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OPTIMIZATION OF WEAR PROPERTIES OF EN-31 STEEL USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

The objective of this paper is to predict the wear properties of EN 31 steel. The artificial neural network optimization technique was applied to predict the wear properties of EN 31 steel. Wear experiments are to be conducted by using Pin On Disc wear tester at varying load, Sliding velocity. Fretting wear volume is obtained at different normal loads (ranging between 15N – 75N) for various treated samples were used in the formation of training data of ANN. Based on experimental database for EN 31 steel the specific wear rate are to be calculated by a well-trained ANN (Artificial Neural Network) using Elman back propagation algorithm at MATLAB. A three layer neural network with a back propagation algorithm is used to train the network. ANN can be trained using input and output data can be used to predict for new input values. Results of the prediction of ANN are in good agreement with the experimental results. The predicted results from ANN model are compared with experimental values.

INDEX TERMS ANN (Artificial Neural Network), EN 31 steel, Pin On Disc

I. INTRODUCTION

Steel is defined as an alloy of iron and carbon with the carbon content up to about 2% wt., with a vast application almost in every part of our life. EN31 is a popular grade of alloy steel which is widely used in automobile industry for production of axle, roller bearings, shear blades, spindle , forming , molding dies, ball bearings, spinning tools, beading rolls, punches and dies, shafts, studs, bolts, used in high stress and with a large cross section. It includes aircraft and general engineering applications for propeller or gear components.

By its character this type of steel has high resisting nature against wear and can be used for components which are subjected to severe abrasion, wear or high surface loading. The properties of the carbon steels vary with their composition and microstructure, which are dependent on the alloying elements present in the steel and to the kind of heat treatment process it is subjected to. Steel is heated to the austenitization temperature and then cooled at a faster rate to avoid ferrite or pearlite transformation and allow the formation of bainite and marten site to obtain maximum hardness and strength. The factors that the critical cooling rate is depending upon both the specific heat capacity and thermal conductivity of the steel as well as the quenchants in addition to quench-bath temperature and agitation.
Among the many quenchants used, water is the most common one. Whenever lower cooling rates and more uniform cooling is desired for better distortion control and crack prevention petroleum-oil-derived quenchants are used. Petroleum oil possesses a number of other significant disadvantages, including poor biodegradability, Toxicity, Flammability and Non-renewability in addition to being susceptible to global supply issues. Hence it is of continuing interest to identify alternative quenchants to 2

petroleum oil as a base stock for quenchants formulation. Currently, vegetable oils like Gingelly, canola, soybean, corn, cotton seed and sunflower oils are most commonly available vegetable oils. Out of these, soybean oil and Gingelly oil exhibit a narrow viscosity range, high boiling point, nontoxic, renewable and highly biodegradable. Hence these oils are preferred to be used as quenchants for carbon steels.

OBJECTIVE

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To predict the wear properties of EN 31 steel by using artificial neural network algorithm. Wear ratio are to be conducted by using Pin On Disc (DUCOM) wear tester at varying load. Wear rates and frictional volume are to be calculated by input parameters and the graph has been plotted. Fretting wear volume is obtained at different normal loads (ranging between 15N – 75N) for various treated samples were used. To find out the optimum range of wear rate and frictional volume a well-trained ANN algorithm is used. A three layer neural network with a back propagation algorithm is used to train the network at MATLAB. ANN can be trained using input and output data can be used to predict for new input values. Based on experimental database for EN 31 steel the specific wear rate are to be calculated by a well-trained Artificial Neural Network by using MATLAB.

