Applicability of Hooke's and Jeeves Direct Search Solution Method to Metal cutting [Turning] Operation.

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ABSTRACT

Role of optimization in engineering design is prominent one with the advent of computers. Optimization has become a part of computer aided design activities. It is primarily being used in those design activities in which the goal is not only to achieve just a feasible design, but also a design objective. In most engineering design activities, the design objective could be simply to minimize the cost of production or to maximize the efficiency of the production. An optimization algorithm is a procedure which is executed iteratively by comparing various solutions till the optimum or a satisfactory solution is found. In many industrial design activities, optimization is achieved indirectly by comparing a few chosen design solutions and accepting the best solution. This simplistic approach never guarantees and optimization algorithms being with one or more design solutions supplied by the user and then iteratively check new design the true optimum solution. There are two distinct types of optimization algorithms which are in use today. First there are algorithms which are deterministic, with specific rules for moving from one solution to the other secondly, there are algorithms which are stochastic transition rules. An important aspect of the optimal design process is the formulation of the design problem in a mathematical format which is acceptable to an optimization algorithm. Above mentioned theory (tasks) involve either minimization or maximization of an objectives. Mathematically programming techniques are useful in finding the minimum of a function of several variables under a prescribed set of constraints. Stochastic process techniques can be used to analyze problems described by a set of random variables having known probability distributions statistical methods enable one to analyze the experimental data and build empirical models to obtain the most accurate representation of the physical situation. The purpose of the optimization is to determine such a set of the cutting conditions v (cutting speed), f (feed rate), a (depth of cut), that satisfies the limitation equations and balances the conflicting objectives. Current study presents successful optimization using Hook's and Jeeves method for metal cutting process with the help of MATLAB R2014a(version 8.3).

Keywords: Optimization, Minimization, Maximization, Deterministic, stochastic transition rules, Algorithm, MATLAB R2014a (Version8.3).

RELEVANCE

In this paper extensive literature review has been referred to understand current status of various optimization techniques and their significance. Optimization theories are very much prominent and important aspect in industrial arena. Hooke and Jeeves optimization algorithm is mainly identified because of its simplicity to find best optimum solution. This algorithm provides the exact actual results from the bunch of iterations. Along with which, the use of this kind of algorithm to metal cutting operation provides new dimensions in Mechanical Design engineering by means of effective utilization of $3M^s$ i.e. Manpower, materials and machines.

OPTIMAL DESIGN PROCEDURE:

