Complete Search in Continuous Global Optimization and Constraint Satisfaction

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Abstract. This survey covers the state of the art of techniques for solving general purpose constrained global optimization problems and continuous constraint satisfaction problems, with emphasis on complete techniques that provably find all solutions (if there are finitely many). The core of the material is presented in sufficient detail that the survey may serve as a text for teaching constrained global optimization.

After motivation for and important examples of applications of global optimization, a precise problem definition is given, and a general form of the traditional first order necessary conditions for a solution. Then more than a dozen software packages for complete global search are described.

A quick review of incomplete methods for bound constrained problems and recipes for their use in the constrained case follows, an explicit example is discussed, introducing the main techniques used within branch and bound techniques. Sections on interval arithmetic, constrained propagation and local optimization are followed by a discussion of how to avoid the cluster problem. Then a discussion of important problem transformations follows, in particular of linear, convex, and semilinear (= mixed integer linear) relaxations that are important for handling larger problems.

Next, reliability issues – centering around rounding error handling and testing methodology – are discussed, and the COCONUT framework for the integration of the different techniques is introduced. A list of challenges facing the field in the near future concludes the survey.

Contents

1 Introduction

Consider everything. Keep what is good. Avoid evil whenever you recognize it.
St. Paul, ca. 50 A.D. (The Bible, 1 Thess. 5:21–22)

Early history. As the above quote shows, continuous global optimization or constraint satisfaction and the associated global search methods are since antiquity part of the art of successful living. In the mathematical literature published before 1975, there are occasional references related to the topic, few and important enough to mention them individually. (Please inform me about other significant work on continuous global optimization published before 1975 not mentioned here!) Several independent strands of work (probably done in ignorance of each other) are discernible:

- Markowitz & Manne [213] in 1957, and Dantzig et al. [66, 65] in 1958 and 1960, used piecewise linear approximations for the approximate global minimzation of separable nonconvex programs, formulating them as mixed integer linear programs. Land & Doig [193] and Little et al. [201] introduced in 1960/63 the branch and bound technique for discrete optimization, applicable to mixed integer linear programs. Motzkin & Strauss [233] showed in 1965 that solving the (discrete) maximum clique problem is equivalent to finding the global minimum (or maximum) of a special nonconvex quadratic program. In 1969, Falk & Soland [80] gave the first piecewise linear relaxations of nonconvex problems, thus making them available for obtaining bounds in a branch and bound scheme. In 1970, Beale & Tomlin [26, 312] introduced special ordered sets, defining the way piecewise linear functions are handled till today in mixed integer linear programming solvers. In 1972, McCormick [214] introduced the now frequently used linear relaxations for products and quotients, which made the solution of general factorable global optimization problems accessible to the branch and bound technique.

- MOORE [229] showed in 1962 in Part 4 of his Ph.D. thesis, which introduced interval arithmetic to numerical analysis (following an unpublished 1959 technical report by MOORE & YANG[228]), that by repeated subdivision and simple interval evaluation, the range – hence in particular the global minimum – of a rational function over a box can be determined in principle to arbitrary accuracy. SKELBOE [301] improved 1974 this basic but excessively slow method by embedding it into (what would today be called) a branch and bound scheme for continuous variables, giving (what is now called) the Moore-Skelboe algorithm. Moore's thesis [229] also showed that interval methods can be used to prove the nonexistence of solutions of nonlinear systems in a box (which nowadays is used to discard boxes in a branch and bound scheme) and to reduce the region where a solution can possibly lie (which is now used to avoid excessive splitting). KAHAN [168] discovered in 1968 that interval techniques can also be used to prove the existence of solutions of nonlinear systems in a box (and hence to verify feasibility). KRAWCZYK [188] simplified in 1969 Moore's methods for systems of equations; the Krawczyk operator based on his paper is used in several state of the art global solvers. (See also the historical remarks in [129, 205].) In 1972, PIYAVSKII [272] introduced complete global optimization methods based on Lipschitz constants, which are in flavor similar to interval methods.

- In 1964, TSUDA & KIONO [319] introduced the Monte Carlo method for finding solutions of systems of equations; and in 1966, the thesis by MOCKUS [223] applied it to global optimization. BECKER & LAGO [27] first used clustering methods in 1970, and TÖRN [314, 315] suggested in his 1974 thesis to combine these with local optimization, a combination which currently defines the most efficient class of stochastic global optimization algorithms [151]. HOLLAND [139] introduced in 1973 genetic algorithms, till today a popular (although usually slow) stochastic heuristics for global optimization.

As a recognizable mathematical discipline with diverse solution methods for precisely formulated problems involving continuous variables, the field essentially dates back to 1975 when the first book containing exclusively global optimization papers appeared, the volume 'Towards Global Optimization', edited by DIXON & SZEGÖ [69]. In the almost 30 years since the publication of this landmark volume, tremendous progress has been made, and many signs indicate that the field is now ripe for manifold applications in science and engineering.

Scope. Global optimization is the task of finding the absolutely best set of admissible conditions to achieve an objective under given constraints, assuming that both are formulated in mathematical terms. It is much more difficult than convex programming or finding local minimizers of nonlinear programs, since the gap between the necessary (Karush-Kuhn-Tucker) conditions for optimality and known sufficient conditions for global optimality is tremendous.

Many famous hard optimization problems, such as the traveling salesman problem or the protein folding problem, are global optimization problems. The truth of the famous unresolved conjecture $P \neq NP$ [101] would imply [236, 264] that there are no general algorithms that solve a given global optimization problem in time polynomial in the problem description length. However, some large-scale global optimization problems have been solved by current methods, and a number of software packages are available that reliably solve most global optimization problems in small (and sometimes larger) dimensions. The author maintains a web site on Global (and Local) Optimization [108] that contains many links to online information about the subject.

The different algorithms can be classified according to the degree of rigor with which they approach the goal:

- An **incomplete** method uses clever intuitive heuristics for searching but has no safeguards if the search gets stuck in a local minimum.
- An **asymptotically complete** method reaches a global minimum with certainty or at least with probability one if allowed to run indefinitely long, but has no means to know when a global minimizer has been found.
- A **complete** method reaches a global minimum with certainty, assuming exact computations and indefinitely long run time, and knows after a finite time that an approximate global minimizer has been found (to within prescribed tolerances).
- A **rigorous** method reaches a global minimum with certainty and within given tolerances even in the presence of rounding errors, except in near-degenerate cases, where the tolerances may be exceeded.

(Often, the label **deterministic** is used to characterize the last two categories of algorithms; however, this label is slightly confusing since many incomplete and asymptotically complete methods are deterministic, too.)

Complete search. Complete methods (and a fortiori rigorous ones) are (in exact arithmetic) guaranteed to find the global minimizer (within some tolerances) with a predictable amount of work. Here predictable only means relative to known problem characteristics such as Lipschitz constants or other global information (needed for the convergence proof, but usually not for the algorithm itself). The bound on the amount of work is usually very pessimistic – exponential in the problem characteristics. It is only a weak guarantee that does not ensure that the algorithm is efficient in any sense, but it guarantees the absence of systematic deficiencies that prevent finding (ultimately) a global minimizer.

The simplest complete method for bound constrained problems is **grid search**, where all points on finer and finer grids are tested, and the best point on each grid is used as a starting point for a local optimization. Since the number of points on a grid grows exponentially with the dimension, grid search is efficient only in one and two dimensions. More efficient complete methods generally combine branching techniques with one or several techniques from local optimization, convex analysis, interval analysis and constraint programming.

Generally, complete methods (including approximation methods that reduce the problem to one treated by complete methods) are more reliable than incomplete methods since, to the extent they work (which depends on the difficulty of the problem), they have built in guarantees.

Complete methods with finite termination require more or less detailed access to global information about the problem. In most complete codes, this is obtained using interval arithmetic (which provides global control of nonlinearities) in an automatic-differentiation-like manner (cf. Section 16), traversing a computational graph either explicitly, or implicitly by operator overloading. If only black box function (and sometimes gradient) evaluation routines are available, complete methods will find the global minimizer with certainty after a finite time, but will know when this is the case only after an exponentially expensive dense search, cf. Theorem 9.1 below. Thus for complete black box algorithms, stopping must be based on heuristic recipes.

Good heuristics and probabilistic choices (similar to but usually simpler than those for incomplete methods) also play a role in complete methods, mainly to cheaply provide good feasible points that benefit the complete search.

About the contents. In this survey, the reader will be introduced to theory and techniques that form the backbone of the packages implementing complete or even rigorous algorithms. The core of the material is presented in sufficient detail that the survey may serve as a text for teaching constrained global optimization.

Deliberately excluded are methods that are specific to special problem classes (such as distance geometry or protein folding [246]), and methods specific to combinatorial optimization [239, 240]. Moreover, the discussion of incomplete methods is limited to a short overview, and to techniques that remain useful for complete methods.

No attempt has been made to be objective in selection and evaluation of the material; even for the topics I discuss, there is often much more in the references quoted. Instead I have tried to give personal value judgments whenever I found it appropriate. At the present state of the art, where so many methods compete and reliable comparative information only just begins to become available, this seems justified. Thus I discuss the methods that I find most interesting, most useful, and most promising. I hope that my selection bias will be justified by the future. Also, while I try to give accurate references, I do not always refer to the first paper discussing a concept or method but rather quote convenient books or articles summarizing the relevant information, where available.

As one can see from the list of current codes for complete global optimization given in Section 6, none of these codes makes use of all available state-of-the-art techniques. Indeed, in the past, many research groups on global optimization worked with little knowledge of or care for what is going on in related areas. It is hoped that this survey helps to change this lack of communication across the borders of the various traditions in global optimization.

Reviews from other perspectives, less emphasizing the complete search aspect, are given in [117, 270, 316, 318]. For recent books and other basic references, see Section 3.

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2 Why global optimization?

Superficially, global optimization is just a stronger version of local optimization, whose great usefulness in practice is undisputed. Instead of searching for a locally unimprovable feasible point one wants the globally best point in the feasible region. In many practical applications, finding the globally best point is desirable but not essential, since any sufficiently good feasible point is useful and usually an improvement over what is available without optimization. For such problems, there is little harm in doing an incomplete search; and indeed, this is all that can be achieved for many large-scale problems or for problems where function values (and perhaps derivatives) are available only through a black box routine that does not provide global information.

However, there are a number of problem classes where it is indispensable to do a complete search. This is in particular the case for

- hard feasibility problems (e.g., robot arm design, cf. Lee et al. [197, 198]), where local methods do not return useful information since they generally get stuck in local minimizers of the merit function, not providing feasible points (though continuation methods are applicable for polynomial systems in low dimensions);
- computer-assisted proofs (e.g., the proof of the Kepler conjecture by Hales [128]), where inequalities must be established with mathematical guarantees;
- safety verification problems, where treating nonglobal extrema as worst cases may severely underestimate the true risk (emphasized in the context of robust control by Balakrishnan & Boyd [19]);
- many problems in chemistry (cf. below), where often only the global minimizer (of the free energy) corresponds to the situation matching reality;
- semi-infinite programming, where the optimal configuations usually involve global minimizers of auxiliary problems.

These problems, as well as the fact that algorithms doing a complete search are significantly more reliable and give rise to more interesting mathematics, justify our focus on complete solution techniques.

To show the relevance of global optimization for both pure and applied mathematics, we sketch here a number of typical applications. Of course, this is only the tip of an iceberg. . . .

(i) Many problems in graph theory are global optimization problems. For example, the **maximum clique problem** asks for the maximal number of mutually adjacent vertices in a given graph. By a well-known theorem of Motzkin & Strauss [233], an equivalent formulation is the indefinite quadratic program

$$\begin{array}{ll} \max & x^T A x \\ \text{s.t.} & e^T x = 1, \quad x \geq 0, \end{array}$$

where A is the adjacency matrix of the graph and e is the all-one vector. Since the maximum clique problem is NP-hard, the same holds for all classes of global optimization problems that contain indefinite quadratic programming.

(ii) **Packing problems**. The problem is to place a number of k-dimensional ($k \leq 4$) objects of known shape within a number of larger regions of k-space of known shape in such a way that there is no overlap and a measure of waste is minimized. The simplest packing problem is the **knapsack problem** where a maximal number of objects of given weights is to be placed into a container with given maximum weight capacity. Many packing problems arise in industry; but there are also a number of famous packing problems in geometry, of which the 300 year old **Kepler problem** of finding the densest packing of equal spheres in Euclidean 3-space was only solved recently by Hales [128] (reducing the problem to several thousand linear programs and some interval calculations to ensure rigorous handling of rounding errors). (The proof is still disputed because of the difficulty to check it for correctness; cf. Lagarias [191]. A proof based on rigorous global optimization algorithms would probably be more transparent.)

(iii) **Scheduling problems**. The problem is to match tasks (or people) and slots (time intervals, machines, rooms, airplanes, etc.) such that every task is handled in exactly one slot and additional constraints are satisfied. If there are several feasible matchings, one which minimizes some cost or dissatisfaction measure is wanted. Simple scheduling problems such as the **linear assignment problem** can be formulated as linear programs and are solved very efficiently, but already the related **quadratic assignment problem** is one of the hardest global optimization problems, where already most instances with about 30 variables are at the present limit of tractability, cf. Anstreicher [16].

(iv) **Nonlinear least squares problems**. In many applications, one needs to fit data to functional expressions. This leads to optimization problems with an objective function of a form such as

$$f(\theta) = \sum_l \|y_l - F(x_l, \theta)\|^2,$$

where x_l, y_l are given data vectors and θ is a parameter vector. Under certain assumptions, the most likely value of θ is the global minimizer; it generally must have a small objective function value at noise level if the model is to be deemed adequate. If the F_l are nonlinear in θ, a nonconvex optimization problem results that frequently has spurious local minima far above the noise level. A particularly obnoxious case is obtained for data fitting problems in **training neural networks**.

(v) **Protein folding**. The protein folding problem [246] consists in finding the equilibrium configuration of the N atoms in a protein molecule with given amino acid sequence, assuming the forces between the atoms are known. These forces are given by the gradient of the $3N$-dimensional potential energy function $V(x_1, \ldots, x_N)$, where x_i denotes the coordinate vector of the ith atom, and the equilibrium configuration is given by the global minimizer of V. Because short-range repulsive forces act like packing constraints, there are numerous local minima.

(vi) **Chemical equilibrium problems** [87, 216]. The task here is to find the number and composition of the phases of a mixture of chemical substances allowed to relax to equilibrium. Local optimization of the associated Gibbs free energy is notorious for giving wrong (nonglobal) solutions, and the need to solve such problems was one of the main driving forces for the development of constrained global optimization packages in the chemical engineering community, which till today is among the leaders in the field.

(vii) For applications in **robotics**, see NEUMAIER [251]. Many more applications can be found in the books by PINTER [269], FLOUDAS & PARDALOS [88, 92], JAULIN et al. [158].

3 Basic ideas

In the following, we discuss complete methods for finding the global minimizer(s) of an objective function subject to constraints. Such problems are typically much more difficult than local optimization problems, since it is often hard to decide whether a local minimizer found is global, and since one needs nonlocal space covering techniques to avoid being trapped in a region with only nonglobal local minimizers.

Basic to almost all complete global optimization algorithms is the **branching principle** (Section 9). This technique consists in splitting (branching) the original problem recursively into subproblems which are sooner or later easy to solve. In pure branching methods, the more prospective branches are split more frequently, while in **branch and bound methods** one computes for each subproblem bounds on the objective function in the hope of being able to eliminate many subproblems at an early stage.

The very useful technique of **constraint propagation**, discussed in Section 14, allows to reduce the feasible region in many cases by exploiting properties of **separable constraints** of the form

$$\sum_{k \in K} q_k(x_k) \in \mathbf{b}$$

with simple, often linear or quadratic functions q_k of a single variable only. This technique may save a lot of branching steps and thus speeds up the branch and bound procedure. This is a reason why special care should be taken in presenting (or transforming) the problem in a form which has as much separability as possible, and we introduce the notion of a **semiseparable program** adapted to this feature. Section 18 addresses ways to transform general problems into semiseparable form by introducing appropriate extra variables. Semiseparable programs are also amenable to approximation by a **mixed integer linear program** (MILP), the only class of global optimization problems that has a long reputation of being successfully solvable even for large problem instances. We shall not discuss techniques for solving MILPs (see, e.g., [34, 239, 240, 338]), but we show how to approximate (and indeed rigorously relax) general global optimization problems by MILPs in Sections 17 and 18.

In order to be able to quickly eliminate subproblems it is important that one can easily locate good feasible points. This is usually done by local optimization (often in a somewhat rudimentary form); see Section 13. However, especially for problems with many local extrema, it is important to use some heuristics which (hopefully) prevents that a local method is trapped in a high-lying local minimum. A suitable such tunneling technique is discussed in Section 13.

Another basic principle, discussed in Section 16, is that of **outer approximation** of the feasible domain and **underestimation** of the objective function, in order to obtain **relaxed problems** which are convex and hence solvable by local methods. Indeed, this is the traditional way to obtain the bounds on the subproblem. In particular, we consider the use of **cutting planes** and more general cutting surfaces. **Nonconvex relaxations** are also of interest if they can be solved efficiently.

A useful tool for the automatic construction of tight bound constraints, outer approximations and underestimating functions in nonlinear problems is **interval arithmetic**. Though little known in the optimization community, interval arithmetic is an elegant way of calculating with bound constraints, intervals, and simple higher dimensional geometric shapes like boxes and parallelepipeds. Its most prominent feature is that it allows strict estimates of the approximation error in linear and quadratic approximations of nonlinear functions over a box, thereby providing non-local information even in large boxes. In Section 11, we shall give a very short introduction to this subject (just sufficient for writing programs); a more leisurly introduction embedded into a standard numerical analysis course can be found in NEUMAIER [250], and a much more extensive treatment is in NEUMAIER [243]. Interval arithmetic can also be used to rigorously certify the validity of calculations with finite precision arithmetic, and some such applications to optimization are briefly treated in Section 20. The state of the art in 1996 of certified global optimization with interval methods is in KEARFOTT [173].

Basic references. A basic reference on most aspects of global optimization is the *Handbook of Global Optimization* by HORST & PARDALOS [142]. It contains chapters written by the experts in the respective subfields, on global optimality conditions, complexity issues, concave minimization, dc methods, indefinite quadratic programming, complementarity problems, minimax problems, multiplicative programming, Lipschitz optimization, fractional programming, network problems, continuation methods, interval methods, and stochastic methods (including simulated annealing).

Some more recent books present the state of the art in deterministic global optimization from different perspectives: The interval point of view is in KEARFOTT's 1996 book *Rigorous Global Search* [173]. The constraint propagation point of view is in the book *Numerica* by VAN HENTENRYCK et al. [328]; see also the tutorial by LUSTIG & J.-F. PUGET [204]. The convex analysis point of view is in the books *Deterministic Global Optimization* by FLOUDAS [86] and *Convexification and Global Optimization in Continuous and Mixed-Integer Nonlinear Programming* by TAWARMALANI & SAHINIDIS [309]. An attempt to give a synthetic view of the field (but mostly restricted to discrete optimization) is in the book *Logic-based Methods for Optimization* by HOOKER [141]; see also his survey [140].

A comprehensive background on local optimization (needed as part of most good global optimization algorithms) can be found in the book *Numerical Optimization* by NOCEDAL & WRIGHT [256]. For interior point methods, this should be complemented by [339].

Other books on global optimization methods include [94, 131, 143, 144, 224, 263, 269, 276, 277, 317, 330, 343], and proceedings of conferences on global optimization include [39, 42, 69, 89, 90, 91, 124]. The *Journal of Global Optimization* is devoted exclusively to papers on global optimization and its applications.

4 Problem formulation

In the present context, a global optimization problem is specified in the form

$$\begin{array}{ll} \min & f(x) \\ \text{s.t.} & x \in \mathbf{x}, \quad F(x) \in \mathbf{F}, \quad x_I \text{ integral.} \end{array} \tag{1}$$

Here

$$\mathbf{x} = [\underline{x}, \overline{x}] = \{x \in \mathbb{R}^n \mid \underline{x} \le x \le \overline{x}\},$$

is a bounded or unbounded **box** in $\mathbb{R}^n$ (with $\underline{x} \in (\mathbb{R} \cup \{-\infty\})^n, \overline{x} \in (\mathbb{R} \cup \{\infty\})^n, \underline{x} \le \overline{x}$), and x_I denotes the subvector $(x_{i_1}, \dots, x_{i_l})^T$ of x when $I = (i_1, \dots, i_l)$ is a list of indices. Inequalities between vectors are interpreted componentwise. $f : \mathbf{x} \to \mathbb{R}$ is a continuous objective function, $F : \mathbf{x} \to \mathbb{R}^m$ a vector of m continuous constraint functions $F_1(x), \dots, F_m(x)$, and $\mathbf{F}$ is a box in $\mathbb{R}^m$ defining the constraints on $F(x)$.

$$C = \{x \in \mathbf{x} \mid x_I \text{ integral}, F(x) \in \mathbf{F}\} \tag{2}$$

is the **feasible domain.** Points $x \in C$ are called **feasible**, and a **solution** of (1) is a feasible point $\hat{x} \in C$ such that

$$f(\hat{x}) = \min_{x \in C} f(x). \tag{3}$$

A **local minimizer** only satisfies $f(\hat{x}) \le f(x)$ for all $x \in C$ in some neighborhood of $\hat{x}$, and the solutions are precisely the **global minimizers**, i.e., the local minimizers with smallest objective function value. A **local (global) solver** is an algorithm or programming package designed for finding a local (global) minimizer. (We avoid the ambiguous term *optimizer* which may denote either a minimizer or a solver.)

The difficulties in global optimization stem mainly from the fact that there are generally many local minimizers but only one of them is the global minimizer (or just a few), and that the feasible region may be disconnected. (Consider, e.g., the set of positions in the Rocky Mountains above a certain altitude.) Already a linear objective function has one minimizer in each connected component of the feasible domain, and local descent methods usually fail if they start in the wrong component.

