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Optimization of Constrained Machining Parameters in Turning Operation Using Firefly Algorithm

S. Bharathi Raja, N. Sathiya Narayanan, C.V. Srinivas Pramod,
Arvind Raguathan, Somala Raju Vinesh and K. Vamshee Krishna
School of Mechanical Engineering, SASTRA University, Thanjavur-613 401, Tamil Nadu, India

Abstract: Turning is a widely used machining operation when compared to other manufacturing processes. The finished component is subjected to dimensional accuracy, required surface finish and the tool is subjected to less cutting force, minimum possible temperature and maximum tool life. In order to achieve these desired performance measures in any machining operation, proper selection of machining parameters is very essential. The present method of selection of machining parameters by trial and error, previous work experiences of the process planner and machining handbooks are time consuming and very tedious process. There is a need to develop a technique that could be able to find the optimal machining parameters for the desired performance measures in minimum production time and minimum production cost. In this work, Firefly Algorithm (FA) is implemented to select the optimal machining parameters such as cutting speed, feed and depth of cut in minimum possible production time and production cost on turning process. The result of FA has been compared with other optimization techniques and discussed.

Key words: Turning operation, machining parameters, firefly algorithm, production time, production cost

INTRODUCTION

Selection of appropriate machining parameters is an important step in the process planning of any machining operation. The present method of selection of machining parameters mainly depends either on previous work experience of the process planner or thumb rule or any machining data handbook. But it is a known fact that the machining parameters obtained from these resources are far below the optimal parameters and may be very much useful for theoretical investigations. The other possibility of selecting machining parameters is by conducting 'trial and error' experiments (Bharathi Raja and Baskar, 2012). But this act of experiments is purely non-technical moreover, time and cost is unnecessarily wasted for this purpose. In today's manufacturing environment, the cost of Computer Numerical Control (CNC) machines are very high and so there is a need to utilize the CNC machines as economic as possible in order to get the required payback (Bharathi Raja and Baskar, 2010a). Economic operation of CNC machines mainly depends on minimized machining time which once again depends on proper selection of machining parameters.

Production time and production cost are two of the important factors in manufacturing industries. Improperly selected machining parameters leads to increase in production cost and time. To achieve the desired objective in machining, machining parameters such as

cutting speed, feed, depth of cut, tool nomenclature, cutting force and rigidity of the machine can be considered. Among these cutting parameters, cutting speed, feed and depth of cut are parameters which are the most influencing and easily controllable during the process of machining moreover, time and cost is not involved in indulging in such changes whenever necessary (Bharathi Raja and Baskar, 2012).

At this juncture, it is necessary to find a suitable method to select the appropriate machining parameters for any machining. In the recent years, non-traditional optimization techniques such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and so on have become very popular due to its versatile usage in various engineering applications especially in machining problems. Many researchers have developed and adopted traditional and non-traditional optimization techniques for solving optimization problems in various applications. They have also compared the end results of one technique with the other techniques (Bharathi Raja and Baskar, 2010b). This was done to explore the best performing technique among the available techniques. The best optimization technique should be efficient than the present method of machining parameters selection.

In this study a recently developed non-traditional optimization technique named as Firefly Algorithm (FA)

was implemented in a mathematical from available in the literature. This was done to compare the robustness of the proposed FA with other well-proven techniques in the same literature. The objective was to minimize total production time and cost subjected to constraints such as cutting speed, feed, depth of cut, surface roughness, power, temperature and cutting force.

LITERATURE REVIEW

Agapiou (1992) determined the optimum machining conditions for single-pass operation using Nelder-Mead simplex method. The objective function was a combination of minimum product cost and minimum production time prioritized through their weight coefficients. The superiority of the combined objective function over single objective, sensitivity analysis for the weighted coefficients and the constant multiplier used to normalize the objective function are also discussed via numerical examples. Bharathi Raja and Baskar (2010a) investigated optimum machining parameters for turning operation using non-traditional optimization techniques and compared the results with traditional Nelder-Mead Simplex (NMS) method. Non-traditional optimization techniques such as SA, PSO, GA, Hybrid Algorithm (HA) and Memetic Algorithm (MA) were used to optimize the machining parameters. PSO has yielded best result among the non-traditional optimization techniques. The result of PSO is 8% better than NMS method and 4.7% better than the least result obtained from non-traditional techniques. Bharathi Raja and Baskar (2010b) examined SA, GA and PSO in three different mathematical models such as single pass turning operation, multi-pass turning operation and grinding operation. The authors found that PSO outperformed the other optimization techniques in all the cases. Bharathi Raja and Baskar (2012) applied PSO to find optimum cutting parameters for desired surface roughness in minimum machining time. The predicting accuracy of PSO was found to be 96% for machining time and 85% for surface roughness with respect to the measured values.

