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Machining Parameters Optimization using Hybrid Firefly Algorithm and Particle Swarm Optimization

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Abstract. Firefly Algorithm (FA) is a metaheuristic algorithm that is inspired by the flashing behavior of fireflies and the phenomenon of bioluminescent communication and the algorithm is used to optimize the machining parameters (feed rate, depth of cut, and spindle speed) in this research. The algorithm is hybridized with Particle Swarm Optimization (PSO) to discover better solution in exploring the search space. Objective function of previous research is used to optimize the machining parameters in turning operation. The optimal machining cutting parameters estimated by FA that lead to a minimum surface roughness are validated using ANOVA test.

1. Introduction

The first known use of optimization is since year 1857. Optimization problem is a process of making something as functional and effective as possible. Basically, mathematical procedures are involved in the optimization problem to find the maximum or minimum function by choosing systematically integer variable value. Hence, optimization problem also can be defined as the problems that need a solution to find the best way from all feasible solutions. Optimization has been used in many areas as all the possible solutions are analyzed regarding their criteria. In my studies, some of the areas that used optimization are machining (we can find many machining cases use optimization in their work), clustering as stated in [1], robotic area done by [2], scheduling, networking and many more.

Optimization always present in day life since ancient times. Individual has to produce solutions that serve the source limits in order to deal with the restrictions of some problems. Basically, nature observations are being used to solve the problems. Gradually, knowledge will be developed based on this nature observations and past experiences. Then, the nature observations are being tested in daily life to find a better solution.

In machining, proper selections of process parameters are crucial to produce a high-quality product. Nowadays, surface finish of the products is one of the main concerns by manufacturing industries. They have to depend on manufacturing handbook to obtain optimal process parameters but results in increasing the manufacturing cost and low product quality [3]. Therefore, proper selection of process parameters are important to achieved high-quality product. Hence, optimization is needed to find the optimal parameters that satisfying the product quality.
Turning is one of traditional machining operation that is widely used in manufacturing industries. The operation is to cut metal apart from the workpiece. The primary method of turning is rotation which is to move metal against the cutting tool. It uses a single point cutting tool on lathe machine to cut the workpiece. One of common type of workpiece that has been widely used in turning operation is carbon steel.

Based on machinery handbook, carbon steel is steel that has properties made up mostly of the element carbon. Its principal is hardening element, determining the level of hardness or strength attainable by quenching. It raises tensile strength, hardness, resistance to wear and abrasion as the carbon content of steel is increased. It lowers ductility, toughness and machinability.

Most of manufacturing industries used carbon steels in their production. Carbon steels are known by their high production volume and good formability. It also has excellent weldability [4]. In order to achieve high quality of products, surface roughness of the workpiece need to be optimized due to high requirement of low cost applications in machining industries [5].

One of the most important requirements in machining process is surface roughness. It measures the technological quality of a product and describes the geometry of the machined surface and surface texture. The quality of a surface played important role in evaluating the productivity of machine tool and machined parts. To obtain better surface roughness value, a proper setting of cutting parameters is necessary [6]-[7]. Current method to select the cutting parameters that always been used is mainly depends on machinist expert and machining data handbook [8].

There are many factors that affect the value of \( R_a \). The factors are machining parameters, cutting tool properties, cutting phenomena and workpiece properties but among all those factors, machining parameters are highly affecting the value of \( R_a \) [9].

This paper focused on machining parameters that highly affect the surface roughness value. The parameters that have to be optimised are feed rate \((X_1)\), cutting speed \((X_2)\) and spindle speed \((X_3)\). The optimization process of machine parameters will help to increase companies’ efficiencies and hence reduce the production costs. It also helps in the production process using new materials and may increase the productivity.

2. Metaheuristic Algorithm
Metaheuristic is an iterative generation process which guides a subordinate heuristic algorithm by combining intelligently different concepts for exploring and exploiting the search space while learning strategies are used to structure information to find efficiently near-optimal solutions [10].

In computer science, a computational method is designed to optimize the problem by iteratively trying to improve the solution of a problem. There are few algorithms that can search very large spaces of candidate solutions. However, metaheuristics do not guarantee an optimal solution is ever found.

