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# **A Review on Structural Optimization Techniques**

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**ABSTRACT:** Optimal structural design is becoming increasingly important due to the limited material resources, environmental impact and technological competition, all of which demand lightweight, low-cost and high-performance structures. Structural optimization seeks to achieve the best performance for a structure while satisfying various constraints such as a given amount of material. Conventional optimization techniques suffer from drawbacks such as difficult gradient calculations, converging to local optimum without exploring the design space adequately, too much dependency on the starting solutions, lacking capabilities to treat discrete and mixed design variables. The drawbacks of conventional optimization techniques lead to development of metaheuristic algorithms and hybrid algorithms. These algorithms have been applied to many structural optimization problems and proved effective for solving some specific kinds of problems. In this paper, a review of the most popular optimization algorithms used in structural optimization are presented.

KEYWORDS: Structural Optimization, review, Optimization algorithms

### I. INTRODUCTION

In structural optimization, the design process as announced by professor Uri Kirsch in 80's, can be classified into four stages: formulation of functional requirements, the conceptual design stage, optimization and detailing. Iterative procedures or the application of algorithms are necessary before the final solution is achieved. Almost all engineering design and decision-making problems have an objective of minimizing or maximizing a function (usually cost or profit function) and simultaneously have a requirement for satisfying some constraints arising due to space, strength or stability consideration [Rao, 2006].

Structural optimization seeks to achieve the best performance for a structure while satisfying various constraints such as a given amount of material. Optimal structural design is becoming increasingly important due to the limited material resources, environmental impact and technological competition, all of which demand lightweight, low-cost and high-performance structures.

The types of structural optimization may be classified into three categories, i.e. size, shape and topology optimization. Size optimization is to find the optimal design by changing the size variables such as the cross-sectional dimensions of trusses and frames, or the thicknesses of plates. This is the easiest and earliest approach to improving structural performance. Shape optimization is mainly performed on continuum structures by modifying the predetermined boundaries to achieve the optimal designs. Topology optimization for discrete structures, such as trusses and frames, is to search for the optimal spatial order and connectivity of the bars. Topology optimization of continuum structures is to find the optimal designs by determining the best locations and geometries of cavities in the design domains [Huang, X., Xie, Y. M., 2010]. This paper aims to collect the recent advances in optimization algorithms for structural optimization

#### **II. OPTIMIZATION TECHNIQUES**

Optimization can be defined as the process of the finding the conditions that give the maximum or minimum value of a chosen objective function. Optimization can also be taken to mean minimization since the maximum of a function can be found by seeking the minimum of the negative of the same function. There is no single method available for solving all optimization problems efficiently. Hence a number of optimization techniques have been developed for solving different types of optimization problems [Rao, 2006].



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The optimum seeking methods are also known as mathematical programming techniques. Mathematical programming techniques are useful in finding the minimum of a function of several variables under a prescribed set of constraints. Some of the mathematical programming methods are calculus method, nonlinear programming method, geometric programming, quadratic programming, network methods like CPM and PERT, simulated annealing, neural network etc. Statement of an optimization problem

An optimization or a mathematical programming problem can be stated as follows.

Find

		( X <sub>1</sub>
Х		x <sub>2</sub>
	=	) i
		$(x_n)$

which minimizes f(x)

Subject to the constraints

$gj(x) \le 0$ ,	j = 1,2, m	inequality constraint
hj(x) = 0	j = 1,2, p	equality constraint

where, X is an n-dimensional vector called the designed vector and f(x) is termed the objective function. The number of variables n and the number of constraints m and/or p need not be related in any way. The problem stated is called a constrained optimization problem. Some optimization problem does not involve any constraints. Such problems are called as unconstrained optimization problems.

Any engineering system or component is defined by a set of quantities some of which are viewed as variables during the design process. In general, certain quantities are usually fixed at the outset and these are called preassigned parameters. All other quantities are treated as variables in the design process and are called design or decision variables. The design variables are collectively represented as a design vector.

In many practical problems, the design variables cannot be chosen arbitrarily; rather, they have to satisfy certain specified functional and other requirements. The restrictions that must be satisfied to produce an acceptable design are collectively called design constraints.

