Journal of Social Sciences and Technical Education, 3(1), 46-51
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# Selection of EDM Die Sinking Optimal Condition of Machine AISI L3 Tool Steel Material Using Ant Colony Optimization

(Pemilihan Kondisi Optimal EDM Die Sinking bagi Memesin Bahan AISI L3 Tool Steel Menggunakan Ant Colony Optimization)

*SAIPUL AZMI MOHD HASHIM[1], AHMAD AZLAN MOHAMAD[2], NUR MARINI MOHD ZAIN[3]
Manufacturing Technology Unit, Kolej Komuniti Kepala Batas, Malaysia[1]
Light Vehicle Service Unit, Kolej Komuniti Kepala Batas, Malaysia[2]
General Study Unit, Kolej Komuniti Kepala Batas, Malaysia[3]

* Corresponding author: saipulneural@gmail.com

ARTICLE INFO

*Article History:*
Received 11.08.2022
Accepted 11.10.2022
Published 22.11.2022

**Abstract**

The leading use of tool steel material as cutting tool material because of its good qualities and economical in the production line. Besides, the common use of EDM Die Sinking of machine tool steel material makes machining preferred by the industry. Therefore, a study that correlates input-output parameters of EDM Die Sinking is urged to estimate the good quality machined tool steel workpiece such as an optimization study. This study estimates the good qualities as the outputs, with the benefit of knowing the machining parameters. Therefore, this paper aims to optimize EDM Die Sinking input parameters by using the Ant Colony Optimization algorithm, an approach based on soft computing. This paper's step begins with experimental data and mathematical model application, then running the algorithm to gain the minimum outputs and optimized inputs, and ends with evaluation and validation. The selected input parameters are Current, Pulse on time, and Pulse off time; and the outputs are Material Removal Rate, Electrode Wear Rate, and Surface Roughness. The comparative study is made based on other references, and the result finds that the proposed approach outperforms the result by 3D Response Surface, Tabu Search, Genetic Algorithm, and Particle Swarm Optimizations approaches applied in previous studies. Moreover, the predicted optimized input parameters suggest more economical production expenses, by running at a lower rate of current supply for having better outputs.

Keywords: EDM Die Sinking, Multi-Objective Optimization, Ant Colony Optimization, Tool Steel.

## INTRODUCTION

Tool steel is commonly used as cutting tool materials by manufacturers. This discerned material of good hardness, wear resistance, and high temperature is workable (Mandaloi et al., 2015). Furthermore, tool steels are much cheaper compared to other tool materials, such as carbides, titanium, and Inconel. The most common grade given to tool steel is based on AISI-SAE, such as water-hardening (W), cold-working (O, A, D), shock resisting (S), high speed (T, M), hot-working (H), plastic mould (P), and special purpose (F, L). L2, L3, and L6 are L-grade variants for high-precision applications.

Specifically, the L3 grade applies mainly to engine pistons, valves, and moulds. These products with bad qualities have a serious impact on the user's safety, thus this need for good quality attention. The critical flaws of the machined tool steel workpiece of conventional machining include dimension inaccuracies, residual stresses, high surface roughness, and excessive tool wear. Machining by Abrasive Water Jet Machining, Laser Machining, and Electro Discharged Machining (EDM) can solve these disadvantages. For instance, EDM minimizes chattering, residual stresses, and mechanical vibration (Niamat et al., 2020). Hence, EDM Die Sinking to machine the selected material, i.e. AISI-SAE L3 tool steel, is this paper's interest. EDM Die Sinking began operation by supplying current to its electrode and workpiece that generate electric sparks once the electrode and workpiece get close. Therefore, proper electrical current supply is the main parameter that determines the machined workpiece qualities. The sparks make the workpiece cut in fine form; hence, the machining output is defined by the current supply for the whole operation. Current supply patterns depend on the quantity of pulse on time (Pon) and pulse off time (Poff), which is have a peak current supplied and no current durations to workpiece consecutively.

