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Neural Network Modeling of Cutting Force and Chip Thickness Ratio For Turning Aluminum Alloy 7075-T6

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Abstract

The turning process has various factors, which affecting machinability and should be investigated. These are surface roughness, tool life, power consumption, cutting temperature, machining force components, tool wear, and chip thickness ratio. These factors made the process nonlinear and complicated. This work aims to build neural network models to correlate the cutting parameters, namely cutting speed, depth of cut and feed rate, to the machining force and chip thickness ratio. The turning process was performed on high strength aluminum alloy 7075-T6. Three radial basis neural networks are constructed for cutting force, passive force, and feed force. In addition, a radial basis network is constructed to model the chip thickness ratio. The inputs to all networks are cutting speed, depth of cut, and feed rate. All networks performances (outputs) for all machining force components (cutting force, passive force and feed force) showed perfect match with the experimental data and the calculated correlation coefficients were equal to one. The built network for the chip thickness ratio is giving correlation coefficient equal one too, when its output compared with the experimental results. These networks (models) are used to optimize the cutting parameters that produce the lowest machining force and chip thickness ratio. The models showed that the optimum machining force was (240.46 N) which can be produced when the cutting speed (683 m/min), depth of cut (3.18 mm) and feed rate (0.27 mm/rev). The proposed network for the chip thickness ratio showed that the minimum chip thickness is (1.21), which is at cutting speed (683 m/min), depth of cut (3.18 mm) and feed rate (0.17 mm/rev).

Keywords*: Machining forces, chip thickness ratio, neural network, optimization, turning operation.*

1. Introduction

The turning process is among the most significant cutting operation. It would once generate a variety of cylindrical products like solid, hollow, profile shafts and threads, etc. Due to its important, a lot of scientists considered the parameter which impacting the process either to generate a good finished product, improve tool life or both. Additionally, they examined the power usage reduction and the production time [1].

The machining force (F_u) in turning operation is a three-dimensional vector. Three components represent it, namely, the cutting force(F_c) which is in the direction of cutting axis, the passive force (F_p) in the direction of radial axis and feed force (F_f) in the direction of feed axis as shown in Fig. **1**. 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 [1] applied mathematical models to estimate the cutting forces during machining two materials, aerospace aluminum alloy 2024 and T6AISI bearing steel E52100. Agustina, et al. [3] implemented a design of experiment to evaluate the impact of cutting factors to the cutting force when turning aluminum alloy (UNS A97075) in dry conditions. They examined the influence of micro grove size and shape on the cutting temperature, cutting force and tool wear. C.X.Yue, et al. [4] produced a three-dimensional model by using

Abaqus/Explicit to simulate the cutting operation of hardened steel GCr15. For their model the cutting temperature, surface residual stresses, cutting force and the side flow were investigated.

The chip thickness ratio (CTR) gives essential indication for the cutting process stability. It can be explained as the ratio relating the chip thickness to the undeformed chip thickness. It is usually greater than unity (CTR>1) [5]. Through the definition, the higher CTR means that the chip is thicker. The reason is the limitation to the chip movement, that in turns, can cause rise in the machining power and vice versa. Santos, et al. [5] researched the machining force (Fu), chip thickness ratio (CTR) and chip disposal during turning ductile (1350-O grade) and high strength (7075-T6 grade) aluminum alloys at different cutting conditions. Astakhov and Shvets [6] investigated the chip compression ratio with several cutting parameters.

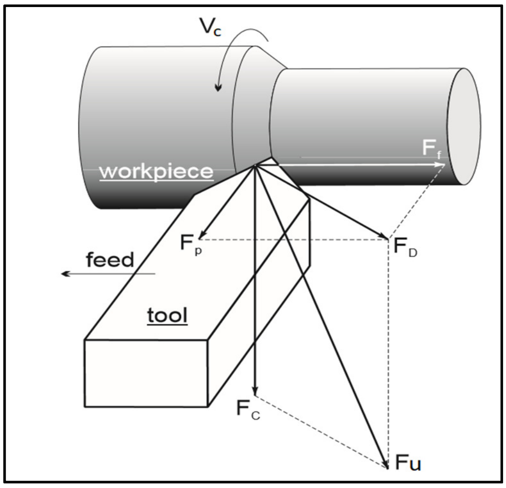

Fig. 1. Machining force and its components.

