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Optimization and Prediction of Cutting Parameters in the End Milling Process for Cast Aluminium B_4C Based Composite

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End milling process is a very common and important machining process not only due to its ease of machining but also due to the availability of various cutter profiles and curved surfaces. This research work investigates the effect of various process parameters, such as rotational speed of the cutting tool, feed rate, depth of cut on the machined surface of the composite, experimentally. The composite material is synthesized by using the stir casting process with reinforcement of B_4C particulate into Al5083 aluminium alloy. The Taguchi design of experiments is used to calculate the optimum process parameters for machining with minimum variability. In this study, RSM (Response surface methodology) based equation is applied to Teaching-Learning-Based Optimization (TLBO) algorithm to optimize the process parameters. The mathematical model is developed with a confidence level of 95% with a prediction error of less than ±5%. The efficiency and effectiveness of the TLBO algorithm has been observed with the help of convergence graph of the value outcome from experiment. The optimized results obtained from TLBO are almost nearer to the average results of 10 runs.

Keywords: End Milling , TLBO , RSM , Al5083, Taguchi

Introduction

Aluminium alloy, Al5083 (Al-Mg) is a well-known non-heat treatable alloy. The Al-Mg alloy is achieving its strength by the use of solid-solution strengthening technique, in the presence of Magnesium. It is best suited for marine and automobile industry due to its better design efficiency, good welding properties, good resistance against corrosion, high strength to weight ratio, and low cost. In any machining operation, the performance of machining operation is evaluated in terms of its power consumed, tool wear, cutting force (CF), and surface finish, of which the quality of surface finish plays an important role in any machined component. Develop a mathematical model for surface quality by using parameters, such as rotational speed of the tool, feed rate, and depth of cut, and then applying the TLBO optimization technique to analyse the cutting parameters. In addition, analysis of variance (ANOVA) is applied to determine the effects of other diverse factors on the cutting parameters.

Materials

There has been an increase in demand by the present-day manufacturing industry for parts with high accuracy. To full fill this demand for high accuracy parts, it is necessary for manufacturers to make high quality components, such that those parts can better achieve the functional as a well as the operational requirements of the components[1]. Masmiati *et al*. investigated the influence of machined surface inclination, depth of cut rotational speed of tool and feed rate in inclined end milling process and found that machined surface inclination angle had high impact on micro hardness and residual stress along the feed direction [2]. Saharea *et al*. examined the optimum coating condition for the quality of surface finish and metal removal rate by varying cutting speed, feed rate, and depth of cut[3]. Gopal & Prakash examined the effect of material and machining parameters on the surface roughness and CF[4]. Suresh *et al.* studied the hybrid metal matrix composite (Al-SiC-Gr) where the reinforced graphite particle is mainly to improve the machinability and tribological properties of the composite. In their results they found that the Al-10% (SiC-Gr) composite shows better properties when compared with Al-5% (SiC-Gr) and Al-7% (SiC-Gr) [5]. Maher *et al.* studied the adaptive neuro-fuzzy inference system (ANFIS) which is used as prediction tool to predict the surface roughness of end milling process in CNC milling and the predictor variables are rotational speed of tool, feed rate and

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depth of cut, their findings show maximum prediction error of 6.25% for surface roughness and average prediction error was (2.75%) [6]. Zhang *et al.* studied the prediction of three dimensional cutting forces component in micro end milling. The proposed cutting forces model is validated through the value obtained from experiment and they found that the experimental data is very close to simulation results[7].Khanna and Davim study the effect of controlling machining parameters cutting speed and feed rate on different grade of titanium alloys and they found that the feed rate was the most influencing factors for cutting and feed forces whereas the cutting speed has most significant influence on the temperature of tool[8].Singaravel and selvaraj study the effects of machining variables on cutting force, specific cutting pressure, coefficient of friction and shear energy and they found that this are essential variables to evaluate the machinability.[9] Rao and Padmanabhan study the effect of machining performance with the presence of reinforcement content in the matrix and responses of output optimized by response surface methodology (RSM)[10].Devinder and Sharma study the effect of input variables in turning process of (Al6061-SiC-Gr) hybrid composite. The Predicted value and experimentally obtained are close to each other with an error of less than 5%[11].Singh *et al.* review the process and advantages of different process for manufacturing and machining of composite and concluded from their work that aluminium is favourable material for matrix of the composite and the reason is due to its high strength weight ratio[12].Nataraj and Balasubramanian study the effect of vibration in CNC lathe and temperature between the work and tool and also developed a mathematical model to generate improved surface finish[13].Kumar and Patel reviewed the modification technique to the machined surface which is used to decreases the friction during the machining process and this reduction directly affect the tool life. From their review the nanocomposite and nanocrystalline coating is superior coating during hard turning [14].Gupta and Sood investigated the effect of process parameters of turned AISI 4340 steel[15].Rajkumar *et al*. implies (DFA) for optimizing the process parameters on microdrilling (CFRP) composite[16]. Natraj and Balasubramanian investigated about the methods to optimising the process parameter for machining LM6 to achieved minimum surface finish[17].There are several factors that affect the tool wear and surface finish, such as tool geometry, workpiece material, tool material, and coolant. End milling machining is actually a material removal process. In the end milling operation, a multi-tooth device with cutting edges rotates in different axes with respect to the workpiece. The key objective of the current research is to:

