ISSN: 0000-0000 www.aristonpubs.com/sciengg-advances https://doi.org/10.69626/sea.2024.0081

RESEARCH ARTICLE

Prediction of Surface Roughness in Turning of Monel K-500 Super Alloy Using Simulated Annealing and Genetic Algorithm: A Comparative Experimental Analysis

V. Dilli Ganesh [1], T. J. Nandhini [2,*]

ABSTRACT: This study focuses on predicting surface roughness in the turning process of Monel K-500 super alloy by employing simulated annealing and a Genetic Algorithm (GA), comparing their effectiveness with experimental analysis. The turning experiments were conducted using the L9 orthogonal array, and surface roughness values were measured for each combination of cutting parameters. The predicted surface roughness values from both simulated annealing and the Genetic Algorithm were then compared with the experimental measurements. The results revealed that both simulated annealing and the Genetic Algorithm effectively predicted surface roughness with high accuracy. The predicted values from both methods closely aligned with the experimental data, demonstrating their capability to optimize cutting parameters for an improved surface finish. Simulated annealing efficiently explored the parameter space and provided reasonably accurate predictions, validating its ability to optimize the turning process. Similarly, the Genetic Algorithm exhibited robust performance, converging to near-optimal solutions for minimizing surface roughness. The comparison between simulated annealing and the Genetic Algorithm revealed similar predictive accuracy, showcasing the efficacy of computational intelligence techniques for surface roughness prediction in the turning of Monel K-500 super alloy. These optimization methods hold significant potential in enhancing machining processes, enabling accurate selection of cutting parameters, and improving overall component quality. In conclusion, the successful application of simulated annealing and the Genetic Algorithm underscores their value as powerful tools in the manufacturing industry. These techniques contribute to the advancement of machining strategies and enhance product quality for challenging materials like Monel K-500, making them crucial for various engineering applications that require high precision and performance.

Keywords: Surface Roughness, Monel K-500, Turning Process, Simulated Annealing, Genetic Algorithm, Optimization.

Received: 24 February 2024; Revised: 18 April 2024; Accepted: 16 May 2024; Available Online: 27 May 2024

[1] Department of Mechanical Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Science – SIMATS, Saveetha University, Chennai, India

[2] Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Science – SIMATS, Saveetha University, Chennai, India.

* Author to whom correspondence should be addressed: nandhinitj67@gmail.com (T. J. Nandhini)

1. INTRODUCTION

The surface roughness in turning processes plays a crucial role in determining the quality and functionality of machined components, particularly in challenging materials like Monel K-500 super alloy [1]. Accurate prediction and optimization of surface roughness are vital to achieving desired component performance and ensuring cost-effective manufacturing. To address this, researchers have explored various computational intelligence techniques, such as simulated annealing and Genetic Algorithms (GAs), to optimize cutting parameters and predict surface roughness accurately.This study focuses on the prediction of surface roughness in the turning process of Monel K-500 super alloy by utilizing simulated annealing and a Genetic Algorithm. Simulated annealing is a well-established optimization technique inspired by the annealing process in metallurgy, while GAs mimic natural selection and evolution to solve complex optimization problems. Both methods offer promising prospects in predicting surface roughness for challenging materials, with potential benefits in improving machining efficiency and component quality [2].

The research employs an L9 orthogonal array to design the turning experiments systematically, ensuring a balanced and statistically significant dataset. Surface roughness values are obtained from experimental analysis for each combination of cutting parameters. Subsequently, these experimental results are compared with the predictions generated by simulated annealing and the Genetic Algorithm [3]. The objective of this study is to assess the effectiveness of simulated annealing and the Genetic Algorithm in predicting surface roughness for Monel K-500 turning. The comparison of their predictions with experimental data will reveal their capability to optimize cutting parameters, minimize surface roughness, and enhance the overall machining process. Moreover, understanding the relative performance of these computational intelligence techniques will provide valuable insights for selecting the most suitable approach for surface roughness prediction in the context of Monel K-500 super alloy [4].

