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Multi objective optimization of machining parameters by using weighted sum genetic algorithm approaches

Narasimha Kasyap Sai[@] T.N.Charyulu[#] M.Siva Nayak[$]

[@]PG Student, Department of MECHANICAL, Nova College of Engg & Tech, JANGAREDDYGUDEM.
[#] HOD, Department of MECHANICAL , Nova College of Engg & Tech, JANGAREDDYGUDEM.
[$]Associate Professor, Rise Groups Of Institution , Ongole.

ABSTRACT

Optimization machining parameters are most important in manufacturing world considering economic reason. Economy of machining operation plays a key role in competitiveness in the market. All CNC Machines produce finished components from cylindrical bar. Finished profiles consist of straight turning, facing, taper and circular machining. Finished profile from a cylindrical bar is done in two stages, rough Machining and finish machining. Numbers of passes are required for rough machining and single pass is required for the finished pass. The machining parameters in multi pass turning are depth of cut, cutting, speed and feed. The machining performance is measured by the minimum production time. In this paper the optimal machining parameters for continuous profile machining are determined with respect to the minimum production time, subject to a set of practical constraints, cutting force ,power and dimensional accuracy and surface finish. Due to complexity of this machining optimization problem, a genetic algorithm (GA) and resolve the problem and the results obtained from GA.

OPTIMIZATION:

It has been recognized that conditions during cutting such as feed rate, cutting speed and depth of cut should be selected to optimize the economics of machining operations as assessed by the productivity and total manufacturing cost per component or some other criteria. The selection of efficient machining parameters such as machining speed, feed rate and depth of cut has a direct impact on production economics in the metal cutting processes. Dimensional accuracy is significantly affected by tool wear. Therefore to improve dimensional accuracy one or more tool adjustments may be desirable before a tool is replaced. Taylor showed that an optimum or economic cutting speed exists which will increase the maximum material removal rate.Manufacturing industries have long depended on the skill and the experience of the shop floor machine tool operators for optimal selection of cutting conditions and tools. Considerable efforts are still in progress on the use of hand book-based conservative cutting conditions and cutting tool selection at the process planning level.

The need for selecting and implementing optimal machining conditions and the most suitable cutting tool has been felt over the last few decades. Further more for realistic solutions the many constraints met in practice such as low power, torque, force limits and component surface roughness must be overcome**.**

While the major efforts of earlier works were concentrated on optimization of a single objective function. Various multi-objective optimization approaches have been proposed in recent years for optimizing machining parameters.

Q. Meng [2] has used machining theory for calculating optimum cutting conditions in turning. The method uses a variable flow stress machining theory to predict cutting forces, stress etc. which are then used to check process constraints such as machine power, tool plastic deformation and built-up edge formation. Their results indicate that the method is capable of selecting the appropriate cutting conditions.

Nafis Ahmad and Dr. A. F. M. Anwar ul Haque [3] outlined the use of genetic algorithm to find out the optimum machining parameters. In this work, machining parameters for the turning rotational components are optimized by a genetic algorithm optimization toolbox developed in MATLAB environment. Here machining time is considered as the objective function and constraints are machining capacity, limits of feed rate, depth of cut and cutting speed. Machining time is minimized through a series of generations while some genetic operators are applied at each generation. The result of the work shows how a complex optimization problem is handled by a genetic algorithm and converges very quickly.

GENETIC ALGORITHM:

Genetic algorithms have been developed by John Holland his colleagues and his students at the University of Michigan .Genetic algorithms are adaptive methods which may be used to solve search and optimization problems. Over many generations natural populations evolve according to the principles of natural selection and "survival of the fittest", which clearly stated by Charles Darwin in the origin of species. By minimizing this process GAs are able to evolve solutions to real world problems, if they have been suitably encoded. For example GAs can be used to design bridge structures for maximum strength/weight ratio. They can also be used for online control such as in a chemical plant (or) load balancing on a multi processor computer system .Genetic algorithms are search algorithms based on the mechanics of natural selection and natural genetics. They combine with the survival of the fittest among string structures with a structure at randomized information exchange to form a search algorithm with some of the innovative flair of human search. In every generation a new set of artificial creatures (strings) are created using bits and pieces of the fittest of the old. While randomized genetic algorithms have a number simple random walk. They efficiently exploit historical information to speculate on new search points with expected improved performance.

