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Estimation of optimal cutting parameters of plane turning using quantum inspired evolutionary algorithm

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ABSTRACT

Turning is a versatile machining process that involves different cutting parameters and conditions. The surface finish is the vital design requirement as it is a key indicator of quality of the work piece. This work, presents the application of Quantum Inspired Evolutionary Algorithm (QIEA), that essentially exploits some principles of quantum mechanics such as Q-bits, superposition, quantum gate and quantum measurement, for the process optimization of plane turning. The QIEA estimated optimal cutting parameters i.e., cutting speed, feed rate, tool nose radius and depth of cut of plane turning for improved surface finish within the operating conditions. The results are compared with real coded genetic algorithm (RCGA) and differential evolution algorithm (DEA). The results obtained by Quantum Inspired Evolutionary Algorithm are better than those reported with RCGA and are comparable to those of DEA.

Keywords – **Differential evolution, Plane turning, Quantum Inspired Evolutionary Algorithm, Surface finish**

I. INTRODUCTION

The key attribute of any machined part is its surface finish, which is a technical requirement as the machined part necessarily have to interact with other parts of the larger mechanical system per se. Surface finish is actually the degree of smoothness of a machined part, which is the result of the surface roughness. Surface roughness is undesirable, but difficult and expensive to control during manufacturing. Decreasing roughness of a surface will usually exponentially increase its manufacturing costs. Optimizing any machining process in want of better surface finish using experimental methods is very difficult and cost intensive, and often fail to achieve good repeatable optimal or near optimal results. Plane turning is an indispensible metal removing process that finds wide applications in all the manufacturing industries. In plane turning, the cutting tool establishes contacts with workpiece, at a single point, and resulting, heat and wear at the contact point between cutting tool and workpiece. Consequentially, tool life gets affected and surface roughness increases. Thus, it is imperative to select optimal cutting parameters, such as cutting speed, feed rate, and depth of cut, that are known to have a significant impact on surface quality of the workpiece [1].

To address the limitations of laborious, cost intensive traditional techniques, soft-computing techniques are increasingly inviting the attention of researchers, as they are capable of handling highly non linear complex real world machining optimization problems [2]. The problem of plane turning process optimization was attempted using binary coded genetic algorithms (BCGA) to estimate optimal cutting conditions for the process [3, 4]. An empirical surface roughness model of plane turning was enumerated and solved using real coded genetic algorithm (RCGA), which does not suffer from imprecision and premature convergence, unlike BCGA [5, 6].The differential evolution algorithm (DEA) was also applied on the same optimization problem in order to reduce the surface roughness [7]. Although Quantum Inspired Evolutionary Algorithm was firstly introduced by Narayanan and Moore to solve TSP [8], in which the crossover operation was performed based on the concept of interference. Ever since, Han and Kim exploited the quantum mechanics principles such as Q-bits, superposition, quantum gates and quantum probabilistic measurement and developed a more practical algorithm, Quantum Inspired Evolutionary Algorithms gained greater attention of the scientific fraternity.

Quantum Inspired Evolutionary Algorithm was applied on some engineering optimization problems. However, the problem of process optimization of turning was not solved yet, using Quantum Inspired Evolutionary Algorithm. On the other hand, Gexiang Zhang, reported that, although Quantum Inspired Evolutionary Algorithm is reportedly better than genetic algorithm (GA), there are a few comparisons made between Quantum Inspired Evolutionary Algorithm and Differential Evolution Algorithm [11]. Therefore this work presents the performance comparison of Quantum Inspired Evolutionary Algorithm on the process optimization of plane turning. The paper is further organized as follows. In section II, the empirical model of plane turning is presented. Quantum Inspired Evolutionary Algorithm is explained in detail in section III. In section IV results of the experiments conducted on Quantum Inspired Evolutionary Algorithm for process optimization plane turning are compared with the results of Differential Evolution Algorithm. The conclusions are presented in section V.

