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Prediction of Cutting Force in Turning Process by Using Artificial Neural Network

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Abstract

Cutting forces are important factors for determining machine serviceability and product quality. Factors such as speed feed, depth of cut and tool noise radius affect on surface roughness and cutting forces in turning operation. The artificial neural network model was used to predict cutting forces with related to inputs including cutting speed (m/min), feed rate (mm/rev), depth of cut (mm) and work piece hardness (Map). The outputs of the ANN model are the machined cutting force parameters, the neural network showed that all (outputs) of all components of the processing force cutting force FT (N), feed force FA (N) and radial force FR (N) perfect accordance with the experimental data. Twenty-five samples of experimental data were used, including nineteen to train the network. Moreover six other experimental tests were implemented to test the network. The study concludes that ANN was a dependable and precise method for predicting machining parameters in CNC turning operation.

Keywords: Cutting force, ANN, turning operation.

1. Introduction

Turning operation is a very rife material removal technique in manufacturing field; Researches treat with several sides like: geometric and metallurgical feature of the cutting tool, work piece material effect on the operation and process parameters like (cutting speed, feed rate, and depth of cut). hard turning operation produce high cutting forces and temperatures that effect on cutting parameters , The influence of all these factors give rise to concatenation of physical, chemical and thermo-mechanical phenomena that effect on metal so modeling of cutting forces is necessary [1].

The machining force in turning process is a three-dimensional vector. Three components represent it, namely the cutting force Ft which is in the direction of cutting axis, the radial force Fr in the direction of radial axis and feed force Fa in the direction of feed axis the cutting force has the biggest value in the three force components. Several researchers learned such components and taking into accounts the effect of cutting variables Stachurski, et al. [2] utilized a power polynomial to model the cutting force during turning steel C45.

Astakhov and Xiao [3] applied mathematical models to estimate the cutting forces during machining two materials, aerospace aluminum alloy 2024 and T6AISI bearing steel E52100.

Hrinath Gowd et al. [4] performed experiments involving the effect of cutting forces and surface roughness, which were appreciably influenced by cutting speed, feed and depth of cut, then developed a second order polynomial model in which studied The effect of operating parameters on cutting forces and surface roughness and used RSM for the prediction of mathematical models for estimation of Fx, Fy, Fz and surface roughness.

Bouacha et al. [5] during machining of AISI 52100 Steel with CBN tool show the effect of operating parameters speed, feed and depth of cut on cutting forces and surface roughness by Using three level factorial design , the study showed that surface roughness effected by feed rate and cutting speed ,while cutting forces influenced by depth of cut.

In this work, an ANN process is suggest to predict cutting force components in hard turning feed force Fa, radial force Fr and cutting force Ft. An artificial neural network model is a powerful method to deal with nonlinear functions or to model systems with unknown input–output relations [6-7].

In experimental procedures a lot of money is wasted as well as time. Used (ANN) as a powerful and accurate tool for machining process modeling to avoid this, where it succeeded in providing an accurate theoretical model and showed accuracy in the modeling of cutting forces quicker than numerous methods that used in complex machining operations such as milling and turning Budak et al. [8].

Szecsi et al. [9], an analytical model was used which gave the average predictive error (9.5%) on the cutting forces and also provided a neural network for training with an average error rate (3.5%.) where the cutting forces were modeled based feed-forward multilayered neural networks were trained by BP algorithm that inspected the effect of two main factors affecting on error convergence namely education rate η and momentum term α.

The neural network is trained on the cases that are reversed during the training process as it is distinguishing by being able to find a base linking outputs to inputs through training operation [10, 11].

Mohanned H.AL-Khafaji[12], built a neural network model in which the cutting parameters were optimize to produce the lowest machining force and the study showed compatibility with experimental data and the calculated correlation coefficients were equal to one.

This paper aims to build a neural network model to link the cutting variables, work piece hardness, cutting speed, cutting depth, feed rate, to the machining Force during machining of AISI 52100 bearing steel and providing an accurate model for modeling cutting forces faster relying on operating parameters and creating a rule that connects inputs and outputs through training operations.

2. Experimental Work

An empirical data set of cutting forces measured through hard turning of AISI 52100 bearing steel with CBN tool.

2.1 Work Piece Material

AISI 52100 steel is great used for a diversity of applications that used in bearings and rotating machinery. Like valve bodies, pumps and fittings, etc. schedule (1, 2) display the mechanical properties and chemical composition of AISI 52100 steel respectively.

Experiments were accomplished dry straight turning operation using lathe type SN 40 and AISI 52100 bearing steel as a work piece material with round bars (40 mm diameter and 250 mm length) with chemical composition in schedule (2) . Tool used is CBN 7020, the rake angle γ = 12 °, clearance angle α = 9 °, helix angle λ = 25°, the cutting zone shown in Figure (1), Figure (2) shows components of machining force.

Table 1,
Mechanical properties AISI 52100 bearing steel.

Tensile	Yield	Bulk modulus	Shear modulus	Poisson's ratio	Thermal conductivity
MPa	Mpa	Gpa	Gpa		W/m.K
520	415 Min	140	80	0.27-0.30	46.6

Table 2,
The typical Chemical composition of AISI 52100 bearing steel.

