Turning processes investigation of materials austenitic, martensitic and duplex stainless steels and prediction of cutting forces using artificial neural network (ANN) techniques

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In this study focus on the performance of machining parameters that are cutting forces and surface roughness when the turning processes AISI 304 (Austenitic), AISI 420 (Martensitic) and AISI 2205 (Duplex) stainless steels have been explored the machinability performance and cutting forces. The machining tests have been conducted on a CNC turning center using coated cemented carbide tools. Machining parameters have been chosen cutting speeds (120, 150, 180 and 210 m/min), feed rate (0.1 mm/rev) and depth of cut (1 mm/rev) according to cutting tool manufacturer recommendation catalog. Machining forces and surface roughness variables have been measured when the turning processes. It has also been investigated the worn of cutting tools and explored under the scanning electron microscope (SEM). An ANN model has been developed using experimental results. Experimental results and ANN model results have been compared with each other. It seemed that cutting forces have been modeled using ANN techniques and ANN results have been very close to experimental results.

Keywords: Stainless steels, Machining, Surface roughness, Cutting force, Artificial neural networks (ANN)

1 Introduction

Stainless steels are a group of highly alloyed steels which have corrosion resistance properties. In addition, these groups of metals have high tensile strength, low thermal conductivity, high ductility and the high degree of work hardening\textsuperscript{1,3}. They are used especially demanding corrosion resistance states. These materials are used in chemical and food processing equipment, various machinery parts, jet engine parts and medical equipment\textsuperscript{2,4}.

Stainless steels have high work hardening tendency and poor thermal conductivity\textsuperscript{1,5}. It reveals the problems like poor surface finish and high tool wear\textsuperscript{6}. A low thermal conductivity of these materials increases the temperatures at the primary and secondary deformation zones. This, in turn, results in rapid tool wear. High ductility of stainless steels is the reason for the poor surface finish and poor chip breakability. High ductility together with high work hardening rate contributes to built up edge (BUE) formation at the tooltip even at high cutting speeds. The presence of BUE at the tooltip deteriorates noticeably the surface finish\textsuperscript{1}.

The quality of surface roughness is very important. This quality effects machine performance and machine part life. Surface roughness is a significant design specification and also manufacturing dimensions. It impacts on wear resistance and fatigue strength. Because all of the machine parts work with each other. The lower surface roughness value has resulted in the less wear on the machine parts\textsuperscript{1}. Many of the publications on the machining of stainless steels are interested in austenitic grades steels\textsuperscript{4,6,8-12}.

Ozkan et al.\textsuperscript{13} have been investigated the coated carbide and cermet cutting tools performance and modeling with the ANN techniques. They have measured the cutting forces and surface roughness according to manufacturing parameters. Ozkan\textsuperscript{14,15} has investigated coated cermet/carbide cutting tool performance on surface roughness and cutting forces. Both studies contain ANN modeling. Ulas\textsuperscript{16} has investigated coated and uncoated carbide cutting tools performance when the processing turning operation. He also measured cutting forces and surface roughness. And, then he has improved a new ANN model to predict to surface roughness.

Kaladhar et al.\textsuperscript{17} have explored the AISI 304 workpiece machinability performance in turning

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operations. They have used AISI 304 as a workpiece and on (CVD) coated cemented carbide cutting insert as a cutting tool. They have used ANOVA analysis for determining to influence of cutting parameters. Cutting parameters have been optimized. Kaladhar et al.\textsuperscript{18} have used the method of Taguchi to determine the cutting process parameters. That has machined AISI 304 on turning operations. They have used CVD cutting inserts. They have researched the surface roughness and material removal rate (MRR). They have tried to determine significant factors of cutting parameters. Dhananchezian et al.\textsuperscript{19} have investigated the effect of cutting parameters using the liquid nitrogen as a coolant. In these processes, they have used AISI 304 stainless steel as a workpiece and PVD TiAlN turning tool inserts on the turning operations.

