Multi-objective Optimization of Hard Milling Process using Evolutionary Computation Techniques

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Abstract: This paper focuses on determination of optimum cutting conditions for the efficient hard milling performance of the selected process parameters using hybrid method of response surface methodology and evolutionary computing approaches. A central composite rotatable design is used to design the experimentations. The responses of cutting temperature, tool wear and metal removal rate are measured and analysed the data to develop the mathematical models. The adequacies of the models are tested at 95% confidence level. To achieve the set goal of this study, genetic and simulated annealing algorithms are used for predicting and optimizing the process parameters. The result shows that the simulated annealing algorithm is effectively produced better optimal solutions than the genetic algorithm. The actual experimental results were in agreement with the prediction.

Keywords: Hard milling, central composite rotatable design, cutting temperature, tool wear, metal removal rate, optimization, genetic and simulated annealing algorithms

I. INTRODUCTION

During past few decades, the field of metal cutting witnessed numerous developments. In this sense, hard milling is an emerging technology to machine the steels with hardened (i.e more than 45HRC) state. The potential advantages are to eliminate many process chains during the manufacturing of a component as compared with conventional route [1].Recently, few research studies related to implementation of experimental design for hard milling process have been reported by many researchers [2-5]. The empirical models have been developed to predict the cutting forces and surface roughness in terms of cutting speed, feed, radial depth of cut and axial depth of cut in hard milling of AISI H13 steel [3]. The cutting performance of PVD coated carbide and CBN tools in hard milling of JIS S55C was studied by Okada et al. [4]. Çaliskan et al. [5] experimentally investigated the influence of type of coating, cutting speed, feed rate and depth of cut on the cutting forces and surface roughness in hard milling of AISI O2 (~61 HRC) cold work tool steel using coated carbide inserts. Therefore, the industrial research on hard milling is considerably important in order to understand the effectiveness of the process. The quality and productivity of hard milled surface depends on three main parameters such as cutting temperature, tool wear and MRR. These characteristics are controlled by a number of process parameters like cutting speed, feed per tooth, width and axial depth of cut, tool geometry and work piece hardness etc. Nowadays, modeling and optimization methodology have become vital play role in the manufacturing industry to meet required product quality and productivity. Therefore, proper setting of hard milling process parameters is essential to ensure production efficiency. The present work deals with optimization of hard milling process parameters in order to enhance the surface quality as well as to obtain the best parameters of the hard milling covers in terms of cutting temperature, tool wear and metal removal rate. A Central Composite Rotatable Design (CCRD) was used to design the experimentations. Design-expert version 6.0.8 package was used to analyze the data and to develop the models. The adequacy of the model was tested at 95% confidence level. Further, the developed models were employed with Genetic Algorithm (GA) and Simulated annealing Algorithm (SA) to determine the optimal process parameters resulting in minimum cutting temperature, tool wear and maximum metal removal rate. The evolutionary approaches widely applied to solve single and/or multi-objective problems in various fields [6-23].

II. MODELING AND OPTIMIZATION OF HARD MILLING PROCESS

A. Response Surface Methodology

Response Surface Methodology (RSM) is a combination of statistical experimental design fundamentals, regression modeling techniques, and optimization methods [24]. The main advantage of RSM is the reduced number of experimental runs needed to provide sufficient information for statistically acceptable results. It is a faster and less expensive method for gathering research results than the classical method. The CCRD design is one of the most important experimental design used in process optimization studies. This design was applied in the present work with the objective to develop an empirical model of the process and to obtain a more precise estimate of the optimum operating conditions for the factors involved. The data obtained from the CCRD design was fitted with a second order polynomial equation to evaluate the parametric influences on the various hard milling criteria as follows

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_{i} \sum_{j} \beta_{ij} X_i X_j + \varepsilon \qquad (1)$$

where y denotes the predicted response of the process, X_i refers to the coded levels of the factors, β_0, β_i, β_{ii}, and β_{ij} are the regression coefficients, and ε is the statistical error.The adequacy of the model was determined by evaluating the lack of fit, coefficient of regression (R^2) and the Fisher test value (F-value) obtained from the analysis of variance (ANOVA).Statistical significance of the model and model variables was determined at the 5% probability level ($p < 0.05$). The software uses the quadratic model equation shown above to build response surfaces.

