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# CUTTING PARAMETERS OPTIMIZATION TO MINIMIZE THE SURFACE ROUGHNESS AND CARBON EMISSION IN TURNING PROCESS USING AI TOOLS AND INTELLIGENT ALGORITHMS

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**Abstract-** Surface roughness *Ra* is an important factor in the manufacturing sector, this characteristic is taken into consideration when evaluating the quality of manufactured parts, but it also has significant effects on the Carbon Emissions *CE* associated with the manufacturing process, as noted in this article which aims to closely examine the relationship between surface roughness and carbon emissions resulting from this process. The purpose of this study is to achieve minimal surface roughness while at the same time reducing carbon emissions. based on experimental data ($ap, f, V_c, D, L_c, F_c, F_a$) made on a CNC machine and analytical cutting models, *Ra* and *CE* roughness modelling is performed by a set of artificial intelligence tools namely LR (Linear Regression), SVM (Support Vector Machine), KNN (K Nearest Neighbors), ANN (Artificial Neural Network), DT (Decision Tree), GPR (Gaussian Process Regression), GBoost (Gradient boosting), and ANFIS (Neuro-Fuzzy), which are assembled in a way to have the most accurate *Ra* and *CE* model. the outputs of the most accurate tools are combined by a MODE function, which allows selection of the repetitive value, followed by an optimization of cutting conditions $ap$, $V_c$, $f$ to minimize surface roughness and Carbon Emissions is performed by intelligent algorithms such as GA and Particle Swarm. the optimum values of cutting conditions for best roughness and minimum *CE* are $ap$=0.20368 mm for depth of cut, a cutting speed of $V_c$=324.4422 mm/min, and a tool feed speed of $f$=0.08518 mm/rev.

**Keywords:** Surface Roughness, Carbon Emissions, Cutting Parameters, Turning Process, IA Tools, Intelligent Algorithms.

## 1. INTRODUCTION

Machining is an essential process in the industrial manufacturing sector, but it also has a considerable footprint in terms of carbon emissions. Carbon emissions from machining processes arise from the use of energy-intensive machine tools $CE_{elec}$, as well as from the production of raw material $CE_m$, from production of cutting tools $CE_{tool}$, lubricants, and coolants $CE_{fluid}$. Additionally, machining processes can generate substantial amounts of waste, including metal chips $CE_{chip}$ and other materials as shown in Figure 1, which can contribute to environmental pollution if not properly disposed of. As such, reducing carbon emissions from machining processes is a vital step in the manufacturing industry's efforts to mitigate its impact on the environment. In this context, there has been increasing interest in the development of sustainable machining practices that reduce carbon emissions while maintaining or improving productivity and product quality. For this purpose, several studies conducted on reducing Carbon emissions in machining processes are made, as presented in Table 1, these studies use statistical or mathematical methods to model either roughness, machining cost, carbon emissions, cutting noise, or tool wear, then applying a tool to achieve optimal cutting conditions.

According to these studies, the cutting factors used in manufacturing may affect the carbon footprint in a different way. As is known, metal cutting can be considered as the removing of material from a workpiece, which require machines, tools, and other equipment. Cutting factors which can affect carbon emissions include:

- Cutting speed: Higher speeds mean that parts can be produced more rapidly, but can also result in higher energy consumption by the machine, which can increase carbon emissions [1].
- The cutting tool type: according to [2], using more efficient cutting tools can reduce the time required to manufacture parts and thus decrease carbon emissions. More efficient cutting tools can reduce the energy required to cut the raw material, which can also potentially reduce carbon emissions.
- The workpiece material: according to [3] The cutting material can also affect $CO_2$ emissions. For example, using a harder material may require using more power to cut, which can increase $CO_2$ emissions. Carbon emissions.
- The final part quality: to achieve a high level of quality, can increase energy consumed and therefore increase carbon released levels [4].

In other words, the impact of cutting parameters on $CO_2$ emissions depends on the specific properties of the production process and the decisions made by the manufacturing company in terms of technology and environmental practices.

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Cutting parameters that affect carbon emissions can also affect the quality of the workpiece, more precisely the roughness of surfaces according to several studies [5-7], for this reason, a roughness modelling will be done in parallel with the carbon emission modelling, in order to improve the cutting parameters for optimal results while minimizing surface roughness and the carbon emission in a cutting phase for a turning operation. In this paper, different artificial intelligence tools namely SVM, KNN, GBoost, GPR, Neuro-Fuzzy, and ANN, will be used for modelling surface roughness as well as Carbon emission, in order to generate the appropriate objective functions to be minimized. The data used in this study is generated by experiments [8] performed on a ROMI E280 CNC turning machine on specimens of AISI H13 material with a TNMG 16 04 04-PF 4425 tool, these data are the surface roughness, and the cutting forces from which the carbon emissions are calculated.

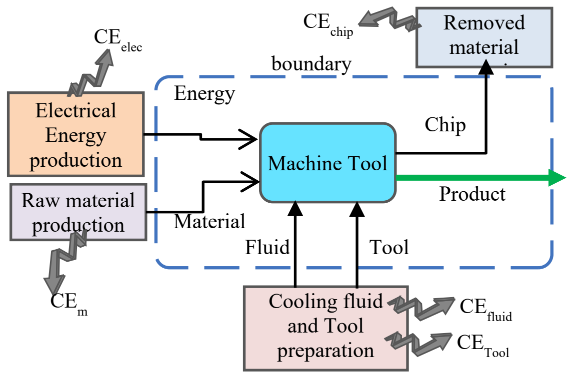



Figure 1. Carbon emission categories in a CNC machine-tool [13]

