# A Hybrid ANN coupled NTOPSIS Approach: An Intelligent Multi-Objective Framework for solving Engineering Problems

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*Abstract*— **Optimization is a group of mathematical strategies for resolving quantitative issues in a variety of fields. The industries are relentlessly working to optimize more than one objective which are often conflicting in nature. Hence researchers are shifting their focus towards the multi-objective optimization algorithm which computes a set of Non-dominated solutions (NDS) which predominates other solutions in the search space. Non-dominated Sorting Genetic Algorithm II (NSGA-II) is one such multi-objective optimization algorithm but it fails to compute an accurate result when applied to rocky datasets. In order to overcome the difficulties, we have integrated the Artificial Neural Network (ANN) and TOPSIS with NSGA-II. The ANN algorithm creates the objective functions and the TOPSIS algorithm creates a trade-off between the NDS for better exploration. For testing the applicability of our approach we have applied it for computing the machining parameters for turning Aluminum alloy 6061-T6 using a high speed steel tool so that the objective performances namely machining time, material removal rate (MRR) and surface roughness (SR) are optimized. For validating the approach two experiments are conducted at the optimized parameters and the parameters obtained by the traditional NSGA-II approach. The computed the relative error (RAE) between the simulated and the first experimental values which is 1.87% for machining time, 4.2% for MRR and 4.3% for SR and the simulated and the second experimental values which is 14.8% for machining time, 12% for MRR and 11.2% for SR. The RAE value is very less and within the acceptable limit for the result computed by the proposed approach. The strength of our proposed algorithm is its practical applicability and ability to provide an accurate solution to an industry problem and hence our model is suitable for industrial applications.**

***Keywords— Multi-Objective Optimization Algorithm, Hybrid algorithm, Non-dominated Sorting Genetic Algorithm II, Artificial Neural Network, TOPSIS, Non-dominated solutions***

## I. Introduction and Objectives

In the field of mathematics, optimization is a group of mathematical ideas and strategies for resolving quantitative issues in a variety of fields, such as physics, biology, engineering, economics, business etc. The topic developed as a result of the discovery that quantitative issues in ostensibly unrelated fields share significant mathematical components. Because of this similarity, the area of optimization's unified principles and techniques can be used to construct and solve a wide variety of problems.

However, in the modern technologically advanced world, industries are relentlessly working to optimize more than one objective which are often conflicting in nature at a time. Hence researchers and academicians are shifting their focus towards the multi-objective optimization algorithm (MOOA). Mostly, researchers study multi-objective optimization problems with the viewpoint of finding the best set of solutions which are not dominated by other solutions in the search space. These solutions are called Non-dominated (ND) solutions that form the Pareto Optimal front.

The MOOA that uses ND sorting and sharing have been criticized mainly for their computational complexity, their non-elitism approach and the need to specify a sharing parameter. These are overcome by the development of Non-dominated Sorting Genetic Algorithm II (NSGA-II). In spite of this, NSGA-II fails to compute a good solution when applied to a rocky dataset and the strategy applied for selecting the best NDS. In order to address the difficulties in the NSGA-II algorithm and make it widely accepted for industrial purposes, we have integrated the Artificial Neural Network (ANN) and TOPSIS method with NSGA-II.

### *A. Motivation and Novelties*

The goal of the present study is develop an efficient as well as effective MOOA for application in the problems that have a high level nonlinearity in the performance parameters. Mostly, the engineering problems shows high level of non-linearity and because of this reason ANN is the best mathematical model for developing the objective functions. On the other hand, the TOPSIS algorithm is employed to create a trade-off between the non-dominated solutions, to select the optimal solution from the Pareto-optimal front. The proposed approach hybridizes the exploration capability of the NSGA-II algorithm with the exploitation capability of the TOPSIS algorithm. The intelligibility, rationality, comprehensibility, and ability to measure the relative performance for each of the non-dominated solutions makes the TOPSIS method the best strategy employed for selecting the optimal solution by creating a trade-off between the non-dominated solutions that forms the Pareto optimal front. In order to test the efficacy of the algorithm it is applied for selecting the machining parameters for turning Aluminum