B. Genetic Algorithm

The genetic algorithm is a global search algorithm, which is designed to mimic the principles of biological evolution in natural genetic systems [8]. At first, the fitness of each individual is determined according to their closeness to the optimum solution, and individuals are categorized according to their fitness. After that, the reproduction, crossover, and mutation operators are applied to each generation to evolve a new generation. Reproduction is the random selection of copies of the solution from the population according to their fitness value to create one or more offspring variables. The parameters of individuals that perform well are crossed to try to create better-performing individuals. The new set of individuals is called the first generation and each individual is evaluated for a new fitness value. This process is repeated until the population cannot create better performing individuals. The general flow chart for genetic algorithm optimization as shown in Fig.1.

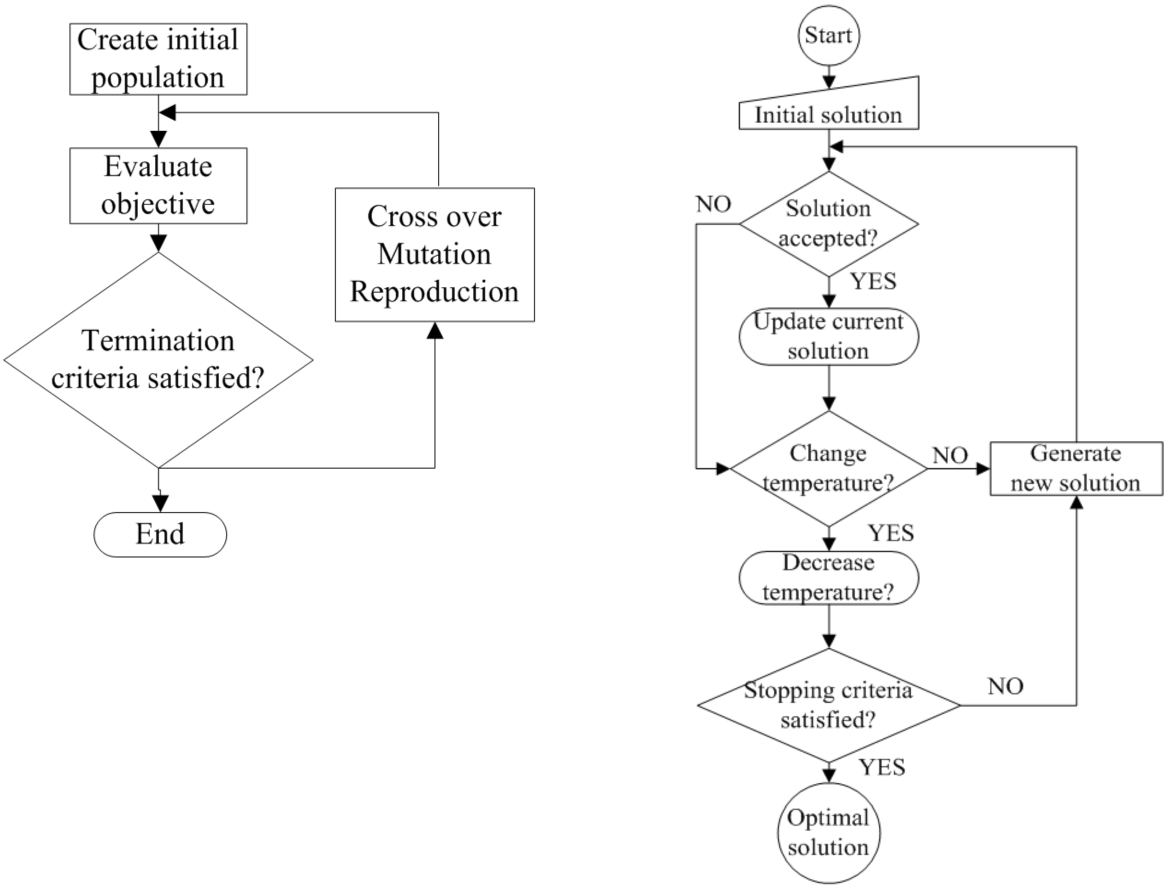

Figure 1: GA and SA flow chart

C. Simulated Annealing Algorithm

Simulated annealing is derived from the physical process of heating to a high temperature and slowly lowering the temperature to reach a minimum energy state [11]. Simulated annealing is a point-by-point method. The algorithm starts with an initial point (either randomly or heuristically constructed) and a high temperature T. A second point is created at random in the vicinity of the initial point and the difference in the function values (ΔE) is calculated. If the second point has a smaller function value, the point is accepted; otherwise, the point is accepted with a probability exp $(-\Delta E/T)$. This completes one iteration of the SA procedure. In the next generation, another point is created at random in the neighborhood of the current point and the metropolis algorithm is used to accept or reject the point. That is, the probability of the next point being a minimum value depends on the difference in function values on these two points, or on $\Delta E = E\ (t + 1) - E\ (t)$, and is calculated using the Boltzmann probability distribution: $P\ (E\ (t + 1)) = \min\ [1, \exp\ (-\Delta E\ kT)]$. In order to simulate the thermal equilibrium at every temperature, a number of points (n) are usually tested at a particular temperature before reducing the temperature. The flow chart for optimization using SA as depicted in Fig.1.