	Si	Mn	P	S	C	Cr
MIN～MAX%	0.15～0.35	0.25～0.45	≤0.015	≤0.015	0.95～1.10	1.35～1.60

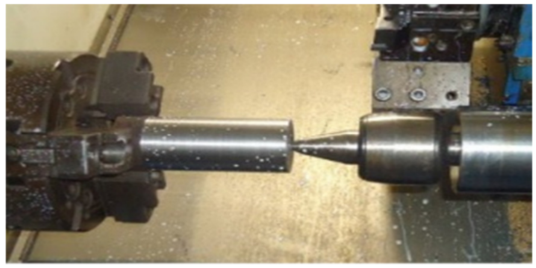


Fig. 1. Cutting zone.

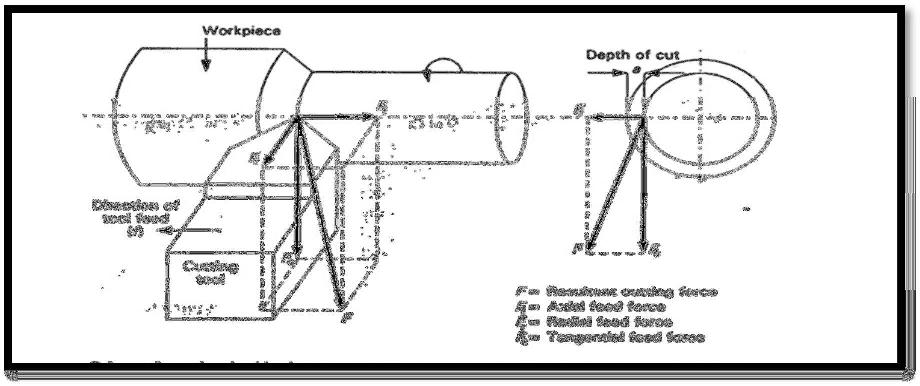


Fig. 2. Components of machining force [13].

2.2 Artificial Neural Network

After execution the experiments at design matrix, output response Measured and recorded be obvious in the schedule (3) cutting speed, feed, cutting depth and work piece hardness are taken as input parameter.

Table 3,
Experimental dataset.

	HRC	Speed	Feed	Depth of cut	FT(N)	FR(N)	FA(N)
1	45	100	0.05	0.15	55.325	100.3	15.4
2	50	150	0.10	0.15	81.205	85.505	25.905
3	52	200	0.15	0.15	105.297	83.725	28.153
4	54	250	0.20	0.15	129.389	35.945	29.156
5	56	300	0.30	0.15	164.9	122.2	32.604
6	52	150	0.05	0.20	72.172	73.06	34.313
7	54	200	0.10	0.20	96.264	94.28	35.316
8	56	250	0.15	0.20	120.4	85.5	35.316
9	45	300	0.20	0.20	136.7	123.59	36.319
10	50	100	0.30	0.20	201.92	189.84	47.98
11	56	200	0.05	0.25	7.231	81.835	42.479
12	45	250	0.10	0.25	113.6	109.5	40.245
13	50	300	0.15	0.25	145.895	114.175	39.55
14	52	100	0.20	0.25	167.247	154.395	52.698
15	54	150	0.30	0.25	216.979	198.615	56.146
16	50	250	0.05	0.30	96.33	80.51	48.155
17	52	300	0.10	0.30	120.422	101.73	49.158
18	54	100	0.15	0.30	158.214	141.95	59.861
19	56	150	0.20	0.30	172.3	103.2	60.864
20	45	200	0.30	0.30	224.29	194.26	61.075
21	54	300	0.05	0.40	126.804	97.82	65.431
22	56	100	0.10	0.40	164.596	183.04	76.134
23	45	150	0.15	0.40	180.94	146.13	73.9
24	50	200	0.20	0.40	206.8	194.4	79.7
25	52	250	0.30	0.40	256.432	214.6	79.338

Neural network models are used to predict FT, FR and FA respectively Levenberg Marquardt algorithm was chosen due to its high accuracy in similar function approximation [14] that used to train the networks in order to improve the generalization of the network, a regularization" scheme was used in conjunction with the Levenberg-Marquardt algorithm. The input/output dataset was divided randomly into two categories: training dataset and test dataset. The automatic Bayesian Regularization was used for training with Levenberg Marquardt combined with Bayesian regularization.

Two steps were used to model ANN; First for training, whereas second for testing the network. two layer back propagation network was employed As a tool for mapping the complex and highly inter-active process parameters such as cutting speed, feed, depth of cut and work piece hardness.
The Input data, target data set and testing data used in ANN modeling are shown in Tables (4&5) respectively

