

Wire Electrical Discharge Machining (WEDM) optimization process: A conceptual view

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Abstract. Optimization technique are solutions for finding for specific problems and solved existing limitation on common problems. This are especially in improving the output of WEDM processing where it involves more than a single objective or multiple output to be optimized synchronously. WEDM machining process usage increased rapidly as its capability in cutting complicated design formation. Thus the precision of the work piece is required. Therefore, this paper aims to provide a quick conceptual view of optimizing WEDM process by providing fundamentals parameters involved. Henceforth, perspective on WEDM optimization process on this paper may be use for future reference.

1. Introduction

Optimization is a method to maximize performance of machining process. The optimization method often involves with real experiment or computational simulation. Prior to the utilization of machine learning into machining process optimization, the parameters were control based on experimental result and advices from expert. Furthermore, there are factors that were consider by previous studies ranging from the input settings, the servo voltage and also the chemical component of the material used. This however does not find near optimal solution to reach for the best output for the machining process as the correlation between the input and output is unclear.

WEDM is a method to cut exotic metal or alloy with complicate design formation by using wire electrode. It is preferable method for parts use in automotive, aerospace, medical and surgical industry where precision is required [1]. Additionally, the process in WEDM manufacturing is still evolving and consist a lot of affecting factors and the process is random [2].The work piece used in WEDM process were often differs in previous studies. Figure 1(a) display illustration of WEDM cutting process while Figure 1(b) shows the direction cutting the work piece and display the locations of the upper and lower nozzles for injection electric fluid.



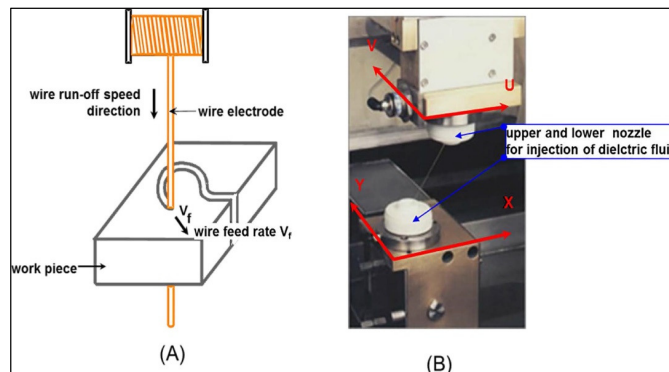


Figure 1. WEDM Schematic Diagram [3]

2. WEDM Optimization Flow

In order to find the optimum parameters, previous studies share similar flows to comprehend the optimization of WEDM parameters. Figure 2 shows the steps taken in WEDM parameters optimization. The steps start by feeding selected WEDM machining data and follows with modelling the data. This steps are mostly supervised learning where it learned the pattern of input and output parameters and deduct the possible range of input and out based on the model created using the datasets. The steps continue with find the optimum input parameters to provide the best output required.

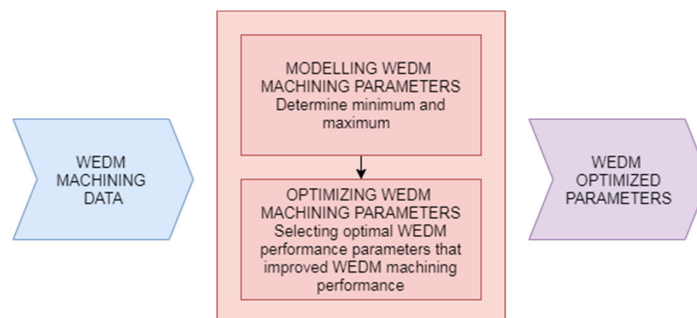


Figure 2. WEDM parameter optimizations steps

3. WEDM Optimization

Generally, optimization is an approach to find the best solution for producing a high quality product and reduce production cost [3]. There are 2 main method used in optimization where it is either computer simulation or experiment. Simulation is computational approach by utilizing mathematical model or soft computing optimization technique such as metaheuristic, swarm technology and neural network. While an experiment is run by using real work piece and machinery to validate hypothesis.

