International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 07 Issue: 04 | Apr 2020 www.irjet.net p-ISSN: 2395-0072

Study of Surface Roughness based on Tool Wear in SS304

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Abstract

In modern manufacturing industries, they aim to increase the production rate with less production cost and high quality. The exterior look refers to surface roughness which is one of the most important property of the machined components

AISI 304 austenite stainless steel is popularly used grade in the various field of manufacturing because of its high ductility, high durability and excellent corrosion resistance.

Turning operation is conducted as numerous experiments and tests with cutting parameters such as speed, feed of cut and depth of cut to determine the surface roughness of the material. Then, tool wear is measured using profile projector, the artificial neural network determines and establishes a proper relationship between the surface roughness and tool wear of the material,

1.Introduction

Machining is any of various processes in which a piece raw material is cut into a desired final shape and size by a controlled material-removal process. The processes that have this common theme, controlled material removal, are today collectively known as subtract manufacturing, in distinction from processes of controlled material addition, which are known as additive manufacturing. Exactly what the "controlled" part of the definition implies can vary, but it almost always implies the use of machine tools.

Around the middle of the 19th century, the latter words were coined as the concepts that they described evolved into widespread existence. Therefore, during the Machine Age, machining referred to the “traditional” machining processes like turning, boring, drilling, milling, broaching, sawing, shaping, planning, boring, drilling, milling, broaching, sawing, shaping. In these "traditional" or "conventional" machining processes, machine tools, such as lathes, milling machines, drill presses, or others, are used with a sharp cutting tool to remove material to achieve a desired geometry. Much of modern-day machining is carried out by computer numerical control (CNC), in which computers are used to control the movement and operation of the mills, lathes, and other cutting machines.

2. Experimental Study

2.1 Material Used

The material chosen for this project study is SS304 and its chemical composition is given in below table. The size is yet to decided.

Element	C	S	Ni	Si	Mo	Mn	Cr
Weight	0.06	0.005	8.03	0.47	0.03	1.40	18.95

Table 1. Composition of AISI 304 Austenitic Stainless Steel (wt%)

Fig 1. Workpiece (SS304)

2.1.1 Characteristic

Grade 304 stainless steel is the most versatile and the most widely used of all stainless steels. Its chemical composition, mechanical properties, weldability and n corrosion/oxidation resistance provide the best all-round performance stainless steel at relatively low cost. It also has excellent low temperature properties and responds well to hardening by cold working. If inter granular corrosion in the heat affected zone may occur.

	304	
	Typical	Minimum
Tensile strength Mpa	600	515
Proof Strength (Offset 0.2%) MPa	310	205

Elongation (Percent in 50mm)	60	40
Hardness (Brine ll)	170	-
Endurance (fatigue) limit Mpa	240	-

Table 2. Mechanical property at room temperature

2.2 Machining Process

We selected turning operation which was done using a carbide tool in a CNC. Th entire stainless-steel work piece which-is used for the study of our project underwent CNC turning operation with a carbide tool.

The CNC used was in the Machine shop for machining. After the finishing of CNC operation process the material is checked for finishing and for the dimensions required.

2.2.1 CNC Machining

Machining is any of various processes in which a piece of raw material is cut into a desired final shape and size by a controlled material removal process. Much of modern-day machining is carried out by computer numerical control (CNC) in which computers are used to control the movement and operation of the mills, lathes and other cutting machines.

The turning processes are typically carried out on a lathe, considered to be the oldest machine tools and can be of four different types such as straight turning processes can produce various shapes of materials such as straight, conical, curved or grooved work piece. In general, turning uses simple single point cutting tools. Each group of work piece materials has an optimum set of tools angles which have been developed through the years.

2.2.2 Turning Operations

Turning is a form of machining, a material removal process, which is used to create rotational parts by cutting away unwanted material. The turning process requires a turning machine or lathe or CNC, work piece, fixture and cutting tool.

Turning is used to reduce the diameter of the material. Turning is a machining process in which a cutting tool, typically a non-rotary tool bit, describes a helix tool path by moving more or less linearly while the work piece rotates. The tools axes of movement may be literally a straight line or they may be along some set of curves or angles, but they are essentially linear.

