An overview of GA technique for Surface Roughness Optimization in Milling Process

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Abstract

Optimization of parameters in machining is a nonlinear model with constraints, so it is difficult to be conducted using conventional approaches. As alternative, non conventional approaches become useful approaches to conduct machining parameter optimization problem. Genetic Algorithm (GA) is one of the well known techniques classified as non conventional approaches with intelligent in human behavior that is mostly applied to ensure efficient and fast selection of the optimum cutting conditions for parameters in machining process. This paper outlines an understanding of how GA system operates in order to optimize the surface roughness performance measure in milling process. Example of works that applied GA technique for machining optimizing problem for surface roughness is also given.

1. Introduction

In many real machining applications, three conflicting objectives are often considered; these are the minimum production rate, minimum operational cost, and quality of machining. In term of quality of machining, the criterion for the assessment is usually referred to the surface quality of the machined part. Improvement of the quality could be indicated by referring to a performance measure known as surface roughness.

Several optimization techniques that can be classified as non conventional techniques include Genetic Algorithm (GA), Simulated Annealing (SA), Tabu Search (TS), Ant Colony Algorithm (ACO), and Particle Swarm Optimization (PSO) [1, 2, 3]. Most of these techniques are suitable and have the potential to be applied for cutting parameters optimization problems during machining. Among these techniques, GA is widely used by most researchers for the optimization objectives which include minimizing production cost and maximizing material removal rate, and improving product quality [4]. With consideration that GA is able to handle machining optimization problem, this paper outlines an understanding of how GA system operates in order to optimize the surface roughness in milling operation. Application example of GA technique for machining optimizing problem for surface roughness is also given with reference to previous works.

2. Optimization of cutting conditions for surface roughness

This section discusses the basis measurement of surface roughness performance with its mathematical model. In machining, the surface roughness is generally specified mathematically in terms of the arithmetic average deviation from the mean line and which is also known as $R_a$ using the following equation:

$$R_a = \frac{1}{L} \int_0^L Y(x) \, dx.$$  (1)

where $L$ is the sampling length, and $Y$ is the ordinate of the profile curve. In other word, $R_a$ is the area between the roughness profile and its mean line in $\mu$m, or the integral of the absolute profile height over
into a set of genetic characteristics (parameters to be optimized) that will survive in the best possible manner in the environment. The parameters of the search identified as $x_1$, $x_2$, $x_3$, $x_4$, and $x_5$ which are called the phenotypes. In GA, the phenotypes (parameters) are usually converted to genotypes (chromosome) by using a coding procedure. Knowing the ranges of $x_1$, $x_2$, $x_3$, $x_4$, and $x_5$ each variable is to be presented using a suitable binary string. The representation using binary coding makes the parametric space independent of the type of variables used.

3. Relationship between modeling and optimizing phase for $R_d$ prediction

Generally, there are two phases needed in optimizing the machining process parameters which are modeling and optimizing [2]. The first phase involves the development of models to predict the values of response or performance measure such as $R_d$ value. It also can be defined as modeling phase of machining processes which is important to provide the basis mathematical model for formulation of the objective function. Second phase is the determination of optimization conditions for the objective function. It is also called optimizing phase which is important to obtain the optimal solution of the predicted value obtained from the modeling phase. Figure 2 illustrates an example of the flow relation between modeling and optimizing phase in machining parameters optimization.

Based on Figure 2, surface roughness, labeled as $R_d$ is one of the important responses or performance measure to be measured in machining to indicates the surface quality of the machined workpiece. Normally, the predicted model of surface roughness value for milling process in relation to the independent variables investigated can be expressed as:

$$R_d = kv^{x_1}f^{x_2}a^{x_3}.$$

From Equation (2), $R_d$ is the predictive surface roughness in µm, $v$ is the cutting speed, $f$ is the feed per tooth, $a$ is the cutting depth and $k$, $x_1$, $x_2$, $x_3$ are the model parameters to be estimated using the experimental data. Then, all the parameters that affect the predicted $R_d$ value obtained from modeling phase must be optimized by using conventional or non conventional approaches. The standard mathematical equation of surface roughness to be optimized in milling is expressed in the Equation (1).