Even the **constraint satisfaction problem**, i.e., the problem of deciding whether the feasible set is nonempty (and finding a feasible point) is frequently highly nontrivial, and may be essentially as difficult as the optimization problem itself (cf. Section 13). The usual device of minimizing a suitable measure of infeasibility does not work when the constraints are sufficiently nonlinear since this measure has itself local minima in which descent methods often get stuck.

Usually, it is possible to reformulate a global optimization problem such that f and F are **smooth**, i.e., twice continuously differentiable. Note that (1) is sufficiently flexible to take care of

- free variables x_i: take $\underline{x}_i = -\infty$, $\overline{x}_i = \infty$;
- nonnegative variables x_i: take $\underline{x}_i = 0$, $\overline{x}_i = \infty$;
- binary variables x_i: take $\underline{x}_i = 0$, $\overline{x}_i = 1$, $i \in I$;
- equality constraints $F_i(x) = 0$: take $\underline{F}_i = \overline{F}_i = 0$;
- inequality constraints $F_i(x) \leq 0$: take $\underline{F}_i = -\infty$, $\overline{F}_i = 0$.

If I is not empty then, if f and F are linear then (1) is called a **mixed integer linear program (MILP)**; and if f and F are convex, and $\underline{F}_i = -\infty$ for all nonlinear F_i, (1) is called a **mixed integer nonlinear program (MINLP)**. Strictly speaking, this term should apply for all problems (1); however, the current techniques for MINLP use the convexity in an essential way, so that it is appropriate to reserve the term for the convex case. Nonconvex mixed integer global optimization problems have received little attention, but see, e.g., [85, 284, 309]

The only class of global optimization problems that can be reliably solved for many large problem instances (say, $\approx 10^5$ variables and $|I| \approx 10^3$) is the class of MILPs. This is due to the fact that after fixing the integer variables one is left with a linear program, which can be solved efficiently. Instead of trying all integer combinations separately, branching techniques (branch and bound, branch and cut) combined with preprocessing the resulting linear programs drastically cut down the number of cases to be looked at. MINLP shares with MILP the feature that fixing all integer variables leads to a tractable problem, in this case a convex nonlinear program, for which every local minimizer is a solution; however, the dimensions are here more limited since nonlinear programming codes are significantly slower than their linear counterparts.

Most of constrained global optimization is nowadays best viewed as an adaptation of mixed integer programming technology to nonlinear problems. Historically, however, many of the techniques were devised independently by groups working in integer programming, combinatorial optimization, unconstrained optimization, interval analysis, and constraint logic programming.

Other important classes of global optimization problems:

- **simply constrained**: if $\dim F = 0$,
- **continuous**: if $I = \emptyset$,
- **bound constrained**: if simply constrained and continuous,
- **separable**: if $f(x) = \sum_{k=1}^{n} f_k(x_k)$ and $F(x) = \sum_{k=1}^{n} F_k(x_k)$,
- **factorable**: if f and F are obtained by applying a finite sequence of arithmetic operations and unary elementary functions to constants and the x_k,
- **reverse convex**: if f, F are concave, and $\underline{F}_i = -\infty$ for all nonlinear F_i,
- **DC**: if f, F are differences of convex functions.

5 First order optimality conditions

Traditional nonlinear programming provides the following necessary **(Karush-John) optimality conditions** for local minimizers. We assume that f, F are continuously differentiable, and denote by $f'(x)$ and $F'(x)$ the derivatives at x. Note that $f'(x)$ is a row vector and $F'(x)$ a matrix, the **Jacobian**.

5.1 Theorem. (Karush [170], John [162])

For every local minimizer $\hat{x}$ of (1) *(which defines the notation) there are a number $\kappa \geq 0$ and a vector y, not both zero, such that the row vector*

$$g^T = \kappa f'(\hat{x}) + y^T F'(\hat{x}) \tag{4}$$

satisfies

$$g_i \begin{cases} \geq 0 & \text{if } \underline{x}_i = \hat{x}_i < \overline{x}_i, \quad i \notin I, \\ \leq 0 & \text{if } \underline{x}_i < \hat{x}_i = \overline{x}_i, \quad i \notin I, \\ = 0 & \text{if } \underline{x}_i < \hat{x}_i < \overline{x}_i, \quad i \notin I, \end{cases} \tag{5}$$

$$y_i \begin{cases} \geq 0 & \text{if } \underline{F}_i < F_i(\hat{x}) = \overline{F}_i, \\ \leq 0 & \text{if } \underline{F}_i = F_i(\hat{x}) < \overline{F}_i, \\ = 0 & \text{if } \underline{F}_i < F_i(\hat{x}) < \overline{F}_i. \end{cases} \tag{6}$$

Note that there is no restriction on g_i if $i \in I$ or $\underline{x}_i = \overline{x}_i$, and no restriction on y_i if $\underline{F}_i = F_i(\hat{x}) = \overline{F}_i$. Buried implicitly in results of MANGASARIAN [209], and spelled out explicitly in NEUMAIER & SCHICHL [254], is the observation that one may in fact assume that either κ or the subvector y_J of y is nonzero, where J is the set of indices i such that either $F_i(x)$ is nonconvex and $F_i(\hat{x}) = \underline{F}_i$ or $F_i(x)$ is nonconcave and $F_i(\hat{x}) = \overline{F}_i$. (In particular, J does not contain any index i such that $F_i(x)$ is linear.) In view of the homogeneity of the statement of the theorem, one can therefore scale the multipliers such that

$$\kappa + y_J^T D y_J = 1, \tag{7}$$

where D is an arbitrary diagonal matrix with positive entries. This condition is relevant for the application of exclusion box techniques (cf. Section 15).

We say that $\hat{x}$ satisfies a **constraint qualification** (CQ) if (4)–(6) hold for some $\kappa > 0$. In this case, one can scale g, κ, y to enforce $\kappa = 1$ and obtains the more frequently used **Kuhn-Tucker conditions** (KUHN & TUCKER [189, 190]). A sufficient condition for the constraint qualification is that the rows of $F'(\hat{x})$ are linearly independent; various weaker conditions guaranteeing CQ are known.

If $\kappa = 1$ then y is called an optimal **Lagrange multiplier** corresponding to $\hat{x}$ (it need not be unique). In this case, g is the gradient of the associated **Lagrangian** (LAGRANGE [192])

$$L(x, y) = f(x) + y^T F(x)$$

at $x = \hat{x}$.

Note that minimizers with huge Lagrange multipliers are best considered as points nearly violating the constraint qualification, so that (4) holds with $y = O(1)$ and tiny κ.

If there are only nonnegativity constraints and equality constraints,

$$C = \{x \geq 0 \mid F(x) = b\},$$

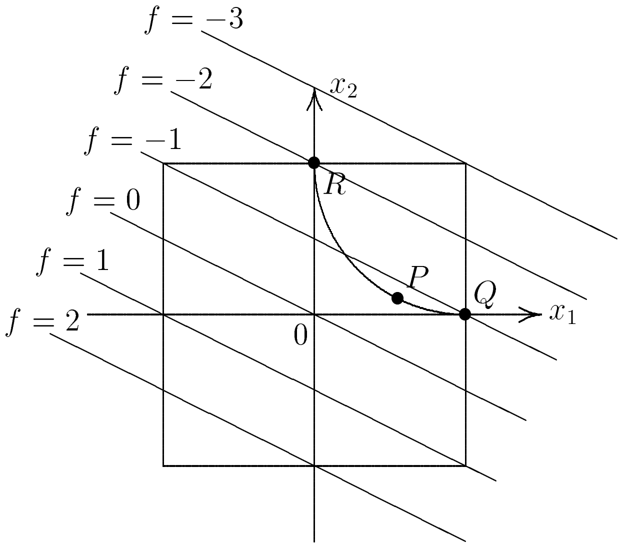
corresponding to $\underline{x}_i = 0$, $\overline{x}_i = \infty$, $\underline{F}_i = \overline{F}_i = b_i$ then the conditions (6) are vacuous, and (5) reduces to the traditional **complementarity condition**

$$\min(g_i, x_i) = 0 \quad \text{for all } i.$$

5.2 Example. We consider the problem

$$\begin{array}{ll} \min & f(x) = -x_1 - 2x_2 \\ \text{s.t.} & F(x) = (x_1 - 1)^2 + (x_2 - 1)^2 = 1, \quad x_1, x_2 \in [-1, 1]. \end{array} \tag{8}$$

Figure 1: Feasible region and contour lines for Example 5.2.



The feasible region is a quarter circle, and the contour lines of the objective function are linear, decreasing in the direction indicated in Figure 1. This implies that there is a unique maximizer at P, a local minimizer at Q and a global minimizer at R. The solution is therefore $\hat{x} = \binom{0}{1}$. Since there are only two variables, we analyzed the problem graphically, but we could as well have proceeded symbolically as follows.

Assuming for simplicity the validity of the CQ, we find for the gradient of the Lagrangian

$$g = \begin{pmatrix} -1 \\ -2 \end{pmatrix} + y \begin{pmatrix} 2x_1 - 2 \\ 2x_2 - 2 \end{pmatrix}.$$

The Kuhn-Tucker conditions require that $g_i \geq 0$ if $\hat{x}_i = -1$, $g_i \leq 0$ if $\hat{x}_i = 1$, and $g_i = 0$ otherwise. This leaves three cases for each component, and a total of $3 \cdot 3 = 9$ cases. If we assume $|\hat{x}_1|, |\hat{x}_2| < 1$ we must have $g = 0$, hence $\hat{x}_1 = 1 + 1/2y$, $\hat{x}_2 = 1 + 1/y$. Since $\hat{x}$ must be feasible, $y < 0$, and since $F(\hat{x}) = 1$, $y = -\frac{1}{2}\sqrt{5}$, $\hat{x} = (1 - 1/\sqrt{5}, 1 - 2/\sqrt{5})^T$, which is the local maximizer P. If we assume $\hat{x}_1 = -1$ or $\hat{x}_2 = -1$, or $\hat{x}_1 = \hat{x}_2 = 1$, we find a contradiction with $F(\hat{x}) = 1$. (These are 6 cases!) If we assume $|\hat{x}_2| < 1 = \hat{x}_1$ we find Q, and for $|\hat{x}_1| < 1 = \hat{x}_2$ we find R. Thus we have three feasible points satisfying the Kuhn-Tucker conditions, and a comparison of their function values shows that R is the global minimizer.

In general, we have three cases for each two-sided inequality and two for each one-sided inequality; since the number of independent choices must be multiplied, the total number of cases grows exponentially with the number of inequalities in the problem formulation. Hence this symbolical approach is limited to problems with few inequality constraints. Even then it only works if the resulting nonlinear equations are symbolically solvable and have few solutions only. Thus, in general, we need to resort to numerical methods.

We draw several conclusions from the example. First, there is a combinatorial aspect to the continuous global optimization problem, so that it resembles a mixed integer problem.

Second, several cases can often be excluded by a single argument, which is the basis for the branch and bound approach to global optimization. Third, the Karush-John or Kuhn-Tucker conditions do not distinguish between maxima and minima (and other "stationary" points); all these would have to be enumerated in a naive approach. Since there may be an exponential number of Kuhn-Tucker points, additional techniques are needed to reduce the search space. Lagrange multiplier techniques involving second order conditions will address this last point; cf. Theorem 15.1.

6 Software for complete global optimization

Here we list some of the better complete global optimization codes available on the WWW, with short comments on scope and method. Several of the codes (LGO, BARON, SBB, DICOPT) can be called from the GAMS modeling system [100], allowing for very convenient input. Input from the AMPL modeling system [97] will be possible through an AMPL to GAMS translator available within the COCONUT environment; cf. Section 22. Only two of the codes (GlobSol and Numerica) are rigorous solvers.

Some branching codes using function values only. The codes listed use black box function evaluation routines, and have heuristic stopping rules, so that the actual implementation yields an incomplete search only.

(i) **DIRECT, Divide Rectangles** (in Fortran, by Gablonsky [99])
`ftp://ftp.math.ncsu.edu/FTP/kelley/iffco/DIRECTv204.tar.gz`

Direct.m, a Matlab implementation of DIRECT
`http://www4.ncsu.edu/~definkel/research/`

Implementations of a simple and efficient global optimization method by Jones et al. [165] for bound constrained problems. DIRECT is based on branching and a Pareto principle for box selection.

(ii) **MCS, Multilevel Coordinate Search** (by Huyer & Neumaier [145])
`http://www.mat.univie.ac.at/~neum/software/mcs/`

A Matlab program for bound constrained global optimization using function values only. MCS is based on branching and sequential quadratic programming.

(iii) **LGO, Lipschitz Global Optimization** (commercial, by Pintér [269, 271])
`http://is.dal.ca/~jdpinter/l_s_d.htm`

An integrated development environment for global optimization problems with Lipschitz continuous objective and constraints. LGO is based on branching and stochastic estimation of Lipschitz constants; constraints other than simple bounds are handled by L_1 penalty terms, but interior convex constraints by projection penalties. (LGO also has options for incomplete search methods; these give generally better results than the branching option.)

Some branch and bound codes. The codes listed use global information (generally from required symbolic problem input). They have finite termination with guarantee that the global minimizer is found within certain tolerances; in difficult cases storage or time limits may be exceeded, however, leading to appropriate error messages. All codes use at least basic constraint propagation, but differ considerably in the other techniques implemented.

Not listed are the many MILP codes available (see the Global Optimization Web Page mentioned in the introduction).

(i) **BARON, Branch-And-Reduce Optimization Navigator** (commercial, by Sahinidis et al. [282, 284, 285, 286, 309, 310])
`http://archimedes.scs.uiuc.edu/baron/baron.html`

A general purpose solver for optimization problems with nonlinear constraints and/or integer variables. Fast specialized solvers for many linearly constrained problems. BARON is based on branching and box reduction using convex and polyhedral relaxation and Lagrange multiplier techniques.

(ii) **GlobSol, Global Solver** (in Fortran 90, by Kearfott [173, 174])
`http://www.mscs.mu.edu/~globsol/`

Branch and bound code for global optimization with general factorable constraints, with rigorously guaranteed results (even roundoff is accounted for correctly). GlobSol is based on branching and box reduction using interval analysis to verify that a global minimizer cannot be lost.

(iii) **LINGO** (commercial, by Gau & Schrage [103])
`http://www.lindo.com/cgi/frameset.cgi?leftlingo.html;lingof.html`

Branch and bound code for global optimization with general factorable constraints, including nondifferentiable expressions. LINGO is based on linear relaxations and mixed integer reformulations. C and Excel interfaces are available.

(iv) **Frontline Interval Global Solver** (commercial, by Nenov & Fylstra [241])
`http://www.solver.com/technology5.htm`

This solver is based on interval methods and linear relaxations. Visual Basic and Excel interfaces are available.

(v) **ALIAS** (in C, by Merlet [7, 218])
`http://www-sop.inria.fr/coprin/logiciels/ALIAS/ALIAS-C++/ALIAS-C++.html`

Branch and bound environment for solving constraint satisfaction problems (and rudimentary global optimization). A toolkit of interval analysis and constraint programming techniques with a Maple interface for symbolic preprocessing.

(vi) **Numerica** (by van Hentenryck, Michel & Deville [328])

Branch and bound code for constrained optimization (with mathematically rigorous results). This code (no longer available) was based on branching and box reduction using interval

analysis and deeper constraint propagation techniques. The box reduction and interval analysis algorithms of Numerica are now available in **ILOG Solver** (commercial) at
`http://www.ilog.com/products/solver/`

(vii) α**BB** (by Adjiman, Floudas and others [3, 2, 4, 15])
`http://titan.princeton.edu/soft.html#abb`

Branch and bound code for nonlinear programs. The site has currently the description only; no code. αBB is based on branch and bound by convex underestimation, using interval analysis to write nonlinearities in DC (difference of convex functions) form.

(viii) **LaGO** (by Nowak, Alperin & Vigerske [257])
`http://www-iam.mathematik.hu-berlin.de/~eopt/#Software`

Branch and bound code for mixed integer nonconvex nonlinear programming, using block-separable structure and convex underestimation. The site has currently the description only; no code.

(ix) **GloptiPoly** (in Matlab, by Henrion & Lasserre [135, 136, 137])
`http://www.laas.fr/~henrion/software/gloptipoly/`

Global optimization of polynomial nonlinear programs, using semidefinite relaxations. Currently limited to problems with less than 20 variables.

(x) **SOSTOOLS** (in Matlab, by Prajna et al. [273])
`http://control.ee.ethz.ch/~parrilo/sostools/index.html`

Matlab toolbox for solving sums of squares (SOS) optimization programs. Allows the solution of polynomial global optimization problems.

(xi) **cGOP** (by Visweswaran & Floudas [83, 84])
`http://titan.princeton.edu/soft.html`

Branch and bound code for linearly constrained global optimization problems with an objective containing linear, bilinear, and convex terms, using convex relaxations.

(xii) **MINLPBB** (commercial, by Fletcher & Leyffer [83, 84])
`http://www-unix.mcs.anl.gov/~leyffer/solvers.html`

Branch and bound code for mixed integer nonlinear programming; finding the global optimum is guaranteed only if all constraints become convex when all integer variables are fixed. Problems with AMPL input can be solved online via **NEOS** at
`http://www-neos.mcs.anl.gov/neos/solvers/MINCO:MINLP-AMPL/`
MINLP uses standard mixed integer programming techniques and filter methods for the local subproblems.

(xiii) **DICOPT** (commercial, by Grossmann [74, 182])
`http://www.gams.com/solvers/dicopt/main.htm`

Solver for mixed integer monlinear programming (MINLP) problems. Finding the global optimum is guaranteed only if all constraints become convex when all integer variables are fixed.

(xiv) **SBB** (commercial, by BUSSIEK & DRUD [47])
`http://www.gams.com/solvers/solvers.htm#SBB`

Branch and bound code for mixed integer nonlinear programming; finding the global optimum is guaranteed only if all constraints become convex when all integer variables are fixed. Problems with GAMS input can be solved online via **NEOS** at
`http://www-neos.mcs.anl.gov/neos/solvers/MINCO:SBB-GAMS/`
SBB uses standard mixed integer programming techniques and sequential quadratic programming methods for the local subproblems.

MINLPBB, DICOPT and SBB are borderline cases in our list since they do not use truly global techniques for the continuous variables, and will not be discussed further.

7 Incomplete methods for simple constraints

As mentioned in the introduction, numerical methods for global optimization can be classified into four categories according to the available guarantees. We shall be mainly concerned with complete methods; however, since incomplete and asymptotically complete methods are frequently successful and, for many difficult problems, the only feasible choice, we give an overview of the main possibilities. In these categories are several deterministic and most stochastic methods. For some of the latter, it is possible to prove convergence with probability arbitrarily close to 1 (if running arbitrarily long), but this does not yet guarantee convergence. (Moreover, the assumptions underlying the convergence proofs are frequently not verifiable for particular examples.)

The simplest incomplete method is **multiple random start**, consisting of picking random starting points and performing local optimizations from these points, in the hope that one of them is in the basin of attraction of the global minimizer. Most stochastic techniques can be regarded as devices for speeding up this basic method, by picking the points more carefully and by doing only rudimentary local optimization, or optimizing only selectively.

Most of the research on incomplete search has been concentrated on global optimization methods for simply constrained problems only. Many different incomplete methods are known for simply constrained problems, and we sort them into four categories: **local descent techniques**, including among others multiple random start, clustering [41], tunneling [200], and smoothing methods [126, 187, 232, 304]; **response surface techniques**, including Bayesian stochastic techniques [224, 225] and related techniques [35, 164, 166]; **nonmonotonic search techniques**, including among others tabu search [111, 112], simulated annealing [181, 149, 330], and deterministic variants such as threshold accepting [73]; **ensemble methods**, including genetic algorithms [139, 95, 221] and variants such as ant colony minimization [72].

No attempt is made to be representative or complete on referencing or describing the large literature on incomplete techniques; we only mention the 1975 book by Dixon & Szegö [69], which marks the start of a tradition of comparing different global optimization methods, an excellent exposition of stochastic global optimization methods for bound constrained problems on the WWW by Törn [316], and another WWW-survey of (mainly incomplete) methods by Hart [117]. For incomplete search in combinatorial optimization (where the underlying ideas are also called **metaheuristics**), see, e.g., [1, 340].

Instead of describing technical details of the various methods (these vary from author to author and even from paper to paper), we give an informal view of the ideas, strengths and weaknesses of one method from every category, each based on analogies to natural processes where more or less global optima are reached. While these techniques are motivated by nature it is important to remember that processes in nature need not be the most efficient ones; at best they can be assumed to be efficient *given the conditions under which they have to operate* (namely an uncertain and changing environment that is potentially hazardous to those operating in it). Indeed, much of our present technology has vastly surpassed natural efficiency by unnatural means, and it would be surprising if it were different in global optimization. Even assuming that nature solves truly *global* optimization problems (a disputable assumption), simple lower estimates for the number of elementary steps – roughly corresponding to function evaluations – available to natural processes to converge are (in chemistry and in biology) in the range of 10^{15} or even more. This many function evaluations are unacceptable for present day computers, and will be so in the near future.

With a limited number of function evaluations, the quality of incomplete methods depends a lot on details of the implementation; comparisons on relative efficiency are virtually missing. Indeed, the techniques must generally be tuned to special classes of applications in order to be fast and competitive, which makes general purpose comparisons difficult and inconclusive.

Smoothing (= **homotopy** = **continuation**) **methods** are based on the intuition that, in nature, macroscopic features are usually an average effect of microscopic details; averaging smoothes out the details in such a way as to reveal the global picture. A huge valley seen from far away has a well-defined and simple shape; only by looking more closely, the many local minima are visible, more and more at smaller and smaller scales. The hope is that by smoothing a rugged objective function surface, most or all local minima disappear, and the remaining major features of the surface only show a single minimizer. By adding more and more details, the approximations made by the smoothing are undone, and finally one ends up at the global minimizer of the original surface.