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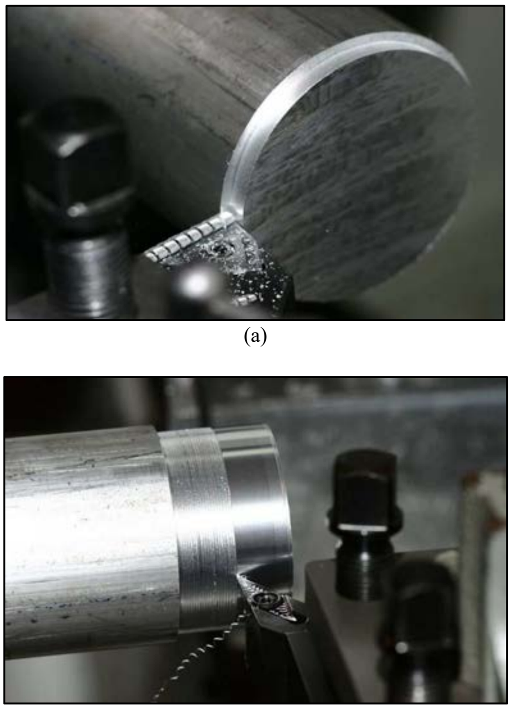
alloy 6061-T6 using a high speed steel tool so that the objective performances namely machining time, material removal rate (MRR) and surface roughness (SR) are optimized. The machining time is the time taken to give the workpiece a desired shape. Whereas the MRR is the mass of the workpiece removed per unit time in minute and SR is irregularities on the surface of the final workpiece. The turning operation and idealized SR model is shown in figure 1 and 2 respectively.



(a)

(b)

Figure 1: Figure showing (a) Rough and (b) Fine turning operation

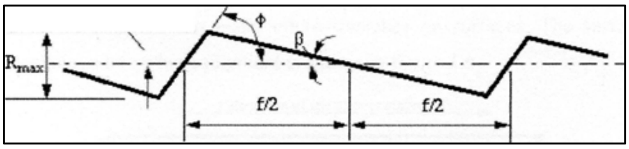



Figure 2: Idealized SR model

## II. Literature Review

Stainless steel turning was presented by Leksycki et al. [9] for the three cutting force components. Both the feed rate and the depth of cut have an impact, and as they rise, the reactions rise along with them. The study's key finding is that an improved feed rate and depth of cut boost each cutting force component independently of the cooling conditions. An experimental research on the finish hard turning of MDN250 steel was conducted by Lalwani et al. [10]. The key finding is that cutting forces are not affected by cutting speed, that the axial cutting force is affected by cutting depth, and that the tangential cutting force is affected by both feed rate and depth of cut. A Nimonic 80A superalloy material was examined by Korkmaz et al. [11] during turning. The authors' most significant finding was that while feed rate predominates over radial cutting force, depth of cut affects tangential and axial force. Optimizing the cutting force has numerous benefits for turning processes, including increased productivity and a better understanding of the systems involved in cutting. The MRR stands for productivity that includes the eliminated material in a given unit of time. As a result, it immediately takes into account how much surface material is eliminated, making it one of the most sought-after optimization parameters. The volume of the removed material at any particular time might be included in the definition. As a result, from the past to the present, producers and researchers have found MRR optimization concerns to be interesting.

