Optimization of Machining Parameters in Turning Process Using Genetic Algorithm & Artificial Neural Network

A Project Report

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S. Suresh - 71205402009

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BONAFIDE CERTIFICATE

Certified that this project report entitled **"Optimization of Machining Parameters in Turning Process Using Genetic Algorithm & Artificial Neural Network"** is the bonafide work of

Mr. S. Suresh - Register No. 71205402009

Who carried out the project work under my supervision.

Signature of the Head of the Department

28/5/07

Signature of the supervisor
Dr. P. PALANISAMY

9/7/07

Internal Examiner

4/7/07

External Examiner

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CADAM '07

llege of Engineering and Technology

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ABSTRACT

The ultimate aim of turning is to remove work piece material in a single cut rather than a lengthy grinding operation in order to reduce processing time, production cost, surface roughness and setup time and to remain competitive. The process of turning offers many potential benefits compared to conventional grinding operation. Optimization of cutting parameters is valuable in terms of providing high precision and efficient machining. Optimization in turning means determination of the optimal set of machining parameters to satisfy the objectives within the operational constraints. In the present work, an attempt is made to minimize the unit production cost as an objective function subjected to a set of constraints such as tool life, power, cutting force and surface roughness in turning by using a genetic algorithm. The main machining parameters which are to be considered as the variables of the turning process are cutting speed, feed and depth of cut. The result of the work shows how a complex optimization problem is handled by a genetic algorithm and converges very quickly. The proposed algorithm is found to perform better than a goal programming technique. This work also presents the artificial neural network model for the prediction of surface roughness and tool wear in turning operation. Cutting speed, feed and depth of cut were taken as input parameters while surface roughness and tool wear were taken

ஆய்வுச்சுருக்கம்

போட்டிகள் நிறைந்த சந்தையில் கடைசலின் முக்கிய நோக்கம் பணிப் பொருளை ஒரே முறை வெட்டுதல் மூலம் நீக்குதல் ஆகும். இந்த முறையில் உற்பத்தி விலை, செய்முறை பணி கால அளவு, மேற்பரப்பின் கரடுமுரடான தன்மையைக் குறைத்தல், ஆகிய அனைத்தையும் கிரைண்டிங் முறையை விட எளிதாக குறைக்க இயலும்.

பழைமையான கிரைண்டிங்கை விட நவீன கடைசல்கள் முறை பல நன்மைகளைக் கொண்டது.நுட்பமான மற்றும் திறன் உடைய பொருள் நீக்குதல் வேண்டும் போது வெட்டுதலின் மிக முக்கிய காரணிகளை ஆட்டிமைசேஷன் செய்தல் மிகவும் பொக்கிஷமான ஓர் முறையாகும்.பணி இடத்தில் உள்ள குறைந்த பட்ச வசதிகளைக் கொண்டு பொருள் நீக்கும் காரணிகளை தேர்ந்து எடுத்து அவற்றை ஆப்டிமைஸ் செய்வது கடைசல்கள் முறையின் நோக்கம் ஆகும்.

பொருளுக்கான உற்பத்தி செலவை குறைப்பது என்ற லட்சியத்தோடு இந்த ஆய்வு முயற்சியில் கடைபிடித்த ஜெனடிக் அல்காரிதம் மூலம் வெட்டுக் கருவியின் ஆயுள், மின் சக்தி, வெட்டுவிசை, மற்றும் சொரசொரப்பான பரப்பு ஆகிய காரணிகளை கருத்தில் கொண்டு ஒரு சீரிய முயற்சி கடைசலில் மேற்கொள்ளப்பட்டுள்ளது.

பொருள் நீக்குதலின் முக்கிய அம்சங்களை வெட்டு வேகம், வெட்டு ஆழம், உட்செலுத்துதல் வீதம் ஆகியவற்றை கருத்தில் கொண்டு கடைசல் முறை கையாளப் படுகிறது.சிக்கலான ஆப்டிமைசேஷன் முறையில் கையாளப்பட்டு ஒரு பணியை சுலபமாக விரைவாக ஜெனடிக் அல்காரிதம் மூலம் சரி செய்யப்பட்டு உள்ளது. இந்த அல்காரிதம் முறை கோல் பிரோகிராமிங் முறையை விட மிகச் சிறந்ததாகும்.

இந்த ஆய்வில் கடைசல் பணியில் ஏற்படும் வெட்டுக் கருவியின் தேய்மானம், மேற்பரப்பு ஆகியவற்றை முன் கூட்டியே கண்டறியும் செயற்கை நரம்புசார் ஒருங்கிணைப்படி கையாளப்பட்டது.கடைசல் பணியின் போது வெட்டு வேகம், வெட்டு ஆழம், உட்செலுத்துதல் முறை ஆகியவை இன்புட் பராமீட்டர்கள் மேற்பரப்பின் கரடு முரடு மற்றும் வெட்டுக் கருவியின் தேய்மானம் அவுட்புட் பராமீட்டர்கள் ஆக எடுத்துக் கொள்ளப்படுகிறது.

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CONTENTS

LIST OF TABLES

LIST OF PHOTOS & FIGURES

LIST OF SYMBOLS & ABBREVATIONS

ANN	-	Artificial Neural Network
DOE	-	Design of Experiments
GA	-	Genetic Algorithm
d	-	Depth of cut (mm)
P	-	Power (kw)
D	-	Diameter of the work piece (mm)
T_{tcb}	-	Tool changing time (min / edge)
f	-	Feed rate (mm / rev)
T_l	-	Loading / Unloading time (min)
F_c	-	Cutting force (N)
R	-	Surface roughness (μm)
L	-	Length of the work piece (mm)
P_c	-	Crossover probability
r_e	-	Tool nose radius (mm)
P_m	-	Mutation probability
T	-	Tool life (min)
T_m	-	Machining time (min)
V	-	Cutting speed (m / min)
C_{pr}	-	Unit cost of production (Rs / work piece)
N	-	Speed of work piece (rpm)
C_t	-	Tool cost (Rs / edge)
C_0	-	Unit cost of operation (Rs / min)
k_s	-	Specific cutting resistance (N/ mm^2)

Chapter 1

1.1 TURNING PROCESS

Turning is the process of reducing the outer diameter of the work piece in which the tool is moved parallel to the lathe axis. Turning is performed on a machine called lathe in which the work piece is rotated while the tool travels at transverse or longitudinal direction. Work pieces, small and large can be machined in one setup through multi-tasking capabilities on single and multi-spindle machines. For larger work pieces, engine lathes, vertical turning centers, and a new generation of computer numerical control lathes are used. Automation is provided by bar feeders, robots and pallet delivery systems.

1.2 GENETIC ALGORITHM

It is a population-based search optimization and has been used as a powerful tool for optimizing cutting parameters. The data processed by GA includes a set of strings (or chromosomes) with an infinite length in which each bit is called an allele (or a gene). A selected number of strings are called as population and the population at a given time is a generation. Generation of the initial population of strings is done randomly. Since the binary alphabet offers the maximum number of schemata per bit of information of any coding, a binary encoding scheme is traditionally used to represent the chromosomes using either zeros or ones. Thereafter the fitness value (objective function value) of each member is computed. The population is then operated by the three main operators namely, reproduction, cross-over and mutation to create a new population. The new population is further evaluated and tested for determination.

1.3 DESIGN OF EXPERIMENTS

1.4 ARTIFICAL NEURAL NETWORKS

Artificial neural network is an information processing paradigm and is highly interconnected network of large number of processing element. Non-linear mapping systems consist of neurons, linked by weighted connections. In ANN, the processing elements (organized in layers) perform the task of combining several inputs into a weighed output.

1.5 IMPORTANCE OF THE PROJECT

Optimum machining parameters are of great concern in manufacturing environments, where economy of machining operation plays a key role in competitiveness in the global market. Optimization analysis of the machining process is usually based on either minimizing production rate, or obtaining the finest possible surface finish by using the empirical relationships between tool life and the operating parameters. Most of the researchers have published a number of such equations for the practical turning process in which numerous process variables are involved. Some researchers reported in the literature attempted to solve problems for machining conditions by using linear programming.

For solving machining optimization problems, various conventional techniques had been used so far, but they are robust and have problems when applied to turning process which involves number of variables and constraints. To overcome the above problems, genetic algorithm is used in this work it goes through solution space starting from a group of points and not from a single point.

1.6 OBJECTIVES OF THE PROJECT

1. To optimize the cutting parameters in turning process using genetic

Chapter 2

Chattopadhyay et al. (1996) has used neural network for evaluation of wear in carbide inserts. He has taken cutting speed, feed, and depth of cut as input parameters to develop the model. The feed forward back propagation artificial neural network has been used and the model results come closer to the actual values. He has suggested that the accuracy of the model can be improved by increasing the number of nodes in the hidden layer.

Choudhary et al. (1999) predicted tool wear using neural network and design of experiments. He analyzed the role of temperature in tool wear. He used the experimental data from the conducted experiments as per design of experiments methodology and developed a regression model and neural network model. In his work, he has considered temperature along with other machining parameters like feed and cutting speed as input parameters and tool wear as the output parameter. His results prove that the neural network model is the better model. But one limitation in his work is that he has not considered tool geometry as an input parameter.

