# A Real Coded Genetic Algorithm for Optimization of Cutting Parameters in Turning

**T. Srikanth† and Dr V. kamala††**

Asso. Prof.,Dept. of Mech. Engg. G.I.E.T, Rajahmundry, A.P, India†
DGM (Retd.), B.H.E.L, R&D, Balanagar, Hyderabad, A.P, India††

**Abstract**

Surface roughness, an indicator of surface quality is one of the most specified customer requirements in a machining process. For efficient use of machine tools, optimum cutting parameters (speed, feed and depth of cut) are required. So it is necessary to find a suitable optimization method which can find optimum values of cutting parameters for minimizing surface roughness. The turning process parameter optimization is highly constrained and nonlinear, so this paper proposes a real coded genetic algorithm (RCGA) to find optimum cutting parameters. This paper explains various issues of RCGA and its advantages over the existing approach of binary coded genetic algorithm. The results obtained, conclude that RCGA is reliable and accurate for solving the cutting parameter optimization.

***Key words:*** *Real Coded Genetic Algorithm, Turning, Cutting Parameters, Optimization, Surface roughness.*

## 1. Introduction

In turning operation, it is an important task to select cutting parameters for achieving high cutting performance. Usually, the desired cutting parameters are determined based on experience or by use of hand book. But the ranges given these sources are actually starting values and are not the optimal values. However, this does not ensure that the selected cutting parameters have optimal or near optimal cutting performance for a particular machine and environment.

The traditional methods used for solving this kind of optimization problems include calculus based searches, dynamic programming, random searches and gradient methods whereas modern heuristic methods include artificial neural networks [1], Lagrangian relaxation approaches [2] and simulated annealing [1]. Some of these methods are successful in locating the optimal solution, but they are usually slow in convergence and require much computing time. Other methods may risk being trapped at a local optimum which fails to give best solution.

The performance of conventional genetic algorithm (CGA) precedes mainly traditional optimization method in aspect of global search, but CGA suffers also premature convergence problem and expensive computing time, therefore many researchers proposed different methods to solve these problems and have obtained an amount of achievements. The purpose of these methods is centralized into three aspects, i.e., decrease computing burden, speed up convergence rate and enhance global search capability. CGA use binary code, which needs a lot of time to code and decode the values.

To improve the final local tuning capabilities of a binary coded genetic algorithm, which is a must for high precision problems, real coded genetic algorithm (RCGA) is introduced. The main objective behind RCGA implementation is to move the genetic algorithm closer to the problem space. For most applications of GA, constrained optimization problems, the real coding is used to represent a solution to a given problem to decrease computing burden. Such coding is also known as floating-point representation or real number representation.

Michaelewicz [3] indicated that for real valued numerical optimization problems, floating-point representations outperforms binary representation because they are more consistent, precise and lead to faster execution. For most applications of GAs to optimization problems, the real coding technique is used to represent a solution to a given problem. Hence, GA with real values, for solving the optimal control problem is used.

Optimization of machining parameters not only increases the utility for machining economics, but also the product quality to a great extent. In this context, an effort has been made to estimate the minimum surface roughness in turning operation using real coded genetic algorithm.

## 2. Literature Review

Since turning is the primary operation in most of the production processes in the industry, surface finish of turned components has greater influence on the quality of the product. Surface finish in turning has been found to be influenced in varying amounts by a number of factors such as feed rate, work material characteristics, work hardness, unstable built-up edge, cutting speed, depth of cut, cutting time, tool nose radius.

Manuscript received June 5, 2008.
Manuscript revised June 20, 2008.

Franic Cus [4] used binary coded genetic algorithm for the optimization of cutting parameters. This genetic algorithm optimizes the cutting conditions having an influence on production cost, time and quality of the final product. P.V.S. Suresh [5] developed optimum surface roughness predictive model using binary coded genetic algorithm. This GA program gives minimum and maximum values of surface roughness and their respective optimal machining conditions. W.H. Yang [6] used the Taguchi method for design optimization on quality. It is used to find the optimal cutting parameters for turning operations. An orthogonal array, the signal-to-noise (S/N) ratio, and the analysis of variance (ANOVA) are employed to investigate the cutting characteristics. Uros Zuperl[7] proposed a neural network-based approach to complex optimization of cutting parameters is proposed. It describes the multi-objective technique of optimization of cutting conditions by means of the neural networks taking into consideration the technological, economic and organizational limitations. H. Oktem [8] utilized response surface methodology to create an efficient analytical model for surface roughness in terms of cutting parameters: feed, cutting speed, axial depth of cut, radial depth of cut and machining tolerance.

