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Multi – Objective Parametric Optimization of Milling on AMMC using Supervised Machine Learning Techniques

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ABSTRACT: Aluminium Metal Matrix Composites (AMMC) have recently gained importance inproduction technology.The presence of hard reinforcements in the composites makes the machining process (milling, turning and drilling) quite difficult.Experimentation determination of optimum parameters for machining AMMC is expensive and time intensive.This can be substituted by using machine learning techniques.This study aims to optimize the input parameters such as depth of cut, feed and cutting speed in the milling for differentmass fraction and particle size of SIC. This is achieved by predicting the output parameters by using supervised machine learning techniques - LASSO Regression, KNN Regressionand Artificial Neural Network Regression.The results of the various models are compared using metrics like MSE and R^2.The sustainable impacts of incorporating artificial intelligence with manufacturing techniques(Industry 4.0) are thus demonstrated.

KEYWORDS: Industry 4.0, Sustainable manufacturing, CNC Milling, Supervised Machine Learning, AMMC.

I. INTRODUCTION

Aluminium Metal Matrix Composites (AMMCs) are a class of materials which find extensive applications where light-weight, high stiffness and moderate strength are required properties [1]. Metal matrix composites are metals reinforced with other metals, ceramics or organic compounds. Reinforcements are dispersed in the matrix and are majorly included to improve or enhance the properties of base metal like strength, stiffness, conductivity, etc. Aluminium as base metal has attracted the most attention in such composites. The reinforcements must be stable and non-reactive in the working temperature. Silicon Carbide (SiC) and Aluminium Oxide (Al_2O_3) are the most commonly used reinforcements; SiC increases the tensile strength, hardness, density and wear resistance of aluminium alloys while Al_2O_3 imposes excellent compressive strength and wear resistance. Boron Carbide's (B_4C) addition also enhances the hardness but doesn't improve the wear resistance [2]. Thus, with a variety of reinforced materials and flexibility in their primary processing, AMMCs offer great potential for the development of composites with the desired properties for certain applications [3]. In the last few years, AMMCs have largely replaced the conventional ferrous materials in automobile, marine, and aerospace industries owing to its higher wear resistance and strength to weight ratio [4].

Milling is one of the most extensively used machining process which may be employed in at least one stage of fabrication in the manufacturing industries. CNC Milling machines are most commonly used as they are versatile, flexible and allow the manufacturing of products in shorter duration of time at reasonable costs along with great surface finish [5]. It is also capable of producing complex geometric surfaces with reasonably high accuracy and surface finish.Milling process removesmaterial by cutting repeatedly into small bits.Milling cutter is a rotary tool with multiple cutting points and it is usually moved perpendicular to the axis of workpiece so that cutting occurs on the circumference only [6]. The various input or response parameters involved in CNC Milling are explained below:

Particle size: - Particle size is defined as the dimensions of reinforcements in aluminium metal matrix composites. It is measured in µm. SiC particles of 10, 20, 40 µm were reinforced [7].

Mass Fraction: - Mass Fraction is defined as the ratio of weight percentage of the reinforcements used to that of the metal matrix composite.

Feed Rate: -It is the speed with which the cutting tool is fedagainst the workpiece.It is measured in mm/min.

Depth of Cut: - Depth of cut also known as Axial or Radial Depth of cut is the total thickness of the cut when viewing the cutting tool from above. It can never exceed the cutter's diameter and is measured in mm.

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Cutting Velocity: - Cutting velocity is the tangential velocity at the periphery of rotating cutter or workpiece. It is measured in rpm.

The output variables obtained in the CNC milling process are:

Surface Roughness (Ra): - Measure of irregularities on machined surfaces or the measure of vertical aberrations along a flat surface. It is measured in μm using a surface roughness comparator or profilometer.