I.WEAR TESTING

Wear is the damaging, gradual removal or deformation of material at solid surfaces. Causes of wear can be mechanical or chemical. Wear in machine elements, together with other process such as fatigue and creep causes functional surfaces to degrade eventually leading to material failure or loss of functionality. wear of metal occurs by plastic displacement of surface and near-surface material and by detachment of particles that form wear debris. The particle size may vary from millimeters to nanometers. the wear rate is affected by factors such as types of loading (e.g., impact, 4 static, dynamic),type of motion (e.g., sliding, rolling) and temperature. Wear test is carried out to predict the wear performance and to investigate the wear mechanism. When friction is the predominant factor causing deterioration of your materials, abrasion and wear testing will give you data to compare materials are coatings and can help you predict the life time of a material are coating. A customized wear testing program on the other hand, can be configured to closely operating condition including temperatures and fluids and directions of wear. This custom approach will result in wear testing data that is much more relatable to the specific work environment. Element has a range of unique wear testing methods, including pin on disc, blade on block and medical device wear testing. Pin on disc wear testing is a method of characterizing the coefficient of friction, frictional force and rate of wear between two materials. As particularly versatile method for testing wear resistance, pin on disc can be configured in multiple scenarios. Common types of wear include;

(1) Adhesive wear
(2) Abrasive wear
(3) Surface fatigue
(4) Fretting wear
(5) Erosive wear

Corrosion and oxidation wear Pin on disc testing can simulate multiple wear modes, including unidirectional, bidirectional, omnidirectional and quasi rotational wear. Our equipment allows as testing virtually any combination of materials to determine the effect of wear on a medical device. After completing pin on disc testing the mass loss evaluations and differential analysis of test fluids to characterize wear properties. In some cases metallurgical evaluations of the posttest wear scaring can also be performed. Two specific reasons are as follows:

From a material point of view, the test is performed to evaluate the wear 5 Property of a material so as to determine whether the material is adequate for a Specific wear application. From a surface engineering point of view, wear test is carried out to evaluate the potential of using a certain surface engineering technology to reduce wear for a specific application, and to investigate the effect of treatment conditions (processing parameters) on the wear performance, so that optimized surface treatment conditions can be realized.

Three levels of wear testing

(1) Laboratory test,
(2) Component simulation test,
(3) In-service test.

We may use an example to describe the difference among each type of test. A new surface engineering (SE) technology has been developed, which could be potentially used to improve the wear resistance of parts for a metal on-metal hip joint (for human body). Perhaps the ideal and logical sequence of wear testing in this example will be as follows:

Laboratory test with small samples are initially carried out under testing conditions simulated insofar as conveniently possible to determine whether the surface engineering technology warrants further consideration, and if so, to find out under what treatment conditions, the highest wear resistance improvement can be achieved.

II. *ARTIFICIAL NEURAL NETWORK*

are An ANN is a biologically inspired mathematical model. Similar to the brain, a neural network is a massively parallel collection of small and simple processing units. An ANN collects its knowledge by detecting the patterns and relationships in data and learns through experience, not from programming. Thus, while it may interpolate between data with some con-fidence, it cannot accurately extrapolate, and any trials at 6 such predictions should be viewed with great care. Based on the fact that an

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ANN learns by example, it is not necessary for it to know the theory behind a phenomenon. The modeling process is opaque similar to a ‘‘black-box’’ operation, therefore it is difficult to ascertain any physical relationships within the dataset using an ANN. The main advantage of the neural network approach over conventional regression analysis is that the net- work constructs a solution without the need to specify the relationships or the form of relationships between variables. This feature inputs and outputs are not clear enough or the solutions are not easily formulated in a short time. The structure of an ANN (Fig. 1) is organized in layers of units (called neurons), namely the input layer, hidden layer(s), and output layer. The numbers of units (neurons) in the input and output layer are fixed to be equal to that of input and output
variables. The hidden layer can contain more than one layer, and in each layer the number of units (neurons) is flexible.

