ANALYSIS AND OPTIMIZATION OF MACHINING PROCESS USING EVOLUTIONARY ALGORITHMS

A thesis

submitted in partial fulfillment of the degree of

DOCTOR OF PHILOSOPHY

by

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Dedicated
in
loving memory of my
son **Aldo Ansalam**
who is safe in the arms of God.

DECLARATION

I hereby declare that the work presented in the thesis entitled "Analysis and Optimization of Machining Process Using Evolutionary Algorithms" is based on the original work done by me under the supervision and guidance of DR.V.N.Narayanan Namboothiri, Division of Mechanical Engineering, School of Engineering, Cochin University of Science and Technology. No part of this thesis has been presented for any other degree from any other institution.

T.G.Ansalam raj

Kochi-22

19.08-2011

CERTIFICATE

This is to certify that the thesis entitled “Analysis and Optimization of Machining process using Evolutionary Algorithms” is a report of the original work done by T.G.Ansalam Raj under my supervision and guidance in the School of Engineering, Cochin University of Science and Technology. No part of this thesis has been presented for any other degree from any other institution.

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19.08.2011

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Abstract

To ensure quality of machined products at minimum machining costs and maximum machining effectiveness, it is very important to select optimum parameters when metal cutting machine tools are employed. Traditionally, the experience of the operator plays a major role in the selection of optimum metal cutting conditions. However, attaining optimum values each time by even a skilled operator is difficult. The non-linear nature of the machining process has compelled engineers to search for more effective methods to attain optimization. The design objective preceding most engineering design activities is simply to minimize the cost of production or to maximize the production efficiency. The main aim of research work reported here is to build robust optimization algorithms by exploiting ideas that nature has to offer from its backyard and using it to solve real world optimization problems in manufacturing processes.

In this thesis, after conducting an exhaustive literature review, several optimization techniques used in various manufacturing processes have been identified. The selection of optimal cutting parameters, like depth of cut, feed and speed is a very important issue for every machining process. Experiments have been designed using Taguchi technique and dry turning of SS420 has been performed on Kirlosker turn master 35 lathe. Analysis using S/N and ANOVA were performed to find the optimum level and percentage of contribution of each parameter. By using S/N analysis the optimum machining parameters from the experimentation is obtained.

Optimization algorithms begin with one or more design solutions supplied by the user and then iteratively check new design solutions, relative search spaces in order to achieve the true optimum solution. A mathematical model has been developed using response surface analysis for surface roughness and the model was validated using published results from literature.

Methodologies in optimization such as Simulated annealing (SA), Particle Swarm Optimization (PSO), Conventional Genetic Algorithm (CGA) and Improved Genetic Algorithm (IGA) are

applied to optimize machining parameters while dry turning of SS420 material. All the above algorithms were tested for their efficiency, robustness and accuracy and observe how they often outperform conventional optimization method applied to difficult real world problems. The SA, PSO, CGA and IGA codes were developed using MATLAB. For each evolutionary algorithmic method, optimum cutting conditions are provided to achieve better surface finish.

The computational results using SA clearly demonstrated that the proposed solution procedure is quite capable in solving such complicated problems effectively and efficiently. Particle Swarm Optimization (PSO) is a relatively recent heuristic search method whose mechanics are inspired by the swarming or collaborative behavior of biological populations. From the results it has been observed that PSO provides better results and also more computationally efficient.

Based on the results obtained using CGA and IGA for the optimization of machining process, the proposed IGA provides better results than the conventional GA. The improved genetic algorithm incorporating a stochastic crossover technique and an artificial initial population scheme is developed to provide a faster search mechanism.

Finally, a comparison among these algorithms were made for the specific example of dry turning of SS 420 material and arriving at optimum machining parameters of feed, cutting speed, depth of cut and tool nose radius for minimum surface roughness as the criterion. To summarize, the research work fills in conspicuous gaps between research prototypes and industry requirements, by simulating evolutionary procedures seen in nature that optimize its own systems.

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Abbreviations

OA	Orthogonal Array
DOE	Design Of Experiments
S/N	Signal to Noise Ratio
ANOVA	Analysis of Variance
RSM	Response Surface Methodology
SAA	Simulated Annealing Algorithm
PSO	Particle Swarm Optimization
CGA	Conventional Genetic Algorithm
IGA	Improved Genetic Algorithm
CAPP	Computer Aided Process Planning

Chapter 1 - Introduction

The cost of machining amounts to more than 20% of the value of manufactured products in industrialized countries. It is therefore imperative to investigate the machinability behavior of different materials by changing the machining parameters to obtain optimal results. The machinability of a material provides an indication of its adaptability to manufacturing by a machining process. Good machinability is defined as an optimal combination of factors such as low cutting force, good surface finish, low tool tip temperature, and low power consumption.

Process modeling and optimization are the two important issues in manufacturing products. The selection of optimal cutting parameters, like depth of cut, feed and speed, is a very important issue for every machining process. In workshop practice, cutting parameters are selected from machining databases or specialized handbooks, but the range given in these sources are actually starting values, and are not the optimal values. Optimization of machining parameters not only increases the utility for machining economics, but also the product quality to a great extent.

In today's manufacturing environment, many industries have attempted to introduce flexible manufacturing systems (FMS) as their strategy to adapt to the ever changing competitive market requirements. To ensure quality of machined products to reduce the machining costs and to increase the machining effectiveness, it is very important to select appropriate machining parameters when machine tools are selected for machining.

1.1. Optimization

The design objective preceding most engineering design activities is simply to minimize the cost of production or to maximize the production efficiency. An optimization algorithm is a procedure which is executed iteratively by comparing various solutions till the optimum or satisfactory solution is found. Accepting the best solution after comparing a few design solutions is the indirect way of achieving optimization in many industrial design activities. There is no way of guaranteeing an optimal solution with this simplistic approach. Optimization algorithms on the contrary, begin with one or more design solutions supplied by the user and then iteratively check new design solutions, relative search spaces in order to achieve the true optimum solution.

In optimizing the economics of machining operations, the role of cutting conditions such as feed rate, cutting speed and depth of cut have long been recognized. F.W.Taylor (1907) showed that an optimum or economic cutting speed exists which would maximize material removal rate.

Gilbert (1950) studied the optimization of machining parameters in turning taking maximum production rate and minimum production cost as criteria. Armarego & Brown(1969) investigated unconstrained machine-parameter optimization using differential calculus. Brewer & Rueda (1963) carried out simplified optimum analysis for non-ferrous materials. For Cast Iron (CI) and steels, they employed the criterion minimum machining cost.

Some of the widely used techniques in optimization are conventional Genetic Algorithm, , Particle Swarm Optimization and Simulated Annealing which will be illustrated in the forthcoming chapters

1.2. Surface roughness

Surface finish is an essential requirement in determining the surface quality of a product. Surface roughness in metal cutting is defined as irregularities on any material resulting from a machining operation. Average roughness Ra is the arithmetic average of departure of the profile from the mean line along a sampling length. Surface finish has a great influence on the reliable functioning of two mating parts. In this work optimum machining parameters for minimum surface roughness on the machining of SS420 material is investigated. It has a large number of applications in industries such as the aerospace, petrochemicals, forging, medical, dental and surgical equipment industries, electrical and electronic components, food industries, tractor and tool production and automotive industries, where surface quality is an important factor.

During the initial period of the past century, tactual standards were used to measure the surface roughness; this involved the use of a series of specimens that had different finishes. The man in the shop used these specimens by running his fingernail first across standard tactual surface and then across the surface he was producing. The work piece was considered to be smooth enough when the two surfaces were felt to have the same roughness. In the modern times however stylus instruments are used with a diamond stylus which traverses a surface. These utilize transducers to convert the vertical and horizontal motions of the diamond stylus into recorded traces.

Surface roughness is usually measured in characteristic peak-to-valley roughness (R_t) or arithmetic average roughness (R_a). Arithmetical average (AA) roughness (R_a) or centerline average (CLA) is obtained by measuring the mean deviation of the peaks from the centerline of a trace, the centerline being established as the line above and below which, there is an equal area between the centerline and the surface trace.

1.3. Thesis Outline

The thesis is organized in nine chapters.

Chapter 1 gives an introduction to the Thesis.

Chapter 2 contains literature survey, motivation and objectives of the thesis.

Chapter 3 contains the experimental setup, Design of Experiments and analysis using Signal to Noise ratio (S/N) and Analysis Of Variance (ANOVA).

Chapter 4 contains the formulation of mathematical model using Response Surface Methodology (RSM) and its analysis

Chapter 5 presents the Simulated Annealing based optimization of machining process.

Chapter 6 presents the Particle Swarm based machining process Optimization.

Chapter 7 presents the Genetic and Improved genetic algorithm based optimization of machining process.

Chapter 8 Results and Discussions

Chapter 9 presents conclusions.

Chapter 2 - Literature Review

This chapter sets the background for up-coming sections. It is basically an assessment of the present state of art of the wide and complex field of evolutionary algorithms and its application. Also this chapter separately reviews what has been done in the past in the area of application of evolutionary algorithms in machining process.

Tarng. Y.S , S.C. Juang and C.H. Chang [1] proposes the use of grey-based Taguchi methods for the optimization of the Submerged Arc Welding (SAW) process parameters in hard facing with considerations of multiple weld qualities. In this new approach, the grey relational analysis is adopted to solve the SAW process with multiple weld qualities. A grey relational grade obtained from the grey relational analysis is used as the performance characteristic in the Taguchi method. They found that a grey relational analysis of the S/N ratios can convert the optimization of the multiple performance characteristics into the optimization of a single performance characteristic called the grey relational grade. As a result, the optimization of the complicated multiple performance characteristics can be greatly simplified through this approach. Their study showed that the performance characteristics of the SAW process such as deposition rate, dilution, and hardness are improved together by using the method proposed.

Vijayan. P and V. P. Arunachalam [2] reported research in their work Taguchi's off-line quality control method applied for determines the optimal process parameters which maximize the mechanical properties of squeeze cast LM24 aluminum alloy. For this purpose, concepts like orthogonal array, S/N ratio and ANOVA were employed.

Nihat Tosun Cogun and Gul Tosun [3] investigated the effect and optimization of machining parameters on the kerf (cutting width) and material removal rate (MRR) in wire electrical discharge machining (WEDM) operations. The experimental studies were conducted under varying pulse duration, open circuit voltage, wire speed and dielectric flushing pressure. The settings of machining parameters were determined by using Taguchi experimental design method. The level of importance of the machining parameters on the cutting kerf and MRR was determined by using analysis of variance (ANOVA). The optimum machining parameter combination was obtained by using the analysis of signal-to-noise (S/N) ratio. The variation of kerf and MRR with machining parameters is mathematically modeled by using regression analysis method.

The purpose of optimization of a process is that we need a solution which is as close as possible to the target and as robust as possible, i.e. with minimum variation. Dual response methodology has been successfully used for optimization in various cases [4–7].

The study of Baek et al. [8] presented a surface roughness model for face-milling operations considering the profile and the run out error of each insert in the cutter body. It was stated that because of manufacturing errors in making the cutters, axial (affecting the depth of cut) and radial (affecting the surface roughness) run out errors exist. The feed rate was also taken into account so as to formulate a geometric model. After the model validation with experimental cutting data, the material removal rate was maximized through optimization of the feed rate with the surface roughness as a constraint by means of a bisection optimization algorithm.

Tzeng. Y.-F and N.-H. Chiu [9] presents the application of a Taguchi dynamic experiment in developing a robust high-speed and high-quality electrical-discharge machining (EDM) process. In their study, a two-phase parameter design strategy coupled with a double- signal ideal function methodology is proposed. In the first phase, the ideal function of the EDM process is designed as a linear relationship between the main input signal (machining time) and the first output (material removal rate). This model seeks to develop a robust machining process that leads to a high material removal rate. In the second phase, the ideal function is particularly designed as a linear relationship between the adjustment signal (electrode dimension) and the second output (product dimension). The purpose is to adjust machined product dimension of the

EDM through optimized process parameters obtained in the first phase, to the desired dimension to provide an allowance for subsequent fine- polishing.

For solving an optimization problem need to have estimates of S/N ratio and the average out of roundness error. Lucas [10] has suggested that an equation for predicting S/N ratio can be used for direct minimization of variance. To obtain the estimates of S/N ratio and the average response, analysis was performed on the responses for each run of the experiment.

Kim and Chu [11] stated that the surface roughness could be determined by the maximum height of the effective scallop including the effects of cutter marks and conventional scallops. Through a texture superposition procedure, 3D surface texture, according to the given cutting conditions and cutter types, could be formed. The run out effect (classified as geometric runout caused by the eccentricity of the cutter axis and the irregularity of the cutting edges and as dynamic runout caused by vibration, chatter and the tool deflection) was included to make the predicted surface closer to the actual machined surface.

Jianxin Roger Jiao and Petri T. Helo [12] propose an algorithm for the optimal design of a CUSUM control chart detecting process shifts in the mean value. The algorithm optimizes the sample size, sampling interval, control limit and reference parameter of the CUSUM chart through minimizing the overall mean value of a Taguchi's loss function over the probability distribution of the random process mean shift.

Hasan Oktem ,Tuncay Erzurumlu and Mustafa C [13] developed a Taguchi optimization method for low surface roughness in terms of process parameters when milling the mold surfaces of 7075-T6 aluminum. Considering the process parameters of feed, cutting speed, axial and radial depth of cut, and machining tolerance, they performed a series of milling experiments to measure the roughness data. Regression analysis was performed to identify whether the experimental measurements represent a fitness characteristic for the optimization process. For this purpose, a Taguchi orthogonal array, the S/N ratio, and an ANOVA were used.

A new method was introduced by Ehmann and Hong [14] to represent the surface generation process. Their system basically consisted of two parts, one that modeled the machine tool kinematics and another that modeled the cutting tool geometry. Specific interest for the latter was given in the area of the cutting edge that was described as the intersection of the tool's face and flank surfaces along with the respective angles.

Palanikumar. K [15] discusses the use of Taguchi and response surface methodologies for minimizing the surface roughness in machining glass fiber reinforced (GFRP) plastics with a polycrystalline diamond (PCD) tool. The experiments were conducted using Taguchi's experimental design technique. He concluded that for achieving good surface finish on the GFRP work piece, high cutting speed, high depth of cut and lower feeds are preferred.

George. P.M, B.K. Raghunath, L.M. Manocha and Ashish M. Warrier [16] determined the optimal setting of the process parameters on the electro-discharge machining (EDM) machine while machining carbon–carbon composites. The parameters considered were pulse current, gap voltage and pulse-on-time; whereas the responses were electrode wear rate (EWR) and material removal rate (MRR). The optimal setting of the parameters are determined through experiments planned, conducted and analyzed using the Taguchi method. It was found that the electrode wear rate reduces substantially, within the region of experimentation, if the parameters are set at their lowest values, while the parameters set at their highest values increase the MRR drastically.

Mahapatra. S. S and Amar Patnaik [17] attempted to determine the important machining parameters for performance measures like MRR, SF, and kerf separately in the WEDM process. Taguchi's experimental design method was used to obtain optimum parameter combination for maximization of MRR, SF as well as minimization of kerf. The optimal levels of the factors for all the objectives were shown to differ widely. In order to optimize for all the three objectives, mathematical models were developed using the non-linear regression method.

Beggan. C et al. employed acoustic emission analysis [18] to predict surface quality. Acoustic emission (AE) is defined as the class of phenomena whereby transient elastic waves are generated by the rapid release of energy from localized sources within a material. In the case of turning such sources can be found in the primary (due to chip formation), secondary (due to friction between cutting tool and chip) and tertiary (due to friction between cutting tool flank and workpiece) cutting zones. Instead of using the RMS value of the AE measured signals; a new quantity called AERMS20 was introduced in the paper and correlated with surface roughness.

Sahin. Y [19] developed weight loss model of aluminium alloy composites with 10wt.% SiC particles by molten metal mixing method in terms of abrasive grain size, reinforcement size used in the composite, applied load and sliding distance using the Taguchi method. The two-body abrasive wear behavior of the specimen was investigated using pin-on-disc method where the samples slid against various size of SiC abrasive grits under different conditions. The orthogonal array, signal-to-noise ratio and analysis of variance were employed to study the optimal testing parameters on composites with 50µm and 100µm particle sizes. The experimental results demonstrate that the abrasive grain size was the major parameter on abrasive wear, followed by reinforcement size.

Implementations of the RSM can be found in the works of M. Alauddin et al. [20] where a surface roughness model is developed for end milling of 190 BHN steel and Inconel 718. It was found that first- and second-order models constructed along with contour plots, easily enable the selection of the proper combination of cutting speed and feed to increase the metal removal rate without sacrificing surface quality.

Lung Kwang Pana, Che ChungWangb, Ying Ching Hsiaoc and Kye Chyn Ho [21] optimized the use of an Nd:YAG laser for thin plate magnesium alloy butt welding using the Taguchi analytical methodology. The welding parameters governing the laser beam in thin plate butt welding were evaluated by measuring of the ultimate tensile stress. The effectiveness of the Taguchi method lies in clarifying the factor that dominates complex interactions in laser welding. The factors can be the shielding gas, laser energy, convey speed of work piece, point at which the laser is focused, pulse frequency, and pulse shape. Furthermore, 18 combinations of these six essential welding parameters were set and Taguchi's method followed exactly. The optimal result was confirmed with a superior ultimate tensile stress of 169 MPa, 2.5 times larger to that from original set for laser welding.

An approach that used a criterion for determining a network's architecture automatically can be found by W.S. Lin et al [22]. A prediction model was developed prior to the implementation of the actual machining process to determine certain cutting conditions (cutting speed, feed rate and depth of cut) in order to obtain a desired surface roughness value and cutting force value.

Suresh et al. [23] adopted a two stage approach towards optimizing for surface roughness. Experimental results were used to build two mathematical models for surface roughness by a regression method according to RSM. The second-order mathematical model obtained was then taken as an objective function and optimized with a GA to obtain the machining conditions for a desired surface finish.

Suresh Kumar Reddy. N and P. Venkateswara Rao [24] discuss the advantages of dry machining over wet machining by selecting proper cutting tools and tool geometry. The optimization, carried out in their work, gives an opportunity for the user to select the best tool geometry and cutting condition so as to get the required surface quality. Their work emphasizes that proper selection of parameters eliminates the use of cutting fluids during machining and hence makes machining more environmentall friendly.

Jeyapaul. R, P. Shahabudeen and K. Krishnaiah [25] presented the use of genetic algorithm and ANOVA for the optimization of the gear hobbing process with multiple performance characteristics. They demonstrated that a multiple response optimization problem can be effectively tackled by using genetic algorithm to generate a single weighted SN ratio (WSN) as a performance indicator.

Rajesh Krishnan and Carla C. Purdy [26] applied both simulated annealing and a genetic algorithm to optimize the output of the TNF α -mediated NF-kB pathway and compared the results. They found that the algorithms had similar execution time. The genetic algorithm out-performs simulated annealing in both the constrained and the unconstrained experiments. In both cases, the output is maintained at a much higher level than was achieved by the method of Cho et al (2003). Future work includes application of both the algorithms to additional biological pathways such as glycolysis and HIV-1 protease pathways and comparison of the optimizations produced by both the algorithms. They concluded that if the genetic algorithm performs better than simulated annealing in all these cases, we will have good evidence that the genetic algorithm is preferable to simulated annealing for the Box algorithm, and it will then be used as the default optimization algorithm in Box.

Heikki Orsila, Tero Kangas, Erno Salminen and Timo D. H¨am¨al¨ainen [27] discuss a way to minimize optimization effort and application execution time in mapping an application on Multiprocessor System-on-Chip (MPSoC) using simulated annealing which is a versatile algorithm for hard optimization problems, such as task distribution on MPSoCs. The proposed new method of automatically selecting parameters for a modied simulated annealing algorithm to save optimization effort. The method determines a proper annealing schedule and transition probabilities for simulated annealing, which makes the algorithm scalable with respect to application and platform size. Applications are modeled as static acyclic task graphs which are mapped to an MPSoC.

Vincent A. Cicirello [28], in his work illustrates the ease in which an adaptive simulated annealing algorithm can be designed. He uses the adaptive annealing schedule known as the modified Lam schedule to apply simulated annealing to the weighted tardiness scheduling problem with sequence-dependent setups. The modified Lam annealing schedule adjusts the temperature to track the theoretical optimal rate of accepted moves. Employing the modified Lam schedule allows to avoid the often tedious tuning of the annealing schedule; as the algorithm tunes itself for each instance during problem solving. He discovered that for short searches, the adaptive SA outperforms the current best metaheuristic for this NP-Hard scheduling problem; while for slightly longer searches, the highly-tuned GA is still better although SA is competitive.

Abido. M. A [29], presents the robust design of multi-machine Power System Stabilizers using Simulated Annealing (SA) optimization technique. This approach employs SA to search for optimal parameter settings of a widely used conventional fixed-structure lead-lag PSS (CPSS). The parameters of the proposed simulated annealing based power system stabilizer are optimized in order to shift the system electromechanical modes at different loading conditions and system configurations simultaneously to the left in the s-plane. Incorporation of SA as a derivative-free optimization technique in PSS design significantly reduces the computational burden. One of the main advantages of this approach is its robustness to the initial parameter settings.

Andreas Efstratiadis and Demetris Koutsoyiannis [30] proposed evolutionary annealing-simplex algorithm (EAS) to try to couple the robustness of SA in rough problems, with the efficiency of the downhill simplex method in simple search spaces. By enhancing the typical Nelder-Mead procedure with new movements such as climbing and mutation, and by introducing to the original movements a stochastic component, it not only makes possible to easily escape from local optima but also to accelerate the searching procedure, especially in high-dimensional applications. After extended analysis, the algorithm was proved at least as effective and efficient as the SCE method, which is now widely used in the region of water resources systems optimisation.

Anshuman Sahu and Rudrajit Tapadar [31] attempts to solve the generalized “Assignment problem” through genetic algorithm and simulated annealing. The generalized assignment problem is basically the “N men- N jobs” problem where a single job can be assigned to only one person in such a way that the overall cost of assignment is minimized. While solving this problem through genetic algorithm (GA), a unique encoding scheme is used together with Partially Matched Crossover (PMX).

Ruhul SARKER and Xin YAO [32],developed a general cost model model for a two-stage batch environment considering both raw materials and finished products which in turn was used to develop a simulated annealing approach to determining an optimal ordering policy for procurement of raw materials and also for the manufacturing batch size to minimize the total cost for meeting customer demands in time. The solutions obtained were compared with those of traditional approaches.

Farhad Kolahan, and Mahdi Abachizadeh [33] developed a simulated annealing algorithm to optimize machining parameters in turning operation on cylindrical workpieces. The computational results clearly showed that the proposed optimization procedure has considerably reduced total operation cost by optimally determining machining parameters and also demonstrated that the proposed solution procedure was quite capable in solving such complicated problems effectively and efficiently.

Janaki Ram. D, T. H. Sreenivas, and K. Ganapathy Subramaniam [34] present two general algorithms for SA in their work. The algorithms have been applied to job shop scheduling problem (JSS) and the traveling salesman problem (TSP) and it has been observed that it is possible to achieve super linear speedups using the algorithm.

William L. Goffe ,Gary D. Ferrier and John Rogers [35] tested a simulated annealing, on four econometric problems and compare it to three common conventional algorithms. Not only can simulated annealing find the global optimum, it is also less likely to fail on difficult functions because it is a very robust algorithm. The promise of simulated annealing is demonstrated on the four econometric problems. They found that SA could be used as a diagnostic tool to understand how conventional algorithms fail. They also found that, it could "step around" regions in the parameter space for which the function does not exist. And most importantly, it could optimize functions that conventional algorithms have extreme difficulty with or simply cannot optimize at all.