The very first step of a GAs is the random selection of initial search points from the total search space. Each and every point in the search space corresponds to one set of values for the parameters of the problem. Each parameter is coded with a string of bits. The individual bit is called "gene". The content of each gene is called "allele". The total string of such genes of all parameters written in a sequence is called a "chromosome". So there exists a chromosome for each point in the search space. The set of search points selected and used for processing is called "population" i.e. population is set of chromosomes. The number of chromosomes in a population is called "population size" and the total number of genes in a string is called "string length". The population is processed and evaluated through various operators of GAs to generate a new population and this process is carried out till global optimum point is reached. The two parts of this process are called "Generation' and "Evaluation".

In the Evaluation of GAs, we can define a fitness function and evaluate the fitness function for each chromosome of the population. This fitness is an indication of the suitability of the values of the parameters as represented by that chromosome, as a solution to the optimization problem under consideration. This fitness is used as bias for selecting the parents and generating a new population from the existing one. As obviously evident, here we are testing a significant number of solutions simultaneously since each chromosome represents a solution. This is referred to as "Implicit Parallelism". GA is the only search technique that employs implicit parallelism..

Genetic operation:

In this phase, the objective is the generation of new population from the existing population with the examination of fitness values of chromosomes and application of genetic operators. These genetic operators are

1. Reproduction
2. Crossover
3. Mutation

CROSSOVER AND MUTATION

A new population of off springs is generated using crossover and mutation operators. The parents for crossover are selected from the previous population of chromosomes on the basis of the statistics and the selection operator in which the probability of selection of each parent is directly proportional to its fitness values. The crossover operator is applied on the mating sites of the parents. Then the mutation operator is applied so as to avoid the entrapment in the local optima. Then a complete new population is obtained.

MULTI-OBJECTIVE OPTIMIZATION FORMULATION:

Consider a decision maker who wishes to optimize K objectives such that the objectives are non-commensurable and the decision-maker has no clear preference of the objectives relative to each other. Without loss of generality, all objectives are of the minimization type. A minimization type objective can be converted to a maximization type by multiplying negative one. A minimization multi-objective decision problem with K objectives is defined as follows: Given an n-dimensional decision variable vector $x = (x_{1 \ldots\ldots\ldots} x_n)$ in the solution space X, find a vector x^* that minimizes a given K functions $z(x^*) = (z^1(x^*) \ldots . z^k(x^*))$.

In many real-life problems, objectives under consideration conflict with each other. Hence, optimizing x with respect to a single objective often results in unacceptable results with respect to the other objectives. Therefore, a perfect multi-objective solution that simultaneously optimizes each objective function is almost impossible. The classical approach to solve a multi-objective optimization problem is to assign a weight w_i to each normalized objective function $z_i(x)$ so that the problem is converted to a single objective problem with a scalar objective function as follows:

$$\min z = w_1 z_1(x) + w_2 z_2(x) + \cdots\cdots w_k z_k(x)$$

Where is $z_i(x)$e normalized objective function z and $\sum wi = 1$ This approach is called the priori approach since the user is expected to provide the weights.

Solving a problem with the objective function for a given weight vector $w = (w_{1,} w_{2 \ldots\ldots} w_n)$ yields a single solution and if multiple solutions are desired the problem must be solved multiple times with different weight combinations. The main difficulty with this approach is selecting a weight vector for each run.

FORMULATION OF THE OPTIMIZATION PROBLEM:

The formulation of the optimization problem requires the knowledge of mathematical equations, which represent the economical and physical parameters for the machining process and the whole machine-tool system.

FORMULATION OF THE OBJECTIVE FUNCTION:

Both the production cost and total production time are considered in the formulation of the objective function. The sum of the costs for tooling, machining, tool changing time, handling time and quick return time:

$$time\ of\ machining\ T_m - \frac{L}{fN}$$

$$V = \frac{\pi dl}{1000 fv}$$

$$cost\ of\ cutting\ action = C_0\ T_m$$

$$cost\ of\ tool\ machining = C_0 \frac{Tm T_{cs}}{T} \mathrm{S}$$

$$Total\ time = T_u = T_m + T_h + \frac{T_m}{T} T_s + T_r$$

$$cost\ of\ tooling = C_t \frac{T_m}{T}$$

$$handling\ cost = C_o\, T_h$$

$$quick\ return\ time = T_r$$

Total cost of production=

$$C_o T_m + C_o \frac{T_m}{T} T_w + C_r \frac{T_m}{T} + C_o T_h + C_o T_r$$

Taylor' s expanded tool life equation is

$$V * f_a * d_b * j_c = K$$

total cost of production as an objective function can be written as:

$$C_u = c_o * v_{-1} * f_{-1} + A * v(1/_c - 1) * f(^a/_c) * d(^b/_c) * k(-1/_c) * (c_o + T_{cs} + c_t) + c_o * (T_h + T_r)$$

