An Enhanced Prediction Model for Environmentally Friendly MQL Machining of AISI Grade 4340 Composite with Nano-Lubricants Based a Novel Optimizer Technique

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The milling of AISI 4340 with nano-lubricants and Minimum Quantity Lubrication (MQL) offers a viable path toward green production. Because of the complex interactions between several variables, including the rate of feeding, cutting rate and quantity of the nano-lubricant, optimizing the procedure is difficult. Current forecasting techniques frequently lack the accuracy needed for efficient optimization and traditional optimization methods can find it difficult to handle the complicated parameter space. This study proposes an innovative parallel red deer optimized AdaBoost (PRDO-AB) approach for optimum milling of AISI 4340 with nano-lubricants and it resolves the requirement for an improved prediction framework. The addition of PRDO, which is used to determine the ideal AB's settings, improves the preciseness of the AB approach. In this study, a greener Nano-Fluid (NF) with improved thermo-physical properties is produced by combining CuO with rice bran vegetable oil. Comprehensive experimental information is used to confirm the suggested model and the outcomes show notable gains in tool life, surface polish and machining effectiveness over standard techniques. In addition, the environmental impact evaluation shows a significant decrease in waste production and resource usage.

Keywords: MQL machining, nano lubricants green production and parallel red deer optimized ada boost (PRDO-AB).

1. Introduction

The industrial sector is experiencing an important change at environmentally conscious and sustainable practices due to the fast advancement of these innovations. When contrasted with conventional machining techniques, MQL cutting has demonstrated great promise in terms of significant savings in ecological effects and operating costs [1]. The milling of substances such as AISI Grade 4340, strong, low-alloying steel that is utilized in aircraft and automotive industries, underscores the importance of this change. AISI Grade 4340 is a highly favored option for vital components exposed to stressful conditions because of its well-known durability [2]. But the traditional machining methods used for these kinds of materials sometimes need large coolant use that raises concerns about the environment and drives up expenses. Incorporating MQL cutting, on the other hand, is an unusual strategy to deal with these problems and adopt a more environmentally conscious production ethic. Because of the small size of their particles and great lubrication qualities, nano-lubricants work better than their traditional substitutes [3]. These small lubricants not just assist with extending tool life but also decrease wastage as well as use of resources, yet additionally reduce wear and friction. MQL processing decreases the negative impacts of liquid manufacturing, destruction and the total ecological imprint of machining procedures by lowering the amount of liquid used [4, 5]. This decrease in consumption of fluids is in line with the worldwide movement to environmentally friendly production practices as it minimizes the discharge of hazardous compounds into the environment while conserving valuable assets. Additional benefits of using MQL for cutting in AISI Grade 4340 milling include increased dimensional accuracy and exterior polish [6, 7]. A more focused and regulated lubrication process is ensured by the accurate usage of nano-lubricants in small amounts, leading to better product qualities. An additional instance of the possibility for higher energy efficiency is the use of nano-lubricants in MQL machining for AISI Grade 4340. The entire electrical usage of the machining method is decreased with less wear and friction [8].

Through reduced energy expenditures and increased total energy efficiency of machining processes, this additionally conforms to environmental sustainability goals but also has financial implications [9].

The study [10] proposed that Grey Wolf Optimization (GWO) method were used to improve the machining parameters of the AISI 4340 alloy to improve cutting force, roughness of the surface and wear of the tool. In accordance with published results, turning experiments were carried out using MQL-assisted CuO and Al_2O_3 NF. It implies that the GWO technique was a feasible alternative for optimizing the AISI 4340 alloy's reactions throughout machining processes. The paper [11] investigated the use of MQL in a variety of machining techniques, cutting, rotating, milling and drilling, with an emphasis on difficult-to-machine metals. Optimization of aerosol-supply pathways, tool geometry, tip substances and tool body design was critical to improve the efficacy of the MQL system. The research [12] examined the effectiveness of NF when they were sprayed into the tool–work connection utilizing the MQL misting system after that is combined in various ratios with coconut oil. The combination of coconut oil and Nano-Al_2O_3 revealed enhanced efficiency, leading to an improved surface.