In recent years, the scientific approaches such as neural network, fuzzy logic, genetic algorithm, ant colony or combinations of them, are used to model nonlinear, complicated and multi parameters system. In addition, they are used in the optimization of such systems. The neural network is miming human brain. It consists of an input layer to presents data to the network, output layer to produces the network response, and one or more hidden layers. The hidden and output layers' topology, weights and activation functions are the network characterization. A neural network is trained with various data sets and tested with other testing data sets to reach an optimum topology and weights. Once the network is trained, it can be used for prediction, simulation, monitor and control complicated system [7].

Sick [8], used the neural network to estimate the development of tool wear. Sharma, et al., [9] utilize the neural network to model the cutting force and surface roughness as a response to the approach angle, cutting speed, feed rate and depth of cut. Chen, et al., [10] constructed nested artificial neural network. Their model consists from two networks, the first one is the enclosed network which take the cutting parameters to predict the cutting force and tool vibration, and the second is the output network which take the outputs of the first network and the cutting parameters as inputs and give the surface roughness as output. Sangwana, et al., [11] optimized the surface roughness during turning of Ti-6Al-4V titanium alloy by integrating feed forward neural network and the genetic algorithm. AL-Khafaji, et al., [12] applied Levenberg-Marquardt algorithm for backpropagation training algorithm to train four feed forward neural network. Their networks were constructed to different insert type. The network takes the cutting speed, feed rate and depth of cut as input and predict the surface roughness. These networks are used to optimize the cutting parameters for minimizing surface roughness. Mia and Dhar, [13] presented an artificial neural network based model to predict the surface roughness of EN 24T steel in turning operation. Their model take the cutting speed, feed rate, material hardness and the machining environment, coolant or dray conditions, as input. The model output was surface roughness.

This paper aims to build neural network model to correlate the cutting variables, cutting speed (V_c), depth of cut (a), and feed rate (f), to the machining force (F_u) and the chip thickness ratio during machining aluminum alloy 7075-T6.

2. Experimental Data

The implemented experimental data are conducted by Santos, et al. [5]. The workpieces are artificially aged aluminum alloy 7075-T6, they are cylindrical extruded bars (Ø 101×2,000 mm) in dimension. Their chemical composition is 1.20–2.00 % Cu, 0.40 % Si, 2.10–2.90 % Mg, and 5.10–6.10 % Zn. The experiments had been executed on CNC lath machine ROMI Multiplic 35D applying 6% concentration of soluble oil with 360 l/h. The cutting tool implemented comes with ISO designation of (TCGT16T308-AZ HTi10) which is cemented carbide inserts. The tool holder utilized in the experiments is made by Mitsubishi which has a designation of (STGCR2020K16Z). The applied tool geometries have been: rake angle, $\gamma_0 = 15°$;

relief angle, $\alpha_0 = 7°$and approach angle, $\chi_r = 90°$. These angles have been estimated after installing the tool on the tool holder. The forces measuring system is made up from three elements, a force sensor which is force dynamometer, a signal conditioning and USB 6251 data acquisition board. The force sensor and a signal conditioning element are made by Kistler company both have model no. (9265B) and (5019B), respectively. The USB 6251 data acquisition board made by National Instruments controlled by LabVIEW® 9.0 software were applied for data recording. When the cutting conditions are getting a steady-state stage, the data recorded for a 10s interval at 6kHz as sample rate. The system has been calibrated prior to conducting the experiments. The machining variables that will be considered in this paper are cutting speed (v_c) depth of cut (a) and feed rate (f). Five level were given for each variable, for cutting speed, v_c, (117, 200, 400, 600, and 683 m/min), for depth of cut, a, (0.38, 1.00, 2.50, 4.00, and 4.62 mm) and for feed rate, f, (0.170, 0.200, 0.275; 0.350; and 0.380 mm/rev). The experimentation output were cutting force, F_c, passive force, F_p, feed force, F_f, and chip thickness ratio, CTR.The experimental data shown in table 1. The tests no. 8, 9, 10 and 11 shown in the table1 duplicated so that average of their results has been utilized in the modeling.