II. MODEL OF PLANE TURNING

The problem of prediction of optimal cutting parameters for plane turning may be enumerated as objective minimization problem as

$$\text{Min} \quad R_a \; (v, \; f, \; d, \; r)$$

The average surface roughness Ra [6] is calculated by the following empirical formula

$$\mathbf{R_a = (1.0632 \; x \; f^{1.0198} \; x \; d^{0.0119} \; x \; H^{0.5234} \; x \; r^{0.1388}) \; x \; 1/v^{0.229}} \qquad \text{------ (1)}$$

Subject to the boundary conditions [12]

$v_{min} \le v \le v_{max}$; $f_{min} \le f \le f_{min}$

$d_{min} \le d \le d_{min}$; $r_{min} \le r \le r_{min}$

Table no 1. Boundary conditions of plane turning

Cutting parameter	Range	
	Min	Max
Cutting Speed ***v*** in m/min	30	90
	90	180
Feed ***f*** in mm/rev	0.2	0.4
	0.4	0.8
Depth of cut ***d*** in mm	0.5	1.0
	1.0	1.5
Tool nose radius ***r*** in mm	0.4	0.8
	0.8	1.2
Material hardness constant ***H*** in BHN	125	

Where v is the cutting speed (m/min), f is the feed rate (mm/rev), d is the depth of cut (mm), r is the nose radius of the tool (mm) and H is hardness constant of the material. Based on the above mentioned different machining conditions sixteen combinations of different operating conditions were indentified for this study. They are:

Table no 2 Ranges of cutting parameters

S. No.	*v* m/min	*f* mm/rev	*d* mm	*r* mm
1	30-90	0.2-0.4	0.5-1.0	0.4-0.8
2	30-90	0.2-0.4	0.5-1.0	0.8-1.2
3	30-90	0.4-0.8	0.5-1.0	0.4-0.8
4	30-90	0.4-0.8	0.5-1.0	0.8-1.2
5	30-90	0.2-0.4	1.0-1.5	0.4-0.8
6	30-90	0.2-0.4	1.0-1.5	0.8-1.2
7	30-90	0.4-0.8	1.0-1.5	0.4-0.8
8	30-90	0.4-0.8	1.0-1.5	0.8-1.2
9	90-180	0.2-0.4	0.5-1.0	0.4-0.8
10	90-180	0.2-0.4	0.5-1.0	0.8-1.2
11	90-180	0.4-0.8	0.5-1.0	0.4-0.8
12	90-180	0.4-0.8	0.5-1.0	0.8-1.2
13	90-180	0.2-0.4	1.0-1.5	0.4-0.8

S. No.	*v* m/min	*f* mm/rev	*d* mm	*r* mm
14	90-180	0.2-0.4	1.0-1.5	0.8-1.2
15	90-180	0.4-0.8	1.0-1.5	0.4-0.8
16	90-180	0.4-0.8	1.0-1.5	0.8-1.2

III. Quantum Inspired Evolutionary Algorithm

Quantum Inspired Evolutionary Algorithm is essentially a stochastic population based evolutionary algorithm that exploits some principles of quantum mechanics, such as Q-bits, superposition, quantum gates and quantum measurement [12].In conventional EAs, encoding the solutions onto chromosomes uses many different representations, which may be generally grouped into three classes: symbolic, binary, and numeric. In contrast, a Quantum Inspired Evolutionary Algorithm uses novel probabilistic representation called as Q-bit. Q – bit is a smallest unit of information that can be in superposition of basis states in a quantum system. Q- Bits are generally represented by a vector in Hilbert space with |0> and |1> as basis states. The Q-bit can be represented as:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \qquad .....(2)$$