- Explore parameters, such as surface quality, (MRR) material removal rate, and (K) kerf thickness, and determine the CF of the machined surface of the composite material. This composite material is reinforced with B_4C particle into an Al5083 aluminium alloy, which is produced in an induction furnace by stir casting method.

Methods

Preparation of MMC (Metal Matrix Composite)

The Al5083 alloys and B_4C reinforcement was used to make an MMC with a stir casting process. The temperature of the induction furnace (Megatherm, SR NO.400914000093- India) for the casting of MMC was maintained at 750^0C. Further Al5083 ingot was brought down to a temperature of 680^oC, The preheated boron carbide at 500^0C then added to the liquid aluminium at the rate of 1gram /sec, with the help of mechanical stirrer and the mixture was endlessly stirred at the speed of 350-500 rpm for several minute for the proper homogenization of mixture, K_2TiF_6 was used to increase the wettability of the melt. Afterwards degasser (Hexachloroethane) was added to the molten aluminium alloy at 680^oC and the molten material was stirred for few seconds for the proper mixing of degasser. It was kept for 2 to 3 minutes to permit the reaction to remove the dissolved gases. Subsequently the hot liquid melt was casted into square metallic mould for carrying out the end milling process.

Machine setup and experimental details

A square cross-section specimen (40mm× 40mm×20mm) of the Al5083/7% B_4C composite was machined by using a CNC vertical milling machine fabricated by MTAB Engineers Pvt. Ltd. (3-axis FANUC control series). The CF in the direction of tool travel was measured with the help of a dynamometer. Surface roughness was measured with the help of a 2D profilometer Form Talysurf FTS INTRA 2 (M 112-3346-02, system No-635, Taylor Hobson Ltd). The surface roughness was measured for a length of 7mm at three different locations and then an average value was determined. The probe of

2D profilometer moved at a speed of 0.5 mm/s. Machining process was done with a high-speed steel (HSS) end mill cutter without the use of any fluid. The material removal rate was measured using a digital mass balance with precision of 0.001g by taking the difference in mass of the sample, before and after machining, and dividing it by machining time. The quality characteristics of the machining surface were controlled by process parameters, such as speed (N), feed-rate (f) and depth of cut (d). The exploratory machining try-out were carried out to lessen the allowable range of process input variables and to categorize the tolerable upper and lower bounds of input parameters for which the surface quality of machined surface remains sizable. The input process parameters were mixed at five levels and Taguchi L_{25} (5^3) of DOE (design of experiments) was considered to conduct the experiments. Taguchi "Orthogonal Array" Table 1 was used to design the various combinations of input variables for the experiment thereby reducing the number of experiments being conducted. The use of Orthogonal Array Table 1 also resulted in reduced time, effort, and experimental cost. Taguchi was applied for experimental design in order to get the aims of how the controlled input factor affect the output response and what are the optimum end milling controlled parameters to obtain minimum force and roughness and maximum MRR and kerf i.e., CF, MRR, Kerf, and surface roughness were selected as output responses. Width and length of the cut were fixed for all the experiments at 5 mm and 20 mm, respectively.