Yee-Ming Chen & Chun-Ta Lin [36] through their work presents an adaptive particle swarm optimization (APSO) approach to optimize the sequence of component placements on a PCB and the assignment of component types to feeders simultaneously for a pick-and-place machine with multiple heads. APSO proposed in the paper incorporates three heuristics, namely, head assignment algorithm, reel grouping optimization and adaptive particle swarm optimization. Comparing with the results obtained by other research, they concluded that performance of APSO is not worse than the performance of genetic algorithms (GA) in terms of the distance traveled by the placement head. Their results lead to minimize the total assembly time of assignment sequencing time of the placements of component on the PCB board. Considering other applications, they suggest it is easy to modify the APSO approach for the different applications in practice and the other research, for example, a further consideration of component placement for multiple printed circuit boards operation simultaneously and with the time limitation of operation.

The basic PSO algorithm that is described in the works of Venter. G. and Sobieski, J (37). The basic algorithm is first described, followed by a discussion on side and functional constraint handling, and finally, a discrete version of the algorithm is presented.

Hong Zhang, Member IAENG and Masumi Ishikawa [38] proposes a new method to prevent premature convergence and for managing the exploration-exploitation trade-off in PSO search, Particle Swarm Optimization with Diversive Curiosity (PSO/DC). They applied PSO/DC to a 2-dimensional multimodal optimization problem to well demonstrate its effectiveness. The ratio of success in finding the optimal solution to the given optimization problem is significantly improved, which reaches 100% with the estimated appropriate values of parameters in the internal indicator.

Arvind Mohais, Alexander Nikov, Ashok Sahai, and Selahattin Nesil [39] suggested an optimization approach for product design parameters based on emotive responses by combining Kansei techniques and particle swarm optimization algorithm (PSO). The approach involves designing a Kansei survey for collecting data on customers' affective responses to various aspects of a product, using several exemplars of the product. After information gathering, the PSO algorithm is employed to build a prediction binary linear model that aggregates the survey data. Subsequently, another binary linear model links product design. Parameters to the outputs of the first model to establish mathematical connections between the subjective impression of a product (Kansei) and its properties.

ZHAO Bo and CAO Yi-jia [40] proposes a multi-objective particle swarm optimization (MOPSO) approach for multi-objective economic load dispatch problem in power system. The proposed MOPSO approach handles the problem as a multi-objective problem with competing and non-commensurable fuel cost, emission and system loss objectives and has a diversity-preserving mechanism using an external memory (call "repository") and a geographically-based approach to find widely different Pareto-optimal solutions. In addition, fuzzy set theory is employed to extract the best compromise solution. Several optimization runs of the proposed MOPSO approach were carried out on the standard IEEE 30-bus test system. The results revealed the capabilities of the proposed MOPSO approach to generate well-distributed Pareto optimal non-dominated solutions of multi-objective economic load dispatch. They also found that the non-dominated solutions in the obtained Pareto-optimal set are well distributed and have satisfactory diversity characteristics.

Jialin Zhou, Zhengcheng Duan, Yong Li, Jianchun Deng and Daoyuan Yu [41] presented particle swarm optimization (PSO) technique in training a multi-layer feed-forward neural network (MFNN) which is used for a prediction model of diameter error in a boring machining. Experimentally they established that compared to the back propagation (BP) algorithm, the present algorithm achieved better machining precision with a fewer number of iterations. Their work showed that the networks for diameter error prediction trained by the PSO algorithm or by the BP algorithm both improve the precision of the boring machining, but the neural networks trained by the PSO algorithm perform better than those trained by the BP algorithm.

Abido. M. A [42], a novel evolutionary algorithm-based approach to optimal design of multi-machine power-system stabilizers. The designed approach employs a particle-swarm-optimization (PSO) technique to search for optimal settings of PSS parameters. Two Eigen value-based objective functions to enhance system damping of electromechanical modes are considered. The robustness of the proposed approach to the initial guess is demonstrated.

Jong-Bae Park, Ki-Song Lee, Joong-Rin Shin, and Kwang Y. Lee [43] proposed a new approach to economic dispatch (ED) problems with non-smooth cost functions using a particle swarm optimization (PSO) technique. In their work, a modified PSO (MPSO) mechanism is suggested to deal with the equality and inequality constraints in the ED problems. A constraint treatment mechanism is devised in such a way that the dynamic process inherent in the conventional PSO is preserved. Moreover, a dynamic search-space reduction strategy is devised to accelerate the optimization process. To show its efficiency and effectiveness, the proposed MPSO is applied to test ED problems, one with smooth cost functions and others with non-smooth cost functions considering valve-point effects and multi-fuel problems. A position adjustment strategy is incorporated in the PSO framework in order to provide the solutions satisfying the inequality constraints. The equality constraint in the ED problem is resolved by reducing the degree of freedom by one at random. The strategies for handling constraints are devised while preserving the dynamic process of the PSO algorithm. Additionally, the dynamic search-space reduction strategy is applied to accelerate the convergence speed.

Cui-Ru Wang, He-Jin Yuan, Zhi-Qiang Huang, Jiang-Wei zhang and Chen-Jun Sun [44] presented in their work a modified particle swarm optimization algorithm and a new application of it for solving the OPF problem in power system. As a representative method of swarm intelligence, MPSO supplies a novel thought and solution for nonlinear, non-differential and multi-modal problem. For solving the OPF problem, numerical results on the 5-bus system demonstrated the feasibility and effectiveness of the proposed MPSO method, and the comparison showed its validity and superiority over EP and HEP.

Rania Hassan, Babak Cohanim and Olivier de Weck [45] discussed the comparison between the computational effectiveness and efficiency of the GA and PSO using a formal hypothesis testing approach. The motivation was to validate or refute the widely speculated hypothesis that PSO has the same effectiveness as the GA (same rate of success in finding true global optimal solutions) but with better computational efficiency. The results of this test could prove to be significant for the future development of PSO. It appeared that PSO outperformed the GA with a larger differential in computational efficiency when used to solve unconstrained nonlinear problems with continuous design variables and less efficiency differential when applied to constrained nonlinear problems with continuous or discrete design variables.

Jong-Bae Park, Young-Moon Park, Jong-Ryul Won, and Kwang Y. Lee [46] developed an improved genetic algorithm(IGA) for a long-term least-cost generation expansion planning (GEP) problem. The proposed IGA includes several improvements such as the incorporation of an artificial initial population scheme, a stochastic crossover technique, elitism and scaled fitness function. The IGA has been successfully applied to long-term GEP problems. It provided better solutions than the conventional SGA. Moreover, by incorporating all the improvements (IGA3), it was found to be robust in providing quasi-optimums within a reasonable computation time and yield better solutions compared to the TCDP employed in WASP. Contrary to the DP, computation time of the proposed IGA is linearly proportional to the number of stages. The developed IGA method can simultaneously overcome the “curse of dimensionality” and a local optimum trap inherent in GEP problems. The proposed IGA approach can be used as a practical planning tool for a real-system scale long-term generation expansion planning.

Yiğit Karpat and Tuğrul Özel [47] introduces a procedure to formulate and solve optimization problems for multiple and conflicting objectives that may exist in finish hard turning processes using neural network modeling together with dynamic neighborhood particle swarm optimization technique. They indicated through their results that the proposed swarm intelligent approach for solving the multi-objective optimization problem with conflicting objectives is both effective and efficient, and can provide intelligence in production planning for multi-parameter turning processes.

Williams, E. A., and Crossley, W. A. (48), "Empirically-Derived Population Size and Mutation Rate Guidelines for a Genetic Algorithm with Uniform Crossover," *Soft Computing in Engineering Design and Manufacturing*, P. K. Chawdhry, R. Roy and R. K. Pant (editors), Springer-Verlag, 1998, pp. 163-172.

Hassan R. and Crossley, W.(49,50) defines the problem involving designing the payload and bus subsystems of a commercial communication Geosynchronous satellite with given payload requirements. The design objective is to minimize the spacecraft overall launch mass, which is a surrogate for cost, given design constraints on payload as well as overall system reliability. The problem also involves geometrical constraints imposed by the choice of the launch vehicle. The problem includes six functional constraints and 27 discrete design variables representing the technology choices and redundancy levels of the satellite payload and bus subsystems.

Ramón Quiza Sardiñas, Marcelino Rivas Santana, Eleno Alfonso Brindis [51] suggested that a posteriori multi -objective optimization offers greatest amount of information in order to make a decision on selecting cutting parameters in turning. By means of Pareto frontier graphics, several different situations may be considered, facilitating the choice of right parameters for any condition. They proposed a micro-GA that was shown to obtain several, uniformly distributed points, in order to arrange the Pareto front, at a reasonably low computational cost. Aspects like diversity maintenance and constraints handling have been successfully sorted for their studied problem in turning operation. Cost analysis can complement the Pareto front information, and it helps the decision-making process. The proposed model must be enlarged to include more constraints, such as cutting surface temperature.

Paulo Davim. J and C. A. Conceicao Antonio [52] proposed a methodology aiming at the selection of the optimized values for cutting conditions in machining process, as turning and drilling aluminium matrix composites is proposed. An hybrid technique based on an evolutionary search over a design space obtained by experimental way is considered. The machining forces, the surface finish and the tool wear are experimentally measured considering the feed and the cutting velocity as predefined parameters. The optimization based on genetic algorithms has proved to be useful dealing with discrete variables defined on a population of cutting condition values obtained from time scale dependent experiments. The obtained results show that machining (turning and drilling) of composite material made of metal matrices with PCD tool is perfectly compatible with the cutting conditions for cutting time of industrial interest and in agreement with the optimal machining parameters (cutting forces , work piece surface finish and tool wear).They cited the importance of optimisation of machining parameters using numerical and experimental models based on genetic algorithms in matters of scientific interest and large industrial applications.

Abdel-Magid. Y. L, M. A. Abido, et.al, [53], demonstrates the use of genetic algorithms for the simultaneous stabilization of multi-machine power systems over a wide range of operating conditions via single-setting power system stabilizers. The power system operating at various conditions is treated as a finite set of plants. The problem of selecting the parameters of power system stabilizers which simultaneously stabilize this set of plants is converted to a simple optimization problem which is solved by a genetic algorithm with an Eigen-value based objective function. Two Objective functions are presented, allowing the selection of the stabilizer parameters to shift some of the closed-loop Eigen values to the left-hand side of a vertical line in the complex s-plane, or to a wedge-shape sector in the complex s-plane.

Mahapatra. S. S & Amar Patnaik [54],in their work, attempted to determine the important machining parameters for performance measures like MRR, SF, and kerf separately in the WEDM process. Factors like discharge current, pulse duration, and dielectric flow rate and their interactions have been found to play a significant role in rough cutting operations for maximizations of MRR, minimization of surface roughness and minimization of cutting width.Taguchi’s experimental design method was used to obtain optimum parameter combination for maximization of MRR, SF as well as minimization of kerf. Interestingly, the optimal levels of the factors for all the objectives differed widely. In order to optimize for all the three objectives, mathematical models were developed using the non-linear regression method.

Chiuh-Cheng Chyu & Wei-Shung Chang [55] presents a genetic-based algorithm to determine the feeder arrangement and CPS for a chip shooter type machine with the objective of minimizing the cycle time per board. The algorithm has considered several factors in real situations: different machine velocity settings for component types, X–Y table movement time is nonlinear and concave, and feeder duplications. Such a study is very helpful when a manufacturer is requested to produce thousands of PCBs of identical design. The performance of the proposed algorithm, including the effect of feeder duplications, is presented and analyzed in their study. The results indicate that the algorithm produces promising solutions evaluated on the basis of a lower bound on cycle time per board, which is computed by a conservative formula. An estimate of average cycle time per board based.

Kuriakose. S, M.S. Shunmugam [56] suggests use of Non-Dominated Sorting Genetic Algorithm in optimizing the Wire-EDM process parameters to obtain a non dominated solution set . The sorting procedure employs a fitness assignment scheme which prefers non-dominated solutions and uses a sharing strategy which preserves diversity among the solutions. Also, none of the solution in the Pareto-optimal set is better than any other solution in the set. The process engineer can select optimal combination of parameters from the Pareto optimal solution set, depending on the requirements. They implemented the NSGA algorithm using TurboC and ran on Pentium IV PC.

Several efforts were made by various researchers to design a suitable model for grinding process such as, using parameter optimisations [57,58], analytical and numerical approaches.

Noorul Haq, K. Balasubramanian , Sashidharan & R. B. Karthick [59] solves the problem of parallel line job shop scheduling problem using the genetic algorithm optimization technique. It arrives at the optimal allocation and schedule of given jobs for each of the given processing lines. The C program code is written in LINUX platform and is user friendly. It can be executed for any number of lines, jobs, and machines per line. It also gives the minimum make span for a given problem. Their work may be further extended for varying set up times in each line and also for unequal number of machines in each line. Also the randomization algorithm for the initial population can be made less complicated without sacrificing its accuracy.

Chao-Lung Chiang [60] presents an improved genetic algorithm with multiplier updating (IGA_MU) to solve power economic dispatch (PED) problems of units with valve-point effects and multiple fuels. The proposed IGA_MU integrates the improved genetic algorithm (IGA) and the multiplier updating (MU). The IGA equipped with an improved evolutionary direction operator and a migration operation can efficiently search and actively explore solutions, and the MU is employed to handle the equality and inequality constraints of the PED problem. Few PED problem-related studies have seldom addressed both valve-point loadings and change fuels. proposed algorithm is highly promising for the large-scale system of the actual PED operation.

2.1. Motivation

Based on the literature survey performed, venture into this research was amply motivated by the fact that a little research has been conducted to obtain the optimal levels of machining parameters that yield the best machining quality in machining of SS 420. Most of the researchers have investigated influence of a limited number of process parameters on the performance measures of turning process. In this work, tool nose radius (one of the tool geometry) has been incorporated to enhance the effectiveness of the machining process, which is one of the most influential parameter in machining. A suitable optimization technique or algorithm can be chosen based on the output performance of the optimization technique and the best one can be selected to maximize the production efficiency. This is possible only by evaluating the performance of different algorithm. No such performance evaluation is conducted throughout the literature. Majority of the works are concentrating only on particular method or technique. This has been rectified by employing different set of algorithms in this work. More over no study has been performed in turning process using Improved Genetic Algorithm (IGA). The study, it is hoped will lead to theorising efficient monitoring and diagnostics in cutting processes.

The non-linear nature of the machining process has compelled engineers to search for more effective methods to attain optimization. Researchers have found efficient optimized processes in nature itself. Biological systems provide ample insight into their workings; each when applied to mechanical systems help in converging towards the optimum value more accurately.

The studies indicate the importance in analyzing the problem and efforts done to improve the performance of the production or design system even under disturbed conditions. Researchers are responsible to conceive new and improved analytical tools to solve a problem. When a new tool is available the problem should be re-examined to find better and more economical solutions.

In recent years evolutionary algorithms have been gaining more importance and giving promising results in industrial applications. These issues motivate in applying such paradigms for analyzing and improving the performance of machining process system for enhancing quality and economy.

2.2. Objective of the Thesis

- To conduct experiments in dry turning process using Taguchi method.
- To perform statistical analysis using S/N and ANOVA technique.
- To develop a mathematical model using Response Surface Methodology.

- To determine the optimum machining parameters using evolutionary algorithms.

- To identify the best optimization method in finding the optimum machining parameters based on the minimum surface roughness.

- Make use of other published work in the literature in order to prove the effectiveness of the proposed algorithms.

Chapter 3 - Experimental details

Experiments are performed by investigators in virtually all fields of inquiry, usually to discover something about a particular process or system. More formally experiment is a test or series of tests in which purposeful changes are made to the input variables of a process or system so that one can observe or identify the reasons for changes that may be observed in the output response. In this work to test the various algorithms actual experimental data should be available. In order to do that experiments in dry turning of SS 420 have been performed.

When developing models on the basis of experimental data, careful planning of experimentation is essential. Experiment helps us in understanding the behavior of mechanical system. Data collected by systematic variation of influencing factors helps us to quantitatively describe the underlying phenomena. The factors considered for experimentation and analysis were cutting speed, feed rate, depth of cut and cutting tool nose radius. A large number of experiments have to be carried out when the number of process parameters increases. To solve this problem Taguchi method has been implemented in this context.

3.1. Overview of the Taguchi method

Taguchi's comprehensive system of quality engineering is one of the greatest engineering achievements of the 20^{th} century. His methods focus on the effective application of engineering strategies rather than advanced statistical techniques. It includes both upstream and shop-floor quality engineering. Upstream methods efficiently use small-scale experiments to reduce variability and remain cost-effective, and robust designs for large-scale production and market place. Shop-floor techniques provide cost based real time methods for monitoring and maintaining quality in production. The farther upstream a quality method is applied, the greater leverages it produces on the improvement, and the more it reduces the cost and time. Taguchi proposes an “off-line” strategy for quality improvement as an alternative to an attempt to inspect quality into a product on the production line. He observes that poor quality cannot be improved by the process of inspection, screening and salvaging. No amount of inspection can put quality back into the product. In the present work Taguchi’s parameter design approach is used to study the effect of process parameters on the various responses of the dry turning of SS 420.

Quality improvement programmers are very much part of the strategic planning process of successful companies (McKeown, [61]). Alongside the strategic planning issues are the importance of design and the idea of designing quality into products and processes.

The Taguchi philosophy and its associated experimental design method has been extensively used in the manufacturing environment to improve production processes, for example a metal injection molding process (Fox and Lee, [62]) and a plasma deposition process in device fabrication (Logothetis et al. [63]). In such environments, careful planning of the experiment is important if the full benefits of the experimental methods are to be realized (Coleman and Montgomery [64]). Other examples of manufacturing related applications of the Taguchi method include scheduling (Dooley and Mahmoodi [65]) and optimization of a robot's performance capability for continuous path operation (Wu et al. [66]). Despite the successful applications of the Taguchi method, a wider use of the approach and its associated techniques is only possible by gaining a better understanding of the method and its analysis. The success and failure of the Taguchi approach to parameter design have been widely discussed ,Nair [67]; Lochner [68]; Pignatiello and Ramberg [69]; Antony [70]. In summary, Taguchi's main success have been to emphasize the importance of quality in design and to simplify the use of experimental design as a general purpose tool for quality engineers. Amongst the many criticisms of the Taguchi method is the use of the signal-to- noise (S/N) ratio as a performance measure statistic. S/N ratio measures the functional robustness of products and processes. The S/ N ratios have been criticized as providing misleading results in certain cases. Although the classical experimental design has a much wider appeal than the Taguchi method, the Taguchi method does provide the practical engineer with an useful starting point for quality improvement. This is fundamentally because the former is more focused on the statistical aspects whereas the latter is primarily focused on the engineering aspects of quality. The beauty of Taguchi method lies in the fact that it integrates statistical methods into the powerful engineering process.

3.2. Design of Experiments

In this process four factors at three levels are chosen which is given in Table 1. The fractional factorial design used is a standard L_{27} (3^{13}) orthogonal array [71]. This orthogonal array is chosen due to its capability to check the interactions among factors. Each row of the matrix represents one trial.

The basic principle in using any design of experiment (DOE) technique is to first identify the key variables in the process and then actively probe those variables to determine their effects on the process output. A typical DOE process consists of three distinct phases, screening, characterization and optimization, although not all three phases are used in every study. Orthogonal designs are particularly useful because the estimate of the effect of a factor is unaffected by which other factors are under consideration. Factorial designs, which involve all possible combinations of levels of all the factors, can be investigated simultaneously**.** This technique also saves time and money because large number of factors can be investigated simultaneously.

One type of complete factorial experiment is 2^k factorial designs; k is the number of factors investigated at two levels. In order to calculate the number of runs, e.g. if k=7 then the number of runs is 2^7 =128 experimental runs. The number of run increases as the k value increases. In order to reduce the number of experimental runs, fractional factorial was introduced which use only a fraction of the total possible combinations of levels. The number of run is given by 2^{k-1}, e.g. if k=7, $2^{(7-1)}$ =2^6 =64 experimental runs. By using the fractional factorial the number of run has been reduced by half. Taguchi's method adopts the fundamental idea of DOE but simplifies and standardized the factorial and fractional factorial designs so that experiments conducted will produce more consistent results.

3.2.1 Parameter Design Based on the Taguchi method

The Taguchi philosophy proposes that the task of assuring quality must begin with the engineering of quality-product and process design optimization for performance quality and cost. Quality engineering must be completed before the product reaches its production stage. 'Quality', defined by Taguchi as the deviation from on-target performance appears at first to be a paradox. According to him the quality of a manufactured system is the total loss generated by that product to society from the time it is shipped. The robust design method which is the key QA procedure put forth by Taguchi is a systematic method for keeping the producer's costs low while delivering the highest quality to the consumer. Taguchi's robust design experiments for most part use only orthogonal arrays rather than full factorial design.

Modeling provides reliable equations obtained from the data of properly designed experiments. Therefore, it is essential to have a well-designed set of experiments. A well-designed experiment can substantially reduce the number of experiments required. Several types of experimental results have been reported. In this research, the design suggested by Taguchi is used.

3.2.2 Orthogonal Array Experiment

Classical experimental design methods are too complex and are not easy to use. A large number of experiments have to be carried out when the number of process parameters increases. To solve this problem, the Taguchi method uses a special design of orthogonal arrays to study the entire parameter space with only a small number of experiments. According to the Taguchi method, a robust design and an L_{27} orthogonal array are employed for the experimentation. Four machining parameters are considered as controlling factors – namely, cutting speed, feed rate, depth of cut and nose radius and each parameter has three levels – namely low, medium and high, denoted by 1,2 and 3, respectively. Table 3.1 shows the cutting parameters and their levels considered for the experimentation. The experimental design considered for the investigation to achieve an optimal surface finish during the turning of SS 420 steel is based on the L_{27} orthogonal array shown in Table 3.2. Based on this, a total number of 27 experiments in dry machining condition is done, each having a different combination of levels of factors as shown in Table 3.1 were carried out.

Orthogonal arrays are special standard experimental design that requires only a small number of experimental trials to find the main factor effects on output. Before selecting an orthogonal array, the minimum number of experiments to be conducted shall be fixed which is given by:

$N_{Taguchi} = 1 + NV (L – 1)$

$N_{Taguchi}$ = Number of experiments to be conducted

NV = Number of variables

L = Number of levels

In this work

NV = 4 and L = 3 , Hence

$N_{Taguchi} = 1 + 4 (3-1) = 9$

Hence at least 9 experiments are to be conducted. Based on this orthogonal array (OA) is to be selected which has at least 9 rows i.e.,9 experimental runs. Standard OAs available are L4, L8, L9, L12, L16, L18, L27, etc. In this work L9 is sufficient, but since interaction effects are also to be considered, L27 array is selected.

Based on main factor, interaction effects between variables, the variables are assigned at columns, as stipulated by orthogonal array. Some columns can be kept dummy, but no row should be left out.

Once the orthogonal array is selected, the experiments are selected as per the level combinations. It is important that all experiments are conducted. The interaction effect columns can be kept dummy while conducting experiments, but to be considered for analysis. The performance parameter (out put) is noted for each experimental run for analysis.

