A Neural Network Cutting Fluid Effect on Surface Roughness and Tool Life

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Abstract:-

Is the refrigerant of the important factors affecting the cutting process as the use of fluids and in different proportions with water used in the cutting process has a clear influence on both the roughness of the surface of the metal to be used and the age of many because of that importance was the use of neural networks to predict the impact of the proportion of mixtures of different and find the best rate of mixing terms of access to the best surface roughness and longer life for many.

Keywords: Neural Network, Cutting, Roughness, Tool Life.

1. Introduction.

For purposes of this document, metalworking fluids (MWFs) are fluids used during machining and grinding to prolong the life of the tool, carry away debris, and protect the surfaces of work pieces .These fluids reduce friction between the cutting tool and the work surface, reduce wear and galling, protect surface characteristics, reduce surface adhesion or welding and carry away generated heat. Workers can be exposed to MWFs by inhaling aerosols (mists) and by skin contact with the fluid .Skin contact occurs by dipping the hands into the fluid, splashes, or handling workpieces coated with the fluids .The amount of mist generated and the resulting level of exposure depends on many factors :the type of MWF and its application process; the MWF temperature; the specific machining or grinding operation; the presence of splash guarding; and the effectiveness of the ventilation system in capturing and removing the mist.Substantial scientific evidence indicates that workers currently exposed to MWF aerosols have an increased risk of respiratory (lung) and skin diseases .These health effects vary based on the type of MWF, route of exposure, concentration, and length of exposure. To reduce the potential health risks associated with occupational exposures to metalworking fluids (MWFs), NIOSH recommends an exposure limit (REL) for MWF aerosol of (0.4 mg/m^3)for thoracic particulate mass the portion of the aerosol that penetrates below the larynx in the respiratory system as a time-weighted average (TWA) concentration for up to 10 hours per day during a
40-hour work week. Because of the limited availability of thoracic samplers, measurement of total particulate mass is an acceptable substitute.
The REL of 0.4 mg/m^3 is based on four major considerations:

- The adverse respiratory health effects of MWF exposure;
- The selection of an index for measuring MWF aerosol exposure;
- The universal applicability of the REL to all types of MWFs; and,
- The technological feasibility of the REL.

NIOSH also recommends the development and implementation of occupational safety and health programs, engineering controls, fluid management and medical monitoring to reduce MWF exposures.These recommendations are intended to prevent or greatly reduce respiratory disorders causally associated with MWF exposure .Whenever possible, reduce MWF aerosol levels below (0.4 mg/m^3) thoracic particulate mass (because some workers have developed work-related asthma or hypersensitivity pneumonitis at MWF exposures below the NIOSH recommended exposure level .It is also important to limit exposure levels based on the association between some past MWF exposures and various cancers and because the minimization of exposures by skin contact helps prevent allergic and irritant skin disorders [1].

To estimate optimum cutting condition or to detect effect of cutting flowed on surface roughness and tool life there two traditional methods 1.using practical testes on several flowed ratio with several cutting conditions then analyze the recorded results to explain flowed ratio effect to surface roughness and tool life [2]. Using empirical equations to calculate the theoretical surface roughness and tool life, the first method is too expensive and take long time to caver all cutting conditions also the second method isn't careful. Due to this reasons Neural Network used to work with limited data of cutting condition to estimate effect of cutting flowed on surface roughness and tool life [3].

There are Four Different Classes Metal Working Fluids.

1. **Straight oil (neat oil) MWFs** are severely solvent-refined petroleum oils (lubricant-base oils) or other animal, marine, vegetable, or synthetic oils used singly or in combination and with or without additives .Straight oils are not designed to be diluted with water.

2. ***Soluble oil (emulsifiable oil) MWFs*** are combinations of 30 %to 85% severely refined lubricant-base oils and emulsifiers that may include other performance additives .Soluble oils are diluted with water at ratios of 1 part concentrate to (5B40) parts water.

3. ***Semisynthetic MWFs*** contain a lower amount of severely refined lubricant-base oil in the concentrate (5% to 30%) a higher proportion of emulsifiers, and (30 %to 50 %)water .The transparent concentrate is diluted with (10 to 40) parts water.

4. ***Synthetic MWFs*** contain no petroleum oils and may be water soluble or water dispersible . The synthetic concentrate is diluted with (10 to 40) parts water [4].

2. Functions of a Cutting Fluid.

Cutting fluids used in machine shops help to improve the life and function of cutting tools .The two most important functions of a cutting fluid are to provide cooling and lubrication .A good cutting fluid, in addition to prolonging cutting-tool life, should resist rancidity and provide rust control.