Response surface methodology

The relationship between the various independent input variables and dependent output responses was done with the help of Response Surface Methodology (RSM). The key objective of RSM is to apply a set of planned researchers to attain a best possible response. Central Composite Design (CCD) was used to get a second-degree polynomial model that is still an estimate, at most excellent. To determine the outcome of the various end milling parameters on the above-declared machining criteria, second order polynomial response surface mathematical model will be developed.

Table 1 — Various Input Parameters along with their Outcomes

	Design of Experiment			Output after Machining				
S.No.	Spindle speed (RPM)	Feed rate (mm/min)	Depth of cut (mm)	Y(CF) (N)	Y(Kerf) (mm/min)	Y(MRR) (gram/min)	Y(R_a) (μm)	Y(R_t) (μm)
1	500	15	0.2	15.1085	0.010633	0.040714	1.353533	26.79887
2	500	20	0.3	10.2415	0.015918	0.091429	1.002070	17.73887
3	500	25	0.4	6.2162	0.017657	0.135223	1.010500	16.39003
4	500	30	0.5	7.8779	0.021378	0.204643	1.187167	22.71803
5	500	35	0.6	14.3800	0.025245	0.290000	1.781967	35.60197
6	600	15	0.3	8.6327	0.010493	0.072321	1.061267	25.97303
7	600	20	0.4	5.3520	0.011737	0.107857	1.050533	27.00630
8	600	25	0.5	6.8582	0.015981	0.183581	1.102900	26.29120
9	600	30	0.6	13.0501	0.018577	0.256071	1.529200	30.59770
10	600	35	0.2	7.8582	0.023940	0.110000	1.027833	24.00630
11	700	15	0.4	6.3536	0.008195	0.087857	1.105767	25.92337
12	700	20	0.5	6.0546	0.010446	0.140000	1.011467	22.48403
13	700	25	0.6	12.8430	0.012362	0.198805	1.451333	27.63707
14	700	30	0.2	8.3034	0.014191	0.076071	1.120267	31.79373
15	700	35	0.3	7.2877	0.017411	0.14000	0.926367	19.30723
16	800	15	0.5	9.0711	0.007100	0.108750	1.173467	18.39473
17	800	20	0.6	14.8398	0.009327	0.171429	1.469667	20.42883
18	800	25	0.2	9.2369	0.011401	0.069851	1.224900	31.10267
19	800	30	0.3	10.0440	0.012941	0.118929	1.114600	20.14910
20	800	35	0.4	12.3676	0.017037	0.208750	1.213533	15.20183
21	900	15	0.6	13.5219	0.006244	0.129107	1.748033	13.88497
22	900	20	0.2	9.8567	0.007980	0.055000	1.780867	35.58997
23	900	25	0.3	10.3645	0.009875	0.102089	1.434067	20.63280
24	900	30	0.4	12.3633	0.011892	0.163929	1.449133	10.13447
25	900	35	0.5	20.2339	0.013421	0.231250	1.647367	10.57127

In general, the response surface is expressed using the following equation:

$$y = a_0 + \sum_{j=1}^{k} a_j x_j + \sum_{j=1}^{k} a_{jj} x_j x_j + \sum_{j=1}^{k} \sum_{j<i}^{k} a_{ij} x_i \, x_j \quad \ldots (1)$$

Where, Y is the respective responses, such as CF, kerf thickness, MRR (Material removal rate), R_a, and R_t (Maximum Height of the roughness Profile), generated by a range of input variables of x_j (1, 2, 3…... k) that are the coded levels of quantitative process variable, k. The term a_0, a_j, a_{jj} and a_{ij} are the second order regression coefficients. The second term in polynomial Equation 1 with the summation sign is ascribed to linear effect, while the third term represents the higher-order effects. The fourth term of the polynomial Equation 1 represents the interactive outcomes of the process parameters.

The polynomial Equation 1 can be re-written as:

$$Y = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + a_{11}x_{12} + a_{22}x_{22} + a_{33}x_{32} + a_{12}x_1x_2 + a_{13}x_1x_3 \, a_{23}x_2x_3 \quad \ldots (2)$$

Where x_1, x_2, and x_3 are the input parameters i.e., Spindle speed, feed rate, and depth, respectively.

