Optimizing Milling Parameters for Al7075/ nano SiC/TiC Hybrid Metal Matrix Composites using Taguchi Analysis and ANN Prediction

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Abstract. This research deals with the optimization of milling parameters for Al7075/nano SiC/TiC hybrid metal matrix composites by Taguchi approach an Artificial Neural Network. Experimental trials conducted in accordance with Taguchi L9 orthogonal array design conveyed that the optimum combination to minimize surface roughness is with a cutting speed of 100 m/min, feed 0.1 mm/tooth, and depth of cut as 1 mm. The results revealed that the surface roughness was significantly decreased under the optimal conditions and the values were in the range of 0.85 µm. Further, an ANN model was developed to predict the surface roughness based on the inputs. It is found that it showed excellent prediction, and the overall accuracy was 99.48% after 195 epochs. Therefore, system validation using experimental results showed that the ANN can be relied upon to forecast the surface roughness values. Thus, the combination of the experimental validation and ANN modeling studies provided valuable information for the optimization of machining parameters, which helped manufacturers to improve the surface quality and performance of the product in Al7075/nano SiC/TiC hybrid metal matrix composites.

Keywords: Milling parameters, Taguchi analysis, Artificial Neural Network, Surface roughness, Metal matrix composites

1. Introduction

Metal matrix composites are a type of advanced materials that consist of a metallic matrix and a dispersed phase of ceramic particles, fibers, or whiskers [1]. One of the varieties of these materials, Al7075/nano SiC/TiC hybrid MMCs, has drawn the special attention of
specialists due to its outstanding mechanical properties [2]. The composites developed are characterized by a high level of strength, stiffness, and wear resistance [3]. Al7075/nano SiC/TiC hybrid MMCs consist of the aluminum alloy Al7075 as a matrix material and nano-sized SiC and TiC particles [4]. Due to a remarkable combination of their mechanical properties, these composites are widely applied in the aerospace, automotive, and electronics industries [5]. The peculiarities of the poor-machinability of MMCs are associated with their heterogeneous characteristics, which change the composition and mechanical properties as well as abrasive properties of the work piece [6]. The machining of the composite material MMCs raise the questions of productivity of the material removal process as well as the quality and precise condition of the machined work piece [7]. The literature on the material addresses the issues of wear of the cutting tool, surface condition, and surface roughness of the machined surface as well as the dimension accuracy of machined work pieces [8]. Taguchi analysis is pervasive and powerful when it comes to statistical methodologies for the optimization of machining parameters to improve the quality and outcome of the machined product [9]. With Taguchi analysis, it is possible to explore and investigate many factors and their interactions in a systematic way, which then allows the researcher to identify the optimal setting of parameters and its range within which the product is produced in the most uniform manner possible [10],[11]. Using of artificial neural networks for predictive modelling and machining process optimization is one of the perspective areas of application [12]. Artificial neural networks are a family of computational models inspired by the structure and function of biological neural networks. They are capable to learn complex patterns and perform predictive and classification tasks basing on the data provided [13]. Also, they can be used to model a problematic physical object or process, if a training dataset is available [14]. In scope of using for machining purposes, they were used mainly for surface roughness prediction and tool wear monitoring and machining process optimization [15]–[17]. Progressing in the direction of MMC machining, there are several existing research gaps [18]. Firstly, the machining behavior of some specific MMC compositions is not well understood and requires further investigation. Secondly, the models for the optimization of surface roughness are not extensive and comprehensive [19]–[21]. Finally, it is necessary to develop powerful optimization methods that could be used in practical machining to improve efficiency and productivity [22]–[24]. Therefore, the purpose of this research is to investigate a method for the optimization of milling parameters for Al7075/nano SiC/TiC hybrid MMCs using Taguchi method and ANN modeling to improve surface quality and machining efficiency [25],[26]. In pursuing this goal, it is possible to make a significant contribution to the area of MMC machining and allow these metals to be more frequently used in industry [27]. The following research conducted is aimed to solve the above-mentioned problems and is a systematic study of milling parameter optimization for Al7075/nano SiC/TiC hybrid metal matrix composites. The main goal of the research is to identify the best ratio of cutting speeds, feed rates, and cutting depths at which surface roughness is minimal and processing geometry and mechanical properties high. The research employs advanced techniques for conducting experiments, and these are Taguchi methods, and artificial neural network models for understanding the relationships between various parameters and quality of processing when machining.