Cooling

Laboratory tests have proved that the heat produced during machining has a definite bearing on cutting-tool wear .Reducing cutting-tool temperature is important to tool life .Even a small reduction in temperature will greatly extend the life of a cutting tool .For example, if tool temperature were reduced only(500 F^o) from (9500 to 9000 F^o), cutting tool life would be increased by five times, from (19.5 to 99) minutes .Water is the most effective agent for reducing the heat generated during machining. Since water alone causes rusting, soluble oils or chemicals which prevent rust and provide other essential qualities are added to make it a good cutting fluid.

Lubricating

The lubricating function of a cutting fluid is as important as its cooling function .The effective life of a cutting tool can be greatly lengthened if the heat and friction generated by the cutting process are reduced.When cutting fluids are used, faster speeds and feeds can be used in the machining process resulting in increased production and a reduction in the cost per piece.

Rust Control

Cutting fluids used on machine tools should inhibit rust from forming; otherwise machine parts and work will be damaged .Cutting oil prevents rust from forming but does not cool as effectively as water .Water is the best and most economical coolant but causes parts to rust unless rust inhibitors are added .All chemical cutting fluids now contain rust inhibitors, which inhibit or prevent the process of rusting.

Rancidity Control

In the early days of the industrial revolution lard oil was the only cutting fluid used .After a few days lard oil would start to spoil and give off an offensive odor .This rancidity is caused by bacteria and other microscopic organisms that grow and multiply .Modern synthetic fluids are susceptible to the same problem; therefore, most cutting fluids contain some type of bactericide Which controls the growth of bacteria and makes the fluid more resistant to rancidity Bactericides too high in concentration can be harmful to the skin.No matter how good the engineering qualities of a coolant, if it develops an offensive odor, it can cause problems for management .The material may become a hazardous waste and may create disposal costs greater Than the fluid's worth [5].

3. Benefits and Saving.

A successful fluid management program provides [6]:

- Longer fluid life;
- A cleaner, safer and more environmentally sound work environment;
- Improved productivity)less downtime(;
- Reduced costs)increased machine and fluid life, reduced purchase and waste disposal cost(;
- Reduced labor)fewer fluid change-out, less maintenance/repair,
- Environmental compliance and reduced environmental liability; and
- Consistently manufactured quality products.

A machine shop that installed a settling tank to remove contaminant from coolants is now saving more than (26,800$) a year in reduced material, labor and disposal costs.A shop that installed filter units for $9,000 to recycle the spent coolants has dropped its coolant use and disposal cost from (10,800$) per year to (500$) .The shop also estimates another (10,000 $)annual savings on grinding wheels due to expended wheel life.

The four components of a successful fluid management program are:

- Product selection

- Inventory management and chemical handling
- Fluid monitoring
- Contamination removal and prevention

Factors to be considered when selecting a Fluid [7]:

- Fluid's cost and life expectancy;
- Fluid's cutting and grinding abilities;
- Fluid's resistance to bacterial attack;
- Chemical restrictions and reactivity of fluids;
- Biodegradability;
- Ease of fluid recycling and disposal;
- Ease of fluid maintenance and quality control;
- The corrosion protection the fluid offers;
- Speed, feed and depth of the cutting operation;
- Type, hardness and microstructure of the metal being machined;
- Ability to separate fluid from the work and cuttings;
- The product's applicable temperature operating range; and
- Optimal concentration and pH ranges.

4. Artificial Neural Networks ANN.

ANN offers a computational approach that is quite different from conventional digital computation. Digital computers operate sequentially and can do arithmetic computation extremely fast. Biological neurons in the human brain are extremely slow devices and are capable of performing a tremendous amount of computation tasks necessary to do everyday complex tasks, commonsense reasoning, and dealing with fuzzy situations. The underlining reason is that, unlike a conventional computer, the brain contains a huge number of neurons, information processing elements of the biological nervous system, acting in parallel. ANNs are thus a parallel, distributed information processing structure consisting of processing elements interconnected via unidirectional signal channels called connection weights. Although modeled after biological neurons, ANNs are much simplified and bear only superficial resemblance. Some of the major attributes of ANNs are: (a) they can learn from examples and generalize well on unseen data, and (b) are able to deal with situation where the input data are erroneous, incomplete, or fuzzy [7].