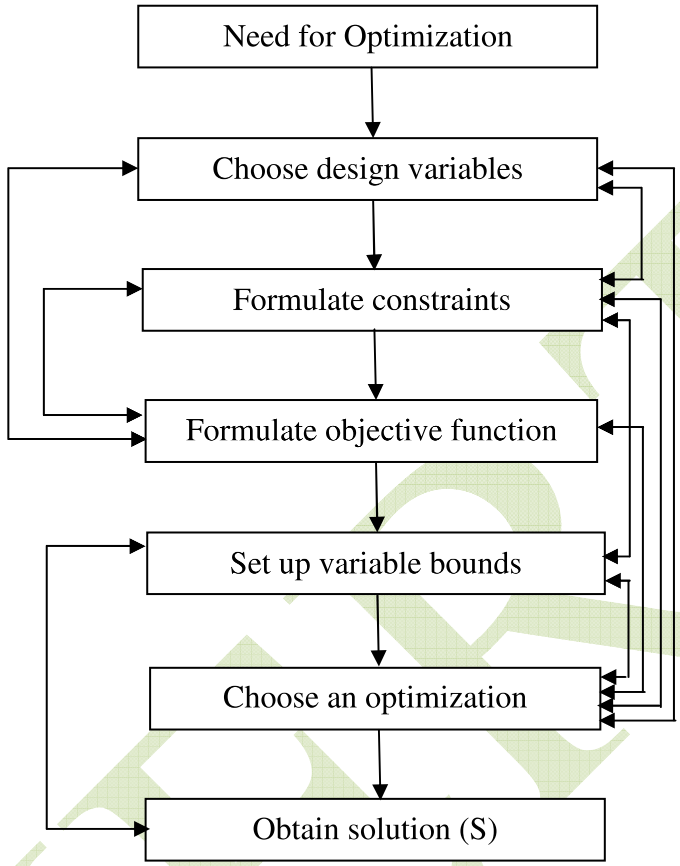

Fig 1. A flow chart of the Optimal design Procedure

Following are the present practices for application of the "Hooke and Jeeves Direct search solution method" in Mechanical Design Engg. Certain problems involve linear terms for constraints and objective function but certain other problems involve non-linear terms for them. In some problems, the terms are not explicit functions of the design variables, there does not exist a single optimization algorithm which will work in all optimization problems equally efficiently. In order to use optimization algorithms in engineering design activities, the first task is to formulate the optimization problem. The formulation process begins with identifying the important design variables that can be changed in a design. The other design parameters are usually kept fixed. Thereafter, constraints may arise due to resource limitations such as deflection limitations, strength limitations, frequency limitations, & other. Constraints may also arise due to codal restrictions that govern the design. The next task is to formulate the objective function which the designer is interested in minimizing or maximizing the final task of the formulation phase is to identify some bounding limits for the design variables [1]. Many engineering optimization problems contain multiple optimum solutions among which one or more is the absolute min. or max. Solutions these optimum solutions are known as global optimal solutions and other optimum solutions are known as local optimum solution. The rudimentary information of success or failure is utilized by combining it into a "pattern" which indicates a probable direction for a successful move. As set up each pattern move is followed by a sequence of exploratory moves which continually revise the pattern.

DIRECT SEARCH METHODS

Introduction:

We use the phrase "direct search" to describe sequential examination of trial solutions involving comparison of each trial solution with the "best" obtained up to that time together with a strategy for determining (as a function of earlier results) what the next trial solution will be. The phrase implies our preference, based on experience, for straightforward search strategies which employ no techniques of classical analysis except where there is a demonstrable advantage in doing so. [1] to a modern reader, this preference for avoiding techniques of classical analysis except where there is a demonstrable advantage in doing so" quite likely sounds odd. After all, the success of quasi-Newton methods, when applicable, is now undisputed. But consider the historical context of the remark by Hooke and Jeeves. Hooke and Jeeves' paper appeared ve years before what are now referred to as the Armijo Goldstein Wolfe conditions were introduced and used to show how the method of steepest descent could be modified to ensure global convergence. Their paper appeared only two years after Davidon's unpublished report on using secant updates to derive quasi-Newton methods, and two years before Fletcher and Powell published a similar idea in The Computer Journal. So in 1961, this preference on the part of Hooke and Jeeves was not without justification. Forty years later, the question we now ask is: why are direct search methods still in use? Surely this seemingly hodge-podge collection of methods based on heuristics, which generally appeared without a large extent direct search methods have been replaced by more sophisticated techniques. As the field of numerical optimization has matured, and software has appeared which eases the ability of consumers to make use of these more sophisticated numerical techniques, many users now routinely rely on some variant of a globalized quasi-Newton method. Yet direct search methods persist for several good reasons. First and foremost, direct search methods have remained popular because they work well in practice. In fact, many of the direct search methods are based on surprisingly sound heuristics that fairly recent analysis demonstrates guarantee global convergence behavior analogous to the results known for globalized quasi-Newton techniques. Direct search methods succeed because many of them including the direct search method of Hooke and Jeeves can be shown to rely on techniques of classical analysis in ways that are not readily apparent from their original specifications. Second, quasi-Newton methods are not applicable to all nonlinear optimization problems. Direct search methods have succeeded when more elaborate approaches failed. Features unique to direct search methods often avoid the pitfalls that can plague more sophisticated approaches. Third, direct search methods can be the method of first recourse, even among well-informed users. The reason is simple enough: direct search methods are reasonably straightforward to implement and can be applied almost immediately to many nonlinear optimization problems. The requirements from a user are minimal and the algorithms themselves require the setting of few parameters. It is not unusual for complex optimization problems to require further software development before quasi-Newton methods can be applied (e.g., the development of procedures to compute derivatives or the proper choice of perturbation for nit difference approximations to gradients). For such problems, it can make sense to begin the search for a minimize using a direct search method with known global convergence properties, while undertaking the preparations for the quasi-Newton method. When the preparations for the quasi-Newton method have been completed, the best known result from the direct search calculation can be used as a hot start" for one of the quasi-Newton approaches, which enjoy superior local convergence properties. Such hybrid optimization strategies are as old as the direct search methods themselves. We have three goals in this review. First, we want to outline the features of direct search that distinguish these methods from other approaches to nonlinear optimization. Understanding these features will go a long way toward explaining their continued success. Second, as part of our categorization of direct search, we suggest three basic approaches to devising direct search methods and explain how the better known classical techniques t into one of these three camps. Finally, we review what is now known about the convergence properties of direct search methods. The heuristics that first motivated the development of these techniques have proven, with time, to embody enough structure to allow in most instances analysis based on now standard techniques. We are never quite sure if the original authors appreciated just how reliable their techniques would prove to be; we would like to believe they did. Nevertheless, we are always impressed by new insights to be gleaned from the discussions to be found in the original papers. We enjoy the perspective of forty intervening years of optimization research. Our intent is to use this hindsight to place direct search methods on arm standing as one of many useful classes of techniques available for solving nonlinear optimization problems. Our discussion of direct search algorithms is by no means exhaustive, focusing on those developed during the dozen years from 1960 to 1971. Space also does not permit an exhaustive bibliography. Consequently, we apologize in advance for omitting reference to a great deal of interesting work. [1] [10] [11]

