

Surface Roughness Optimisation by ALO in CNC

Vinay Singh¹, Mr. Sanjeev²

¹M.Tech. Scholar, CBS College, Jhajjar, Haryana, India

²Assistant Professor, CBS College, Jhajjar, Haryana, India

ABSTRACT

This work discusses the reducing the surface roughness of jobs used on CNC milling machine. For this purpose optimisation algorithms are a choice which gives optimal set of values of CNC machine parameters which affect the surface roughness during milling operation. In this work, we have proposed a algorithm name Ant Lion Optimisation (ALO). As per previous work, GSA gives better results than TLBO but the convergence speed is lesser, so our suggested ALO will improves the result and speed to. For this we have developed the MATLAB script and compared the results with the paper.

I. INTRODUCTION

People engaged in manufacturing research and industries are continuously improving the manufacturing systems to produce parts or products that are good in quality, delivered on time and lower in cost. This will not only make the company to survive in the today's competitive world but it will also delight the customer. A manufacturing system is defined as, a complex arrangement of the following four physical elements;

- Machine tool
- Tools and tooling
- People
- Material handling equipments

The measureable output of a manufacturing system can be characterized by the following measurable parameters;

- Productivity
- Defects rate
- Unit cost, etc

The manufacturing system will be highly effective and cost efficient if integration of the above four physical elements is good. Machine tool, among above four physical elements, in particular plays a very important role because its function is to add value in term of quality, cost and time in manufacturing. There are improvements going on in technologies in manufacturing to make a machine tool more precise and efficient. Numerical control, NC, refers to the automated machine tool that is operated by coded programmed commands. With the development of technologies in computer, the NC machine was further developed to computer numerical control, CNC, machine in the 1970s. The CNC machine is not intelligent enough to act and achieve the required surface roughness. For example, if the feed rate is too low to have a surface roughness value that was achievable at some higher feed rate, may result in lost productivity, cost, and time. In dealing with the accuracy of a machine, for example, an important discovery from experience is that a machine tool is deterministic in nature. By deterministic in nature, it is meant that accuracy of a machine tool follows cause effect relationship. Therefore, accuracy of a machine tool will be disturbed only if it has some problems. Surface roughness is one of the most important parameters to determine the quality of a product. Surface roughness consists of the fine irregularities of the surface texture, including feed marks generated by the machining process. The quality of a surface is significantly important factor in evaluating the productivity of machine tool and machined parts. The mechanism behind the formation of surface roughness is very dynamic, complicated, and process dependent. Several factors will influence the final surface roughness in a CNC end milling operation such as controllable factors like CNC cutting speed, feed, depth of cut and step over ratio. Because of these dependencies researchers used several optimisation algorithms and latest gravitational search algorithm (GSA) was used to tune these parameters for optimum surface roughness of material. It has been seen that although GSA gave better results than rest four but number of iterations required in GSA was very high so the convergence time. Whereas TLBO (teacher learner

based algorithm) algorithm gives almost equal result (though less than GSA) but convergence time is very less [10]. So in our work we will try to remove this issue with less convergence time and better surface roughness by using a more efficient optimisation algorithm Ant Lion optimisation (ALO) algorithm.

II. ANT LION OPTIMISATION ALGORITHM

Ant lion optimizer(ALO) is new meta heuristic algorithm. This is motivated from the hunting mechanism of ant lions .Inherit steps of hunting prey such as the random walk of ants, building traps, entrapment of ants in traps, catching preys, and re-building are simulated to find the optimal solution of real life problems.