3. Neural Netowrk Modelling

The feedforward networks have number of neurons in their layers, the layers arrange sequentially. The outputs of one layer are inputs to the next layer neurons. As mentioned in advance that the feedforward neural network consists from one or more hidden layer. These layers are characterized by their activation function and neurons number [13]. The network training is a process to adjusts the networks' weights to reach the minimum error between the network output and the target, the experimental data. The most common algorithm used to train neural network, adjusting weights, is the Backpropagation algorithm. [7].

Table 1,
Machining experimental results taken from Santos, et al. [5]

No	Input			Measured			
	$V_c(\frac{m}{min})$	a (mm)	$f\ (\frac{mm}{rev})$	$F_c(N)$	$F_p(N)$	$F_f(N)$	CTR
1	117	2.5	0.275	564	-24.9	158	1.32
2	200	4	0.2	749	-1.9	233	1.69
3	200	4	0.35	1150	-23.1	222	1.71
4	200	1	0.2	167	-5.76	31.5	1.5
5	200	1	0.35	257	-11.4	30.5	1.96
6	400	4.6	0.275	923	-40.4	134	1.45
7	400	2.5	0.17	377	-9.5	133	1.48
8	400	2.5	0.275	518	-30.7	112	1.45
9	400	2.5	0.275	518	-31	113	1.45
10	400	2.5	0.275	522	-32.7	114	1.45
11	400	2.5	0.275	520	-27.9	115	1.45
12	400	2.5	0.38	636	-51.1	101	1.41
13	400	0.38	0.275	84.8	28.6	14	1.14
14	600	4	0.2	678	4.51	185	1.5
15	600	4	0.35	992	-28	167	0.75
16	600	1	0.2	153	-8.64	24.9	1.5
17	600	1	0.35	238	-19.1	11.8	1.61
18	683	2.5	0.275	491	-29.5	106	1.36

The radial basis function (RBF) neural networks type is fundamental categories of neural networks. The primary features of the RBF model are its efficiency, the implementation simplicity. In addition, good learning and generalization capabilities. The radial basis function network construction requires two different layers, a single hidden layer and the output layer. The hidden layer has nonlinear processing neuron, which provides an alternative goal from that in the feedforward multilayer perceptron MLP network. The output layer has neurons to compute the scalar product of its inputs and provides the response of the network. The input space transformation to the hidden-unit space is nonlinear, whereas it is linear from the hidden-unit space to the output space. It can be concluded that the RBF network is a feedforward neural network with single hidden-layer [14].

The RBFs are generally proven to have universal approximation capabilities. They are suitable for solving pattern classification and function approximation problems because of their uncomplicated topology and their capability to show the learning proceeds in an explicit manner [14]. The hidden layer activation function in the radial basis neural network is radial function. The most radial basis function used is Gaussian function. In a RBF network having k radial units in the intermediate layer and one output [15]. The weights connecting the hidden and output units are estimated either by the least mean square (LMS) or the gradient descent method [14]. Radial basis networks might need more neurons compared to standard feedforward backpropagation networks, although they can be designed with a less time that it takes to train standard feedforward networks. They operate most effective when many training vectors are implemented [16].

In this work a RBF neural network were used to model the cutting parameters against machining force components and chip thickness ratio. Four models were constructed using MATLAB neural network toolbox. The input to all networks are cutting speed V_c, depth of cut and feed rate f. The first three networks' responses are cutting force F_c, passive force F_p and feed force F_f, respectively. Whereas, the fourth network's response is chip thickness ratio CTR.

As stated in advance the RBF network is like feedforward MLP network in architecture with only one hidden layer. The function, newrb, in Matlab neural toolbox used in this work to generate the models networks is conducting it calculates the distance of network input from the weights' matrix rows, rather than matrix multiplication as in MLP network. In addition, it multiplies the bias instead of adding it. Therefore, the input of hidden layer j^{th} neuron is computed by (1) [16] [17].

$$y_j^1 = \|p - w_j^1\|.b_j^1 \quad \text{... (1)}$$

Where, p is the input vector, w^1 is the weights' matrix and b^1 is the bias. Each weights' matrix element is considered as center point, a point at which the net input is zero. Whereas, the bias is used to scale the output of the hidden layer transfer function (the radial basis function) output either stretching or compressing it.

