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A Comparative Study Of Firefly Algorithm And Cuckoo Search Algorithm In Optimizing Turning Operation With Constrained Parameters

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Abstract

Turning is one of the most widely used machining operations. It is the process of removing sections of unwanted material from the raw work piece to a finished product. Optimum quality and production time at reliable production cost must be achieved in any machining operation. This is achieved by proper selection of tool, cutting fluid and machining parameters like cutting speed, feed and depth of cut. Non-traditional algorithms like genetic algorithm (GA), simulated annealing (SA), ant colony optimization (ACO) and particle swarm optimization (PSO) are now widely used in predicting the best combination of machining parameters for achieving near expected quality and production cost. In this work, recently developed Nature-Inspired Metaheuristic Algorithms namely firefly algorithm and cuckoo search algorithm which are less implemented in optimization of machining parameters is implemented in selecting optimal machining parameters for turning operation. The results are compared and discussed.

Keywords:*Turning, production cost, Non-traditional algorithm, Firefly algorithm, Cuckoo search algorithm.*

1. Introduction

Selection of machining parameters for a machining process is an important criterion in achieving optimum production time and production cost. Of all machining parameters, cutting speed, feed and depth of cut are the most influential factors. Selection of these parameters for a machining process is usually done either by trial experiments or from the experience of related machining process.

Manufacturing industries thrive for minimum production cost, minimum production time and less wastage due to high capital and high prices of fuel and raw materials. For the recent years, non-traditional optimization techniques like Genetic algorithm (GA), simulated annealing (SA), particle swarm optimization (PSO), ant colony optimization (ACO) are effectively used in proper selection of machining parameters. The results have proved that they can be effectively used in selecting optimal machining parameters to achieve minimum production cost and minimum production time. Many hybrid and memetic algorithms were also developed which showed good improvements than normal algorithms.

Many research works related to implementation of algorithms in selection of optimal parameters in different engineering problems have been done and the results were compared with various algorithms. In this work, firefly algorithm and cuckoo search algorithm were taken for comparison. Three mathematical model of single pass turning operation is taken from literature. It was implemented to both the algorithms and the results were compared between them and from the literature review.

2. Literature review

Ermer DS [2] and Petropoulos [6] have discussed about the optimal selection of machining parameters using geometric programming. Ermer et al. [3] made a detailed study of multi-pass turning optimization with different aspects in modeling of multi-pass operations. A combination of linear and geometric programming to optimize machining conditions was proposed by them in their work. Z. Khan et al. [5] made a detailed study of implementing Genetic algorithm and simulated annealing in machining parameters optimization. An improved continuous simulated annealing was also used and the results were compared with the results from literature. K. Deep et al. [4] developed a Real Coded Genetic Algorithm (RCGA) named Laplace Crossover Power Mutation (LXPM). Five models of minimization of objective function were taken from literature and optimization was done. Results were compared with literature and it proved to be a success in terms of better optimized results and minimum number of function evaluation. Xin-She Yang [10] developed and explained firefly algorithm and Xin-she Yang and Deb [8], [9] developed the cuckoo search algorithm and provided an insight for solving minimization objective function with constrained parameters using these algorithms. S. Bharathi Raja et al. [7] have discussed about the implementation of firefly algorithm in optimization of constrained machining parameters for turning operation. Ali R. Yildiz [1] is the first of its kind in implementing cuckoo search algorithm in machining parameters optimization problem. The effective way of implementing cuckoo search algorithm in milling operation was discussed and compared with other optimization technique.