Table 3.1 – Cutting parameters and levels

Levels	Feed F in mm/rev	Cutting velocity V in m/min	Depth of cut D in mm	Nose radius R in mm
1	0.059	39.269	0.4	0.4
2	0.159	60.475	0.8	0.8
3	0.26	94.247	1.2	1.2

Table 3.2- L_{27} Orthogonal array

Runs	F **1**	**2**	D*F **3**	**4**	D **5**	F*V **6**	F*R **7**	V*R **8**	V **9**	D*V **10**	**11**	D*R **12**	R **13**
1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2	2	2	2	2	2
3	1	1	1	1	3	3	3	3	3	3	3	3	3
4	1	2	2	2	1	1	1	2	2	2	3	3	3
5	1	2	2	2	2	2	2	3	3	3	1	1	1
6	1	2	2	2	3	3	3	1	1	1	2	2	2
7	1	3	3	3	1	1	1	3	3	3	2	2	2
8	1	3	3	3	2	2	2	1	1	1	3	3	3
9	1	3	3	3	3	3	3	2	2	2	1	1	1
10	2	1	2	3	1	2	3	1	2	3	1	2	3
11	2	1	2	3	2	3	1	2	3	1	2	3	1
12	2	1	2	3	3	1	2	3	1	2	3	1	2
13	2	2	3	1	1	2	3	2	3	1	3	1	2
14	2	2	3	1	2	3	1	3	1	2	1	2	3
15	2	2	3	1	3	1	2	1	2	3	2	3	1
16	2	3	1	2	1	2	3	3	1	2	2	3	1
17	2	3	1	2	2	3	1	1	2	3	3	1	2
18	2	3	1	2	3	1	2	2	3	1	1	2	3
19	3	1	3	2	1	3	2	1	3	2	1	3	2
20	3	1	3	2	2	1	3	2	1	3	2	1	3
21	3	1	3	2	3	2	1	3	2	1	3	2	1
22	3	2	1	3	1	3	2	2	1	3	3	2	1
23	3	2	1	3	2	1	3	3	2	1	1	3	2
24	3	2	1	3	3	2	1	1	3	2	2	1	3
25	3	3	2	1	1	3	2	3	2	1	2	1	3
26	3	3	2	1	2	1	3	1	3	2	3	2	1
27	3	3	2	1	3	2	1	2	1	3	1	3	2

3.3. Experimental details

The experiment is performed on SS 420 of size 25 mm diameters which contains 12% of chromium sufficient enough to give corrosion resistance property and good ductility. Its chemical composition is given as 0.15% C, 12.0-14.0% Cr , < 1.0% Si , <0.04% P ,<1.0% Mn, <0.03% S and remaining as Fe . The physical and mechanical properties of the SS420 are given in Table 3.3. The cutting tool for turning with rhombic tooling system is uncoated tungsten carbide having zero rake angle,7^{o} clearance angle and 55^{o} cutting edge angle and of nose radii 0.4,0.8 and 1.2 have been used for experiment. The different sets of dry turning experiments are performed using a Kirlosker centre lathe. The machined surface is measured at three different positions and the average values are taken using a RUGOSURF 10G surface texture measuring instrument, which has diamond stylus tip with accuracy of 0.005µm and resolution of 0.05 µm and having a maximum measuring range of 300 µm. The photograph of the experimental set-up is shown in fig.3.1.

Table 3.3 – Physical and Mechanical properties of specimen SS420

Grade	Density (kg/m^3)	Elastic Modulus (GPa)	Mean Coefficient of Thermal Expansion (µm/m/°C)			Thermal Conductivity (W/m.K)	Specific Heat 0-100°C (J/kg.K)	Electrical Resistance (nΩ.m)
			0 to 100°C	0 to 315°C	0 to 538°C	At 100°C		
420	7750	200	10.3	10.8	11.7	24.9	460	550

(a)

(b)

Fig.3.1. Experimental Setup (a) Machining Trial (b) Roughness Measurement

3.4. S/N Analysis

The S/N ratio is a concurrent quality metric linked to the loss function (Barker, 1990). By maximizing the S/N ratio, the loss associated can be minimized. The S/N ratio determines the most robust set of operating conditions from variation within the results. The S/N ratio is treated as a response (transform of raw data) of the experiment. In the present investigation, the S/N data analysis have been performed. The effects of the selected turning process parameters on the selected quality characteristics have been investigated through the plots of the main effects based on raw data. The optimum condition for each of the quality characteristics has been established through S/N data analysis aided by the raw data analysis.

Taguchi recommends the use of the loss function to measure the performance characteristic deviating from the desired value. The value of the loss function is further transformed into a signal-to-noise (S/N) ratio. The rationale for this switch over to S/N ratios instead of working directly with the quality characteristic measurement is, the S/N ratio is a concurrent statistic –a special kind of data summery. A concurrent statistic is able to look at two or more characteristics of distribution and roll these characteristic into a single number or figure of merit. Usually, there are three categories of performance characteristic in the analysis of the S/N ratio. The loss function for the lower gives better performance characteristic and can be expressed as

$$L_{ij} = \frac{1}{n}\sum_{k=1}^{n} y_{ijk}^{2} \tag{3.1}$$

where L_{ij} is the loss function of the i^{th} performance characteristic in the j^{th} experiment, y_{ijk} the experimental value of the i^{th} performance characteristic in the j^{th} experiment at the k^{th} trial, and n the number of trials.

The loss function is further transformed into an S/N ratio. In the Taguchi method, the S/N ratio is used to determine the deviation of the performance characteristic from the desired value. The S/N ratio L_{ij} for the i^{th} performance characteristic in the j^{th} experiment can be expressed as

$$\eta_{ij} = -10\log(L_{ij}) \tag{3.2}$$

In contrast, the S/N ratio is a predictor of quality loss that isolates the sensitivity of the products function to noise factors. In robust design one minimizes the sensitivity of noise by seeking combinations of the design parameters setting that maximize the S/N ratio.

The evaluation of surface roughness performed using signal to noise ratio analysis is to determine, which settings of the controllable factors results in the mean as close as possible to the desired target and a maximum value of the signal- to - noise (S/N) ratio. An analysis of variance (ANOVA) is used to estimate the variance of independent factors. Moreover the response surface methodology (RSM) and residual analysis is used to validate the robustness of the experiment.

3.5. Influence of the Cutting Parameters on the Surface Roughness (Ra)

Since each experiment is the combination of different factor levels, it is essential to segregate the individual effect of independent variables. This is done by summing up the performance values for corresponding level setting and then mean is found. Then sum of squares of deviation of each of mean value from grand mean value is calculated.

This sum of squares of deviation of a particular variable indicates whether the performance parameter is sensitive to the change of level setting. If the sum of square deviation is close to zero or insignificant , one may conclude that design variable is not influencing the performance process (i.e.) by performing ANOVA, one can conclude which factor is dominating over other and the percentage contribution of that particular independent variable can be found.

The S/N ratio for each parameter level is calculated by averaging the S/N ratios obtained when the parameter is maintained at that level. The experimental results for surface roughness and its S/N ratio are shown in Table 3.4.

The average S/N ratios using smaller the better characteristics to find arithmetic average roughness (Ra) and significant interactions are shown in Fig.3.2. Study of Fig.3.2 suggests that feed rate (F), nose radius (R) and interaction between depth of cut and feed rate (*DF*) are more significant. Cutting velocity (V) and depth of cut (D) are marginally significant. The lowest feed rate of level 1 (F_1=0.059) and highest nose radius of level 3 (R_3= 1.2 mm) appear to be the best choice to get low value of surface roughness or high value of surface finish and thus making the process robust to the feed rate in particular. The cutting velocity and depth of cut are insignificant on the average S/N response. Table 3.5 shows Response table for S/N analysis of surface roughness.

Table 3.6 shows the optimum level of process parameters to achieve high surface finish or low surface roughness. Therefore, the optimal combination to get low value of surface roughness (Ra) is 1-2-1-3 (F_1-V_2-D_1-R_3) within the tested range.

Table 3.4 Experimental Results and S/N ratio for surface roughness Ra

Experiment runs	Feed F mm/rev	Depth of cut DOC mm	Cutting velocity V m/min	Nose radius R mm	Test result of Ra(µm) y_1	y_2	y_3	Average Surface roughness Ra microns	Calculated S/N ratio for Ra (db)
1	1	1	1	1	1.38	1.545	1.455	1.46	-1.0956
2	1	2	2	2	0.971	0.908	1.039	0.972667	0.0802
3	1	3	3	3	1.706	1.787	1.365	1.619333	-1.3955
4	1	1	2	3	0.893	0.971	0.81	0.891333	0.3330
5	1	2	3	1	1.921	1.762	1.933	1.872	-1.815
6	1	3	1	2	2.617	2.692	2.72	2.676333	-2.850
7	1	1	3	2	1.334	1.243	1.347	1.308	-0.777
8	1	2	1	3	0.88	0.876	0.861	0.872333	0.3954
9	1	3	2	1	1.148	1.273	1.621	1.347333	-0.8631
10	2	1	2	3	1.465	1.281	1.248	1.331333	-0.82857
11	2	2	3	1	2.273	2.169	2.232	2.224667	-2.3150
12	2	3	1	2	1.512	1.869	2.365	1.915333	-1.881
13	2	1	3	2	1.201	1.11	1.09	1.133667	-0.3632
14	2	2	1	3	1.353	1.211	1.137	1.233667	-0.6079
15	2	3	2	1	2.046	1.959	1.894	1.966333	-1.9577
16	2	1	1	1	2.133	1.908	2.11	2.050333	-2.0788
17	2	2	2	2	1.785	1.988	1.537	1.77	-1.6531
18	2	3	3	3	1.13	1.41	1.36	1.3	-0.7596
19	3	1	3	2	2.637	3.475	3.491	3.201	-3.3685
20	3	2	1	3	1.746	1.763	1.753	1.754	-1.6268
21	3	3	2	1	5	4.566	4.817	4.913667	-4.6093
22	3	1	1	1	5.832	5.743	5.657	5.744	-5.0614
23	3	2	2	2	3.163	3.116	3.2	3.159667	-3.3309
24	3	3	3	3	2.358	2.23	2.399	2.329	-2.4477
25	3	1	2	3	1.941	2.107	1.853	1.967	-1.9586
26	3	2	3	1	4.99	5.957	5.358	5.435	-4.9013
27	3	3	1	2	3.186	2.944	3.042	3.057333	-3.2356

Table 3.5 Response table for S/N analysis of surface roughness

Parameters	Level 1	Level 2	Level 3
Feed,F	-0.88763	-1.38287	-3.3934
cutting velocity,V	-2.00476	-1.64315	-2.016
Depth of cut,D	-1.68882	-1.75278	-2.22231
Nose radius,R	-2.74422	-1.93117	-0.98851
FV	-1.4462	-1.51301	-2.7047
FR	-1.76797	-1.65702	-2.19096
VR	-2.37449	-1.78716	-1.50226
DF	-1.28822	-1.7973	-2.69269
DV	-1.84679	-1.69797	-2.11915
DR	-2.21652	-1.85558	-1.54791

Table 3.6.The optimum level for the surface roughness Ra

Parameters	Optimum Level of cutting parameters	S/N Response value for Ra
Feed- mm/rev	1	-0.88763
cutting velocity-m/min	2	-1.64315
Depth of cut-mm	1	-1.68882
Nose radius	3	-0.98851

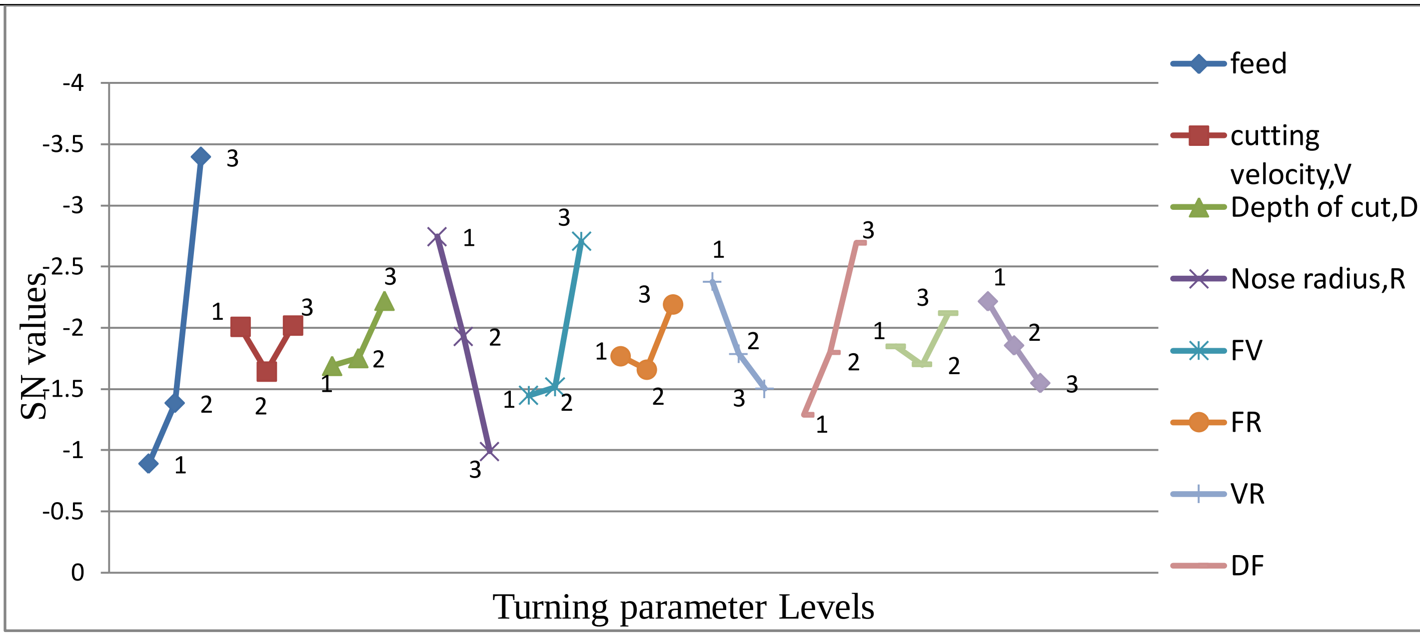


Fig.3.2. S/N ratio for surface roughness, Ra.

Fig.3.3 represents the percentage of contribution of process parameters and the interactions among them. This reveals that the feed factor (F = 54.863%) and the nose radius (R= 24.051%) have statistical and physical significance on the surface roughness, Ra. The interactions of feed/cutting velocity (FV= 15.62%) and depth of cut /feed (DF= 22.541%) have statistical and physical significance on arithmetic average roughness (Ra) in work piece. The interaction of velocity /nose radius (VR= 6.162%) presents percentage of marginal physical significance. The interactions of feed/nose radius (FR= -0.335%), depth of cut/cutting velocity (DV=1.421%) and depth of cut/nose radius (DR=0.917%) do not present percentages of physical significance of contribution on arithmetic average roughness (Ra) in work piece.

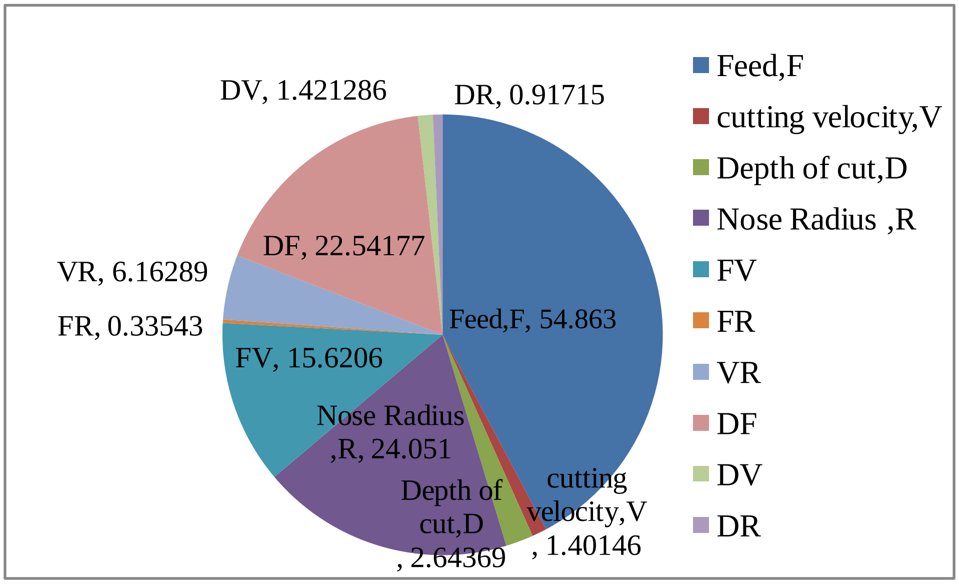


Figure 3.3. Pie- chart showing percentage contribution of surface roughness, Ra

The main purpose of the analysis of variance (ANOVA) is the application of a statistical method to identify the effect of individual factors. Results from ANOVA can determine very clearly the impact of each factor on the process results [77].Table 3.7 shows the analysis of variance with arithmetic average roughness (Ra). This analysis is carried out for a 5% significance level, i.e. for a 95% confidence level. From table 3.7, it is clear that F calculated value for feed rate is 5.62, which is the most significant parameter and also nose radius have considerable influence on surface roughness. F calculated value is more than the table value; $F_{0.05, 2, 20}$= 3.49) at 95%

Table 3.7 – Results of ANOVA for S/N ratio of Ra

Parameters	Sum of squares	Degrees of freedom	Varian ce	F-Test	F,5%	% Contribution
Feed, F	31.69	2	15.849	5.620	3.36	54.86
cutting velocity, V	0.809	2	0.4048	0.144	3.36	1.40
Depth of cut, D	1.527	2	0.7637	0.271	3.36	2.643
Nose Radius ,R	13.89	2	6.9482	2.464	3.36	24.05
FV	9.0252	4	2.2563	0.800	2.74	15.62
FR	0.1938	4	0.0484	0.017	2.74	0.335
VR	3.560783	4	0.8901	0.316	2.74	6.162
DF	13.02414	4	3.2560	1.154	2.74	22.54
DV	0.821188	4	0.2052	0.072	2.74	1.421
DR	0.529911	4	0.1324	0.046	2.74	0.917
Error	-16.9225	-6	2.8204			-29.28
total	57.77779	26				100

3.6 Analysis of Data for Interaction Effects (S/N Ratio)

Interaction effects represent the synergetic effect of two or more factors in the OA experiment. The effect of one factor depends on the other factor.

Interaction effect between variables F and D (FD), F and V (FV) ,F and R (FR) , V and R (VR) , D and V (DV) and D and R (DR) on the output surface roughness (Ra) are analyzed from Table 3.4. The following table shows the results of the interactions (FV), (FD), (FR),(DV),(DR) and (VR) on the surface roughness (Ra) and S/N values of Ra.

Table 3.8- Interaction effects of (FV) on the surface roughness (Ra) and S/N values of Ra.

PARAMETERS AND ITS LEVELS		INTERACTION RESULTS (FV)	
F	V	Ra	Ra (S/N)
1	1	1.669556	-1.1835
1	2	1.070444	-0.14995
1	3	1.599778	-1.32944
2	2	1.689222	-1.47982
2	3	1.552778	-1.14599
2	1	1.733111	-1.52281
3	3	3.655	-3.57257
3	1	3.518444	-3.30797
3	2	3.346778	-3.29967

Table 3.9- Interaction effects of (FD) on the surface roughness (Ra) and S/N values of Ra.

PARAMETERS AND ITS LEVELS		INTERACTION RESULTS (FD)	
F	D	Ra	Ra (S/N)
1	1	1.219778	-0.44656
1	2	1.239	-0.51333
1	3	1.881	-1.703
2	2	1.742778	-1.52541
2	3	1.727222	-1.53299
2	1	1.505111	-1.09021
3	3	3.433333	-3.43093
3	1	3.637333	-3.4629
3	2	3.449556	-3.28638

Table 3.10- Interaction effects of (FR) on the surface roughness (Ra) and S/N values of Ra.

PARAMETERS AND ITS LEVELS		INTERACTION RESULTS (FR)	
F	R	Ra	Ra (S/N)
1	1	1.559778	-1.25808
1	2	1.652333	-1.18247
1	3	1.127667	-0.22235
2	2	1.606333	-1.29934
2	3	1.288333	-0.73206
2	1	2.080444	-2.11721
3	3	2.016667	-2.01112
3	1	5.364222	-4.85738
3	2	3.139333	-3.31171

Table 3.11- Interaction effects of (DV) on the surface roughness (Ra) and S/N values of Ra.

PARAMETERS AND ITS LEVELS		INTERACTION RESULTS (DV)	
D	V	Ra	Ra (S/N)
1	1	1.669556	-1.1835
1	2	1.286667	-0.61313
1	3	1.880889	-1.50306
2	2	1.967444	-1.63462
2	3	3.177222	-3.0106
2	1	1.396556	-0.81807
3	3	1.749444	-1.53433
3	1	2.549667	-2.65584
3	2	2.742444	-2.47675

Table 3.12- Interaction effects of (DR) on the surface roughness (Ra) and S/N values of Ra.

PARAMETERS AND ITS LEVELS		INTERACTION RESULTS (DR)	
D	R	Ra	Ra (S/N)
1	1	3.084778	-2.74531502
1	2	1.880889	-1.50306399
1	3	1.286667	-0.61313308
2	2	1.967444	-1.63461904
2	3	1.396556	-0.81806959
2	1	3.177222	-3.01060076
3	3	1.749444	-1.53433133
3	1	2.742444	-2.47675086
3	2	2.549667	-2.65583858

Table 3.13- Interaction effects of (VR) on the surface roughness (Ra) and S/N values of Ra.

PARAMETERS AND ITS LEVELS		INTERACTION RESULTS (VR)	
V	R	Ra	Ra (S/N)
1	1	3.084778	-2.74531502
1	2	2.549667	-2.65583858
1	3	1.396556	-0.81806959
2	2	1.967444	-1.63461904
2	3	1.286667	-0.61313308
2	1	2.742444	-2.47675086
3	3	1.749444	-1.53433133
3	1	3.177222	-3.01060076
3	2	1.880889	-1.84717705

3.6.1 DISCUSSION ON INTERACTION EFFECT

Surface finish is one of the main aspects of machinability. In this work , the effect of various main machining parameters viz., Feed (F), Cutting velocity (V), Depth of cut (D) , Tool nose radius (R) and Interaction effect between variables F and D (FD) , F and V (FV) ,F and R (FR) , V and R (VR) , D and V (DV) and D and R (DR) on the output surface roughness (Ra) and S/N values of Ra are analyzed.

High surface finish or low surface roughness is obtained at low levels of Feed and Depth of cut and high level of Tool nose radius and at medium Cutting velocity (Table 3.5 and Fig. 3.2).

Feed and Tool nose radius influencing more in the surface roughness and interaction DF an FV is contributing more in the surface roughness (Table 3.6 and Fig. 3.3).

INTERACTION EFFECTS

Considering the interaction effect FV, when F is at level 1 and V is at level 2 minimum surface roughness value of 1.070444 is obtained among all other combinations (Table 3.7).

For interaction FD when F is at level 1 and D is at level 1 minimum surface roughness value of 1.219778 is obtained among all other combinations (Table 3.8).

Lowest surface roughness value of 1.127667 occurs when F is at level 1 and R is at level 3 for interaction FR obtained among all other combinations (Table 3.9).

For interaction DV when D is at level 1 and V is at level 2 minimum surface roughness value of 1.286667 is obtained among all other combinations (Table 3.10).

For interaction DR when D is at level 1 and R is at level 3 minimum surface roughness value of 1.286667 is obtained among all other combinations (Table 3.11).

For interaction VR when V is at level 2 and R is at level 3 minimum surface roughness value of 1.286667 is obtained among all other combinations (Table 3.12).

Considering the Interaction effect between variables F and D (FD), F and V (FV) ,F and R (FR) , V and R (VR) , D and V (DV) and D and R (DR) on the S/N values of Ra, it is found that the levels obtained are same as that of surface roughness. This shows the noise has lesser effects at these levels.

