

# HARD TURNING OPTIMIZATION USING NEURAL NETWORK MODELING AND SWARM INTELLIGENCE

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## KEYWORDS

Hard turning, optimization, neural networks, swarm intelligence.

## ABSTRACT

In this paper, multi-objective optimization of hard turning has been reported. A neural network model was developed in order to model the surface roughness and tool wear characteristics of hard turning when CBN tools are used. Objective is to obtain optimum process parameters, which satisfies given limit, tool wear and surface roughness values and maximizes the productivity at the same time. A recently developed optimization algorithm called particle swarm optimization is used to find optimum process parameters. Accordingly, the results indicate that a system where neural network is used to model and predict process outputs and particle swarm optimization is used to obtain optimum process parameters can be successfully applied to multi-objective optimization of hard turning.

## INTRODUCTION

Machining of hardened steels into finished components by turning is receiving increasing attention in especially automotive and bearing industries. In general, hard turning process can be defined as machining already hardened parts into finished components that are typically machined from alloy steels with hardness between 50 and 70 HRc [1]. Recent developments in machine tool technology and ceramic cutting tools have enabled hard turning

to compete with grinding applications. Energy and cost savings realized with dry hard turning is substantial and contributes to keep the environment clean. The most important surface quality requirement in hard turning is surface roughness, which is mainly influenced by tool wear. Therefore, it is important to address the factors affecting surface quality and tool wear mechanism in hard turning [2-8].

Cutting parameters (cutting speed and feed rate), hardness of workpiece material, and cutting tool material (including tool edge type) are important to understand wear mechanisms of advanced cutting tools. Cubic boron nitride (CBN) tools are commonly used in hard turning and exhibit unpredictable wear behavior, result in premature tool failure “chipping” and the cost of downtime for tool changing affects the economic advantage of the process. Therefore it is important to understand the effect of tool wear on the hard turning process and on the quality of machined surfaces and relate it to changing process conditions. Edge geometry of the CBN tool is an important factor affecting surface quality [3-8]. In order to improve the strength of cutting edges, honed edges with large nose radii and chamfered edges with large wedge angles are used (see Fig.1).

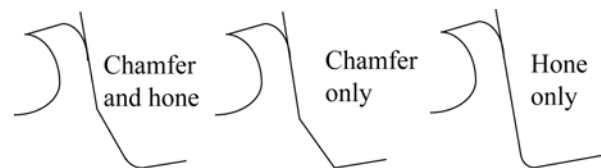


FIGURE 1. TYPES OF CUTTING EDGE GEOMETRY USED IN CBN TOOLS [14]

In literature, chamfered and honed cutting edges are compared in many studies [1-8, 19]. Koenig et al. [1] suggested that honed or sharp edges are favorable in terms of attainable surface finish. Theile et al. [4] showed that cutting edge geometry has significant impact on surface integrity and residual stresses. Chou et al. [6] tested three types of edge preparation and found that the performance of honed cutting edge is worse than chamfered and sharp cutting edges. Cutting conditions have a profound effect on tool wear and surface quality [2,4,6]. Increasing cutting speed and feed rate increases tool wear but decreases surface roughness [8,14]. The surface roughness decreases with increasing workpiece hardness, whereas, workpiece hardness deeply influences cutting life of the CBN tools [5,6].

A number of researchers have investigated various factors affecting tool wear, surface roughness and surface integrity [1-8]. From these studies, it is concluded that it is highly difficult to develop a comprehensive analytical model that considers all the factors affecting tool wear, surface roughness and surface integrity. On the other hand, a large number of researchers reported on the benefits and the application of neural network models, which have the ability to model, mathematically calculate, match non-linear relationships of complex systems, in predicting tool wear and tool life. Many researchers have used neural network systems in tool condition monitoring and predicting tool life as well as surface roughness [9-14].

Neural network models which are developed for a better understanding of the effects of process conditions on the wear behavior of cutting tools and the resultant surface quality of hard turning can be combined with optimization methods in order to determine optimum machining parameters for different objectives such as minimizing manufacturing cost or maximizing productivity. Evolutionary computation algorithms such genetic algorithms and particle swarm optimization are usually utilized for optimization of neural network based models. Tandon et al [15] optimized machining parameters in end milling to minimize machining time by combining a feed forward neural network force model with particle swarm optimization.