Material Removal Rate (MRR): - Material removed per unit time. It is measured in mm^3/min.

$$MRR = kerf\ width\ (k) * thickness\ of\ workpiece\ (t) * cutting\ velocity\ (V_c)$$

Experimental determination of the optimum input parameters for desired Ra and MRR in CNC milling is an effective and accurate method. But due to the slow rate of MRR, a lot of time is consumed in the process, especially for large sized workpieces. Also, excessive power is consumed in the milling operation. Moreover, a large capital is required for the experimentation. Substitution of experimental analysis by supervised machine learning algorithms for the prediction of Ra and MRR resolves these issues. In Supervised Machine Learning, computational or mathematical algorithms are trained using "labelled" training data. Labelled data comprises a collection of input variables along with their corresponding output variables. This enables the algorithms to predict the output for unseen data having input and output fields similar to the training data. Therefore, the aim of supervised machine learning algorithm is to generate a mapping function that can accurately match the input variables to the output variables. The performance of machine learning models isdetermined using Evaluation Metrics. It is necessary to use multiple evaluation metrics to evaluate the model. This is because a model may perform well on one evaluation metric, but may perform poorly on another. Evaluation metrics are used for critical analysisto ensure that the model functions optimally. So, we have used MSE metric and R^2 score to check the validity of the model. Mean Squared Error is the mean of square of errors produced. It is calculated by

$$\text{MSE} = \sum_{i=1}^{n} (y_i - \hat{y})^2$$

The lower the MSE score, the better is the model. R^2 score is a statistical measure that represents the proportion of the variance for a dependent variable that's explained by an independent variable or variables in a regression model. It is given by

$$R^2 = 1 - \frac{RSS}{TSS}$$

RSS standsfor residual sum of squares andTSS stands for total sum of squares. The higher the R^2 score, the better is the model.

The objective of the study is to map the response parameters – Particle Size, Mass Fraction, Feed Rate, Depth of Cut and Cutting Velocity to Surface Roughness and MRR using several supervised machine learning models - LASSO Regression, KNN regression and Neural Network regression. Thus, optimization of multiple input parameters (Multi - Parametric optimization) for desired output parameters - Surface Roughness and MRR is performed simultaneously (Multi - Objective optimization) for milling of AMMC. The performance of ML models is evaluated using the metric - Mean Squared Error (MSE) and R^2 score, and the technique which most accurately models the milling process, for such a small dataset is identified.

II. RELATED WORK

In recent years, many researches have been performed to optimize response parameters of CNC milling process for different materials either using analytical Taguchi's method or machine learning techniques. K.G. Prasad utilized Data Envelopment Analysis (DEA) based Taguchi method in order to optimize CNC End Milling Process Parameters. V. Mundada et.al performed the optimization of milling operations using Artificial Neural Network (ANN) and Simulated Annealing Algorithm (SAA) and Response Surface Methodology (RSM) was used to formulate its objective function [8]. P. Saini et.al used Taguchi's Grey Relational Analysis so as to optimize end milling parameters for rough and finish machining of Al-4032 with 3% SiC metal matrix composite [9]. E. Mounayri et.al provided a detailed study on multi parametric ANN model for flat milling of aluminium grade 7075T6 [10]. Daniel et. al optimised the control parameters in CNC milling of AMMC using ANN and used Taguchi -grey relational analysis for optimization [7].

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III. METHODOLOGY

3.1 Dataset Description

The dataset was obtained from milling experiments onAluminumhybrid MMC from literature [7]. The dataset consists of 27 runs or experiments with 3 levels of 5 input parameters –Cutting Speed, Feed rate, Depth of cut, mass fraction and particle size of SiC andthe corresponding 2 output parameters – R_a and MRR obtained from the experiments. The response parameters along with their levels are:

Levels	SIC (%)	SIC Size (micrometres)	Cutting Speed (Rpm)	Feed Rate (mm/min^{-1})	Depth of Cut (mm)
1	5	10	500	200	0.5
2	10	20	1000	400	1
3	15	40	1500	600	1.5