In addition, there are studies about turning processes in the literature. In some of these studies the surface roughness and cutting forces were investigated according to test parameters. These parameters are especially, cutting tool, cutting speed, feed rate, material, depth of cut, etc. Some studies were performed to investigate the cutting tool performance and effective tool life\textsuperscript{13-16,20-27}. The aim of the present study is to investigate cutting forces and surface roughness when the turning of AISI 304, 420 and 2205 materials. The machining tests were conducted on a CNC turning center using coated cemented carbide tools. Machining parameters have cutting speeds (120, 150, 180 and 210 m/min), feed rate (0.1 mm/rev) and depth of cut (1 mm/rev). Cutting tool manufacturer proposed parameters have been put into effect on the experiments. These values have been chosen as common cutting speed values of stainless steel materials. Cutting force and surface roughness variation have been explored by changing the cutting speeds. Feed rate and depth of cut have been taken as constant. So cutting speed and material type parameters have been examined deeply on the cutting forces and surface roughness. Machining forces and surface roughness values have been determined. An ANN model was developed. An ANN results and the experimental result were compared.

2 Experimental Procedures
2.1 Mechanical and metallurgical examination of the workpiece materials

The commercially available AISI 304, AISI 420 grade and AISI 2205 stainless steels were selected as the workpiece materials. The chemical properties (weight %) of the workpiece materials are given in Table 1 (a & b).

In order to determine the tensile strength of the workpiece, the tensile test samples were prepared according to TS-138 standard. The samples were subjected to a tensile test at ambient temperature using a SHIMADZU type testing device with a crosshead speed of 2 mm/min. At least, three types of specimens were tested and average values were measured. The hardness values of the workpiece materials were also determined. Four hardness readings were performed per each workpiece.

All the test specimens were grounded and polished to 1µm finish for metallographic examination. Test samples were electronically etched in 100 ml of distilled water with 10 g oxalic acid at 5V for 45s. The etching revealed the microstructures of the austenite, ferrite and martensite phases of the workpieces. Nickel (Ni) and nitrogen (N) are widely used for alloying element for stainless steels. These two elements improve the mechanical properties of material. Ni and N elements bring almost the same features to the material. Nitrogen and nickel have provided more corrosion, wear and fatigue resistant to stainless steels. The price of nickel has increased 5 times in the last 10 years. Nitrogen is cheaper than nickel. So, nitrogen has been used widely instead of nickel.

2.2 Machining tests

The machining tests were performed by single point continuous turning of AISI 2205, AISI 304 and AISI 420 stainless steel workpieces in cylindrical form on a Johnford TC-35 CNC turning center. It has a variable spindle speed of up to 4000 rpm and a power rating of 10 kW. Coolant fluid was not used during the tests. The coated cemented carbide inserts were used on the tests. These cutting tools were produced by WIDIA with the geometry of CNMG120404. Cutting tool manufacturer proposals have been put into effect on the experiments while machining the austenitic, martensitic and duplex stainless steels. AISI 304 provides higher machining rates and lower tool wear in manufacturing processes. AISI 420 has easily machined specification. But when the hardness of AISI 420 above 30HRC, machining of this material has become more difficult. AISI 2205 has high strength material. So it's machinability specification is very hard. AISI 2205 cutting speeds are about 20% slower than for AISI 304.
CNMG120404 inserts were attached mechanically on a rigid tool holder. The tests were performed in accordance with ISO 3685 standards. Cutting speeds were selected between 120 to 210 m/min interval. The cutting speed was tried in steps of 30 m/min. Feed rate and depth of cut were chosen constant, 0.1 mm/rev and 1.0 mm, respectively. Surface roughness has been measured using a Mitutoyo Surftest 211 instrument. Three measurements were performed on the each surface. Cutting forces were measured with a Kistler 9257A three component piezoelectric dynamometer. Kistler 9257A was connected with 5019 B130 charge amplifiers. Data collected in PC using Kistler Dynoware force measurement software. The worn cutting tools were also explored under a JEOL JSM 6360 LV type scanning electron microscope (SEM).

