

Selection of Optimal Cutting Condition for Wear, Friction and Lubricant using Hybrid Intelligent System

تحديد ظروف القطع المثلى للأسطح الهندسية بناءً على التآكل والاحتكاك والتزييت باستخدام نظام ذكاء مختلط

N. A. El-Hamshary, T. T. El-Midany, I. M. Eliwa, A.S.Gad El-Mawla, O. B. Abouelatta
Production Dept., Faculty of Engineering, Mansoura University, EGYPT.

الملخص العربي

تقدم تكنولوجيا السطح معلومات قيمة في التطبيقات العملية و النظرية للأسطح المصنعة كما تلعب ظروف القطع دوراً هاماً في تقييم الأداء الوظيفي للأسطح الهندسية. أيضاً هناك ارتباط قوي بين شكل الأسطح و الأداء الوظيفي لها، حيث تؤثر هندسة السطح تأثيراً كبيراً على أداءه الوظيفي. ومن خلال ما قدمته الأبحاث السابقة من دراسة العلاقات بين عوامل خشونة السطح و الأداء الوظيفي للسطح المشغل فقد وجد أن عوامل خشونة السطح والتي تحدد مواصفات السطح المشغل ترتبط ارتباطاً مباشراً بكل من ظروف القطع و الأداء الوظيفي للسطح. ولذلك فإن البحث يركز في البداية على تحليل طبوغرافية السطح لتحديد مواصفاته من خلال عوامل خشونة السطح. ثم استخدام المعلومات الناشئة عنها للتحكم في ظروف عملية إنتاج السطح للتنبؤ بالأداء الوظيفي له عند استخدامه. يقدم البحث دراسته من خلال أنواع مختلفة للأداء الوظيفي للسطح هي التآكل و الاحتكاك و التزييت والتي تسمى الخواص التريبولوجية للسطح. تم بناء نظام ذكاء صناعي مختلط لاختيار ظروف القطع المثلى باستخدام الشبكات العصبية الاصطناعية وتم عمل دراسة عملية للحصول على عوامل خشونة السطح المطلوبة لبناء الشبكة العصبية الاصطناعية عن طريق تشغيل 65 عينة من الصلب 37 و قطر العينة 40 مم. تم تقسيم العينات المستخدمة إلى ثلاث مجموعات، شغلت المجموعة الأولى باستخدام عملية الخراطة بينما شغلت الثانية باستخدام عملية التفرير والثالثة باستخدام عملية التجليخ. كل عينة من العينات تم تشغيلها بظروف قطع مختلفة (سرعة قطع و عمق قطع و تغذية). تم قياس العينات باستخدام جهاز قياس خشونة السطح Mitutoyo Surf Test SJ201 والذي يعطي شكل السطح بالإضافة إلى بعض عوامل خشونة السطح. تم إنشاء برنامجين للحصول على عدد كبير من عوامل خشونة السطح اللازمة لإنشاء الشبكة العصبية باستخدام برنامج Matlab[®]. الأول *SurfTest SJ201P* وهو يختص بالحصول على طبوغرافية السطح المقاس بواسطة جهاز قياس خشونة السطح Mitutoyo Surf Test SJ201. أما الثاني *SRCP* فيقوم بقراءة وعرض نتائج البرنامج الأول والحصول على عدد كبير من عوامل خشونة السطح. تم بناء برنامج الشبكة العصبية الاصطناعية عن طريق برنامج Matlab[®] وأيضاً بناء برنامج *OSSC* والذي يستخدم في إيجاد ظروف القطع المثلى باستخدام Matlab[®]. وقد تم اختبار دقة النظام فكانت دقة النظام التي تم الحصول عليها 99.75% ±. كما تم قياس معاملات الارتباط بين ظروف القطع الحقيقية و ظروف القطع الناتجة من النظام المقترح وتراوحت بين (0.975-0.999).