Classical direct search methods:

We organize the popular direct search methods for function-strained minimization into three basic categories. For a variety of reasons, we focus on the classical direct search methods, those developed during the period 1960-1971. The restriction is part practical, part historical. On the practical side, we will make the distinction between pattern search methods, simplex methods (and here we do not mean the simplex method for linear programming), and methods with adaptive sets of search directions. The direct search methods that one finds described most often in texts can be partitioned relatively neatly into these three categories. Furthermore, the early developments in direct search methods more or less set the stage for subsequent algorithmic developments. While a wealth of variations on these three basic approaches to designing direct search methods have appeared in subsequent years largely in the applications literature these newer methods are modifications of the basic themes that had already been established by 1971. Once we understand the motivating principles behind each of the three approaches, it is a relatively straightforward matter to devise variations on these three themes. There are also historical reasons for restricting our attention to the algorithmic developments in the 1960s. Throughout those years, direct search methods enjoyed attention in the numerical optimization community. The algorithms proposed were then (and are now) of considerable practical importance. As their discipline matured, however, numerical optimizers became less interested in heuristics and more interested in formal theories of convergence. At a joint IMA/NPL conference that took place at the National Physics Laboratory in England in January 1971, W. H. Swann surveyed the status of direct search methods and concluded with this apologia: Although the methods described above have been developed heuristically and no proofs of convergence have been derived for them, in practice they have generally proved to be robust and reliable in that only rarely do they fail to locate at least a local minimum of a given function, although sometimes the rate of convergence can be very slow. Swann's remarks address an unfortunate perception that would dominate the research community for years to come: that whatever successes they enjoy in practice, direct search methods are theoretically suspect. Ironically, in the same year as Swann's survey, convergence results for direct search methods began to appear, though they seem not to have been widely known, as we discuss shortly. Only recently, in the late 1990s, as computational experience has evolved and further analysis has been developed, has this perception changed. [13] [14]

- **Pattern search**

In his belated preface for ANL 5990, Davidson described one of the most basic of pattern search algorithms, one so simple that it goes without attribution: Enrico Fermi and Nicholas Metropolis used one of the first digital computers, the Los Alamos Maniac, to determine which values of certain theoretical parameters (phase shifts) best t experimental data (scattering cross sections). They varied one theoretical parameter at a time by steps of the same magnitude, and when no such increase or decrease in any one parameter further improved the t to the experimental data, they halved the step size and repeated the process until the steps were deemed sufficiently small. Their simple procedure was slow but sure Pattern search methods are characterized by a series of exploratory moves that consider the behavior of the objective function at a pattern of points, all of which lie on a rational lattice. In the example described above, the unit coordinate vectors form a basis for the lattice and the current magnitude of the steps (it is convenient to refer to this quantity as k) dictates the resolution of the lattice. The exploratory moves consist of a systematic strategy for visiting the points in the lattice in the immediate vicinity of the current iterate. It is instructive to note several features of the procedure used by Fermi and Metropolis. First, it does not model the underlying objective function. Each time that a parameter was varied, the scientists asked: was there improvement in the t to the experimental data. A simple yes" or no" answer determined which move would be made. Thus, the procedure is a direct search. Second, the parameters were varied by steps of predetermined magnitude. When the step size was reduced, it was multiplied by one half, thereby ensuring that all iterates remained on a rational lattice. This is the key feature that makes the direct search a pattern search. Third, the step size was reduced only when no increase or decrease in any one parameter further improved the t, thus ensuring that the step sizes were not decreased prematurely. This feature is another part of the formal definition of pattern search in and is crucial to the convergence analysis presented therein. [1]