The paper [13] assessed to discover further about the physicochemical characteristics and atomizing efficiency of NF to understand their function in processing different materials. Cutting fluids that utilized vegetable oil as well as water were shown to be more effective than those relying on mineral-based oils for dealing with environmental and health problems. These changes guaranteed strong ecological sustainability in addition to high-performance machining. The study [14] proposed an optimization strategy based on Grey Relational Analysis (GRA) that predicted the values of the Grey Relational Grade (GRG) and optimized the parameters used for machining by applying predictive algorithms such as RSM and support vector machine (SVM). The results showed that when it came to cutting parameter prediction, Artificial Neural Networks (ANN) and SVM models outperformed the response surface method (RSM) model in terms of accuracy in forecasting. The article [15] discussed the investigation of a Computer Numerical Control (CNC) lathe's manufacturing of reinforced steel to maximize the parameters for cutting while minimizing surface roughness and energy use. In the optimization process, input parameters, such as the rate of feed, tool type and cutting speed, were considered. Given that the percentage error in allowable bounds, the results of the verification tests indicated effective optimization.

The research [16] proposed a technique that used regression analysis (RA) and ANN to forecast the surface roughness during severe machining of AISI 52100 steel. Through an examination of correlation coefficients, the results indicated a strong correlation, with an ANN model surpassing the RA model in predicting surface roughness. The paper [17] discussed heat, pressure and roughness of surfaces as instances of numerous reactions. That requires the adoption of multiple factors optimization approaches and the MQL method was investigated as an effective means of maximizing the fluid for cutting usage to improve milling efficiency. The response settings produced excellent outcomes, based on the experimental information. The study [18] used an Metal-Organic Chemical Vapor Deposition (MTCVD) multilayer-coated carbide insertion (TiN/TiCN/Al2O3) to estimate wear on the flanks and roughness of the surface during dry hard machining of AISI 52100 steel (55 ± 1 HRC). Following Pearson correlation coefficient accuracy testing, Multiple Linear Regression (MLR) and Multiple Quantile Regression (MQR) prediction models were developed using parameters from machining and signals from vibrations. The article [19] utilized statistical models to examine how trimming specifications affect surface irregularities and the average square root of piece motion in metallic drilling. A mixed-level design of tests included slicing rates, feed velocity and radius of the nose, affecting both surface roughness and work-piece vibrations speed root mean square. The study [20] employed Taguchi design, ANOVA and modeling to examine how machining factors affect the surface roughness and cutting force during dry turning of martensitic metal. In comparison to multiple regressions, ANN prediction results were found to be superior.

This paper's aim is to improve prediction model for environmentally friendly MQL machining of AISI Grade 4340 composite using nano-lubricants, employing a novel optimizer technique to enhance machining efficiency and sustainability.

The remaining segments of the study were classified into the following categories: The methodology is discussed in Section 2. Section 3 includes results. Section 4 ends with conclusion.

2. METHODOLOGY

In this study, we present Parallel Red Deer optimized AdaBoost (PRD-AB), a novel technique for eco-friendly MQL machining integrating nano-lubricants for enhanced sustainability and performance.

2.1Design for MQL machining of AISI 4340

The experiments were carried out on AISI 4340 Steel blends, measuring 650 mm in length and 50 mm in diameter, was used for the experimentation. 45 ± 2 HRC is the alloy's hardness. This alloy, that is utilized in the device tool, motoring and air force sectors, is categorized as high-strength and challenging to process. The AISI 4340 steel's chemical constitution and biomechanical and thermo-physical characteristics are shown in Tables 1 and 2.

Table 1. AISI 4340 steel's chemical composition.

(Source: author)

Element	Nickel (%)	Carbon (%)	Chromium (%)	Molybdenum (%)	Manganese (%)	Silicon (%)	Copper (%)	Iron(%)
Weight	1.62	0.42	1.02	0.295	0.81	0.38	0.18	Bal.

Table 2. AISI 4340 steel's mechanical specifications.

(Source: author)

Property	Tensile Force (MPa)	Hardness of Yield (MPa)	Flexible Modulus (GPa)	Ratio of Poissons	Intensity (kg/m^3)	Conductivity of Heat	The Ratio of Heat Growth	Particular temperature (J/kg.K)
Value	920	670	205	0.28	7900	45.2	12.8e−6	480

Supplying the drilling of the NF to the cutting zone was done using the MQL-turning with nano-lubricants (MQL-TNL) approach. Cupric oxide (CuO) was treated with two slicing NF. Because rice bran oil is a vegetable oil that has superior thermo-physical qualities to other vegetable-based oils including a sunflower olive, canola and soy beans, it is considered as environmentally beneficial and it was utilized as an organizing fluids. The oil's rice bran thermo-physical characteristics are shown in Table 3. To achieve complete variation, tiny particles were mixed with the base oil at 2% per volume under a stirrer with a magnet for 60 min. Finally, the produced solution was sterilized for three hours using an ultrasonic sonicator. With a high-pressure nozzle that produced NF are applied over the splitting area.

