# Multi-objective optimization using Fuzzy Evolutionary Strategies Optimization

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***Abstract*—** This paper proposes EDiM*f*ESO (Electrical Discharge Machine using Fuzzy Evolutionary Strategies Optimization) as a multi-objective optimization to control parameters in Electrical Discharge Machine (EDM). EDM is engineering machinery which is widely used in manufacture mould, die, automotive, aerospace and surgery components. EDM performance is measured by three output performance which is Material Removal Rate (MRR), Tool Wear Rate (TWR) and Surface Roughness (SR). EDiM*f*ESO learning rate is calculated based on performance of the input parameter setting involving the calculation of current (A), pulse time on (µs) and pulse time off (µs) while other parameters are set to constant. EDiM*f*ESO is a hybrid of evolutionary strategies (ES) technique (as the multi-objective algorithm) and dynamic fuzzy (as the fitness to predict the most appropriate multi-objective optimization parameter setting). EDiM*f*ESO multi-objective is proven to be successful in achieving multi – objective optimization.

***Keywords*—** Evolutionary Strategies, Electrical Discharge Machine (EDM), Dynamic Fuzzy, multi – objective optimization, Material Removal Rate (MRR), Tool Wear Rate (TWR), Surface Roughness (SR)

## I. Introduction

INDUSTRIES usually comprises of processes that are large scale, multidimensional, high uncertainty which requires highly complex skilled operators to control process plant. Frequently this 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.

Advanced industries such as automobile, aeronautics, nuclear, mould, tools and die making often uses advance materials with high strength, high hardness, temperature resistance and high strength. This materials inturn need advance machineries for manufacturing processes to create complex shapes and geometries [1]. Conventional machines such as turning, milling and drilling are often used but it is difficult to attain good surface finish, close tolerance and high manufacturing cost thus the advent of a more accurate machine called Electrical Discharge Machining (EDM) [2].

EDM uses energy-based technique that work with high-strength in contactless manner [1] [3]. EDM erodes materials from the work piece via sequence of discrete sparks between electrode tool and work piece that pass through electrical discharges which causes the work piece to plunge in a liquid dielectric medium [4]. EDM is desirable due to its ability to mould advance materials into desired shape and size that require dimensional accuracy and productivity. Futhermore this machine is suitable to shape conductive material such as metals, metallic alloys, graphite, or ceramic materials [5]. Generally, there are 2 types of EDM which is Sinker EDM and Wire EDM.

However achiving the optimum outputs is not easy because the EDM manufacturing process involves more complex parameter control which can affect the efficiency and stability of the process. The parameters adjustment affects 3 important output objectives which is material removing rate (MRR), Tool/electrode wear ratio (TWR) and surface roughness (SR) [6]. Mehta suggested that the characteristics of MRR can be improved by optimum control of manufacturing conditions such as work-tool combination, electrode polarity, peak current, pulse ON/OFF time, duty cycle factor, flushing pressure and process stability. On the other hand the Tool Wear Rate (TWR) involves the use of a set of electrodes consisting of copper, graphite or copper tungsten. Three main factors that affect the TWR is intensity, pulse time and flushing pressure. Finally SR and the diameter of discharge point increases with higher in pulse-ON time and discharge current. The best result of EDM output objective can be achieved by increasing MRR, decreasing EWR and reducing the SR [7]. Thus optimizing the parameters to achive the three objectives involves is not an easy tasks.

Oduguwa regards engineering process as chaotic disturbances, unpredictable with complex non-linear dynamic parameters [8]. Objectives compete with each other in the optimization process which means that the optimization of one objective might cost the degradation of others [6]. Optimizing the EDM outputs requires highly skilled operators to control multidimensional parameters and high uncertainty process. Obviously this method produces inconsistent machining performance and apparently has many limitations and shortcomings . Frequently this riveted into multi-objective problem that are usually solved by conventional trial and error method which are tedious, slow, costly and inefficient.

Many attempts have been done to automatically optimize the parameters to produced maximum outputs namely multi objective optimization (MOO). Previous techniques exerimented to solve the MOO are such as Genetic Algorithm [9][25], Grey Relational Analysis [10], Taguchi Method [4], Artificial Neural Network [11], Pareto-optimal [12][27], Non-dominated Sorting Genetic Algorithm [12], Fuzzy Logic [13][26][29], Particle Swarm Optimization[28], evolutionary algorithm[30] and Evolutionary Strategies [14] [15] [16].

Initially Evolutionary strategies (ES) is design for engineering field to improved aerodynamic shapes [14]. ES generally is applied to real value representation of optimization problem [17]. In addition, ES technique is non-dominating other individual during selection [18]. Finally, ES characteristic strongly emphasis on mutation for creating offspring is really helpful for continuous parameter optimization [9]. However, the implementation and research on ES is rare being use because its complexity.These positive characteristic of ES makes it suitable in solving multi-objective optimization problems [17] [18] [19].

As described in the previous paragragh numerous experiments and method had been used to predict the most desirable parameters for EDM. Thus this paper proposes evolutionary strategies (ES) in the attempt to automatically optimize the three outputs of the Sinker EDM which is MRR,TWR and SR. The parameters that need to be set are limited to amount of current, the length of pulse on time and the length of pulse off time.

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 in crating various shape template holes on various types of work-piece.