Usually the "turning" is reserved for the generation of external surfaces by this cutting action, whereas this same essential cutting action when applied to internal surfaces is called "boring". Thus, the phrase "turning and boring" categorizes the larger family of processes known as lathing. The cutting of faces on the work piece, whether with a turning or boring tool, is called "facing", and may be lumped into either category as a subset.

Today the most common type of such automation is computer numerical control, better known as CNC. When turning, a piece of relatively rigid material is rotated and a cutting tool is traversed along 1,2 or axes of motion to produce precise diameters and depths. Turning can be either on the outside of the cylinder or on the inside to produce tubular components to various geometries even the platonic solids, although since the advent of CNC it has become unusual to use non-computerized tool path control for this purpose.

The turning processes are typically carried out on a lathe, considered to be the oldest machine tools an can be of four different types such as straight turning, taper turning, profiling or external grooving. Those types of turning process can produce various shapes of materials such as straight, conical, curved or grooved workpiece. In general, turning uses simple single point cutting tools. Each group of workpiece materials has an optimum set of tools angles which have been developed through the years.
Computer numerical control (CNC) is the automation of machine tools by means of computers executing pee-programmed sequences of machine control commands. This is in contrast to machines that are manually controlled by hand wheels or leaves or mechanically automated by cams alone.

In modern CNC systems, the design of a mechanical part and its manufacturing program is highly automated. The part mechanical dimensions are defined using computer aided design (CAD) software. The resulting directives are transformed into the specific commands necessary for a particular machine to produce the component, and then are loaded into the CNC machine.

2.2.3 Carbide Tool

Carbide as a tool material was discovered in the search for a replacement for expensive diamond dies used in the wire drawing of tungsten filaments. Carbide tool materials include silicon and titanium carbides and tungsten carbides and titanium carbides as well as other compounds of a metal (Ti,W,Cr,Zr) or metalloid (B,Si) and

carbon. Carbides have excellent wear resistance and high hot hardness.

The terms tungsten carbide and sintered carbide for a tool material describe a comprehensive family of hard carbide composite used for metal cutting tools dies of various types and wear parts. Carbides are excellent substrates for all coatings such as TiN, TiAIN, TiCN, solid lubricant coatings and multilayer coatings. Coatings considerably improves tool life and boost the performance of carbide tools in high productivity, high speed and high feed cutting or in dry machining and when machining and when machining of difficult to machine materials.

2.3 Surface Roughness Testing

Surface roughness of each work piece is then measured using the surface roughness measuring tester. The surface roughness is to be measured at 3 points at each work piece so as to obtain the equivalent roughness values of the work piece. The roughness tester was available in the department of mechanical engineering at Sri Manakula Vinayagar Engineering College.

A roughness tester is used to quickly and accurately determine the surface tester or surface roughness of a material. A roughness tester shows the measured roughness depth as well as the mean roughness value in micrometers or microns.

2.3.1 Roughness Tester Specification

Roughness Parameter: Ra (ISO), Rz(DIN)
Ra: 0.05-10.0❍m/ Rz 0.1-50 ❍m
Measuring range: 50❍m
Cut-off lengths: 0.25 mm/0.8mm/2.50m
Accuracy: Conform ISO Class 3
Power: 3.6 V/ 2x Ni MH-Batteries
Weight: 200g

2.4 Profile projector

Profile projector is widely used for complex shape stampings, gears, cams, threads and comparing the measured contour model. It's easy to use and highly efficient.

It is a commonly used measurement of optical instruments. Thus, profile projector is widely used in major machinery manufacturing including aviation, aerospace industry, watches and clocks, electronics, instrumentation industry, research institutes and detection metering stations at all levels and etc. The projector magnifies the profile of the specimen, and displays this on the built-in projection screen. On this screen there is typically a grid that can be rotated 360 degrees so the X-Y axis of the screen can be aligned with a straight edge of the machined part to examine or measure. This projection screen displays the profile of the specimen and is magnified for better ease of calculating linear measurements.

An edge of the specimen to examine may be lined up with the grid on the screen. From there, simple measurements may be taken for distances to other points. This is being done on a magnified profile of the specimen.

