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Chair's Column

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Dear Fellow IOS Members:

The annual INFORMS meeting is coming! We look forward to Houston and, in our small way, to helping the city recover after Hurricane Harvey.

This newsletter marks the first time that the INFORMS Optimization Society has published two newsletters in a year! Many thanks to IOS Newsletter Editor Marina Epelman for making this happen. We plan to continue with both fall and spring

2016 IOS Prizes winners (left to right): Sven Leyffer, Gonzalo Muñoz, Aharon Ben-Tal, Parikshit Shah, Hamza Fawzi, and Venkat Chandrasekaran newsletters, and this is but one indicator of the growth of the field of optimization and the Optimization Society.

IOS Sessions in Houston: I look forward to seeing you in Houston, where the Optimization Society is sponsoring a record-breaking 93 sessions.

Business meeting: The IOS Business Meeting at the annual conference will be held on Sunday, October 22, 6:15–7:15pm in the Convention Center, Grand Ballroom, Level 3. Light refreshments, along with beer and wine, will be provided.

IOS prizes: Congratulations to the winners of the 2017 INFORMS Optimization Society prizes:

- Robert Vanderbei: Khachiyan Prize
- Kim-Chuan Toh: Farkas Prize
- Alberto Del Pia and Aida Khajavirad: Prize for Young Researchers
- Frans de Ruiter: Student Paper Prize
- Will Ma: Student Paper Prize, honorable mention.

The winners will receive their prizes at the IOS Business Meeting. Please join us for a special prize session, immediately prior to the business meeting, in which the prize recipients will present their award-winning work: SD76, Sunday, October 22, 2017, 4:30-6:00pm, in Room 372E of the Convention Center.

We are grateful to the prize committees for their work: *Khachiyan Prize*: Gerald Brown (chair), Bill Cook, Andrzej Ruszczyński, and Yinyu Ye; *Farkas Prize*: Margaret Wright (chair), Patrick Jaillet, Zhi-Quan (Tom) Luo, and Pascal Van Hentenryck; *Young Researchers Prize*: Michael Ferris (chair), Jonathan Eckstein, Simge Küçükyavuz, and Suvrajeet Sen; *Student Paper Prize*: Vineet Goyal (chair), Kiavash Kianfar, Javier Peña, and Ermin Wei.

IOS board transitions: IOS officer elections were held last month. We welcome our new vice-chairs, who will be assuming their responsibilities on January 1, 2018:

- Computational Optimization and Software: Dimitri Papageorgiou;
- Integer and Discrete Optimization: Akshay Gupte;
- Linear and Conic Optimization: Somayeh Moazeni;
- Network Optimization: Jorge Sefair.

I'm also very happy to report that Burcu Keskin was elected to continue as Treasurer/Secretary.

After eight years of service, which included the nontrivial transition to the new format and structure of the INFORMS Web sites, Pietro Bellotti is stepping down as the IOS Web Editor. His role will be filled by Sertalp Çay. Please join me in thanking Pietro and the vice chairs who complete their terms this year: Hande Benson (Computational Optimization and Software), Amitabh Basu (Integer and Discrete Optimization), Sauleh Siddiqui (Linear and Conic Optimization), and Austin Buchanan (Network Optimization). Further thanks to Austin for serving as the IOS Representative on the INFORMS Subdivision Council.

INFORMS Optimization Society Conference: Our biennial conference will take place March 23–25, 2018 in Denver, Colorado. The team of Steve Billups, Steffen Borgwardt, Manuel Laguna, and Alexandra Newman has a great lineup of plenary and tutorial speakers as detailed in this issue. *The deadline for abstract submissions is December 12.* If you would like to organize a session, please contact Alexandra newman@mines.edu, who is serving as Program Chair.

INFORMS Journal on Optimization: IJOO is "open for business." We are grateful for the leadership of Suvrajeet Sen in shepherding the journal through the INFORMS approval process. Dimitris Bertsimas serves as the journal's founding Editor-in-Chief. He recently launched the journal, which is now accepting submissions. Please see further details in this issue.

NONLINEAR OPTIMIZATION AND BEYOND

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I am deeply honored and grateful for receiving the 2016 Farkas Prize from the INFORMS Optimization Society. Throughout my career, I had the great fortune to work with some of the brightest optimizers, and this article is a tribute to their influence, guidance, and inspiration. The remainder of this article provides a personal view of three topics in nonlinear optimization. Starting with filter methods for global convergence of nonlinear solvers, we consider two extensions of nonlinear optimization, namely mixed-integer nonlinear programming (MINLP), and mathematical programs with equilibrium constraints. Each topic concludes with a brief outlook for future research challenges.

Sven Leyffer and Ariela Sofer

1 Filter Methods

Nonlinearly constrained optimization, or nonlinear programming (NLP), problems are a fundamental class of optimization problems that underpin many applications and more complex optimization problems. NLP problems can be compactly stated as

$$\begin{cases} \underset{x}{\text{minimize}} & f(x) \\ \text{subject to} & c(x) \geq 0, \end{cases} \tag{1.1}$$

where the objective function $f(x)$ and the constraint functions $c(x)$ are smooth.

Many methods for solving (1.1) are based on Newton's method and are iterative. Given an estimate $x^{(k)}$ of the solution x^* of (1.1), a simpler (linear or quadratic) approximation of (1.1) is solved for a new and, one hopes better, estimate $x^{(k+1)}$. Near a solution, this process is guaranteed to converge. Far from the solution, however, the sequence $\{x^{(k)}\}$ generated in this way may not converge.

