A contribution concerning trends in modelling of Wire-micro EDM of Titanium alloys- A review

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Abstract. The era is shifting towards the manufacturing idea of converting raw form of material into finalized part in minimum step and lesser machining operation. Manufacturing processes like 3D printing and additive manufacturing are achieving the criteria but they requires high capital investment and are sophisticated in its operation which need next to zero possibility of error. Alloying of materials yield high derivative properties like hardness, temperature resistance and extreme strength to weight ratio like in Titanium, Nickel and their alloys and super alloys. Specialized feature at micro level, complex and intricate geometries in the part are difficult to produce via traditional machining processes than non-contact machining process at cost effectiveness. This paper reviews the modelling related studies done in the processing of Titanium alloys through Wire- micro electrical discharge machining (Wire-\textmu EDM) process. Most of the research done in the Wire EDM domain, experimented with the wire of copper and brass with diameter range in microns, thus resulting micro-machining phenomenon. Since Ti alloys find the most of the applications in field of aerospace, automobile, nano tech due to excellent performance at elevated temperature and pressure, than other alloying materials. The summarized should provide an overview on modelling techniques used by the re-searchers for measuring and predicting the parametric values for the optimization of WEDM process.

1. Introduction
Titanium and its alloys are known for their high mechanical properties like extreme hardness, strength, resistance to creep and fatigue and temperature resistance. And their extensive applications in industries like aerospace, ballistics, automobile, etc. to manufacture intricate parts like gears. Since these alloys are very costly, these material are to be handle with care and efficient machining operations must be utilized for their fabrication. Machining process utilizing tool for material removal are ineffective due to high tool wear and energy loss in form of friction between tool and workpiece which led to wastage of material and time both. Thus, advanced machining methods like EDM, LBM, WEDM, etc. are required for machining at faster rate with desirable quality.

Due to ease of availability and machinability of WEDM of electrically conductive material, it can almost machine every Ti alloy easily without significant tool or energy loss. Controlling and monitoring of input variables in WEDM is comparatively easier than other processes. In order to achieve higher machining rate different configuration of WEDM are used along with the change in composition of tool wire material. Response factors like machining rate, surface integrity, wear ratio and dimensional accuracy are highly dependent on the input variables like pulse on/off time, spark gap voltage, current, etc. as shown in figure 1 [1-3].
2. Mechanism of Wire micro EDM
The material removal mechanism of wire-micro EDM is similar as that of Wire EDM. Similarly this process utilizes tool electrode in the form of electrical conductive wire through which spark generation take place for erosion of material from the work, refer figure 2. Wire in this process is continuously fed through the spool in tension. Wire diameter range is in the order of 0.1mm to 0.02mm as to remove material of minimal width or for internal cutting. The movement and automated feed of wire is generally programmable through CNC along with the service of guides in order to inhibit wire lag and wire breakage. Flushing system are implied for the application and pressure control of dielectric fluid required in the process for removal of debris along with heat dissipation.

3. Parametric Studies of Wire-μEDM
Process parameters of Wire μ-EDM are discharge current, voltage, feed rate, capacitance, wire tension, pulse on time($T_{on}$), type of circuit, etc. which were being used by the different researchers for evaluation and optimization of performance characteristics. The deviation in performance characteristics like geometrical accuracy, surface roughness and cutting rate was observed, by Bergs, with respect to discharge current, pulse interval time and flushing condition and found that accuracy is affected by increased flushing due to wire vibration and lead to high cutting rate while pulse interval time and discharge current had no significant effect. Surface roughness was lowered by decreasing the current and increasing the pulse interval time and flushing pressure than standard [4]. Tsai et al. describes the effect of vibration of tool wire with the help of auxiliary device on the machining rate and relates that increased vibration increases the removal rate of material additionally machining depth in-increases with discharge time due to unusual debris flow [5].Beside this, Han et al. used ultrasonic assisted WEDM which describes the vibration of workpiece along horizontal direction and its effect which increases MRR and surface roughness while reduces kerf width [9]. Increment in feed rate decrease the kerf width, increase the MRR and surface roughness was increased has been discussed by Alias et al. using brass wire electrode with constant current of 4A and 6A in order to find best combination of process inputs and optimize cost with quality [6-7]. Majumder et al. also discussed effect $T_{on}$, $T_{off}$, wire feed and tension
on machining time, Kerf width plus surface roughness and concluded that response parameters were increase with increase in $T_{on}$ while decreases with $T_{off}$ and wire feed and tension had minimum effect on them [8]. Study of surface integrity with low speed WEDM using brass wire was experimentally studied by Gong et al. with the comparison of trim cuts to machined main cut for the investigation of surface roughness and found out to be fine of about 0.67μm. This was possible by decreasing the discharge current, $T_{on}$ wire speed and increasing wire tension [10].

4. Modelling related Studies
Chalisgaonkar et al. used coated and uncoated zinc electrodes for the trim cuts on commercial pure Titanium (CPTi) and evaluated variation of the MRR through mathematical modelling using Buckingham’s $\pi$ theorem and ANOVA. It predict values of MRR over significant process parameters like peak current, wire offset and wire type, shown in figure 3 [11].