Where $|\alpha|^2$ and $|\beta|^2$ are the probability amplitudes of the Q-bit that may exist in state '0' or in state '1' so that it satisfies the normal condition

$$|\alpha|^2 + |\beta|^2 = 1 \qquad ...... (3)$$

Quantum Inspired Evolutionary Algorithm uses a better characteristic of diversity than classical approaches, since it can represent superposition of states. Convergence is also achieved with such representation. As a Q-bit tends towards 1 or 0 during the process of probabilistic observation, the Q-bit converges to a single state and the property of diversity disappears gradually. That is, the Q-bit representation is able to possess the two characteristics of exploration and exploitation, simultaneously. The basic structure of Quantum Inspired Evolutionary Algorithm [13] is presented below:

begin

$t \leftarrow 0$

initialize *Q(t)*

make *P(t)* by observing *Q(t)* states

evaluate *P(t)*

store the best solution among *P(t)*

While (**not** termination – condition) **do**

begin

$t \leftarrow t+1$

make *P(t)* by observing *Q(t-1)* states

evaluate *P(t)*

update *Q(t)* using quantum gates *U(t)*

store the best solution among *P(t)*

end

end

Pseudo code of QIEA

Initialize: Initialize the population Q_{ij}, where i = 1, 2... *n*, j = 1, 2..*q* , and *n*, *q* are population size and number of parameters respectively. Assign equal probabilities to α and β of each Q-bit, so that normal condition $|\alpha|^2 + |\beta|^2 = 1$, is satisfied. And set the generation number to 0.

Observe: Observe all the Q-bits. That is, if $|\beta_i|^2 >$ rand, where rand Є [0, 1], then, the observed state would be '1', else, the observed state would be '0'. Decode the binary bits and if necessary employ a repair algorithm to correct boundary violations.

Evaluate: Evaluate the fitness.

Store: Store the best result of generation 0, as f (b). Increment the generation by one and repeat observe and evaluate processes, and store the best result as f (x).

***Update*:** Compare each Q-bit of all the parameters pertaining to the best solutions of f (b) and f (x_1). Based on the quantum rotation gate lookup Table 3 and by employing the equation (4), and update the Q-bits. Now repeat *observe*, *evaluate*, and *update* processes until requirements are met.

$$\begin{bmatrix} \alpha'i \\ \beta'i \end{bmatrix} = \begin{bmatrix} \cos\theta i & -\sin\theta i \\ \sin\theta i & \cos\theta i \end{bmatrix} \begin{bmatrix} \alpha i \\ \beta i \end{bmatrix} \quad \text{.... (4).}$$

Once we determine the number of Q-bits per variable, i.e., in this case of plane turning, the cutting speed v is a parameter which varies from 30 to180 m/min, requires eight Q-bits, but for all the other cutting parameters such as feed rate f, depth of cut d, tool nose radius r, we need only four Q-bits. Randomly generate population of parameters, in this case population size is 20, and assign equal probabilities to α and β of each Q-bit of every parameter and conduct probabilistic measurement for observed states of Q-bits, by generating a random number and comparing it with $|\beta|^2$. If rand > $|\beta|^2$ consider the Q-bit as 1 otherwise as 0. Now, boundary violations are checked and repaired, if necessary, by using a repair algorithm.

Table no. 3. Quantum rotation gate lookup table [14]

x_i	b_i	$f(x) \geq f(b)$	Δθ	$S(\alpha_i\ \beta_i)$			
				$\alpha_i\ \beta_i > 0$	$\alpha_i\ \beta_i < 0$	$\alpha_i = 0$	$\beta_i = 0$
0	0	F	0	0	0	0	0
0	0	T	0	0	0	0	0
0	1	F	0	0	0	0	0
0	1	T	0.05 Π	-1	+1	±1	0
1	0	F	0.01 Π	-1	+1	±1	0
1	0	T	0.025 Π	+1	-1	0	±1
1	1	F	0.005 Π	+1	-1	0	±1
1	1	T	0.025Π	+1	-1	0	±1

Now, evaluate the fitness and *store* the best solution among the twenty solutions of generation 0, f (b). Now repeat *observe, repair, evaluate* processes and *store* the best solution among the twenty solutions of generation 1, f (x). Now compare the corresponding Q-bits of all the parameters of best solution f (b) and best solution f(x), to update Q-bits, by determining rotation angle using quantum rotation gate Table no. 3 and employing equation (4). Here such iterative process of observing, repairing, evaluating and updating is continued till maximum number of cycle is not met, which is sixty in this study.