The conventional design procedures aim at finding an acceptable or adequate design which merely satisfies the functional and other requirements of the problem. In general, there will be more than one acceptable design, and the purpose of optimization is to choose the best one of the many acceptable designs available. Thus, a criterion has to be chosen for comparing the different alternative acceptable designs and selecting the best one. The criterion, with respect to which the design is optimized, when expressed as a function of the design variables, is known as the objective function [Rao, 2006].



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Fig. 2.1. Taxonomy of optimization methods.

### III. OPTIMIZATION ALGORITHMS

#### CLASSICAL METHODS

The classical methods of optimization are useful in finding the solution of continuous and differential functions. These methods are analytical and make use of the techniques of differential calculus in locating the optimum points. Since some of the practical problems involve objective functions that are not continuous and/or differentiable, the classical optimization techniques have limited scope in practical applications. However, a study of the calculus methods of optimization forms a basis for developing most of the numerical techniques of optimization. [Rao, 2006].

Four main types of problems can be handled by the classical optimization techniques as listed below:

- Single variable optimization problem
- Multivariable optimization with no constraints.
- Multivariable optimization with equality constraints.
- Multivariable optimization with inequality constraints

#### NUMERICAL METHODS OF OPTIMIZATION

The numerical optimization methods are broadly classified into two groups viz, one dimensional and multidimensional. As the one-dimensional problems have little practical importance, they are not discussed here. One dimensional problems can be solved by Exhaustive search, Golden section, Interpolation methods etc. Multidimensional optimization techniques of continuous variables are divided into unconstrained and constrained techniques [Arora, 2004, Rao, 2006].

Some of the unconstrained optimization techniques are listed below [Rao, 2006].

- 1. Direct Search Methods
  - a. Random search method
  - b. Grid search method
  - c. Univariate method
  - d. Pattern search method



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- e. Powell's method
- f. Simplex method
- 2. Descent Methods
  - a. Steepest descent method
  - b. Conjugate gradient (Fletcher Reeves) method
  - c. Newton's method
  - d. Marquardt method
  - e. Quasi-Newton methods

Although direct search methods do not use the derivatives of the functions, they suffer from the following drawbacks. [Rao, 2006]

- The random search methods are not efficient by themselves, but they can be used in early stages of optimization to detect the region where global minimum is likely to be found. Once this region is found, some of the more efficient techniques can be used to find precise location of the global minimum point.
- The minimum of any function that possesses continuous derivatives can be found easily. However, if the function has a steep valley, it may not even converge to optimum point (univariate method).
- Even the most widely used Powell's method suffers from the drawbacks of convergence, and dependent search direction which leads to local minima.

Some constrained optimization techniques are listed below.

- 1. Direct methods
  - a. Random search method
  - b. Heuristic search method
  - c. Sequential linear programming
  - d. Generalized reduced gradient method
  - e. Sequential quadratic programming
  - f. Methods of feasible directions
- 2. Indirect methods
- 3. Sequential unconstrained minimization techniques
- 4. Interior penalty function method
- 5. Exterior penalty function method
- 6. Augmented Lagrange multiplier method

### **EVOLUTIONARY ALGORITHMS**

Evolutionary algorithms are based upon Darwin's Natural Selection (survival of the fittest) theory of evolution, where a population is progressively improved by selectively discarding the worse individuals and breeding new children from the better ones obtained in the previous sequence.

The toughness of solving many design optimization problems by conventional optimization techniques led the researchers to develop new techniques. Evolutionary algorithms, which simulate the natural evolution processes of living organisms are the most promising ones. An evolutionary algorithm (also EA, Evolutionary Computation, Artificial Evolution) is an algorithm using evolutionary techniques inspired by mechanisms from biological evolution such as natural selection, mutation and recombination to find an optimal configuration for a specific system within specific constraints

#### Evolutionary Algorithms include:

i)Genetic Programming and Genetic Algorithms which use the gene transmission and mutation mechanism as an optimization technique,

ii)Evolutionary Programming (EP), which allows one to parameterize computer programs to find optimal solutions according to a goal function,



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iii)Evolutionary Strategies (ESs), which work with vectors of real numbers as representations of optimization problems; selection and mutation are important working mechanisms in this method.

