Adaptive Surface Roughness Prediction in Turning Processes with Dynamic Lubrication Using Fish Swarm-Intelligent Modified Xgboost Approach

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Accurately anticipating Surface Roughness (SR) throughout turning operations is a continuous difficulty for the machining industry, particularly under variable lubrication circumstances. Surface finish quality is sometimes subpar because of standard models' low responsiveness to changes in lubrication conditions and machining settings. The present research introduced a novel Artificial Fish Swarm-Intelligent Modified XGBoost (AFSI-MX) methodology to tackle this problem by combining the XGBoost technique's potent prediction powers with the collective thinking of fish swarm behavior. First, the dataset is collected to assess the suggested AFSI-MX technique in relation to SR prediction. This study is carried out using the AFSI-MX approach on the Matlab platform. The suggested AFSI-MX technique is effective in forecasting SR in turning procedures over variable lubrication, as demonstrated by expserimental findings. The suggested AFSI-MX technique outperforms conventional methods in comparison when it comes to managing the complexity and unpredictability present in machining situations

Keywords: Turnin, Surface Roughness (SR), Machining Industry, Lubrication Conditions, Artificial Fish Swarm-Intelligent Modified Xgboost (AFSI-MX).

1. Introduction

The enhancement of machining operations efficiency is crucial in contemporary manufacturing as it directly impacts cost-effectiveness, heightened productivity and improved product quality (Das et al 2022; Nguyen et al 2022; Huang et al 2023). The fundamental process of machining, known as turning, plays a crucial role in the formation of various materials, encompassing metals and composites. The surface roughness of the final product is a crucial determinant of the efficiency of turning operations. In industries that demand high levels of quality and precision, such as the aerospace, automotive and medical sectors, obtaining the necessary surface polish is of utmost importance (Tian et al 2022; Afzal et al 2022; Prashanth et al 2023). The phenomenon of surface roughness is a multifaceted process influenced by various factors, such as material properties, lubrication conditions, cutting settings and tool geometry (Wang et al 2022). The continuous prediction and control of roughness on the surface during turning operations provide significant challenges in scenarios involving dynamic lubrication. Traditional strategies for predicting surface roughness in machining settings struggle to account for the fluctuating nature of these parameters, leading to subpar results and increased production costs (Yao et al 2023).

Ulas et al (2020) proposed a Wire Electrical Discharge Machining (WEDM) that was used to machine the aluminum alloy Al7075 with a variety of parameters to predict the surface roughness, which is important for material properties. Dubey et al (2022) presented to estimate the surface roughness and assess its consistency with expected values, namely“linear regression (LR)," “random forest (RF)" and “support vector machine (SVM)” be employed. Zeng et al (2023) presented the “convolutional neural networks (CNN)”, “gated recurrent units (GRU)” method as the main model for predicting the roughness of the surface. Pimenov et al (2018) proposed the application of “artificial intelligence (AI)” approaches for the real-time prediction of surface roughness variations.Karim et al (2018) presented an “Adaptive Neurofuzzy Inference System (ANFIS)” and an “Artificial Neural Network (ANN)" for the prediction of surface roughness in turning SiC-Al Alloy composite. Motta et al (2022) presented machine learning techniques, Random Forest (RF) and Gaussian Process Regression (GPR), for the prediction of surface roughness in cylindrical turning operations. Pelayo et al (2021) presented two methodologies: a geometric framework for characterizing the surfaces generated by barrel-end mills. The methodology relies on the simulation of tool-induced marks on the machined surface and the utilization of empirical models to forecast surface characteristics using cutting parameters. Steege et al (2023) proposed two machine learning algorithms, artificial neural network (ANN) and random forest (RF), which were examined to assess their effectiveness in predicting surface roughness Steege et al 2020).