Experiments on Quantum Inspired Evolutionary Algorithm: The experiments are conducted on a Laptop machine equipped with the processor Intel Core 2 Duo, 4GB RAM and 150 GB HDD. The software is developed in MATLAB 7.0. The program parameters of Quantum Inspired Evolutionary Algorithm (QIEA) are: population size is 20 and maximum generation number 60 and the number of independent simulation runs are 30. The program parameters of Differential Evolution Algorithm (DEA) are: Population size 20, maximum generation number 60, and cross over rate 0.9, mutation rate 0.8, and the number of independent runs are 30.

IV. Results and Discussion

Quantum Inspired Evolutionary Algorithm is applied on the machining model, referred in section II, for minimum average surface roughness of plane turning, to determine optimal cutting parameters such as cutting speed, feed rate, depth of cut and tool nose radius, for corresponding sixteen operating conditions referred in Table 2.

Table no 4. QIEA determined surface roughness

S. No.	RCGA [6]	DEA [7]	**QIEA**
1	0.857260	0.8035080	**0.803017**
2	0.928069	0.8846534	**0.884113**
3	1.786641	1.6292232	**1.628231**
4	1.880024	1.7937567	**1.792665**
5	0.851825	0.8101631	**0.809668**
6	0.928080	0.8919806	**0.891436**
7	1.836571	1.6427173	**1.641714**
8	1.878548	1.8086136	**1.807512**
9	0.766149	0.685574	**0.685155**
10	0.817921	0.7548094	**0.754348**

S. No.	RCGA [6]	DEA [7]	**QIEA**
11	1.512453	1.3900957	**1.389251**
12	1.690667	1.5304801	**1.529550**
13	0.738389	0.6912523	**0.690832**
14	0.810552	0.7610611	**0.760596**
15	1.504253	1.4016093	**1.400753**
16	1.687547	1.5431564	**1.542211**

Table no 5. QIEA determined optimal cutting speed

S. No.	*v* m/min RCGA [6]	*v* m/min DEA [7]	*v* m/min QIEA
1	82.717673	89.9996112	90.000000
2	86.577654	89.9912760	90.000000
3	62.817164	89.9975154	90.000000
4	87.211219	89.9993688	90.000000
5	85.125584	89.9993875	90.000000
6	89.252907	89.9994307	90.000000
7	87.040925	89.9993405	90.000000
8	85.768303	89.9999034	90.000000
9	173.232215	180.000000	180.000000
10	160.781579	180.000000	180.000000
11	138.670919	180.000000	180.000000
12	156.988433	179.999994	180.000000
13	147.707450	179.999989	180.000000
14	172.982269	179.999997	180.000000
15	179.980773	179.999991	180.000000
16	158.174993	180.000000	180.000000

The average surface roughness as determined by QIEA algorithm is presented in Table no 4. The average surface roughness predicted by QIEA is compared with the estimations of real coded genetic algorithm (RCGA) and differential evolution algorithm (DEA). The results demonstrates that, QIEA has outperformed RCGA and improved results over DEA in achieving better surface quality, for plane turning, in every given operating environment. The below shown figure no 1, depicts the improved performance of Quantum Inspired Evolutionary Algorithm over Real Coded Genetic Algorithm and Differential Evolution Algorithm