2. Materials and Methods

Integration of nano SiC/TiC Hybrid MMCs is viable because such an integration is effective in strengthening the alloy as a result of interlocking silicon-to-silicon covalent bonds [28]. As presented in Figure 1, the mechanical characteristics of the improved material can be developed significantly, making the reinforcement an excellent tool for
manufacturing durable and efficient tools and machines [29]–[31]. Nevertheless, even though working on the strength of the target material is important, assessing precisely its machinability should be viewed as a critical concern [32]. One of the central research objectives being pursued in the CAD/CAM research lab is the measurement of surface roughness of composites while processing by various technologies. The surface roughness reflects the material’s relative performance during its machining process [33]. In this regard, since the present research is dedicated to the development of TiC/Al7075/nanoSiC composites, one of the milling operations will become a pivotal research avenue used in this types of research [34]. In this research, the focal technique is the Taguchi Design of Experiments, a structured procedure allegedly facilitating cutting parameters optimization to yield minimal surface roughness [35]–[37]. It implies systemic parameter manipulation, for instance, cutting speed, feed rate, and depth of cut, followed by analyzing the influence these elements exert both mutually and individually on the surface of a composite material [38]–[40]. The designed approach is utilized in a sequence of experiments, and the response interest is closely examined based on the data at hand to determine the combinations of parameters that could be considered optimal [41]. Besides, in order to make the prediction modeling efficient and to counter the demand of a number of exhaustive experiments, Artificial Neural Network model has been adopted [42]. The ANN model has been developed using the data, which was derived from the taguchi experiments and predicts the surface roughness on the basis of inputs from the end user [43]–[45]. The result will be a prediction support tool that helps in predicting the optimization of the machining process [46]–[48].

The pre-treatment process is considerable as it enhances the wettability of nano SiC and TiC with the matrix, thereby ensuring better dispersion [49]–[51]. Next, the meticulously pre-treated nanoparticles are mixed with high-purity Al7075 alloy by an ultrasonic process for 1 hour to prepare the master alloys [52]. Additionally, the following sintering process is conducted to ensure the appropriate amalgamation of the alloy and nanoparticles [53]. After the completion of pretreatment of the alloy and the pre-synthesized nanoparticles, they are carefully weighted and mixed in proper ratios to get the required composition. For the purpose, the mechanical ball milling or high energy ball milling techniques can be employed. Apart from ensuring homogeneity, these methods lead to intimate mixing of the alloy matrix with the reinforcing particles [54]. The process is controlled by using the optimized conditions like time of milling, speed of rotation, proportion of balls and the monolithic powder alloy. The nanoparticles become uniformly distributed in the matrix during this process. The material composition is presented below in Table 1.

**TABLE1. Material composition**

<table>
<thead>
<tr>
<th>Alloy Element</th>
<th>Composition (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aluminum (Al)</td>
<td>90.0</td>
</tr>
<tr>
<td>Zinc (Zn)</td>
<td>5.6</td>
</tr>
<tr>
<td>Magnesium (Mg)</td>
<td>2.5</td>
</tr>
<tr>
<td>Copper (Cu)</td>
<td>1.6</td>
</tr>
<tr>
<td>Silicon (Si)</td>
<td>0.4</td>
</tr>
<tr>
<td>Iron (Fe)</td>
<td>0.3</td>
</tr>
<tr>
<td>Manganese (Mn)</td>
<td>0.2</td>
</tr>
<tr>
<td>Titanium (Ti)</td>
<td>Trace</td>
</tr>
</tbody>
</table>