Rajesh et al (2022)proposed that a ML methodology known as the nonlinear autoregressive network (NRAX) model was utilized to develop prediction and logistic regression models for the dry turning process of Inconel 625. The Alajmi and Almeshal (2020)presented the ML technology employed in this approach is the "Adaptive Neuro-Fuzzy Inference System-Quantum Particle Swarm Optimization (ANFIS-QPSO)" to forecast surface roughness measurements in the specific scenario of dry and cryogenic turning of stainless steel AISI 304. Hu et al (2023) presented a suggest framework that combines Transfer Learning (TL) and Gaussian Process (GP) to improve the reliability of surface roughness prediction. Li et al

(2021) proposed the method “particle swarm optimization least squares support vector machine (PSO-LSSVM)” and it is designed to enable high-speed precision milling surface roughness prediction. The aim is to implement using artificial fish swarm-intelligent with modified xgboost (AFSI-MX) to improve the predictions of surface roughness. Our goal is to increase accuracy and efficiency by analyzing a dataset of metal matrix composites that were constructed using SiC as the support material and Al alloy as the lattice material, as demonstrated by better performance metrics (ARE and RMSE) compared to current techniques.

2. Materials and Methods

This research proposed to predict Surface Roughness Prediction in Turning Processes with Dynamic Lubricationusing an Artificial Fish Swarm Algorithm With Modified Xgboost (AFSI-MX).

2.1 Dataset

The dataset was gathered in Karim et al (2018). Metal matrix composites were constructed using SiC as the support material and Al alloy as the lattice material. Al-6061-based Metal Matrix Composite (MMC) consists of 98% of aluminium, 0.8% of magnesium, 0.50 percent iron, 0.2% of zinc, 0.2 percent chromium and 0.2% of copper. Furthermore, it includes 10% aluminium 6061 and 90% of silicon carbide (SiC).

2.2 Machining parameters

2.2.1 Speed

The variability in spindle speed has a direct influence on the workpiece's roughness on the surface. Titanium alloys exhibit favorable machinability characteristics when subjected to high cutting speeds, whereas softer materials like aluminum are best processed at lower cutting rates. In contrast to various other aspects, the speed and feed of the machining process exhibit interdependence. When operating at low speeds and high feed rates, it is possible to achieve higher surface roughness values, resulting in a greater surface polish. This can be accomplished by using low feed rates and high speeds. Nevertheless, the pace at which material is removed is quite low in the second case. The adjustment of speed on a machine is contingent upon the cutting tool employed for the cutting process. Tools that are designed for softer materials are meant to achieve a high-quality surface finish when rotated at modest rates. When employing tools equipped with carbide materials that possess higher hardness or increased speed capabilities, it is possible to alter the operating speeds to achieve superior surface quality.

2.2.2 Feed

The advancement of the length tool in the cutting direction is determined by the feed, which is measured in millimeters per revolution of the spindle. The role of feed is of utmost importance in establishing the surface quality of the machined product. The relationship between feed and speed is elucidated in the preceding discussion. There's a chance that applying excessive feed at a slow speed will cut the machine's surface threads. It is not recommended to use low feeds while working at high speeds, as this leads to a large fall in the “Material Removal Rate (MRR)," which is undesirable.

2.2.3 Depth of the cut

The surface roughness is affected by the cutting depth when the operation involves substantial cutting depths. The poor surface quality is a consequence of increased strain at the interface due to the significant cut depth, which is caused by the contact area of the tool material.

2.3 Materials properties

2.3.1 Tensile strength and Yield strength

The manufacturing of a given work is ascertained based on the workpiece's production and strength of tensile. When making a decision about the choice of tools and lubricants, it is imperative to consider these criteria. The cutting forces exerted and the amount of heat generated in the cutting zone can be estimated based on the material's strength. Considering the aforementioned factors, the heat conductivity qualities of both the tool and material are of interest, it is possible to ascertain the appropriate amount of cooling required and the specific cooling method to be utilized to achieve a desirable surface quality.