Table 2.1. Four levels of response parameters

3.2 Supervised Machine Learning Models

3.2.1 LASSO Regression

Least Absolute Shrinkage and Selection operator (LASSO)regression is form linear regression that uses shrinkage. Shrinkage operation promotesdata values to get shrunktowards a central point such as the mean. The lasso procedure thus encourages simple, sparse models (i.e. models with fewer parameters). Lasso regresion achieves this by perfroming regularization, in which a penalty term is added to residual sum of squares term [11]. For LASSO, absolute magnitude of coefficents is taken as the penalty. This is known as theL1 regularization technique [12].The objective of the algorithm is to minimize [13]:

$$\sum_{i=1}^{n}(y_i - \sum_{j} x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p} |\beta_j|$$

Where λ is a tuning parameter that regulates the effect of L1 penalty term [14]. When some of the βs are minimized to zero, the regression model becomes computationally cheap and easier to interpret. Thus, LASSO regression is mostly employed in models having large multicollinearity.

3.2.2 K Nearest Neighbors Regression

The KNN algorithm uses “feature similarity” in order to determine new data points. The value of a new point is evaluated based on the resemblance to the points in training set. The average of the values is taken as final prediction. KNN regression can be explained as a non-parametric method which intuitivelyformulates a relation between independent variables and the continuous outcomes by averaging observations belonging to the same neighborhood [15]. Size of neighborhood is chosen using cross-validation in which sizeproducing the least mean-squared error is selected. Our KNN model uses Euclidean distance metric which is calculated as [16]:

$$\sqrt[2]{\sum_{i=1}^{k}(x_i - y_i)^2}$$

Where x is a point in the training set, y is a point in test set and K is the number of neighbors. The method is unfeasible for data having large dimensions ornumerous independent variables. For a low k-value, overfitting occurs on training set leading to poor results on test set [17]. On the other hand, for a high k-value, model produces poor

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results on testing as well as training dataset. Thus, the error curve is minimum only for a specific k-value. It is evaluated as 4 for the milling model.

