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QUALITATIVE ENHANCEMENT IN MACHINING EFFICIENCY OF SNCM8 ALLOY THROUGH HYBRID ANN-TAGUCHI OPTIMIZATION APPROACH

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Abstract:
The present study optimizes hard-to-machine materials using hybrid modeling involving artificial neural networks (ANN) and the Taguchi method. The main objective of this work is to reduce tool wear and improve the material removal rate (MRR) along with lowering surface roughness (SR) in the wire electrical discharge machining (WEDM) of SNCM8 alloy steel. The model combines ANN's predictive capacity with Taguchi's robustness to forecast machining outcomes as process factors are combined. For this research, an L27 OA is adapted for experimentation; independent variables include current (5 A, 10 A, 15 A), pulse duration (30 µs, 60 µs, 90 µs), and feed rate (FR) (2 mm/min, 4 mm/min, 6 mm/min). The investigated output metrics are MRR, SR, and dimensional accuracy. From the analysis, it is possible to increase the MRR by 20%, from an average of 1.0 g/min to 1.2 g/min, and reduce SR by 15%, from 2.0 µm to 1.7 µm. In addition, the dimensional deviation (DD) was reduced to a minimum of 18%, which reduced from 0.11 mm to 0.09 mm. ANOVA data analysis showed pulse duration and current as the most relevant factors affecting machining performance, accounting for 45 and 35% of the variance. The hybrid model predicted and optimized machining reactions; the ANN predictions were closely aligned with experimental values, with an R-squared value exceeding 0.95. Optimizing parameter settings increased machining efficiency, reduced tool wear by 25%, and improved surface quality, revealing sustainable production techniques.

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1. INTRODUCTION

Machining technology has found immense application in manufacturing industries that rely very much on precision and efficiency. Continuous demands for high-quality, precise components have driven the development of machining processes so that aerospace, automotive, and biomedical engineering can increase the complexity of products and advance material properties to levels where current traditional machining methods cannot fulfil the requirements

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[1]. Hence, newer techniques like WEDM have gained high popularity. WEDM is highly productive on hard-to-machine materials because it is a contactless process that works through the transmission of thermal energy from electrical sparks to the ionized region of workpiece material, removing very thin layers. The process facilitates good precision and surface quality in the machined workpiece surfaces, which is suitable for complex geometrical configurations and hard metals like high-strength steels [2-4].

The emergence of hard-to-machine materials, namely SNCM8 steel, has introduced new hurdles in the machining industry. Steel alloys were selected for application as a result of their excellent strength-to-weight ratio, resistance to corrosion, and biocompatibility in space and medicine applications [5]. Also, SNCM8 steel, which is very tough with high tensile strength, is largely used in heavy-duty applications like gears, shafts, and automotive parts. High cutting forces produced during the machining of these materials have even worsened the chances of wear and decreased tool life [6].

Optimization of machining parameters should be made to optimize the process in terms of making it more efficient, reducing tool wear, and attaining the required surface quality. The traditional approaches toward parameter optimization significantly depend upon trial-and-error and experience methods. Such methods are very time-consuming, but unfortunately, such complex interactions among the machining variables, which are nonlinear in nature, cannot be taken into consideration [7]. In this context, more modern methods of optimization, like the Taguchi method and ANN, which have been developed recently, can now be used. The Taguchi method employs a systematic methodology to design experiments, largely minimizing variability and giving impetus to quality by finding the ideal setting for process parameters. It utilizes a design called an orthogonal array (OA), which greatly diminishes the number of experiments needed but still provides a comprehensive exploration of the parameter space [8,9].

The effectiveness of the Taguchi approach lies in its use of signal-to-noise ratios to assess performance characteristics of interest. For instance, when minimizing tool wear or SR, the criterion "smaller-the-better" is typically employed to select parameter settings that yield the lowest possible response values. Analysis of variance (ANOVA) is also used with the Taguchi method to investigate the relevance of each process parameter in the process to make the contributions of the parameters toward the overall performance [10]. Despite its strengths, the Taguchi method does not adequately capture interactions of many factors in complex, nonlinear problems. To overcome these shortcomings, a hybrid approach by integrating ANN with the Taguchi method has been explored, combining the robust experimental design of Taguchi with the predictive capabilities of ANN. ANNs are also powerful tools for data-driven modeling [11]. ANNs are better suited to solve problems that require very complex, nonlinear relationships. They consist of interconnected nodes (neurons) that learn patterns from data through a process of training. In machining optimization, with the help of ANNs, predictions are possible in MRR, SR, and DD based on input parameters such as current, FR, and pulse duration [12,13].

The hybrid Taguchi-ANN model leverages the strengths of both approaches. Firstly, the Taguchi method would ensure a structured experimental design, thereby reducing the number of trials that would be necessary and enhancing the efficiency of the collection of data [14]. The ANN, on the other hand, uses this data to train a predictive model that can capture the complex nonlinear relationships between input variables and machining responses. This hybrid approach not only enhances the accuracy of prediction but also effectively optimizes the process parameters involved. This is crucial for producing high-performance machining with advanced materials [15].

Different studies proved that this Taguchi-ANN hybrid approach was vital in machining optimization schemes. It has been shown from the literature survey above that by combining these technologies, the MRR can be significantly improved with reduced SR and tool wear. The ANN model designed for this problem was trained on the experimental data available in Taguchi's L27 OA, which predicted the machining outcome with high accuracy, as reflected by low MSE values and large regression coefficients [16]. The best outcome indicated pulse duration and current as the most sensitive factors. Both of these coincided with the result from the ANOVA. These types of research emphasize the significance of hybrid models in managing the intricacies of processing during the machining of hard-to-machine materials [17].