The hardness of the workpiece:

The hardness of the material has an impact on various other qualities. The machining properties, specifically the speed, are influenced by the hardness of the workpiece. It is generally advised to employ lower speeds when turning softer workpieces, as this tends to yield more favorable results. Higher speeds are recommended for turning harder workpieces, as this is more likely to ensure a superior surface quality. The hardness of the part has an impact on some attributes of the tool, including the tool's hardness and nose radius. In order to achieve cutting, it is essential for the tool to possess greater toughness than the workpiece. Additionally, the utilization of blunt tools is necessary to ensure the anticipation of a superior surface quality.

2.4 Tool properties

2.4.1 Tool coating and rack angle

The thermal ability to absorb the cutting region is determined by the coating used on a tool. The tool's coating exhibits significant heat absorption in the cutting zone, reflecting the surface roughness caused by heat-induced material loss. The rake angle plays a crucial role in the formation of the chip and serves to reduce the probability of built-up edge formation, which in turn contributes to the generation of surface roughness.

2.4.2 Tool hardness

The hardness of a tool has an indirect impact on the surface roughness of a material, which is mediated by many processing characteristics like speed, feed rate and the hardness of the substance are worked on. It is imperative that the crushing force of the device surpasses that of the workpiece. When engaging in turning activities, high-speed tools, typically hard tools, are utilized to enable turning operations at elevated speeds. Typically, the utilization of robust tools is observed for the purpose of machining materials like titanium alloys and hardened steel.

2.4.3 Tool nose radius

The feed rate for machining is influenced by the tool. The utilization of a blunt tool and the allocation of substantial resources give rise to disharmony. The occurrence of rubbing or sliding during the machining process can be attributed to the large radius and feed rate. Based on the conducted research investigating the relationship involving feed rate and nose radius, it is observed that to eradicate chat markings, it is advised to restrict the rate of feed to no over fifty percent of the nose circumference. The region where the tool and workpiece make contact, which offers valuable information regarding the heat generation and removal rate, is determined by the nose radius.

2.5 Cooling system

Heat is produced by the friction between the tool and the workpiece. Ignoring the heat created might have numerous negative effects on the workpiece's surface quality. For your investigation, below are a few different refrigeration systems.

2.5.1 Dry

Dry turning is a machining technique characterized by the absence of coolant in the cutting process. The “Surface Roughness (SR)” measurements of the end product exhibit higher values when compared to processes employing alternative cooling techniques. Significant amounts of thermal energy are generated as well as absorbed by the work-piece and the tool. The occurrence of tool malfunction or local welding at the interface of tool parts can be attributed to the temperature exceeding the melting point of the working component. In a dry lubricating system, the values of thermal conductivity are assumed to be 0 W/m^2K.

2.5.2 Flooded cooling

In the process of immersing a coolant in the workpiece to facilitate cooling is referred to as flooded lubrication in the context of turning operations. The coolant has the potential to exhibit homogeneity or exist as an emulsion of oil and water. Non-corrosive workpieces are cooled using water and the coolant's heat absorption capacities are communicated through emulsions. The heat conductivity of the coolant is a crucial factor in the process of heat absorption. This study investigates the thermal conductivity of two fundamental fluids and their weight ratio, which is contingent upon the composition of the mixture. In the absence of additional liquid substances containing nano particles, the analysis account is equal to the base fluid's thermal conductivity when there is a 1 blending ratio.

2.5.3 Minimal Quantity of Lubricant (MQL)

Reducing the amount of coolant needed to reduce the heat generated in the area of cutting is the primary goal of MQL. A key feature of MQL is the precise mist-like release of the coolant at the area of cutting, which is achieved by spraying small atomized particles from a nozzle under excessive pressure. Their ability to absorb heat is increased since they have been atomized into little molecules. At the same time, a significant amount of coolant is preserved since the workpiece does not submerge large volumes of coolant. To improve the absorption of heat in the cutting region, the refrigerant in the MQL tank can be mixed with various oils or nanoparticles. The weight combination, nano-partitions and the thermal properties of the base fluid are taken into account when predicting the surface roughness.

With the least amount of surface roughness possible, the cloth is twisted with the help of MQL to achieve the best surface quality.