Table 3. The Rice bran oil's thermo-physical characteristics.

(Source: author)

Dampness (%)	Turning Point (ºC)	Intensity (20ºC)	Motion-Based Viscosity (mm²/s)	Value of Saponification	Refractive Index
0.12	190	900	42.0	195	1.475

2.2 Enhancements in AISI 4340 Machining

In this section we integrate Red Deer algorithm, which is recognized for imitating the behavior of deer herds, is utilized to optimize machining parameters, ensuring effective and sustainable procedures. Through utilizing parallel computing capabilities, PRDO accelerates the tuning process further. In addition, machining conditions are optimized by the AdaBoost method that is recognized for its stability in classification tasks. These developments attempt to reduce the negative effects on the environment and increase the effectiveness of AISI Grade 4340 machining processes using nano-lubricants.

2.3 Red Deer Algorithm (RDA)

The RDA stands out, obtaining inspiration from deer herds' collective behavior. This technique, when applied to AISI Grade 4340 composite machining, dynamically refines cutting parameters, assuring maximum effectiveness while reducing environmental effect. RDA starts with a starting group of Red Deer (RD). Male RDs were selected from the population as they were considered some of the best, with the remaining RD generally referred to as hinds. We create harems after already roared and fought. A harem is a collection of hinds. The mentioned male RD split all of the population's harems according to their skill, elegance and strength. In Genetic Algorithm GA, the male RD's refinement and strength are inversely related to his physical rating.

2.3.1 Creating foundational Red Deer.

We create a value for a variable array that needs to be improved. Although this array is known as a genetic material in GA communication system, RD is a term utilized to this. RD therefore represents the opposite of the solution. $\mathrm{M_{var}}$, $1 \times \mathrm{M_{var}}$ Array represents a RD in a $\mathrm{M_{var}}$–dimensional optimization issue. In order to define this array,

$$\mathrm{RedDeer} = \left[\mathrm{W_1, W_2, W_3, \dots, W_{M_{var}}}\right] \quad (1)$$

Additionally, every Red Deer's functional value can be assessed in the manner described below:

$$\mathrm{Value} = \mathrm{e\ (RedDeer)} = \mathrm{e}\left(\mathrm{W_1, W_2, W_3, \dots, W_{M_{var}}}\right) \quad (2)$$

To start the optimization algorithm we generate the initial population of size $\mathrm{M_{pop}}$. We select the best Red Deers to $\mathrm{M_{male}}$ and the rest of to $\mathrm{M_{hind}}$.

We create the original group of size $\mathrm{M_{pop}}$to begin with the optimization method. We give $\mathrm{M_{male}}$ the best RD and $\mathrm{M_{hind}}$ the remaining ones.

2.3.2 Manly roar RD

In this step, the male RD is shouting in an attempt to show off their grace. That indicates whether or not male RD is superior to females. In actuality, we let any male RD to shift places. Female RD is attracted to roaring males.

2.3.3 Choose γ proportion of the top male Red Deer leaders

The differences between male RD are enormous. Of them, a few have achieved greater success than the others.

The position of males in nature is actually different; some of them take control of harems. We distinguish two categories of male red deer: There are both stags and male commanders, hence the quantity of male commanders is connected with γ, will be:

$$\mathrm{M.male.Com} = \mathrm{round}\,\{\gamma . \mathrm{N_{male}}\} \quad (3)$$

Here $\mathrm{M.male.Com}$ is the quantity of men grabbing the harems. We choose this male RD as the greatest, while the rest are stags. The quantity of stags is calculated as follows:

$$\mathrm{M.stag} = \mathrm{M_{male}} - \mathrm{M.male.Com} \quad (4)$$

Where, Male population stag count is $\mathrm{M.stag}$.

2.3.4 Conflict involving deer and male commanders

We allowed random fighting between stags and leader males. Yet choose them following a battle if the goal function outperforms the previous ones.