## II. Data Collection

EDiM***f***ESO is trained using two sets of data that is secondary data obtained from [9] and 20 data from experiment done in the mechanical engineering Lab in University Technology Mara Malaysia. These data are used as fitness function which provides the benchmark for EDiM***f***ESO to find better solution and propose alternatives of parameter setting that meet the multi-objective optimization. The test data are based on three types of work piece which is stainless steel, carbon steel and SDK61 while the electrode tool used are copper, copper tungsten and graphite. Each workpiece and tool are bounded with fixed melting point values as shown in Table 1.

Table I Melting point for workpiece and tool

| Workpiece | Melting Point (˚C) | Tool | Melting Point (˚C) |
|---|---|---|---|
| **Stainless Steel** | 1510 | **Copper** | 1084 |
| **C40 Carbon Steel** | 2600 | **Copper Tungsten** | 3410 |
| **SKD61** | 2600 | **Graphite** | 3500 |

### A. Primary data

The primary data is obtained from trial and error experiments done using die-sinking Electrical Discharge Machine (EDM). The EDM model used is NC Electric Discharge Machine Mitsubishi EX30 E. Fig 1 is the picture of NC EDM.

Fig. 1 NC EDM EX-30 from Mitsubishi

Twenty pieces of stainless steel plat samples of stainless steels are use as work-piece and four coppers are used as electrode. These samples undergo EDM machining process with manually set parameters and materials selection. During the process, all the parameters are set to constant values except for three parameters which us current, pulse time on and pulse time off. These parameters are varied randomly during the experiments to provide a diversified range of the final results. The time constraints for the machining samples are fixed at 30 minutes per sample. Table 2 shows 20 samples for variation of parameter used.

Table II selected current, pulse time on and pulse time off

The plate machining involves the measurements of the before

| Specimen | Current | Pulse Time on | Pulse Time off |
|---|---|---|---|
| 1 | 3.5 | 8.0 | 9.5 |
| 2 | 3.2 | 7.3 | 5.0 |
| 3 | 1.5 | 5.5 | 4.0 |
| 4 | 2.3 | 6.5 | 5.0 |
| 5 | 2.5 | 7.0 | 5.0 |
| 6 | 1.3 | 6.0 | 5.0 |
| 7 | 4.2 | 8.0 | 10.0 |
| 8 | 4.4 | 8.0 | 9.5 |
| 9 | 5.2 | 9.0 | 9.5 |
| 10 | 5.5 | 9.0 | 9.5 |
| 11 | 6.2 | 10.0 | 12.9 |
| 12 | 6.5 | 10.0 | 12.9 |
| 13 | 7.2 | 10.0 | 12.5 |
| 14 | 7.5 | 10.1 | 12.7 |
| 15 | 8.2 | 10.3 | 11.7 |
| 16 | 8.5 | 10.1 | 12.8 |
| 17 | 0.1 | 12.9 | 4.0 |
| 18 | 0.4 | 12.8 | 1.0 |
| 19 | 5.3 | 9.0 | 10.0 |
| 20 | 7.3 | 10.0 | 8.0 |

and after weight of work pieces and tools. Both the selected parameters (current, pulse time on and pulse time off) and the measured weights are used to calculate the MRR, TWR and SR values.
Equation (1) shows the equation for MRR.

$$MRR = \frac{(W_i - W_f)}{\rho_s t} \tag{1}$$

where,

*Wi* *is* the weight before the experiment
*Wf* is weight after the experiment.
$P_s$ is the density of the stainless steel give is 0.0078 g/mm3.
t is the time of machining sample.

The machining evaluation of TWR also can be expressed in the same way of MRR as shown in in equation 2.

$$TWR = \frac{(E_i - E_f)}{\rho_{Cu} t} \tag{2}$$

where,

$E_i$ *is* weight initial before machining sample,
$E_f$ *is* weight after the machining sample.
$\rho_{cu}$ is the density of the cooper give is 0.00894g/mm3.
T is the time of machining sample.

Finally the SR measurement are obtained from the experiments conducted using the ALICONA 3D Optical Measurement Machine. The surface roughness of the sample is taken as Ra value. The SR values are determined by first capturing the image of the surface texture and image processing method. The fig. 1 shows an example of surface roughness image captured for specimen 1.

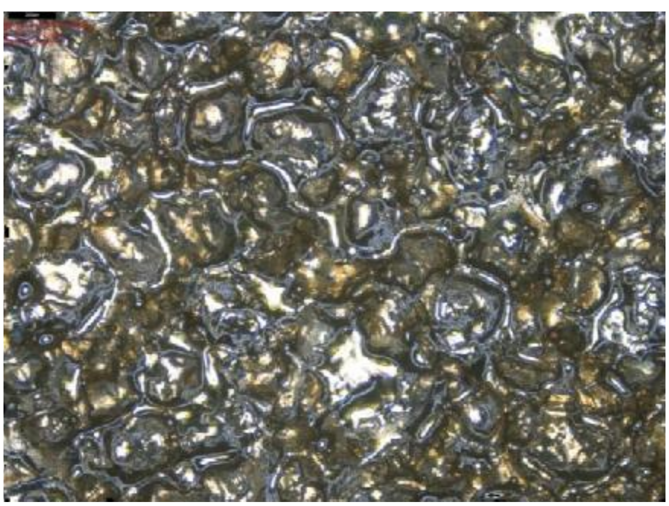

Fig. 1 image captured for surface roughness from specimen 1

Figure 2 shows the graph produced using image processing method that enables ALINOCA 3D Optical Measurement Machine to determine depth against path length. These measurements indicates the SR values