### Table 1(a) — Chemical compositions of the work piece materials.

<table>
<thead>
<tr>
<th>Material</th>
<th>C%</th>
<th>Si%</th>
<th>Mn%</th>
<th>P%</th>
<th>S%</th>
<th>Cr%</th>
<th>Mo%</th>
<th>V%</th>
<th>Ni%</th>
<th>Cu%</th>
<th>W%</th>
<th>Co%</th>
</tr>
</thead>
<tbody>
<tr>
<td>AISI 2205</td>
<td>0028</td>
<td>0365</td>
<td>143</td>
<td>0023</td>
<td>0001</td>
<td>2353</td>
<td>318</td>
<td>0065</td>
<td>628</td>
<td>0163</td>
<td>0073</td>
<td>0049</td>
</tr>
<tr>
<td>AISI 304</td>
<td>0033</td>
<td>042</td>
<td>145</td>
<td>0046</td>
<td>0021</td>
<td>1966</td>
<td>0318</td>
<td>0061</td>
<td>834</td>
<td>0487</td>
<td>0034</td>
<td>0136</td>
</tr>
<tr>
<td>AISI 420</td>
<td>0184</td>
<td>0364</td>
<td>072</td>
<td>0037</td>
<td>0031</td>
<td>13919</td>
<td>0012</td>
<td>0027</td>
<td>0067</td>
<td>001</td>
<td>001</td>
<td>0016</td>
</tr>
</tbody>
</table>

### Table 1(b) — Mechanical properties of work piece materials.

<table>
<thead>
<tr>
<th>Material</th>
<th>Tensile Strenght (MPa)</th>
<th>% Extension amount</th>
<th>Yield Strenght (MPa)</th>
<th>Creş</th>
<th>Nieş</th>
</tr>
</thead>
<tbody>
<tr>
<td>AISI 2205</td>
<td>640</td>
<td>25</td>
<td>460</td>
<td>27,0</td>
<td>8,0</td>
</tr>
<tr>
<td>AISI 304</td>
<td>510</td>
<td>35</td>
<td>230</td>
<td>19</td>
<td>10</td>
</tr>
<tr>
<td>AISI 420</td>
<td>760</td>
<td>&gt;12</td>
<td>600</td>
<td>13</td>
<td>0.05</td>
</tr>
</tbody>
</table>

**Fig. 1** — Stress-strain curves of AISI 304, AISI 2205 and AISI 420 stainless steels stress-strain curves.

Stainless steels, which are indispensable materials of the industrial society, are essentially alloys containing iron, carbon and most of the time nickel, mainly chrome-plated. Corrosion resistance in stainless steels increases with increasing chromium content. There are many opinions about the stainless steel's stainless ability, but the most recognized of them is that a thin and thin chromium oxide layer is formed on the stainless steel, which prevents the oxidation and corrosion of this layer. Stainless steel corrosion resistance requires at least 12% Cr content and oxygen in the environment. Another effect of chromium is to increase the strength of the steel under heat at a great rate. This effect manifests itself, especially in tensile and friction strengths.

In terms of corrosion resistance, austenitic stainless steels have more advantages than others. Ferritic and martensitic steel types are only alloyed with chromium. The most commonly used austenitic stainless steel is 18/8 (18% Cr - 8% Ni) steel. These alternatives are usually sulfur or selenium. Additives improve processability and reduce corrosion resistance. This feature reduces tool life to minimize problems such as burr formation, poor surface quality, stacking chip formation and negative screw pull conditions. Austenitic steels are characterized by a high deformation hardening rate and low thermal
conductivity. Materials with these properties are more difficult to process other than steels. The shavings from these materials tend to stick to the cutting edge and cause a BUE, which may cause the cutting tool to break. The austenitic materials themselves have a high rate of deformation hardening. If this effect is excessive, the processed surfaces of the workpiece will have areas of very high hardness. In this case, the surface of the material is at least twice as hard as the interior. These materials must be selected in such a way as to ensure that the cutting depths to be selected during processing and the feed rates allow the cutting edge to penetrate this hard plate on the surface. It is advantageous to process the austenitic steels in cold drawn conditions. In this case, agglomerate chip formation, poor surface quality, problems are significantly reduced. When ordinary carbon steels are machined, a large part of the heat energy formed is removed with the sawdust. The low thermal conductivity of austenitic steels results in high cutting temperatures. The most important step to increase machinability is addition of sulfur to steel.