Traditionally, penalty or merit functions have been used to enforce convergence from remote starting points. These functions are a linear combination of the objective function and a measure of the constraint violation such as $h(x) := \|c(x)^-\|$, where $\|a^-\| = \|\min(a, 0)\|$ for some norm. An example is the ℓ_1 exact penalty function, $p(x; \pi) := f(x) + \pi h(x)$, where $\pi > 0$ is the penalty parameter. Provided π is sufficiently large, we can use this penalty function to ensure progress in our iterative scheme by enforcing sufficient decrease in each step. Unfortunately, in classical penalty methods, a suitable penalty parameter depends on the solution of (1.1), namely, $\pi > \|y^*\|_D$, where y^* are the optimal multipliers and $\|\cdot\|_D$ is the dual norm. If the penalty parameter is too large, then any monotonic method would be forced to follow the nonlinear constraint manifold very closely, resulting in much shortened Newton steps and slow convergence.

Roger Fletcher had been unhappy with the performance of classical penalty functions for NLP, and had been playing around with methods that instead use the Lagrangian as a merit function within a tolerance tube around the constraints [43], similar to the funnel ideas [24] developed later by Nick Gould and Philippe Toint. Our filter method [17] grew out of these early experiments.

Filter methods avoid the pitfalls of penalty function methods. Instead of combining the objective and constraint violation into a single function, we borrow the concept of domination from multiobjective optimization and say that a point $x^{(k)}$ *dominates* a point $x^{(l)}$ if and only if $f(x^{(k)}) \le f(x^{(l)})$ and $h(x^{(k)}) \le h(x^{(l)})$. We define a *filter* as a list of pairs $\big(h(x^{(l)}), f(x^{(l)})\big)$ such that no pair dominates another pair. A typical filter is illustrated in Figure 1, where the shaded area shows the region dominated by the filter entries. The contours of the ℓ_1 exact penalty function are the purple lines with slope $-\pi$ in this plot.

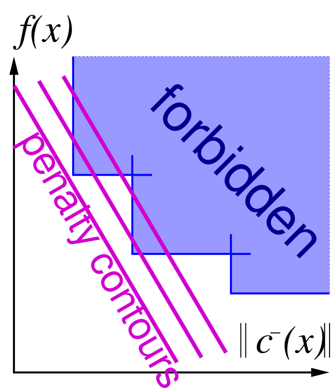

Figure 1: A typical filter. All pairs $(f(x), h(x))$ that are below and to the left of the shaded area are acceptable to the filter.

A rough outline of a filter trust-region method is as follows. At iteration $k = 0$, we initialize the filter $\mathcal{F}_k = \big\{(U, -\infty)\big\}$, where U is an upper bound on the acceptable constraint violation. We proceed by accepting only steps, s, that are not dominated by the current filter. If a point is acceptable, then we set $x^{(k+1)} = x^{(k)} + s$ and possibly increase the trust-region radius, and update the filter (adding $(h^{(k)}, f^{(k)})$ from the previous iterate and removing any dominated entries). If, on the other hand, the step is dominated by the current filter, then we reject it, set $x^{(k+1)} = x^{(k)}$, reduce the trust-region radius, and resolve the trust-region subproblem.

This simple description of a filter method requires a number of refinements to ensure convergence:

1. *Filter Envelope.* To avoid convergence to infeasible limit points where $h^* > 0$, we add an envelope around the current filter. A new iterate is acceptable if, $\forall (h^{(l)}, f^{(l)}) \in \mathcal{F}_k$,
$$h^{(k+1)} \le \beta h^{(l)}, \quad \text{or} \quad f^{(k+1)} \le f^{(l)} - \gamma h^{(k+1)}, \tag{1.2}$$
holds, where $0 < \beta, \gamma < 1$ are constants, see [8, 7]. In [8, Lemma 1] it is shown that if an infinite number of points are added to the filter, and $f(x)$ is bounded below, then the limit point must be feasible.
2. *Sufficient Reduction.* The filter alone cannot ensure convergence to stationary points. For example, if the sequence satisfies $h^{(k+1)} \le \beta h^{(k)}$, then the iterates could converge to an arbitrary feasible point. Therefore, if constraint violation becomes small, we enforce a sufficient reduction condition similar to unconstrained optimization. We denote the predicted reduction by $\Delta q_k := -\nabla f^{(k)^T} s - \frac{1}{2} s^T H^{(k)} s$ and introduce the following *switching condition*:
$$\begin{array}{l} \text{if } \ (\ \Delta q_k > 0\ ) \ \text{ then} \\ \qquad \text{check } \ f^{(k)} - f^{(k+1)} \ge \sigma \Delta q_k, \end{array} \tag{1.3}$$
where $\sigma \in (0, 1)$ is a constant.
3. *Feasibility Restoration.* As the trust-region radius is reduced, the subproblem may become inconsistent and we take this inconsistency as an indication that the current point is too far from the feasible set to make meaningful progress to optimality. Hence we invoke an SQP-like algorithm that minimizes the constraint violation $h(x)$, and we exit the restoration phase once a filter-acceptable point has been found.

Successful steps that satisfy (1.3) are called *f-type steps* and all other steps are called *h-type* steps. The first global convergence proof of a filter method was developed by Roger and Philippe in the context of sequential linear programming (SLP) methods, see [22], and I still regard this as the most easily understood proof. This proof was later generalized to sequential quadratic programming (SQP) methods in [21, 15] together with Nick Gould and Andreas Wächter, who corrected many errors in the early proof.