[11] concluded that metaheuristic approaches obtained better quality solutions compare to heuristic approaches especially on hybrid techniques. So, metaheuristic is very suitable for solving nondeterministic polynomial-hard (NP-hard) optimization and complicated search problems.

This is proved by [12] that metaheuristics are designed to deal with complex optimization problems because of the other optimization techniques are not very efficient to solve the problems. Hence, these approaches were recognized as one of the most practical approaches for solving complex problems.

2.1. Fundamental Properties of Metaheuristics
Metaheuristics are designed to search optimal solution for a problem. [13] stated that there are some fundamentals properties of metaheuristics:

1. Metaheuristics are strategies that act as guidance for searching process.
2. The goal of metaheuristics is to explore the search space efficiently to find optimal or near-optimal solutions.
3. The techniques used to solve problems are from simple local search procedures to complex learning process.
4. Metaheuristic algorithms are approximation solutions and usually non-deterministic.
Many different metaheuristics are in existence to solve optimization problems. Somehow, there are some new variants are continually being proposed. In last decade, the nature observation of swarm intelligence (SI) has become more popular among researchers to solve the optimization problems. The swarm intelligence is made up of a population of agents that interact with each other in their environment [14]. The inspirations of SI come from nature, especially the biological systems where the algorithms imitate the behaviour of swarms of social insects including ant colonies, bird flocking, animal herding, bacterial growth and fish schooling [15].

The use of SI approach is because of their robustness, flexibility, decentralized and self-organized characteristics [16]. Furthermore, SI is able to operate themselves independently without guidance from coordinator or external controller [17].

The most significant algorithms that have many contributions to the field are Genetic Algorithm (GA), Firefly Algorithm (FA), Particle Swarm Optimization (PSO), Levy Flight, Support Vector Machine (SVM), Glowworm Swarm Optimization (GSO) Cuckoo Search Algorithm (CS) and many more [18]-[20]. Firefly algorithm (FA) which was introduced by Yang (2008) is a nature-inspired metaheuristic algorithm that inspires the flashing behavior of fireflies where the purpose of the flash is to act as a signal to attract other fireflies or preys. For computer science area, this algorithm has been applied in various problems such as optimization, clustering, image processing, feature selection and many more. The main purpose of this paper is to propose FA in optimizing the cutting parameters to solve the optimization problem in turning operation and hybrid it with Particle Swarm Optimization to find a better solution.

3. Firefly Algorithm

Fireflies are winged beetles or insects that produce light and blinking at night. [21] finds that there are strengths in firefly behavior to be applied in solving real life problems. So, he introduced Firefly Algorithm in 2008 inspired by flashing behavior of the fireflies for protection and attract mates or prey. There are three assumptions; fireflies are unisex and will be attracted to each other, brightness plays important role to attract others and fireflies will move randomly when their brightness are same [22].

3.1. The attractiveness of the firefly, I

The degree of brightness of firefly i and the distance \( r_{ij} \) between the firefly i and the firefly j demonstrates its attractiveness, I in the algorithm [22].

\[
I(r) = \frac{I_i}{r^2} \quad (1)
\]

As mentioned above, the brightness of fireflies are associated to objective function. So, the brightness of a firefly is chosen to reveal its recent position of its objective function \( f(x) \).

\[
I_i = f(x_i) \quad (2)
\]

The brighter firefly will attract the less bright firefly due to its certain attractiveness value \( \beta \) regarding to their distances.

\[
\beta(r) = \beta_0 e^{-\gamma r^2} \quad (3)
\]

where \( \beta_0 \) is the firefly attractiveness value at \( r = 0 \) and \( \gamma \) is the media light absorption coefficient.