#### **Evolutionary Strategies**

Evolution strategies were developed by Rechenberg (1965, 1973) and Schwefel (1981) in Germany. The first applications of ES were experimental and attempted to solve the shape optimization of bended pipe (Lichtfuss, 1965), the drag minimization of jointed plate (Rechenberg, 1965), and the shape optimization of flashing nozzle (Schwefel 1968), along with various other problems. They are similar to Genetic Algorithms, but originally did not use crossover operator. ES have very complex mutation and replacement functions. Mutation is the main operator while recombination is the secondary in ES. ESs use real parameter values.

#### **Evolutionary Programming**

Evolutionary programming (EP) is a mutation based evolutionary algorithm applied to discrete search spaces. It was originally developed by Fogel et al (1966) and refined by Fogel (1991). It is possibly the first genetic approach to artificial intelligence. This technique does not use crossover operator. Mutation is the main operator in EP. Recombination is even omitted in this technique. Probabilistic selection schemes are used in EP. Like ES, real variables are used in EP.

#### **Genetic Algorithms**

Genetic Algorithms were first introduced by Holland (1975) and further developed by De Jong (1975). Unlike ES and EP, recombination is the main variation in GAs. Probabilistic selection schemes and binary coding in representation are used in GAs. Genetic Algorithms are discussed in detail in next section.

Evolutionary algorithms have certain advantages over the conventional techniques. These advantages can be listed as follows:

i)Evolutionary algorithms are easy to use and program since they do not require use of gradients of cost or constraint functions.

ii)A population of candidate solutions is used to explore the design space.

iii)Discrete and non-continuous problems can be handled easily.

iv)Several near optimum solutions can be obtained yielding alternative designs to the engineer.

Besides the advantages; EAs have some minor drawbacks. The performance of the technique depends mostly on choosing appropriate values of parameters. But it is difficult to choose appropriate values unless the preliminary knowledge is available for the characteristics of the optimization problem. Second drawback is that finding the global optimum cannot be ensured with evolutionary algorithms. Third drawback is the large computation time to obtain a good optimum solution for complex problems [Yavuz, 2005, Back, 1996].

#### **METAHEURISTIC ALGORITHMS**

In the past four decades, from about 1980 to 2018, metaheuristic methods have been rapidly developed to solve optimization problems. These methods are principally intuitive and do not have theoretical support. Metaheuristic methods such as GAs, Simulated Annealing (SA), and Tabu Search (TS) provide general ways to search for a good but not necessarily the best solution.

The arrival of the metaheuristics mark a reconciliation of both domains: indeed, those apply to all kinds of discrete problems and they can also adapt to the continuous problems. Moreover, these methods have in common the following characteristics [Dreo et al, 2006]:

i)They are, at least to some extent, stochastic: this approach makes it possible to counter the combinatorial explosion of the possibilities;



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iii)Generally, of discrete origin, they have the advantage, decisive in the continuous case, to be direct, i.e. they do not resort to often problematic calculations of the gradients of the objective function.

iii) They are inspired by analogies: with physics (simulated annealing, simulated diffusion. . . ), with biology (evolutionary algorithms, tabu search. . . ) or with ethology (ant colonies, particle swarms. . . ).

iv)They share also the same disadvantages: difficulties of adjustment of the parameters of the method and the large computation time.

In brief the metaheuristic algorithms are discussed below:

#### Genetic Algorithm (GA)

Genetic algorithms were introduced by Holland in the 1960s. With the aid of his colleagues and students, he further developed these algorithms during the 1970s at the University of Michigan. He summarized the results of his research in the book, Adaptation in Natural and Artificial Systems (Holland, 1975). GAs are numerical optimization techniques inspired by the natural laws of evolution. A GA starts searching the design space with a population of individuals (designs), which are initially created over the design space at random. In the basic GA, every individual of the population (design) is described by a binary string (encoded form).