Table 1. Published studies about the modelling of carbon emissions

| Ref. | Cutting parameters | Modelled output | Modelling and Optimizing tools |
|---|---|---|---|
| [9] | $V_c$, $f$, $ap$, *material* | *E*, *CE*, *cost*, *Ra* | RSM and NSGA-II |
| [10] | $f$, $ap$, $N$ | *CE*, *Ra*, *T* | RSM and NSGA-II |
| [11] | $V_c$, $f$, $ap$ | *CE*, *VB* | NSGA-I and MOPSO |
| [12] | $V_c$, $f$, $ap$, *material* | *E*, *CE*, *cost*, *VB* | MOGA |
| [13] | $V_c$, $f$, $ap$, *material* | *E*, *CE*, *cost*, *VB* | Mathematical methods |

## 2. METHODOLOGY

As shown in Figure 2, the working method starts with a collection and preparation of training data, then an application of artificial intelligence tools to model the surface roughness and carbon emissions, an application of an optimization algorithm on the good model found will allow to achieve optimal cutting parameters for a good surface condition and minimal carbon emissions. Before collecting the data, it is important to clearly define the objective. In this case the objective is modelling the Surface Roughness, and Carbon emission in cutting phase by AI tools, this requires training inputs and targets. The dataset is produced by experiments on a CNC turning machine and a cylindrical multi-flange workpiece, with cutting parameters in three levels each, as shown in Table 2, the total factorial design gives a number of 45 experiments, these experiments are repeated twice with different cutting diameters which gives a total of 90 experiments, the surface roughness is measured 6 times in different angles of the machined surface, the cutting forces are also measured in three directions during the cutting process with a dynamometer.

The Carbon emission *CE* during the cutting process is calculated from the measured data (forces, cutting parameters and others), details of the calculation of the Carbon emission will be in the following sections. The selection of the artificial intelligence model is based on its performance by taking the Mean Squared Error, and the regression coefficient, once it is properly selected objective functions are generated in order to apply an optimization tool on it.

Table 2. Different levels of cutting settings

| Cutting parameters | Units | Levels |
|---|---|---|
| Depth of cut (*ap*) | mm | [0.25;0.5;0.8] |
| Cutting speed ($V_c$) | m/min | [310;350;390] |
| Feed rate (*f*) | mm/rev | [0.07;0.09;0.1;0.11;0.13] |
| Initial diameter ($D_i$) | mm | Variable in each pass |

## 3. QUANTITATIVE MEASURES OF CARBON EMISSIONS CE

As mentioned earlier, to model the surface roughness, and the carbon emission by AI tools as a result of cutting parameters, it is necessary to have the features and the targets data. In this case, the $CO_2$ emissions are calculated using the method described below. The carbon footprint of a CNC machine according to C. Li [13] is a sum of the carbon emissions for each component associated with the machine as shown in Figure 1, i.e., the emissions caused by electricity consumption $CE_{elec}$, the emissions generated by the tool $CE_{tool}$, the emissions from lubrication $CE_{fluid}$, the emissions produced by the raw material $CE_m$, and those caused by the chip $CE_{chip}$, these emissions are calculated by the following Equation (1).

$$CE = CE_{elec} + CE_{tool} + CE_{fluid} + CE_m + CE_{chip} \quad (1)$$

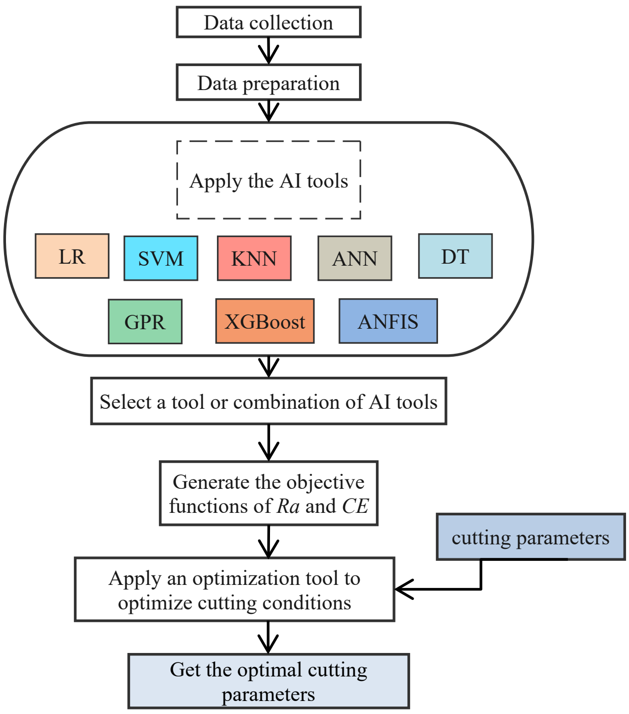



Figure 1. The graph of the steps followed

Calculating the carbon emissions of a CNC machine involves calculating each component of Equation (1), for this purpose, the steps shown in Figure 3.

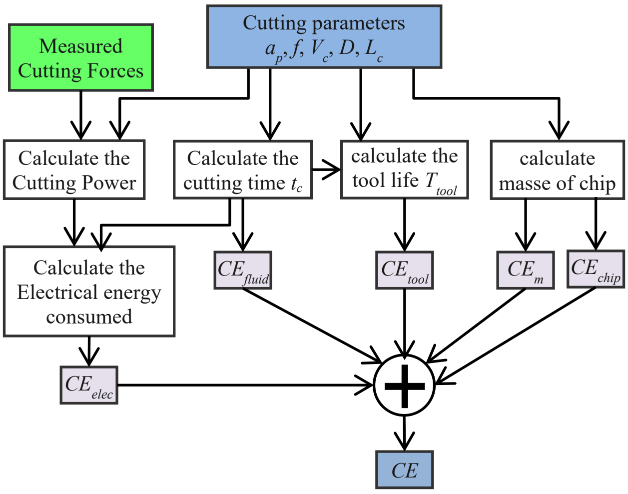



Figure 3. Carbon Emissions calculation method

### 3.1. Cutting Power and Electrical Energy Consumed

The electrical energy consumed during the cutting phase is calculated by the Equation (2), $P$ is the power needed for cutting, of which it includes the power to remove the material from the workpiece and the tool advance power.