III. HARD MILLING EXPERIMENTS

A CCRD was used to investigate the effects of four independent variables, feed per tooth (A), radial depth of cut(B), axial depth of cut(C) and cutting speed(D), on the dependent variables, CT,TW and MRR. The factors and levels used during the milling experiments are listed in Table I. Typical hardened and tempered 100MnCrW4 (AISI O1) tool steel (50HRC) was taken for analysis. The main applications are making molds, dies, gauges and bushings etc. All the specimens were in the form of 150 mm×150mm×25mm blocks. A series of 30 experiments with three replications was performed on CNC Mazak-Nexus 510C-II machine equipped with 12000rpm and 25KW power drive motor is used. A photograph of experimental setup is shown in Fig.2.

Table 1: Parameters and levels

Levels	**Process Parameters**			
	A(mm/z)	**B(mm)**	**C(mm)**	**D(m/min)**
-2	0.05	0.2	0.2	200
-1	0.1	0.3	0.4	250
0	0.15	0.4	0.6	300
+1	0.2	0.5	0.8	350
+2	0.25	0.6	1.0	400

A Taegu Tec cutter body, 2S-TE90AP 320-W20-09, is used to hold the inserts. The coated (TiN+TiAlN) carbide tool insert, Taegu Tec APKT 09T320R-EM with 2mm nose radius is used in this study. All of the experiments were run under dry conditions and each test was started with a new cutting edge. During machining, a cutting temperature was captured using non-contact fluke type (Type 8839) pyrometer with an emissivity value of 0.19 (i.e. Rake face of the tool).Tool wear was measured by means of a toolmaker's microscope and was examined by the use of SEM and EDAX on JSM-6510LV unit. The observed tool wear for 4th experiment as depicted in Fig.3. MRR is calculated from the difference in weight of the workpiece before and after machining divided by the total machining time. In the experiment, the workpiece was weighed using a digital balance with 0.001 gram accuracy.

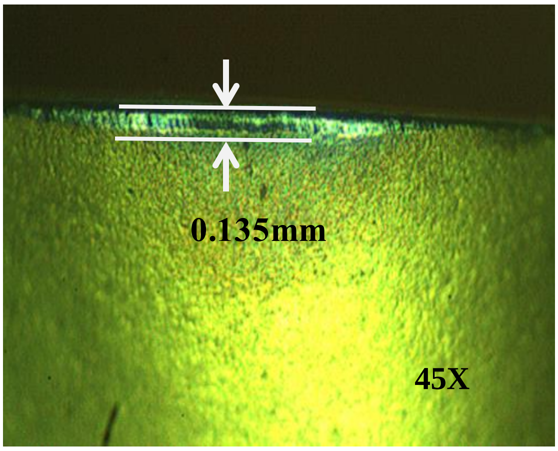

Figure -2: Mazak VMC and cutting zone Figure-3- Tool wear for 4th Experiment

IV. RESULTS AND DISCUSSIONS

A. Empirical Regression Equations

The Table II summarizes experimental design matrix with the results. A second order quadratic model has been intended to develop which will take into account the quadratic and interactive effects beside the individual factors. With the help of Design Expert software, the final mathematical models of the actual values of the CT in °C, TW in mm and MRR in g/min obtained at 95% confidence interval as follows:

