Comparative Experimental Analysis of ML Based Surrogate Models for Predicting MR and PRR In WEDM of Shape Memory Alloys

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Abstract

Wire electro discharge machining i.e. WEDM of shape memory alloys (SMA) involves complex experimental processes, making optimization time-consuming and expensive. To address this, machine learning-based models trained using limited experimental data are employed as surrogate systems to predict machining responses. In this study, ML models most suitable for EDM output prediction, i.e., Adaptive-Neuro-Fuzzy-Inference -System (ANFIS), Support-Vector-Regression (SVR) and Gaussian-Process-Regression (GPR) were comparatively evaluated as surrogate models for predicting product removal rate (PRR) and material roughness (MR) during WED machining of $Ti_{50}Ni_{40}Co_{10}$ SMA . Experimental data were divided into 70% training and 30% testing sets. Model performances were assessed using square root of mean error i.e. RMSE, R^2 error or the determination coefficient error, and average percent accuracy. Analysis presents that, among all models, GPR shows meaningful confidence intervals and achieved the highest accuracy (85.78%) for MR prediction due to the smooth behaviour of MR, and ANFIS demonstrated the most superior performance accuracy (65.55%) for PRR prediction despite localized nonlinear relationships and a small experimental dataset. Both SVR and GPR showed limited robustness for PRR prediction due to its highly nonlinear nature. ANFIS avoided overfitting in PRR prediction by reducing fuzzy rules but captured limited details for modelling material roughness variations, leading to lower MR prediction accuracy. The study concludes that ANFIS and GPR are best suited as surrogate modelling frameworks for PRR and MR prediction during WEDM of $Ti_{50}Ni_{40}Co_{10}$ shape memory alloys. These frameworks can be combined into a hybrid model to make a complete surrogate of the WEDM process of SMAs. The study shows how machine learning–based surrogate models can significantly reduce experimental effort while maintaining reliable prediction accuracy.

Keywords: WEDM, Shape Memory Alloys, Surrogate Modelling, ANFIS, GPR, SVR

1 Introduction

Shape memory alloys have a unique ability-to return to their original shape after any deformation upon the application of certain thermal or mechanical inputs (Soni et al., 2017). Among the shape memory alloys, the nickel-titanium Ti-Ni-Co-based alloys

A. Agnihotri et al. (eds.), *Proceedings of the Conference on Bridging Engineering Disciplines with AI and Machine Learning (BEDAIML 2026)*, Advances in Intelligent Systems Research 209,
https://doi.org/10.2991/978-94-6239-697-5_16

have been the focus of extensive research due to the presence of favourable characteristics like super-elasticity, resistance to corroding, non-toxicity, high breakpoint, and low weight. Due to hardening of these alloys during machining, the machining of shape memory alloys such as $Ti_{50}Ni_{40}Co_{10}$ using conventional machining methods such as milling, turning, or drilling is difficult (Pušavec et al., 2011). Therefore, application of unconventional techniques of shaping such as the Wire-Electro-Discharge-Machining (WEDM) method has been recognized as a viable solution for machining electrically conductive as well as difficult-to-machine alloys. It is a thermal-electric discharge machining method in which the material removal occurs due to a repetition of electric discharge in controlled manner between the electrode (wire) and the machined material dipped in a dielectric medium. However, its downside is the presence of a number of shaping parameters such as pulse on-time or T_{on}, pulse off-time or T_{off}, and servo voltage that affect the output parameters i.e. product removal rate (PRR) and material roughness (MR) (Chaudhari et al., 2019; Kibe et al., 2007; Liu et al., 2021).