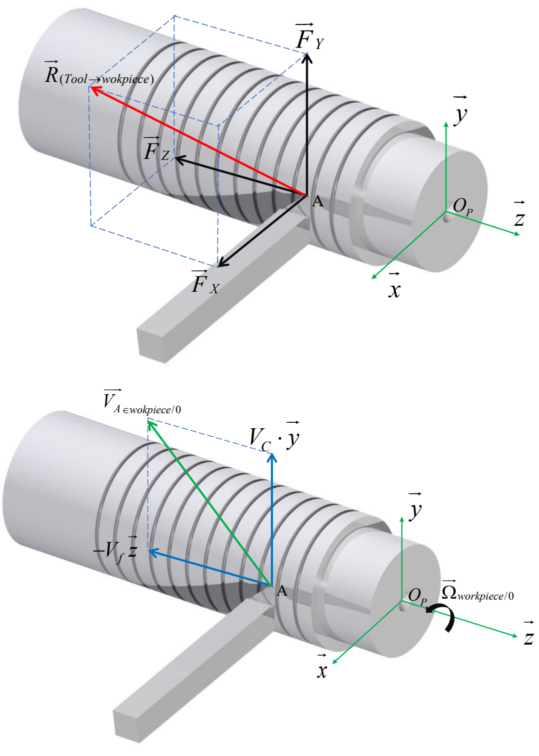



Figure 4. Cutting forces and velocity in turning process

Based on Figure 4 which represents the different forces applied to the material and the speed of the tool relative to the workpiece, the power required for cutting (including the cutting power and the feed power) is calculated by Equation (3), the cutting time $t_c$ is the ratio between the cutting length $L_c$ and the feed speed which is represented by Equation (4).

$$E_{elec} = \frac{P}{\eta_{machine}} \times t_c \tag{2}$$

$$P = V_c \times F_Y + V_f \times F_Z \tag{3}$$

$$t_c = \frac{L_c}{V_f} = \frac{\pi D L_c}{1000 V_c f} \tag{4}$$

### 3.2. Calculate the Tool Life

The life of a tool cutting edge is determined by the generalized Taylor Equation (5) [13], The cutting tool or tool inserts generally have several cutting edges, so the tool life of an n edge insert is calculated by Equation (6).

$$T_0 = \frac{C}{V_c^x \times f^y \times a_p^z} \tag{5}$$

$$T_{tool} = n \times T_0 \tag{6}$$

R. Suresh [14] modelled the tool wear for the same material used in the experiment with different tool materials (multilayer coated carbide, uncoated ceramic tool, and coated ceramic tool), by the RSM method, he found a regression model (7), that is used in our study for a Carbide tool by using a $VB_{\max}$=0.3 mm [15]. Hence the duration of a cutting edge is calculated by Equation (8).

$$\begin{aligned} VB_{\max} &= 1.847\times10^{-3} - 0.899\times10^{-3}\times V_c + \\ &+0.207422\times f - 7.6667\times10^{-2}\times a_p + \\ &+1.6458\times10^{-2}\times T_0 + 3\times10^{-6}\times V_c^2 - \\ &-0.706\times f^2 + 1.094\times10^{-3}\times V_c\times f \end{aligned} \tag{7}$$

$$\begin{aligned} T_0 &= 18.115992 + 5.467\times10^{-3}\times V_c - 12.603111\times f + \\ &+ 4.658342\times a_p - 1.8228217\times V_c^2 + \\ &+ 42.897071\times f^2 - 6.6472.10^{-2}\times V_c\times f \end{aligned} \tag{8}$$

### 3.3. Calculate the Masse of Chip

The material mass cut during a cutting time is calculated by equation. The mass is a result of the three adjustable cutting settings, the density of the material being cut, and the cutting time.

$$m_{chip} = f \times a_p \times V_c \times \rho t_c \tag{9}$$

### 3.4. Calculation of Various Carbon Emitted by Cutting Process

The various Carbon emissions represented by Equation (1) are calculated using the factors shown in Table 3. The quantity of carbon produced by the electricity $CE_{elec}$ depends on the total electrical energy consumed and an emission factor for carbon associated with the generation of electrical energy through the electricity production process.

$$CE_{elec} = CEF_{elec} \times E_{elec} \tag{10}$$

The cutting tool carbon emission is determined by multiplying the tool carbon emission factor $CEF_{tool}$, the tool mass, and number of consumed tools by the ratio of cutting time to tool life. The tool used is a 3 edges tool with a mass of 7g.

$$CE_{tool} = CEF_{tool} \times m_{tool} \times \frac{t_c}{T_{tool}} \quad (11)$$

According to Q. Yi [16] the carbon quantity emitted by the fluid is calculated by Equation (12), where, $d$ is the oil concentration, $V_{in}$, $V_{ad}$, are respectively the initial quantity of fluid and the additional quantity in Table 4.

$$CE_{fluid} = \frac{t_c}{T_{fluid}} \times [CEF_{oil} \times (V_{in} + V_{ad}) + CEF_{wat-c} \times (\frac{V_{in} + V_{ad}}{\delta})] \quad (12)$$

The calculation of carbon emissions generated by the raw material is performed using Equation (13). The carbon emission factor for steel production, denoted as $CEF_m$, is subject to variation due to several factors such as the energy source utilized during the production process, the efficiency of the production process, and other relevant variables.

