THE USE OF TABU SEARCH AND PARTICLE SWARM ALGORITHM IN OPTIMIZING EDM INPUT PARAMETERS TO MACHINED AISI L3 TOOL STEEL

(PENGGUNAAN ALGORITHM TABU SEARCH AND PARTICLE SWARM BAGI MENGOPTIMUMKAN PARAMETER-PARAMETER INPUT PEMESINAN EDM UNTUK MEMESIN AISI L3 TOOL STEEL)

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Abstract

Tool steel material is dominating as cutting tool material because of its good qualities and economical in production line. Besides, EDM Die Sinking is one of the common non-conventional machining in the industry that machine tool steel material. In order to obtain good machined tool steel work piece, and align in this case, the influence input parameters to machine by EDM Die Sinking must be studied. This context is ideal for the study of optimization, which optimized input parameters can be obtained to result good output parameters. Therefore, this paper aims to optimized EDM Die Sinking input parameters by using two soft-computing approached namely Tabu Search and Particle Swarm Optimization. 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. Result from this study finds that the proposed approaches are successfully obtained better results than through 3D Response Surface approach used in previous study. In addition, the predicted optimized input parameters are more economical to be applied in production line. Overall, this study helps manufacturers reduce production expenses for having a good output at lower rate of current supply.

Keywords: EDM die sinking, multi-objective optimization, tabu search, particle swarm optimization, tool steel

Abstrak

Bahan *Tool steel* mendominasi sebagai bahan alatan pemotongan kerana kelebihan kualiti dan ekonomi dalam barisan pengeluaran. Di samping itu, *EDM Die Sinking* adalah satu daripada mesin bukan konvensional yang biasa memesin bahan *tool steel*. Bagi mendapatkan benda kerja tool steel termesin yang baik, dan selari dengan kes ini, pengaruh parameter-parameter masukan bagi memesin dengan *EDM Die Sinking* mestilah dikaji. Konteks ini sesuai dengan kajian pengoptimuman, di mana parameter-parameter masukan teroptimum boleh diperoleh bagi menghasilkan parameter-parameter keluaran yang baik. Oleh yang demikian, kertas kajian ini bertujuan mengoptimumkan parameter-parameter masukan *EDM Die Sinking* dengan menggunakan dua kaedah *soft-computing* yang dinamakan *Tabu Search* dan *Particle Swarm Optimization*. Parameter-parameter masukan yang terpilih adalah Arus, Denyut Masa *On*, dan Denyut Masa *off*; dan parameter-parameter keluaran adalah Kadar Pembuangan Bahan, Kadar Penggunaan Elektod, dan Kekasaran Permukaan. Keputusan daripada kajian ini mendapati kaedah yang dicadangkan berjaya menghasilkan keputusan yang lebih baik berbanding kaedah kajian *3D Response Surface* yang digunakan dalam kajian lepas. Tambahan pula, parameter-parameter keluaran yang dijangkakan adalah lebih ekonomi digunakan dalam barisan pengeluaran. Keseluruhannya, kajian ini membantu pengilang-pengilang mengurangkan perbelanjaan barisan pengeluaran untuk mendapatkan hasil yang baik pada penggunaan arus yang lebih rendah.

Kata kunci: EDM die sinking, pulse on time, pulse off time, current, tabu search, particle swarm optimization

Introduction

Carbon steel and alloy steel can be made for cutting tools, also known as tool steel. The tool steel generally well known of good hardness, wear resistance, and able to work at high temperature (Mandaloi et al., 2015). Besides, tool steels are much economical compared to other material tool types such as carbides, titanium, and Inconel. L-type is one of tool steel grade material for special purpose tool steel application. The application mainly in precision gauges, bearings, rollers, cold-heading dies, jigs, shears, punches, and drills (Alavudeen, Venkateshwaran, & Jappes, 2006). This widely applied in various application attracted many manufacturers to use the material to process in their production.