EDM and tool steel correlation study in modelling and optimization is reviewed literately as follows. Mandaloi et al. (2015) used the Taguchi approach to determine the optimum machining input parameters by EDM to machine AISI M2 tool steel. Alternatively, by a soft-computing approach, Baraskar, Banwait, and Laroiya (2013) have interested to apply a Multi-Objective Genetic Algorithm, and Kanlayasiri & Jattakul (2013) used Desirability Function in their study. Besides, the blended method of Grey Relational Analysis and Fuzzy Logic is applied to optimize the machining (Lin & Lin, 2005). It is also recorded that by statistical approach, i.e. Response Surface Methodology, Sultan, Kumar, & Gupta (2014) used the approach to optimize the EDM machining. These listed down studies a machined variety of tool steel grade materials, and Material Removal Rate (MRR), Electrode Ware Rate (EWR), and Surface Roughness (SR) are the main input parameters. These (Niamat et al. 2020, Baraskar, Banwait, & Laroiya, 2013, Kanlayasiri & Jattakul, 2013, Lin & Lin, 2005) have proven that through soft-computing optimization, better MRR, EWR, and SR value is obtainable.

This literature review study on MRR, EWR, and SR in relation to L-grade tool steel justifies the study by the finding that there is no similar research has been conducted. This paper aims to optimize the input parameters, i.e. MRR, EWR, and SR via Ant Colony Optimization (ACO) approach. The remaining section includes methodology, finding enlightened in the result and discussion section, and finalized with a concluding section.

## METHODOLOGY

Experiment Data → Mathematical Model → ACO Optimization → Evaluation & Validation

Figure 1. The Methodology

Figure 1 is the methodology flow which began by applying experiment data (Niamat et al., 2020) based on three input parameter levels as in Table 1. The effective input parameters for EDM include Pulse on time (Pon), and Current (C) because the inputs are directly proportionate to MRR, EWR, and SR (Mandaloi et al., 2015). Besides, MRR, EWR, and SR are inverse proportionate to Pulse off Time (Poff) (Sultan, Kumar, & Gupta, 2014). Furthermore, a study (Padhi et al., 2018) also confirmed that EDM performance can be measured by MRR, EWR, and SR. Besides, this study's output-input values finding are like the Travelling Salesman problem.

Table 1. The input parameter settings

| Process Parameter [Symbol, unit] | Low Level | Middle Level | High Level |
|---|---|---|---|
| Pulse on Time [Pon, μs] | 200 | 400 | 600 |
| Current [C, A] | 10 | 13 | 16 |
| Pulse off Time [Poff, μs] | 50 | 100 | 150 |

Source: Niamat et al. (2020)

$$MRR = -22.22697 + 0.043425 \times Pon + 1.88978 \times C + 0.089232 \times Poff + 1.54167x10^{-3} \times Pon \times C + 6.225x10^{-5} \times Pon \times Poff - 3.46667x10^{-3} \times C \times Poff - 7.57938x10^{-5} \times Pon^2 - 0.063806 \times C^2 - 4.027x10^{-4} \times Poff^2 \quad (1)$$

$$WR = -0.54243 + 6.462940^{-3} \times Pon - 0.023750 \times C - 4.06579x10^{-4} \times Poff + 5.66667x10^{-4} \times Pon \times C + 4.95x10^{-5} \times Pon \times Poff - 1.68651x10^{-5} \times Pon^2 - 7.68421x10^{-5}\ Poff^2 \quad (2)$$

$$SR = -1.71756 + 6.795x10^{-3} \times Pon - 0.12989 \times C + 0.015330 \times Poff - 8x10^{-6} \times Pon \times Poff - 5.775x10^{-6} \times Pon^2 + 0.02044 \times C^2 - 8.84x10^{-5} \times Poff^2 \quad (3)$$