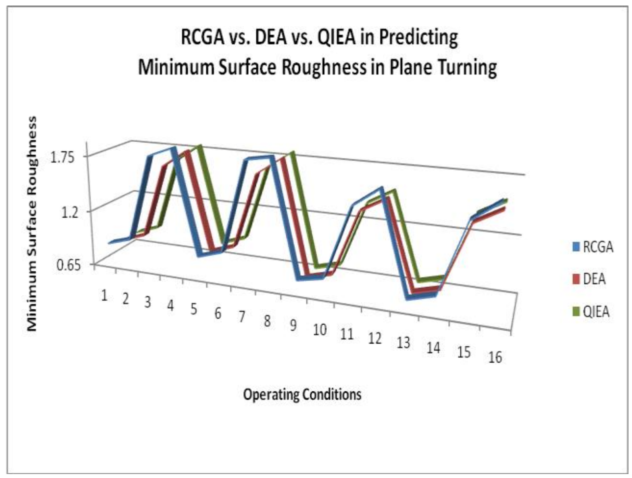

Figure no1. RCGA vs DEA vs QIEA in predicting minimum surface roughness in plane turning

Table no 6. QIEA determined optimal feed rate

S. No.	*f* mm/rev RCGA [6]	*f* mm/rev DEA [7]	*f* mm/rev QIEA
1	0.200012	0.200053	0.200000
2	0.204248	0.200034	0.200000
3	0.401709	0.400031	0.400000
4	0.402454	0.400060	0.400000
5	0.205896	0.200000	0.200000

S. No.	f mm/rev RCGA [6]	f mm/rev DEA [7]	f mm/rev QIEA
6	0.206922	0.200079	0.200000
7	0.432032	0.400013	0.400000
8	0.409876	0.400005	0.400000
9	0.200159	0.200000	0.200000
10	0.207935	0.200000	0.200000
11	0.405750	0.400000	0.400000
12	0.420301	0.400000	0.40000
13	0.203143	0.200000	0.200000
14	0.202057	0.200000	0.200000
15	0.408081	0.400000	0.400000
16	0.419410	0.400000	0.400000

Reaffirming the findings [5, 6, 7], the important cutting parameters, cutting speed and feed rate, that are significantly affect the surface roughness are tabulated in Table no 5 and 6, as predicted using QIEA algorithm. These results confirm that, at higher cutting speed and at lower feed rate minimum surface roughness can be achieved.

Table no 7. QIEA determined optimal depth

S. No.	d mm RCGA [6]	d mm DEA [7]	d mm QIEA
1	0.720191	0.5007623	0.500000
2	0.913816	0.5000292	0.500000
3	0.726173	0.5000123	0.500000
4	0.817698	0.5001041	0.500000
5	1.168371	1.0003244	1.000000
6	1.005707	1.0033508	1.000000
7	1.272668	1.0003603	1.000000
8	1.151006	1.0002004	1.000000
9	0.898267	0.000003	0.500000
10	0.696722	0.5000003	0.500000
11	0.650456	0.5000001	0.500000
12	0.697592	0.5000000	0.500000
13	1.012772	0.5000002	1.000000
14	1.230903	1.0000006	1.000000
15	1.375683	1.0000008	1.000000
16	1.069231	1.0000004	1.000000

The other two cutting parameters, depth of cut and tool nose radius are presented in the Table no 7 and 8. At minimal settings of these two parameters the improved surface finish is achieved by the algorithm. With help of these results of QIEA estimations of plane turning, it is observed that at higher cutting speeds and at lower feed rate, and at minimal settings of other two parameters, best surface roughness can be achieved.

Table no 8. QIEA determined nose radius

S. No.	r mm RCGA [6]	r mm DEA [7]	r mm QIEA
1	0.537565	0.4001902	0.400000
2	0.862380	0.8004704	0.800000
3	0.403186	0.4000622	0.400000

S. No.	r mm RCGA [6]	r mm DEA [7]	r mm QIEA
4	0.976519	0.8000915	0.800000
5	0.417408	0.4000517	0.400000
6	0.817481	0.8000086	0.800000
7	0.470266	0.4001726	0.400000
8	0.802100	0.8000237	0.800000
9	0.790576	0.4000000	0.400000
10	0.864846	0.8000000	0.800000
11	0.420508	0.4000000	0.400000
12	0.883425	0.8000000	0.800000
13	0.413575	0.4000000	0.400000
14	1.074825	0.8000000	0.800000
15	0.559014	0.4000000	0.400000
16	0.864284	0.8000000	0.800000