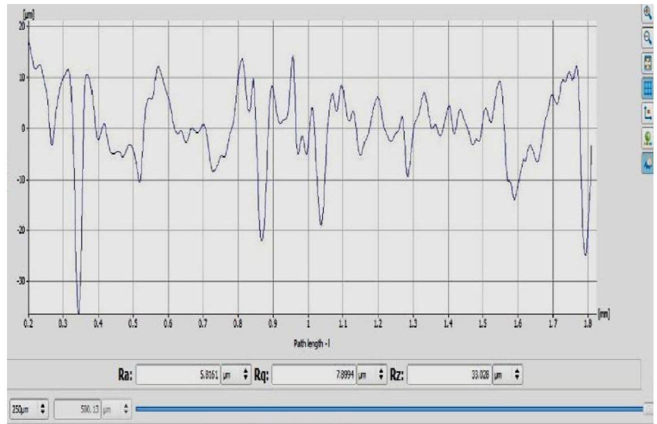

Fig. 2 depth against path length graph produced by ALINOCA 3D Optical Measurement Machine

Finally the total parametric data needed in the multi-objective optimization process are complete to be used as the learning process in EDiM*fESO*. Table III shows the tabulated primary data.

Table III. example of parametric input for EDM parameter setting

| Test | Current | Pulse Time On | Pulse Time Off | MRR (g) | TWR (g) | SR (μm) |
|---|---|---|---|---|---|---|
| 1 | 3.5 | 8.0 | 9.5 | 11.87 | 0.13 | 5.81 |
| 2 | 3.2 | 7.3 | 5.0 | 9.74 | 0.12 | 3.66 |
| 3 | 1.5 | 5.5 | 4.0 | 2.21 | 0.03 | 2.50 |
| 4 | 2.3 | 6.5 | 5.0 | 3.71 | 0.03 | 3.68 |
| 5 | 2.5 | 7.0 | 5.0 | 7.84 | 0.18 | 4.78 |
| 6 | 1.3 | 6.0 | 5.0 | 2.52 | 0.12 | 3.40 |
| 7 | 4.2 | 8.0 | 9.5 | 15.70 | 0.030 | 7.82 |
| 8 | 4.4 | 8.0 | 9.5 | 7.85 | 0.02 | 5.87 |
| 9 | 5.2 | 9.0 | 9.5 | 15.70 | 0.03 | 7.82 |
| 10 | 5.5 | 9.0 | 12.0 | 16.54 | 0.33 | 8.34 |
| 11 | 6.2 | 10.0 | 12.9 | 7.69 | 0.17 | 8.68 |
| 12 | 6.5 | 10.0 | 12.9 | 8.44 | 0.40 | 9.01 |
| 13 | 7.2 | 10.0 | 12.5 | 23.78 | 1.65 | 10.34 |
| 14 | 7.5 | 10.1 | 12.7 | 17.37 | 1.71 | 10.19 |
| 15 | 8.2 | 10.3 | 11.7 | 24.45 | 3.27 | 10.10 |
| 16 | 8.5 | 10.1 | 12.8 | 25.76 | 6.75 | 10.67 |
| 17 | 0.1 | 12.0 | 4.0 | 0.02 | 0.06 | 1.36 |
| 18 | 0.4 | 12.8 | 1.0 | 0.37 | 0.05 | 2.72 |
| 19 | 5.3 | 9.0 | 10.0 | 13.70 | 0.93 | 8.07 |
| 20 | 7.3 | 10.0 | 8.0 | 14.10 | 0.51 | 7.08 |

### *B. Secondary data*

The secondary data consists of 78 experimental to evaluate the MRR and TWR obtained of 10 sample raw data as organize in Table IV. These data are secondary data obtained from [9] and will be used as additional test data set. Mandal [9] in his work described the importance of *three* input parameter which is current, time on and time off. Current is the amount of electrical energy that is force onto the workpiece by EDM. "Time on" is the duration for EDM to force current on work piece , while time off is the duration where the EDM stop the force current on the work piece. Table IV show the sample of the secondary data.

Table IV experiment sample of secondary data [9]

| Current | Time on | Time off |
|---|---|---|
| 4 | 58 | 59 |
| 6 | 58 | 59 |
| 8 | 58 | 59 |
| 10 | 58 | 59 |
| 12 | 58 | 59 |
| 1 | 58 | 59 |
| 16 | 58 | 59 |
| 18 | 58 | 59 |
| 4 | 166 | 128 |
| 6 | 166 | 128 |

These data are also used as the parameters to produce the MRR and TWR values as in the primary data. Table V shows the complete parametric values that are used to predict optimum setting by EDiM*f*SO.