3.2.3 Artificial Neural Network Regression

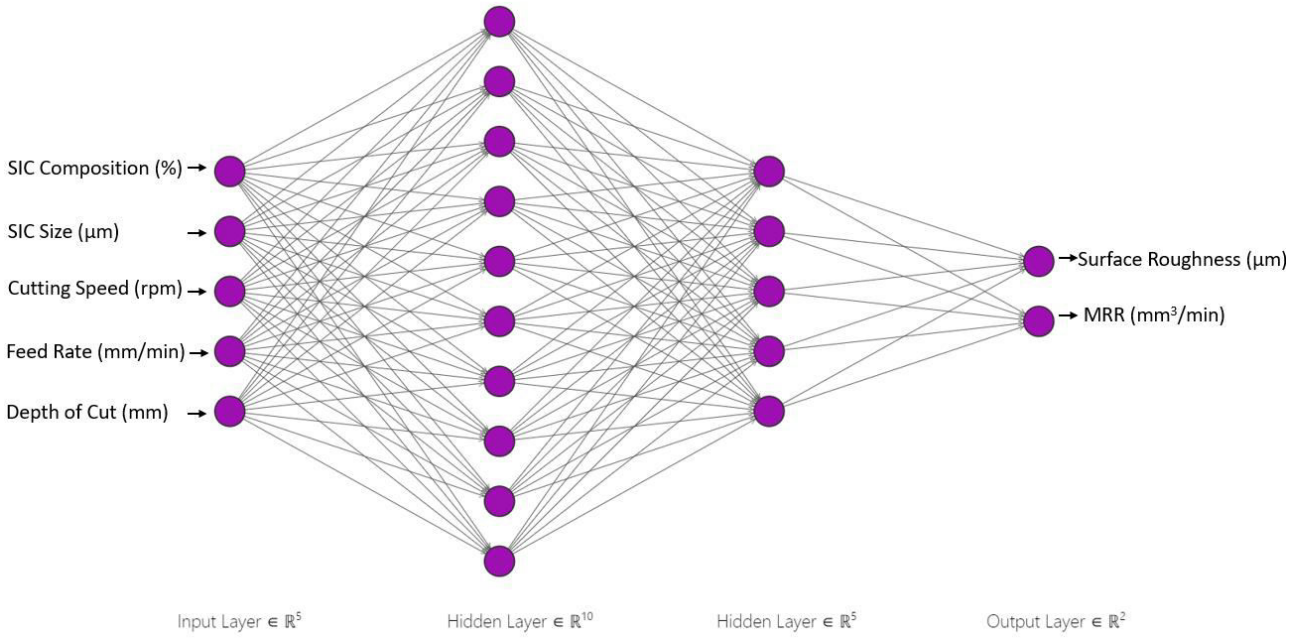

Figure. 1. Artificial Neural Network Structure for modelling milling

Artificial Neural Network (ANN) is a set of computational functions which helps to mapthe input data to the output. Neural networks consist of neurons arranged in sequential layers having weights and biases assigned to them. Weights and biases are learnable parameters that are multiplied and added respectively with the inputs received to the neuron from the previous layer. These weights are updatedas the learning progresses [18]. In the milling model there are four layers, the Input layer consisting of 5 neurons (for the five input parameters), the Output layer providing the required outputs consisting of 2 neurons (for R_a and MRR), and 2 Hidden layers for processing, consisting of 10 and 5 neurons. The output generated from each neuron is passed to an activation function (ReLU) which then passes the obtained output to next layer.

$$Layer\ Output = f(\sum_{i=1}^{n} w_i x_i + b_i)$$

Where x is the input to neuron, w and b are the weights and biases, n is the number of inputs to this neuron and f () is the activation function [19]. On each iteration during training of the network, Gradient based optimizers(Adam) adjust the weights to improve the accuracy by minimizing the error obtained by loss function (Mean squared error). The training process is repeated for 2000 epochs after whichMSE does not reduce further.

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IV. EXPERIMENTAL RESULTS

4.1 LASSO Regression

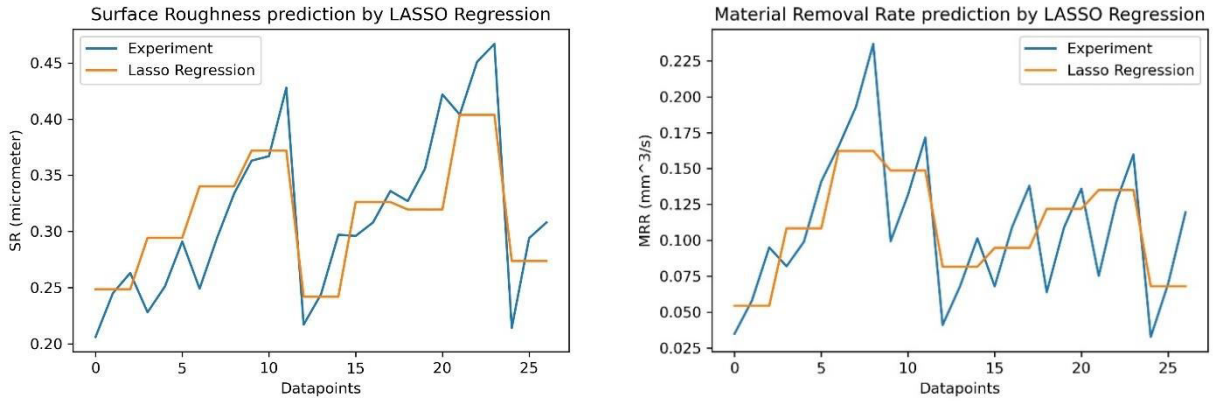

Figure. 2. Actual (experiments) and predicted values (LASSO Regression) for R_a (left) and MRR (right)

The MSE values for R_a and MRR produced by LASSO regression are 0.0018and 0.0011 respectively. The R^2 score for R_a and MRR are 0.65 and 0.52 respectively. Though the error is highly reduced (Fig 2), the predicted values do not overlap with the extreme experimental values present in dataset (Fig 2). This happened because LASSO regression objective is to minimize the residual sums of square loss and thus ends up predictingvalues near to the mean of the dataset. This way a low MSE value is produced but the prediction is not correct for data points in which the values deviate significantly from the mean.