| Symbol | Description |
|---|---|
| $n_1$ | ant to choose the first route |
| $n_2$ | ant to choose the second route |
| $P_{1(n+1)}$ | the probability for $(n+1)^{th}$ ant to choose the first route |
| $P_{2(n+1)}$ | the probability for $(n+1)^{th}$ to choose the second route |
| $k$, $h$, $Q$ | constants to fit the experiment model and pheromone update model |
| $T_{ij}$ | the pheromone update |
| $\rho$ | evaporation rate |
| $m$ | number of ants |
| $L_k$ | the tour length of $k_{th}$ ant |
| $\Delta T_{ij}^k$ | the quantity of pheromone per unit length laid on edge $(i,j)$ by $k_{th}$ ant |

(a)

```
Set_parameters, initialize_pheromone_routes
while termination_do_not_met do
   Schedule_Activities
      Constuct_Ant_Solution
      Update_Pheromones
   end Schedule_Activities
endwhile
```

(b)

Figure 2. (a) ACO Symbol Description; (b) Standard ACO Algorithm

$$P_{1(n+1)} = \frac{(n_1 + k)^h}{(n_1 + k)^h + (n_2 + k)^h} \quad (4)$$

$$P_{2(n+1)} = 1 - P_{1(n+1)} \quad (5)$$

$$T_{ij} = (1 - \rho).T_{ij} + \sum_{k=1}^{m} \Delta T_{ij}^k \quad (6)$$

$$\Delta T_{ij}^k = \begin{cases} \frac{Q}{L_k}, \\ 0, \end{cases} \quad (7)$$

Niamat et al. (2020) begins the study with a set of experiment to produce data, then Empirical Model Analysis to develop three mathematical models as in equations Eq. 1, Eq.2, and Eq.3. Then, optimization by 3D Response Surface (3DRS) determines a set of optimized input parameters is taken place in Table 1 and output in Table 2. As the optimization approach (Niamat et al., 2020) is different than this paper and other reference (Mohd Hashim, Mohaiyiddin, & Talib, 2021) hence the optimization approach outcomes from different sources are compared in this paper.

Statistical and soft-computing are the commonly used approach to optimization study. Comparatively, specific optimal parameter values are obtainable by soft-computing approach, but by statistical approach only explicit value set while in experimental stage is obtainable. Furthermore, determination of the multiple inputs the minimum point ($x_1$, $x_2$, …) to single output correlation requires a high mathematical order problem solving and required for soft-computing approach using an algorithm. The algorithm finds the most minimum output point or global optima out of other minimum points or local optima, by repetitive calculations. This paper used the three equations from Niamat et al. (2020), as optimization fitness functions using ACO algorithm. As this study requires multi-objective optimization, fortunately ACO is robust and versatile in multi-objective optimization, good solution rapid discovery, and efficient for the Travelling Salesman problem (Dorigo, Maniezzo, & Colorni, 1996).

ACO algorithm is inspired by ants' behavior to find the best food source interact through pheromone trails. Based on these ants' behavior and two routes selection assumption, the following equations, i.e. Eg. 4, Eq. 5, Eq. 6 and Eq. 7 are applied, refer Figure 2(a) for the symbol used. These are the schedule activities that involved in the ACO algorithm. Similarly, to El Baradie (1996) study, Monte Carlo is used for model simulation, with k ≈ 20 and h ≈ 2 were found very good for fitting.

Previous studies by Dorigo & Di Caro (1999) validated that the ACO is appropriate multi-objective optimization. Besides, ACO usage is set by the selected inputs, inputs constrain, and fitness function. These are set in the algorithm before the pheromone update setting as shown in Figure 2(b). Moreover, ACO replicates the pheromone update model, i.e. Eq. 6 designed by Dorigo, Maniezzo, and Colorni (1996), is a part of the full algorithm. If the probability aforementioned about the route, the pheromone update model selects a route from the joint of two cities, i.e. $i$ and $j$. The $T_{ij}$ model updates the pheromone values and controlled by the evaporation rate ($\rho$) with the two conditions of pheromone quantity between $i$ and $j$ by $k_{th}$ ant ($\Delta T_{ij}^{k}$). These features influence all the ants (m) with two conditions are either the use of $k$, and edge $(i,j)$ in the tour or return to zero for no use.