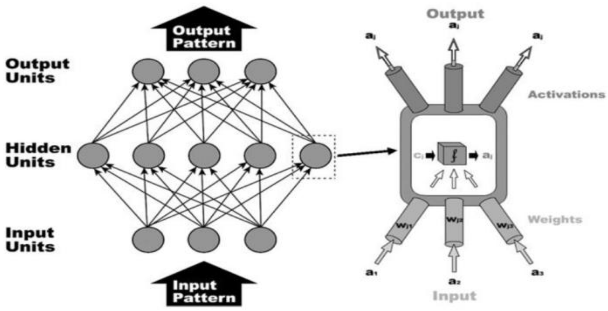

FIGURE 1. **Schematic Representation of Artificial Neural Network**

III. SELECTION OF MATERIALS

EN 31 STEEL

En 31 is a excellent high carbon alloy steel which offers a high measure of hardness with compressive strength and abrasion resistance. By its character this type of steel has high resisting nature against wear and can be used for components which are subjected to severe abrasion, wear or high surface loading. The properties of the carbon steels vary with their composition and microstructure, which are dependent on the alloying elements present in the steel and to the kind of heat treatment process it is subjected to. Steel is heated to the austenitization temperature and then cooled at a faster rate to avoid ferrite or pearlite transformation and allow the formation of bainite and martensite to obtain maximum hardness and strength. The factors that the critical cooling rate is depend upon are both the specific heat capacity and thermal conductivity of the steel as well as the quenchants in addition to quench-bath temperature and agitation.

Table 1. Mechanical properties of EN 31 steel

Element	Mechanical Properties
Tensile strength	750 N/mm2
Yield stress	450 N/mm2
Reduction of area	45%
Elongation	30%
Modulus of elasticity	215000 N/mm2
Density	7.8 Kg/m3
Hardness	63HRC

Table 3. Chemical Composition of EN-31 Steel

Element	Chemical Composition (wt%)
C	1.08%
Si	0.25%
Mn	0.53%
S	0.015%
P	0.022%
Ni	0.33%
Cr	1.46%

Mo	0.06%

HEAT TREATMENT OF EN - 31

Element	**Heat Treatment**
Hardening temperature	802° – 860 °c
Quenching medium	Oil
Tempering temperature	180° - 225°c
Brinell Rockwell hardness	59 – 65

SAMPLE SPECIMEN OF EN-31 STEEL

FIG 3.1 SHOWS THE SAMPLE SPECIMEN OF EN-31 STEEL

TABLE I

Table 2. Physical Properties

Thermal conductivity at °c	20	350	700
Physical Properties	44.5	45.0	46.0

WEAR TEST ON PIN ON DISC APPARATUS

This test method describes a laboratory procedure for determining the wear of materials during sliding using a pin-on-disk apparatus. Materials are tested in pairs under nominally non-abrasive conditions. The principal areas of experimental attention in using this type of apparatus to measure wear are described. The coefficient of friction may also be determined. In a pin on disc wear tester, a pin is loaded against a flat rotating disc specimen such that a circular wear path is described by the wear and friction properties of materials under pure sliding conditions. Either disc or pin serves as specimen while the other as counter face. Pin with various geometry can be used. A continent way is to use ball of commercially available carbide or alumina as counter face show that the name of ball on disc is used.

SUMMARY OF TEST METHOD

For the pin-on-disk wear test, two specimens are required. One, a pin with a radiused tip, is positioned perpendicular to the other, usually a flat circular disk. A ball, rigidly held, is often used as the pin specimen. The test machine causes either the disk specimen or the pin specimen to revolve about the disk center. In either case, the sliding path is a circle on the disk surface. The plane of the disk may be oriented either horizontally or vertically. Wear results may differ for different orientations. The pin specimen is pressed against the disk at a specified load usually by means of an arm or lever and attached weights. Other loading methods have been used, such as, hydraulic or pneumatic. Wear results may differ for different loading methods. Wear results are reported as volume loss in cubic millimeters for the pin and the disk separately. When two different materials are tested, it is recommended that each material be tested in 27 both the pin and disk positions. The amount of wear is determined by measuring appropriate linear dimensions of both specimens before and after the test, or by weighing both specimens before and after the test. If linear measures of wear are used, the length change or shape change of the pin, and the depth or shape change of the disk wear track (in millimeters) are determined by any suitable metrological technique, such as electronic distance gaging or stylus profiling. Linear measures of wear are converted to wear volume (in cubic millimeters) by using appropriate geometric relations. Linear measures of wear are used frequently in practice since mass loss is often too small to measure precisely. If loss of mass is measured, the mass loss value is converted to volume loss (in cubic millimeters) using an appropriate value for the specimen density. Wear results are usually obtained by conducting a test for a selected sliding distance and for selected values of load and speed. Other test conditions may be selected depending on the purpose of the test. Wear results may in some cases