These interdependent parameters in WEDM machining have a nonlinear influence on the machining responses, making it difficult to determine the optimum machining parameters using traditional empirical approaches. Such approaches also increase the machining time, material, and cost (Forrester et al., 2008; Shahriari et al., 2016) However, using the ML approach, the machining responses are predicted using the surrogate model, eliminating the need for experimental approaches and hence reducing the machining time and cost (Jiang et al., 2021; Panda & Bhoi, 2005; Phate & Toney, 2019; Saha et al., 2022; Takei et al., 2020; *Pattern Recognition and Machine Learning*, 2006). Several ML approaches are used in the surrogate modelling in the manufacturing domain. This study used the Adaptive-Neuro-Fuzzy-Inference-System (ANFIS), Support-Vector-Regression (SVR) and Gaussian-Process-Regression (GPR) approaches (Ulas et al., 2020; Wang et al., 2003).

SVR uses support vector machines that performs regression by identifying an optimal hyperplane capable of minimizing prediction error while maintaining model generalization. GPR is a probabilistic regression approach based on Bayesian inference, which models input-output relation as a range of possible functions, allowing not only predictions but also estimation of prediction uncertainty. In contrast. The adaptive-neuro-fuzzy-inference-system (ANFIS) is based on combining artificial neural networks ability of learning with the logic of fuzziness to model complex relationships, thus allowing for the modelling of complex, non-linear relationships through fuzzy rules(Jang, 1993). These powerful machine learning techniques are being actively pursued for their ability to predict machining performance.(Lalwani et al., 2020)

Qasem et al. (Qasem & Alsakarneh, 2025) conducted a comparative study to identify the most effective machine learning techniques for predicting the maximum PRR and MR in the EDM process. In their work, The performance of models such as feedforward artificial neural networks (FNN), Support-Vector-Regression (SVR), decision tree regression (DTR), random forest regression (RFR), Gaussian-Process-Regression (GPR) and k- nearest neighbours regression have been compared. It was observed that the models, such as GPR and SVR, were efficient in dealing with nonlinear relationships and limited amounts of experimental data generally encountered during the investigation of EDM operations. In the research by Kumar et al. (Kumar et al., 2025) the prediction and optimization of the parameters of the wire EDM process for machining Ti-Ni-Co shape memory alloys were carried out by utilizing the Adaptive-Neuro-Fuzzy-Inference-System (ANFIS). The hybrid architecture of the ANFIS that uses artificial neural networks ability of learning with the logic of fuzziness, is quite efficient in dealing with the uncertainties and nonlinear relationships encountered during the machining operations. So, compared to other conventional machine learning models, ANFIS stood out as a reliable approach for the modelling of the WEDM process. Since earlier research has identified GPR and SVR as highly accurate regression models for EDM processes, while ANFIS has also emerged as a powerful predictive model in WEDM applications*, the present study focuses on comparing these three high-performing approaches to evaluate their effectiveness as surrogate models for predicting accurate machining responses.*

2 Methodology

2.1 Material Collection and Analysis

The experiment material used for present work is based on the research conducted by Soni et al. (Soni et al., 2017), which studied the machinability of $Ti_{50}Ni_{40}Co_{10}$ SMA using the Wire EDM technique. The alloy used for the experiment was prepared by the vacuum arc melting method by mixing titanium, nickel, and cobalt, and cast into rectangular blocks of size fifty cross twelve cross ten cubic millimetres. The machining experiment was conducted using the ELPULS-15 CNC WEDM machine with a brass wire of diameter zero point two-five millimetres and deionised H_2O as the dielectric fluid. The input parameters selected for the experiment were wire speed, servo voltage, pulse-on time (T_{on}), pulse-off time (T_{off}) and servo feed and the machining responses obtained were product removal rate (PRR) and material roughness (MR). The input-output parameters from the experiment has been pre-processed by using the feature scaling technique, which is based on the standard scaler method, to normalize the input variables, prevent unstability and attain efficient performance of the ML models. After pre-processing, the data has been split into 70% training and 30% testing sets in using the train-test split technique.