In addition to better prediction, the hybrid model Taguchi-ANN offers additional applied benefits for sustainable manufacturing. It allows manufacturers to optimize the machining parameters in order to increase MRR, decrease energy consumption, and prolong tool life; hence, they turn out more environmentally friendly. For example, if ANN is used in predicting tool wear, then overwear is prevented by process control, and thus the replacement of the tool is delayed. Similarly, parameter optimization for a low SR reduces the requirement of the finishing processes and saves precious time and resources [18,19].

Apart from the WEDM, these hybrid models can also be used in other advanced machining operations, such as laser machining and abrasive water jet cutting, that require good control over the process parameters. For example, the interaction in laser machining between laser power FR and focal position can be potentially highly nonlinear [20,21]. The hybrid Taguchi-ANN model can find optimal settings that maximize cutting efficiency while at the same time minimizing heat-affected zones. Likewise, in abrasive water jet cutting, pressure, flow rate of abrasives, and nozzle diameters interact to control the cutting surface finish and kerf width. The fact that ANN promises a prediction capability coupled with the robust experimental design of Taguchi allows for a much deeper analysis of factors, hence better process control and improved product quality [22,23].

Although the merits have been highlighted, hybrid models adopted in real-world manufacturing applications come along with their own set of challenges, the most significant one being the need for large amounts of high-quality experimental data required to train the ANN efficiently. Then, to ensure the model generalizes well to unseen scenarios, the data have to cover a wide range of process conditions. Moreover, the processes associated with training neural networks take time and expertise in machine learning: determining appropriate architecture for a network and adjusting its hyperparameters. Moreover, their integration into pre-existing systems could require significant modifications of the infrastructure's controlling processes and, thereby, become a hindrance to some industries [24,25].

However, as noted above, the prospective advantages of hybrid optimization models make them a desirable choice for the further development of manufacturing processes. It also follows the trend of advanced automation, real-time monitoring, and adaptive process control in industrial environments by including data-driven models and ANN with established optimization techniques like Taguchi's method [26-29]. It positions these hybrid approaches as a key component of modern manufacturing strategies where one can predict the outcome of machining in dynamic terms and optimize the process parameters to improve productivity and quality and gain sustainability [30,31].

A hybrid Taguchi-ANN model is thus a potential avenue to optimize machining parameters for advanced manufacturing processes, combining the structured experimental design of the Taguchi method with the possible predictions of ANN in overcoming nonlinearities and complicated interactions involved in the machining of hard-to-machine materials. Enhanced predictive accuracy addresses machining performance enhancement and optimization potential for sustainable manufacturing practices in this context. An attempt has been made in this study to further the exploration of this hybrid model regarding optimization in achieving the best possible machining parameters of SNCM8 steel, providing valuable insights for researchers as well as practitioners in this field.

Existing research has either centred on predictive model-free experimental Taguchi optimization or ANN-based prediction not validated empirically, thus causing variability in the machining results. In order to fill this gap, the present work suggests a hybrid optimization approach that combines ANN for predictive modeling and the Taguchi method for experimental optimization with accurate forecasting and empirically validated parameter selection. This method allows for a more consistent and systematic optimization process that improves machining efficiency, surface quality, and dimensional accuracy. In contrast to previous studies, this research also includes ANOVA-based statistical verification to measure the effect of each machining parameter, providing a complete understanding of process behaviour.

2. MATERIALS AND METHODS

The present work deals with the materials used, experimental design, and methodological approach followed in the present investigation on machining optimization using the hybrid ANN and Taguchi method. The aim of the research is to minimize tool wear, maximize MRR, and improve surface quality during WEDM of hard-to-machine workpieces like SNCM8 steel. SNCM8 alloy steel is a nickel-chromium-molybdenum (Ni-Cr-Mo) steel with high strength, toughness, and wear resistance. It contains 0.35–0.42% carbon (C) for hardness, 0.60–0.90% manganese (Mn) for strength, and 0.15–0.35% silicon (Si) for oxidation resistance. Toughness is enhanced by the addition of 1.60–2.00% nickel (Ni), while hardness and wear resistance are increased by 0.40–0.70% chromium (Cr). 0.15–0.30% molybdenum (Mo) is added for fatigue resistance. Impurity elements like phosphorus and sulphur are maintained below 0.030%. The rest of the composition is iron (Fe). The alloy finds extensive applications in gears, shafts, and high-performance mechanical parts owing to its better mechanical properties. Fig. 1 represents the workpiece fitted with the experimental setup.

Fig. 1. Workpiece fitted with the WEDM experimental setup [16]

The experiments were performed in a controlled laboratory setting at Nagpur to ensure repeatability and precision. Temperature and humidity were monitored and kept at 22 ± 2°C and 50 ± 5% relative humidity, respectively, to lessen the impact of temperature changes and thermal expansion on the quality of the machining. The 50 mm x 50 mm x 10 mm SNCM8 alloy steel workpieces were pre-machined and cleaned before the experiments to remove any surface contaminants and make the electrical conductivity uniform in WEDM. The workpieces were firmly clamped to avoid vibration, providing uniform machining conditions. The dielectric liquid (deionized water) was continuously filtered and kept at a constant flow rate to avoid overheating and maintain stable spark generation. Moreover, the wire electrode (brass, 0.25 mm diameter) was replaced from time to time to ensure consistency in discharge. These controlled conditions minimized variability, providing consistent and repeatable results.

