OPTIMISATION OF MACHINING PARAMETERS IN ALUMINIUM ALLOY COMPOSITE USING GENETIC ALGORITHM

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Abstract

Aluminum alloy composites have emerged as an important class of materials, which are increasingly being utilized in recent years. Application of these materials in certain areas is limited due to difficulties in machining. The principal machining parameters that control machinability characteristics are extrinsic parameters (cutting speed, feed rate, depth of cut, and type of cutting tools) and intrinsic parameters (particulate size, volume fraction, and type of reinforcement).

Using genetic algorithms for the optimal search of cutting conditions, the chromosomes represent cutting conditions defined according to a temporal scale and are composed by random keys. The present review is focused on the influence of cutting parameters of reinforcement on the surface finish. This review will provide an insight into selecting the optimum machining parameters for machining metal matrix composites.

Author Keywords: Machining; Aluminium alloy composites; Optimisation; Genetic algorithm

Introduction

It has long been recognized that conditions during cutting, such as feed rate, cutting speed and diameter of cut, should be selected to optimize the economics of machining operations. Taylor showed that an optimum or economic cutting speed exists which could maximize material removal rate. Considerable efforts are still in progress on the use of hand book based conservative cutting conditions and cutting tool selection at the process planning level. The need for selecting and implementing optimal machining conditions and most suitable
cutting tool has been felt over the last few decades. Despite Taylor’s early work on establishing optimum cutting speeds in machining, progress has been slow since all the process parameter need to be optimized. Furthermore, for realistic solutions, the many constraints met in practice, such as low machine tool power, torque, force limits and component surface roughness must be overcome. Aluminum alloy composites have been increasingly used in industry because of their improved properties over those of non-reinforced alloys. Among the various types of composites, aluminium based composites have found in various engineering applications such as for cylinder block liners, vehicle drive shafts, automotive pistons, bicycle frames, etc. (Rohatgi, 1991; Dinwoodie, 1987; Joshi et al., 1995; Kocazac et al., 1993; Chadwick and Heath, 1990). High hardness aluminium oxide (Al2O3) or silicon carbide (SiC) particles are commonly used to reinforce aluminium alloys, but the full application of such composites is cost sensitive because of their high machining cost (Hung et al., 1995). Machinability of composites has received considerable attention because of the high tool wear associated with machining. Although efforts have been made to produce near-net-shape composites products by casting or hot forging, the need for machining cannot be completely eliminated and the resulting near-net-shape products still have to be machined to the designed shape and dimension. Composites reinforced with Al2O3 particles are extremely difficult to machine (turning, milling, drilling, threading) due to their extreme abrasive properties (Durante et al., 1997; Sahin et al., 2002). Therefore, the available literature has concentrated on the study of wear characteristics of various tool materials during machining aluminium alloy composites (Sahin et al., 2002; Lane, 1990; Monaghan and O’Reilly, 1992; Tomac and Tonnessen, 1992; Finn and Srivastava, 1996; Yanning and Zehna, 2000; Quan et al., 1999; Joshi et al., 1999; El-Gallab and Sklad, 1998; Hung et al., 1994;). Composites cause extremely rapid wear of the cutting tools and consequently high tool cost. The reason for this is the presence of the hard Al2O3 particles in the aluminium matrix. Studies on machinability of light alloy composites reinforced with Al2O3/SiC fibres/particles (Chadwick and Heath, 1990; Lane, 1990; Tomac and Tonnessen, 1992; Cronjager and Meister, 1992; Saga and Ikeda, 1991; Chandrasekaran and Johansson, 1997) indicate poor machinability due to abrasive wear of tools. Moreover, quality of the machined surface also deteriorates with tool wear (Chadwick and Heath, 1990). With existing tools such as cemented carbides coated with titanium nitride (TiN) or titanium carbides (TiC), the wear rate of the tools is so high that machining is extremely expensive.