## 3. Methodology

The main objective of the present paper is to determine the optimal machining parameters that minimize the surface roughness without violating any imposed cutting constraints. The present paper uses the real number genetic algorithm.

In real-coded genetic algorithm (RCGA), the solution is directly represented as a vector of real parameter decision variables, representation of the solutions very close to the natural formulation of many problems. The use of real-parameter makes it possible to use large domains (even unknown domains) for variables. Capacity to exploit the graduality of the functions with continuous variables is another advantage. Every good GA needs to balance the extent of exploration of information obtained up until the current generation through recombination and mutation operators with the extent of exploitation through the selection operator. If the solutions obtained are exploited too much, premature convergence is expected. On the other hand, if too much stress is given on a search (i.e. exploration), the information obtained thus far has not been used properly. Therefore, the solution time may be enormous and the search exhibits a similar behaviour to that of a random search. The issue of exploration and exploitation makes a recombination and mutation operator dependent on the chosen selection operator for successful GA run.

### 3.1 Reproduction

This is the first of the genetic operators. It is a process in which copies of the strings are copied into a separate string called the ‘mating pool’, in proportion to their fitness values. This implies that strings with higher fitness values will have a higher probability of contributing more strings as the search progresses. The present paper uses the roulette wheel method [9] for the reproduction. In this method, each individual in the population is assigned a space on the roulette wheel, which is proportional to the individual relative fitness. Individuals with the largest portion on the wheel have the greatest probability to be selected as parent generation for the next generation.

### 3.2 Crossover

Crossover is the main genetic operator and consists of swapping chromosome parts between individuals. Crossover is not performed on every pair of individuals, its frequency being controlled by a crossover probability (Pc). The present paper uses arithmetic crossover operator (AMXO). The basic concept of this operator is borrowed from the convex set theory. Simple arithmetic operators are defined with the combination of two vectors (chromosomes) as follows:

$$s' = (\lambda \times s) + ((1-\lambda) \times t) \quad (1)$$

$$t' = ((1-\lambda) \times \mathrm{s}) + (\lambda \times \mathrm{t}) \quad (2)$$

Where λ is uniformly distributed random variable between 0 and 1.

### 3.3 Mutation

Let us suppose $C=(c_1,\ldots c_i,\ldots c_n)$ is a parent chromosome, $C_i \in [a_i, b_i]$ is a gene to be mutated and $a_i$ and $b_i$ are the lower and upper ranges for gene $c_i$. A new gene in the offspring chromosomes, $c_i$ may arise from the application of two different mutation operators respectively. The present paper uses uniform mutation operator. This operator is single point random mutation, in which a single gene $c_i$ is randomly chosen number from range $[a_i, b_i]$ to replace $c_i$ and to form new chromosome C'. It is controlled by mutation probability ($M_c$).

### 3.3 Objective Function

The problem of the optimization of cutting parameters can be formulated as the following objective optimization problem:

min $R_a(v, f, d, r)$

The surface roughness [10] is calculated by Equation (3).

$$R_a = \frac{1.0632 \times f^{1.0198} \times d^{0.0119} \times H^{0.5234} \times r^{0.1388}}{v^{0.229}} \quad (3)$$

Where v is the cutting speed (m/min), f is the feed (mm/rev), d is the depth of cut (mm), r is the tool radius (mm) and H is material hardness (125BHN).

### 3.4 Constraints

Due to the limitations on the machine and cutting tool and due to the safety of machining the cutting parameters are limited with the bottom and top permissible limit. There are several factors limiting the cutting parameters. Those factors originate usually from technical specifications and organizational considerations. The following limitations are taken into account as given by Equation (4)-(7).

$$v_{min} \leq v \leq v_{max} \quad (4)$$

$$f_{min} \leq f \leq f_{max} \quad (5)$$

$$d_{min} \leq d \leq d_{max} \quad (6)$$

$$r_{min} \leq r \leq r_{max} \quad (7)$$

### 3.5 Decision variables

In the construct optimization problem four decision variables are considered. These decision variables are cutting speed, feed, depth of cut and nose radius.

The procedure of optimization of cutting parameters by using real coded genetic algorithm is explained in Fig 1.