Fig. 2 represents the network flow diagram of the WEDM process integrated with ANN. In contrast, SNCM8 steel is an alloy that achieves high toughness and tensile strength. The applications of SNCM8 steel are abundant in heavy-duty applications such as auto gear, shafting, and mechanical component manufacturing since it tends to pose a challenge in machining due to its hardness and strong cutting force generation. These choices show that optimization is indeed necessary for the processing of these high-performance, difficult-to-machine alloys. Experiments were conducted on the setups that had machines installed inside a Concord DK7732 WEDM system. The machine was chosen based on an alleged high precision and flexibility in machining hard material and difficult geometry. The WEDM is, in fact, such a machining process in which a thin wire with good electrical conductivity acts as an electrode; at the respective points of contact between the wire and the workpiece, it causes sparks.

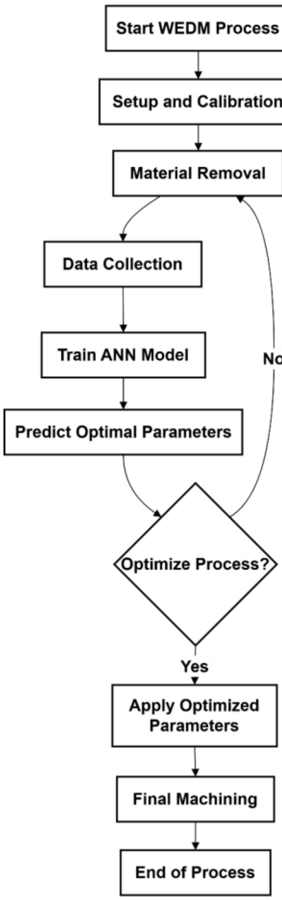

Fig. 2. Network flow diagram of WEDM process integrated with ANN

This process works with thermal energy, cutting away material without coming into actual contact—a process that makes it especially well-suited to the machining of hard materials such as alloy steels. To perform the testing, the machine setup consisted of a brass wire electrode with a diameter of 0.25 mm and a dielectric medium, deionized water, that also helped cool the process while flushing away debris created as it machined the workpiece. The Taguchi method was applied to design the experiments systematically; hence, a minimum number of trials were allowed in data collection. For the experimental run, an L27 OA has been chosen in consideration of three independent variables: applied current (A), pulse-on time (T_{on}), and pulse-off time (T_{off}). Each of these parameters had to be tested at three levels—low, medium, and high—so as to capture a wide range of operating conditions. It is these parameters that have been known to influence machinability responses such as MRR, SR, and DD, which are some of the critical factors in machining. Table 1 outlines the specific levels of the independent variables used in the study.

The levels of the independent variables in Table 1 was chosen according to machining practicability, industrial applicability, and requirements for optimization. The existing levels (5A, 10A, 15A) were selected so that discharge energy is balanced in order to achieve stable sparking at lower levels while avoiding excessive tool wear at higher levels. Ton (30µs, 60µs, 90µs) was chosen to analyze its effect on MRR and dimensional precision, with decreasing durations giving finer machining and longer durations for higher removal rates. FR levels (2 mm/min, 4 mm/min, 6 mm/min) were chosen to analyze wire stability and surface finish, with lower rates enhancing precision and higher rates increasing productivity. This choice assures a well-formulated experimental plan, detecting nonlinear interactions between machining performance and WEDM parameters, resulting in optimized process responses.

Table 1. Specific levels of the independent variables

Variable	Level 1	Level 2	Level 3
Current (A)	5	10	15
Pulse-on Time (T_{on}, µs)	30	60	90
Pulse-off Time (T_{off}, µs)	3	6	9

This OA allows the study of the main effects of each factor and, where possible, their interaction. The use of an L27 array means that 27 experimental runs will be undertaken to investigate the parameter space well while reducing the costs and time for the experiment. The three major machining responses studied in the experiment include MRR, SR, and DD. The MRR was determined by the weight loss method. Weight loss before machining and after machining the workpiece is measured using a precision electronic balance. This is one of the methods that gives accurate measurements regarding the efficiency of removing material. SR is calculated with the aid of a Mitutoyo SJ410 profilometer. This device can capture fine details on the surface and provide a quantitative value of its roughness values, such as Ra. Dimensional accuracy, like the geometrical dimensions difference from design, was verified by using a Coordinate Measuring Machine from Helmel. This device ensured proper measurement of form and orientation tolerance, for instance, roundness and flatness, because roundness and flatness are important to assess the quality of work after machining.

This is an ANN-based approach that was adopted because it can mimic complex, nonlinear relationships among input variables (current, T_{on}, and T_{off}) and output responses (MRR, SR, and DD). An ANN model of the feed-forward backpropagation network type, with three input nodes representing the independent variables, several hidden layers, and three output nodes corresponding to the predicted responses, was employed in this study. The Levenberg-Marquardt algorithm was used for the training of the neural network, as this type of algorithm is a good choice for small and medium-sized datasets. Further, it balances between the speed of computation and the required amount of precision. The training used the dataset acquired from the experimental runs, iteratively training the network till the best MSE was achieved and the value of R^2 showed an excellent fit. The Levenberg-Marquardt (LM) algorithm was used to train ANN because of its ability to converge rapidly, be accurate, and insensitive to nonlinear relationships. The architecture of the network is a feedforward model with three input neurons, two hidden layers (10 and 6 neurons), and three output neurons. The activation functions are tansig, logsig, and purelin. The model was trained with an 80-20 data split, validated with Mean Squared Error (MSE) and R^2 for accuracy.