The prime measures for optimizing is setting conditions for evaluation. Here, multi-objective optimization with three objectives, i.e. MRR, EWR, and SR, so three minimum conditions must be evaluated. For a wider perspective of comparative analysis, other reference's result (Mohd Hashim, Mohaiyiddin, & Talib, 2021) also referred into this paper, which using two soft-computing approaches, i.e. Tabu Search (TS) and Particle Swarm Optimization (PSO). Due to it is economical the three objectives in low values, hence the results evaluation concerning are as follows: (1) The MRR, EWR, and SR optimized values are expected to be lower than the value by the 3DRS and other approaches applied in previous studies, (2) The EDM Die Sinking optimized input parameters are accepted to be within the range of experimental values that also reflecting the acceptable machinability conditions. Then, the finding is valid if the optimized values are similar to the value generated by the fitness functions (Zain, Haron, & Sharif, 2010) as in Eq.1, Eq.2, and Eq.3 – validation stage.

## RESULT

Validation test (T) in Table 2 shows Mathematical Model based on the input values of ACO. Comparatively, Mathematical Model and ACO different output value is insignificant. Besides, Fig. 3 summarizes the optimization result values by 3D Response Surface (3DRS) (Niamat et al., 2020), PSO and TS (Mohd Hashim, Mohaiyiddin, & Talib, 2021), and ACO by this paper. This clearly visualized by bar chart in Figure 3 that the most efficient output values for MRR, EWR, and SR by ACO is 1.61855 $mm^3$/min, 1.28418 $mm^3$/min, and 0.70131 μm – ACO outperforms the results through 3DRS, GA, TS, and PSO.

Generally, the most efficient of optimum point does not always correlate with the maximum input value. For instance, the maximum value of the Pon is set to 600 μs but the average optimum point is 214.96 μs; for the Current is set to maximum of 16 A but the average optimum point is 11.76 A; and the set a maximum Poff is 150 μs, but the average optimum point is 59.4 μs. All of these scores are listed in Table 1 and pictured in Figure 3. Furthermore, the Pareto-Front for ACO result with the most efficient point shown is shown in Figure 4. By the result of this approach, it is clearly shown the all objectives are agreed with the selection of the most efficient point.

Table 2. Validation Result

| T | Pon [μs] | Poff [μs] | C [A] | SR [μm] ACO | SR [μm] Model |
|---|---|---|---|---|---|
| I | 213.89 | 73 | 13.07 | 2.0074 | 2.0061 |
| II | 203.47 | 58 | 12.58 | 1.3222 | 1.3257 |
| III | 229.32 | 67 | 10.74 | 1.9332 | 1.9381 |
| IV | 225.58 | 54 | 11.37 | 1.5038 | 1.5012 |