2.5 Collected data

CUTTING PARAMETERS			SURFACE ROUGHNESS	FLANK WEAR
SPEED(RPM)	FEED(MM)	DEPTH OF CUT(MM)		
700	0.1	0.3	1.1967	0.4
700	0.3	0.5	2.8633	0.4
700	0.5	0.7	2.75	0.4
900	0.1	0.3	0.5467	0.4
900	0.3	0.5	1.4467	0.4
900	0.5	0.7	2.5833	0.4
1100	0.1	0.3	1.6333	0.4
1100	0.3	0.5	3.2233	0.4
1100	0.5	0.7	2.72	0.4

3. Method of Analyzing

3.1 Artificial Neural Network (ANN)

The idea of ANNs is based on the belief that working of human brain by making the right connections, can be imitated using silicon and wires as living neurons and dendrites. The human brain is composed of 86 billion nerve cells called neurons. They are connected to other thousand cells by Axons. Stimuli from external environment or inputs from sensory organs are accepted by dendrites. These inputs create electric impulses, which quickly travel through the neural network. A neuron can then send the message to other neuron to handle the issue or does not send it forward. ANNs are composed of multiple nodes, which imitate biological neurons of human brain. The neurons are connected by links and they interact with each other. The nodes can take input data and perform simple operations on the data. The result of these operations is passed to other neurons. The output at each node is called its activation or node value.

Each link is associated with weight. ANNs are capable of learning, which takes place by altering weight values.

In the topology diagrams shown, each arrow represents a connection between two neurons and indicates the pathway for the flow of information. Each connection has a weight, an integer number that controls the signal between the two neurons.

If the network generates a "good or desired" output, there is no need to adjust the weights. However, if the network generates a "poor or undesired" output or an error, then the system alters the weights in order to improve subsequent results.

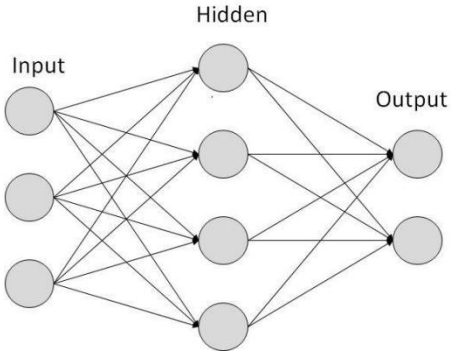

Fig 2. ANN Model

3.2 MODELING OF MACHINING PROCESSES USING NEURAL NETWORKS

In recent years, modeling techniques using NNs have attracted attention of practitioners and researchers. The learning ability of nonlinear relationship in a cutting operation without going deep into the mathematical complexity, or prior assumptions on the functional form of the relationship between inputs, in-process parameters and outputs makes NN an attractive alternative choice for many researchers to model cutting processes. This type of modeling is often called direct modeling. NNs are massive parallel systems made up of simple processing units (neurons) there are linked with weighted connections where the knowledge possessed by the networks is held.

NNs are characterized by their topology, weight vectors, and activation functions there are used in hidden and output layers of the network. The neurons in the input layer are fed with input data. Each neuron sums its inputs, with one input per neuron in the input layer but many inputs per neuron in the hidden layer. The bias (threshold) is used to scale the input to a useful range to improve the convergence properties of the neural network. Each neuron transfers the data, according to a transfer function (activation function), to all the elements in the next layer. However, each neuron receives a different signal due to different connection weights between the neurons. Finally, the output of each neuron in the output layer is compared to the desired output. In order to minimize the difference between these outputs, weights of the connections between the neurons must be adjusted. There are numerous methods of determining the weights of the connections. Especially there are used some variations of back propagation (BP) learning algorithm, conjugate gradient algorithms, quasi- Newton algorithms and Levenberg–Marquardt (LM) method. A NN is trained using some learning (training) algorithm with a number of data to arrive at an optimum set of weights and tested with other set of data. Once trained, the NN can be used for prediction of output parameters.