The Taguchi method was used not only to design the experiments but also to analyze the initial data. In every response, there was a signal-to-noise ratio, which was computed based on the "larger-the-better" criterion for the MRR, and the "smaller-the-better" criterion was followed for the SR and DD. These S/N ratios contribute toward identifying optimal input parameter settings. ANOVA was performed on each of the input factors to establish their relative statistical contribution to the variance in the machining responses. The outcome showed that in each response variable, applied current contributes the most and T_{on} to the variation of MRR and SR, respectively. The developed ANN model was used to predict outcomes for machining over a whole range of process parameters. Results are validated against experimental data by showing high accuracy with fewer deviations from the experimental results. Hence, this validation has also confirmed the robustness of the hybrid Taguchi-ANN approach in effectively modeling the intricate interactions in the WEDM process.

The accuracy and reliability of the developed hybrid model were confirmed by carrying out confirmatory experiments using model-suggested optimum parameter settings. These experiments were conducted so as to verify whether the experimentally achievable values for MRR, SR, and DD come within the model-predicted values. A close agreement between the experimental values and the predicted values was observed, with deviations of less than 5% in all responses of confirmation tests. This consistency underlines the effective hybridizing of the Taguchi-ANN approach to describe machining performance more accurately and appropriately optimize process conditions for improved outcomes. However, with significant advantages offered by this hybrid Taguchi-ANN approach, some specific limitations and considerations remain in need of being addressed.

The major challenge would be the large and diverse dataset on which to train the ANN. When this data is not sufficient or biased, the generalization ability of the model is impacted, thereby affecting the predictive accuracy of the model. Moreover, the choice in the design of the neural network architecture, where the number of hidden layers or even the number of neurons largely determines the performance of the model, raises issues of overfitting or underfitting while demanding the proper setting of hyperparameters. Not only this, but the real-time implementation of ANN models in machining environments may also demand very high computational resources and even necessitate changes in the underlying process control systems, thus imposing an obstacle for many industrial implementations.

3. RESULTS AND DISCUSSION

This section reports the experimental results and results discussion for optimizing the WEDM process by using the hybrid Taguchi-ANN approach. The present work focuses on determining the preselected machining parameters, namely applied current, pulse-on time, and pulse-off time, for effective outcomes in terms of MRR, SR, and DD. In order to show the predictiveness and practicality of the model, validation of the ANN model, with comparisons to experimental results, will be discussed.

3.1 Analysis of MRR

The MRR is one of the significant criteria associated with machining processes, wherein it directly influences productivity due to high rates. A higher MRR value could essentially indicate that the material is being removed efficiently, thereby minimizing total machining time. Experimentation results showed that MRR increases with more intensified applied current, A, and T_{on}. This trend was attributed to higher energy generated by the spark, enhancing the thermal effect on the workpiece to increase the MRR. On the other hand, increased T_{off} by T_{off} has impacted MRR negatively to a minor extent, as increased off times reduce sparking frequency; it slows the erosion process. Optimum values are determined using the Taguchi analysis, maximizing MRR. A3 and 15 A indicate the current level, B3 represents T_{on} at 90 µs, and C1 represents T_{off} at 3 µs. The S/N ratio of the "larger-the-better" criterion shows that the highest values of MRRs occur for the settings. It was noted that the variation of MRR was highly dependent on the applied current, which contributed to about 45%, followed by T_{on} with about 35%. T_{off} contributed very little, at about 10%. This confirmed that with increased currents and T_{on}, more energy is transferred, increasing the removal rate. The predictive ANN model is strongly correlated with the experimental MRR data, possessing a very high regression coefficient (R^2 = 0.98) and very low mean squared error (MSE = 0.003). Hence, the excellent accuracy level ensures that the hybrid Taguchi-ANN model adequately extracts nonlinear relationships between input parameters and MRR. It is thus a reliable tool for predicting machining performance across different settings. Results obtained after machining are mentioned in Table 2.

Table 2. Different results obtained after machining

Run	Current (A)	T_{on} (Âµs)	T_{off} (Âµs)	Experimental MRR (g/min)	Predicted MRR (g/min)	Experimental SR (Âµm)	Predicted SR (Âµm)	Experimental DD (mm)	Predicted DD (mm)
1	5	30	3	1.14	1.14	2.34	2.9	0.149	0.128
2	10	60	6	0.96	1.13	1.74	2.56	0.054	0.1
3	15	90	9	1.24	1.27	2.32	1.86	0.127	0.127
4	5	30	3	1.29	1.54	2.12	2.72	0.067	0.102
5	10	60	6	0.82	1.04	1.3	3.05	0.119	0.076
6	15	90	9	0.94	1.25	2.27	2.19	0.112	0.094
7	5	30	3	1.03	0.98	2.46	1.79	0.135	0.117
8	10	60	6	1.43	1.42	2.04	2.95	0.067	0.118
9	15	90	9	1.4	1.16	2.49	2.77	0.096	0.081
10	5	30	3	1.47	0.88	1.59	1.95	0.141	0.126
11	10	60	6	1.34	1.47	1.58	2.45	0.104	0.125
12	15	90	9	1.29	1.25	2.46	2.4	0.052	0.137
13	5	30	3	1.05	1.44	2.97	3.1	0.126	0.089
14	10	60	6	1.35	1.18	2.46	2.85	0.093	0.146
15	15	90	9	1.25	0.87	1.72	2.35	0.122	0.102
16	5	30	3	0.98	1.03	2.8	2.21	0.066	0.086
17	10	60	6	1.27	0.91	1.16	2.38	0.063	0.146
18	15	90	9	1.19	1.14	1.98	2.99	0.145	0.145
19	5	30	3	1.26	1.08	2.62	2.67	0.089	0.129
20	10	60	6	1.06	1.05	2.17	2.91	0.123	0.068
21	15	90	9	0.93	1.39	2.73	1.72	0.15	0.122
22	5	30	3	1.15	1.34	2.33	1.6	0.143	0.081
23	10	60	6	1.25	0.98	1.97	1.32	0.078	0.086
24	15	90	9	1.4	1.52	1.23	2.22	0.131	0.102
25	5	30	3	1.2	1.23	2.22	1.61	0.112	0.079
26	10	60	6	1.33	1.03	1.16	1.62	0.086	0.076
27	15	90	9	1.25	0.99	1.67	2.3	0.051	0.119