Mathematical model for responses

Optimization is the process of either minimizing the undesirable effects or maximizing the favorable effects. The S/N ratio measures the difference in the responses with respect to the maximum or minimum value under different noise situation. The results of output responses are converted to S/N ratio using conversion method of larger is the best and smaller is the best.

CNC milling machining is completely dependent on its input parameters, such as spindle speed, feed rate, depth of cut, etc. and these parameters influence the output responses, such as CF, kerf, MRR, etc. By using Equation 1 and 2 in the MINITAB-17 software and feeding these equations with data from Table 1, the magnitude of CF and all other responses has been calculated,

Main effect plot and anova

The observational outcomes were analyzed with ANOVA to determine the influence of the cutting input parameters (i.e., control factors) cut in the Al5083/7% B_4C matrix that affects the performance measure. Through ANOVA, you can forecast the control input factors that dominate over other factors along with the percentage of that control input factor on the output responses. In this study, the investigation was performed at the significance level of P = 0.05, i.e., the confidence level of 95%. In the ANOVA result, P-value less than 0.05 was regarded as a noteworthy involvement to the performance measures.

The last column of ANOVA of CF in Table 2 suggests that each value of P is less than 0.05. This essentially means that each input parameter plays a major role in estimating the CF. Figure 1(a) shows the main effect plot of CF , and the impact of each input parameter on CF. It is observed that when spindle speed, feed rate, and depth of cut is 700, 25 and 0.4, respectively then CF is at its minimum. The last column of ANOVA Table of kerf thickness and MRR

Table 2 — ANOVA test results for C.F., MRR, K, Ra and Rt.

Source of variation	Out put parameters	Regression	Error	Total
Degree of Freedom		8	16	24
Sum of Squares	C.F	295.711	13.449	309.160
	MRR	0.076510	0.004550	0.081061
	K	0.000599	0.000014	0.000613
	Ra	1.63863	0.05653	1.69516
	Rt	1126.81	63.15	1189.96
Mean squares	C.F	36.964	0.841	
	MRR	0.009564	0.000284	
	K	0.000075	0.000001	
	Ra	0.204828	0.003533	
	Rt	140.851	3.947	
F-ratio	C.F	43.98		
	MRR	33.63		
	K	84.76		
	Ra	57.97		
	Rt	35.69		

shows that the value of P is less than 0.05 for spindle speed, for kerf and MRR the value of P is less than 0.05, for feed rate and depth of cut and from the main effect plot of kerf thickness, the kerf thickness increases with increase in feed rate and depth of cut and decreases with spindle speed. In the main effect plot of MRR, MRR increases with increase in depth of cut and feed rate, and has intermittent effect with the spindle speed i.e., sometimes it increases and sometimes it decreases.

The last column of ANOVA of Ra and Rt shows that all the three input parameters i.e., spindle speed, feed rate, and depth of cut had a greater impact on the output responses. Figure 1(b) shows the main effect plot of Ra, Ra first decreases with increase in all three input parameters and reaches to a minimum and later, it increases with increase in all three input parameters. As per the main effect plot of Rt, shows the intermittent effect with all three input parameters.

Results and Discussion

Application of TLBO algorithm to optimize CNC milling characteristics

TLBO is a recently evolved optimization technique and has been used to optimize numerous problems. The technique has evolved from day to day life of interaction between teacher and the learner to enhance the knowledge of the learner. TLBO consists of two phases, the teacher phase and the learner phase. In the first phase, there is interaction between teacher and the learner to enhance the knowledge of the learner. In the learner phase, the learner interacts with other learners to enhance its knowledge as each learner would have different level of knowledge. TLBO optimization technique gives the best results among available optimization techniques. Hence, in this current study, the author applied TLBO algorithm to enhance the manufacturing capability of CNC milling processes. Here, three input parameters were selected to optimize. The TLBO code was developed and run in MATLAB2015 software. TLBO was run for all objective function to obtain the maximum and minimum value of milling performance characteristics. To run the TLBO algorithm for individual objective optimization, population size and number of runs have been defined on several numbers of trials as follows:

- Number of iterations = 200
- Population size = 10

Confirmation experiments have been conducted by using the optimal parameters of CF, kerf thickness, MRR, Ra, and Rt. The percentage error (Equation 3) was calculated by the deviations from predicted results and experimental results.

$$\%\text{Error} = \frac{\text{Experimental value} - \text{Predicted value}}{\text{Experimental value}} \times 100 \quad \dots (3)$$

Table 3 shows the optimum results of CF, kerf thickness, MRR, R_a, and R_t, which was obtained from TLBO optimization algorithm. The TLBO predicted results were compared with experimental results.