2.6 Surface Roughness Prediction

In this research, we integrate the "artificial fish swarm algorithm (AFSA)" and modified XGboost (MX) for surface roughness prediction in turning processes with dynamic lubrication.

2.7 Artificial fish swarm algorithm

The implementation of the artificial fish swarm method is employed to optimize parameters in the prediction of surface roughness during dynamic lubrication. This approach attempts to enhance comprehension and regulation of frictional behavior, leading to increased performance and longevity of machinery as shown in Figure 1.

AFSA is a swarm intelligence program that can solve optimization problems by mimicking the swarming, pursuing and preying actions of artificial fishes. Let $\mathbf{W_j}$represent the current position of one artificial fish, $\mathbf{W_u}$represent the viewpoint of one artificial fish at one time, visual represents the visual scope of each individual, $\mathbf{W_a}$and $\mathbf{W_b}$represent fishes inside the visual of$\mathbf{W_j}$, Step represent the largest step of artificial fish and $\boldsymbol{\delta}$represent the fish swarm congestion factor. The following behaviors of fish swarms can be described.

Behavior of swarms: Swarming activity is to be carried out if$\mathbf{e}(\mathbf{W_d}) > \mathbf{e}(\mathbf{W_j})$, where $\mathbf{W_d}$is the focal point inside the point $\mathbf{W_j}$visual. Assume $\mathbf{W_d}$to be$\mathbf{W_u}$. The fish at $\mathbf{W_j}$ will move in the direction of point$\mathbf{W_d}$.

Behavior of chasing: If the point $(\mathbf{denotedby W_{max}})$ that has the highest value for the objective function in the visual satisfies the condition$\mathbf{e}(\mathbf{W_{max}}) > \mathbf{e}(\mathbf{W_j})$ and if the visuals of $\mathbf{W_j}$is not crowded, the chasing behavior is to be implemented. Let $\mathbf{W_u}$be denoted as$\mathbf{W_{max}}$. The fish located at $\mathbf{W_j}$will proceed to move one step closer to the $\mathbf{W_{max}}$location.

Behavior of Preying: The following circumstances are where preying behavior is used:

$\mathbf{e}(\mathbf{W_d}) < \mathbf{e}(\mathbf{W_j}), \mathbf{e}(\mathbf{W_{max}}) < \mathbf{e}(\mathbf{W_j})$and the visual representation exhibits a lack of overcrowding.The visual representation exhibits a high level of crowding.

In this context, a point $\mathbf{W_i}$is randomly chosen from the visual representation of $\mathbf{W_j}$. If the value of $\mathbf{e}(\mathbf{W_i}) > \mathbf{e}(\mathbf{W_j})$, the preying action is to be performed. Let $\mathbf{W_i}$be denoted as $\mathbf{W_u}$. The fish located at $\mathbf{W_j}$will proceed by taking towards the point$\mathbf{W_i}$. On the other hand, the entity will transition to a random position inside its visual field.

The optimal answer achieved in each iteration is denoted as the "board." Once the designated number of iterations has been completed, the search process is over and the outcome displayed on the "board" is considered to be the definitive solution. In the context of artificial preying fishes, the process of updating their position can be expressed as Eq. (1),

$$\mathbf{W_{next}} = \mathbf{W_j} + \mathbf{rand}.\frac{\mathbf{step}\times(\mathbf{W_i}-\mathbf{W_j})}{\mathbf{norm}\ (\mathbf{W_i}-\mathbf{W_j})} \quad (1)$$

Where, $\mathbf{W_j}$ the artificial fish's present position, $\mathbf{W_{next}}$ is its next position and $\mathbf{W_i}$ is the position with the highest objective function value in terms of computational intelligence and neuroscience; In $[-\mathbf{1},\mathbf{1}]$, rand represents a random number and norm$(\mathbf{W_i}-\mathbf{W_j})$ represents the separation between two position vectors.