The individual processing unit in ANNs receives input from other sources or output signals of other units and produces an output as shown in **Fig.(1)**. The input signals (x_i) are multiplied with weights (w_{ji}) of connection strength between the sending unit "i" and receiving unit "j". The sum of the weighted inputs is passed through an activation function. The output may be used as an input to the neighboring units or units at the next layer. Assuming the input signal by a vector x (x1, x2… xn) and the corresponding weights to unit "j" by w_j (wj1, wj2… wjn), the net input to the unit "j" is given by Equation 1. The weight wj0(=b) is a special weight called bias whose input signal is always +1. [2, 3, 8]

$$net_j = \sum_n \mathrm{w}_{jn}\mathrm{x}_n + \mathrm{w}_{j0} = \mathbf{w}_j\,\mathbf{x} + \mathrm{b} \quad (1)$$

The computed weighted sum of inputs is transformed into an output value by applying an activation function. In most cases, the activation function maps the net input between (-1 to +1) or (0 to 1)[8]. This type of activation function is particularly useful in classification tasks. Since the most real-world problems are nonlinearly separable, nonlinearity in the intermediate layer is essential for modeling complex problems. There are many different activation functions proposed in the literature that are often chosen to be monotonically increasing functions. A recent study [9]. Has shown that approximately 95% of the reported neural network business applications utilize multilayer feed-forward neural networks with Back propagation learning algorithm. Backpropagation [10] is a feed-forward network as shown in **Fig.** (**2**) that updates the weights iteratively to map a set of input vectors (x1, x2… xp) to a set of corresponding output vectors (y1,y2,…,yp).

The input xp corresponding to pattern or data point "p" is presented to the network and multiplied by the weights. All the weighted inputs to each unit of the upper layer are summed up, and produce an output governed by the following equations:

$$\mathbf{y}\mathrm{p} = f(\mathbf{W}\mathrm{o}\ \mathbf{h}\mathrm{p} + \mathrm{o}), \quad (2)$$

$$\mathbf{h}\mathrm{p} = f\mathbf{W}\mathrm{h}\mathbf{x}\mathrm{p} + \mathrm{h} \quad (3)$$

where **Wo** and **Wh** are the output and hidden layer weight matrices, hp is the vector denoting the response of hidden layer for pattern "*p*", θ**o** and θh are the output and hidden layer bias vectors, respectively and $f(.)$ is the sigmoid activation function. The cost function to be minimized in standard Backpropagation is the sum of squared error defined as:

$$\mathrm{E} = \frac{1}{2}\sum_{\mathrm{p}} (\mathbf{t}_{\mathrm{p}} - \mathbf{y}_{\mathrm{p}})^{\mathrm{T}} (\mathbf{t}_{\mathrm{p}} - \mathbf{y}_{\mathrm{p}}) \quad (4)$$

Where tp is the target output vector for pattern "*p*" [11]. The algorithm uses gradient descent technique to adjust the connection weights between neurons. Denoting the fan-in weights to a single neuron by a weight vector **w**, its update in the *t-th* epoch is governed by the following equation:

$$\Delta \mathbf{w}_t = -\eta \nabla E(\mathbf{w})\big|_{w = w(t)} + \alpha \Delta \mathbf{w}_{t-1} \quad (5)$$

The parameters η and α are the learning rate and the momentum factor, respectively. The learning rate parameter controls the step size in each iteration. For a large-scale problem, Backpropagtion learns very slowly and its convergence largely depends on choosing suitable values of η and α by the user

5. ANN Cutting Fluid Effect on Surface Roughness and Toll Life NNCFE.

In the field of research oriented on cutting of metal control with the aim to optimize the industrial process and to increase a quality of metal cutting roughness and increasing cutting tool life by applying artificial intelligent element, particular models of artificial neural networks for prediction metal cutting the proposed neural network model is supervised learning back propagation network . the NNCFE architecture consist of three layers, the first layer (input layer) has three nodes to inter values of cutting fluid ratio R , velocity of cutting Vc, and feed rate f, the second layers (hidden layer) with two hidden layers having three and two nodes respectively due to optimum learning rate **Fig.** (**3**) that selected from several neural network architecture such as(3,3 -4,3 -3,4- 4,2) where weight fitness value equal to (٠.9%) , and the third layer (output Layer) has two node to predicate surface roughness (μm) and tool life(min).

The input values and target output values having several types such as 1:10 for oil water mixed ratio, (66.88 m/min) cutting speed, (0.72 mm/rev) feed rate,(395 min) target tool life, and (0.038 μm) target surface roughness, from that, all input and output adopted with same range having four floating number (0.0000) due that, the output with positive values sigmoid function used as transfer function.