Moreover, the convergence graph for CF as shown in Figure 2(a), kerf thickness Figure 2(b), MRR, and surface roughness showing the effectiveness of TLBO algorithm. To find out the consistency of TLBO, the algorithm was run ten times and the average was calculated. For CF and kerf thickness, the average result was same i.e., no changes. Similarly, there was no change in the average result for MRR, R_a, and R_t.

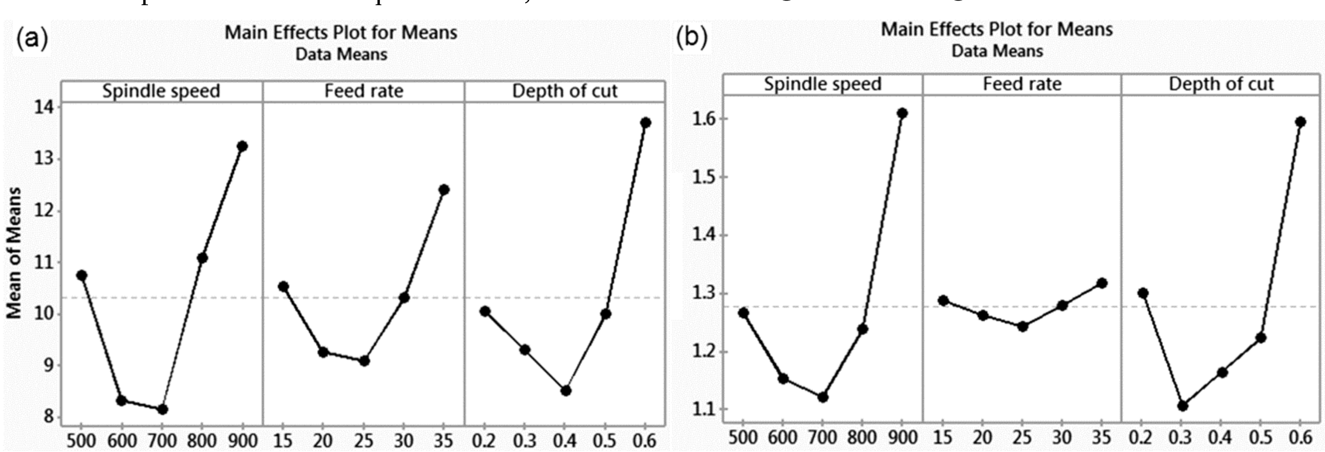

Fig. 1 — Main effect plot for (a) Ra (b) C.F.

Table 3 — Comparison of TLBO predicted CF., Kerf thickness, MRR, Ra, and R_t respectively with the experimental value.

Trait	Input	TLBO	Experimental Value	Errors
CF.	Spindle speed (rpm)	612.7934	613	
	Feed rate (mm/min)	27.5870	28	
	Depth of cut (mm)	0.3464	0.35	
	Cutting force (N)	3.9905	4.2312	5.69%
Kerf thickness	Spindle speed (rpm)	500	500	
	Feed rate (mm/min)	35	35	
	Depth of cut (mm)	0.2654	0.27	
	Kerf thickness (mm/min)	0.02061	0.02142	3.78%
MRR	Spindle speed (rpm)	500	500	
	Feed rate (mm/min)	35	35	
	Depth of cut (mm)	0.6	0.6	
	MRR(gm/min)	0.19807	0.2046	3.1%
Ra	Spindle speed (rpm)	610.1559	610	
	Feed rate (mm/min)	28.38057	28	
	Depth of cut (mm)	0.33012	0.33	
	Ra (µm)	0.7671	0.7782	1.426%
Rt	Spindle speed (rpm)	900	900	
	Feed rate (mm/min)	27.66992	28	
	Depth of cut (mm)	0.51902	0.52	
	Rt (µm)	7.06670	7.2856	4.911%