Recent analysis:
Recently, a general theory for pattern search extended a global convergence analysis of the multidirectional search algorithm. Like the simplex algorithms, multidirectional search proceeds by reflecting a simplex (n + 1 points in Rn) through the centroid of one of the faces. However, unlike the simplex methods discussed, multidirectional search is also a pattern search. In fact, the essential ingredients of the general theory had already been identified by First, the pattern of points from which one selects trial points at which to evaluate the objective function must be sufficiently rich to ensure at least one direction of descent if xk isn't a stationary point of f. For Cea and Polak, this meant a pattern that included points of the form x0k = xk k ei, i 2 f1; : : : ; ng, where the ei are the unit coordinate vectors. For Berman, it meant requiring being the lattice of integral points of Rn, i.e., requiring that the basis for the lattice be the identity matrix I 2 Rn n.In these conditions were relaxed to allow any nonsingular matrix B 2 Rn n to be the basis for the lattice. In fact, we can allow patterns of the form x0k = xk + k Bγk0, where γk0 is an integral vector, so that the direction of the step is determined by forming an integral combination of the columns of B. The special cases studied by Cea and Polak are easily recovered by choosing B I and γk0 = ei, i 2 f1; : : : ; ng. Second, an essential ingredient of each of the analyses is the requirement that k not be reduced if the objective function can be decreased by moving to one of the x0k. Generalizations of this requirement were considered in and. This restriction acts to prevent premature convergence to a non stationary point. Finally, we restrict the manner by which k is rescaled. The conventional choice, used by both Cea and Polak, is to divide k by two, so that k = 0=2k. Somewhat more generally, Berman allowed dividing by any integer > 1, so that (for example) one could have k = 0=3k. In fact, even greater generality is possible. For > 1, we allow k+1 = w k, where w is any integer in a designated finite set. Then there are three possibilities:

1. w < 0. This decreases k, which is only permitted under certain conditions (see above). When it is permitted, then Lk Lk+1, the relation considered by Berman.
2. w = 0. This leaves k unchanged, so that Lk = Lk+1.
3. w > 0. This increases k, so that Lk+1 Lk .

It turns out that what matters is not the relation of Lk to Lk+1, but the assurance that there exists a single lattice Li 2 fL0; L1; : : : ; Lk; Lk+1 g, for which Lj Li for all j = 0; : : : ; k + 1. This implies that fx0; : : : ; xk g Li, which in turn plays a crucial role in the convergence analysis. Exploiting the essential ingredients that we have identified, one can derive a general theory of global convergence. The following result says that at least one subsequence of iterates converges to a stationary point of the objective function. Theorem 3.2. Assume that L(x0) = fx j f (x) f (x0) g is compact and that f is continuously differentiable on a neighborhood of L(x0). Then for the sequence of iterates fxk g produced by a generalized pattern search algorithm, lim inf krf (xk) k = 0: k!+1.Under only slightly stronger hypotheses, one can show that every limit point of fxk g is a stationary point of f, generalizing Polak's convergence result. Details of the analysis can be found in provides an expository discussion of the basic argument. [11] [12] [13]

Formulae Used

MRR =1000 × v × f × a [2]

$$T = \frac{k_T}{v^{\alpha_1} \cdot f^{\alpha_2} \cdot a^{\alpha_3}} \qquad T_p = T_s + V \cdot \frac{(1 + \frac{T_c}{T})}{MRR} + T_i$$

Tool life (T).

$$C_p = T_p \cdot \left(\frac{C_t}{T} + C_l + \cdot C_0 \right)$$

Cost per product (Cp).

Roughness $R_a = k \cdot v^{x_1} \cdot f^{x_2} \cdot a^{x_3}$

Cutting power and force $P = \frac{F \cdot v}{6122{,}45 \cdot \eta}$ where f is $F = k_F \cdot f^{\beta_2} \cdot a^{\beta_3}$ [14][20]

RESULTS AND DISCUSSION

For the experiment the Hooks and Jeeves optimization method was used. The Hooks and Jeeves optimization method give more accurate results, but they require more time for result. The C program containing this is slow. Therefore the MATLAB was chosen for application. [14] [19] [20] [21]