GAs differ from the traditional methods of optimization in the following respects:

i)A population of points (trial design vectors) is used for starting the procedure instead of a single design point. If the number of design variables is n, usually the size of the population is taken as 2n to 4n. Since several points are used as candidate solutions, GAs are less likely to get trapped at a local optimum.

ii)GAs use only the values of the objective function. The derivatives are not used in the search procedure.

iii)In GAs the design variables are represented as strings of binary variables that

correspond to the chromosomes in natural genetics. Thus, the search method is naturally applicable for solving discrete and integer programming problems. For continuous design variables, the string length can be varied to achieve any desired resolution.

iv)The objective function value corresponding to a design vector plays the role of fitness in natural genetics.

v)In every new generation, a new set of strings is produced by using randomized parents selection and crossover from the old generation (old set of strings). Although randomized, GAs are not simple random search techniques. They efficiently explore the new combinations with the available knowledge to find a new generation with better fitness or objective function value.

Drawbacks of the algorithms are:

i)They require a large amount of calculation for even reasonable size problems, or for problems where evaluation of functions itself requires massive calculation.

ii)There is no absolute guarantee that a global solution has been obtained.

Simulated Annealing (SA)

The SA algorithm was proposed by Kirkpatrick et al. (1983) and Cerny (1985) independently. The simulated annealing method is based on the simulation of thermal annealing of critically heated solids. When a solid (metal) is brought into a molten state by heating it to a high temperature, the atoms in the molten metal move freely with respect to each other. However, the movements of atoms get restricted as the temperature is reduced. As the temperature reduces, the atoms tend to get ordered and finally form crystals having the minimum possible internal energy. The process of formation of crystals essentially depends on the cooling rate. When the temperature of the molten metal is reduced at a very fast rate, it may not be able to achieve the crystalline state; instead, it may attain a polycrystalline state having a higher energy state compared to that of the crystalline state. In engineering applications, rapid cooling may introduce defects inside the material. Thus, the temperature of the heated solid (molten metal) needs to be reduced at a slow and controlled rate to ensure proper solidification with a highly ordered crystalline state that corresponds to the lowest energy state (internal energy). This process of cooling at a slow rate is known as annealing.



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Some of the features of simulated annealing are as follows [Rao, 2006]:

i)The quality of the final solution is not affected by the initial guesses, except that the computational effort may increase with worse starting designs.

ii)Because of the discrete nature of the function and constraint evaluations, the convergence or transition characteristics are not affected by the continuity or differentiability of the functions.

iii)The convergence is also not influenced by the convexity status of the feasible space.

iv)The design variables need not be positive.

v)The method can be used to solve mixed-integer, discrete, or continuous problems.

vi)For problems involving behavior constraints (in addition to lower and upper bounds on the design variables), an equivalent unconstrained function is to be formulated as in the case of genetic algorithms.

vii)It is also possible to implement the algorithm on parallel computers to speed up the calculations.

The disadvantages of simulated annealing lie on one hand in the "adjustments", like the management of the decrease of the temperature; the user should have the know-how of "good" adjustments. In addition, the computing time can become very significant, which led to parallel implementations of the method.

Tabu Search (TS)

Tabu Search is an iterative procedure appropriate for discrete optimization problems. However, this method, like SA and GA, can be applied to continuous problems. The basic idea of the method has been described by Glover et al. (1993). The method consists of a sequence of exploration movements over the design search space, which is started from a feasible design toward the optimum. To move from one solution to another, the algorithm explores around the point and chooses the best available solution. To avoid retracing the steps used before, the method records recent moves in one particular iteration as a forbidden or tabu list. Tabu moves are based on the short-term and long-term history of the sequence of moves.

For certain optimization problems, the TS method gives excellent results; moreover, in its basic form, the method comprises fewer parameters of adjustment than simulated annealing, which makes it easier to use. However, the various additional mechanisms, like the intensification and diversification, bring a notable complexity.

#### Ant Colony Optimization (ACO)

Ant Colony Optimization was developed by Dorigo and his associates in the early 1990s (Colorni et al, 1991, Dorigo, 1992, Dorigo et al, 1996). The main idea of ACO is to imitate the cooperative behavior of an ant colony, which finds the shortest path to a food source. The ant colony algorithms have several interesting characteristics; to mention in particular high intrinsic parallelism, flexibility (a colony of ants is able to adapt to modifications of the environment), robustness (a colony is ready to maintain its activity even if some individuals are failing), the decentralization (a colony does not obey a centralized authority) and the self-organization (a colony finds itself a solution, which is not known in advance). This method seems particularly useful for the problems which are distributed in nature, problems of dynamic evolution, which require a strong fault-tolerance. [Dreo et al, 2006].