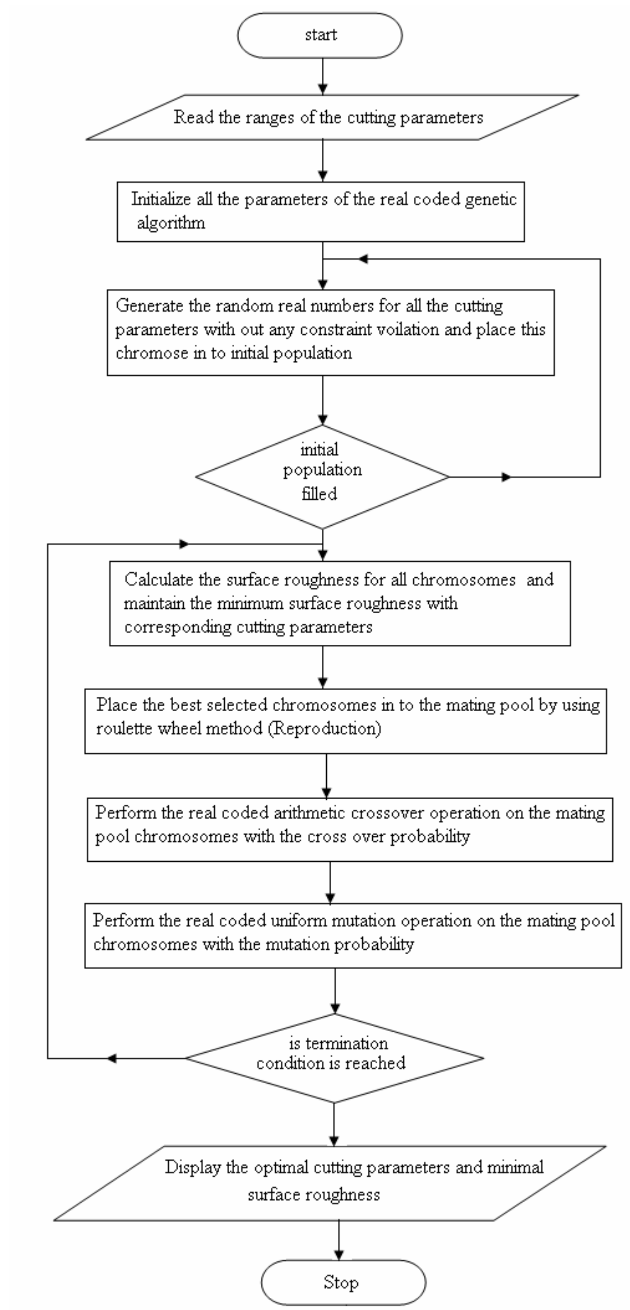


Fig 1: Flow chart for RCGA approach of optimization of cutting parameters

## 4. Results and Discussions

The first step of RCGA is to create an initial population. Individual values for different parameters in the initial population are chosen within their ranges at random. The initial parameters chosen in (Table:1) are depth of cut, feed rate, cutting speed and along with these process parameters nose radius is also chosen. Optimal cutting parameters predicted by RCGA for the minimum surface roughness are given in Table 2.

Table 1: Output values of RCGA with respect to input cutting parameters

| *S. No* | *Speed (m/ min)* | *Depth of cut (mm)* | *Feed (mm/ rev)* | *Nose Radius (mm)* | *Surface roughness (μm)* |
|---|---|---|---|---|---|
| 1 | 30-90 | 0.5-1.0 | 0.2-0.4 | 0.4-0.8 | 0.857260 |
| 2 | 30-90 | 0.5-1.0 | 0.2-0.4 | 0.8-1.2 | 0.928069 |
| 3 | 30-90 | 0.5-1.0 | 0.4-0.8 | 0.4-0.8 | 1.786641 |
| 4 | 30-90 | 0.5-1.0 | 0.4-0.8 | 0.8-1.2 | 1.880024 |
| 5 | 30-90 | 1.0-1.5 | 0.2-0.4 | 0.4-0.8 | 0.851825 |
| 6 | 30-90 | 1.0-1.5 | 0.2-0.4 | 0.8-1.2 | 0.928080 |
| 7 | 30-90 | 1.0-1.5 | 0.4-0.8 | 0.4-0.8 | 1.836571 |
| 8 | 30-90 | 1.0-1.5 | 0.4-0.8 | 0.8-1.2 | 1.878548 |
| 9 | 90-180 | 0.5-1.0 | 0.2-0.4 | 0.4-0.8 | 0.766149 |
| 10 | 90-180 | 0.5-1.0 | 0.2-0.4 | 0.8-1.2 | 0.817921 |
| 11 | 90-180 | 0.5-1.0 | 0.4-0.8 | 0.4-0.8 | 1.512453 |
| 12 | 90-180 | 0.5-1.0 | 0.4-0.8 | 0.8-1.2 | 1.690667 |
| 13 | 90-180 | 1.0-1.5 | 0.2-0.4 | 0.4-0.8 | 0.738389 |
| 14 | 90-180 | 1.0-1.5 | 0.2-0.4 | 0.8-1.2 | 0.810552 |
| 15 | 90-180 | 1.0-1.5 | 0.4-0.8 | 0.4-0.8 | 1.504253 |
| 16 | 90-180 | 1.0-1.5 | 0.4-0.8 | 0.8-1.2 | 1.687547 |