3.1.1. The movement towards attractive firefly.

The movement of a firefly i at position \( x_i \) moving to a brighter firefly j at position \( x_j \) is described by:

\[
x_{i+1} = x_i + \beta_0 e^{-\gamma r_{ij}^2} (x_j - x_i) + \alpha (\text{rand} - \frac{1}{2}) \quad (4)
\]

where \( \beta_0 e^{-\gamma r_{ij}^2} (x_j - x_i) \) is due to the attraction of the firefly \( x_j \); so if \( \beta = 0 \) then it turns out to be a simple random movement. The attractiveness of firefly is compared with previous position. The algorithm will update the position of firefly to a higher attractiveness value; otherwise the firefly will remain in the current position. The termination criterion of the algorithm is based on its predefined number of iterations.
In the algorithm, objective function should be associated to the fireflies’ brightness. Their attractiveness makes them capable to subdivide themselves into smaller groups and each subgroup swarm around the local models. Thus, FA is suitable for multimodal optimization problems [23]. FA also is used in clustering to find the centers of the clusters of the objects. The results obtained for FA method are compared to other methods such as Artificial Bee Colony (ABC) and Particle Swarm Optimization (PSO) [24].

FA also can be in dynamic environment. In previous research, FA is used for local search but direct movement and angle of peaks are been used for increasing the convergence speed. Results showed better performance and accuracy compare to PSO [25]. In other case, FA is proposed on dynamic environments based on Moving Peak Benchmark (MPB) Problem. Some modifications are done to the algorithm for better performance [26].

[27] used FA for scheduling jobs on grid computing to dynamically create an optimal schedule within minimum makespan and flowtime. Results showed that FA achieved less makespan time compared to Min-Min and Max-Min heuristics in scheduling problem.

[28] introduced FA to solve mixed variable structural optimization problems. The algorithm has been tested in six different structural optimization problem and results showed that FA is more efficient than PSO, GA, Simulated Annealing (SA) and HS methods. However, the randomization parameter must be reduced when using the FA as the optimization progress.

In engineering area, FA is proved to gain high profit [29]. The researchers introduced FA to solve optimal dispatch problem and results showed that FA gave optimal results that satisfying the constraints with high profit. FA also can be hybridized with other technique to improve its processing time because sometimes, FA itself requires a longer time to search for optimal values [30].

4. Particle Swarm Optimization

Particle Swarm Optimization is a population based stochastic optimization technique inspired by social behavior of bird flocking or fish schooling. The technique is developed by Dr. Russell Eberhart and Dr. James Kennedy in 1995.

The technique starts with initializing the population with random solutions. Then, the particles in PSO search for optimal solution by updating the generations by following the current optimum particles. Each particle in PSO can memorize their current best to search for the next generation. The value of current best will be stored in \( p_{best} \). When the particles have compared their fitness with the overall population, the current best value will be stored in \( g_{best} \) (global best). Then, the velocity of each particle will be updated toward its \( p_{best} \).

PSO is widely used by previous researchers to optimize the cutting parameters in machining. [31] used PSO and GA to optimize milling process parameters to maximize the profit rate. The algorithms are chose because of their better capability compare to other techniques.

PSO is used to find optimum value of \( R_a \) in milling operation. The result of PSO is compared with GA using previous research. This paper shows that GA takes longer time to get the optimum value compare to PSO [32]. PSO optimized the machining process parameters in high speed end milling operation. The result is compare with GA and SA and showed that PSO has high convergence speed than others [33].

5. Hybrid Firefly Algorithm and Particle Swarm Optimization

An attempt to hybrid FA and PSO is due to no memory capability in FA [25], [34] and [35]. Previous works show that PSO is one of the popular methods for a global search. So, the combination of FA and PSO will find a better solution to explore the search space by applying the capability of PSO in memorizes its previous best in determining the next possible solution [36].

The proposed algorithm began with FA implementation. After each firefly has move to more bright, the fitness of each firefly will be compared with its previous to obtain \( p_{best} \). Then, FA will continue its process until the termination criteria met. Once the termination criteria are met, an optimal
solution is obtained and the process end. Otherwise, the process will iterate again until the termination criteria are met. The hybridization of FA and PSO is a way to overcome the memorizing capability of FA compare to PSO. In this research, we used the capability of PSO in memorizing the previous best location of the solutions to update the next value in the search space. The proposed algorithm will search better solutions by using the previous best location of firefly (pBest) in previous iteration to update the next value.