2.3.5 Build harems

Now, at this stage, we establish the harems. A herd of hinds under the control of a male leader is referred to as a harem. The strength of the male leaders determines that many hinds are in harems. To forming the harems, we determine the normalized worthy of a male commander by dividing hinds among male commanders in a proportional manner by:

$$\mathrm{U_m} = \mathrm{u_m} - \max_{j}\{\mathrm{u_j}\} \quad (5)$$

Where, $\mathrm{u_m}$is the normalized value and $\mathrm{u_m}$is the value of the $\mathrm{n^{th}}$ male commander. Every male commander's normalized power, with the normalized value of all male commanders is defined by:

$$\mathrm{O_m} = \left| \frac{\mathrm{U_m}}{\sum_{j=1}^{\mathrm{M.male.Com}} \mathrm{U_j}} \right| \quad (6)$$

From a different angle, the part of hinds that a male commander should have is the normalized power .After then, a harem's hind population will be:

$$\mathrm{M.harem_m} = \mathrm{round}\,\{\mathrm{O_m} . \mathrm{M_{hind}}\} \quad (7)$$

Where, $\mathrm{M.harem_m}$ is the quantity of hinds of nth harem and $\mathrm{M_{hind}}$ is the amount of all hinds. Allocate the hindquarters among the individual male commanders, we select at random $\mathrm{M.harem_m}$ of the hinds and allow them to handle it. A man and those hinds will form the $\mathrm{n^{th}}$ harem.

2.3.6 Pair the male leader of the harem with $\propto$ percent of the females

In Genetic Algorithms (GA), we have a model of this feature similar to crossover. These parents are the male leader and his harem's hinds are the latest responses to come from the offspring.

The quantity of hinds in a harem that are pairing in their male's leader in proportion to a will be:

$$\mathrm{M.harem}_{\mathrm{m}}^{\mathrm{mate}} = \mathrm{round}\ \{\propto . \mathrm{M.harem}_{\mathrm{m}}\} \qquad (8)$$

Here $\mathrm{M.harem}_{\mathrm{m}}^{\mathrm{mate}}$ is the quantity of hindquarters of n^{th} which are prepared to mating with these individuals harem.

We select at random $\mathrm{M.harem}\ _{\mathrm{m}}^{\mathrm{mate}}$ of the $\mathrm{M.harem}_{\mathrm{n}}$.

2.3.7 Mate a man harem leader with % hinds in the other harem

We randomly select a harem and permit the guy to be the leader to connect with 20% of the harem's hinds. To expand his domain, the male RD actually captures other harem. A single male RD will mate with a specific number of hinds in a harem.

$$\mathrm{M.harem}_{\mathrm{m}}^{\mathrm{mate}} = \mathrm{round}\ \{\beta . \mathrm{M.harem}_{\mathrm{m}}\} (9)$$

Here $\mathrm{M.harem}_{\mathrm{m}}^{\mathrm{mate}}$ is the quantity of hinds of nth harem that are prepared for mating with one male Red Deer. We randomly choose $\mathrm{M.harem}_{\mathrm{m}}^{\mathrm{mate}}$ of the $\mathrm{M.harem}_{\mathrm{n}}$ too.

2.3.8 Mate stag with the nearest hind

At this point, for each stag, mates with the nearest hind in the group. The male Red Deer during the breeding period tends to follow the most hind out of them. This hind can be used to one harem or be in its own. We let a stag to mate with the closest hind. This implies that, in the worst scenario, each male RD has a chance to mate with as few hind as possible. To find the nearest hind, we must first compute the distance among every stag and every hind. We operate as a two-dimensional method. The separation among a male RD and his entire hinds in J-spatial dimension is calculated as follows:

$$c_j = \left(\sum_{i \in I} \left(\mathrm{stag}_i - \mathrm{hind}_i^j\right)^2\right)^{\frac{1}{2}} \qquad (10)$$

2.3.9 Selecting the upcoming generation

We decided the upcoming generation's males red deer as the most suitable solution and hinds for the subsequent generations utilizing matches selection, spinning wheels choice, or every adaptive procedure for fitness-based selection.

2.3.10 Convergence

This stopped condition might be an amount of iterations, the quality of the greatest solution ever identified, or a time period.

2.4 Parallel red deer optimization (PRDO)

MPI library functions provide parallelization, as demonstrated in Figure 1, with SLAVE CPUs collaborating with the MASTER CPU in Red Deer Optimization. RDO uses MPI for CPU coordination and connectivity. The MASTER creates an initial group and assigns portions to SLAVE CPUs to optimize. Customized calculations determine fitness for each SLAVE. The MASTER produces fresh populations for repeated assessments after receiving results. MPI coordinates communication, allowing Red Deer Optimization solves complex optimization problems.