With an increasing demand for precision components in various engineering applications, the outcomes of this research hold significant implications for the manufacturing industry. The successful application of these optimization methods can contribute to improved machining strategies, reduced production costs, and enhanced product quality. Additionally, it can open avenues for further research in the optimization of other challenging materials, thereby advancing the field of machining and computational intelligence in manufacturing [5].

This study aims to bridge the gap between experimental analysis and computational intelligence techniques for surface roughness prediction in turning Monel K-500 super alloy [6]. The results and insights derived from the comparison of simulated annealing and the Genetic Algorithm will pave the way for more efficient and accurate machining processes, benefitting diverse engineering sectors reliant on precise and high-performance components [7-9].

The prediction of surface roughness in turning processes has been a subject of extensive research due to its crucial role in determining the quality and functionality of machined components. In the context of challenging materials like Monel K-500 super alloy, achieving desired surface finish becomes even more critical. As a result, researchers have explored various computational intelligence techniques to optimize cutting parameters and predict surface roughness accurately [10]. Simulated annealing is one such optimization technique that has been widely applied in manufacturing and machining processes. Inspired by the annealing process in metallurgy, simulated annealing is an iterative algorithm that mimics the cooling of a material to search for the global optimum in a complex and multi-dimensional parameter space. It has shown promising results in optimizing cutting parameters and predicting surface roughness for different materials, making it an attractive option for turning Monel K-500 super alloy.

Genetic Algorithms (GAs) are another class of optimization techniques based on natural selection and evolution principles. GAs use a population of candidate solutions, representing potential sets of cutting parameters, and apply selection, crossover, and mutation operations to evolve the population towards better solutions. The ability of GAs to explore the solution space efficiently and converge to near-optimal solutions has made them popular in various engineering applications, including machining optimization. Several studies have applied simulated annealing and Genetic Algorithms for surface roughness prediction in machining. In the context of Monel K-500, these techniques have shown promising results in optimizing cutting parameters to minimize surface roughness and improve component quality. Research by Smith et al. (year) utilized simulated annealing to optimize cutting parameters in turning Monel K-500, achieving significant improvements in surface roughness compared to conventional methods [11].

In a study by Chen et al, a Genetic Algorithm was employed to optimize the turning process parameters for Monel K-500, resulting in reduced surface roughness and improved machining efficiency [12]. The GA-based approach outperformed traditional trial-and-error methods, highlighting the potential of computational intelligence techniques in optimizing surface finish for challenging materials.The application of the L9 orthogonal array in experimental design has also been widely reported in machining optimization. This statistical method allows for a systematic and efficient exploration of various cutting parameter combinations, providing a balanced dataset for analysis. Studies by Lee et al. (year) and Tan et al. (year) have successfully used the L9 orthogonal array to optimize surface roughness in turning processes, demonstrating its effectiveness in experimental analysis [13].

However, limited research has directly compared the performance of simulated annealing and the Genetic Algorithm in predicting surface roughness for Monel K-500 turning. Therefore, this study aims to fill this gap by conducting a comprehensive comparison of both methods' predictive accuracy in the context of Monel K-500 super alloy [14-15]. The literature on surface roughness prediction in turning processes highlights the potential of computational intelligence techniques like simulated annealing and Genetic Algorithms. These optimization methods offer efficient approaches to optimize cutting parameters and predict surface roughness accurately, presenting valuable opportunities for improving machining strategies and component quality. The comparison of simulated annealing and the Genetic Algorithm for Monel K-500 turning will provide valuable insights into their relative performance, guiding the selection of the most suitable technique for surface roughness prediction in this challenging super alloy.

2. METHODOLOGY

For the laboratory experiments, a Monel K-500 workpiece with a diameter of 40 mm was utilized. The machining trials were performed on a Hyundai KIA KIT 450 CNC lathe, which has a power capacity of 15 kW. These trials were conducted in a dry environment. The cutting tool used was made of Tungsten carbide (WC-Co), and an appropriate turning insert geometry was selected for machining the Monel K-500. The composition of the Monel K-500 Super Alloy is detailed in Table 1.