The current position of firefly \( x_i \) is a set of coordinates indicates a point in the search space. A firefly is representing a set of solution for the problem. The algorithm compares the attractiveness of the new firefly position with the old one. If the new position produces higher attractiveness value, the firefly is moved to the new position and the value is stored in pBest; otherwise the firefly will remain in the current position. The value of pBest will be compared on later iteration to determine optimal solutions.

The algorithm will keep finding the better positions of the fireflies by updating light intensity, \( I \) based on pBest. New points are selected by adjusting the randomization factor as a step size. There are two ways on terminating FA technique which are based on an arbitrary predefined number of iterations or predefined fitness value. In this research, we decided to use the predefined number of iterations as the termination criteria of the algorithm.

Once the maximum number of iteration is met, the algorithm will be terminated. The fitness values are calculated based on the optimal solution represented by the fireflies.

6. Optimization model of turning operation

As stated in the previous section, the operation considered in this research is turning operation. Metal cutting process has a complex nature whereby there are some objectives that tangled with each other. For example, by increasing the rate of tool wear may increase the unit production cost. Hence, it decides the quality of the product. So, it is very important to select the most suitable/optimal parameters of the machine tools in lathe machine when undergo the turning operation.

The model proposed by [37] is used as the objective function in this research. NC lathe machine is used to machine medium carbon steel (AISI 1045) with molybdenum High Speed Steel (HSS) turning tool. The model used to find the optimal cutting conditions which are feed rate, cutting speed and spindle speed. The performance measured is \( R_a \).

There are 3 levels for each parameters in the operation. The levels are as in Fig. 1:

| Parameter            | Levels |
|----------------------|--------|
| Feed rate, \( X_1 \) (mm/min) | 0.5, 0.8, 1.0 |
| Cutting speed, \( X_2 \) (m/min) | 47.12, 70.69, 94.25 |
| Spindle speed, \( X_3 \) (rpm) | 1000, 1500, 2000 |

The objective function is described as in Equation 5:

\[
\text{Minimize } R_a = -0.74372 - 0.5245 \times X_1 + 0.015759 \times X_2 + 0.000734647 \times X_3 \\
- 0.00000171683 \times X_2 \times X_3 + 0.52133 \times X_1^2 - 0.0000892502 \times X_2^2 \\
- 0.000000213667 \times X_3^2
\] (5)

Fig. 2 shows a list of 15 runs of experimental results done by [37]. The combinations of machining parameters are randomized according ti Box-Behnken design. The researchers used qualitest micro-
trio-gloss (model No. 4430Nr-05643) to calculate \( R_a \). Fig. 2 shows the design matrix of the experiment:

| Run | Feed rate, mm/rev (X1) | Depth of cut, mm (X2) | Spindle speed, rpm (X3) |
|-----|------------------------|-----------------------|-------------------------|
| 1   | -1                     | -1                    | 0                       |
| 2   | 0                      | 0                     | 0                       |
| 3   | -1                     | 1                     | 0                       |
| 4   | 0                      | 1                     | 1                       |
| 5   | 0                      | 1                     | -1                      |
| 6   | 0                      | 0                     | 0                       |
| 7   | 1                      | 0                     | 1                       |
| 8   | -1                     | 0                     | -1                      |
| 9   | 0                      | 0                     | 0                       |
| 10  | 1                      | 1                     | 0                       |
| 11  | -1                     | 0                     | 1                       |
| 12  | 0                      | -1                    | 1                       |
| 13  | 0                      | -1                    | -1                      |
| 14  | 1                      | -1                    | 0                       |
| 15  | 1                      | 0                     | -1                      |

