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Analysis of Material Removal Rate using Genetic Algorithm Approach

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Abstract— In the present scenario of manufacturing industries particularly in all of the machining processes, the application of various optimization techniques is playing vital role which seeks identification of the best process parametric condition for that particular manufacturing or metal removal process. Manufacturing process involves a number of process parameters (controllable and uncontrollable). Since selection of wrong cutting parameter in any machining process may lead to several negative effects. For example, high maintenance cost of the lathe machine, poor surface finish of the work piece, short tool life, low production rate, material wastage and increased production cost. In this research paper, Genetic Algorithm (GA) has been applied for optimizing of machining parameters during turning operation of mild steel using conventional lathe machines. The purpose of this paper is to find the optimum parameters values for turning operations for maximizing the material removal rate. The machining parameters that been consider in this paper are cutting speed, feed rate and spindle speed. The Turbo C compiler is used to develop the GA simulation. GA can be used in optimization problems such as scheduling, materials engineering, optimal control, and so forth.

Index Terms— Genetic Algorithm, Optimization, Turning operation, turbo c, mild steel, GA optimization technique, material removal rate, machining, process parameters, feed rate, cutting speed, machining time.

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1 Introduction

METAL cutting is one of the important and commonly used manufacturing processes in any metal processing or business industries. By machining processes or manufacturing operations, attempts are made to make a particular product in several steps as of required dimensions and shapes to ensure the quality of machining products for the intended applications made for. The step-by-step machining is done on the material to reduce the machining costs thereby increasing the machining effectiveness. Every manufacturing Industry aims at producing a large number of products within relatively lesser time. It has long been recognized that conditions during cutting, such as feed rate, cutting speed and depth of cut, should be selected to optimize the economics of machining operations, as assessed by productivity, total manufacturing cost per component or some other suitable criterion. The optimization of cutting parameters during machining is a difficult task as it involves a number of aspects such as knowledge of machining, empirical equations of tool life, cutting forces, power consumed, machining surface finish etc. All these aspects should be considered during machining optimization to develop an effective optimization criterion [1]. Manufacturing industries have long depended on the skill and experience of shop-floor machine-tool operators for optimal selection of cutting conditions and cutting tools. Many authors have shown the optimization objective as specific cost from the beginning of the researches in this branch [2] to some of the most recent works [3], [4], [5], [6], and [7]. A review of artificial intelligence techniques for CNC machining parameter optimization in manufacturing industry was presented by [8] for providing a better understanding of these techniques in machining control. Recently a study on manufacturing of freeform surfaces or sculptured surfaces using CNC machines has been performed in [9], which primarily focuses on three aspects in freeform surface machining: tool path generation, tool orientation identification, and tool geometry selection. A standard optimization technique using genetic algorithm was developed by [10] to solve different machining optimization problems such as turning, face milling and grinding [11]. For a machining process such as turning, the cutting conditions play an important role in the efficient use of the machine tool. There is an economic need to operate these machines as efficiently as possible. Since the cost of turning on these machines is sensitive to the cutting condition, so the optimum value have to be determined before a work piece is put for processing. The present study is mainly focused on optimization of process parameters of CNC turning operation considering maximization of material removal rate (MRR) as the objective function. Feed rate, spindle speed and cutting speed are considered as process parameters with specified ranges.

2 Experimental Methodology and Conditions

The experiments are performed on a high precision conventional lathe machine. Fig 1 shows the photographic view of experimental set-up used for the present set of turning operation of mild steel workpiece. A single point high speed steel tool has been used as the cutting tool. The round bar of mild steel material of dimensions 30.4 mm in diameter and 140 mm in length is used as the workpiece. The chemical composition of the mild steel taken for experimentation is shown in Table

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1. The input parameters were considered as spindle speed, cutting speed and feed rate. The considered ranges of these input process parameters are shown in Table 2. The material removal rate (MRR) in turning operations is the volume of material or metal that is removed per unit time in mm3/sec. For each revolution of the workpiece, a ring shaped layer of material is removed. Material removal rate has been calculated as per following equation.

$$MRR = \pi \times \frac{(D_1^2 - D_2^2)}{4} \times f \times N \quad (1)$$

Here, D_1 is the initial and D_2 is the final diameter of work-piece, f is the feed rate and N is the spindle speed. The various adjustable cutting parameters during turning operation is discussed hereunder.

