Electrical Discharge Machine using Fuzzy for Fitness Evolutionary Strategies Optimization (EDiMƒESO)

NOOR ELAIZA ABD KHALID, NORDIN ABU BAKAR, FARIDAH SH. ISMAIL, NOOR SHEERA MOHD DOUT
Faculty of Computer & Mathematical Sciences
Universiti Teknologi MARA (UiTM) Malaysia
40450 Shah Alam, Selangor, Malaysia
elaiza@tmsk.uitm.edu.my http://www.fskm.uitm.edu.my

Abstract: - Electrical Discharge Machine (EDM) is one of the engineering machineries which is widely used in manufacturing mould, die, automotive, aerospace and surgery components. EDM performance was measured in the output performance using factors such as Material Removal Rate (MRR), Tool Wear Rate (TWR) and Surface Roughness (SR). The process also depends on the shape of the current pulses and parameter setup. A complex machine needs a complex control ;for example, EDM requires a complex parameter setting such as current (I), pulse time (t_i), duty cycle (η), open-circuit voltage (U) and dielectric flushing pressure (P) to be taken into account as design factors. This paper proposes EDiMƒESO (Electrical Discharge Machine using Fuzzy Fitness Evolutionary Strategies Optimization). EDiMƒESO learning rate is calculated based on performance of the input parameter setting which involves calculating the current (A), pulse time on (μs) and pulse time off (μs) while other parameters are constant. It employs Evolutionary Strategies (ES) technique and Dynamic Fuzzy to predict the most appropriate multi-objective optimization parameter setting for creating various shape template holes on various types of work piece (example: alloy, graphite, copper, etc). EDiMƒESO multi-objective performance testing has shown that this model has a huge potential in achieving multi – objective optimization. The introduction of Dynamic Fuzzy is very useful to give the optimum weight for ES fitness evaluation in this multi – objective optimization. The results have been compared with Mandal's and proved to be better.

Key-Words: - Evolutionary Strategies, Electrical Discharge Machine (EDM), Dynamic Fuzzy, multi – objective optimization, Material Removal Rate (MRR), Tool Wear Rate (TWR), Surface Roughness (SR)

1 Introduction

According to *Oduguwa V. et al (2005)*, *"real world engineering can be characterized as having chaotic disturbances, randomness and complex non-linear dynamic"*. Industries usually comprise of processes that are large scale, multidimensional, and highly uncertain which requires highly complex skilled operators to control process plant. Frequently this has riveted into multi-objective problem that are usually solved by conventional trial and error method which are tedious, slow, costly and inefficient. Hence, this project proposes to replace this conventional method with automated simulated multi-objective solution.

Objectives compete with each other in the multi-objective problem, which means that the optimization of one objective will cost the degradation of others. Thus, multi-objective optimization for processing parameters has become one of the problems in the development of Electrical Discharge Machine (EDM). Traditionally, the selection of the most favorite process parameters is based on experience, empirical formula and handbook [2]. These methods produce inconsistent machining performance and apparently have many limitations and short comings that the desired results often could not be achieved. Grey relation is currently used, but this method cannot be used in multi-objective environment because only one combination of parameter can be obtained. In EDM process, there may not be one single optimal combination of parameters for all processing objectives, which is the best with respect to all other solutions, so grey relation is also imperfect.

EDM is one of engineering machinery which is widely used to manufacture mould, die, automotive, aerospace and surgery components. A complex machine needs a complex control. EDM performance is measured in the output performance such as Material Removal Rate (MRR), Tool Wear

Rate (TWR) and Surface Roughness (SR), for the same energy depending on the shape of the current pulses and parameters setup. EDM requires complex parameter setting such as current (I), pulse time (t_i), duty cycle (η), open-circuit voltage (U) and dielectric flushing pressure (P) that have only been taken into account as optimization design factors [1].

The most challenging problems in EDM are: the way to increase the Material Removal Rate (MRR), the way to minimize Tool Wear Ratio (TWR) and to improve the smoothness of the surface roughness (Ra). Optimization method helps to select values of each parameter for optimum usage.

