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Quantum Inspired Evolutionary Algorithm for Optimization of Hot Extrusion Process

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Abstract— Quantum Inspired Evolutionary Algorithm (QIEA) is a probability based optimization algorithm which applies quantum computing principles such as qubits, superposition, quantum gate and quantum measurement to enhance the properties of classical evolutionary algorithms. This work presents the application of QIEA, for the optimization of hot extrusion process i.e., for finding optimum value of die angle, co-efficient of friction and temperature of billet for minimizing the extrusion load. The optimal process parameters are compared with Finite Element (FE) simulation results conducted in FORGE-3 environment, which is a domain specific software designed to simulate hot, warm and cold forging. The results show the efficacy of QIEA in terms of good global search ability and fast convergence to the best solution due to its highly probabilistic nature and better characteristics of population diversity since it can represent linear superposition of states.

IndexTerms— Finite Element Simulation, FORGE-3, Optimization, QIEA.

I. INTRODUCTION

Quantum Inspired Evolutionary Algorithm (QIEA) falls under a new class of metaheuristics which draw their characteristics mainly from two fields: Evolutionary and Quantum Algorithms. Evolutionary Algorithms (EAs) are inspired by principles of natural evolution and adopts three main mechanisms of natural evolution which are reproduction, mutation, and natural selection (i.e., the Darwinian principle of survival of the fittest) in a simplified way and breed progressively towards better solutions. On the other hand, quantum computation is an emerging field in which the principles of quantum mechanics are employed to store and process information for solving computational problems extremely efficiently. The integration of evolutionary and quantum computation has resulted in quantum evolutionary algorithms. QIEA incorporates some of the key features of quantum mechanics such as quantum bits and superposition of states (quantum parallelism) and quantum gates. Apart from the classical bit which could be in one of the two states, 0 or 1, a quantum bit (called as 'qubit') may be in the '1' state, in the '0' state, or in any superposition of the two states with certain probability. This probabilistic mechanism which gives rise to the superposition of states is known as quantum parallelism and in turn is responsible for inherit advantages which QIEA possess over conventional evolutionary algorithms.

This concept of incorporating quantum computing concepts in evolutionary algorithms was first introduced by Han et al. [1, 2]. In these algorithms, the individuals are represented as a string of quantum-bits or qubits. Quantum gates are then used to modify these individuals. The power of these algorithms comes from the great diversity they provide by using quantum coding. Each single quantum individual in reality represents multiple classical individuals giving rise to linear superposition of states.

In the past one decade QIEA has received a lot of attention and demonstrated its superiority over classical evolutionary algorithms for solving a class of complex benchmark problems of combinatorial optimization including traveling salesman problem [3], [4], knapsack problem [1] [5], filter design problem [6], numerical optimization problems [7], network design problems [8, 9], flow shop scheduling problems [10], power system optimization [11] and training fuzzy neural networks [12].

However, to author's knowledge QIEA is not applied to manufacturing process optimization problems (especially metal forming). In this endeavor QIEA is applied for process optimization of hot extrusion (optimal die angle, co-efficient of friction and temperature of billet that minimize extrusion load).

The paper is organized as follows: A brief overview of quantum computation is presented in section II. Structure of QIEA is explained in section III. Finite element simulation of hot extrusion is presented in section IV. Application of QIEA to hot extrusion is shown in section V and finally in section VI conclusions are presented.

II. BRIEF OVERVIEW OF QUANTUM COMPUTATION

QIEA is essentially a stochastic population based evolutionary algorithm that exploits some principles of quantum mechanics such as qubits, superposition, quantum gates and quantum parallelism. In conventional evolutionary algorithms encoding the solutions into chromosomes uses many different representations which can be generally grouped into three classes: symbolic, binary and numeric. In contrast, a QIEA uses novel probabilistic representation called qubit. Qubit is a smallest unit of information that can be in superposition of basis states in a quantum system. Qubits are generally represented by a vector in Hilbert space with $|0\rangle$ and $|1\rangle$ as basis states. The qubit can be represented as:

$$|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

where α and β are probability amplitudes of the qubit that may exist in state '0' or in state '1' so that it satisfies the normalization condition:

$$|\alpha|^2 + |\beta|^2 = 1$$

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A qubit individual as a string of *m* qubits is defined as follows:

$$\left[\begin{array}{c|c|c|c}\alpha_1 & \alpha_2 & \ldots & \alpha_m \\ \beta_1 & \beta_2 & \ldots & \beta_m\end{array}\right]$$

where $|\alpha_i|^2 + |\beta_i|^2 = 1,\ i = 1, 2, \ldots, m$

QIEA uses a better characteristic of diversity than classical approach since it can represent superposition of states. In classical bit string, a string of length *m* can represent 2^m possible states. However, a quantum space of *m* qubits has 2^m dimensions. Thus, a single qubit of length *m* can simultaneously represent all possible bit strings of length 2^m, for example, an 8 qubit system can simultaneously encode 256 distinct strings. This implies that it is possible to modify standard evolutionary algorithms to work with very few, or even a single quantum individual, rather than having to use a large population of solutions encodings. The qubit representation can also help to maintain exploration and exploitation of entire search space due to its capability to represent multiple system states simultaneously. Convergence is also better achieved with such representation.

III. STRUCTURE OF QIEA

The pseudo code algorithm for QIEA is illustrated in Fig. 1. The algorithm is developed in MATLAB 7.0 environment and the experiments are conducted on a laptop computer equipped with Intel core i3 processer @ 2.10 GHz, 4 GB RAM and 500 GB of HDD.

Each step of this algorithm is described below:

(i) In the first step "initialize $Q(t)$", a population $Q(0)$with *n* multi qubit individuals is generated, $Q(t)=\{q^t_1, q^t_2, \ldots, q^t_n\}$, at the generation moment $t=0$, where $q^t_1(i = 1, 2, \ldots, n)$ is an arbitrary individual in $Q(t)$, represented as:

$$q_i^t = \left[\begin{array}{c|c|c|c}\alpha_{i1}^t & \alpha_{i2}^t & \ldots & \alpha_{im}^t \\ \beta_{i1}^t & \beta_{i2}^t & \ldots & \beta_{im}^t\end{array}\right]$$

where *m* is the number of qubits used in each individual's representation, i.e., the string length of the qubit individual. The value α^t_{ij} and β^t_{ij}, $j = 1, 2, \ldots, m$, $t=0$, are initialized to the same probability amplitude$1/\sqrt{2}$, so that all possible states are superposed with the same probability at the beginning.

Begin

$t \leftarrow 0$

(i) **initialize** $Q(t)$

(ii) **observe** $P(t)$ by observing the states of $Q(t)$

(iii) **repair** $P(t)$

(iv) **evaluate** $P(t)$

(v) Store the best solutions among $P(t)$ into $B(t)$ and best solution *b* among $B(t)$

while (t < MAXGEN) **do**

begin

$t \leftarrow t + 1$

(vi) **observe** $P(t)$ by observing the states of $Q\ (t\text{-}1)$

(vii) **evaluate** $P(t)$

(viii) **update** $Q(t)$ using quantum rotation gate

(ix) Store the best solutions among $P(t)$ and $B(t\text{-}1)$ into $B(t)$ and the best solution *b* among $B(t)$

(x) **if** (global migration condition)
then migrate *b* to $B(t)$ globally
else if (local migration condition)
then migrate b^t_j to $B(t)$ locally
end
end

Fig. 1 Pseudo code of QIEA

(ii) By independently observing each qubit of $Q(t)$ (where at this stage $t=0$), binary solutions in $P(t)$, $P(t) =\{x^t_1, x^t_2, \ldots, x^t_n\}$, are obtained where each $x^t_1(i = 1, 2, \ldots, n)$ is a binary solution with m bits. Each bit '0' or '1' is the observed value of a qubit $[\alpha^t_{ij}\ \ \beta^t_{ij}]^T$ in q^t_i, respectively, $j = 1,2,\ldots,m$.

