# A NEURAL NETWORK PREDICTION MODEL FOR SURFACE FINISH IN TURNING PROCESS

**Dr. Bahaa Ibraheem Kazem**

Department of Mechatronic Eng., Al-khwarizmi college of Eng. , University of Baghdad , Al- Jadiryah campus , AL- Jadiryah Baghdad , IRAQ .

E. mail : bahaa51170@hotmail.com

## ABSTRACT

This paper presents a neural network based surface finish Prediction model in turning operation , Orthogonal cutting tests were performed on mild steel using H.S.S cutting tool with different cutting parameters cutting speed , feed and nose radius of the cutting tool . The collected data was used to train feed forward back propagation neural network. The developed model has been tested to predict surface finish for various cutting conditions. The model was found to be powerful & capable of accurate surface finish prediction for the range it had been trained but the accuracy deteriorated as the cutting conditions were changed significantly.

## الخلاصة

يتضمن هذا البحث تصميم نموذج لشبكة عصبية للتنبأ بخواص انهاء السطوح في عمليات القطع حيث تمت دراسة عمليات قطع عمودي على عينات من سبائك الحديد المطاوع وبأستخدام عدة قطع فولاذ السرع العالية ولظروف قطع مختافة (سرعة قطع وتغذية ونصف قطر مقدمة قلم القطع). تم استخدام المعلومات المستخلصة لتعليم شبكة عصبية ذات تغذية امامية مرتدة. تم اختبار النموذج للتنبأ بخواص انهاء السطوح لظروف قطع مختلفة حيث وجد ا ن للنموذج قابلية عالية ودقيقة للتنبأ بانهاء السطوح ضمن المدى الذي تم تدريبه عليه وان الدقة تتلاشى عند تغيير ظروف القطع تغيرا جذريا.

## KEY WORDS

Surface finish, neural net work, prediction model

## INTRODUCTION

Machining or metal removal processes such turning are widely used in Manufacturing. Productivity and quality in the finish turning of hardened steels can be improved by optimum selection of the cutting conditions, and because of the complicated relationships between the parameters of cutting operation, the machining process is hard to be decomposed or described by classical differential equations due to larger number of variables & their stochastic, nonlinear relations.

The effect of the cutting parameters on the surface roughness in a turning operation has been investigated [M Hasegawa, 1976]. The mathematical prediction models for surface roughness have been obtained for common mild steel.

Neural networks have achieved in recent years a high degree of importance. The availability of process control computers as well as data historians made it easy to develop neural network solutions for process modeling and control. From medical to industrial application, neural networks have been applied in countless number of situations. Lately, mainly due to the increasing pressure from consumption markets a lot of research has been done under the field of fault detection, diagnosis and quality control. The needs produce more and better, informed markets, has had to the investigation of new methodologies in the quality control area [N. Costa, 1998 ] Neural computing , as one of such techniques , became an attractive approach in this area, since neural networks are adaptable to an involving environment and are able to take a quick decision once they have learned the proper control function . Artificial neural networks ( ANN ) because they are cost – effective , easy to understand and because of their ability to learn from examples, have found many applications in process modeling and control as intelligent sensors, to estimate variables that usually can be measured on - line in dynamic system identification in fault defection diagnosis and finally . in process control [ N.Costa,1998].

Tugral et.al. [Tugral Ozel,2002] Outlined a neural network based tool condition monitoring system, (TCMS), for cutting tool state classification. Orthogonal cutting tests were performed on H13 steel using PCBN inserts and on line cutting forces data was acquired with a piezoelectric force dynamometer. Simultaneously flank wear data was measured using a tool maker's microscope and along with the processed data were fed to aback propagation neural network to be trained. The developed system then was tested to predict flank wear for various cutting condition. The system was found to be capable of accurate tool wear prediction for the range it had been trained but the accuracy deteriorated as the cutting condition were changed significantly.

R.G. Khunchustombham et.al [R.G. Khunchustombham,2001] showed that it can use a neural network approach to on tina monitoring of a turning process emphisis is given to applying neural networks to perform information processing and to recognize the process abnormalities in a machining operation . A neural network monitor based on a feed forward back- propagation algorithm is developed. The monitor is trained by detect cutting force signal and measured surface finish.

Ahmad Ghasempoor [Ahmed Ghasempoor,1997] described a methodology for on – line adjustment of cutting conditions in a turning operation. The system presented consists of on – line wear monitoring and optimal adjustment of cutting conditions. A practical optimization goal has been defined. Simulation results the feasibility of the proposed method.

Sarah. et.al. [Sara S.Y,] discussed the preliminary development of a neural network based process monitor and off – line controller for abrasive flow machining of automotive engine intake manifolds. The process is only observable indirectly, yet the time at which machining achieves the specified air flow rate must be estimated accurately. A neural network model is used to estimate when the process has achieved air flow specification so that machining can be terminated. This model uses surrogate process parameters as inputs because of the inaccessibility of the product parameter of interest, air flow rate through the manifold.