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be reported as plots of wear volume versus sliding distance using different specimens for different distances. Such plots may display non-linear relationships between wear volume and distance over certain portions of the total sliding distance, and linear relationships over other portions. Causes for such differing relationships include initial “break-in” processes, transitions between regions of different dominant wear mechanisms, etc. The extent of such non-linear periods depends on the details of the test system, materials, and test conditions.

PROCEDURE

Immediately prior to testing, and prior to measuring or weighing, clean and dry the specimens. Take care to remove all dirt and foreign matter from the specimens. Use non-chlorinated, non-film-forming cleaning agents and solvents. Dry materials with open grains to remove all traces of the cleaning fluids that may be entrapped in the material. Steel (ferromagnetic) specimens having residual magnetism should be demagnetized. Report the methods used for cleaning.

Measure appropriate specimen dimensions to the nearest 2.5 µm or weigh the specimens to the nearest 0.0001 g. Insert the disk securely in the holding device so that the disk is fixed perpendicular (61°) to the axis of the resolution. Insert the pin specimen securely in its holder and, if necessary, adjust so that the specimen is perpendicular (61°) to the disk surface when in contact, in order to maintain the necessary contact conditions. Add the proper mass to the system lever or bale to develop the selected force pressing the pin against the disk. Start the motor and adjust the speed to the desired value while holding the pin specimen out of contact with the disk. Stop the motor. Set the revolution counter (or equivalent) to the desired number of revolutions. Begin the test with the specimens in contact under load. The test is stopped when the desired number of revolutions is achieved. Tests should not be interrupted or restarted. Remove the specimens and clean off any loose wear debris. Note the existence of features on or near the wear scar such as: protrusions, displaced metal, discoloration, micro cracking, or spotting. Remeasure the specimen dimensions to the nearest 2.5 µm or reweigh the specimens to the nearest 0.0001 g, as appropriate. Repeat the test with additional specimens to obtain sufficient data for statistically significant results.

RESULTS AND DISCUSSION

Comparison of experimental results versus Artificial Neural Network Algorithm

The wear rate for EN-31 steel for various specimen is calculated by varying load, time, sliding velocity, speed on Pin on disc apparatus as shown in below the table.

Table 7 Shows the Wear Ratio of EN-31 Steel

Levels	**Sliding velocity**	**Normal load**	**Exp Duration**	**Disc Speed**	**Tool wear rate for En 31 steel**
Units	**m/s**	**N**	**S**	**rpm**	**g**
1	1.0	15	400	191	0.014
2	1.25	30	320	239	0.029
3	1.50	45	266.67	287	0.030
4	1.75	60	228.57	334	0.028
5	2.0	75	200	382	0.029

Specimen 1

Before wear: 22.219g , After wear: 22.205g 36

Wear rate: 0.014g

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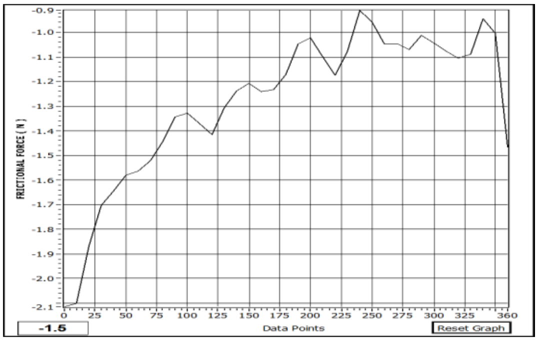