Originally, we had believed that filter methods avoid the Maratos effect [34], which rejects Newton steps arbitrarily close to a solution, destroying the second-order convergence properties of Newton's method. However, Nick and Philippe developed an example that showed that filter methods also suffer from the Maratos effect:

$$\begin{cases} \underset{x}{\text{minimize}} & 2(x_1^2 + x_2^2 - 1) - x_1 \\ \text{subject to} & x_1^2 + x_1^2 - 1 = 0. \end{cases}$$

The starting point $x = (\cos(t), \sin(t))$ for $t > 0$ small and multipliers $y = 3/2$ shows that the SQP step increases *both* $f(x)$ and $\|c(x)\|$, leading to a filter-rejected step. We can avoid the Maratos effect by using second-order correction steps, and this approach was analyzed in [41]. However, a more appealing approach is to use a nonmonotone filter, developed by Chungen Chen at Argonne, see [38]. The method uses two filters: a standard, global filter for global convergence, and a local nonmonotone filter that allows us to establish fast local convergence. The switching mechanism between the filters can be analyzed to show both global and fast local convergence.

Originally, filter methods were developed in the context of SQP methods. However, they were quickly extended to interior-point methods [40, 9, 42], and augmented Lagrangian methods [23, 30]. Filter methods have also become popular in other areas, such as the solution of systems of equations [18, 25], derivative-free optimization [2], and mathematical programs with equilibrium constraints (see Section 3) [29].

Conclusions. Following the development of filter methods, modern penalty functions methods emerged. Most notable are the steering methods developed by Byrd, Nocedal, and Waltz, see [6, 5]. These methods adjust the penalty parameter to ensure sufficient reduction in a measure of constraint violation. At this point, I do not believe that there exists a big difference between filter methods and modern penalty function methods, and the choice of method is really a question of personal preference.

2 MINLP

Many optimal decision problems in scientific, engineering, and public sector applications involve both discrete decisions and nonlinear system dynamics that affect the quality of the final design or plan. Mixed-integer nonlinear programming (MINLP) problems combine the combinatorial difficulty of optimizing over discrete variable sets with the challenges of handling nonlinear functions. MINLPs are one of the most general modeling paradigms in optimization and are conveniently expressed as

$$\begin{cases} \underset{x}{\text{minimize}} & f(x), \\ \text{subject to} & c(x) \le 0, \\ & x \in X, x_i \in \mathbb{Z},\ \forall i \in I, \end{cases} \tag{2.4}$$

where $f : \mathbb{R}^n \to \mathbb{R}$ and $c : \mathbb{R}^n \to \mathbb{R}^m$ are twice continuously differentiable *convex* functions, $X \subset \mathbb{R}^n$ is a bounded polyhedral set, and $I \subseteq \{1, \ldots, n\}$ is the index set of integer variables.

During my PhD studies with Roger Fletcher, we generalized outer approximation by Duran and Grossmann [13], see [16], "simplified" its convergence analysis, and provided a one-dimensional example where outer approximation visits all integer points. Later, Bonami et al. corrected our convergence proof [4], and Pierre developed a much nicer example that showed that outer approximation can take an exponential number of iterations [26].

Over the last 10 years or so, I have been fortunate to collaborate with some very smart discrete optimizers. With a student of Jeff Linderoth's, we built FilMINT [1], which efficiently implements the Quesada-Grossmann algorithm [36], which is arguably the best approach to solving MINLPs. FilMINT creates an initial outer approximation of a convex MINLP by linearizing $f(x)$ and $c(x)$ around $x^{(k)}$,

$$z \ \ge\ f^{(k)} + \nabla f^{(k)^T}(x - x^{(k)}), \tag{2.5}$$

$$0 \ \ge\ c^{(k)} + \nabla c^{(k)^T}(x - x^{(k)}), \tag{2.6}$$

where z is the objective value. FilMINT then starts an MILP tree-search using MINTO. Whenever this tree search finds a new integer assignment, we (approximately) solve an NLP obtained by fixing the integer variables in (2.4), and add linearizations about its solution to the MILP, and resume the tree search. FilMINT implements a number of computational refinements that proved critical to its performance, such as efficient cut management to remove redundant cuts and a more aggressive cut generation strategy that generates cuts at non-integer points, and it takes full advantage of the modern MIP techniques within MINTO.

Most solution methods for MINLP apply some form of tree-search, and we can distinguish two broad classes of methods: single-tree and multitree methods. Classical single-tree methods include nonlinear branch-and-bound and branch-and-cut methods, while classical multitree methods include outer approximation and Benders decomposition. The most efficient class of methods for convex MINLP are hybrid methods that combine the strengths of both classes of classical techniques.

All these MINLP algorithms share a range of common building blocks, namely *relaxation* and *constraint enforcement*. A relaxation is obtained by enlarging the feasible set of the MINLP, and is used to compute a lower bound on the optimal solution of (2.4). Typically, we are interested in relaxations that are substantially easier to solve than the MINLP itself. Together with upper bounds, which can be obtained from any feasible point, relaxations allow us to terminate the search for a solution whenever the lower bound is larger than the current upper bound. Constraint enforcement refers to procedures used to exclude solutions that are feasible to the relaxation but not to the original MINLP. Constraint enforcement may be accomplished by refining or tightening the relaxation, often by adding valid inequalities, or by *branching*, where the relaxation is divided into two or more separate problems.