In this paper the tool box function **newrb** is implemented to generate the radial basis neural network models. The network generated by this function use the Gaussian function shown in

Fig. **2** as a transfer function and defined by (2)

$$\theta_j^1 = e^{-y_j^2} \quad \text{...(2)}$$

An essential property of the Gaussian function, it is local. Which indicate that the output is near to zero if n moves extremely far in either direction from the center point. In addition, it is global function. It is opposed to the global sigmoid functions used in the multilayer perceptron MLP whose output remain near to 1 when the net input goes toward infinity. The output layer in RBF network is pure line given by (3) [16] [17]

$$\theta^2 = \sum_{i=1}^{n} w_i^2 \theta_i^1 + b^2 \quad \text{...(3)}$$

Where, n is the number of neurons in the hidden layer, w^2 is the weights' vector connecting the hidden layer and the output layer and b^2 is the bias of the network output layer. The model of the proposed radial basis models is shown in .٣fig. The vector p in equation (1) is consist of three components which are cutting speed, depth of cut and feed rate. The number of hidden layer neurons (n) is 18 for all four models. The weights matrix w^1 has size of 18 rows and 3 columns and the bias vector b^1 has 18 elements. The w^2 has 18 elements too.

Table 2 to table 5 show the network weights matrices and bias for F_c, F_p, F_f and CTR models, respectively. It should be noted that the value of second layer bias b^2 for F_c, F_p, F_f and CTR networks are scalar values equal to (-1058.152), (-15.3309), (557.1898) and (0.8283), respectively.

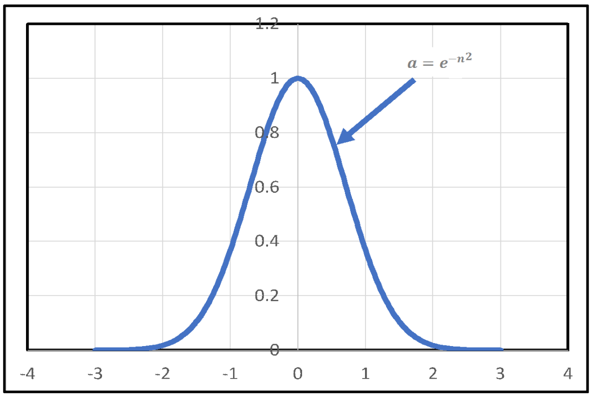

Fig. 2. Gaussian function.

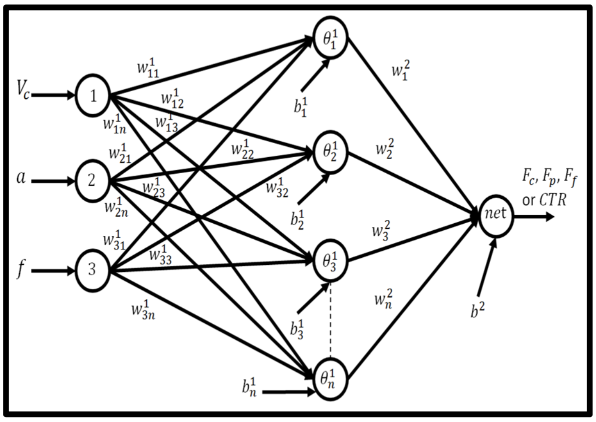

Fig. 3. The proposed neural network model.

4. Results and Discussion

The networks outputs are extremely matching the experimental data. The correlation coefficient R is computed for all networks using equation (4)

$$R = \frac{n\sum x_i y_i - \sum x \sum y}{\sqrt{[n\sum x_i^2 - (\sum x_i)^2][n\sum y_i^2 - (\sum y_i)^2]}} \quad \ldots (4)$$

All networks responses gave value of R equal to one. This is a perfect match.