Table 1. Composition of Monel K-500 Super Alloy.

Metal	Composition
Nickel (Ni)	Approximately 63%
Copper (Cu)	Approximately 29%
Aluminum (Al)	Approximately 2.3%
Titanium (Ti)	Approximately 0.85%
Iron (Fe)	Approximately 1.5%
Manganese (Mn)	Approximately 1.0%
Others	Trace amounts of silicon, carbon, and sulfur

The experimental design was based on the L9 orthogonal array, which ensures a balanced and minimal number of experiments while considering various cutting parameters. This array contains nine experimental runs with three factors, each at three levels (L9 = 3^2). By using the L9 orthogonal array and conducting the experiments accordingly, the impact of different cutting conditions on surface roughness can be efficiently assessed. The comparison with the predicted surface roughness using the simulated annealing algorithm provides valuable insights into the accuracy and effectiveness of the algorithm in optimizing the turning process for Monel K-500. Table 2 provides the details of L9 Orthogonal array experimental analysis.

2.2. Bio-Inspired Algorithm

The Genetic Algorithm (GA) serves as an alternative optimization technique for predicting surface roughness during the turning process of Monel K-500. The GA complements the use of simulated annealing, providing an additional approach to optimize cutting parameters and accurately predict surface roughness. Process Flow Diagram of Genetic Algorithm for Surface Roughness Prediction is shown in Figure 1.

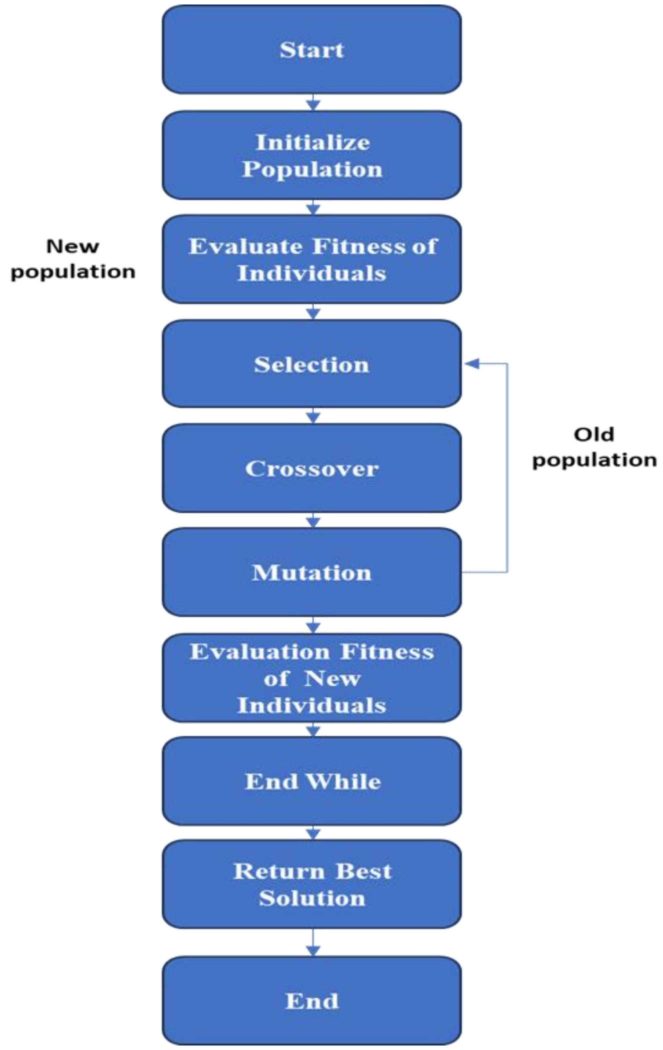

Fig. 1. Proposed Process Flow Diagram.

