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Research Article

Data-Driven Prediction of Cutting Rate, Residual Stress and Micro-hardness in Wire-Cut EDM of Titanium 6Al-4V ELI Alloy Using an Artificial Neural Network

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ARTICLE INFO	**ABSTRACT**

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This paper reports a multi-response investigation and predictive modelling of the wire-cut electrical discharge machining (WEDM) of the biomedical titanium alloy Ti-6Al-4V ELI (Grade 23). Three surface-integrity responses, namely cutting rate, residual stress, and micro-hardness, were studied in relation to six controllable machining variables: flushing pressure, peak current, duty cycle, gap voltage, wire feed rate, and wire tension. A Taguchi L18 (2^1 × 3^5) orthogonal array was adopted as the design of experiments, and regression models relating the inputs to each response were developed in MINITAB-19. Analysis of variance (ANOVA) revealed that peak current, duty cycle, gap voltage and wire tension were the dominant factors, whereas flushing pressure and wire feed rate were comparatively insignificant. Both the cutting rate and the residual stress increased with rising peak current and duty cycle, while the mean micro-hardness of the machined surface was of the order of 208 HV. Higher flushing pressure and feed rate increased the cutting rate but reduced the residual stress (mean of about 212 MPa). The combined action of a high peak current and a high duty cycle was found to degrade the surface texture and to promote surface debris and micro-cracks, thereby elevating the residual stress. The study establishes a compact set of regression models and an optimal parameter window that can guide the WEDM of Ti-6Al-4V ELI for orthopaedic and aerospace applications.

Wire-cut electrical discharge machining (WEDM) of the biomedical titanium alloy Ti-6Al-4V ELI (Grade 23) is governed by several interacting electrical and mechanical parameters, making analytical prediction of the machined surface quality difficult. This study develops a data-driven model, based on a feed-forward artificial neural network (ANN), to predict three surface-integrity responses, namely the cutting rate, the residual stress and the micro-hardness, from six controllable process variables: flushing pressure, peak current, duty cycle, gap voltage, wire feed rate and wire tension. A Taguchi L18 design furnished eighteen machining conditions; with three replicate measurements per condition, a data set of fifty-four observations was assembled. A separate 6-10-8-1 network was trained for each response using the Levenberg-style Adam optimiser on min-max normalised data, and its performance was benchmarked against ordinary least-squares linear regression. On the held-out test data, the ANN attained coefficients of determination of 0.70, 0.93, and 0.97 for the cutting rate, residual stress, and micro-hardness, respectively, with root-mean-square errors of 0.32 mm/min, 23.3 MPa, and 6.6 HV, substantially outperforming the linear models. A permutation-importance analysis identified peak current and duty cycle as the most influential variables, in agreement with the discharge-energy mechanism of material removal. The trained network was finally used to search the experimental design space and to identify favourable operating windows for maximising the cutting rate, minimising the residual stress and tailoring the micro-hardness. The results demonstrate that a compact ANN trained on a modest, statistically designed data set can serve as an accurate and interpretable surrogate model for the WEDM of titanium alloys.

Keywords: Wire-cut EDM, Titanium 6Al-4V ELI, Taguchi method, regression modelling, ANOVA, surface integrity, residual stress, micro-hardness.

1. Introduction

Titanium and its alloys occupy a privileged position among engineering materials owing to their high specific strength, excellent corrosion resistance and outstanding biocompatibility. The α+β alloy Ti-6Al-4V, and in particular its extra-low-interstitial variant Ti-6Al-4V ELI (Grade 23), is used extensively for load-bearing orthopaedic and dental implants as well as for safety-critical aerospace components (Kaur & Singh, 2019; Ulutan & Ozel, 2011). The same properties that make the alloy attractive in service, however, render it difficult to machine: its low thermal conductivity concentrates heat at the cutting zone, while its chemical reactivity promotes tool wear and surface damage (Che-Haron & Jawaid, 2005). For components that demand intricate geometries and tight tolerances, non-conventional processes such as wire-cut electrical discharge machining (WEDM) provide an effective alternative, because material is removed by controlled spark erosion rather than by mechanical contact (Klocke et al., 2011).