Table 4,
Input Dataset and Target data

Input Dataset					**Target data.**		
Exp No.	**HRC**	**Speed**	**Feed**	**Depth of cut**	**FT(N)**	**FR(N)**	**FA(N)**
2	50	150	0.10	0.15	81.2	85.5	25.9
3	52	200	0.15	0.15	105.3	89.7	28.2
4	54	250	0.20	0.15	129.4	95.9	29.2
6	52	150	0.05	0.20	72. 2	73.1	34.3
7	54	200	0.10	0.20	96.3	94.3	35.3
9	45	300	0.20	0.20	136.7	123.6	36.3
10	50	100	0.30	0.20	161.9	189.8	47.9
11	56	200	0.05	0.25	87.2	81.8	42.5
13	50	300	0.15	0.25	145. 9	114.2	39.6
14	52	100	0.20	0.25	167.2	154.4	52.7
15	54	150	0.30	0.25	176.9	99.6	56.1
16	50	250	0.05	0.30	96.3	80.5	48.2
17	52	300	0.10	0.30	130.4	98.7	49.2
18	54	100	0.15	0.30	158.2	141.9	59.9
20	45	200	0.30	0.30	184.3	190.3	63.1
21	54	300	0.05	0.40	126.8	97.8	65.4
22	56	100	0.10	0.40	164.6	146.0	76.1
23	45	150	0.15	0.40	180.9	184.1	77.9
25	52	250	0.30	0.40	189.4	198.6	82.3

Table 5,
Testing data

Exp No	**HRC**	**Feed**	**Speed**	**Depth of cut**
1	45	0.05	100	0.15
5	56	0.30	300	0.15
8	56	0.15	250	0.20
12	45	0.10	250	0.25
19	56	0.20	150	0.30
24	50	0.20	200	0.40

3. Results and Discussion
3.1 Analysis of Variance

The experimental results were from table (3) analyzed with an analysis of variance (ANOVA), which they are used to determine the factors that most influence the performance characteristics (cutting forces) are shown in Table (6, 7, and 8) respectively.

The overall significant of mathematical model can be seen in table (6,7,8) respectively ,the greatest value of F ratio among the variables was (18.88) for feed accordingly the mostly effected variable on FR with p-value (0.000) and R-sq(adj)= 85.15% as see in schedule(6).

From schedule (7) the most influence variable is depth of cut with F ratio (333.46), p-value(0.000)and R-sq(adj)= 98.40% for FA . From schedule (8)the most influence variable on FT value was fee with F ratio (861.72), p-value (0.000) and R-sq(adj)= 99.51% **.**

Figure (3,4,5), illustrate the Residual Plot for FR,FA,FT respectively .

Table 6,
Analysis of variance for FR

Source	DF	Adj-SS	Adj-MS	F-Value	P-Value
Speed	4	7163	1790.8	5.24	0.023
Feed	4	25800	6449.9	18.88	0.000
Depth	4	17599	4399.7	12.88	0.001
HRC	4	1900	475.0	1.39	0.320
Error	8	2733	341.6		
Total	24	55194			

R-sq= 95.05% R-sq(adj)= 85.15% R-sq(pred)= 71.65%

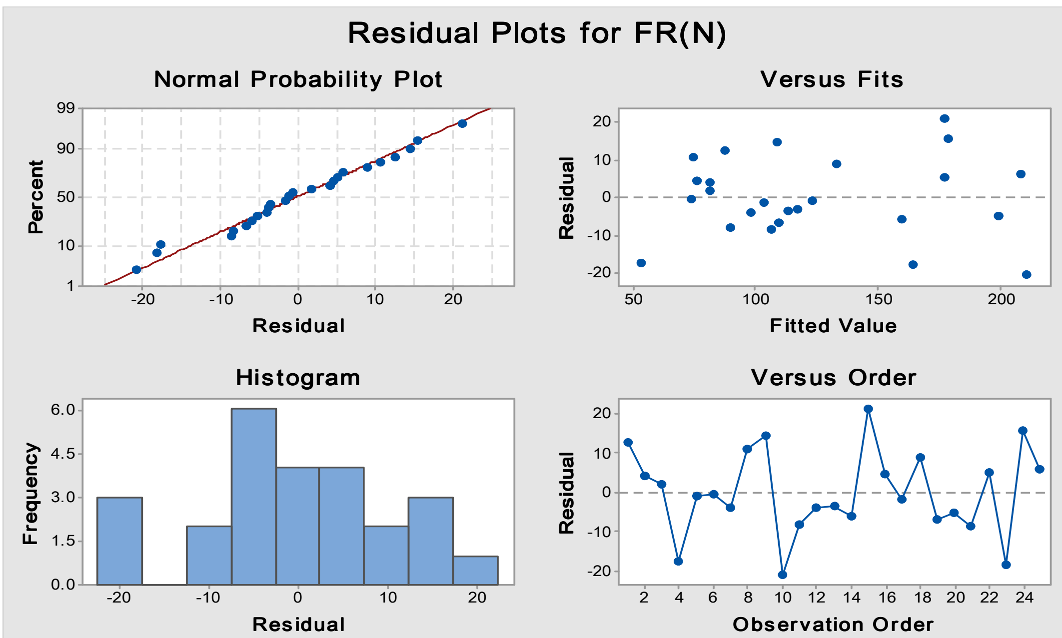


Fig. 3. Residual Plot for FR

Table 7,
Analysis of variance for FA

Source	DF	Adj-SS	Adj-MS	F-Value	P-Value
Speed	4	131.39	32.85	6.42	0.013
Feed	4	616.43	154.11	30.14	0.000
Depth	4	6820.81	1705.20	333.46	0.000
HRC	4	53.98	13.49	2.64	0.113
Error	8	40.91	5.11		
Total	24	7663.52			