Fig. 4-7) which showing the networks responses compared with the experimental data taken from Santos, et al. [5] for F_c, F_p, F_f, and CTR, respectively. It can be seen from those figures that all networks outputs are perfectly coincide with the experimental data given by Santos, et al. [5]. The machining force F_u is the resultant of the three components as mentioned in advanced. It can be computed using equation (5). According to the perfect matching between experimental and networks outputs of the machining forces' components, the machining force F_u computed from the networks outputs is perfectly coincide with the experimental F_u. Fig. 8 shows the perfect match of the computed F_u versus the experimental F_u from Santos, et al. [5].

$$F_u = \sqrt{F_c^2 + F_p^2 + F_f^2} \quad \ldots (5)$$

Table 2,
The F_c network weights matrices and bias.

no.	w^1			b^1	w^2
1.	200	4.00	0.350	0.833	13961.3
2.	400	2.50	0.380	0.833	0
3.	600	4.00	0.350	0.833	11092.91
4.	400	4.60	0.275	0.833	1913.422
5.	117	2.50	0.275	0.833	1622.152
6.	683	2.50	0.275	0.833	1549.152
7.	200	1.00	0.350	0.833	3520.709
8.	600	1.00	0.350	0.833	3356.444
9.	200	4.00	0.200	0.833	-11940.5
10.	600	4.00	0.200	0.833	-9187.46
11.	400	2.50	0.170	0.833	-8603.13
12.	400	0.38	0.275	0.833	1079.067
13.	200	1.00	0.200	0.833	-2244.6
14.	600	1.00	0.200	0.833	-2096.74
15.	400	2.50	0.275	0.833	9977.41
16.	400	2.50	0.275	0.833	0
17.	400	2.50	0.275	0.833	0
18.	400	2.50	0.275	0.833	0

Table 3,
The F_p network weights matrices and bias.

no.	w^1			b^1	w^2
1.	400	2.5	0.38	0.8326	0
2.	400	4.6	0.275	0.8326	-24.312
3.	400	0.38	0.275	0.8326	44.644
4.	683	2.5	0.275	0.8326	-14.169
5.	400	2.5	0.17	0.8326	1381.82
6.	117	2.5	0.275	0.8326	-9.569
7.	600	1	0.35	0.8326	-335.18
8.	200	4	0.35	0.8326	-683.21
9.	600	4	0.35	0.8326	-1047.9
10.	600	4	0.2	0.8326	1051.56
11.	200	4	0.2	0.8326	686.05
12.	200	1	0.35	0.8326	-177.49
13.	600	1	0.2	0.8326	336.650
14.	200	1	0.2	0.8326	184.293
15.	400	2.5	0.275	0.8326	-1387.3
16.	400	2.5	0.275	0.8326	0
17.	400	2.5	0.275	0.8326	0
18.	400	2.5	0.275	0.8326	0

Table 4,
The F_f network weights matrices and bias

no.	w^1			b^1	w^2
.	200	4	0.2	0.833	189.7411
2.	400	2.5	0.17	0.833	1062.935
3.	600	4	0.2	0.833	389.2137
4.	117	2.5	0.275	0.833	-399.19
5.	400	4.6	0.275	0.833	-404.308
6.	683	2.5	0.275	0.833	-451.19
7.	200	1	0.2	0.833	-233.206
8.	600	1	0.2	0.833	150.9871
9.	400	2.5	0.275	0.833	-1456.21
10.	600	4	0.35	0.833	-772.317
11.	400	0.38	0.275	0.833	-525.381
12.	600	1	0.35	0.833	-693.28
13.	200	4	0.35	0.833	-520.967
14.	400	2.5	0.38	0.833	0
15.	200	1	0.35	0.833	-296.439
16.	400	2.5	0.275	0.833	0
17.	400	2.5	0.275	0.833	0
18.	400	2.5	0.275	0.8325	0

Table 5,
The CTR network weights matrices and bias.

no.	w^1			b^1	w^2
1.	400	2.5	0.17	0.8326	0
2.	200	1	0.35	0.8326	15.3151
3.	200	4	0.35	0.8326	1.05552
4.	600	1	0.35	0.8326	3.96737
5.	600	4	0.2	0.8326	24.3887
6.	400	4.6	0.275	0.8326	0.59432
7.	683	2.5	0.275	0.8326	0.53165
8.	117	2.5	0.275	0.8326	0.49165
9.	400	0.38	0.275	0.8326	0.28587
10.	600	4	0.35	0.8326	-24.091
11.	200	1	0.2	0.8326	-14.408
12.	600	1	0.2	0.8326	-3.2356
13.	400	2.5	0.275	0.8326	2.88848
14.	400	2.5	0.38	0.8326	-2.3251
15.	200	4	0.2	0.8326	-0.1788
16.	400	2.5	0.275	0.8326	0
17.	400	2.5	0.275	0.8326	0
18.	400	2.5	0.275	0.8326	0