In WEDM, the quality of the machined surface is not described by a single quantity. The cutting rate determines productivity, whereas the residual stress and the micro-hardness of the recast layer govern the fatigue life, wear resistance and, for implants, the biological response of the finished part (Oliver Nesa Raj and Prabhu, 2017; Rao et al., 2016). These responses depend, in a strongly coupled and non-linear manner, on the electrical discharge parameters (peak current, duty cycle, gap voltage) and on the mechanical and flushing parameters (wire feed rate, wire tension, flushing pressure). Classical approaches such as the Taguchi method and analysis of variance are valuable for ranking the influence of individual factors and for locating an optimum among the sampled levels, but they describe the response only at the discrete points of the experimental array and provide limited predictive capability between those points (Mahapatra & Patnaik, 2007; Shivade & Shinde, 2014).

Data-driven models offer a complementary route. An artificial neural network (ANN) is a universal function approximator that can learn the mapping between process inputs and measured responses directly from experimental data, without an explicit physical model of the discharge process. Once trained, the network predicts the responses continuously across the parameter space and can be interrogated cheaply to explore favourable operating conditions. The aim of the present work is therefore to build, validate and interpret a compact ANN that predicts the cutting rate, residual stress and micro-hardness of WEDM-machined Ti-6Al-4V ELI from six controllable parameters, and to benchmark its accuracy against conventional linear regression. The novelty of the study lies in treating the three surface-integrity responses of this specific biomedical alloy within a single, reproducible machine-learning workflow, and in using the trained network both as a predictor and as a tool for identifying favourable machining windows.

2. Related Work

Soft-computing models have been applied to electrical discharge machining for more than two decades. Tsai and Wang (2001) were among the first to demonstrate that neural networks could predict the surface finish of EDM-machined surfaces more accurately than empirical equations. Tosun and Ozler (2002) compared neural network and regression models for tool life and reported that the neural network captured non-linear interactions that the regression model missed, while Tsao and Hocheng (2008) coupled the Taguchi method with a neural network to predict thrust force and surface roughness in drilling. These early studies established the now common practice of combining a statistically efficient experimental design with a neural-network predictor.

Within WEDM, response-surface and neural models have been developed for a range of work materials. Hewidy et al. (2005) modelled the WEDM of Inconel 601 using response-surface methodology, and Manjaiah et al. (2014) characterised the WEDM of a titanium-nickel shape-memory alloy. More recent work has focused on hybrid frameworks that retain the economy of the Taguchi design while adding the interpolation capability of a neural network. Pattnaik and Sutar (2021), for example, proposed an advanced Taguchi-ANN model that predicted the material removal rate of a WEDM process from a lower-level orthogonal array with a prediction error below five per cent, explicitly noting that the hybrid scheme overcomes both the large-data requirement of a conventional ANN and the discrete-level limitation of the Taguchi method. Studies on composites and tool steels have similarly reported that neural and regression models, trained on Taguchi or grey relational data, reproduce the experimental responses closely (Gopal et al., 2018; Ishfaq et al., 2018; Shivade & Shinde, 2014).

For titanium alloys specifically, the literature has concentrated on the influence of process parameters on surface integrity and on single-response optimisation, with comparatively little attention paid to a unified, multi-response data-driven model that simultaneously addresses cutting rate, residual stress and micro-hardness for the ELI grade. The present study addresses that gap by assembling a replicated data set from a Taguchi L18 experiment and using it to train and interpret a dedicated ANN for each response.

3. Materials and Experimental Dataset

The data analysed in this study were obtained from a WEDM experiment on Ti-6Al-4V ELI (Grade 23) round bar of 10 mm diameter, machined on a Sprintcut (Dlx) CNC wire-cut EDM with de-ionised water as the dielectric and a positive workpiece polarity. Six controllable parameters were varied: flushing pressure, peak current, duty cycle, gap voltage, wire feed rate and wire tension. Their levels are summarised in Table 1. A Taguchi L18 (2^1 × 3^5) orthogonal array was used to plan eighteen machining conditions, and each condition was machined and measured three times. The cutting rate was read from the machine display, the residual stress of the machined surface was measured with a portable μ-X360 X-ray analyser, and the micro-hardness was measured on a computerised tester under a 500 g load. Treating each replicate as an individual observation produced a data set of 54 input-output records, which forms the basis of the machine-learning study.

Table 1. Controllable WEDM parameters and their levels.