Yang (2009) developed and described a new meta-heuristic optimization technique named as Firefly Algorithm (FA). The results of the developed FA depicts that it is very much suitable for any engineering optimization as it outperformed the proven and most efficient Particle Swarm Optimization (PSO) technique. Sayadi *et al.* (2010) presented FA to minimize the makespan for the permutation flow shop scheduling problem. The authors concluded that the proposed FA performs better than Ant Colony Optimization for some well known benchmark problems. Yang (2009) demonstrated FA to solve non-linear design problems.

Experimental results based on FA for standard pressure vessel design optimization has produced better results when compared to best solution obtained previously in the literature. Apostolopoulos and Vlachos (2011) applied FA to minimize fuel cost and emission from the power production units. The results obtained by other techniques for the same problem available in the literature are compared with the proposed FA. The author concluded that FA could yield the best optimal solution when compared to other techniques.

In this study, recently developed FA was adopted for finding optimal machining parameters to minimize production time and production cost in single pass turning operation. The result of FA was compared with SA, GA, PSO, MA and HA and discussed.

MATHEMATICAL MODEL

The mathematical model for single pass turning operation proposed by Agapiou (1992) is considered in this work. It is concerned with the optimal selection of machining parameters such as cutting speed, feed rate and depth of cut to minimize production time and cost. Since these parameters strongly affect the cost, time, productivity and quality of the machined parts, determining the optimal machining parameters is an essential step in machining operation.

Formulation of objective function: Minimization of total production time and total production cost is taken as the objective function. Table 1 shows the values for the machining parameters like length and diameter of the work piece, minimum and maximum values of machining parameters, maximum limits of various performance measures. They are obtained from the knowledge of the machine limitations and from the handbooks.

Production cost: Production cost is a function of time and cost. It is given in Eq. 1:

$$C_u = C_o \cdot tm + (tm/T) C_o \cdot t_{cs} + C_t + C_o (t_h + t_p) \tag{1}$$

Table 1: Values of machining parameters

Parameters	Values	Parameters	Values
L	203 mm	HP _{max}	5 KW
D	152 mm	T _{max}	500°C
v _{min}	30 m min ⁻¹	a ₁	0.29
v _{max}	200 m min ⁻¹	a ₂	0.35
f _{min}	0.254 mm rev ⁻¹	a ₃	0.25
f _{max}	0.762 mm rev ⁻¹	K	193.3
d _{min}	2 mm	C _o	0.1 min ⁻¹
d _{max}	5 mm	C _t	0.5 edge ⁻¹
t _{cs}	0.5 min edge ⁻¹	t _h	1.4999 min Pieces ⁻¹
t _t	0.13 min pass ⁻¹	SR _{max}	8 μm
F _{max}	1100 N		

The machining time per pass in single pass turning is given in Eq. 2:

$$t_m = (\pi DL)/(1000 vf) \quad (2)$$

Tool life is given in Eq. 3:

$$T = (K/(vf^a_1 d^a_2))^{1/a_3} \quad (3)$$

Production time: Production time is a function of machining time, tool handling. It is given in Eq. 4:

$$t_u = t_m + t_{cs} (t_m/T) + t_h + t_r \quad (4)$$

Practical constraints: Practical constraints always exist in any machining which has to be considered to get real time performance measures. In this work, seven different practical constraints are considered before calculating production time and cost:

- Parameter constraints

$$v_{min} \leq v \leq v_{max} \quad (5)$$

$$f_{min} \leq f \leq f_{max} \quad (6)$$

$$d_{min} \leq d \leq d_{max} \quad (7)$$

- Power constraint

$$0.0373 v^{0.91} f^{0.78} d^{0.75} \leq HP_{max} \quad (8)$$

- Surface finish constraint

$$14785 v^{-1.52} f^{1.004} d^{0.25} \leq SR_{max} \quad (9)$$

- Temperature constraint

$$74.96 v^{0.4} f^{0.2} d^{0.105} - 17.8 \leq T_{max} \quad (10)$$

- Cutting force constraint

$$844 v^{-0.1013} f^{0.725} d^{0.75} \leq F_{max} \quad (11)$$

FIREFLY ALGORITHM

Firefly Algorithm (FA) is a nature inspired algorithms which is based on the flashing light of fireflies. Yang (2009) formulated firefly algorithm by assuming all artificial fireflies are unisexual, so that one firefly will be attracted to all other fireflies, attractiveness is proportional to their brightness and for any two fireflies,

the less brighter one will be attracted by (and thus move to) the brighter one however, the brightness can decrease as their distance increases. If there are no fireflies brighter than a given firefly, it will move randomly.

The flashing light helps fireflies for finding mates, tracking their potential prey and protecting themselves from their predators. The swarm of fireflies will move to brighter and more attractive locations by the flashing light intensity that associated with the objective function of problem considered in order to obtain efficient optimal solutions. Steps involved in FA is described in the subsequent section.

Population initiation: Cutting speed is calculated randomly within the limits using Eq. 12:

$$v = v_{min} + (v_{max} - v_{min}) * rand() \quad (12)$$

Similarly feed is calculated randomly within the limits using Eq. 13:

$$f = f_{min} + (f_{max} - f_{min}) * rand() \quad (13)$$

Similarly depth of cut is also calculated randomly within the limits using Eq. 14:

$$d = d_{min} + (d_{max} - d_{min}) * rand() \quad (14)$$

Distance: The distance between any two fireflies *i* and *j* at x_i and x_j , respectively, can be defined as a Cartesian distance (r_{ij}) using equation (15), where x_i, k is the *k*th component of the spatial coordinate x_i of the *i*th firefly and *d* is the number of dimensions:

$$r_{ij} = |x_i - x_j| = \sqrt{\sum_{k=1}^d (x_{i,k} - x_{j,k})^2} \quad (15)$$

Attractiveness: The calculation of attractiveness function of a firefly is performed using Eq. 16:

$$\beta = \beta_0 \cdot e^{-\gamma r^m} \text{ where } m \geq 1 \quad (16)$$

where, *r* is the distance between any two fireflies, β_0 is the initial attractiveness at $r = 0$ and γ is an absorption coefficient which controls the decrease of the light intensity.

Movement: A firefly moves towards a brighter or more attractive firefly. Firefly movement can be calculated using the Eq. 17:

$$v_{np} = [v_{cp}(1 - \beta)] + [v_b \cdot \beta] + [\alpha (rand() - 0.5)] \quad (17)$$

New position of a firefly can be updated by adjusting the current position of the same firefly. After satisfying all the physical constraints given in equations from (5) to (11), the machining parameters such as cutting speed, feed, depth of cut values are substituted in the equations from (1) to (4) to get the minimum production cost and minimum production time.

RESULTS AND DISCUSSION

FA is implemented in the mathematical model available in the literature. MATLAB software was used to execute the algorithm with population size as 100 in 1000 iterations. The convergence to the optimal point appeared at 56th iteration. Table 2 shows the values of optimised machining parameters and its corresponding production time and cost. Computational time taken for execution of single run is observed to be 12 seconds in an average.

Figure 1 shows the convergence of production time at the optimal point in 56th iteration. Figure 2 shows the convergence of production cost at the optimal point in 56th iteration. From 56th iterations onwards, there is no specific change in the objective function value till the last iteration.

Table 3 shows the results of various algorithms performed in the adopted mathematical model. It is obvious that PSO has proved to be the best performing technique when compared to the other techniques considered. The proposed FA could not outperform PSO, GA, MA and HA but could perform better than SA and NMS method.

Table 3 shows the results of FA is 5% better than SA and 9.8% better than NMS method. But the result of PSO is 2.35% better than the proposed FA. The execution time for PSO is 11 seconds and that of FA is 12 seconds which is again better the proposed FA in computation execution time.