In mathematical terms, one has to define a homotopy by introducing an additional parameter t into the problem in such a way that $t = 0$ gives the original problem, while $t = 1$ gives either a related convex problem or a related problem with a unique and known global minimizer. (There are various ways of doing this; homotopies whose parameter has a natural interpretation in the context of the original problem usually perform better.) Then a sequence of local problems is solved for $t = t_1, t_2 \ldots, t_N$, where the t_i form a decreasing sequence starting at 1 and ending at 0. Each time, the solution of the previous problem is taken as the starting point for the current problem. The quality of the final local minimizer depends on the homotopy, and frequently is the global or at least a good local minimizer.

There is no theoretical work on conditions that would ensure convergence to the global minimum. In particular, it is quite possible for such a method to miss the global minimum. However, for properly chosen homotopies, smoothing methods at least give good local minima with a small number of function evaluations. (For more theory on homotopy methods, see, e.g., [126, Section 6.3].)

Response surface techniques are designed specifically for the global optimization of functions that are very expensive to evaluate. They construct in each iteration an interpolation or approximation **surrogate function** of known analytic form. The surrogate function is then subjected to global optimization, e.g., by some form of multiple random start (started at a selection of the current points). The resulting optimizers (or some points where the feasible region has been only sparsely explored) are taken as new evaluation points. Since this is sequential global optimization, each step is much more expensive than the others, but the reduction of the number of function values needed gives (for sufficiently expensive function evaluations) a net gain in speed.

In principle, these methods may have convergence guarantees if the point selection strategy is well-chosen; but this is irrelevant in view of the fact that for expensive functions, only few (perhaps up to 1000) function evaluations are admissible.

Simulated annealing takes its intuition from the fact that the heating (annealing) and slow cooling of a metal brings it into a more uniformly crystalline state that is believed to be the state where the free energy of bulk matter takes its global minimum. (Incidentally, even for the simplest potential energy functions, it is still an unsolved problem whether this is indeed true with mathematical rigor. Apart from that, even very pure crystals still have defects; i.e., the global minimum is not quite achieved in nature.) The role of temperature is to allow the configurations to reach higher energy states with a probability given by Boltzmann's exponential law, so that they can overcome energy barriers that would otherwise force them into local minima. This is quite unlike line search methods and trust region methods on which good local optimization programs are based.

In its original form, the simulated annealing method is provably convergent in a probabilistic sense but exceedingly slow; various ad hoc enhancements make it much faster. In particular, except for simple problems, success depends very much on the implementation used.

Genetic algorithms make use of analogies to biological evolution by allowing mutations and crossing over between candidates for good local optima in the hope to derive even better ones. At each stage, a whole population of configurations is stored. Mutations have a similar effect as random steps in simulated annealing, and the equivalent of lowering of the temperature is a rule for more stringent selection of surviving or mating individuals.

The ability to leave regions of attraction to local minimizers is, however, drastically enhanced by crossing over. This is an advantage if, with high probability, the crossing rules produce offspring of similar or even better fitness (objective function value); if not, it is a severe disadvantage. Therefore the efficiency of a genetic algorithm (compared with simulated annealing type methods) depends in a crucial way on the proper selection of crossing rules. The effect of interchanging coordinates is beneficial mainly when these coordinates have a nearly independent influence on the fitness, whereas if their influence is highly correlated (such as for functions with deep and narrow valleys not parallel to the coordinate axes), genetic algorithms have much more difficulties. Thus, unlike simulated annealing, successful tuning of genetic algorithms requires a considerable amount of insight into the nature of the problem at hand.

Both simulated annealing methods and genetic algorithms are, in their simpler forms, easy to understand and easy to implement, features that invite potential users of optimization methods to experiment with their own versions. The methods often work, if only slowly, and may be useful tools for applications where function values are not very expensive and the primary interest is to find (near-)solutions *now*, even when the reliability is uncertain and only subglobal optima are reached.

To make simulated annealing methods and genetic algorithms efficient, clever enhancements exploiting expert knowledge about the problem class at hand are essential. Theoretical work on explaining the effectiveness of useful enhancements is completely lacking. I also haven't seen careful comparisons of the various options available and their comparative evaluation on standard collections of test problems.

In general, incomplete methods tend to fail systematically to find the global optimum on the more difficult problems in higher dimensions, but they frequently give relatively good points with a reasonable amount of effort. Beyond a certain number of function evaluations (that depends on the problem), progress slows down drastically if the global optimum has not yet been located already. This is unlikely to change in the future, although new heuristics and variations of old ones are discovered almost every year.

For general purpose global optimization, the most promising incomplete methods appear to be clustering methods (see the recent comparison by Janka [151]), being fairly robust and fast. In particular, the multilevel clustering algorithm by Boender et al. [41], as implemented by Csendes [62], can be recommended. Among incomplete algorithms adapted to problem structure, I would favor smoothing methods (if a natural homotopy is available) and tabu search like strategies (since these have a kind of memory).

8 Bound constrained approximation

For general constraints, incomplete techniques are much less developed. Only the smoothing techniques extend without difficulties to general constraints. To use the other incomplete techniques, it is customary to rewrite problems with general constraints in an equivalent or approximately equivalent form with either simple constraints only, for which the methods of the previous section apply, or into a mixed integer linear problem (MILP), since highly efficient software is available for solving the latter [34]. Both transformations are of great practical importance and widely used. Solving the transformed (equivalent or approximate) problem yields an approximate solution for the original problem, and local optimization from this approximate solution gives the global minimizer of the original problem if the approximation was good enough, and usually a good local minimizer otherwise.

In this section we treat the approximation of general constrained problems by bound constrained problems using penalty and barrier functions. The approximation of nonlinear problems by mixed integer linear programs is treated in Section 18.

Penalty and barrier formulations. Traditionally (see Fiacco & McCormick [82]), constraints that cannot be handled explicitly are accounted for in the objective function, using simple l_1 or l_2 penalty terms for constraint violations, or logarithmic barrier terms penalizing the approach to the boundary. In both cases, the reformulation changes the solution, so that this is an instance of an approximation method, and the result should be used as a starting point for a subsequent local optimization of the original problem. There are also so-called exact penalty functions whose optimization gives the exact solution (see, e.g., Nocedal & Wright [256]); however, this only holds if the penalty parameter is large enough, and what is large enough cannot be assessed without having global information.

The use of more general transformations gives rise to more precisely quantifiable approximation results. In particular, if it is known in advance that all constraints apart from the simple constraints are soft constraints only (so that some violation is tolerated), one may pick a transformation that incorporates prescribed tolerances into the reformulated simply constrained problem, using the following variation of a similar, but less flexible result of Dallwig et al. [64], given in Huyer & Neumaier [147].

8.1 Theorem. (Soft optimality theorem)

Given $\Delta, \underline{\sigma}_i, \overline{\sigma}_i > 0, f_0 \in \mathbb{R}$, let

$$q(x) = \frac{f(x) - f_0}{\Delta + |f(x) - f_0|},$$

$$\delta_i(x) = \begin{cases} (F_i(x) - \underline{F}_i)/\underline{\sigma}_i & \text{if } F_i(x) \le \underline{F}_i, \\ (F_i(x) - \overline{F}_i)/\overline{\sigma}_i & \text{if } F_i(x) \ge \overline{F}_i, \\ 0 & \text{otherwise}, \end{cases}$$

$$r(x) = \frac{2\sum \delta_i^2(x)}{1 + \sum \delta_i^2(x)}.$$

Then the merit function

$$f_{\text{merit}}(x) = q(x) + r(x)$$

has its range bounded by $]-1, 3[$, *and the global minimizer* $\hat{x}$ *of* f_{merit} *in* $\mathbf{x}$ *either satisfies*

$$F_i(\hat{x}) \in [\underline{F}_i - \underline{\sigma}_i, \overline{F}_i + \overline{\sigma}_i] \quad \text{for all } i, \tag{9}$$

$$f(\hat{x}) \le \min\{f(x) \mid F(x) \in \mathbf{F}, x \in \mathbf{x}\}, \tag{10}$$

or one of the following two conditions holds:

$$\{x \in \mathbf{x} \mid F(x) \in \mathbf{F}\} = \emptyset, \tag{11}$$

$$f_0 < \min\{f(x) \mid F(x) \in \mathbf{F}, x \in \mathbf{x}\}. \tag{12}$$

(9) says that a soft version of the constraints is satisfied. The numbers $\underline{\sigma}_i$ and $\overline{\sigma}_i$ measure the degree to which the lower and upper bounds in the constraint $F_i(x) \in \mathbf{F}_i$ may be softened; suitable values are in many practical applications available from the meaning of the constraints.

(10) says that f_{merit} has a lower global minimum value (attained at a point satisfying the soft constraints) than the global minimum value of the original problem (on the hard version of the constraints). Thus little is lost from a practical point of view.

The degenerate cases (11)–(12) account for the possibility of an empty feasible set (11), and for a choice of f_0 that was too small. If a feasible point is already known we may choose f_0 as the function value of the best feasible point known (at the time of posing the problem), thus eliminating the possibility (11). If none is known, f_0 should be chosen as a fairly large value to avoid (12); it can be reset (and the optimization restarted) when a feasible point becomes available during the search.

In spite of the absolute value in the definition of $q(x)$, f_{merit} is continuously differentiable if f and F have this property. A suitable value for Δ is the median of the values $|f(x) - f_0|$ for an initial set of trial points x (in the context of global optimization often determined by a space-filling design [217, 260, 261, 283, 306]).

Projection penalties. A little known result by PINTER [269] may be used to get in certain cases (in particular, for linear and convex quadratic constraints) an exact reformulation as a nonsmooth but Lipschitz continuous simply constrained problem. The idea is to project infeasible points to the feasible domain.

To accommodate linear constraints (or convex quadratic ones), Pinter assumes that x_0 is a known interior point. For arbitrary $\gamma > 0$ he now defines the modified objective function

$$\overline{f}(x) := f(\overline{x}) + \gamma\|\overline{x} - x\|^2, \tag{13}$$

where

$$\overline{x} = \lambda x_0 + (1 - \lambda)x \tag{14}$$

and $\lambda = \lambda_x \geq 0$ is smallest such that $\overline{x}$ satisfies the linear constraints. This is well-defined, since $\lambda = 1$ always works by the choice of x_0. Each constraint contributes a lower bound $\in [0, 1]$ for λ, and the largest of these bounds is the desired value. In particular, a linear constraint $a^T x \leq \alpha$ contributes a nonzero lower bound

$$\lambda \geq (a^T x - \alpha)/(a^T x - a^T x_0)$$

if both numerator and denominator of the right hand side are positive. A convex quadratic constraint similarly yields a quadratic inequality that can easily be solved for λ. (Convexity can be weakened to star-shapedness with respect to x_0.)

The modified objective function (13) is Lipschitz continuous, but nonsmooth at all points where the ray (14) hits a lower-dimensional face of the feasible domain. Note that to evaluate (13), function values are needed only at points satisfying the linear (or convex quadratic) constraints.

An interior point can be found by solving a linear program or a convex second order cone program. If no interior point exists since the feasible set is in a lower-dimensional subspace, each feasible point has the form $x = x_0 + Cz$ with $z \in \mathbf{z}$, where x_0 is in the relative interior of the feasible domain, and $\mathbf{z}$ a box with $0 \in \operatorname{int} \mathbf{z}$. Both x_0 and C can be found by techniques from convex analysis for finding a maximal independent set of points in the affine subspace spanned by the feasible set. Reposing the optimization problem in terms of z reduces the dimension and yields a problem in which 0 is an interior point.

9 Pure branching methods

We begin our analysis of complete methods for global optimization by looking at the options for methods that can access no global information about a problem. The information is made available via black box routines that provide **local information** only, i.e., function values and possibly gradients or Hessians at single points. A necessary and sufficient condition for complete methods based on local information only is given by the following important **density theorem** due to Törn & Zilinskas [317]. It formalizes the simple observation that after finitely many local evaluations there are still many 'holes', i.e., balls not containing an already evaluated point, and there are many functions [249] that have the known function values, gradients and Hessians at the evaluation points but an arbitrarily low function value at the center of such a ball.

9.1 Theorem. *Any method based on local information only that converges for every continuous f to a global minimizer of f in a feasible domain C must produce a sequence of points $x^1, x^2, \ldots$ that is dense in C.*

Conversely, for any such method,

$$\liminf_{l \to \infty} f(x^l) = \min\{f(x) \mid x \in C\}.$$

A global optimization method based on local information only is called **convergent** if it satisfies the hypothesis of the density theorem. (Actual implementations of a convergent global optimization method usually are not truly convergent since they must have built in termination criteria that are necessarily heuristic.)

Convergence is a **minimal** requirement and does not make an algorithm good! For example, exhaustive grid search is convergent but far too slow in dimensions > 2. (Compare with local optimization with line searches along the steepest descent direction, which is globally convergent but frequently very slow.) In a sense, the density theorem says that any convergent method must be ultimately exhaustive, though it may delay the detailed exploration of unpromising regions. Since, in practice, only a limited number of points can be explored, the behavior of a pure branching method is governed by its ability to find a good ordering of the points to be evaluated for which premature termination has no severe effect.

Three good complete general purpose global optimization algorithms based on local information only are currently available: DIRECT [165], MCS [145] and LGO [269]. All work for bound constrained problems only and need the approximation techniques of Section 8 for more general problems. (Some of these are built in into LGO, but must be coded by the user for DIRECT and MCS.) All three algorithms enforce convergence by employing a branching scheme. They differ in how and when to split, and what is done within each box.

A **branching scheme** generates a sequence of rooted trees of boxes whose leaves cover the feasible set. At least one point in each box is evaluated. The first tree just has the original box as root and only leaf. Each other tree is obtained from the previous one by splitting one or several leaves. If the diameters of all boxes at all leaves converge to zero, convergence of the algorithm is straightforward.

The convergence to zero of the diameters is ensured by appropriate **splitting rules** that define when and how a box is split. For example, convergence is guaranteed when in each of a sequence of rounds, one

- always splits the oldest box along the oldest side, and possibly splits finitely many other boxes, or
- always splits the longest box along the longest side, and possibly splits finitely many other boxes (where length = sum of length of sides),

provided that each split of the oldest (or longest) box produces boxes whose volume is at most a fixed fraction < 1 of the unsplit box. The possibility of 'and finitely many other boxes' (but not many if the code is to be robust!) can be used with considerable flexibility without destroying the convergence property.

Apart from the convergence requirement, the key to efficiency is a proper balance of global and local search. This is achieved in DIRECT by splitting in each round all boxes for which the pair (v, f) (where v is the volume and f the midpoint function value) is not dominated by another such pair. Here (v, f) is dominated by (v', f') if both $v' < v$ and $f' > f$. In particular, the box of largest volume and the box with the best function value are never dominated and hence always split. MCS uses instead domination of pairs (l, f), where l is a suitably assigned level, and in addition employs local optimization steps (using line searches and sequential bound constrained quadratic programs) from appropriate candidate points. LGO uses lower bounds

$$L \geq \max_{k,l} \|f(x_k) - f(x_l)\| / \|x_k - x_l\|$$

on Lipschitz constants L obtained from the previous function evaluations to decide on the promising boxes to split first. (Upper bounds on L, and hence bounds on function values, cannot be obtained from local information only.)

The combination of a suitable branching strategy with the heuristic methods discussed earlier would make the latter complete, and appears to be a fruitful research direction.

To improve on the density theorem we must find ways to throw away irrelevant parts of the feasible domain that are guaranteed not to contain a global minimizer. To be able to do this reliably, some kind of global information is necessary. This is utilized by box reduction techniques, discussed in Section 10 using a simple example, and afterwards in more depth.

10 Box reduction – an example

Box reduction techniques are based on a more or less sophisticated interplay of several components: logical constraint propagation, interval analysis, convex relaxations and duality arguments involving Lagrange multipliers. Before giving a more formal treatment, we illustrate simple arguments of each of these components by reconsidering Example 5.2.

Suppose that a local solver has already produced the local minimizer $\hat{x} = \binom{0}{1}$ for the problem (8) discussed in Example 5.2, perhaps as the best local minimizer found by minimizing from a few random starting points. We use box reduction to check whether there is possibly a better feasible point. In fact, we know already that this is not the case, but we obtained this knowledge in a way that works only for very simple problems. Thus we want to do it again, using only techniques of wide applicability.

The idea of box reduction is to use various arguments that allow to shrink the box without losing any feasible point that is at least as good as the best point found already. Since $\hat{x}$ is feasible with objective function value -2, any such point satisfies

$$f(x) = -x_1 - 2x_2 \le -2, \tag{15}$$

$$F(x) = (x_1 - 1)^2 + (x_2 - 1)^2 = 1, \tag{16}$$

$$x_1 \in [-1, 1], \quad x_2 \in [-1, 1]. \tag{17}$$

Constraint propagation (see Section 14) is a very cheap and easily formalizable process that gives important initial range reductions in many otherwise difficult problems. It consists in deducing better bounds for a variable by using the other bounds and one of the constraints. In particular, (15) implies $x_2 \ge 1 - x_1/2 \ge 0.5$ since $x_1 \le 1$, and $x_1 \ge 2 - 2x_2 \ge 0$ since $x_2 \le 1$, reducing the bounds to

$$x_1 \in [0, 1], \quad x_2 \in [0.5, 1].$$

Similarly, (16) implies $(x_1 - 1)^2 = 1 - (x_2 - 1)^2 \ge 1 - 0.25 = 0.75$, hence $x_1 \le 1 - \sqrt{0.75} < 0.14$, giving the improved bound

$$x_1 \in [0, 0.14].$$

This bound could be used to improve again x_2 using (15); and by alternating use of (15) and (16) one would obtain a sequence of boxes shrinking towards $\hat{x}$. This is a special feature of this simple example. In most cases, this simple substitution process gives no or only very little improvements after the first few good reductions. (Look at a problem with the constraints $x_1 + x_2 = 0$, $x_1 - x_2 = 0$, $x_1, x_2 \in [-1, 1]$ to see why.)

Interval analysis (see Section 11) can be applied in a number of different ways. Here we use it to produce linear relaxations of the nonlinear constraint. The Jacobian of $F(x)$ at $x \in \mathbf{x} = ([0, 0.14], [0.5, 1])^T$ is

$$F'(x) = (2x_1 - 2, 2x_2 - 2) \in ([-2, -1.72], [-1, 0]) = F'(\mathbf{x}).$$

The mean value theorem implies that, for any $\tilde{x} \in \mathbf{x}$,

$$F(x) \in F(\tilde{x}) + F'(\mathbf{x})(x - \tilde{x}) \quad \text{if } x \in \mathbf{x}.$$

Using $\tilde{x} = \hat{x}$ we find

$$1 \in 1 + [-2, -1.72]x_1 + [-1, 0](x_2 - 1) = [1 - 2x_1, 2 - 1.72x_1 - x_2];$$

the interval evaluation needs no case distinction since x_1 and $x_2 - 1$ happen to have constant sign. The lower bound gives no new information, but the upper bound leads to the new constraint

$$1.72x_1 + x_2 \leq 1.$$

By its derivation, this constraint is weaker than (16).

But since it is linear, the constraint is quite useful for **relaxation techniques** (see Section 16). It allows us to create a convex relaxation of the problem. Indeed, we may look at the relaxed linear program

$$\begin{array}{ll} \min & -x_1 - 2x_2 \\ \text{s.t.} & 1.72x_1 + x_2 \leq 1, \quad 0 \leq x_1 \leq 0.14, \quad 0.5 \leq x_2 \leq 1. \end{array} \tag{18}$$

By construction, every feasible point better than the best point is feasible for (18), hence the minimum of (18) will be a **lower bound** on the best possible objective function value of the original problem. Solving (18) gives the solution $\hat{x} = \binom{0}{1}$ with function value -2. Since this lower bound equals the best function value found so far for the original problem, the original problem has global minimum -2. This is a happy accident due to special circumstances: Our problem had already a linear objective function, and the global minimizer was at a corner of the feasible set. (But as we shall see, we can adapt the technique to work much more generally if the box is narrow enough.)

It might still be the case that there is a second, undiscovered global minimizer. This can be checked with **multiplier techniques**. We use the Lagrange multiplier $\hat{\lambda} = 2$ associated with the linear constraint of (18) at the solution. The associated linear combination $-x_1 - 2x_2 + 2(1.72x_1 + x_2 - 1)$ is bounded by the best known function value -2 of the original problem, giving $2.44x_1 - 2 \leq -2$, hence $x_1 \leq 0$. Thus we must have $x_1 = 0$, and constraint propagation using (15) implies $x_2 = 1$. Thus the box has been reduced to $\hat{x}$, showing that it is the only global minimizer.

What generalizes? The problem discussed was deliberately kept simple so that the complete solution process could be demonstrated explicitly. In general, constraint propagation only gives limited reduction. Similarly, relaxed linear or convex programs usually only give a lower bound on the smallest possible objective function value, but the linear combination derived from the Lagrange multipliers frequently contains useful information that can be exploited by constraint propagation to get a further significant box reduction.

If the reduction process stalls or becomes slow, the box is split into two or more smaller boxes. On the smaller boxes, the same techniques may prove effective, and one alternates box reduction and box splitting until all box sizes are below some termination threshold. Usually, only very few boxes remain if good enough reduction techniques are used (pathological exceptions include min $x - x$ s.t. $x \in [0, 1]$). If no box remains, the problem is guaranteed to have no feasible point.

The total number of boxes processed is a measure of the difficulty of a problem for the particular algorithm used. Simple problems (like the example discussed above) only need a single box; in the worst case, an exponential number of boxes may be needed. In the latter case, time and storage limitations may force a premature termination; in this case the best point found is not verified to be a global minimizer.

11 Interval arithmetic

Interval analysis, the study of theory and algorithms for computing with intervals, is a large subject; see Moore [230] (introductory), Neumaier [250] (embedded in a numerical analysis context) and Neumaier [243] (advanced). Its importance for global optimization stems from several, interrelated facts:

- Interval analysis gives easily computable (though sometimes only very crude) bounds on the range expressions.
- Interval analysis allows one to control nonlinearities in a simple way (via centered forms).
- Interval analysis extends classical analysis in its ability to provide *semilocal* existence and optimality conditions, valid within a *pre-specified* local region around some point, while classical analysis generally only asserts the existence of such neighborhoods without providing a simple way to find them.