2.2 Surrogate Models Training

After data preprocessing, after data preprocessing, surrogate models were developed to establish a correlation between WEDM machining parameters and responses. The mathematical equations of the models used in the current research are given in the following subsections. All models are appropriate for use in training a continuous and relatively small WEDM data set (Forrester et al., 2008; Jones et al., 1998; Queipo et al., 2005)

2.2.1 Support-Vector-Regression (SVR)

Support-Vector-Regression (SVR) aims to create a regression function by finding the model of minimum complexity where the error between predictions and observations does not exceed a predefined value ε. The regression function can be written as:

$$f(x) = w^T x + b$$

here, w is weight vector and b is bias. The optimization problem of SVR can be written as

$$\min \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{n} 1 \,.\, (\xi_i + \xi_i^*)$$

with constraints

$$y_i - (w^T x_i + b) \le \varepsilon + \xi_i$$
$$(w^T x_i + b) - y_i \le \varepsilon + \xi_i^*$$

Here, C is the parameter for regularizing model complexity, ε is the width of the ε-insensitive tube, and the slack variables ξ_i and ξ_i^* measure the deviation of the predictions from the ε tube. The kernel function used in SVR is the radial basis function (RBF) kernel, which enables SVR to learn nonlinear models by mapping parameters to multi-dimensional space. For present study, an RBF-kernel SVR model was implemented with hyperparameters C, ϵ, and γ optimized through Grid-Search-CV using five-fold cross-validation (Aich & Banerjee, 2014; Klopfenstein & Vaiter, 2021; Smola & Schölkopf, 2004)

2.2.2 Gaussian-Process-Regression (GPR)

Gaussian-Process-Regression (GPR) is a kernel-based regression technique using probability as a base to model input-output relation as a range of possible functions. The predictive model is defined as

$$f(x) \sim GP\big(m(x), k(x, x')\big)$$

GPR describes the probability distribution over a set of relations in coherence with the experimental data. The function $m(x)$ and its kernel $k(x, x')$ represents the model. Kernel describes the similarity between the input data points and allows non-linearity prediction in responses. Current work presents a composite kernel given by the product of a constant kernel and a radial basis function (RBF) kernel and further augmented with a white noise kernel for the smooth as well as the noisy variations in the data set (Rasmussen & Williams, 2005; Shahriari et al., 2016).

2.2.3 Adaptive-Neuro-Fuzzy-Inference-System (ANFIS)

ANFIS is based on combining artificial neural network with the logic of fuzziness to model complex relationships. It is based on the Takagi-Sugeno model and has five computational layers. These include fuzzification, rule evaluation, normalization, de-fuzzification, and aggregation. Rule weight of rule i is calculated as:

$$w_i = \mu_{A_i}(x)\mu_{B_i}(y)$$

normalized rule weight is

$$\bar{w}_i = \frac{w_i}{\sum w_i}$$

End-result is taken out by combining the weighted rule outputs:

$$f = \frac{\sum w_i f_i}{\sum w_i}$$

Where f_i is the linear consequent function of each fuzzy rule. Gaussian membership functions are applied for fuzzy representations of linguistic variables. This facilitates a smooth transition between fuzzy regions. A least squares learning method is applied for estimation of the parameters.(Jang, 1993; Kumar et al., 2025; Maher et al., 2015; Surajudeen-Bakinde et al., 2022)

2.3 Models Testing

Models trained using 70% of the data were used to predict the results using the remaining 30% of data. The models' ability to predict the output using the machining parameters is then evaluated. Each model's accuracy is determined using three different metrics: R^2, Average Accuracy and RMSE. The R^2 value indicates the level of explanation of the variability of response values. The RMSE measures the prediction error using the square root of mean of the residuals, that measures accuracy of given models. The percentage prediction accuracy measures the closeness of the prediction to the actual values. These metrics help access efficiency of models as surrogates in machining studies. Results from prediction are shown in Table 2. The metrics' formulas are given below (Draper & Smith, 1998; Hastie et al., 2009; Montgomery et al., 2012).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} 1.(y_i - \hat{y}_i)^2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} 1.(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} 1.(y_i - \bar{y})^2}$$

$$Accuracy(\%) = 100 - (\frac{100}{n} \sum_{i=1}^{n} | \frac{y_i - \hat{y}_i}{y_i} |)$$

where,

y_i– Actual experimental value of the response
$\hat{y}_i$– Predicted value of response obtained from the surrogate model
$\bar{y}$– Mean of the actual values of response variables
n– Total entries in the testing data
i– Index of each observation