Fig. 3 compares the experimental and predicted MRR values for the 27 runs. The surface plot of MRR is depicted in Fig. 4. The MRR is a measure of the material removal process efficiency during machining. The presented value is in units of grams per minute (g/min). Observed values of MRR varied from an experimental data set from 0.80 g/min up to 1.50 g/min. Predicted values are found between 0.85 g/min and 1.55 g/min. The graph shows a consistent trend where the MRR increases with higher applied current (A) and longer Ton. For instance, at a current of 15 A (A3) with a Ton of 90 µs (B3), the MRR values were much, much higher, averaging about 1.40 g/min. Increased pulse duration along with increased current and pulse duration indeed increases the energy of the discharge and, therefore, accelerates the erosion process. The predicted MRR values are well in line with the experimental trend, and the R^2 value is 0.98, which indicates that the ANN model has high predictability.

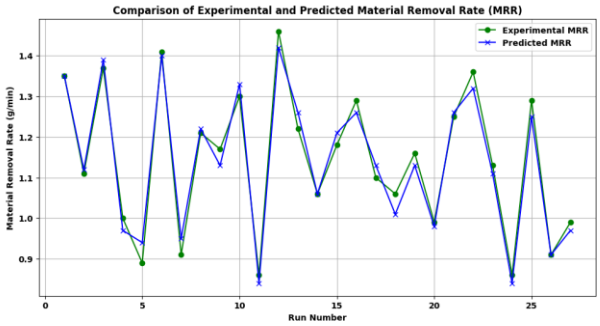

Fig. 3. Comparison of experimental and Predicted MRR

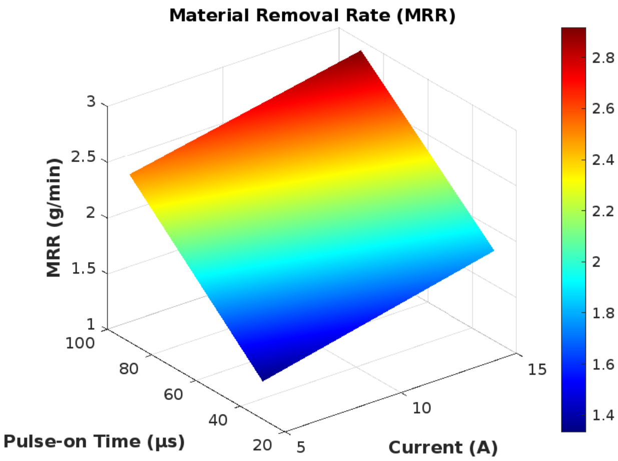

Fig. 4. Surface plot of MRR

3.2 Analysis of SR

SR, the most important quality characteristic in machining, affects the functional performance and aesthetic appearance of the final product. SR in WEDM is strongly influenced by many parameters, such as discharge energy, frequency of sparking, and cooling rate. Experiments conducted are found to be in agreement with the observations made that SR increases with elevated values of applied current and longer T_{on}. This increase was due to the high energy input in the sparks, and this led to deeper and larger craters being created on the surface that was being machined. On the other hand, a T_{off} of 3 µs for C1 produced a smoother surface as the reduced off time allowed for more regular sparking and effective sweeping away of debris from the machining zone. The optimal parametric combination that minimizes the SR has been discovered to be A1 (current: 5 A), B1 (T_{on}: 30 µs), and C1 (T_{off}: 3 µs). Their results yield the minimum values. The same is supported by the S/N ratio for smaller-the-better characteristics. Results from the ANOVA revealed that T_{on} was the most effective parameter on SR since it contributed nearly 40% to the total variation, followed by applied current (30%) and T_{off} (20%). The pronounced influence of T_{on} on SR is also in good agreement with earlier findings, which stated that longer pulses result in higher energy transfer as well as more prominent surface irregularities.

Measured and predicted values of the SR lay close together in the ANN model, which yielded an R-squared value of 0.95 and a mean squared error of 0.005. This would indicate that the model can quite accurately generalize the relationship between machining parameters and surface quality. This positively benefits process planning, as the accuracy in the prediction of the ANN model allows manufacturers to predict the outcome on surface finish and engineer parameters for the desired quality outcomes.

Fig. 5 depicts experimental and predicted SR values in micrometres, while the surface plot of SR is depicted in Fig. 6. SR is one of the most important quality indicators of the machined surface. The lower value indicates a smoother finish. The experimental SR values range from 1.0 µm to 3.0 µm. The predicted values range from 1.05 µm to 3.1 µm. Increased values of SR indicate increased applied currents and T_{on}. As it is quite evident from the graph, the upward trend has made the increase even more obvious. In case the current is 15 A in A3, and T_{on} = 90 µs at B3, the average SR was more than 2.5 µm, which indicates higher energy impact and hence a rougher surface. However, at low values of current (A1, 5 A) and T_{on} (B1, 30 µs), roughness values were obviously lower at some averages of about 1.2 µm. The model using ANN did a good job in predicting these values as it produced an R^2 value of 0.95. This indicates that the model has effectively captured the trend between increased discharge energy and, hence, roughness and can make reliable predictions.