R-sq= 99.47% R-sq(adj)= 98.40% R-sq(pred)= 94.79%

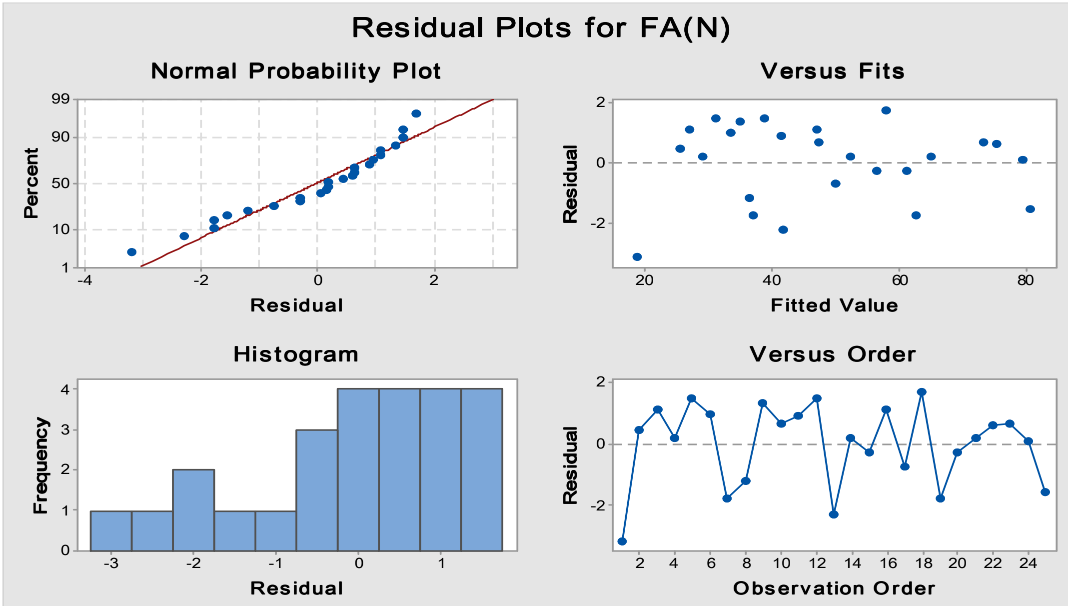


Fig. 4. Residual Plot for FA.

Table 8,
Analysis of variance for FT

Source	DF	Adj-SS	Adj-MS	F-Value	P-Value
Speed	4	282.3	70.6	5.34	0.022
Feed	4	45527.4	11381.9	861.72	0.000
Depth	4	18325.3	4581.3	346.85	0.000
HRC	4	80.7	20.2	1.53	0.282
Error	8	105.7	13.2		
Total	24	64321.4			
R-sq=99.84% R-sq(adj)= 99.51% R-sq(pred)= 98.40%					

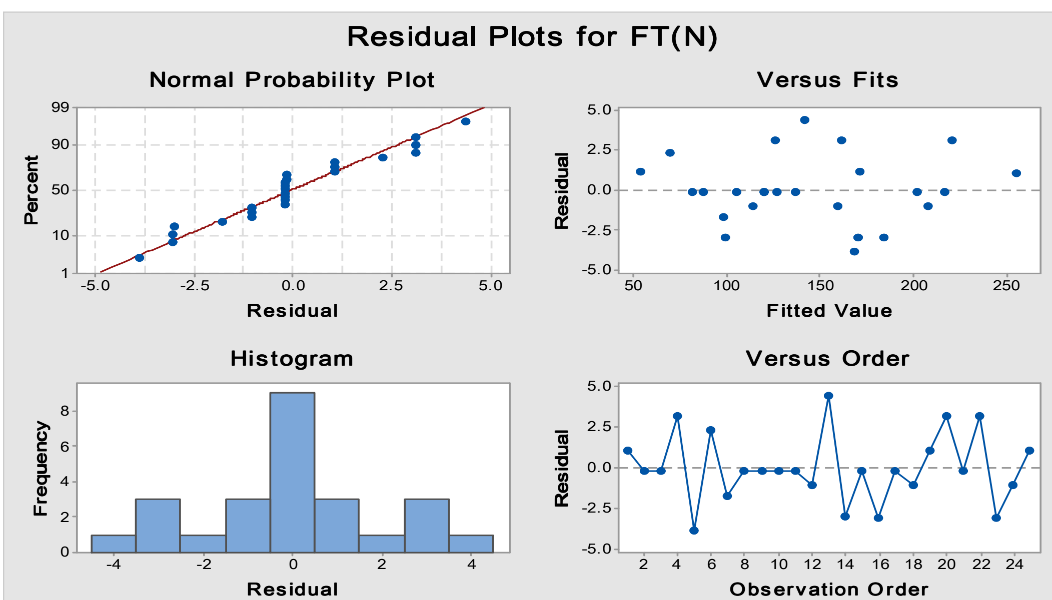


Fig. . 5. Residual Plot for FT.