$$CT(°C)=1207.1727+1996.746429\times A+55.7226\times B+529.527\times C+6.51711\times D-849.125\times AC+2.2335\times BD-0.897375\times CD-3289.571429\times A^2-744.2678571\times B^2-0.00739\times D^2 \quad (R^2=0.9896) \tag{2}$$

$$TW(mm)=+0.06604+0.1275\times A-0.635833\times B-0.21645\times C+0.0010575\times D-0.175\times AC-0.0001625\times CD+2.358\times A^2+0.8395\times B^2+0.266145833\times C^2-0.0000012\times D^2 (R^2=0.9975) \tag{3}$$

$$MRR(g/min)=-26.331+25.3575\times A+1.5279\times B-5.3404\times C+0.14648\times D+41.675\times AC+15.19375\times BC-77.725\times A^2-0.000213475\times D^2 \quad (R^2=0.9697) \tag{4}$$

The goodness of the fit was expressed by the coefficient of determination (R^2), which was 0.9896, 0.9975 and 0.9697 for CT, TW and MRR respectively. This indicates that 98.96%, 99.75% and 96.97% of variability in the each response could be explained by the model. This shows that the second-order model contains both quadratic and interaction terms and, thus, is more accurate.

B. Single Objective Optimization with GA and SA

Regression models are as a fitness function in both algorithms and so, the accuracy of these models is very vital in the performance of standard optimization. The GA and SA optimization of the hard milling process of regression models was simulated using a matlab codes. In both optimization procedures, the lower bound values and upper bound values are used as LB= [0.05 0.2 0.2 200] and UB= [0.25 0.6 1.0 400] respectively. The iteration in GA begins with a population of random strings representing the design or decision variables. Thereafter, each string is evaluated to find fitness value. The critical parameters in GA are the population size number of generations, mutation rate, etc. In case of SA, the parameters are varied one at a time randomly to obtain a new set of parameters. With each set of parameters, the objective function was determined and the difference in the objective function (Δf) with the old and new sets of parameters was calculated. If the new set of values improved the objective function, the move was accepted. Otherwise, the move was accepted with a probability of exp ($\Delta f/T$), where T is the simulated annealing temperature, a dummy variable that is used to control the acceptance of uphill moves. Initially, T was fixed at a higher value and periodically annealed by a proportional cooling schedule in the outer loop.

Table 2: Experimental design matrix with results

Std	A(f_z) mm/z	B(a_e) mm	C(a_p) mm	D(V_c) m/min	CT °C	TW mm	MRR g/min
1	0.20	0.30	0.40	250	407.01	0.183	2.282
2	0.15	0.40	1.00	300	591.67	0.199	8.424
3	0.20	0.50	0.40	350	693.78	0.213	6.175
4	0.10	0.30	0.40	350	575.26	0.135	2.696
5	0.15	0.40	0.60	300	574.94	0.143	4.664
6	0.15	0.40	0.60	300	559.81	0.142	4.93
7	0.20	0.30	0.40	350	650.84	0.209	3.885
8	0.15	0.40	0.20	300	491.55	0.175	2.178
9	0.20	0.50	0.80	250	460.71	0.201	7.981
10	0.20	0.50	0.80	350	705.47	0.219	9.64
11	0.10	0.50	0.40	350	609.02	0.139	3.237
12	0.10	0.30	0.40	250	334.09	0.107	1.196
13	0.20	0.30	0.80	350	673.63	0.210	7.77
14	0.15	0.40	0.60	200	244.02	0.112	1.088
15	0.20	0.50	0.40	250	378.68	0.191	4.055
16	0.15	0.40	0.60	300	567.64	0.148	5.865
17	0.10	0.50	0.80	350	696.61	0.153	6.475
18	0.15	0.40	0.60	300	552.28	0.145	5.554
19	0.10	0.50	0.40	250	349.57	0.113	2.027