## NEURAL NETWORK MODEL

In this study two neural network models are used. The first model is the back propagation training neural network (BPTNN) and the second one is the back propagation prediction neural network (BPPNN)

### Neural Network Layers

The network always consists of at lest three layers of processing elements **Fig (1)**. This model has three layers of processing elements: a) The input layer b) The middle layer c) the output layer (as shown in **Fig. (2)**)

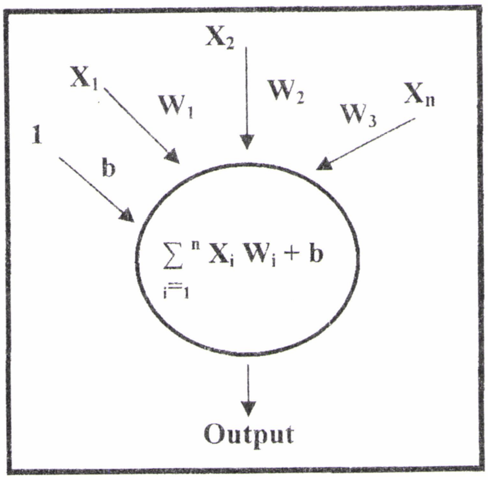


Fig. (1) Illustration of
a processing element

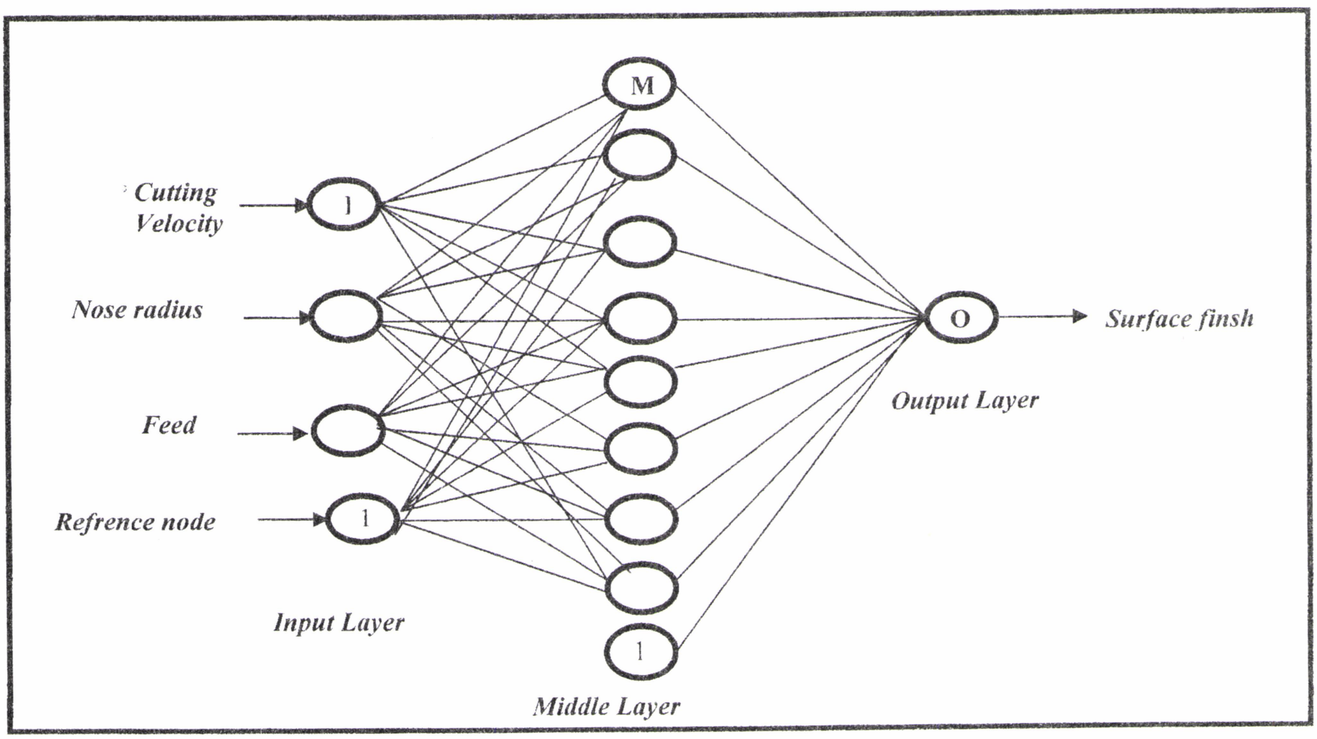


Fig. (2) NETWORK ARCHITCTURE

The input variable is cutting velocity, feed, and nose radius the depth of cut was 0.25 mm. Each input variable is assigned to a single input layer-processing element. The output value at the output layer processing elements is represented as O the surface roughness

The input variable values are carried over to the output of the input layer without any processing. The output values of the input layer processing units are represented by I, (where I=1, 2, 3…) the number of middle layer processing elements is determined by trial and error after testing the model