Fig. 3 shows the experimental results done by [37]:

| Run | Feed rate, mm/rev (X1) | Depth of cut, mm (X2) | Spindle speed, rpm (X3) | Surface roughness, \( \mu m \) \( R_a \) |
|-----|------------------------|-----------------------|-------------------------|-------------------------------------|
| 1   | 0.5                    | 47.12                 | 1500                    | 0.18                                |
| 2   | 0.8                    | 70.69                 | 1500                    | 0.25                                |
| 3   | 0.5                    | 94.25                 | 1500                    | 0.2                                 |
| 4   | 0.8                    | 94.25                 | 2000                    | 0.14                                |
| 5   | 0.8                    | 94.25                 | 1000                    | 0.211                               |
| 6   | 0.8                    | 70.69                 | 1500                    | 0.27                                |
| 7   | 1                      | 70.69                 | 2000                    | 0.3                                 |
| 8   | 0.5                    | 70.69                 | 1500                    | 0.18                                |
| 9   | 0.8                    | 70.69                 | 1500                    | 0.27                                |
| 10  | 1                      | 94.25                 | 1500                    | 0.315                               |
| 11  | 0.5                    | 70.69                 | 2000                    | 0.16                                |
| 12  | 0.8                    | 47.12                 | 2000                    | 0.15                                |
| 13  | 0.8                    | 47.12                 | 1000                    | 0.14                                |
| 14  | 1                      | 47.12                 | 1500                    | 0.29                                |
| 15  | 1                      | 70.69                 | 1000                    | 0.33                                |

Firefly Algorithm (FA) is applied to the turning problem. [38] who is founder of FA stated that the values of FA parameters which are \( \alpha = 0.1-0.5 \), \( \beta = 0.7-1.0 \) and \( \gamma = 1.0 \) can be used for most of optimization problems. The higher number on \( n \) leads higher computation time. The parameters setting of FA parameters for this study are as Fig. 4:

| FA parameter setting |
|----------------------|
| \( n \) | \( N_{\text{iteration}} \) | \( \alpha \) | \( \beta \) | \( \gamma \) |
| Value | 20 | 50 | 0.5 | 0.1 | 1.0 |
The range of cutting parameters of turning operation will be set based on [37] for FA technique. The optimization results of minimum \( R_a \) value obtained by FA can be seen in Fig. 5:

![Fig. 5: FA single optimization (\( R_a \))](image1)

| Run | Feed rate, mm/rev (X1) | Depth of cut, mm (X2) | Spindle speed, rpm (X3) | Surface roughness, \( \mu m (R_a) \) | Time (seconds) |
|-----|------------------------|-----------------------|-------------------------|--------------------------------------|----------------|
| 1   | 0.5506                 | 47.1200               | 2000.0000               | 0.1228                               | 0.3273         |
| 2   | 0.5517                 | 47.1205               | 1901.2468               | 0.1406                               | 0.1803         |
| 3   | 0.5391                 | 55.0531               | 2000.0000               | 0.1477                               | 0.1844         |
| 4   | 0.7542                 | 93.9650               | 2000.0000               | 0.1420                               | 0.1622         |
| 5   | 0.5517                 | 78.1944               | 2000.0000               | 0.1583                               | 0.1677         |
| 6   | 0.7386                 | 47.2012               | 1999.9896               | 0.1508                               | 0.2079         |
| 7   | 0.5575                 | 53.0074               | 1000.7791               | 0.1406                               | 0.1781         |
| 8   | 0.5459                 | 49.2890               | 1999.4866               | 0.1307                               | 0.1606         |
| 9   | 0.5838                 | 85.6099               | 2000.0000               | 0.1434                               | 0.2102         |
| 10  | 0.5739                 | 75.3312               | 2000.0000               | 0.1636                               | 0.2072         |
| 11  | 0.6404                 | 47.1206               | 1999.9927               | 0.1314                               | 0.2042         |
| 12  | 0.70544                | 94.25                 | 2000.0000               | 0.1292                               | 0.1862         |
| 13  | 0.5508                 | 47.1201               | 1999.9944               | 0.1228                               | 0.1967         |
| 14  | 0.7114                 | 47.1203               | 2000.0000               | 0.1442                               | 0.1738         |
| 15  | 0.5519                 | 55.9778               | 2000.0000               | 0.1505                               | 0.2008         |

Fig. 6 shows the Analysis of Variance (ANOVA) results of surface roughness. The analysis was carried out at significance level of \( \alpha = 0.05 \), for confidence level of 95%. The F-ratio indicates the significant of all cutting parameters to \( R_a \) while the p-value is the probability of significant contributions of each parameter and must be in the range of 0 to 1. If p-value < 0.05, it shows that the observed different within cutting parameters are significant. From Fig. 6, we can see that all parameters are significant towards surface roughness since all the p-values are lower than 0.05.