3.7. Summary

Experiments have been designed using Taguchi technique and dry turning of SS420 has been performed on Kirloskar turn master 35 lathe. Analysis using S/N and ANOVA were performed to find the optimum level and percentage of contribution of each parameter. By using S/N analysis the optimum machining parameters from the experimentation is obtained. To find out the optimum machining parameter, which were not used for experimentation but within the limits (lower and upper levels) effective optimization technique is required. In order to this evolutionary algorithms are used for further analysis.

Chapter 4 - Mathematical model

For high quality demands of production process in the micro range, the modeling of machining parameters is necessary. Non linear regression as mathematical modeling tool is found economical to well detect the functional non linearity and interaction features involved in the experimental data.

The various methods for doing mathematical models are Power equation, Exponential, logarithmic, Linear, Regression, Polynomial etc.

In this work, the experimental results were used for modeling using response surface methodology. The purpose of developing mathematical models was to relate the machining responses to the parameters and thereby to facilitate the optimization of the machining process. With these mathematical models, the objective function and process constraints can be formulated, and the optimization problem can then be solved by using Evolutionary algorithms. In the constructed optimization problem, four decision variables are considered: cutting speed (V), feed (F), cutting depth (D) and cutting tool nose radius (R). These are the important cutting parameters of the process.

4.1 Mathematical Formulation

4.1.1. Response Surface Methodology (RSM)

Experimentation and making inferences are the twin features of general scientific methodology. Statistics as a scientific discipline is mainly designed to achieve these objectives. Planning of experiments is particularly very useful in deriving clear and accurate conclusions from the experimental observations, on the basis of which inferences can be made in the best possible manner. 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 of appropriate statistical methods to them are satisfied. Lastly, techniques for proper interpretation of results are devised.

The RSM is an empirical modeling approach for determining the relationship between various processing parameters and responses with the various desired criteria and searches for the significance of these process parameters in the coupled responses [78]. It is a sequential experimentation strategy for building and optimizing the empirical model. The objective of the response surface methodology is to develop the mathematical link between the responses and predominant machining parameters. Cochran & Cox [79] proposed response surface methodology for the optimization of experiments. In many experimental situations, it is possible to represent independent factors in quantitative form. Then these factors can be thought of as having a functional relationship or response:

$$Y = \phi(X_1, X_{2,}......., X_k) \pm e_r, \tag{4.1}$$

between the response Y and X_1,X_2, . . . X_k of k quantitative factors. The function ϕ is called response surface or response function. The residual e_r measures the experimental error. For a given set of independent variables, a characteristic surface responds. When the mathematical form of ϕ is not known, it can be approximated satisfactorily within the experimental region by a polynomial. The higher the degree of the polynomial the better is the correlation, though at the same time the costs of experimentation become higher.

The methodology may be applied for developing the mathematical models in the form of multiple regression equations correlating the dependent parameters such as cutting force, power consumption, surface roughness, tool life etc. with more than two independent parameters, viz. cutting speed, feed rate, depth of cut and tool nose radius, in a turning process. In applying the response surface methodology, the dependent parameter is viewed as a surface to which a mathematical model is fitted. For the development of regression equations related to various quality characteristics of turned parts, the second-order response surface may be assumed as:

$$\mathrm{Y}_u = \beta_0 + \sum_{i=1}^{k} \beta_i x_{iu} + \sum_{i=1}^{k} \beta_{ii} x_{iu}{}^2 + \sum_i \sum_j \beta_{ij} x_{iu} x_{ju} \pm e_r \tag{4.2}$$

This assumed surface Y_u contains linear, squared and cross-product terms of variables Xi 's. where Y_u represents the corresponding response, the surface roughness Ra in the present research. The code values of i^{th} machining parameters for u^{th} experiment are represented by x_{iu}. The values of n indicate the number of machining parameters. The terms β_i, β_{ii} and β_{ij} are the second order regression co-efficient. The second term under the summation sign of this polynomial equation attributes to linear effects, whereas the third term of the above equation corresponds to the higher order effects and lastly the fourth term of the equation includes the interactive effects of the parameters.

Response Surface Methodology (RSM) combines mathematical and statistical techniques for empirical model building and optimization. By conducting experiments and applying regression analysis, a model of the response to certain independent input variables can be obtained. The mathematical models commonly used are represented by:

$$Y = \phi(V,F, D, R)+\in \tag{4.3}$$

Where Y is the machining response (surface finish), φ is the response function and V,F , D, R are turning variables and $\in$ is the error that is normally distributed about the observed response Y with a zero mean. The general second-order polynomial response is as given below:

$$\mathrm{Y}u = \beta_0 + \sum_{i=1}^{k} \beta_i x_{iu} + \sum_{i=1}^{k} \beta_{ii} x_{iu}{}^2 + \sum_i \sum_j \beta_{ij} x_{iu} x_{ju} \tag{4.4}$$

where Y_u represents the corresponding response, the surface roughness R_a in the present research. The code values of i^{th} machining parameters for u^{th} experiments are represented by x_{iu}.The values of k indicate the number of machining parameters. The terms β_i, β_{ii} and β_{ij} are the second order regression co-efficient. The second term under the summation sign of this polynomial equation attributes to linear effects, whereas the third term of the above equation corresponds to the higher order effects and lastly the fourth term of the equation includes the interactive effects of the parameters.

It also confirms that this model provides an excellent explanation of the relationship between the independent factors and the response arithmetic average roughness (R_a). The second order response surface representing the surface roughness, R_a can be expressed as a function of cutting parameters such as feed (F), cutting speed (V), depth of cut (D) and nose radius (R). The relationship between the surface roughness and machining parameters has been expressed as follows [71].

$$R_a = \beta_0 + \beta_1(F) + \beta_2(D) + \beta_3(V) + \beta_4(R) + \beta_5(FD) + \beta_6(FV) + \beta_7(FR) + \beta_8(DV) +$$
$$\beta_9(DR) + \beta_{10}(VR) + \beta_{11}(F^2) + \beta_{12}(D^2) + \beta_{13}(V^2) + \beta_{14}(R^2) \qquad (4.5)$$

To obtain practical predictive quantitative relationships, it is necessary to model the turning responses and the process variables. In the present work, the mathematical models were developed on the basis of dry machining experimental results as shown in Table 3.4. The experimental results were used to model the response using response surface methodology. From the observed data for surface roughness, the response function has been determined using RSM is,

$$R_a = -4.89 + 2.49F - 38.0D + 0.599V + 3.27R - 5.38F*D + 0.0140F*V - 18.2F*R +$$
$$0.0097D*V + 15.8D*R - 0.232V*R + 80.5F^2 + 16.5D^2 - 0.00318V^2 \qquad (4.6)$$

From the relation developed for surface roughness using RSM (equation-4.6), the term R^2 is highly correlated with depth of cut (D^2) and hence R^2 has been removed from the equation. R-Sq values of RSM model for first order, second order with only interaction and second order with interaction and quadratic terms are 66.3%, 82.6% and 93.4% respectively. This shows the second order RSM model contains both quadratic and interaction terms and thus is more accurate.

Result of ANOVA for the RSM model is represented in Table 4.1. This analysis is carried out for a level of significance of 5%, i.e., for a level of confidence of 95%. From the analysis of Table 4.1, it is apparent that, the calculated F value is greater than the table F value ($F_{0.05,\ 13,13}$=2.575) and hence the second order response function developed is quite adequate.

Table 4.1 Results of ANOVA for response function of Ra

Source	DF	SS	Variance	F-Test
Regression	13	42.0678	3.2360	14.24
Residual Error	13	2.9545	0.2273	
Total	26	45.0223		

The comparison of the predicted and experimental values of surface roughness as per the Taguchi array is shown in Table 4.2 and Fig. 4.1.

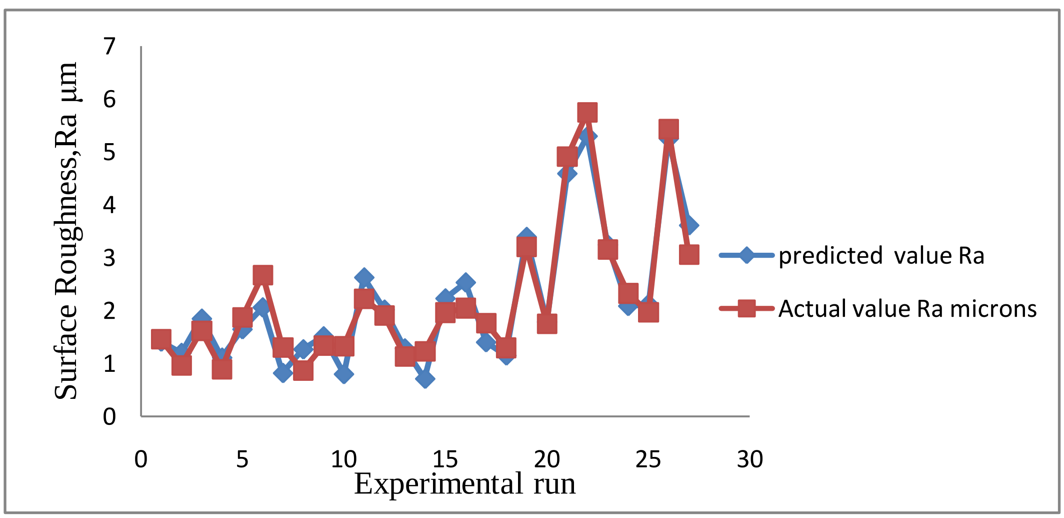


Fig 4.1 RSM Predicted and Experimental values of Ra

Table 4.2. Experimental and Predicted values of Ra

Experimental Run	Actual value,Ra	Predicted value,Ra
1	1.460	1.415914
2	0.973	1.201805
3	1.619	1.847592
4	0.891	1.112467
5	1.872	1.648305
6	2.676	2.060945
7	1.308	0.821878
8	0.872	1.269779
9	1.347	1.515143
10	1.331	0.801833
11	2.225	2.625752
12	1.915	2.018223
13	1.134	1.286525
14	1.234	0.714256
15	1.966	2.230109
16	2.050	2.531592
17	1.770	1.403971
18	1.300	1.153839
19	3.201	3.390049
20	1.754	1.78741
21	4.914	4.586455
22	5.744	5.292657
23	3.160	3.242389
24	2.329	2.087378
25	1.967	2.122323
26	5.435	5.247204
27	3.057	3.609304

4.2. Analysis of the model developed

4.2.1 Residual analysis

The analysis of variance assumes that the model errors are normally and independently distributed with the same variance in each factor level. These assumptions can be checked by examining the residuals. Residual is the difference between the actual observation and the value that would be obtained from the analysis of variance model to the experimental data.

By constructing a normal probability plot of the residuals, the normality assumptions can be checked. To check the assumption of equal variances at each factor level residual against factor levels can be plotted and spread in the residuals may be compared.

The independence plotting can be checked by plotting the residuals against the run order in which the experiment was performed. Simply the residuals from a design of experiment play an important role in assessing model adequacy. The analysis was made using the popular software, specifically used for design of experiment applications, known as MINITAB 14.

It is also necessary that residuals be normally distributed in order that the regression analysis to be valid [80].Residuals are the best estimates of error. The individual deviations of the observations Y_i from their fitted values are known as residuals. Residual plots can also help to examine the assumptions about the regression model .The analysis of variance assumes that the model errors are normally and independently distributed. These assumptions can be checked by residuals. In this paper normal probability plot of the residuals ,residuals versus fits, residuals versus experimental run, residuals versus the variables and four-in-one residual plot for first order and second order response models are discussed.

The first and second order response surface model representing the surface roughness, Ra can be expressed as a function of cutting parameters such as feed (F), cutting speed (V), depth of cut (D) and nose radius (R). The relationship between the surface roughness and machining parameters has been expressed as follows [81].

$$Ra = \beta_o + \beta_1(F) + \beta_2(D) + \beta_3(V) + \beta_4(R) + \epsilon \qquad \text{(first order RSM model)} \qquad (4.7)$$

$$Ra = \beta_o + \beta_1(F) + \beta_2(D) + \beta_3(V) + \beta_4(R) + \beta_5(FD) + \beta_6(FV) + \beta_7(FR) + \beta_8(DV) + \beta_9(DR) + \beta_{10}(VR) + \epsilon \qquad \text{(second order RSM model with only interaction)} \qquad (4.8)$$

$$Ra = \beta_o + \beta_1(F) + \beta_2(D) + \beta_3(V) + \beta_4(R) + \beta_5(FD) + \beta_6(FV) + \beta_7(FR) + \beta_8(DV) + \beta_9(DR) + \beta_{10}(VR) + \beta_{11}(F^2) + \beta_{12}(D^2) + \beta_{13}(V^2) + \beta_{14}(R^2) + \epsilon \text{ (second order RSM model with quadratic)} \qquad (4.9)$$

The corresponding RSM models of the experimental values are as follows

$$Ra = 1.87 + 10.3\ F + 0.283\ D + 0.00001\ V - 1.90\ R \qquad \text{(first order RSM model)} \qquad (4.10)$$

$$Ra = -\ 0.21 + 28.2\ F - 0.05\ D - 0.0040\ V + 0.40\ R - 5.38\ f{*}d + 0.0140\ f{*}v - 18.2\ f{*}r + 0.0056\ d{*}v + 1.04\ d{*}r - 0.0040\ v{*}r \text{ (second order RSM model with only interaction)} \qquad (4.11)$$

$$Ra = -\ 4.89 + 2.49\ F - 38.0\ D + 0.599\ V + 3.27\ R - 5.38\ F{*}D + 0.0140\ F{*}V - 18.2\ F{*}R + 0.0097\ D{*}V + 15.8\ D{*}R - 0.232\ V{*}R + 80.5\ F^2 + 16.5\ D^2 - 0.00318\ V^2 \qquad \text{(second order RSM model with quadratic)} \qquad (4.12)$$

R-Sq values of RSM model for first order , second order with only interaction and second order with interaction and quadratic terms are 66.3%, 82.6% and 93.4% respectively. This shows the second order RSM model contains both quadratic and interaction terms are more accurate

The normal probability plots of the response; Ra is depicted in Figs. 4.2. The graph shows that the data closely follow the straight lines, denoting a normal distribution.

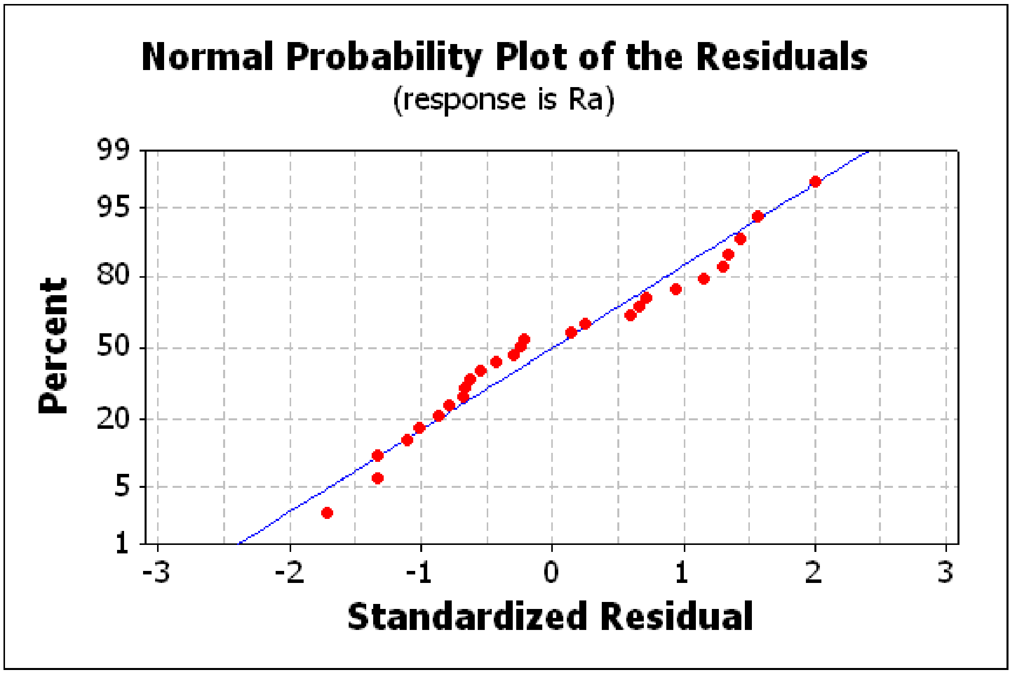


Fig.4.2 Normal probability plot of residuals

Figures 4.3(a), 4.3(b), 4.3(c) and 4.3(d) plot the residual versus the levels of feed, depth of cut, cutting velocity and tool nose radius respectively. There are some indications that levels of 1, 1, 2 and 3 of feed, depth of cut, cutting velocity and tool nose radius have slightly lower variability in response, than other levels of the cutting parameters.

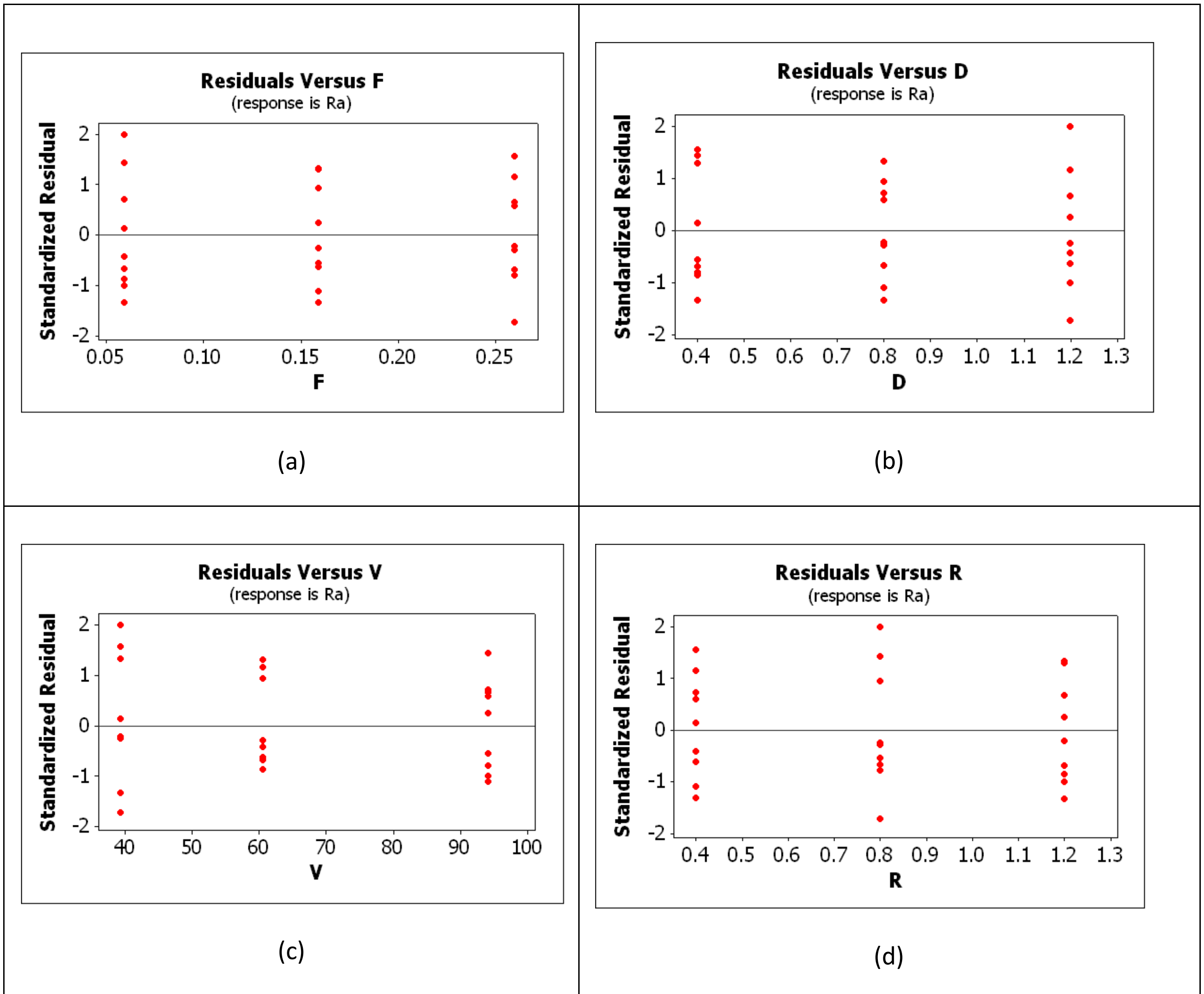


Fig.4.3. Plots of residuals versus (a) feed (b)depth of cut (c) cutting velocity (d) tool nose radius

4.2.2 Response surface analysis for Ra

The interactions between controllable and noise factors are the key to a process robustness study. Therefore, it is logical to utilize a model for the response that includes both controllable and noise factors and also their interactions. Once we are in the region of optimum by S/N analysis a very precise estimate of the optimum operating condition is attained using RSM methodology. It also confirms that this model provides an excellent explanation of the relationship between the independent factors and the response arithmetic average roughness (Ra). The fitness of the model is ascertained by comparing linear and non-linear response equations.

Based on the analysis conducted, Fig.4.4 gives the contour plots of the response model and Fig.4.5 is the three dimensional response surface plot for the model (equation 4.6).The curvature to the response surface is due to the interaction effect; in effect the plane is twisted. The rising ridge shape of surface plot is due to quadratic effect. The plots are created by considering the middle level values as the hold values of the independent variables such as feed, speed, depth of cut and nose radius. From the contour plot, it is observed that, at lower values of the cutting feed and depth of cut, and mid-value of cutting velocity and for maximum value of tool nose radius, minimum surface roughness can be obtained. The response surface plot reveals the interaction and quadratic effect of the model .Each contour corresponds to particular height of the response surface. The contour plot is helpful in analyzing the levels of independent variables that result in changes in the shape or height of the response surface. Also these plots are helpful in validating the S/N and ANOVA analysis. In this analysis the above plots satisfy the analysis.

4.3. Determining the model accuracy

The model accuracy percentage for all data sets can be found by [82]

$$\Delta = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_{i,\exp t} - y_{i,pred}}{y_{i,pred}}\right| \tag{4.13}$$

where $y_{i,expt}$ measured response corresponding to data set i, $y_{i,pred}$ predicted response corresponding to data set i and n the number of data sets = 27. Equation (The average error rate of this model (equation-4.4) with the experimental data is within 4.7%. The mathematical model is applied to various evolutionary algorithms as explained in the succeeding chapters.

4.4. Validation of mathematical model

The developed mathematical model has been validated with the experimental results of Paulo Davim. J [123], Ersan Aslan , Necip Camuscu , Burak Birgo¨ren [124] and J. Paulo Davim, V. N. Gaitonde and S. R. Karnik [125]. The percentage error obtained is 4.7% as such in table 4.3, which shows that the developed model will yield reasonably good result with percentage error less than 5%.

Table 4.3 Validation of the proposed mathematical model

Sl.No.	Name of the author	Reported error (%)	Error obtained from the proposed mathematical model (%)
1	Paulo Davim. J,2003,[123]	10	4.7
2	Ersan Aslan , Necip Camuscu , Burak Birgo¨ren,2007[124]	28	4.7
3	J. Paulo Davim, V. N. Gaitonde and S. R. Karnik,2008,[125]	12	4.7

4.5. Summary

A mathematical model has been developed using response surface methodology and the analysis of the model was carried out. The model accuracy is determined and validation of the mathematical model has been carried out with the experimental results of various research work published in international journals. In forth-coming sections the developed mathematical model is used for further analysis in the optimization of machining parameters to achieve minimum surface roughness in the evolutionary algorithms.