In this section, the conceptual properties of WEDM optimization such as WEDM modelling techniques, the input and output parameters, the WEDM optimization techniques and validation is listed as:

3.1. WEDM Modelling

WEDM modelling is the process to build an estimated dynamic mathematical model from WEDM machining process. Modelling in machining process are known as Design of Experiment (DOE). Listed in Table 1 are the WEDM modelling technique used by previous researcher for their DOE. From the table, in recent years RSM and Taguchi orthogonal array are preferable in manifesting DOE [4, 5].

Table 1. WEDM Modelling Technique

Modelling Method	
Respond Surface Method (RSM)	[6, 7]
General Regression Neural Network (GRNN)	[8]
Taguchi Orthogonal Array	[9, 10]
Gaussian Process Regression (GPR)	[11]

3.2. Work Piece Material

WEDM optimization process faces additional parameters where only 1 researcher conclude the work piece material as one of parameter component. Work piece used in WEDM machining is Alloy, Alloy is a mixed a combination of metal each work piece material is different from each other. Work piece Alloy may contain silicon(SiC), titanium(Ti), Aluminum (Al), Nickel (Ni) and much more. The work piece listed in table 2 lists the work piece material used by previous study.

Table 2. Work piece material

Material	
Nimonic C-263	[6]
Nano-Sic MMC (100% Mg + 0% SiC, 99.5% Mg + 0.5% SiC, 99% Mg + 1% SiC)	[7]
Ni-Ti shape memory alloy	[8]
Aluminium alloy AA7075	[9]
SiCp/Al metal matrix composite (MMC)	[11]
Nimonic-75	[12]

3.3. Input Parameters

In WEDM Machining, there are few machining parameters was considered for machining process. For an example, every researcher consider pulse on time as machining parameters. Pulse on and pulse off is a controllable electrical pulses where the pulse on with the length of time the pulses was on while the pulse off is the idle time. As conclusion from input parameters listed in Table 3; it is unanimously all research uses Pulse on time as it input parameters so does pulse off time. The other machining parameters such as flow rate, current discharge, wire speed, flushing pressure are the least favourable input considered. Additionally, Wire Feed Rate (Wfr) [7] and Wire Tension both were suggested to have a very little effect on performance [6]. While the significant process parameters are Pulse On Time (TON) [8], Wire feed rate [9], water pressure [11] and wire ware rate [9]. However, it was also suggested that different input parameters affected different output. As an example, pulse on time and servo voltage are significantly affecting the value of MRR, while wire feed rate is influencing surface roughness [9]. Other least significant information gather is Kerf Width(Kw) [12], Wire Diameter (dw), thickness (d), and density (ρ_w).

Table 3. WEDM Input parameters

Input	Pulse On Time (T _{ON} , μ s)	Pulse Off Time (T _{OFF} , μ s)	Servo Voltage (SV, (V))	Flow Rate (FR, (L/min))	Discharge current (I,A)	Wire Speed (WS,mm/s)	Wire Tension (WT, N/gm)	Flushing Pressure (FP, Bar)	Wire Feed Rate (m/min)
[3]	✓	✓	✓	✓					
[6]	✓	✓	✓						✓
[7]	✓				✓	✓	✓	✓	
[8]	✓	✓							✓
[10]	✓	✓					✓	✓	
[9]	✓	✓	✓		✓		✓		✓

3.4. Output Parameters

The focus from past researcher were divided into either single objective output or multiple objective output. Based on Table 4 below, it is safe to conclude that the major objective of optimization of WEDM process output were surface roughness and square roughness which are the final product quality appearances.