The initial population is spread over the whole solution space instead of being localized because initial population is created randomly. This diversity of the population increases the region under search to find the global optima. From the initial set of data, RCGA starts to converge very quickly by using genetic operators such as reproduction, crossover, and mutation**.**

The surface roughness prediction model developed, takes into account cutting speed, feed rate, depth of cut, cutting tool, nose radius and their interactions. With the known boundaries of surface roughness and machining conditions, optimal values of these parameters are generated by RCGA for minimum surface roughness.

The effect of surface roughness with speed with constant feed of 0.2-0.4 mm is shown in Fig. 2. It is observed that with constant feed minimum surface roughness values are observed at high speeds, whereas as the speed decrease the surface roughness increases. The effect of surface roughness with feed is shown in Fig. 3. It is observed that at low feed minimum surface roughness is produced, whereas at high feed the surface roughness increases. Where as from the Table:1 depth of cut and nose radius have moderate effect on surface roughness. Hence in order to achieve better surface finish, a combination of high speed and low feed, with moderate depth of cut and nose radius are to be selected for the machining process.

Table 2: Optimum values of cutting parameters predicted by RCGA for minimum values of surface roughness in Table 1.

| *S. No* | *Speed (m/ min)* | *Depth of cut (mm)* | *Feed (mm/ rev)* | *Nose Radius (mm)* |
|---|---|---|---|---|
| 1 | 82.717673 | 0.720191 | 0.200012 | 0.537565 |
| 2 | 86.577654 | 0.913816 | 0.204248 | 0.862380 |
| 3 | 62.817164 | 0.726173 | 0.401709 | 0.403186 |
| 4 | 87.211219 | 0.817698 | 0.402454 | 0.976519 |
| 5 | 85.125584 | 1.168371 | 0.205896 | 0.417408 |
| 6 | 89.252907 | 1.005707 | 0.206922 | 0.817481 |
| 7 | 87.040925 | 1.272668 | 0.432032 | 0.470266 |
| 8 | 85.768303 | 1.151006 | 0.409876 | 0.802100 |
| 9 | 173.232215 | 0.898267 | 0.200159 | 0.790576 |
| 10 | 160.781579 | 0.696722 | 0.207935 | 0.864846 |
| 11 | 138.670919 | 0.650456 | 0.405750 | 0.420508 |
| 12 | 156.988433 | 0.697592 | 0.420301 | 0.883425 |
| 13 | 147.707450 | 1.012772 | 0.203143 | 0.413575 |
| 14 | 172.982269 | 1.230903 | 0.202057 | 1.074825 |
| 15 | 179.980773 | 1.375683 | 0.408081 | 0.559014 |
| 16 | 158.174993 | 1.069231 | 0.419410 | 0.864284 |

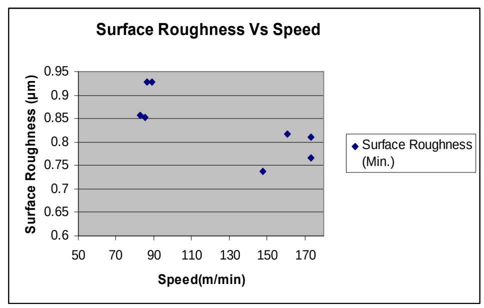


Fig. 2 Surface Roughness Vs Speed

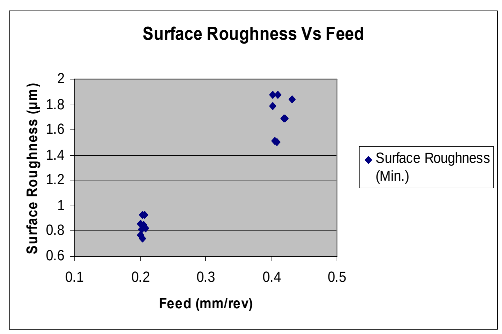


Fig. 3 Surface Roughness Vs Feed

The advantages of this RCGA approach for optimization of cutting parameters are summarized below.

- The use of real- values for cutting parameters makes it possible to use large domains for variables.
- Fast optimization with less computation burden.
- Capacity to exploit the graduality of the functions with continuous variables.