The position-updating for fish that artificially swarm can be expressed as Eq. (2-3),

$$\mathbf{W_{next}} = \mathbf{W_j} + \mathbf{rand}\frac{\mathbf{step}\times(\mathbf{W_d}-\mathbf{W_j})}{\mathbf{norm}(\mathbf{W_d}-\mathbf{W_j})} \quad (2)$$

The position-updating might be formulated as follows for artificial chasing fish:

$$\mathbf{W_{next}} = \mathbf{W_j} + \mathbf{rand}\frac{\mathbf{step}\times(\mathbf{W_{max}}-\mathbf{W_j})}{\mathbf{norm}(\mathbf{W_{max}}-\mathbf{W_j})} \quad (3)$$

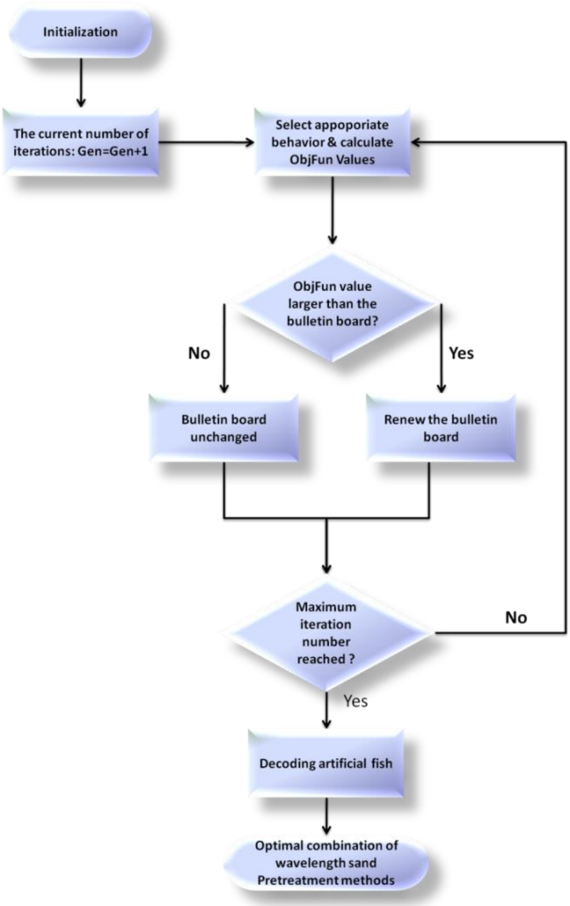

Figure 1The flow chart of AFSI [Source: Author]

2.8 Modified XGBoost

Modified XGBoost is used for predicting surface roughness in dynamic lubrication situations. It optimizes surface quality predictions by capturing complicated interactions and improving accuracy through the use of ensemble approaches.XGBoost, known as Extreme Gradient Boosting, was employed to produce an efficient model with quick computation times and good performance. To maximize the accuracy of future forecasts, the formula models the expected errors of decision trees using a combination technique. A value report on each feature's impact in predicting the final building performance score is part of the model's creation process. The impact of each attribute on the overall prediction of learning outcomes is indicated by this feature value. Decision trees are generated by XGBoost, which makes parallelization easier. The algorithm has the important property of distributed computing, which allows it to process large and complex models efficiently. The examination of extensive and varied datasets defines it as an out-core computing. This analytical technique is used to control resource use in an efficient manner. After every iteration, a new model must be incorporated to reduce errors.

At iteration t, the goal of the XGBoost function is Eq. (4-8):

$$\mathbf{L(t) = \sum_{k=1} L(z_{out_j}, z_{out_k^{(t-1)}} + f_t(x_k) + i(h_t)} \quad (4)$$

The variable $\mathbf{y_{out}}$ h indicates a known true value from the training data. The combined component is indicated by$\mathbf{f(x + dx)}$, where x equals $\mathbf{y = S\,Out1_k^{(t-1)}}$. Using the Taylor approximation is required. The simplest linear approximation of the function $\mathbf{f(x)}$is as follows:

$$\mathbf{f(x) = f(b) + f(b(x - b)dx = g_t(z_k)} \quad (5)$$

The loss equation$\mathbf{K}$, represented as$\mathbf{f(x)}$, is assessed in this situation. The intended result from the previous operation $\mathbf{t - 1}$is represented by the variable a and the additional learning that must be included in step $\mathbf{s}$ is denoted by the variable$\mathbf{dx}$.