$$CE_m = CEF_m \times m_{chip} \quad (13)$$

The same applies to chip carbon emissions, which are calculated by the following Equation (14), Where, $CEF_{chip}$ and $m_{chip}$ are successively the chip carbon emission factor and the chip mass.

$$CE_{chip} = CEF_{chip} \times m_{chip} \quad (14)$$

Table 3. Carbon mission factor [13]

| Carbon Emission Factor | Values |
|---|---|
| $CEF_{tool}$ | 29.6 $kgCO_2/kg$ |
| $CEF_{oil}$ | 2.85 $kgCO_2/l$ |
| $CEF_{wat-c}$ | 0.2 $kgCO_2/l$ |
| $CEF_m$ | 2.68 $kgCO_2/kg$ |
| $CEF_{chip}$ | 0.361 $kgCO_2/kg$ |

The Ministry for Energy Transition and Sustainable Development and the International Energy Agency [17, 18], report that, the carbon emission factor for electricity generation in Morocco is estimated at around 0.723 and 0.8 kg of $CO_2$ per kWh. It is important to note that this number may change as a result of the country's increasing efforts to implement and improve its energy strategies and technologies.

Table 4. Fluid properties [19]

| Fluid Properties | Values |
|---|---|
| Initial coolant quantity | 8.75 L |
| Additional fluid | 4.3 L |
| Mean interval between each replacement | 3 months |
| Concentration of oil | 8% |

Table 5. Other properties related to the tool, material, and machine

| Properties | Values |
|---|---|
| Tool weight | 7g [20] |
| Material density | 7.76 $kg/m^3$ [21] |
| Machine efficiency | around 80% [12] |

## 4. SURFACE ROUGHNESS AND CARBON EMISSION AI MODELS

In this section, the focus is on developing a model that relates the cutting parameters of $ap$, $f$, and $V_c$ to the surface roughness and carbon emissions in a cutting process. To improve the training efficiency and stability according to [22, 23], a data normalization technique is employed as shown in Figure 5. The ultimate objective of this modelling is to establish a function that relates the cutting parameters to the output variables of surface roughness and carbon emissions. This function can then be used to optimize the cutting process, with the aim of reducing surface roughness and carbon emissions. Overall, this section provides valuable insights into the development of a data-driven approach for optimizing cutting processes.

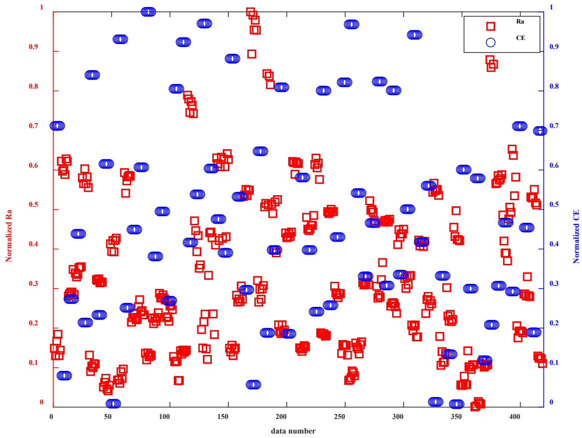



Figure 5. Normalized data for $Ra$ and $CE$

The modelling will be performed using various artificial intelligence tools, including ANN, KNN, GPR, SVM, DT, GBoost, and ANFIS. These tools are designed to analyze the complex data sets and make predictions efficiently and accurately. Each tool has its own specific qualities and limitations, the choice of the most suitable tool is contingent upon the modelling task in question. The ultimate idea is to build a robust that can accurately predict the outcomes of the cutting process. The training data inputs comprise the cutting velocity, feed speed, and depth of cut, while the training data targets are the machined surface roughness and carbon emission. The data used for the Roughness and Carbon Emissions Modelling, which employs artificial intelligence tools, is split into three parts: 80% for training, 10% for testing, and 10% for validation, within the suite. The 8 models are trained with the same training data, tested with the same test data, and validated with the same validation data to see the ability of each tool to model the surface roughness and Carbon emissions per mm of cut in the turning operation.

### 4.1. Backpropagation Neural Network (ANN)

A backpropagation Neural Network is created through the utilization of an algorithm developed in article [24]. This algorithm enables the modification of hyperparameters through a complete factorial design, followed by the selection of the most effective hyperparameters based on the mean squared error MSE. The number of hidden layers, the neuron count within each hidden layer, the learning rate, as well as the activation function and training algorithm are the four key hyperparameters of ANN. The available options for the number of hidden layers are constrained to either 1 or 2, in order to prevent the model from becoming overly deep.

Meanwhile, all other parameters have four levels. On a logarithmic scale, the *MSE* for each ANN training is depicted in the Figures 6 and 7, for modelling Ra, the optimal hyperparameters are: 2 hidden layers with 10 neurons in each layer, a learning rate of 0.02, a Logsig activation function and BR training algorithm. On the other hand, for modelling *CE*, the recommended hyperparameters are: 2 hidden layers with 12 neurons in each layer, a learning rate of 0.001, a tensing activation function and trainer as a training algorithm.