The NNCFE software consists of three windows the first is a mean control window from this window the user select training to learn the NNCFE **Fig.** (**4**) by selected several neural network architecture number of hidden layers and number of nods in each layer, then the learning phase stated by pushing start bottom, where the input vector and target output value selected randomly entail the neural reach to minimum mean square error, where the target output and estimated values will be contacted as shown in **Fig.** (**4,5**) respectively.

The window in **Fig.** (**5**) is NNCFE Test window, where the user enter the values of cutting fluid mixed rate, cutting speed, and feed rate then the NNCFE estimate Tool life and surface roughness or make generate all cutting condition to select several optimum conditions.

6. Results and Discussion.

Cells work the Neural Network through a few experiments to infer the conditions of the pieces to several types of refrigerants and Bsra different feeding multiple knowledge roughness surface the best and the age of preparing the longest as well as the work of simulation of the practical

experience to the circumstances of the pieces other than the circumstances that have been used in practical experiments.
Show in **Fig. (6,7)** The best surfaces roughness are in (1:20) flooding at cutting speed of (94.2 m/min) and average feeding (0.72 mm/rev) .Which gives surface roughness of (0.01µm) compared with other values obtained.
Show in **Fig. (*8,9*)** The longer tool life is in (1:20) flooding at cutting speed of (66.88 m/min) and average feeding (0.72 mm/rev).Which gives tool life of (748.9 mint) for all values of cutting process.

7. Conclusion.

The practical tests to determine cutting condition and effect of cutting fluid is two expansive with mach time so that the using of neural network is simulate to the cutting operation to study cutting in environment to :

1. NNCFE estimate the cutting condition from limited partial tests to determine effect of cutting fluid.
2. By using the NNCFE can be generate huge of cutting data and represented on chart and annulling this data to estimate the near optimum condition data.
3. The NNCFE reduce the time and cost to determine tool life and surface roughness.

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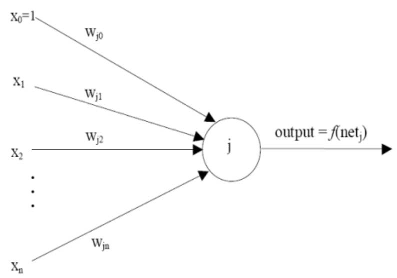


Figure: (1): Simple neuron.

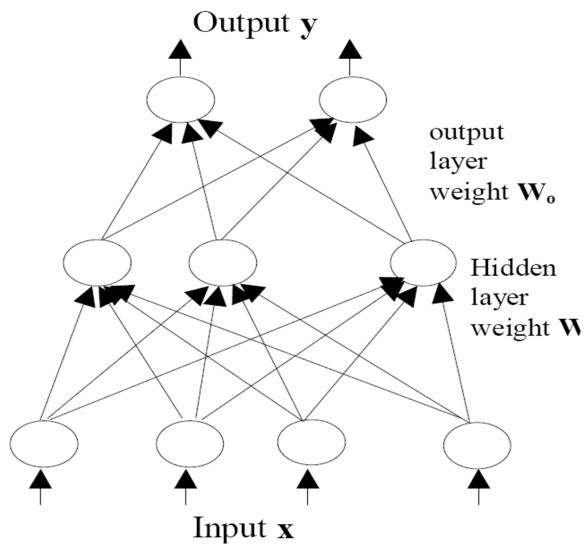


Figure (2): General back propagation malty layers neural network architecture.