Abstract

Surface technology provides an important and valuable insight into the practical and theoretical applications of a manufactured surface. Cutting conditions play an important role in assessment of functional performance for engineering surfaces. Also, there is an important relation between the surfaces geometry and the functional performance of the surface. The geometry of the surface has a large influences of the surface performance. Topography analysis is primarily concerned with describing a surface in terms of its features. Then the knowledge gained about the geometry of the surface is used to control the surface production process to predict the performance of the component in its functional environment. Roughness parameters which characterize machined surfaces affect on both cutting conditions and functional performance. Previous researches introduced a relations between roughness parameters and functional performance of machined surfaces. In present study, three of the surface functional performance that are friction, wear, and lubrication which known as the tribological properties are concerned. A hybrid Artificial Neural Network (ANN) is used for selection of optimal cutting conditions. Experimental study is made to obtain the required parameters for the constructed ANN. The experimental study is made on 65 specimens free cutting steel 37, 40 mm in diameter. The specimens are divided into three groups, one of them is machined by turning operation. The second group is machined by milling

and O. B. Abouelatta

operation. The third group is machined by grinding operation. All specimen are machined at various cutting conditions (feed, speed, depth of cut). All specimens are measured using Mitutoyo SurfTest-SJ201 that give the surface profile and some of roughness parameters of the measured surface as a result. A developed Matlab[®] programs *SurfTest SJ201P* and *SRCP*, are used to give a full assessment of surface roughness parameters from the resulted surface profile of the Mitutoyo SurfTest-SJ201. An introduced neural network is modeled by computer programs written in Matlab[®]. Also, *OSCC* program made by Matlab[®] is developed for selection of optimal cutting conditions. The maximum difference between measured data and data obtained from introduced hybrid ANN is of $\pm 0.25\%$.

Keywords: Optimal, ANN, Cutting conditions, Roughness parameters and Functional performance

1. Introduction

Metal cutting is one of the important and widely used manufacturing processes in engineering industries. The study of metal cutting focuses, among others, on the features of tools, input work materials, and machine parameter settings influencing process efficiency and output quality characteristics. A significant improvement in process efficiency may be obtained by machining process optimization that identifies and determines the regions of critical process control factors leading to desired outputs. The technology of metal cutting has grown substantially over time owing to the contribution from many branches of engineering with a common goal of achieving higher machining process efficiency. Selection of optimal machining conditions is a key factor in achieving this condition. In any multi-stage metal cutting operation, the manufacturer seeks to set the process-related controllable variables at their optimal operating conditions with minimum effect of uncontrollable variables on the levels and variability in the output. It has long been recognized that conditions during cutting, such as feed rate, cutting speed and depth of cut, should be selected to optimize the economics of machining operations, as assessed by productivity, quality of component or some other suitable criterion. At last manufacturing industries have long depended on the skill and experience of shop-floor machine-tool operators for optimal selection of cutting conditions and cutting tools. Various conventional techniques employed for cutting conditions optimization include geometric programming, geometric plus linear programming, goal programming,

sequential unconstrained minimization technique, dynamic programming etc. the latest techniques for optimization include many techniques for example genetic algorithm, fuzzy logic, taguchi technique and response surface methodology. The following review the literature on optimization techniques for cutting conditions in various machining operations: A. B. Abouelatta and A. A. Tharwat., [1]investigated the significance of surface texture on wear, friction and lubrication. The optimal values of the cutting variables that maximize/minimize surface roughness parameters, minimize wear rate, maximize/minimize friction, and maximize lubrication were evaluated as a single- and multi-objective functions. N. Tayebi and A. A. Polycarpou [2]extended a model to include asymmetric distributions of asperity heights using the Pearson system of frequency curves. This method allows the study of the effects of skewness and kurtosis independently from each other, and also can be used to generate the exact density function of asperity heights with the exact skewness and kurtosis values of a measured surface roughness. It is found that positive skewness values predict higher contact force, real area of contact, number of contacting asperities, tangential and adhesion forces than the Gaussian case, while negative skewness values predict lower values and larger deviations from the Gaussian case. It is also found that distributions with kurtosis higher than three predict higher contact and friction parameters with larger deviations compared to the Gaussian case, while distributions with kurtosis lower than three predict lower values than the Gaussian case. D. Novovic et al.,[3]