4.2 K – Nearest Neighbor Regression

The MSE values for R_a and MRR produced by KNN regression are 0.0021 and 0.0008 respectively. The R^2 score for R_a and MRR are 0.61 and 0.65 respectively. The error is quite high for most data points and the predicted values do not overlap with experimental values as well (Fig 3). This occurred because KNN regression requires large amounts of good quality data. Distribution of all datapoints very closely deteriorates the results of KNN.

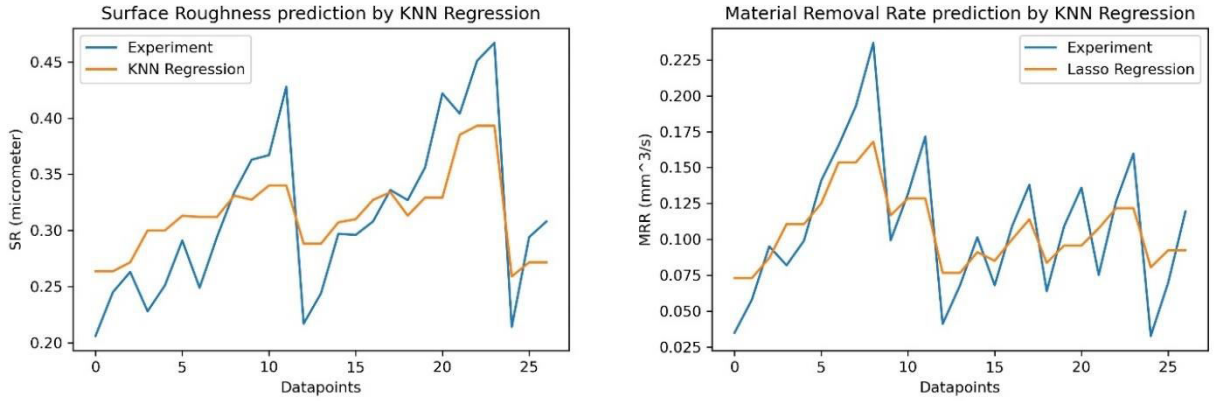

Figure. 3. Actual (experiments) and predicted values (KNN) for R_a (left) and MRR (right)

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4.3 Artificial Neural Network Regression

The MSE values for R_a and MRR produced by ANN are 0.0015 and 0.0005 respectively. The R^2 score for R_a and MRR are 0.71 and 0.76 respectively. The error values are minimized and the predicted values overlap with the experimental values as well (Fig 4). Thus, ANN accurately models the milling process, even for such a small dataset. ANN is capable of modeling complex nonlinear functions because of different weights and biases associated with the neurons and the activation functions of the layers. After the neural network is trained for a sufficient number of epochs, the optimizer is able to set the weights so as to precisely map any continuous function, which has been proved using the universal approximation theorem [20]. Accuracy of the model will further increase with increase in size of dataset and possible overfitting will also be avoided.