(iii) When the binary string violates the boundary constraint, the random repair method of $P(t)$ is employed.

(iv) The binary solution $x^t_i\ (i = 1, 2, \ldots, n)$ in $P(t)$ is evaluated thus obtaining its fitness.

(v) In this step, all solutions in $P(t)$ are stored into $B(t)$, where $B(t) = \{b^t_1, b^t_2, \ldots, b^t_n\}$, and $bt_1 = x^t_1\ \ (i = 1, 2, \ldots, n)$ (again at this stage, $t = 0$), Furthermore, the best binary solution *b* in $B(t)$ is also stored.

(vi) This step is similar to step (ii). Observation of the states of $Q(t\text{-}1)$ produces the binary solutions in $P(t)$.

(vii) This step is similar to step (iv).

(viii)In this step all the individuals in $Q(t)$ are modified by applying Q-gate. The QIEA uses a quantum rotation gate as a Q-gate. To be specific, the j^{th} qubit in the i^{th} qubit individual q^t_1, $j = 1,2,\ldots,m$, $i = 1,2,\ldots,n$, is updated by applying the current quantum rotation gate $G^t_{ij}(\theta)$

$$G_{ij}^t(\theta) = \begin{bmatrix}\cos\theta_{ij}^t & -\sin\theta_{ij}^t \\ \sin\theta_{ij}^t & \cos\theta_{ij}^t\end{bmatrix}$$

where θ^t_{ij} is an adjustable Q-gate rotation angle. Thus the update procedure for the qubit $[\alpha^t_{ij}\ \ \beta^t_{ij}]^T$ can be described as:

$$\begin{bmatrix}\alpha_{ij}^{t+1} \\ \beta_{ij}^{t+1}\end{bmatrix} = G_{ij}^t(\theta)\begin{bmatrix}\alpha_{ij}^t \\ \beta_{ij}^t\end{bmatrix}$$

where θ^t_{ij} is defined as

$$\theta_{ij}^t = s(\alpha_{ij}^t, \beta_{ij}^t)\Delta\theta_{ij}^t$$

$s(\alpha_{ij}^t, \beta_{ij}^t)$ and $\Delta\theta_{ij}^t$ are the sign and the value of θ_{ij}^t respectively.

(ix) This step is similar to step (v). The better candidate between x^t_i in $P(t)$ and $b_i(t\text{-}1)$ in $B(t\text{-}1)$, $i = 1,2,\ldots,n$, is selected and stored into $B(t)$. Simultaneously, the best candidate *b* in $B(t)$ is also stored.

(x) This step includes local and global migrations, where a migration in this algorithm is defined as the process of copying b^t_j in $B(t)$ or *b* to $B(t)$.

A global migration is realized by substituting *b* for all the solutions in *B(t)*, and a local migration is realized between each pair of neighboring solutions in *B(t)*, i.e., by substituting the better one of two neighboring solutions for the other solution.

Fig. 2 depicts the polar plot of the rotation gate for qubit individuals. The change in the values of (α_i, β_i) to $(\alpha_i^{'}, \beta_i^{'})$ by rotation angle of $\Delta\theta_i$ is clearly seen.

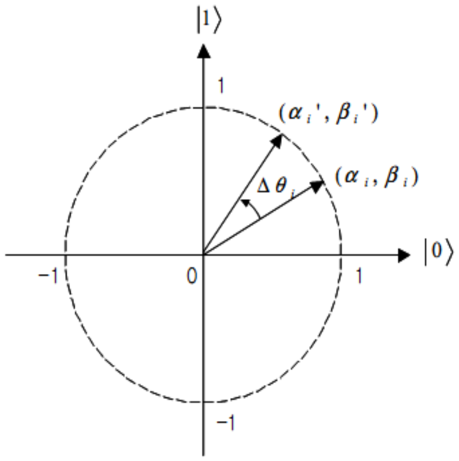


Fig. 2 Polar plot of rotation gate for qubit individuals

Table1 Look up table for rotation gate

x_i	b_i	*f(x)< f(b)*	$\Delta\theta_i$
0	0	*true*	θ_1
0	0	*false*	θ_2
0	1	*true*	θ_3
0	1	*false*	θ_4
1	0	*true*	θ_5
1	0	*false*	θ_6
1	1	*true*	θ_7
1	1	*false*	θ_8