published data which address the effect of machining (conventional and non-conventional processes) and the resulting workpiece surface topography/integrity on fatigue performance, for a variety of workpiece materials. The effect of postmachining surface treatments, such as shot peening, are also detailed. D. Umbrello et al., [4] This paper presents a predictive hybrid model based on the artificial neural networks (ANNs) and finite element method (FEM) that can be used for both forward and inverse prediction. The former is able to determine a residual stresses profile corresponding to a given tool, material and process conditions, the latter is able to determine these conditions when a constraint on the residual stresses distribution is given. F. Mata et al., [5] aimed at studying the impact of cutting conditions on surface roughness in turning of polyetheretherketone (PEEK) composites. They found that At higher feeds the profiles become more periodic and empty of material, a fact that contributes to the tribological function of these surfaces, in the case they will experience contact. C. S. glu et al., [6] presented an analysis of the pressure development of journal bearing in a various shaft surface texture and velocity variations using a proposed neural network. The effects of the parameters, which act on performances of journal bearing, on the pressure development and load-carriage capacity had been examined such as the number of revolution and shaft surface texture. The data from the experiments are used as learning information for the neural network to establish a reliable prediction model that can be applied to journal bearings and the model's performance was verified. W. z. Wang et al., [7] developed a computer program to generate non-Gaussian surfaces with specified standard deviation, autocorrelation function, skewness and kurtosis, based on digital technique. A thermal model of mixed lubrication in point contacts is proposed, and used to study the roughness effect. The area ratio, load ratio, maximum pressure, maximum surface temperature and average film thickness as a function of skewness and kurtosis are studied at different value of rms. Numerical examples show that skewness and

kurtosis have a great effect on the contact parameters of mixed lubrication. L. Xiao et al., [8] studied a rough friction in lubricated sliding of roller surfaces, which were manufactured to simulate the real gear surfaces. By examining 3D surface topography of two mating bodies, both surface roughness and its effect on friction behavior was studied. A. C. Basheer et al., [9] presented an experimental work on the analysis of machined surface quality on Al/SiCp composites leading to an artificial neural network-based (ANN) model to predict the surface roughness. The predicted roughness of machined surfaces based on the ANN model was found to be in very good agreement with the unexposed experimental data set. A. Y. Suh et al., [10] Detailed studies of the surface topography line and areal (usually referred as one dimensional (1D) and two dimensional (2D), respectively) analyses. Simple amplitude roughness parameters as well as more detailed spatial, hybrid, and functional parameters were calculated and used to track detailed roughness changes as the Al390-T6 samples undergo progressive wear until scuffing occurs. One-dimensional amplitude descriptors, such as the root-mean-square value, were not reliable in tracking surface topographic changes. However, 2D functional parameters, such as the surface bearing index and the fluid retention index, clearly showed progressive changes as the surfaces wear and reach scuffing. G.P. Petropoulos et al., [11] presented a method for characterizing machined surface textures corresponding to varying cutting conditions, which lead to differing profile shapes. Through a proper multi-parameter analysis carried out on turned steel specimens, it is indicated that statistical functions and parameters are the most effective towards relative discrimination and control.

2. Experimental study

The experimental study is made on 65 specimens free cutting steel 37, 40 mm in diameter. The specimens are divided into three groups, one of them is machined by turning operation. The second group is machined by milling operation. The third

and O. B. Abouelatta

group is machined by grinding operation. All specimens are machined at various cutting conditions. All specimens are measured using Mitutoyo SurfTest-SJ201 that give the surface profile and four roughness parameters of the measured surface as a result. A developed Matlab[®] programs SurfTest SJ201P and SRCP, are used to give a full assessment of surface roughness parameters from the resulted surface profile of the Mitutoyo SurfTest-SJ201.

2.1 Specimens preparation:

Workpiece material is a steel bar (free cutting steel 37 with 45mm in diameter. Then, it is machined by turning into 65 specimens 40 mm in diameter as shown in figure (1).

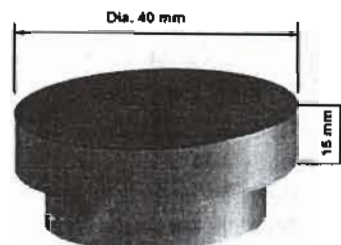


Fig. (1) Machined specimen

The first group of 20 specimens are machined by facing (turning operation). The used cutting tool for turning operations has tips of commercial type Widadur coated hard metal (TNMG160412P25) with nose radius of 1.2 mm. The second group of 20 specimens are machined by milling operations. The used milling cutter has 50 mm external diameter and 36 mm length. It belongs to the plain milling cutters, which have only peripheral cutting edges. The number of teeth is 20. They are used for roughing and finishing of plain surfaces on the horizontal milling machine. The Third group of 25 specimens are machined by grinding operation. The used cutting tool for grinding operations is aluminum oxide grinding wheels (38A60KK5VBE).