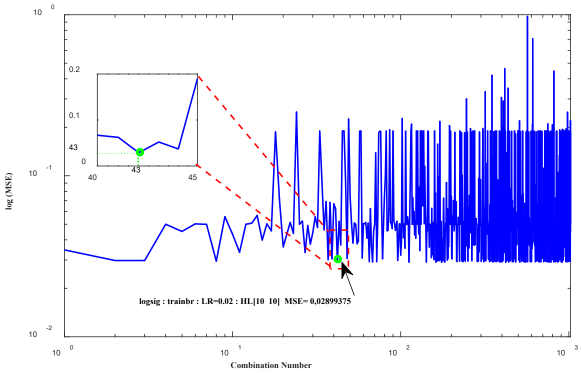



Figure 6. The optimal hyperparameter configuration with a fall factorial design to Tuning a *Ra* model

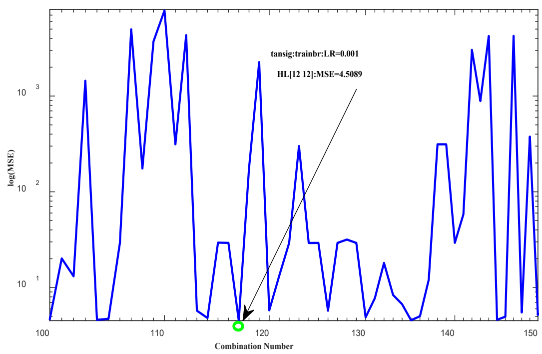



Figure 7. The optimal hyperparameter configuration with a fall factorial design to Tuning a *CE* model

### 4.2. K-Nearest Neighbors

K-Nearest Neighbors is an artificial intelligent tool for regression and classification problems. The aim is to discover the K data points closest to a given input and then generating predictions based on the labels of these nearest neighbors. The KNN algorithm's hyperparameters include the number K of nearest neighbors, the distance metric, and the weighting function. Tuning these hyperparameters can significantly affect the performance of the KNN algorithm. The optimum training hyperparameters of KNN models with MATLAB program using Bayesian Optimization function are; K neighbors equal 9 with "Seuclidean" distance for modelling *Ra*, and 3 nearest neighbors with a "Euclidean" distance for *CE* modelling.

### 4.3. Support Vector Machine

The Support Vector Machine is a robust artificial intelligence tool used for classification and regression analysis problems. The adjustment of SVM parameters, including the Epsilon parameter, the kernel function type, and the C coefficient of the box constraint, is important to obtain optimal SVM model on a particular dataset. After splitting the data. The *Ra*'s SVM model underwent 30 iterations of training with a variety of hyperparameters. The 15th iteration yielded the best result who gives a minimal mean squared error equal to 0.051339 for *Ra* model, and 7.48815 for CE model. The same set of hyperparameters were utilized to model carbon emission. The optimized hyperparameters are detailed in Table 6.

Table 6. Optimized hyperparameters of the *Ra* and *CE* models

| Hyperparameter | Optimized hyperparameters for Ra | Optimized hyperparameters for Carbon Emission |
|---|---|---|
| Box constraint | 0.02878 | 1.5746 |
| Kernel scale | 0.76464 | 1 |
| Epsilon | 0.00953 | 0.86746 |
| Kernel function | Gaussian | Quadratic |

### 4.4. Gaussian Process Regression

This is a probabilistic machine learning tool that can be applied to regression analysis, as in the present study. The hyperparameters of this tool comprise the Kernel function, the Sigma noise variance parameter, the optimizer option, and others. The optimization of these hyperparameters is crucial to ensure that GPR can accurately capture the data models involved and generate accurate predictions. By using automated hyperparameter tuning in MATLAB 2021, the GPR model was optimized to determine the optimal hyperparameters for training. The optimized hyperparameters for Ra were kernel function set to 'SquaredExponential', optimizer option set to 'quasinewton', and sigma set to 0.11199. For *CE*, the optimized hyperparameters were kernel function set to 'Noninotropic Exponential', optimizer option set to 'quasinewton', and sigma set to 90.0801.

### 4.5. Decision Trees DT

DT is a tool used in machine learning for both classification and regression applications. They are widely used for decision-making in many fields, including data science, artificial intelligence, and data analysis. The most significant hyperparameters of a decision tree are the maximum depth of the tree, the minimum number of samples required to split an internal node and the splitting criterion. These hyperparameters have a considerable effect on the tree's efficiency and the potential for overfitting. using a Bayesian optimization in range 1 to 168 of leaf size. After conducting hyperparameter optimization, the appropriate parameters for the decision tree have been identified. For *CE*, the optimized minimum leaf size is 2, while for *Ra*, the optimized minimum leaf size is 3.

### 4.6. Gradient Boosting (GBoost)

GBoost is identical to random forests, both being ensemble methods that use multiple decision trees to increase the accuracy of predictions. The main differences between random forests and gradient boosting are as follows: Random forests construct multiple trees in an independent manner, whereas gradient boosting constructs

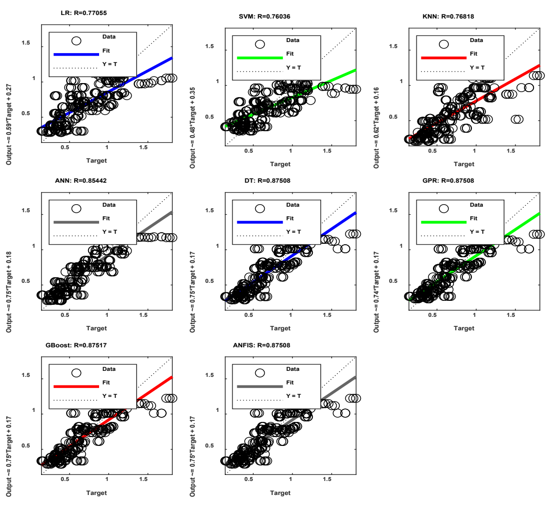
trees sequentially, and random forests take the mean of the tree's predictions, whereas gradient boosting sums the predictions. Both methods are in general use and have their advantages and disadvantages. The choice between the two depends on the specific problem and the data available. The optimized hyperparameters for *CE* and *Ra* have been identified as follows:
- For *Ra*, the minimal size of the leaf is 1, the learners are 60, the rate of training is 0.21938, the predictors are 3 and the ensemble method is LSBoost.
- For *CE*, the minimal size of the leaf is 10, the learners are 78, the rate of training is 0.076428, the predictors are 3 and the ensemble method is LSBoost.