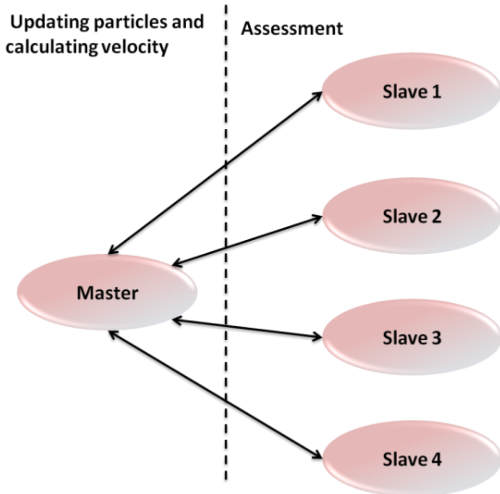

Fig.1.MPI library Function

(Source:https://www.sciencedirect.com/science/ar ticle/abs/pii/S0149197014001334)

2.5 Adaptive Boosting (AdaBoost)

Adaboost is a powerful ensemble learning algorithm, plays a crucial role in streamlining machining procedures and advancing environmentally friendly methods for treating AISI Grade 4340 steel using MQL techniques. Its ability to adapt and enhance predicted performance.

The structure of AdaBoost can be summarized as follows. AdaBoost computed the average weighted classification error per learner s utilizing the subsequent equation:

$$f_s = \sum_{m=1}^{M} c_m^{(s)} J\big(z_m \neq g_s(w_m)\big) \qquad (11)$$

Where, w_m is the prediction vector value for the observations m, z_m represents the actual class label and g_s represents the hypothesis (learner predictor). In step s, J is the value of the indicator variable and $c_m^{(s)}$ is the measurement weight. AdaBoost instructs individuals consecutively. AdaBoost calculates prediction utilizing the subsequent equations during the conditioning stage:

$$e(w) = \sum_{s=1}^{S} \propto_s g_s(w) \qquad (12)$$

$\propto_s = \frac{1}{2}\log\frac{1-\varepsilon_s}{\varepsilon_s}$ (13)

Where $\propto_s$ is the ensemble's weak hypotheses weight, AdaBoost retraining can be thought of as the minimizing of an exponential loss utilizing the equation below.

$\sum_{m=1}^{M} x_m \exp^{(-z_m e(w_m))}$ (14)

Given that, $z_m \epsilon \{-1,1\}$ is the real class, x_m are the normalized observed weights and $e(w_m)\epsilon(-\infty,+\infty)$is the projected classification.

2.6 ParallelRed deer optimized Adaboost (PRDO-AB)

AdaBoost and Parallel Red Deer Optimization (PRDO) are used to create a reliable prediction model for MQL machining of AISI Grade 4340 that is ecologically friendly. AdaBoost increases the predicted accuracy, whereas PRDO improves the optimization process. Through ensuring effective resource utilization, minimizing lubrication needs and optimizing machining parameters, this synergistic method seeks to minimize environmental impact. When these algorithms are combined, an effective and ecologically friendly prediction model for sustainable milling methods on AISI Grade 4340 is produced. Algorithm 1 shows the pseudo code for PRDO-AB.

Algorithm 1: pseudocode for Parallel Red deer optimized adaboost

```
# Assuming a dataset X_train, y_train for training and X_test for testing

# Step 1: Apply Parallel Red Deer Optimization (PRDO) for parameter optimization

optimized_params = PRDO(X_train, y_train, other_parameters)

# Step 2: Train a base model with the optimized parameters

base_model = train_base_model(X_train, y_train, optimized_params)

# Step 3: Apply AdaBoost to boost the base model

boosted_model = AdaBoost(base_model, X_train, y_train, other_parameters)

# Step 4: Make predictions on the test set

predictions = boosted_model.predict(X_test)

# Evaluate the model, e.g., using accuracy, precision, recall, etc.

evaluation_result = evaluate_model(predictions, y_test)
```

3. RESULT AND DISCUSSION

In this study, three procedure parameters with four levels were considered: Nourish (0.08, 0.12, 0.16 and 0.20 mm/rev), cutting speed (90, 110, 130, 150 m/min) and thickness of cutting (0.2, 0.4, 0.6, 0.8). As the rate of cutting fluid flow (200 ml/h) and particle concentration (0.2%) were kept continuous throughout every experiment. Rough milling is done before the tests to eliminate the exterior, a component layer that might include undesired substances such as oxide. An overview of the cutting circumstances is shown in

Table 4.

