International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Numerical Method in Finding Optimizing Design

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A B S T R A C T

Numerical optimization techniques start with optimizing univariate, dichotomous, Fibonacci, and Newtonian functions. Successful application of model-based simulation and dynamic process optimization requires accurate tuning of the underlying mathematical models. An important task here is to estimate the unknown, naturally-given model coefficients from actual observations. After suitable numerical treatment of the differential system, the parameters can be estimated as solutions to finite-dimensional nonlinear finite-parameter estimation problems. As measurements always contain errors, the resulting parameter estimates cannot be treated as definitive and require sensitivity analysis to verify their statistical accuracy. The goal of optimizing test design is to identify measurement times and test conditions that allow parameter estimation with maximum statistical accuracy. Furthermore, the design of the optimization experimental problem can be formulated as an optimization problem whose objective function is given by an appropriate quality criterion based on sensitivity analysis of the parameter estimation problem.

Next, the function of some variables plays a major part and is divided into the direct search method and the gradient method. Many methods have been proposed for direct searches, such as the simplex method, Hooke and Jeeves method, Powell method, Rosenbrock method, Nelder-Mead method, box composition method, and genetic algorithm with sub-global optimization. Gradient methods are first described in general terms for quadratic and non-quadratic functions, including gradient descent, conjugate gradient, Newton-Raphson, quasi-Newton, Gauss-Newton, and Levenberg-Marquardt. It describes the problems that solve large systems. All these methods are illustrated with important numerical examples.

Keywords: Numerical methods, optimization, design product

1. Introduction

Analytic methods are an important theoretical basis of optimization, but especially when dealing with large problems, optimization is performed by the cyclic number method (Kelly, 1999b). For example, engineering problems (Edgar and Hinmelblau, 2001; Rao, 2009; Ray and Szekely, 1973) and economics. Digital optimization can be done in many ways. For example, linear programming and quadratic programming. However, the most common problem in optimizing multivariable nonlinear functions under nonlinear conditions is called nonlinear programming. online. Here programming means optimization.

The concept of optimal structural design is common to many disciplines. In addition to economic cost savings, especially for engineering applications, the optimized results also improve performance. Sources of uncertainty are everywhere. For example, material properties. Boundary conditions, geometric dimensions, payload, etc. for best results. The design process should fully consider the effects of uncertainties. Many existing engineering methods use traditional methods to describe uncertainty. However, we simplify the uncertainty by adding minor corrections (for example, using very high values and safety factors). These methods are simply simplistic by various kinds of uncertainties. Performance levels and dimensional changes in the final design.

Second sensitivity analysis to better evaluate the statistical accuracy of parameter estimation. In the case of highly nonlinear model functions, the newly recommended sensitivity analysis is based on the square of the approximate confidence interval. This expands the commonly used linear confidence range. The square of the approximate confidence area was extensively analyzed and sufficient boundaries were determined. It shows that the exact range of quadratic elements can be found by solving the symmetric eigenvalue problem. One of the main results of this paper is that the square part is surrounded by two lipid constants. κ also. ω This is the unique characteristic of Gauss-Newton convergence. This range can also be used to estimate the precision of the linear confidence range of the error, We also calculate the square approximation of the common variance matrix. This provides another possibility for the statistical evaluation of parameter estimation solutions. The good estimation characteristics of the new recommended sensitivity analysis are shown in several digital samples.

The part secondly presents some practical applications that I have studied over the years. In this part, we will show you step-by-step how to apply different optimization techniques to some test cases. Methods are presented for solving various optimization problems. Optimization is a very powerful tool for designers. This is a highly interdisciplinary subject and can be applied to almost any kind of problem. It still makes starting difficult. The purpose of this study is to prove the practicality of using optimization techniques for design purposes. Provide general guidance to virtual end users on how to implement the optimization process. The latter is usually required as each optimization algorithm has its own peculiarities. This may be more appropriate than other approaches to solving your particular problem. The work consists of two parts. The first part focuses on optimization theory. Understanding it from a mathematical point of view can be very complicated. Although these can be found in many books on optimization theory. I think the theoretical overview is very important because when we talk about optimization, we have to be ready to understand what we are saying.

1.1 Flow of Optimize design

Design optimization is a design methodology that uses a mathematical formulation of the design problem to help select the optimal design among many alternatives. Design optimization includes the following phases:

Figure 1 – Phases of Design Optimization

Variables: Describe design alternatives

Goal: Combination of functions of selected variables (maximize or minimize)

Constraints: Variables combination. Satisfied Acceptable Design Alternatives

Feasibility: A set of variable values that satisfy all constraints and minimize/maximize goals

2. Design Optimization

Depending on your design goals, you can use one or more of the following design optimization processes: End of support programs for emulation and optimization. Design optimization is used to change the shape and size to reduce weight. It also optimizes materials to meet design requirements such as density versus model frequency, fatigue resistance, and crash resistance.