### 4.7. Neuro-Fuzzy

Neuro-fuzzy is a hybrid computing technique that integrates a fuzzy logic and artificial neural networks to create a more powerful and accurate model of a complex problem. To tune a neuro-fuzzy system for regression, the appropriate input and output variables need to be identified and converted into fuzzy sets. Next, the fuzzy rules that describe the input-output relationships must be defined and the system must be trained by optimizing its parameters using a training algorithm. The performance of the system should then be evaluated using a validation dataset and the parameters refined if necessary. A neuro-fuzzy model can be effectively tuned using a genetic algorithm, as stated in reference [25]. Additionally, there is another optimization technique called particle swarm optimization (PSO) that can also employed to adjust the hyperparameters of a neuro-fuzzy model, as mentioned in reference [26]. These hyperparameter tuning algorithms are very slow in this case of study, The current study employs 'ANFIS' method for hyperparameter tuning.

### 4.8. Linear Regression LR

Linear regression is also used with its four types, namely, Linear, Linear Interaction, Robust Linear, and Stepwise Linear. It is found that Linear interaction is the most accurate in this case of study for roughness modelling, and Stepwise Linear the most efficient for *CE* modelling.



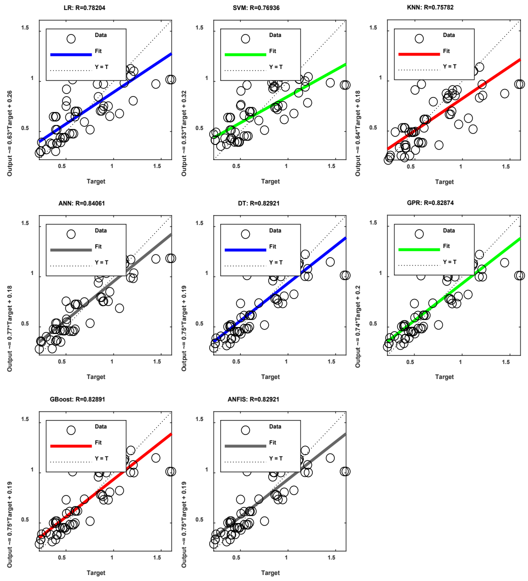




Figure 8. *Ra* Models' regression (training and validation)

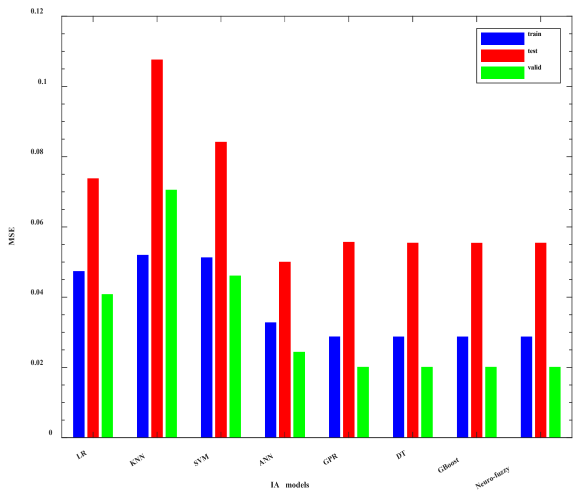



Figure 9. The *MSE* of *Ra* model

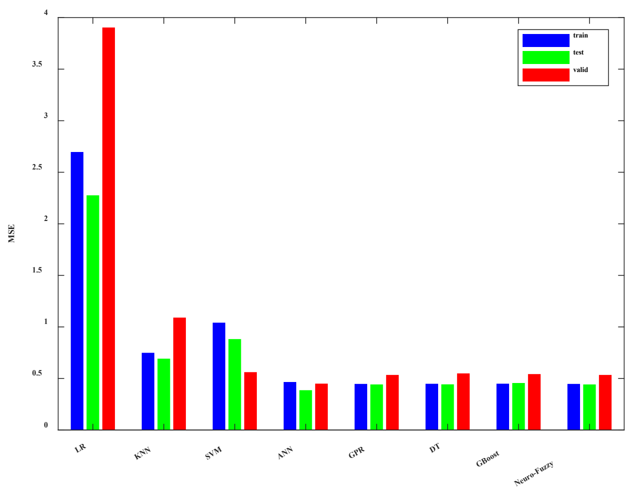



Figure 10. The *MSE* of *EC* model

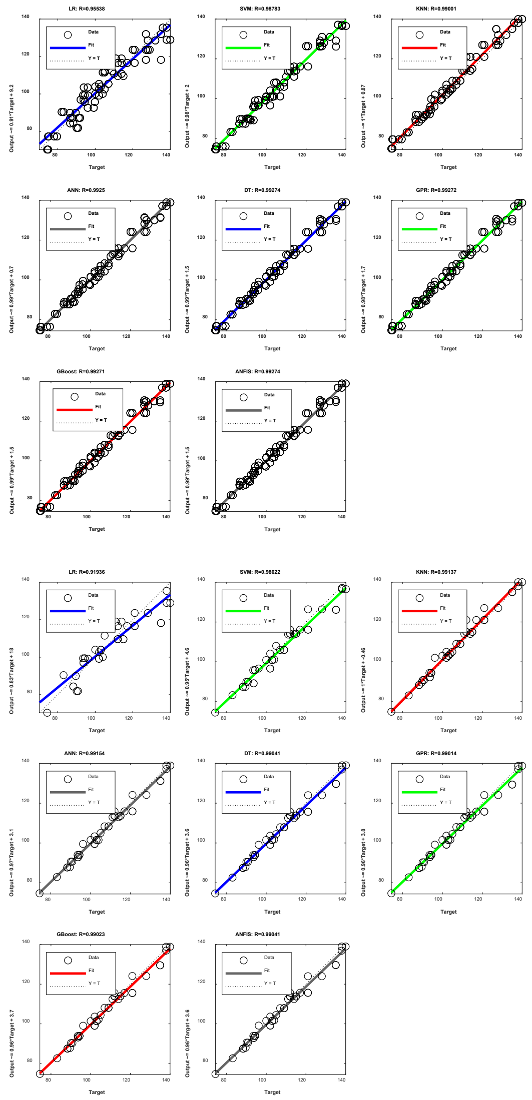


Figure 11. *CE* Models' regression (training and validation)