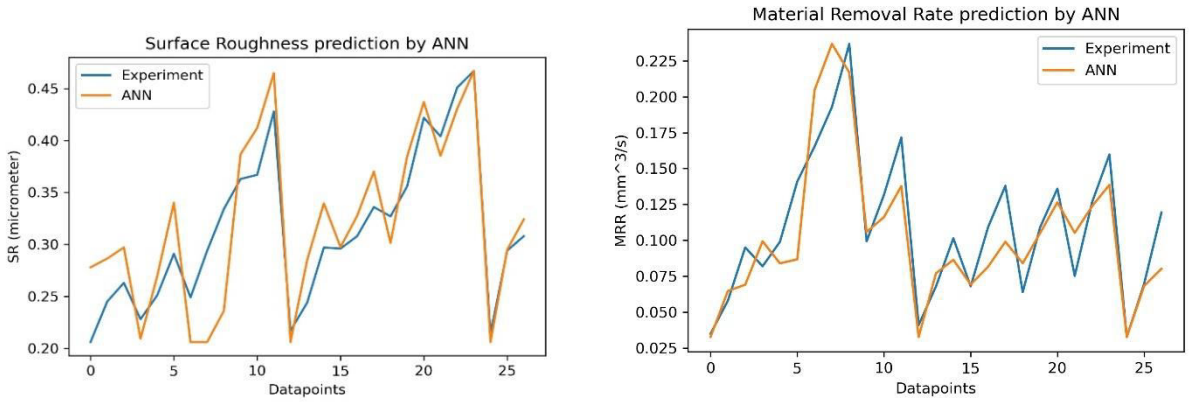

Figure. 4. Actual (experiments) and predicted values (ANN) for R_a (left) and MRR (right)

V. CONCLUSION

The mean squared error for the predicted surface roughness and MRR values are 0.0018, 0.0011 for LASSO regression, 0.0021, 0.0008 for KNN and 0.0015, 0.0005 for ANN respectively.The R^2 Score for the predicted surface roughness and MRR values are 0.65, 0.52 for LASSO regression, 0.61, 0.65 for KNN and 0.71, 0.76for ANN respectively. Among all the supervised machine learning algorithms utilized in the study, the Artificial Neural Network model predicted the surface roughness as well as MRR with highest accuracy or overlap, least MSE and produced the highest R^2 Score. Although training of neural networks requires a greater computation time and power than other algorithms, the difference is insignificant for smaller datasets. Therefore, it can be concluded that artificial neural networks are capable of accurately modelling the CNC Milling process and effectively replaces the experimental analysis required for the optimum parameter determination. The study thus highlights the sustainable impacts of incorporating artificial intelligence with manufacturing techniques, which not only cut-down the time and costs required for the experimentation but also produces parts with high quality surface finish and dimensional accuracy.

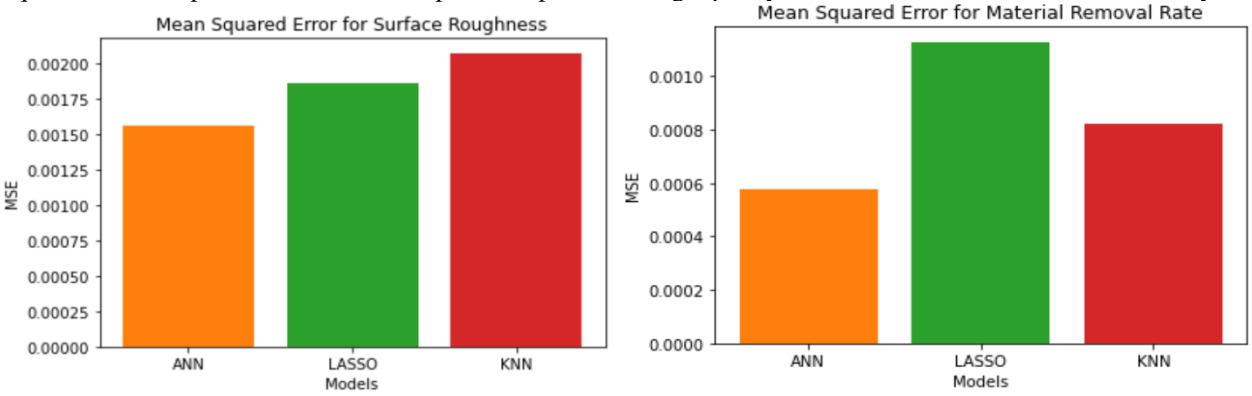

Figure. 5. MSE between actual (experiments) and predicted values (ML models) for R_a (left) and MRR (right)