A. Operators of the ALO algorithm

The ALO algorithm mimics interaction between antlions and ants in the trap. To model such interactions, ants are required to move over the search space, and antlions are allowed to hunt them and become fitter using traps. Since ants move stochastically in nature when searching for food, a random walk is chosen for modeling ants' movement as follows:

$$x(t) = |0; \text{cumsum}(2r(t1) - 1); \text{cumsum}(2r(t2) - 1); \dots; \text{cumsum}(2r(tn) - 1)| \quad (1.1)$$

wheremcumsum calculates the cumulative sum, n is the maximum number of iteration, t shows the step of random walk (iteration in this study), and r(t) is a stochastic function defined as follows:

$$r(t)=\begin{cases} 1 & \text{if rand} > 0.5 \\ 0 & \text{if rand} \leq 0.5 \end{cases} \quad (1.2)$$

$$M_{\text{ant}} = \begin{bmatrix} A_{1,1} & \dots & A_{1,d} \\ \vdots & \ddots & \vdots \\ A_{n,1} & \dots & A_{n,d} \end{bmatrix} \quad (1.3)$$

where M_{ant} is the matrix for saving the position of each ant, $A_{i,j}$ shows the value of the j-th variable (dimension) of ith ant, n is the number of ants, and d is the number of variables. The position of an ant refers the parameters for a particular solution. Matrix M_{ant} has been considered to save the position of all ants (variables of all solutions) during optimization.

For evaluating each ant, a fitness function is used during optimization and following matrix stores the fitness value of all ants:

$$M_{\text{OA}} = \begin{bmatrix} f(A_{1,1}, \dots, A_{1,d}) \\ \vdots \\ f(A_{n,1}, \dots, A_{n,d}) \end{bmatrix} \quad (1.4)$$

where M_{OA} is the matrix for saving the fitness of each ant, $A_{i,j}$ shows the value of jth dimension of ith ant, n is the number of ants, and f is the objective function. In addition to ants, we assume the antlions are also hiding somewhere in the search space. In order save their positions and fitness values, the following matrices are utilized:

$$M_{\text{antlion}} = \begin{bmatrix} (A_{L1,1}, \dots, A_{L1,d}) \\ \vdots \\ (A_{Ln,1}, \dots, A_{Ln,d}) \end{bmatrix} \quad (1.5)$$

where M_{antlion} is the matrix for saving the position of each antlion, $AL_{i,j}$ shows the jth dimension's value of ith antlion, n is the number of antlions, and d is the number of variables.

$$M_{\text{OAL}} = \begin{bmatrix} f(A_{L1,1}, \dots, A_{L1,d}) \\ \vdots \\ f(A_{Ln,1}, \dots, A_{Ln,d}) \end{bmatrix} \quad (1.6)$$

where M_{OAL} is the matrix for saving the fitness of each antlion, $AL_{i,j}$ shows the jth dimension's value of ith antlion, n is the number of antlions, and f is the objective function. During optimization, the following conditions are applied:

- Ants move around the search space using different random walks.
- Random walks are applied to all the dimension of ants.

- Random walks are affected by the traps of antlions.
- Antlions can build pits proportional to their fitness (the higher fitness, the larger pit).
- Antlions with larger pits have the higher probability to catch ants.
- Each ant can be caught by an antlion in each iteration and the elite (fittest antlion).
- The range of random walk is decreased adaptively to simulate sliding ants towards antlions.
- If an ant becomes fitter than an antlion, this means that it is caught and pulled under the sand by the antlion.
- An antlion repositions itself to the latest caught prey and builds a pit to improve its chance of catching another prey after each hunt.

B. Random walks of ants

Ants update their positions with random walk at every step of optimization. Since every search space has a boundary (range of variable). In order to keep the random walks inside the search space, they are normalized using the following equation (min–max normalization):

$$x_i^t = (x_i^t - a_i) \times \frac{d_i - c_i^t}{d_i^t - a_i} + c_i \quad (1.7)$$

where a_i is the minimum of random walk of i th variable, b_i is the maximum of random walk in i th variable, c_i^t is the minimum of i th variable at t th iteration, and d_i^t indicates the maximum of i th variable at t th iteration. Eq. (3.7) should be applied in each iteration to guarantee the occurrence of random walks inside the search space.