In current hard turning practice, industry chooses the correct tool geometry less than half

of the time, uses proper machining parameters only half of the time, and uses cutting tools to their full life capability only one third of the time. These sub-optimal selections cause loss of productivity for the manufacturing industry.

We modeled tool wear behavior of honed and chamfered CBN tools (honed inserts with a radius of 0.01 mm and chamfered inserts with 0.1 mm chamfer land and 20° chamfer angle, and all of the inserts have 1.19 mm nose radius) and surface roughness characteristics of finish hard turning of H13 steel using neural networks and determined optimum process parameters according to user specified limit tool wear and surface roughness values by integrating neural network model with the particle swarm optimization method. Optimal cutting speed, feed rate and most suitable edge geometry for the given limits are the outputs of the algorithm.

## **NEURAL NETWORK MODELING OF TOOL WEAR AND SURFACE ROUGHNESS**

It has been shown that the actual surface roughness in experiments does not match the theoretical values because of adhesion and ploughing effects, which cannot be easily modeled with analytical models. To overcome this problem, neural networks, which are known to have great capability of capturing actual process information, are designed with data obtained from surface roughness and tool wear experiments. In this study, the neural network models developed in Özel and Karpaz [14] are utilized. Experimental data reported in [8,14] for turning of hardened AISI H13 steel was used in this study.

### **Neural Network Model Prediction Results**

Surface roughness and tool wear values are predicted with a feed-forward multilayer neural network as shown in Fig 2. Tool edge geometry, Rockwell-C hardness of workpiece, cutting speed, feed rate and cutting length are used as inputs to train neural networks. The Levenberg-Marquardt method is used together with Bayesian regularization to train neural networks in order to obtain good generalization capability. A 5-15-2-network structure was chosen by trial and error. Training of the neural network was performed by using 173 data points covering the cutting speed range (100-200 m/min) and feed rate range (0.05-0.2 mm/rev) and generalization testing of the neural network was tested with 36

data points which were never used in training. High accuracy in predicting surface roughness (Ra) and, depth of tool flank wear (VB) was obtained with the designed neural network model of the system. Therefore, neural network models were experimentally verified by using 36-data-point independent data sets.

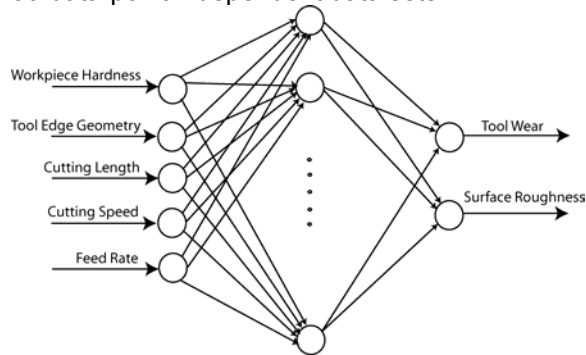


FIGURE 2. NEURAL NETWORK STRUCTURE USED IN MODELING TOOL WEAR AND SURFACE ROUGHNESS

Prediction simulations are performed with respect to axial cutting distance to demonstrate the tool wear and surface roughness development in finish hard turning. All of the simulations are performed under two different cutting conditions with the data never used in neural network training to verify the robustness of the system. In Fig 3 and 4, tool wear developments for honed and chamfered tools are shown. As expected, tool wear values increase with increasing cutting distance, cutting speed and workpiece hardness.

Surface roughness development simulations are shown in Fig 5 and 6. It is seen that decreasing feed rate and increasing cutting speed improves surface finish quality. However, it should be noted that increasing cutting speed adversely affects tool wear and decreasing feed rate may hinder productivity. In some cases surface roughness improved with increasing tool wear therefore attention should be paid on the relation between tool wear and surface roughness.