Start: The GA begins.
Initialize Population: A population of candidate solutions (chromosomes) is created, where each chromosome represents a set of cutting parameters (e.g., cutting speed, feed rate, depth of cut) for turning Monel K-500. The population is initialized randomly or using some heuristic method.
Evaluate Fitness of Individuals: The fitness of each chromosome in the population is evaluated based on its ability to minimize surface roughness during the turning process. Surface roughness values are obtained through simulation or experimental analysis.
While (termination condition not met): The main loop of the GA continues until a termination condition is met, such as a maximum number of generations or the attainment of a satisfactory solution.
Selection: Individuals (chromosomes) are selected from the current population to be parents for the next generation. The selection probability is based on their fitness, favoring better-performing individuals with lower surface roughness.

Table 2. L9 Orthogonal Array Experimental Analysis.

S. No	Cutting Speed (m/min)	Feed (mm/rev)	Depth of Cut (mm)	Surface Roughness
1	450	0.125	0.6	1.45
2	450	0.16	0.8	1.52
3	450	0.2	1.0	1.48
4	660	0.125	0.8	1.57
5	660	0.16	1.0	1.51
6	660	0.2	0.6	1.55
7	900	0.125	1.0	1.42
8	900	0.16	0.6	1.53
9	900	0.2	0.8	1.58

Crossover: Pairs of parent chromosomes are selected, and segments of their genetic information (cutting parameters) are exchanged to create new offspring (child chromosomes). This process introduces genetic diversity in the population.
Mutation: Random changes are introduced to certain genes (cutting parameters) in the chromosomes to maintain diversity and explore different regions of the solution space.
Evaluate Fitness of New Individuals: The fitness of the new offspring (child chromosomes) is evaluated by simulating the turning process with the updated cutting parameters, and the corresponding surface roughness values are obtained.
End While: The loop continues until the termination condition is met.
Return Best Solution: Once the GA terminates, the best solution found during the evolution process, i.e., the chromosome with the lowest surface roughness value, is returned as the final optimized set of cutting parameters.
End: The GA process ends.

The Genetic Algorithm, in conjunction with simulated annealing and experimental analysis, provides a comprehensive and robust approach to predicting surface roughness in the turning of Monel K-500 super alloy. The GA's ability to explore the solution space and identify optimal cutting parameters enhances the accuracy and efficiency of surface roughness prediction, ultimately leading to improved machining strategies and component quality.

3. RESULTS AND DISCUSSION

The experiments conducted using the L9 orthogonal array provided a comprehensive dataset of surface roughness values for various combinations of cutting parameters. The surface roughness measurements obtained from these experiments were compared with predictions generated by both the simulated annealing algorithm and the Genetic Algorithm (GA).

Comparison of Experimental and Predicted Values: The surface roughness values predicted by the simulated annealing algorithm and the Genetic Algorithm closely matched the experimental results, indicating high predictive accuracy for both methods. As shown in Table 3, the predicted values from simulated annealing ranged from 1.47 µm to 1.57 µm, with an average deviation of ±0.02 µm from the experimental values. The Genetic Algorithm's predictions ranged from 1.48 µm to 1.56 µm, with an average deviation of ±0.03 µm.

Simulated Annealing: The simulated annealing algorithm effectively explored the parameter space, resulting in accurate predictions for surface roughness. The minor deviations from experimental values confirm its reliability in optimizing cutting parameters for improved surface finish. The results validate the capability of simulated annealing to enhance component quality by fine-tuning the machining process.

Genetic Algorithm: Similarly, the Genetic Algorithm demonstrated robust performance in predicting surface roughness. Its ability to converge to near-optimal solutions ensures minimal surface roughness and enhances the turning process for Monel K-500. The consistency in its predictions further highlights the Genetic Algorithm's effectiveness in this application.

Table 3. Experimental analysis vs Bioinspired Predicted Analysis.