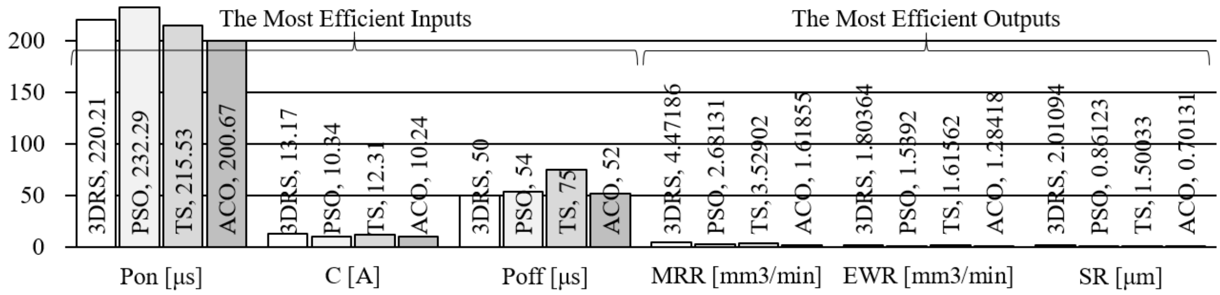

Figure 3. The Bar Chart for Inputs and Outputs Based on The Most Efficient Result

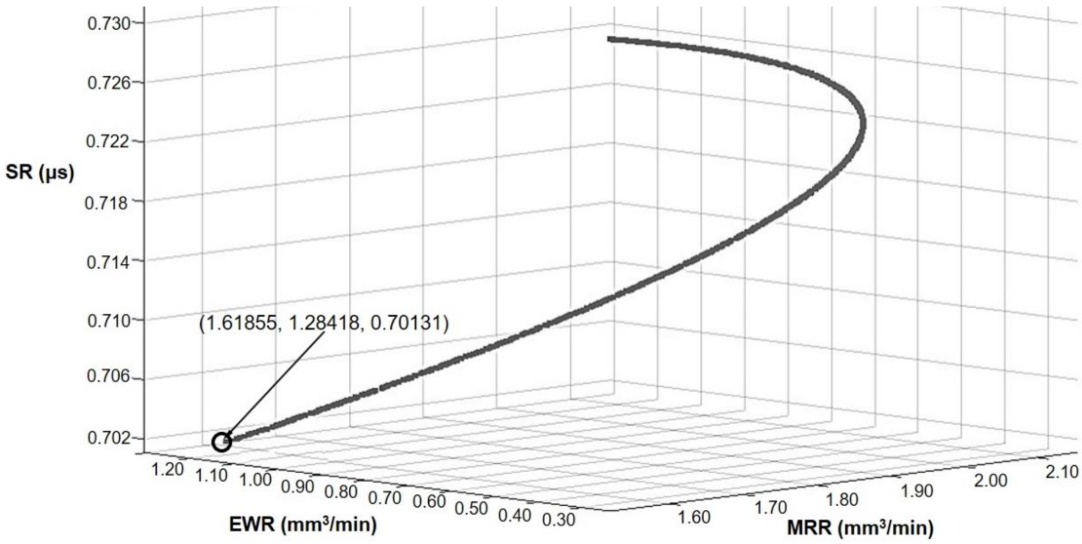

Figure 4. The Pareto-Front for the Output with the Most Efficient Point

## CONCLUSION

Based on the result, it is confirmed that the ACO is effective to estimate better results in searching the MRR, EWR, and SR minimum point compared to 3DRS result (Niamat et al., 2020) and other approach soft computing approach (Mohd Hashim, Mohaiyiddin, & Talib, 2021). This result also, approved that the used of k ≈ 20 and h ≈ 2 in the Monte Carlo simulation model is very good for fitting. Furthermore, ACO is better due to its robust, versatile, and efficient approach in finding the solution to this study problem.

This paper suggests that the finding is not being consistent with the literature finding, i.e. Pon and Current are equivalent to the output and Poff is inversely equivalent to the output. This paper finds that even at low values of Pon, Current, and Poff; still the optimum value of MRR, EWR, and SR can be obtained through PSO and TS. This finding also suggests that manufacturers can obtain the best outputs at lower input values. This is due to, the inputs Pon and Current higher value, required higher production expenses.

In future works some improvements could be made to discover the wider potential in this scope of study, such as under wider constrained inputs are applied to the value of Pon, Current, and Poff. This can help the algorithm to search wider space for a more efficient solution. Besides, outputs, i.e. dimensional accuracy, depth of heat affected zone, and white layer thickness should be applied.

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