As discussed in detail earlier, hard turning machining exhibits a unique behavior, which is different than conventional turning operations. Application of hard turning technology can be improved by utilizing advanced optimization algorithms, which helps manufacturers to make educated decisions in the presence of multiple objectives to be satisfied.

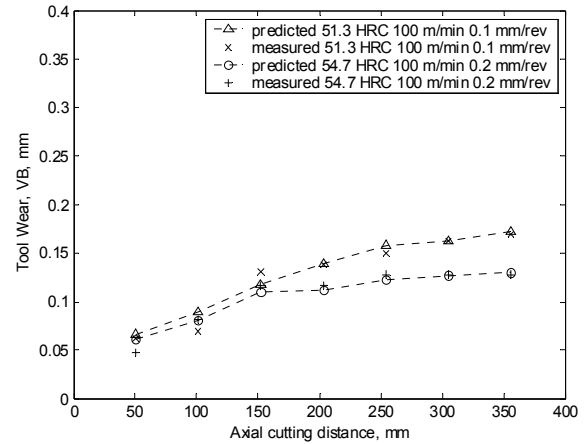


FIGURE 3. PREDICTED TOOL WEAR PATTERN FOR HONED EDGE GEOMETRY CBN TOOL

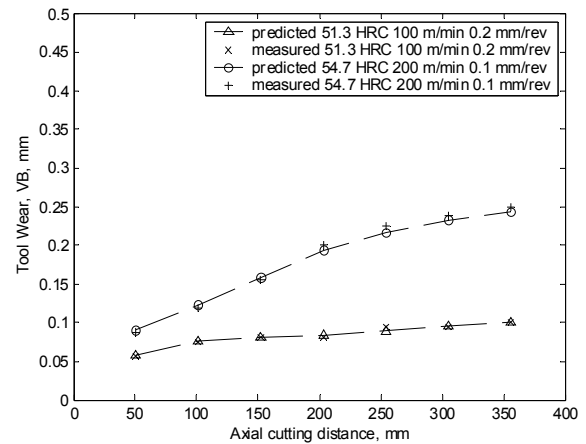


FIGURE 4. PREDICTED TOOL WEAR PATTERN FOR HONED EDGE GEOMETRY CBN TOOL

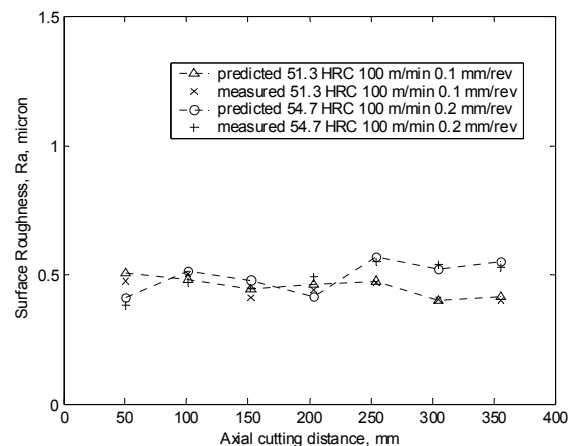


FIGURE 5. PREDICTED SURFACE ROUGHNESS PATTERN FOR HONED EDGE GEOMETRY CBN TOOL

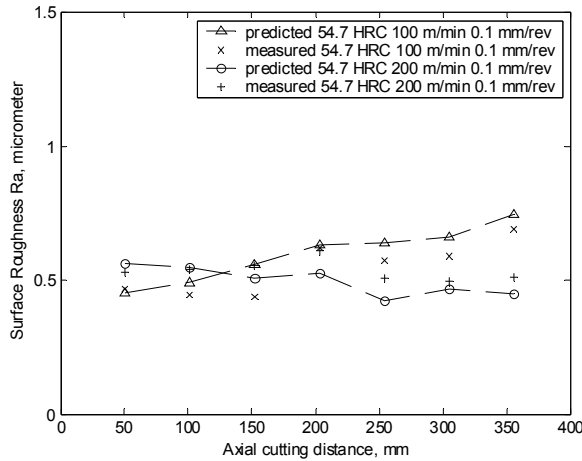


FIGURE 6. PREDICTED SURFACE ROUGHNESS PATTERN FOR CHAMFERED EDGE GEOMETRY CBN TOOL

At this point our goal is to present preliminary results of optimization of hard turning rather than providing results, which can be directly used in shop floor. To obtain general results with this approach extensive experimentation is required which emphasizes the importance of analytical force, tool wear and surface roughness models.