Fig.1 The experimental setup used for lathe turning operation

TABLE 1

CHEMICAL COMPOSITION OF MILD STEEL

Elements	Carbon (C)	Manganese (Mn)	Silicon (Si)	Others
Percentage	0.25	0.4-0.7	0.1-0.5	Balance

TABLE 2

PROCESS PARAMETERS AND THEIR RANGES

Parameters	Unit	Range
Feed rate	mm/rev.	0.62, 0.73, 0.77, 0.82, 0.86, 0.89, 0.98
Spindle speed	rpm	40, 90, 200, 400, 600
Cutting speed	m/min	$=(\pi \times D \times N)/1000$, where, D is the diameter of workpiece and N is the spindle speed
Depth of cut	mm	1
Cutting fluid	---	tap water

2.1 Depth of cut

It is the thickness of the layer being removed (in a single pass) from the workpiece or the distance from the uncut surface of the work to the cut surface, expressed in mm. It is important to note that the diameter of the work piece is reduced by two times the depth of cut because this layer is being removed from both sides of the work. It is expressed in mm. Depth of cut can be calculated as per following equation, where D_1 is the initial and D_2 is the final diameter of workpiece.

$$DOC = \frac{D_1 - D_2}{2} \quad (2)$$

2.2 Spindle Speed

The rotational speed of the spindle and the workpiece is in revolutions per minute (rpm). The spindle speed is equal to the cutting speed divided by the circumference of the work-piece where the cut is being made. In order to maintain a constant cutting speed, the spindle speed must vary based on the diameter of the cut. If the spindle speed is held constant, then the cutting speed will vary.

2.3 Feed Rate

Feed always refers to the cutting tool, and it is the rate at which the tool advances along its cutting path. On most power-fed lathes, the feed rate is directly related to the spindle speed and is expressed in mm (of tool advance) per revolution (of the spindle), or mm/rev. The feed rate is calculated by using the relation of machining time.

2.4 Cutting Speed

Speed always refers to the spindle and the workpiece. When it is stated in revolutions per minute (rpm), it tells their rotating speed. But the important feature for a particular turning operation is the surface speed, or the speed at which the workpiece material is moving past the cutting tool. It is simply the product of the rotating speed times the circumference of the work-piece before the cut is started. It is expressed in meter per minute (m/min), and it refers only to the workpiece. Every different diameter on a workpiece will have a different cutting speed, even though the rotating speed remains the same. The equation of evaluating of cutting speed is already given in Table 2.

3 RESULT AND DISCUSSION

Lathe turning experiments on mild steel workpiece have been conducted by varying the spindle speed and cutting speed at different feed rate values. Fig. 2 shows the variation of material removal rate (MRR) at various spindle speed while varying the feed rate parameters in the considered range. From this figure, it is evident that at low spindle speed of rotation i.e. at lower value of rotation of workpiece, the material removal rate slightly increases with the increase of feed rate. As the feed rate increases, the amount of material sheared off by the cutting tool is high, resulting in higher material removal rate. However, at higher setting of rotation of the workpiece, i.e. at spindle speed rotations of 600 rpm, the material removal rate increases rapidly. It is due to the fact that, at higher speed of rotation, the material is sheared off from the workpiece sur-

face very quickly due to higher cutting force.
The influence of feed rate on machining rate is shown in Fig. 3 at different spindle speed values. From this figure, it is revealed that at low spindle speed of rotation, the cutting duration or the machining time is very high for a particular length of turning operation. However, at high spindle speed i.e. high cutting speed, the machining time is less due to more amount of removal of material from the workpiece. The figure also depicts that with increasing value of feed rate, the machining time is decreasing rapidly.

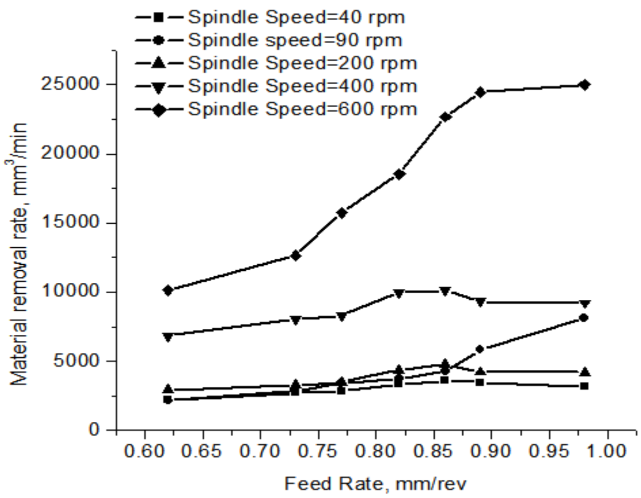


Fig. 2 Influence of feed rate and spindle speed on material removal rate (MRR)