2.2 Experimental setup

The introduced system consists of two major parts, hardware and software. The hardware consists of two main items shown in figure (2) Mitutoyo SurfTest-SJ201 and personal computer (PC).

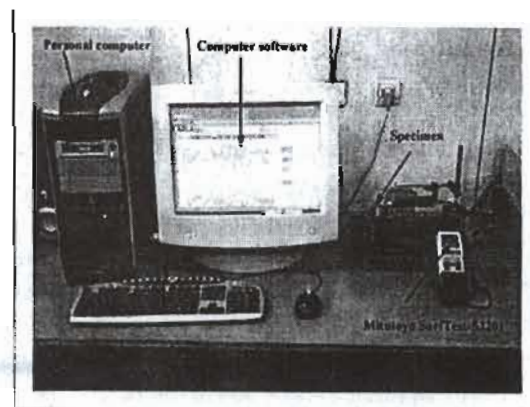


Fig. (2) Photograph of the introduced system

Mitutoyo SurfTest-SJ201 is surface measuring instrument, used in contact method surface assessment.

SurfTest SJ201P is a developed Matlab[®] program used to read the obtained surface profile from Mitutoyo SurfTest-SJ201, then, convert it to Matlab[®] program code that can be processed and evaluated wide range of roughness parameters. Also, SRCP program give a full assessment of surface roughness parameters from the resulted surface profile of the Mitutoyo SurfTest-SJ20.

2.3 Numerical work (Artificial Neural Network Program for Optimization)

The neural network is modeled by computer programs written in Matlab[®]. The training and testing of the artificial neural network is performed using the experimental results. So, all the experimental data are divided into two groups, one for the training of the network and the other group for the testing of the trained network for every group of experimental data (Turning, Milling and Grinding).

2.4 Optimization procedure using trained ANN

Based on the previous researches it found that the factors of roughness parameters affecting wear, lubrication and friction areas follow the relations shown in table (1).

Table(1) The effecting of roughness parameter in wear, lubrication and friction

Operation	parameters	Max/Min
wear	<i>Rsk</i>	Min
	<i>Rz</i>	Min
	<i>tp%</i>	Max
lubrication	<i>Rku</i>	Max
	<i>Vo</i>	Max
	<i>tp%</i>	Min
Maximum friction	<i>Vo</i>	Max
	<i>HSC</i>	Min
	Δq	Max
	<i>Pc</i>	Min
Minimum friction	<i>Vo</i>	Min
	<i>HSC</i>	Max
	Δq	Min
	<i>Pc</i>	Max

a developed program *OSCC* made by Matlab© is used for selection of optimal cutting conditions .

3. Result and discussion

3.1 Experimental results

Using Mitutoyo SurfTest-SJ201 and the developed Matlab© programs *SurfTest SJ201P* and *SRCP*, The three specimen groups are measured. One of turning group measurements is shown in figure (3) which contain the interfaces of *SurfTest SJ201P* and *SRCP* programs.