Stainless steel turning was the subject of Taguchi S/N-based optimization studies by Bouzid et al. [12]. The paper used Taguchi and grey relational analysis to demonstrate the significance of MRR employing both mono- and multiobjective optimizations. Another Taguchi-based S/N optimization in hard turning was described by Mia et al. [13]. The study sought to optimise resource use while taking into account a variety of characteristics, including MRR. Cutting speed, feed rate, depth of cut, nose radius, and coating kinds were all incorporated by Kaladhar [14] when converting AISI 304 steel. According to the author's findings, the third level of cutting speed, combined with the maximum depth of cut and feed rate, should be chosen in order to achieve the highest MRR. The influence of turning parameters and their optimization during the machining of reinforced polymer pipes was investigated by Kini and Chincholkar [15]. An important finding of the study was that the nose radius and depth of cut were the two parameters that had the greatest impact on MRR. In a micro-turning operation, Kumar [16] employed C360 copper alloy while taking MRR into account. In the micro-turning operation, Taguchi optimization proved to be helpful for process optimization. The use of the maximum depth of cut to maximise MRR without considering the method is a common theme among the publications presented. A general agreement regarding the value of MRR optimization and its contribution to the machining economy was also noted. One of the naturally inspired algorithms that is widely utilised in literature is the Artificial Bee Colony (ABC) algorithm. The strategy used by bees to find fertile blossoms served as the model for the ABC algorithm. In a similar vein, the ABC algorithm looks for the ideal parameters to maximise an objective function. Researchers drew conclusions on the efficacy and inefficacy of the ABC algorithm in experiments looking into cutting parameter optimization.

By contrasting it with nine other nature-inspired algorithms from the literature, Yildiz et al. [17] contributed a hybrid ABC method that was enhanced. They concentrated on locating better ideal solutions faster. As a result, they included Taguchi's resilient parameter design in the ABC's first step of swarm generation. As a result, they enhanced the ABC algorithm's performance. However, the identification of numerous limits made their approach exhaustive. Using the ABC algorithm, Prasanth et al. [18] looked for the best parameter designs for the cutting speed, feed rate, depth of cut, and tool nose radius. A comparison of the ABC algorithm, genetic algorithm, and ant colony algorithm was presented. They came to the conclusion that the ABC algorithm outperformed the other two. These two results motivated us to concentrate on the ABC algorithm's searching method in order to enhance it. A contradictory multi-objective function was optimised for cutting speed, feed rate, and cutting depth using a bee algorithm by ztürk et al. [19]. The use of quadratic regression models of the cutting forces can be used in place of their method of combining two objectives into one fitness function. In terms of an algorithm created to optimise competing objectives, such as cutting forces and MRR, this work differs from the literature. The ABC algorithm's searching phases merely incorporated a harmony memory, and the restrictions were established in accordance with the experimental input range for cutting speed, feed rate, and cutting depth. A study on a comparative optimization technique for these response parameters was not found, despite numerous initiatives about cutting forces and MRR in the open literature. In the open literature, Taguchi-based optimization and RSM were frequently mentioned as optimization methodologies. In the past [17–21], some research used nature-inspired algorithms to turn for the application of crucial response parameters, but none of them simultaneously took into account the three elements of cutting forces and MRR. The popular optimization techniques Taguchi S/N ratio, RSM, and nature-inspired algorithms, HBA and H-ABC, were suggested in this work to discover the best levels of cutting speed, feed rate, and depth of cut values. The techniques described in this work are anticipated to significantly advance the time and cost minimization strategy used in actual implementations of multiple optimizations.

## III. Proposed Methodology

The first step of the proposed approach is to develop the objective function by ANN. The data collected from the experimentation is normalized so that the data are squeezed and transform them into dimensionless number of the same range. Then the ANN parameters such as the number of hidden layers and hidden neurons are optimized. In the study, the number of hidden layers are varied in between 1 and 2 and the number of hidden neurons are varied in between 1 to 15. The parameter of the ANN that showed the best performance is considered as the optimal. Figure 3 and 4 shows a typical ANN structure and an artificial neuron respectively.

