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TECHNICAL PAPER

Chip load-responsive optimization of micro-milling of engineering materials

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Abstract The miniaturization of machine component is perceived by many as requirement for the future technological development of a broad spectrum of products. Micro-component fabrication requires reliable and repeatable methods, with accurate analysis tools. Surface roughness is one of the most important parameter in machining process. This study presents the results of test done with high-speed face milling tool. Also this research discusses an experimental approach to the development of mathematical model for surface roughness prediction before milling process by using ant colony optimization algorithm. This mathematical model is validated by optimization of cutting parameters for minimum surface roughness.

Keywords High-speed machining · Micro-milling · Chip load · ACO · Surface roughness

1 Introduction

Micro-machining, or miniature machining, refers to the machining of very small parts and consisting micro-features. Micro-machining not only offers quality and reliability for conventional products, but also makes possible better performing products, especially where mechatronics, miniaturization and critical functionality are important. The emergence of new manufacturing technologies, spurred by intense competition, will lead to dramatically new products, processes and process pull. It is widely appreciated that the development of micro-machining has greatly changed human lives in terms of increased standards, as an example of process pull. Uses of high-accuracy miniaturized components have been increased, such as in aerospace, biomedical, electronics, environmental, communications, and automotive components [1].

In the present-day manufacturing industry, high-speed milling (HSM) plays an important role. The key benefit of HSM is that a large amount of material can be cut in a short time span with relatively small tools due to the high rotational speed of the tool. This results in relatively low forces, which allows one to mill large and complex thin-walled structures from a single block of material, instead of assembling the same structure from several parts. In order to improve the production rates. The selection of optimal cutting parameters is a very important issue for every machining process in order to enhance the quality of machining products, to reduce the machining costs and to increase the production rate. Due to machining costs of numerical control a machine (NC), there is an economic need to operate NC machines as efficiently as possible in order to obtain the required pay back. In workshop practice, cutting parameters are selected from machining databases or specialized handbooks, but they do not consider economic aspects of machining. The cutting conditions set by such practices are too far from optimal. Therefore, a mathematical approach has received much attention as a method for obtaining optimized machining parameters [1, 2].

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2 Literature review

Micro-milling is one of the technologies widely used for manufacture of microstructures and tooling inserts for microinjection molding and hot embossing. For example, important application areas are the manufacture of micro-parts for watches, keyhole surgery, and housings for micro-engines and also tooling inserts for fabrication of micro-filters, housings and packaging solutions for micro-optical and microfluidic devices [2, 3].

The conduction of experiments for the characterization of surface quality for the micro-end milling shows that the chip load is by far the most dominant factor of that surface quality. Cutting speed and its interaction with chip load were also having significant effect. Run-out appears to play a significant role in the surface quality of micro-milled parts. The dominant cutting marks have a period of twice the chip load, meaning that one cutting edge is making deeper cut that the other cutting edge. The cutting marks of the non-dominant edge are also visible as small steps on the surface roughness profiles. This effect is most likely due to run out [4]. A small run-out that affects cutting profiles of conventional end milling very little creates drastic force variation in micro-end milling. In micro-end milling, the tool run-out to tool diameter ratio becomes relatively big compared to conventional end milling [5].

Significant difference in the chip loads varies from location to location; the surface generation mechanism and surface roughness are also expected to exhibit significant differences. Periodic variations in the chip load and force, as well as increased machined surface roughness causes premature cutting edge failure. When chip load increases then the total cutting force also increases. The radial force has more effect with change in chip load as compared to the tangential force. The minimum chip thickness and micro-burr formation along with the process parameters and machining conditions have major influence on surface generation. The chip load is one of the important factors which play the role in surface generation [6–8].

Many researchers focused their research on optimization of cutting parameters in machining. Yang and Tarng [9] used three cutting parameters; speed, feed and depth of cut for achieving quality surface finish and improve tool life and using Taguchi technique for optimization of cutting parameters obtained the optimum result. Aslan et al. [10] use the optimization for to getting the minimum tool flank wear using Taguchi technique. K. Vijayumar work to find the optimum cutting parameters for multipass turning to produce component at minimum production cost by using ant colony algorithm (ACO) tool. Researchers compared their result with the result obtained by other technique such as GA, PSO, etc., and found that the result obtained by ACO is good as compared to others. Research has experimentally proved that the setting of optimum parameter during the machining will increases the tool life [11].