20	0.15	0.20	0.60	300	505.2	0.169	2.674
21	0.25	0.40	0.60	300	575.46	0.243	7.348
22	0.10	0.50	0.80	250	438.82	0.129	4.355
23	0.15	0.40	0.60	300	560.73	0.148	5.038
24	0.20	0.30	0.80	250	441.52	0.195	4.866
25	0.05	0.40	0.60	300	469.66	0.093	1.696
26	0.15	0.40	0.60	400	719.09	0.152	5.241
27	0.15	0.40	0.60	300	568.37	0.142	5.839
28	0.10	0.30	0.80	250	419.04	0.125	2.433
29	0.15	0.60	0.60	300	546.17	0.187	7.581
30	0.10	0.30	0.80	350	600.35	0.144	3.085

At any specific temperature, the parameters were randomly varied a number of times in the inner loop. Thus, the optimum parameter values were obtained after *T* reached a desired lower value. The results of single objective optimization of the responses are presented in Table 3 and 4. From the Tables 3 and 4, it is observed that different combinations of the optimal hard milling process parameters are attained by GA and SA for individual response.

Table -3- Results of Single objective optimization using GA

S. No.	**Response**	**Objective**	**Optimal value**	**Input parameters**			
				f_z**(mm/z)**	a_e**(mm)**	a_p**(mm)**	V_c**(m/min)**
1	*CT*	Minimize	332.3596	0.1	0.3	0.4	250
2	*TW*	Minimize	0.0979	0.1	0.379	0.516	250
3	*MRR*	Maximize	9.9937	0.2	0.5	0.8	343.087

Table 4: Results of Single objective optimization using SA

S. No.	**Response**	**Objective**	**Optimal value**	**Input parameters**			
				f_z**(mm/z)**	a_e**(mm)**	a_p**(mm)**	V_c**(m/min)**
1	*CT*	Minimize	332.3596	0.1	0.3	0.4	250
2	*TW*	Minimize	0.099	0.101	0.366	0.525	251.597
3	*MRR*	Maximize	8.7118	0.2	0.499	0.8	265.797

C. Multi-objective optimization with GA and SA

The CT, TW and MRR have been expressed separately as the non-linear functions of input variables, such as f_z, a_e, a_p and V_c. Now, the goal was to minimize CT, TW and maximize MRR simultaneously, in the hard milling process. In order to find the set of input variables to satisfy both the above criteria, the problem formulation becomes a multi-objective optimization by considering three objective functions. The following combined objective function (i.e. minimization problem) is developed.

$$Min(Z_1) = \frac{w_1 Y_u(CT)}{CT_{min}} + \frac{w_2 Y_u(TW)}{TW_{min}} - \frac{w_1 Y_u(MRR)}{MRR_{max}} \quad (5)$$

Where W_1, W_2 and W_3 are the weight values assigned to CT, TW and MRR respectively, and CT_{min} and TW_{min} are the minimum values of CT and TW respectively, and MRR_{max} is the maximum value of MRR. The minimum and maximum values of the responses are obtained from the single objective optimization results in both GA and SA. In this present optimization study, for each response the equal priority was considered, i.e. W_1=W_2=W_3=0.333. The convergence history of the GA is illustrated in Fig.4.

It is clear from the figure that no substantial change in the fitness value is observed after 38 generations. This indicates that, the parameters have reached the optimum values, ensuring minimum cutting temperature, tool wear and maximum material removal rate. The suitable parameters for GA computations as population size, number of generations, scattered crossover, uniform mutation and selection are 160, 90, 0.75, 0.20 and tournament selection respectively. Similarly, the convergence history of the SA is illustrated in Fig.5. The best fitness attained during each iteration of the simulated annealing algorithm optimization decreased till it became relatively constant after 750 generations. In case of SA computations, the parameters are annealing function, annealing interval, initial temperature and data type set as Boltzmann annealing, 100,100 and double respectively. The desired optimal values for GA and SA are shown in Table 5. The objective solution of SA is better than GA was observed in Table 5.

D. Verification

A verification of the results using the set of optimized parameters was accomplished by performing the experiments incorporating the optimized variables. The experiments were conducted in triplicate and the average values of each response as shown in Table 6 .These experimental findings were in close agreement with the GA and SA based optimal solutions. The error between the theoretically predicted value and the experimental measurement is less than 5%. This confirms the applicability of these evolutionary computational techniques are reasonable for optimization of process parameters in the hard milling process.