Table V example of variable input for EDM parameter setting

| Experiment | Current (A) | $T_{ON}$ (μs) | $T_{OFF}$ (μs) | MRR | TWR |
|---|---|---|---|---|---|
| 1 | 4 | 58 | 59 | 0.64 | 0.05 |
| 2 | 6 | 58 | 59 | 1.33 | 0.18 |
| 3 | 8 | 58 | 59 | 2.66 | 0.61 |
| 4 | 10 | 58 | 59 | 4.81 | 1.57 |
| 5 | 12 | 58 | 59 | 5.82 | 1.57 |
| 6 | 1 | 58 | 59 | 5.86 | 2.72 |
| 7 | 16 | 58 | 59 | 6.07 | 3.05 |
| 8 | 18 | 58 | 59 | 7.59 | 4.10 |
| 9 | 4 | 166 | 128 | 1.09 | 0.01 |
| 10 | 6 | 166 | 128 | 4.88 | 0.04 |

## III. Dynamic Fuzzy

The parameters setting and objectives involved in the control of the EDM are represented in real numbers and can be categorized as high or low it is very difficult to determine the boundary between the high and low. Thus the best solution to determine the level of each parameters and objective values is using membership values that can be calculated using fuzzy logic as shown in Fig. 3 where else Fig. 4 shows the pseudocode used in conjunction with the illustrated fuzzy logic.

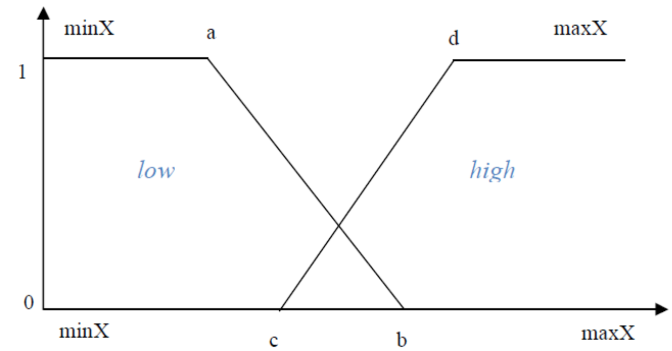


Fig. 3 illustration of Dynamic Fuzzy set

**Begin**
Object := $B_n^g\{(x_i^g, \sigma_i^g, y_i^g, w),\ n = 1..\mu,\ i = 1,2,3\}$;
minX := $y_n^g$;
maxX := $y_n^g$;

**Repeat**
**For** $n = 1$ **To** μ **Do Begin**
**If** minX $_n$ <= minx
minx := minX $_n$;
**If** maxX $_n$ >= maxX
maxX := maxX $_n$ ;
**End;**
range := maxX – minX;

initial trapezoidLow (minX, minX, (a = range), (b = range + (range * 0.8)));

initial trapezoidHigh (c = range + (range * 0.2)), (d = range * 2 ), maxX, maxX);
**Fuzzification :=** $y_i^g$**;**
**Rule evaluation;**
**Aggregation of rule output;**
$w_n$ **:= Defuzzification;**

**Return** $w_n$;

Fig. 4 pseudocode of dynamic fuzzy for fitness evaluation

In this work, dynamic fuzzy technique is used to produce single weighting fitness (*w)*.The dynamic fuzzy algorithm is designed based on the standard fuzzy where the membership is calculated as a membership in the trapezoid and triangle. However in EDiM***f***ESO fitness evaluation the fuzzy membership range is dynamically changed with every generation. This satisfies the rule of the of ES algorithm where the fitness values must change in every generation to ensure the diversity of the individual of each generations. The highest *w* is consider the as the most optimal solution for the multi – problem.

The 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 based on rules set. Fig. 4 shows some of the dynamic fuzzy rules. These fuzzy memberships are then used in the dynamic fuzzy rules as shown in Fig. 5.

1. *If MRR is Low and TWR is Low and SR is Low then Output is High*
2. *If MRR is Medium and TWR is Medium and SR is Medium then Output is Medium*
3. *If MRR is High and TWR is High and SR is High then Output is Low*
4. *If MRR is Low and TWR is Low and SR is Medium then Output is Medium*
5. *If MRR is Low and TWR is Medium and SR is Medium then Output is Medium*

Fig 5 dynamic fuzzy rules

Finally, the rule aggregations of output are calculated to produce weighted average (WA). The rule aggregation use in this work is based on Sugeno fuzzy algorithm shown in equation (7).

$$WA = \sum_{i=0}^{n} \frac{(rule\ (n) * singleton\ value)}{\sum rule} \tag{3}$$

The singleton values obtained from fuzzy set are categorized as 1 that denotes poor, 2 as average and 3 as good. Once the WA is calculated, these values are than defuzzified and are considered as weighted average fitness which is μ.

## IV. Evolutionary Strategies Architecture

Historically, this algorithm is developed more or less independently and in very different direction as other evolutionary algorithm. ES generally apply to real value representation for optimization problem, and tend to emphasize mutation over crossover [22].

In order to perform this research, a prototype of EDiM*f*ESO is develop based on basic ES [24] inspired by Multi-objective Elitist Evolutionary Strategies [18]. EDiM*f*ESO is developed based on the basic ES [20] inspired by Multi-objective Elitist Evolutionary Strategies [18]. This algorithm consists of individual representation, mutation and selection. However, it is enhanced using elitism and ranking selection using tournament to achieve MOO. There are five basic steps in ES algorithm which is representation, initial population, fitness, mutation and selection. The flowchart of the algorithm is shown in Fig. 6.