3. Single pass turning optimization models

3.1 Model 1:

The model taken first was developed by Ermer [2] for single pass turning machine operation. Minimization of production cost in dollars/piece is taken as the objective function subject to surface finish and horse power as constraints. Objective function is defined as:

$$Min.Cost = 1.25\, V^{-1} f^{-1} + 1.8\times10^{-8} V^{3} f^{0.16} + 0.2 \quad (1)$$

The constraints are:

(i) Surface Finish (R_a)

$$SF \leq 100\ \mu in$$

$$Where\ SF = 1.36 \times 10^{8}\, V^{-1.52} f^{1.004} \quad (1a)$$

(ii) Horse Power (HP)

$$HP \leq 2\ hp$$

$$Where HP = 3.58 \times V^{0.91} f^{0.78} \quad (1b)$$

The range of cutting speed and feed rate are taken as

$$0 \leq V \leq 400 \text{ and } 0.0 \leq f \leq 0.01$$

3.2 Model 2:

The second model taken for consideration is a single pass turning of a medium carbon steel work piece using a carbide tool developed by Petropoulos [6]. Similar to the previous model this also minimizes the production cost in dollars/piece. The constraints are cutting power and surface finish. The objective function is defined as:

$$Min.\ Cost = 452\, V^{-1} f^{-1} + 10^{-5} V^{2.33} f^{0.4} \quad (2)$$

The constraints are:

(i) Surface Finish (R_a)

$$SF \leq 2\ \mu in$$

$$Where\ SF = 2.2 \times 10^{4}\, V^{-1.52} f \quad (2a)$$

(ii) Cutting Power (P_c)

$$P_c \leq 5.5$$

$$Where P_c = 10.6 \times 10^{-2}\, V f^{0.83} \quad (2b)$$

The range of cutting speed and feed rate are taken as

$$0 \leq V \leq 500 \text{ and } 0.0 \leq f \leq 0.5$$

3.3 Model 3:

The third model considered is a single pass turning developed by Ermer and Kromodihardjo [3]. Similar to the previous models this also minimizes the production cost in dollars/piece. The constraints are Horse power and surface finish. The objective function is defined as:

$$Min.Cost = 1.2566 V^{-1} f^{-1} + 1.77\times10^{-8} V^{3} f^{0.16} + 0.2 \quad (3)$$

The constraints are:

(i) Surface Finish (R_a)

$$SF \leq 50\ \mu in$$

$$Where\ SF = 204.62\times10^{6}\, V^{-1.52} f^{1.004} d^{0.25} \quad (3a)$$

(ii) Horse Power (HP)

$HP \leq 4\ hp$

$$\text{Where}\ HP = 2.39 \times V^{0.91} f^{0.78} d^{0.75} \quad (3b)$$

The value of depth cut (d) is taken as 0.2 as given in (Khan et al. [5], K.Deep et al. [4]) for simplification.

The range of cutting speed and feed rate are taken as

$0 \leq V \leq 500$ and $0.0 \leq f \leq 0.1$

4. Firefly algorithm

Firefly Algorithm (FA) is a nature inspired algorithms based on the bioluminescence process of fireflies to produce rhythmic flashes. The most important reason for this natural effect by fireflies is to attract the opposite sex and potential prey. Xin-She Yang [10] formulated firefly algorithm by idealizing three rules:

1. All fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex;
2. Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the lesser bright one will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If there is no brighter one than a particular firefly, it will move randomly;
3. The brightness of a firefly is affected or determined by the landscape of the objective function.

4.1 Steps involved in Firefly algorithm

(i) Population initiation

$$X = X_{min} + (X_{max} - X_{min}) * rand\,(\,) \quad (4)$$

(ii) Distance

The distance between any two fireflies i and j at x_i and x_j, respectively, is the Cartesian distance and is given by,

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2} \quad (5)$$

Where $x_{i,k}$ is the k^{th} component of the spatial coordinate x_i of i^{th} firefly and d is the number of dimensions.

(iii) Attractiveness

The attractiveness function of a firefly is calculated using equation (6),

$$\beta = \beta_0 e^{-\gamma r^m} \quad (6)$$

Where r is the distance between any two fireflies, $\beta 0$ is the initial attractiveness at $r = 0$ and γ is an absorption coefficient which controls the decrease of the light intensity and $m \geq 1$.