Alloys in stainless steels with martensitic structure contain 0.1-1 % C and 12-17 % Cr. The most important features distinguishing martensitic stainless steels from other stainless steels are; carbon percentage is low and it is possible to harden by heat treatment. These steels, like the carbon steels, form a very rigid structure by performing a quenching phase transformation. The corrosion resistance of these steels is less than that of austenitic stainless steels, although it is very high compared to mild steels. If it contains 1% C, and if heat treatment is applied under favorable conditions, very high hardnesses can be obtained. The addition of a small number of other alloys increases the toughness, strength and corrosion resistance. Martensitic steels are magnetic; heat treatment is used in areas exposed to corrosion requiring strength. The most commonly used types are 410 and 420.

Duplex stainless steels have a double-phase internal structure, and duplex stainless steels with ferrite grains containing austenite or ferrite in austenite grains have twice the yield strengths compared to austenitic stainless steels. Duplex stainless steels have good corrosion resistance and mechanical properties. Important characteristics of duplex stainless steel are high resistance to rust, high strength, high hardness, good weldability, and good machinability. The resistance to high stiffness and corrosion is provided by the austenite phase, while the resistance to corrosion and corrosion is provided by the ferrite phase. Resistance to rust is mainly due to high Cr, Mo, and N content. The ferrite-austenite balance has a critical effect on the properties of the duplex stainless steel. When the austenite ratio increases, the strength decreases. The best properties of these steels are in the microstructure when the ferritesite phases are almost equal. Ni and Cr ratios and phase structures are shown in Fig. 2.

The ductility values of as-received AISI 304, AISI 420 and AISI 2205 were found to be 22, 62 and 44 %, respectively. Annealing gives the maximum softening for wrought martensitic stainless steel. The hardness values of 84, 95 and 98 HRB were determined for AISI 304, AISI 420 and AISI 2205, respectively.

![Fig. 2 — Schaffler - Delong diagram](image-url)
The microstructures of the workpiece materials were also evaluated. The results are shown in Fig. 3. As seen in Fig. 3(a), the microstructure of as-received AISI 304 grade austenitic stainless steel consists of equiaxed austenite grains and annealing twins. The microstructures of as-received AISI 420 grade martensitic stainless steel consist of mainly ferrite phase and carbide in the annealed condition (Fig. 3(b)). These steels contain chromium sufficiently high carbon and most, but not all, contain less amount of nickel (Table 1 (a and b)). The martensitic stainless steels are normally supplied in the annealed condition and they were generally heat treated after forming process in order to improve mechanical properties. The microstructures of AISI 2205 grade duplex stainless steel consist of the austenite phase and ferrite phase (Fig. 3(c)). The high strength of duplex stainless steel comes from austenite phase while the ferrite phase provides good ductility.

3.2 Cutting forces

Figure 4 shows the effects of cutting speed and workpiece materials on the cutting forces produce when machining three different types of stainless steels. When Fig. 4 is investigated, it was seen that the cutting forces decreased when cutting speed was increased to 150 m/min from 120 m/min for AISI 304 and cutting forces firstly decreased until 150 m/min then increased between 150 and 210 m/min for AISI 420. Cutting forces were firstly increased at 150 m/min then began to reduce at 210 m/min for AISI 2205. This decrement in the cutting forces were partly reasoned by a reduction in the contact area and partly by a drop in shear strength in the flow zone as its temperature steps up with increasing cutting speed. Similar findings were also reported by Korkut et al. and Ciftci for AISI 304 stainless steel. However, such a decrease in the cutting forces with escalation cutting speed is not observed for AISI 2205. This can be attributed to its duplex structure.

When a comparison was made among the forces generated while machining the three workpiece materials, the highest cutting forces were observed for AISI 2205 that the lowest cutting forces for AISI 304 at all the cutting speeds (Fig. 4). Workpiece strength and ductility are important factors for determining the cutting forces. Higher strength requires higher forces to shear the workpiece in the primary and secondary deformation zones. However, the tensile strength of AISI 2205 is lower than that of AISI 304 (Fig. 4). Therefore, the higher cutting forces for AISI 2205 can be explained by its high yield strength, nitrogen contained austenite phase, low sulfur content, high level of initial work hardening rate and relatively higher ductility (Fig. 4). The ductility values of AISI 304 and AISI 2205 are 24 and 44 %, respectively.