- Dimensional optimization determines the best performance of the part, such as dimension thickness and part shape. Meet specified design goals related to bending, stretching, etc.
- Topology optimization determines the correct distribution of material over the available design packing area and specific load conditions.
- Shape optimization provides the best geometry in the available design space. and under load conditions and specified limits.
- Terrain optimization is an advanced size optimization technique used to change gauge element thickness per element instead of the area in the finite element code.
- Terrain optimization is used to modify the topology and shape of surfaces to increase structural stiffness, for example by adding stiffeners or layers at optimal locations.

3. Functions for one variable

For a function of one variable, the problem is to find the zero of the derivatives an optimization problem without constraints.

$f'(x) = 0$ (1)

3.1 Bisection Method:

In the case of finding the optimal value of a unimodal function, so that it has only one minimum or maximum in the initial interval [a, b], the derivative f'(x) replaces the function f(x). If a numerical approximation of the derivative is used instead of an analytical expression of the derivative, three numerical analyzes of the derivative are required, each analysis representing the derivative function at two different points. Thus, this type of procedure requires at least six function values at each step, two of which are new. but the most general problem of optimization of a nonlinear function of several variables subject to nonlinear constraints is called nonlinear programming here means optimization.

The bisection method is thus achievable according to the following algorithm. In the case of root-finding for a function, the bisection method required the knowledge of three values of the function. points by a centrally divided difference formula;

$$f'(x) \approx \frac{f(x(1+\epsilon))-f(x(1-\varepsilon))}{2x\epsilon} \quad (2)$$

Estimation of the second derivative according to the centrally divided difference formula;

$$f''(x) \approx \frac{f(x(1+\epsilon))-2f(x)+f(x(1-\epsilon))}{(x\epsilon)^2} \quad (3)$$

3.2 Bisection method Optimizations:

The bisection method is used to search the minimum of the following function of one variable:

$$f(\mathcal{X}) = \sqrt{exp((\mathcal{X}-0.5)^2)} - x^2 \quad (4)$$

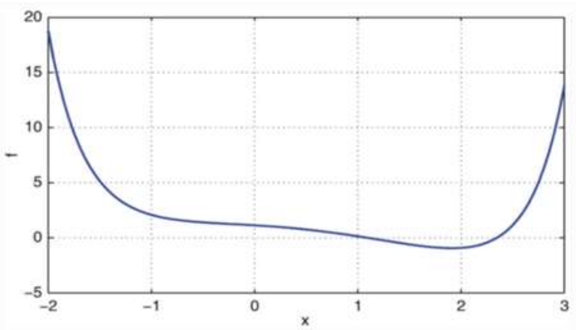

Figure 2 - Function of one variable used for the search of a minimum

3.3 Newton's Method:

The first derivative and that of the first derivative by the calculation of the second derivative so that Newton's algorithm which was In the case of Newton's method, the calculation of the function is replaced by the calculation of the first derivative.

$$x_{k+1} = x_k - \frac{f\,(x_k)}{f(x_k)} \quad (5)$$

optimization without constraints,

$$x_{k+1} = x_k - \frac{f'\,(x_k)}{f''(x_k)} \quad (6)$$

When the derivatives are not available analytically, it is possible to use a numerical estimation of the derivatives as a central divided difference of order 2 to apply Newton's method;

$$f'(x) \approx \frac{f(x(1+\epsilon))-f(x(1-\varepsilon))}{2x\epsilon} \quad (7)$$

which implies to use at least three points to estimate the second derivative, for example, as a central divided difference;

$$f''(x) \approx \frac{f(x(1+\epsilon))-2f(x)+f(x(1-\epsilon))}{(x\epsilon)^2} \quad (8)$$

where ϵ is small with respect to 1 and the increase of x is calculated in a relative way.

4. Function of Several Variables:

All methods lie on several common principles:

Selection of base point:

- The objective function is now calculated.

- Select another feasible point according to the given method.
- The objective function is now calculated.
- a set of feasible values of variables must be found, which belong to the domain and meet the constraints.
- If the second point is better, it will create a new foundation. If the starting point is better, modify the search direction or strategy or stop.
- Compare the value of the objective function at another point with the base point.

5. Methods of Direct Research:

Direct search does not require knowledge of the gradient of the objective function (Lewis et al., 2000; Fletcher, 1965). Depending on the method chosen, it is enough to know the value of the function in some places. Most of them have a stronger rationale and are being gradually abandoned in favor of more effective methods (such as conjugate gradients and quasi-Newtonian).

5.1 Simple One Variable Search:

A simple search with one variable alternates the value of only one variable. For example, a translation parallel to the Ox_1 axis, then a translation parallel to the Ox_2 axis, and so on.