The purpose of conducting this research is to overcome the three challenges of EDM as stated above using Evolutionary Strategies (ES) since study on ES is very rare as compared to Genetic Algorithm (GA) in multi-objective optimization [3].

This paper proposes EDiM*f*ESO (Electrical Discharge Machine using Fuzzy Fitness Evolutionary Strategies Optimization) as parameter optimization technique. EDiM*f*ESO learning rate is calculated based on performance of the input parameter setting which involves calculating the current (A), pulse time on (µs) and pulse time off (µs) while other parameters are constant. EDiM*f*ESO employ Evolutionary Strategies (ES) technique and Dynamic Fuzzy for fitness to predict the most appropriate multi-objective optimization parameter setting for creating various shape template holes on various types of workpiece (example: alloy, graphite, copper, etc).

2 Data Collection

EDiM*f*ESO is trained using two set of data from primary (own experiment) and secondary (experiment by [8]) sources. For the initial population, 78 data has been taken from [8] and 20 data from experiment.

Then, all data will be used as input for EDiM*f*ESO to measure the accuracy. All the input data will be used as the threshold values for EDiM*f*ESO to find better solutions and propose another set of parameters to optimize the multi-objectives.

3 Methods

3.1 Evolutionary Strategies

Evolution strategies (ES), the third main variant of Evolutionary Algorithm (EA), were founded by Ingo Rechenberg, students at the Technical University of Berlin (TUB). In the beginning, ES were not devised to compute minima or maxima of real-valued static functions with fixed numbers of variables and without noise during their evaluation. The usual goal of an ES is to optimize (some) given objective or quality function(s) *F* with respect to a set of decision variables or control parameters [4].

Historically, this algorithm develops more or less independently and in very different direction. ES generally apply to real value representation of optimization problem, and tend to emphasize mutation over crossover [5]. The main reason of employing ES technique is because of the ability using real number representation that makes it more precise for floating number.

In order to perform this research, a prototype of EDiM*f*ESO is developed based on basic ES [6] inspired by Multi-objective Elitist Evolutionary Strategies [3]. There are four basic steps in ES algorithm.

3.1.1 Representation

The individual, a, consists of 10 genes with each gene represents parameter setting, sigma for mutation, objective function and weighted average respectively. Fig. 1 is the illustration of individual representation.

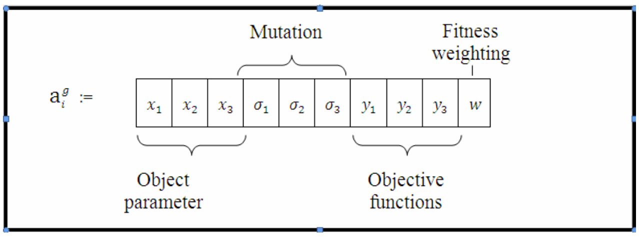

Figure 1: Individual representation in EDiM*f*ESO

Object parameter involved are x_1 which represents current, x_2 as pulse on time, x_3 as pulse off time. Mutation representations are σ1, σ2 and σ3 for each parameter. Objective functions MRR, TWR and SR are represented by y_1, y_2 and y_3 respectively. Meanwhile *w* weighted average imposes for multi-objective optimization.

3.1.2 Initial Population

EDiM*f*ESO begins with 98 individuals for the initial population plus 1 individual from user import.

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Hence, 99 individuals have been selected for initial population which is marked as generation 0. Then, this initial population will be evaluated through its fitness to achieve multi-objective optimization using Dynamic Fuzzy technique. All fit individual, a, will be declared as parents and labelled as μ.

3.1.3 Fitness Evaluation

EDiMfESO will evaluate the fitness for multi-objective optimization of initial population by calculating a weighted average using dynamic fuzzy (as discussed in Section 2.1.1).