Several strategies are used to obtain relaxations of MINLPs.

1. *Relaxing integrality.* Integrality constraints $x_i \in \mathbb{Z}$ can be relaxed to $x_i \in \mathbb{R}$ for all $i \in I$. This procedure yields a *nonlinear relaxation* of MINLP. This type of relaxation is used in branch-and-bound algorithms.
2. *Relaxing convex constraints.* Constraints $c(x) \leq 0$ and $f(x) \leq z$ containing convex functions c and f can be relaxed with a set of supporting hyperplanes obtained from first-order Taylor series approximation, (2.5) and (2.6), for a set of points $x^{(k)},\ k = 1, \dots, K$. This class of relaxations is used in the outer approximation methods.
3. *Relaxing nonconvex constraints.* Constraints $c(x) \leq 0$ and $f(x) \leq z$ containing nonconvex functions require more work to be relaxed, e.g., by deriving convex underestimators.

Given a point $\hat{x}$ that is feasible to a relaxation but is not feasible to the MINLP, the goal of constraint enforcement is to exclude this solution, so that the algorithm can eventually converge to a solution that satisfies all the constraints. Two broad classes of constraint enforcement strategies exist: relaxation refinement and branching. Most modern MINLP algorithms use both classes.

Algorithmic advances over the last decade or so have often taken advantage of the special structure of problems, which motivated us to develop the Minotaur software framework [33]. Minotaur stands for Mixed-Integer Nonlinear Optimization Toolkit: Algorithms, Underestimators, and Relaxations. It was developed by Ashutosh Mahajan at Argonne together with Jeff Linderoth, Jim Luedtke, and Todd Munson. The goal of Minotaur is to (1) implement a range of algorithms in a common framework; (2) provide fast and usable MINLP solver; (3) provide flexibility for developing new efficient algorithms; and (4) reduce the burden of developing new algorithms by providing a common software infrastructure. Our vision is to enable researchers to implement new algorithms that take advantage of problem structure, by providing a general framework that is agnostic of problem type or solvers.

Minotaur allows us to exploit problem structure in new algorithmic developments, by making it easier to be tailored to special problem classes and nonconvex structures. In particular, Minotaur can evaluate, examine, and possibly modify the nonlinear problem description, which is significantly more complex than LP or QP problem specifications. In addition, a single MINLP algorithm may require several types of LP, QP, NLP, or MILP relaxations or approximations to be solved as subproblems. Different nonconvex structures benefit from tailored branching, bound tightening, and cut-generation routines, as well as requiring possibly novel separation routines.

In general, nonconvex forms are more challenging and diverse than integer variables, which motivates a more tailored approach. Minotaur provides an extensible toolkit that enables researchers to implement new algorithms, taking advantage of problem structure by providing a general framework that is agnostic of problem type or solvers.

Conclusions and Outlook. There has been tremendous progress in solving MINLP problems over the past decade (and this short note does not do justice to the many clever developments in the field). In addition, new classes of MINLPs are emerging, such as MIPs with second-order cone constraints [12, 11] and MINLPs with partial-differential equation constraints [31], which necessitate novel approaches.

3 Complementarity Constraints

Mathematical programs with equilibrium constraints (MPECs) are a class of problems that generalize nonlinear programs. Until recently, it had been assumed that these problems were too difficult for standard nonlinear solvers. However, as long as we take care with the problem formulation and the algorithm design, modern NLP solvers can tackle these problems.

MPECs arise in a variety of applications, see the surveys [14, 32, 35], and the test problem libraries [27, 10]. The most famous set of applications are leader-follower games (also known as Stackelberg games [39]), which result in optimization problems that contain optimality conditions of the follower's problem as constraints, including the complementarity conditions. In general, MPECs can be expressed as

$$\left\{\begin{array}{lll} \text{minimize} & f(x) & \\ \text{subject to} & c_i(x) = 0, & i \in \mathcal{E} \\ & c_i(x) \geq 0, & i \in \mathcal{I} \\ & 0 \leq x_1 \perp x_2 \geq 0, & \end{array}\right. \tag{3.7}$$

where $x = (x_0, x_1, x_2)$ is a decomposition of the problem variables into controls $x_0 \in \mathbb{R}^n$ and states $(x_1, x_2) \in \mathbb{R}^{2p}$. The objective function, $f(x)$, and the constraint functions, $c_i(x)$, are twice continuously differentiable.

The complementarity constraint involving x_1 and x_2 means that for all $i = 1, \ldots, p$, $x_{1i} \geq 0$ and $x_{2i} \geq 0$ and that $x_{1i} = 0$ or $x_{2i} = 0$, i.e., x_{1i} and x_{2i} cannot both be non-zero. Clearly, an MPEC with a more general complementarity condition such as

$$0 \leq G(x) \perp H(x) \geq 0 \tag{3.8}$$

can be written in the form (3.7) by introducing slack variables. One can easily show that the reformulated MPEC has the same properties (such as constraint qualifications or second-order conditions) as the original MPEC. In this sense, nothing is lost by introducing slack variables. *However, we show below that the simpler form of complementarity is necessary for the convergence of NLP solvers.*

One attractive way of solving (3.7) is to replace the complementarity condition by a set of nonlinear inequalities, such as $x_1^T x_2 \leq 0$, and then solve the equivalent nonlinear program (NLP),

$$\left\{\begin{array}{lll} \text{minimize} & f(x) & \\ \text{subject to} & c_i(x) = 0, & i \in \mathcal{E} \\ & c_i(x) \geq 0 & i \in \mathcal{I} \\ & x_1,\ x_2 \geq 0, & x_1^T x_2 \leq 0. \end{array}\right. \tag{3.9}$$

Unfortunately, it has been shown [37] that (3.9) violates the Mangasarian-Fromowitz constraint qualification (MFCQ) at *any* feasible point. This failure of MFCQ implies that the multiplier set is unbounded, the central path fails to exist, the active constraint normals are linearly dependent, and linearizations of (3.9) can become inconsistent *arbitrarily close* to a solution. In addition, early numerical experience with this approach has been disappointing [3] with failure on 50–70% of some bilevel problems. As a consequence, solving MPECs via NLPs such as (3.9) has been commonly regarded as numerically unsafe.