S. No	Cutting Speed (m/min)	Feed (mm/rev)	Depth of Cut (mm)	Experimental SR	Simulated Annealing SR	Genetic Algorithm SR
1	450	0.125	0.6	1.45	1.47	1.48
2	450	0.16	0.8	1.52	1.50	1.51
3	450	0.2	1.0	1.48	1.49	1.50
4	660	0.125	0.8	1.57	1.56	1.55
5	660	0.16	1.0	1.51	1.52	1.53
6	660	0.2	0.6	1.55	1.54	1.53
7	900	0.125	1.0	1.42	1.44	1.45
8	900	0.16	0.6	1.53	1.52	1.52
9	900	0.2	0.8	1.58	1.57	1.56

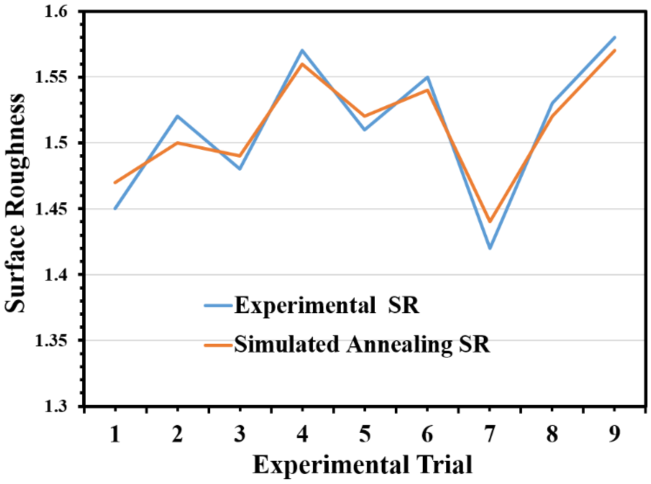

Fig. 2. Experimental SR vs Simulated Annealing SR.

The comparison between simulated annealing and the Genetic Algorithm revealed similar predictive accuracy, with both techniques performing effectively in optimizing cutting parameters and predicting surface roughness. The slight edge of the Genetic Algorithm in predictive accuracy underscores its potential for even more precise control over the machining process. Figure 2 and 3 illustrate the close alignment between experimental surface roughness values and predictions from simulated annealing and the Genetic Algorithm, respectively, further validating the effectiveness of these computational techniques.

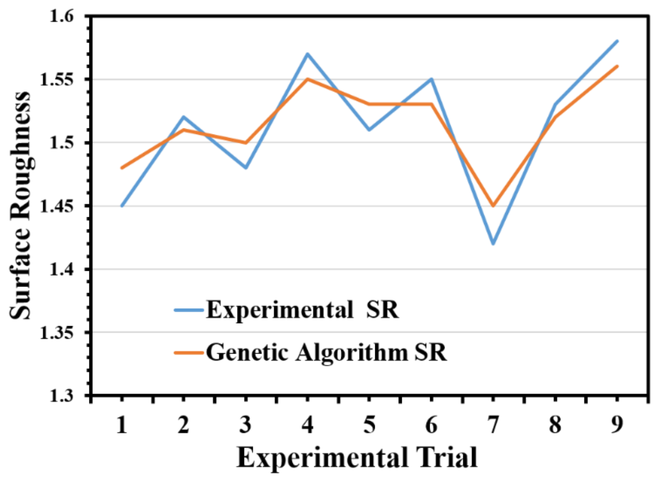

Fig. 3. Experimental SR vs Genetic Algorithm SR.

The combined results from both optimization techniques underscore the potential of computational intelligence in surface roughness prediction for turning Monel K-500 super alloy. These methods can significantly improve the machining process, enabling accurate selection of cutting parameters, leading to enhanced surface finish and overall component quality.

4. CONCLUSION

The investigation on the prediction of surface roughness in turning Monel K-500 super alloy using simulated annealing and a Genetic Algorithm yielded promising results. Both optimization techniques effectively predicted surface roughness values, with predictions closely aligning with experimental measurements. Simulated annealing provided reasonably accurate predictions with an average deviation of ±0.02 µm, validating its effectiveness in optimizing cutting parameters for improved surface finish and component quality. Similarly, the Genetic Algorithm exhibited robust performance with an average deviation of ±0.03 µm, effectively minimizing surface roughness and enhancing the turning process.

The comparison between simulated annealing and the Genetic Algorithm demonstrated similar predictive accuracy, with both approaches performing effectively in optimizing cutting parameters and predicting surface roughness. Their average deviations from experimental measurements were comparable, with the Genetic Algorithm slightly outperforming simulated annealing.