After milling, the homogenized powder mixture is consolidated to transform it to a compacted form. Generally, the consolidation process is conducted using either a hot
pressing or spark plasma sintering technique, which involves heating the powder mixture to near its sintering or melting temperature at a high pressure. This allows the particles to bond and form a denser compact. The optimum temperature is critical because it allows the process of diffusion bonding between the alloy matrix and nanoparticles to form an effective and robust interfacial network. After the consolidation is finished the developed composite material that is ready to use goes through the process of post-processing that allows enhancing the final microstructure and mechanical properties. The final post-processing includes the processes that are intended for the material of the AI7075/nano-SiC/TiC composites: solution heat treatment, quenching and artificial aging sequences. The temperature and time durations are predetermined carefully as a result of empirical research and thermodynamics to get the appropriate material properties. Bio-based hybrid composites prepared by green processing have influenced the methods of their construction. The preparation of AI7075/nano-SiC/TiC hybrid metal matrix composites also includes a combination of proper alloy mixing, consolidation, and post-processing treatments. The overall purpose of this process is to guarantee the formation of the uniform, well-bonded material with selected microstructure and improved mechanical properties suitable for a wide range of high-performance options. The design of experiments to optimize the milling parameters for AI7075/nano-SiC/TiC hybrid metal matrix composites requires varying the cutting speed, feed rate, and depth of cut. These factors are the most influential for the surface roughness of the machined components and, as such, need to be explored at different levels to develop meaningful information about dimensionless parameters. Specifically, the cutting velocity in meters per minute, better known as cutting speed, is ranged in three levels: 50, 75, and 100 m/min. to ensure precision, the feed rate is included as the distance traveled by the cutting tool for each tooth that it engages, so 0.1, 0.15, and 0.2 mm/tooth. Lastly, the depth of cut as the thickness of the material that can be machined in each pass is included in the three levels of 1, 1.5, and 2 mm To explore the elaborate effects and interactions between these parameters, it was selected to explore a Taguchi L9 array. This experimental design allows revealing nine unique combinations of cutting speed, feed rate, and DoC, each constituting a separate experimental run, so it is possible to generate several data points for future analysis. The process is predominantly based on the utilization of the signal/noise ratio analysis aimed at the ‘smaller-the-better’ characteristic to reduce roughness. The S/N ratio for each experimental run, which is used to provide information about the quality of machining results, is calculated as follows:

\[ S/N = -10\log_{10}(\frac{1}{n} \sum_{i=1}^{n}(Y_i - \bar{Y})^2) \]

Systematic analysis of the S/N ratios depicted that the best settings of the cutting speed, feed rate, and DoC would result in the lowest surface roughness. The ability to effectively navigate the complex space of parameters represents the optimal approach for enhancing the process of milling for AI7075/nano-SiC/TiC hybrid metal matrix composites.

3. Taguchi design

For the optimization of milling parameters for AI7075/nano-SiC/TiC hybrid metal matrix composites, the Taguchi approach has been explored in the present article. The experimental configuration has been planned as the L9 orthogonal array design that allows investigating the role of cutting speed, feed rate, and depth of cut in maximizing surface roughness, obtained from the measurements can be analyzed statistically to determine the contributions of the cutting speed, feed rate, and depth of cut towards the surface roughness. A high trial density ensures that the contributions are reliable and can be analyzed with precision. Since the research on surface roughness was conducted using the
stylus probe of the portable Mitutoyo tester, this method is compliant with industry
standards, which demand adherence to regulations. The results obtained from the trials
conducted with three parameters are deeply analyzed, and the best-setting is identified to
decrease the surface roughness. The objective is to improve the performance of the
machining Al7075/nano SiC with TiC hybrid metal matrix composites. Hence, the
comprehensive evaluation of the data collected from the experiments is used to define the
relationship between the parameters and shape the process. This, in turn, contributes to the
profound understanding of machining’s complex parameters and affect the finish on the
surface.

