.7	1.1	1.5	1.7	0.4
Predicted S_w (μm)	0.779	0.816	0.764	0.655	0.644
Actual S_w (μm)	0.721	0.828	0.721	0.630	0.599
% Error	-2.98	9.96	9.96	9.95	10.12

Fig. 3 Residual plot for response



Optimization by Advanced Algorithms:

In this research, advanced algorithms such as TLBO,' JAYA' and GA are executed in the turning of hard material (Ti alloys) for better finishing of workpiece. For these algorithms, objective function was developed using methodology of response surface as discussed in the above section. Work speed, tool feed and tool depth are defined as control parameters for design of experiments. For each advanced algorithm, the population size and number of generations are the same, for proper judgment. Table 6 displays the execution of proposed algorithms for varying population size and number of generations and the related design variables and performance function. In matlab 2014a algorithm codes for new algorithms are generated, whereas GA is implemented in matlab optimum toolbox. It is evident from table 6 that JAYA algorithm outperforms GA and TLBO in terms of computational time due to lower roughness values of workpiece at lower population size and generations. The levels of cutting parameters for minimizing roughness of workpiece also confirm the influence of cutting parameters over surface roughness on the RSM analysis. Consequently, it is verified that minimal roughness of workpiece can be observed at higher work speed, lower tool feed and tool depth mid values.

Table VI Results Obtained For Optimum Roughness Of Machined Surface Using Ga, Tlbo And Jaya

Strategy		Genetic Algorithm				TLBO				JAYA			
Pop	Gen.	Z	G	U	S_w	Z	G	U	S_w	Z	G	U	S_w
10	50	145	65	1.29	0.809	162.6	63	1.09	0.612	163.5	63	1.03	0.608
15	50	155.3	63	1.13	0.609	163.2	63	1.09	0.598	163.5	63	1.06	0.597
20	50	132.6	63	1.13	0.616	163.2	63	1.12	0.599	163.5	63	1.12	0.591
30	50	161.4	63	1.12	0.611	163.5	63	1.13	0.591	163.5	63	1.12	0.591
10	100	144.5	63	1.14	0.658	162.3	63	1.10	0.628	163.5	63	1.24	0.591
15	100	148.3	63	1.15	0.70	163.4	63	1.12	0.596	163.5	63	1.12	0.591
20	100	159.4	63	1.14	0.678	163.1	63	1.13	0.597	163.5	63	1.12	0.591
30	100	163.4	63	1.12	0.601	163.4	63	1.13	0.592	163.5	63	1.12	0.591

It is evident from table 6 that TLBO and Jaya display minimal values compared with GA algorithms. This is because Jaya and TLBO are easy to apply as it require very less information related to optimization. Nevertheless, the Jaya algorithm makes the solution converge faster than the TLBO algorithm. This is due to simple and less number of steps Jaya algorithms. It is inferred from above discussion that JAYA and TLBO perform better than GA algorithm.

Affirmation test was performed for substantiation of the result obtained from JAYA and TLBO algorithm. Results from Jaya algorithms are considered i.e. Z = 163.5 m/min, G = 63 mm/min and U= 1.1 mm and average roughness of machined surface was found to be 0.59 µm after confirmation test. The average absolute error between results obtained from JAYA and actual experiment is found to be 13 per cent. Key explanation for the above error is due to real machining conditions and errors of measurement.

4. CONCLUSIONS

The above results and discussion can established that newly developed advanced algorithms can be successfully implemented for optimizing machining responses. Response can be well predicted through RSM model for the processes for which physical mechanism is not clear. Subsequent remarks can be drawn after the study:

- Design of experiments is a systematic method of finding out effect of individual and combined input variables over the response.
- Analysis of variance (ANOVA) is a well statistical tool to find out important input variables for response.
- Correlation coefficient with higher value suggests that these model values are approximate to experimental values.
- This methodology helps to improve machining response to achieve higher productivity.
- It is observed that for lowering of roughness value of hard materials (Ti alloys), JAYA algorithm performed better in terms of calculation time compare to TLBO however they are equal for calculating optimal results. Both algorithms are better than GA algorithm in terms of optimal results. Also JAYA algorithm moves faster towards optimum results than TLBO algorithms.

From the above results, it is concluded that newly developed algorithms i.e. JAYA and TLBO can provide information on input cutting parameters which can reduce the roughness values of workpiece in the machining of hard materials (Ti alloys). Such algorithms can enable operator to obtain realistic cutting parameters for minimal roughness of the workpiece exterior. Jaya and TLBO are able to solve other response, as well as multi-objective machining problems.

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