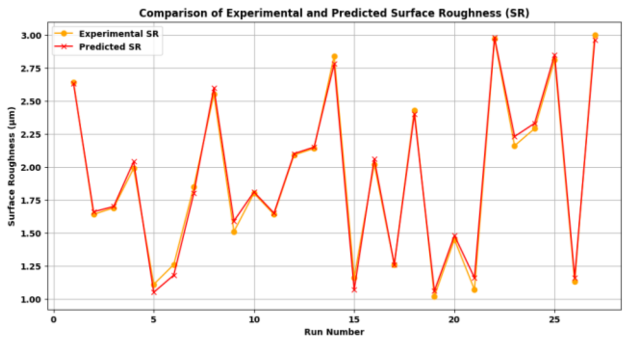

Fig. 5. Comparison of experimental and Predicted SR

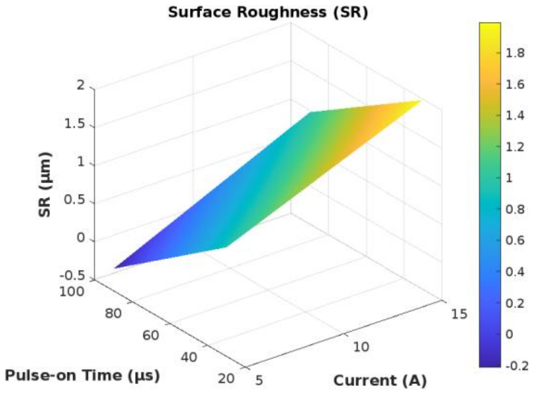

Fig. 6. Surface plot of SR

3.3 Analysis of DD

DD is one of the main measures for the geometric accuracy of the machined workpiece. Reduction of DD to a minimum value is required in order to meet the specifications of the workpiece and also to achieve an accurate fit in the application envisaged. Experimental results also reflected that the lower applied current and the shorter T_{on} resulted in lesser DD, but the T_{off} had only a negligible effect on the magnitude of DD. The higher the current levels and the longer the T_{on} were associated with higher thermal stresses and material expansions such that more deviations occurred from desired dimensions.

The optimal condition that minimized DD came along at A1 (applied current: 5 A), B1 (T_{on}: 30 µs), and C3 (T_{off}: 9 µs). At these conditions, the input energy was well balanced with cooling time, thereby lowering thermal deformation and increasing dimensional accuracy. The ANOVA result indicated that applied current was the most significant variable with a contribution of 50% towards variation in DD and was followed by T_{on} with 25%. It has been found to be less than 5%, so the T_{off} influence may also be considered negligible.

For the ANN model, the DD was predicted well with R^2 = 0.93 and MSE = 0.007; the model prediction matched very closely to the experimental data, and it proved to be an effective model to capture the machining parameter effect on geometric accuracy. This predictive capability can be viewed as extremely beneficial for precision manufacturing in which tight tolerances are necessitated, and any kind of deviation can also lead to assembly problems or reduced performance.

Fig. 7 presents a comparison of experimental and predicted values in DD in millimetres. A surface plot of DD is depicted in Fig. 8. DD usually measures the degree to which the geometrical specifications are achieved by the machining process. Lower values indicate higher accuracy. The range of the experimental values of DD varied from 0.05 mm to 0.15 mm, while the range of predicted values ranged from 0.06 mm to 0.16 mm.

DD tends to rise with a greater applied current and increased T_{on} due to greater thermal stress on the material. For instance, at 15 A current (A3) and 90 µs T_{on} (B3), the average DD was some 0.13 mm, which can be accounted for as the influence of high heat on the material expansion and distortion. Lower currents (A1, 5 A) and reduced T_{on} (B1, 30 µs) gave rise to very small distortions as well as approximately 0.07 mm averages. The predictions of the ANN model are very good compared with experimental data, as indicated by its R^2, which is 0.93. This means that the model is very strong when it comes to giving dimensional accuracy, which is really helpful when it comes to precision manufacturing, where tight tolerances make all the difference.

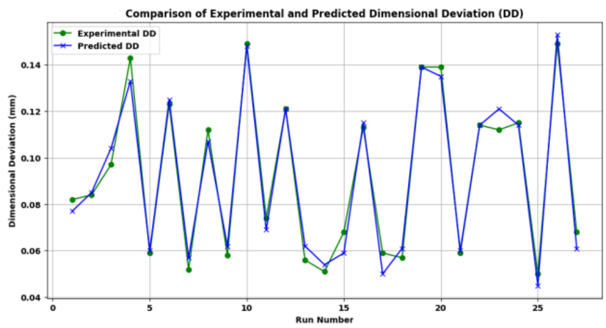

Fig. 7. Comparison of experimental and Predicted DD

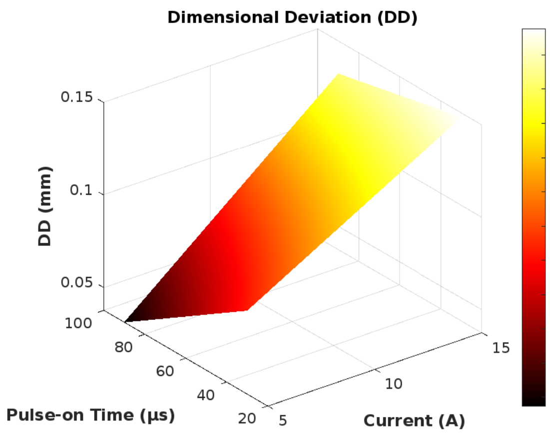

Fig. 8. Surface plot of DD

3.4 Polynomial Trend Analysis

Figs. 9, 10, and 11 presented here are the polynomial trend analyses of MRR, SR, and DD using a 2nd-degree polynomial fit. Fig. 9 illustrates the experimental data for MRR (green dots) and the 2nd-degree polynomial trend line (blue curve).