C. Trapping in antlion's pits

As discussed above, random walks of ants are affected by antlions' traps. In order to mathematically model this assumption, the following equations are proposed:

$$c_i^t = \text{antlion}_j^t + c^t \quad (1.8)$$

$$d_i^t = \text{antlion}_j^t + d^t \quad (1.9)$$

where c^t is the minimum of all variables at t th iteration, d^t indicates the vector incorporating the maximum of all variables at t th iteration, c_j^t is the minimum of all variables for i th ant, d_j^t is the maximum of all variables for i th ant, and Antlion_j^t shows the position of the selected j th antlion at t th iteration. Eqs. (3.8) and (3.9) show that ants randomly walk in a hyper sphere defined by the vectors c and d around a selected antlion.

D. Building trap

In order to model the antlions' hunting capability, a roulette wheel is employed. Ants are assumed to be trapped in only one selected antlion. The ALO algorithm is required to utilize a roulette wheel operator for selecting antlions based on their fitness during optimization. This mechanism gives high chances to the fitter antlions for catching ants.

E. Sliding ants towards antlion

With the mechanisms proposed so far, antlions are able to build traps proportional to their fitness and ants are required to move randomly. However, antlions shoot sands outwards the center of the pit once they realize that an ant is in the trap. This behaviour slides down the trapped ant that is trying to escape. For mathematically modelling this behaviour, the radius of ants' random walks hyper-sphere is decreased adaptively. The following equations are proposed in this regard:

$$\begin{aligned} c^t &= c^t / I \\ d^t &= d^t / I \end{aligned}$$

where I is a ratio, c^t is the minimum of all variables at t th iteration, and d^t indicates the vector including the maximum of all variables at t th iteration. T is the maximum number of iterations, and w is a constant defined based on the current iteration ($w = 2$ when $t > 0.1T$, $w = 3$ when $t > 0.5T$, $w = 4$ when $t > 0.75T$, $w = 5$ when $t > 0.9T$, and $w = 6$ when $t > 0.95T$). Basically, the constant w can adjust the accuracy level of exploitation.

F. Catching prey and re-building the pit

The final stage of hunt is when an ant reaches the bottom of the pit and is caught in the antlion's jaw. After this stage, the antlion pulls the ant inside the sand and consumes its body. For mimicking this process, it is assumed that catching prey occur when ants becomes fitter (goes inside sand) than its corresponding antlion. An antlion is then required to update its position to the latest position of the hunted ant to enhance its chance of catching new prey. The following equation is proposed in this regard:

$$\text{Antlion}_j^t = \text{Ant}_i^t \text{ if } \text{Ant}_i^t > f(\text{Antlion}_j^t)$$

where t shows the current iteration, Antlion_j^t shows the position of selected jth antlion at tth iteration, and Ant_i^t indicates the position of ith ant at tth iteration.

III. PROPOSED STEPS

In this work we worked towards improving the surface roughness of aluminium silicon carbide (Al-SiC) composite using CNC milling machine. Our work is mainly focused on the optimising the machine parameters to get the maximum surface smoothness of job. For this purpose we have picked the necessary values for our experiment from [10]. In the paper they have done experiment on Al-SiC composite and recorded four readings of surface roughness depending upon the different sets of machine parameters which affects the surface roughness. This experiment is the base of our research as it gives an allowable range, within which our optimisation gives the tuning parameters' optimal value. A mathematical relationship is developed in [10] based on their experiment between surface roughness and optimising parameters if CNC machine. The linear equation which relates the surface roughness with four optimising parameters is given in equation 1.10.

$$R_a = 0.893 - 0.0028x_1 + 0.00186x_2 + 1.19x_3 + 3.39x_4 \quad \dots\dots 1.10$$

Where R_a is surface roughness in μm

x₁ is speed in m/min

x₂ is the feed in μm /rev

x₃ is the depth of cut mm

x₄ is the step over ratio

Here these four variant of 'x' are input parameters if CNC machine whereas surface roughness is the output parameter observed over processed job on CNC. Similarly non linear relation between them is also established which is represented in equation 1.11.

$$R_a = 1.99 - 0.454\log_{10}x_1 + 0.124\log_{10}x_2 + 0.157\log_{10}x_3 + 0.794\log_{10}x_4 \quad \dots\dots 1.11$$

All notations have same significance as in equation 1.10.