While, the mathematical model for FR,FA,FT are developed as shown in equations (1,2,3) to represent the relationship between the input parameters speed(S), feed(F),depth of cut(D) ,work piece hardness (HRC) and the response FR,FA,FT

FR(N)=124.40+ 29.50 S-100 - 3.10 S-150 + 5.30 S-200- 19.19 S-250- 12.50 S-300- 37.70 F-0.05- 9.59 F_0.10- 10.11 F-0.15- 2.10 F-0.20 + 59.50 F-0.30- 38.87 D-0.15- 11.15 D-0.20+ 7.30 D-0.25- 0.07 D-0.30+ 42.79 D-0.40+ 10.35 HRC-45 + 8.48 HRC-50 + 1.10 HRC-52 - 10.68 HRC-54 - 9.25 HRC-56 ...(1)

FA(N)=48.208+ 2.207 S-100+ 2.018 S-150 + 1.137 S-200 - 1.766 S-250- 3.595 S-300- 7.052 F-0.05- 2.856 F-0.10- 0.852 F-0.15+ 3.540 F-0.20+ 7.221 F-0.30- 21.964 D-0.15- 10.359 D-0.20- 1.984 D-0.25+ 7.615 D-0.30+ 26.693 D-0.40- 2.820 HRC-45+ 0.050 HRC-50+ 0.524 HRC-52 + 0.974 HRC-54 + 1.272 HRC-56 ...(2)

FT(N)=144.066+ 5.39 S-100 + 0.65 S-150 - 0.09 S-200- 0.84 S-250- 5.12 S-300- 56.49 F-0.05- 28.85 F-0.10- 1.92 F-0.15+ 18.42 F-0.20 + 68.84 F-0.30- 36.84 D-0.15- 18.57 D-0.20+ 2.12 D-0.25+ 10.25 D-0.30+ 43.05 D-0.40- 1.90 HRC-4+ 2.36 HRC-50+ 0.25 HRC-52 + 1.46 HRC-54 - 2.18 HRC-56 ...(3)

3.2 Development of ANN Modelling

Neural Network model consist of four input neurons and three output corresponding to cutting speed (S), feed–rate (F),work piece hardness (HRC),depth (D) and (FT,FR,FA) respectively by used Hebbian learning rule . The number of the hidden layer and the number of neurons equal to (2) and (4) respectively. Number of input parameters is equal to 4; Figure (6) shows the schematic view of the neural network used.

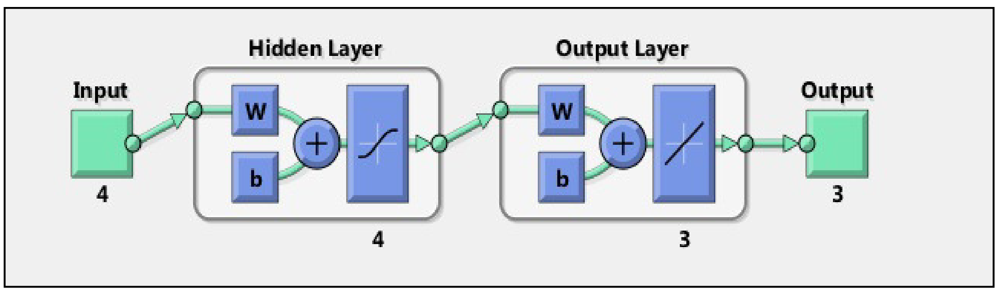


Fig.. 6. the schematic view of the neural network used.

<u>Network Model</u>

Network Kind: Feed Forward Back Propagation
Training: Levenberg Maquardtl Algorithm
Number Of Layers: 2
Output Layer: 3
Number OF Neurons: 4
Performance: Mean Square Error
Transfer Function For Hidden Layer: Tran Sigmoid Transfer Function for Output: Pure Linear
Adaption of Learning Rate: LEARNGDM

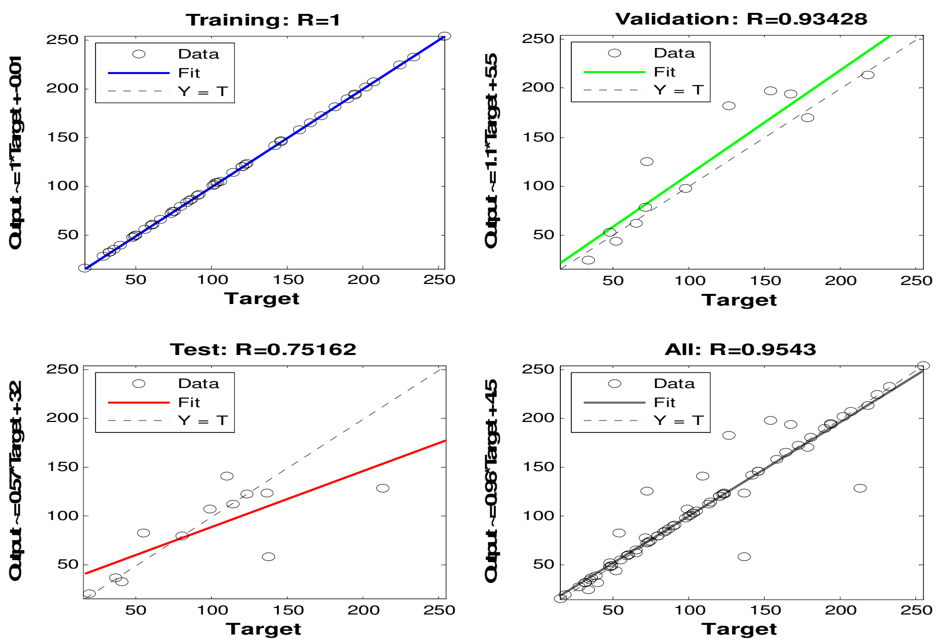


Fig. .7. the graphical representation of the proposed network.