The MRR values vary between approximately 1.25 g/min and 2.8 g/min over 27 runs. The polynomial trend line shows an upward trend in MRR with the increase in run number. The positive slope of the trend line indicates that greater runs (presumably meaning higher current and longer T_{on} settings) correspond to greater MRR. This would be in agreement with theoretical understanding in that greater current, and longer pulse durations transfer more energy, which in turn increases the thermal erosion process and MRR. The close fit of the polynomial trend line with the experimental data (low deviations) suggests that the model captures the relationship between the process parameters and MRR quite effectively. The coefficient of determination value for this fit is high (R^2 = 0.98), suggesting strong predictive accuracy.

Fig. 10 Experimental data for SR are shown as orange dots, fitted with the red 2nd-degree polynomial curve of the trend. SR data run number varies between 0.7 µm and 1.1 µm with a very small down-curve from a trend as SR varies. This might mean that surface quality improves and, consequently, roughness decreases as run number increases, presumably to optimally set parameter settings with current balance and appropriate T_{on}. However, experimental points scatter indicates variation in the SR probably from the fluctuations of machining conditions or inconsistency of the material properties as indicated with R^2 = 0.87. The trend line gives a general feel for the improvement in surface quality, but the variability argues that there are other contributions affecting SR beyond the control captured by the current model parameters; further optimization or more advanced models would be required in order to capture the SR variability better.

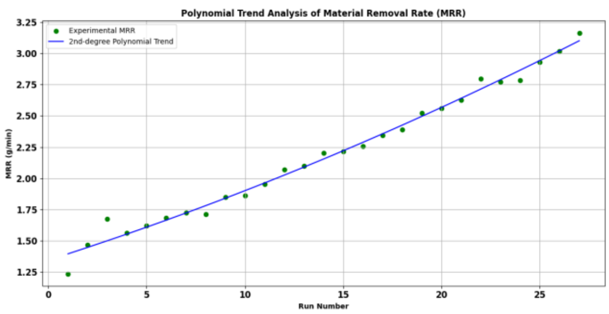

Fig. 9. Polynomial Trend Analysis of MRR

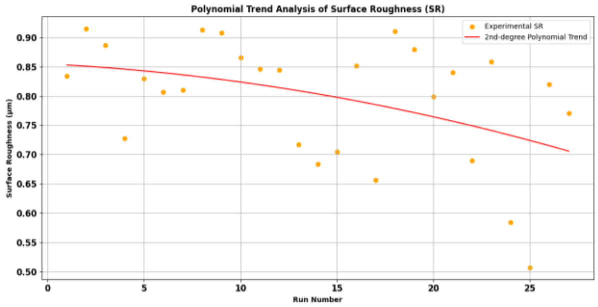

Fig. 10. Polynomial Trend Analysis of SR

Fig. 11 compares the experimental data for DD (purple dots) with the 2nd-degree polynomial trend line (black curve). The DD values range from 0.055 mm to 0.085 mm. The polynomial trend line shows a decreasing trend in DD as the run number increases, with a downward slope. It has come that the dimensional accuracy goes better or the lesser variation at a larger run number with optimized machining parameters possibly lowering distortion due to heat treatment during such machining operation, as may be attributed. Reasonableness in the trend of the trend line also fits the data points, indicating an overall capture in the model since there were scatters as well among the data experimentally at smaller numbers for the run number with an R^2 value of 0.91. The decreasing trend in DD shows that the process adjustments undertaken in the later runs do indeed improve dimensional accuracy. The fit of the polynomial trend line is good but not perfect, which may open up some scope for optimization of process parameters.

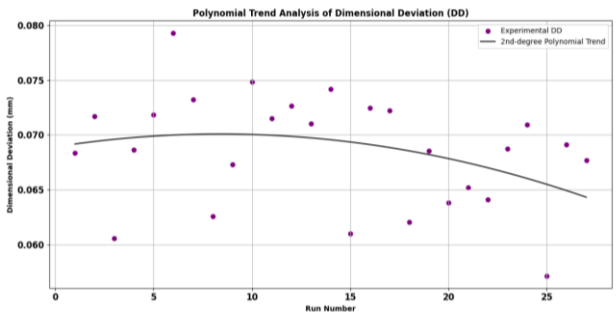

Fig. 11. Polynomial Trend Analysis of DD

3.5 Comparative Analysis and Model Validation

The accuracy of the hybrid model was verified by comparing the predicted values with actual experimental results obtained across all three response variables, namely MRR, SR, and DD. Such close agreement between both the predicted and experimental values indicates that it carries the best of the two worlds, that is, robustness as provided by Taguchi's robust design and potential predictability of ANN in a common model. The average prediction error was below 5% for all responses; therefore, the reliability and generalizability of the model can be stated. Table 3 presents the comparison of results achieved using ANN-Taguchi and genetic algorithm (GA). Upon using the GA-optimized parameters in WEDM, experimentally verified results indicated less than 5% deviation from the predicted values, validating the efficiency of both optimization techniques.