The most used NNs for modeling of machining processes are: MLP also known as multilayer feed forward networks, adaptive resonance theory models (ART), self-organizing maps (SOM), radial basis function network (RBFN), etc. The most popular NN for modeling machining processes is MLP with BP training algorithm. MLP BP is adopted by most researches since MLP models are general- purpose models and have good generalization capabilities. The MLP BP networks are most popular in practice due to their easiness to understand and implement. The standard BP technique with momentum is adopted by most researchers. MLP uses BP algorithm for training the network in a supervised manner. BP algorithm is a steepest descent method, where weight values are adjusted in an iterative fashion while moving along the error surface to arrive at minimal range of error, when input patterns are presented to the network for learning the network. A complete description of the BP algorithm can be found in numerous sources, including (Hay kin, 1999). Figure 3 shows three-layered MLP architecture based on the input, hidden and output layers for modeling machining process. The first layer is an input layer where external data are received. The last layer, separated from the input layer by one or more intermediate layers called the hidden layers, computes the network outputs.

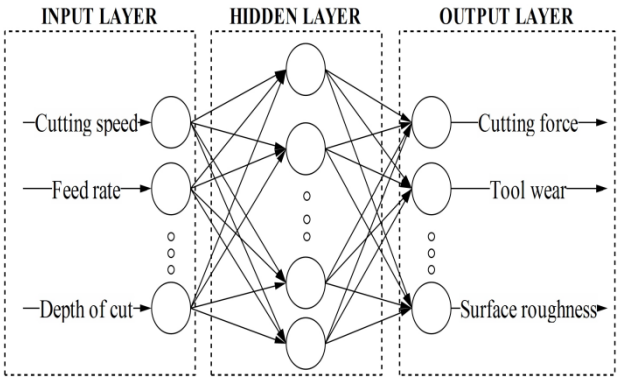

Fig 3. MLP topology for modeling machining processes

According to the network structure, decision variables in modeling machining problem could be assigned as the set of input neurons such as the value of cutting speed, feed rate, depth of cut, etc. Response variables are assigned as the set of output neurons such as cutting force, tool wear, surface roughness, etc.

3.3 MODELING METHODOLOGY OF NEURAL NETWORKS

Development of NN predictive model is a nontrivial task. Modeling issues that affect the performance of an NN must be considered carefully. In order to ensure good performance of an MLP BP models, it is inevitable to develop them in a systematic manner. Such an approach needs to address major factors such as the determination of adequate model inputs, data division and pre-processing, the choice of suitable network architecture, choice of training parameters, etc. Namely, two crucial processes are of importance: model development and issues in selecting MLP parameters, i.e. determining training parameters of BP and topology of MLP.

3.3.1 Selection of MLP BP network parameters

Configuring MLP architecture usually comprises the decisions about the internal architecture and training parameters.

Internal architecture:

Specifying the internal architecture requires determining the number of hidden layers, the number of hidden neurons and transfer functions of the neurons in hidden and output layer. First two parameters especially affect the overall performance of NN i.e. generalization ability of the NN model.

Number of layers.

The role of the hidden layers is to map complicated input-output relationships between network inputs and outputs. Until now, no general method for determining the number of hidden layers was proposed. Increasing the number of hidden layers increases the network's processing power, but on the other hand the training time is increased along with more required training examples. Reviewing the literature, it could be seen that at most two hidden layers are used. When talking about using NN in machining process modeling and prediction, most authors used only one hidden layer.

Number of hidden neurons.

The issue of determining the optimal number of hidden neurons is of crucial importance since the number of neurons determines the "expressive power" of the network. The number of neurons in the hidden layers influences the generalization ability of the network. Adding hidden neurons always results in reduction of the training error, but error decreasing or increasing on test is in direct relationship with actual number of hidden neurons. A typical approach would be to start with a small number of hidden neurons and to slightly increase the number until no significant improvement in model performance is achieved. Using the NN model with minimal number of hidden neurons i.e. simplest architecture is always desirable for both practical and theoretical reasons. It should be underlined that the number of neurons in the hidden layers is data dependent. If the network has more degrees of freedom (the number of connection weights) than the number of training samples, the network is mathematically undetermined. The number of weights is equal to the sum of the product between the numbers of neurons in each layer.

Activation function.

The activation function, also called the transfer function, is a mathematical formula that gives the output of a neuron as a function of its input signals. The most used activation functions are: sigmoid (logistic or squashing) function, hyperbolic tangent function, sine or cosine function and linear function. Typically, the activation function is chosen based on the kind of data used and type of the layer. For prediction purposes it is common to use a sigmoid or hyperbolic tangent function in both hidden and output layer or sigmoid or hyperbolic tangent function in hidden layer and linear in the output layer.

Training parameters.