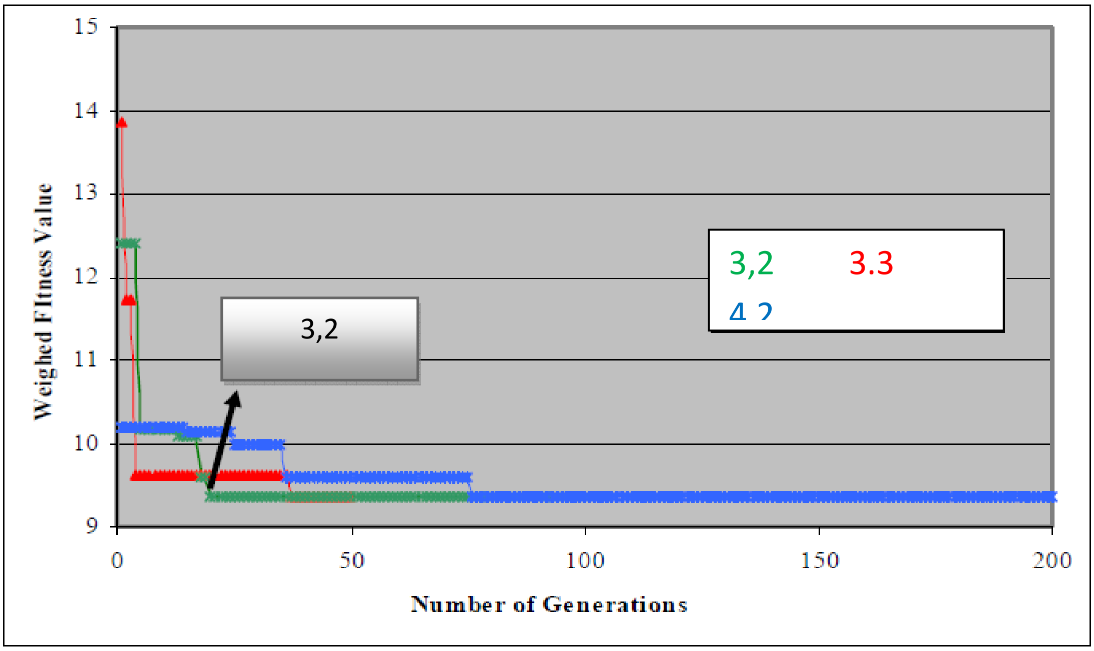
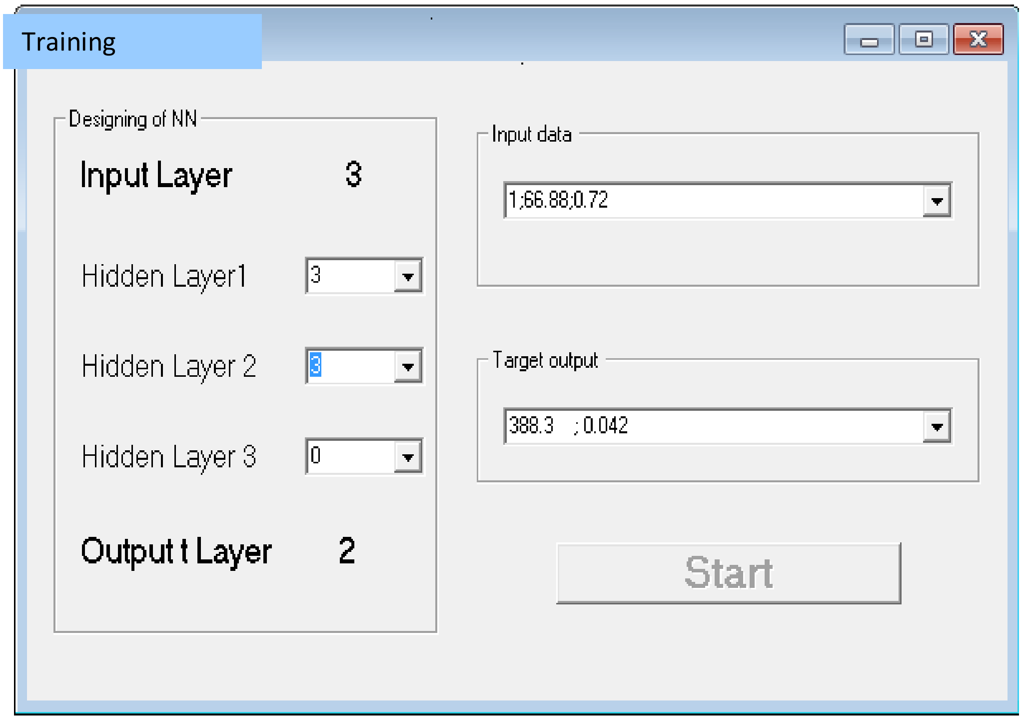
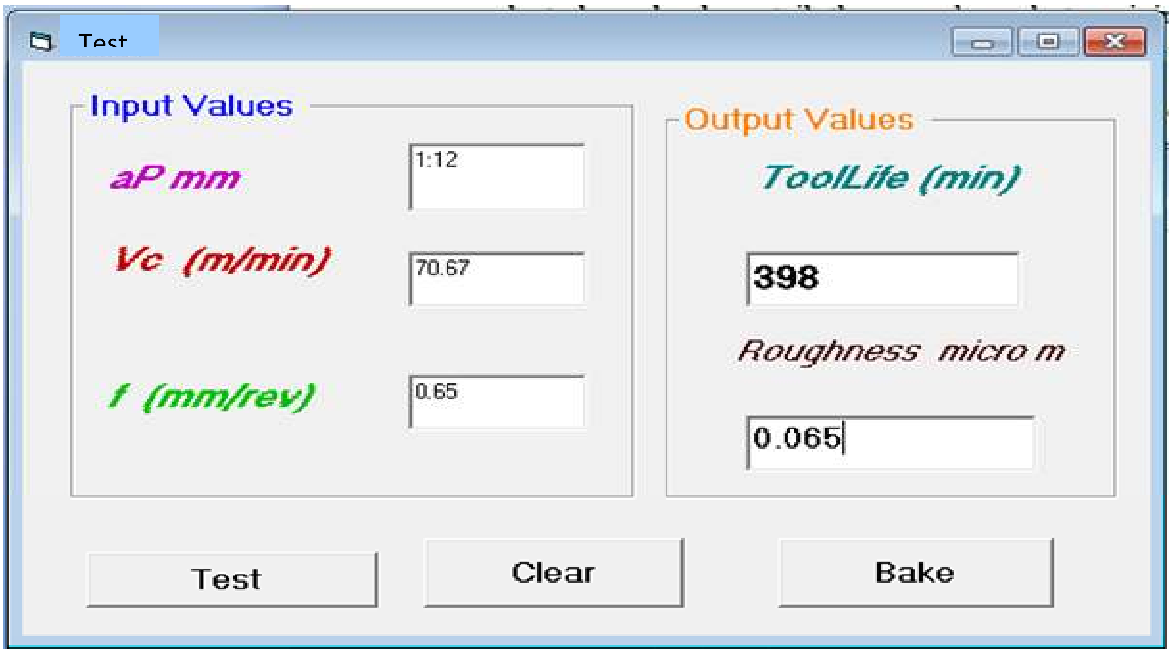