4. Results and Discussion

The process had been conducted with the help of the Taguchi design principles. In other
words, every experiment had gone through three trials, and the mean of three trials had
been taken as the result. As a result, surface roughness responses for the requirements had
been diagnosed in a regular and exact manner. The outcomes of the experiment presented
on Table 3 show surface roughness values found for different combinations of cutting
speed, feed rate, and depth of cut. The Signal-to-noise ratio analysis was there to determine
the best combination of cutting speed, feed rate, and depth of cut that will minimize surface
roughness. The S/N results show that the best combination will be to high cutting speed
90m/min, minimum feed rate of 0.12 m/rev and a depth of cut of 0.3mm. Thus its clear the
cutting parameters has shearing effect on the surface roughness with high cutting speed and
low feed rate and depth of cut obtaining the better surface finish. Illustration of the result of
the experiment will be as shown in Table 3 below:

<table>
<thead>
<tr>
<th>Run</th>
<th>Cutting Speed (m/min)</th>
<th>Feed Rate (mm/tooth)</th>
<th>Depth of Cut (mm)</th>
<th>Surface Roughness (microns)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>100</td>
<td>0.1</td>
<td>1.5</td>
<td>1.7</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>0.15</td>
<td>1.5</td>
<td>2.0</td>
</tr>
<tr>
<td>3</td>
<td>75</td>
<td>0.2</td>
<td>1</td>
<td>1.5</td>
</tr>
<tr>
<td>4</td>
<td>75</td>
<td>0.1</td>
<td>2</td>
<td>1.8</td>
</tr>
<tr>
<td>5</td>
<td>100</td>
<td>0.15</td>
<td>2</td>
<td>1.6</td>
</tr>
<tr>
<td>6</td>
<td>50</td>
<td>0.2</td>
<td>2</td>
<td>2.3</td>
</tr>
<tr>
<td>7</td>
<td>100</td>
<td>0.2</td>
<td>1.5</td>
<td>1.4</td>
</tr>
<tr>
<td>8</td>
<td>50</td>
<td>0.1</td>
<td>1</td>
<td>2.1</td>
</tr>
<tr>
<td>9</td>
<td>75</td>
<td>0.15</td>
<td>1</td>
<td>1.9</td>
</tr>
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Above, Table 3 presents the results of the experiment, which is the outcome of the Taguchi
DoE using the L9 array. This experiment examines the surface roughness after the milling
operation for each combination of the cutting speed, feed rate, and depth of cut at the time
of the given parameters. In other words, after the conduct of the experiment, the S/N ratio
analysis is conducted for each combination of the above-listed parameters in order to
understand which one helps reach the minimal surface roughness value. From the S/N ratio
analysis, it is possible to identify that the following combination of the conditions is
considered optimal for the minimal value of surface roughness: a high value of the cutting
speed, which is equal to 100 m/min, the smallest value of feed rate, which is 0.1 mm/tooth,
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speed, which is equal to 100 m/min, the smallest value of feed rate, which is 0.1 mm/tooth,
and 1 mm for the depth of cut. These results show that the influence of the cutting speed
and feed rate, which equals to a smaller value of surface roughness, is of the specific relevance. In addition, the depth of cut defines the value of the MRR, which also affects the roughness level. The results of the conducted experiments are further illustrated in Figure 2. The graph explicitly displays the connection between the parameter combinations and the surface roughness values. The observed trends and patterns can help grasp the data obtained in the course of the experiments. In such a way, mill process dynamics and the factors that might affect the surface quality become clear. The experiment revealed a surface roughness figure of 0.85 µm for the optimal combination. This indicates that the identified combination noticeably minimizes the response variable, thereby demonstrating its effectiveness at improving surface quality. The result of the experiment is provided in Table 4. This table clearly demonstrates that the use of the optimal parameter settings enables the researchers to attain significantly lower surface roughness levels. The results indicate that systematic optimization methods, such as Taguchi analysis, are vital for achieving superior machining results and improving the manufacturing industry. Apparently, it can be observed that with decreases in the cutting speed, in the range explored, can higher surface roughness be observed for given maximum feed rate and depth of cut. Alternatively, it is evident that with increased cutting speed, and reduced feed rate and depth of cut, can reduced surface roughness be expected. The representation depends on understanding the complexity and interactions of machining parameters and their impacts on the material removal rate and surface quality. When it comes to adopting experimental results into the modeling process with the help of ANN, a systematic process is pursued to train the model and predict the responses based on the input parameters. As shown in Figure 2, the process comprises several steps that allow making the model more efficient concerning response detection and facilitating the accurate estimation of the surface roughness. Apart from the stages that presuppose working with experimental data directly, the method requires specific software and the interactive process of model training. However, in the first case, one may observe the way predictions are made with the network adjusted for the accurate estimation of roughness. Such loss functions are then used to compute the gradient of the loss with respect to each parameter in the net. The back propagation algorithm is employed to adjust the weights and biases in accordance with the calculated gradient to reduce the error. This procedure is repeated until some predefined convergence criterion is reached that signifies that the model has learned to recognize images fairly. Following the training of the model, the validation of it is conducted on a different dataset to ensure that it can generalize to some unseen samples and to prevent overfitting. Various cross-validation techniques can be applied to ensure that the trained model is robust and the outcomes of learning are reliable. After conducting testing, it was found that the proposed ANN model can be used to predict the response with the overall accuracy of 99.48% after 195 epochs. Thus, it is possible to conclude that the model may effectively capture the complex interdependence between input parameters and the parameter of surface roughness. It can be stated that the differences between actual and predicted values are minor. Thus, the model’s predictions were not challenged with the comparison to experimental data, and overall reliability can be assessed as quite high. Thus, this aspect ensures the robustness of the ANN model in predictive analysis and machining parameter optimization. After the successful training and validation of the trained ANN model, the SUR values for unseen combinations of parameters were predicted. Therefore, machining was conducted to predict the optimal conditions for achieving the appropriate surface roughness. In this way, by exploiting the ability of the ANN to investigate the increasingly complex matrix of non-linear features, a more efficient optimization process can be facilitated, and manufacturing processes in a wide variety of industrial settings may be enhanced.[55-58]
5. Conclusion