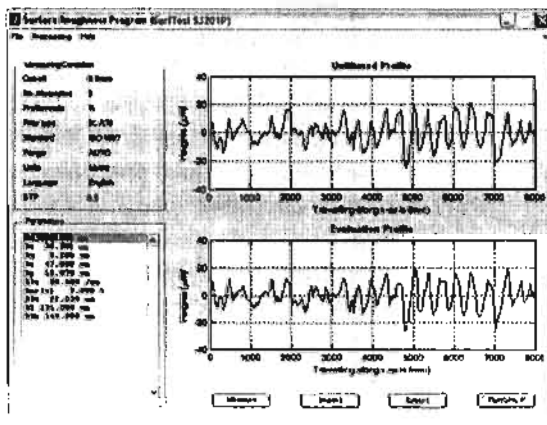


Fig. (3a) Interfaces of *SurfTest SJ201P* for turning operation

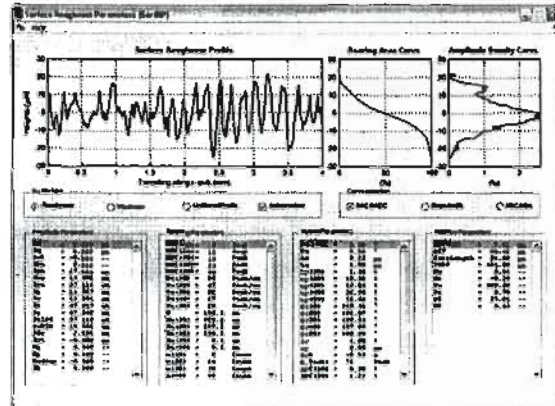


Fig. (3b) Interfaces of *SRCP* programs for turning operation

3.2 Artificial Neural Network Construction and Learning

The feed forward back propagation network is used for the required introduced system (neural network). Back propagation training algorithm is used to train the multiple-layer networks and nonlinear differentiable transfer functions. Neural network training can be made more efficient if certain processing steps are performed on the network inputs and targets. Before training, it is often useful to scale the inputs and targets so that they always fall within a specified range. A certain function can be used to scale inputs and targets so that they fall in the range (-1 ,1). The input and output patterns include nine input and three output variables. The roughness parameters (*Ra*, *Rz*, *Rsk*, *Rku*, *HSC*, *Pc*, *Vo*, Δq , *tp%*) are used as the input variables. The cutting conditions (cutting feed, cutting speed, depth of cut) are used as output variables. Some of the inputs and outputs sets obtained from experimental work are used as training input patterns. The rest are used as testing input patterns.

3.3 System Verification

To verify the accuracy of the introduced system, training and testing for the introduced system are made by changing number of hidden layers and number of neurons in each layer until reaching the acceptable difference as shown in figure (4).

$$\text{max. dif. \%} = \frac{(\text{cutting condition})_{\text{actual}} - (\text{cutting condition})_{\text{ANN}}}{(\text{cutting condition})_{\text{actual}}}$$

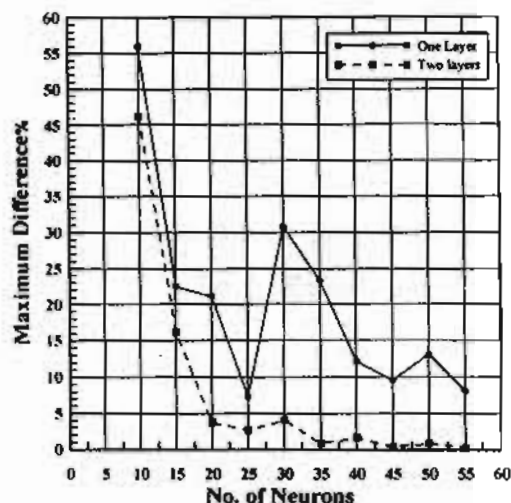


Fig. (4) Maximum difference at various number of neurons and various number of hidden layer

3.4 Correlations for optimal selection of cutting conditions

The correlations coefficient between estimated cutting conditions resulted from the introduced system and the actual values of cutting conditions are calculated and plotted for different machining operations turning, milling and grinding as shown in figure (5) for estimated depth of cut for grinding versus actual depth of cut for grinding.

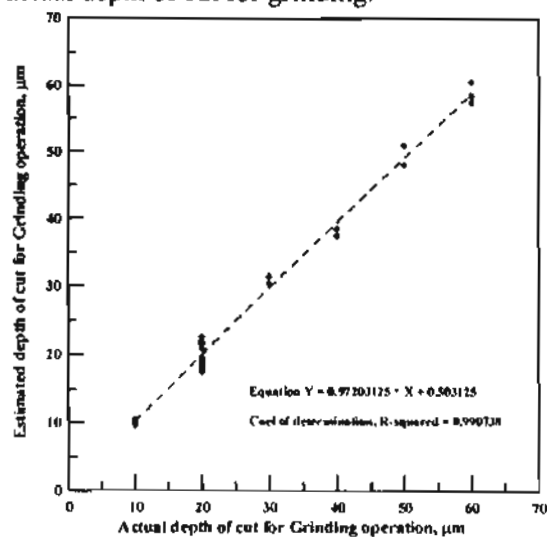


Fig. (5) Estimated depth of cut for grinding versus actual depth of cut for grinding

The maximum correlation coefficients between measured data and ANN optimal selection data are in the range of 0.9750 to 0.9993.

3.5 Optimal selection of cutting conditions based on functional performance

Because of the introduced system is trained and correlated, one can use it for optimal selection of cutting conditions for every machining operation based on desired functional performance. Figure (6) shows the result of the introduced system in case of milling operation.