$$\mathbf{f(x) = f(b) + f(b)(x - b) + 0.5f'(b)(y - b)\hat{}2} \quad (6)$$

$$\mathbf{L(t) = \sum_{i=1}[L\left(z_{out_j}, z_{out_i^{(t-1)}}\right) + h_k f_t(x_i) + 0.5k_k f_t\,\hat{}2(x_k)] + i(f_t)} \quad (7)$$

The deleted objectives that must be minimized at step $\mathbf{s}$ remain after the constant components have been removed.

$$\mathbf{L1(t) = \sum_{k=1}[h_i f_t(x_k) + 0.5k_k f_t\,\hat{}2(x_k)] + i(f_t)} \quad (8)$$

2.9 Hybrid of Artificial Fish Swarm-Intelligent with Modified Xgboost (AFSI-MX)

The Artificial Fish Swarm-Intelligent (AFSI) and modified XGBoost are used to predict surface roughness in dynamic lubrication settings. The AFSI algorithm imitates foraging behavior in fish, enhancing its predictive accuracy. The XGBoost method, a gradient boosting technique, is known for its exceptional forecasting capabilities, capturing complex patterns and interdependencies. The hybrid methodology uses AFSI to improve hyperparameters of the XGBoost model, adjusting learning rates and tree depths to suit the surface roughness prediction in turning processes with dynamic lubricationchallenge. This integration enhances the model's efficiency and precision, improving machine dependability and effectiveness in practical contexts. The algorithm for AFSI-MX is shown in algorithm (1).

Algorithm 1: Pseudocode for AFSI-MX

```
% Objective function for surface roughness prediction
obj_fun = @(params) surface_roughness_prediction(params);
% AFSA parameters
num_agents = 50; max_iter = 100;
lb = [lower_bound_param1, lower_bound_param2, ...];
ub = [upper_bound_param1, upper_bound_param2, ...];
% Initialize AFSA agents
agents = struct('position', [], 'fitness', []);
agents = repeat(agents, num_agents, 1);
[agents. position] = deal(lb + rand(1, numeral(lb)) .* (ub - lb));
% AFSA optimization loop
for iter = 1: max_iter
    [agents.fitness] = arrayfun(@(a) obj_fun(a.position), agents);
    [~, sorted_indices] = sort([agents.fitness]);
agents = agents(sorted_indices);
xgboost_params = agents(1). position;
xgboost_model = train_xgboost_model(training_data, xgboost_params);
predictions = predict(xgboost_model, test_data);
mse = mean_squared_error(predictions, true_labels);
fprintf('Iteration %d, MSE: %f\n', iter, mse);
agents = update_afsa(agents);
end
```

3. Results and discussion

The material has a yield strength that varies from 190 MPa to 1145 MPa. The material's tensile strength ranges from 235 MPa to 1354 MPa. The Brinell Hardness Number (BHN), which represents the hardness of the workpiece, varies from 245 to 920.

The range of the tool rake angle is 3 to 20 degrees. The range of the tool nose radius is 0.3

mm to 2.3 mm. The material's basal thermal conductivity is between 0 and 0.9 W/m^2.K. The material's nano-thermal conductivity ranges from 0 to 0.3112 W/m^2.K. Some other characteristics are shown in Table 1. In Table 2, the experiment's data findings are displayed. Figure 2 displays the surface imperfection results.