Homell Tester made in Germany was used for surface roughness measurement in experimental work at NABL certified Dimensional Metrology Lab of Indo-German Tool Room, Aurangabad. The device has cut-off length 0.8 mm so that the sample length is "$0.8 \times 5 = 4$ mm". Five small regions on the machined surface were determined for measurement and average value of these measurements was recorded as the Ra value [12].

For the optimization the experimental data and the mathematical model given in [12] are used as it is. The obtained mathematical models for all three materials are as below [12]:

for ETP copper:

$$\mathrm{Ra} = 1.0631 + 0.0227 \times \mathrm{Vc} - 0.2458 \times \mathrm{Ft} + 0.4258 \times d \quad (1)$$

for Al V-95:

$$\mathrm{Ra} = 1.5643 + 0.0285 \times \mathrm{Vc} - 1.1887 \times \mathrm{Ft} + 0.22505 \times d \quad (2)$$

for HcHcr steel:

$$\mathrm{Ra} = 0.0359 + 0.0592 \times \mathrm{Vc} - 2.1515 \times \mathrm{Ft} - 0.0025 \times d, \quad (3)$$

where Ra, surface roughness (µm); d, depth of cut (µ); Vc, cutting velocity (m/s); Ft, chip load (µm).

2.1 Validation of empirical mathematical model by optimization using Ant Colony Optimization

Optimal cutting parameters are obtained by application of ACO algorithm for which the above mathematical models are used to determine surface roughness for intermediate values of the cutting parameters. Formulation of problem is as discussed below.

2.2 Objective variable

For this analysis we considered main three machining parameters as objective variables, i.e., cutting speed (V), chip load (f) and depth of cut (d).

2.3 Objective function

The aim is to obtain the cutting parameters for minimum surface roughness value. So, the required objective function is

Min. $\mathrm{Ra} = f(V, f, d)$.

2.4 Constraints

Optimum results are obtained under the constraints of:

$\mathrm{Vmax} > V > \mathrm{Vmin}$

$\mathrm{fmax} > f > \mathrm{fmin}$

$\mathrm{dmax} > d > \mathrm{dmin}$.

2.5 Ant colony optimization methodology

Ant colony optimization is a new approach to solve complex optimization problem. It is a population-based technique. This technique is based on behavior of real ants. Researchers are surprised by seeing that the ability of the almost blind ants in establishing the shortest route from their nest to food source and back. These ants secrete a chemical on their path which is called as 'Pheromone'. This pheromone is a communication media between the ants. Real ants follow the route which has more pheromone deposition [13].

Many researchers tried this algorithm to solve engineering problem. Basically it is suitably used for traveling salesman routine problem. Its use is not limited to that only, but can be used for solving other engineering problem also. ACO was presented as an effective optimization procedure by introducing bi-level search procedure called local and global search.

2.6 Steps followed in ACO

The proposed ACO algorithm for optimization of cutting conditions in micro-milling is shown as scheme in Fig. 2. The distribution of ants is shown in Fig. 1.

The proposed ACO algorithm for optimization of cutting parameters with objective of minimizing surface roughness value will go through the following steps [14].