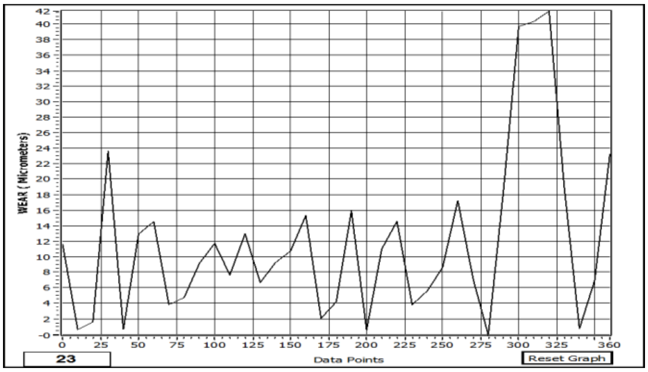


FIGURE 2.The Frictional Force And Wear Rate For The Specimen En-31

Specimen 2
Before wear: 22.164g , After wear: 22.135g
Wear rate: 0.029g

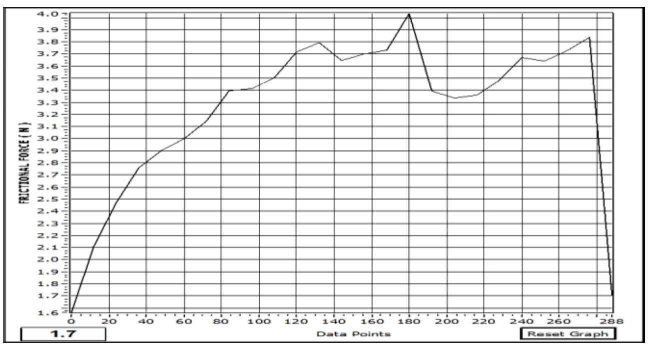
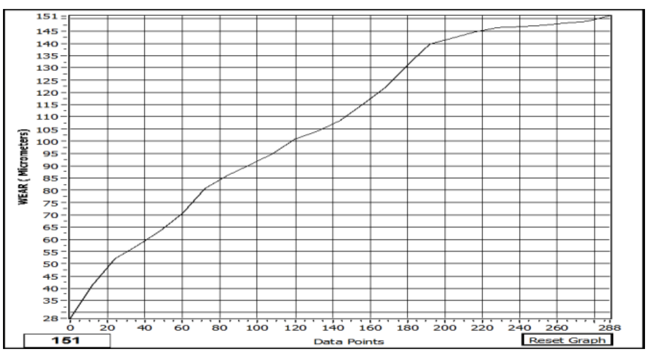


FIGURE 3.The Frictional Force And Wear Rate For The Specimen En-31



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Specimen 3
Before wear: 22.668g , After wear: 22.638g
Wear rate: 0.030g

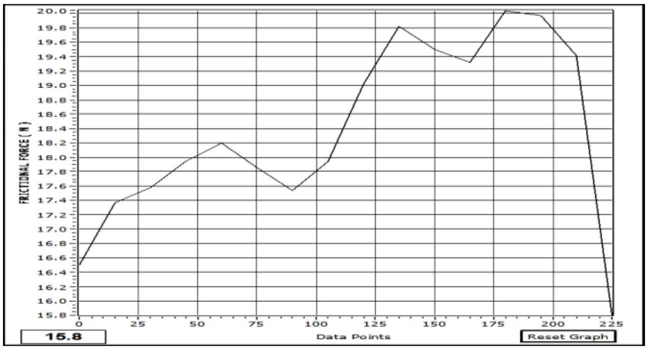
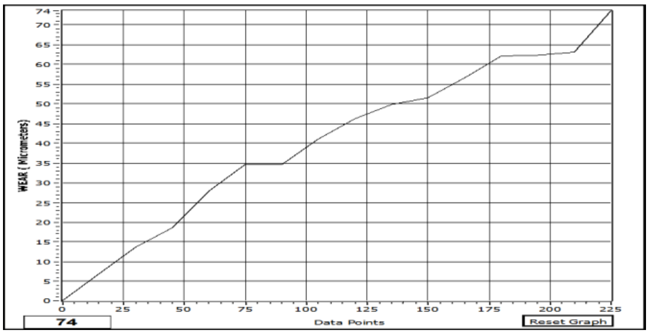