Table . Input Parameters, Actual PRR and Predicted PRR values

Ton	Toff	SV	SF	WS	Actual PRR	Predicted PRR (SVR)	Predicted PRR (GPR)	Predicted PRR (ANFIS)
115	28	40	2180	4	5.44	2.90720342	3.717437644	3.623223776
120	35	30	2170	3	5.25	3.455835593	4.5823855	5.074133381
115	42	20	2180	4	5.32	3.683764535	4.208113843	4.632175544
115	42	40	2180	4	4.57	3.279936634	3.188778037	3.053931304
120	49	30	2170	5	5.37	3.086925999	3.697782404	4.288347276
120	49	50	2190	5	2.73	2.800086862	2.973664857	3.480349049
120	49	30	2190	3	5.53	3.274406194	4.119125552	5.041136486
120	35	50	2190	3	4.11	2.89483942	3.739391011	4.101206927
110	49	30	2190	5	1.88	3.105780511	2.89302221	2.636087067
120	35	50	2170	5	1.26	2.777058337	3.345315884	3.335053072

Table . Input Parameters, Actual MR and Predicted MR values

Ton	Toff	SV	SF	WS	Ac-tual PRR	Predicted MR (SVR)	Predicted MR (GPR)	Predicted MR (ANFIS)
115	28	40	2180	4	5.44	2.72165816	2.773043478	2.824256754
120	35	30	2170	3	5.25	2.928055541	2.773043467	1.896672808
115	42	20	2180	4	5.32	2.444209834	2.770124048	1.736649068
115	42	40	2180	4	4.57	2.704696704	3.329989164	3.100982543
120	49	30	2170	5	5.37	2.51413629	2.773043467	2.092218981
120	49	50	2190	5	2.73	2.935787485	2.773043478	2.728216051
120	49	30	2190	3	5.53	2.841471235	2.773043467	3.617939216
120	35	50	2190	3	4.11	2.99221127	2.773043478	3.064189474

110	49	30	2190	5	1.88	2.7325031	2.773043468	2.903989947
120	35	50	2170	5	1.26	2.711323442	2.773043478	1.602801732

3 Experimental Outcomes and Discussion

3.1 Material Roughness (MR) Prediction

3.1.1 Average Accuracy

The average prediction accuracy measures closeness of predicted values to the experimental ones. In this study, GPR's predictions were on average closest to the true values (85.78%), while SVR was slightly lower (85.05%). ANFIS lagged behind (65.55%). Higher accuracy of GPR suggests that its kernel-based Bayesian approach captured the underlying MR trends more reliably. High accuracy implies that the model behaves well on unseen data, which parallels with prior work showing GPR's effectiveness in WEDM modelling. The comparatively poor accuracy of ANFIS implies that its fuzzy-rule structure did not fit the MR behaviour very well. This is because of its capability to perform better on non-linear and complex data rather than simple and linear data. The ε-insensitive loss function and limited flexibility for highly nonlinear relationships lead to SVR behaving moderately in accuracy.