Table 4. WEDM Output parameters

Output	Cutting Rate (V_c)	Surface Roughness (R_a)	Spark Gap (S_g)	WWR	Square Roughness (R_q)	maximum peak-to-valley height (R_z)	Micro-Hardness (MH)	MRR
[3]	✓	✓	✓	✓				
[7]		✓			✓	✓	✓	
[8]		✓			✓	✓		✓
[10]		✓			✓			✓
[6]		✓						✓
[9]		✓						✓

3.5. Optimization Method

The modelling technique provides the minimum and maximum approximation of the WEDM processing which depends on parameters that has been considered from field expert and the modelling shows the correlations of the inputs and outputs parameter. From the modelling process the steps resume with optimization of the output parameters by understanding the near optimum combination of inputs parameters. For example, Majumder uses Desirability Function Analysis (DFA) where the combination for optimum input parameters depends on large value of average cutting speed, small value for average kerf width and average for surface roughness [12]. The calculation used different equation and the overall desirability grade (d_G) was calculated to grade response and highest d_G value accepted as the optimal parameters. Similar to Majumder, Mandal [6] uses desirability grade to select best optimal parameter combination. However, the implementation was different where the setting was to receive 95% confident value using ANOVA to find the effects of each parameters towards the output. The study concludes that in order to simultaneously solve the 3 WEDM responses is to divide the desirability grading into two groups; optimizing rough cutting or finish cutting operations. This however, is not conclusively similar to other approach, for example Ramanujam, et al, suggested by using Grey Relation Coefficient and grading, the respond number is not limited to 2 or 3 but more and the grade performance shows ranks of best response therefore the best optimum condition [9]. Evidently, desirability grade has respond number limitation which would be suitable for small number of machining respond. Contrary, the Grey Coefficient Grade were more suitable for small number of parameters. This signifies the optimization process also not only depended on the number of response but also the number of parameter selected for the process.

Table 5. WEDM Optimization approach

Optimization Method	
Polynomial Second Order	[6]
RSM based desirability function method	[7]
Multivariate VIKOR-Fuzzy	[8]
Grey Relation Analysis/Grade	[9]
Hybrid GPR and Wolf Pack Algorithm	[11]
Desirability Function Analysis	[12]

3.6. Performance Evaluation

Performance evaluation is important steps to verified the estimated model received from undergone the parameter optimization model. Based on recent studies, Analysis of Variance (ANOVA) analysis F-value is mostly know statistical validation in the optimization process [2, 7, 8]. ANOVA statistical

methods provides figurative understanding on input parameters contribution on output parameters required. The calculation starts with calculating the sum of means from observation among parameters which commonly known as the grand mean. Subsequently, the calculation continues with varieties prediction among parameter which know as $SS_{parameters}$ and continues with the calculation of sum of parameter's squares $SS_{withinparameters}$. All the calculation mention above is important steps to calculate the ANOVA F-Value. The calculation of F-Value is represented as follows:

$$F\text{-Value} = \frac{SS_{parameters}/a-1}{SS_{withinparameters}/a(n-1)} \quad (1)$$

where:

a	is the number of groups
n	is the number of observations within each parameters
$SS_{parameters}$	varieties prediction among parameter
$SS_{withinparameters}$	Sum of parameter's squares

The F-value shown the ratio of variation among parameters to the variations within parameters. If $SS_{parameters}$ is larger than $SS_{withinparameters}$ and vice versa. Addition to F-Value, the modelling and optimization estimation requires for validation. The validation process compares the estimation to the real model by calculating its error in percentage (%) value as follows:

$$Error(\%) = \left| \frac{Result\ of\ conformation\ tests - Predicted\ value}{Result\ of\ conformation\ tests} \right| \times 100 \quad (2)$$

4. Conclusion

Starts from point 2 this paper describes the concept of WEDM optimization, start with the flow of the optimization process and end with evaluation methods use by previous researcher. The paper however intentionally did not cover single objective optimization as more and more researcher prefers to solved WEDM optimization output simultaneously. The main objective is of this paper is to layout the WEDM optimization process for readers' perusal with the hope that by understand slightly of the element involved in WEDM optimization will assist in improvement of the optimization.

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