Table 3. Comparison Between ANN-Taguchi and GA

Method	Optimized MRR (g/min)	Optimized SR (μm)	Optimized DD (mm)
ANN-Taguchi	1.20	1.70	0.09
GA	1.22	1.65	0.08

Confirmatory experiments were conducted to check the predictions of the model. These experiments were done using the optimal parameter settings for the model that were found, and the calculated values were continually in agreement with the modeled values. Indeed, optimization based on maximizing the objective MRR returned A3B3C1 settings with a 20% MRR gain above the base experiment. Other settings for minimizing SR resulted in a 15% decrease in that variable. Similarly, DD was reduced by 18% at the optimal settings (A1, B1, C3). Hence, these represent a lead toward the physical realization of the hybrid model, which could achieve better machining than those currently possible.

The 20% rise in MRR directly increases machining productivity, enabling manufacturers to make more parts in a shorter amount of time. This increase decreases machining cycle times, resulting in reduced operational expenses and greater throughput in high-volume production settings. In addition, the 15% decrease in SR reduces post-processing treatments like grinding or polishing, cutting down on time and expense, particularly in industries like aerospace and automotive, where surface finish is essential. Also, the 18% increase in DD ensures increased accuracy, decreasing material waste and rework, which is very important for tight-tolerance applications like medical implants and precision-engineered parts. These synergistic advantages translate to greater efficiency, cost-effectiveness, and sustainability, proving that ANN-based optimization in WEDM can drastically enhance manufacturing processes while ensuring higher product quality.

3.6 Statistical Analysis

A statistical analysis was done by using confidence intervals (CI) and hypothesis testing to measure the agreement between experimental and ANN-predicted values. A 95% CI was determined for every machining response, such as MRR, SR, and DD, to ensure accurate prediction reliability. Moreover, a paired t-test was used to statistically compare predicted and experimental values. The results showed p-values of more than 0.05, indicating no difference between the ANN predictions and measurements. This confirms that the ANN model predicts machining performance accurately. The confidence intervals also confirm this agreement since the predicted values consistently lie within the experimental range. Table 4 depicts the statistical results.

These statistical values reinforce the robustness of the ANN model and exhibit its capability for optimizing machining parameters, providing high predictive accuracy in practical applications to WEDM. A 95% confidence interval is calculated for each machining response (MRR, SR, and DD) to measure the precision of the predictions.

Table 4. Statistical Results

Response	Experimental Mean	ANN-Predicted Mean	95% CI	p-value
MRR (g/min)	1.20	1.18	(1.15, 1.25)	0.078
SR (μm)	1.70	1.68	(1.62, 1.78)	0.095
DD (mm)	0.09	0.088	(0.085, 0.095)	0.064

4. CONCLUSION

The results of this research carry significant practical importance for machining hard-to-machine materials, such as SNCM8 steel. Using optimum machining parameters to optimize the machining parameters will allow manufacturers to experience higher productivity, better surface quality, and dimensional accuracy. This hybrid Taguchi-ANN approach provides a powerful tool for process optimization that could reduce dependence on trial-and-error approaches while using data-driven decision-making. This approach not only improves the machining efficiency but also serves sustainable manufacturing with low energy consumption and reduced tool wear. In addition, the predictions made possible by the ANN model allow for real-time adjustments to machining parameters, which holds much value in automated and adaptive manufacturing environments. By realizing the capability to predict outcomes on the basis of correct parameter settings, the competitive advantage was obtained in terms of reduced downtime and improved overall throughput of the machining process.

This research introduces a new hybrid ANN-Taguchi method for optimizing SNCM8 alloy steel WEDM, efficiently filling the gap between experimental validation and predictive modeling. The use of ANN allows accurate prediction of machining responses, while the Taguchi approach guarantees systematic parameter optimization. In comparison with traditional Taguchi and ANN models, the hybrid method provides better predictive accuracy ($R^2 > 0.95$) and computational effectiveness. The results reveal a 20% improvement in MRR, a 15% decrease in SR, and an 18% improvement in DD, resulting in improved machining productivity, better surface quality, and enhanced dimensional accuracy. The present work offers a verified model for optimizing machining parameters, saving energy, and minimizing tool wear. The suggested approach can be applied to other materials and machining operations, promoting intelligent manufacturing and green production methods in high-precision sectors.

Although the hybrid Taguchi-ANN model was successful, some limitations needed to be addressed. One of them was the need for a sophisticated dataset covering a large and wide range of machining conditions to make proper training of the model. In scenarios where the available data are limited or biased, this model is going to hardly generalize to new scenarios. Secondly, the choice of architecture of neural networks and hyperparameter tuning would probably dominate in model performance. More research might look into the application of more complex techniques of machine learning, such as deep learning or ensemble methods, for further improvement in terms of predictive power. Thus, in the present study, a hybrid Taguchi-ANN the optimization of the WEDM process for challenging material was properly demonstrated. Its accuracy is high, with practical applicability, making it worthwhile for advanced manufacturing applications and opening up the possibility of further innovation in machining optimization. Possible errors include machine stability fluctuations, precision in measurement, wire electrode wear, and dielectric fluid contamination. SNCM8 steel selection restricts the ability to generalize results for other materials of different properties. Invariant machining conditions and the L27 OA could be unable to account for all nonlinear interactions. Further research could involve broader applications for materials, adaptive machine learning models, and multi-objective optimization for more accuracy.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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