Machining tool steels by conventional machining resulted dimension inaccuracies, residual stresses, and high surface roughness and excessive tool wear (Shrivastava & Pandey, 2018). Alternative machining to avoid these disadvantage are the use of a non-conventional machining such as Abrasive Water Jet Machining, Laser Machining, and Electro Discharged Machining (EDM). The advantage used of EDM is minimum chattering, residual stresses, and mechanical vibration (Niamat et al., 2020). The most common type in EDM is Wire-Cut and Die Sinking. In this paper, the interest is on EDM Die Sinking to machine AISI L3 tool steel material. By EDM Die Sinking, electrode shapes the work piece through generating electric sparks once the electrode and the work piece get close. The sparks are the formation of work piece in fine pieces, and this resulted the cut of the work piece. Hence, the machining output is dominated by current supply to generate the sparks the whole operation (Khajuria et al., 2019). The pattern of the current supply depending on the quantity of pulse on time and pulse off time. Pulse on time is a duration which peak current is supplied to work piece. On the contrary, pulse off time is a duration which no current supply or no machining take place (Uthayakumar et al., 2019). Current, pulse on time, and pulse off time are these paper input parameters.

Study in relation between EDM and tool steel in modelling and optimization is literature reviewed as follows. Mandaloi et al., (2015) and Dhobe, Chopde, & Gogte (2014) using Taguchi approach to determine the optimum machining input parameters by EDM to machine AISI M2 tool steel. The used of soft-computing approach has interest Baraskar, Banwait, & Larois (2013) applied Multi-Objective Genetic Algorithm and Kanlayasiri & Jattakul (2013) applied by Desirability Function in their study. In addition, the fused method of Grey Relational Analysis and Fuzzy Logic is applied by Lin & Lin (2005) to optimize the machining. Also recorded that by statistical approach Sultan, Kumar, & Gupta (2014) and Vates & Singh (2013) optimized the EDM machining using Response Surface Methodology. All of these studies 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.

According to Niamat et al. (2020), based on his literature review study, it is found that MRR, EWR, and SR in related to L-type tool steel is too limited or no research has been conducted especially on optimization of input parameters. Thus, this justifies this paper, to study in this line with other alternative approach. This paper aims to optimize the input parameters, i.e. MRR, EWR, and SR through two soft-computing approaches namely Tabu Search and Particle Swarm Optimization. The remaining sections of this paper includes materials and methods to discuss the methodology applied, discussion of the finding explained in result and discussion section, and end up with a section of the conclusion.

Materials and Methods

The methodology in this paper is organised as in Figure 1. The experimental data is applied from paper Niamat et al. (2020) that conducted based on three levels of machining input parameters as shown in Table 1. The input parameters are based on Mandaloi et al. (2015) and Mondal et al. (2015) studied concluded that input parameters influence the Pulse on time (Pon), and Current (C) significantly response through EDM operation. Their study concluded that MRR, EWR, and SR are proportional to Pon and Current applied. In addition, studied by Pellicer, Ciurana, & Delgado (2011) and Sultan, Kumar, & Gupta (2014), suggested that MRR, EWR, and SR are inversely proportional to Pulse off Time (Poff). Thus, these are the three parameters that will be used in the study. Besides, for output parameters, previous studied such as Padhi et al., (2018) had conducted a study on EDM performance, concluded that it can be measured by MRR, EWR, and SR. The study is based on the EDM with Rapid Tooling Electrode to machined AISI D2 tool steel material, which is parallel and replicate to this study.

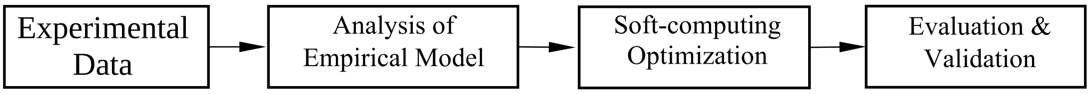


Figure 1: The Methodology

Table 1: The process Parameter (Source from: Niamat et al., 2020)

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

Table 2: The Initial Result (Source from: Niamat et al., 2020)