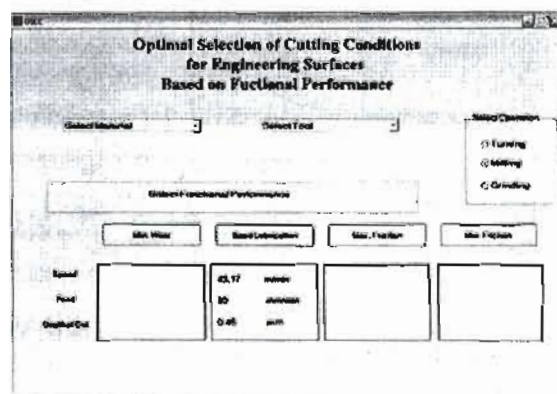


Fig. (6) Estimated cutting conditions in case of milling operation

4. Conclusion

From the present work, it can be concluded the following:

- Experimental study is made to obtain the required parameters for the constructed ANN.
- 65 specimens free cutting steel 37, 40 mm are divided into three groups, one of them is machined by turning operation, the second is machined by milling operation, while the third group is machined by grinding operation.
- All specimen are machined at various cutting conditions (feed, speed, depth of cut) and are measured using Mitutoyo SurfTest-SJ201 that give the surface profile and some of roughness parameters of the measured surface as a result.
- Full assessment of surface roughness parameters from the resulted surface profile of the Mitutoyo SurfTest-SJ20 is obtained using a developed Matlab[®] programs SurfTest SJ201P and SRCP.

- A numerical study is made by modeling neural network using computer programs written in Matlab[®].
- Also, OSCC program made by Matlab[®] is developed for selection of optimal cutting conditions.
- The artificial neural networks ANN have the lowest mean square error MSE of 5.0427×10^{-7} and the highest accuracy over the linear and nonlinear regression analysis of $\pm 99.75\%$.
- The maximum correlation coefficients between measured data and ANN optimal selection data are in the range of 0.9750 to 0.9993.
- It is recommended that, multilayer feed forward neural network is more suitable for solving multi inputs – multi outputs problems.

5. References

- [1] B. Abouelatta and A. A. Tharwat "Multi-criteria surface roughness and its application in tribology", journal of the Egyptian society of tribology, Vol.2, PP.26-38, January 2005.
- [2] N.Tayebi and A. A. Polycarpou "Modeling the effect of skewness and kurtosis on the static friction coefficient of rough surfaces", Tribology International Vol. 37, PP. 491–505, 2004.
- [3] D. Novovic, R.C. Dewes, D.K. Aspinwall, W. Voice and P. Bowen "The effect of machined topography and integrity on fatigue life", International Journal of Machine Tools & Manufacture, Vol. 44, PP. 125–134, 2004.
- [4] D. Umbrello, G. Ambrogio, L. Filice and R. Shivpuri, "A hybrid finite element method-artificial neural network approach for predicting residual stresses and the optimal cutting conditions ,during hard turning of AISI 52100 bearing steel" Materials and Design . Vol.29, PP. 873–883, 2008.
- [5] F. Mata , J. Paulo Davim and G. Petropoulos, "Statistical study of surface roughness in turning of peek composite", Materials and Design, Vol. 29, PP. 218–223, 2008.
- [6] C. S.glu, F. Nair and M. B. Karamus" Effects of shaft surface texture on journal bearing pressure distribution", Journal of Materials Processing Technology, Vol. 168, PP.344–353, 2005.
- [7] W .z. Wang, H. C., Y. z.Hu, H. Wang , "Effect of surface roughness parameters on mixed lubrication characteristics", Tribology International, Vol. 39 , PP.522–527, 2006.
- [8] L. Xiao, B. G. Rosen , N. Amini and P. H. Nilsson, "A study on the effect of surface topography on rough friction in roller contact", Wear , Vol. 254 , PP.1162–1169, 2004.
- [9] A. C. Basheer, U.A. Dabadea, S. S. Joshi V.V. Bhanuprasad and V.M. Gadre "Modeling of surface roughness in precision machining of metal matrix composites using ANN
- [10] A.n Y. Suh, A.A. Polycarpou and T. F. Conry "Detailed surface roughness characterization of engineering surfaces undergoing tribological testing leading to scuffing", Wear, Vol. 255 ,PP. 556–568, 2003.
- [11] G.P. Petropoulos, N.M. Vaxevanidisb, C.N. Pandazaras and A.T. Antoniadisc "Control of representative turned surface textures", Wear Vol. 257 , PP.1270–1274, 2004.