### OPTIMIZATION OF HARD TURNING MACHINING PARAMETERS

Optimal selection of machining parameters of hard turning can be formulated and solved as a multiple objective optimization problem. In practice, efficient operation of hard turning operation requires the simultaneous consideration of multiple objectives, including maximum tool-life, desired roughness of the machined surface, target operation productivity, etc. In some instances, parameter settings that are optimal for one defined objective function may not be particularly suited for another objective function. This results in an important optimization problem to define parameter settings given multiple conflicting objectives, with different relative priorities.

The general multi-objective optimization of hard turning problem can be formulated as:

$$\begin{aligned} & \min \{f_1(x), f_2(x), f_3(x), \dots\} \\ & \text{s.t. } g_i(x) \leq b_i \text{ for } i = 1, \dots, m \\ & \quad g_i(x) = b_i \text{ for } i = m + 1, \dots, m + k \\ & \quad x \in X \end{aligned}$$

where

$$f_1(x) = \text{tool wear}$$

$$f_2(x) = \text{roughness of machined surfaces}$$

...

$$g_i(x) = i^{\text{th}} \text{ constraint}$$

$$b_i = i^{\text{th}} \text{ constraint limit}$$

$$x = \text{decision variable vector} = (x_1, x_2, \dots, x_n)$$

$$x_1 = \text{cutting speed (m/min)}$$

$$x_2 = \text{feed rate (mm/rev)}$$

$$x_3 = \text{tool edge type (chamfered or honed)}$$

$$x_4 = \text{workpiece hardness (HRC)}$$

$$x_5 = \text{cutting distance (m)}$$

$X$  = solution space of possible parametric values, not considering  $g_i(x)$  constraints

In this formulation, the objective is to simultaneously optimize, minimize in this case, each objective function. The constraints are related to machine cutting speed and feed rate related limits. Determination of the relative priority of the multiple objective functions depends on the producers' and customer needs.

There are two primary general approaches to solve multiple objective problems. They are (1) to combine the multiple objectives into a single objective through the use of "weights" or utility functions, or (2) to produce a Pareto-optimal set of non-dominated decision variable settings. The combined objectives approach yields a unique solution that can be readily implemented, but largely depends on numerical weights that are often difficult to select, and often somewhat selected arbitrarily, in practice. The selection of a Pareto-optimal set avoids this problem, but may provide numerous prospective solutions that must be considered. Since neural networks are used as the models for tool wear and surface roughness, gradient-based nonlinear programming methods are not practical. In this study, a recently developed optimization algorithm, PSO, which offers distinct advantages especially in terms of computation time, is used.

### Particle Swarm Optimization

PSO is an evolutionary computation (EC) method inspired by flocking birds. This population based stochastic optimization technique developed by Eberhart and Kennedy [16] and applied to many different systems including machining. El-Mounayri et al [17] used PSO to optimize the coefficients of a surface roughness model. Scheffer et al. [13] performed

on-line optimization of the dynamic neural network models by PSO to estimate the wear values and by minimizing the difference between on-line measurements and the output of the static networks.

PSO is initialized with a population of random solutions and this initial population evolves over generations to find optima. However, in PSO, each particle in population has a velocity, which enables them to fly through the problem space instead of dying and mutations. Therefore, each particle is represented by a position and a velocity. Modification of the position of a particle is performed by using its previous position information and its current velocity. Each particle knows its best position (personal best) so far and the best position achieved in the group (group best) among all personal bests. These principles can be formulated as:

$$v_i^{k+1} = wv_i^k + c_1rnd_1(pb_{best_i} - x_i^k) + c_2rnd_2(gbest - x_i^k) \quad (1)$$

where

$v_i^k$ : velocity of agent  $i$  at iteration  $k$

$x_i^k$ : current position of agent  $i$  at iteration  $k$

$pb_{best_i}$ : personal best of agent  $i$

$gbest$ : best position in group

$rnd$ : random number between 0 and 1

$w$ : weighting function

$c_j$ : weighing factor  $j=1,2$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (2)$$