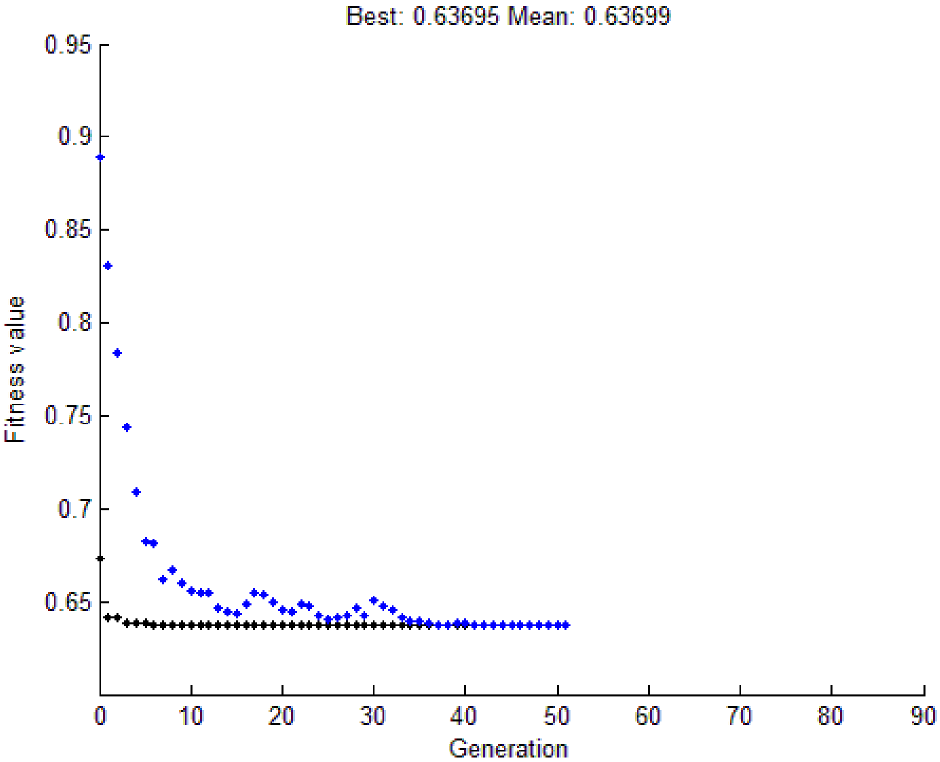

Figure 4: Best fitness (lowest MSE value) versus generation during the optimization procedure of GA