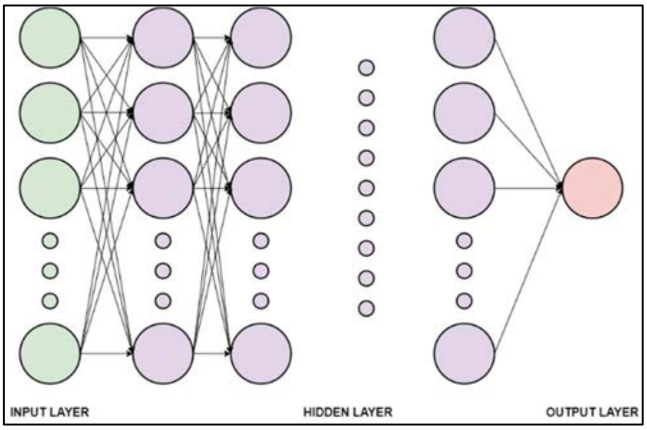



Figure 3: Representation of ANN

The objective function for ANN can be mathematically expressed as:

$$h_{iu} = \sum_{j=1}^{m}\left(w_{ju} \times x_j\right) + b_u; u = (1,2,3, \cdots p) \tag{1}$$

$$h_{ou} = (h_{iu})^{tr}; u = (1,2,3, \cdots p) \tag{2}$$

$$y_{iv} = \sum_{k=1}^{p}(w_{kv} \times h_{ou}) + b_v;\ v = (1,2,3, \cdots q) \tag{3}$$

$$y_{pred} = (y_{iv})^{tr};\ u = (1,2,3, \cdots p);\ v = (1,2,3, \cdots q) \tag{4}$$

General form:

$$y_{pred} = \left[\sum_{k=1}^{p}\left\{w_{kv} \times \left(\sum_{j=1}^{m}\langle w_{ju} \times x_j\rangle + b_u\right)^{tr}\right\} + b_v\right]^{tr} \tag{5}$$

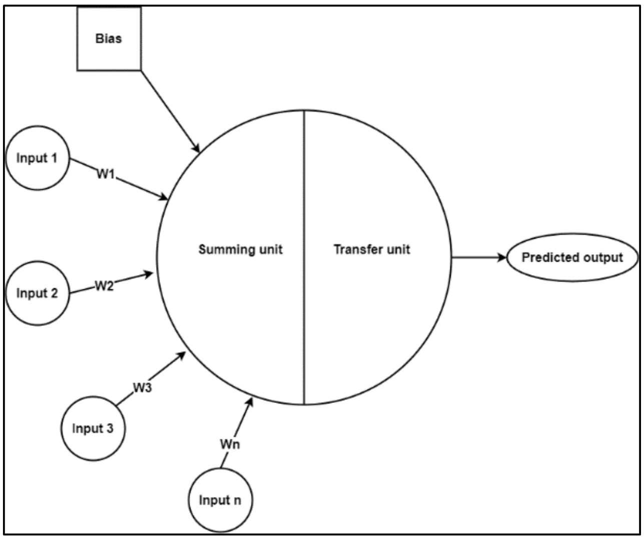



Figure 4: Representation of artificial neuron

Where $m$ is the number of input variables, $p$ is the number of hidden neurons, $q$ is the number of performance measures, $y_{pred}$ represents the predicted output value from the ANN model. Then in the second step NSGA-II is applied to determine the NDS that forms the Pareto Optimal front. Steps for NSGA-II is shown in figure 5.

The third step is employing the exploitation capability of TOPSIS method for selecting the optimal solution from the set of NDS. The flowchart of the hybrid algorithm is shown in figure 6.

## IV. Results

Following the steps as shown in figure 6, we have conducted the experimentation and collected the dataset. Then determined the optimal ANN parameter settings for each performance measures. Table 1 shows the optimal ANN parameter settings and the figure 7 shows the accuracy graph between the target and predicted values for each performance measures.