Tool-chip contact length on the cutting tool rake face increases with increasing workpiece ductility. Increasing tool-chip contact length, in turn, requires higher forces to shear the workpiece material on the cutting tool rake face (secondary deformation zone). In addition, tool wear also increases the cutting forces.
Figure 4 shows the cutting force fluctuations (amplitude) for the three different stainless steels at 180 m/min cutting speed. As seen from Fig. 5, the range of fluctuations obtained with AISI 2205 is significantly larger than those obtained with AISI 304 and AISI 420. The structure of AISI 2205 is different from those of AISI 304 and AISI 420. The structures of AISI 304 and annealed AISI 420 consist mainly of austenite, ferrite, and carbide, respectively, while the structure of AISI 2205 having high strength austenite and high ductility ferrite phases. This duplex structure of AISI 2205 is considered to result in much larger fluctuations. Low strength ferrite phase and high strength austenite phase lead to variations in the cutting forces when shearing takes place in the primary and secondary shear zones.

Three SEM images are given in Fig. 5 for AISI 304, 420 and 2205. These images were taken from the worn tools used to cut the three grades of stainless steels. Figure 5(c) shows the tool used to cut AISI 2205. When compared to the other two images (Fig. 5 (a and b)), higher flank wear is seen from this image. Therefore, the high cutting forces generated when cutting AISI 2205 can also be attributed to high flank wear.

Built up edge (BUE) appears as a result of cutting speed, temperature, and wear. BUE formation occurs depending on the relationship between the cutting tool material and the workpiece material. The chips formed in the case of low-temperature and high-pressure, removal from material microparts adhere to the cutting tool surface as adhesion. This has resulted in both surface roughness or dimensional accuracy. It causes the increase in the manufacturing costs.

The SEM images of the worn cutting tools in Fig. 6 show considerable end cutting edge wear for all the three grades of stainless steels. The images in the right column were the magnified views of the worn end cutting edges in the left column. It has been observed to compatible with experimental results and literature results.\textsuperscript{24-27}

3.3 Surface roughness

Surface roughness measurements were made by taking the arithmetic average of the measurements taken from 5 different points on the referenced circle on the same part of the cylindrical workpiece. Surface roughness values were obtained on the test sample at three different distances at different distances.

Figure 7 shows workpiece surface roughness values saved when machining AISI 304 austenitic, AISI 420 martensitic and AISI 2205 duplex stainless steels with coated carbide tools at various cutting speeds. The average values were measured three points for each cutting condition.
The surface roughness values obtained are quite high as shown in Fig. 7. These high surface roughness values can be clarified by the highly tender nature of stainless steels, which increases the trend to form a large and unstable built-up edge (BUE) on the cutting edge. The asset of the large and non-stable BUE reasons poor surface finish.

Austenitic stainless steels bond extremely vigorous to the tool during cutting and this bonding is clearer than when cutting other steels because the chips more often remain squeeze to the tool after cutting. When the chip is broken away, it may bring away with it a fragment of the tool, particularly when cutting with cemented carbides. This, in turn, results in rapid tool wear. In addition, a rough tool surface is obtained. A rough tool surface especially at the end cutting edge results in a high surface roughness value since the edge is indirectly contacted with the newly machined surface. Ciftci reported end cutting edge wear for carbide tools in the turning of AISI 304 austenitic stainless steels. The curves in Fig. 7 show that lower surface roughness values were generated for AISI 304 and AISI 2205 when machining at 150 and 180 m/min cutting speeds while higher values were generated at 210 m/min cutting speed. At the cutting speed of 120 m/min, the lowest cutting speed employed in this study, somewhat higher surface roughness values were generated than those generated at 150 m/min cutting speed. With increasing cutting speed from 120 m/min to 150 m/min, a drop in the surface roughness values for AISI 304 and AISI 2205 workpiece materials were observed.

However, further increase beyond 150 m/min increased the surface roughness values of all the workpiece materials. The decrease in surface roughness with increasing cutting speed can easily be clarified by decreasing built-up edge formation trend with increasing cutting speed. However, further increase in surface roughness with increasing cutting speed can be referred to enhancement cutting tool wear at more excessive cutting speeds.