Table 4 .Test conditions for cutting.

(Source: author)

Cutting Tool	High-Tech CNC Milling Device
manufacturing process	Precision Milling
raw material	Titanium Alloy (Ti-6Al-4V)
tool mount	High-Performance Carbide Insert Holder
Instrument composition.	Coated Cermet (SNMG 120408)
Slicing Velocity (m/min)	90, 110, 130, 150
Nourish (mm/rev)	0.08, 0.12, 0.16, 0.20
Slicing depth (mm)	0.2, 0.4, 0.6, 0.8
Slice Agent	Coatings (CuO) + Renewably Sourced Oil extracted from "rice bran".
Distribution approach	MQL
Rate of flow	200 ml/hr
distance of Machining	150 mm
% of nano-material	0.2%

This section describes an experiment using AISI 4340 alloy steel with dimensions of 650 mm in length and 50 mm in diameter. To minimize experimental error, the trial was conducted three times and average responses were calculated. Table 5 illustrates the test setup and the measured reactions.

Table 5. Experimental setup and measurement responses.

(Source: author)

Exp. No.	Cutting Velocity	Nourish	Depth of Cut	Machining Force (N)	Surface Unevenness a(μm)	Tool Degradation (mm)
				CuO	CuO	CuO
1	90	0.08	0.6	135	0.382	0.041
2	90	0.12	0.8	142	0.395	0.042
3	90	0.16	0.2	149	0.405	0.043
4	90	0.20	0.4	154	0.418	0.046
5	110	0.08	0.6	161	0.428	0.048
6	110	0.12	0.8	166	0.415	0.052
7	110	0.16	0.2	168	0.452	0.053
8	110	0.20	0.4	176	0.464	0.055
9	130	0.08	0.6	185	0.473	0.057
10	130	0.12	0.8	189	0.478	0.060

The cutting force metric specifies the speed that the work-piece is manipulated by the milling tool. This crucial parameter affects removal of materials rates and tool wear, shaping MQL effectiveness and sustainability. The surface roughness metric is an accurate measure of the variations and irregularities on the AISI Grade 4340 composite's milled surfaces. This metric is a critical instrument for assessing that MQL machining with nano-lubricants is operating with its enhanced predictive model that calculates and maximizes surface roughness. Tool wear metric refers to the measurement of wear and tear on the cutting tool utilized in MQL machining operations. This metric predicts and evaluates tool cutting edge degradation during ecologically friendly AISI Grade 4340 machining, especially with nano-lubricants. Table 6 depicts the cutting replies based on various levels.

Table 6. Cutting replies based on various levels.

(Source: author)

Adjustable parameter	Condition of cutting	Level	Machining Force (N)	Surface Unevenness (μm)	Tool Degradation (mm)
Cutting speed	CuO-NF	1	6.238322	0.01787	0.002944
		2	8.062258	0.017462	0.003948
		3	8.693868	0.024515	0.00216
		4	14.59166	0.051983	0.011434

Feed rate	CuO-NF	1	34.10279	0.071705	0.010664
		2	35.75262	0.075525	0.012285
		3	38.30905	0.080571	0.013938
		4	40.4753	0.105351	0.019909
Cutting depth	CuO-NF	1	31.58586	0.066695	0.010773
		2	37.22454	0.08074	0.012856
		3	38.43935	0.080129	0.012447
		4	41.89272	0.106525	0.020869

In this section, six statistical metrics, including the determination coefficient (R^2), root mean square error (RMSE), mean absolute error (MAE), were employed to assess the performance of the proposed model.

The experimental results and data anticipated by the generated models cutting depth variations. Feed and speed in the "MQL-TNL" procedure using CuO, NF are presented. Figure 2 plots the results, demonstrating the high exactness of the PRDO-AB model. The dispersed dots representing estimated data are entirely in the region of the line (Destination).