TABLE I: OPTIMAL ANN ARCHITECTURE

| **Performance measure** | **Number of** | | **Transfer function** | **Error** | ***R*** | **Computation time(s)** |
|---|---|---|---|---|---|---|
| | ***Hidden layer*** | ***Hidden neuron*** | | | | |
| Machining time | 1 | 10 | Logsig–tansig | 0.291 | 0.8933 | 1.35 |
| MRR | 2 | 9-1 | logsig–tansig–tansig | 2.34 | 0.8507 | 2.12 |
| SR | 2 | 10-6 | logsig–logsig–logsig | 1.58 | 0.876 | 2.22 |

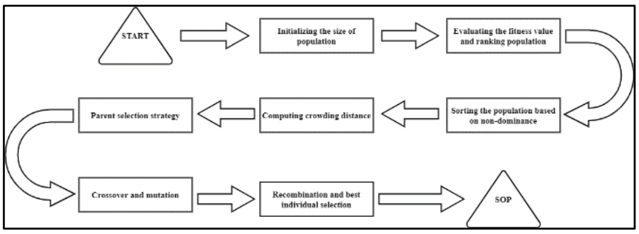



Figure 5: Steps for NSGA-II

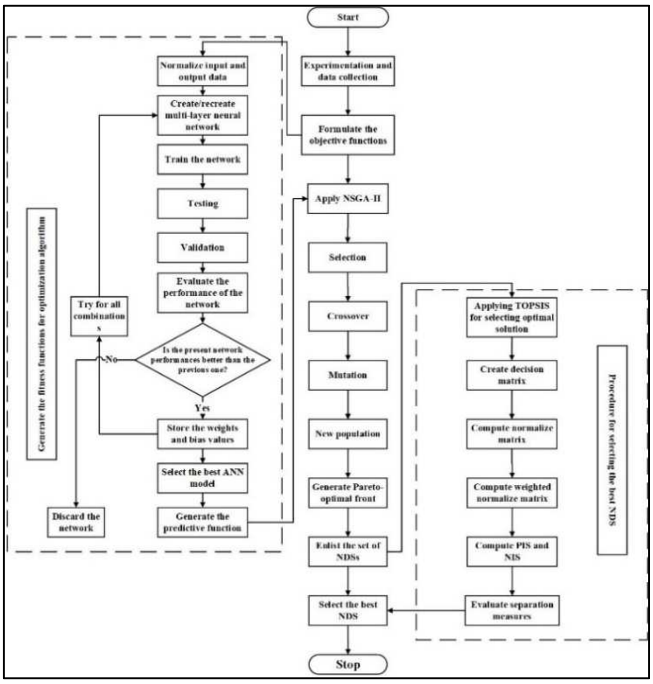
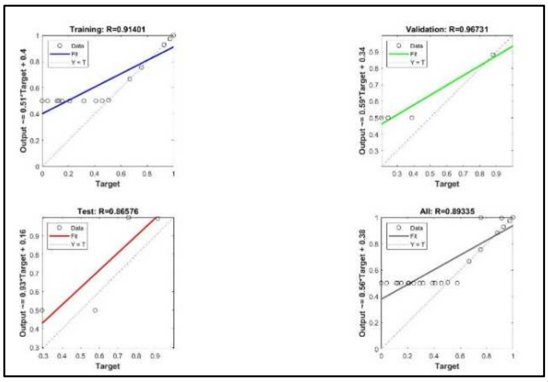
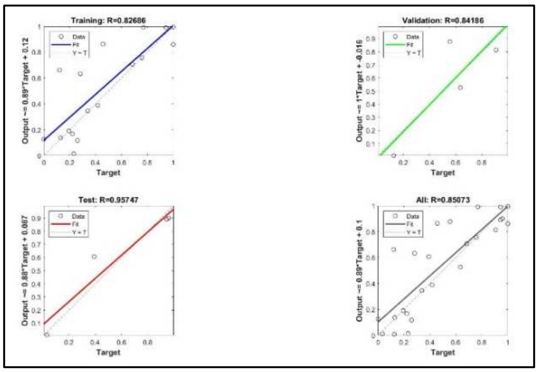



Figure 6: Flowchart of proposed approach




(a)