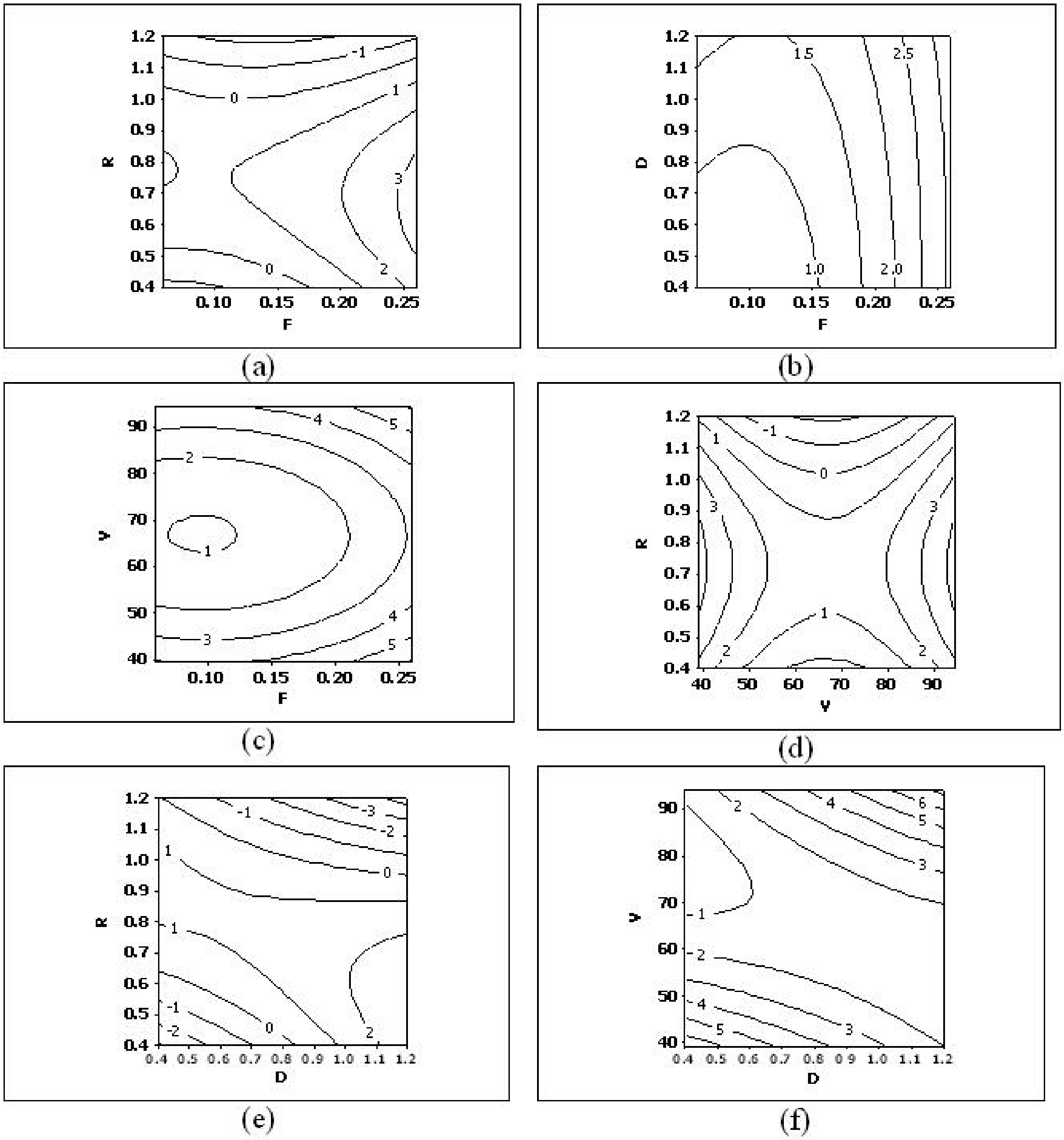


Figure 4.4 – Contour plots for the RSM model (a) Ra Vs R,F (b) Ra Vs D,F (c) Ra Vs V,F (d) Ra Vs R,V (e) Ra Vs R,D (f) Ra Vs V,D

(The values shown on the contour lines indicates surface roughness)

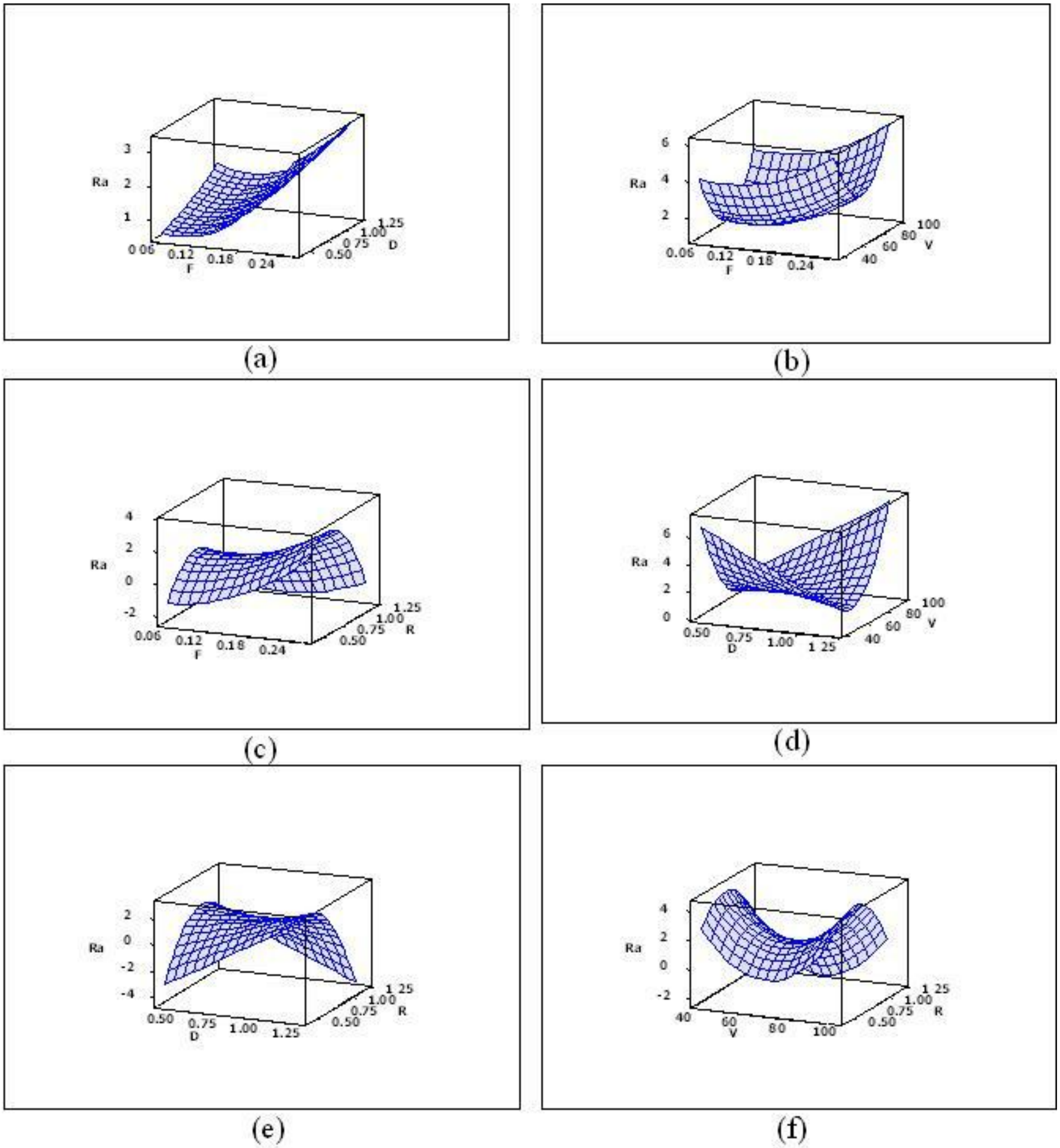


Figure 4.5- Response surface graph for the RSM model (a) Ra Vs D,F (b) Ra Vs V,F

(c) Ra Vs R,F (d) Ra Vs V,D (e) Ra Vs R,D (f) Ra Vs R,V

Chapter 5 - Simulated Annealing Based Optimization of Machining Process

In simulated annealing (SA) method, an exponential cooling schedule based on Newtonian cooling process is employed and experimentation is done on choosing the number of iterations (m) at each step. The SA approach is applied to predict the influence of tool geometry (nose radius) and cutting parameters (feed, speed and depth of cut) on surface roughness in dry turning of SS 420 materials conditions based on Taguchi's orthogonal array method.

5.1. Simulated Annealing method (SA)

Simulated annealing was developed in 1983 to deal with highly nonlinear problems. SA appears rapidly to be becoming an algorithm of choice when dealing with financial instruments [83].Standard nested regression and local-search methods usually are applied to develop hybrid securities, e.g. combining markets in interest rates, foreign exchange, equities and commodities by linking them via options, futures, forwards, and swaps, to increase profits and reduce risks in investments as well as in trading [84].However, simulated annealing has been reasonably successfully used in the solution of a complex portfolio selection model [85,86]. The algorithm was able to handle more classes of constraints than most other techniques. One study has used SA on a set of several econometric problems [87], including cost functions arising in the monetary theory of exchange rate determination, a study of firm production efficiency, and a neural net model which generates chaos reputed to mirror some economic and financial series.

SA approaches the global maximization problem similar to using a bouncing ball that can bounce over mountains from valley to valley. It begins at a high "*temperature*" which enables the ball to make very high bounces, which helps it to bounce over any mountain to access any valley, given enough bounces. As the temperature declines the ball cannot bounce so high and it can also settle to become trapped in relatively small ranges of valleys. A generating distribution generates possible valleys or states to be explored. An acceptance distribution is also defined, which depends on the difference between the function value of the present generated valley to be explored and the last saved lowest valley. The acceptance distribution decides probabilistically whether to stay in a new lower valley or to bounce out of it. All the generating and acceptance distributions depend on the temperature. It has been proved that by carefully controlling the rate of cooling of the temperature, SA can find the global optimum. SA's major advantage over other methods is an ability to avoid becoming trapped in local minima.

The general SA algorithm involves the following three steps. First, the objective function corresponding to the energy function must be identified. Second, one must select a proper annealing scheme consisting of decreasing temperature with increasing of iterations. Third, a method of generating a neighbor near the current search position is needed. In single objective optimization problems, the transition probability scheme is generally selected by the Metropolis and logistic algorithms [88, 89,90]. Simulated annealing (SA) is based on an analogy with the homonymous thermo dynamical process. For slowly cooled thermo dynamical systems (e.g., metals), nature is able to find the minimum state of energy, while the system may end in an amorphous state of higher energy if it is cooled quickly. This principle is expressed by the Boltzmann probability distribution.

The energy of a system in thermal equilibrium at a given temperature T is probabilistically distributed among all different states E. The parameter K is the Boltzmann constant and the exponential term is the Boltzmann coefficient. With the decrease of temperature, the Boltzmann distribution focuses on a state with lowest energy and finally as the temperature comes close to zero, this becomes the only possible state (see Fig.5.1).The system may switch to a new energy state with probability p, irrespective of whether it is higher or lower. Therefore, nature’s minimization strategy is to allow the system sometimes to go uphill as well as downhill, so that it has a chance to escape from a local energy minimum in favor of finding a better, more global minimum. However, the lower the temperature, the less likely is a significant uphill step.

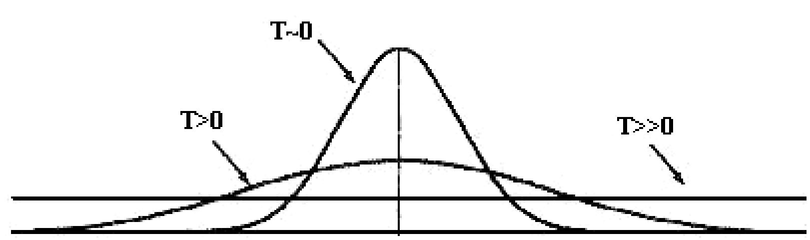


Fig. 5.1 Distribution of probability for three different temperatures

Simulated annealing presents an optimization technique that can: (a) process cost functions possessing quite arbitrary degrees of nonlinearities, discontinuities, and stochasticity; (b) process quite arbitrary boundary conditions and constraints imposed on these cost functions; (c) be implemented quite easily with the degree of coding quite minimal relative to other nonlinear optimization algorithms; (d) statistically guarantee finding an optimal solution. Simulated annealing combines a downhill search with a random search. In order not to be trapped in a locally optimum region, this procedure sometimes accepts movements in directions other than steepest ascend or descend. The acceptance of an uphill rather that a downhill direction is controlled by a sequence of random variables with a controlled probability. Simulated annealing (SA) is a powerful stochastic search method applicable to a wide range of problems for which little prior knowledge is available. It can produce high-quality solutions for hard combinatorial optimization.

The process of slow cooling is known as annealing in metallurgical process. The simulated annealing procedure simulates this process of slow cooling of molten metal to achieve the minimum function value of surface roughness in the problem of minimization. It is a point-by-point method. The algorithm begins with an initial point and a high temperature T. A second point is taken at random in the vicinity of the initial point and the difference in the function values (ΔE) at these two points is calculated. Suppose that initially we have a point x_k in the search space and that the cost at that point is $f(x_k)$. A new point x_{k+1} is randomly generated that is "nearby" in some sense; we will call this a "trial point". The cost there is $f(x_{k+1})$. Next we decide whether to move to x_{k+1}, that is whether to replace x_k by x_{k+1} as the current approximation. If $f(x_{k+1}) < f(x_k)$ then the move is definitely accepted. If $f(x_{k+1}) \geq f(x_k)$ then also the move is accepted with a probability of

$$P_{r(move\_accepted)} = \exp\left(\frac{f(x_{k+1}) - f(x_k)}{T} \right) \qquad (5.1)$$

This completes an iteration of this simulated annealing procedure. In the next generation another point is created at random in the neighborhood of the current point and the Metropolis algorithm is used to accept or reject it. In order to simulate the thermal equilibrium at every temperature the number of points (n) is usually tested at a particular temperature before reducing the temperature. The algorithm is terminated when a sufficiently small temperature is obtained are a small enough change in function value is obtained. The structure of the proposed simulated annealing algorithm (SA) is as follows and is shown in figure 5.2.

Step-1: Initialization

Choose a start point (x) and set a high starting temperature (T), number of iterations to be performed at a particular temperature K; (K=1 to n)

*Step-2: Generation of neighborhood seed and evaluation (*Evaluate objective function E= f(x))

Step-3: Find new point $X_{i(k+1)} = X_{i(k)} + \lambda_i (X_{i\max} - X_{i\min})$ (5.2)

$$\lambda_i \in (-1,1)$$

$$\lambda_i = sign(U_i - 0.5) * T_i \left[(1 + 1/T_i)^{|2U_i - 1|} - 1 \right] \tag{5.3}$$

U_i = random variable between 0 and 1

Select Δ_x with probability determined by $g(\Delta_x, T)$. Set the new point $\mathbf{X}_{\mathbf{new}} = \mathbf{X} + \Delta_\mathbf{X}$

$$g(\Delta_x, T) = (2\pi T)^{-n/2} \exp\left[-|\Delta_x|^2 / 2T \right] \tag{5.4}$$

n = dimension of space under exploration**.** The new point should be between the maximum and minimum limit.

Step-4: Calculate the new value of the objective function using fitness equation.

$$E_{new} = f(X_{new}) \tag{5.5}$$

Step-5: Calculation of uphill and downhill move acceptance parameter ΔE

Set X to X_{new} and E to E_{new} with probability determined by acceptance function , h (ΔE, T)

$$h(\Delta E, T) = \frac{1}{\left[1 + \exp(\Delta E / T)\right]} \tag{5.6}$$

T= Current temperature, $\Delta E = E_{new} - E$

Step-6: Increment the iteration count K, if K reaches the maximum stop iteration; otherwise go back to STEP-3.

Step-6: Reduce the temperature according to annealing schedule $=T_0 * \alpha$, α=cooling rate [91], usually between 0 and 1 and when T is small, terminate; Else go to step 2.

The cooling schedule is an important feature of this algorithm, in the generalized approach, α may vary with respect to the temperature which is as follows:

$$\left(\frac{\min T}{T_0}\right)^{1/\max no.of\ iteration} \tag{5.7}$$

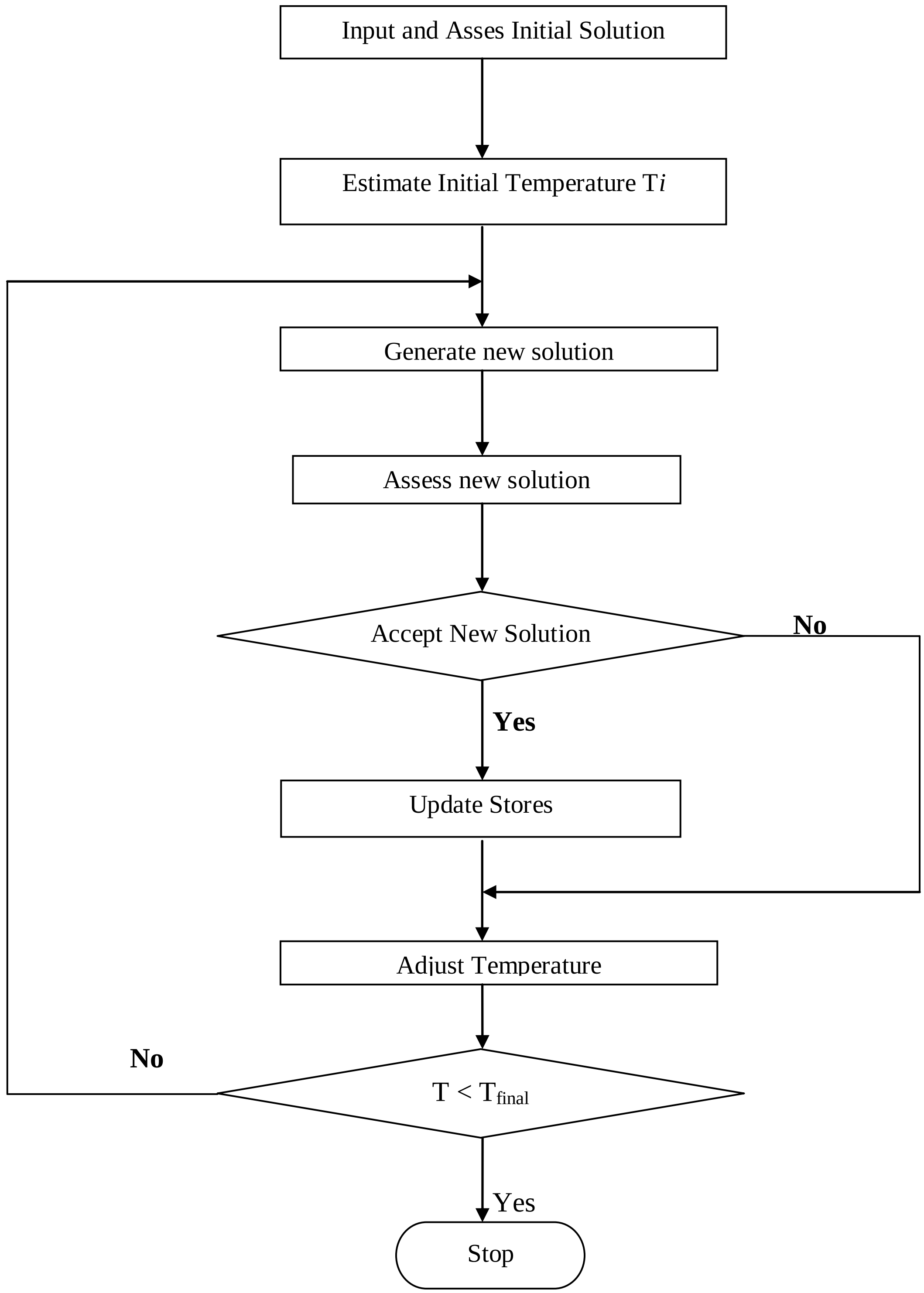


Fig.5.2 Simulated Annealing Structure

In order to optimize the present problem using simulated Annealing algorithms (SAs), the constrained optimization problem is stated as follows:

From the observed data for surface roughness, the response function has been determined using RSM and fitness function, defined as

Minimize,

$$R_a = -4.89 + 2.49F - 38.0D + 0.599V + 3.27R - 5.38F*D + 0.0140F*V - 18.2F*R +$$
$$0.0097D*V + 15.8D*R - 0.232V*R + 80.5F^2 + 16.5D^2 - 0.00318V^2 \qquad (5.8)$$

subject to

39.269 m/min $\leq V \leq$ 94.247 m/min

0.059 mm/rev $\leq F \leq$ 0.26 mm/rev

0.4 mm $\leq D \leq$ 1.2 mm

0.4mm$\leq R \leq$ 1.2mm

$xil \leq xi \leq xiu$

where xil and xiu are the upper and lower bounds of process variables xi . x_1, x_2, x_3, x_4 are the cutting speed, feed, depth of cut and nose radius respectively. In order to optimize the present problem using IGAs, the following parameters have been selected to obtain optimal solutions with less computational effort.

Initial Temperature T_i= 1^{o}C

Final Temperature T_i= 1*10^{-20} ^{o}C

Maximum no. of iterations = 10000

5.2. Simulation Studies and Performance Evaluation

The SA code was developed using MATLAB. The input machining parameter levels were fed to the SA program. Table 5.1 shows the minimum values of surface roughness with respect to input machining parameters SA. It is possible to determine the conditions at which the turning operation has to be carried out in order to get the optimum surface finish. Fig.5.3 shows the Performance of SAA and Fig.5.4 shows the Cooling diagram of SAA. Hence, it can be concluded from the optimization results of the SA program that it is possible to select a combination of cutting speed, feed, depth of cut and nose radius to achieve the better surface finish.