## 4.9. Ensemble Models

In this part, an assembly of the models (Figure 12) is done in a way to have a more accurate ensemble for predicting the surface roughness, also the quantity of carbon emitted per mm of cut. Several tests are made to aggregate the five most accurate models in order to generate an output (*Ra*, and *CE*) with a good accuracy, using the functions such as; average of the outputs, the max or min of the models outputs, the MODE function which allows to return the most frequent or repetitive value, the median, the average of the *k* max (*k*=4), and the average of the *k* min (*k*=4), the results of *MSE* and the regression coefficient of the aggregate are represented in Figure 13.

According to Figures 13 and 14, it is noticed, that the aggregation of the models with a MODE function gives a minimal MSE whether it is for training, testing, and validation (The mode function allows to choose the most repetitive output).

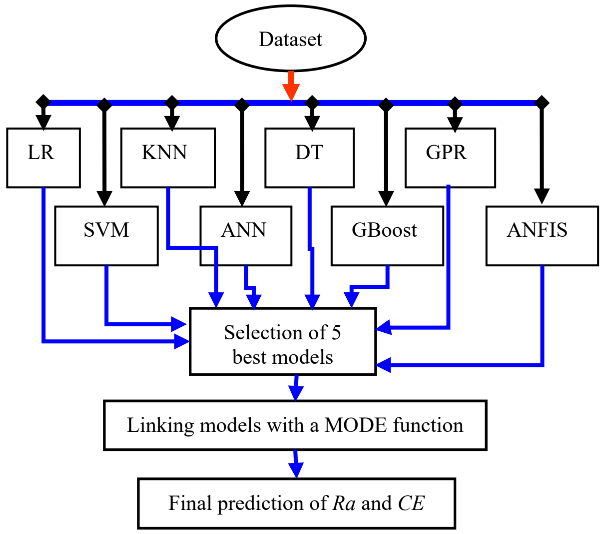



Figure 12. Ensemble of models

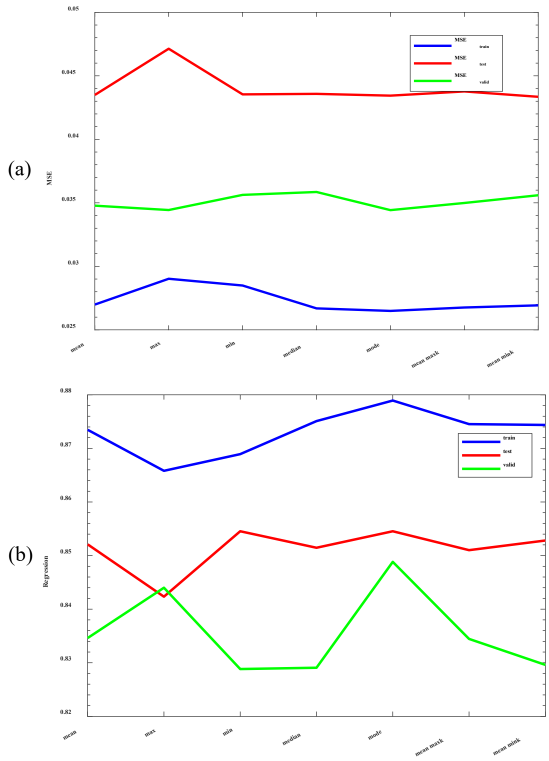



Figure 2. a) *MSE* for different assembly functions, b) Regression coefficient

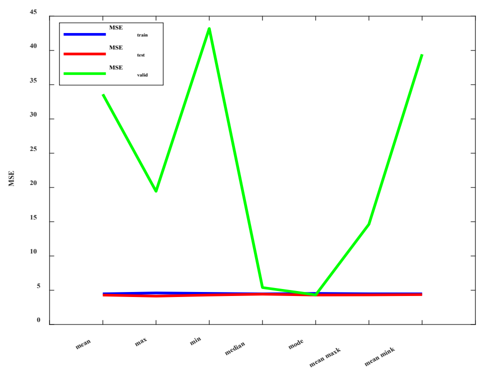


Figure 14. *CE* / *MSE* for the different assembly functions

## 5. CUTTING PARAMETERS OPTIMIZATION

In the manufacturing of precision workpieces, the surface roughness is potentially the most significant parameter to be minimized. By means of the artificial model of *CE* and *Ra* constructed in the previous sections. A random generation of 1000 inputs are done and then fed back into the constructed artificial model which will generate outputs *Ra*, and *CE*, the aim is to examine the influence of the three cutting parameters on surface roughness, and the quantity of carbon released into the environment. The most important parameter affecting roughness is the feed rate *f* according to several studies [27, 28], a minimum feed rate gives a minimum roughness, in this study scenario the carbon emissions are also affected by the feed per revolution as shown in Figure 15, increasing *f* provides less Carbon contrary to the roughness of the surface. Figure 16 shows the surface roughness versus the carbon emissions, it is clear that an improvement in the precision of the machined surface will increase carbon emissions in the same way.