Choudhuri et al. (2002) optimized the machining parameters in turning process by using genetic algorithm while taking the multi-objective function as minimization of production cost per piece, minimization of production time per piece or any weighted combination both. He used the optimum set of three input parameters which are cutting speed, feed and depth of cut, after satisfying the constraints such as power availability, surface roughness condition, tool life, dimensional tolerance and rigidity. But the limitation is that parameters like tool geometry, tool material and cutting temperature can also influence the metal cutting to a great extent.

measure the surface roughness, cutting force and vibration for the optimized cutting parameters.

Ramon Quiza Sardinas et al. (2006) optimized machining parameters in turning process by using genetic algorithm while taking multi-objective functions as minimization of production time per part and maximization of the tool life and used three input parameters which are cutting speed, feed and depth of cut, after satisfying the constraints such as power, surface roughness and cutting force. An application sample is developed and its results are analyzed for several different production conditions.

Radhakrishnan, (2005) have developed a good empirical relationship between the cutting force in an end milling operation and the cutting parameters such as speed, feed and depth of cut, by using both multiple regression and neural modeling processes. He analyzed that milling force data using conventional regression can lead to a more accurate neural networks model for force prediction.

Asokan et al. (2005) optimized the machining parameters in grinding process by using particle swarm optimization while taking the multi-objective function as minimization of unit production cost per piece and minimization of unit production time. He used the optimum set of four input parameters which are wheel speed, work piece speed, depth of dressing and lead of dressing, after satisfying the constraints such as thermal damage constraint, wheel wear parameter constraint, machine tool stiffness constraint and surface constraint.

Palanisamy et al. (2006) have developed two different models regression model different grades of polycrystalline cubic boron nitride as the cutting tool. He described the various characteristics in terms of component quality, tool life, tool wear, and effects of individual parameters on tool life, material removal and economics of operation. The hardened material selected for hard turning is commercially available engine crank pin material.

Choudhury et al. (1999) predicted the tool wear in turning process using neural network He has taken cutting speed, feed, and depth of cut as input parameters to develop the model and used an optoelectronic sensor system for monitoring the tool wear without interrupting the machining process. For the experiments used for validating the system, the predicted values were found to be within an error of 6 % of the actual measured values.

Tugrul Ozel et al. (2002) has developed exponential regression model and neural network model to predict surface roughness and tool wear in finish hard turning using Carbide tools. In the work, material hardness, Carbide content in tool material, cutting speed, feed and cutting time have been considered as the process parameters and has found their influence on tool wear and surface finish. He has compared the neural network model with regression model and found that the ANN model provided better prediction capabilities because they generally offer the ability to model more complex non-linearity's and interactions than linear and exponential models.

Gopalakrishnan et al. (1991) described the design and development of an analytical tool for the selection of machining parameters in turning process. Geometric programming was used as a basic methodology to determine the values on a single variable by considering a single constraint. In the present work, efforts have been made to study the influence of feed, depth of cut and cutting speed during machining on the tool life and surface finish while minimizing the unit production cost.

Chapter 3

3.1 INTRODUCTION

Optimization analysis of the machining process is usually based on minimizing production cost, maximizing production rate, or obtaining the finest possible surface finish by using the relationships between tool life and the operating parameters.

3.2 NEED FOR OPTIMIZATION

Optimization algorithms are becoming increasingly popular in engineering design activities, primarily because of the availability and affordability of high-speed computer. They are extensively used in those engineering problems where the emphasis is on maximizing or minimizing a certain goal. For example, optimization is routinely used in aerospace design activities to minimize the overall weight of the aircraft. Thus the minimization of the weight of the aircraft components is of major concern to aerospace designers. Chemical engineers, in the other hand, are interested in designing and operating a process plant for an optimum rate of production. Mechanical engineers design mechanical components for the purpose of achieving either a minimum manufacturing costs or a maximum component life.

Production engineers are interested in designing optimum schedule of the various machining operations to minimize the ideal time of machines and the overall job completion time. Civil engineers are involved in designing buildings, bridges, dams and other structures in order to achieve a minimum overall cost or maximizing safety or both. Electrical engineers are interested in designing communication networks so as to achieve minimum time for communication from

3.3 TYPES OF OPTIMIZATION TECHNIQUES

The types of optimization techniques are given below

- Single or multi variable optimization
- Single or multi objective optimization
- Constrained or unconstrained optimization
- Linear or non-linear optimization
- Non-traditional optimization algorithms

Non-traditional optimization algorithms are fuzzy logic, genetic algorithm, scatter search technique, particle swarm optimization technique, taguchi technique, response surface methodology.

3.3.1 Fuzzy logic

Fuzzy logic has great capability to capture human commonsense reasoning, decision-making, and other aspects of human cognition. Fuzzy logic overcomes the limitations of classic logical systems, which impose restrictions on representation of imprecise concepts. Vagueness in the coefficients and constraints may be naturally modeled by fuzzy logic. Modeling by fuzzy logic opens up a new way to optimize cutting conditions and tool selection.

3.3.2 Genetic algorithm

The algorithms are based on mechanics of natural selection and natural genetics, which are more robust and more likely to locate global optimum. Genetic algorithm goes through solution space starting from a group of points and not from a single point. The cutting conditions are encoded as genes by binary various economic criteria and numerous practical constraints. It can obtain near-optimal solutions within reasonable execution time on computer.

3.3.4 Particle swarm optimization technique

This technique simulates the behavior of bird flocking. Suppose a group of birds is randomly searching for food in an area and there is only one piece of food in the area being searched. All the birds do not know where the food is. The effective one is to follow the bird that is nearest to the food and each single solution is a "bird" in the search space. This is called as "particle". All of the particles have fitness values, which are evaluated by the fitness function to be optimized, and have velocities, which direct the flying of the particles. The particles are flown through the problem space by following the current optimum particles.

3.3.5 Taguchi technique

Taguchi methods refer to parameter design, tolerance design, quality loss function, on-line quality control, design of experiments using orthogonal arrays, and methodology applied to evaluate measuring systems.

3.3.6 Response surface methodology

Experimentation and making inferences are twin features of general scientific methodology. Statistics as a scientific discipline is mainly designed to achieve these objectives. The methodology for making inferences has three main aspects. First it establishes methods for drawing inferences from observations when these are not exact but subject to variation, because inferences are not exact but probabilistic in nature. Second it specifies methods for collection of data appropriately, so that assumptions for the application appropriate statistical

3.4 SUMMARY OF MACHINING OPTIMIZTION TECHNIQUES

The summary of the machining optimization techniques have been given in the table below.

TABLE 3.1 SUMMARY OF MACHINING OPTIMIZTION TECHNIQUES

Technique	Reference	Tools used	Remarks
Lagrange's Method	Brewer (1966); Bhattacharya (1970)	Lagrange's multiplier	Used for constrained optimization
Geometric Programming	Walvekar & Lambert (1970): Gopalakrishnan & Khayyal (1991)	Theory is based on the arithmetic-geometric mean inequality	Developed for solving a class of nonlinear optimization problem found in engineering design and manufacture
Goal programming	Sundaram (1978)	Goal programming combines the logic of optimization in mathematical programming with the decision maker's desire to satisfy several goals	Form of multi-objective optimization
Dynamic programming	Agapiou (1992)	A collection of algorithms used to compute optimal polices given a perfect model of environment	Solving sequential or multi-stage decision problems by solving a series of single variable problems

Technique	Reference	Tools used	Remarks
Genetic Algorithm	Kuo (2002): Wang (2004)	A CGI (common gateway interface) program	Based on machining model developed from theoretical analysis, experimental database and numerical methods
Scatter search	Chen (2003)	A program designed by Laguna and Marti in C code	A generalized optimization methodology for machining Problems that have no restrictive assumption about objective function, parameter set and constraint set
Taguchi technique	Pignatiello (1993): Tsui (1999): Singh & Kumar (2003, 2004, 2005)	Design of experiments, Orthogonal arrays, ANOVA	Based on actual experimental work and determination of optimum conditions using statistical tools
Response surface methodology	Taraman (1974): Hassan & Suliman (1990): Baradie (1993); Noordin (2004)	Design expert software (DX6)	Based on machining model developed by mathematical and statistical techniques

Genetic algorithms use only the values of the objective function. The derivatives are not used in the search procedure. A population of points is used for the starting procedure instead of a single design point. Since several points are used as

Chapter 4

4.1 INTRODUCTION

Genetic algorithm simulates the survival of the fittest among individuals over consecutive generation for solving a problem. Each generation consists of a population of character. Each individual represents a point in a search space and a possible solution. The individual in the population are then made to go through a process of evaluation. The basic idea of genetic algorithm is to use the power of evolution to solve optimization problems.

The basic concept of genetic algorithm is to encode a potential solution to a problem as a series of parameters. A single set of parameter value is treated as the genome of an individual solution. An initial population of individuals is generated at random or statically. Every generation the individuals in the current population are decoded according to a fitness function. The chromosomes with the highest population fitness are selected for mating.

The genes of the two parents are allowed to exchange to reproduce off springs. These children then replace their parents in the next generation. Thus the old population is discarded and the new population becomes the current population. The current population is checked for acceptability of solution. The iteration is stopped after the completion of maximal number of generations or on the attainment of the best results.