Table 5.1 Output values of simulated annealing algorithms with respect to input machining parameters

Machining Parameters	Method SAA
Feed,F(mm/rev)	0.12722
Depth of cut,D(mm)	1.19947
Cutting Velocity,(m/min)	47.4072
Nose Radius,R(mm)	0.45422
Min. Surface Roughnes,Ra(microns)	$4.94068*10^{-7}$

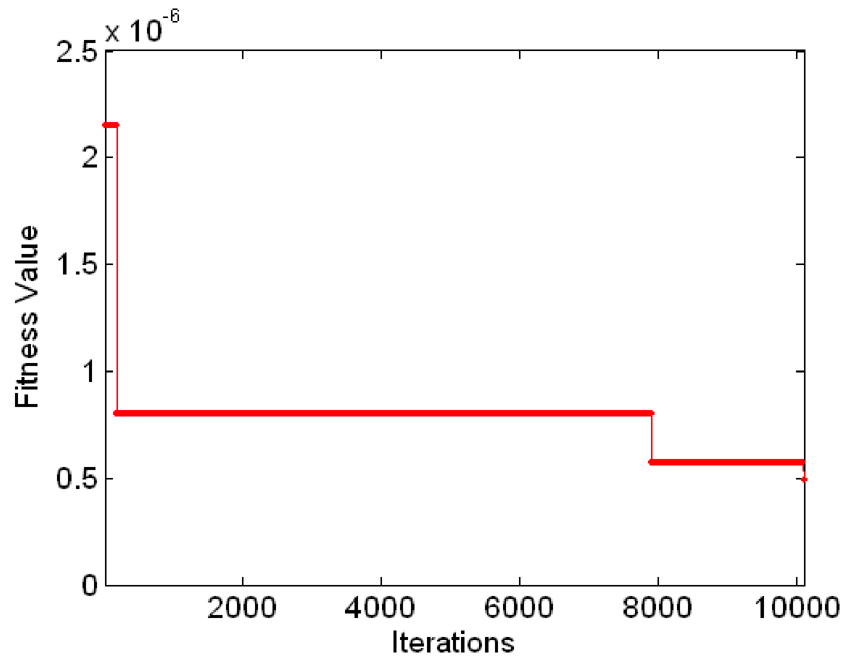


Fig.5.3. Performance of SAA

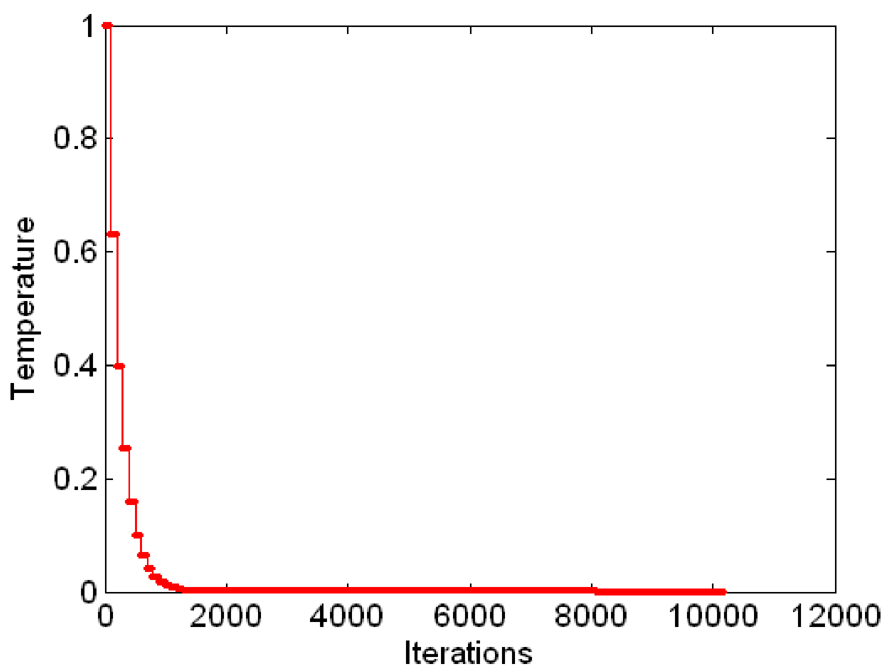


Fig.5.4. Cooling diagram of SAA

5.3. Summary

In this part, the problem of minimizing the surface roughness in turning operation has been investigated. To model the machining process, several important operational constraints have been considered. These constraints were taken into account in order to make the model more realistic. To optimally determine machining parameters (cutting speed, feed rate, depth of cut and tool nose radius), a simulated annealing method has been employed. The computational results clearly demonstrated that the proposed solution procedure is quite capable in solving such complicated problems effectively and efficiently. A major advantage of SA is its flexibility and robustness as a global search method and good performance will be obtained when the size of problem is small. It can deal with highly nonlinear problems and non-differentiable functions as well as functions with multiple local optima. Even though SA gives good result, for better performance different algorithm named PSO is applied, which is discussed in the next chapter.

Chapter 6 - Particle Swarm based machining porcess optimization

Eberhart and Kennedy [92] suggested a particle swarm optimization (PSO) based on the analogy of swarm of bird and school of fish. The PSO mimics the behavior of individuals in a swarm to maximize the survival of the species. In PSO, each individual makes his decision using his own experience together with other individuals' experiences [93]. The algorithm, which is based on a metaphor of social interaction, searches a space by adjusting the trajectories of moving points in a multidimensional space. The individual particles are drawn stochastically toward the position of present velocity of each individual, their own previous best performance, and the best previous performance of their neighbors [94]. The main advantages of the PSO algorithm are summarized as: simple concept, easy implementation, robustness to control parameters, and computational efficiency when compared with mathematical algorithm and other heuristic optimization techniques.

PSO have been successfully applied to various fields of power system optimization [95], reactive power and voltage control [96, 97, 98, 99]. The original PSO mechanism is directly applicable to the problems with continuous domain and without any constraints. Therefore, it is necessary to revise the original PSO to reflect the equality/inequality constraints of the variables in the process of modifying each individual's search. Yoshida et al. [100] suggested a modified PSO to control reactive power and voltage considering voltage security assessment. Since the problem was a mixed-integer nonlinear optimization problem with inequality constraints, they applied the classical penalty method to reflect the constraint- violating variables. Abido [94] developed a revised PSO for determining the optimal values of lag-lead design parameters of multi-machine power system stabilizers. In this study, the velocity of each parameter is limited to a certain value to reflect the inequality constraint problem in the dynamic process.

6.1. PSO in Machining Parameter Optimization

Particle Swarm Intelligent technique combines social psychology principles in socio-cognition human agents and evolutionary computations. PSO has been motivated by the behavior of organisms, such as fish schooling and bird flocking. Generally, PSO is characterized as a simple concept, easy to implement, and computationally efficient. Unlike the other heuristic techniques, PSO has a flexible and well-balanced mechanism to enhance the global and local exploration abilities. Thus, a PSO algorithm can be employed to solve an optimization problem.

The PSO coding scheme is to be defined and the initial population is produced. The computation with particle swarm intelligent operators is used to evaluate fitness with respect to the objective function. Fig 6.1 shows the PSO based optimization procedure.

The Swarm Intelligent is designed for optimization of four inputs, the feed (F), speed (V) depth of cut (D) and tool nose radius (R) and surface roughness (Ra) as output.

Accordingly in the proposed approach each particle (agent) represents a possible solution to the optimization task at hand. Initially a random set of 20 population is created for the particles to be optimized (i.e. feed, speed, depth of cut and nose radius). Each particle accelerates in the direction of its own personal best solution found so far during each iteration cycle, as well as in the direction of the global best position discovered so far by any of the particles in the swarm. If a particle discovers a promising new solution, all the other particles will move closer to it, exploring the region more thoroughly in the process. From this grouped population equal numbers of new populations are generated.

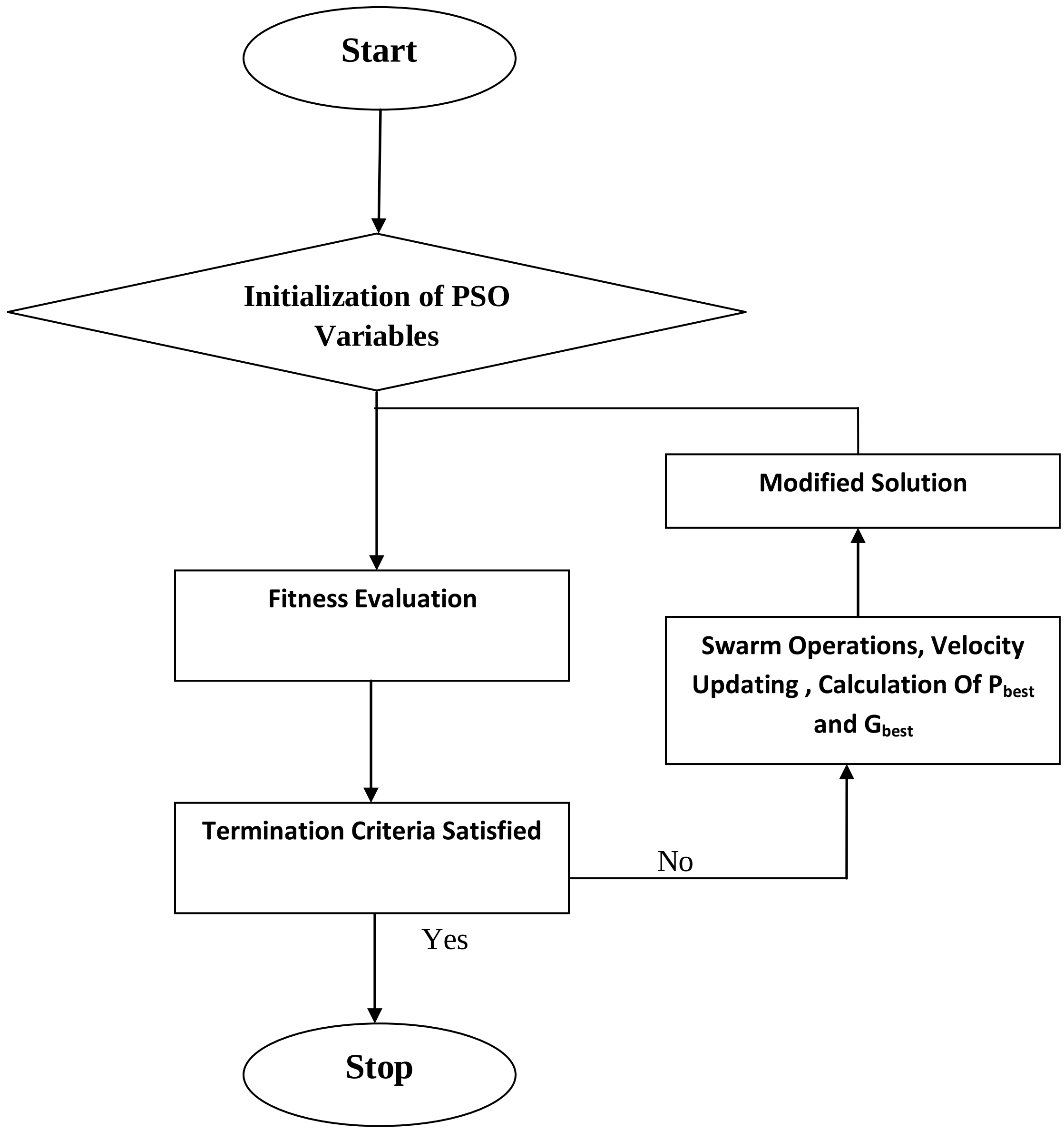


Fig. 6.1 PSO Optimisation Algorithm

6.2. Swarm Intelligent Optimization

From a view of social cognition, each individual in PSO can benefit from both its own experience and group findings. In its theoretical base, some factors [101,102] are included: i) evaluation of stimulation; ii) influence to its behavior hereafter by its own experience; iii) influence to its behavior by other particles' experience. The principle of PSO algorithm is as follows [103]. Let X and V denote the particle's position and its corresponding velocity in search space respectively. The PSO algorithm models the exploration of a problem space by a population of individuals; individual's successes influence their searches and those of their peers.

The PSO algorithm searches in parallel using a group of individuals similar to other AI-based heuristic optimization techniques. An individual in a swarm approaches to the optimum or a quasi-optimum through its present velocity, previous experience, and the experience of its neighbors. In a physical n-dimensional search space, the position and velocity of individual i are represented as the vectors $X_i=(x_{i1},\ldots\ldots x_{in})$,and $V_i=(v_{i1},\ldots\ldots v_{in})$, respectively, in the PSO algorithm. Let $Pbest_i = (x_{i1}^{Pbest}, \ldots\ldots, x_{in}^{Pbest})$ and $Gbest_i = (x_{i1}^{Gbest}, \ldots\ldots, x_{in}^{Gbest})$, respectively, be the best position of individual and its neighbors' best position so far. Using the information, the updated velocity of individual i is modified under the following equation in the PSO algorithm:

$$V_{k+1}^{i} = wV_k^i + c_1 rand_1 * (P_k^{besti} - X_k^i) + c_2 rand_2 * (G_k^{best} - X_k^i) \tag{6.1}$$

where

V_k^i : velocity of individual at iteration ;

w : weight parameter;

c_1, c_2 : weight factors;

$rand_1$, $rand_2$: random numbers between 0 and 1;

X_k^i : Position of individual at iteration k;

P_k^{besti} : Best position of individual until iteration k;

G_k^{besti} or P_k^g : Best position of the group until iteration k .

The steps involved in PSO algorithms are:

1. Initialize an array of particles with random positions and velocities on D dimensions (parameters to be optimized i.e F,D,V,R).

   Set constants k_{max}, C_1, C_2.

   Initialize particle position X_0^i $$X_0^i = X_{min} + rand(X_{max} - X_{min}) \quad (6.2)$$

   Initialize particle velocity V_0^i

   $$V_0^i = X_{min} + rand(X_{max} - X_{min}) \quad (6.3)$$

   Set k=1

2. Evaluate the desired minimization function (F_k^i).

   (a) $$If \quad F_k^i \le F_{best}^i \quad then \quad F_{best}^i = F_k^i, P_k^i = X_k^i \quad (6.4)$$

   (b) $$If \quad F_k^i \le F_{best}^g \quad then \quad F_{best}^g = F_k^i, P_k^g = X_k^i \quad (6.5)$$

   (c) If stopping condition is satisfied then go to 3.

3. Update particle velocities V_{k+1}^i

$$V_{k+1}^i = wV_k^i + c_1 rand_1 * (P_k^{besti} - X_k^i) + c_2 rand_2 * (G_k^{best} - X_k^i) \quad (6.6)$$

4. Update particle positions X_{k+1}^i

$$X_{k+1}^i = X_k^i + V_{k+1}^i \quad (6.7)$$

5. Evaluate the objective function (F_k^i).

(a) $If \quad F_k^i \le F_{best}^i \quad then \quad F_{best}^i = F_k^i, P_k^i = X_k^i$ (6.8)

(b) $If \quad F_k^i \le F_{best}^g \quad then \quad F_{best}^g = F_k^i, P_k^g = X_k^i$ (6.9)

(c) If stopping condition is satisfied then go to 7, otherwise go to 5.

6. Increment K

7. Go to next iteration.

8. Terminate.

The search mechanism of the PSO using the modified velocity and position of individual based on (6.2), (6.3) ,(6.6) and (6.7) is illustrated in Fig. 6.2.

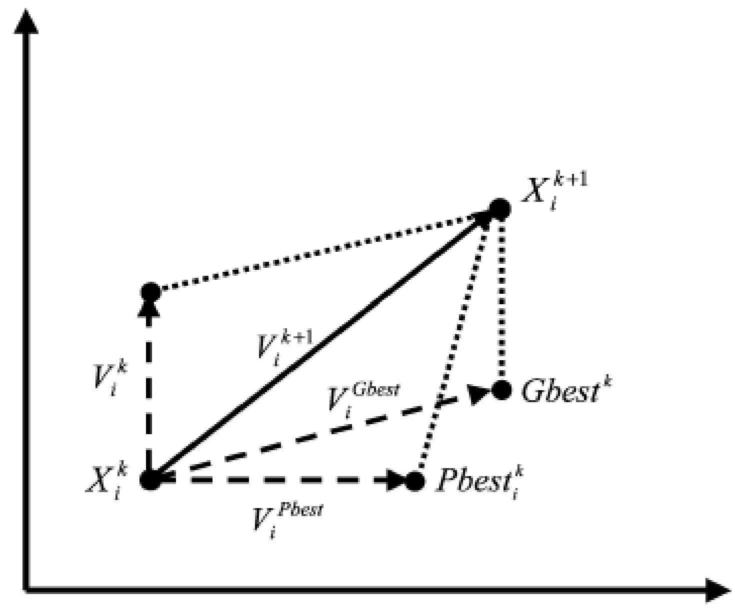


Fig. 6.2 The search mechanism of the particle swarm optimization.

(X and Y axis represents direction of motion of particle)

Stopping criteria

There are many number of stopping criteria reported such as Maximum number of functional evaluation, Convergence criteria, computation time etc. In this work, Maximum number of functional evaluations has been used as stopping criteria. The detailed flow chart of the proposed PSO design is shown in Fig. 6.3.

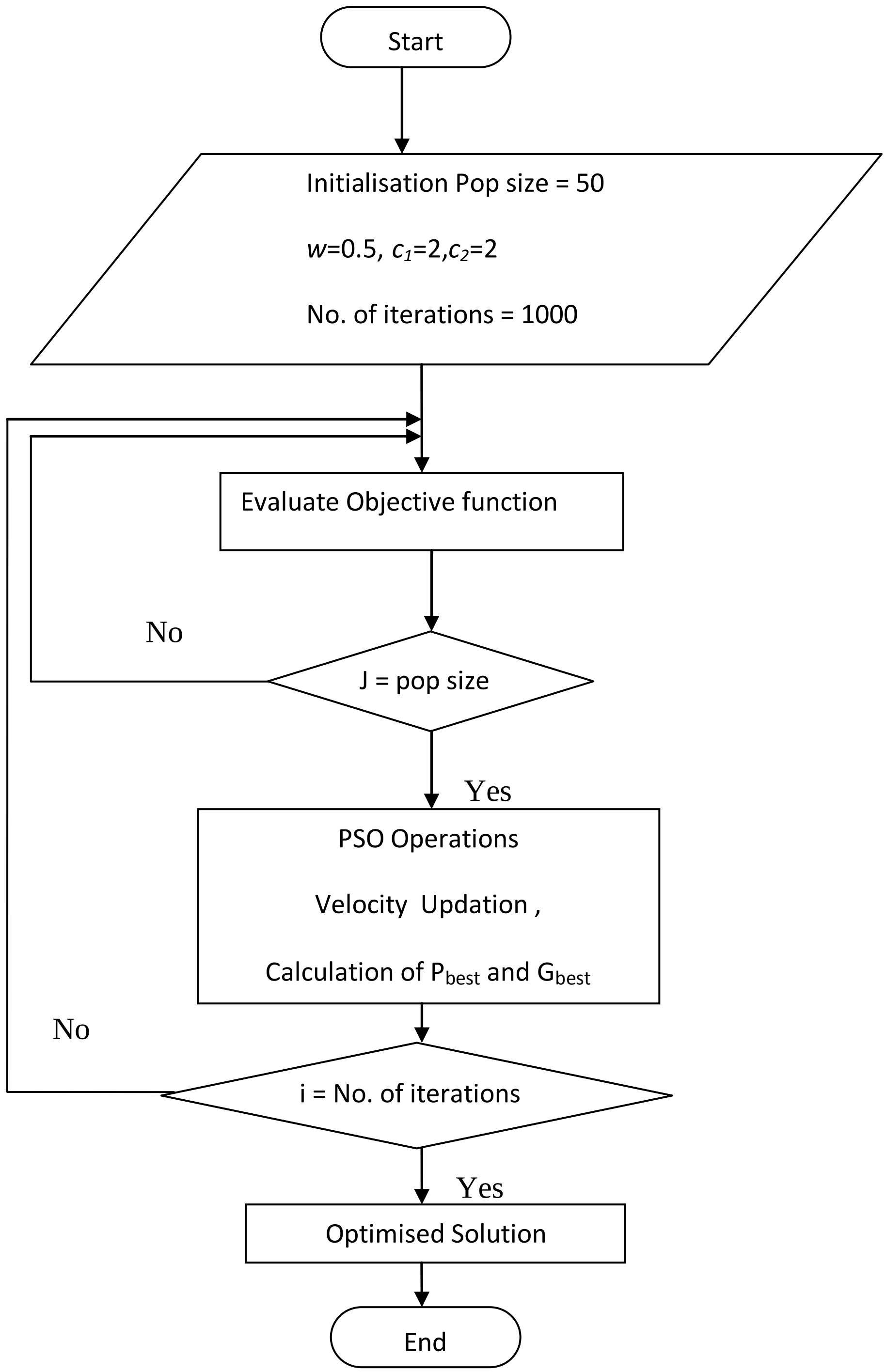


Fig 6.3. Flowchart of the PSO design.

In order to optimize the present problem using PSO, the following parameters have been selected to obtain optimal solutions with less computational effort.

- No.of iterations-1000
- c_1=2
- c_2=2
- w=0.5

From the observed data for surface roughness, the response function has been determined using RSM and fitness function , defined as Minimize,

$$R_a = -4.89 + 2.49F - 38.0D + 0.599V + 3.27R - 5.38F*D + 0.0140F*V - 18.2F*R + \\ 0.0097D*V + 15.8D*R - 0.232V*R + 80.5F^2 + 16.5D^2 - 0.00318V^2 \tag{6.10}$$

subject to

$39.269 \text{ m/min} \leq V \leq 94.247 \text{ m/min}$

$0.059 \text{ mm/rev} \leq F \leq 0.26 \text{ mm/rev}$

$0.4 \text{ mm} \leq D \leq 1.2 \text{ mm}$

$0.4\text{mm} \leq R \leq 1.2\text{mm}$

6.3. Simulation Studies and Performance Evaluation

The PSO code was developed using MATLAB. The input machining parameter levels were fed to the PSO program. It is possible to determine the conditions at which the turning operation has to be carried out in order to get the optimum surface finish. The fitness evaluation is described in figure 6.4. Table 6.1 shows the performance of surface roughness with respect to input machining parameters for PSO.

Table 6.1. Output values of the PSO with respect to input machining parameters

Machining Parameters	Method PSO
Feed,F(mm/rev)	0.127395
Depth of cut,D(mm)	0.718475
Cutting Velocity,(m/min)	43.8783
Nose Radius,R(mm)	0.941211
Min. Surface Roughnes,Ra(microns)	$1.9938*10^{-7}$

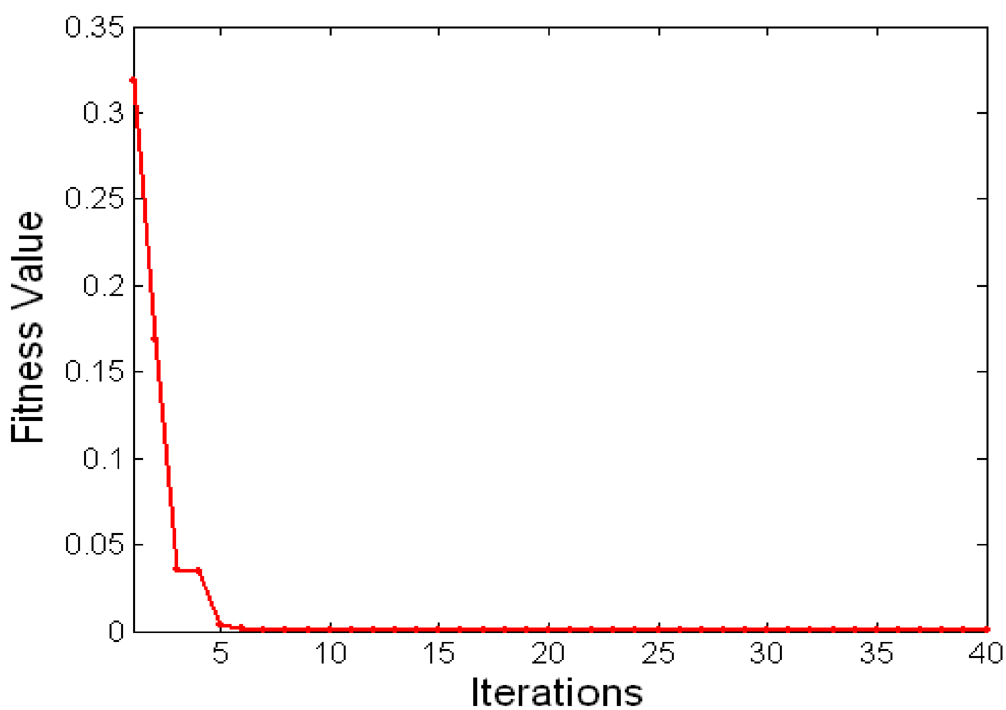


Fig.6.4. Performance of PSO

6.4. Summary

Based on this PSO algorithm the following conclusions may be drawn from the optimization results of the PSO program. Particle Swarm Optimization (PSO) is a relatively recent heuristic search method whose mechanics are inspired by the swarming or collaborative behavior of biological populations. PSO is more computationally efficient (uses less number of function evaluations).The basic PSO algorithm consists of three steps, namely, generating particles' positions and velocities, velocity update, and finally, position update. Here, a particle refers to a point in the design space namely feed, speed, depth of cut and nose radius, that changes its position from one move (iteration) to another based on velocity updates. Even though PSO gives better result than SA, for improving the output results different algorithms named CGA and IGA is applied, which is discussed in the coming chapter.