Selection of training parameters is very important for proper training of NN. The most important training parameters are: learning coefficient, momentum, epochs and initial weights.

Learning coefficient.

Learning coefficient is the rate, at which the network adjusts its weights during training. A high learning coefficient allows the network to learn faster, hence providing faster convergence. With a small learning coefficient, training time is increased, but the probability of reaching the global minimum is increased. Practical guidelines for selecting learning coefficient values are given in

Momentum.

Momentum is a training parameter used to reduce training time of the BP algorithm and to enhance the stability of the learning. The method involves adding a term to the weight adjustment that is proportional to the amount of the previous weight change. A high momentum reduces the risk of the network being stuck in local minimum, but it increases the risk of skipping over the solution. Using a small value for momentum will lead to prolonged training. The values of 0.01 for learning rate and 0.9 for momentum are adopted by most researchers because a BP network with these settings has the best prediction performance with the least number of epochs.

Epochs.

The epochs of the training cycle is the number of times the training data has been presented to the network. The BP algorithm guarantees that total error in the training set will continue to decrease as the number of epochs increases. With each epoch, the weights are modified to decrease the error on the training patterns. As training progresses, the amount of change in the error function becomes smaller. Convergence occurs when the change in the error function is less than a specified threshold. Similar to the problem of over-fitting, the problem of over- training may occur if the number of epochs is considerably high. The number of epochs required for proper generalization is often determined by trial and error method and cross validation method.

Initial weights.

BP network is sensitive to initial values of weights. Too small initial weights will the training time and difficulties in converging to an optimal solution may occur. If initial weights are too large the network may get unstable weights. The initial connection weights must also be specified prior to training. The weight initialization can be set in random way or using evolutionary algorithms. Typically, weights and biases are initialized uniformly in a relatively small range within ±0.5 or ±1.

3.3.2 NN model development

Several steps need to be considered when developing NN models. Generally, the developing process include: selection of input and output parameters, data collection, data filtering, data pre-processing, selection of training and testing set and model validation and performance measures.

Selection of input and output parameters.

The idea of using NN to model the process is to create network that take process parameters as inputs and produces process responses as outputs. In order to developed optimal NN model it is necessary to identify process parameters that affect the process response and to assign them as network inputs. The selection of the suitable response for network outputs requires understanding of the given process. NN can be trained to predict both single- response and multi-purpose.

Data collection:

For a successful application of NN modeling, it needs to collect as much data as. Instead of volume, the quality and representative of the collected data is important when NN performance is considered. It is not possible to say how many data items are appropriate, because this depends on the complexity of the modeling problem. Data can be collected in various ways: from simulation, by experimental research or actual process data. In any case, it is necessary to filter and pre-process the data.

Data filtering:

Data filtering include data integrity check and extreme data removal. Errors such as incorrectly entered data, duplicated and missing data have to be corrected, because the NN model performance in direct link with the quality of the data. Very extreme data should be also removed because it can interfere with the training process.

Data pre-processing:

The NN can only work with data within certain ranges and in specified formats. Data pre-processing usually speeds up the learning process and it usually

performed. Pre-processing can be in the form of data scaling (normalization) and transformation. Scaling the data is essential and is closely related to the activation function used. Scaling to [-1,1] for the hyperbolic tangent transfer function and to [0,1] for the sigmoid transfer function is often applied. However, some researchers recommended that the data be normalized between slightly offset values such as [0.1, 0.9] or [0.2, 0.8] rather than between 0 and 1 to avoid saturation of the sigmoid function leading to slow or no. In some situations, where parameters have an exceptionally large range, it may be beneficial to take logarithm of data prior to scaling.

Selection of training and testing set:

After data collection and pre-processing, all the data should be randomly divided into two sets: training set and testing set. The training set is used for NN model development and the test set is used for estimating the prediction ability of the model. If enough data is available, it is recommended to divide the data set into a training set, a validation set, and a test set. The, validation set (stopping set) is not used for weights update, but to assess the performance of the model. By using a validation set, over-fitting and over- training problems could be avoided. The proportion of training to testing data varied considerably in the published research. It is common to divide all available data so that 90, 80 or 70% are selected for training purposes and the remaining for testing. When using a validation set, dividing the data into the three parts: 50% for training, and 25% each for validation and testing could be reasonably.