Pon (μs)	C (A)	Poff (μs)	MRR (mm^3/min)	EWR (mm^3/min)	SR (μm)
220.21	13.17	50	4.47186	1.80364	2.01094
220.13	13.21	50	4.48082	1.80449	2.02074
215.90	13.28	50	4.45033	1.7644	2.03568

$$\begin{aligned} MRR = & -22.22697 + 0.043425 \times Pon + 1.88978 \times C + 0.089232 \times Poff \\ & + 1.54167x10^{-3} \times Pon \times C + 6.225x10^{-5} \times Pon \times Poff \\ & - 3.46667x10^{-3} \times C \times Poff - 7.57938x10^{-5} \times Pon^2 - 0.063806 \times C^2 \\ & - 4.027x10^{-4} \times Poff^2 \qquad Eq.1 \end{aligned}$$

$$\begin{aligned} EWR = & -0.54243 + 6.462940^{-3} \times Pon - 0.023750 \times C - 4.06579x10^{-4} \times Poff \\ & + 5.66667x10^{-4} \times Pon \times C + 4.95x10^{-5} \times Pon \times Poff \\ & - 1.68651x10^{-5} \times Pon^2 \\ & - 7.68421x10^{-5} \times Poff^2 \qquad Eq.2 \end{aligned}$$

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

This study used the three equations from Niamat et al. (2020) for optimization study. For the matter, this paper acts as a new perspective of study by applying other potential optimization approaches. Niamat et al. (2020) optimized the input vector of a machining system, i.e. Current, Pon, and Poff by the used of Analysis of Empirical Model to develop three machining models and 3D Response Surface to determine a set of optimized input parameters. The study used Die Sinking EDM with a round copper electric rod to machine AISI L3 material. By the Analysis of Empirical Model, the three equations are generated as per Eq. 1, Eq.2, and Eq.3. Then, the 3D Response Surface (3DRS) the optimum value is obtained and the result is shown in Table 2. In this paper, the study is to optimized the input machining parameters by soft-computing approaches i.e. Tabu Search and Particle Swarm Optimization.

The optimization study can be generalized into statistical and soft-computing. The justification for the use of soft-computing due to the approach resulted with specific optimal parameter values. Contrariwise, the statistical approach result is explicitly on the value set while in experiment stage. Fundamentally, one input (x) to one output (f(x)) correlation is simple to obtain the minimum point by a differential equation (df(x)/dx). However, minimum point of multiple input (x_1, x_2, …) to single output correlation is a complex and long problem solving by manual calculation. Therefore, by soft-computing approach, an algorithm searches automatically the most minimum output point or global optima out of other minimum points or local optima, by repetitive calculations. Here, the selected soft-computing approaches are Particle Swarm Optimization (PSO) and Tabu Search (TS). This paper is multi-objective optimization study, hence the algorithm variants that suited for multi-objective are selected.

Kennedy & Ebenhart (1995) coined the PSO that inspired by a group of animal searching for the best source of food. The algorithm advantage includes it is a recent trend of optimization algorithm with anti-local optimum trap strategy. Besides, PSO is a simple implementation, parallel computation, short computational time, and efficient in finding solution for complex model (Abdmouleh et al., 2017). Hence, these advantages back the algorithm used in this study. There are variant algorithms for multi-objective of PSO available, and the selected variant is multi-objective PSO based on Dynamic Neighbourhood. By the generated data, i.e. particles through the algorithm, the information is gathered that known as a solution. Because of there are solutions generated, thus by Pareto-Front is used so that the best particles among the non-dominated solutions i.e. optimal solution, can be selected. From the selected particles, then a leader is selected is stored in an archive. Leaders are selected from an archive using the neighbourhood information mechanism. This is done by adopting additional information from the neighbourhood in the archive. In this paper, the information is the distance between the archive particles neighbourhood. Based on this distance, the nearest distance out of this leader particles are selected as the solutions used for this study.

```
Particle initial Setting
Initialize an archive = 0
Repeat compute fitness value for each
  particle setting
    compute the best fitness value
    Begin perform PSO operation
        compute Speed
        compute Position
        perform Stored the best fitness value
    Update the content of the archive
    Calculate new position in archive after select Leader
        End
    Set n = n + 1
Until termination criteria satisfied
```