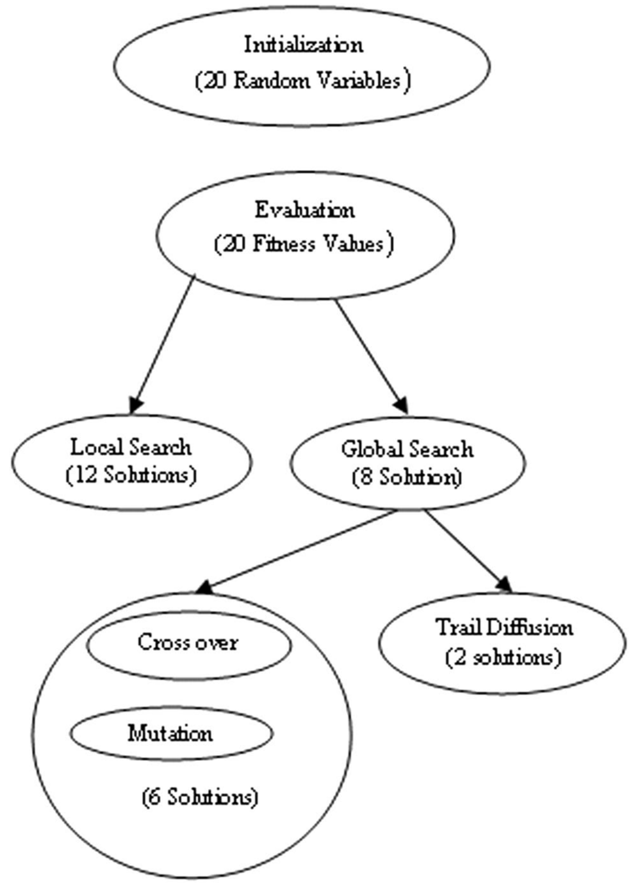

Fig. 1 Artificial ant distribution

2.7 Step 1: initial solution

In first step 20 solutions are generated randomly, with the values that lie within the given constraints. After this these 20 solutions are arranged in ascending order. The region which has lower roughness value is referred as superior solution, while region having larger roughness value is called inferior solution.

2.8 Step 2: global search

Global search is applied on only inferior solutions. Following three operators are to be performed on the randomly generated solutions.

(a) Cross over
(b) Mutation
(c) Trail diffusion

2.9 Cross over

Cross over is divided in three sections. Firstly generate two random numbers and select the initial solution form superior region corresponding to these random numbers. These solutions are noted as parent1 and parent2. Secondly generate another integer random number and according to it the position of digit in solutions of parent1 and parent2 are interchanged to get child1 and child2. In last section of cross over the solution of child1 and child2 are decoded and its fitness value is assessed. The solution which has closer fitness value will replace the inferior solution.

2.10 Mutation

In this step also the inferior solution obtained after cross over is repaired. Randomly adding or subtracting a value to each variable newly creates solution in the inferior region with a suitably defined mutation probability.

2.11 Trail diffusion

It is another element in global search. This is applied on inferior solutions which were yet not considered for cross over or mutation. Here two parents are selected at random from superior solutions obtained child can have either:

Table 1 Optimum cutting parameters and surface roughness value

Material	Optimum parameter				Validation by experimental results
	Spindle speed (rpm)	Depth of cut (μ)	Chip load (μm)	Ra value using ACO (μm)	Average of surface roughness after machining (μm)
Al V-95	8000	1	1.01	0.67	0.728
ETP copper	8000	1	1.5	1.26	1.246
HcHcr	8000	2.74	0.02	0.134	0.13

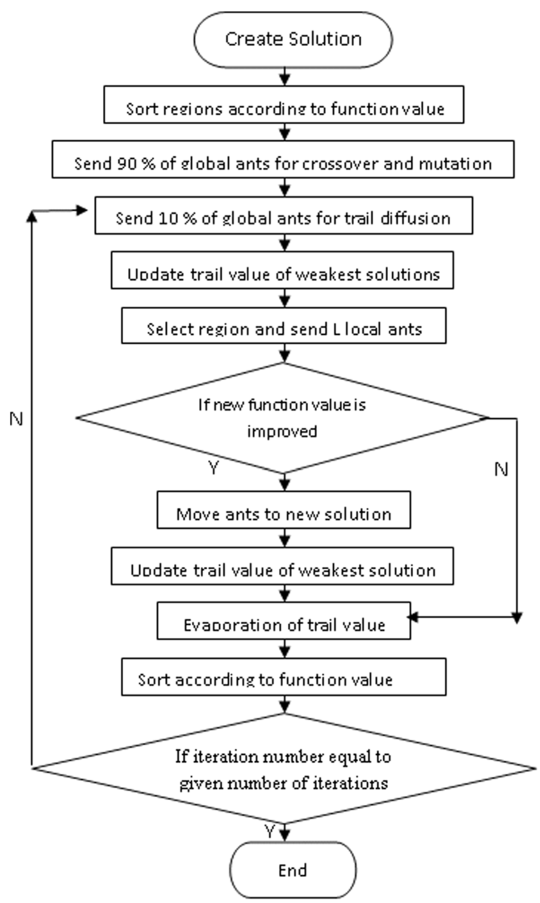

Fig. 2 Flow chart for the ACO algorithm [11]

1. The value of corresponding variable from the first parent
2. The corresponding value of the variable from second parent
3. Or a combination arrived from a weighted average of the above.

$$\text{Xchild} = \alpha \cdot \text{Xi(parent1)} + (1-\alpha) \cdot \text{Xi (parent2)},$$

where α is uniform random number between 0 and -1.