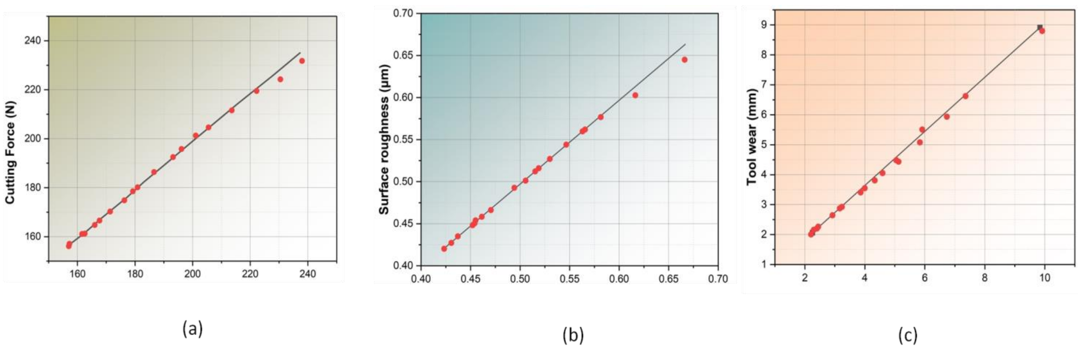

Fig.2. Outcome of machining force, finishing quality and tool integrity.

(Source: author)

CuO NF in the MQL-TNL cutting process, cutting force has an outcome of R^2 value of 0.997, 0.995 and 0.970 for Ad+PRD, RD and Adaboost, in that order. Regarding surface roughness, the corresponding outcome of R^2 values for Ad+PRD, RD and Adaboost are 0.994, 0.988 and 0.959, respectively. The outcome of R^2 values for the tool wear is 0.988, 0.977 and 0.955 for Adaboost, RD and Ad+PRD, respectively. In comparison to RD and Adaboost, the anticipated and measured outcomes of Ad+PRD exhibit a fit correlation, as indicated by the higher value of R^2. Figure 3 and Table 7 depict the R^2 of the proposed method.

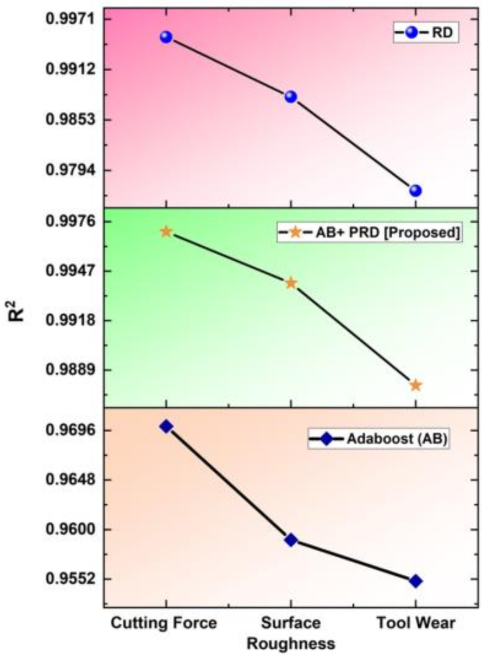

Fig.3.Outcome of R^2

(Source: author)

Table 7. Outcome of R^2

R^2			
Measurements	Adaboost (AB)	RD	AB+ PRD [Proposed]
Cutting Force	0.970	0.995	0.997
Surface Roughness	0.959	0.988	0.994
Tool Wear	0.955	0.977	0.988

CuO- NF is used in the MQL-TNL cutting process. The corresponding RMSE values of cutting force are 11.031, 12.262 and 30.955. For Ad+PRD, RD and Adaboost, the corresponding RMSE values for surface roughness are 0.038, 0.045 and 0.104. For Ad+PRD, RD and Adaboost, the corresponding RMSE values for tool wear are 0.002, 0.008 and 0.013. The cutting force RMSE value for the hybrid Ad+PRD is less than the Adaboost and RD. Furthermore, RMSE values of Ad+PRD are below than that of RD and Adaboost. The minimalistic values of the RMSE validate the precision of the forecast of the hybrid Ad+PRD algorithm over RD and Adaboost. Figure 4 and Table 8 demonstrate the outcome of RMSE.