Recently, non conventional approaches are mostly used by researchers to find the optimal value of the predicted model obtained from the modeling phase. In
the next section, the potential of GA technique to be applied for optimizing cutting conditions for surface roughness performance measures is highlighted.

4. GA for Optimization Problem

The machining optimization problem becomes complicated when a large number of constraints are involved. Conventional optimization approaches are useful for specific problems and are inclined to provide local optimal solution [1, 2]. Non conventional approaches consist of a variety of methods including optimization paradigms that are based on evolution mechanisms such as biological genetics and natural selection. These methods use the fitness information instead of the functional derivatives making them more robust and effective. Non conventional approach such as GA is widely used for solving optimization problems.

Generally, some steps are taken in order to apply GA in optimizing problem. The performance measures to be optimized is based on several variables, as given in the following steps [8]:

[i] The variables should be coded. An appropriate coding for the variables should be such that the new variables appear as strings consisted of integers. These strings will be used by the GA to lead the optimization in areas that give a high value to the quantity under optimization. A widely applied coding is the transformation of the variables into binary numbers. These binary numbers may be seen as strings consisted of the integers 0 and 1.

[ii] A set of randomly-selected strings is created. This set of strings is called the initial population 1. The size of the initial population varies from several tens even to several thousands, depending on the application. The size of the population is usually set after testing, since there is not a criterion that gives the best size of the population for a GA. An average size for a population is usually 50 strings.

[iii] For each string of the population, the value of the quantity to be optimized is calculated. Then, based on this value, an objective function value (fitness) is assigned to the string. This objective function value is usually a multiple of the quantity value divided by the average of the quantity values of the strings of the population.

[iv] A set of GA operators is applied to the population. This set of operators, based on the strings of the existing population and their corresponding objective function values, will hopefully provide a new population whose strings will be better. The new population replaces the old one. This procedure, namely the creation of a new population, based on the old one, and the replacement of the old population, is called generation.

[v] A predefined stopping criterion is checked. This criterion is usually a pre-set maximum number of generations that should be performed. If this
criterion is not satisfied, then the GA continues with step 3 (the application of the GA operators on the new population), otherwise it terminates.

An example of pseudo code for the GA algorithm in obtaining a global optimum solution is given as in Figure 3. Based on the pseudo code given, there are five main parameters affecting the performance of GA: population size, number of generations, crossover rate, offspring, and mutation rate. Example of flow for the GA algorithm in obtaining optimal cutting conditions in metal cutting problem is given in Figure 4.

![Figure 3. Pseudo code for the GA algorithm for global optimum solution [9]](image)

![An empirical input-output and in-process parameter relationship(s) model(s) developed and single objective function f(x) formulated.](image)

**Initializing search algorithm:**
1. Choose for feasible operating region of each input decision variable (vector x).
2. Select encoding of process decision variables vector x, population size P, length of the spring, selection criteria, crossover and mutation probability, and number of generation (say Gen\textsuperscript{max}). Set initial number of generation as Gen=0.

**Create as many feasible random encoded decision vector strings (combination level of decision variables, such as speed and feed rate value) as the current population size.**

**Gen= Gen+1**

**Update current population (The best P chromosomes from parent and offspring population)**

**Perform mutation operation offspring based on mutation probability.**

**Perform crossover of random pair of string from mating pool, to form new offspring, based on crossover probability.**

**Select populations by suitable selection method, to form mating pool of same population size.**

**Assign fitness value of each string in current population based on single objective function f(x).**

**Is Gen > \text{Gen}_{\text{max}}**

**No**

**Yes**

**Decode current population of strings, which are the near optimal cutting conditions.**

![Figure 4. GA-based optimization technique for metal cutting process problems [2]](image)
Table 1. Application of GA for $R_a$ values optimization in milling process