These networks are used to optimize the cutting parameters that produce lowest machining force and chip thickness ratio. To do that, a Matlab function has been written. The function creates two three-dimension arrays with (60, 60, 60) in size and initialized with zeros. The first array stores the results of F_u and the second stores CTR. In addition, its creates three vectors using the **linspace** MATLAB function. Each vector has 60 elements for the three parameters cutting speed, depth of cut and feed rate. The range of the cutting speed vector is (117 – 683) m/min, for depth of cut is (0.38 – 4.62) and for feed rate is (0.170 – 0.380). Then it performs loops to execute the networks with different parameters. The optimum parameters are founded by searching for minimum F_u and minimum CRT arrayes.

Table **6** presents the optimum parameters that gives lowest F_u and CTR. The optimum parameter for both the F_u and CTR are differ only in the feed. A surface drawn when taking the optimum cutting speed value as constant and changing the remaining for both the computed F_u from the networks output and CTR are shown in Fig. 9 and

Fig. **10**, respectively.

The square correlation coefficients of the proposed models are compared to those given by Santos, et al. [5] as shown in Table 7.

Table 6,
The optimum parameters and their corresponding optimum values from F_u and CTR

	$V_c\left(\frac{m}{min}\right)$	$a(mm)$	$f\left(\frac{mm}{rev}\right)$	Optimum value
F_u	683	3.18	0.27	240.46 N
CTR	683	3.18	0.17	1.21

Table 7,
RBF neural network R^2 versus R^2 from [5].

	R^2 for F_u	R^2 for CTR
Proposed RBF networks	1	1
Results from Santos, et al. [5]	0.998	0.9661

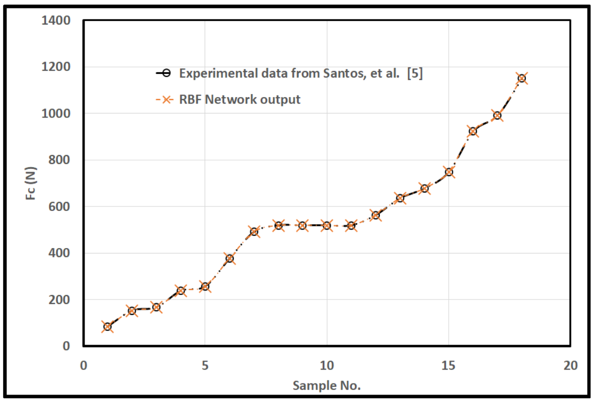

Fig. 4 The neural network for F_c response against the experimental data from Santos, et al. [5].

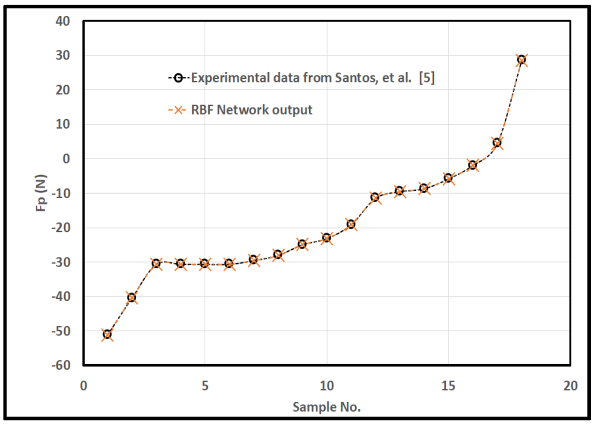

Fig. 5 The neural network for F_p response against the experimental data from Santos, et al. [5].