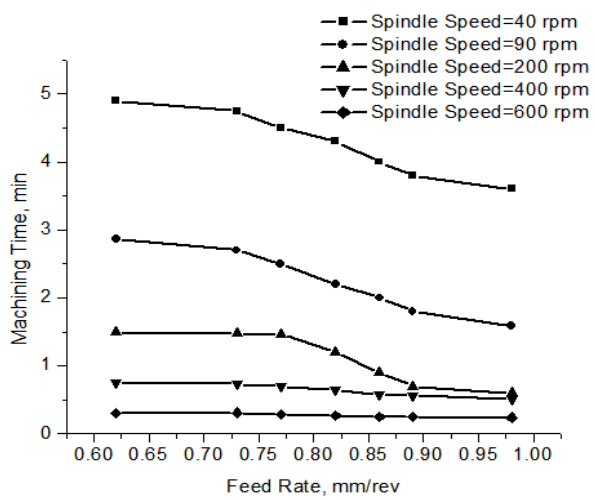


Fig. 3 Influence of feed rate and spindle speed on machining time

TABLE 3

RANGES OF CONSTRAINTS (VARIABLE BOUNDS)

Sl. No.	Ranges	Spindle speed (rpm)	Cutting speed (m/min)	Feed rate (mm/rev.)
1.	Maximum	1000	95.5	0.98
2.	Minimum	40	3.5	0.62

4 DEVELOPMENT OF REGRESSION EQUATION FOR MRR

4.1 Constraints and their Ranges

For developing the regression model of material removal rate and further optimization of MRR, a separate set of experiments have been conducted using the same set-up and tool-workpiece configurations. During machining, some constraints are imposed on machining processes and parameters, which effect the optimal selection of machining conditions and therefore need to be handled carefully while optimizing the machining model. In the constructed optimization problem, three decision variables are considered as cutting speed, feed rate and spindle speed. The parameters spindle speed, feed rate and cutting speed are bounded by upper and lower limits, specified by machinist or tool maker. These bounds are enlisted in Table 3. Table 4 shows the machining parametric combinations and the corresponding values of material removal rate and machining time.

TABLE 4

MACHINING PARAMETRIC COMBINATIONS AND RESULTS OF RESPONSES

Expt.no	Feed Rate	Depth of cut	Spindle speed	Cutting speed	MRR	Machining time
	mm/rev.	mm	rpm	m/min	mm3/sec	Min
1	0.73	1	40	3.82	2696.99	4.75
2	0.86	1	60	5.73	4765.92	2.70
3	0.98	1	90	8.59	8146.39	1.58
4	0.89	1	135	12.89	11097.3	1.16
5	0.76	1	200	19.10	14039.1	0.91
6	0.62	1	300	28.65	17179.4	0.75
7	0.84	1	400	38.20	31033.3	0.42
8	0.82	1	675	64.46	51122.8	0.25
9	0.77	1	1000	95.50	71119.3	0.18

4.2 Regression Analysis

The first necessary step for process parameter optimization in any metal cutting process is to understand the principles governing the cutting processes by developing an explicit mathematical model. Here, statistical regression technique has been used to model the equation using Analysis of Variance (ANOVA).
The objective consists of adjusting the parameters of a model function to best fit a data set. A simple data set consists of n points (data pairs) (xi, yi) i = 1, ..., n, where xi is an independent variable and yi is a dependent variable whose value is found by observation. The model function has the form f(x, β), where the m adjustable parameters are held in the vector β. The goal is to find the parameter values for the model which "best" fits the data. The least squares method finds its optimum when the sum, S, of squared residuals

$$S = \sum_{i=1}^{n} r_i^2 \tag{3}$$

is a minimum. A residual is defined as the difference between the actual value of the dependent variable and the value predicted by the model.

$$r_i = y_i - f(x_i, \beta) \tag{4}$$

An example of a model is that of the straight line. Denoting the intercept as β0 and the slope as β1, the model function is given by

$$f(x, \beta) = \beta_0 + \beta_1 x \tag{5}$$

A data point may consist of more than one independent variable. For an example, when fitting a plane to a set of height measurements, the plane is a function of two independent variables, x and z, say. In the most general case there may be one or more independent variables and one or more dependent variables at each data point.
The minimum of the sum of squares is found by setting the gradient to zero. Since the model contains m parameters there are m gradient equations.