The experimental database is utilized to construct the neural network. About 24% of data are utilized for model testing, whereas 76% of data are utilized for model training. Figure (7) show the graphical representation of the proposed network while figure (8) shows the best validation performance was (727.3687) at epoch 6.

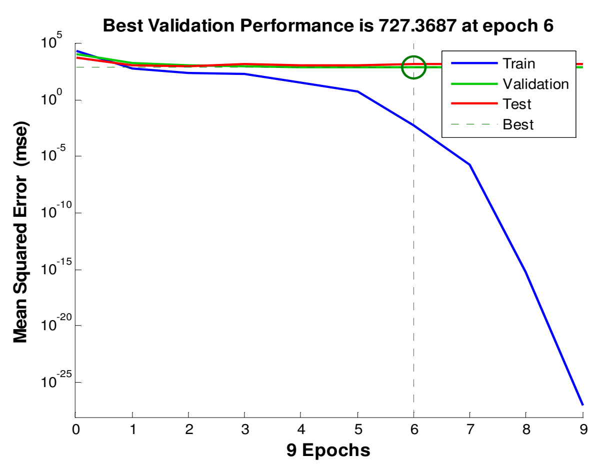


Fig. 8. Mean Square Error-Number of Epochs

Error % = (Measured- Predicted)/ Measured *100%)| ... (4)

MSE = ∑ (Measured- Predicted) ^2/ number of experiments ... (5)

Table (9) shows the measured and predicted cutting forces obtained in testing, as well as the mean square error (MSE) values. It can be seen from this table that the average prediction error($\overline{\phi}$) found (4.57%, 4.925%, and 4.62%) the accuracy was (95.43%, 95.075%, and 95.38%) and MSE (2.345, 40.2, and 85.37%) relative to FA, FR, FT respectively.

Table 9.
Results testing dataset

Input testing data					FA(N)			FR(N)			FT(N)		
exp No	**depth of cut**	**speed**	**feed**	**HRC**	**Measured**	**Predicted**	**Error (%)**	**Measured**	**Predicted**	**Error (%)**	**Measured**	**Predicted**	**Error (%)**
1	0.15	100	0.05	45	15.4	17.5	13.64	100.3	105.1	4.79	55.3	54.7	1.08
5	0.15	300	0.30	56	32.6	31.1	4.60	122.2	111.6	8.67	164.9	179.7	8.98
8	0.20	250	0.15	56	35.3	35.1	0.57	85.5	75.9	11.22	120.4	126.9	5.40
12	0.25	250	0.10	45	40.2	42.3	5.22	109.5	113.3	3.47	113.6	117.2	3.17
19	0.30	150	0.20	56	60.9	61.9	1.64	103.2	102.4	0.78	172.3	169.2	1.80
24	0.40	200	0.20	50	79.7	81.1	1.76	194.4	195.6	0.62	206.8	221.9	7.30
					$\overline{\phi}$(%)=4.57, MSE=2.345, Accuracy (%)=95.43			$\overline{\phi}$(%)=4.925, MSE=40.2, Accuracy (%)=95.075			$\overline{\phi}$(%)=4.62, MSE=85.37, Accuracy (%)=95.38		

The expected and empirical values of FA, FR and FT as shown in the testing results in Table (9), which was represented in figures(9, 10, & 11) respectively show that the network gave good interaction with the test data .

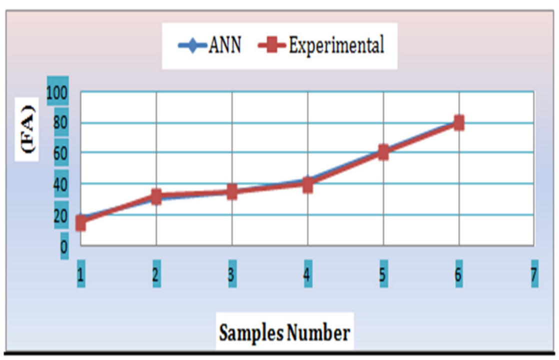


Fig. 9. Experimental & Predicted FA values for testing data set.

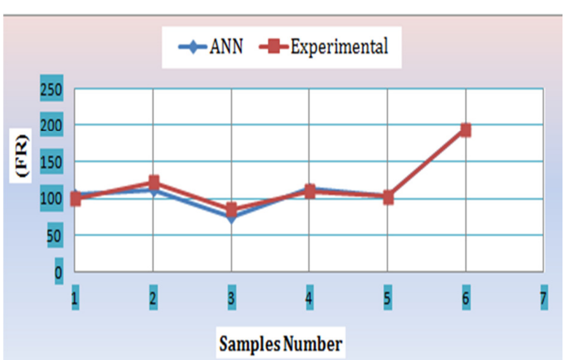


Fig. 10. Experimental & Predicted FR values for testing data set.