Figure (3): Learning rate for deferent neural network architecture.



Figure(4): NNCFE Training window.



Figure(5): NNCFE Test window.

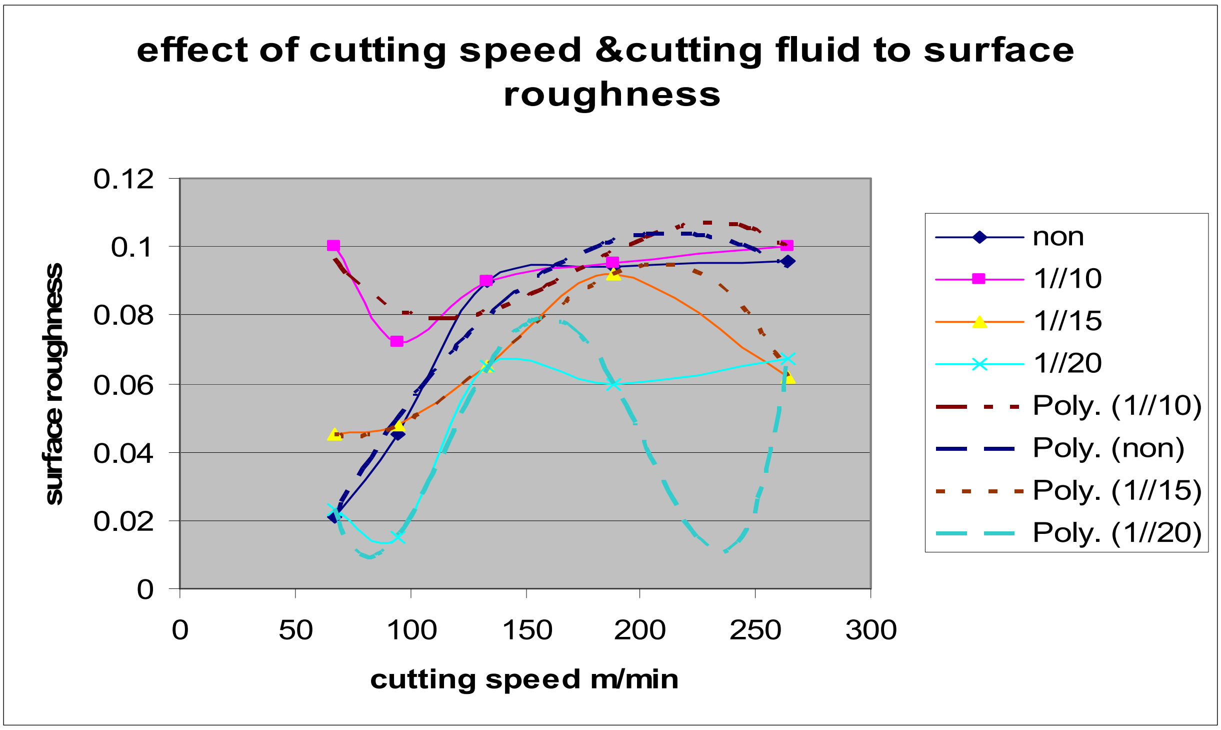


Figure (6): Effect of cutting speed &cutting fluid to surface roughness.