Chapter 7 - Genetic algorithm based optimization of machining process

GA is a search algorithm based on the hypothesis of natural selections and natural genetics also the GA is a parallel and global search technique that emulates natural genetic operations [104]. GA can find a global solution after sufficient iterations, but has a high computational burden. Recently, a global optimization technique using GA has been successfully applied to various areas of power system such as economic dispatch [105,106], unit commitment [107,108], reactive power planning [109-111], and power plant control [112,113]. GA-based approaches for optimization of machining parameters have several advantages. Naturally, they can not only treat the discrete variables but also overcome the dimensionality problem. In addition, they have the capability to search for the global optimum or quasi optimums within a reasonable computation time. To enhance GA's computational efficiency, an improved evolutionary direction operator (IEDO) modified from [114] and a migration operator [115] are embedded in GA to form the IGA. On the contrary, studies on evolutionary algorithms have shown that these methods can be efficiently used to eliminate most of the above-mentioned difficulties of classical methods [116]. The selection of optimal cutting parameters, like depth of cut, feed and speed, is a very important issue for every machining process. In workshop practice, cutting parameters are selected from machining databases or specialized handbooks, but the range given in these sources are actually starting values, and are not the optimal values [106]. In any optimization procedure, it is a crucial aspect to identify the output of chief importance, the so-called optimization objective or optimization criterion.

In this section, an improved genetic algorithm (IGA), which can overcome the aforesaid problems of the conventional GA to some extent, is developed to obtain the optimal parameters in turning processes. The proposed IGA incorporates the following two main features. First, an artificial creation scheme for an initial population is devised, which also takes the random creation scheme of the conventional GA into account. Second, a stochastic crossover strategy is developed. In this scheme, one of the three different crossover methods is randomly selected from a biased roulette wheel where the weight of each crossover method is determined through pre-performed experiments. The stochastic crossover scheme is similar to the stochastic selection of reproduction candidates from a mating pool. The IGA requires only a small population, and it is more efficient than GA. The results of the IGA are compared with those of the conventional simple genetic algorithm.

Genetic algorithms are very different from most of the traditional optimization methods. Genetic algorithms need design space to be converted into genetic space. So, genetic algorithms work with a coding of variables. The advantage of working with a coding of variable space is that coding discretizes the search space even though the function may be continuous. A more striking difference between genetic algorithms and most of the traditional optimization methods is that GA uses a population of points at one time in contrast to the single point approach by traditional optimization methods. This means that GA processes a number of designs at the same time. As we have seen earlier, to improve the search direction in traditional optimization methods, transition rules are used and they are deterministic in nature but GA uses randomized operators. Random operators improve the search space in an adaptive manner.

Three most important aspects of using GA are:

1. definition of objective function
2. definition and implementation of genetic representation
3. definition and implementation of genetic operators.

Once these three have been defined, the GA should work fairy well beyond doubt. We can, by different variations, improve the performance, find multiple optima (species if they exist) or parallelize the algorithms.

Genetic algorithms are computerized search and optimization algorithms based on the mechanics of natural genetics and natural selection: Prof. Holland of University of Michigan, Ann Arbor, envisaged the concept of these algorithms in the mid-sixties and published his work [117].

Thereafter, a number of students and other researchers have contributed to the development of this field.

To date, most of the GA studies are available by Davis [118], Goldberg [119], Michalewicz [120] and Deb [121] and through a number of conference proceedings. The first application towards structural engineering was carried by Goldberg. He applied genetic algorithms to the optimization of a ten-member plane truss. P. Ju [122] applied genetic algorithm for the design of Static Compensator in an integrated power system. Apart from structural engineering there are many other fields in which GA's have been applied successfully. It includes biology, computer science, image processing and pattern recognition, physical science, social sciences and neural networks. In this chapter, we will discuss the basic concepts, representatives of chromosomes, fitness functions, and genetic inheritance operators with example and how this will be adopted for the power system stability low frequency damping problem.

7.1. Genetic Algorithm Based Optimization

First, coding scheme is to be defined and the initial population is produced. The computation with genetic operators is used to evaluate fitness with respect to the objective function [79]. Fig 7.1 shows the GA based optimization procedure.

The genetic algorithm (GA) has gained momentum in its application to optimization problems. Unlike strict mathematical methods, the GA does not require the condition that the variables in the optimization problem be continuous and different; it only requires that the problem to be solved can be computed. So, the GA has an apparent benefit to adapt to irregular search space of an optimization problem [79]. Therefore, in this approach, the GA has been used for optimization of surface roughness for the machining process. The basic operators in the GA include reproduction, crossover, and mutation. The input gains and output gain are taken as individuals in GA, and are represented by a binary string of length 200 with 50 bit for each individual.

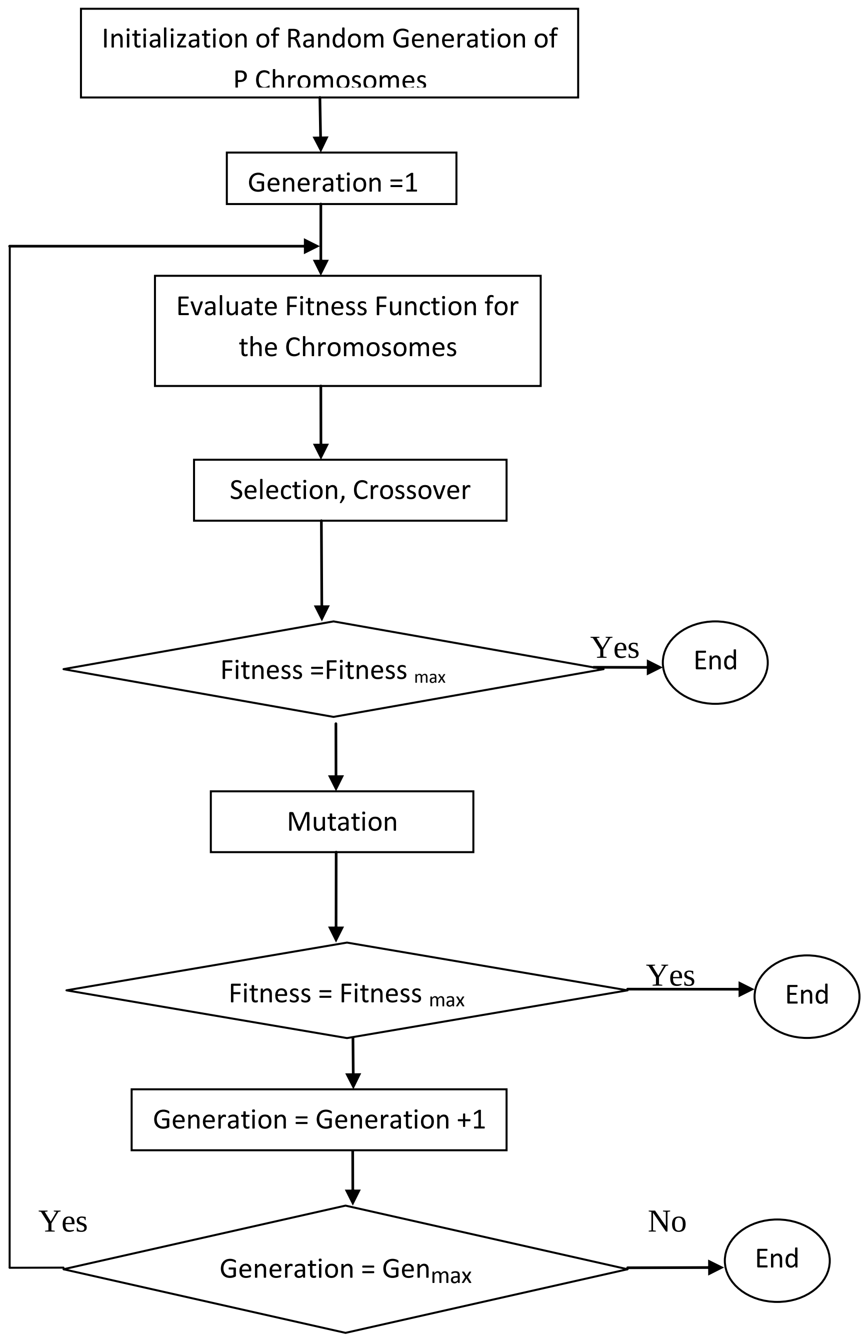


Fig. 7.1. GA Optimisation Algorithm

Steps in Genetic Algorithm

- Create the initial population.
- Evaluate the fitness of each individual.
- Select the best individuals and perform recombination.
- Mutate the new generation.
- If termination condition is not reached, go back to step 2.

The calculation can be terminated for example when a certain fitness level is reached or after a certain number of iterations is performed. Also, if it seems that the solutions will not get any better for a long time, it can be deduced that it is best to stop the calculation.

Selection

The main idea behind the selection mechanism is better individuals get higher chance. There are many methods reported such as Roulette Wheel selection, Stochastic Universal sampling and Tournament selection, etc. In this approach, Tournament selection method which is one of the most widely used selection schemes. In tournament selection a specified number of individuals are selected from the current population size. The best individuals out of the best individuals get copy in a mating pool. The selection of individuals can be performed either with replacement or without replacement. In selection with replacement the individuals selected for the current tournament are candidate for other tournaments. On the other hand, if selected without replacement the individuals once selected are not candidates for other tournaments. Tournament selection can be implemented very efficiently as no sorting of the population is required. The advantages of Tournament selection are No premature convergence, No stagnation, No global reordering is required and explicit fitness is not needed.

Crossover

Crossover is a mechanism, which creates new individuals by combining parts from two individuals. Crossover is explorative; it makes a big jump to an area somewhere “in between” two (parents) areas. Single point, multi point and uniform crossovers are available. In this work, simulated binary crossover (SBX) proposed by Deb and his students has been used. SBX crossover creates children solutions in proportion to the difference in parent solutions.

Mutation

Mutation is a mechanism, which creates new individual by making changes in a single individual. Mutation is explorative, it creates random small deviations, thereby staying near (in the area of) the parent. Only mutation can introduce new information. In this work polynomial mutation has been applied.

Stopping criteria

There are many no of stopping criteria are reported such as Maximum number of generation, Maximum number of functional evaluation, Convergence criteria, computation time etc. In this work, Maximum number of generations has been used as stopping criteria.

In order to optimize the present problem using genetic algorithms (GAs), The fitness function for the surface roughness is taken as the constrained optimization problem is stated as follows:

From the observed data for surface roughness, the response function has been determined using RSM and fitness function , defined as Minimize,

$$R_a = -4.89 + 2.49F - 38.0D + 0.599V + 3.27R - 5.38F*D + 0.0140F*V - 18.2F*R + 0.0097D*V + 15.8D*R - 0.232V*R + 80.5F^2 + 16.5D^2 - 0.00318V^2 \tag{7.1}$$

subject to

39.269 m/min $\leq V \leq$ 94.247 m/min

0.059 mm/rev $\leq F \leq$ 0.26 mm/rev

0.4 mm $\leq D \leq$ 1.2 mm

0.4mm$\leq R \leq$ 1.2mm

$x_{il} \leq x_i \leq x_{iu}$

where x_{il} and x_{iu} are the upper and lower bounds of process variables x_i . x_1, x_2, x_3, x_4 are the cutting speed, feed, depth of cut and nose radius respectively. In order to optimize the present problem using GAs, the following parameters have been selected to obtain optimal solutions with less computational effort.

Population size = 50

Maximum number of generations = 1000

Total string length = 50

Crossover probability (Pc) = 0.9

Mutation probability (Pm) = 0.01

Initially, a set of 50 random pairs of the coefficients are created, discarding the unstable cases. These 50 pairs of coefficients are converted into binary codes to construct the initial population termed as “old pop.” From this grouped population and by using the usual GA operators, equal numbers of new populations are generated. A specific probability of each operator is fixed, keeping the “mutation” probability sufficiently small. The crossover and mutation probabilities are taken as 0.9 and 0.01, respectively [79]. To select two strings of population for either mutation or crossover, the roulette wheel technique is used [79]. The technique specified that for selection, a random number between 0 and 1 is multiplied with the sum of fitness of all the “old pop” strings. When this value is greater than or equal to the cumulative fitness of the i^{th} string, this string is selected from the “old-pop.” In this manner, two strings (mate-1 and mate-2) are selected to the mating pool. Using the GA operators, two new strings (child-1 and child-2) are created out of these mates. This process is continued until 50 new strings of population are generated. Out of the original 50 strings and newly created 50 strings (a total of 100 strings), the most-fit 50 population strings are retained. These strings are replaced into the “old-pop” to represent the second generation “old- pop.” In this manner, 1000 generations are continued, before the algorithm converges into the fit unique solution. The binary data in the solution are decoded to provide the optimized machining parameters. The detailed flow chart is shown in Fig. 7.2.

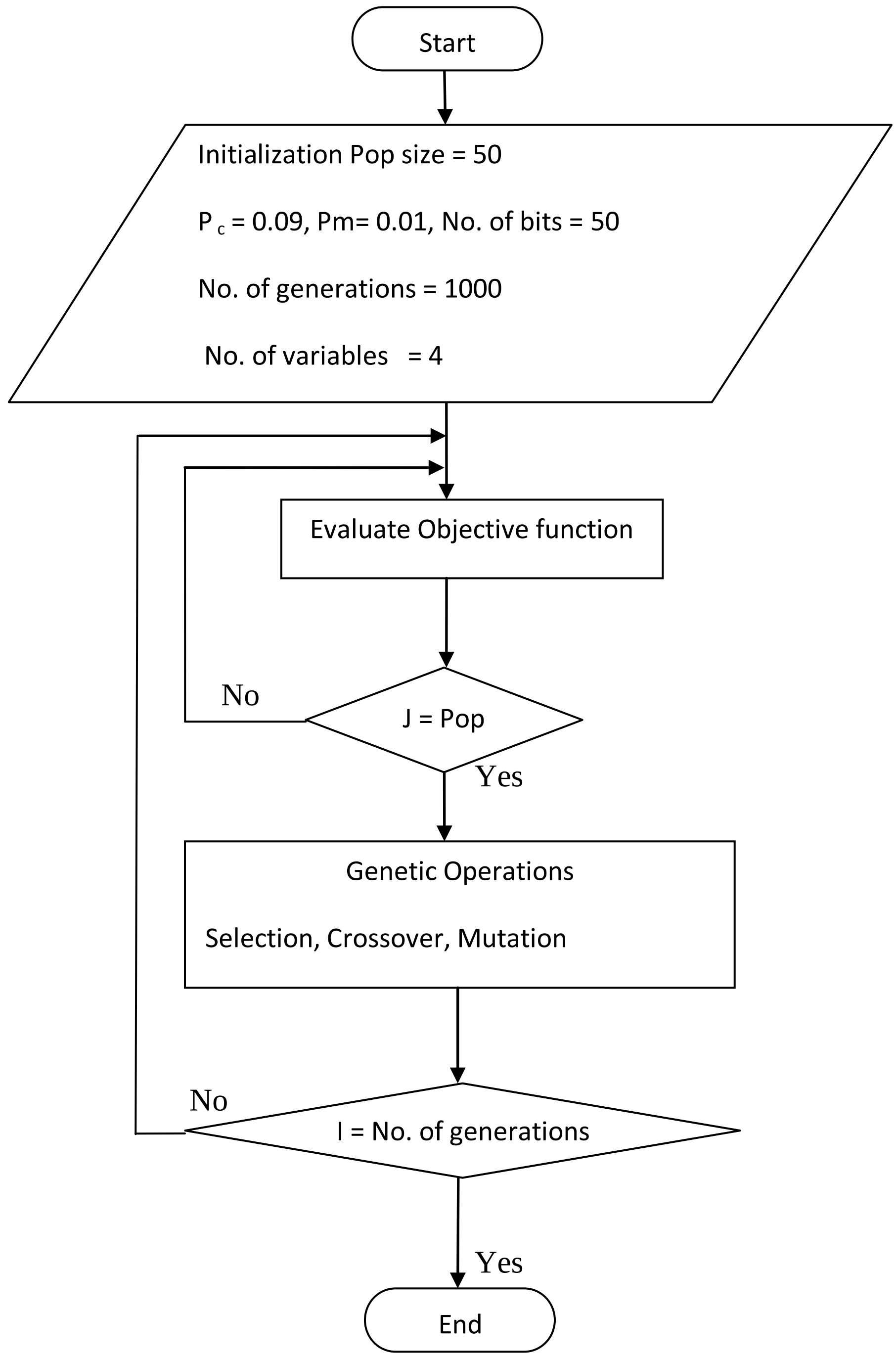


Fig. 7.2. The detailed flow chart of GA Optimisation Algorithm

7.1.1. Simulation Studies and Performance Evaluation

The CGA code was developed using MATLAB. The input machining parameter levels were fed to the CGA program. The CGA program uses different types of crossover and mutation operators to predict the values of tool geometry and cutting conditions for minimization of surface roughness. Table 7.1 shows the minimum value of surface roughness with respect to input machining parameters for CGA. It is possible to determine the conditions at which the turning operation has to be carried out in order to get the optimum surface finish. The genetic evolution history is described in figure 7.3 for CGA. The given problem is converted to a maximization problem and solved using CGA.

Table 7.1 – Output values of the genetic algorithm with respect to input machining parameters

Machining Parameters	CGA Method
Feed,F(mm/rev)	0.161564
Depth of cut,D(mm)	0.583087
Cutting Velocity,V(m/min)	39.985
Nose Radius,R(mm)	0.967974
Min. Surface Roughnes,Ra(microns)	$1.62085*10^{-10}$

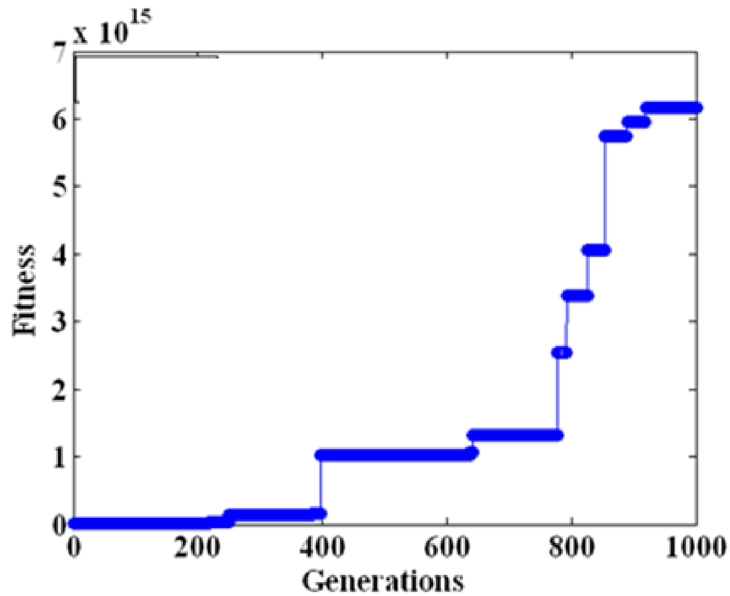


Fig.7.3 Genetic evolution of CGA

7.2. Improved Genetic Algorithm (IGA)

The main advantage of the IGA approach is that the "curse of dimensionality" and a local optimal trap inherent in mathematical programming methods can be simultaneously overcome. This section describes the proposed IGA. First, a brief overview of the IGA is provided then the solution procedures of the proposed IGA are stated.

The IGA is a parallel direct search algorithm that uses N_P vectors of variables in the nonlinear programming problem, namely, $X^G = \{X_i^G, i = 1,........, N_p\}$ as a population in generation G. For convenience, the decision vector (chromosome) x_i, is represented as $(x_{1i}...x_{ji}...x_{n_{ci}})$. Here, the decision variable (gene), x_{ji} is directly coded as a real value within its bounds.

7.2.1. Improved Evolutionary Direction Operator (IEDO)

The main shortcoming of the evolutionary direction operator (EDO) [114] is that it creates a new chromosome from three arbitrary chromosomes in each generation, making this search operator blind. The improvement of the IEDO is to choose three best solutions in each generation to implement the improved evolutionary direction operation, and then obtain a new solution that is superior to the original best solution. The IEDO is introduced below.

A chromosome which carries a set of solutions with n_c optimizing parameters may be expressed as $x_j = \{C_1, C_2, ..., C_P, ..., C_{nc}\}$. Each C_P represents a continuous decision variable, and is limited by its lower and upper bounds (C_P^{MIN} and C_P^{MAX}). Three sets of optimal chromosomes are obtained after a generation. These three preferred chromosomes are ascended according to their fitness and called the "low," "medium," and "high" chromosomes, respectively.

Three inputs (preferred) and the output (created) chromosomes are denoted below.

Inputs:

"low" chromosome, $z_l = \{C_{l1}, C_{l2}, ...C_{in_C}\}$, with Fitness F_l

"medium" chromosome, $z_m = \{C_{m1}, C_{m2}, ..., C_{mnc}\},$, with fitness F_m

"high" chromosome, $z_h = \{C_{h1}, C_{h2}, ..., C_{hnc}\},$ with fitness F_h

Output chromosome, $\{C_{o1}, C_{o2}, ..., C_{on_C}\}$, with fitness, F_{new}

The IEDO can significantly reduce the effort in searching for the optimal solution because it enhances the local searching capability for GA. Fig. 7.4 shows the flowchart of the minimum optimization for IEDO.