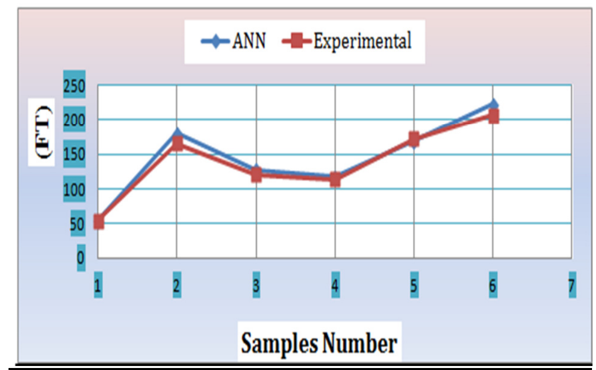
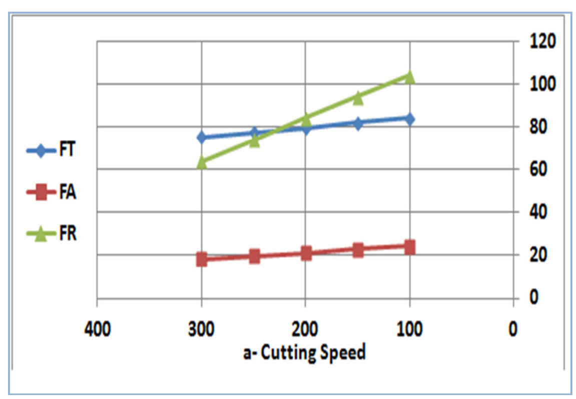
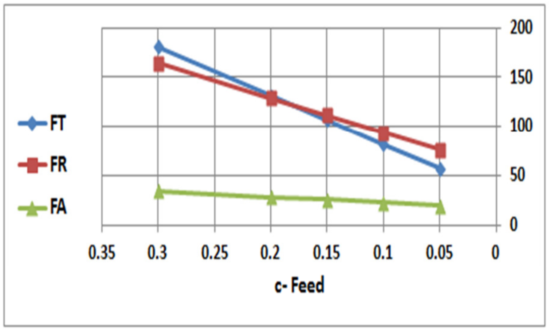


Fig. 11. Experimental & Predicted FT values for testing data set.





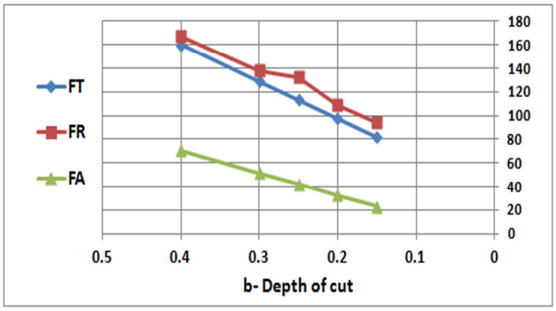


Fig. 12. Experimental testing cutting force components as a function of:

a- Cutting speed (F=0.1; D=0.15; HRC=45)
b- Depth of cut (F=0.1; S= 150; HRC=45)
c- Feed (S= 150; D= 0.15; HRC= 45)

As mentioned previously, there are many parameters of the process that have a significant impact on the experimental cutting forces, figure (12) shows the difference of cutting forces with the cutting speed, feed and depth of cut, which can be observed through Figure (12 a, b , c), so it is natural to prefer numerical techniques such as Artificial Neural Networks or Multiple Regression or Genetic algorithm to describe the efficiency of a complex process.

Table 10,
Comparison between ANN vs. Experimental values for cutting forces in training

No	Depth of cut	Feed	Speed	HRC	ANNFA	Exp FA	Error(%)	ANN FR	Exp FR	Error(%)	ANN FT	Exp FT	Error(%)
1	0.15	0.10	150	50	25.2	25.9	2.70	85.5	85.5	0.00	81.5	81.2	0.36
2	0.15	0.15	200	52	28	28.2	0.70	89.7	89.7	0.00	105.3	105.3	0.00
3	0.15	0.20	250	54	29.2	29.2	0.00	95.9	95.9	0.00	129.4	129.4	0.00
4	0.20	0.05	150	52	34.3	34.3	0.00	73.1	73.1	0.00	72.2	72.2	0.00
5	0.20	0.10	200	54	35.3	35.3	0.00	86.3	94.2	8.38	100.3	96.3	4.15
6	0.20	0.20	300	45	36.3	36.3	0.00	123.6	123.6	0.00	136.6	136.6	0.00
7	0.20	0.30	100	50	47.9	47.9	0.00	189.8	189.8	0.00	161.9	161.9	0.00
8	0.25	0.05	200	56	42.7	42.5	0.81	82.3	81.8	0.61	87.3	87.2	0.11
9	0.25	0.15	300	50	39.6	39.6	0.00	114.2	114.2	0.00	145.9	145.9	0.00
10	0.25	0.20	100	52	52.7	52.7	0.00	154.4	154.4	0.00	167.2	167.2	0.00
11	0.25	0.30	150	54	56.1	56.1	0.00	99.6	99.6	0.00	176.9	176.9	0.00
12	0.30	0.05	250	50	48.2	48.2	0.00	80.5	80.5	0.00	96.1	96.3	0.21
13	0.30	0.10	300	52	49.2	49.2	0.00	98.7	98.7	0.00	130.4	130.4	0.00
14	0.30	0.15	100	54	59.8	59.9	0.16	141.9	141.9	0.00	158.1	158.2	0.06
15	0.30	0.30	200	45	63.1	63.1	0.00	190.3	190.3	0.00	184.3	184.3	0.00
16	0.40	0.05	300	54	66.2	65.4	1.22	97.8	97.8	0.00	126.8	126.8	0.00
17	0.40	0.10	100	56	75.9	76.1	0.26	146.1	146	0.06	164.6	164.6	0.00
18	0.40	0.15	150	45	75.1	77.9	3.68	184.1	184.1	0.00	180.9	180.9	0.00
19	0.40	0.30	250	52	82.7	82.3	0.48	198.6	198.6	0.00	189.4	189.4	0.00