2. Problem Formulation

In machine tools, the finished component is obtained by a number of rough passes and finish passes. The roughing operation is carried out to machine the part to a size that is slightly larger than the desired size, in preparation for the finishing cut. The finishing cut is called single-pass contour machining, and is machined along the profile contour. In this paper, during the turning operation carried out in lathe how long the tool last under variation of the parameters such as speed, feed, depth of cut in order to achieve maximum tool life.

2.1 Machining Model

The objective of this model is to minimize the surface roughness [4]. The formula [8] for calculating the above surface roughness is as given by,

\[
R_a = -0.309 + 0.675V_c + 0.870f + 0.175d - 0.234V_c f - 0.002f d - 0.143V c d
\]

Finally, by using the above mathematical processes, Surface roughness is obtained.

Where,

\[V = \text{Cutting Speed (m/min)}\]
f = Feed Rate \ (\text{mm/rev})

d = Depth of Cut \ (\text{mm})

3. Genetic Algorithm

Genetic algorithm is an adaptive search and optimization algorithm that mimics the principles of natural genetics. GA’s are very different from traditional search and optimization methods used in engineering design problems. Because of their simplicity, easy of operations minimum requirements and global perspective, GA’s has been successfully used in a wide variety of problem domains. GA work through three operators, namely reproduction, cross over and mutation. In this paper an attempt is made to use of genetic algorithm to maximize the tool life by optimizing the depth of cut, feed rate and cutting speeds.

Steps in the Genetic Algorithm Method

Step 1
(Initialization) Randomly generate an initial population of \( N \) chromosomes and evaluate the fitness function to a function to be maximized for the encoded version) for each of the chromosomes.

Step 2
(Parent Selection) Set if elitism strategy is not used; otherwise. Select with replacement parents from the full population (including the elitist elements). The parents are selected according to their fitness, with those chromosomes having higher fitness value being selected more often.

Step 3
(Crossover) For each pair of parents identified in Step 1, perform crossover on the parents at a randomly (perhaps uniformly) chosen splice point (or points if using multi-point crossover) with probability. If no crossover takes place (probability), then form two offspring that are exact copies (clones) of the two parents.

Step 4
(Replacement and Mutation) While retaining the best chromosomes from the previous generation, replace the remaining chromosomes with the current population of offspring from Step 2. For the bit-based implementations, mutate the individual bits with probability; for real coded implementations, use an alternative form of "small" modification (in either case, one has the option of choosing whether to make the elitist chromosomes candidates for mutation).

Step 5
(Fitness and End Test) Compute the fitness values for the new population of \( N \) chromosomes. Terminate the algorithm if the stopping criterion is met or if the budget of fitness function evaluations is exhausted; else return to Step 1.

3.1 Working Principle

1. The decision variables \( X_i \) are coded in some string structure, binary coded string having zeros and one’s are mostly used.
2. The length of the string is usually determined according to the desired solution accuracy. For example, the strings (0000) and (1111) represent the point \((X_1^{(L)}, X_2^{(L)})\) and \((X_1^{(u)}, X_2^{(u)})\), the sub string has the minimum and maximum decoded values.
3. The parameter values are calculated by using the following formula,
\[ X = X_i^{(l)} + \frac{X_j^{(l)} - X_i^{(l)}}{2^n - 1} \quad (\text{Decoded value}) \]

(Or)

\[ X = \text{Min} \left( \frac{\text{Max} - \text{Min}}{2^n - 1} \right) \times \text{(Decoded value)} \]

### 3.2 Fitness Function [7]

1. Genetic Algorithm mimics the survival of the fittest principle of nature to make search procedure.
2. The fitness function \( F(x) \) is first derived from the objective function and used in successive genetic operation.
3. For minimization problems, the fitness function is an equivalent maximization problem such that the optimum point remains unchanged.

\[ F(x) = \frac{1}{1 + g(x)} \]

### 3.3 Operation of genetic Algorithm

Genetic Algorithm begins with population of random strings representing design and decision variables thereafter each string is evaluated to find the fitness value.