## 5. Conclusions

This paper outlines the development of RCGA approach for optimization of cutting parameters in turning. This RCGA approach is quite advantageous in order to have the minimum surface roughness values, and their corresponding optimum cutting parameters, for certain constraints. This work shows that in constrained optimization problem like turning process, RCGA approach is necessary to get the optimum solutions faster. This would be helpful for a manufacturing engineer to choose machining conditions for desired machining performance of a product. With the known boundaries of surface roughness and machining conditions, machining could be performed with a relatively high rate of success, with selected machining conditions. Integration of the proposed approach with an intelligent manufacturing system will lead to reduction in production cost, reduction in production time, flexibility in machining parameter selection and overall improvement of the product quality.

## References


[1] Pandey PPC, Pal S. In: Proceedings of Third International Conference in Computer Integrated machining Sigapore, Vol.1, 1995.pp812-819.

[2] Hsu VN, Daskin M, Jones PC, Lowe TJ. Tool selection for optimal part production : a Lagrangian relaxation approach. I I E Trans 1995;27: pp 417-426.

[3] Mitsuo Gen and Runwei Cheng, Genetic Algorithms and Engineering Design, John Wiley & Sons, Inc., 1997.

[4] Franci Cus, Joze Balic ," Optimization of cutting process by GA approach", Robotics and Computer Integrated manufacturing 19 (2003), pp113-121.

[5] P.V.S. Suresh, P. Venkateswara Rao, S.G. Deshmukh," A genetic algorithmic approach for optimization of surface roughness prediction model", International Journal of Machine Tools & Manufacture 42 (2002), pp 675–680.

[6] W.H. Yang, Y.S. Tarng, "Design optimization of cutting parameters for turning operations based on the Taguchi method", Journal of Materials Processing Technology 84 (1998), pp122–129.

[7] Uros Zuperl, Franci Cus, "Optimization of cutting conditions during cutting by using neural networks", Robotics and Computer Integrated Manufacturing 19 (2003) pp189–199.

[8] H. Oktem, T. Erzurumlu, H. Kurtaran, "Application of response surface methodology in the optimization of cutting conditions for surface roughness", Journal of Materials Processing Technology 170 (2005), pp11–16.

[9] Genetic Algorithms in search, optimization & Machine learing by David E.Goldberg, Pearson Education.

[10] T. Srikanth, Dr V. kamala, "Experimental determination of optimal speeds for alloy steels in plane turning", Proceedings of the 9th Biennial ASME Conference on Engineering Systems Design and Analysis,ESDA2008, Haifa, Israel.

[11] F. Herrera, M.Lozano and J.L. Verdegay, "Tackling Real Coded Genetic Algorithms: Operators and tools for behaviour Analysis". Artificial Intelligence Review, Volume 12, Number 4 / August, 1998, pp: 265-319.


**T. Srikanth** received his B.E degree in mechanical engineering from Bangalore University, India in 1997. He received his M.tech degree in advanced manufacturing from REC, warangal, A.P, India in 2002. He is pursuing Ph.D degree from Osmania University in Mechanical Engineering under the guidance of Dr V. kamala. He worked as engineer in bottling company, samarlakota, A.P, India (1998-200). He is working as Associate Professor in Mech. Dept., G.I.E.T, Rajahmundry, A.P, India (2002-2008).His research interests include condition monitoring, metal cutting and optimization techniques.

**V. Kamala** received B.E degree in mechanical engineering from Osmania University, Hyderabad, A.P, India in 1966. She received her M.Tech degree in machine design from IIT Madras, India in 1970 and Ph.D degree from IIT Madras in 1977. She had worked as lecturer in REC Warangal, A.P, India for one year. She is a permanent member of FIEM and ASME. She is ASME zonal coordinator, Indian chapter. She was a research associate in IIT Madras for 5 years. She worked as Prof. and Head of Mech. Dept. in C.B.I.T, Hyderabad for 1 year. She was a visiting research scientist in department of mechanical engineering at Carleton University, Ottawa, Canada during 1987-89. She worked as D.G.M in B.H.E.L corp. R&D division, Hyderabad, A.P, India for 29 years. She acted as technical program committee member of 12$^{th}$ ASME technical conference, Montreal, Quebec, Canada. She published around 75 papers in conferences and journals at national and international levels. She received Best citizen of India award in 1998 and received 20$^{th}$ century award for achievement given by International Biographical centre, Cambridge, London. She received best paper award at international conference on industrial tribology in 1999, and also best design paper award for achievement at XI AIMTDR conference held at IIT, Madras in 1984. Her research interests include condition monitoring, magnetic bearings and vibrations.