4.2 OBJECTIVE FUNCTION

The objective functions and constraints of this optimization problem have been formulated as below, considering a practical problem of D = 35 mm, L = 100 mm, T_{tcb} = 0.5 min / edge, T_1 = 15 min

Tool life, T is obtained from the tool life equation as given by [2]

$$T = \frac{48.24 \times 10^{11}}{V^{5.263} f^{1.894} d^{0.421}} \tag{3}$$

Substituting equations (2) and (3) in equation (1) and using the values of C_0 and C_t as Rs 3 / min and Rs 15 / edge, respectively, the expression of unit production cost C_{pr} is [4]

$$C_{pr} = (45 + 32.987 V^{-1} f^{-1} + 3.761 \times 10^{-11} V^{4.263} f^{0.894} d^{0.421}) \tag{4}$$

4.3 CONSTRAINTS

There are four constraints that must be satisfied to give the optimal of feed, depth of cut and cutting speed. These constraints are tool life, power, cutting force and surface roughness

4.3.1 Tool life

Tool life (T) can be defined as a tool's useful life until it no longer produces satisfactory parts. When the wear reaches a certain value the tool is not capable of further cutting unless it is resharpened. Life of the tool is affected by various parameters such as cutting speed, depth of cut, feed, tool geometry and cutting fluid. [2]

$$T = \frac{48.24 \times 10^{11}}{V^{5.263} f^{1.894} d^{0.421}} \geq 30 \min \tag{5}$$

4.3.2 Power

The power consumed during a turning operation is given by the equation [15]

$$P = \frac{k_s \times f \times d \times V}{60 \times 1020} \leq 2.2 kw \tag{6}$$

4.3.4 Surface roughness

Surface roughness can be defined as an integral of the absolute value of the roughness profile measured over evaluation length. It is expressed in thousands of millimeter [16]

$$R = \frac{125 \times f^2}{r_e} \le 3.2 \mu m \tag{8}$$

4.4 WORKING PRINCIPLE OF GA

The genetic algorithm (GA) is a population-based search optimization technique and has been used as a powerful tool for optimizing cutting parameters in turning operations. The data processed by GA includes a set of strings (or chromosomes) with an infinite length in which each bit is called an allele (or a gene). A selected number of strings are called as population and the population at a given time is a generation. Generation of the initial population of strings is done randomly. Since the binary alphabet offers the maximum number of schemata per bit of information of any coding, a binary encoding scheme is traditionally used to represent the chromosomes using either zeros or ones.

Thereafter, the fitness value (objective function value) of each member is computed. The population is then operated by the three main operators, namely, reproduction, crossover, and mutation to create a new population. The new population is further evaluated and tested for determination. One iteration of these three operators is known as a generation in the parlance of GA. The range of cutting parameters variables are given in Table 4.1.

TABLE 4.1 CUTTING PARAMETERS

4.5 IMPLEMENTATION OF GA

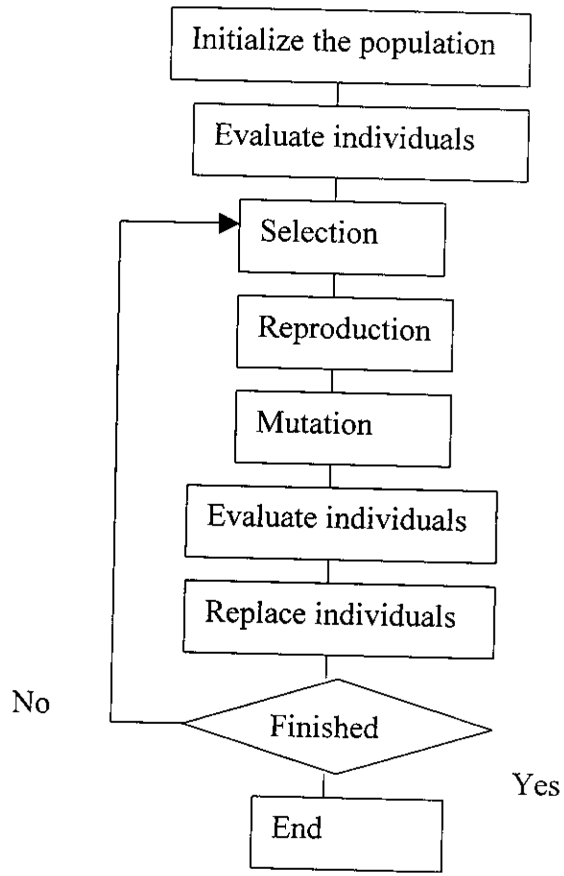


FIGURE 4.1 FLOWCHART OF GENETIC ALGORITHM

4.5.1 Coding

In order to use Genetic algorithms to solve the problem, variables are first coded in some string structures. Binary-coded strings having ones and zeros are primarily used. The length of the string is usually determined according to the desired solution accuracy. In order to solve this problem using GA, binary coding function F(x) is derived from the objective function and is used in successive genetic operations. For maximization problems, fitness function can be considered the same as the objective function. The minimization problem is an equivalent maximization problem such that the optimum point remains unchanged. A number of such transformations are possible.

4.5.3 Basic operators of GA

1. Reproduction

Reproduction is the first operator applied on a population. In this process individual strings are copied into a separate string called the 'mating pool' according to their fitness values, i.e. the strings with a higher value have a higher probability of contributing one or more offspring in the next generation. A reproduction operator can be implemented in algorithmic form in a number of ways. The easiest way is to create a biased roulette wheel where each current string in the population has a roulette-wheel-slot-size in proportion to its fitness. In this way more highly fit strings have higher numbers of offspring in the succeeding generation. Once the string has been selected for the reproduction an extra replica of the string is made. The string is entered into the mating pool.

2. Crossover

After reproduction, the population is enriched with good strings from the previous generation but does not have any new string. A crossover operator is applied to the population to hopefully create better strings. The total number of participative strings in crossover is controlled by crossover probability, which is the ratio of total strings selected for mating and the population size. The crossover operator is mainly responsible for the search aspects of GA.

4.6 TOURNAMENT SELECTION

The fitness-proportionate described requires two passes through the population at each generation. One pass to compute the mean fitness (for sigma scaling and the standard deviation.) and one pass to compute the expected value of each individual. Rank scaling requires sorting the entire population by rank a potentially time consuming procedure. Tournament selection is similar to rank selection in terms of selection pressure, but it is computationally more efficient and more amenable to parallel implementation. Two individuals are chosen at random from the population. A random number is then chosen between 0 and 1; if individuals are selected to be parent otherwise the less fit individual is selected. The two are then returned to the original population and can be selected again. An analysis of this method was presented by Golgberg and Deb.

4.7 GA PARAMETERS

The GA parameters are given in the table 4.2

TABLE 4.2 GA PARAMETERS

Number of digits	10 (for variables d, f & V)
Sample size	30
Selection operator	Tournament selection
Crossover probability P_c	0.7
Mutation probability P_m	0.1
No of generations	100

4.8 OPTIMIZATION RESULTS

The optimization results are given in the table 4.3

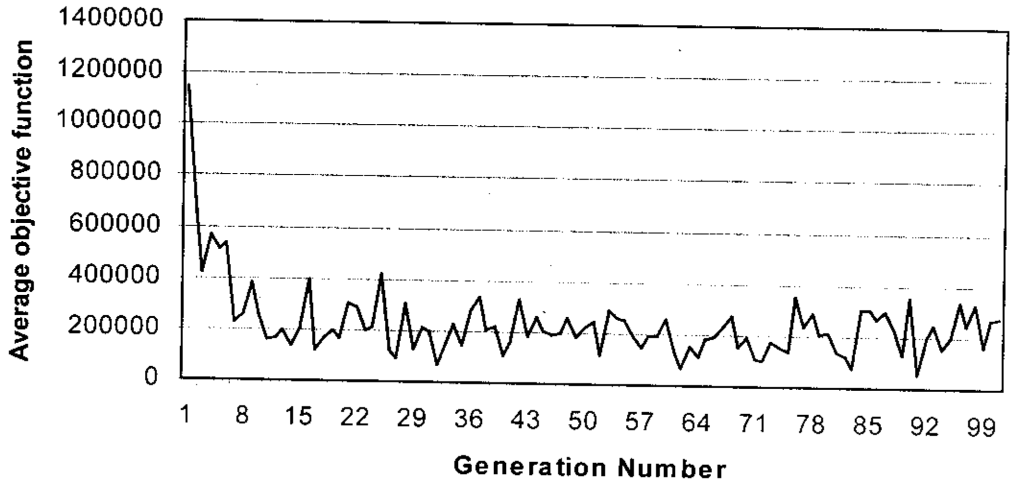
TABLE 4.3 OPTIMIZATION RESULTS

Gen. No	Min Objective Function Unit Production Cost (Rs)	Average Objective Function (Rs)
0	47.295	1151029.5
1	47.038	689079.938
2	46.496	417058.875
3	50.093	566485.688
4	49.967	510474.938
5	47.721	539199.438
6	47.56	226317.438
7	46.892	261489.312
8	46.895	381357
9	46.484	262605.844
10	47.668	157106.109
11	47.6	164805.797
12	47.223	198362.734
13	47.222	134977.172
14	46.988	206690.5
15	46.493	395687.469
16	46.492	120553.469
17	46.499	170834.641
18	46.53	201050.609
19	46.393	166951.391
20	46.743	302559.094
21	46.4	[illegible]

30	47.085	199731.797
31	46.838	72647.758
32	46.807	161553.391
33	46.536	229631.109
34	46.597	145701.703
35	46.482	281040.125
36	46.555	334291.312
37	47.091	204113.641
38	46.636	220203.594
39	46.725	110579.789
40	46.379	160066.562
41	46.868	330565.656
42	46.377	185892.734
43	46.377	259356.094
44	47.618	208443.328
45	46.887	191521.078
46	47.395	197744.062
47	46.792	262406.594
48	46.907	186171.5
49	46.645	223493.719
50	46.372	246352.641
51	46.374	115562.398
52	46.373	288520.938
53	46.372	256811.859
54	46.356	250022.719
55	46.851	194026.516
56	46.364	144599.938
57	47.078	189437.891
58	47.636	189460.859

67	46.748	277033.844
68	46.669	154733.688
69	46.568	189973.859
70	46.545	104762.461
71	46.528	98730.555
72	46.536	175159.75
73	46.392	150163.359
74	46.387	134920.734
75	46.47	350949.688
76	46.738	233852.766
77	46.649	291737.062
78	46.49	204026.047
79	46.615	215088.906
80	46.657	134052.953
81	46.749	124643.273
82	46.812	78529.398
83	46.566	303234.188
84	46.846	306623.344
85	46.968	267917.219
86	46.927	298190.531
87	46.867	228334.312
88	46.998	131366.297
89	47.612	353540.469
90	47.497	50130.195
91	47.197	195709.781
92	46.345	245675.047
93	46.348	149800.359
94	46.507	195497.047
95	46.37	333348.594

The results are explained in the following graphs



FIGUERE 4.2 GENERATION NUMBER VS AVERAGE OBJECTIVE FUNCTION

Figure 4.2 shows that generation number is taken in the x axis and average objective function is taken in the in y axis.