Table 1. Some other characteristics[Source: Author]

Characteristics	Ranges
Speed (revolutions per minute)	236.74 - 3256.7
Feed (revolution /mm)	0.05 - 0.6
Tool Coating	/×
Depth of Cut (mm)	0.3-3

Table 2. Result of Test Data [Source: Author]

Machining Parameters			Workpiece properties			Tool properties				Cooling system		
speed	feed	Depth of cut	Yield Strength	Tensile Strength	Hardness	Coating	Hardness	Nose radius (mm)	Rake angle	Base T.C.(k)	Nano T .C.(k)	Weight ratio
535.25	0.25	0.3	190	235	245		850	0.6	20	0.9	0.201	10
720.65	0.2	0.3	190	210	245		850	0.6	20	0.9	0.201	10
741.65	0.32	0.3	190	210	245		850	0.5	20	0.9	0.201	10
741.65	0.23	0.3	190	210	245		850	0.5	20	0.9	0.201	10
741.65	0.25	0.3	190	210	245		850	0.5	20	0.9	0.201	10
1684.66	0.24	2	489	485	300	×	760	0.5	8	0.2564	0.3112	43.44
2168.75	0.05	2	489	485	300	×	760	0.5	8	0.2564	0.3112	43.44
1896.66	0.3	2	489	485	300	×	760	0.5	8	0.2564	0.3112	43.44
1845.36	0.24	2	489	485	300	×	760	0.5	8	0.2564	0.3112	43.44
1896.77	0.17	2	560	745	456		720	0.9	14	0.356	0.256	354
1896.77	0.17	1	560	745	456		720	0.9	14	0.356	0.256	354
1893.77	0.2	2.6	560	745	456		720	0.9	14	0.2356	0.256	354
3256.7	0.2	2.6	384	490	456	×	720	0.5	10	0	0	0
3256.7	0.24	2.6	384	490	456	×	720	0.5	10	0	0	0
3256.7	0.3	2.6	384	490	456	×	720	0.5	10	0	0	0

756.51	0.35	1	1145	895	920	×	901	0.7	11	0.25	0	0
1856.33	0.43	0.5	1145	895	920	×	901	0.3	11	0.25	0	0
1647.33	0.43	0.7	1145	895	920	×	901	0.3	11	0.25	0	0
1675.33	0.43	1	1145	895	920	×	920	0.3	11	0.25	0	0
236.74	0.5	3	754	1354	365		760	2.3	3	0	0	0

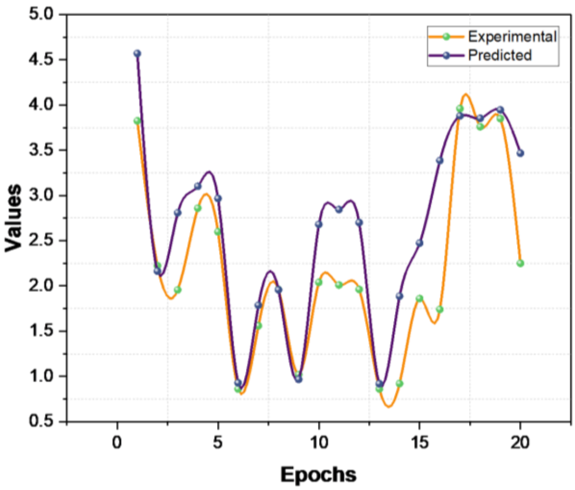

Figure 2. Results of surface roughness (experimental and predicted)[Source: Author]

We implemented our approach in Matlab (v 2021) on Windows 10 OS. The system is powered by an Intel Core i3 processor and it is equipped with a high-performance IRIS graphics card, providing robust capability for performing intensive machine learning tasks. Using metrics like ARE and RMSE, the suggested method (AFSI-MX) was evaluated in terms of performance against the current approaches, which include ("Particle Swarm Optimization - Least Squares Support Vector Machine (PSO-LSSVM)," "Support Vector Machine (SVM)," and "Response Surface Method (RSM)" (Li et al 2021)).

The percentage difference between expected and actual values is measured by the “Absolute Relative Error (ARE)” in Surface Roughness Prediction in Turning Processes with Dynamic Lubrication, which indicates how accurate the predictive model performs. The results of ARE are shown in Figure 3 and Table 3. AFSI-MX obtains the value of 0.0299, then the current technique, such as PSO-LSSVM (0.0326), SVM (0.03861) and RSM (0.0365).The results show that the ARE of Surface Roughness Prediction in Turning Processes with Dynamic Lubrication is much lower than that of the existing method.