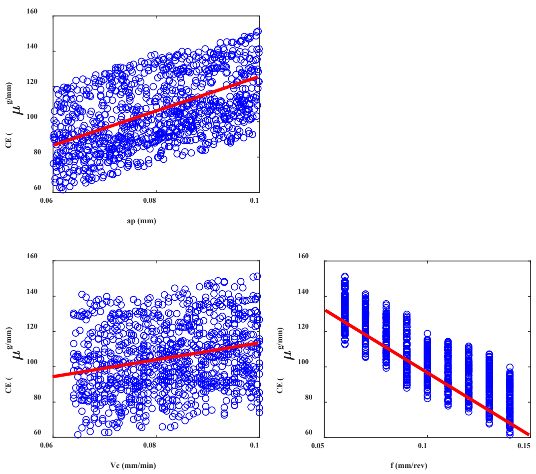



Figure 15. Cutting parameters effect on CE

The cutting conditions are optimized to minimize carbon emissions and machined surface roughness using the most accurate artificial model of *Ra* and *CE* as objective functions. After saving the five most accurate models as functions and coupling them by a MODE function, that equation becomes the objective function to be optimized using MOGA and PSO optimization tools.

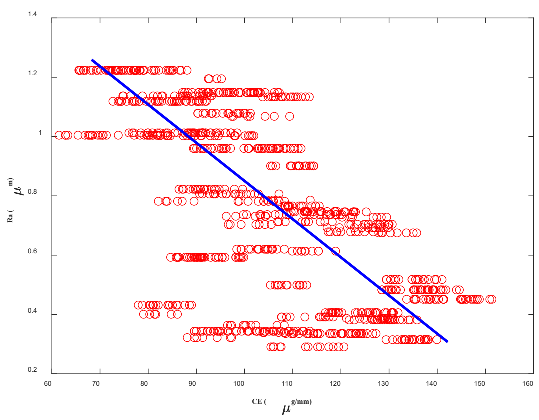



Figure 16. *Ra* according to *CE*

In this optimization section, two algorithms are used separately to validate the best cutting conditions for minimizing carbon emissions and machined surface roughness: the first is the GA genetic algorithm that has been used to optimize the Ra functions generated by the neural network, as was done in our last study [22, 29], the second is the PSO Particle Swarm optimization. Optimization of cutting parameters by MOGA under optimal options, results several solutions, represented by Pareto front (Figure 17). the smoothest surface finish has a roughness of 0.3947 µm with the following cutting conditions: *ap*=0.2146 mm, $V_c$= 333.8326mm/min, and *f*=0.0882 mm/rev. The *CE* is minimum ($CE_{min}$=77.1643 µg/mm) under cutting conditions; *ap*=0.2mm, $V_c$= 310 mm/min, and *f*=0.07 mm/rev. From the Pareto front shown in Figure 17, it is perfectly understandable that the surface roughness and carbon emissions are functions of inverse variation.

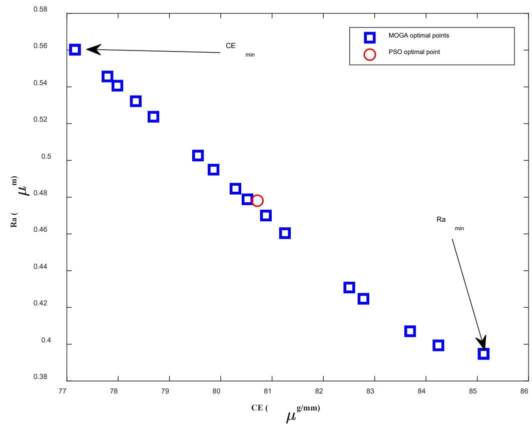



Figure 17. Pareto front (minimum points)

Particle Swarm Optimization (PSO) is an optimization algorithm that uses the collective intelligence of a group of particles to find the optimal solution. It is similar to the way birds flock and fish school together and works by refreshing the particle location and speed to the best solution found so far by any particle in the swarm. PSO is simple to implement, computationally efficient and effective for solving optimization problems in various fields such as finance, engineering, and data science. It has been shown to perform well for problems with many variables and non-linear search spaces. After setting bounds of the 3 variables (*ap*, $V_c$, *f*), and choosing options in MATLAB using a function called; particleswarm. By using this intelligent tool, the minimum of surface roughness *Ra*=0.478 mm and *CE*=80.7197 mg/mm, for the optimal parameters following, *ap*=0.20368 mm, $V_c$=324.4422 mm/min, and *f*=0.08518 mm/rev. The optimization result is almost the same as the result found by the GA.

## 6. CONCLUSION

In this paper, the surface roughness of a CNC turning machine and the quantity of carbon emitted by each millimeter of machining are modelled by several artificial intelligence tools, followed by a coupling of the 5 most highly accurate AI tools (ANN, GPR, DT, GBoost, and ANFIS) by a MODE function (is used to select the repeating value) to achieve the most accurate model, which is then used to optimize the three cutting factors; Cutting speed, feed rate per tool revolution, and depth of cut. The Multi-Objective Genetic Algorithm, and Particleswarm algorithm are used to optimize the cutting conditions to minimize machined surface roughness and carbon emission per millimeter of cut, the optimum cutting conditions to achieve a minimum of objective functions (Ra and CE) are then: $ap$=0.20368 m, $V_c$=324.4422 mm/min, and $f$=0.08518 mm/rev. Ultimately, this study shows the importance of taking surface roughness into account as a key parameter for the search of more sustainable solutions in the turning machining field. Efficient monitoring of surface roughness can not only improve product quality, but also help to reduce the industry's carbon footprint.

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