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An Interior Point Method for Nonlinear Programming with Infeasibility Detection Capabilities

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Abstract This paper describes interior point methods for nonlinear programming endowed with infeasibility detection capabilities. The methods are composed of two phases, a main phase whose goal is to seek optimality, and a feasibility phase that aims exclusively at improving feasibility. A common characteristic of the algorithms is the use of a step-decomposition interior-point method in which the step is the sum of a normal component and a tangential component. The normal component of the step provides detailed information that allows the algorithm to determine whether it should be in main phase or feasibility phase. We give particular attention to the reliability of the switching mechanism between the two phases. The two algorithms proposed in this paper have been implemented in the KNITRO package as extensions of the KNITRO/CG and KNITRO/DIRECT methods. Numerical results illustrate the performance of our methods on both feasible and infeasible problems.

Keywords infeasibility detection · interior point · feasibility restoration

Mathematics Subject Classification (2000) 90C30 · 90C51

1 Introduction

This paper describes the design and implementation of interior point methods for nonlinear programming that are efficient when confronted with both feasible and infeasible problems. Our design is based on a step-decomposition approach in which the total step of the algorithm is the sum of a normal and a tangential component. The algorithms employ feasibility-improvement information

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provided by the normal component of the step to determine whether the algorithm should be in a feasibility or an optimality phase. Feasibility-improvement information of this type is not readily available in line search primal-dual methods [28,20,31,11,30,29,27], and this provides the main motivation for our choice of the step-decomposition approach.

Infeasible problems arise often in practice. They are sometimes generated by varying model parameters to observe system response. They also arise when nonlinear optimization is a subproblem of another algorithm, such as branch-and-bound or branch-and-cut methods. In that context, the efficiency and reliability of the nonlinear optimization algorithm on feasible or infeasible problems becomes very important since the optimization solver is typically run thousands of times in the course of the solution of a master problem, with many infeasible subproblems generated.

Various infeasibility detection mechanisms have been proposed in the nonlinear programming literature, with varying degrees of success. Let us begin by considering SNOPT [16] and FILTER [15], two of the most popular active-set methods. SNOPT uses a switch that transforms the standard sequential quadratic programming (SQP) algorithm into an SL_1QP penalty method [14] when the problem is deemed to be infeasible, badly scaled or degenerate. FILTER uses a more robust diagnostic — the infeasibility of a trust region problem — to invoke a feasibility restoration phase whose objective is to minimize constraint violations. Both of these methods include a main mode and a feasibility mode, together with a switching mechanism. SQP approaches based on a single optimization phase are described by Gould and Robinson [19,18] and Byrd, Curtis and Nocedal [2], who propose an exact penalty SQP method that automatically varies its emphasis from optimality to feasibility, and vice versa, using so-called steering rules [6]. Another penalty-SQP method with a single optimization phase is described by Yamashita and Yabe [32].

Sequential linear-quadratic programming (SLQP) methods have emerged as an attractive alternative to SQP methods for solving problems with a large number of degrees of freedom. The method described by Chin and Fletcher [8] employs a filter and a feasibility restoration phase to deal with infeasibility, whereas the SLQP method proposed by Byrd et al. [4], which is implemented in the KNITRO/ACTIVE code, follows a penalty approach.

Interior point methods with infeasibility detection mechanisms have also been proposed in the literature. LOQO [28] employs a penalty approach, whereas IPOPT [29] uses a filter and a feasibility restoration phase. Curtis [2] proposes an interior-penalty method based on a single optimization phase that balances the effects of the barrier and penalty functions through an extension of the steering rules mentioned above. Methods based on augmented Lagrangian approaches, such as LANCELOT [10] and MINOS [25], are endowed with infeasibility detection mechanisms through the presence of a quadratic penalty term.

The interior point algorithms described in this paper contain an optimality mode and a feasibility mode, but are distinct from other methods proposed in the literature. We have implemented them in the KNITRO package [7], and report their performance on a large collection of feasible and infeasible problems.

The paper is divided into 7 sections. In Section 2, we present numerical results for several popular nonlinear programming solvers on a set of infeasible problems. Section 3 describes a mechanism for determining whether the algorithm should be in an optimality or feasibility phase. The proposed algorithm is stated and discussed in Section 4, and numerical results on both feasible and infeasible problems are presented in Section 5. Our infeasibility detection approach is extended in Section 6 to a primal-dual line search interior point method, and concluding remarks are given in Section 7.