The look up table used for the rotation gate is shown in Table. 1. Let *f(x)* and *f(b)* are the binary and the best solutions *x* and *b*, and x_i and b_i are the i^{th} bits of the binary and best solutions *x* and *b* then if x_i and b_i are 0 and 1, respectively, and if the condition *f(x)< f(b)* is true then:

1. If the qubit is located in the first or the third quadrant in fig. 2, θ_3, the value of $\Delta\theta_i$ is set to a positive value to increase the probability of the state $|1\rangle$.
2. If the qubit is located in the second or the fourth quadrant, - θ_3, should be used to increase the probability of the state $|1\rangle$.

If x_i and b_i are 1 and 0, respectively, and if the condition *f(x) < f(b)* is true then:

1. If the qubit is located in the first or the third quadrant, θ_5, is set to a negative value to increase the probability of the state $|0\rangle$.
2. If the qubit is located in the second or the fourth quadrant, -θ_5, should be used to increase the probability of the state $|0\rangle$.

In this QIEA, $\theta_1 = 0$, $\theta_2 = 0$, $\theta_3 = 0.06\pi$, $\theta_4 = 0$, $\theta_5 = -0.06\pi$, $\theta_6 = 0$, $\theta_7 = 0$, $\theta_8 = 0$ are used. If it is ambiguous to select a positive or a negative number for the values of the angle parameters it is set to 0. The magnitude of $\Delta\theta_i$ has an effect on the speed of convergence, but if it is too big, the solutions may diverge or converge prematurely to a local optimum. It is worth mentioning here that the sign of $\Delta\theta_i$ determines the direction of convergence.

Termination is the criterion by which the algorithm decides whether to continue searching or stop the search. Each of the enabled termination criterion is checked after each generation to see if it is time to stop. The termination criterion is the maximum number of generations (MAXGEN), which can be decided by the user.

IV. FINITE ELEMENT (FE) SIMULATION OF HOT EXTRUSION

Hot extrusion is a metal forming process of forcing a heated billet to be reduced in its cross section by forcing it to flow through a shaped die opening under high pressure. During extrusion metal billet is under compression stress state in all three directions and shear forces, Fig. 3. No tensile force is produced, which makes high deformation possible without tearing the metal. The hot extrusion process is widely used due to its relative low deformation resistance of the metal for production of long straight metal products of constant cross section (such as bars, solid and hollow sections, tubes, wires and strips) from materials that cannot be formed by cold extrusion. Hot extrusion is an attractive process in industry due to its ability to achieve energy and material savings, quality improvement and development of homogeneous properties throughout the component.