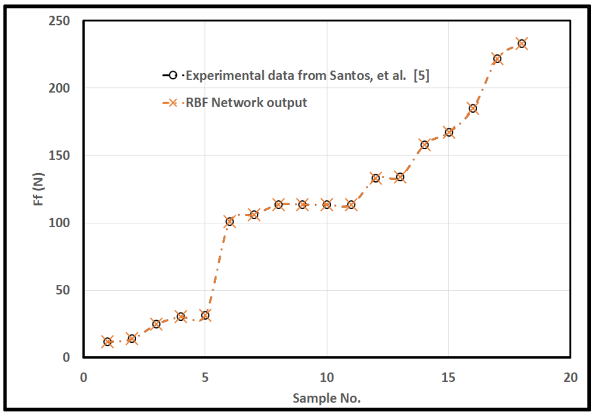

Fig. 6. The neural network for F_f response against the experimental data from Santos, et al. [5].

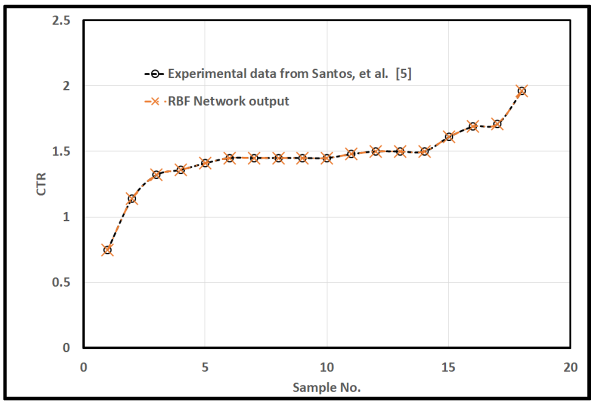

Fig. 7. The neural network for CTR response against the experimental data from Santos, et al. [5].

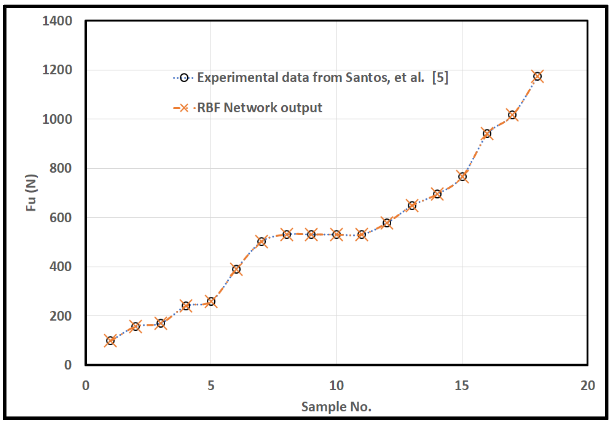

Fig. 8. The F_u computed from the networks outputs against the experimental data from Santos, et al. [5].

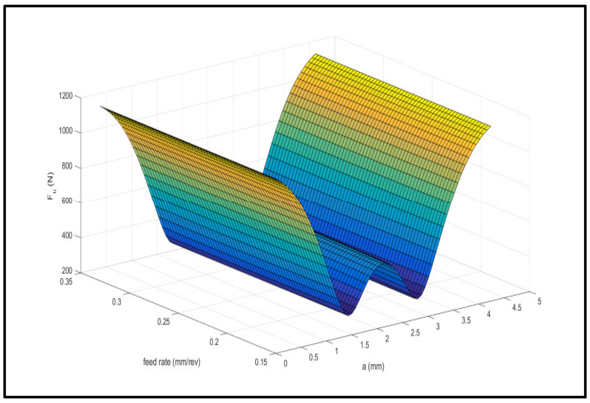

Fig. 9. Fu surface when cutting speed is (683 m/min)

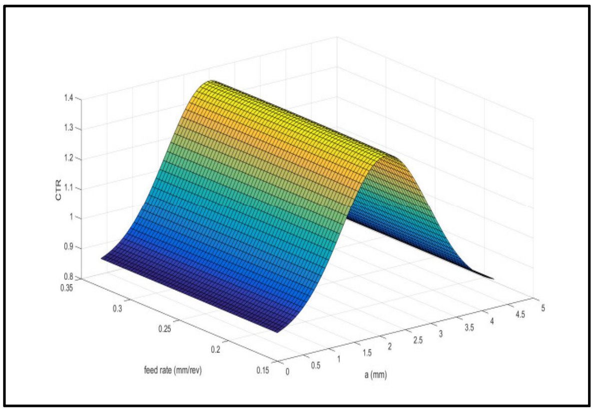

Fig. 10. CRT surface when the cutting speed is (683 m/min).