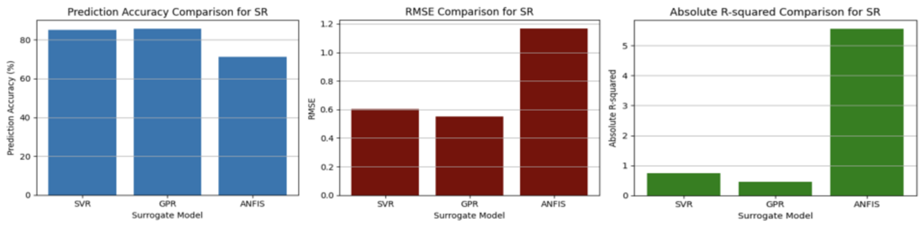
3.1.2 RMS Error

Low RMSE is generally correlated with high prediction precision. GPR produced the smallest RMSE (≈0.55 μm), SVR was intermediate (≈0.60 μm), and ANFIS was much larger (≈1.16 μm). This result is consistent with other WEDM studies, where GPR models often yield the lowest error metrics (i.e., highest precision) when predicting MR. ANFIS's RMSE being roughly double that of GPR and SVR's intermediate RMSE reflects that GPR and SVR were significantly better at minimizing residuals for MR due to their robust and more flexible fit.

3.1.3 R^2 Error

R^2 error represents the proportion of variance within the parameter being measured. High R^2, along with low values of RMSE, represents a good model fit. The GPR model captured most of the variability in the data by achieving the highest R^2 for MR (-0.45). SVR's R^2 was slightly lower (-0.74) but still relatively high, whereas ANFIS's much smaller R^2 (-5.56) showed its failure to learn MR trends due to the smoothness of MR values.

Fig. 1 (a), (b), (c) Accuracy, RMSE and Absolute R^2 Comparison of SVR, GPR and ANFIS MR Predictions



3.2 Product Removal Rate (PRR) Prediction

3.2.1 Average Accuracy

In contrast to MR average accuracy values, ANFIS achieved the highest average accuracy for PRR (65.55%), followed by GPR (61.05%), with SVR lowest (55.92%). Thus, ANFIS model's adaptive fuzzy inference captured the complex relation of input parameters to PRR effectively which is consistent with various prior studies. the product removal rate exhibits localized nonlinear variations due to complex interactions between machining parameters and spark energy distribution. As a result, GPR, having kernel-based architecture good at capturing linear or smooth non-linearity fails. SVR gives lowest accuracy due to its failure to capture non-linearities and requiring more training for better predictions.

3.2.2 RMS Error

In terms of RMSE for PRR, ANFIS had the lowest error (~1.10 units), GPR's error was moderate (~1.30), and SVRs was highest (~1.70). The relatively small RMSE of ANFIS means it had smaller residuals on average. SVR's larger RMSE shows it had greater deviation and GPR's RMSE in the middle reflects a reasonable model but still worse than ANFIS. Low RMSE is generally correlated with high prediction precision, so ANFIS clearly produced the tightest fit.

3.2.3 R^2 Error

The ANFIS model achieved the highest R^2 for PRR (~0.45), compared to GPR (~0.28) and SVR (~0.26). While these R^2 values are not high in absolute terms due to higher variance, ANFIS clearly explained more of the PRR variability than the other models. This aligns with its superior accuracy and lower RMSE. The lower R^2 for SVR and GPR models can be attributed to their smooth regression structures limit their ability to represent localized nonlinear variations as in the highly nature of the PRR, resulting in lower explanatory power compared to the ANFIS model

Fig. 2 (a), (b), (c) Accuracy, RMSE and Absolute R^2 Comparison of SVR, GPR and ANFIS PRR Predictions