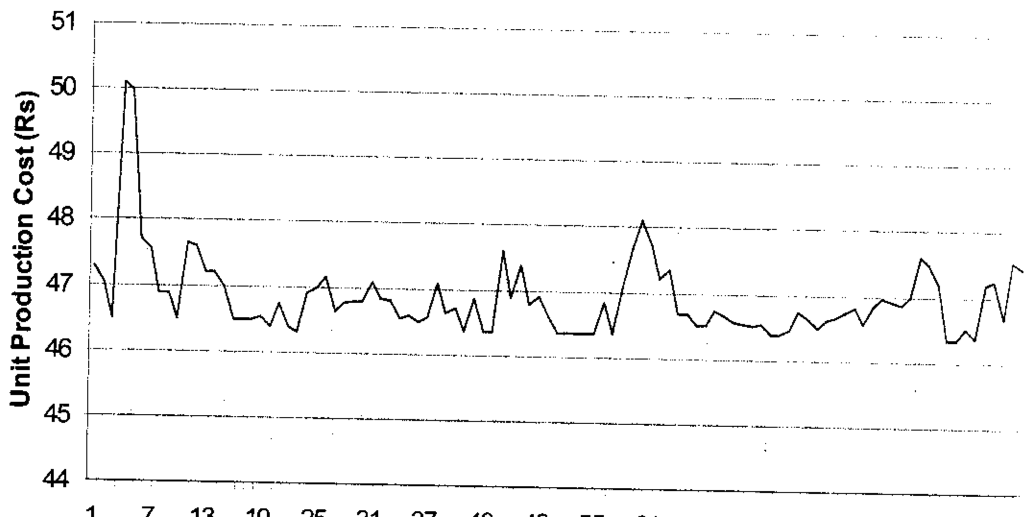


TABLE 4.4 OPTIMIZATION RESULTS

Gen. No	Tool life (min)	Power (kw)	Cutting force (N)	Surface roughness (μm)
0	873.92	0.85	348.60	1.27
1	453.30	0.96	336.38	1.27
2	286.27	1.32	473.91	2.60
3	21368.11	0.25	183.90	0.64
4	177514.46	0.32	529.02	2.52
5	1062.43	0.91	386.39	0.90
6	666.88	1.32	531.20	0.90
7	1399.73	0.34	138.51	2.33
8	969.84	0.80	361.25	2.33
9	16201.31	0.30	229.92	1.63
10	7133.44	0.52	377.78	2.52
11	4880.90	0.82	592.45	2.40
12	2144.69	0.94	550.17	2.40
13	2249.22	0.84	485.85	2.40
14	1592.00	0.52	247.36	2.40
15	378.82	0.94	340.20	2.81
16	392.25	0.86	310.59	2.81
17	477.41	0.59	206.56	2.81
18	413.85	0.87	318.78	2.72
19	234.01	0.98	313.83	2.81
20	334.16	0.91	315.09	2.72
21	248.45	0.96	310.06	2.72
22	214.84	1.08	347.46	3.11
23	857.87	1.01	456.97	2.25

32	1303.26	0.78	389.81	3.11
33	413.96	1.22	483.46	2.93
34	493.36	0.72	261.72	2.52
35	518.35	0.49	169.46	2.93
36	472.37	1.04	415.88	2.93
37	446.59	0.87	290.13	1.13
38	759.99	0.42	153.00	2.60
39	339.22	0.88	289.07	1.72
40	241.03	1.55	559.97	3.11
41	494.73	0.95	353.50	1.72
42	334.99	0.65	210.33	3.02
43	337.29	0.64	206.61	3.02
44	10851.68	0.32	244.93	3.02
45	330.62	1.21	411.27	1.41
46	1795.91	0.47	213.38	1.50
47	444.60	0.63	206.03	1.63
48	1557.26	0.46	212.71	2.60
49	366.00	0.61	196.61	2.60
50	246.99	1.19	406.59	3.02
51	251.11	1.17	399.20	3.02
52	259.48	1.08	366.41	3.02
53	263.44	1.04	352.20	3.02
54	237.86	1.13	377.47	3.02
55	1358.29	0.45	200.03	2.60
56	313.26	0.67	215.80	3.02
57	498.36	0.77	261.06	1.21
58	2544.49	0.35	157.96	1.27

67	418.59	1.13	414.92	1.79
68	424.40	1.22	474.68	2.33
69	513.90	1.11	461.29	3.02
70	273.56	1.32	459.84	2.33
71	336.93	0.74	241.90	2.33
72	346.34	0.74	242.26	2.33
73	260.33	1.47	533.66	3.11
74	217.28	1.52	525.90	2.93
75	358.61	1.37	538.75	3.11
76	411.31	1.08	398.35	1.96
77	304.73	1.61	596.74	2.14
78	413.02	0.35	103.82	2.33
79	297.16	1.54	568.16	2.25
80	736.17	0.92	406.52	3.02
81	546.02	0.61	213.35	1.96
82	1024.55	0.36	135.57	2.25
83	501.66	0.48	159.32	2.40
84	849.81	0.42	153.18	1.96
85	918.62	0.73	309.00	1.96
86	806.42	0.91	390.39	2.07
87	644.29	1.26	549.97	2.14
88	1421.83	0.72	354.93	2.40
89	5546.64	0.64	452.57	2.40
90	591.71	1.30	503.39	0.90
91	598.28	0.62	207.50	1.08
92	183.81	1.33	423.80	2.81
93	195.08	1.20	380.14	2.81

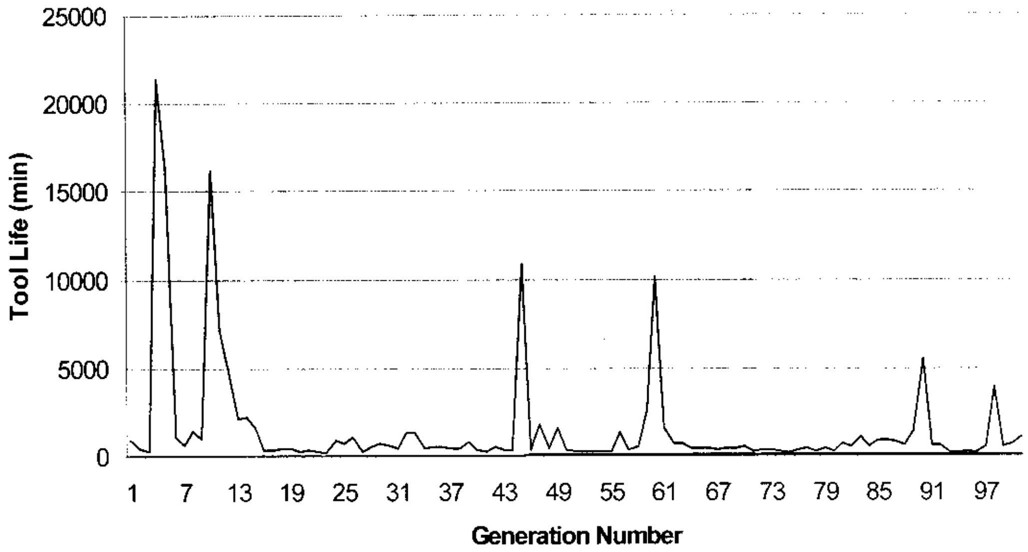
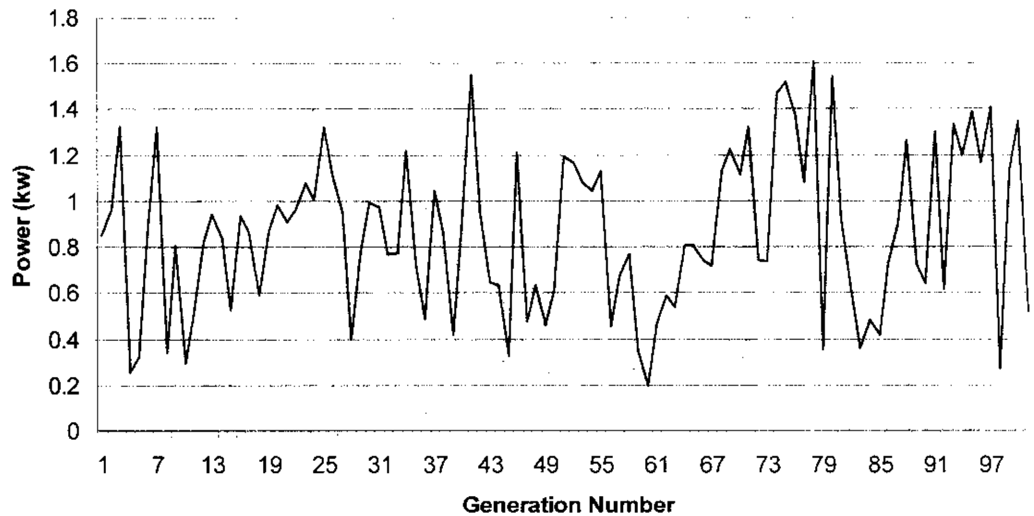


FIGURE 4.4 GENERATION NUMBER VS TOOL LIFE

Figure 4.4 shows that generation number is taken in the x axis and tool life is taken in y axis. The tool life is 214.84 min at the optimum point.