We give here a short introduction to the basics and mention the main techniques useful for global optimization. General references on interval methods in global optimization include [4, 29, 30, 31, 64, 77, 78, 152, 156, 157, 130, 131, 173, 176, 245, 276, 277, 328].

If $\mathbf{a}$ and $\mathbf{b}$ are two intervals we define for $\circ \in \{+, -, *, /, \hat{}\ \}$ the binary operation

$$\mathbf{a} \circ \mathbf{b} := \square\{\tilde{a} \circ \tilde{b} \mid \tilde{a} \in \mathbf{a}, \tilde{b} \in \mathbf{b}\}, \tag{19}$$

provided the right hand side is defined. Here

$$\square S = [\inf S, \sup S]$$

denotes the **interval hull** of a set of real numbers, i.e., the tightest interval containing S. A monotonicity argument gives for addition and subtraction

$$\mathbf{a} + \mathbf{b} = [\underline{a} + \underline{b}, \overline{a} + \overline{b}], \tag{20}$$
$$\mathbf{a} - \mathbf{b} = [\underline{a} - \overline{b}, \overline{a} - \underline{b}], \tag{21}$$

and for multiplication and division

$$\begin{aligned} \mathbf{a} * \mathbf{b} &= \square\{\underline{a}\underline{b}, \underline{a}\overline{b}, \overline{a}\underline{b}, \overline{a}\overline{b}\}, & (22) \\ \mathbf{a}/\mathbf{b} &= \square\{\underline{a}/\underline{b}, \underline{a}/\overline{b}, \overline{a}/\underline{b}, \overline{a}/\overline{b}\} \quad \text{if } 0 \notin \mathbf{b}; & (23) \end{aligned}$$

in most cases only two of these products or quotients need to be computed. We also define elementary functions $\varphi \in \{\mathrm{sqr}, \mathrm{sqrt}, \exp, \log, \sin, \cos, \mathrm{abs}, \ldots\}$ of an interval $\mathbf{a}$ (and similarly $-\mathbf{a}, \mathbf{a}_+$, etc.) by

$$\varphi(\mathbf{a}) := \square\{\varphi(\tilde{a}) \mid \tilde{a} \in \mathbf{a}\} \tag{24}$$

whenever the right hand side is defined. Again $\varphi(\mathbf{a})$ can be computed from the value of φ at the endpoints of $\mathbf{a}$ and the interior extremal values, depending on the monotonicity properties of φ. Note that, however, $|\mathbf{a}|$ is defined as $\sup \mathrm{abs}(\mathbf{a})$, since this expression figures prominently in estimates involving interval techniques.

For interval vectors (=boxes) $\mathbf{x}$, analogous definitions apply. We also need the **interior**

$$\mathrm{int}\ \mathbf{x} = \{\tilde{x} \in \mathbb{R}^n \mid \underline{x} < \tilde{x} < \overline{x}\}$$

of a box $\mathbf{x} \subseteq \mathbb{R}^n$.

For details and a systematic study of interval operations see NEUMAIER [243]; we only remark here that some rules familiar from real arithmetic fail, and in particular the interval evaluation of different expressions equivalent in real arithmetic may give different results. E.g., (with $-\mathbf{a} := 0 - \mathbf{a} = [-\overline{a}, -\underline{a}]$)

$$\mathbf{a} + (-\mathbf{a}) = \mathbf{a} - \mathbf{a} \neq 0 \quad \text{except when } \underline{a} = \overline{a}.$$

Therefore, we also use the converse **inner operations**

$$\mathbf{a} \oplus \mathbf{b} := [\underline{a} + \overline{b}, \overline{a} + \underline{b}], \tag{25}$$

$$\mathbf{a} \ominus \mathbf{b} := [\underline{a} - \underline{b}, \overline{a} - \overline{b}]. \tag{26}$$

Here, expressions of the form $\pm\infty \mp \infty$ in (25) or (26) must be interpreted as $-\infty$ for the lower bounds and as $+\infty$ for the upper bounds. Note that the result of an inner operation is not necessarily an interval since it may happen that the lower bound is larger than the upper bound; giving an empty "interval".

All these operations are very simple to program. Note that many implementations of interval arithmetic are rather slow since they take care to guarantee correct (and often optimal) outward rounding, needed when interval arithmetic is used for mathematically rigorous certification (see Section 20). For global optimization without certification, **unsafe** interval arithmetic, which uses the standard rounding for floating point operations, and hence is significantly faster but may lose containment of points that lie too close to the boundary, usually suffices if certain safety measures are taken. But it is significantly harder to ensure robust behavior with unsafe interval arithmetic since occasionally the solution is lost, too.

Important: When using unsafe interval arithmetic, proper safeguards must be taken at places (such as inner operations and intersections) where intervals might become (spuriously) empty due to accumulation of roundoff errors. In place of an empty result, a thin interval formed from the arithmetic mean of the two intersecting bounds should be returned in a safe implementation.

As already mentioned, an interval evaluation $f(\mathbf{x})$ of some expression f often overestimates the desired **range**

$$\mathrm{Range}(f, \mathbf{x}) = \{f(x) \mid x \in \mathbf{x}\}$$

of a function. However, under very mild conditions [243, Section 1.4], the evaluation over small boxes satisfies

$$f(\mathbf{x}) \subseteq \mathrm{Range}(f, \mathbf{x}) + O(\varepsilon) \quad \text{if } \overline{x} - \underline{x} = O(\varepsilon);$$

we refer to this as the **linear approximation property** of simple interval evaluation.

Better enclosures, especially for small ε, can be obtained by **centered forms**; the simplest of these (but not the most efficient one, see [243, Chapter 2] for better methods based on slopes) is the **mean value form**: Due to the mean value theorem, we have

$$f(x) \in f(z) + f'(\mathbf{x})(x - z) \quad \text{if } x, z \in \mathbf{x}. \tag{27}$$

In particular, $\mathrm{Range}(f, \mathbf{x})$ is contained in $f(z) + f'(\mathbf{x})(\mathbf{x} - z)$, and it can be shown that, under mild conditions,

$$f(z) + f'(\mathbf{x})(\mathbf{x} - z) \subseteq \mathrm{Range}(f, \mathbf{x}) + O(\varepsilon^2) \quad \text{if } \overline{x} - \underline{x} = O(\varepsilon);$$

we say that the mean value form (as other centered forms) has the **quadratic approximation property**. Recently, centered forms based on higher order Taylor expansions have found considerable attention; these are able to give significantly sharper bounds in cases where simple interval evaluation suffers from severe dependence. See the survey NEUMAIER [252] and the numerical comparisons in MAKINO & BERZ [208]; cf.also CARRIZOSA et al. [50].

Apart from interval evaluation and centered forms, we need **interval Newton methods** for verifying solutions of nonlinear systems of equations. The prototype (but again not the most efficient method; see [243, Chapter 5] for better methods based on slopes and Gauss-Seidel iteration) is KRAWCZYK's [188] method. To check for solutions of $F(x) = 0$ with $x \in \mathbf{x}$, Krawczyk multiplies the vector version of (27) by a matrix C and subtracts it from x to find

$$x \in K(\mathbf{x}, z) := z - CF(z) + (I - CF'(\mathbf{x}))(\mathbf{x} - z).$$

For $z \in \mathbf{x}$, the resulting **Krawczyk operator** $K(\mathbf{x}, z)$ (cf. KRAWCZYK [188], KAHAN [168]) has the following properties, typical for interval Newton operators:

(i) Any zero $x \in \mathbf{x}$ of F lies in $\mathbf{x} \cap K(\mathbf{x}, z)$.

(ii) If $\mathbf{x} \cap K(\mathbf{x}, z) = \emptyset$ then $\mathbf{x}$ contains no zero of F.

(iii) If $K(\mathbf{x}, z) \subseteq \mathrm{int}\,\mathbf{x}$ then $\mathbf{x}$ contains a unique zero of F.

(i) and (ii) follow directly from the above derivation, while (iii) is a simple consequence of Banach's fixed point theorem.

The most important part is (iii), since, applied to the Karush-John conditions, it allows the elimination of large regions around a local minimizer; cf. Section 15. However, (i) and (ii) are also useful as ways of reducing a box or eliminating it, if it contains no zero. This is implemented in GlobSol [173] and Numerica [328].

Another useful interval Newton operator with analogous properties is

$$x \in N(\mathbf{x}, z) := z - (CF[\mathbf{x}, z])^H (CF(z)),$$

where C is an approximate inverse of the interval slope $F[\mathbf{x}, z]$ and $\mathbf{A}^H\mathbf{b}$ is an enclosure for the set of solutions of $Ax = b, A \in \mathbf{A}, b \in \mathbf{b}$ computed, e.g., by the Hansen-Bliek method [36, 132, 248].

Convexity check. Interval analysis can be used to check the convexity of a function $f : \mathbf{x} \to \mathbb{R}$ in some box $\mathbf{x}$. Let $\mathbf{G}$ be a matrix of intervals (usually simply called an *interval matrix*), calculated as an enclosure of $f''(x)$ for $x \in \mathbf{x}$, then, with $r = \max\{\overline{x}_k - \underline{x}_k \mid k = 1, \ldots, n\}$, the linear approximation property implies that $|\overline{G} - \underline{G}| = O(r)$. Such a statement implies that $|\mathbf{G} - \tilde{G}| = O(r)$ for all individual matrices $\tilde{G} \in \mathbf{G}$, with absolute values taken componentwise. In particular, if $\hat{G}$ is positive definite then, provided the underlying box is not too wide, all matrices in $\mathbf{G}$ are definite, too; and if this is the case, f is convex in $\mathbf{x}$. The following constructive criterion for simultaneously checking the definiteness of all members of an interval matrix was given in Neumaier [245].

11.1 Theorem. (Sufficient conditions for convexity)

Let $f : \mathbf{x} \to \mathbb{R}$ be twice continuously differentiable on the compact box $\mathbf{x}$, and suppose that $\mathbf{G}$ is a symmetric interval matrix such that

$$f''(x) \in \mathbf{G} \quad \text{for all } \ x \in \mathbf{x}. \tag{28}$$

(i) If some symmetric matrix $G_0 \in \mathbf{G}$ is positive definite and all symmetric matrices in $\mathbf{G}$ are nonsingular then they are all positive definite, and f is uniformly convex in $\mathbf{x}$.

(ii) In particular, this holds if the midpoint matrix

$$\check{G} = (\sup \mathbf{G} + \inf \mathbf{G})/2$$

is positive definite with inverse C, and the preconditioned radius matrix

$$\Delta = |C| \operatorname{rad} \mathbf{G},$$

where $|C|$ is the componentwise absolute value of C and

$$\operatorname{rad} \mathbf{G} = (\sup \mathbf{G} - \inf \mathbf{G})/2,$$

satisfies the condition

$$\|\Delta\| < 1 \tag{29}$$

(in an arbitrary norm).

Proof. (i) Since the eigenvalues are continuous functions of the matrix entries and the product of the eigenvalues (the determinant) cannot vanish, no eigenvalue changes sign. Hence the eigenvalues of all matrices in $\mathbf{G}$ are positive, since this is the case for the positive definite member. Thus all symmetric matrices in $\mathbf{G}$ are positive definite. By well-known results, uniform convexity of f now follows from (28).

(ii) $G_0 = \check{G}$ belongs to $\mathbf{G}$, and condition (29) implies strong regularity of the interval matrix $\mathbf{G}$ ([243], Section 4.1) and hence nonsingularity of all matrices in $\mathbf{G}$. Thus (i) applies. □

In many cases, the Hessian of the augmented Lagrangian can be shown to have the form

$$f''(x) = \sum u_i A_i, \quad u_i \in \mathbf{u}_i,$$

with constructively available real matrices A_i and intervals $\mathbf{u}_i = [\check{u}_i - r_i, \check{u}_i + r_i]$. In this case, the above result can be strengthened (with virtually the same proof) by replacing $\check{G}$ and Δ with

$$\check{G} = \sum \check{u}_i A_i$$

and

$$\Delta' = \sum r_i |CA_i|,$$

respectively. Indeed, it is not difficult to see that for $\mathbf{G} = \sum \mathbf{u}_i A_i$, we always have $0 \le \Delta' \le \Delta$, so that the refined test is easier to satisfy.

Other sufficient conditions for convexity based on scaled Gerschgorin theorems and semidefinite programming, form the basis of the αBB method [2, 15] and are given in ADJIMAN et al. [4, 3].

12 The branch and bound principle

The branch and bound principle is a general label (invented in [193, 201]) to denote methods to split a problem recursively into subproblems which are sooner or later eliminated by showing that the subproblem cannot lead to a point better than (or as least as good as) the best point found so far. The latter is often checked by computing lower bounds on the objective function, and the splitting produces new branches in the tree of all subproblems tried, according to so-called **branching rules**; hence the name "branch and bound". But in practice, the subproblems are best treated in a more flexible fashion, allowing also to eliminate subproblems only partially.

General references for branch and bound in global optimization include [23, 24, 31, 77, 78, 85, 123, 143, 156, 173, 269, 328]. A thorough discussion of branch and bound in discrete optimization, with many algorithmic choices that are of potential interest in general global optimization, is given in PARKER & RARDIN [265].

For a global optimization problem

$$\begin{array}{ll} \min & f(x) \\ \text{s.t.} & x \in \mathbf{x}^{\text{init}}, \quad F(x) \in \mathbf{F}, \quad x_I \text{ integral}, \end{array} \tag{30}$$

a natural way to define subproblems is to choose boxes $\mathbf{x} \subseteq \mathbf{x}^{\text{init}}$ of the initial box $\mathbf{x}^{\text{init}}$, and to consider the subproblems

$$\begin{array}{ll} \min & f(x) \\ \text{s.t.} & x \in \mathbf{x}, \quad F(x) \in \mathbf{F}, \quad x_I \text{ integral}, \end{array} \tag{31}$$

i.e., each subproblem is characterized by (and stored as) the box over which the problem is solved. The branching process then consists in splitting a box $\mathbf{x}$ into two or several smaller boxes whose union is $\mathbf{x}$. The most typical branching rule is to select a **bisection coordinate** j and to split the j-th component of the box at a **bisection point** ξ. Thus, the current box $\mathbf{x}$ is replaced by two subboxes $\mathbf{x}^{\text{low}}, \mathbf{x}^{\text{upp}}$ with

$$\begin{array}{l} \mathbf{x}_k^{\text{low}} = \mathbf{x}_k^{\text{upp}} = \mathbf{x}_k \quad \text{if } k \neq j, \\ \mathbf{x}_j^{\text{low}} = [\underline{x}_j, \xi], \quad \mathbf{x}_j^{\text{upp}} = [\xi, \overline{x}_j]. \end{array} \tag{32}$$

This branching rule is termed **bisection**. The bisection point ξ is often taken as the **midpoint** $\xi = (\overline{x}_j + \underline{x}_j)/2$ of the interval $\mathbf{x}_j$; but this fails when there are infinite bounds and is inefficient when the interval ranges over several orders of magnitude. In this case, a more useful bisection point is a **safeguarded geometric mean**, defined by

$$\xi = \operatorname{sign} \underline{x}_j \sqrt{\underline{x}_j \overline{x}_j} \quad \text{if } 0 < \underline{x}_j \overline{x}_j < \infty,$$

and otherwise

$$\begin{array}{ll} \xi = 0 & \text{if } \underline{x}_j < 0 < \overline{x}_j, \\ \xi = \min(\mu, q\overline{x}_j) & \text{if } \underline{x}_j = 0, \\ \xi = \max(-\mu, q\underline{x}_j) & \text{if } \overline{x}_j = 0, \\ \xi = q^{-1}\underline{x}_j & \text{if } \underline{x}_j > 0, \\ \xi = q^{-1}\overline{x}_j & \text{if } \overline{x}_j < 0, \end{array}$$

where $q \in \;]0, 1[$ is a fixed constant (such as $q = 0.01$) and variables whose initial interval contains 0 are assumed to be most likely of magnitude μ.

The branching coordinate is more difficult to choose, but the speed of a branch and bound algorithm may be heavily affected by this choice. For a good algorithm, the choice should be scaling invariant, but the details depend on how the algorithm treats the individual subproblems.

Sometimes, a **trisection** branching rule is used which splits some component of a box into three intervals. Also, **multisection** branching rules may be employed; only one natural choice is described here. Suppose we know that a subbox $\mathbf{x}^0$ of $\mathbf{x}$ cannot contain a solution of (30). (In practice, $\mathbf{x}^0$ would be the intersection of an exclusion box, cf. Section 11, with $\mathbf{x}$.) Then we can cover $\mathbf{x} \setminus \mathbf{x}^0$ by (at most) $2n$ subboxes, namely, for $j = 1, \ldots, n$,

$$\begin{array}{l} \mathbf{x}_k^{2j-1} = \mathbf{x}_k^{2j} = \mathbf{x}_k^0 \quad \text{if } k < j, \\ \mathbf{x}_j^{2j-1} = [\underline{x}_j, \underline{x}_j^0], \quad \mathbf{x}_j^{2j} = [\overline{x}_j^0, \overline{x}_j], \\ \mathbf{x}_k^{2j-1} = \mathbf{x}_k^{2j} = \mathbf{x}_k \quad \text{if } k > j. \end{array} \tag{33}$$

However, this may yield long and thin slices and is then rather inefficient.

For a comparison of some branching rules for bound constrained problems see [63, 278, 279].

The **bounding rule** in its classical variant requires the solution of a **convex relaxation**, i.e., a convex (and often linear) optimization problem whose feasible set contains the feasible set of the subproblem (**outer approximation**) and whose objective function is at no feasible point larger than the original objective function (**underestimation**). If the convex problem is infeasible, the subproblem is infeasible, too, and can be discarded. If the convex problem is feasible, its solution provides a lower bound on $f(x)$, and when this lower bound is larger than the value of f^{best} for some feasible point x^{best} known (stored in a list of **best feasible points found so far**) we conclude that the subproblem does no longer contribute to the solution of the global optimization problem and hence can be discarded.

Clearly, this procedure is equivalent to adding the constraint $f(x) \le f^{\text{best}}$ to the definition of the subproblem and checking infeasibility of the resulting reduced subproblem. This suggests a more general approach to defining subproblems by adding other **cuts**, i.e., derived inequalities that have to be satisfied at a global minimizer. If these inequalities are linear, the cuts define hyperplanes and are referred to as **cutting planes**, cf. Section 16. Branch and bound methods using cuts are frequently labelled **branch and cut**.

Another important approach to handling subproblems uses constraint propagation and related techniques that define **reduction** (also called **tightening**, **narrowing**, **filtering** or **pruning**) **rules** which serve to reduce (as much as easily possible) the box defining a subproblem without changing its feasible set. If reduction results in an empty box, the subproblem is eliminated; if not, the subproblem may still have been reduced so much that many branching steps are saved. Fast and simple reduction rules use constraint propagation, discussed in Section 14; more expensive rules are discussed in Section 15. The balancing of work done in reduction versus work saved through less branching is a delicate matter, which at present more or less depends on ad hoc recipes.

Note that reduction techniques may be applied not only to the original constraints but to all constraints that must be satisfied at the global minimizer. This includes cutting planes (see Section 16) and the equations and inequalities derived from the Karush-John optimality conditions (see Section 5). In particular, software based on interval techniques (GlobSol [173], Numerica [328]) make essential use of the latter.

13 The role of local optimization

Local optimization routines are an important part of most global solvers. They are used for two different purposes:

(i) to find feasible points if the feasible domain has a complicated definition, and to find better local minimizers when (after successful tunneling) a feasible point better than the previously best local minimizer has been found;

(ii) to solve auxiliary optimization problems such as relaxations of the original problem (for generating improved bounds) or bound constrained approximations (for tunneling).

Relaxation. The auxiliary local optimization problems that need to be solved are simpler in structure since they 'relax' the problem in some way. A **relaxation** is a modification of the original problem whose solution is tractable and gives some information about the possible location of the global minimizer. In the past, mainly linear and convex relaxation have been used, since for these, local optimization provides global solutions, which usually implies useful global information about the original problem. We shall discuss various ways of obtaining and using linear and convex relaxations in Section 16. Nonconvex relaxations may be useful, too, if they are reliably solvable to global optimality. We therefore discuss semilinear relaxations – which can be solved by MILP techniques – in Section 18.

Tunneling. One may consider solving a global optimization problem as a **sequential nonlinear programming method** (SNLP), where local optimization (NLP) steps that improve a feasible point to local optimality alternate with tunneling steps that produce better (nearly) feasible points by some **tunneling procedure**. For complete methods based on branching, the 'tunneling' is done by finding nearly feasible points during inspection of the subproblems.

The success of the tunneling step depends on the details of looking for such points. One strategy (Dallwig et al. [64]) proceeds by solving on selected subboxes nonlinear least squares problems that minimize the sum of squares of the constraint violations, and (if a best feasible point with function value f^{best} is already available) the violation of $f(x) \le f^{\text{best}} - \Delta$, where $\Delta \ge 0$ is some measure of minimal gain in function value. Alternatively, one may use the soft optimality theorem (Theorem 8.1) in place of least squares. (See also [126] for tunneling by continuation.) Thus, in a sense, the global optimization of (1) consists in solving a sequence of harder and harder feasibility problems

$$\begin{array}{ll} \text{find} & x \\ \text{s.t.} & x \in \mathbf{x}, \quad F(x) \in \mathbf{F}, \quad x_I \text{ integral}, \\ & f(x) \le f^{\text{best}} - \Delta. \end{array} \tag{34}$$

Typical global optimization methods spend perhaps 5% of their time on finding a global minimizer, and the remaining 95% on the verification that there is no significantly better feasible point, i.e., showing that the feasibility problem (34) has no solution. Also, hard problems need a significant amount of time to find the first feasible point. Thus the initial and final (dominant) stages of a global optimization solution process are essentially identical with that for a feasibility problem.