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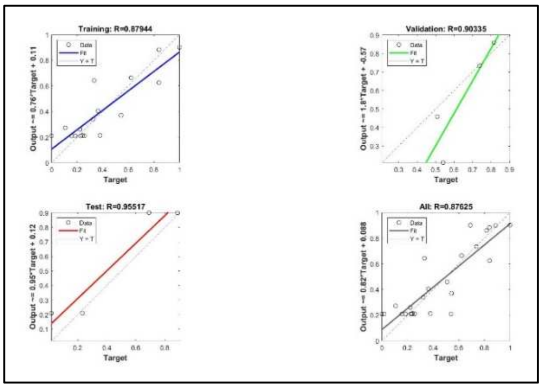
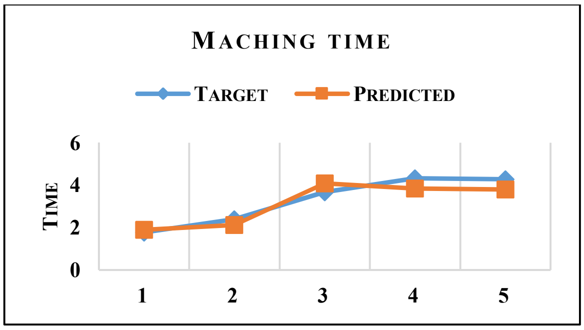


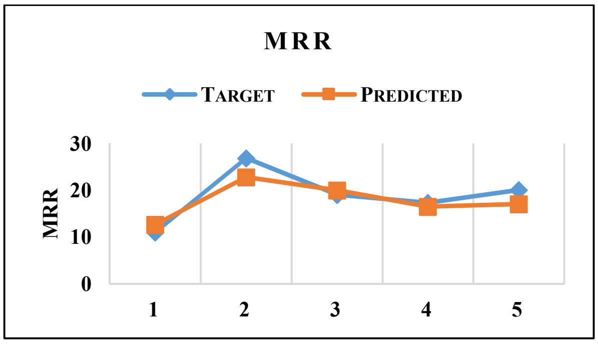

(c)

Figure 7: Accuracy graph

Figure 8 shows the variation graph between the target and predicted values for each performance measures.




(a)

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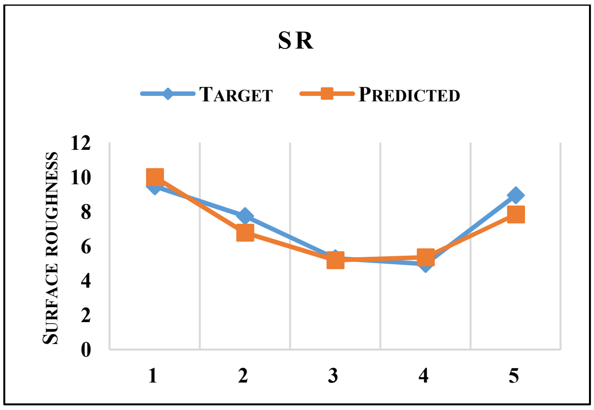


(c)

Figure 8: Graph showing the target vs predicted for the test data

In the next step the set of NDS are computed using the NSGA-II model. The parametric configuration for the NSGA II is shown in Table 2**.**

TABLE II: PARAMETRIC CONFIGURATION FOR NSGA II

| Parameter | Values |
|---|---|
| No. of population | 50 |
| No. of generations | 250 |
| Parent selection strategy | Binary tournament selection |
| Mutation | 0.3 |
| Crossover | 0.8 |

Then the TOPSIS is applied to select the optimal solution from the PO front. Figure 9 shows the PO front.

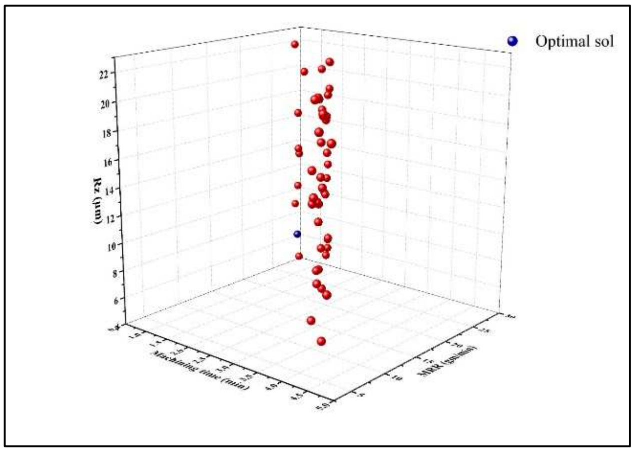


Figure 9: Pareto optimal front

The optimal solution obtained from the proposed approach is shown in table 3.