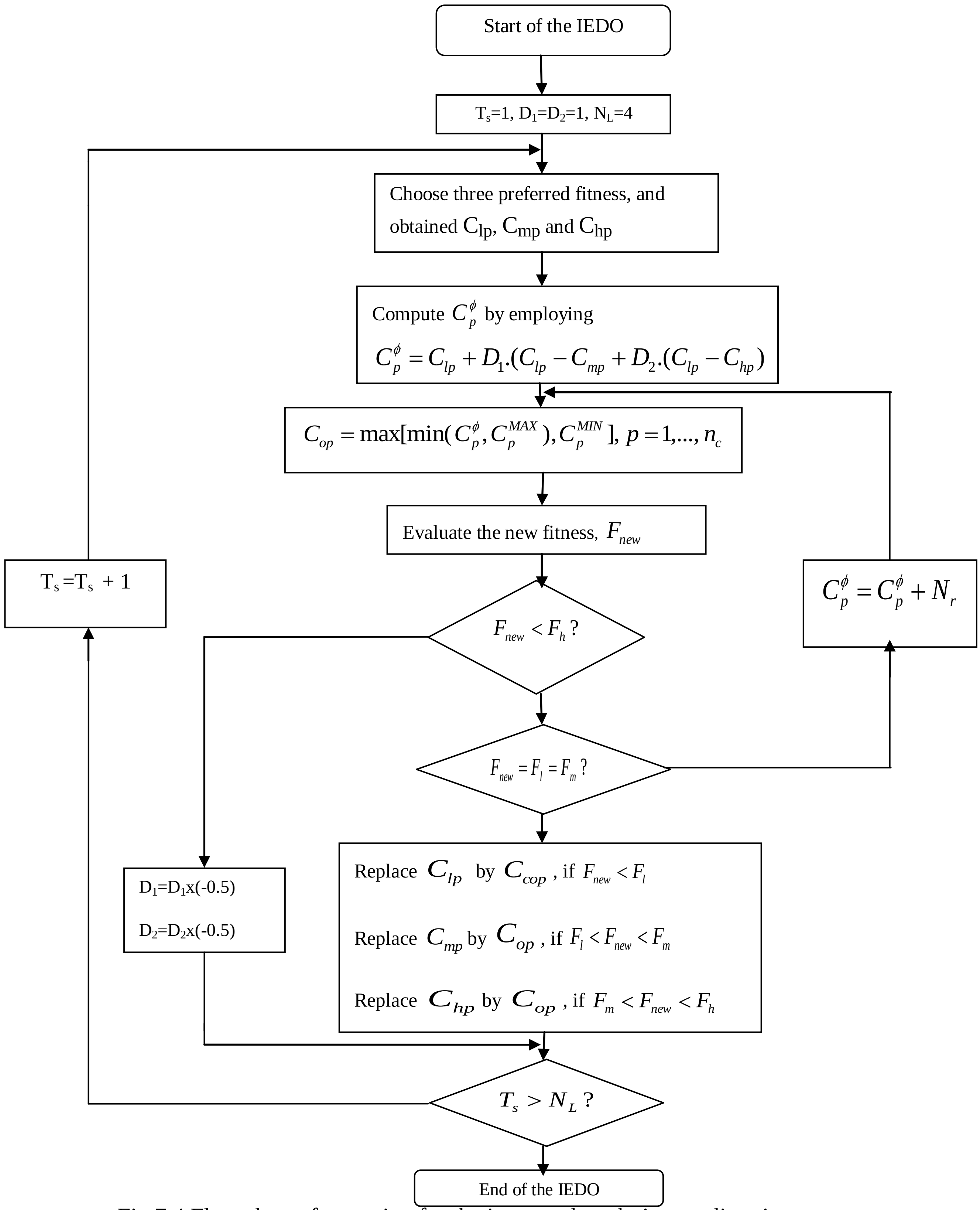


Fig.7.4 Flow chart of operation for the improved evolutionary direction operator

Step 1. The magnitudes of the two evolution directions is set to 1 (i.e., $D_1 = 1$, $D_2 = 1$). Then, set the initial index of the IEDO to 1 ($T_s = 1$), and set the number of the IEDO loop to 4 (i.e., $N_L = 4$).

Step 2. Choose three preferred fitness values (F_l ,F_m and F_h) and find their associated chromosomes (Z_l,Z_m and Z_h). Then, obtain three preferred decision variables (Clp , Cmp , and Chp , p = 1; . . . ; nc) from these three preferred chromosomes.

Step 3. Compute C_p^{ϕ} by $C_p^{\phi} = C_{lp} + D_1.(C_{lp} - C_{mp} + D_2.(C_{lp} - C_{hp})$

Starting from the base point C_{lp} and using two difference vectors, $D_1.(C_{lp} - C_{mp})$ and $D_2.(C_{lp} - C_{hp})$, the next evolutionary direction and the next evolutionary step-size can be determined by this parallelogram. The point C_p^{ϕ} can be then created along the evolutionary direction with the evolutionary step-size.

Step 4. $C_{op} = \max[\min(C_p^{\phi}, C_p^{MAX}), C_p^{MIN}], p = 1,..., n_c.$.The value of C_{op} must be kept within its set bounds.

Step 5. Evaluate the new fitness (F_{new}) of the newly created output chromosome.

Step 6. If $F_{new} < F_h$,then go to next step; otherwise, go to Step 8.

Step 7. If $F_{new} = F_l = F_m$, add a random number $(N_r \in [0,1])$ to C_p^{ϕ} and go to Step 4, then recomputed F_{new} ; otherwise, go to Step 9.

A random number is added to prevent the algorithm from falling into a local optimum.

Step 8. Let $D_1=D_1*(-0.5)$, $D_2=D_2*(-0.5)$, then go to Step 10.

Use the opposite direction and reduce the half step-size to search the new solution.

Step 9. Replace C_{lp} by C_{cop}, if $F_{new} < F_l$,Replace C_{mp} by C_{op} , if $F_l < F_{new} < F_m$ Replace C_{hp} by C_{op} , if $F_m < F_{new} < F_h$, and go to Step 10.

To search a minimum extreme, use three cases of replacements mentioned above to choose the best three individuals, given as Z_l, Z_m and Z_h for the IEDO operation.

Step 10. If the last iterative loop of the IEDO is reached, then go to Step 11; otherwise, $T_s = T_s + 1$, and go to Step 2.

Step 11. Terminate the IEDO operation.

7.2.2. Reproduction, Crossover, and Mutation

Three preferred individuals generated by the IEDO are selected for reproduction. Reproduction probabilities of the three chosen individuals are set as follows: the first preferred unit 35%; the second preferred unit 25%, and the third preferred unit 15%. The remainder 25% of population is generated using the randomly created feasible individual. A binomial mutual crossover is adopted to raise the local diversity of individuals. For a small population (e.g. $N_P = 50$), the crossover probability is set to 0.9 which is enough to create new individuals and to avoid high diversity resulting in divergence of the population. The purpose of mutation is to introduce a slight perturbation to increase the diversity of trial individuals after crossover, preventing trial individuals from clustering and causing premature convergence of solution. The probability of mutation is set to 0.01.

7.2.3. Migration

A migration is included in the IGA to regenerate a newly diverse population, which prevents individuals from gradually clustering and thus greatly increases the amount of search space explored for a small population. The migrant individuals are generated based on the best ind ividual, $x_b^{G+1} = (x_{1b}^{G+1}, x_{2b}^{G+1}, ..., x_{n_C b}^{G+1})$ by non- uniformly random choice. Genes of the i^{th} individual are regenerated according to

$$x_{ki}^{G+1} = \begin{cases} x_{kb}^{G+1} + \rho(x_K^L - x_{kb}^{G+1}), \\ x_{kb}^{G+1} + \rho(x_k^U - x_{kb}^{G+1}), \end{cases} \quad \text{if} \quad r_1 < \frac{x_{kb}^{G+1} - x_k^L}{x_k^U - x_k^L} \tag{7.2}$$

Where $k = 1,..., n_C; i = 1,..., N_P, r_{1,}$ and ρ are random numbers in the range of [0,1]. The migration may be performed if only the best fitness has not been improved for over 500 generations running, and the migrant population will not only become a set of newly promising solutions but also easily escape the local extreme value trap.

The procedure used in the optimization using improved genetic algorithm is shown in Fig.7.5. The problem of optimization of the turning process can be described as minimizing the surface roughness subject to a set of constraints as shown in equation (7.3).

In order to optimize the present problem using improved genetic algorithms (IGAs), the constrained optimization problem is stated as follows:

From the observed data for surface roughness, the response function has been determined using RSM and fitness function, defined as

Minimize,

$$R_a = -4.89 + 2.49F - 38.0D + 0.599V + 3.27R - 5.38F*D + 0.0140F*V - 18.2F*R +$$

$$0.0097D*V + 15.8D*R - 0.232V*R + 80.5F^2 + 16.5D^2 - 0.00318V^2 \tag{7.3}$$

subject to

39.269 m/min $\leq V \leq$ 94.247 m/min

0.059 mm/rev $\leq F \leq$ 0.26 mm/rev

0.4 mm $\leq D \leq$ 1.2 mm

0.4mm$\leq R \leq$ 1.2mm

$xil \leq xi \leq xiu$

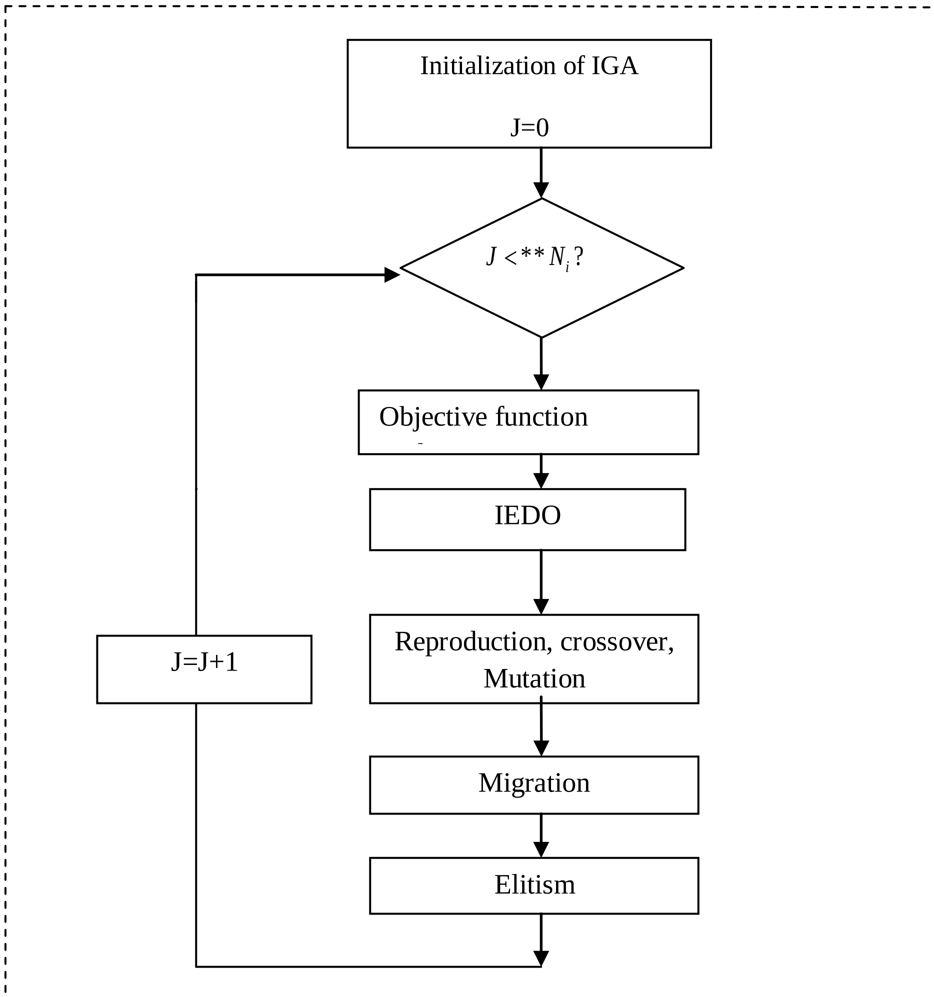
where xil and xiu are the upper and lower bounds of process variables xi . $x1$, $x2$, $x3$, $x4$ are the cutting speed, feed, depth of cut and nose radius respectively. In order to optimize the present problem using IGAs, the following parameters have been selected to obtain optimal solutions with less computational effort.

Maximum number of generations = 1000

Total string length = 50

Crossover probability (Pc) = 0.9

Mutation probability (Pm) = 0.01



**N_i: Maximum number of iterations of inner loop

Fig.7.5 Flowchart of the Improved Genetic Algorithm (IGA)

7.3. Simulation Studies and Performance Evaluation

The possibility of a SS 420 machining optimization procedure using genetic algorithm is investigated in this work. The optimisation based on genetic algorithm has proved to be very useful in dealing with discrete variables defined on a population of cutting condition obtained from the experiment. The search for the optimum was based on the minimization of an objective function. It was found that the GA can be a powerful tool in experimental machining optimization of scientific interest and large industrial applications. However, the optimization by GA technique requires a good setting of its own parameters, such as population size, number of generations, etc.

An improved evolutionary direction operator (IEDO) is embedded in GA to form the IGA so as to enhance GA's computational efficiency. The IEDO can significantly reduce the effort in searching for the optimal solution because it enhances the local searching capability for GA. IGA is the algorithm based on mechanics of natural selection and natural genetics, which are more robust and more likely to locate global optimum and a local optimal trap inherent in mathematical programming methods can be overcome. The IGA code was developed using MATLAB. The genetic evolution histories are described in figure 7.6 for IGA and table 7.2 shows the minimum values of surface roughness with respect to input machining parameters.

Moreover, the proposed IGA approach has the following merits: simple concept; easy implementation; greater effectiveness than previous methods; better efficiency than the conventional genetic algorithm (CGA); robustness of algorithm; applicable to the larger-scale system; and the requirement for only a small population to prevent the dimensionality problem. The comparative results demonstrate that the proposed algorithm has the advantages mentioned above for solving the optimization problem.

7.4. Summary

Both CGA and IGA is applied for the optimization of machining problem. The proposed IGA provides better solutions than the conventional GA. The improved genetic algorithm incorporating a stochastic crossover technique and an artificial initial population scheme is developed to provide a faster search mechanism. The main advantage of the IGA approach is that the "curse of dimensionality" and a local optimal trap inherent in mathematical programming methods can be simultaneously overcome. The IGA equipped with an improved evolutionary direction operator and a migration operation can efficiently search and actively explore solutions.

Moreover, by incorporating all the improvements, it was found to be robust in providing optimum solution within a reasonable computation time and yield better solutions. Contrary to the dynamic programming, computation time of the proposed IGA is linearly proportional to the number of stages.

Table 7.2 – Output values of Improved genetic algorithm with respect to input machining parameters

Machining Parameters	Method IGA
Feed,F(mm/rev)	0.0755067
Depth of cut,D(mm)	0.564062
Cutting Velocity,V(m/min)	42.7725
Nose Radius,R(mm)	0.649459
Min. Surface Roughnes,Ra(microns)	$4.88498 * 10^{-14}$

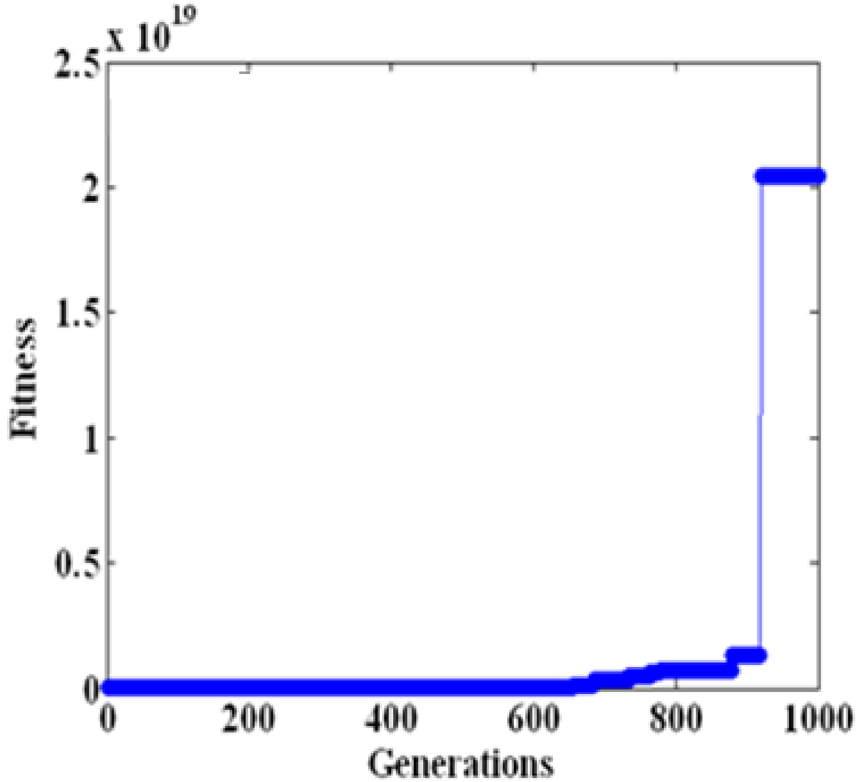


Fig.7.6 Genetic evolution of IGA

Chapter 8 – Results and Discussion

Determination of optimal cutting parameters is one of the most important elements in any process planning of metal parts. This work presents a development of an improved genetic algorithm (IGA) and its application to optimize the cutting parameters for predicting the surface roughness is proposed.

Before that experimentation is done and statistical analysis such as S/N and ANOVA has been performed. Mathematical model is developed using RSM and which has been applied in further analysis.

The SA, PSO, CGA and IGA codes were developed using MATLAB. The input machining parameter levels were fed to the respective programs. Each program used their own specific types of operators to predict the optimized values of tool geometry and cutting conditions for minimization of surface roughness. Table 8.1 shows the comparison of minimum values of surface roughness with respect to input machining parameters for SA, PSO, CGA and IGA. It is possible to determine the conditions at which the turning operation should be carried out in order to get the optimum surface finish. Hence, it can be concluded from the optimization results of each program that it is possible to select a proper combination of cutting speed, feed, depth of cut and nose radius to achieve better surface finish.

Table 8.1. Comparison of Results

Parameter	Evolutionary Methods			
	Simulated Annealing (SA)	Particle Swarm Optimization (PSO)	Genetic Algorithm (GA)	Improved genetic Algorithm (IGA)
Feed(mm/rev)	0.12722	0.127395	0.161564	0.0755067
Depth of cut (mm)	1.19947	0.718475	0.583087	0.564062
Speed (mm/min)	47.4072	43.8783	39.985	42.7725
Nose radius (mm)	0.45422	0.941211	0.967974	0.649459
Surface roughness, Ra (micro meter)	$4.94068*10^{-7}$	$1.9938*10^{-7}$	$1.62085*10^{-10}$	$4.88498* 10^{-14}$

Table 8.1 shows the comparison of surface roughness values obtained by the various evolutionary methods investigated in this work. From the results it can be observed that SA and PSO give almost the same values for the surface roughness. GA method gives a better value for Ra than SA and PSO. Out of the different methods analyzed IGA method has been observed to give the best results.

It appears that IGA outperforms the CGA, PSO and SA with a larger differential in computational efficiency when used to solve constrained nonlinear problems with continuous or discrete design variables.

8.1 Validation of Evolutionary Algorithms

The algorithms has been validated with the experimental results and mathematical model developed of Paulo Davim. J [123] and Ersan Aslan , Necip Camuscu , Burak Birgo¨ren [124].

The surface roughness obtained in IGA method is minimum than CGA is shown in table 8.2, which shows that the proposed IGA method will yield reasonably good result and it can be applied to any process.

Table 8.2 Validation of the algorithms

Paulo Davim. J,2003,[123]		
Parameter	Genetic Algorithm (GA)	Improved genetic Algorithm (IGA)
Feed(mm/rev)	0.0555742	0.0628178
Time(sec)	1.59365	1.42633
Velcity (mm/min)	472.427	482.971
Surface roughness, Ra (micro meter)	$1.22621*10^{-9}$	$1.9762*10^{-13}$
Ersan Aslan , Necip Camuscu , Burak Birgo¨ren,2007[124]		
Feed(mm/rev)	0.129632	0.105255
Depth of cut(mm)	0.564215	0.742634
Velocity (mm/min)	197.201	222.167
Surface roughness, Ra (micro meter)	$1.0125*10^{-8}$	$2.93043*10^{-12}$

Chapter 9 - Conclusions

Based on the experimental results, S/N and ANOVA analysis performed, RSM based mathematical model developed and application of evolutionary algorithms such as SA, PSO, CGA and IGA for the optimization of machining of SS 420, the following conclusions have been arrived to obtain optimal machining parameter to achieve better surface finish characteristics during turning:

The surface roughness in the turning process has been measured for machining of SS 420 under different cutting conditions with a rhombic tooling system having uncoated tungsten carbide tool using Taguchi's orthogonal array. Comparison of the experimental and analytical results has been carried out.

By incorporating the tool geometry in the model, the validity of the model has been enhanced.

The accuracy of mathematical model developed using response surface methodology shows the effectiveness of the model.

The optimization, carried out in this work, gives an opportunity for the user to select the best tool geometry and cutting condition so as to get the optimum surface quality.

The proposed IGA includes several improvements such as the incorporation of an artificial initial population scheme, a stochastic crossover technique, elitism and scaled fitness function. The IGA has been successfully applied to machining problems. It provided better solutions than the conventional GA.

Moreover, by incorporating all the improvements, it was found to be robust in providing quasi-optimum within a reasonable computation time and yield better solutions. Contrary to the dynamic programming, computation time of the proposed IGA is linearly proportional to the number of stages. The developed IGA method can simultaneously overcome the "curse of dimensionality" and a local optimum trap inherent non -linear problem. The IGA helps the proposed algorithm to efficiently search and actively explore the solution. Therefore, the proposed IGA approach can be used as a practical planning tool for a real problem like machining process. Moreover, the proposed approach has the following merits: simple concept; easy implementation; better effectiveness than previous methods; better efficiency than the CGA. This research presents an improved genetic algorithm optimization approach for solving the machining operations problem with turning of SS 420. The results obtained from comparing the proposed genetic algorithm optimization approach with those taken from recent literature prove its effectiveness. The results of the proposed approach are compared with results of simulated annealing, particle swarm optimization and conventional genetic algorithm. The implication of the encouraging results obtained from the present approach is that such approach can be integrated on-line, with an intelligent manufacturing system for automated process planning. Since the genetic algorithm-based approach can obtain near-optimal solution, it can be used for machining parameter selection of complex machined parts that require many machining constraints. Integration of the proposed approach with an intelligent manufacturing system will lead to reduction in production cost, reduction in production time, flexibility in machining parameter selection, and improvement of product quality.

The application of each approach to obtain optimal machining conditions will be quite useful at the computer-aided process planning (CAPP) stage in the production of high-quality goods with tight tolerances by a variety of automated machining operations, and in adaptive control based machine tools. With the known boundaries of surface roughness and machining conditions, machining can be performed with a relatively high rate of success with the selected machining conditions.

This research definitely indicates some directions for future work. The application of the improved genetic algorithm-based approach in complex as well as flexible machining systems and automated process planning-systems is one of the directions for future research work.

Publication Based On The Thesis

International Journal (published)

T. G. Ansalam Raj & V. N. Narayanan Namboothiri (2009) "An Improved genetic algorithm for the prediction of surface finish in dry turning of SS 420 materials". International Journal of Advanced Manufacturing Technology- Springer publications;pp:313—324.

International Journal (Communicated)

1. T. G. Ansalam Raj & V. N. Narayanan Namboothiri (2010) **A Hybrid Particle Swarm Optimization of Surface finish in turning of SS420 materials.** In International Journal of Materials and Manufacturing Process- Taylor & Francis publications .

2. T. G. Ansalam Raj & V. N. Narayanan Namboothiri (2010) **Analysis of Dry Turning of SS 420 Material Using Evolutionary Algorithms.** In International Journal of Soft Computing-Springer publications .

3. T. G. Ansalam Raj & V. N. Narayanan Namboothiri (2010) **Optimization of Surface finish in dry turning of SS 420 using Simulated Annealing Algorithm.** In International Journal of Advanced Manufacturing Technology- Springer publications .

International Conferences

1. T. G. Ansalam Raj & V. N. Narayanan Namboothiri (2007) Application of Taguchi Method in the Optimisation of Cutting Conditions in Turning Process' at International Conferences on Modeling and Simulation (CITICOMS 2007), CIT Coimbatore.

2. T. G. Ansalam Raj & V. N. Narayanan Namboothiri (2007) Application of Grey Analysis in Optimisation of Cutting Conditions in Turning Process for Multi Process Response' at International Conferences on Advaced Design and Manufacturing (ICADM 2007) ,SIT Virudunagar Madurai.

National Conferences

1. T. G. Ansalam Raj & V. N. Narayanan Namboothiri (2010) Application of Simulated Annealing in the Optimisation of Cutting Conditions in Turning Process' at National Conferences on Modeling and Simulation (MIS 2010), LGCET Nagercoil.
2. T. G. Ansalam Raj & V. N. Narayanan Namboothiri (2010) Application of Particle Swarm Optimisation in the Optimisation of Cutting Conditions in Turning Process at National Conferences on Global Technologies in Manufacturing and Thermal Sciences (GTMTS 2010) ,SIT Virudunagar Madurai.

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