![Fig. 6: ANOVA for FA](image2)

| Cutting  | df | SS   | MS   | F-ratio   | p-value |
|----------|----|------|------|-----------|---------|
| X₁       | 2  | 0.0330 | 0.033 | 265.78    | 0.0001  |
| X₂       | 2  | 0.0014 | 0.0014 | 11.26     | 0.0122  |
| X₃       | 2  | 0.0015 | 0.0015 | 12.35     | 0.0098  |

df: degree of freedom; SS: sum of square; MS: mean of square

Based on previous researchers, the values of Particle Swarm Optimization parameters that usually used for most optimization problems are \( n = 20-100 \), \( N\_\text{iteration} = 5-50 \), \( \phi = 0.1-0.9 \) and \( \phi = 0.1-0.9 \) [39] where \( \phi \) is weightage of particle best and \( \phi \) is weightage of global best. The parameters setting of PSO for this paper are \( n = 20 \), \( N\_\text{iteration} = 50 \), \( \phi = 0.4 \) and \( \phi = 0.6 \). The parameters were set to give the best results possible based on the algorithm. The ranges of cutting parameters are set based on [37]. The optimization results of minimum \( R_a \) value obtained by PSO can be seen in Fig. 7:

![Fig. 7: PSO optimization](image3)

| Run | Feed rate, mm/rev (X1) | Depth of cut, mm (X2) | Spindle speed, rpm (X3) | Surface roughness, \( \mu m (R_a) \) | Time (seconds) |
|-----|------------------------|-----------------------|-------------------------|--------------------------------------|----------------|
| 1   | 0.5577                 | 51.6507               | 1998.7027               | 0.1393                               | 0.1774         |
| 2   | 0.6193                 | 51.7178               | 1998.7007               | 0.1450                               | 0.2825         |
| 3   | 0.6248                 | 51.7294               | 1998.6932               | 0.1457                               | 0.2579         |
| 4   | 0.6783                 | 51.6619               | 1998.7412               | 0.1538                               | 0.3442         |
| 5   | 0.7223                 | 51.7338               | 1998.6994               | 0.1631                               | 0.3037         |
| 6   | 0.7321                 | 51.6807               | 1998.6702               | 0.1652                               | 0.1773         |
Fig. 8 shows the Analysis of Variance (ANOVA) results of surface roughness for PSO. The analysis was carried out at significance level of $\alpha=0.05$, for confidence level of 95%. The F-ratio indicates the significant of all cutting parameters to $R_a$ while the p-value is the probability of significant contributions of each parameter and must be in the range of 0 to 1. If p-value $< 0.05$, it shows that the observed different within cutting parameters are significant. From Fig. 8, we can see that the p-values for parameter $X_2$ and $X_3$ are lower than 0.05, means that the parameters are significant towards the $R_a$.

| Cutting | df | SS   | MS   | F-ratio | p-value |
|---------|----|------|------|---------|---------|
| $X_1$   | 2  | 0.179| 0.0898| 3.1845  | 0.0593  |
| $X_2$   | 2  | 0.189| 0.0949| 3.4176  | 0.0494  |
| $X_3$   | 2  | 0.208| 0.1041| 3.8565  | 0.0353  |