TABLE III: SUMMARY TABLE

| Input | | | | Performance measures | | |
|---|---|---|---|---|---|---|
| ***Spindle speed (rpm)*** | ***Feed Rate (mm/min)*** | ***Depth of Cut (mm/min)*** | ***% of Cutting Fluid*** | ***Machining time*** | ***MRR*** | ***SR*** |
| 500 | 0.1 | 0.3424 | 15.76 | 1.04 | 25.6 | 7.25 |

## V. CONCLUSIONS

The results obtained from the proposed approach needs to be validated before applying it for industrial use and this will also test the suitability of our approach. For this reason we have conducted two experiments. The first experiment (Exp 1) is conducted at the optimized parameters obtained from our approach and the second experiment (Exp 2) is conducted at the optimized parameters obtained from the traditional NSGA-II approach and then computed the Relative absolute error (RAE) between the simulated and the experimental values as per Eq. (6).

$$RAE = \frac{|y_i - p_i|}{y_i} * 100\% \qquad (6)$$

Where $y_i$ and $p_i$ is the output for the i$^{th}$ observation. The table IV shows the RAE computed between the simulated and the experimental values.

From table IV it is observed that the proposed approach is far superior in comparison to the traditional approach. The propose approach hybridizes the exploration capability of NSGA-II and the exploitation capability of TOPSIS method. Together it is called NTOPSIS. Our approach formulates the objective function using the ANN and hence it is suitable for application to highly nonlinear dataset. From the overall observation, it can be concluded that with the proposed model we have achieved the aims and objective of the study.

TABLE IV: RAE COMPUTED BETWEEN THE SIMULATED AND THE EXPERIMENTAL VALUES.

| **Exp.** | **Input** | | | |
|---|---|---|---|---|
| | ***Speed*** | ***Feed*** | ***DOC*** | ***Cutting fluid %*** |
| Exp. 1 | 500 | 0.1 | 0.35 | 15.76 |
| Exp. 2 | 300 | 0.2 | 0.6 | 0.00 |

| **Exp.** | **Simulated** | | |
|---|---|---|---|
| | ***MC time (min)*** | ***MRR (gm/min)*** | ***SR (μm)*** |
| Exp. 1 | 1.04 | 25.6 | 7.25 |
| Exp. 2 | 1.85 | 23.8 | 9.53 |
| **Exp.** | **Experimental** | | |
| | ***MC time (min)*** | ***MRR (gm/min)*** | ***SR (μm)*** |
| Exp. 1 | 1.06 | 26.7 | 7.57 |
| Exp. 2 | 2.17 | 27.0 | 10.7 |
| **Exp.** | **Error** | | |
| | ***MC time*** | ***MRR*** | ***SR*** |
| Exp. 1 | 1.87 | 4.22 | 4.29 |
| Exp. 2 | 14.8 | 12.0 | 11.2 |

## REFERENCES


[1] Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. A. M. T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE transactions on evolutionary computation*, *6*(2), 182-197.

[2] Deb, K., Agrawal, S., Pratap, A., & Meyarivan, T. (2000, September). A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. In *International conference on parallel problem solving from nature* (pp. 849-858). Springer, Berlin, Heidelberg.

[3] Deb, K. (2005). Multi-objective optimization. In Search methodologies (pp. 273-316). Springer, Boston, MA

[4] Medhi, T., Hussain, S. A. I., Roy, B. S., & Saha, S. C. (2021). An intelligent multi-objective framework for optimizing friction-stir welding process parameters. *Applied Soft Computing*, *104*, 107190.