(iv) Movement

A firefly i moves towards a brighter or more attractive firefly j. The firefly adjusts itself from its current position to a better position. It is given by,

$$x_{i\,(new\ point)} = x_{i\,(current\ point)} + \beta\,(x_j - x_{i\,(current\ point)}) + [\alpha\,(rand\,(\,) - 0.5)] \quad (7)$$

The pseudo code of firefly algorithm is as follows:

Start
Objective function f(x), $x = (x_1, x_2, ..., x_d)^T$
Generate initial population of fireflies x_i
$(i = 1, 2, ..., n)$
Light intensity I_i *at* x_i *is determined by* $f(x_i)$
Define light absorption coefficient
While *(t <MaxGeneration)*
For *i = 1: n all n fireflies*
For *j = 1: n all n fireflies (inner loop)*
If $(I_i < I_j)$*, Move firefly i towards j;* ***end if***
Vary attractiveness with distance r via exp[−r]
Evaluate new solutions and update light intensity
End *for j*
End *for i*
Rank the fireflies and find the current best
End while
Postprocess results and visualization

5. Cuckoo search algorithm

Cuckoo search algorithm (CS) is a nature inspired algorithm based on the brood parasitism behaviour of cuckoo birds. Female cuckoo birds (brood parasite) lays and abandons its eggs in the nest of another species (host species). They do not rear their off springs but spend their energy in choosing host nests and laying eggs. Some species even have the ability to mimic the colour and shape of some species of host birds so that their eggs are least likely to be identified as alien eggs by the host birds. Cuckoo birds sometimes throw away host bird's eggs so that the probability of hatching of their eggs is increased. Cuckoo chicks also have the ability to mimic the call of host bird's chick so that they get the most of the feeding from the host bird. Some host birds counter attack when they discover alien eggs in their nest. They either throw away the alien eggs or simply abandon the nest. Xin-She Yang et al. [8] formulated cuckoo search algorithm by idealizing three rules:

1. Each cuckoo lays only one egg at a time and dumps it in a randomly chosen nest.

2. Nest with high quality eggs are the best nest and they are carried over to the next generation.

3. The number of host nests available is fixed. The probability of the discovery of an alien egg in its nest by a host bird is taken as p_a ϵ [0, 1]. The host birdeither gets rid of the egg or abandons the nest and builds a new nest.

The last assumption can be approximated by the fraction of $p_a$of n nests that are replaced by new nests with new random solutions.The pseudo code for cuckoo search algorithm is as follows:

Start
Objective function f(x), $x= (x_1, x_2 \ldots x_d)^T$
Generate initial population of n host nests x_i
(i=1,2,…n)
While *(t<MaxGenerations) or (stop criterion)*
Move a cuckoo randomly via Lévy flights
Evaluate its quality/fitness Fi
Choose nest randomly among n available nests
(for example j)
If*(Fi >Fj) Replace j by the new solution;*
Fraction p_a *of worse nests are abandoned and*
new nests are being built;
Keep the best solutions or nests with quality
solutions;
Rank the solutions and find the current best
End while
Post process and visualization of results
End

A new solution $x^{(t+1)}$for cuckoo $i$is generated using a Lévy flight according to the following equation:

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \wedge Lévy\ (\lambda) \qquad (8)$$

Where α (α>0) represents a step scaling size. The parameterαshould be chosen to the scales of problem which is to be solved. The random walk described in Eq. (8) is a *Markov chain.* The first term in Eq. (8) is the current location and second term is the transition probability. The Markov chain's next location is dependent on these two elements. For the levy flight random step length is drawn from a Lévydistribution. It has an infinite variance with an infinite mean:

$$Lévy \sim u = t^{-\lambda} (9)$$

In the actual scenario, if the egg of a cuckoo in the host bird's nest is very similar to the eggs of the host bird, then this cuckoo's egg is less likely to be discovered. Thus the fitness should be related to the difference in solutions. Therefore random walk can be performed in a biased way with some random step sizes. Eq. (10) describes how step size can be performed.

*Step size =r*nests[perm(n)]-nests[perm(n)]*(10)

Where ris random number in [0, 1] range, *nests*is matrix which contains candidate solutions along with their variables, *perm* is different rows permutation functions applied on nestmatrix.