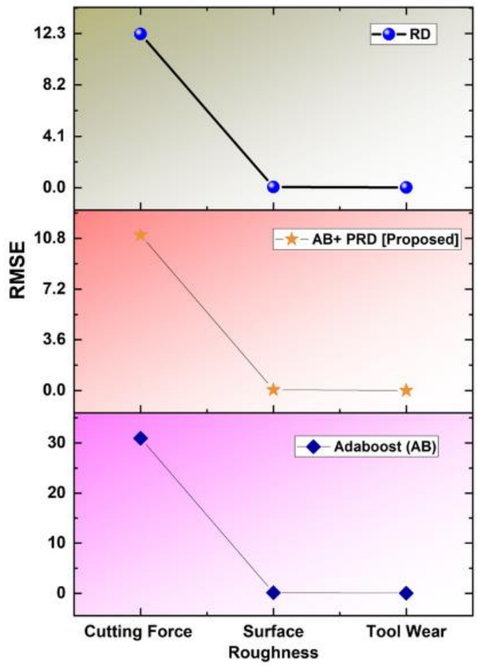

Fig.4. Outcome of RMSE

(Source: author)

Table 8. Outcome of RMSE

(Source: author)

RMSE			
Measurements	Adaboost (AB)	RD	AB+ PRD [Proposed]
Cutting Force	30.955	12.262	11.031
Surface Roughness	0.104	0.045	0.038
Tool Wear	0.013	0.008	0.002

Figure 5 and Table 9 depict the proposed method's MAE. The MAE cutting force magnitude equals to 10.650, 11.226 and 28.461 for Ad+PRD, RD and Adaboost, respectively, The "surface roughness", principles of MAE are 0.022, 0.045 and 0.094 for Ad+PRD, RD and Adaboost, sequentially, For the "tool wear", the principles of MAE are 0.002, 0.005 and 0.003 for Ad+PRD, RD and Adaboost. Furthermore MAE values of Ad+PRD are below than that of RD and Adaboost. Minimalistic values of the MAE validate the precision of the forecast of hybrid Ad+PRD method over RD and Adaboost.

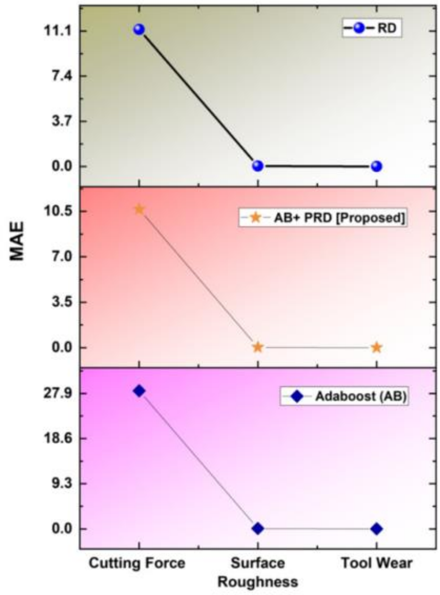

Fig.5.MAE

(Source: author)

Table 9.MAE

(Source: author)

MAE			
Measurements	Adaboost (AB)	RD	AB+ PRD [Proposed]
Cutting Force	28.461	11.226	10.65
Surface Roughness	0.094	0.045	0.022
Tool Wear	0.003	0.005	0.002

4. CONCLUSION

The nano-MQL technique replaced traditional cooling through flooding during the turning process of AISI 4340 alloy, employing eco-friendly rice bran oil as a slicing agent. The oil's thermo-physical properties were enhanced by introducing CuO nano-particles. A novel Parallel Red Deer optimized Adaoost (PRDO-AB) approach was anticipating and forecasting process outcomes. Key findings indicate that the CuO- NF yielded a smooth surface, preserving the tool due to enhanced thermo-physical properties. The nano-fluid's higher thermal conductivity improved cooling, lower viscosity enhanced flow, reduced contact angle and surface tension contributed to favorable characteristics. CuO NF showed increased “surface roughness and tool wear with higher cutting speed”, moderate increase with feed and decreased cutting depth. Optimal parameters recommended for minimizing cutting force, surface roughness and tool wear, while maintaining a high material removal rate, were “high cutting depth, moderate feed rate and high cutting speed”. A high R^2 of 0.998 was acquired by employing the created PRDO-AB model that is greater than that of AB (0.955) and RD (0.977) for the predicted findings. The prediction model's applicability can be limited to specific machining conditions and its generalizability to diverse scenarios and materials might be a challenge. In future, research could focus on optimizing nano-lubricant formulations for different materials and machining conditions. This could involve exploring various nano-particle concentrations, sizes and compositions to maximize lubrication efficiency.

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