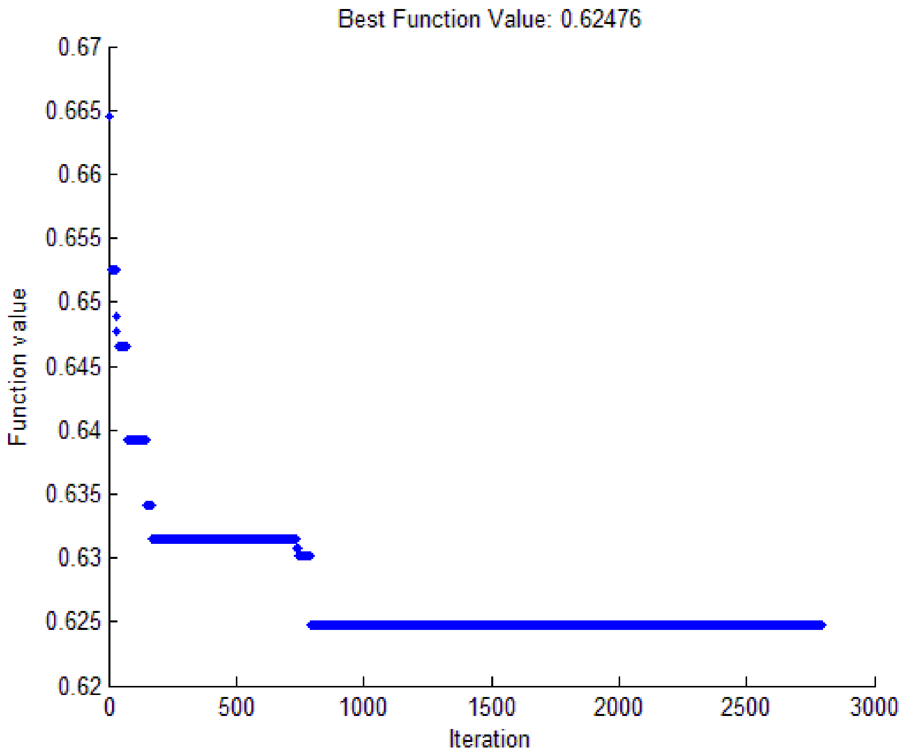

Figure 5: Best function value versus Iteration during the optimization procedure of SA

Table 5: Multi-objective optimization results using GA and SA

Optimization method	***Z***	**Optimal values**			**Input parameters**			
		CT	***TW***	***MRR***	f_z	a_e	a_p	V_c
		°C	***mm***	***g/min***	***mm/z***	***mm***	***mm***	***m/min***
GA	0.63695	362.238	0.10145	2.1169	0.1	0.438	0.495	250
SA	0.62476	367.916	0.10541	2.58054	0.1	0.469	0.523	250.412

Table 6: Optimal conditions and confirmation runs of two different approaches

Optimization method	**Optimal values**				**Input parameters**		
	f_z	a_e	a_p	V_c	***CT(°C)***	***TW(mm)***	***MRR(g/min)***
					Pred./Exp.	**Pred./Exp.**	**Pred./Exp.**
GA	0.1	0.438	0.495	250	362.237/361.543	0.101/0.093	2.116/2.104
SA	0.1	0.469	0.523	250.4	367.915/365.647	0.105/0.089	2.58/2.234

V. CONCLUSION

The present article investigates multi-objective optimization of process parameters in hard milling of 100MnCrW4 (Type O1) cold work tool steel using evolutionary algorithms. Following conclusions can be drawn on the basis of results obtained:

1. A central composite rotatable design was effectively used for experiments and to develop the regression models.
2. The predicted values match the experimental values reasonably well, with R^2 of 0.9896 for CT, R^2 of 0.9975 for TW and R^2 of 0.9697for MRR.
3. The GA and SA offer simple and effective tools for searching the optimal cutting conditions effectively.
4. The objective solution of SA is better than GA was obtained.
5. The validity of the optimized results was checked by conducting conformity test, and the error is less than ±5% achieved.
6. The selection of optimum values is essential for the process automation and implementation of a computer-integrated manufacturing system.

REFERENCES

[1] Lobanov, AA. (2007). Technological Advantages of Hard Milling, Russian Engineering Research, Vol. 27, No. 6, pp. 396-397.

[2] Gopalsamy, B.M.; Mondal, B.; Ghosh, S.; Arntz, K.; Klocke, F. (2009). Investigations on hard machining of Impax Hi Hard tool steel, International Journal of Material forming, Vol.2, pp.145-165.

[3] Ding, T.; Zhang, S.; Wang, Y.; Zhu, X. (2010). Empirical models and optimal cutting parameters for cutting forces and surface roughness in hard milling of AISI H13 steel, International Journal of Advanced Manufacturing Technology, Vol.51, pp.45-55.

[4] Okada, M.;Hosokawa, A.; Tanaka R.; Ueda, T. (2011). Cutting performance of PVD-coated carbide and CBN tools in hard milling, International Journal of Machine Tools & Manufacture, Vol. 51, pp.127-132.

[5] Çalışkan, H.; Kurbanoğlu, C.; Panjan, P.; Kramar, D.(2012). Investigation of the performance of carbide cutting tools with hard coatings in hard milling based on the response surface methodology, International Journal of Advanced Manufacturing Technology, Vol.66, Nos. 5-8, pp.883-893.

[6] Sivasakthivel, P.S.; R. Sudhakaran,R. (2013). Optimization of machining parameters on temperature rise in end milling of Al 6063 using response surface methodology and genetic algorithm, International Journal of Advanced Manufacturing Technology, Vol.67, pp.2313-2323.

[7] Suresh Kumar Reddy, N.; VenkateswaraRao,P. (2006). Selection of an optimal parametric combination for achieving a better surface finish in dry milling using genetic algorithms, International Journal of Advanced Manufacturing Technology, Vol.28, pp.463-473.