Model validation and performance measures.

Once the model is developed, the performance of the trained model should be validated. The purpose of the model validation phase is to assess the model generalization ability. This is achieved by measuring the performance of trained NN on test set, which contain the data that NN has not seen. The most important measure of performance is the prediction accuracy. An accuracy measure is often defined in terms of the prediction error which is the difference between the actual (desired) and the predicted value. There are a number of measures of accuracy in the literature and each has advantages and limitations. They are listed in (Zhang e al., 1998).

The coefficient of correlation (R), the root mean squared error (RMSE) and the mean absolute percentage error (MAPE) are the main criteria that are often used to evaluate the prediction performance of NNs models. The coefficient of correlation is a measure that is used to determine the relative correlation and the goodness-of-fit between the predicted and observed data.

The interpretation of correlation coefficient is as follows:

|R|>=0.8 – strong correlation exists
0.8>=|R|>=0.2 – correlation exists
|R|<=0.2 – weak correlation exists

The RMSE and has the advantage that large errors receive much greater attention than small errors. MAPE is scale less and therefore useful for ease of interpretation, but in contrast to RMSE does not treat small errors symmetrically with large errors. A good NN model should have a correlation coefficient over |0.8| and RMSE and MAPE should be as close to 0 as possible.

3.4 Weka Software

Waikaro Environment for Knowledge Analysis (Weka) is a suite of machine learning software written in Java developed at the University of Waikaro, New Zealand. It is free software licensed under the GNU General Public License.

Weka contains a collection of visualization tools and algorithms for data analysis and predictive modeling, together with graphical user interfaces for easy access to these functions. The original non-Java version of Weka was a Tcl/Tk front-end to (mostly third party) modeling algorithms implemented in other programming languages, plus data processioning utilities in C and a Make file-based system for running machine learning experiments.

Weka supports several standard data mining tasks, more specifically, data processing, clustering, classification, regression, and visualization and feature selection. All of Weka techniques are predicated on the assumption that the data is available as one flat file or relation, where each data point is described by a fixed number of attributes (normally, numeric or nominal attributes, but some other attribute types are also supported). Weka provides access to SQL databases using Java Database Connectivity and can process the result returned by a database query.

Weka provides access to deep learning with Deep learning. It is not capable of mufti-relational data mining, but there is separate software for converting a collection of linked database tables into a single table that is suitable for processing using Weka. Another important

area that is currently not covered by the algorithms included in the Weka distribution is sequence modeling. Weka is data mining software that uses a collection of machine learning algorithms. These algorithms can be applied directly to the data or called from the Java code. Weka is a collection of tools for:

- Regression
- Decision
- Clustering
- Data pre-processing
- Visualization

Weka formats

Weka uses the Attribute Relation File Format for data analysis, by default. But listed below are some formats that Weka supports, from where data can be imported:

- CSV
- ARFF
- Database using ODBC

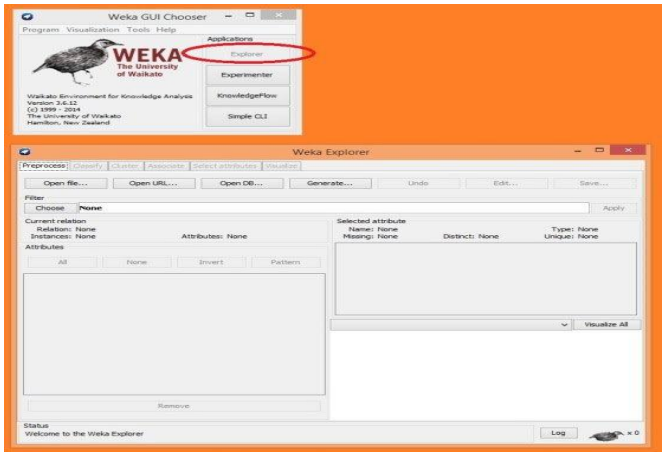

Fig 4 Weka Explorer

3.4.1 Multilayer Perceptron

A multilayer perceptron (MLP) is a class of feed forward artificial neural network. A MLP consists of, at least, three layers of nodes: an input layer, a hidden layer and an output layer. Except for the input nodes, each node is a neuron that uses a nonlinear activation function. MLP utilizes a supervised learning technique called back propagation for training. Its multiple layers and non-linear activation distinguish MLP from a linear perceptron. It can distinguish data that is not linearly separable.