On the other hand, for the iterated fitness evaluation inside ES, EDiMfESO needs to define the new output (MRR, TWR, SR) after μ being mutated, it will become λ (child). Calculating λ objective function will impose on empirical equation stated by [7]. The following formulas are the empirical equation for calculating MRR, TWR and SR.

$$\text{MRR} = (4 * 10^4) * i * Tw^{-1.23} \tag{1}$$

$$\text{TWR} = (11 * 10^3) * i * Tt^{-2.38} \tag{2}$$

$$\text{SR} = 0.0225 * i^{0.29} * (y + z)^{0.38} \tag{3}$$

Where,
i = current (A)
T_w = melting point of work piece (˚C)
T_t = melting point of tool (˚C)
T_{on} = pulse on time (μs)
T_{off} = pulse off time (μs)

The research covers three types of workpiece (stainless steel, carbon steel and SDK61) and electrode tool (copper, copper tungsten and graphite) with fixed melting point values.

3.1.4 Mutation

Mutation is the main operator in an ES algorithm. In this phase, all μ will be mutated by random σ. New mutated λ must obey the density function as stated in [6]. This λ is generating through mutation as below.

$$\hat{y} := y + z \tag{4}$$

with

$$z := \sigma((N_1(0,1) \dots N_N(0,1)) \tag{5}$$

where N will obey density function (7) for self adaptive and reduce the possibilities of convergence.

$$f(\hat{y}i) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(\hat{y}i - yi)^2}{2\sigma^2}} \tag{7}$$

3.1.5 Selection

In selection , this research used Multi-objective Elitist Evolutionary Strategies, where it maintains old generation called elitist. Hence, the selection will use (μ+λ)-ES. It is referred to as "*plus selection*". It notices that both parent and child are copied into the selection pool(ρ). Therefore , ρ = μ + λ. According to [6], plus selection suits for combinatorial problem and should have finite size search space.

3.2 Dynamic Fuzzy

Since EDM's objectives involve combination of high and low values, dynamic fuzzy technique is used to produce single weight fitness noted as *w*.

Standard fuzzy initializes the fuzzy set of trapezoid or triangle in the beginning. In spite of this, EDiMfESO fitness evaluation has modified the standard fuzzy technique where the fuzzy set ranges change with every generation. The reason for constructing this kind of technique is to meet the nature of ES which evolves through generation. If the ranges are constant, it cannot return the fittest weight for each individual. After going through dynamic fuzzy process, EDiMfESO considers the highest *w* as the most optimal for multi – objective solution and vice versa.

Fuzzy algorithm has four steps which is fuzzification, rule evaluation, aggregation of rule output and defuzzification. After the fuzzy set has been initialized, each objective function will be set as input for each fuzzy set respectively. The membership function (mf) value will be evaluated in rule evaluation step. Finally, the rule aggregation of output will calculate and produce weighted average (WA). All WA is calculated based on Sugeno style as shown in equation (6).

$$WA = \sum_{i=0}^{n} \frac{(rule\ (n) * singleton\ value)}{\sum rule} \tag{6}$$

Singleton value is obtained from fuzzy set, where 1 denotes poor, 2 is average and 3 is good. Once the WA is calculated, that value will be defuzzification and considered as weighting fitness for μ. Fig. 4 is the example of fitness measure for 100 generation. The value with weight more than or equal to 2.5 is consider as fit.

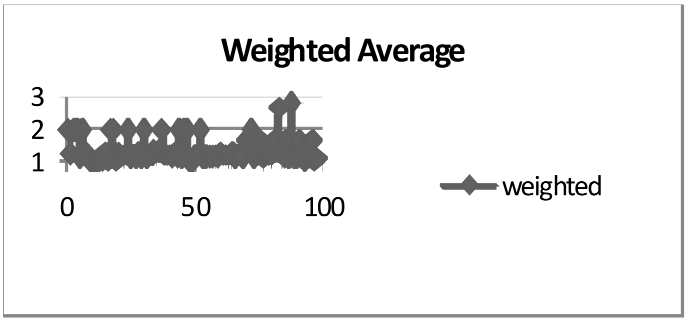

Figure 4 : Example of individual fitness in 100 generation.