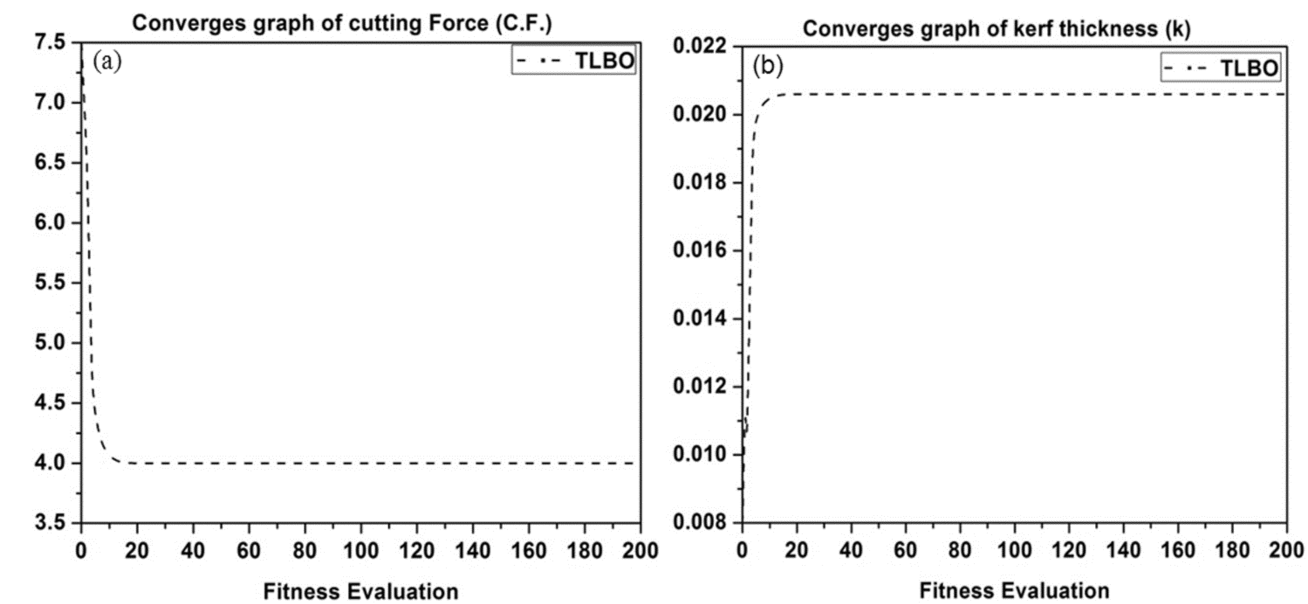

Fig. 2 — Convergence graph of (a) CF (b) kerf Thickness

In all the above five cases, an average result of 10 runs is almost equal to the best solutions thereby showing the efficiency and effectiveness of TLBO algorithm for CNC milling performance optimization.

Conclusions

After analyzing the experimental data, it is evident that the CF, kerf thickness, MRR, as well as surface roughness of the specimen, are greatly affected by input parameters of the CNC milling operations.

- The mathematical equation developed by RSM using MINITAB-17 software was used as a fitness function in TLBO algorithm. The efficiency and effectiveness of the TLBO algorithm have been verified by using a convergence graph of CF, kerf thickness, and Ra.
- Initially, C.F. decreases with increase in all three-input parameter and reaches to a minimum and again increases after further increases in all three input parameters.

- Kerf thickness is reduced with increase in spindle speed, feed rate and depth of cut.
- MRR increases with increase in depth of cut and feed rate and had intermittent effect with an increase in spindle speed, i.e., MRR sometimes increases and sometimes decreases.
- The value of Ra decreases and reaches to a minimum with an increase in all three input parameters. Later, the Ra value increases with further increase in all input parameters. The value of Rt first increases and reaches to maximum with an increase in spindle speed and feed rate. Later, the Rt value decreases and have an opposite effect with an increase in depth of cut.
- TLBO algorithm has shown experimental error of 5.69%, 3.78%, 3.192%, 1.426% and 4.911% for CF, kerf thickness, MRR, Ra, and Rt, respectively. However, TLBO predicted results are almost nearer to the average results of 10 runs.

When compared to many other optimization techniques, TLBO algorithm does not demand selection of the algorithm-specific parameter. It makes this algorithm to be easily and affectively applicable to optimize real life scenarios. The TLBO algorithm requires only 20 to 30 iterations for convergence to the optimal solution.

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