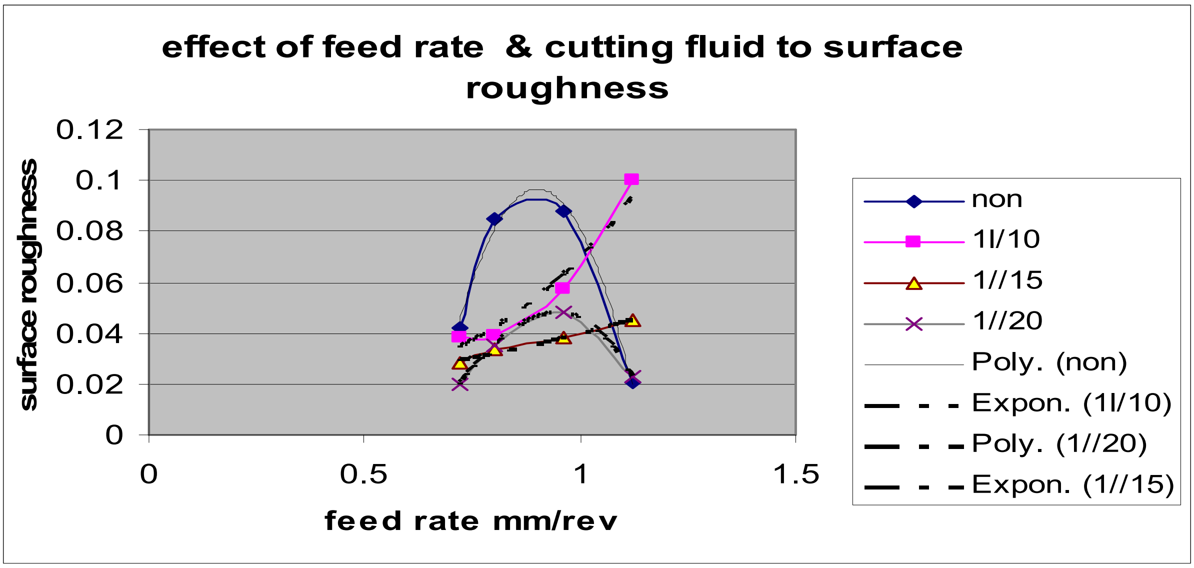


Figure (7): effect of feed rate & cutting fluid to surface roughness.