In contrast, our initial numerical experience with filterSQP was very positive [19], and we investigated the convergence of SQP methods applied to (3.9) together with Roger Fletcher, Danny Ralph, and Stefan Scholtes [20]. Our analysis starts by considering the two index sets $\mathcal{X}_1,\ \mathcal{X}_2 \subset \{1, \ldots, p\}$ with

$$\mathcal{X}_1 \cup \mathcal{X}_2 = \{1, \ldots, p\}; \tag{3.10}$$

we denote their respective complements in $\{1, \ldots, p\}$ by $\mathcal{X}_1^\perp$ and $\mathcal{X}_2^\perp$. For any such pair of index sets, we define the *relaxed NLP corresponding to the MPEC* (3.7) as

$$\begin{array}{lll} \underset{x}{\text{minimize}} & f(x) & \\ \text{subject to} & c_i(x) = 0 & i \in \mathcal{E} \\ & c_i(x) \geq 0 & i \in \mathcal{I} \\ & x_{1j} = 0 & \forall j \in \mathcal{X}_2^{\perp} \\ & x_{2j} = 0 & \forall j \in \mathcal{X}_1^{\perp} \\ & x_{1j} \geq 0 & \forall j \in \mathcal{X}_2 \\ & x_{2j} \geq 0 & \forall j \in \mathcal{X}_1. \end{array} \quad (3.11)$$

Concepts such as constraint qualifications, stationarity, and a second-order condition for MPECs can be defined in terms of the relaxed NLPs. The term "relaxed NLP" stems from the observation that if x^* is a local solution of a relaxed NLP (3.11) *and* satisfies complementarity ${x_1^*}^T x_2^* = 0$, then x^* is also a local solution of the original MPEC (3.7).

Our results relate to the following notion of strong stationarity.

Definition 1. *A point x^* is called* strongly stationary *if there exist multipliers λ of $c(x)$ and $\hat\nu_1$ and $\hat\nu_2$ of x_1 and x_2, respectively, such that the KKT conditions of the relaxed NLP,* (3.11)*, hold.*

We note, that some of the multipliers ν_1, ν_2 may be negative, and we only require that $\nu_{1i}, \nu_{2i} \geq 0$ if $x_{1j}^* = x_{2j}^* = 0$.

We can then show that SQP methods converge quadratically near a strongly stationary point under mild conditions. In particular, we are interested in the situation where $x^{(k)}$ is close to a strongly stationary point, x^*, but ${x_1^{(k)}}^T x_2^{(k)}$ is *not* necessarily zero. SQP then solves a sequence of quadratic programming approximations, given by

$$(QP^k)\left\{\begin{array}{ll} \underset{d}{\text{minimize}} & {g^{(k)}}^T d + \frac{1}{2} d^T W^{(k)} d \\ \text{subject to} & c_{\mathcal{E}}^{(k)} + {A_{\mathcal{E}}^{(k)}}^T d = 0 \\ & c_{\mathcal{I}}^{(k)} + {A_{\mathcal{I}}^{(k)}}^T d \geq 0 \\ & x_1^{(k)} + d_1 \geq 0 \\ & x_2^{(k)} + d_2 \geq 0 \\ & {x_1^{(k)}}^T x_2^{(k)} + {x_2^{(k)}}^T d_1 \\ & \quad + {x_1^{(k)}}^T d_2 \leq 0, \end{array}\right.$$

where $W^{(k)} = \nabla^2 \mathcal{L}(x^{(k)}, \mu^{(k)})$ is the Hessian of the Lagrangian of (3.9) and $\mu^{(k)} = (\lambda^{(k)}, \nu_1^{(k)}, \nu_2^{(k)}, \xi^{(k)})$.

The last constraint of (QP^k) is the linearization of the complementarity condition $x_1^T x_2 \leq 0$. Under reasonable assumptions we can show the following result.

Theorem 2. *Let the following assumptions hold: (1) f and c are twice Lipschitz continuously differentiable; (2) x^* is a strongly stationary point of* (3.7)*, which satisfies an MPEC-LICQ (linear independence constraint qualification); (3) strict complementarity holds for the MPEC multipliers; and (4) our QP solver always chooses a linearly independent basis. Then it follows that SQP applied to the NLP formulation (3.9) of the MPEC (3.7) converges quadratically near a solution (x^*, μ^*).*

The proof is divided into two parts. First, it is shown that if ${x_1^{(k)}}^T x_2^{(k)} = 0$ at some iteration k, then the SQP approximation of (3.9) about this point is equivalent to the SQP approximation of the relaxed NLP. Since the latter is a well-behaved problem, superlinear convergence follows. The second part of the proof assumes that ${x_1^{(k)}}^T x_2^{(k)} > 0$, and it is shown that each QP basis remains bounded away from singularity. Again, convergence can be established by using standard techniques.