![Figure 3](image_url)

**Figure 3.** Comparative bar chart between predicted and experimental values of MRR for $T_{on}$ and Wire offset [11]

Mathematical linearized equation model using logarithmic transformation was used by Raj et al. for predicting surface roughness and MRR using two configuration of electrode wire i.e. brass and molybdenum (Mo). Input parameters were pulse current, $T_{on}$ and $T_{off}$. The maximum test errors for surface roughness were 12.005% and 10.78% for brass and Mo wire and for MRR, 27.65% for brass wire and 11.04% for Mo wire. Regression model depicts the deviation of actual surface roughness and MRR with anticipated values and indicate fit of the model [12]. Analysis of machining parameters of WEDM process were done by the Kumar et al. using RSM modelling in order to obtain relationship between machining rate and overcut. A micro-model has been utilized for predicting MRR of the process using dimensional analysis. Spark gap voltage, current, $T_{on}$, $T_{off}$, wire tension and feed were taken as input parameters. The model was efficient in showing the closeness in the predicted values and experimented values across $T_{on}$ and peak current obtained using brass wire and pure titanium specimen, refer figure 4 [13].
Kumar et al. discussed the RSM for obtaining MRR and wire wear ratio through WEDM of pure titanium and zinc coated brass wire. Input parameters were peak current, $T_{\text{on}}$, $T_{\text{off}}$, wire tension and feed. Regression technique was used to compare the experimental value and predicted values obtained through modelling. It also visualizes the impact of input variables over MRR signifying $T_{\text{on}}$ and $T_{\text{off}}$ as the peak significant factors [14]. Liao et al. adopted back propagation neural network (BPNN) for building the relationship between machining parameters like Specific discharge energy, $T_{\text{on}}$, $T_{\text{off}}$ and servo voltage on the cutting speed, spark frequency, groove width and surface irregularities during the WEDM using brass wire and Ti6Al4V specimen. BPNN outperformed other modelling techniques yielding more accurate result with lesser error percent of 2.74 [15]. Process parameters like discharge current, $T_{\text{on}}$, wire tension, wire speed and flushing pressure were adopted to obtain performance parameters like Surface roughness and micro hardness during WEDM of NiTi smart alloy was described by Majumder et al.. A general regression neural network (GRNN) was adopted for modelling and visualized through regression analysis of experimental and predicted values, as shown in figure 5 [16].

Sarkar et al. proposed second order polynomial mathematical model with RSM to weigh the effect of process constraints on machining criteria like cutting speed, surface integrity and dimensional shift during WEDM of Y-TiAl alloy with brass wire. Here log transformation technique effectively fit the model to give response value of surface roughness to 95.6% with error value of 0.07571 which was within permissible limits [17]. During WEDM of TiC /Fe in situ metal matrix composites with uncoated brass wire of 250$\mu$m, Saha et al. proposed normalized radial basis function network (NRBFN) with enhanced k-means clustering technique for modelling of process using $T_{\text{on}}$, $T_{\text{off}}$, wire feed rate and average gap voltage on the performance entities like kerf width and cutting speed. The enhanced k-means clustering techniques yield superior responses based on dynamic adjustments rather than traditional k-means clustering technique which focuses on local optimality. The model signified better fit of response parameters in enhanced technique rather than with the traditional approach [18]. Saha et al. adopted BPNN model for obtaining functional relationship between process parameters and responses like kerf width and cutting speed by using non-dominated sorting algorithm (NSGA-II). Fitness evaluation of BPNN can be seen in figure 6 [19].
Artificial neural network with feed forward propagation is used to model to predict performance parameters like cutting speed, surface finish and wire offset for all potential combination of process factors by Sarkar et al.. Major observation was that surface roughness increases with increase in cutting speed and 27 parametric combinations were found to fit the responses from the total combination of 15625 [20]. Ghodsiyeh et al. proposed a second order mathematical model of RSM for determining the relation between response output and variable input parameters during machining of Ti6Al4V through zinc coated brass wire of 250μm in 5-axis WEDM. Responses machining rate and surface irregularity were predicted within permissible limit when compared to experimental value showing minute deviation [21]. Machining of shape memory alloy Ni49.4Ti50.6 by WEDM for manufacturing the dynamic compression plate using zinc coated brass wire of 250μm. A finite element model was used for depicting the shape recovery near the WEDMed surface of NiTi alloy. To manufacture dynamic compression plate, process parameters were T_{on} 115 machine units, T_{off} 40 machine units, spark gap set voltage 90 V, wire feed 6 m/min and wire tension 6 machine units. The improvement in performance characteristics is done with the implication of Grey Relation Analysis and experimentation [22]. Yusoff et al. proposed orthogonal based ANN modelling along with multiple polynomial regression (MPR) for selecting and recognition of network parameters during the WEDM of Ti–48Al intermetallic alloy with brass wire of diameter 200μm. Due to the special logical characteristic of ANN which was based on the input and output training data denotes the integration of the two models. ANN–MPR predicted improved ideal machining performances and input factors, as shown in figure 7 [23].

Figure 6. Model comparing experimental and predicted values of cutting speed and kerf width [19]

Figure 7. Comparison between experimental, MPR MultiGA and Ortho ANN-MPR-MultiGA on R_{a} and Kerf width [23]
5. Conclusion
From the survey of these modelling papers on WEDM process, we can conclude that WEDM process can be modelled using both analytical and mathematical model maintaining the optimal limit of performance outputs. And, following other conclusion were,

- Performance characteristic of WEDM, like MRR, SR, cutting speed and kerf width were mostly affected by the $T_{on}$, $T_{off}$, discharge current and servo voltage.
- With the increase in $T_{on}$ and current MRR increases and surface roughness value increases with increment in $T_{on}$ and wire feed.
- ANN modelling yields the better result than any other mathematical model for predicting the performance characteristics.
- Hybridization of ANN along with other models like GA, NSGA-II and MPR yields much better result than the ANN alone.
- With the mixing of two algorithms, the number of optimal solution increases rapidly which satisfies the limiting constraints.

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