(a)

```
Sbest = S0
bestSol = Sbest %%% Sol = Solution
TabuList ← [ ]
while (NOT StoppingSol ()) do
   Generate solutions in the neighborhood of Sbest
   set SSol as the first candidate in the Sbest Neighborhood
   for (SSol in Sbest Neighborhood) do
       if (SSol NOT in TabuList AND fitness SSol) > fitness(bestSol)
          then bestSol ← SSol
       end if
   end for
   if (fitness(bestSol) > fitness (Sbest) then
       Sbest ← bestSol
   end if
   Update Tabulist (switch the bestSol)
   if (tabuLength > maxTabuLength) then
     Remove the first element from TabuList
   end if
end while
return Sbest
```

(b)

Figure 2: Standard Algorithm for (a) Particle Swarm Optimization and (b) Tabu Search

Another selected algorithm is Tabu Search, that proposed by Glover (1986) in solving combinatorial optimization problems i.e. multi-objective. The search technique used is the steepest going down to pair wise that switch analytically. TS uses an initial solution at the beginning for searching the improved solution within different neighbourhoods (Aljarah et al., 2020). In the case of Multi Objective for TS in this paper, it still follows the standard algorithm to generate solutions. The changed is, the models or fitness functions i.e. MRR, EWR, and SR are modified into single fitness function. Initially, the developed fitness functions or models will be normalized from MRR, EWR, and SR into MRR", EWR", and SR" are developed with the total coefficient value must be equal to one i.e 0.3 + 0.3 + 0.4 = 1.0. This technique suggested by Sadeghi et al. (2011), resulted a new objective function *Min(f(x))* expressed by an equation as follows Eq.4. Thus, the single solution later generated a set of three outputs and optimized input. Similarly, as in PSO, the best solution is selected though Pareto-Front.

$$Min\big(f(x)\big) = 0.3MRR'' + 0.3\mathrm{EWR}'' + 0.4SR'' \qquad Eq.4$$

Pareto-Front is used when a multi-objective problem is applied to optimization study. This is due to, there are plural optimal solutions obtained from these multi-objective problems (Kirwin et al., 2020). By Pareto-Front a graph that depicted an objective for each axis is developed. Here, three dimensional graph is developed with each axis represent MRR, EWR, and SR. Hence, the most efficient point i.e. optimal front is selected from the graph.

In optimization, the prime element is making a decision of conditions for evaluation. Here, in multi-objective optimization with three objectives, i.e. MRR, EWR, and SR, hence three conditions of minimum or maximum objectives must be evaluated. Due to the three objectives are economical in low values, hence the points and the results evaluation concerning the issues are as follows:

(1) The optimization minimum MRR, EWR, and SR values are expected to be lower than the value by the 3DRS approach applied in previous study.

(2) The optimal EDM input parameters by the used optimization are expected to be within the range of experiment values that also reflecting the acceptable machinability conditions. Take note that

the based on literature review, it is found that MRR, EWR, and SR are proportional to Pon and Current applied; and Poff is inversely proportional for the three inputs.

Besides, validation of the finding is conducted by comparing the optimized data generated by the optimization study and this is used to generate values by objective functions or the systems' models. (Zain, Haron, & Sharif, 2010) as in Eq.1, Eq.2, and Eq.3.