2.12 Step 3: local search

In ACO local ants select a region with a probability:

$$P_i(t) = \frac{\tau_i(t)}{\sum \tau_k(t)},$$

where 'I' is the region index and $\tau_i(k)$ is the pheromone trail on region 'i' at time 't'. After selecting the region ant moves through a short distance (finite random increment). If the fitness is improved, the new solutions are updated to the current region. Correspondingly, the regions position vector is updated.

In continuous algorithm, the pheromone values are decreased after each iteration by:

$$\tau_i(t+1) = \rho\tau_i(t),$$

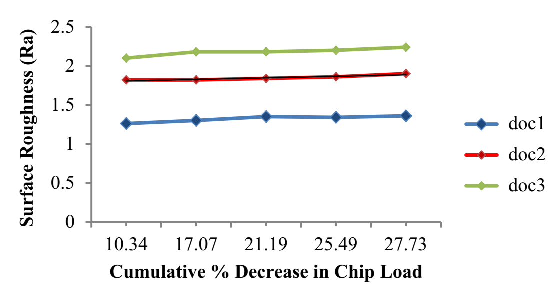

Fig. 3 Cumulative % decrease in chip load vs surface generation for ETP copper

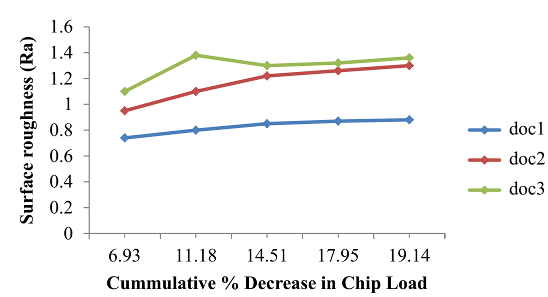

Fig. 4 Cumulative % decrease in chip load vs surface generation for Al V-95

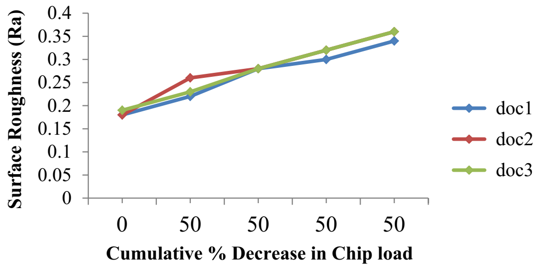

Fig. 5 Cumulative % decrease in chip load vs surface generation for HcHcr

where 'ρ' is the evaporation rate which is assumed to be 0.2 on trial basis and $\tau_i(t)$ is the trail associated with solution at time 't' [11].

The final optimum result is obtained after 500 iterations. The final number of iterations is decided by trial and error method and the program will give constant result for 500 iterations. Confirmation experiment is conducted for validation of optimum surface finish using optimum parameters. The five samples of each studied materials are machined. Surface finish is measured at five regions of machined surface and average of these values recorded as Ra value. The result of optimum parameters and surface finish by ACO and validation result of experimentation are summarized in Table 1.

3 Results and discussion

The F-test results for validation of the models For ETP copper, Al V-95 and HcHcr steel the standard error of the estimate is 0.0014, 0.056 and 0.074 as well as the coefficient of determination, i.e., R^2 values are 0.9808, 0.9018 and 0.9152, respectively. This shows that regression models for these materials as a whole are suitable estimating models which have less standard error of the estimate. At 5 % level of significance the critical value for F distribution is 3.34, as calculated value for the same is significantly greater than critical F value so that regression models for these materials as a whole are significant.

To solve the ACO algorithm a program is prepared in Mat-LAB by attempting the steps in flowchart as shown in Fig. 2.

The final optimum result is obtained after 500 iterations. The final number of iterations is decided by trial and error