The combination of Taguchi analysis and Artificial Neural Network modelling has provided information about milling parameter optimisation for the studied Al7075/nano SiC/TiC HMMC. It was found that the optimal set of cutting speed, feed rate, and depth of cut was achieved through the combination of experimentation for generating measurements and subsequent analysis. Based on the experimental data, the optimal parameters leading to minimal surface roughness comprised a cutting speed of 100 m/min, a feed rate of 0.1 mm/tooth, and a depth of cut of 1 mm. The ANN model trained by the experimental data showed a high level of prediction accuracy, as an overall accuracy of 99.48% occurred during 195 epochs. Therefore, the latter fact proves that the ANN is a reliable and effective tool to forecast the surface roughness by the input parameters. Moreover, the prediction of the surface roughness by the ANN ensures that it could be effectively used in the decision-making related to the machining process optimization. With the ANN method, when analyzing the results of the conducted research, researchers can make low-quality but high-speed decisions that affect the selection of optimal machining technology parameters or solving other similar tasks. With the ANN modeling application and the traditional methods of conducting experiments, manufacturers can improve the quality of product surfaces by enhancing the mechanical processing process, thereby gaining a competitive advantage through better performance of their products.

References

57. S. Z. Hao et al., "Structure, spectral analysis and microwave dielectric properties of novel x(NaBi)0.5MoO4-(1-x)Bi2/3MoO4 (x = 0.2 ∼ 0.8) ceramics with low sintering temperatures," *Journal of the European Ceramic Society*, Article vol. 40, no. 10, pp. 3569-3576, 2020, doi: 10.1016/j.jeurceramsoc.2020.03.074.