FIGURE 3.The Frictional Force And Wear Rate For The Specimen En-31



Specimen 4
Before wear: 22.159g , After wear: 22.131g
Wear rate: 0.028g

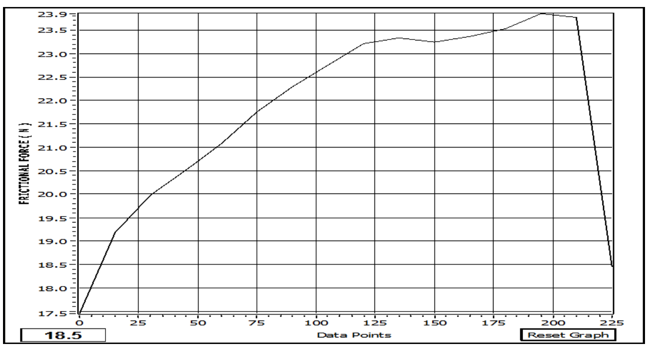


FIGURE 4.The Frictional Force And Wear Rate For The Specimen En-31

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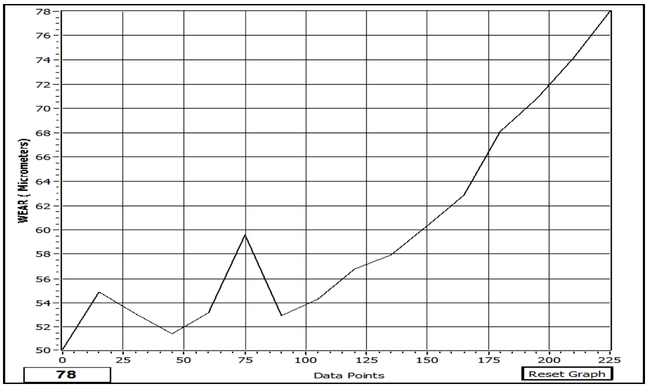


Specimen 5
Before wear: 22.218g , After wear: 22.189g
Wear rate: 0.029g

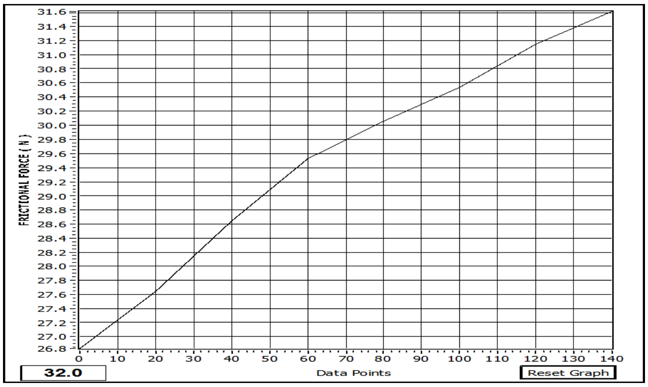
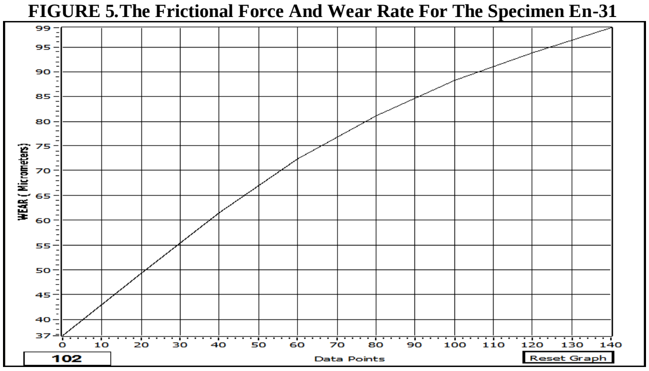