We selected lion ant optimisation (LOA) algorithm which fulfils our both requirements of least surface roughness and convergence time. Since these algorithms are optimisation algorithms and can be used in various research fields where providing the solution to any mathematical problem is not easy and problem is NP hard problem, so the significance of terms of used in these changes with every application area. In our case their significance in terms of our CNC machine is tabulated in 1.

Table 1: Technical counterpart of optimisation variables

Variable in ALO	Terms in our technical concept
1 Position of lion ants	Values of four tuning variables: speed, feed, depth of cut and step over ratio
2 Number of dimension of searching space	Total number of tuning variables. In our case it is 4
3 Update in positions	Change in the values of above four parameters

In each iteration an objective function is evaluated which is based upon equation 4.1 and 4.2 and this objective function is called every time in each iteration and for every lion ant. The minimum of all objective function values calculated for all ants in each iterations is saved and updated by process defined in the algorithm. In next iteration this updated value will be the current values of four tuning parameters and again objective function is called for every lion ant and minimum value amongst all is saved again. This process keeps on repeating till last iteration. At the end, tuning variables' values for which surface roughness settles to a minimum value in all iterations is considered as the final set of variables.

IV. RESULTS

In our work we have developed the MATLAB script to tune the tuning variables of CNC machine whose description is provided in previous chapters. MATLAB R2013a is used in our implementation and testing work. During the ALO implementations we have to provide the input of number of agents, total number of iterations and range to the ALO. m script. The values of these inputs are tabulated in table 2.

Table 2: input variables set in ALO optimization

Input	Value
Total number of ants	10
Total iterations	100
Upper Range	[6000,200,0.4,0.6] for speed of m/c, feed rate, depth of cut and step in ratio
Lower Range	[2000,100,0.2,0.5] for speed of m/c, feed rate, depth of cut and step in ratio
Dimension of searching space	4

The optimisation algorithms compared in our work are ALO, and GSA. An optimisation algorithm will be said good if quickly settles to an optimum value. For example the figure 1 shows the objective function curve for same CNC machine parameters with number of iterations.

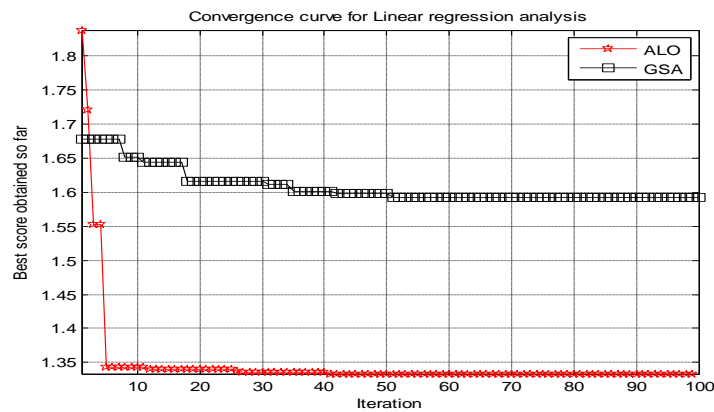


Figure 1: optimisation curve for linear analysis for ALO,GSA

The curve in above figure is for linear equation 1.10, tuned by three different algorithms. It can be analysed that for each algorithm, the fitness function value is decreasing and after some iterations it is settled to a minimum value. The lowest fitness value algorithm is the best algorithm for our test case and that is the ALO. The surface roughness value comparison for all the algorithms (as in reference paper) is shown in bar graph 2. it clearly shows that ALO gives the minimum value and which is 1.332 μm . Table 3 lists all final tuned values for these three algorithms.