Table No. 1 Project Result Analysis Sheet

Inputs			**Outputs**							
v	**f**	**A**	**T_Prod**	**Whole tool life**	**Material Removal rate**	**v1**	**f1**	**a1**	**Fc**	**P**
400	0.55	1.6	0.8436	9.402	3.52E+05	400	0.55	1.6	1146	7.5
358	0.55	1.7	0.8708	6.926	3.35E+05	358	0.55	1.7	1264	7.5
294	0.55	1.9	0.9238	4.018	3.07E+05	294	0.55	1.9	1512	7.408
261	0.55	2.1	0.9352	2.84	3.02E+05	261	0.55	2.1	1746	7.5
250	0.55	2.1	0.9667	2.555	2.89E+05	250	0.55	2.1	1768	7.366
250	0.53	2.2	0.9595	2.519	2.92E+05	250	0.53	2.2	1799	7.494
250	0.45	2.5	0.9869	2.471	2.81E+05	250	0.45	2.5	1782	7.424
250	0.38	2.9	1.003	2.401	2.76E+05	250	0.38	2.9	1796	7.485
250	0.32	3.3	1.038	2.36	2.64E+05	250	0.32	3.3	1769	7.37
250	0.29	3.7	1.024	2.286	2.68E+05	250	0.29	3.7	1833	7.5
250	0.24	4.3	1.057	2.232	2.58E+05	250	0.24	4.3	1818	7.5
250	0.2	4.9	1.102	2.199	2.45E+05	250	0.2	4.9	1776	7.398
250	0.18	5.5	1.093	2.133	2.48E+05	250	0.18	5.5	1831	7.5
250	0.16	6	1.121	2.109	2.40E+05	250	0.16	6	1808	7.5

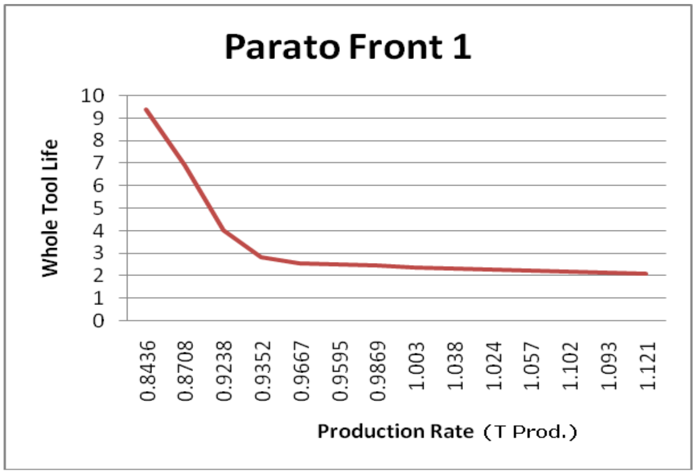

Fig No. 2 Production Rate (T Prod.) vs Whole Tool Life

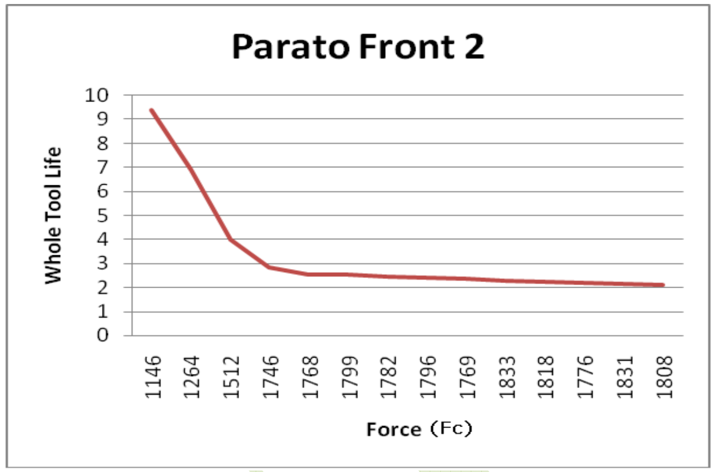

Fig No.3 Cutting Force (Fc) vs Whole Tool Life

CONCLUSION AND SCOPE FOR FUTURE WORK

This chapter summarizes the conclusions of this study and outlines scope for future work.

Conclusions:

Major conclusions for present study are listed as below:

- Successfully validated optimization results of metal cutting process subjected to optimize for objective function.
- Analytically calculated optimum solution is best matched with current optimization method. This ensures optimization of metal cutting process by using proceeding method provides finite solution for finite set of data.
- Successfully used Hooks and Jeeves optimization algorithm in the optimum solution of metal cutting process.
- Optimum solution obtained by implementing MATLAB program for optimization of metal cutting process is best possible optimum solution.
- Percentage error in analytical and MATLAB results is depend on the number of iteration steps, length of data sets, objective function and constrained for optimization.

Scope for Future Work:

Although current study presents successful optimization using Hook's and Jeeves method for metal cutting process, there are various algorithms which can be considered as future scope of the work. Some of the important scope for future work is as mentioned below:

- There are several other algorithms (methods) for optimization which can be studied using similar approach.
- Mathematical analysis of Metal cutting process also can be carried out considering various parameters to check validity of process under several conditions.
- Optimization can be carried out using advanced neural network or genetic algorithm based methods.

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