[5] Petkovic, D., & Radovanovic, M. (2013). Using genetic algorithms for optimization of turning machining process. *journal of engineering studies and research*, *19*(1), 47.

[6] Gupta, M. K., Boy, M., Korkmaz, M. E., Yaşar, N., Günay, M., & Krolczyk, G. M. (2022). Measurement and analysis of machining induced tribological characteristics in dual jet minimum quantity lubrication assisted turning of duplex stainless steel. *Measurement*, *187*, 110353.

[7] Braspenning, P. J., Thuijsman, F., & Weijters, A. J. M. M. (1995). *Artificial neural networks: an introduction to ANN theory and practice* (Vol. 931). Springer Science & Business Media.

[8] Zou, J., Han, Y., & So, S. S. (2008). Overview of artificial neural networks. *Artificial Neural Networks*, 14-22.

[9] Leksycki, K.; Feldshtein, E.; Lisowicz, J.; Chudy, R.; Mrugalski, R. Cutting forces and chip shaping when finish turning of 17-4 ph stainless steel under dry, wet, and mql machining conditions. Metals 2020, 10, 1187.

[10] Lalwani, D.; Mehta, N.; Jain, P. Experimental investigations of cutting parameters influence on cutting forces and surface roughness in finish hard turning of mdn250 steel. J. Mater. Process. Technol. 2008, 206, 167–179.

[11] Korkmaz, M.E.; Ya¸sar, N.; Günay, M. Numerical and experimental investigation of cutting forces in turning of nimonic 80a superalloy. Eng. Sci. Technol. Int. J. 2020, 23, 664–673.

[12] Bouzid, L.; Boutabba, S.; Yallese, M.A.; Belhadi, S.; Girardin, F. Simultaneous optimization of surface roughness and material removal rate for turning of x20cr13 stainless steel. Int. J. Adv. Manuf. Technol. 2014, 74, 879–891.

[13] Mia, M.; Dey, P.R.; Hossain, M.S.; Arafat, M.T.; Asaduzzaman, M.; Ullah, M.S.; Zobaer, S.T. Taguchi s/n based optimization of machining parameters for surface roughness, tool wear and material removal rate in hard turning under MQL cutting condition. Measurement 2018, 122, 380–391.

[14] Kaladhar, M. Evaluation of hard coating materials performance on machinability issues and material removal rate during turning operations. Measurement 2019, 135, 493–502.

[15] Kini, M.V.; Chincholkar, A. Effect of machining parameters on surface roughness and material removal rate in finish turning of ±30 glass fibre reinforced polymer pipes. Mater. Des. 2010, 31, 3590–3598.

[16] Kumar, S.L. Measurement and uncertainty analysis of surface roughness and material removal rate in micro turning operation and process parameters optimization. Measurement 2019, 140, 538–547.

[17] Yildiz, A.R. Optimization of cutting parameters in multi-pass turning using artificial bee colony-based approach. Inf. Sci. 2013, 220, 399–407.

[18] Prasanth, R.S.S.; Raj, K.H. Optimization of straight cylindrical turning using artificial bee colony (abc) algorithm. J. Inst. Eng. (India) Ser. C 2017, 98, 171–177.

[19] Öztürk, O.; Kalyoncu, M.; Ünüvar, A. Multi objective optimization of cutting parameters in a single pass turning operation using the bees algorithm. In Proceedings of the 1st International Conference on Advances in Mechanical and Mechatronics Engineering, Ankara, Turkey, 8–9 November 2018.

[20] Bhor, Y.; Kakuste, N.S.; Gaynar, S. Optimization of Turning Parameters Using Taguchi's Method and Artificial Bee Colony Algorithm; IOP Conference Series: Materials Science and Engineering; IOP Publishing: Bristol, UK, 2020; p. 012064.

[21] Shettigar, A.K.; Patel, G.M.; Chate, G.R.; Vundavilli, P.R.; Parappagoudar, M.B. Artificial bee colony, genetic, back propagation and recurrent neural networks for developing intelligent system of turning process. SN Appl. Sci. 2020, 2, 1–21.