### 3.4 Artificial neural network (ANN) model

ANN, a subdivision of artificial intelligence, has both learning and predictive abilities. ANN works with different learning algorithms. A neuron is the basic element of ANN. Neurons duties, shapes and size can be varied. Neurons activities are important. An ANN may be seen as a black box which contains hierarchical sets of neurons (e.g. processing elements) producing outputs for certain inputs. A neural network consists of inputs layer, hidden layers, and output layers (Fig. 8). Each processing element consists of data collection, processing the data and sending the results to the relevant consequent element. The whole process may be viewed in terms of the inputs, weights, the summation function, the activation function and outputs (Fig. 9).

To realize the learning function, a database with inputs and outputs is needed. Using these data in different mathematical functions, it is derived a conclusion based on hidden layers and network model in the process. An output value is obtained corresponding to the input value of the function. A converged result is obtained by testing the functions and algorithms of the inputs against the inputs to the values of the learning data. This process continues until the output values match the values in the database in response to inputs that are closer to the actual data. When the convergence value reaches the desired value, the test and validation process is executed. Unused learning in the learning function is determined by the fact that memorization is performed in a real learning environment. If the learning action has taken place, the test data and ANN output values derive values that are compatible with each other. If the memorization action is performed, i.e., the test data and the ANN output are not compatible with each other, a new ANN algorithm needs to be developed.

In this study, cutting forces changes when the turning processing the materials AISI 304, AISI 420 and AISI 2205. The processing parameters were changed in the duration of experiments. Material types (AISI 304, AISI 420 and AISI 2205), cutting speeds (120, 150, 180 and 210 m/min), feed rate (0.1 mm/rev), depth of cut (1 mm/rev), time (s) were taken.

![Fig. 7 — Surface roughness data versus cutting speed for turning AISI 304, AISI 420 and AISI 2205 stainless steels using coated carbide tools at a feed rate of 0.1 mm/rev and depth of cut of 1.0 mm.](image)
as inputs data and Fx, Fy and Fz were taken as output data (Table 2). An ANN database was created using these data and a new ANN model was developed. The data were obtained according to study parameters that have 355 lines x 6 columns. Among them, 30% data have been randomly selected for usage of the test data and other 70% data were used as training data. 70% of the data consist of the ANN model original database. The remaining 30% of the unused portion of the learning process was used to validate the ANN model's test and prediction results. The accuracy of the developed model was determined by looking at the predictive ability, which is an important feature of the ANN model.

Material types, cutting speed, feed rate and duration of processes time were used as input layers, and cutting forces (Fx, Fy and Fz) were used as output layers. Levenberg-Marquardt (LM) algorithm and Multi Layer Perception (MLP) were used in the ANN model. In the ANN model, tansig, logsig and purelin transfer functions (f) have been used and expressed as follows (Eqs (1-4)):

\[ \text{NET}_i = \sum w_{ij}x_j + w_{bi} \] … (1)

\[ a = \text{tansig}(n) = \frac{2}{1+e^{-2n}} - 1 \] … (2)

Table 2 — Turning processes input and output parameters.

<table>
<thead>
<tr>
<th>INPUTS</th>
<th>OUTPUTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Materials</td>
<td>Force (N)</td>
</tr>
<tr>
<td>AISI 304</td>
<td>120</td>
</tr>
<tr>
<td>AISI 420</td>
<td>150</td>
</tr>
<tr>
<td>AISI 2205</td>
<td>180</td>
</tr>
<tr>
<td>210</td>
<td></td>
</tr>
<tr>
<td>Cutting speed (mm/min)</td>
<td>Time for Fx (s)</td>
</tr>
<tr>
<td>AISI 304</td>
<td>0.1</td>
</tr>
<tr>
<td>AISI 420</td>
<td>duration of duration of duration of processes processes processes</td>
</tr>
<tr>
<td>AISI 2205</td>
<td>180</td>
</tr>
</tbody>
</table>

Fig. 8 — Cutting force amplitudes for (a) AISI 304, (b) AISI 420 and (c) AISI 2205 stainless steels at 180 m/min.
\[ a = \text{logsig}(n) = \frac{1}{1 + e^{-n}} \]  
\[ a = \text{purelin}(n) \]  
\[ n: \text{number of processing elements in the previous layer where NET is the weighted sum of the input.} \]

An ANN model was developed using MATLAB NN tool. For this aim a new ANN code has been prepared and developed. Different models have been tested. Best model was determined. Figure 10 shows improved an ANN Model using MATLAB.