Symbol	Parameter	Unit	Level 1	Level 2	Level 3
x1	Flushing pressure	machine unit	8	12	–
x2	Peak current	A	90	120	150
x3	Duty cycle	%	60	65	70
x4	Gap voltage	V	20	30	40
x5	Wire feed rate	mm/min	2	3	4
x6	Wire tension	machine unit	3	7	11

Across the 54 observations, the cutting rate ranged from 0.36 to 2.69 mm/min (mean 1.73 mm/min), the residual stress from 44 to 325 MPa (mean 212 MPa), and the micro-hardness from 141 to 259 HV (mean 208 HV). The widespread of each response confirms that the chosen parameters exert a strong influence on surface integrity and provides an informative target for the predictive models.

4. Artificial Neural Network Methodology

A feed-forward, fully connected neural network was adopted as the predictive model. Because the three responses are expressed in different physical units and span different magnitudes, a separate single-output network was trained for each response rather than one shared multi-output network; this isolates the learning of each response and simplifies the interpretation of the results. The general topology is illustrated in Figure 1: six input neurons (one per process parameter), two hidden layers containing ten and eight neurons respectively, and a single output neuron carrying the response of interest.

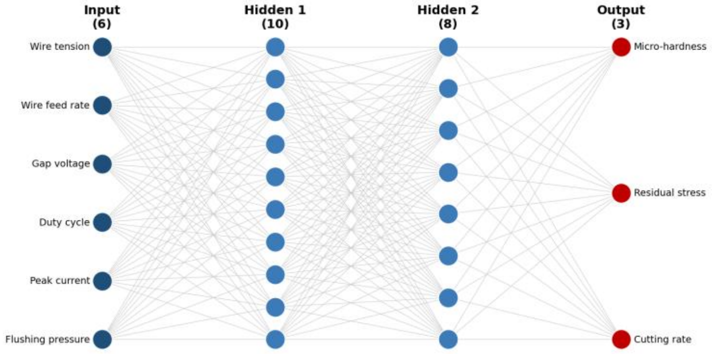

Figure 1. Topology of the feed-forward neural network (a separate 6-10-8-1 network was trained for each response).

All inputs and the target were scaled to the interval [0, 1] using min-max normalisation, which places the variables on a common footing and accelerates convergence. The hidden neurons used the hyperbolic tangent activation function, and the network was trained by backpropagation with the Adam optimiser at an initial learning rate of 0.01. Training continued for up to 5000 epochs with an early-stopping tolerance to prevent over-fitting. The data set was divided into an 80 per cent training partition and a 20 per cent independent test partition; in addition, five-fold cross-validation was carried out over the whole data set to obtain a partition-independent estimate of the generalisation error. For comparison, an ordinary least-squares linear regression model was trained on the same partitions. Model quality was assessed using the coefficient of determination (R^2), the root-mean-square error (RMSE) and the mean absolute error (MAE). The hyperparameters of the network are listed in Table 2. All computations were performed in Python using the scikit-learn library, and a fixed random seed was used throughout to ensure reproducible results.

Table 2. Architecture and training hyper-parameters of the neural network.

Setting	Value
Network type	Feed-forward multilayer perceptron
Input neurons	6 (process parameters)
Hidden layers	2 (10 and 8 neurons)
Output neurons	1 (per response model)
Hidden activation	Hyperbolic tangent (tanh)
Optimiser	Adam (adaptive moment estimation)
Initial learning rate	0.01
Maximum epochs	5000 (with early stopping)
Input/target scaling	Min-max normalisation to [0, 1]
Train / test split	80% / 20% (plus 5-fold cross-validation)

5. Results and Discussion

5.1 Network training and convergence

Figure 2 shows the evolution of the training loss for the three response networks. In every case the mean-squared error fell rapidly during the first few hundred epochs and then flattened to a low, stable plateau, indicating that the optimiser reached a well-converged solution without oscillation. The micro-hardness and residual-stress networks converged in fewer than 1,000 epochs, while the cutting-rate network required slightly more time, which is consistent with the greater scatter of the replicated cutting-rate measurements.

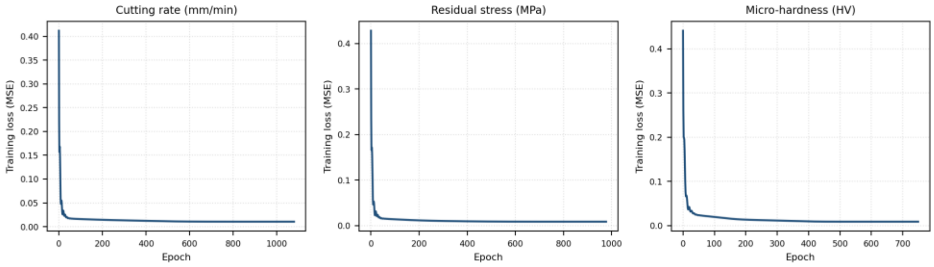

Figure 2. Training-loss convergence of the neural networks for the three responses.