Multilayer perceptional are sometimes colloquially referred to as "vanilla" neural networks, especially when they have a single hidden layer.

3.4.2 Linear Regression

in statistics, linear regression is a linear approach to modelling the relationship between a scalar response (or dependent variable) and one or more explanatory variables (or independent variables). The case of one explanatory variable is called simple linear regression. For more than one explanatory variable, the process is called multiple linear regression.[1] This term is distinct from multivariate linear regression, where multiple correlated dependent variables are predicted, rather than a single scalar variable.[2]

In linear regression, the relationships are modeled using linear predictor functions whose unknown model parameters are estimated from the data. Such models are called linear models.[3] Most commonly, the conditional mean of the response given the values of the explanatory variables (or predictors) is assumed to be an affine function of those values; less commonly, the conditional median or some other quantile is used. Like all forms of regression analysis, linear regression focuses on the conditional probability distribution of the response given the values of the predictors, rather than on the joint probability distribution of all of these variables, which is the domain of multivariate analysis.

3.5 Comparing parameters

3.5.1 Correlation coefficients

A correlation coefficient is a numerical measure of some type of correlation meaning a statistical relationship between two variables. The variables may be two columns of a given data set of observations often called a sample, or two components of a multivariate random variable with a known distribution.

Several types of correlation coefficient exist, each with their own definition and own range of usability and characteristics. They all assume values in the range from -1 to +1, where +1 indicates the strongest possible agreement and -1 the strongest possible disagreement. As tools of analysis, correlation coefficients present certain problems including the propensity of some types to be distorted by outlines and the possibility of incorrectly being used to infer a causal relationship between the variables.

3.5.2 Mean Absolute Error (MAE)

Mean absolute error (MAE) is the average of the difference between predicted and actual value in all test cases, it is the average prediction error. In statistics, mean absolute error (MAE) is the measure of difference between two continuous variables. Assume X and Y are variables of paired observations that express the same phenomenon.

Examples of Y versus X include comparisons of predicted versus observed, subsequent time versus initial time and one technique of measurement versus and alternative technique of measurement.

3.5.3 Rooted Mean Squared Error (RMSE)

RMSE is frequently used measure of difference between values predicted by a model or estimator and the values actually observed from the thing being modeled or estimated. The mean-squared error is one of the most commonly used measures of success for numeric prediction. This value is computed by taking the average of the squared difference between each computed value and its corresponding correct value. The root mean-squared error is simply the square root of the mean-squared-error. The root mean squared error gives the error value the same dimension as the actual and predicted values.

3.5.4 Relative Absolute Error

The relative absolute error is very similar to the relative squared error in the sense that it is also relative to a simple predictor, which is just the average of the actual values. In this case, though, the error is just the total absolute error instead of the total squared error. Thus, the relative absolute error takes the total absolute error and normalizes it by dividing by the total absolute error of the simple predictor.

3.5.5 Root Relative Squared Error

Thus, the relative squared error takes the total squared error and normalizes it by dividing by the total squared error of the simple predictor. By taking the square root of the relative squared error one reduces the error to the same dimensions as the quantity being predicted.

4. Conclusion

From the Previous Chapter, dates analyzed for multilayer Perceptron and Linear Regression the values of the parameter are tabulated as follow:

PARAMETERS	**Multilayer Perceptron**	**Linear Regression**
Correlation coefficient	**0.9332**	**0.6802**
Mean absolute error	**0.3128**	**0.4998**
Root mean squared error	**0.3954**	**0.6263**

Table 4 Comparison Between multilayer Perceptron and Linear Regression

From the above table it can be clearly seen that correlation coefficient of multilayer perceptron is greater than that of linear regression, which is more accurate and closer to 1. At the same time the value of mean absolute error and root mean squared error for multilayer perceptron is less when compared to linear regression since all values of error is less and correlation coefficient is more in multilayer perceptron, so it is considered as accurate model.

The relation between input and output parameters are studied using multilayer perceptron. Thus, the relation can be used to find the influence of tool wear and other parameters on surface roughness. This helps in improve product quality. It also improves the productivity and reduce production time.

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