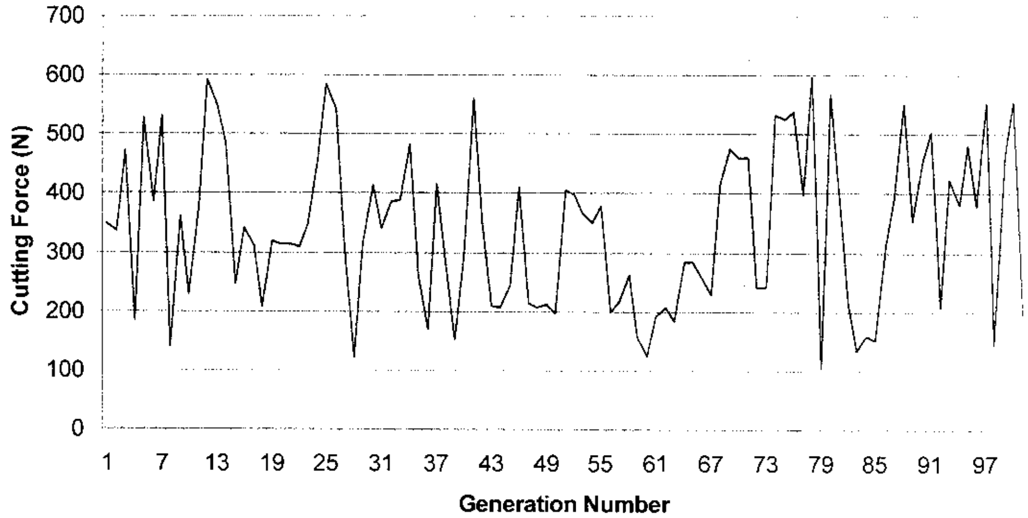
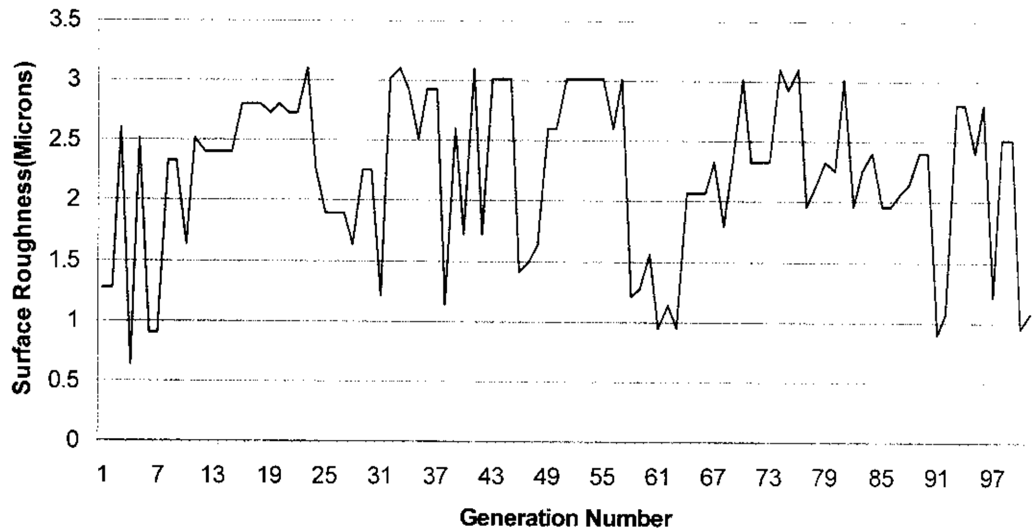


FIGURE 4.6 GENERATION NUMBER VS CUTTING FORCE

Figure 4.6 shows that generation number is taken in the x axis and cutting force is taken in y axis. The cutting force is 347.46 N at the optimum point.



The optimum point is at generation number 22, where the unit production cost is minimum. The optimal values are given below.

- Minimum unit production cost = 46.309 Rs
- Cutting speed = 182.81 m / min
- Feed = 0.141 mm /rev
- Depth of cut = 1.372 mm
- Tool life = 214.84 min
- Power = 1.08 kw
- Cutting force = 347.46 N
- Surface roughness = 3.11 μm

Chapter 5

5.1 INTRODUCTION

The design of experiments is one of the statistical analysis technique widely used to develop the statistical mathematical models. The experiment should provide the required information with minimum time and effort. Therefore, the experimental plan and program must be well prepared and designed to conduct experiments. Experimental design is an important tool to aid in coping with the complexities of technical investigation. This is an organized approach to the collection of information.

The various steps involved in the design of experiments are given below

- Identifying the important process control variables
- Finding the upper and the lower limits of the selected control variables
- Development of the design matrix
- Conducting the experiments as per the design matrix

5.2 IDENTIFICATION OF THE PROCESS VARIABLES

This is the first step in process of developing the mathematical model. This step deals with the selection of the input parameters or the variables that has to be used during the experimentation. These input parameters would vary depending upon the problem that is handled. The input variables have to be chosen depending upon the output responses that is to be considered. The process parameters are those, which affect the output variables to some considerable extent. Normally there would be a lot of process variables that might affect the output variables. But only a limited number of parameters which substantially influence the responses of the process have to be chosen so as to avoid the state of considering many input

It is not a good practice to conduct a large experiment involving many factors or process variables. If none of the factors or process variables is significant, the experiment would then be a waste of time and money. Screening experiments are widely accepted in industries for screening out the key factors, which influence the quality characteristic of a product from a large number of factors. For example, one may be able to study seven factors using just eight experimental trials.

Usually the process of identifying the important process variables is also done by the experimenter's previous experience in that particular field. It reduces the cost and time consumption. It is advisable not to invest more than 25 percent of the experimental budget in the first phase of experimentation such as screening. By this experimental scheme, one may be able to develop the regression based mathematical model that depicts the relationship between the key process variables and the process response. This model can then be used to predict the values of the responses at different variable settings.

In this work, the selected machining process, input parameters and responses were as follows

Machining process : Turning process.

Input parameters : Cutting speed (m/min), Feed (mm/rev) & Depth of cut (mm)

Responses : Tool wear (mm) and Surface finish (Microns)

5.3 FINDING THE LIMITS OF THE PROCESS VARIABLES

The working ranges of all process variables selected had to be determined to fix their levels and to develop the design matrix. In conducting the experiment, the where X_i is the required coded value of a variable X, X is any value of the variable from X_{min} to X_{max}, X_{min} is the lower limit of the variable and X_{max} is the upper limit of the variable. The selected process parameters of the experiment for tool wear and surface roughness, with their limits, units and notations, are given in Table 5.1.

TABLE 5.1 PROCESS VARAIABLES AND THEIR LEVELS

Process Parameters	Units	Notation	Limits				
			-1.682	-1	0	+ 1	+ 1.682
Cutting speed	m / min	V	75	87.5	162.5	237.5	400
Feed	mm / rev	f	0.025	0.0375	0.0675	0.0875	0.15
Depth of cut	mm	d	0.25	0.375	0.675	0.875	1.5

After selecting the working range of the experimentation, the intermediate process variables are selected and all the actual variables are converted into the coded variables.