5.2 Prediction accuracy and comparison with linear regression

The predictive accuracy of the trained networks is summarised in Table 3 and visualised in Figures 3 and 4. On the independent test data, the ANN achieved coefficients of determination of 0.695, 0.933, and 0.974 for the cutting rate, residual stress, and micro-hardness, respectively, with corresponding root-mean-square errors of 0.32 mm/min, 23.3 MPa, and 6.6 HV. The agreement between the predicted and experimental values is evident in Figure 3, where the data cluster closely about the line of equality for all three responses. The five-fold cross-validated R² values (0.47, 0.69 and 0.56) are lower than the single-split test values, as expected for a modest data set, but they remain clearly positive and confirm that the networks generalise rather than memorise.

Table 3. Predictive performance of the ANN and the linear-regression (LR) benchmark.

Response	Model	Test R²	Test RMSE	Test MAE	5-fold CV R²
Cutting rate (mm/min)	ANN	0.695	0.315	0.143	0.471
Cutting rate (mm/min)	LR	−0.103	0.600	0.431	0.154
Residual stress (MPa)	ANN	0.933	23.26	17.20	0.689
Residual stress (MPa)	LR	0.324	74.12	60.68	0.289
Micro-hardness (HV)	ANN	0.974	6.61	5.06	0.563
Micro-hardness (HV)	LR	0.297	34.18	28.12	0.216

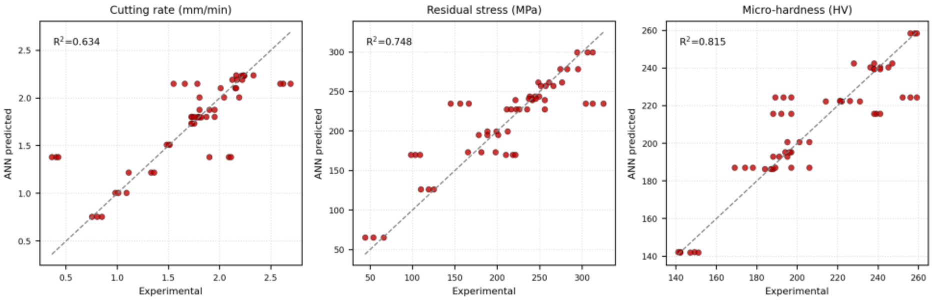

Figure 3. ANN-predicted versus experimental values for the three responses (dashed line denotes perfect agreement).

The benefit of the non-linear model is most apparent when it is compared with linear regression. As Figure 4 and Table 3 show, the linear model explained little of the variance in the test data and even produced a negative R² for the cutting rate, signifying a prediction worse than the response mean. The ANN improved the test R² by between three- and several-fold across the responses and reduced the test RMSE by roughly a factor of two to three. This gap reflects the genuinely non-linear and interactive nature of the WEDM responses, which a first-order linear model cannot represent, but which the network's hidden layers capture effectively.

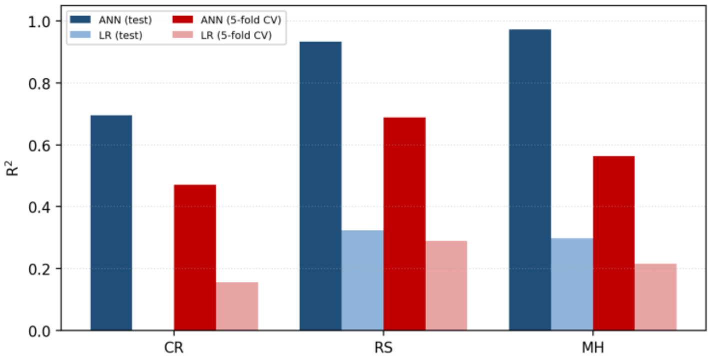

Figure 4. Coefficient of determination of the ANN and the linear-regression model on the test set and under five-fold cross-validation.