Since the performance details of the Real Coded Genetic Algorithm (RCGA) and Differential Evolution Algorithm on this plane turning optimization of problem, in terms of its standard deviation, mean of worst and mean of best is not reported [], in this work an effort is made to bring out such results for DEA and compare the same with Quantum Inspired Evolutionary Algorithm The thirty independent experiments carried out on Quantum Inspired Evolutionary Algorithm are compared with the thirty independent runs carried out on Differential Evolution Algorithm (DEA) for the same problem in order to ascertain the performance of QIEA.

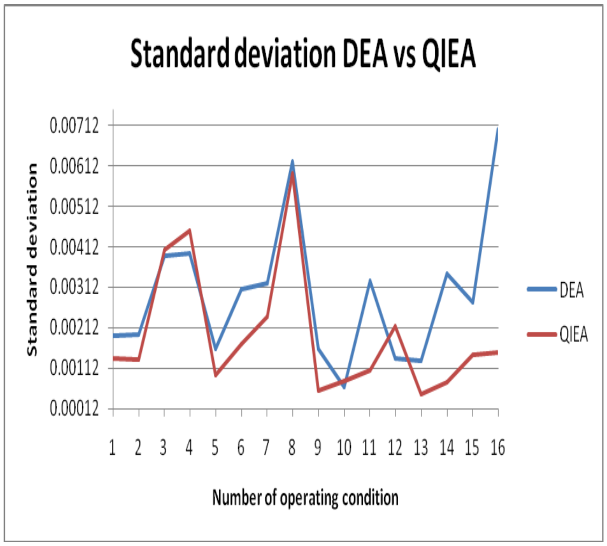

Figure no2. Standard deviation of DEA vs.QIEA

Table no 9. Standard deviation - DEA vs. QIEA

S. No.	DEA Standard deviation	QIEA Standard deviation
1	0.0019217	0.00136438
2	0.0019474	0.00134163
3	0.0038966	0.00403858
4	0.0039486	0.00450954
5	0.0015856	0.00096127
6	0.0030712	0.00170577
7	0.003215	0.00238215
8	0.0062272	0.00591869
9	0.0016095	0.00057922
10	0.0006445	0.00081122

S. No.	DEA Standard deviation	QIEA Standard deviation
11	0.003263	0.00105965
12	0.00137	0.00216368
13	0.00131	0.00047915
14	0.003457	0.00078677
15	0.002739	0.00143839
16	0.007009	0.00150446

The comparisons are drawn between QIEA and DEA by presenting the contrasts of different statistical parameters i.e., standard deviation, mean of worst, mean of best. The results of such independent experimental runs of DEA and QIEA are presented in Table no 9 and 10. The following figure no 2, depicts the comparison of standard deviation between Quantum Inspired Evolutionary Algorithm and Differential Evolution Algorithm.

Table no 10. Mean of worst and best DEA vs. QIEA

S. No	Mean Worst		Mean Best	
	DEA	QIEA	DEA	QIEA
1	0.8109615	0.8443	0.8035781	0.803017
2	0.8922561	0.972828	0.8849536	0.884113
3	1.6443363	1.78902	1.6293654	1.62831
4	1.8091721	2.04418	1.7943654	1.79266
5	0.8165556	0.946924	0.8103791	0.809668
6	0.9043026	0.93703	0.8921801	0.891436
7	1.6556791	1.97014	1.6431554	1.641715
8	1.8335982	1.92121	1.809018	1.807513
9	0.6929077	0.733505	0.685813	0.685152
10	0.7583466	0.781242	0.755081	0.754341
11	1.404966	1.60212	1.39058	1.38925
12	1.537652	2.03124	1.531031	1.52955
13	0.698588	0.69718	0.691327	0.690831
14	0.780506	0.787425	0.76114	0.760592
15	1.416483	1.56292	1.401761	1.400831
16	1.582584	1.63311	1.543315	1.54221