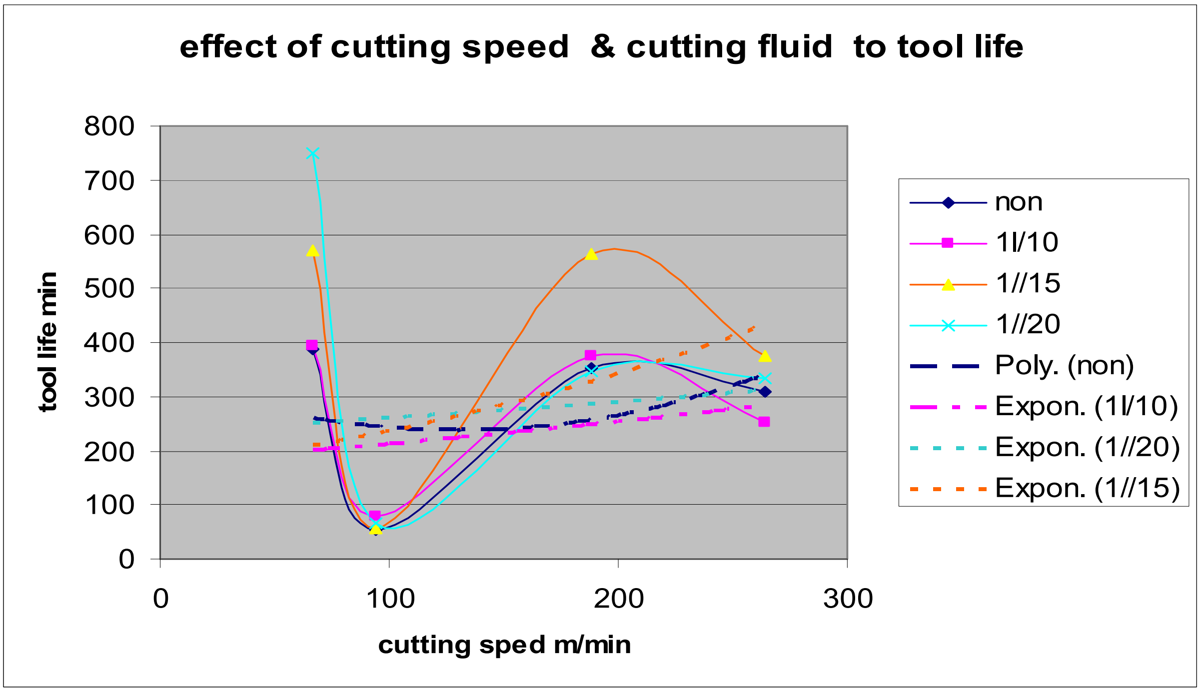


Figure (8): Effect of cutting speed & cutting fluid to tool life.

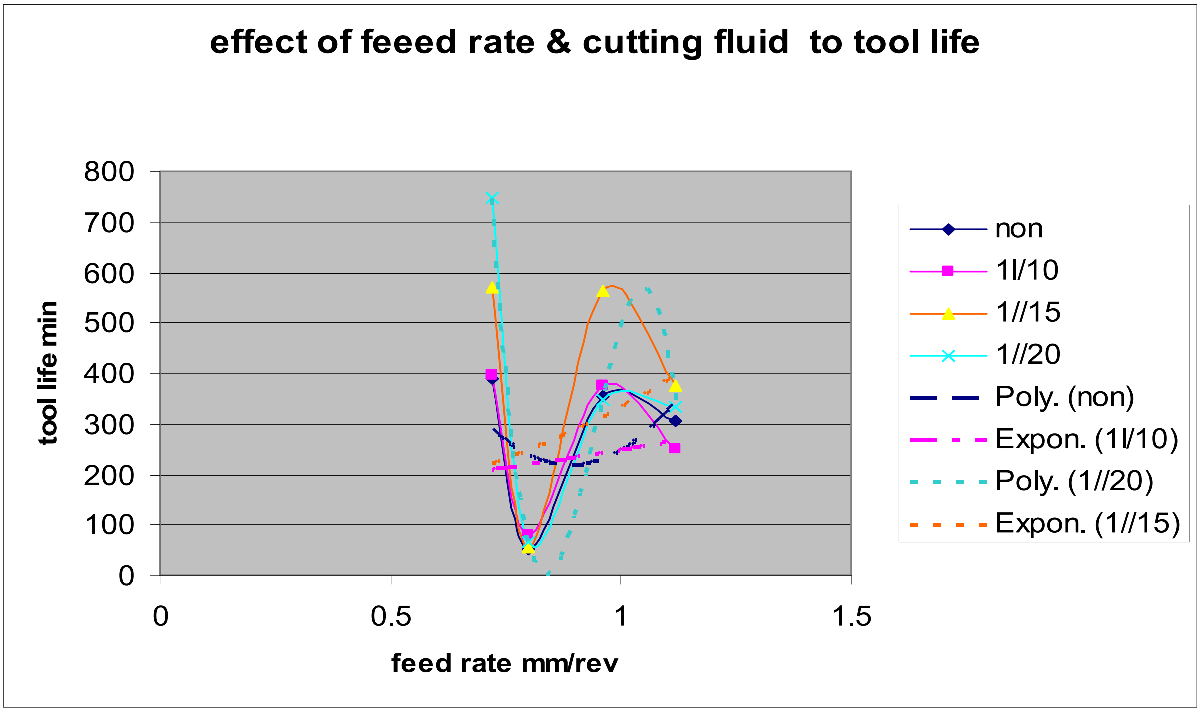


Figure (9): effect of feed rate & cutting fluid to tool life.

الشبكات العصبية لسوائل التبريد الموثرة على خشونة السطح وعمر أداة القطع

د. صلاح كريم جواد

قسم هندسة الانتاج والمعادن ـ الجامعة التكنولوجية

الخلاصة .

تعد سوائل التبريد من العوامل المهمة والمؤثرة على عملية القطع حيث ان استخدام السوائل وبنسب مختلفة مع الماء المستخدم في عملية القطع له التأثير الواضح على كل من خشونة سطح المعدن المستخدم وعمر العدة نظراً لتلك الاهمية تم استخدام الشبكات العصبية للتنبؤ بتأثير نسبة الخلطات المختلفة وايجاد افضل نسبة خلط من حيث الحصول على افضل خشونة السطح واطول عمر للعدة.

الكلمات الدالة: الشبكات العصبية، القطع، الخشونة، عمر العدة.