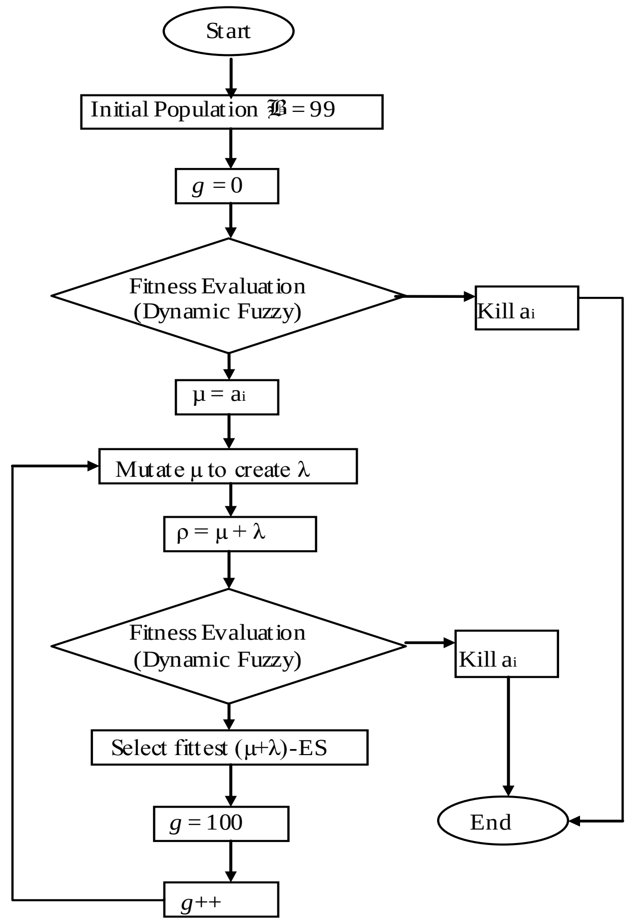


Fig. 6 flow chart of EDiM*f*ESO prototype design

The development of ES is similar to other evolutionary algorithms, where initial values needs to be given to parameters such as chromosomes, initial population, and number of generation allowed and the maximum population allowed. This algorithm is based on the MEES proposed algorithm inspired by Costa[18] to achieve MOO for EDM. Besides this the method used in determining the mutation, density distribution function, population selection, multi-objective fitness function and stopping criteria needs to be specified. Both the parameter initialization and the method specification needed for each steps are tabulated in Table VI.

Table VI ES algorithm initialization

| CATEGORY | INITIALIZATION |
|---|---|
| Data representation | Real number (floating) |
| Initial Population (μ) | 99 individual |
| Generation (g) | 100 generation |
| Maximum population | 200 individual |
| Mutation (σ) | Random but obey density function |
| Density Function | Normal Distribution |
| Selection (elitism) | (μ + λ)-selection using K – tournament |
| Fitness for multi - objective | Weighted average from Dynamic Fuzzy |
| Stopping Criteria | Global fittest individual or reach maximum population |

This will be explained in more detailed in the following sections.

### A. Representation

The individual consists of 10 genes with each gene representing parameter setting, sigma for mutation, objective function and weighted average respectively. Fig. 7 is the illustration of individual representation.

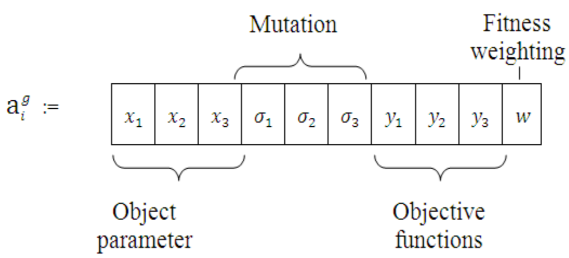


Fig. 7 individual representation in EDiM***f***ESO

The ES chromosome consists of three parts which is the object parameters, mutation, objective functions and the Fitness weighted average. The object parameters involved are $x_1$ which represents current values, $x_2$ as time pulse on and $x_3$ as time pulse off. Mutation genes representations are σ1, σ2 and σ3 for each of the three object parameters. The objective function represents the MRR, TWR and SR values which are labels as $y_1$, $y_2$ and $y_3$ respectively. Meanwhile $w$ is the weighted average that imposes for multi-objective optimization.

### B. Initial Population

EDiM***f***ESO begins with 98 initial populations plus 1 individual from user import marked as generation 0. These populations are evaluated through its fitness to achieve multi-objective optimization using the Dynamic Fuzzy technique as the objective function. The fittest individual, ą, are declared as parent noted with the μ value. The process will only stops when either the stopping criteria is met or reach maximum population which was set to 200 individuals.

### C. Fitness Evaluation

EDiM***f***ESO evaluates the fitness for multi-objective optimization of initial population by giving weighted average values using the Dynamic fuzzy algorithm. The Fitness function changes for every generation iteration thus producing new MRR, TWR, SR values for the child chromosomes (λ). λ objective functions are calculated based on the empirical equation stated in [7]. MRR, TWR and SR are calculated with Equation (3), Equation (4) and Equation (5) respectively.

$$\text{MRR} = (4 * 10^4) * i * Tw^{-1} \tag{3}$$

$$\text{TWR} = (11 * 10^3) * i * Tt^{-2} \tag{4}$$

$$\text{SR} = 0.0225 * i^{0.29} * (y + z)^0 \tag{5}$$

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)

Optimizing the machine setting process involves balancing the MRR, TWR and SR values where the high the MRR and SR values the better the product but this is the reverse for the TWR values. To simplify the process of determining the most suitable solution, weighted average is used to normalize the MRR, TWR and SR values. The weighted average given is tabulated in Table VII.