In this ANN model (5 Inputs+9 tansig+15 tansig+17 logsig+3 purelin+3 outputs) has been used. Figure 11 shows best training performance of ANN model. This figure has emphasised the best training performance of the model (0.00089709). This means; the best training result is different from the original experimental data. This is precision of the model's best training performance.

Figure 12 shows training performance of ANN (R=0.99974) and Fig. 13 shows best validation performance of ANN. According to figure; training performance has under the $10^{-4}$, test performance has under the $10^{-2}$ and validation performance has under the $10^{-2}$.

Figure 14 shows error histogram of ANN and Fig. 15 shows the ANN predictions; training, test and validation performance. These figures have been getting from prepared MATLAB code. ANN model results were compared with the statistically. Table 3 shows statistical performance of training step. The back propagation learning algorithm has been used with scaled conjugate gradient (SCG) learning algorithm and Levenberg-Marquardt (LM) learning algorithm versions at the training and testing stages of the Networks. The number of hidden layers and the number of neurons for each hidden layer were determined. Then, the numbers of iterations were entered by the user, and the training starts. The training continues either to the end of the iterations or reaching the target level of errors.

### 3.5 Testing the accuracy of ANN modelling

In order to understand an ANN modeling performance, the test data which has never been
processed the ANN and compared with the experimental results. The statistical methods of $R^2$, RMSE and MEP values have been used for making comparisons\textsuperscript{13,16,28-30}. The same data obtained from the regression analysis is used to determine the mentioned values. These values are determined by the following Eqs (5-7):

$$\text{RMSE} = \left( \frac{1}{p} \sum_{j} |t_j - o_j|^2 \right)^{1/2} \quad \ldots (5)$$

$$R^2 = 1 - \frac{\sum (t_j - o_j)^2}{\sum (t_j - \bar{o}_j)^2} \quad \ldots (6)$$

$$\text{MEP} = \frac{\sum \left| \frac{t_j - o_j}{t_j} \times 100 \right|}{p} \quad \ldots (7)$$

Using the trial error method, the structure of the network (i.e., the number of neurons and hidden layers) were altered and the training operation was repeated. Number of neurons have changed at each
hidden layer (e.g. from 5 to 150) for determination and find the best performance of ANN model. Experimental results and ANN model results have been compared with each other (Table 4 and Fig. 15). As view of the Table 4 and Fig. 16 results are compatible with each other. Table 3 shows the statistical reliability of the model also.

4 Conclusions

Turning tests were accomplished on AISI 304, AISI 420 and AISI 2205 stainless steels using coated cemented carbide cutting tools. According to material type AISI 304, 420 and 2205, machining parameters effects have been examined on surface roughness and cutting forces. Cutting tool manufacturer proposals have been accepted as machining parameters (cutting speed, cutting depth, feed rate). According to the results acquired, the following results can be drawn:

(i) Cutting forces varied depending on the cutting speed and the work piece material. Generally, increasing the cutting speed decreased the cutting forces. The highest cutting forces were obtained for AISI 2205 due to its mechanical properties. The lowest cutting forces were obtained for AISI 304.

(ii) The surface roughness values were found to be quite high in most cases though the work piece...
material and cutting speed influenced the surface roughness of the machined work pieces.

(iii) These higher surface roughness values were attributed to the high ductility of the work piece materials and the cutting edge wear which was indirectly contacted with newly operated surface. It has been observed, surface roughness was increased between 120-210 m/min for AISI 420 but surface roughness was fluctuated between 120-210 m/min for AISI 304 and 2205.

(iv) Best surface roughness values were obtained at cutting speeds of 180 m/min for AISI 304 and AISI 304 and 120 m/min for AISI 420.

In this study has been revealed the material type and cutting parameters effects on the cutting forces and surface roughness. The main aims of the scientific studies are gaining efficiency. ANN model and experimental studies results were compared with each other. Experimental studies are both costly and time consuming. A separate experiment is required for every each experimental condition. One of the most important features of ANN is to learn the procedure, and the other is to predict the result of a set of input parameters that have never been tested, with high accuracy, depending on the learning ability obtained. Thus, it is possible to produce the result values against the input sets in the boundary range. Using this method saves both time and effort. ANN techniques can be used in machining sector without any trouble.

References

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