From table (10) the average prediction error($\overline{\phi}$) values are found for FA, FR and FT predictions. It was 0.526%, 0.476%, and 0.257%, respectively

Figure (13) shows the final graphical comparison between experimental and predicted cutting forces in training. as shown in Table 10, a good and comprehensive match was found between numerical and experimental results , however a variation in results was observed, as the MAPE was from 0.16 to 3.68% for the FA and from 0.61 to 8.38% for FR while for FT was from 0.21 to 4.15% essentially,

The ANN model appears to have proven to be effective, however its accuracy can be further enhanced by improving some ANN parameters, such as learning rate and momentum

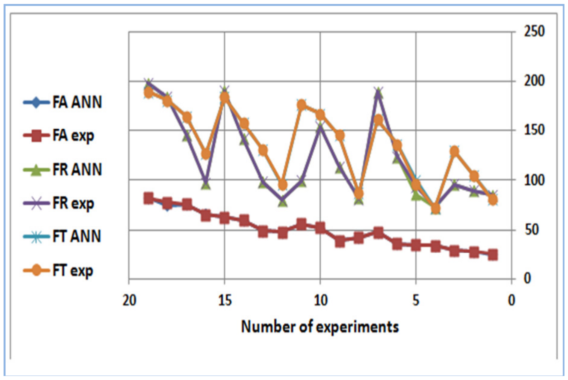


Fig. 13. Comparison between experimental vs. ANN for training

4. Conclusions

A model for predicting values of FA, FR and FT were developed by Artificial neural Networks techniques, full factorial design used to implement the empirical design.(ANN) program in MATLAB used to find the relation between the input process parameters and the output variables.

From the ANOVA analysis, found that the most influencing factor on the FR values was the feed with F-ratio (18.88), followed by the depth of the cut with F-ratio (12.88) while the most influence variable on FA was depth of cut with F-ratio (333.46) and for FT was feed with F-ratio (861.72).

The better model were chosen dependent on the best performance error for different network components then plotted the graphs between the measured and predicted values in the ANN results, models have been estimated by means of the Percentage deviation between the predict values and the actual values. From training results the average prediction error ($\overline{\phi}$)found (0.526%, 0.476%, and 0.257%) the accuracy was (99.474%, 99.524%, 99.743%) and MSE (0.487%, 3.298%, 0.850%) relative to FA, FR, FT respectively.

It is clear that the ANN predicted results shows perfect correspond with the empirical results, ANN demonstrate its qualification in optimizing the Turning process parameters. The sophisticated ANN model can be further joined with optimization algorithms like GA to improve the End milling parameters.

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التنبؤ بقوى القطع في عملية الخراطة باستخدام الشبكة العصبية الاصطناعية

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الخلاصة

تعد قوى القطع من العوامل المهمة لتحديد امكانية تشغيل الماكينة وجودة المنتج . تؤثر عوامل مثل السرعة والتغذية وعمق القطع وصلابة الأداة على خشونة السطح وقوى القطع في عملية الخراطة .تم استخدام نموذج الشبكة العصبية الاصطناعية للتنبؤ بقوى القطع مع المدخلات ذات الصلة بما في ذلك سرعة القطع ومعدل التغذية وعمق القطع وصلابة قطعة العمل. قوى القطع الألية كانت تمثل مخرجات الشبكة العصبية الاصطناعية ، اظهرت الشبكة العصبية ان جميع (المخرجات) لجميع مكونات قوى المعالجة قوة القطع وقوة التغذية والقوة الشعاعية متطابقة تماما مع البيانات التجريبية. تم استخدام خمسة وعشرون عينة من البيانات التجريبية ، بما في ذلك تسعة عشر كانت لتدريب الشبكة، علاوة على ذلك ستة لاختبار الشبكة . ولخصت الدراسة الى ان الشبكة العصبية الاصطناعية طريقة موثوقة ودقيقة للتنبؤ بمعلمات القطع في عملية الخراطة