$$\frac{\partial S}{\partial \beta_j} = 2 \sum_i r_i \frac{\partial r_i}{\partial \beta_j} = 0 \text{ , j = 1, ..., m} \tag{6}$$

From equations (4) and (6), the gradient equation can be written as

$$-2 \sum_i \frac{\partial f(x_i, \beta)}{\partial \beta_j} r_i = 0 \text{ , j = 1, ..., m} \tag{7}$$

The gradient equations apply to all least squares problems. Each particular problem requires particular expressions for the model and its partial derivatives. A regression model is a linear one when the model comprises a linear combination of the parameters, i.e.

$$f(x_i, \beta) = \sum_{j=1}^{m} \beta_j \phi_j (x_i) \tag{8}$$

Here the coefficients, ϕj, are functions of xi.
Letting

$$X_{ij} = \frac{\partial f(x_i, \beta)}{\partial \beta_j} = \phi_j (x_i) \tag{9}$$

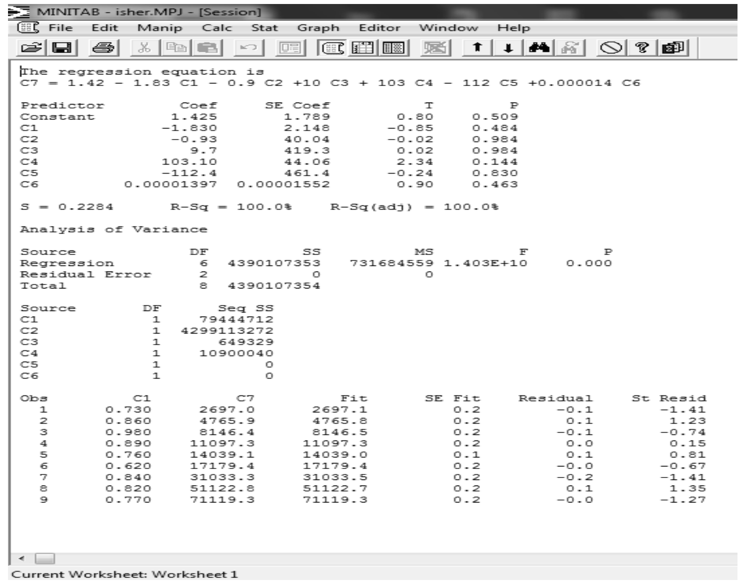
In case the least square estimate (or estimator, in the context of a random sample),β is given by

$$\hat{\beta} = (X^T X)^{-1} X^T y \tag{10}$$

The following regression equation has been developed based on the experimental results shown in Table 4. This regression equation is achieved by feeding the experimental data to the statistical Minitab software. In Fig. 4, the snapshot view of the results of regression analysis from Minitab software is shown. The regression equation developed for material removal rate is as follow.

$$\text{MRR (Y)} = 1.42 - 1.83 X_1 - 0.9 X_2 + 10 X_3 + 103 X_1X_2 - 112 X_1X_3 + 0.000014 X_2X_3 \tag{11}$$

Here, X_1, X_2 and X_3 correspond to the process parameters feed rate, spindle speed and cutting speed in uncoded values.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The regression equation is
C7 = 1.42 - 1.83 C1 - 0.9 C2 +10 C3 + 103 C4 - 112 C5 +0.000014 C6

Predictor         Coef      SE Coef        T       P
Constant         1.425        1.789     0.80   0.509
C1              -1.830        2.148    -0.85   0.484
C2               -0.93        40.04    -0.02   0.984
C3                 9.7        419.3     0.02   0.984
C4              103.10        44.06     2.34   0.144
C5              -112.4        461.4    -0.24   0.830
C6          0.00001397   0.00001552     0.90   0.463

S = 0.2284      R-Sq = 100.0%    R-Sq(adj) = 100.0%

Analysis of Variance

Source           DF          SS         MS          F       P
Regression        6  4390107353  731684559  1.403E+10   0.000
Residual Error    2           0          0
Total             8  4390107354

Source       DF      Seq SS
C1            1    79444712
C2            1  4299113272
C3            1      649329
C4            1    10900040
C5            1           0
C6            1           0