From Table 3, it is obvious that the result of proposed FA is very closer to PSO which has topped the table. The parameters to adjust to get the optimum solution are fewer and so the procedure of FA is simple. Moreover, convergence to global optimum solution is also very quicker when compared to SA, GA, MA, HA and NMS method. Hence FA could also be considered for solving machining problems. On the other hand, percentage of superiority of PSO is 2.35% better than FA. Normally, an algorithm which could able to give superior results, will only normally considered for solving machining problems. Based on this fact, Bharathi Raja and Baskar (2012) have selected PSO for solving their machining problem.

Table 2: Results of FA

Optimized machining parameters			Objective function	
Cutting speed (m min ⁻¹)	Feed (m rev ⁻¹)	Depth of cut (mm)	Machining time (sec)	Production cost (\$ piece ⁻¹)
125.2	0.7518	2.09	2.8418	0.7842

Table 3: Results of various algorithms

Optimization technique	Production time (min)	Production cost (\$ piece ⁻¹)
PSO	2.774	0.7774
HA	2.781	0.7781
MA	2.814	0.7814
GA	2.818	0.7818
FA (Proposed)	2.841	0.7842
SA	2.993	0.7994
NMS	3.150	0.8151

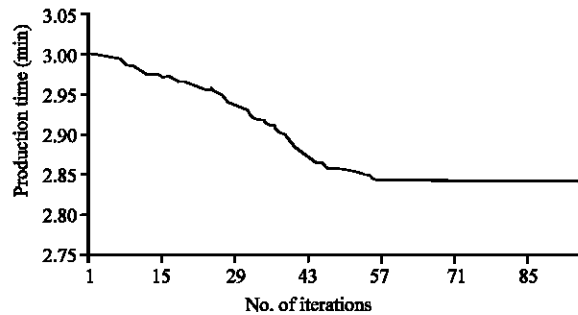


Fig. 1: No. of iterations vs. production time (min)

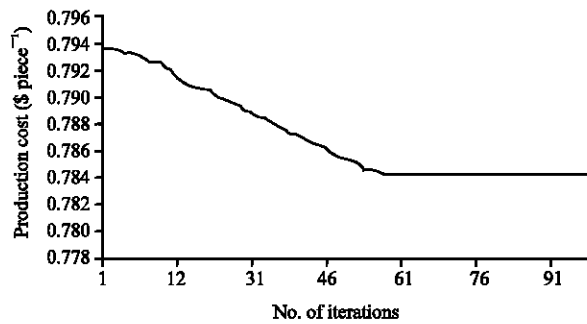


Fig. 2: No. of iterations vs. production cost (\$ piece⁻¹)

CONCLUSION

The problem of selection of proper machining parameters is very predominant in all manufacturing industries. Many attempts have been done so far to identify a methodology to explore the optimal machining parameters for a machining operation. In this work, yet another attempt has been made using a recently developed non-traditional optimization technique named as FA. The proposed technique is implemented in the mathematical model available in the literature. This was done to compare the end result of the proposed technique with the other techniques implemented in the

literature. From the results, it is observed that PSO is proved to be the best performing technique when compared to SA, GA, FA, MA, HA and NMS. The proposed FA outperformed SA and NMS technique but lags behind PSO, GA, MA and HA in the implemented model.

NOMENCLATURE

v	=	Cutting speed (m min ⁻¹)
f	=	Feed rate (mm rev ⁻¹)
d	=	Depth of cut (mm ⁻¹)
c _a	=	Production (cost, \$ piece ⁻¹)
t _a	=	Production time (min ⁻¹)
t _m	=	Machining time (min ⁻¹)
t _{cs}	=	Tool change time (min edge ⁻¹)
t _h	=	Loading and unloading time (min piece ⁻¹)
t _r	=	Quick return time (min pass ⁻¹)
C _o	=	Operating cost (min ⁻¹)
C _t	=	Tool cost per cutting edge (\$ edge ⁻¹)
D	=	Outside diameter (mm ⁻¹)
L	=	Length of the part (mm ⁻¹)
T	=	Tool life (min ⁻¹)
K, a ₁ , a ₂ , a ₃	=	Empirical Constants
r	=	Distance between any two fireflies
p	=	Population size
b	=	Best particle
α	=	Randomization parameter
β	=	Attractiveness
β ₀	=	Initial attractiveness at r = 0
γ	=	Light absorption co-efficient
np	=	New position
cp	=	Current position

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