#### Particle Swarm Optimization (PSO)

Particle swarm optimization, abbreviated as PSO, is based on the behavior of a colony or swarm of insects, such as ants, termites, bees, and wasps; a flock of birds; or a school of fish. The particle swarm optimization algorithm mimics the behavior of these social organisms. The word particle denotes, for example, a bee in a colony or a bird in a flock. Each individual or particle in a swarm behaves in a distributed way using its own intelligence and the collective or group intelligence of the swarm. As such, if one particle discovers a good path to food, the rest of the swarm will also be able to follow the good path instantly even if their location is far away in the swarm. Optimization methods based on swarm intelligence are called behaviorally inspired algorithms as opposed to the genetic algorithms, which are called evolution-based procedures. The PSO algorithm was originally proposed by Kennedy and Eberhart in 1995.



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#### Artificial Neural Networks (ANN):

Artificial neural networks emerged as a result of simulating a biological nervous system. The ANN method was developed in the early 1940s by McCulloch and coworkers [Perlovsky, 2001]. The first studies were focused on building simple neural networks to model simple logic functions. At present, ANNs have been applied to problems that do not have algorithmic solutions or problems with complex solutions. In this study, the approximation ability of two of the most well-known ANN architectures, multi-layer perceptron (MLP) and radial basis function (RBF), are investigated.

Moses (1964) : He applied sequential linear programming (SLP) for a simple planar truss and a planar frame. In this method, the objective function and constraints can be linearized using a Taylor series expansion about an initial guess,  $X_0$ . This approximate linear optimization problem can be solved by a linear programming technique. Then,  $X_0$  is replaced by the obtained solution and linearization is repeated about this new obtained point. This process is continued until the difference between two sequential solutions is less than a predefined value. He concluded that the initial guess plays a crucial role not only in terms of convergence to an unfeasible solution but also in terms of increasing the computational effort.

Krishnamoorthy and Mosi (1981): They used Sequential unconstrained minimization technique (SUMT) for optimization of two-dimensional (2D) frames with rectangular cross-sections. In this method a sequence of unconstrained optimization problems with different values of imposed penalty are solved to find the solution of a constrained optimization problem. Their cost function includes only the material costs of concrete, steel reinforcement, and formwork. They considered nonlinear constitutive relationships but no actual design code.

Rajan, S.D. (1995): He applied the genetic algorithm for simultaneous sizing, shape, and topology design optimization of trusses. For this study, He has taken the 6 - node and 14 - node truss test problems. The cross – sectional areas are considered both as discrete and continuous design variables. He discussed the critical issues in the application of genetic algorithm such as, effect of population size, convergence criteria and the effect of probability values of crossover and mutation. He concluded that a dynamically changing penalty approach is needed to preserve sufficient diversity. The drawback is that, no clear guidelines for generating the ground structure are available which would strongly influence the final solution. The quality and diversity of the initial population has a large effect on the direction that the genetic algorithm takes. From this paper, it can be concluded that robust the initial population better the solutions can be obtained efficiently.

Kaveh, A. and Servati, H. (2001): They applied the efficient backpropagation neural networks for design of double layer grids by incorporating the codal provisions of AISC (American Institute of Steel Construction). Square diagonal on diagonal with spans varying between 26.5 and 75 m are considered. Backpropagation algorithm is employed for training neural networks for evaluation of the maximum deflection, weight, and design of double layer grids. They concluded that the dynamic adjustments of momentum  $\alpha$  and learning rate  $\eta$  should be done wisely either both parameters can accelerate the convergence or lead to instability in the update process.