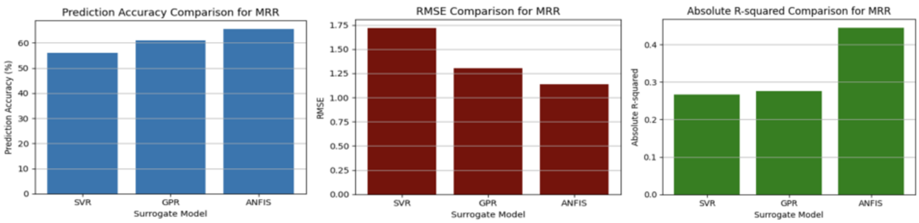
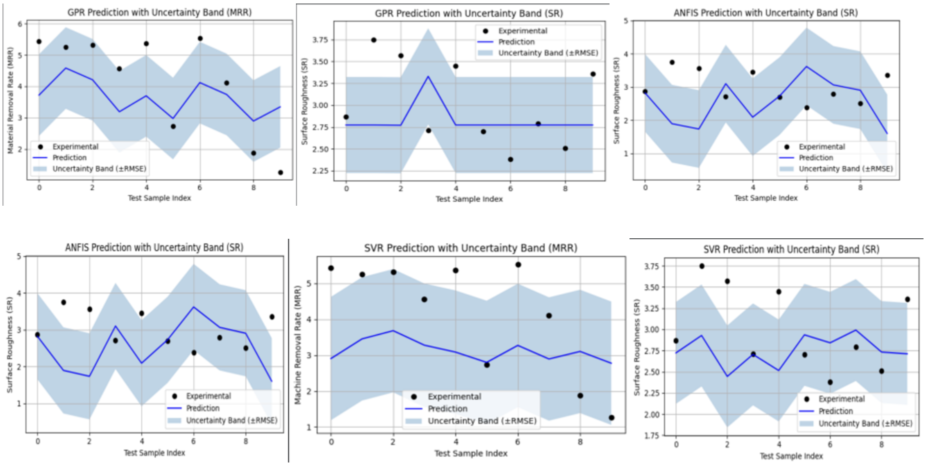


Fig. 3: (a), (b), (c), (d), (e), (f) PRR/MR vs Test Sample Index uncertainty band plots for GPR, SVR and ANFIS models



3.3 Models Error Distributions

To evaluate the reliability of prediction of the surrogate models, the distribution of prediction errors for each model was analyzed to get insight into the bias, spread, and consistency of model predictions. Ideally, prediction errors should be centered around zero with minimal spread, indicating accurate and unbiased predictions.

3.3.1 Error Distribution for SVR

In predicting PRR, the error distribution interval of −1.5 to +2.5 for the SVR model shows a widespread range of prediction errors. This relatively broad distribution explains the higher RMSE and lower R^2 values obtained for SVR in PRR prediction. Overall, the error pattern indicates moderate predictive stability but limited precision. For MR prediction, the SVR error distribution appears more concentrated around the zero-error line with a narrow interval of −0.4 to +1.

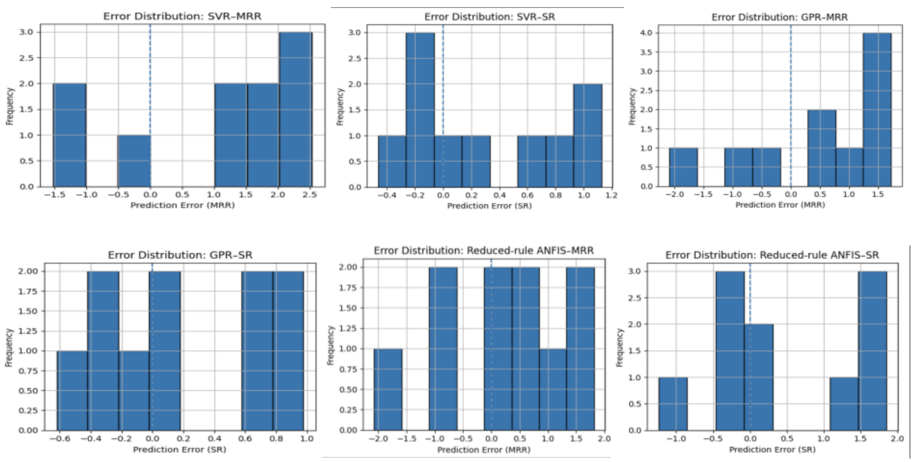
3.3.2 Error Distribution for GPR

The error distribution for the GPR model in PRR prediction shows a more balanced distribution around zero, ranging approximately between −2.0 and +1.7. The model tends to slightly overestimate PRR values, indicated by most errors lying on the positive side of the zero-error line. The presence of larger negative errors for certain samples suggests that the model occasionally underestimates the actual PRR. For MR prediction, the error distribution within the range of approximately −0.6 to +0.9 appears more evenly distributed around the zero line, indicating relatively unbiased predictions.