Result and Discussion

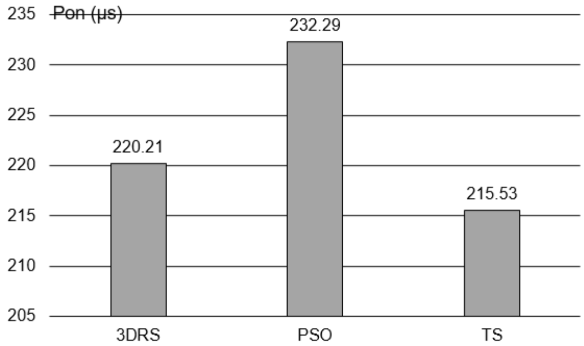
The result of the optimization is summarized in Table 3, it shows three classes of results, i.e. 3D Response Surface (3DRS), PSO, and TS. In this paper, multi-objective optimization focus on three output parameters, namely MRR, EWR, and SR, which concerned of their minimum values. The best minimum value for the MRR, EWR, and SR are obtained through PSO, i.e. 2.68131 mm^3/min, 1.53920 mm^3/min, and 0.86123 μm in sequence. By comparison the minimum of these values, TS is the second efficient, and the third efficient is through 3DRS.

Table 3: The Most Preferred Result from 3DRS (Niamat et al., 2020) and the Top Three Most Efficient Result by PSO and TS

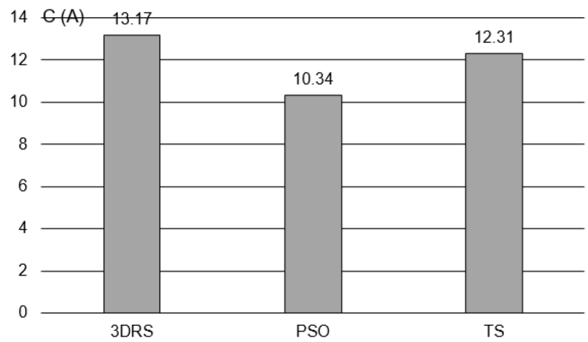
Optimi-zation	Input Parameters			Output Parameters			Most Preferred / Efficient
	Pon (μs)	C (A)	Poff (μs)	MRR (mm^3/min)	EWR (mm^3/min)	SR (μm)	
3DRS	220.21	13.17	50	4.47186	1.80364	2.01094	✓
PSO	232.29	10.34	54	2.68131	1.53920	0.86123	✓
	222.45	10.76	73	2.97497	1.52615	0.99519	-
	213.47	13.17	55	3.65403	1.67538	1.78626	-
TS	215.53	12.31	75	3.52902	1.61562	1.50033	✓
	223.09	12.92	57	3.9136	1.74311	1.72959	-
	209.63	12.95	77	3.53416	1.61414	1.72601	-

Note: 3DRS – 3D Response Surface; PSO – Particle Swarm Optimization; TS – Tabu Search

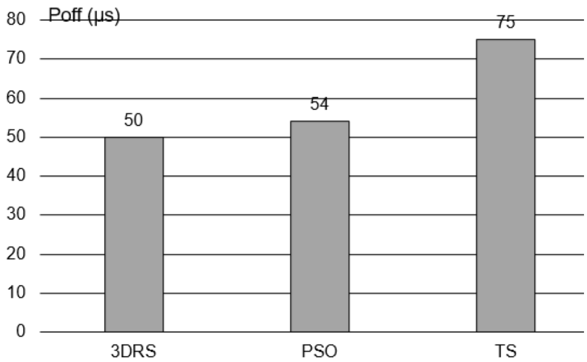
The input parameters can be generalized that in order to obtain the most efficient optimum point, the value for the inputs do not have to be at the maximum value. For instance, the maximum value for the Pon is set to 600 μs but the average optimum point is 222.68 μs; for the Current is set to maximum of 16 A but the average optimum point is 11.94 A; and the set maximum Poff is 150 μs, but the average optimum point is 60 μs. As aforementioned, the maximum setting for the inputs are shown in Table 1. All of these scores are pictured in Figure 3. In addition, generalization can be made that these input results do not suggest which optimization approach perform the best, since the minimum and maximum values distribute unevenly through these approaches.