V. CONCLUSION

Quantum Inspired Evolutionary Algorithm which essentially exploits some quantum mechanics principles such as Q- bit, superposition, quantum measurement, quantum gate is successfully implemented in MTALAB 7.0 environment. The QIEA is applied on a machining model of turning to estimate optimal cutting parameters, such as cutting speed, depth of cut, feed rate, nose radius of the tool, for sixteen different operating conditions, to achieve improved surface finish. Estimations of Quantum Inspired Evolutionary Algorithm, suggest that the surface roughness in turning operation is significantly affected by cutting speed and feed rate. It is observed that low feed rate would give better surface quality. These observations are in concurrence to the reported findings [6]. The results obtained by QIEA are better than RCGA and are comparable to those of DEA. QIEA is found to be computationally efficient and suitable for machining optimization. The statistical results of independent experiments reveal that Quantum Inspired Evolutionary Algorithm is comparably effective in terms of stability when compared to Differential Evolution Algorithm. Therefore, Quantum Inspired Evolutionary Algorithm is a promising heuristic for intelligent manufacturing.

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REFERENCES

[1] A. Bhattacharya, R. Faria-Gonzalez and I. Ham, "Regression analysis for predicting surface finish and its application in the determination of optimum machining conditions", *ASME Journal of Engineering for Industry, 4, pp. 711–714*, 1970.

[2] Chandrasekaran, M. Muralidhar, C. Murali Krishna, U. S. Dixit, "Application of soft computing techniques in machining Performance prediction and optimization: A literature review," *Int J Adv Manuf Technol, 46:445–464.*, 2010.

[3] Suresh, P.V.S., Venkateswara P. Rao, S. G. Deshmukh,, "A Genetic Algorithmic Approach for Optimization of Surface Roughness Prediction Model", *International Journal of Machine Tools & Manufacture, 42, p: 675–680*, 2002.

[4] Franci Cus, Joze Balic,, "*Optimization of cutting process by GA approach"*, Robotics and Computer Integrated manufacturing 19, pp.113-121, 2003.

[5] 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., 2008.

[6] T. Srikanth, Dr V. kamala, *"A Real Coded Genetic Algorithm for Optimization of Cutting Parameters in Turning"* International Journal of Computer Science and Network Security, VOL.8 No.6, June 2008, pp. 189-193, 2008.

[7] R.S.S. Prasanth, K. Hans Raj, "Application of differential evolution algorithm for optimizing orthogonal cutting". *Proceedings of International conference on Systemics, Cybernetics, and Informatics. Pp 122 – 126.* 2011.

[8] Narayanan, A., Moore, M.: Quantum-inspired genetic algorithms. *In: Proc. CEC, pp. 61–66*, 1996.

[9] Ashish Mani and C. Patvardhan., "An adaptive quantum evolutionary algorithm for Engineering optimization problems". *International Journal of Computer Applications, 1(22):43–48.*, 2010

[10] Ashish Mani and C. Patvardhan., "Solving Ceramic Grinding Optimization Problem by Adaptive Quantum Evolutionary Algorithm", *Intelligent Systems, Modeling and Simulation, International Conference on, 0:43–48*, 2010.

[11] Gexiang Zhang**,**"Quantum-inspired evolutionary algorithms: a survey and empirical study", *J Heuristics, 17: 303–351*, 2011.

[12] K.H. Han and J.H. Kim., "Genetic quantum algorithm and its application to combinatorial optimization problem". *In Proceedings of the 2000 Congress on Evolutionary computation, volume 2, pages 1354–1360*. Citeseer, 2000.

[13] *K.H. Han and J.H. Kim*, "Quantum-inspired evolutionary algorithm for a class of combinatorial optimization" *IEEE transactions on evolutionary computation, 6(6):580–593*, 2002.

[14] Kuk-Hyun Han., *"Quantum-inspired Evolutionary Algorithm. PhD thesis",* Korea Advanced Institute of Science and Technology (KAIST), 2003