4 Result

The result of EDiM*f*ESO is measured in 2 phases. Firstly, the accuracy of EDiM*f*ESO with actual experiment (primary and secondary data). Secondly is to measure the performance of EDiM*f*ESO to propose better parameter setting in order to achieve multi-objective optimization.

4.1 Evaluation Results

Result for the model evaluation is important to show the persistence performance of EDiM*f*ESO with actual EDM. This outcome will be the threshold for EDiM*f*ESO to find better parameter setting in order to achieve optimum multi-objectives.

4.1.1 Primary data comparison

Fig. 5 shows the comparison between EDiM*f*ESO predicted outcomes with experiment result on MRR.

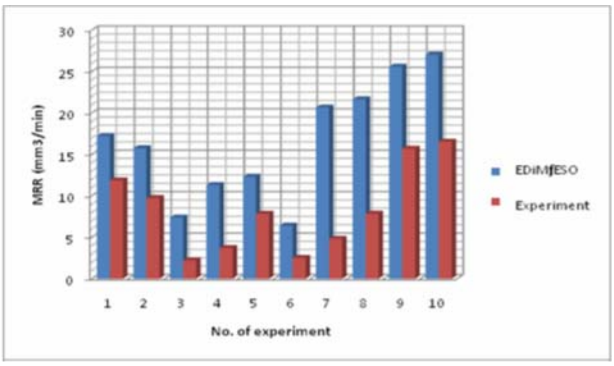

Figure 5 : Comparison of experiment and EDiM*f*ESO for MRR

Results from EDiM*f*ESO show persistence with experiment result. Root Mean Square Error (RMSE) is used to measure the error percentage. The outcome for MRR RMSE is 9.13. This result is acceptable due to the 10% reservation for errors in engineering Therefore, it can be concluded that EDiM*f*ESO result is quite accurate .

Comparison for TWR is shown in Fig. 6.

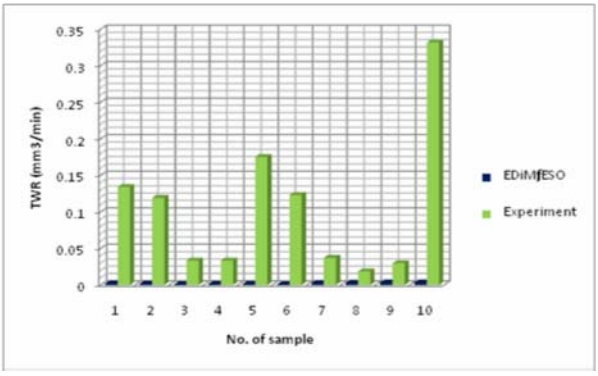

Figure 6 : Comparison of experiment and EDiM*f*ESO for TWR

The graph above shows huge differences between EDiM*f*ESO and experiment result for TWR. RMSE calculation obtained 0.14. Although the error is small,it is not so well because the range of maximum TWR (mm3/min) is also small. It can be considered that formula (2) used to calculate TWR is not suitable and result of EDiM*f*ESO for TWR accuracy is also not precise.

Lastly,the accuracy of EDiM*f*ESO for SR is shown in Fig. 7. The experiment has measured the SR using ALICONA 3D Optical machine.

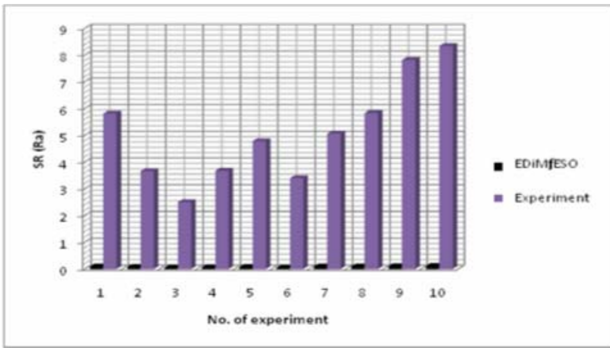

Figure 7 : Comparison of experiment and EDiM*f*ESO for SR

The difference from experiment and EDiM*f*ESO is clearly shown. RMSE is recorded as 5.32. The formula used (3) might also be considered as less suitable for predicting EDM result on SR. As a conclusion, result of EDiM*f*ESO for SR accuracy is also not promising.