<table>
<thead>
<tr>
<th>No</th>
<th>Author, Year</th>
<th>Modeling technique</th>
<th>Remark</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>H. Oktem et al, 2006 [6]</td>
<td>ANN</td>
<td>Feed, cutting speed, axial depth of cut, radial depth of cut, machining tolerance. GA produces the $R_a$ value that is lower than the values of experimental results.</td>
</tr>
<tr>
<td>2.</td>
<td>P.V.S. Suresh et al, 2002 [10].</td>
<td>RSM</td>
<td>Speed, feed, depth of cut, nose radius. $R_a$ decreases with an increase in cutting speed, and increases as feed increases. $R_a$ increases with an increase in depth of cut, and nose radius.</td>
</tr>
<tr>
<td>4.</td>
<td>H. Oktem et al, 2005 [12]</td>
<td>RSM</td>
<td>Feed, cutting speed, axial depth of cut, radial depth of cut, machining tolerance. GA reduces the $R_a$ value in the mold cavity from 0.412(\mu m) to 0.375(\mu m) corresponding about 10 percents (%) improvement.</td>
</tr>
<tr>
<td>7.</td>
<td>P. Palanisamy et al, 2007 [15]</td>
<td>DP</td>
<td>Cutting speed, feed rate, depth of cut. GA reduces the $R_a$ value on the mild steel from 2.60(\mu m) to 0.71(\mu m).</td>
</tr>
</tbody>
</table>

5. Example works of Application of GA for $R_a$ optimization

GA technique could be effectively applied for different types of milling operations such as single-pass, two-pass, three-pass and multiple-pass [4]. For surface roughness optimization in milling process, it was found that usage of non conventional approaches to model and optimize surface roughness was very limited [10]. Examples of applications of GA-based technique conducted by several researchers for $R_a$ values optimization problem in milling operation given in Table 1.

There are various parameters that influence $R_a$ value such as cutting speed, feed rate, axial depth of cut, radial depth of cut, machining tolerance, nose radius, and vibrations. The table also shows the various techniques such as Respond Surface Methodology (RSM), ANN (Artificial Neural Network), DP (Dynamic Programming) and GA could be used as the effective approaches to model the predicted $R_a$ value that to be optimized by GA techniques in milling.

6. Conclusion

This paper discussed on how GA system operates in order to optimize the surface roughness performance measure in milling process. The application of GA technique for machining optimizing problem specifically to optimize the $R_a$ value is also given by referring to the example of works. Based on the discussion made in this paper, GA could be used to obtain the optimal $R_a$ values based on various cutting conditions (parameters) in milling operation mainly cutting speed, feed rate, tool geometry and depth of cut.

The study shows that GA technique can be applied for different predicted $R_a$ values that are modeled by using different conventional approaches (such as DP, and RSM) and non conventional approaches (such as ANN, and GA itself). In other word, GA technique does not strictly state particular modeling approaches in order to be coupled with it in finding the optimal $R_a$ value. It is important for researchers to provide many alternatives by using various matching approaches between modeling and optimizing approaches to give the best result of $R_a$ value in optimization problem.

GA also has its own genetic expression programming which makes a global function search for problem, developed as a resultant of GA and Genetic Programming (GP). GP algorithms try to find a suitable solution using parse tree which they created to define relations between different non-linear models.
Advantages of GA and GP algorithms are combined in the GEP (Genetic Expression Programming). The effectiveness of the GEP for optimization problem of $R_a$ value in milling process has been proven by the works conducted by O. Colak et al. [11] and M. Brezocnick et al. [13].

To conclude, the study has shown and has proven the capability of GA in solving surface roughness performance measure by providing the optimal combination of cutting condition value compared to the result estimated by intuitive method obtained in the actual experiment. An issue also could be highlighted from this study relates to the capability of one the established non conventional techniques, ANN, as modeling technique to be coupled with GA optimizing technique. It is unexpected to find that there is little published work relates on this issue yet. In future, consideration should be taken to study the feasibility of coupling the ANN and GA.

7. References