In particular, general feasibility problems, also called **constraint satisfaction problems**, can be as hard as general global optimization problems, and the techniques needed for solving constraint satisfaction problems are essentially the same as those for solving global optimization problems.

General considerations. Considerations of superlinear convergence of local optimization algorithms imply that one generally uses **sequential quadratic programming** (SQP) techniques, which solve a sequence of related quadratic programs whose solution converges (under certain conditions, cf. below) to a local minimizer of the original problem; if the starting point is feasible (which, initially, need not be the case), the function value of the local minimizer is at or below that of the starting point.

To give the reader a rough idea of times and difficulties, here are some (completely unreliable but catchy) rules of thumb. If the time needed to solve a linear program of a certain size is LP then solving a problem of comparable size and sparsity structure may take perhaps the time

$$QP = 5 * LP$$

for a convex quadratic program,

$$QP' = 10 * LP$$

for a local minimizer of a nonconvex quadratic program,

$$SQP = 30 * QP$$

for a convex nonlinear program,

$$SQP' \geq 200 * QP$$

for a local minimizer of a nonconvex nonlinear program,

$$GLP_f \geq 100 * SQP$$

for *finding* a global minimizer of a nonconvex nonlinear program, and

$$GLP_v \geq 1000 * SQP$$

for *verifying* that it is a global minimizer.

We now comment on the properties of local optimization software that are important for their use in global optimization. Usually, it is more important that the local solver is fast than that it is very robust (i.e., guaranteed to succeed), since lack of robustness in some of the local optimizations is made up for by the structure of the global solution process. To help control the amount of work done in the local part, it should be possible to force a premature return with a less than optimal point when some limit (of time or number of function values) is exceeded. Nevertheless, the local solver should be good to ensure that solving a problem with a unique minimizer (which is automatically global) by the global solver does not take much longer than a good local solver would need.

Modern nonlinear programming codes are usually "globally convergent" in some sense. The global convergence proofs (to a **local** minimizer only!) usually make more or less stringent assumptions that imply the absence of difficulties in finding feasible points. Formally, we may say that a local optimization algorithm is **globally convergent** if there is a continuous function $d_{\text{feas}} : \mathbb{R}^n \to \mathbb{R}$ (defining a 'distance to feasibility') such that

$$d_{\text{feas}}(x) \geq 0, \quad \text{with equality iff } x \text{ is feasible}$$

and the algorithm produces for arbitrary continuous problems and arbitrary starting points a sequence of $x^l \in \mathbb{R}^n$ satisfying one of the following conditions:
(i) x^l converges to the set of points satisfying the Karush-John conditions (and, possibly, second order necessary conditions);
(ii) $d_{\text{feas}}(x^l) \to 0$ and $f(x^l) \to -\infty$;
(iii) x_l converges to the set of points where the objective or some constraint function is not continuously differentiable;
(iv) $d_{\text{feas}}(x^l) \to 0$, $\|x^l\| \to \infty$;
(v) $d_{\text{feas}}(x^l)$ converges to a nonzero local minimum of d_{feas}.

Conditions (i) and (ii) characterize the achievement of the optimization goal, while conditions (iii)–(v) characterize various modes of unavoidable failure. Failures of type (iii) or (iv) are usually attributed to bad modeling or bad choice of the optimization methods. Some methods such as bundle methods can cope with lack of differentiability hence do not lead to case (iii).

A failure of type (v) is unavoidable if there is no feasible point. However, failures of type (v) may happen for problems with nonconvex constraints even though feasible points exist. One could say that from a local point of view, an optimization problem is **easy** (for an algorithm) if (v) cannot occur whenever a feasible point exists. A local algorithm may be considered good if among its easy problems are all problems with convex constraints only, and all problems satisfying certain strong versions [46] of the Mangasarian-Fromovitz [210] constraint qualification. Ideally, a good local algorithm would provide in these cases a certificate of infeasibility whenever it detects case (v).

14 Constraint propagation

In many cases, general constraints can be used to reduce the size of a box in the branching scheme. The general technique is called **constraint propagation** and was pioneered in constraint logic (Cleary [53], Older & Vellino [258]) and interval analysis (Neumaier [242]), but has also forerunners in presolve techniques in mathematical programming (Mangasarian & McLinden [211], Lodwick [202], Anderson & Anderson [14]). See [18, 29, 30, 51, 127, 148, 171, 326, 327, 328] for further developments, and the COCONUT report [38] for an extensive recent survey.

We follow here the setup by DALLWIG et al. [64], which handles linear constraints (and more generally block separable constraints) without the need to decompose the constraints into primitive pieces defined by single operations. (In the following, if J is a list of indices, x_J denotes the subvector of x formed by the components with index in J.)

14.1 Proposition. *Let the q_k be real-valued functions defined on $\mathbf{x}_{J_k}$.*

(i) If (for suitable $\overline{q}_k, \overline{s}$)

$$\overline{q}_k \geq \sup\{q_k(x_{J_k}) \mid x_{J_k} \in \mathbf{x}_{J_k}\}, \quad \overline{s} \geq \sum_k \overline{q}_k, \tag{35}$$

then, for arbitrary $\underline{a}$,

$$x \in \mathbf{x}, \quad \underline{a} \leq \sum_k q_k(x_{J_k}) \quad \Rightarrow \quad q_k(x_{J_k}) \geq \underline{a} - \overline{s} + \overline{q}_k \quad \text{for all } k. \tag{36}$$

(ii) If

$$\underline{q}_k \leq \inf\{q_k(x_{J_k}) \mid x_{J_k} \in \mathbf{x}_{J_k}\}, \quad \underline{s} \leq \sum_k \underline{q}_k, \tag{37}$$

then, for arbitrary $\underline{a}$,

$$x \in \mathbf{x}, \quad \sum_k q_k(x_{J_k}) \leq \overline{a} \quad \Rightarrow \quad q_k(x_{J_k}) \leq \overline{a} - \underline{s} + \underline{q}_k \quad \text{for all } k. \tag{38}$$

Proof. The assumptions of (i) imply

$$q_k(x_{J_k}) \geq \underline{a} - \sum_{l \neq k} q_l(x_{J_l}) \geq \underline{a} - \sum_{l \neq k} \overline{q}_l \geq \underline{a} + \overline{q}_k - \overline{s},$$

hence the conclusion in (36) holds. (ii) is proved in the same way. □

The proposition is applied as follows to reduce the size of boxes by tightening bound constraints. Suppose that $x \in \mathbf{x}$. For any constraint of the form

$$\underline{a} \leq \sum_k q_k(x_{J_k}) \tag{39}$$

we form the quantities (35). (This is straightforward if the q_k depend on a single variable x_k only, $J_k = \{k\}$; in the most important cases, q_k is linear or quadratic in x_k, and the supremum is very easy to calculate; in more complicated cases, upper resp. lower bounds can be calculated with interval arithmetic.) Then one checks the condition

$$\underline{a} \leq \overline{s}\ ; \tag{40}$$

if it is violated then (39) is clearly inconsistent with $x \in \mathbf{x}$ (and in the branch and bound application, the corresponding subproblem can be discarded). If (40) holds, one can exploit the conclusion in (36), provided that one can compute the set of $x_{J_k} \in \mathbf{x}_{J_k}$ (or a superset) such that

$$q_k(x_{J_k}) \geq \overline{q}_k + \underline{a} - \overline{s}. \tag{41}$$

If $\underline{a}$ is sufficiently close to $\overline{s}$ then x_{J_k} will be forced to be close to the global maximum of q_k over the interval $\mathbf{x}_{J_k}$, thus reducing the component $\mathbf{x}_{J_k}$ and hence the box $\mathbf{x}$. This procedure can be applied for each k in turn to get an optimally reduced box. One can similarly proceed for block separable constraints of the form $\sum q_k(x_{J_k}) \leq \overline{a}$. (The reader might wish to reconsider the example in Section 10 in the light of the above result.)

In the separable case ($J_k = \{k\}$), computing the set of x_k with (41) is easy, especially for linear or quadratic q_k. If q_k is nonmonotonic, it may happen that the resulting set is disconnected; then one has to make a choice between taking its convex hull – which is an interval –, or of considering splitting the box into subboxes corresponding to the connected components.

In case of two-sided constraints $\sum q_k(x_{J_k}) \in \mathbf{a}$, which includes the equality constraint $\sum q_k(x_{J_k}) = q_0$ for $\mathbf{a} = q_0$, one can combine (36) and (38) using interval arithmetic as follows. (See (25) for the inner addition $\oplus$.)

14.2 Proposition. *Suppose that*

$$\mathbf{q}_k \supseteq \square\{q_k(x_{J_k}) \mid x_{J_k} \in \mathbf{x}_{J_k}\}, \quad \mathbf{r} \supseteq \mathbf{a} - \sum_k \mathbf{q}_k. \tag{42}$$

(i) If $0 \notin \mathbf{r}$ then the conditions

$$x \in \mathbf{x}, \quad \sum_k q_k(x_{J_k}) \in \mathbf{a} \tag{43}$$

are inconsistent.

(ii) Any x satisfying (43) also satisfies

$$q_k(x_{J_k}) \in \mathbf{r} \oplus \mathbf{q}_k \quad \text{for all } k. \tag{44}$$

Proof. (43) implies $0 \in \mathbf{a} - \sum q_k(x_{J_k}) \subseteq \mathbf{a} - \sum \mathbf{q}_k$, hence $0 \in \mathbf{r}$. Now suppose that $0 \in \mathbf{r}$. In the notation of the previous proposition we have

$$q_k(x_{J_k}) \in [\underline{a} - \overline{s} + \overline{q}_k, \overline{a} - \underline{s} + \underline{q}_k] = [\underline{a} - \overline{s}, \overline{a} - \underline{s}] \oplus \mathbf{q}_k,$$

and since $\mathbf{r} = \mathbf{a} - [\underline{s}, \overline{s}] = [\underline{a} - \underline{s}, \overline{a} - \overline{s}]$, this implies (44). $\square$

Again, condition (44) can be used to reduce $\mathbf{x}_{J_k}$ whenever

$$\mathbf{q}_k \not\subseteq \mathbf{r} \oplus \mathbf{q}_k. \tag{45}$$

We give details for the most important case of quadratic (and including linear) functions, dropping indices for a moment.

14.3 Proposition. *Let* $\mathbf{c}$ *be an interval,* $a, b \in \mathbb{R}$*, and put*

$$\mathbf{d} := (b^2 + 4a\mathbf{c})_+, \quad \mathbf{w} := \sqrt{\mathbf{d}} \ (\textit{if } \mathbf{d} \neq \emptyset)$$

Then

$$\{x \in \mathbb{R} \mid ax^2 + bx \in \mathbf{c}\} = \begin{cases} \emptyset & \textit{if } \mathbf{d} = \emptyset, \\ \emptyset & \textit{if } a = b = 0 \notin \mathbf{c}, \\ \mathbb{R} & \textit{if } a = b = 0 \in \mathbf{c}, \\ \dfrac{\mathbf{c}}{b} & \textit{if } a = 0, \\ \dfrac{-b - \mathbf{w}}{2a} \cup \dfrac{-b + \mathbf{w}}{2a} & \textit{otherwise.} \end{cases}$$

Proof. $ax^2 + bx = \tilde{c} \in \mathbf{c}$ is equivalent to $x = \tilde{c}/b$ when $a = 0$, and to $x = (-b \pm \sqrt{b^2 + 4a\tilde{c}})/2a$ otherwise; in the latter case, the expression under the square root must be nonnegative and hence lies in $\mathbf{d}$. Since the varying $\tilde{c}$ occurs in these formulas only once, the range over $\tilde{c} \in \mathbf{c}$ is given by $\mathbf{c}/b$ if $a = 0$ and by $(-b \pm \sqrt{\mathbf{d}})/2a$ otherwise (use monotonicity!). □

Note that the differences in Proposition 14.1 and the numerators in Proposition 14.3 may suffer from severe cancellation of leading digits, which requires attention in an actual implementation.

In the application to reducing boxes, one must of course intersect these formulae with the original interval. If the empty set results, the subproblem corresponding to the box $\mathbf{x}$ can be eliminated. (But remember to be cautious when using unsafe interval arithmetic!) If a disjoint union of two intervals results one either splits the box into two boxes corresponding to the two intervals or one leaves $\mathbf{x}_k$ unchanged; the first alternative is advisable only when the gap in the interval is quite large.

All reduction techniques may be used together with the technique of **shaving**, which may be seen as an adaptation of the probing technique in mixed integer programming. The idea is to try to remove a fraction of the range $[\underline{x}_i, \overline{x}_i]$ of some variable x_i by restricting the range to a small subrange $[\underline{x}_i, \xi]$ or $[\xi, \overline{x}_i]$ at one of the two end points of that variable, and testing whether reducing the small slab obtained in this way results in an empty intersection. If this is the case, the range of x_i can be restricted to the complementary interval $[\xi, \overline{x}_i]$ and $[\underline{x}_i, \xi]$, respectively. While more expensive, it reduces the overestimation in the processing of constraints which contain a variable several times. In practice, one would perhaps try to shave away 10% of the length of an interval.

Consistency concepts. In constraint logic programming (see the book [328] and the references at the beginning of this section), there are a number of consistency concepts that describe the strength of various reduction techniques. Essentially, a box is **consistent** with respect to a set of reduction procedures if their application does not reduce the box. A simple recursive argument invoking the finiteness of machine-representable boxes shows that every box can be reduced to a consistent box with finitely many applications of the reduction procedures in an arbitrary order. (Depending on the rules used, the resulting reduced box –

called a **fixed point** of the reduction procedures – may or may not depend on the order of applying the rules.)

From a practical point of view, it is not advisable to apply the available rules until the fixed point is reached. The reason is that frequently the first few reductions are substantial, and later ones only reduce the box by tiny fractions; the convergence speed may be arbitrarily slow. For example, for the pair of constraints $x_1 + x_2 = 0, x_1 - qx_2 = 0$ with $q \in]0,1[$, where the unique fixed point (with respect to the simple reduction described above) reduces the volume in each step by a factor of q. For q close to one, this is very inefficient compared to, say, a linear programming relaxation (which gives the result immediately).

Thus one has to be selective in practice, using suitable strategic rules for when to use which reduction strategy. The choice is usually done by various ad hoc recipes that balance the likely gain and the amount of work needed. Moreover, fine-grained interaction between different computations to avoid some unnecessary computation, such as that described in Granvilliers [116] may be decisive in getting optimal performance.

Semiseparable constraints. With some more work, the above techniques can be utilized also for semiseparable constraints. We need the following result.

14.4 Lemma. *If A is a rectangular matrix such that A^TA is nonsingular then*

$$|u_k| \leq \sqrt{((A^TA)^{-1})_{kk}}\|Au\|_2 \quad \textit{for all } u.$$

Proof. Let $A = QR$ be an orthogonal factorization of A with $Q^TQ = I$ and R square nonsingular. Then $A^TA = R^TR$ and $\|Au\|_2 = \|Ru\|_2$. Since

$$|u_k| = |(R^{-T}e^{(k)})^TRu| \leq \|R^{-T}e^{(k)}\|_2\|Ru\|_2,$$

$$\|R^{-T}e^{(k)}\|_2^2 = (e^{(k)})^TR^{-1}R^{-T}e^{(k)} = ((R^TR)^{-1})_{kk},$$

the assertion follows. □

Now suppose that we have a semiseparable inequality of the form

$$\sum_k q_k(x_k) + (x - x^0)^TH(x - x^0) \leq \overline{a}, \tag{46}$$

with possibly nonsymmetric H. Using a modified Cholesky factorization [107, 290]

$$H + H^T = R^TR - D$$

with a (nonnegative) diagonal matrix D, we can rewrite (46) as

$$0 \leq \frac{1}{2}\|R(x - x^0)\|_2^2 \leq \overline{a} - \sum_k q_k(x_k) + \frac{1}{2}(x - x^0)^TD(x - x^0). \tag{47}$$

The right hand side of (47) is a separable quadratic form, hence can be written as $\overline{a}-\sum \tilde{q}_k(x_k)$ with $\tilde{q}_k(x_k) = q_k(x_k) - \frac{1}{2}D_{kk}(x_k - x_k^0)^2$. Therefore, Proposition 14.1(ii) applies. Moreover, one gets the extra inequality

$$\|R(x - x^0)\|_2^2 \leq 2(\overline{a} - \underline{s}),$$

which, together with the lemma gives the further inequalities

$$|x_k - x_k^0| \leq \sqrt{2(\overline{a} - \underline{s})((R^T R)^{-1})_{kk}}, \tag{48}$$

which may help to reduce $\mathbf{x}_k$.

Block separable constraints. For only block-separable constraints ($|J_k| > 1$), the q_k are multivariate, and one needs to resort to suboptimal interval techniques.

How to exploit the enclosures from Proposition 14.1 and 14.2 to reduce the box depends on the special form of the q_k. In many cases, one can in turn solve the conditions directly for each variable involved, substituting an enclosing interval for all other variables.

If this is not possible directly one can use the mean value form (or another centered form) to rewrite a constraint $F_i(x) \in \mathbf{F}_i$ as

$$F_i(\xi) + F'(\mathbf{x})(x - \xi) \cap \mathbf{F}_i \neq \emptyset;$$

this is now a separable expression with interval coefficients that can be processed as above to reduce the box. This way of proceeding, dating back to NEUMAIER [242], is called **conditioning** in [328], and used in the Numerica [328] package. Similarly, by using a Taylor expansion to second order with an interval Hessian, one gets a semiseparable expression with interval coefficients that can in principle be processed as above. (However, the interval coefficients cause here additional complications.) In the context of Taylor models of arbitrary order, a variation of this (with thin coefficients and an interval remainder term) has been used in the linear dominated bounder of MAKINO [207]; cf. the discussion in [208, 252].

15 The cluster problem and second-order information

When programming a simple branch and bound algorithm for global optimization, one quickly notices that it is fairly easy to eliminate boxes far away from the global minimizer, while, especially in higher dimensions, there remains a large cluster of tiny boxes in a neighborhood of the global minimizer that is difficult to eliminate. The occurrence of this situation is called the **cluster problem**. Often, algorithms try to avoid the cluster problem by providing only a Δ-optimal solution; i.e., the program stops when it has shown that there is no feasible point with an objective function value of $f^{\text{best}} - \Delta$, where f^{best} is the function value of the best feasible point found so far. However, when Δ is small (as one wants to have it) then the cluster problem is still present, although to a less pronounced degree.

KEARFOTT & DU [175] studied the cluster problem for unconstrained global optimization, and discovered that the source of the problem was the limited accuracy with which the function values were bounded. In particular, they showed that the cluster problem disappears if, for x in a box of diameter $O(\varepsilon)$, one can bound the overestimation of $f(x^{\text{best}}) - f(x)$ by $O(\varepsilon^3)$. Here we give a simplified version of their result.

Let $\widehat{x} \in \mathbb{R}^n$ be a global minimizer of $f(x)$, and let $\widehat{G}$ be the Hessian at $\widehat{x}$. Near the global minimizer, we have

$$f(x) = f(\widehat{x}) + \frac{1}{2}(x - \widehat{x})^T \widehat{G}(x - \widehat{x}) + O(\|x - \widehat{x}\|^3)$$

since the gradient vanishes at $\widehat{x}$. Suppose we can bound the objective function value over a box of diameter ε with an accuracy of $\Delta = K\varepsilon^{s+1}$, $s \le 2$. Then no box of diameter ε containing a point x with $\frac{1}{2}(x - \widehat{x})^T \widehat{G}(x - \widehat{x}) + O(\|x - \widehat{x}\|^3) \le \Delta$ can be eliminated. For sufficiently small Δ, this describes a nearly ellipsoidal region with volume proportional to $\sqrt{(2\Delta)^n / \det \widehat{G}}$, and any covering by boxes of diameter ε contains at least $const\sqrt{(2\Delta)^n/(\varepsilon^n \det \widehat{G})}$ boxes. The number of uneliminated boxes is therefore proportional to at least

$$\begin{array}{ll} (const/\varepsilon)^{n/2}/\sqrt{\det \widehat{G}} & \text{if } s = 0, \\ \sqrt{const^n/\det \widehat{G}} & \text{if } s = 1, \\ \sqrt{(const \cdot \varepsilon)^n/\det \widehat{G}} & \text{if } s = 2. \end{array}$$

We see that for $s = 0$, the number grows immensely as ε gets small. For $s = 1$, the number of boxes needed – while (for small ε) essentially independent of ε – may still grow exponentially with the dimension, and it is especially large for problems where the Hessian at the solution is ill-conditioned. However, the number is guaranteed to be small (for small ε) when $s = 2$.

For pure constraint satisfaction problems, a similar cluster effect is present (Schichl & Neumaier [288]), but with order reduced by one; thus the quadratic approximation property available from methods exploiting first order information only (such as centered forms) already avoids the cluster effect, except in degenerate cases. However, especially near poorly conditioned solutions, the size of boxes that can be eliminated is significantly larger if second-order information is used [288]. In case of nonisolated solution sets, some clustering seems unavoidable, but Lyapunov-Schmidt reduction techniques (Neumaier [247]) might prove useful. The problem of covering nonisolated solution sets efficiently with a small number of boxes is discussed in considerable algorithmic detail by Vu et al. [332, 333] for the case of pure constraint satisfaction problems; see also Chapter 7 of the COCONUT report [38].

For constrained global optimization, similar arguments as for the unconstrained case apply in a reduced manifold with the result that, in the formulas, n must be replaced by $n - a$, where a is the maximal number of constraints active at the solution, with linearly independent constraint gradients.

Clearly, to bound the overestimation over a box of diameter $O(\varepsilon)$ by $O(\varepsilon^3)$ requires that one knows the Hessian up to $O(\varepsilon)$, and that one is able to bound the deviation from a quadratic model. (Actually, the above argument shows that $o(\varepsilon^2)$ is sufficient, but this still requires the knowledge of the Hessian up to $o(1)$.) Thus it is necessary to have access to second-order information. Unfortunately, in higher dimensions, no cheap method is known that bounds function values over an arbitrary narrow box of diameter $O(\varepsilon)$ close to a minimizer by $O(\varepsilon^3)$. In a single dimension, cheap methods are known; see CORNELIUS & LOHNER [58] and [243, Section 2.4]. In dimension > 1, peeling methods together with Taylor expansions work with an effort that grows like $O(n^3 \cdot 3^n)$; see the discussion in NEUMAIER [252, Section 5].