Later, together with Jorge Nocedal and Gabriel López-Calva, we extended the analysis to interior-point methods (IPMs) [28]. IPMs require an additional reformulation of the equivalent NLP (3.9), in order to mitigate the effect of the loss of MFCQ. Two alternative approaches are relaxation, where we use

$$x_{1i} x_{2i} \leq \theta, \quad i = 1, \ldots, p, \qquad (3.12)$$

or penalization, which replaces the objective by

$$f(x) + \pi x_1^T x_2, \qquad (3.13)$$

where $\pi > 0$ is a penalty parameter. If π is chosen large enough, the solution of the MPEC can be recast as the minimization of the penalty function. With both approaches, we can analyze methods that control the regularization or penalty parameters at the same time as the barrier parameter, resulting in a single loop for convergence.

The Importance of Being Slack. The use of slacks in (3.9) is critical for the convergence of SQP methods. In [20] we give an example that shows that an SQP method applied to a nonlinear complementarity constraint can converge to a nonstationary point. We also provide an example that shows that SQP converges linearly to a spurious stationary point if we use $x_1^T x_2 = 0$ instead of the relaxation $x_1^T x_2 \le 0$.

Beyond NLP Solvers. Despite the success of NLP solvers in tackling a wide range of MPECs, there are still classes of problems where these solvers fail. In particular, problems whose stationary points are B-stationary [37], but not strongly-stationary, will cause NLP solvers to fail or exhibit slow convergence.

One idea is to extend SQP methods by taking special care of the complementarity constraint. Stefan suggested a sequential quadratic programming with equality constraints (SQPEC) approach, where we minimize a quadratic approximation of the Lagrangian subject to a linearized feasible set, and a copy of the complementarity constraint. Remarkably, this approach can be shown to fail for MPECs as demonstrated by the following example:

$$\min_{x,y} \; (x-1)^2 + y^3 + y^2 \quad \text{s.t. } 0 \le x \;\perp\; y \ge 0.$$

Starting from any point $x = 0, y > 0$, SQPEC converges quadratically to a spurious stationary point at $x = (0, 0)$, and fails to detect the descend direction $(1, 0)$.

Todd Munson suggested a sequential linear programming with equality constraints (SLPEC) approach [29] to avoid this issue. By interpreting the B-stationarity conditions as the optimality conditions of an LPEC, we can define an algorithm that solves a sequence of LPECs inside a trust region of radius $\Delta > 0$ around the current point x:

$$\left\{ \begin{array}{ll} \underset{d}{\text{minimize}} & g(x)^T d \\ \text{subject to} & c_{\mathcal{E}}(x) + A_{\mathcal{E}}(x)^T d = 0, \\ & c_{\mathcal{I}}(x) + A_{\mathcal{I}}(x)^T d \ge 0, \\ & 0 \le x_1 + d_{x_1} \;\perp\; x_2 + d_{x_2} \ge 0, \\ & \|d\| \le \Delta. \end{array} \right.$$

We can add an EQP phase to accelerate convergence. Global convergence is promoted through the use of a three-dimensional filter that separates the complementarity error and the nonlinear infeasibility.

Conclusions and Outlook. Software and solvers for MPECs are far less mature than NLP or MINLP. In my opinion, reliable NLP solvers are still the best approach for solving MPECs despite the potential problems with slow convergence or convergence to spurious stationary points. To develop better solvers we need to build on our existing NLP solver infrastructure.

Acknowledgments

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My Life as an Optimizer

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My venture into "optimization land" started in 1970. During my senior year in Tel Aviv University, I read a 1958 paper by Herbert Scarf. In that paper, the expectation of a simple one-variable piecewise linear equation was to be maximized in the face of uncertain random demand d for which only its mean and variance were known. Scarf modeled the problem as a max-min and derived the exact probability function which minimized the expectation. In today's terminology, he solved a *distributionally robust optimization problem.* Looking for a subject for my Master thesis, I decided to look at a significant extension of Scarf's results in which the objective function is a *general convex function* of n decision

Aharon (Ronny) Ben-Tal and Tamás Terlaky variables and m random variables. In my first attempt to follow Scarf's research, I assumed that for each random variable, just the mean and variance are known, and soon came to a dead end. I then remembered that in such cases, one should "think outside the box" and change the setting: Instead of knowledge of mean-variance (mean *square* deviation), I assumed knowledge of mean-mad (mean *absolute* deviation). Amazingly, that led to powerful results in which tight upper and lower bounds were explicitly obtained for the expectation of a general convex (or concave) function of m independent random variables. These results were co-authored with my Master thesis advisor, Eithan Hochman, and were first published in 1972, in *Journal of Applied Probability*, and later applied to stochastic programming problems in a 1976 paper published in *Operations Research*.

I completed my Ph.D. studies in Applied Mathematics at Northwestern University in 1973. I then spent one year at McGill University and another year at the University of Texas at Austin, working with the great Abe Charnes. After that, I joined the Technion.

Frequently, my research interests were evoked by some discrepancies in a theory which make it less than perfect. The KKT optimality condition for convex programming problems is such a case. Indeed, the necessary condition needs the assumption of constraint qualification (CQ), such as the Slater condition, while the sufficient conditions are free from this requirement. This, I observed, is the reason why full characterization of Pareto-optimality was not available until 1976. Together with my Ph.D. advisor, Adi Ben-Israel, and later with Sanjo Zlobec, we developed in 1976–1979 the so-called BBZ (Ben-Tal, Ben-Israel, Zlobec) optimality conditions for convex programming problems, not requiring CQ. This led to a full characterization of Pareto Optimality in a 1977 paper, with Ben-Israel and Charnes, published in *Econometrica*.