5.3.1 Specification of CNC 110 Turning Centre

Capacities:

Type of bed – Inclined 45 deg to vertical

Swing over bed covers – 215 mm

Maximum turning diameter – 110 mm

Maximum turning length – 210 mm

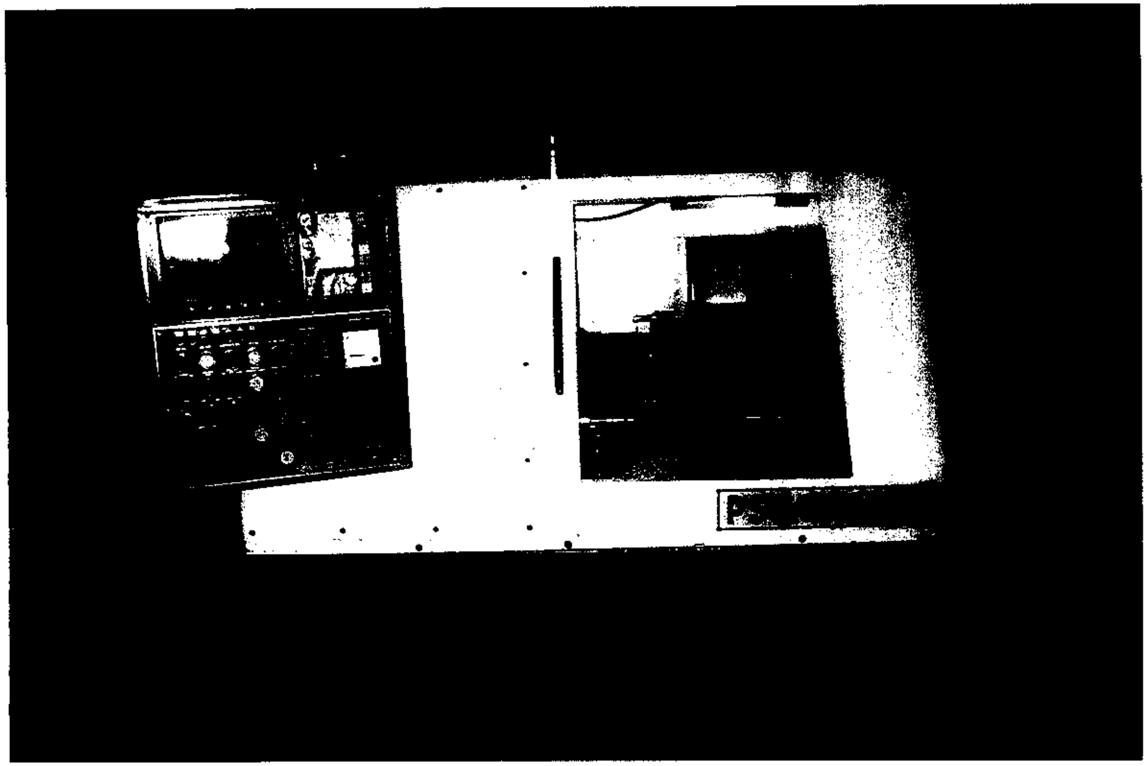
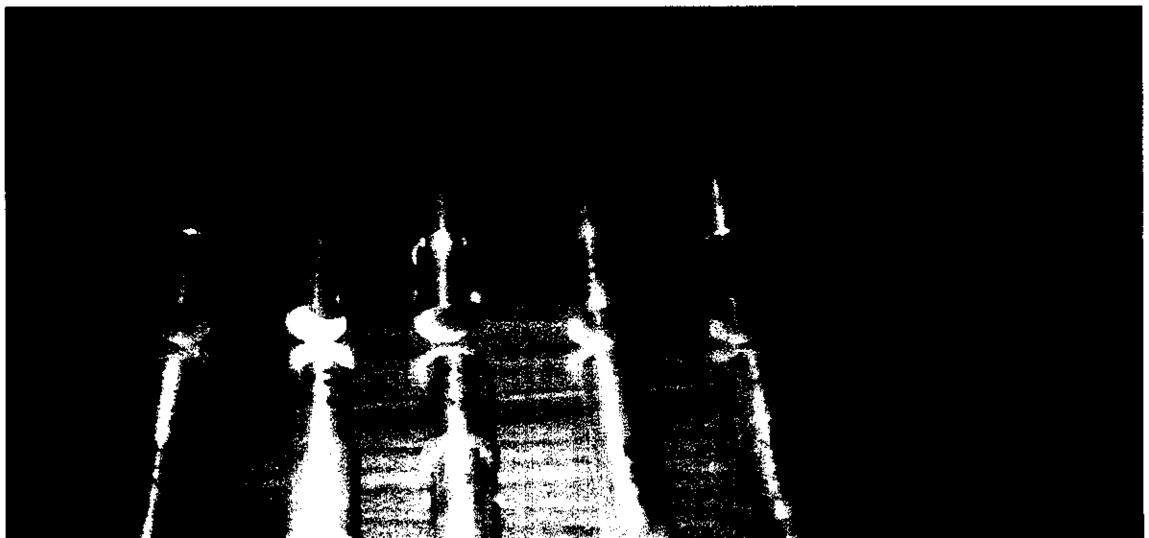


FIGURE 5.1 PSG CNC 110 TURNING CENTRE



Tailstock:

Tailstock spindle diameter – 50 mm

Tailstock spindle stroke – 60 mm

Tailstock spindle taper – 50 mm

Axes travel:

Feed range X and Z axis – 1 to 3750 mm/min

Rapid traverse rate X and Z axis – 5m/min

Threading pitch – 0.25 to 16 mm

Cross slide stroke – 80 mm

Turret:

Number of tools – 8 (4 internal & 4 external tools)

Turret indexing positions – 8

Turret tool shank size – 12 x 12 mm

Maximum shank diameter of boring tool – 20 mm

Indexing time 45 degree indexing – 0.6 seconds

Indexing time 180 degree indexing – 2.0 seconds

Power:

Power of the spindle motor – 2.2 kw

Power of the hydraulic motor – 0.75 kw

Power of the coolant pump motor – 0.1 kw

5.4 DEVELOPMENT OF DESIGN MATRIX

In factorial design, the experiments are conducted for all possible combinations of intermediate (0) level constitute the centre points and the combinations of each of the process parameter variables at either it's lowest (-1.682) or highest (+1.682) with two other variables of the intermediate levels constitute the star points. In this matrix, twenty experimental runs provide ten estimates for the effect of three parameters. Thus the design matrix has allowed the estimation of linear, quadratic and two-way interactive effects of the selected process parameter variables on tool wear and surface roughness.

The Central composite design is constructed as per the following procedure:

Step 1: Construct a complete or factorial 2^k factorial layout, describing on the need for efficiency and the ability to ignore interaction effects.

Step 2: Add 2^k axial or star points along the coordinate axes. Each pair of star points is denoted using coded levels as follows:

$$(\pm a, \quad 0, \quad 0)$$
$$(0, \quad \pm a, \quad 0)$$
$$(0, \quad 0, \quad \pm a)$$

Where "a" is a constant, which can be chosen to make the design rotatable or to satisfy some other desirable property.

Step 3: Add "m" repeat observations at the deign center:

$$(0, \ 0 \ldots 0)$$

Step 4: Randomize the assignment of factor level combinations to the experimental units or to the run sequence, whichever is appropriate.

TABLE 5.2 DESIGN MATRIX

Ex no	Cutting Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)
1	-1	-1	-1
2	-1	-1	1
3	-1	1	-1
4	-1	1	1
5	1	-1	-1
6	1	-1	1
7	1	1	-1
8	1	1	1
9	-1.682	0	0
10	+1.682	0	0
11	0	-1.682	0
12	0	+1.682	0
13	0	0	-1.682
14	0	0	+1.682
15	0	0	0
16	0	0	0
17	0	0	0
18	0	0	0
19	0	0	0
20	0	0	0

5.6 EXPERIMENT DETAILS

The experimental details are as given below:

5.6.1 Work piece specification

Work piece material : Aluminium (HE- 9)

Length of the work piece : 100 mm

Diameter of the work piece : 35 mm

5.6.2 Composition of the work piece material:

Work piece material is Aluminium HE-9, this alloy which is in accordance with BS 1474 No. 6063 TF, has a 0.2 % proof stress value of 160 Mpa, and a tensile strength of 185 Mpa and an elongation at break of 7 %. The chemical composition of the work piece as shown in table 5.3

TABLE 5.3 WORK PIECE COMPOSITIONS

Si	0.2 -0.6 %
Fe	0.35 %
Cu	0.1 %
Mn	0.1 %
Mg	0.45 -0.9 %
Cr	0.1 %
Zn	0.1 %
Ti	0.1 %

5.6.3 Cutting tool specification

Tool material : Carbide tip

Make : WIDIA

Type : 4035

5.7.1 Surface tester specification

Make	: Hommel
Type	: T 1000
Measuring ranges	: ± 80 μm
Resolution	: 0.01 μm

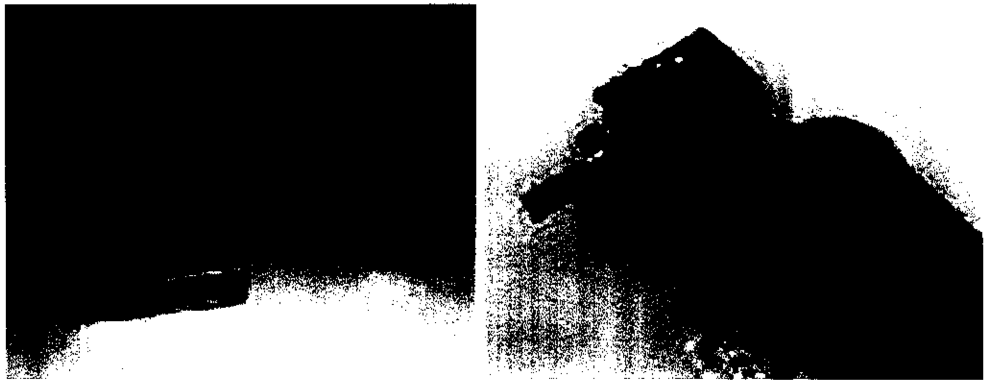


FIGURE 5.3 HOMMEL SURFACE TESTER

5.7.2 Tool maker's microscope specification

The flank wear values have been measured offline with a tool maker's microscope (Metzer-1395, Metzer, India; size travel up to 50 mm in each direction, least count 0.001 mm) for each combination of cutting Conditions Cutting was started with a sharp insert and stopped every 4 runs (passes) of cut for tool flank wear measurement using a toolmaker's microscope.