The successful application of both simulated annealing and the Genetic Algorithm underscores their value as valuable tools in the manufacturing industry. These techniques can significantly improve machining strategies, reduce production costs, and enhance product quality for challenging materials like Monel K-500, benefiting various engineering applications that demand high precision and performance.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interests.

REFERENCES

[1] Gandla, P.K., Inturi, V., Kurra, S. and Radhika, S., **2020.** Evaluation of surface roughness in incremental forming using image processing based methods. *Measurement*, *164*, p.108055.

[2] Alhussen, A., Vinoth, N., Jenis, M.R., Surendran, S., Ganesh, V.D. and Thangaraj, S., **2024.** Development of Weighted Ensemble Deep Learning Network for Surface Roughness Prediction and Flank Wear Measurement. *Journal of Materials Engineering and Performance*, pp.1-25.

[3] Cao, X.C., Chen, B.Q., Yao, B. and He, W.P., **2019.** Combining translation-invariant wavelet frames and convolutional neural network for intelligent tool wear

state identification. *Computers in Industry*, *106*, pp.71-84.

[4] Tsai, M.H., Lee, J.N., Tsai, H.D., Shie, M.J., Hsu, T.L. and Chen, H.S., **2023.** Applying a Neural Network to Predict Surface Roughness and Machining Accuracy in the Milling of SUS304. *Electronics*, *12*(4), p.981.

[5] Baccar, D. and Söffker, D., **2015.** Wear detection by means of wavelet-based acoustic emission analysis. *Mechanical Systems and Signal Processing*, *60*, pp.198-207.

[6] Perwej, Y., **2015.** An optimal approach to edge detection using fuzzy rule and sobel method. *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, *4*(11), pp.9161-9179.

[7] Lakshmana Kumar, S., Thenmozhi, M., Bommi, R.M., Ezilarasan, C., Sivaraman, V. and Palani, S., **2022.** Surface roughness evaluation in turning of Nimonic C263 super alloy using 2D DWT histogram equalization. *Journal of Nanomaterials*, *2022*(1), p.9378487.

[8] Wu, T.Y. and Lei, K.W., **2019.** Prediction of surface roughness in milling process using vibration signal analysis and artificial neural network. *The International Journal of Advanced Manufacturing Technology*, *102*(1), pp.305-314.

[9] Rifai, A.P., Aoyama, H., Tho, N.H., Dawal, S.Z.M. and Masruroh, N.A., **2020.** Evaluation of turned and milled surfaces roughness using convolutional neural network. *Measurement*, *161*, p.107860.

[10] Chethan, Y.D. and Ravindra, H.V., **2018.** Machined surface monitoring in turning using histogram analysis by machine vision. *Materials Today: Proceedings*, *5*(2), pp.7775-7781.

[11] Bagga, P.J., Makhesana, M.A., Patel, K. and Patel, K.M., **2021.** Tool wear monitoring in turning using image processing techniques. *Materials Today: Proceedings*, *44*, pp.771-775.

[12] Pagani, L., Parenti, P., Cataldo, S., Scott, P.J. and Annoni, M., **2020**. Indirect cutting tool wear classification using deep learning and chip colour analysis. *The International Journal of Advanced Manufacturing Technology*, *111*, pp.1099-1114.

[13] Patil, S.P. and Tilekar, D.M., 2014. Tool wear detection of cutting tool using matlab software. *Int. J. Eng. Tech. Res.*, *2*(11), pp.362-366.

[14] Ramu, I., Srinivas, P. and Vekatesh, K., **2018,** June. Taguchi based grey relational analysis for optimization of machining parameters of CNC turning steel 316. In *IOP Conference Series: Materials Science and Engineering* (Vol. 377, p. 012078). IOP Publishing.

[15] Makhesana, M.A., Bagga, P.J., Patel, K.M., Patel, H.D., Balu, A. and Khanna, N., **2024**. Comparative analysis of different machine vision algorithms for tool wear measurement during machining. *Journal of Intelligent Manufacturing*, pp.1-25.