The first term on the right hand side of Eq. (1) is the previous velocity of the particle, which enables it to fly in search space. The second and third terms are used to change the velocity of the agent according to  $pb_{best}$  and  $gbest$ . The iterative approach of PSO can be described as follows:

**Step 1:** Initial position and velocities of agent are generated. The current position of each particle is set as  $pb_{best}$ . The  $pb_{best}$  with best value is set as  $gbest$  and this value is stored. The next position is evaluated for each particle by using Eq. (1) and (2).

**Step 2:** The objective function value is calculated for new positions of each particle. If a better position is achieved by an agent, the  $pb_{best}$  value is replaced by the current value. As in Step 1,  $gbest$  value is selected among  $pb_{best}$

values. If the new  $gbest$  value is better than previous  $gbest$  value, the  $gbest$  value is replaced by the current  $gbest$  value and stored.

**Step 3:** Steps 1 and 2 are repeated until the iteration number reaches a predetermined iteration number.

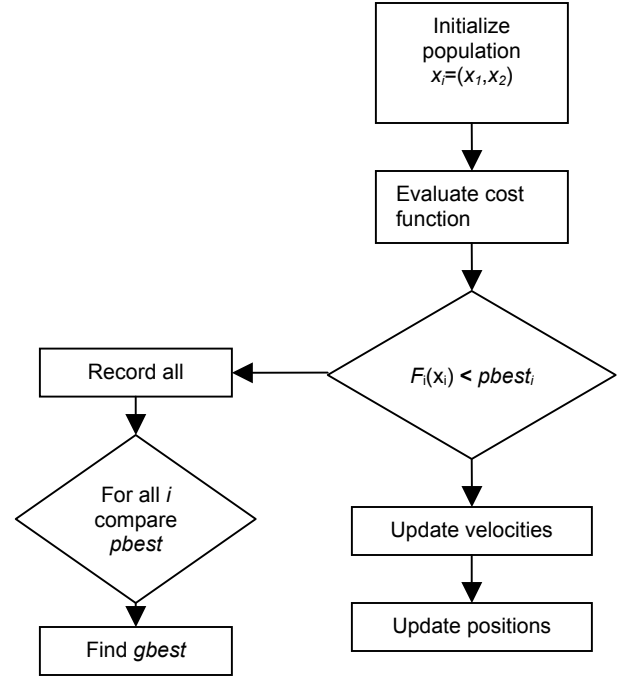


FIGURE 7. FLOWCHART OF PSO ALGORITHM

Success of PSO depends on the selection of parameters given in Eq (1). Shi and Eberhardt [18] studied the effects of parameters and concluded that  $c_1$  and  $c_2$  can be taken around the value of 2 independent from problem. Weighting function  $w$  is usually utilized according to the following formula,

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \quad (3)$$

where

$w_{max}$ : initial weight

$w_{min}$ : final weight

$iter_{max}$ : maximum iteration number

$iter$ : current iteration number

Eq. (3) decreases the effect of velocity towards the end of search algorithm, which confines the search in a small area to find optima accurately. The velocity update step in PSO is stochastic due to random numbers generated, which may cause an uncontrolled increase in velocity and therefore instability in search algorithm. In order to prevent this, usually a maximum and a minimum allowable

velocity is selected and implemented in the algorithm. In practice, these velocities are taken as  $[-4.0, +4.0]$ .

### Optimization of finish hard turning using PSO integrated with neural network

In order to search optimal process parameter sets to satisfy demands, neural network model of tool wear and surface roughness was integrated with particle swarm optimizer. Fig. 8 shows this integrated optimization scheme.