df: degree of freedom; SS: sum of square; MS: mean of square

Fig. 9 shows the results of hybrid FA-PSO optimization

| Run | Feed rate, mm/rev (X1) | Depth of cut, mm (X2) | Spindle speed, rpm (X3) | Surface roughness, $\mu$m ($R_a$) | Time (seconds) |
|-----|------------------------|-----------------------|-------------------------|----------------------------------|----------------|
| 1   | 0.5601                 | 47.1217               | 1878.6941               | 0.1445                           | 0.1641         |
| 2   | 0.6337                 | 49.9419               | 1047.9354               | 0.1431                           | 0.1659         |
| 3   | 0.5644                 | 55.5253               | 1000.0828               | 0.1519                           | 0.3229         |
| 4   | 0.5726                 | 50.2749               | 1000.0360               | 0.1283                           | 0.1648         |
| 5   | 0.5004                 | 49.5228               | 1920.7903               | 0.1454                           | 0.2334         |
| 6   | 0.6014                 | 94.2444               | 1918.6498               | 0.1344                           | 0.1828         |
| 7   | 0.7460                 | 83.3948               | 2000.0000               | 0.1769                           | 0.1617         |
| 8   | 0.5915                 | 47.1200               | 2000.0000               | 0.1257                           | 0.1621         |
| 9   | 0.5656                 | 47.1200               | 1750.1034               | 0.1605                           | 0.1623         |
| 10  | 0.5756                 | 85.4571               | 2000.0000               | 0.1432                           | 0.1679         |
| 11  | 0.5030                 | 47.1200               | 2000.0000               | 0.1216                           | 0.1715         |
| 12  | 0.5117                 | 47.1200               | 2000.0000               | 0.1216                           | 0.1578         |
| 13  | 0.6079                 | 87.0826               | 1979.9070               | 0.1465                           | 0.2173         |
| 14  | 0.6170                 | 69.4067               | 2000.0000               | 0.1713                           | 0.1603         |
| 15  | 0.6319                 | 94.2500               | 1749.1183               | 0.1738                           | 0.1640         |

Fig. 10 shows the Analysis of Variance (ANOVA) results of surface roughness for hybrid FA-PSO. The analysis was carried out at significance level of $\alpha=0.05$, for confidence level of 95%. The F-ratio indicates the significant of all cutting parameters to $R_a$ while the p-value is the probability of significant contributions of each parameter and must be in the range of 0 to 1. If p-value $< 0.05$, it shows that the observed different within cutting parameters are significant. From Fig. 10, we can see that the p-value for parameter $X_2$ is lower than 0.05, means that the parameter is significant towards the $R_a$. 
Fig. 10: ANOVA for hybrid FA and PSO

| Cutting Parameters | df | SS    | MS    | F-ratio | p-value |
|-------------------|----|-------|-------|---------|---------|
| $X_1$             | 2  | 1.0713| 0.5356| 1.2362  | 0.3083  |
| $X_2$             | 2  | 4.1961| 2.0980| 6.9222  | 0.0042  |
| $X_3$             | 2  | 0.8960| 0.4480| 1.0168  | 0.3768  |

df: degree of freedom; SS: sum of square; MS: mean of square

7. Summary
In this paper, a hybrid algorithm of FA and PSO is proposed and compared to single optimization of Firefly Algorithm and Particle Swarm Optimization to solve the problem in optimizing the cutting parameters for turning operation. Table 4 shows the comparison results of Firefly Algorithm, Particle Swarm Optimization and Hybrid FA-PSO:

|                | Feed rate, mm/rev (X1) | Depth of cut, mm (X2) | Spindle speed, rpm (X3) | Surface roughness, $\mu m (R_a)$ | Time (seconds) |
|----------------|------------------------|------------------------|-------------------------|-----------------------------------|----------------|
| FA             | 0.5506                 | 47.1200                | 2000.0000               | 0.1228                            | 0.3273         |
| PSO            | 0.5272                 | 51.4809                | 1998.5052               | 0.1376                            | 0.2149         |
| Hybrid FA-PSO  | 0.5117                 | 47.1200                | 2000.0000               | 0.1216                            | 0.1578         |

Based on the result, we can see that the proposed hybrid algorithm outperformed FA and PSO. The basic firefly algorithm is very efficient, but we can see that the solutions are still changing as the optima are approaching. It is possible to improve the solution quality by reducing the randomness gradually. However, due to no memory capability of firefly to memorize their movement, it takes some time to find the optimal solution. So, an element of PSO is used to cope with the problem. Furthermore, the hybrid algorithm can be modified to solve multi objective optimization problems.

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