[8] Zain, A, M.; Haron, H.; Sharif, S. (2010). Application of GA to optimize cutting conditions for minimizing surface roughness in end milling machining process, Expert Systems with Applications,Vol.37,pp.4650-4659.

[9] Senthilkumar, N.;Tamizharasan, T.; Anandakrishnan, V. (2013). An ANN approach for predicting the cutting inserts performances of different geometries in hard turning, Advances in Production Engineering &Management, Vol. 8, no. 4, pp.231-241.

[10]JaliliSaffar, R.; Razfar, M.R.(2010). Simulation of end milling operation for predicting cutting forces to minimize tool deflection by genetic algorithm, Machining Science and Technology: An International Journal, Vol.14, no.1, pp.81-101.

[11] Zain, A, M.; Haron, H.;Sharif, S. (2010). Simulated annealing to estimate the optimal cutting conditions for minimizing surface roughness in end milling Ti-6Al-4V, Machining Science and Technology: An International Journal, Vol.14, no.1, pp.43-62.

[12] Hrelja, M.; Klancnik, S.; Balic, J.; Brezocnik, M. (2014). Modelling of a turning process using the Gravitational Search Algorithm, International Journal of Simulation Modelling, Vol. 13, No. 1, 30-41.

[13] Oktem, H. (2009). An integrated study of surface roughness for modeling and optimization of cutting parameters during end milling operation, International Journal of Advanced Manufacturing Technology, Vol.43, pp.852–861.

[14] Gaitonde, V.N.; Karnik, S. R.; Davim, J.P. (2012). Optimal MQL and cutting conditions determination for desired surface roughness in turning of brass using genetic algorithms, Machining Science and Technology: An International Journal, Vol.16, no.2, pp.304-320.

[15]Colak, O. (2014). Optimization of machining performance in high-pressure assisted turning of Ti6Al4V alloy, Strojniski vestnik – Journal of Mechanical Engineering, Vol. 60, no. 10, pp.675-681.

[16] Kuruvila, N.; Ravindra H.V. (2011). Parametric influence and optimization of wire EDM of hot die steel, Machining Science and Technology: An International Journal, Vol.15, no.1, pp.47-75.

[17] Edwin Raja Dhas, J.;Kumanan, S. (2011). Optimization of parameters of submerged arc weld using non-conventional techniques, Applied Soft Computing, Vol.11, pp.5198–5204.

[18] Zain, A, M.; Haron, H.; Sharif, S. (2011). Integration of simulated annealing and genetic algorithm to estimate optimal solutions for minimising surface roughness in end milling Ti-6AL-4V, International Journal of Computer Integrated Manufacturing, Vol.24, no.6, pp.574-592.

[19] Suresh, P.;Venkatesan, R.; Sekar, T.; Elango, N.;Sathiyamoorthy, V. (2014). Optimization of intervening variables in micro EDM of SS 316L using a Genetic Algorithm and Response-Surface Methodology, Strojniski vestnik – Journal of Mechanical Engineering, Vol. 60, no. 10, 656-66.

[20] Yang, S.H;, Srinivas, J.; Mohan, S.; Lee, D.M.;Balaji, S.(2009). Optimization of electric discharge machining using simulated annealing, Journal of Materials Processing Technology, Vol.209, pp.4471-4475.

[21] Zain, A, M.; Haron, H.; Sharif, S. (2011). Optimization of process parameters in the abrasive water jet machining using integrated SA–GA, Applied Soft Computing, Vol.11, pp. 5350-5359.

[22] Palanisamy, P.; Rajendran, I.; Shanmugasundaram, S. (2007).Optimization of machining parameters using genetic algorithm and experimental validation for end-milling operations, International Journal of Advanced Manufacturing Technology, Vol.32, pp.644-655.

[23] Liao, H.T.; Chen, Z.W. (2011). A study on fiber laser micro-spot welding of thin stainless steel using response surface methodology and simulated annealing approach, International Journal of Advanced Manufacturing Technology, Vol.11, pp.5350-5359.

[24] Montgomery, D. C. (2005).Design and analysis of experiments, 6th edition, John Wiley and Sons, Hoboken, USA.