4.1.2 Secondary data comparison

Mandal experiment measured the MRR and TWR only, therefore this comparison will also focus on those two objectives as well. Fig. 8 shows the comparison result for MRR between Mandal experiment data and EDiM*f*ESO.

The result of MRR between EDiM*f*ESO and Mandal experiment is not consistent. This might be due to other parameters in Mandal's experiment is unknown making it to be out of control. RMSE calculated for secondary data MRR as 19.26. Subsequently, data comparison for TWR is as shown in Fig. 9. Result of comparison between the two experiments is clearly unjustified. RMSE also show 1.70 errors. However, it is proved that equation used to predict TWR need to be enhanced. Even though EDiM*f*ESO predicted outcome is not convincing, it is accepted because EDiM*f*ESO only used user input values as

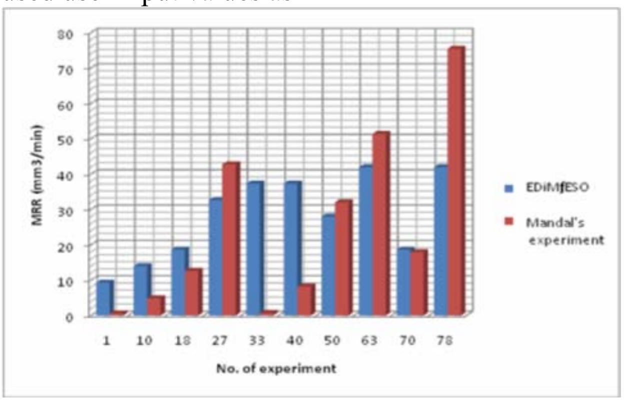

Figure 8 : Comparison of Mandal's experiment and EDiM*f*ESO for MRR

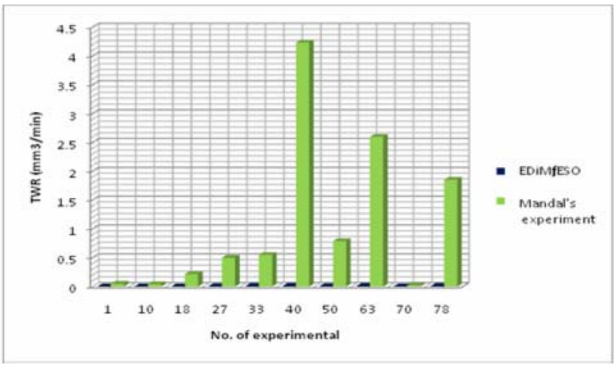

Figure 9 : Comparison of Mandal's experiment and EDiM*f*ESO for TWR

The threshold value to find better multi-objective optimum solution. The result shows that only equation used for MRR is reliable to predict EDM result. TWR and SR equations used are not suitable because that empirical equation is not necessary to be perfect.

There is also other research which used alternative equation for SR, but the result is much worse than the proposed equation. Other factors might be numerous parameter control which effect the result, yet had been disregard in this project scope. Result summary accuracy is reported in Table 1.

Table 1 : Summary of data accuracy comparison result

	MRR	TWR	SR
Data consistency	Average	Poor	Poor
Equation reliability	Reliable	Not reliable	Not reliable

4.2 Result of EDiM*f*ESO for multi-objective

The parameter input data is selected randomly, parallel with its significance for novice user of EDM who has no idea on suitable initial input values. Table 2 is the random parameter input for testing. Meanwhile, Fig. 10, Fig. 11 and Fig. 12 below show the performance of EDiM*f*ESO in proposing suitable input to optimize MRR, TWR and SR respectively.