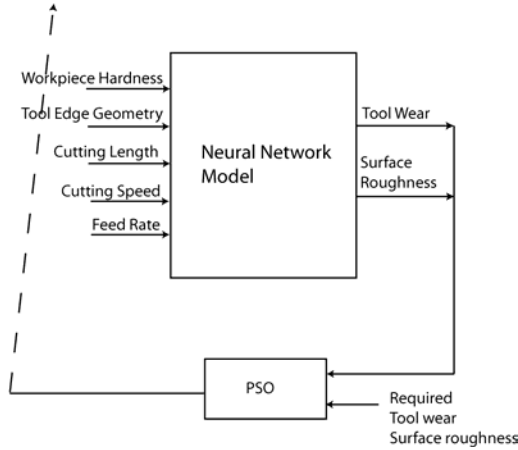


FIGURE 8. PSO BASED NEURAL NETWORK OPTIMIZATION SCHEME

In this scheme, PSO is initiated with randomly generated particles that are optimum solution candidates within the range of inputs. Neural network model predicts tool wear and surface roughness values for each of the particles. Predicted tool wear and surface roughness are used in calculation of objective function in which PSO tries to minimize. The most crucial part of optimization problems is the definition of objective functions. In this study, our objective is to obtain cutting conditions, which yield less tool wear than a limit value after a specified amount of cutting distance and satisfy surface roughness requirements within this cutting distance range without sacrificing maximum productivity. It should be noted that surface roughness should be satisfied all along the specified distance. The proposed objective function for this purpose can be written as:

$$\begin{aligned} \text{minimize } f = & w_1 \times (\min(0, VB_{lim} - VB_{pred}))^2 \\ & + w_2 \times \left( \sum_{l=1}^{l_2} \min(0, Ra_{lim} - Ra_{pred}) \right)^2 + w_3 \times \frac{1}{x_1 x_2} \quad (4) \end{aligned}$$

In Eq. (4),  $VB_{lim}$  is the limit of tool flank wear after given cutting distance and  $VB_{pred}$  is the predicted tool wear at that point by neural network model. Similarly  $Ra_{lim}$  is the limit surface roughness, which is maximum surface roughness allowed within given range and  $Ra_{pred}$  is the prediction of neural network model. According to this objective function, when the neural network predictions are greater than limit values the results will have negative values therefore, minimum function in the objective function will penalize these solutions by multiplying them with penalty coefficients  $w_1$  and  $w_2$ . The third term in the objective function represents productivity and has a penalty coefficient  $w_3$ . The selection of penalty coefficient values depends on the priority of individual objectives.

Among the five inputs of the neural network model, workpiece hardness and cutting distance are assumed to be known in this study. The workpiece hardness can be in the range of 51.3 and 54.7 HRC and cutting distance may be up to 360 m. Consequently, the decision variables; tool edge geometry, cutting speed and feed rate are left as optimization parameters. All the decision variables except tool edge geometry are continuous variables. Tool edge geometry is a binary variable since it can either be honed or chamfered. This presents a typical mixed integer optimization problem. The problem of selecting tool edge geometry can be solved by repeating the optimization algorithm for chamfered and honed tools separately. Tool edge geometry solution which also maximizes material removal rate (MRR) can be chosen as a result due to higher productivity.

$$MRR = d.f.v \quad (5)$$

In Eq. (5),  $d$  is depth of cut which is constant 0.254 mm throughout this study,  $f$  is the optimal feed rate and  $V$  is optimal cutting speed. Since the characteristics of chamfered and honed tools are quite different (Figs. 3-6), it is expected to obtain different optimal solutions for each tool type. Constraints for this optimization problem are cutting speed and feed rate values used in hard turning practice. The constraints can be summarized as follows:

$$\begin{aligned} 0.05 & \leq x_2 \leq 0.2 \\ 100 & \leq x_1 \leq 200 \end{aligned} \quad (6)$$

In order to handle constraints, a simple modification to particle swarm optimization algorithm is sufficient. The additional rules that should be implemented in PSO algorithm are: (1) When updating the memories, only the particles in feasible region should be kept in memory and (2) Particles should be initiated in feasible region. PSO optimization algorithm together with constraints was converted into a code in Matlab® software. In PSO, 40 particles were used and search continues until error gradient is smaller than a specified value. Matlab® code simulates the trained neural network to predict tool wear and surface roughness values at given cutting distances and these values are used to calculate the objective function which PSO algorithm attempts to minimize. In order to test the capabilities of the optimization algorithm two cases are demonstrated here.