Table VII weighted average of the MRR, TWR and SR values

| | MRR | TWR | SR |
|---|---|---|---|
| Low | 1 | 3 | 1 |
| Medium | 2 | 2 | 2 |
| High | 3 | 1 | 3 |

The membership is obtained from the average of the sum of the MRR, TWR and SR weighted. The value with the average weighted average greater than or equal to 2.5 is considered most suitably fit. Fig. 8 shows the fitness weighted average results for 100 chromosomes of a generation.

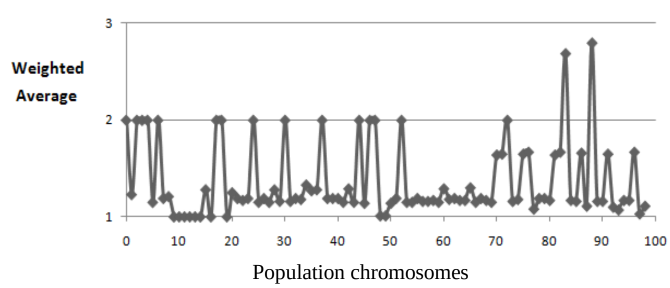


Fig 8. fitness weighted average calculated for in 100 population in a generation.

### *D. Mutation*

The mutation value is based on normal distribution probability density function proposed by Beyer [2]. The probability density function is formulated in equation (6)

$$f(\hat{y}i) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(\hat{y}i - yi)^2}{2\sigma^2}} \tag{6}$$

This mutation values are calculated for each individuals and changes with generation. This is to ensure the diversity of the individuals in the population.

### *E. Selection Method*

The selection method used is K–tournament where EDiM$f$ESO chooses the non-dominated global fittest individual based on a set threshold.

### *F. Stopping Criteria*

Finally, EDiM$f$ESO will be terminating if it reach maximum population on it find the fittest individual. Global fittest individual or reach maximum population

## V. Results

Result of EDiM$f$ESO will be discussed in four parts. The first part discusses the number of generations to achieve the optimum MOO solution. The second part discusses the accuracy of EDiM$f$ESO with actual experiment with the primary data. Second part will compares the accuracy of EDiM$f$ESO with actual experiment with the secondary data. Result comparison is important to show the persistence of EDiM$f$ESO with actual EDM. This outcome will be the benchmark for EDiM$f$ESO to find the most or better parameters setting in order achieve multi-objective optimization. Finally the performance of EDiM$f$ESO is analyzed to propose better parameter setting in order to achieve multi-objective optimization.

### *A. Optimum number of generation determination*

The number of individuals that are in the high fitness zone for 100 generations reaches the highest optimum solution at between 70 to 80 generation and becomes stagnant number of fittest individuals after 88 generations. Thus indicating the learning rate is the best between the 70$^{th}$ to 80$^{th}$ generations as shown in Fig 9.

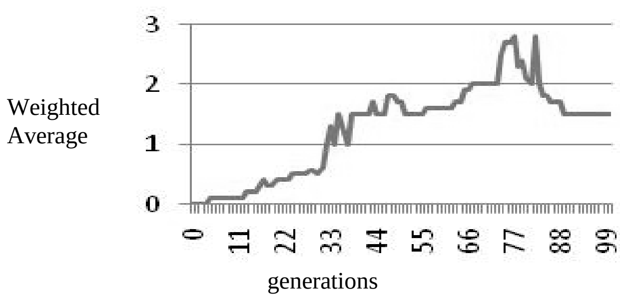


Fig. 9 fitness weighted average calculated for in 100 generation.

### *B. Primary data comparison*

In this section performance comparisons are made between the primary data and the predicted output of EDiM$f$ESO for MRR, TWR and SR.

Fig. 8 shows the comparison between EDiM$f$ESO predicted outcomes with experiment result on MRR. EDiMfESO show a consistent finding compared to the real experimental results.

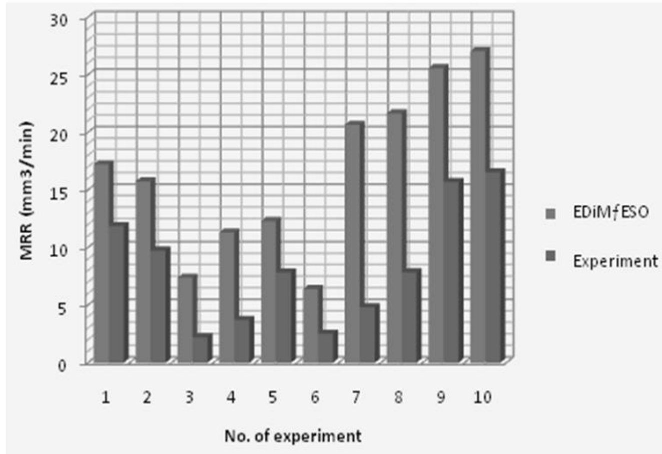


Fig. 8 comparison of experiment and EDiM$f$ESO for MRR.

The margin of error is calculated using Root Mean Square Error (RMSE) in this case. The outcome for MRR RMSE is 9.13 thus it is can be acceptable in engineering where 10% of difference is allowed.

On the other hand there is a huge difference in the findings between EDiM$f$ESO and experiment result for TWR as shown in Fig. 9. The RMSE value is calculated as 0.14. Although this error is small, this result cannot be considered as good because the range of maximum TWR values (mm3/min) is also small.