Fortunately, however, it turns out that by using interval Hessian matrices (which, for 3-times differentiable functions have the required $O(\varepsilon)$ accuracy, see [243, Section 1.4]), there are several ways to avoid the cluster problem, at least when the global minimizer is nondegenerate, i.e., satisfies the second-order sufficient conditions for a local minimizer.

Explicit global Hessian information can be used, as in GlobSol [173] and Numerica [328], by interval Newton methods (see Section 11) applied to the Karush-John conditions discussed in Section 5. These may verify the existence of a unique solution of the Karush-John conditions (Theorem 5.1 and equation (7)) in some box around the best point found, and hence allow to shrink that box to a single point.

Alternatively, one may use global Hessian information to verify the second-order sufficient conditions for a global minimizer given in NEUMAIER [245]. They apply to smooth nonlinear programs of the form

$$\begin{array}{ll} \min & f(x) \\ \text{s.t.} & x \in \mathbf{x}, \quad F(x) = 0. \end{array} \tag{49}$$

Thus it is necessary to introduce slack variables to rewrite general inequality constraints as equality constraints. The sufficient condition is as follows.

15.1 Theorem. *Let $\widehat{x}$ be a Kuhn-Tucker point for the nonlinear program* (49), *with associated multiplier z, and let*

$$y := f'(\widehat{x})^T - F'(\widehat{x})^T z, \tag{50}$$

$$D = \mathrm{Diag}\left(\sqrt{\frac{2|y_1|}{\overline{x}_1 - \underline{x}_1}}, \dots, \sqrt{\frac{2|y_n|}{\overline{x}_n - \underline{x}_n}}\right). \tag{51}$$

If, for some continuously differentiable function $\varphi : \mathbb{R}^m \to \mathbb{R}$ with

$$\varphi(0) = 0, \quad \varphi'(0) = z^T, \tag{52}$$

the **generalized augmented Lagrangian**

$$\widehat{L}(x) := f(x) - \varphi(F(x)) + \frac{1}{2}\|D(x - \widehat{x})\|_2^2 \tag{53}$$

is convex in $[u, v]$, then $\widehat{x}$ is a global solution of (49). *Moreover, if $\widehat{L}(x)$ is strictly convex in $[u, v]$, this solution is unique.*

A choice for φ that works in some neighborhood of a strong global minimizer (i.e., one in which sufficient second-order conditions for local optimality hold) is given in [245], together with further implementation hints. The convexity can be checked by means of interval arithmetic; see Section 11. If these conditions hold in some box, one can shrink this box to a single point.

One can use any of these techniques to construct boxes $\mathbf{y}$ that are guaranteed to contain no global minimizer except if already detected, resulting in exclusion constraints. An **exclusion constraint** is a constraint of the form

$$x \notin \mathbf{y}.$$

It can be used to reduce an arbitrary box $\mathbf{x}$ by intersecting it with $\mathbf{y}$ and taking the interval hull, which may result in a smaller box. If there was no reduction but the intersection is strictly contained in $\mathbf{x}$, one may also want to resort to multisection, cf. (33). Interesting exclusion boxes are those that are constructed around local minimizers, since this helps fighting the cluster problem.

It is possible (though probably not most efficient) to base global optimization algorithms on exclusion methods alone; see the work of GEORG et al. [12, 105, 106], who also give associated complexity results.

Backboxing. Whenever we have a tentative approximate global minimizer $\tilde{x}$, we try to find simultaneously a large box $\mathbf{x}$ and a tiny box $\mathbf{z}$ such that any global minimizer $\widehat{x} \in \mathbf{x}$ satisfies $\widehat{x} \in \mathbf{z}$. This allows to use $\mathbf{x}$ as an exclusion region while $\mathbf{z}$ is stored in an output list as a box containing a putative minimizer. (After terminating the branching process, these boxes need to be checked again for possible elimination.)

Since we expect that $\tilde{x}$ has a function value optimal within $O(\varepsilon)$, but knowing that this only enforces that $\tilde{x}$ has an accuracy of $O(\sqrt{\varepsilon})$ (possibly less in case of singular Hessians), we start with a box

$$\mathbf{x} = [\tilde{x} - \sqrt{\varepsilon}u, \tilde{x} + \sqrt{\varepsilon}u]$$

for some vector u reflecting the scaling of the variables, and apply the available reduction techniques until no significant improvement results. Call the resulting box $\mathbf{z}$. If second-order techniques are used to do the box reduction, then $\mathbf{z}$ is usually a tiny box or empty.

If $\mathbf{z}$ is empty, $\tilde{x}$ was not a good approximation but we know that $\mathbf{x}$ contains no solution. If $\mathbf{z}$ is nonempty, it is likely that $\mathbf{z}$ contains a solution. Indeed this is always the case if *only* interval Newton-like reduction techniques are used and $\mathbf{z} \subseteq \operatorname{int} \mathbf{x}$. (This requires some qualifying conditions that ensure that one can verify sufficient existence conditions such as those in NEUMAIER [243, Chapter 5.3-4].) Thus one may store $\mathbf{z}$ in a list of output boxes together with a flag whether existence (and possibly uniqueness) was verified.

If $\mathbf{z}$ is still a box of significant size, we must have been close to a degeneracy; splitting would probably not improve this and lead to an exponential number of boxes; thus it is preferable to put this box also in the list of output boxes to indicate that a low resolution candidate for a solution has been found. (This way of handling degeneracies is due to KEARFOTT [172].)

No matter what case we have been in, we always know that $\mathbf{x}$ cannot contain a solution not yet in the output list. Therefore, we may add the exclusion constraint $x \notin \mathbf{x}$ to the problem description. However, one can often make $\mathbf{x}$ even bigger. So we try recursively

$$\mathbf{x}^0 = \mathbf{x},\ \mathbf{z}^0 = \mathbf{z}, \qquad \text{but } \mathbf{z}^0 = \mathrm{mid}(\mathbf{x}) \text{ if } \mathbf{z} = \emptyset,$$

$$\mathbf{x}^l = 2\mathbf{x}^{l-1} \ominus \mathbf{z}^{l-1},\ \mathbf{z}^l = \mathrm{reduce}(\mathbf{x}^l);$$

using the available ways of reducing $\mathbf{x}^l$, stopping when $\mathbf{z}^l \subseteq \mathbf{x}^{l-1}$ or $\mathbf{z}^l = \mathbf{x}^l$. (For the inner subtraction $\ominus$, see (26).) Then we have the generally stronger new exclusion constraint $x \notin \mathbf{x}^l$. (This way of generating exclusion constraints, using interval Newton methods, is due to Van Iwaarden [329], who calls the technique **backboxing**, and is part of GlobSol [173].) Recent methods by Schichl & Neumaier [288] for constructing large exclusion boxes can be combined with this iterative approach.

Finite termination. Closely related to the cluster problem is the question of finite termination, i.e., whether branch and bound algorithms find (assuming exact arithmetic) a global optimizer with a finite amount of branching only. This is not easy to achieve, and in practice, most algorithms are content with working towards ε-optimality, i.e., finding a (nearly) feasible point within ε of the true but unknown optimal function value.

Theoretical finite termination guarantees are available only for problems where the optimum is attained at an extreme points (Al-Khayyal & Sherali [11], Shectman & Sahinidis [293]). However, in practice, algorithms based on the explicit use of second-order interval information (either via interval Newton operators or via second-order sufficient conditions) have finite termination behavior on problems with a nondegenerate global minimizer, and it is likely that this can be proved theoretically.

In case of degeneracies, behavior of branch and bound methods can become arbitrarily poor. However, the situation may improve in cases where the degeneracy can be removed by identifying and eliminating redundant constraints causing the degeneracy. To do this rigorously requires care; see Huyer & Neumaier [146] for first results in this direction.

16 Linear and convex relaxations

One of the highly developed sides of global optimization is the use of **linear and convex relaxations** to find a lower bound for the value of the objective function, which makes it possible to discard boxes where this lower bound is larger than the function value f^{best} of the best feasible point found so far. The details are well-covered in several books [85, 86, 309], so we are brief here and only describe the basic issues and recent extensions that are not widely known.

Reformulation-linearization. McCormick [215] introduced the notion of a factorable function (composed of finitely many unary or binary operations), and constructed nonsmooth convex relaxations for such functions. Kearfott [171] (and perhaps others before him) noticed that by introducing intermediate variables, every factorable optimization problem can be rewritten in a form in which all constraints are unary, $z = \varphi(x)$, or binary, $z = x \circ y$. Independently, Ryoo & Sahinidis [282] proposed to use in place of these constraints implied linear constraints (so-called **linear relaxations**) to generate a set of linear inequalities defining a polyhedral outer approximation. Since the objective can be represented by a single variable and another constraint, this allows one to find a linear programming relaxation for arbitrary factorable optimization problems.

Linear relaxations for unary operations are easily found by a simple graphical analysis of the various elementary functions. In particular, for a convex function, the secant between the endpoints of the graph is an overestimate, and any tangent is an underestimate; frequently, taking the two tangents at the end points is already quite useful. For concave functions, the reverse situation holds, and in the general case one also may need to consider bitangents, and tangent secants. Since powers can be written in terms of $\exp, \log$ and the product, the only binary operations that need to be analyzed are products and quotients.

Assuming that bounds $x \in \mathbf{x}$, $y \in \mathbf{y}$ for the factors are available, McCormick proposed for the product $z = xy$ the relaxations

$$\underline{y}x + \underline{x}y - \underline{x}\underline{y} \le z \le \underline{y}x + \overline{x}y - \overline{x}\underline{y},$$

$$\overline{y}x + \overline{x}y - \overline{x}\overline{y} \le z \le \overline{y}x + \underline{x}y - \underline{x}\overline{y},$$

which follow immediately from $(x - \underline{x})(y - \underline{y}) \ge 0$ and three similar inequalities. Al-Khayyal & Falk [9] showed later that these inequalities are indeed best possible in the sense that any other generally valid linear inequality is a consequence of these and the bound constraints. (One says they form the **convex and concave envelope**.)

For the quotient $x = z/y$, exactly the same formulas are valid with $\mathbf{x} = \mathbf{z}/\mathbf{y}$, but remarkably, one does not get the envelope in this way. For example, the following inequality, due to Zamora & Grossmann [342], is not implied.

16.1 Proposition. *Let* $\mathbf{x}, \mathbf{y}, \mathbf{z}$ *be nonnegative intervals. If* $x \in \mathbf{x}$, $y \in \mathbf{y}$, *and* $z = xy \in \mathbf{z}$ *then*

$$xy \ge \Big(\frac{z + \sqrt{\underline{z}\overline{z}}}{\sqrt{\underline{z}} + \sqrt{\overline{z}}}\Big)^2. \tag{54}$$

(54) describes a convex set in the nonnegative orthant of $\mathbb{R}^3$, although the inequality itself is not convex. However, it is the prototype of a convex conic constraint (see below) and can be exploited by solvers for second order cone programs. therefore, adding this constraint gives a relaxation that may be tighter than the McCormick relaxation. The general formulas for the convex envelope of a quotient, derived explicitly in Tawarmalani & Sahinidis [309], are quite complicated.

Crama [60] showed that the following bounds define the optimal convex relaxation of a product of factors bounded in $[0, 1]$.

16.2 Proposition. *If* $x_i \in [0, 1]$ $(i = 1 : n)$ *and* $z = x_1 \cdots x_n$ *then*

$$1 - n + \sum_{k=1}^{n} x_k \le z, \quad 0 \le z \le x_i \le 1 \ (i = 1 : n). \tag{55}$$

More generally, arbitrary multilinear functions have an optimal convex relaxation (the envelope) defined by finitely many linear inequalities. For this result, and for other methods for getting linear relaxations of nonconvex programs based on the **reformulation-linearization** technique, see RIKUN [280], SHERALI et al. [294, 296, 297, 298], and AL-KHAYYAL et al. [10], AUDET et al. [17]. Related is the **lift-and-project** technique in mixed integer linear programming; see, e.g., BALAS et al. [21].

Note that this approach using the factorable or a nearly factorable form generally results in problems with many more variables than in the original problem formulation. Nevertheless, since the resulting linear or convex programs are extremely sparse, the technique can be very useful, especially for larger problems. In particular, this is the main workhorse of the global optimization packages BARON [309] and LINGO [103]. Because linear programming solvers are currently much more reliable and faster than general convex solvers, the convex envelopes used in BARON [309] are in fact approximated by a number of linear constraints computed adaptively with a variant of the sandwich algorithm ROTE et al. [45, 281].

Independent of the way a linear relaxation is produced (see below for alternatives which work without additional variables), the information in the linear relaxation can be exploited not only to get lower bounds on the objective or to eliminate a subproblem, but also to reduce the box. Based on Lagrangian multipliers cheap marginals-based range reduction techniques for doing this are described in TAWARMALANI & SAHINIDIS [309] and are implemented in BARON. Recent results of LEBBAH et al. [195, 196] show that the more expensive approach of minimizing and maximizing each variable with respect to a linear relaxation (which BARON 5.0 did only at the root node of the branch tree) may give a significant speedup on difficult constraint satisfaction problems, and are now part of the default strategy in BARON 6.0.

Semidefinite relaxations. Starting quite recently, a large number of papers, e.g., CHESI & GARULLI [52], JIBETEAN & DE KLERK [161], KOJIMA et al. [98, 178, 179, 180, 183, 184], LASSERRE [194], MEZIAT [220], PARRILO et al. [102, 266, 267, 268], appeared that propose the use of **semidefinite relaxations** or **convex conic relaxations** to solve polynomial constraint satisfaction and global optimization problems. These techniques are implemented in two software packages, GloptiPoly (HENRION & LASSERRE [135, 136, 137]) and SOSTOOLS (PRAJNA et al. [273]). Being developed completely independent from the mainstream in global optimization, these packages do not incorporate any of the other global techniques, and hence are currently restricted to problems with few variables (say, below 20). But since they are able to solve many of these problems to global optimality without doing any branching, their combination with the other techniques, in particular with branch and bound, appears to be highly promising.

The background of these methods is that constraints of the form

$$\sum_k x_k A_k \quad \text{is positive semidefinite,} \tag{56}$$

where the A_k are symmetric (or complex Hermitian) matrices, so-called **semidefinite constraints**, define convex sets, and that constraints of the form

$$\|Ax - b\|_2 \le a^T x + \alpha$$

or

$$\|Ax - b\|_2^2 \le x_i x_j, \quad x_i x_j \in \mathbb{R}_+,$$

so-called **second-order cone constraints**, describe convex conic sections. Problems with a linear or convex quadratic objective and an arbitrary number of such constraints (in addition to linear constraints) can be efficiently solved using interior point methods. Therefore, convex conic and semidefinite relaxations of nonlinear constraints can be efficiently exploited. Books and surveys emphasizing the nonlinear case include [8, 68, 323, 311, 322, 337]; for software, see the semidefinite programming homepage (Helmberg [134]) and the package SEDUMI [291, 305], on which both GloptiPoly and SOSTOOLS are based.

The basic idea behind semidefinite relaxations is the observation that given any set of basis functions $\varphi_i(x)$ and any nonnegative weight function $w(x)$, the matrix M with components

$$M_{ik} = w(x)\varphi_i(x)\varphi_k(x)$$

is always symmetric and positive semidefinite. If the φ_i and w are polynomials then the entries of M are also polynomials, and by introducing auxiliary variables z_j for the elements of a basis of polynomials of sufficiently high degree, one can write both the entries of M and any polynomial objective or constraint as a linear combination of the z_j. The condition that M is positive semidefinite gives therefore rise to a semidefinite constraint. Possible choices for $w(x)$ can be easily made up from the constraints. Moreover, given an equality constraint, any multiple by a polynomial is another equality constraint, and given two inequality constraints $u(x) \ge 0$ and $v(x) \ge 0$, their product is again such a constraint. Thus lots of additional polynomial constraints can be generated and used. Results from algebraic geometry can then be invoked to show that infeasibility and ε-optimality can always be achieved by using sufficiently high degrees, without the need of any problem splitting. Apparently, in many cases, relatively low degrees suffice, which is fortunate since the number of intermediate variables would otherwise become excessively large. Moreover, problem symmetry can be exploited by using basis sets with corresponding symmetry properties (Gatermann & Parrilo [102]).

The conic and semidefinite relaxations produced in this way also result in problems with many more variables than in the original problem formulation, but since semidefinite relaxations are often much stronger than linear relaxations, the effort required to solve these large problems may be well spent if a subproblem is solved without the need of splitting it into many smaller pieces. Since problems with semidefinite constraints involving larger matrices are more expensive to solve than those with convex conic constraints, the latter are in principle preferable, but conclusive results on the best way of using or combining the various possible relaxations are not yet available.

For semidefinite relaxations of certain fractional functions see Tawarmalani & Sahinidis [307, 308].

Relaxations without extra variables. In place of introducing additional variables for nonlinear intermediate expressions, it is also possible to relax the original constraints directly. Apart from McCormick's [215] nonsmooth convex relaxations, which are difficult to use, this can be done in two different ways.

The first possibility is to write the constraints as a difference of convex functions (DC representation). The package αBB (see ADJIMAN et al. [2, 3, 4, 5, 15]) uses DC-techniques, by separating in each inequality constraint $h(x) \leq 0$ a recognizable linear, convex or concave parts from a 'general' remainder. Linear and convex parts are kept, concave parts are overestimated by secant type constructions, and general terms are made convex by adding a nonpositive separable quadratic function. This ensures that a convex underestimating inequality results. More specifically, if $f(x)$ is twice continuously differentiable at all x in a neighborhood of a box $\mathbf{x}$ and D is a diagonal matrix with nonnegative entries then

$$f_{\mathrm{rel}}(x) := f(x) + \frac{1}{2}(x - \underline{x})^T D(x - \overline{x})$$

is an underestimator of $f(x)$ on the box, and the amount of underestimation is bounded by

$$|f_{\mathrm{rel}}(x) - f(x)| \leq \frac{1}{8} \operatorname{rad} \mathbf{x}^T D \operatorname{rad} \mathbf{x}, \tag{57}$$

attained at the midpoint. (At the vertices there is no overestimation.) If the Hessian $G(x)$ lies in the interval matrix $\mathbf{G}$ for all $x \in \mathbf{x}$ (such a $\mathbf{G}$ can be found by interval evaluation of the Hessian, e.g., using automatic differentiation) and all symmetric matrices in $\mathbf{G} + D$ are positive semidefinite then f_{rel} is convex. The latter condition can be checked as in Theorem 11.1; the difficulty is to choose D in such a way that this condition holds and the underestimation bound in (57) is kept small but the work for getting D remains reasonable [3, 4]. Recent, more advanced convexity-enforcing corrections are discussed in AKROTIRIANAKIS & FLOUDAS [6].

More general DC-techniques are treated extensively from a mostly theoretical point of view in the book by HORST & TUY [144]; see also the overview in TUY [320]. Apart from what is used in αBB (and described above), these techniques have not materialized in available codes; however, see, e.g., AN & TAO [13] for some recent numerical results.

General techniques for recognizing convexity automatically are discussed in forthcoming work of FOURER [96] and MAHESHWARI et al. [206]. Other questions related to the semidefiniteness of an interval matrix are discussed in JAULIN & HENRION [159].

The second possibility is to use centered forms. The Frontline Interval Global Solver constructs linear enclosures based on a centered form (in fact a first order Taylor form),

$$f(x) \in \mathbf{f} + c^T(x - z), \tag{58}$$

using forward propagation in an automatic differentiation like manner, described in KOLEV & NENOV [186]. Since the coefficients of the linear term in (58) are real numbers, this directly gives two parallel linear functions which underestimate and overestimate $f(x)$.

$$\underline{f} + c^T(x - z) \leq f(x) \leq \overline{f} + c^T(x - z).$$

The COCONUT environment constructs a centered form using slopes and automatic differentiation like backward propagation according to formulas given in SCHICHL & NEUMAIER [289], from which linear enclosures are constructed. Indeed, given a centered form

$$f(x) = \tilde{f} + \tilde{s}^T(x - z), \quad \tilde{f} \in \mathbf{f},\ \tilde{s} \in \mathbf{s},$$

we have the linear underestimator

$$f(x) \geq \gamma + c^T(x - \underline{x}),$$

where

$$\gamma = \underline{f} + \overline{s}^T(\underline{x} - z), \quad c_i = \frac{\underline{s}_i(\overline{x}_i - z_i) - \overline{s}_i(\underline{x}_i - z_i)}{\overline{x}_i - \underline{x}_i}.$$

A similar formula provides a linear overestimator. Geometrically, the formulas amount to enclosing the double cone defined by the centered form by a pair of hyperplanes; since linear functions are separable, the formulas derived from an analysis of the univariate case can be applied componentwise.

17 Semilinear constraints and MILP

Let us call a constraint **semilinear** if, for arguments x in a *bounded* box $\mathbf{x}$, it is equivalent to a finite list of linear constraints and integer constraints; usually the latter involve additional auxiliary variables. The objective function $f(x)$ is called **semilinear** if the inequality $f(x) \leq x_0$, where x_0 is an additional variable, is semilinear. A **semilinear program** is an optimization problem with a semilinear objective function and a bounded feasible domain defined by semilinear constraints only. Since we can rewrite an arbitrary global optimization problem

$$\begin{array}{ll} \min & f(x) \\ \text{s.t.} & x \in C \end{array}$$

in the form

$$\begin{array}{ll} \min & x_0 \\ \text{s.t.} & x \in C, \ f(x) \leq x_0, \end{array}$$

it is clear from the definition that any semilinear program can be rewritten as a mixed integer linear program by the introduction of additional variables.