Starting in 1980, I turned my efforts to optimality conditions for *nonconvex* optimization problems, more precisely, to second-order optimality conditions for local minimum. I noticed that the classical second-order results (e.g., those given in the Fiacco-McCormick book) may fail to recognize local optimal solutions, for example, that the point $\bar{x} = (0, 0, 0)$ is a local minimizer of the simple problem

$$\min\{x_1^2 + x_1x_2 \mid x_2^2 + x_1x_3 \le 0,\ x_3^2 + x_1x_2 \le 0\}.$$

(In fact, $\bar{x}$ is a global minimizer.) In a 1980 paper in *JOTA*, I derived stronger optimality conditions, both necessary ones and sufficient ones. The next big challenge was to develop a theory for local optimality for problems whose objective function and the constraint functions are not even once differentiable! This new theory was published first in 1980, and a year later, in the second part of my first book (co-authored with Ben-Israel and Zlobec). In that year, my dear colleague and friend Jochem Zowe came for a sabbatical year to the Technion, and this started a 20-year collaboration which resulted in more than 10 papers. The most important of them is the 1981 paper published in *Math. Programming Studies* entitled "A Unified Theory of First snd Second Order Conditions for Extremum Problems in Topological Vector Spaces." This paper has been cited every year in the last 36 years, and continues to be cited. We created in this work the notion of a second-order directional derivative that later became known as the "Ben-Tal–Zowe directional derivative" — a name that was short-lived, since Terry Rockafellar came up with the (better) name, "Parabolic directional derivative." Tragically, Jochem's academic career ended in 2000, due to a serious bike accident.

In the mid-80's, I renewed my interest in stochastic programming. I noticed that economists deal mainly with uncertain *objective functions*, and adopt the Expected Utility paradigm. What could be the corresponding setup for uncertain *constraints*? My first attempt was reported in a 1985 paper in *Math. of OR* entitled "The Entropic Penalty Approach to Stochastic Programming." It resulted in a duality relation between maximizing expected utility of an objective function and penalizing deviations from constraint feasibility — the utility function being *exponential*, and the penalty being a distance-like function associated with *relative entropy*. The natural next step was to consider a general utility function (monotone and concave). I posed this question to Marc Teboulle who had just started his Ph.D. under my supervision. The answer came in a big way in two papers — one in 1986 in *Management Science*, entitled "Expected Utility, Penalty Functions, and Duality in Stochastic Nonlinear Programming," and the second, a year later in *Math. of OR*, entitled "Penalty Functions and Duality in Stochastic Programming via ϕ-Divergence Functionals." In these papers, a new notion of *certainty equivalent* (CE) came out, replacing the classical one ($u^{-1}Eu(x)$). We called it "New CE," but later changed the name to "Recourse CE," and finally it got the name "Optimized CE" (OCE). When u is the exponential utility, OCE $= u^{-1}Eu$; when it is a simple piecewise linear function, OCE is CVaR, and thus the famous formula of Rockafellar–Uryasev is a special case of a result in the OCE theory. The negative of OCE has the properties used to define *risk measures.* In 2005, I met Philippe Artzner, the co-author of the classical paper on coherent risk measures. Hearing about the OCE and our 1986–87 papers, he encouraged us to write a paper extending our results and putting them in the framework of Finance Theory. We did so and the paper was published in 2007 in *Math. Finance.* It shows, among other things, that OCE is a *convex risk measure*, as defined by Follmer and Schild in 2000. Marc and I had a very fruitful collaboration on many other optimization topics, which culminated in 20 joint papers.

In 1986–88, I spent two years as a visiting professor in the IOE department of the University of Michigan (Ann Arbor). This period marked a shift in my career: I started to work in earnest on applications, particularly in engineering. The first works were on optimization of mechanical structures. I was introduced to this area by my colleague, Martin Bendsøe from the Technical University of Denmark. The initial publication on this topic, with Martin and later with Jochem Zowe, Michael Kočvara, Wolfgang Achziger and Arkadi Nemirovski, culminated in a *SIOPT* paper (later published as SIGEST paper in *SIAM Review*) on Free Material Optimization that was the basis of a novel design of part of the new Airbus 380 airplane.

Other important applications to which I contributed are: Medical Imaging (algorithm for recovering images from Positron Emission Tomography), Signal Processing, Designing water distribution networks, Machine Learning, Supply chain management, Use of renewable energy sources in energy systems under uncertainty, and more.

The arrival at Technion of Arkadi Nemirovski in 1992 is another major event in my career. Our collaboration on numerous papers was fruitful right from the start, and not just with regard to Robust Optimization. Our work on RO started on a problem in Truss Topology Design (TTD). We encountered a case where a small unexpected force affecting the optimal truss can cause its collapse. That led to a general question on how to avoid severe infeasibilities in case data is uncertain. Our attempt to answer this question was given in the 1998 *Math. of OR* paper "Robust Convex Optimization," which many consider as the foundation of modern RO. By now, RO is a well-established sub-area of optimization, with a large number of papers, workshops, university courses, and a wide variety of applications. (As of August 2017, writing "Robust Optimization" in Google, one gets 78,000,000 items.)