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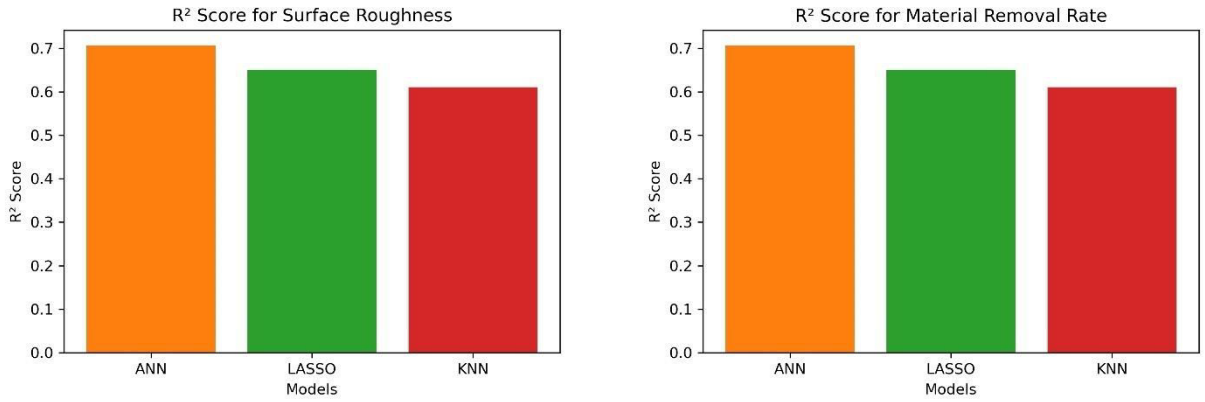

Figure. 6. R^2 between actual (experiments) and predicted values (ML models) for Ra (left) and MRR (right)

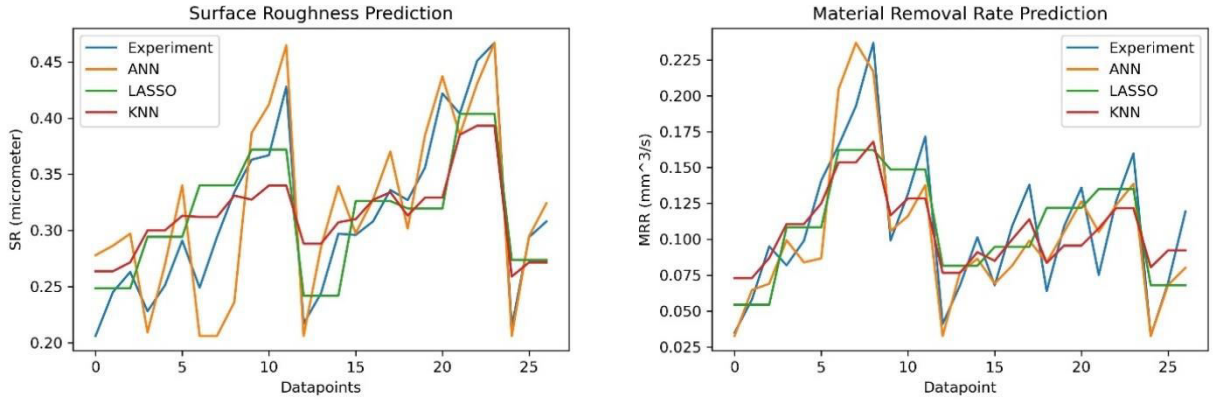

Figure. 4.2. Actual (experiments) and predicted values (ML models) for R_a (left) and MRR (right)

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