Obs      C1       C7      Fit   SE Fit  Residual  St Resid
  1   0.730   2697.0   2697.1      0.2      -0.1     -1.41
  2   0.860   4765.9   4765.8      0.2       0.1      1.23
  3   0.980   8146.4   8146.5      0.2      -0.1     -0.74
  4   0.890  11097.3  11097.3      0.2       0.0      0.15
  5   0.760  14039.1  14039.0      0.1       0.1      0.81
  6   0.620  17179.4  17179.4      0.2      -0.0     -0.67
  7   0.840  31033.3  31033.5      0.2      -0.2     -1.41
  8   0.820  51122.8  51122.7      0.2       0.1      1.35
  9   0.770  71119.3  71119.3      0.2      -0.0     -1.27

Current Worksheet: Worksheet 1
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Fig. 4 The snapshot view of output results of regression analysis from Minitab software

TABLE 5

COMPARATIVE RESULTS OF MRR BASED ON EXPERIMENTAL AND REGRESSION BASED EQUATION

Observation	Experimental Results	Predicted Results from Regression equation
1	2697.0	2697.1
2	4765.9	4765.8
3	8146.4	8146.5
4	11097.3	11097.3
5	14039.1	14039.0
6	17179.4	17179.4
7	31033.3	31033.5
8	51122.8	51122.7
9	71119.3	71119.3

5 OPTIMIZATION BASED ON GENETIC ALGORITHM (GA)

In 1975, Holland developed this idea in his book "Adaptation in natural and artificial systems". He described how to apply the principles of natural evolution to optimization problems and built the first Genetic Algorithms. Holland's theory has been further developed and now Genetic Algorithms (GAs) stand up as a powerful tool for solving search and optimization problems. Genetic algorithms are based on the principle of genetics and evolution [12]. Goldberg, 1989 gives an excellent introductory discussion on GA, as well as some more advanced topics. Genetic algorithms are a probabilistic search approach which is founded on the ideas of evolutionary processes. The GA procedure is based on the Darwinian principle of survival of the fittest. An initial population is created containing a predefined number of individuals (or solutions), each represented by a genetic string (incorporating the varia-

ble information). Each individual has an associated fitness measure, typically representing an objective value. The concept that fittest (or best) individuals in a population will produce fitter offspring is then implemented in order to reproduce the next population. Selected individuals are chosen for reproduction (or crossover) at each generation, with an appropriate mutation factor to randomly modify the genes of an individual, in order to develop the new population. The result is another set of individuals based on the original subjects leading to subsequent populations with better (min. or max.) individual fitness. Therefore, the algorithm identifies the individuals with the optimizing fitness values, and those with lower fitness will naturally get discarded from the population.
Ultimately this search procedure finds a set of variables that optimizes the fitness of an individual and/or of the whole population. As a result, the GA technique has advantages over traditional non-linear solution techniques that cannot always achieve an optimal solution. For the genetic algorithm, the population encompasses a range of possible outcomes. Solutions are identified purely on a fitness level, and therefore local optima are not distinguished from other equally fit individuals. Those solutions closer to the global optimum will thus have higher fitness values. Successive generations improve the fitness of individuals in the population until the optimization convergence criterion is met. Due to this probabilistic nature GA tends to the global optimum, however for the same reasons GA models cannot guarantee finding the optimal solution. The GA consists of four main stages: evaluation, selection, crossover and mutation. These are briefly discussed below.

5.1 Evaluation

The evaluation procedure measures the fitness of each individual solution in the population and assigns it a relative value based on the defining optimization (or search) criteria. Typically in a non-linear programming scenario, this measure will reflect the objective value of the given model. The selection procedure randomly selects individuals of the current population for development of the next generation. Various alternative methods have been proposed but all follow the idea that the fittest have a greater chance of survival.

5.2 Crossover

The crossover procedure takes two selected individuals and combines them about a crossover point thereby creating two new individuals. Simple (asexual) reproduction can also occur which replicates a single individual into the new population.

5.3 Mutation

The mutation procedure randomly modifies the genes of an individual subject to a small mutation factor, introducing further randomness into the population. This iterative process continues until one of the possible termination criteria is met: if a known optimal or acceptable solution level is attained; or if a maximum number of generations have been performed; or if a given number of generations without fitness improvement occur. Generally, the last of these criteria applies as convergence slows to the optimal solution.
Population size selection is probably the most important parameter, reflecting the size and complexity of the problem. However, the trade-off between extra computational `efforts with respect to increased population size is a problem specific decision to be ascertained by the modeler, as doubling the population size will approximately double the solution time for the same number of generations. Other parameters include the maximum number of generations to be performed, a crossover probability, a mutation probability, a selection method and possibly an elitist strategy, where the best is retained in the next generation's population.