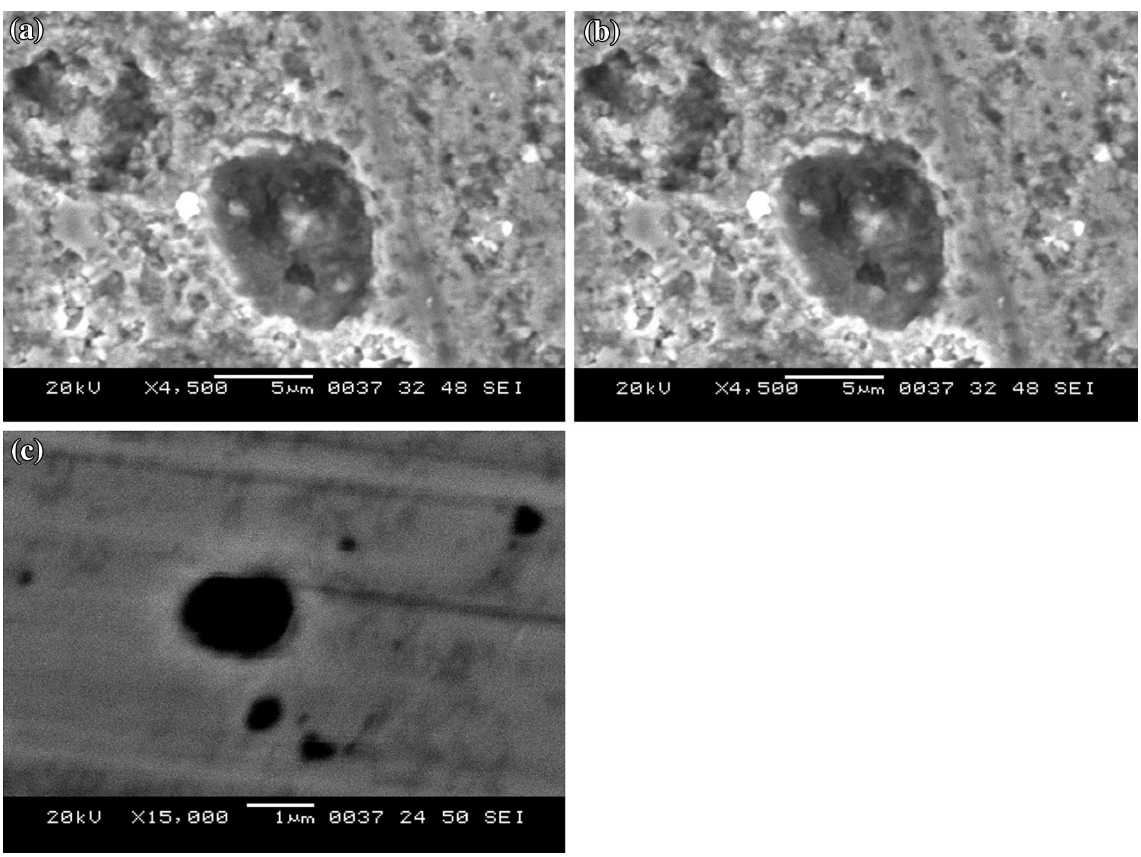

Fig. 6 SEM test results of: **a** ETP copper, **b** Al V-95 and **c** HcHcr

method and the program will give constant result for 500 iterations.

Confirmation experiment is conducted for validation of optimum surface finish using optimum parameters. The five samples of each studied materials are machined. Surface finish is measured at five regions of machined surface and average of these values recorded as Ra value. The result of optimum parameters and surface finish by ACO and validation result of experimentation are summarized in Table 1.

The cumulative % of chip load reduces, the surface finish degraded from the Figs. 3, 4 and 5. To verify the above-mentioned results about degradation of surface finish for the studied material SEM test is carried out for different samples. The result of the same is shown in Fig. 6. The inclusions can be clearly seen in these images varying in different sizes. This test confirms that, for ETP copper the deterioration of surface finish in the rage of 2–3 % is due to the impurities present in the material. Porosity is the major drawback for aluminum alloys so that 4–10 % of surface deterioration is observed. The presence of carbides in HcHcr (D2) which are plugged during machining and hence surface deterioration is in the range of 25–45 %.

4 Conclusion

- The experimental observations shows the interaction between chip load, cutting speed and surface roughness and the chip load (feed/tooth) is dominant factor deciding the surface roughness.
- The chip load value is independent of the depth of cut in high-speed milling. When the spindle speed is increased, the chip load decreases maximally at 25 % for ETP copper and Al V-95 and for HcHcr decrease in chip load is 50 % when spindle speed increases, which is due to high hardness.
- At high chip loads, the contribution of cutting speed was 30–40 % in surface generation which is a considerably more prominent factor.
- ACO algorithm is used to validate the experimental result and the developed mathematical model. Also to determine the exact parameter in the given rate of constraint this gives best surface finish.

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