3.3.3 Error Distribution for ANFIS

In PRR prediction, the error distribution ranging between −2.0 and +1.8 indicates a relatively balanced spread around the zero-error line, showing better capturing of complex PRR parameters by ANFIS than other models. In case of MR prediction, error distribution ranging between −1.1 and +1.8 shows moderate variability around zero. The distribution appears slightly wider compared with to other models, suggesting that ANFIS predictions for MR exhibit somewhat higher variability.

Fig. 4: (a), (b), (c), (d), (e), (f) Frequency vs Prediction Error plots of SVR, GPR and ANFIS for PRR and MR



4 Conclusion

Following can be concluded from the present study:

1) The prediction analysis for **product removal rate (PRR)** demonstrates that the ANFIS model achieved the highest prediction accuracy of **65.55%,** with the lowest RMSE value of approximately **1.14** and the highest determination

coefficient, **$R^2 \approx 0.45$**, among the three taken models, showing its superiority in modelling complex, non-linear interactions in PRR response and machining parameters.

2) The prediction performance for **material roughness (MR)** shows that the GPR or Gaussian-Process-Regression model provides the most reliable predictive capability. The GPR shows prediction accuracy of **85.78%**, maximum among other models compared, with the lowest RMSE of approximately **0.55**, indicating better capturing of the smooth variation patterns present in the MR response.
3) The analysis of **individual prediction error distributions** shows the ANFIS model exhibiting a relatively balanced error distribution for PRR predictions, while the GPR model produced a tighter and more symmetric error distribution for MR predictions. Thus, ANFIS indicates stable modelling of the highly nonlinear material removal process and GPR demonstrates consistent and unbiased prediction behaviour for material roughness. SVR showed comparatively wider error spread in PRR prediction, suggesting limitations in capturing strong nonlinear parameter interactions.

Overall, the comparative evaluation confirms that surrogate model suitability in WEDM prediction is **strongly dependent on the response variable being modelled.** Based on the obtained performance metrics and error analysis, **ANFIS is identified as the most suitable surrogate model for PRR prediction, while GPR provides the most reliable predictions for MR** in machining $Ti_{50}Ni_{40}Co_{10}$ shape memory alloy using the WEDM process.

5 Novelty of Work and Future Scope

The present work compares different high-performance regression approaches for the prediction of key machining responses in shape memory alloys. While several studies have applied individual machine learning techniques to model EDM or WEDM processes, limited research has focused on directly comparing the overall best ones. Another unique feature of this work is the response-specific comparison of surrogate models, demonstrating that different machining responses may require different modelling approaches. While ANFIS was found to be more effective for modelling the highly nonlinear behaviour of PRR, GPR provided superior prediction performance for MR due to its capability to model smooth response variations and provide probabilistic confidence estimation. The study further incorporates prediction accuracy, RMSE, R^2 analysis, and error distribution evaluation to delve deeper into reliability and behaviour of the models. Thus current research shows how machine learning–based surrogate models can significantly reduce experimental effort while maintaining reliable prediction accuracy, thereby contributing to the development of data-driven machining optimization strategies for shape memory alloys.

Although the current research focuses on the prediction of machining responses for the $Ti_{50}Ni_{40}Co_{10}$ shape memory alloy, extending the developed modelling framework to other alloys like Ni-Ti, Inconel and Titanium having a challenging cutting process will enhance its practical applicability. Additionally, further work can be done on developing a hybrid surrogate modelling framework that combines the strengths of both ANFIS and Gaussian-Process-Regression (GPR) for simultaneous prediction of multiple machining responses.

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