The remarkable fact that every factorable optimization problem can be arbitrarily closely approximated by semilinear programs (see Section 18) implies that one can use MILP software to obtain arbitrarily good approximate solutions of factorable optimization problems. To make this observation computationally useful we need to handle two tasks:

(i) Find interesting classes of semilinear constraints and constructive procedures for translating such constraints into linear and integer constraints.

(ii) Show how to approximate factorable constraints by semilinear constraints; see Section 18.

In this section we look at task (i). This is in principle well-known, but usually considered to be part of the modeling process. For good overviews of the modeling related issues see, e.g., Floudas [85, Section 7.4], Williams [336] and (in German) Kallrath [169]. Here we simply give the underlying mathematical substance.

All linear constraints and integer constraints are trivially semilinear. A **binary constraint**

$$z \in \{0,1\}$$

is semilinear since it can be written in the equivalent form

$$z \in [0,1], \quad z \in \mathbb{Z}.$$

We call a list x_K of variables constrained by

$$\sum_{k \in K} x_k = 1, \quad x_k \in \{0,1\} \ (k \in K), \tag{59}$$

where K is some index set, a **binary special ordered set** (BSOS), cf. [66, 26]. Note that a BSOS is a special ordered set of type 1, and can be handled efficiently by most MILP codes. Clearly, the constraint

$$x_K \text{ is a BSOS} \tag{60}$$

is also semilinear. Because (59) can hold only if all but one of the x_k $(k \in K)$ vanish, (60) is equivalent to requiring that

$$x_K = e^{(k)} \quad \text{for some } k, \tag{61}$$

where $e^{(k)}$ is the unit vector with a one in position k and zeros elsewhere. (A binary special ordered set of size two is just a pair of complementary binary variables, and one of its variables is redundant.) Since special ordered sets, defined more generally as sets of variables such that at most one – type 1 – or two (which then must be adjacent) – type 2 – are nonzero, are ubiquitous in MILP formulations, any MILP solver has special facilities to make efficient use of special ordered sets.

Many techniques for translating semilinear constraints are consequences of the following basic result.

17.1 Theorem. *Let $F_k : C_0 \to \mathbb{R}^{m_k}\,(k = 1,\dots,d)$ be scalar- or vector-valued functions such that*

$$F_k(x) \geq \underline{F}_k \quad \textit{for all } x \in C_0 \tag{62}$$

with finite $\underline{F}_k \in \mathbb{R}^{m_k}$. Then there is a point $x \in C_0$ such that

$$F_1(x) \geq 0 \quad \vee \quad \dots \quad \vee \quad F_d(x) \geq 0 \tag{63}$$

if and only if there are $z \in \mathbb{R}^d$ and $x \in C_0$ such that

$$z \quad \textit{is a BSOS}, \tag{64}$$

$$F_k(x) \geq \underline{F}_k(1 - z_k) \quad \textit{for all } k = 1,\dots,d. \tag{65}$$

(The symbol $\vee$ denotes the logical operation **or**. The operation **and** is simply given by the comma, and we follow the convention that the comma is binding stronger than $\vee$.)

Proof. If (63) holds then $F_k(x) \ge 0$ for some k, and $z = e^{(k)}$ satisfies (64) and (65). Conversely, if (64) holds then $z = e^{(k)}$ for some k, and (65) implies $F_k(x) \ge 0$; the other constraints in (65) are automatically satisfied because of (62). □

Note that (62) can always be satisfied if C_0 is bounded and the F_k are continuous.

A constraint of the form (63) is called a **disjunctive constraint**. The theorem implies that **linear** disjunctive constraints, where all $F_k(x)$ are affine functions of x, are semilinear if the F_k have *known*, finite lower bounds on the feasible domain (**bound qualification**), since then (65) consists of linear constraints. In the following, *we shall always silently assume the bound qualification.* (In practice, this is usually enforced where necessary by ad hoc "big M" domain restrictions. In rigorous solvers, this is of course forbidden.)

More generally, linear disjunctive constraints of the form

$$A_1x \in \mathbf{b}_1 \quad \vee \quad \dots \quad \vee \quad A_dx \in \mathbf{b}_d \tag{66}$$

are semilinear since we can rewrite each $A_kx \in \mathbf{b}_k$ in the form

$$\begin{pmatrix} A_kx - \underline{b}_k \\ \overline{b}_k - A_kx \end{pmatrix} \ge 0.$$

Note that we can rewrite (66) in the equivalent form

$$A_kx \in \mathbf{b}_k \quad \text{for some } k \in \{1 : d\}. \tag{67}$$

Since many practically relevant constraints can be cast in the form (66), this makes the theorem a very useful tool for recognizing semilinear constraints and translating them into a MILP formulation. (There is also an extended literature on disjunctive programming not based on transformations to MILP; for pointers see [20, 160, 295].)

For example, **semicontinuous (semiinteger) variables** are variables x_k constrained by

$$x_k = 0 \quad \vee \quad x_k \in \mathbf{a} \tag{68}$$

and

$$x_k = 0 \quad \vee \quad x_k \in \mathbf{a}; \quad x_k \in \mathbb{Z}, \tag{69}$$

respectively, which are semilinear constraints.

A **numerical special ordered set (NSOS)** is a vector $\lambda \in \mathbb{R}^d$ such that

$$\lambda \ge 0, \qquad \sum_{k=1}^{d} \lambda_k = 1,$$

at most two λ_k are nonzero, and nonzero λ_k must have adjacent indices. Since the latter condition can be formulated as

$$\lambda_k + \lambda_{k+1} = 1 \quad \text{for some } k,$$

it is disjunctive; hence the constraint

$$x_K \text{ is a NSOS} \tag{70}$$

is semilinear. Note that a NSOS is a special ordered set of type 2, and can be handled efficiently by most MILP codes.

An **exclusion constraint** of the form

$$x \notin \operatorname{int} \mathbf{x}, \tag{71}$$

where $\mathbf{x}$ is a box, is semilinear since it is a disjunction of the constraints

$$x_k \le \underline{x}_k \quad \vee \quad x_k \ge \overline{x}_k.$$

Propositional constraints. If x_k denotes a binary variable which has the value 1 iff a corresponding logical proposition P_k holds then

$$P_1 \vee \ldots \vee P_K \quad \text{iff} \quad x_1 + \ldots + x_K \ge 1,$$

$$P_1 \wedge \ldots \wedge P_K \quad \text{iff} \quad x_k = 1 \text{ for } k = 1:K,$$

$$P_1 \Leftrightarrow P_2 \quad \text{iff} \quad x_1 = x_2,$$

$$P_1 \Rightarrow P_2 \quad \text{iff} \quad x_1 \le x_2,$$

$$P_1 \vee \ldots \vee P_K \Rightarrow P_{K+1} \vee \ldots \vee P_L \quad \text{iff} \quad x_k \le x_{K+1} + \ldots + x_L \text{ for } k = 1:K.$$

Conditional linear constraints of the form

$$Ax \in \mathbf{a} \quad \text{if } Bx < b \tag{72}$$

are semilinear since (72) is equivalent to

$$Ax \in \mathbf{a} \quad \vee \quad (Bx)_1 \ge b_1 \quad \vee \quad \ldots \quad \vee \quad (Bx)_d \ge b_d,$$

where d is the number of rows of B and b. (Conditional linear constraints with $=$ or $\le$ in place of $<$ in (72) are apparently not semilinear in general since their disjunctive form contains strict inequalities, which – according to our definition – are not regarded as linear constraints. However, conditional linear constraints where the condition involves only integer variables and rational coefficients are semilinear since the condition can be replaced by an equivalent strict inequality condition.)

Certain **minimum and maximum constraints** are also semilinear. A constraint of the form

$$a^T x \le \min_{i=1:d} (Ax - b)_i \tag{73}$$

is equivalent to the linear constraints

$$a^T x \le (Ax - b)_i \quad \text{for } i = 1:d.$$

The reverse constraint

$$a^T x \ge \min_{i=1:d} (Ax - b)_i \tag{74}$$

is equivalent to the linear disjunctive constraint

$$a^T x \geq (Ax - b)_1 \quad \vee \quad \dots \quad \vee \quad a^T x \geq (Ax - b)_d.$$

Similarly, a constraint of the form

$$a^T x \geq \max_{i=1:d} (Ax - b)_i \tag{75}$$

is equivalent to the linear constraints

$$a^T x \geq (Ax - b)_i \quad \text{for } i = 1 : d,$$

and the reverse constraint

$$a^T x \leq \max_{i=1:d} (Ax - b)_i \tag{76}$$

is equivalent to the linear disjunctive constraint

$$a^T x \leq (Ax - b)_1 \quad \vee \quad \dots \quad \vee \quad a^T x \leq (Ax - b)_d.$$

The constraints

$$a^T x = \min_{i=1:d} (Ax - b)_i, \tag{77}$$

$$a^T x = \max_{i=1:d} (Ax - b)_i \tag{78}$$

are also semilinear, since they are equivalent to (73), (74) and (75), (76), respectively. In particular, **linear complementarity constraints** [33], defined by

$$\min(a^T x - \alpha, b^T x - \beta) = 0 \tag{79}$$

are semilinear. Their MILP reformulation needs a single binary variable only since the associated BSOS has size two.

Linear complementarity constraints arise in bilevel programming, see, e.g., [28, 203, 259, 299, 331], in which the inner optimization problem is a linear program. See, e.g., GROSSMANN & FLOUDAS [125] for solving bilevel programs as mixed integer problems.

Constraints of the form

$$a^T x - \alpha \leq |b^T x - \beta|, \tag{80}$$

$$a^T x - \alpha = |b^T x - \beta|, \tag{81}$$

$$a^T x - \alpha \geq |b^T x - \beta| \tag{82}$$

are semilinear since we can write the absolute value in the form $|b^T x - \beta| = \max(\beta - b^T x, b^T x - \beta)$; again a single binary variable suffices for the MILP formulation. In particular, a constraint

$$\alpha \leq |x| \leq \beta \tag{83}$$

can be modeled as

$$(\alpha + \beta) z - \beta \leq x \leq (\alpha + \beta) z - \alpha, \quad z \in \{0, 1\}.$$

Certain other **piecewise linear constraints** are also semilinear. Of particular interest are those of the form

$$a^T x \le \varphi(x_i), \tag{84}$$

where φ is a continuous, piecewise linear function of a *single* variable with a finite number of derivative discontinuities. Let $\xi_0 < \xi_1 < \ldots < \xi_d$ be a list of **nodes** such that $x_i \in [\xi_0, \xi_d]$ and φ is linear in each interval $[\xi_{k-1}, \xi_k]$. Then

$$\varphi(\xi) = \varphi_k + \varphi'_k(\xi - \xi_k) \quad \text{for } \xi \in [\xi_{k-1}, \xi_k], \tag{85}$$

where

$$\varphi_k = \varphi(\xi_k), \quad \varphi'_k = \frac{\varphi(\xi_k) - \varphi(\xi_{k-1})}{\xi_k - \xi_{k-1}}.$$

Therefore, (84) can be rewritten as a disjunction of the d constraints

$$x_i \in [\xi_{k-1}, \xi_k], \quad a^T x \le \varphi_k + \varphi'_k(x_i - \xi_k)$$

for $k = 1, \ldots, d$. Since these are linear constraints, (84) is equivalent to a linear disjunctive constraint. The constraints

$$a^T x \ge \varphi(x_i), \tag{86}$$

$$a^T x = \varphi(x_i), \tag{87}$$

are semilinear by the same argument, with $\ge$ or $=$ in place of $\le$.

Piecewise linear constraints may also be modelled by NSOS (cf. (70)); see BEALE [24, Section 10.3] and [25, 26, 45, 66, 312]. Indeed, if $\varphi(x)$ is piecewise linear with nodes $\xi_{1:d}$ and corresponding function values $\varphi_k = \varphi(\xi_k)$ then we may write an arbitrary argument x as

$$x = \sum \xi_k \lambda_k, \quad \lambda \text{ is a NSOS}, \tag{88}$$

and find

$$\varphi(x) = \sum \varphi_k \lambda_k.$$

Therefore, if we add the semilinear constraints (88), we may replace each occurrence of $\varphi(x)$ by $\sum \varphi_k \lambda_k$. This even works for unbounded variables and for general separable constraints $\sum \varphi_l(x_l) \in \mathbf{a}$ with piecewise linear φ_l. Many modern MILP programs have special features that allow them to handle piecewise linear constraints using special ordered sets of type 2.

Many combinatorial constraints are semilinear. For example, **all-different constraints** of the form

$$\text{the components of } x_K \text{ are distinct integers} \tag{89}$$

are semilinear, since we can rewrite them as

$$x_k \in \mathbb{Z} \text{ for } k \in K; \quad |x_j - x_k| \ge 1 \quad \text{for } j, k \in K,\ j \ne k.$$

A **cardinality constraint**

$$\text{the number of nonzero } x_k \ (k \in K) \text{ is in } \mathbf{s}$$

is semilinear if we know that x_K is integral and nonnegative. Indeed, an equivalent condition is the existence of binary numbers z_k such that

$$\begin{aligned} z_k &= 1 \quad \text{if } x_k > 0, \\ z_k &= 0 \quad \text{if } x_k < 1, \\ \sum_{k\in K} z_k &\in \mathbf{s}, \end{aligned}$$

and these are semilinear constraints.

Cardinality rules (YAN & HOOKER [341]), i.e., constraints of the form

$$\geq j \text{ components of } x_J \text{ equal } 1 \quad \Rightarrow \quad \geq k \text{ components of } x_K \text{ equal } 1$$

for binary $x_{J\cup K}$, can clearly be written in terms of cardinality constraints and hence are semilinear, too.

18 Semilinear relaxations

The preceding results are of importance for general global optimization since every factorable global optimization problem can be approximated arbitrarily well by semilinear programs. Even stronger, these approximations can be made in a way to provide rigorous relaxations, so that solving the resulting semilinear programs after a MILP reformulation can be used to obtain lower bounds in a branch and bound scheme.

The ideas go back to MARKOWITZ & MANNE [213] and DANTZIG [65] for approximate separable nonconvex programming using piecewise linear constraints. (A Lagrangian method by FALK & SOLAND [80] gives piecewise linear relaxations, but in general, these do not yield arbitrarily good approximations.) With a trick due to PARDALOS & ROSEN [263] (for the special case of indefinite quadratic programs, but not in the context of approximations) that allows one to transform multivariate quadratic expressions into separable form, everything extends easily to the semiseparable case; see (92) below. For indefinite quadratic programs, this is discussed in detail in HORST et al. [143].

With a suitable reformulation, arbitrary factorable optimization problems (and many non-factorable ones) can be rewritten in such a way that the objective function is linear and all constraints are either semilinear, or of the form (84), (86), (87) with continuous functions of a single variable. To see this, we introduce an auxiliary variable for every intermediate result; then the objective function is just a variable, hence linear, and the constraints are simple constraints or equations involving a single operation only,

$$x_k = \varphi(x_i), \tag{90}$$

$$x_k = x_i \circ x_j \quad (\circ \in \{+, -, *, /, \hat{}\}). \tag{91}$$

The problem formulation in terms of constraints of the form (90) and (91) together with a simple objective $\min \pm x_i$ and simple bounds (and possibly integrality constraints) is called the **ternary form** of a global optimization problem.

To find a semilinear relaxation, we note that the equations (90) have the form (87) and hence can be handled as in the previous section. The equations (91) are linear if $\circ \in \{+,-\}$. For $\circ = /$, we get equivalent constraints $x_i = x_k x_j$, and for $\circ =\hat{}$ (the power), we can rewrite the constraint $x_k = x_i^{x_j}$ as

$$y_k = x_j y_i, \quad y_k = \log x_k, \quad y_i = \log x_i.$$

(Powers with constant exponents are treated as a case of (90).) It remains to consider products. But $x_k = x_i x_j$ is equivalent to

$$\alpha x_i + \beta x_j = u, \quad \alpha x_i - \beta x_j = v,$$

$$w = v^2, \quad w + 4\alpha\beta x_k = u^2,$$

for arbitrary α, $\beta \neq 0$. The first two are linear constraints in x_i, x_j, u, v, and the others are of the form (87). This proves that the reformulation can always be done.

However, it is clear that in most cases many fewer intermediate variables need to be introduced since affine expressions $a^T x + \alpha$ can be left intact, as can all expressions depending only on a single variable. Moreover, as we shall see in a moment, quadratic and bilinear expressions can be handled more efficiently.

Therefore, it is advisable to do in a first step only those substitutions needed to transform the problem such that the new objective function $f(x) =: F_0(x)$ and the components $F_i(x)$ $(i = 1 : m)$ of the new constraint function vector $F(x)$ are **semiseparable**, i.e., of the form

$$F_i(x) = \sum_{(j,k)\in K_i} \varphi_j(x_k) + x^T H_i x + c_i^T x + \gamma_i \quad (i = 0 : m) \tag{92}$$

with nonlinear univariate functions φ_j and (in general extremely sparse) matrices H_i. Note that linear terms may be absorbed into the sum, and quadratic and bilinear terms into $x^T H_i x$.

In a second step, the quadratic terms are rewritten as a weighted sum of squares,

$$x^T H_i x = \frac{1}{2} \sum_{j\in J_i} d_j (r_j^T x)^2. \tag{93}$$

This is always possible, usually in many ways; e.g., by a spectral factorization

$$H_i + H_i^T = QDQ^T, \quad D \text{ diagonal},$$

which gives

$$2x^T H_i x = (Q^T x)^T D (Q^T x) = \sum D_{kk} (Q^T x)_k^2.$$

(For numerical stability one needs to take care of scaling issues, to ensure that no unavoidable cancellation of significant digits takes place.) Using (93) and substituting new variables for the $r_j^T x$, we see that we can achieve in this second step the **separable form**

$$F_i(x) = \sum_{(j,k)\in K_i} \varphi_j(x_k) + c_i^T x + \gamma_i \quad (i = 0 : m) \tag{94}$$

with increased K_i. Constraints of the form $F_i(x) \le \overline{F}_i$ are now replaced by

$$\sum_{(j,k)\in K_i} y_j + c_i^T x + \gamma_i \le \overline{F}_i,$$

$$y_j \ge \varphi_j(x_k) \quad \text{for} \quad (j,k) \in K_i,$$

and similarly for the objective function. Constraints of the form $F_i(x) \ge \underline{F}_i$ are replaced by

$$\sum_{(j,k)\in K_i} y_j + c_i^T x + \gamma_i \ge \underline{F}_i,$$

$$y_j \le \varphi_j(x_k) \quad \text{for } (j,k) \in K_i.$$

Finally two-sided constraints $F_i(x) \in \mathbf{F}_i$ with finite $\mathbf{F}_i$ are replaced by

$$\sum_{(j,k)\in K_i} y_j + c_i^T x + \gamma_i \in \mathbf{F}_i,$$

$$y_j = \varphi_j(x_k) \quad \text{for} \quad (j,k) \in K_i.$$

Thus, in this third step, the required form has been achieved, and generally much more parsimoniously. (A few more variables could be saved by leaving in each nonlinear $F_i(x)$ one of the nonlinear terms unsubstituted.)

So far, no approximation was done; the reformulated problem is equivalent to the original one. In a final **approximation step**, constraints of the form (84), (86), (87) are replaced by piecewise linear constraints. If (as traditionally done [25]) just an approximation is desired, one simply uses in place of φ the piecewise linear function obtained by interpolating some function values of φ.

However, with little more work only, **outer approximations** can be constructed if we have two piecewise linear approximations $\underline{\varphi}$, $\overline{\varphi}$ with the same nodes $\xi_0 < \ldots < \xi_d$, satisfying

$$\underline{\varphi}(\xi) \le \varphi(\xi) \le \overline{\varphi}(\xi) \quad \text{for} \quad \xi \in [\xi_0, \xi_d]. \tag{95}$$

To get $\xi_0 = \underline{x}_i$ and $\xi_d = \overline{x}_i$, one needs good bounds $\mathbf{x}_i$ on x_i, which can usually be calculated by constraint propagation (see Section 14).

$\underline{\varphi}$ and $\overline{\varphi}$ can be found by exploiting convexity properties of φ, which are well-known for elementary functions and can be determined with interval analysis for factorable univariate functions. Given (95), the constraint (84) *implies* (and not only approximates) the semilinear constraints

$$x_i \in [\xi_{k-1}, \xi_k], \quad a^T x \le \overline{\varphi}_k + \overline{\varphi}'_k(x_i - \xi_k) \quad \text{for some } k,$$

the constraint (86) implies the semilinear constraints

$$x_i \in [\xi_{k-1}, \xi_k], \quad \underline{\varphi}_k + \underline{\varphi}'_k(x_i - \xi_k) \le a^T x \quad \text{for some } k,$$

and the constraint (87) implies the semilinear constraints

$$x_i \in [\xi_{k-1}, \xi_k], \quad \underline{\varphi}_k + \underline{\varphi}'_k(x_i - \xi_k) \le a^T x \le \overline{\varphi}_k + \overline{\varphi}'_k(x_i - \xi_k) \quad \text{for some } k.$$

Moreover, by adaptively adding additional nodes one can make the gap between the bounds in (95) arbitrarily small, and the approximation by these semilinear constraints becomes arbitrarily good (at the cost of higher complexity, of course).

As one can see, the complexity of the resulting MILP formulation depends on the number of nonlinear operations (but in a problem-dependent fashion because of the quadratic bilinear terms), and grows linearly with the number of nodes used in the piecewise linear approximation. Hence it is an efficient technique only if the number of nonlinear operations is not too large, and the approximation not too close.

19 Other problem transformations

Linear or convex relaxations of a global optimization problem may be viewed as transformations of the problem or of its nonlinear (resp. nonconvex) constraints. There are a number of other useful transformations of constraints or groups of constraints.

General cuts. A **redundant constraint**, or simply a **cut**, is an inequality (or sometimes an equation) not in the original problem formulation that must hold for any global minimizer; if the inequality is linear, it is called a **cutting plane** [114]. A lot is known about cutting planes in mixed integer linear programming; see, e.g., [239, 240, 338]; we are here rather interested in techniques for the smooth case.