(a) Pulse on time (Pon)



(b) Current (C)



(c) Pulse off time (Poff)

Figure 3: The Optimized Inputs Based on the most Preferred or Efficient Outputs

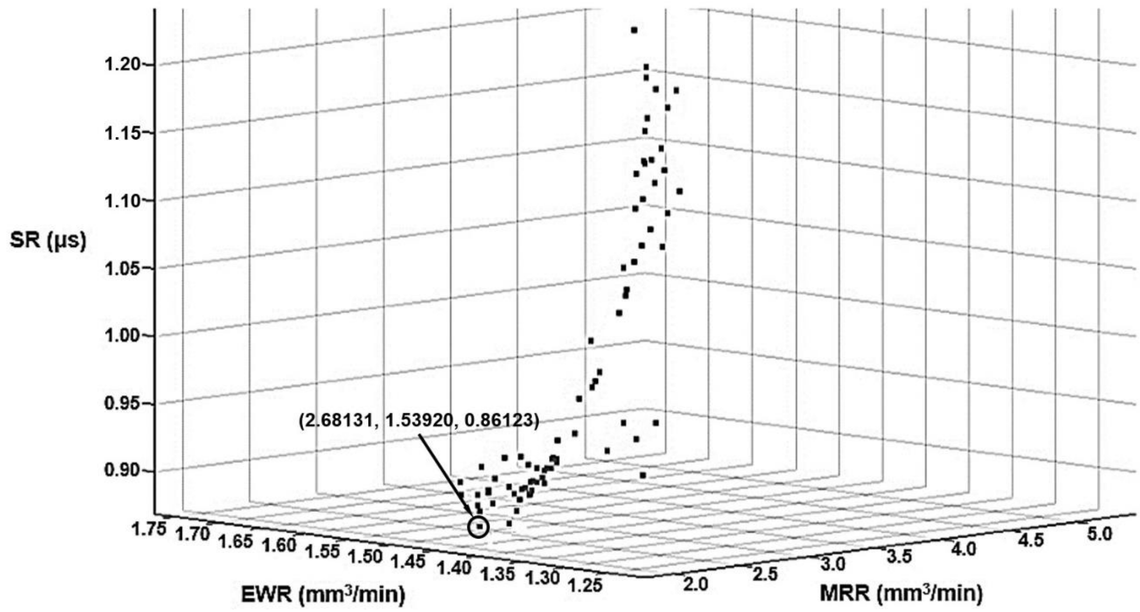


Figure 4: Pareto-Front for PSO with the most efficient point

The Pareto-Front for PSO and TS results are shown in Figure 4 and Figure 5. The most efficient point or optimal is also shown in the figure. By this approach, it is clearly shown the all objectives are agreed with the selection of the most efficient point.