Type	:	Digital microscope.
Magnification factor	:	Maximum of 150 X
Least count	:	0.001 mm
Field of view	:	8 mm diameter
Working distance	:	80 mm (approx)

TABLE 5.4 MEASURED SURFACE ROUGHNESS AND TOOL WEAR VALUES

Ex no	Cutting Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Surface roughness measured values(μm)	Tool wear measured values(mm)
1	87.5	0.0375	0.375	1.1	0.055
2	237.5	0.0375	0.375	0.76	0.075
3	87.5	0.0875	0.375	1.62	0.096
4	237.5	0.0875	0.375	1.28	0.121
5	87.5	0.0375	0.875	1.25	0.092
6	237.5	0.0375	0.875	0.91	0.114
7	87.5	0.0875	0.875	1.76	0.123
8	237.5	0.0875	0.875	1.43	0.142
9	75	0.0625	0.625	1.82	0.086
10	400	0.0625	0.625	1.02	0.154
11	162.5	0.025	0.625	0.86	0.092
12	162.5	0.15	0.625	1.98	0.140
13	162.5	0.0625	0.25	1.17	0.072
14	162.5	0.0625	1.5	1.5	0.112
15	162.5	0.0625	0.625	1.3	0.09
16	162.5	0.0625	0.625	1.3	0.092
17	162.5	0.0625	0.625	1.3	0.091
18	162.5	0.0625	0.625	1.3	0.09
19	162.5	0.0625	0.625	1.3	0.091
20	162.5	0.0625	0.625	1.3	0.093

Chapter 6

6.1 INTRODUCTION

Artificial Neural Networks are relatively crude electronic models based on the neural structure of the brain. The brain basically learns from experience. It is natural proof that some problems that are beyond the scope of current computers are indeed solvable by small energy efficient packages. This brain modeling also promises a less technical way to develop machine solutions. This new approach to computing also provides a more graceful degradation during system overload than its more traditional counterparts.

These biologically inspired methods of computing are thought to be the next major advancement in the computing industry. Even simple animal brains are capable of functions that are currently impossible for computers. Computers do rote things well, like keeping ledgers or performing complex math. But computers have trouble recognizing even simple patterns much less generalizing those patterns of the past into actions of the future.

Now, advances in biological research promise an initial understanding of the natural thinking mechanism. The brains store information as patterns. Some of these patterns are very complicated and allow us the ability to recognize individual faces from many different angles. This process of storing information as patterns, utilizing those patterns, and then solving problems encompasses a new field in computing. This field does not utilize traditional programming but involves the creation of massively parallel networks and the training of those networks to solve specific problems. This field also utilizes words very different from traditional computing, words like behave, react, self-organize, learn, generalize, and forget.

many collateral connections as desired. The most widely used technique, the feed forward back propagation neural network, is adapted for the prediction of tool wear and surface roughness in the turning operation. It is a gradient descent error-correcting algorithm, which updates the weights in such a way that the network output error is minimized. The feed forward back propagation network consists of an input layer (where the inputs of the problem are received), hidden layers (where the relationship between the inputs and outputs are determined and represented by synaptic weights) and an output layer (which emits the outputs of the problem).

6.2 ANALOGY TO THE BRAIN

The exact workings of the human brain are still a mystery. Yet, some aspects of this amazing processor are known. In particular, the most basic element of the human brain is a specific type of cell which, unlike the rest of the body, doesn't appear to regenerate. Because this type of cell is the only part of the body that isn't slowly replaced, it is assumed that these cells are what provides us with our abilities to remember, think, and apply previous experiences to our every action. These cells, all 100 billion of them, are known as neurons. Each of these neurons can connect with up to 200,000 other neurons, although 1,000 to 10,000 are typical. The power of the human mind comes from the sheer numbers of these basic components and the multiple connections between them. It also comes from genetic programming and learning.

The individual neurons are complicated. They have a myriad of parts, sub-systems, and control mechanisms. They convey information via a host of electrochemical pathways. There are over one hundred different classes of was never about replicating human brains. It is about machines and a new way to solve problems.

6.3 ARTIFICIAL NEURONS AND HOW THEY WORK

The fundamental processing element of a neural network is a neuron. This building block of human awareness encompasses a few general capabilities. Basically, a biological neuron receives inputs from other sources, combines them in some way, performs a generally nonlinear operation on the result, and then outputs the final result.

Within humans there are many variations on this basic type of neuron, further complicating man's attempts at electrically replicating the process of thinking. Yet, all natural neurons have the same four basic components. These components are known by their biological names - dendrites, soma, axon, and synapses. Dendrites are hair-like extensions of the soma which act like input channels. These input channels receive their input through the synapses of other neurons. The soma then processes these incoming signals over time. The soma then turns that processed value into an output which is sent out to other neurons through the axon and the synapses.

Recent experimental data has provided further evidence that biological neurons are structurally more complex than the simplistic explanation above. They are significantly more complex than the existing artificial neurons that are built into today's artificial neural networks. As biology provides a better understanding of neurons, and as technology advances, network designers can continue to improve their systems by building upon man's understanding of the biological brain.

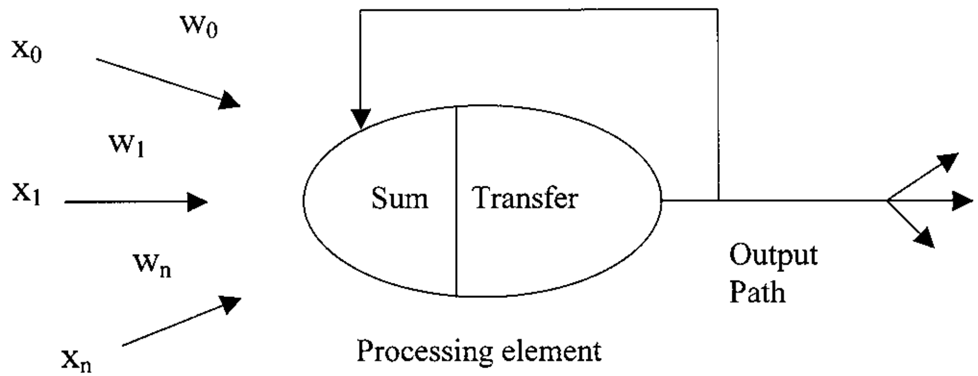


FIGURE 6.1 A BASIC ARTIFICAL NEURON

Figure 6.1 shows a fundamental representation of an artificial neuron. Various inputs to the network are represented by the mathematical symbol, X (n). Each of these inputs is multiplied by a connection weight. These weights are represented by W (n). In the simplest case, these products are simply summed, fed through a transfer function to generate a result, and then output. This process lends itself to physical implementation on a large scale in a small package. This electronic implementation is still possible with other network structures which utilize different summing functions as well as different transfer functions.

Figure 6.2 shows the simlink model where the cutting speed, feed and depth of cut are input parameters while surface roughness and tool wear are the output parameters of the model. Mux combines several input signals into a vector or bus

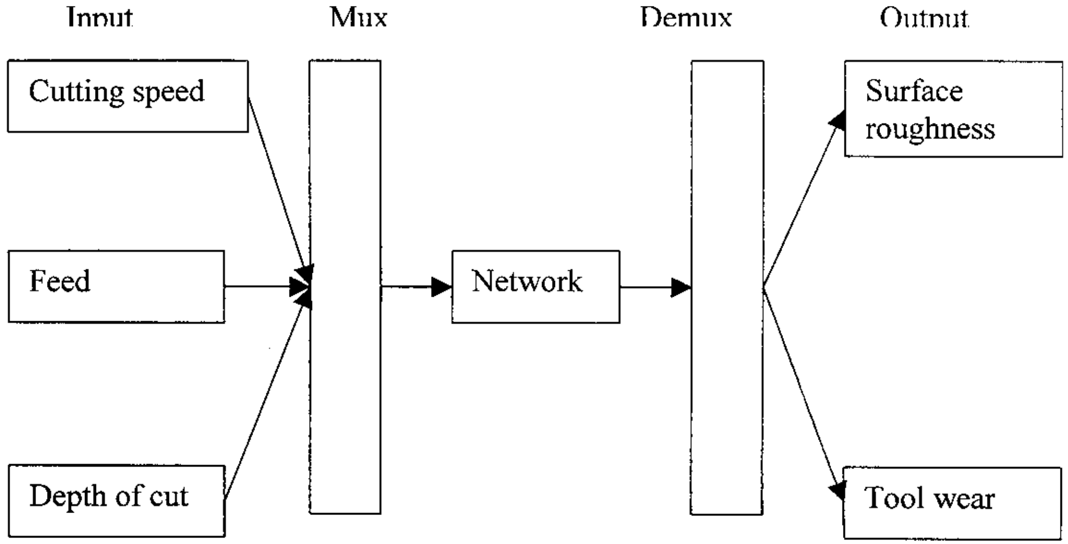


FIGURE 6.2 SIMLINK MODEL

6.4 TYPES OF ANN

Basically there are two types of ANN

1. Supervised Networks
2. Unsupervised Networks

6.4.1 Supervised Networks

Supervised neural networks as in figure 6.3 are trained to produce desired outputs in response to sample inputs, making them particularly well suited to modeling and controlling dynamic systems, classifying noisy data, and predicting future events. Some of the supervised networks available are Feed-forward networks, Radial basis networks, recurrent networks, Learning Vector Quantification values. The aim is to determine a set of weights, which minimize the error. One well-known method, which is common to many learning paradigms, is the least mean square (LMS) convergence.