5.3 Relative influence of the process parameters

To interpret the trained networks, a permutation-importance analysis was carried out: each input was randomly shuffled in turn, and the resulting increase in prediction error was recorded, a large increase indicating an influential variable. The results are shown in Figure 5. Peak current and duty cycle emerged as the dominant variables for all three responses, with gap voltage also important for the residual stress. This ranking is physically reasonable because the peak current and duty cycle jointly govern the discharge energy delivered to the workpiece: a larger discharge energy melts and vaporises more material, raising both the cutting rate and the residual stress through steeper thermal gradients, and modifying the recast layer that determines the micro-hardness. Flushing pressure and wire feed rate were comparatively minor contributors, in agreement with the analysis-of-variance trends reported for the same alloy in earlier work (Oliver Nesa Raj and Prabhu, 2017; Kumar et al., 2018).

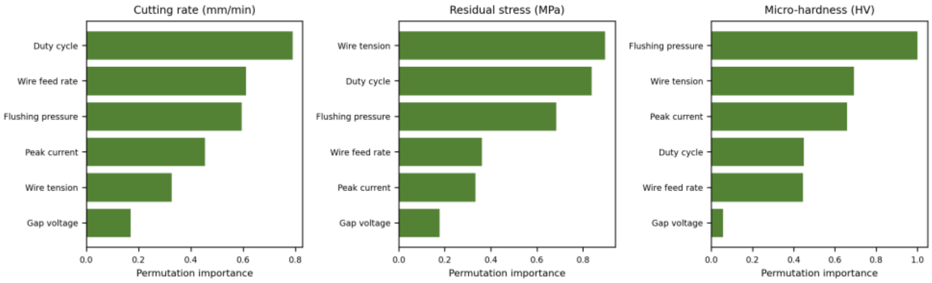

Figure 5. Permutation importance of the process parameters for each response.

5.4 ANN-based identification of favourable operating conditions

Because the trained network predicts each response at any admissible parameter combination, it can be used to search the experimental design space for favourable settings. Evaluating the networks over the eighteen design conditions identified the operating points listed in Table 4: the cutting rate was maximised at a low peak current combined with a high duty cycle, the residual stress was minimised at a moderate peak current with a low duty cycle and gap voltage, and the highest micro-hardness was obtained at a low peak current with an intermediate duty cycle. The search was deliberately confined to the sampled design region; point predictions at unsampled corners of the full factorial grid were found to extrapolate beyond the measured response ranges and were therefore not used as quantitative optima. This conservative use of the model is important for a small data set and is one of the study's practical lessons.

Table 4. ANN-identified favourable operating conditions within the experimental design space.

Objective	Flushing pressure	Peak current (A)	Duty cycle (%)	Gap voltage (V)	Wire feed rate	Wire tension	ANN prediction
Maximum cutting rate	12	90	70	30	3	3	2.24 mm/min
Minimum residual stress	12	120	60	30	4	3	54.5 MPa
Maximum micro-hardness	12	90	65	20	2	11	257.7 HV

6. Conclusions

A compact, reproducible artificial neural network workflow has been developed to predict the cutting rate, residual stress and micro-hardness of wire-cut EDM-machined Ti-6Al-4V ELI alloy from six controllable process parameters. The principal findings are as follows.

First, a 6-10-8-1 feed-forward network trained on a replicated Taguchi L18 data set of fifty-four observations predicted the three responses with test-set coefficients of determination of 0.70, 0.93 and 0.97, and converged smoothly within a few hundred to a thousand epochs. Second, the network substantially outperformed an ordinary least-squares linear regression benchmark, which failed to capture the non-linear behaviour of the responses and yielded a negative test R^2 for the cutting rate; this confirms that the alloy's surface-integrity responses are intrinsically non-linear. Third, a permutation-importance analysis identified peak current and duty cycle as the most influential parameters, consistent with the discharge-energy mechanism of material removal, with gap voltage additionally important for the residual stress. Fourth, the trained network was used to identify favourable operating windows within the sampled design space, while point predictions outside that space were shown to be unreliable for a data set of this size.

Overall, the study shows that a modest, statistically designed experiment combined with a carefully validated neural network provides an accurate and interpretable surrogate model for the WEDM of titanium alloys, and a practical aid to process planning. Future work will enlarge the data set, incorporate additional responses such as kerf width and surface roughness, and couple the trained network with a formal optimisation algorithm to perform genuine multi-objective optimisation.

Declarations

Funding: No external funding was received for this work.

Conflict of interest: The authors declare no competing interests.

Data availability: The experimental data analysed in this study are available from the corresponding author on reasonable request.

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