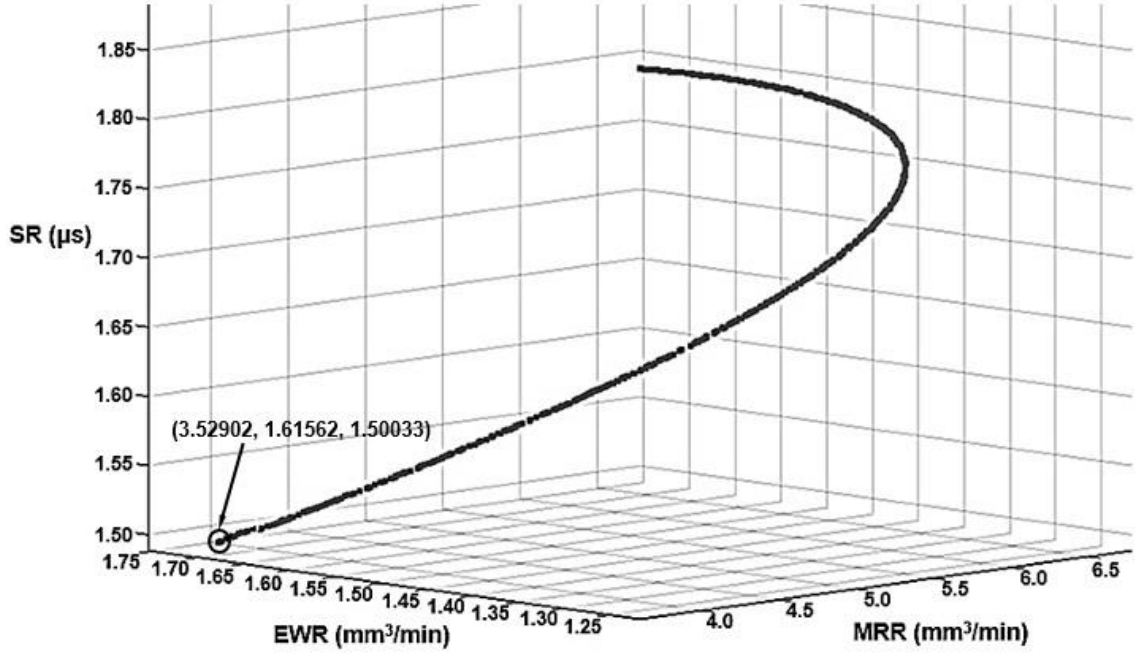


Figure 5: Pareto-Front for TS with the most efficient point

Based on the consideration for evaluation aforementioned, the outputs are found lower than the minimum MRR, EWR, and SR values obtained by the 3DRS approach applied in previous study. In addition, the inputs Pon, Current, and Poff are within the range of experiment values which means acceptable for machining conditions. The validation also conducted by regenerating the obtained valued on the fitness function or the model and the result is matched to the generated values by the used optimization approaches.

Conclusion

Based on the result, it is confirmed that PSO and TS are effective to estimate better results in searching the MRR, EWR, and SR minimum point compared to 3DRS result. The two approaches' search values are lower than the minimum MRR, EWR, and SR values through 3DRS by 4.47186 mm^3/min, 1.80364 mm^3/min, and 2.01094 µm consecutively. The value through PSO for MRR, EWR, and SR minimum values are decreased by 40.04%, 14.66%, and 57.17% in sequence. Besides, the value by PSO for MRR, EWR, and SR minimum values are decreased by 21.08%, 10.42%, and 25.39% successively. This shows the prediction performance of PSO is better than TS.

A conclusion also can be made that this paper finding does not agree with the literature finding – Pon and Current are proportional to the output and Poff is inversely proportional to the output. In this case, 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 too suggest that this finding helps manufacturers to use economical input values and still can obtain the best output. The higher value of input Pon and Current require higher production expenses.

In addition, by the proposed approaches, the recommended machining parameter values are within allowable value range. The allowable range is the experiment set up and acceptable for the Die Sinking EDM machine used in this study. Besides, the proposed optimization approaches result the optimal value beyond the result by 3DRS approach can be achieved. Furthermore, this paper also finds that the input results do not reflect the performance of the approaches performance due to the minimum and maximum input values distribute unevenly through these approaches.

For future works some improvements could be made to discover wider potential in this scope of study, such as under highly constrained cases for the value of Pon, Current, and Poff.

Besides, other output parameters should be considered such as dimensional accuracy, depth of heat affected zone, white layer thickness, and electrode shape. Also suggested that the data model of fuzzy logic and artificial neural network should be applied since the approaches are proven good in data modelling.

References

Alavudeen, A. Venkateshwaran, N., & Winowlin Jappes J. T. (2006). *A Textbook of Engineering Materials and Metallurgy*. Firewall Media.

Aljarah, I., Mafaria, M., Heidari, A. A., Faris, H., & Mirjalili, S. (2020). Clustering analysis using a novel locality-informed grey wolf-inspired clustering approach. *Knowledge and Information System*, *62*(2), 507-539.

Baraskar, S. S., Banwait, S. S., & Laroiya, S. C. (2013). Multiobjective optimization of electrical discharge machining process using a hybrid method. *Materials and Manufacturing Processes*, *28*(4), 348-354.

Dhobe, M. M., Chopde, I. K., & Gogte, C. L. (2014). Optimization of wire electro discharge machining parameters for improving surface finish of cryo-treated tool steel using DOE. *Materials and Manufacturing Processes*, *29*(11-12), 1381-1386.