The total time for machining, work piece handling, tool changing and tool quick return and thus can be written as :

$$T_u = T_m + T_h + \frac{T_m T_s}{T} + T_r$$

For the multi-objective problem, the objective function consists of the sum of the production cost and the production time along with different weight coefficients for each criterion:$m(v, f, d) = w_1 + c_u + w_2 * l * t_u$

Where w1 and w2 are the weight coefficients. These weight coefficients satisfy the following condition:

$w_2 + w_2 = 1, 0 \leq w_1 \leq 0 and 0 \leq w_1 \leq 1$

The objective function would provide the optimum of the individual production cost or time criteria by setting the corresponding weight coefficient equal to zero. The optimum multi-objective function is normalized through the use of a constant multiplier, $= {c_{umin}}/{T_{umin}}$

where, c_{umin} and T_{umin} are the minimum production cost and the minimum production time, respectively. The values are determined by putting the optimum values of the cutting speed V_{opc} and V_{opt} respectively, for the highest possible feed f_h. ForV_{opc} and V_{opt}, we have:

$$V_{opc} = \frac{k}{f_h} * d_b({1}/{c}) * \left(T_{cs} + \frac{c_t}{c_o}\right)$$

$$V_{opt} = {k}/{f_h} * d_b(({1}/{c} - 1) * (T_{cs}))$$

CONSTRAINTS

Practical limitations of the actual cutting conditions always exist for the optimization of the objective function.

Feed and Speed Limitations:

Maximum and minimum feed rate and Cutting speed:

$f_{min} \leq f \leq f_{max}, V_{min} \leq V \leq V_{max}$

Power Limitation:

The power consumption allowed on the material is given as function of feed, speed and depth of cut:

$$0.0373 * V^{0.9} * f^{0.78} * d^{0.75} \leq Hp_{max}$$

Surface Roughness Limitation:

surface roughness allowed for the material is given as a function of feed, speed and depth of cut:

$$1.4785 * V^{-0.52} * f^{1.004} * d^{0.25} \leq SR_{max}$$

Temperature Constraint: The temperature constraint given by inequality is

$$74.96 * V^{0.4} + f^{0.2} + d^{0.1025} - 17.8 \leq T_{max}$$

Cutting Force Constraint: Constraint for the maximum cutting force allowed is:

$$844 * V^{-0.103} * f^{0.725} * d^{0.75} \leq f_{max}$$

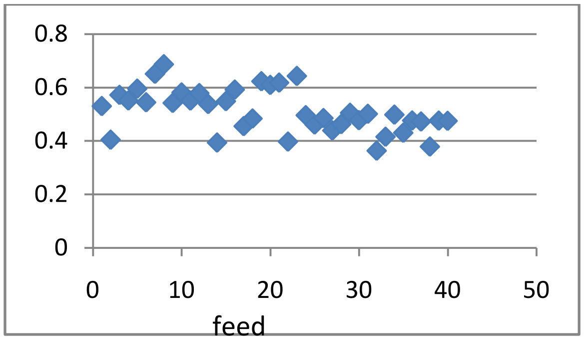
Figure 1. CNC Machine

Output of Optimum Values after Number of Iterations:

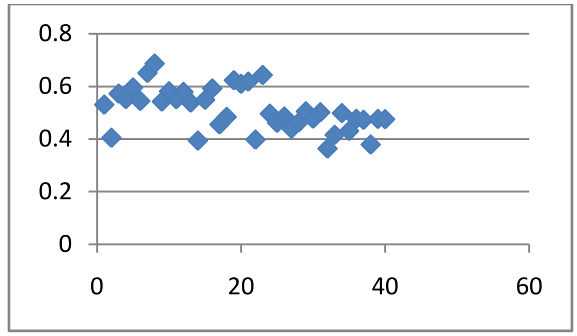
At Weight coefficients w1,w2	Opt feed	Opt speed	Opt Machining time	Opt Tool life	Opt operation cost
0.1-0.9	0.474	136.5	1.08765	1.06	1.0876
0.2-0.8	0.444	109.2	1.9967	1.127	1.3368
0.3-0.7	0.572	121.4	1.3945	1.078	1.0139
0.4-0.6	0.544	97.19	1.8316	1.143	1.2268
0.5-0.5	0.548	93.88	1.8838	1.153	1.2498
0.6-0.4	0.631	122.2	1.25597	1.068	0.9350
0.7-0.3	0.509	111.2	1.7100	1.111	1.1803
0.8-0.2	0.628	82.20	1.87504	1.180	1.2242
0.9-0.1	0.396	107.5	2.27312	1.141	1.4858