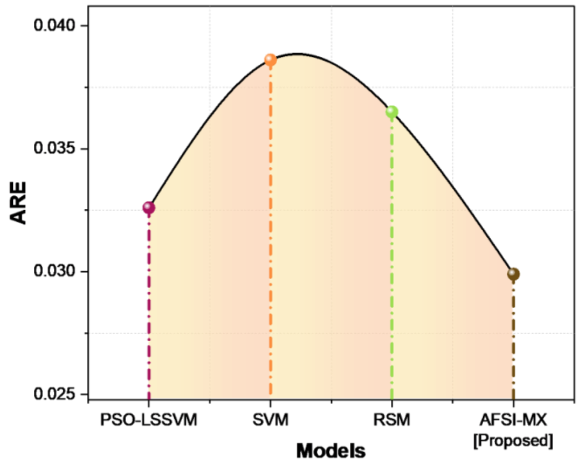

Figure 3. Result of ARE [Source: Author]

Table 3. Results of ARE[Source: Author]

Models	ARE
PSO-LSSVM	0.0326
SVM	0.03861
RSM	0.0365
AFSI-MX [Proposed]	0.0299

The degree of assumption strength is determined by calculating the "Root Mean Square Error (RMSE)" variances between the measured and anticipated surface roughness predictions. The difference between expected and actual surface roughness values in turning processes with dynamic lubrication is depicted by the Root Mean Square Error (RMSE) graph. The result of RMSE is shown in Figure 4 and Table 4. AFSI-MX obtains the value of 0.0201, the current technique, such as PSO-LSSVM (0.0213), SVM (0.0267) and RSM (0.0325). The results show that the RMSE of Surface Roughness Prediction in Turning Processes with Dynamic Lubrication is lower than that of the existing method.

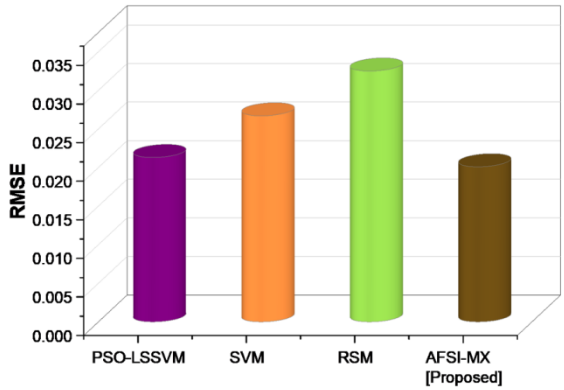

Figure 4. Comparison of RMSE[Source: Author]

Table 4. Results of RMSE[Source: Author]

Models	RMSE
PSO-LSSVM	0.0213
SVM	0.0267
RSM	0.0325
AFSI-MX [Proposed]	0.0201

4. Conclusions

To forecast the texture of machined surfaces, surface roughness prediction uses algorithms. It increases the accuracy and productivity of manufacturing by integrating elements such as material qualities, machining conditions and tool wear. An innovative method, the Artificial Fish Swarm-Intelligent Modified XGBoost (AFSI-MX), is presented in this paper. It combines the powerful predictive powers of modified XGBoost with the collective behavior of fish swarms. The AFSI-MX method is tested using Matlab-collected datasets to show how well it predicts SR in turning processes with different lubrication settings. The investigation evaluated the efficacy of the proposed AFSI-MX technique utilizing multiple criteria, such as ARE (0.0299) and RMSE (0.0201). According to the findings of the experiment, the suggested AFSI-MX approach is more adaptable and predictable in complicated machining environments than traditional methods. A significant factor in determining the model's efficacy could be the level of quality and accuracy of the training dataset. A small or unbalanced dataset can have an effect on how well the model performs in practical situations. Further studies need to concentrate on enhancing the model's durability by overcoming biases and data constraints. To improve the model's flexibility and effectiveness in many real-world circumstances, this involves increasing and diversifying the training dataset.

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