FIGURE 5.The Frictional Force And Wear Rate For The Specimen En-31



The wear rate for the material EN-31 for various specimen is calculated and the graph has been plotted successfully for wear rate and frictional force.

ANN for EN-31 STEEL
Based on the experimental data for the material EN-31 we have to develop a three layer of neural network with a back propagation algorithm is trained using input and output data to find out the optimum range of wear rate.

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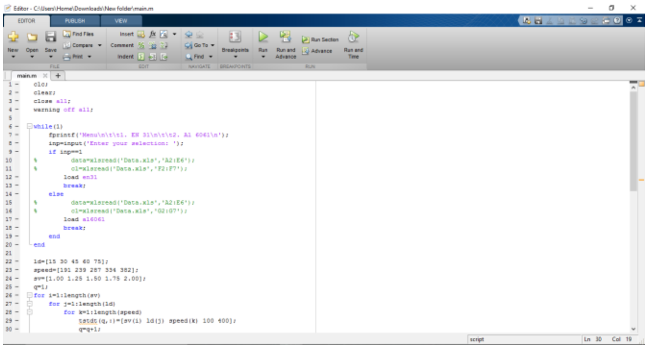

FIGURE 6.The The Back Propagation Neural Network Algorithm is developed to find the optimum wear rate for the material En 31

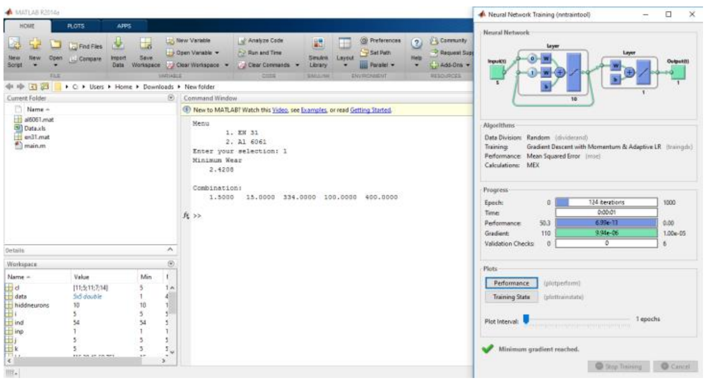

FIGURE 7.Algorithm is coded as input and start to run. Then the above fig shows that the optimum wear rate for the material EN-31

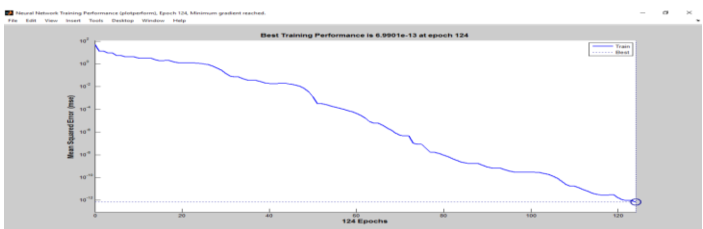

FIGURE 7. Training performance for the algorithm.

CONCLUSION

The experimental test was done with EN-31 steel for the samples at various load, time, speed, sliding velocity on Pin on disc apparatus and the results were obtained. The ANN has shown excellent performance when introduced to optimize wear rate for the material EN-31.By expanding the number of trails and further optimizing the ANN configuration the predicted accuracy would be improved.

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