Table 1. optimum results

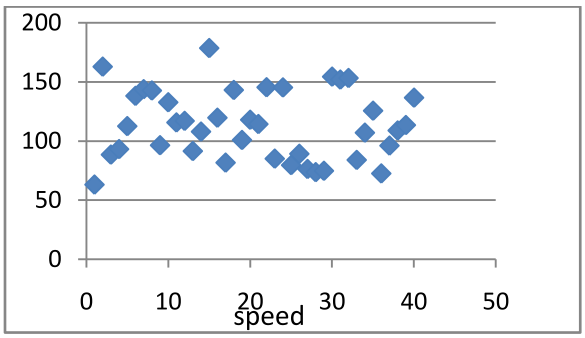
Graphical results for optimum outputs:



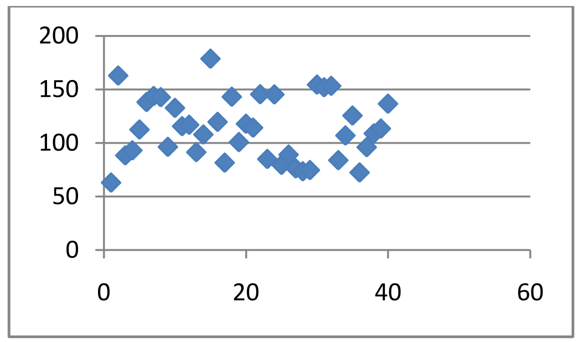
Sample graph for optimum feed at d=2.54



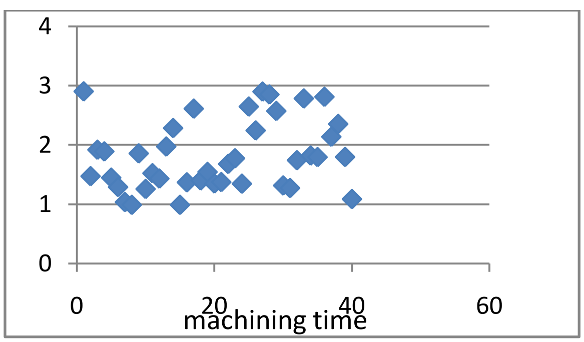
Sample graph for optimum feed at d=5.08



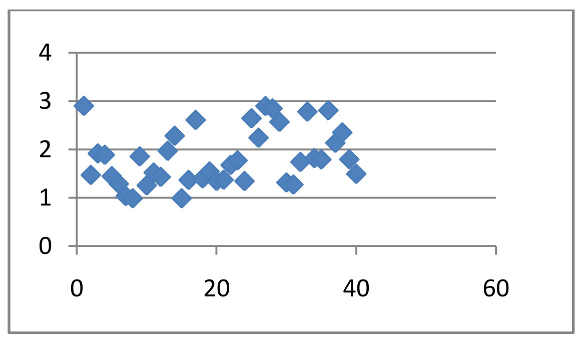
Sample graph for optimum speed at d=2.54



Sample graph for optimum speed d=5.08



Sample graph for optimum machining d=2.54



Sample graph for optimum machining d=5.08

Figure 2.*(At weight factors w1, w2 and optimum graphs for depth of cut d=2.54*)

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Result:

The results obtained from GA are discussed the *optimal cutting parameters such as speed, feed, machining time ,optimum tool life production cost* results are obtained from GA. And the *Optimum time* and great *productivity* are benchmarked. The above *table 1.* Shows optimum parameters values like optimum machining time 1.3945 noted. And the fitness obtained in each iteration of the GA. The plotted graphs are shows above figure 2 at the depth of cut 2.54 and figure 3. Are shows plotted graphs for optimum values of *speed* 121.4, *feed* 0.572 *and machining time* 1.078min at depth of cut 5.08. Finally The GA produces smooth fitness at the initial iteration and varying fitness in the subsequent iterations. Using *MATLAB SOFTWARE* the optimum solutions had obtained.

Conclusion:

All types of CNC are mentioned in Fig 1. Machines have been used to produce continuous finished profiles. A continuous finished profile has many types of operations such as facing, taper turning and circular turning. To model the machining process, several important operational constraints have been considered. These constraints were taken to accounting order to make the model more realistic. A model of the process has been formulated with non-traditional algorithms; GA have been employed to find the optimal machining parameters for the continuous profile. produces better results. Using this technique in GA weight sum method and finally concluded with great optimum *machining time can be further minimized 1.078min.* And productivity will increase to be growth of industries corrigibility.

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