5. Conclusion

This study provided an experimental investigation, via radial basis function RBF network modeling, to estimate the affect of cutting parameters. (cutting speed, depth of cut and feed rate) on machining force (Fu) and chip thickness ratio (CTR) during turning of high strength aluminum alloy 7075-T6. The primary conclusions of the investigation are given following:

1. The proposed RBF networks showed an extreme match to the experimental data and the computed correlation coefficients were equal one. additionally, those networks were used to optimize the cutting process and obtain the optimum cutting parameters.
2. The proposed methodology based on RBF neural network modeling can effectively overcome any complicated function approximation with more than two inputs.
3. The outcome also revealed that the effectiveness of the developed networks was better compared to existing using genetic algorithm (GA).

The present study for optimizing the cutting process is anticipated to open two directions which can be suggested to continue this work. The first is to investigate the effect of more cutting parameters, which include cooling liquids and angles of cutting tools, on machining force and chip thickness ratio.

The second possible direction is to integrate a neural network with fuzzy logic to solve a more complicated function approximation models.

Notation

a	Depth of cut
b^1	Network first layer bias vector
b^2	Network second layer bias vector
CTR	Chip thickness ratio
f	Feed rate
F_c	Cutting force
F_p	Passive force
F_f	Feed force
F_u	Machining Force
p	Network input vector
R	correlation coefficient
V_c	Cutting speed
w^1	Network first layer weights matrix
w^1	Network first layer weights matrix

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نمذجة قوة القطع ونسبة سمك النحاتة باستخدام الشبكات العصبية اثناء خراطة سبيكة الألمنيوم 7075-T6

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الخلاصة

تؤثر الكثير من المتغيرات على عملية القطع والتي يجب دراستها. ومن هذه المتغيرات الخشونة السطحية وعمر عدة القطع واستهلاك الطاقة ودرجة حرارة القطع ومركبات قوى التشغيل وتآكل العدة ونسبة سمك النحاتة. ان عملية القطع تعد معقدة ولا خطية بسبب هذه العوامل. إن الهدف من هذا البحث هو بناء نماذج من الشبكات العصبية لتمثيل العلاقة بين متغيرات القطع (سرعة القطع وعمق القطع ومعدل التغذية) وقوة التشغيل وكذلك مع نسبة سمك النحاتة. عملة الخراطة اجرية لسبيكة الألمنيوم 7075-T6. تم بناء ثلاث شبكات عصبية نصف قطرية لكلٍ من قوة القطع والقوة السلبية وقوة التغذية، فضلاعن ذلك تم انشاء شبكة نصف قطرية لنمذجة نسبة سمك النحاتة. ان مدخلات جميع الشبكات هي ظروف القطع (سرعة القطع وعمق القطع ومعدل التغذية). تم مقارنة أداء (مخرجات) الشبكات لمركبات قوة التشغيل (قوة القطع والقوة السلبية وقوة التغذية) مع التجارب العملية وأعطت تطابقا تاما وكذلك تم حساب معامل العلاقة وجد بأنه مساوٍ للواحد. وكذلك الشبكة التي تم بناؤها لنسبة سمك النحاتة كان معامل الارتباط مساوٍ للواحد ايضاً، بالمقارنة مع النتائج العملية. ان هذه الشبكات (النماذج) استخدمت لإيجاد أفضل ظروف قطع والتي بدورها تعطي اقل قوة قطع وأقل نسبة سمك النحاتة. أظهرت نتائج النماذج بإن افضل قوة تشغيل يمكن الحصول عليها هي (٢٤٠,٤٦ نيوتن) عندما تكون سرعة القطع (٦٨٣ م/د) و عمق القطع (٣,١٨ملم) و معدل تغذية (٠,٢٧ ملم/دورة). وأظهرت الشبكة المقترحة لنسبة سمك النحاتة إن اقل نسبة يمكن الحصول عليها هي (١,٢١) عندما تكون سرعة القطع (٦٨٣ م/د) وعمق قطع (٣,١٨ ملم) و معدل تغذية (٠,١٧ ملم /دورة).