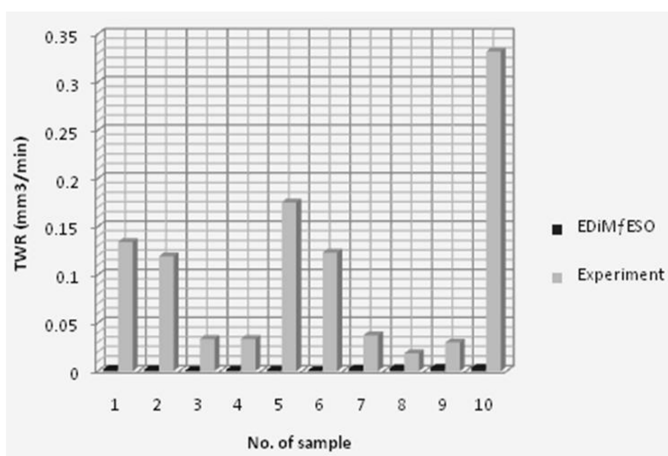


Fig. 9 comparison of experiment and EDiM$f$ESO for TWR

Lastly, is there is a large difference between the results obtained using EDiM$f$ESO and the experimental value for SR as shown in Fig.10.

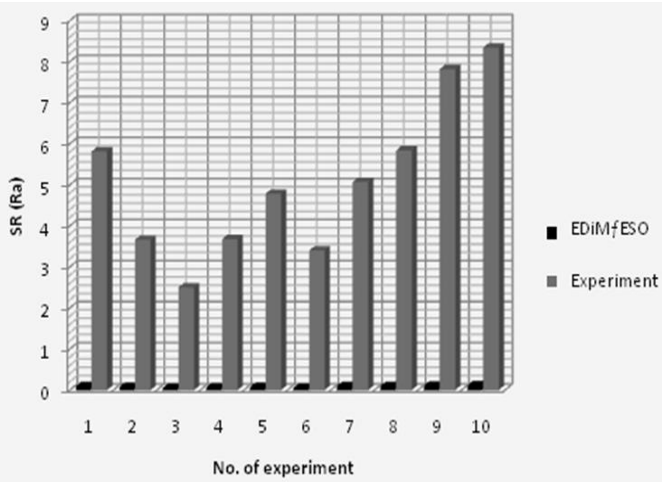


Fig. 10 comparison of experiment and EDiMƒESO for SR

### C. Secondary data comparison

Mandal experiment only measure on MRR and TWR result, therefore this comparison will only focus on those two parameters. Fig. 10 shows the comparison result for MRR between Mandal experiment data and EDiMƒESO. The result of MRR between EDiMƒESO and Mandal experiment is not so consistent as shown in the histograms in Fig. 10. This is might be due to the other parameters setting in Mandal's experiment which is unknown. The RMSE value is calculated for secondary data MRR is 19.26 which are relatively high.

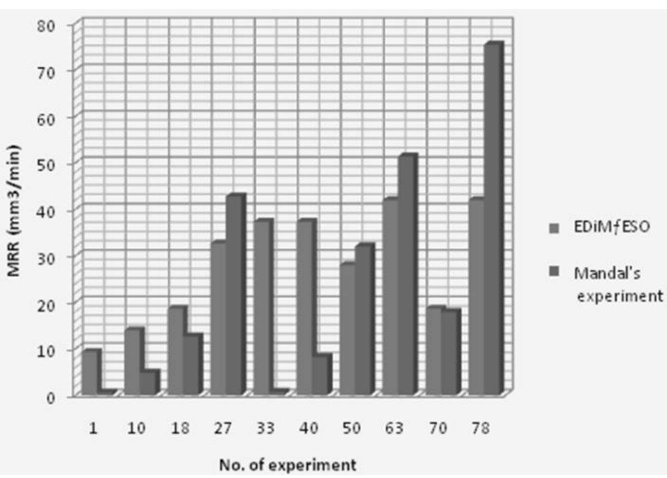


Fig. 10 Comparison of Mandal's experiment and EDiMƒESO for MRR

The results comparison between the Mandal [9] experiments and EDiMƒESO for TWR in Fig. 11 shows poor consistency with the an RMSE of 1.70 errors.

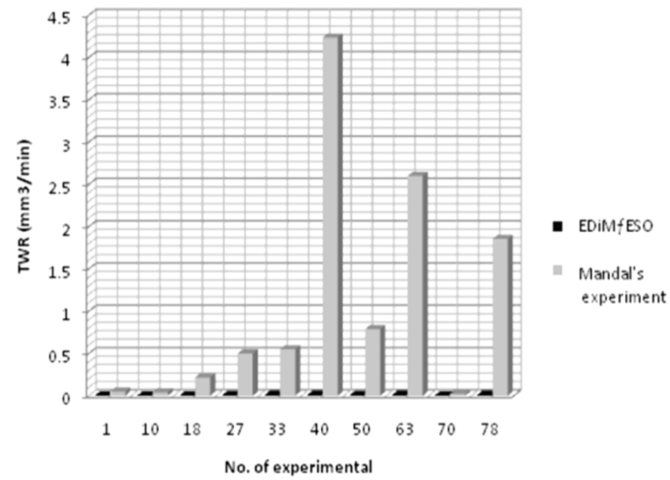


Fig. 11 comparison of Mandal's experiment and EDiMƒESO for TWR

The comparison of both the primary data and secondary data proved that the equation used to predict TWR need to be enhanced for better accuracy. Even though EDiMƒESO predicted outcome is not convincing, however it is acceptable because EDiMƒESO only uses user input values as benchmark to obtain better multi-objective optimal solution.