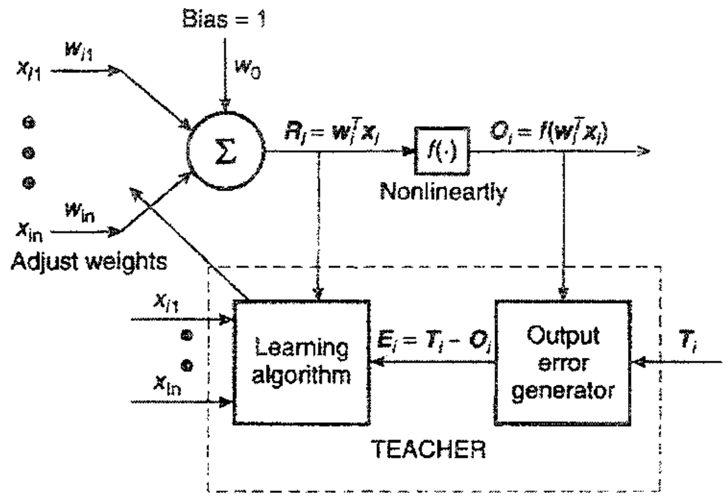


FIGURE 6.3 SUPERVISED LEARNING PROCESS

6.4.2 Unsupervised Networks

Unsupervised neural networks are trained by letting the network continually adjust itself to new inputs. They find relationships within data and can automatically define classification schemes. Some of the available such type of networks are competitive layers, self-organizing maps, etc.

Generally, the learning process of a back-propagation neural network takes place in two phases. In the forward phase, the output of each neuron in each layer and the errors between the actual output from the outer layer and the target outputs are computed; in the backward phase, weights are modified by the back-propagating standard part propagates forward through the entire network to compute the output of each neuron in the hidden and output layer.

For each neuron in the output layer, its output value is compared with the corresponding target value to calculate the error of each neuron of the output layer. If the output error of the training part geometry is within a predefined tolerance, the training of the network is accomplished; otherwise the learning continues, that is, the weights are modified by calculating and propagating the error of each neuron in the output layer backward through the entire network. A similar computation is performed for the output value of each neuron in a forward phase by the new modified weights. In a target pattern representing a part family only one-neuron value is defined as one and the other values are zero. After the neural network ahs been trained, it assigns an input part in the form of a binary image to a family, even if the shape is incomplete.

6.5 FEED FORWARD BACK PROPAGATION NETWORK

Several ANN topologies have been developed for different applications, the most popular being the Feed Forward Back Propagation Network. It is a gradient descent error-correcting algorithm, which updates the weights in such a way that the network output error is minimized. The way that the neurons are organized forms the structure of the neural network, such as single-layer feed forward networks and multilayer-feed forward networks. A feed forward back propagation network consists of an input layer (where the inputs of the problem are received), hidden layers (where the relationship between the inputs and outputs are determined and represented by synaptic weights) and an output layer (which emits the outputs of the problem).

demonstrated their efficacy on many practical problems and have been shown to be relatively easy to use. Hence, this technique is adopted in this study.

6.6 MATLAB SOFTWARE

MATLAB stands for MATrix LABoratory developed by The Mathworks Incorporation, USA and is an interactive system for matrix-based computation designed for scientific and engineering use. It is good for many forms of numeric computation and visualization. Besides dealing with explicit matrices in linear algebra, it can handle differential equations, polynomials, signal processing, and other applications. Results can be made available both numerically and as excellent graphics. It is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation.

Typical uses include:

1. Math and computation
2. Algorithm development
3. Modeling, simulation, and prototyping
4. Data analysis, exploration, and visualization
5. Scientific and engineering graphics
6. Application development, including Graphical User Interface building

In University environments, it is the standard instructional tool for introductory and advanced courses in mathematics, engineering, and science. In industry, MATLAB is the tool of choice for high-productivity research, development, and analysis. MATLAB has hundreds of built-in functions and can be used to solve processing, control systems, neural networks, fuzzy logic, wavelets, simulation, and many others.

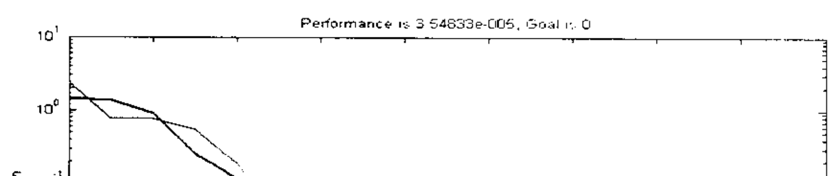
6.7 TRAINING THE NETWORK

MATLAB 6.1 has been used for training the network model for tool wear and surface roughness prediction. There are 20 training patterns considered for prediction of surface finish and tool wear. Each neuron is a processing element, which performs a weighed sum of all input variables that feed it. Depending on the value of weighted sum of the variables, the neuron gives a signal to the neurons in the adjacent layer through a non-linear transfer function. The algorithm used is feed forward backward propagation algorithm'

6.8 RESULTS OF ANN

The result of the ANN is given below

Number of input nodes	3
Number of hidden nodes	27
Number of output nodes	2
Type of learning method	Supervised learning
Algorithm	Back propagation
Learning rule	Gradient descent rule
Number of learning patterns used	20
The leaning parameter used	0.5
Number of epochs	1000



ANN training graph for surface roughness and tool wear for 27 neurons is given in the figure 6.4. The predicted values of surface roughness and tool wear by the ANN model are compared with the experimental values for the validation set of experiments.

TABLE 6.1 COMPARSION OF MEASURED AND PREDICTED SURFACE ROUGHNESS VALUES

Ex no	Cutting speed (m/min)	Feed (mm/ rev)	Depth of cut (mm)	Surface roughness measured values (μm)	Surface roughness predicted values (μm)	% error
1	87.5	0.0375	0.375	1.1	1.12	-1.82
2	237.5	0.0375	0.375	0.76	0.73	3.95
3	87.5	0.0875	0.375	1.62	1.6	1.23
4	237.5	0.0875	0.375	1.28	1.31	-2.34
5	87.5	0.0375	0.875	1.25	1.21	3.33
6	237.5	0.0375	0.875	0.91	0.9	1.10
7	87.5	0.0875	0.875	1.76	1.71	2.84
8	237.5	0.0875	0.875	1.43	1.47	-2.8
9	75	0.0625	0.625	1.82	1.84	-1.1
10	400	0.0625	0.625	1.02	0.99	2.94
11	162.5	0.025	0.625	0.86	0.88	-2.33
12	162.5	0.15	0.625	1.98	1.98	0
13	162.5	0.0625	0.25	1.17	1.12	4.27
14	162.5	0.0625	1.5	1.5	1.49	0.67
15	162.5	0.0625	0.625	1.3	1.29	0.77
16	162.5	0.0625	0.625	1.3	1.29	0.77

TABLE 6.2 COMPARSION OF MEASURED AND PREDICTED TOOL WEAR VALUES

Ex no	Cutting speed (m/min)	Feed (mm/ rev)	Depth of cut (mm)	Tool wear measured values (mm)	Tool wear predicted values (mm)	% error
1	87.5	0.0375	0.375	0.055	0.053	3.64
2	237.5	0.0375	0.375	0.075	0.073	2.67
3	87.5	0.0875	0.375	0.096	0.098	-2.08
4	237.5	0.0875	0.375	0.121	0.121	0
5	87.5	0.0375	0.875	0.092	0.096	-4.35
6	237.5	0.0375	0.875	0.114	0.112	1.75
7	87.5	0.0875	0.875	0.123	0.119	3.25
8	237.5	0.0875	0.875	0.142	0.14	1.41
9	75	0.0625	0.625	0.086	0.089	-3.49
10	400	0.0625	0.625	0.154	0.156	-1.3
11	162.5	0.025	0.625	0.092	0.088	4.35
12	162.5	0.15	0.625	0.140	0.136	2.86
13	162.5	0.0625	0.25	0.072	0.075	-4.17
14	162.5	0.0625	1.5	0.112	0.116	-3.57
15	162.5	0.0625	0.625	0.09	0.089	1.11
16	162.5	0.0625	0.625	0.092	0.089	3.26
17	162.5	0.0625	0.625	0.091	0.089	2.2
18	162.5	0.0625	0.625	0.09	0.089	1.11
19	162.5	0.0625	0.625	0.091	0.089	2.2
20	162.5	0.0625	0.625	0.093	0.089	4.26

Chapter 7

The following conclusions were made from the project.

- An effective method of finding the optimal parameters for turning process using genetic algorithm has been proposed.

- In the turning process parameters cutting speed, feed and depth of cut are used as input parameters to reduce the unit production cost while considering the constraints such as tool life, power, cutting force and surface roughness.

- The optimum point is at generation number 22, where the unit production cost is minimum. The optimal values at generation 22 are

  Minimum unit production cost = 46.309 Rs

  Cutting speed = 182.81 m / min

  Feed = 0.141 mm / rev

  Depth of cut = 1.372 mm

  Tool life = 214.84 min

  Power = 1.08 kw

  Cutting force = 347.46 N

  Surface roughness = 3.11 µm

- This method can be applied to any kind of optimization problems with suitable modifications.

- One of the innovative models, ANN is used for predicting surface roughness and tool wear in turning operation.

- Experiments have been performed to ascertain surface roughness and tool wear in a CNC turning center for machining aluminium HE-9 specimens using Carbide tipped cutter.

- The predictive ANN model is found to be capable of better predictions of surface roughness and tool wear within the range that they had been trained.

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