The success of RO is due to the fact that at the same time *conic optimization*, particularly, *conic quadratic* and *semidefinite* optimization were developed, and thus provided the technical tools needed for developing RO. The two books written by Arkadi and me were instrumental in this respect. In the last seven years, my work on RO continued mainly with Dick den Hertog and his group at Tilburg University. My most recent paper (just accepted to *Operations Research*), with my postdoc Krzysztof Postek, den Hertog, and Bertrand Melenberg, "Robust optimization with ambiguous stochastic constraints under mean and dispersion information," is particularly meaningful to me as it is directly connected to my very first 1970 paper!

I would like to end this brief "scientific biography" of mine with a small poem I read when awarded the 2016 Khachiyan Prize:

What is an Optimizer?

An optimizer is one that will not rest
Until he achieves the very best

His frustration is clearly visible
If his solution is not even feasible

Facing uncertainty he will not trust
A solution that is not robust

He becomes completely ecstatic
If he can prove convergent quadratic

Even if integers come around
He will boldly branch and bound

Multiple criteria, dealing with Pareto?
For him this is small potato

His self-esteem to the sky will rise
If he can win the Khachiyan Prize...

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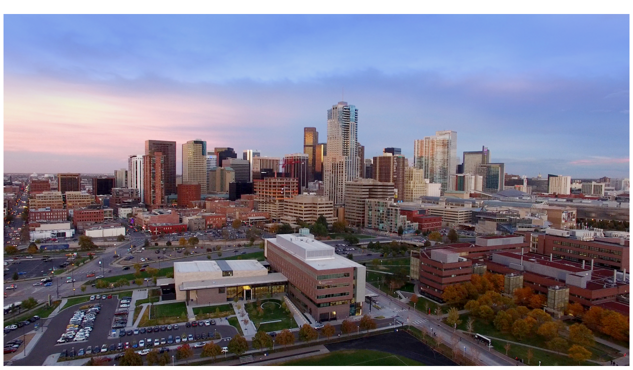
2018 INFORMS Optimization Society Conference: update and call for submissions

The next INFORMS Optimization Society is co-organized by Steve Billups (University of Colorado Denver), Steffen Borgwardt (University of Colorado Denver), Manuel Laguna (University of Colorado Boulder), and Alexandra Newman (Colorado School of Mines). It will take place March 23–25, 2018, on the University of Colorado Denver's downtown campus. The conference theme, *Mountains of Optimization*, is designed to emphasize, in the mountain setting, the myriad of topics, both theoretical and applied, that confront optimizers today.

The conference will feature plenary speakers Shabbir Ahmed (Georgia Tech), Marcos Goycoolea (Universidad Adolfo Ibáñez), Moritz Hardt (Google and UC Berkeley), Illya Hicks (Rice University), Karla Hoffman (George Mason University), John Hooker (Carnegie Mellon University), and Sven Leyffer (Argonne National Labs), as well as tutorials by Bob Fourer (AMPL), Ed Klotz (CPLEX), and Warren Powell (Castle Labs).

Abstract submission is welcome at `https://acgi.informs.org/oasis_login.php?` (before the deadline of Tuesday, December 12, 2017); if you are interested in chairing a session, please contact the chair of the organizing committee Alexandra Newman at newman@mines.edu and provide a tentative session title and list of speakers.



Denver, CO (image used with permission of the University of Colorado)

Important dates to keep in mind:

- December 12, 2017: abstract submission deadline
- February 9, 2018: pre-registration deadline for discounted rates
- February 22, 2018: cutoff date for hotels

Additional details are available on the conference website, `http://orwe.mines.edu/conference/`. The organizers are working hard to make this an exciting conference!

INFORMS Journal on Optimization

INFORMS Journal on Optimization is now accepting submissions! Its home on the web is http://pubsonline.informs.org/journal/ijoo, where you can find more information, submit your manuscript, and in the near future, view published and accepted articles.

Dimitris Bertsimas (Massachusetts Institute of Technology) is serving as the inaugural Editor-in-Chief, and the associate editors are:

- Shabbir Ahmed
- John Birge
- Dick den Hertzog
- Brian Denton
- Laurent El Ghaoui
- Vivek Farias
- Dan Iancu
- Garud Iyengar
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- Andrea Lodi
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- Georgia Perakis
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The journal aims to publish papers in optimization with particular emphasis on data-driven optimization, optimization methods in machine learning, and exciting real-world applications of optimization. The journal also covers more traditional areas such as: convex and linear optimization; general purpose nonlinear optimization; discrete optimization (combinatorial, integer, mixed integer optimization); optimization under uncertainty (dynamic, stochastic, robust, simulation-based optimization); infinite dimensional optimization; and online optimization. Especially welcomed are contributions studying new and significant applications such as: healthcare; inventory and supply chain management; logistics; revenue management and pricing; energy; the Internet; interfaces with computer science; and finance.

The journal welcomes three types of submissions:

- **Regular articles:** These are original papers that build on an area and expand it in different ways. A paper in this category will be published electronically within 1 year of submission. Accepted regular articles are expected to score highly in at least one of the following questions:
  - How new and significant is the application studied?
  - How original/creative is the optimization modeling?
  - How original/creative is the optimization methodology?
  - How significant is the impact in practice?
- **Perspective articles:** These are unusually original papers that initiate an area, typically the first of their kind. A paper in this category will be published electronically within 2 months of submission.
- **Review articles:** These are papers that present a unifying and comprehensive review of an area of optimization. A paper in this category will be published electronically 6 months of submission.