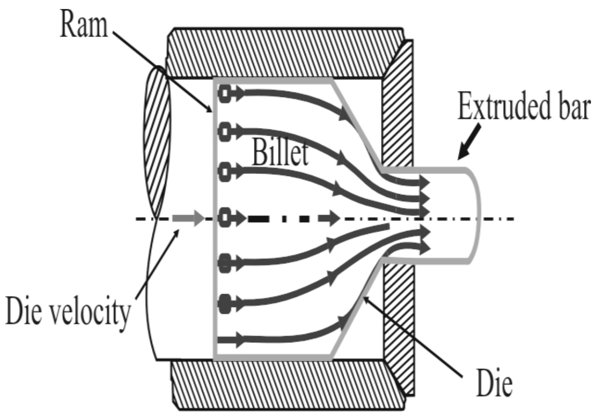


Fig. 3 Metal flow in steady state extrusion process

A number of finite element simulations are performed for forward hot extrusion of a preform for transmission shaft with various die angles (15°, 30°, 45°, 60° and 75°) at temperatures varying from 1000°C to 1260°C using the finite element model in FORGE-3 environment. The dies are kept at constant temperature (350°C). The schematic of die, billet and punch shape are shown in Fig. 4 and the 3 dimensional models of billet, lower die and upper die (punch) for simulation purpose were developed in Solidworks software. The dies are assumed to be rigid pieces and the billet material taken is ck-45 steel. The chemical composition of ck-45 steel in weight % and data pertaining to FE simulation for billet is shown below:

C 0.46	Si 0.40	Mn 0.65	Cr 0.40 max	Mo 0.1 max	Ni 0.40 max
Number of Nodes – 1872		Number of elements - 9943		Type of meshing - Tetrahedral	

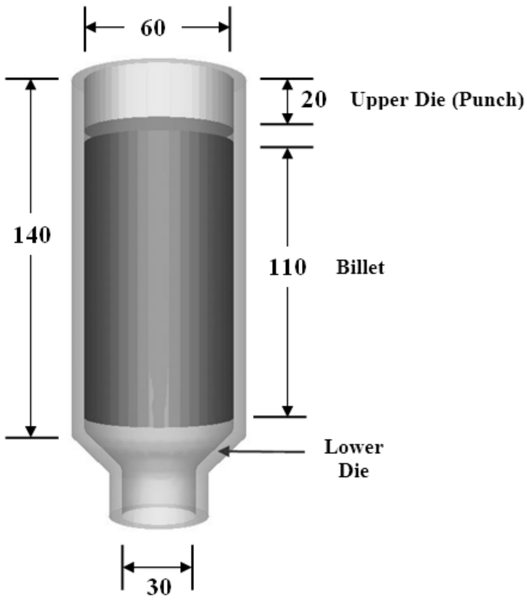


Fig. 4 Schematic of die shape used for simulation of hot extrusion process. (Dimensions are in mm)

Table 2 shows the FE simulation results for extrusion load required to extrude a shaft by 50% reduction in its diameter with various die angles under different process conditions at a punch velocity of 203 mm/sec.

Fig.5 shows the isocontours of equivalent strain evolved during hot extrusion of transmission shaft for 45° and 60° die angles. Fig.6 shows the extrusion load curve with respect to displacement of upper die for 45° angle.

V. APPLICATION OF QIEA TO HOT EXTRUSION

The problem of prediction of optimal extrusion load for hot extrusion process may be enumerated as objective minimization problem as:

$$\text{Min} \quad \text{Load } (\varphi, \mu, \theta)$$

Where φ is the die angle, μ is the co-efficient of friction and θ is the temperature of billet. The data to be optimized is derived from FE simulation results shown in table 2. The extrusion load is calculated by the following empirical formula:

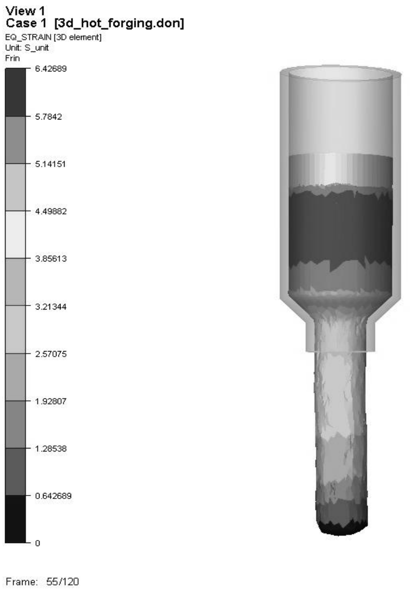
$$\text{Extrusion load} = 405 - 0.562\,\varphi + 14.7\,\mu - 0.135\,\theta \qquad (1)$$

Subject to the boundary conditions:

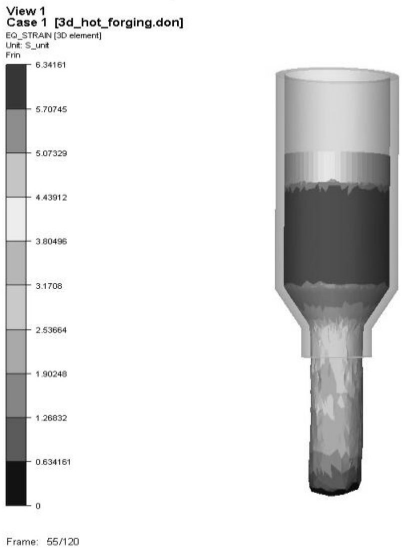
$$\phi_{\min} \le \phi \le \phi_{\max}\,; \quad \mu_{\min} \le \mu \le \mu_{\max}\,; \quad \theta_{\min} \le \theta \le \theta_{\max}$$

Table 2 FE simulation results for extrusion load

Angle (Degrees)	Co-efficient of Friction	Extrusion load (Tones) for following initial temperatures of the ck-45 steel billet			
		1000 °C	1090 °C	1180 °C	1260 °C
15	0.4	270.11	263.07	254.24	252.22
	0.6	273.24	265.80	258.84	257.17
	0.8	275.04	267.90	263.32	262.98
30	0.4	247.92	238.32	230.16	226.13
	0.6	248.50	241.09	235.71	229.78
	0.8	249.87	247.82	240.26	233.67
45	0.4	243.18	236.34	228.19	200.90
	0.6	244.60	240.12	232.54	205.10
	0.8	246.80	243.09	237.92	208.33
60	0.4	234.49	216.18	208.71	181.86
	0.6	236.56	219.27	211.82	184.03
	0.8	238.26	220.72	218.33	185.91
75	0.4	261.93	240.77	220.74	211.77
	0.6	263.35	242.12	222.79	206.75
	0.8	266.07	243.85	223.83	210.82



Isocontour of equivalent strain for 45° die



Isocontour of equivalent strain for 60° die

Fig. 5 Isocontours of equivalent strain evolved during hot extrusion of transmission shaft for different die angles

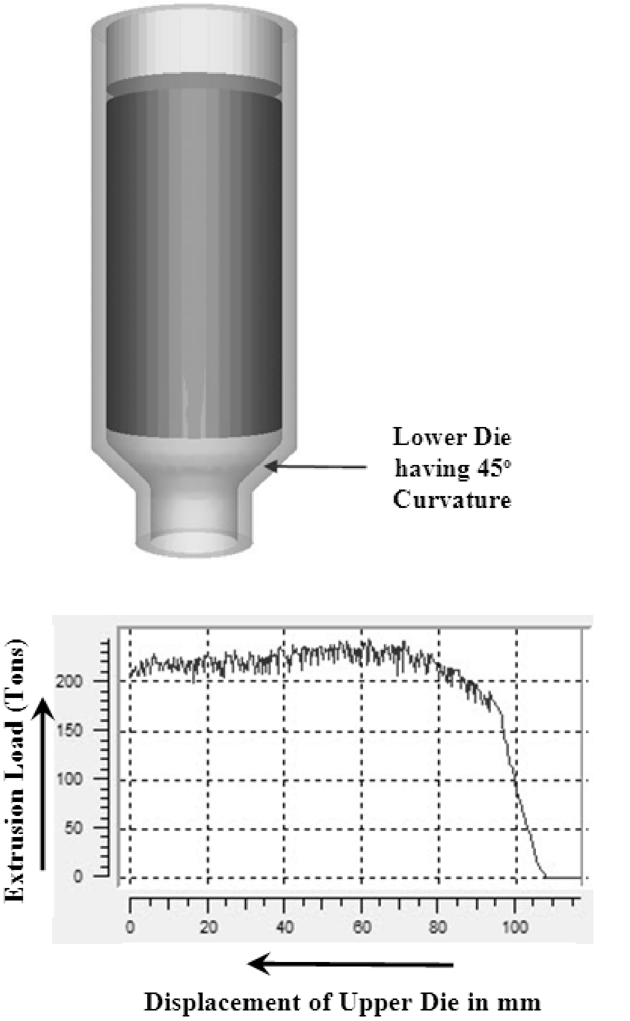


Fig.6 Die with 45° curvature w.r.t. horizontal and its corresponding extrusion load curve w.r.t. displacement of upper die

The range of the boundary conditions is shown in table 3.