**Case 1:** It is required that tool wear after 85th m of cutting should not exceed 0.04 mm and maximum value of surface roughness should not exceed 0.2 micron between 40th and 85th meters. The tool is assumed to be fresh at the beginning. The objective function for this case can be written as:

$$\begin{aligned} \text{minimize } f = & w_1 \times (\min(0, 0.04 - VB_{pred}))^2 \\ & + w_2 \times \left( \sum_{l_1=40}^{l_2=85} \min(0, 0.2 - Ra_{pred}) \right)^2 + w_3 \times \frac{1}{x_1 x_2} \end{aligned} \quad (7)$$

$$0.05 \leq x_2 \leq 0.2$$

$$100 \leq x_1 \leq 200$$

$$x_4 = \text{workpiece hardness } 54.7 \text{ (HRC)}$$

$$x_5 = \text{cutting distance between 40 and 85 (m)}$$

TABLE 1. RESULT SUMMARY OF CASE 1

	Chamfered Tool	Honed Tool
Cutting Speed (m/min)	100	200
Feed rate (mm/rev)	0.1166	0.0683
Objective function	303.18	0.3715
Convergence	63 iterations	51 iterations

The above given objective function is used in Matlab® code and the obtained optimum solutions for chamfered and honed tools are given in Table 1. Because of its relatively high objective value it is understood that chamfered tool could not satisfy the limit tool wear and surface roughness values for given cutting distance range. Honed tool successfully satisfied the given conditions. Another fact can be verified

from the result is, to obtain good surface roughness feed rate must be selected low.

**Case 2:** In the second case, we aim to compare chamfered and honed tools, hence we relax surface roughness and tool wear requirements. This condition can be defined as:

$$VB_{lim} = 0.1 \text{ mm}, Ra_{lim} = 0.5 \mu\text{m}$$

$$l_1 = 40 \text{ m}, l_2 = 85 \text{ m}$$

The objective function can be written as:

$$\begin{aligned} \text{minimize } f = & w_1 \times (\min(0, 0.1 - VB_{NN}))^2 \\ & + w_2 \times \left( \sum_{l=40}^{85} \min(0, 0.5 - Ra_{NN}) \right)^2 + w_3 \times \frac{1}{x_1 x_2} \end{aligned} \quad (8)$$

$$0.05 \leq x_2 \leq 0.2$$

$$100 \leq x_1 \leq 200$$

$$x_4 = \text{workpiece hardness } 54.7 \text{ (HRC)}$$

$$x_5 = \text{cutting distance between 40 and 85 (m)}$$

Optimal cutting speed and feed rates for chamfered and honed tools are shown in Table 2. Since the surface roughness conditions are relaxed, higher feed rates and lower cutting speeds are obtained compared to case 1. Both of the cutting tool edge geometry satisfies the requirements. According to higher productivity criteria related to material removal rate, honed tool is selected.

TABLE 2. RESULT SUMMARY FOR CASE 2

	Chamfered Tool	Honed Tool
Cutting Speed (m/min)	101.01	162.7
Feed rate (mm/rev)	0.1254	0.1893
Objective function	0.396	0.1623
Convergence	78 iterations	156 iterations
MRR	3217.33	7822.9

## CONCLUSION

This study has presented multi-objective optimization of hard turning process by using neural network modeling and particle swarm optimization. A neural network model of hard turning was used to predict surface roughness and tool wear during machining and particle swarm optimization was used to obtain optimum cutting speed, feed rate and tool edge geometry which are main process variables. Two different test cases illustrated that the combined neural network and particle swarm optimization system is capable of generating optimal process

parameters and can be used successfully in the multi-objective optimization of hard turning. Particle swarm optimization is also proved to be an efficient optimization algorithm. For the test cases it yielded optimal parameter around 100 iterations, which take only a little time with today's computers.

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