Kanlayasiri, K., & Jattakul, P. (2013). Simultaneous optimization of dimensional accuracy and surface roughness for finishing cut of wire-EDMed K460 tool steel. *Precision engineering*, *37*(3), 556-561.

Kennedy, J., & Eberhart, R. (1995, November). Particle swarm optimization. In *Proceedings of ICNN'95-International Conference on Neural Networks* (Vol. 4, pp. 1942-1948).

Khajuria, A., Akhtar, M., Pandey, M. K., Singh, M. P., Raina, A., Bedi, R., & Singh, B. (2019). Influence of ceramic Al2O3 particulates on performance measures and surface characteristics during sinker EDM of stir cast AMMCs. *World Journal of Engineering*.

Kirwin, R., Niraula, A., Liu, C., Kovach, L., & Jahan, M. (2020). Optimization of Electric Discharge Machining Based Processes. In *Optimization of Manufacturing Processes* (pp. 29-63). Springer, Cham.

Lin, J. L., & Lin, C. L., (2005). The use of grey-fuzzy logic for the optimization of the manufacturing process. J. Mater. Process. Technol. 2005, 160, 9–14.

Mandaloi, G., Singh, S., Kumar, P., & Pal, K. (2015). Effect on crystalline structure of AISI M2 steel using copper electrode through material removal rate, electrode wear rate and surface finish. *Measurement*, *61*, 305-319.

Mondal, R., De, S., Mohanty, S. K., & Gangopadhyay, S. (2015). Thermal energy distribution and optimization of process parameters during electrical discharge machining of AISI D2 steel. *Materials Today: Proceedings*, *2*(4-5), 2064-2072.

Niamat, M., Sarfraz, S., Ahmad, W., Shehab, E., & Salonitis, K. (2020). Parametric modelling and multi-objective optimization of electro discharge machining process parameters for sustainable production. *Energies*, *13*(1), 38.

Pellicer, N., Ciurana, J., & Delgado, J. (2011). Tool electrode geometry and process parameters influence on different feature geometry and surface quality in electrical discharge machining of AISI H13 steel. *Journal of Intelligent Manufacturing*, *22*(4), 575-584.

Padhi, S.K.; Mahapatra, S.S.; Padhi, R.; & Das, H.C. (2018). Performance analysis of a thick copper-electroplated FDM ABS plastic rapid tool EDM electrode. *Advanced Manufacturing, 6*, 442–456.

Sadeghi, M., Razavi, H., Esmaeilzadeh, A., & Kolahan, F. (2011). Optimization of cutting conditions in WEDM process using regression modelling and Tabu-search algorithm. *Proceeding of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *225*(10), 1825-1834.

Shrivastava, P. K., & Pandey, A. K. (2018). Parametric optimization of multiple quality characteristics in laser cutting of Inconel-718 by using hybrid approach of multiple regression analysis and genetic algorithm. *Infrared Physics & Technology*, *91*, 220-232.

Sultan, T., Kumar, A., & Gupta, R. D. (2014). Material removal rate, electrode wear rate, and surface roughness evaluation in die sinking EDM with hollow tool through response surface methodology. *International Journal of Manufacturing Engineering*, *2014*.

Uthayakumar, M., Babu, K. V., Kumaran, S. T., Kumar, S. S., Jappes, J. W., & Rajan, T. P. D. (2019). Study on the machining of Al–SiC functionally graded metal matrix composite using die-sinking EDM. *Particulate Science and Technology*, *37*(1), 103-109.

Vates, U. K., & Singh, N. K. (2013). Optimization of surface roughness process parameters of electrical discharge machining of EN-31 by response surface methodology. *International Journal of Engineering Research and Technology*, *6*(6), 835-840.

Zain, A. M., Haron, H., & Sharif, S. (2010). Simulated annealing to estimate the optimal cutting conditions for minimizing surface roughness in end milling Ti-6Al-4V. *Machining Science and Technology*, *14*(1), 43-62.