The step length can be calculated based on mantegna's algorithm.

$$s = \frac{u}{|v|^{1/\beta}} \qquad (11)$$

Where β is an indexranging $1 \leq \beta \leq 2$ (β value of 1.5 is recommended.) and u and $v$are drawn from normal distribution.

$$u \sim N(0, \sigma_u^2),\ v \sim N(0, \sigma_v^2) \qquad (12)$$

Where,

$$\sigma_u = \{ \frac{\Gamma(1+\beta)\sin(\frac{\Pi\beta}{2})}{\Gamma[\frac{1+\beta}{2}]\beta 2^{(\beta-1)/2}} \}^{1/\beta},\ \sigma_v = 1 \qquad (13)$$

The evolution of any cuckoo $i$begins with the vector v, where $v = x_i^{(t)}$). Step size is beingcalculated as given in Eq. (14)

$$Stepsize = 0.01 \frac{u^{(t+1)}}{|v^{(t+1)}|^{1/\beta}} (v - x_{best}) \quad (14)$$

The advantage of cuckoo search algorithm is the number of tuning parameters is very less when compared to other algorithms like GA and PSO and hence can be easily applied to a wider range of optimization problem.

6. Parameters settings and optimization

The machining parameters are kept the same as in the literature review. For firefly algorithm, the number of fireflies (n) is taken is taken as 100, the randomization parameter (α) is taken as 0.5, initial attractiveness (β_0) is taken as 0.2 and light absorption coefficient (Γ) is taken as 1. The maximum generation (N) is taken as 1000. For cuckoo search algorithm, the number of nests (n) is taken as 100;the probability of the discovery of an alien egg in its nest by a host bird (p_a) is taken as 0.25 and the maximum generation (N) is taken as 1000. MATLAB program code was developed for both the algorithms.

7. Results and discussion

The results for model 1, model 2 and model 3 optimized by firefly algorithm and cuckoo search algorithm are given and compared with results from literature (Z. Khan et al. [5], K. Deep et al. [4]) in the following tables. For model 1, 2 and 3, the convergence of production cost for FA was found at generation 971, 895 and 763, for CS 780, 397 and 263 respectively. Beyond that there was no significant change in the value of production cost.

Method	V	f	Cost
SA	143.908	0.001439	6.255
Cont. SA	143.914	0.001439	6.2551
GA	145.068	0.0014	6.2758
LXPM	143.901	0.001439	6.254945
FA	143.9157	0.001438919	6.2551
CS	143.9013	0.001439087	6.2549

Table 1. Results for model 1

Method	V	F	Cost
SA	174.394	0.2321	12.097
Cont. SA	174.2229	0.2321	12.096
GA	174.399	0.2321	12.099
LXPM	174.3877	0.232119	12.09707
FA	174.3912	0.2321133	12.0976
CS	174.3878	0.2321196	12.0975

Table 2. Results for model 2

Method	V	F	Cost
SA	433.980	0.003814	1.5526
Cont. SA	440.8529	0.003907	1.5526
GA	434.375	0.003814	1.5536
LXPM	433.318	0.0038053	1.552611
FA	437.5092	0.003861107	1.5531
CS	433.3626	0.003805895	1.5526

Table 3. Results for model 3

The computational time taken for FA is 56, 43 and 52 and for CS is 21, 19 and 23 seconds for model 1, 2 and 3 respectively.

The results of FA and CS in table 1, 2 and 3 shows that they are reliable for optimizing machining operation with constraint parameters. They produced almost the same results as that of LXPM proposed by K. Deep et al. [4] which is the best in the literature. FA and CS outperformed GA and CS produced almost the same results as that of SA and Cont. SA (Z. Khan et al. [5]). In terms of production cost, no of generation and computing time CS outperformed FA proving it more reliable than FA for optimization of machining parameters.

8. Conclusion

Selection of machining parameters for a machining process is an important criterion in achieving optimum production time and production cost. In this study, it is proved that Firefly algorithm and Cuckoo search algorithm can be effectively used in optimization of machining parameters. They are highly reliable as it is proven by implementing to the mathematical models from literature.

9. References

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