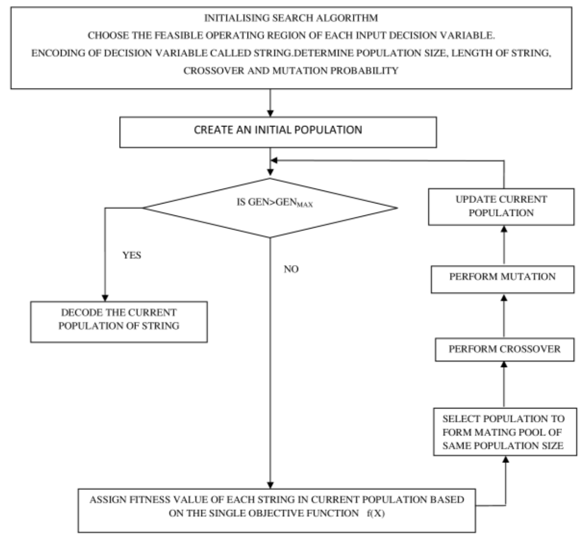

Fig5 Flow chart of Genetic Algorithms

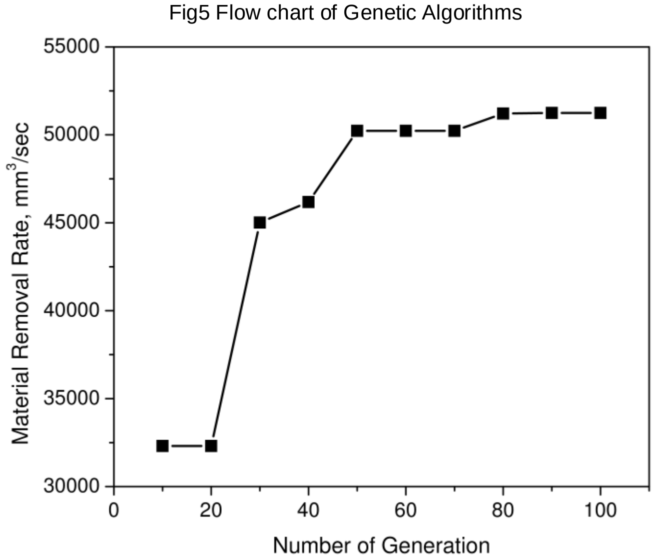

Fig. 6 Plot of Number of Generation Vs Material Removal Rate

Unlike traditional optimization methods, GA is better at handling integer variables than continuous variables. This is due to the inherent granularity of variable gene strings within the GA model structure. Typically, a variable is implemented with a range of possible values with a binary string indicating the number of such values; i.e. if x1 [0,15] and the gene string is 4 characters (e.g. "1010") then there are 16 possibilities for the search to consider. To model this as a continuous variable increases the number of possible values significantly. Similarly, other variable information which aids the search considerably are upper and lower bound values. These factors can affect convergence of the model solutions greatly.

5.4 Results of Optimization

Fig. 6 shows the plot of material removal rate (MRR) for variation of number of generation during GA optimization. From this plot, it is clear that the material removal rate increases with number of generation. However, it is observed that after a certain number of generation (90 generation), material removal rate remains constant. The optimal parametric setting of feed rate, cutting speed and spindle speed for which the material removal rate (MRR) is maximum is shown in table 6.

TABLE 6

OPTIMIZATION RESULTS OF MRR ACHIEVED IN GA

Spindle Speed, rpm	Cutting Speed, m/min	Feed Rate, mm/rev	Best Fitness of MRR, mm3/sec
891.520	25.580	0.582	51247.549

6 CONCLUSIONS

This paper presents a genetic algorithm optimization approach for finding the optimal parameter setting during turning operation in conventional Lathe machine. In this work the experimentation is carried out in mild steel considering three machining parameter, viz. , feed rate, spindle speed and cutting speed. It has been found that material removal rate increases with the increase of feed rate. However, at low spindle speed of rotation, the material removal rate is high compared to high spindle speed of rotation. Based on the results of experiments, the regression equation for material removal rate (MRR) has been developed using statistical Minitab software. The regression equation has been validated through comparative results of MRR achieved during experimentation. Genetic Algorithm (GA) has been used to achieve the optimum machining parametric combination in order to obtain the value of optimal result of material removal rate. The results obtained in this paper can be effectively utilized for machining, particularly turning operation of mild steel material in shop floor manufacturing.

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