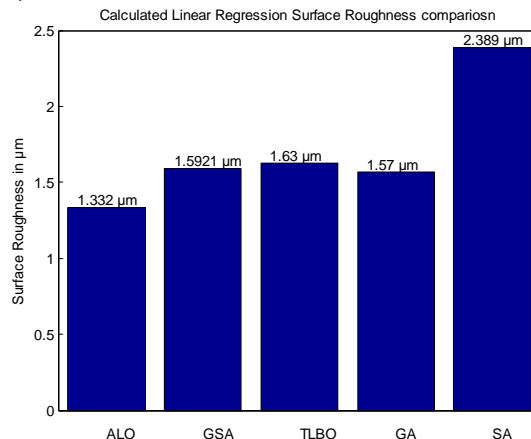


Figure 2: bar graph comparison of surface roughness for linear mathematical formulation

Table 3: Output tuned parameters for two optimisation algorithms by linear analysis

	Speed of m/c in m/min	Feed in $\mu\text{m}/\text{rev}$	depth of cut in mm	step over ratio	Surface Roughness in μm
ALO	6000.000000	100.00000	0.20000	0.50000	1.33200
GSA	5167.776090	113.86687	0.20040	0.50023	1.59207

By above table it can be concluded that we have achieved the improvement of 13.07% from the minimum value (GSA) of paper by ALO algorithm. Similarly for non linear analysis using equation 1.11, the optimisation curve is plotted and shown in figure 3. Again in this curve too, the fitness function value curve which is surface roughness is ALO case and settled to a minimum value earlier than others.

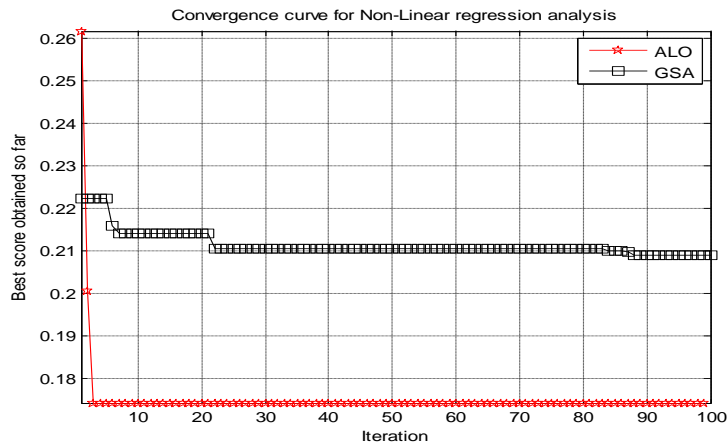


Figure 3: non linear analysis optimisation curve for two algorithms

A bar graph is shown in figure 4 which clearly shows that even in case of non linear analysis, our algorithm is the winner, followed by GSA and TLBO.

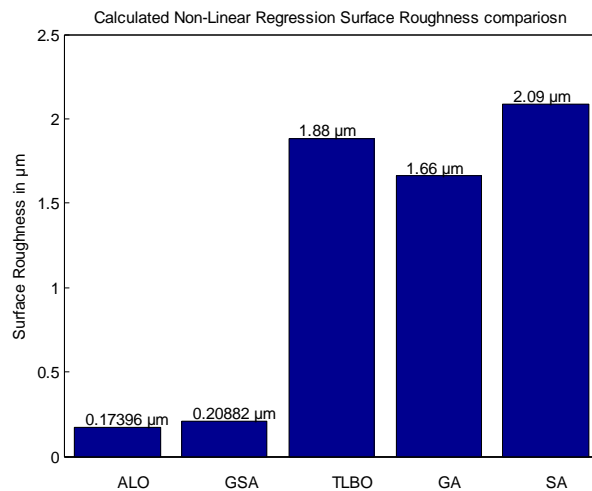


Figure 4: bar graph comparison for non linear analysis of surface roughness

CONCLUSION

This work is targeting the optimisation of milling machine parameters to get minimum surface roughness. To achieve this ALO (ant lion) optimisation algorithm is used in which we behaviour of lion ant and simple ant is used. Four parameters speed of cut, depth of cut, feed rate and step over ratio are the independent variables which affects the dependent surface roughness. So a linear and non linear relationship in between these independent and dependent variables is set and optimised to have minimum surface roughness. In this work we compared both linear and non linear analysis by our proposed optimisation and individual GSA and TLBO. Non linear relation between variables is giving very less surface roughness. An improvement of 88% over single GSA result in paper, by our method is achieved for non linear relation whereas in case of linear this improvement is 13%. But ALO is performing well than single GSA and TLBO in both cases.

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