We have already met several kinds of derived constraints that cut off part of the feasible region:

- The constraint $f(x) \leq f^{\text{best}}$ cuts off points worse than the best feasible point found so far (with function value f^{best}).
- Exclusion constraints, discussed in Section 15, cut off a region around local minimizers that do not contain any other, better minimizer.
- The linear, convex and semilinear relaxations of constraints, discussed in Section 16 and Section 18, are of course special cases of cuts.

For bound-constrained indefinite quadratic programs, Vandenbussche [324] generalized techniques for mixed integer linear programming to find cuts which lead to excellent results on this problem class.

Surely there is much more to be explored here.

Symbolic transformations. The quality of all techniques considered so far may depend strongly on the form in which a problem is posed. Symbolic techniques may be employed to change the given form into another, perhaps more advantageous form. Unfortunately, it is not clear which transformations are most valuable, and the best transformations must usually be found on a problem-specific ad hoc basis. A recent example of a very difficult constraint satisfaction problem in robotics that only yielded to such an approach is described by LEE et al. [198]. We simply list here a few of the techniques that may be of interest.

Frequently, problems involving **trigonometric variables** can be replaced by equivalent problems with only polynomial equations, using (as recommended in ALIAS [7]) the additional constraint

$$s^2 + c^2 = 1$$

together with the substitution

$$s = \sin\varphi, \quad c = \cos\varphi, \quad s/c = \tan\varphi, \quad c/s = \cot\varphi,$$

and similar rules for trigonomentric functions of half or double angles.

Techniques from **algebraic geometry** can be applied to 'solve' polynomial equations symbolically or to bring them into a special form that may be useful. In particular, **Gröbner basis** methods (see, e.g., BUCHBERGER & WINKLER [44], FAUGERE et al. [81], STETTER [303]) provide normal forms that have a triangular structure and thus allow a complete enumeration of solutions for small polynomial problems. The work grows exponentially with the number of variables. Elimination theory (see, e.g., COX et al. [59], EMIRIS et al. [75, 76], JÓNSSON & VAVASIS [167], MOLLER & STETTER [226], MOURRAIN [43, 234, 235]) provides different, often less expensive techniques for potential simplifications by the elimination of variables. The results are often expressed in terms of determinants, and their exploitation by global solution techniques is not well explored. While the matrices arising in elimination theory appear to be realated to those in semidefinite relaxations of polynomial systems, the connection apparently received little attention [67, 133].

Unfortunately, the equations resulting from completely automatic algebraic techniques are often numerically unstable. If this is the case, function evaluations need either rational arithmetic or higher precision. In such cases, interval evaluation including their refinements suffer from excessive cancellation and provide only very weak global information. it would be very desirable to have flexible tools that do only partial elimination but provide stable reduced equations of some sort.

HANZON & JIBETEAN [133] apply these techniques to find the global minimizer of multivariate polynomials, giving attention also to the case where the minimum is achieved at infinity.

Automatic differentiation [32, 57, 119, 120, 121, 122, 321] is a now classical technique for obtaining high quality derivatives analytically and cheaply by transforming a program for function evaluation into a program for the evaluation of derivatives. This technique can be applied directly to create the Karush-John optimality conditions (Theorem 5.1 and equation (7)) as additional constraints for constraint propagation or for verifying optimality, as done in the COCONUT environment (cf. Section 22) and (with a weaker form of (7)) in Numerica [328] and GlobSol [173].

On the other hand, the automatic differentiation techniques can also be adapted to provide evaluations of interval derivatives, slopes (BLIEK [36, 37], with improvements in SCHICHL

& Neumaier [289]), linear enclosures (Nenov & Fylstra [241]), and second-order slopes (Kolev [185]).

20 Rigorous verification and certificates

The reliability of claimed results is the most poorly documented aspect of current global optimization software. Indeed, as was shown by Neumaier & Shcherbina [255], even famous state-of-the-art solvers like CPLEX8.0 (and many other commercial MILP codes) may lose an integral global solution of an innocent-looking mixed integer linear program. In our testing of global solvers within the COCONUT project we noticed many other cases where global solutions were lost or feasible problems were declared infeasible, probably because of ill-conditioned intermediate calculations that lead to rounding errors not covered by the built-in tolerances.

For the solution of precise mathematical problems (such as the Kepler problem [128]), but also for safety-critical optimization problems, it is necessary to have a complete mathematical guarantee that the global minimizer has been found. This requires special attention since numerical computations are affected by rounding errors. Fortunately, interval arithmetic, if performed with directed (outward) rounding, is able to give mathematical guarantees even in the presence of rounding errors.

Rounding in the problem definition. Many problems contain floating-point constants in their formulation. Therefore, frequently, the translation of the problems into an internal format involves floating-point computations which introduce rounding errors. Unfortunately, none of the currently available modeling systems allows one to control these rounding errors or any rounding errors made in a presolve phase used to simplify the problem formulation. The rigorous solvers available (GlobSol and Numerica) have special input modes for constants, but cannot be fed with problems generated from AMPL or GAMS input (the format for most test problems in the collections available, see Section 21). It is hoped that future releases of modeling systems provide options that allow for the passing of either symbolic constants or interval-valued coefficients computed from the input, so that the exact problem or at least nearly exact but rigorous relaxations of the exact problem can be recovered.

Rounding in the solution process. Most current solvers simply implement algorithms valid in exact arithmetic, and do not care about rounding errors, except by allowing for certain nonrigorous ad hoc tolerances in testing feasibility.

On the other hand, certain solvers (in the above list of solvers, GlobSol and Numerica) do only rigorous computations – by enclosing all numbers in intervals accounting for the rounding errors. However, they do not make use of convexity arguments leading to linear or convex programs that can be solved by local techniques, and hence have a competitive disatvantage for numerous problems. The main reason seems to be that until recently making linear (or convex) programming rigorous was very expensive compared to the traditional approximate approach, and time-consuming to implement.

NEUMAIER & SHCHERBINA [255] showed that it is possible to certify the results of linear optimization problems with finite bounds by simple pre- and post-processing, without having to modify the solvers. JANSSON [153, 154] extended this to the case of unbounded variables (where only little more work is needed unless a large number of unbounded variables is present), and JANSSON [155] extended the approach further to the case of convex programs.

The availability of these cheap, easy to use methods for certifying the results of linear and convex optimization programs is likely to change this in the near future. First results in this direction are presented by LEBBAH et al. [195, 196], who report rigorous results for a combination of constraint propagation, interval Newton and linear programming methods that significantly outperform other rigorous solvers (and also the general purpose solver BARON) on a number of difficult constraint satisfaction problems.

Certification of upper bounds. Apart from controlling rounding errors in the computation of bounds, care must also be taken in using objective function values as upper bounds on the objective function. This is permitted only if the argument is feasible. However, especially in the presence of equality constraints, the arguments are often not exactly feasible but satisfy the constraints only within certain tolerances. In these cases, a rigorous upper bound on the objective can be obtained only if the existence of a feasible point in a small box around the approximate point can be proved rigorously, and the objective function is then evaluated at this box. This requires the use of interval Newton techniques (cf. Section 11). However, since there are frequently fewer equality constraints than variables, the standard existence tests must be modified to take account of this, and also to handle inequalities correctly. For a description of the main techniques currently available to certify the existence of feasible points see, e.g., [173, 172].

Certificates of infeasibility. If an optimization problem (or a subproblem in a box generated by branch and bound) has no feasible point, a **certificate of infeasibility** can often be given that allows an easy check that this is the case. For linear constraints, the following result [255], which uses basic interval arithmetic only, applies.

20.1 Theorem. *The set of points satisfying*

$$x \in \mathbf{x}, \quad Ax \in \mathbf{b} \tag{96}$$

is empty if and only if there is a multiplier vector y such that

$$(y^T A)\mathbf{x} \cap y^T \mathbf{b} = \emptyset. \tag{97}$$

Proof. If x satisfies (96) then the left hand side of (97) contains $y^T Ax$ and hence is nonempty. Thus (97) implies that (96) cannot be satisfied. The converse is a simple consequence of the Lemma of Farkas and the fact [243, Section 3.1] that $a^T\mathbf{x} = \{a^T x \mid x \in \mathbf{x}\}$. □

Thus a certificate of infeasibility consists in a multiplier vector y satisfying (97), and is, e.g., a byproduct of phase 1 of a simplex algorithm.

If there are nonlinear constraints, there are simple certificates for infeasibility of

$$x \in \mathbf{x}, \quad F(x) \in \mathbf{F},$$

such as a multiplier vector y with

$$y^T F(\mathbf{x}) \cap y^T \mathbf{F} = \emptyset, \tag{98}$$

where $F(\mathbf{x})$ is an interval evaluation of F at the box $\mathbf{x}$, or

$$y^T F(\xi) + \Big(y^T F'(\mathbf{x})\Big)(\mathbf{x} - \xi) \cap y^T \mathbf{F} = \emptyset, \tag{99}$$

where $F'(\mathbf{x})$ is an interval evaluation of the Jacobian F' at the box $\mathbf{x}$. Similarly, if already a feasible point with objective function value f^{best} is known then a multiplier vector y with

$$\min_{x \in \mathbf{x}} (f(x) + y^T F(x)) > f^{\text{best}} + \sup y^T \mathbf{F} \tag{100}$$

is a certificate that the box $\mathbf{x}$ cannot contain a global minimizer. The left hand side can be bounded from below by interval evaluation or a centered form, giving a verifiable sufficient condition. In the linear case, (100) reduces to half of Theorem 20.1.

It is not difficult to show that for convex constraints, a certificate of infeasibility can be constructed in complete analogy to the linear case. But in the nonconvex case, there is no guarantee that such a certificate exists (or can be found easily if it exists). Moreover, local solvers may fail because they are not able to find a feasible point, even if one exists. Indeed, finding a feasible point is in the latter case already a global problem that cannot be handled by local methods.

Good certificates of infeasibility of the form (99) are, however, available for small boxes not too close to the feasible domain. This follows from the quadratic approximation property of centered forms. A suitable multiplier vector y can be obtained in this case from the linearized problem.

Thus, in combination with branching, we can certify the nonexistence of solution in a covering of almost all of the initial box.

Certification of global minimizers. One may also be interested in providing a minimal number of mathematically rigorous certificates that constitute a proof that some point in a narrow computed box is in fact a global minimizer. These certificates are mathematically valid only if the corresponding conditions have been evaluated in exact arithmetic; and additional safeguards are needed to ensure their validity in finite precision arithmetic. Virtually nothing has been done so far with regard to this problem.

21 Test problems and testing

An important part of the development of global optimization software is the careful testing of proposed methods.

For useful test problem collections, see, e.g., [55, 92, 109, 145, 151, 157, 335]. In particular, [145] contains a test suite containing the traditional global optimization test set of low-dimensional problems by Dixon & Szegö [69], together with test results for DIRECT, MCS, and many incomplete global optimization methods. [151] (see also [177, 227]) contains a comparison of stochastic global optimization routines on a large number of low-dimensional test problems from different sources, and [157, 335] contain test results for some interval methods on a large number of low-dimensional test problems. Testing in higher dimensions has been much more limited, although this is about to change.

The documentation and availability of test problems has been considerably simplified by coding them in one of the widely used modeling languages. AMPL [97] and GAMS [100] are two flexible and convenient algebraic modeling languages enabling rapid prototyping and model development. They are of widespread use in the optimization community, as attested by the large number of existing interfaces with state-of-the-art optimization solvers.

The recent *Handbook of Test Problems in Local and Global Optimization* [92] contains a large collection of test problems for local and global optimization problems, both academic and from real applications. (Unfortunately, the book contains a significant number of inaccuracies [93].) The algebraic test problems of this collection are available in the GAMS modeling language, and the differential-algebraic problems are supplied in the MINOPT modeling language. All test problems can be downloaded from the Handbook's web site. A recent web site by GAMS World [109] started collecting a library GlobalLib of real life global optimization problems with industrial relevance, coded in GAMS, but currently most problems on this site are without computational results. 131 algebraic test problems from the Handbook are all included and constitute about a third of the 397 test problems currently available at GlobalLib.

Test problems for local optimization should also pass global optimization solvers; the traditional test set for low-dimensional unconstrained problems is that by Moré, Garbow & Hillstrom [231], with optional bounds from Gay [104]. A number of these problems have in fact several local minimizers and are therefore global optimization problems. Bob Vanderbei maintains a large collection of AMPL files for constrained nonlinear optimization problems [325] from practical applications; also included are the major part of the CUTE collection and the more academic but useful low-dimensional problem collection of Hock & Schittkowski [138].

The COCONUT benchmark [55] (cf. Shcherbina et al [292]) is a collection of nearly 1300 AMPL models, containing the CUTE part of the Vanderbei test collection, AMPL versions of the problems from GlobalLib (collection from summer 2002), and a large collection of pure constraint satisfaction problems from various places. All problems are annotated with best known function values (or even solutions) and some statistical information such as the number of variables and constraints.

The COCONUT project has extensive test results on the COCONUT benchmark for a number of solvers, which will be made public on the COCONUT website [54] at the end of the COCONUT project (February 2004). Extensive benchmarking results for *local* optimization by Mittelmann [222] are also available online. See also Dolan & Moré [70, 71].

Bussiek et al. [48] report about obtaining reliable and repeatable comparisons in global optimization. The ACM Transaction of Mathematical Software recommends [313] to consider advice in [163] for performing computational experiments. The Mathematical Programming Society has guidelines [150] for reporting results of computational experiments based on [61, 118, 275]. See also [22].

22 The COCONUT environment

This survey is part of an attempt to integrate various existing complete approaches to global optimization into a uniform whole. This is the goal of the COCONUT project [54], sponsored by the European Union. The COCONUT consortium is planning to provide at the end of the project (February 2004) at its homepage [54] a modular solver environment for nonlinear global optimization problems with an open-source kernel, which can be expanded by commercial and open-source solver components (inference engines). The following information is taken from Schichl [287].

The application programming interface (API) of the COCONUT environment is designed to make the development of the various module types independent of each other and independent of the internal model representation. It will be a collection of open-source `C++` classes protected by the LGPL license model [113], so that it could be used as part of commercial software. It uses the `FILIB++` [199] library for interval computations and the matrix template library `MTL` [300] for the internal representation of various matrix classes. Support for dynamic linking will relieve the user from recompilation when modules are added or removed. In addition, it is designed for distributed computing, and will probably be developed further (in the years after the end of the COCONUT project) to support parallel computing as well.

The solution algorithm is an advanced branch-and-bound scheme which proceeds by working on a set of search nodes, each representing a subproblem of the optimization problem to be solved. A complete optimization problem is always represented by a *single* DAG (directed acyclic graph). The vertices of the graph represent operators similar to computational trees. Constants and variables are sources, objective and constraints are sinks of the DAG. This DAG is optimally small in the sense that it contains every subexpression of objective function and constraints only once.

For expression DAGs, special forward and backward evaluators are provided to allow function evaluation and automatic-differentiation-like tasks. Currently implemented are real function values, function ranges, gradients (real, interval), and slopes. In the near future evaluators for Hessians (real, interval) and second order slopes (see, e.g., [253]) will be provided as well.

A strategy engine is the main part of the algorithm. It makes decisions, directs the search, and invokes the various modules. The strategy engine consists of the logic core ("search") which is essentially the main solution loop, special decision makers for determining the next action at every point in the algorithm. It calls management modules, report modules, and inference engines in a sequence defined by programmable search strategies.

The strategy engine can be programmed using a simple strategy language based on the language `Python` [274] (in which, e.g., most of the interface of the web search engine `google` [115] is written). Since it is interpreted, (semi-)interactive and automatic solution processes are possible, and even debugging and single-stepping of strategies is supported. The language is object oriented, provides dynamically typed objects, and is garbage collecting. These features make the system easily extendable. Furthermore, the strategy engine manages the search graph and the search database. The strategy engine uses a component framework to communicate with the inference engines. This makes it possible to launch inference engines dynamically (on need) to avoid memory overload. Since the strategy engine is itself a component, even multilevel strategies are possible.

Corresponding to every type of problem change, a class of inference engines is designed: model analysis (e.g., find convex part), model reduction (e.g., pruning, fathoming), model relaxation (e.g., linear relaxation), model splitting (e.g., bisection), model glueing (e.g., undo excessive splitting), computing of local information (e.g., probing, local optimization). Several state of the art techniqnes are already provided, including interfaces to local nonlinear solvers and linear programming systems, rigorous point verifiers, exclusion box generators, constraint propagation, linear relaxations, a splitter, and a box covering module.

Changes suggested by an inference engine and approved of by the strategy engine are performed by appropriate management modules. Report modules produce human readable or machine readable files for checkpointing or external use.

The open design of the solver architecture, and its extensibility to include both open source modules and commercial programs, was chosen in the hope that the system will be a unique platform for global optimization in the future, serving the major part of the community, bringing their members closer together.

Several researchers and companies from outside the COCONUT project have already agreed to complement our efforts in integrating the known techniques by contributing to the COCONUT environment.

23 Challenges for the near future

We end the survey by listing a number of challenges that researchers in global optimization, and those working on software systems and support, may wish to face to improve the state of the art.

1. Ensuring reliability is perhaps the most pressing issue. While in theory essentially all techniques discussed here can be made fully rigorous, many of them with little computational overhead (cf. Section 20), only very few solvers do this. As a result, even otherwise excellent solvers (such as CPLEX 8.0 for linear mixed integer problems) lose occasionally the solution and give completely misleading results without warning, and global solvers based on these inherit the problems unless properly safeguarded. Safe bounds can guard against all errors due to the finite precision arithmetic. Programming bugs are another possible source of loss of solutions, and can be discovered only through extensive testing on benchmarking suites with known solutions.

Under the heading reliablility fall also improvements relevant for computer-assisted proofs, especially the documentation of certificates that give a short and complete proof (that can be checked independently) that the solution is indeed correct.

2. Better compiler (or even hardware) support for automatic differentiation, outward rounded interval arithmetic, and related techniques [289] based on computational graphs would significantly simplify its use in global optimization codes, and probably speed up the programs. (Code optimization would, however, need to provide an option that ensures that simplifications are only performed if they are mathematically safe even in finite precision arithmetic.) The SUN FORTE compiler [334] already supports interval arithmetic. NAG [56, 237] is investigating the possible integration of automatic differentiation capabilities into its Fortran 95 compiler.

3. Unbounded variables are perhaps the dominant reason for failure of current complete global optimization codes on problems with few variables. Unless the initial constraint propagation phase provides useful finite bounds, interval estimates are frequently meaningless since calculations with unbounded intervals rarely generate tight enclosures. Thus the bounding part of the search remains weak, and an excessive number of boxes is generated. Better techniques for handling problems with unbounded variables are therefore highly desirable. For unconstrained polynomial problems see Hanzon & Jibetean [133].

4. Unconstrained problems and bound constrained problems in higher dimensions are harder for current solvers than highly constrained ones, since the lack of constraints gives little basis for attack with the known methods. In particular, current complete solvers are quite slow on many nonzero residual least squares problems. Until better techniques become available, users should take advantage of available freedom in modeling by providing as many constraints as possible, e.g., by adding for a least squares problem $\min \|F(x)\|_2^2$ the additional constraints $F(x) \in \mathbf{F}$ for some reasonable box $\mathbf{F}$. While this may change the solution, it might be fully adequate from the point of view of the application.

5. Integrating techniques from mixed integer and semidefinite programming into the current solver frameworks appears to be a fertile direction. Work in this direction has begun at various places, and it is already apparent that one can expect major improvements in speed.

6. Problems with symmetries have many solutions that differ only in trivial rearrangements, sign changes, etc. However, it is not easy to avoid finding the solutions repeatedly or having to exclude repeatedly regions equivalent under symmetries. There are significant applications in cluster optimization [49], packing problems, and the optimal design of experiments [302]. A recent paper [212] handles the integer linear programming case, and Gatermann & Parrilo [102] address the case of polynomial systems.

7. The representation of nonisolated solution sets is another challenge where papers are slowly forthcoming (e.g., Vu et al. [332, 333] for the case of continuous constraint satisfaction problems) and which has important application in the modeling of devices with uncertain parameters or flexible parts [251]. Related is the problem of parametric global optimization, where the same parameterized problem needs to be solved in dependence on a few parameters. Apart from some discussion in [126], very little seems to have been done in this area.

8. Problems with severe dependence among the variables have poor interval extensions and hence create difficulties for complete solvers. This applies in particular to problems containing nested functions $f(x)$ such as those arising from volume-preserving discrete dynamics, where $f(x) = f_n(x)$ with $f_1(x) = \varphi(x)$, $f_n(x) = \varphi(f_{n-1}(x))$, which suffer from a severe wrapping effect [238, 244], and problems involving determinants of matrices of size > 3. Taylor methods [208, 252] and reformulation techniques might help overcome these problems.

9. Differential constraints are not of the factorable form that is the basis of all current global solvers. But they arise in optimal control problems, and it is well-known that many of these (especially in space mission design and in chemical engineering) have multiple minima and hence would need a global optimization approach. Recently, some approximate methods [79, 219] and a complete method [262] (for the inverse monotone case) have become available, though these work at present only in very low dimensions.

10. Constraints involving integrals are also not factorable; so far, they have received no attention in a global optimization context. They arise naturally in many stochastic optimization problems defined in terms of continuous random variables, since expectations or probabilities involving these are given by integrals. Examples are probabilistic safety factors in engineering and values at risk in finance.

11. Large-scale problems are obviously hard due to their size and the worst case exponential behavior of branch and bound algorithms. However, like in many combinatorial optimization problems, there may be many large-scale problems that are tractable if their problem structure is exploited. Extending the current methods to take advantage of such structure would make them much more widely applicable. Recent work of Boddy & Johnson [40], who solved to completetion large quadratic constraint satisfaction problems arising in oil refinery, including one with 13 711 variables, 17 892 constraints (of which 2 696 were nonlinear) gives rise to optimism.

All these problems show that much remains to be done and that we can expect much further progress in the future.

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