Table 2 : User random input

No. of experiment	Current (A)	T_{on} (μs)	T_{off} (μs)
1	4.3	53	60
10	6.1	167	130
18	8.2	247	134
27	14.4	502	192
33	16.2	24	27
40	17	34	53
50	12.7	248	49
63	18.5	307	142
70	7.8	491	173
78	17.8	342	79

All testing results produced by EDiM*f*ESO shows extremely superior output. It meets the multi-objective requirement as shown in Fig. 10 where all MRR produce higher values than the thresholds. On the other hand, Fig. 11 and Fig. 12 show the reverse requirement where it produces better optimized result performance than benchmark.

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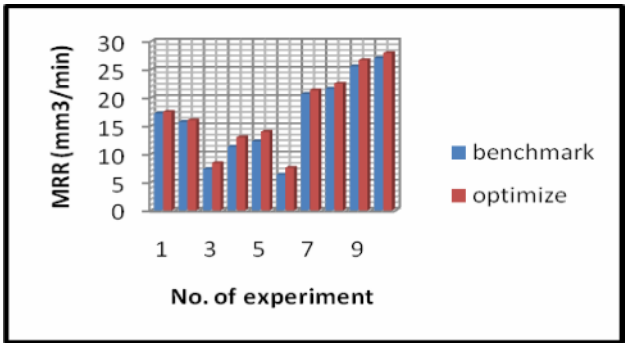

Figure 10 : Testing result to measure MRR

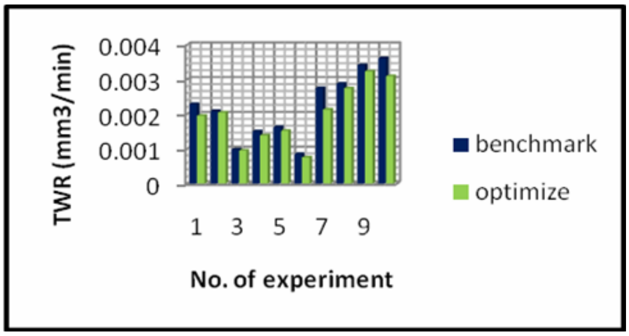

Figure 11 : Testing result to measure TWR

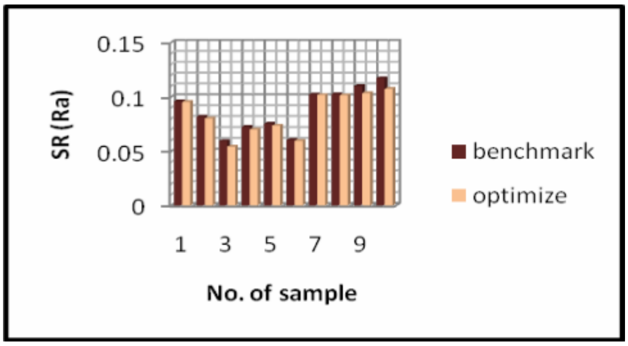

Figure 12 : Testing result to measure SR

5 Conclusion

To conclude, Evolutionary Strategies (ES) technique is admirable in solving multi-objective optimization problems . Although this technique is rarely used , it has huge potential. Since the specialty of ES is its ability in mutation, it can learn and mutate with small changes to make it close to the objective function. As proven in this research, the proposed optimized result has small difference with the original benchmark and gives promising multi-objective optimal solution.

5.1 Recommendation

This research recommends the use of dynamic fuzzy. In a different way of standard fuzzy, the range of fuzzy set must be initialized in the early stage of the experiment. Besides, the fuzzy range is fixed all the way. For Dynamic Fuzzy, the range is set based on MRR, TWR and SR range through out the generations and changes in each generation.

Secondly, engineering expert need to make future study and enhancement on creating formula to calculate MRR, TWR and SR. there are numerous empirical formula recorded, however the formula proposed by [7] only suit for MRR. In this research, most of other parameter setting assumed to remain silent. The parameters used in this model have certainly improved the performance of EDM and proved to be acceptable.

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