Schutte, J. F. and Groenwold, A. A, (2003): They proposed a particle swarm optimization algorithm (PSOA) for optimum sizing design of truss structures. They modified the PSOA algorithm to improve the efficiency; namely, craziness operator, dynamic inertia reduction operator, logical stopping criteria, and social pressure operator. They studied the efficiency of modified algorithm for the 10 –Bar (convex nature), 10 –Bar (non-convex nature), 25 –Bar (non-convex nature), 36 –Bar (convex nature) truss problems. They concluded that inclusion of the dynamic inertia reduction not only increases the convergence rate also reduce the observed constraint violations. They also concluded that social pressure operator increase the likelihood of migration of feasible regions during the initial phases of the swarm search, thereby sacrificing the cognitive learning ability of initially infeasible birds.

Carbas, S. and Saka, M. P., (2009): They employed the harmony search (HS) algorithm for optimum design of single layer network domes. The HS algorithm is a recent addition to stochastic search techniques of combinatorial



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optimization. The algorithm determines the optimum number of rings, the optimum height of crown and sectional designations for the members of a network dome under the external loads. The design limitations including strength and serviceability requirements are imposed according to ASD - AISC (Allowable Stress Design - American Institute of Steel Construction) specification. This metaheuristic algorithm is based on the musical performance process that takes place when a musician searches for a better state of harmony. Jazz improvisation seeks to find musically pleasing harmony similar to the optimum design process which seeks to find optimum solution. It is concluded that HS method is mathematically quite simple but effective in finding the solutions of combinatorial optimization problems. It neither needs initial starting values for the design variables nor a population of candidate solutions for the design problem.

Hasançebi, O., et al, (2010) : They discussed the convergence rates and reliabilities of seven metaheuristic algorithms in their paper. The optimum design of pin-jointed geodesic steel dome structures is investigated using seven metaheuristic search techniques; namely simulated annealing (SA), evolution strategies (ESs), particle swarm optimizer (PSO), tabu search method (TS), ant colony optimization (ACO), harmony search method (HSM) and simple genetic algorithm (SGA). For this study, 130-member geodesic steel dome with eight member groups (design variables) is sized for minimum weight using standard pipe sections by conducting the three independent runs with seven optimization techniques above mentioned. The design limitations including strength and serviceability requirements are imposed according to ASD - AISC specification. The design loads and combined load effects for these systems are computed according to the minimum load requirements as specified by ASCE 7-98. They concluded that ESs, SA and PSO can be characterized as methods that have high convergence reliabilities since they found the same optimum solution in all of their three runs. On the other hand, performance variations are observed for TS, ACO and HS methods associated with their stochastic nature. ESs, TS and ACO method come into prominence in terms of their satisfactory convergence rates, whereas a steady convergence attribute has been observed with PSO, HS and SA methods. Finally, SGA exhibited a satisfactory performance neither in terms of convergence reliability nor its convergence rate.

Dede & Ayvaz (2015) studied the optimization of plane and space trusses with a Teaching-learning-based optimization (TLBO). Cross-sectional areas of bars and nodal coordinates were considered as the design variables. The method was applied to five structures. When compared to results obtained by other studies, it was concluded by the authors that the algorithm can be effectively used to design truss structures.

#### **IV. CONCLUSION**

The conclusions and the surveys given in this study are based on the various references analyzed. There is a widespread information, with too many studies about the argument, and it is not possible to analyze all them in one paper. The different optimization algorithms are used for different applications, but one need not claim any particular optimization algorithm as the "best" algorithm among all the optimization algorithms available in the literature. Some algorithms are more efficient and robust than others . In fact, there may not be any such 'best' algorithm existing! A particular algorithm may not be the "best" for all types of optimization problems.

New algorithms are constantly being developed in the field of size structural optimization. These algorithms make it possible to have faster optimal results. These algorithms can handle problems with a higher number of variables. Some of the most peer reviewed algorithms have been analyzed in this study. The optimization of skeletal structures, was demonstrated to be achieved better with: Simulated Annealing (SA), Genetic Algorithm (GA), Harmony Search (HS), Tabu Search (TS), Ant colony optimization (ACO), Particle swarm optimization (PSO) etc. Also , there is advancement in the hybrid algorithms. Due to the length limitation of the text, other important works were not included in this selection. Anyway, it is remarkable the growing application of optimization to the resolution of real problems.



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