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 4.

Table 4 : Summary of data accuracy comparison result

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

### D. *Result of EDiMƒESO for multi-objective*

The parameter input data is selected randomly which is significance for novice user of EDM who does not know what the suitable input is. Table VIII shows the random parameter input for testing.

Table VIII operators 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 |

Meanwhile, Fig. 11, Fig. 12 and Fig. 13 below show the performance of EDiM***f***ESO in proposing suitable inputs to optimize MRR, TWR and SR respectively.

The MRR test results shows EDiM***f***ESO performs slightly better results against the benchmark to optimized the machine for all the experiments to produce optimum results.

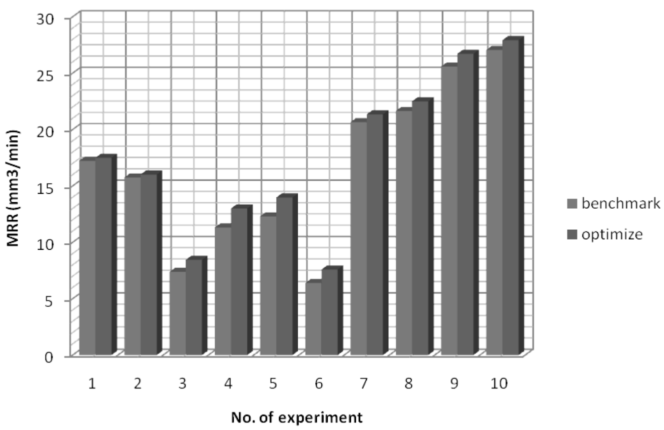


Fig. 12 testing result to measure MRR

The TWR test results shows EDiM***f***ESO performs slightly better against the benchmark to optimized the machine for all the experiments to produce optimum results.

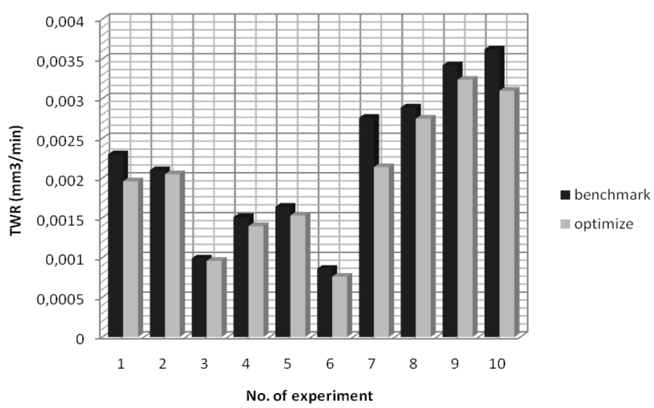


Fig. 13 testing result to measure TWR

The SR test results shows EDiM***f***ESO performs slightly less against the benchmark for all cases except experiment 3, 9 and 10 to optimized the machine for all the experiments to produce optimum results.

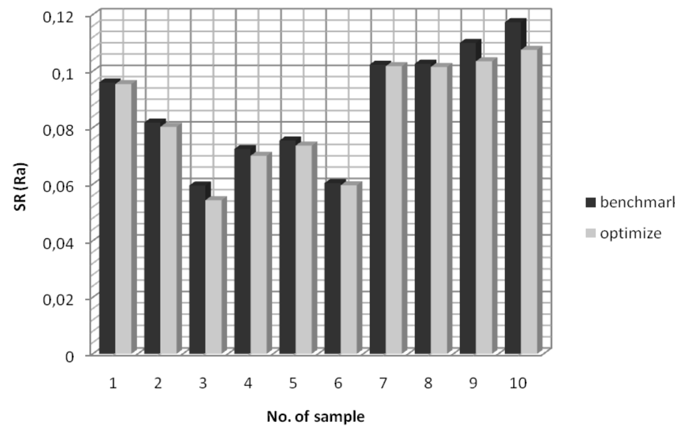


Fig. 14 testing result to measure SR

## VI. Conclusion and Recommendation

To conclude this research, Evolutionary Strategies (ES) is admirable in solving multi-objective problems or optimization. Although this technique is rarely used before, it has been shown to have high potential in solving MOO. Since the specialty of ES is its ability in dynamic mutation, it can also learn and make very small changes during mutation thus make it possible to converge 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.

This research recommends the use of dynamic fuzzy mainly to overcome drawback of standard fuzzy which has a fixed range of fuzzy set. In dynamic fuzzy, the range is initialized in the early stage by experts based on MRR, TWR and SR range changes in every each generation.

Secondly, engineering experts are recommended to formulate better MRR, TWR and SR equation to increase the accuracy of the parameter control setting.

## Acknowledgment

Special thanks to Miss Norliana Mohd Abbas, my Co-Supervisor from Faculty of Mechanical Engineering for all guide and knowledge that had been shared.

The authors acknowledge with gratitude to Research Management Institute (RMI), UiTM and financial support from FRGS RM 89,000 2010-2012, 600-RMI/ST/FRGS 5/3/Fst (223/2010) from the Ministry of Higher Education, ,Malaysia.

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