1. The population is operated by three main operators:
   a. Reproduction
   b. Crossover
   c. Mutation
2. The population formed is further evaluated and tested for termination. If the termination criteria is not met, the population is iteratively operated by the above three operators and evaluated.
3. This procedure is continued until the termination criteria are met.

### 3.4 Genetic Algorithm operators

**Reproduction**

Reproduction selects good strings in a population and forms a mating pool. The reproduction operator is also called a selection operator. In this work rank order selection is used. A lower ranked string will have a lower fitness value or a higher objective function and vice versa. The probability of selection for each string which is calculated, based on the following formula:

Expected value of probability,

\[ \text{Expected value of probability,} \]

\[ \text{Min} + \left( \text{Max} - \text{Min} \right) (\text{rank} - 1) \]

\[ \frac{\text{Min} + \left( \text{Max} - \text{Min} \right) (\text{rank} - 1)}{N - 1} \]

Where,

\[ N = 020 \]

\[ \text{Min} = 0.02 \]

\[ \text{Max} = 0.08 \]

**Crossover**

1. In the crossover operator, exchanging information among strings of the mating pool creates new strings.
2. In most crossover operators, two strings picked from the mating pool at random and some portion of the strings are exchanged between the strings.

**Mutation**

After a crossover is performed, mutation takes place. This is to prevent falling all solutions in population into a Local optimum of solved problem. Mutation changes randomly the new offspring. For binary encoding we can Switch a few randomly chosen bits from 1 to 0 or from 0 to 1. Mutation can then be following:

Original offspring 1 110111000011110
Original offspring 2 11011001001010110

### 4. GA PROCEDURE

**Step1:**
Choose a coding to represent problem parameter, a selection operator, a crossover operator and a mutation operator. Choose population size \( N \), crossover probability \( p_c \), and mutation probability \( p_m \). Initialize a random population of strings of size 10. Set iteration \( t=0 \).

**Step 2:**
Evaluate each string in the population.

**Step 3:**
If \( t > t_{\text{max}} \) (or) other termination criteria is satisfied, terminate.

**Step 4:**
Perform reproduction on the population.

**Step 5:**
Perform crossover on the random pairs of strings.

**Step 6:**
Perform bit wise mutation.

**Step 7:**
Evaluate strings in the new population.
Set \( t \) = \( t + 1 \) and go to step 3.

**Objective function**

The objective of this model is to maximize the Surface roughness. The formula for calculating the Surface roughness is as given by,

\[
R_a = -0.309 + 0.675V_c + 0.870f + 0.175d - 0.234V_c f - 0.002f d - 0.143V_c d
\]

Finally, by using the above mathematical processes, the Surface roughness is obtained.

Where,

- \( V \) = Cutting Speed (m/min)
- \( f \) = Feed Rate (mm/rev)
- \( d \) = Depth of Cut (mm)

**Ra = Surface roughness (m)**

5. **RESULT AND DISCUSSION**

The objective function is the minimization of surface roughness by varying feed, speed, depth of cut. In this work, the optimum surface roughness is obtained by using genetic algorithm at the 5th generation. The optimum value of surface roughness is 7.922869 \( \mu \text{m} \). The corresponding speed is 207.52688 m/min, feed is 0.229912 mm/rev and depth of cut is 2.829912 mm.

6. **CONCLUSION**

A genetic algorithm was proposed for predicting tool life for a turning tool. The main advantage of this approach is that it can be used for any objective function, which was most clearly demonstrated in this example, where the Objective function was the maximization of tool life. In this approach three constraints namely feed, speed and depth of cut are considered for maximizing the tool life. There are many other constraints that affect tool life, which can be solved by using multi objective genetic algorithm in the future.

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