Let $\mathcal{U}_i$ be the unit vector in the Cartesian plane. Note the search direction ξ. A new point is taken by relation from the previous point.

$$\mathcal{X}_{j+1} = \mathcal{X}_j + \alpha_j \xi_j$$

If ξ 1 = $u_1$initially, we are left with a choice of scalar a 1 for which there is no information. The procedure continues by following the general instructions given at the beginning. Performance comparison of new and old points, change of direction.

5.2 Simplex Method

This basic simplex is slightly different from the simplex developed in Chapter 10 for linear programming. Generally speaking, a simplex is an n-dimensional convex polyhedron bounded by n + 1 hyperplanes (Matousek and Gärtner, 2007). Also, Chapter 10 uses the more-or-less simplex method to identify simplexes.

Two-dimensional simplex

The two-dimensional case is the best way to illustrate how this simplex works.

Consider a regular geometric figure as a basis, called a simplex (Walters et al., 1991). In 2D, the simplex is an equilateral triangle. Then proceed according to a set of rules shown in fig below;

Figure 3 - Simplex method

Compute the objective function at the vertices of the triangle

Rule 1: Reject the worst point (in terms of the minimum or maximum value of the objective function).

Replace symmetrically with respect to the centroid of the other two points.

Compute the objective function at this new point.

If this new point gives better results than the discarded point, it is accepted and the third point of the simplex is formed. Reboot on b/. So stay away from bad directions.

Rule 2: If this new point gives a worse result than the rejected point, keep it, choose the second lowest rejected point, continue like b/, reject Replaces the selected point with its center of symmetry. Centroid of the other two points.

Rule 3: Sometimes it can't be done because the new point exceeds one or more constraints. In this case, we cannot accept it. The second worst point is chosen as the worst point.

Finally, we can see that the equilateral triangle figure rotates around the optimal value and progress towards the optimal value is gone. This is the drawback of this method. In this case, the size of the simplex should be reduced. For example, halve the length of one side of a triangle (Rule 4).

The search stops when the vertices are estimated to be placed with sufficient accuracy.

6. Conclusion:

In conclusion, what is the best way to solve an optimization problem? In the spirit of the No Free Lunch Theorem, there is no optimal choice that applies indiscriminately to all problems. However, in technical applications, the can find solutions if you have theoretical knowledge and practical experience. All that is required as hardware is a simulation model or a lab experiment set-up to collect the data. Next you need to select the appropriate optimization process to apply. The optimization process suggested by theoretical knowledge and practical experience is unlikely to be the best possible choice, and I don't know if it is. In any case, it can be a good compromise between the accuracy of the optimal solution and the effort that must be expended to obtain it.

The present invention proposes a number of direct search or gradient type methods. A big advantage of the direct search method is that it only requires the values of the function, not the gradient. A major drawback of all these methods is that the convergence speed is unpredictable and limited to small dimensional problems. Methods of an evolutionary nature, such as genetic algorithms, are very popular because they are easy to understand and have properties of sub-global optimization, but they are not worth using in combination with other more rigorous methods. there is. Gradient methods offer the qualities of robustness and guaranteed convergence and are well adapted to large-scale problems.

Goals and limits are somehow related. In fact, if you're interested in the parameters of the output, you can tweak or constrain them. 4464 Each optimized output variable contributes to the definition of the Pareto frontier, making the problem more general and increasing the optimization complexity. Each constraint reduces the degrees of freedom (like 4663 which restricts the virtual solution space to a sub volume or section), making the optimization problem a little easier to solve, but less general. Choosing an optimization process can be thought of as the optimization problem itself. The goal here is to minimize process effort (time, cost, hardware, people, etc.) and optimization accuracy. Found a solution that maximizes. However, the design space in this case is infinite in size, and the variables are the alternative optimization methods that may be applied, how they are incorporated into the optimization process, and any arbitrary optimizations that govern and define the process. parameter. The design space of the original optimization problem.

Due to the large number of components in large mechanical structural systems, it is not possible to optimize each component individually. Therefore, optimizing reliability design requires comprehensive consideration of multiple failure modes. Nevertheless, stochastic constrained optimization models for structural systems must consider various edge loading conditions, and statistical correlations may exist between multiple failure modes. Therefore, there is an urgent need for optimization design methods for the overall reliability of multi-element, multi-failure mode structures that allow computational accuracy and efficiency to meet the actual needs of the project.

The selection of the optimization process itself can be thought of as an optimization problem. The goal here is the process effort (time, cost, hardware, people, etc.) to be minimized and the accuracy of the optimal solution. is maximized. However, the design space in this case is infinitely large, and the variables are the alternative optimization techniques that can be applied, how they are incorporated into the optimization process, and any parameters that control the process and define the design space. Original optimization problem.

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