Table 3 Range of boundary conditions for hot extrusion

Parameters	Range	
	Minimum	Maximum
Die angle ‘φ’	15	75
Co-efficient of friction ‘μ’	0.4	0.8
Temperature ‘θ’	1000	1260

QIEA is successfully applied to find the best solution i.e., optimum value of die angle, co-efficient of friction and temperature of billet for minimum extrusion load. Equation 1 is used as an objective function to evaluate the fitness of the solution in step (iv) and (vii) of the pseudo-code shown in fig.1. The parameters used in the QIEA are shown in table 4. The optimal die angle and other process parameters obtained by QIEA are shown in table 5 and are compared with FE simulation result. The statistical information after 50 runs of QIEA algorithm is shown in table 6. Fig. 7 shows the convergence graph of optimal values of extrusion load with respect to number of generations.

Table 4 Parameters used in QIEA

Parameters	Values
Population Size	10
Rotation angle	0.06π
Number of qubits	4
Max. number of generations	50
Termination Criterion	Max. Generations
Crossover probability	0.1
Mutation probability	0.01
Number of runs	50

Table 5 Optimal die angle and other process parameters obtained by QIEA

Optimal die angle (°)	Optimal Co-efficient of friction (μ)	Optimal Temp. of billet (°C)	Optimal extrusion load (tones)	
			FEM result	QIEA result
65	0.4	1180	218.71	216.35

Table 6 Statistical information after 50 runs of QIEA

Best	Worst	Mean	Median	Std. dev.
216.35	221.29	219.17	216.35	0.000356

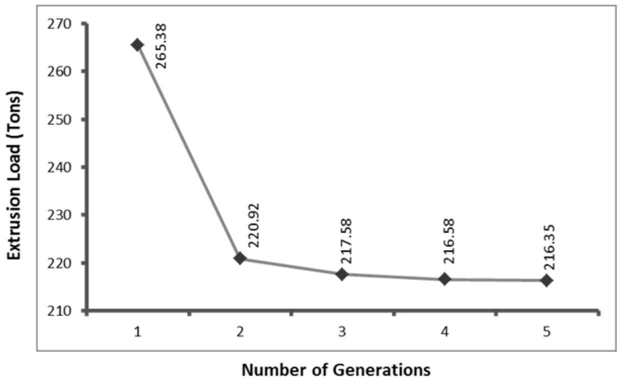


Fig. 7 Convergence graph of optimal values of extrusion load with respect to number of generations.

The results demonstrated by QIEA shows improvement with those predicted by FE simulation as shown in table 5. The QIEA has proved its efficacy in terms of convergence of optimal values. For minimization of extrusion load QIEA has taken just 5 generations to converge to optimal solutions. This fast convergence is due to the probabilistic mechanism which gives rise to the superposition of states and in turn is responsible for inherit advantages which QIEA possess over conventional evolutionary algorithms.

VI. CONCLUSION

In this paper a Quantum Inspired Evolutionary Algorithm (QIEA) is presented for optimizing the process parameters of hot extrusion. The algorithm has been designed with various features of quantum computation such as superposition of states and application of quantum rotation gate in conjunction with evolutionary algorithm that enable it to seek the near global optimum rapidly without getting stuck in the local optima. The algorithm allows a natural coding of variables by considering continuous variables.

This may give designer more flexibility in the optimization problems. QIEA demonstrates promise in optimizing complex industrial processes pertaining to intelligent manufacturing systems for achieving energy and material saving, quality improvement in the end product.

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