Notation. Throughout the paper, $\|\cdot\|$ denotes the Euclidean norm unless stated otherwise. We let $\mathbf{1}$ denote the vector of all ones, and employ superscripts, as in $v^{(i)}$, to indicate the components of vector v.

2 Some Tests On Infeasible Problems

To serve as motivation for this paper, and to provide a snapshot of the state-of-the art in infeasibility detection in nonlinear programming, we present results of several popular solvers on a set of small dimensional infeasible problems. Table 1 lists the problems and their characteristics; there n denotes the number of variables and m the number of constraints. Test Set 1 is taken from [2], and Test Set 2 was designed specifically for this study, and is described in [12].

Table 1 List of test problems

Test Set 1			Test Set 2					
Problem	n	m	Problem	n	m	Problem	n	m
ISOLATED	2	4	BALLS	67	285	SOSQP1_MOD	200	201
NACTIVE	2	3	COVERAGE	10	45	EIGMAXC_TYPE2	22	23
UNIQUE	2	2	PORTFOLIO	30	31	EIGMAXC_TYPE3	22	23
BATCH_MOD	39	49	DEGEN	2	4	SENSITIVE	2	4
ROBOT_MOD	7	3	MCCORMCK_MOD	251	3	LOCATE	20	110
			POWELLBS_MOD	4	8	PEIGEN	28	28

We tested the following solvers, which we group according to the type of algorithm they implement:

a) SNOPT, FILTER, and KNITRO/ACTIVE implement active set methods;
b) LOQO, KNITRO/DIRECT, KNITRO/CG and IPOPT implement interior point methods;
c) LANCELOT , MINOS, and PENNON [23] implement augmented Lagrangian methods.

The results are reported in Tables 2 and 3; they were obtained with the NEOS server using the AMPL interface. We do not provide detailed results for LOQO or PENNON because these two solvers were unable to detect infeasibility for any of the problems tested. For each solver, we report in Tables 2 and 3 whether the code was able to detect that the problem was infeasible (Yes/No), as well as the number of iterations needed to meet its default stop test. `IP` stands for interior point method; `AL` for augmented Lagrangian method; and `SLC` for sequential linearly constrained Lagrangian method. For SNOPT, the number of iterations was determined by the number of Jacobian evaluations; for FILTER, the number in parenthesis gives the total number of iterations in the feasibility restoration phase.

Table 2 Results for Test Set 1 (Infeasibility detection and number of iterations)

Solver	Version	Algorithm	unique		robot_mod		isolated		batch_mod		nactive	
SNOPT	7.2-10	SQP	Y	138	Y	134	Y	83	Y	18	Y	130
FILTER	20020316	SQP	Y	16(7)	Y	23(22)	Y	27(16)	Y	6(2)	Y	15(4)
KNITRO/ACT.	7.0	SLQP	Y	18	Y	22	Y	18	Y	8	Y	12
KNITRO/CG	7.0	IP	N	10000	Y	80	N	10000	Y	1315	Y	343
KNITRO/DIR.	7.0	IP	Y	44	Y	148	Y	47	N	10000	Y	18
IPOPT	3.8.3	IP	N	772	Y	44	Y	65	Y	97	Y	30
LANCELOT	N.A.	AL	Y	23	Y	53	Y	16	N	1000	Y	21
MINOS	5.51	SLC	N	0	Y	202	N	1	Y	200	Y	110

We observe from Tables 2 and 3 that, in these tests, the active set solvers FILTER and KNITRO/ACTIVE are the most efficient and show the most consistent performance. FILTER performs

Table 3 Results Test Set 2 (Infeasibility detection and number of iterations)

Solver	locate		balls		coverage		portfolio		degen		mccormck_mod	
SNOPT	Y	34	Y	46	Y	175	Y	42	Y	17	N	118
FILTER	Y	30(28)	Y	63(62)	Y	2(1)	Y	11(10)	Y	7(6)	Y	13(9)
KNITRO/ACT.	Y	20	Y	15	Y	1	Y	15	Y	26	Y	18
KNITRO/CG	N	10000	Y	1661	N	10000	Y	447	N	10000	N	10000
KNITRO/DIR.	N	10000	N	10000	Y	38	N	211	Y	15	Y	23
IPOPT	Y	105	Y	816	Y	19	Y	47	Y	43	Y	63
LANCELOT	N	?[1]	Y	808	Y	33	Y	651	Y	33	Y	24
MINOS	Y	2104	Y	1458	N	46	N	30	Y	43	Y	462
Solver	**peigen**		**powellbs_mod**		**sosqp1_mod[2]**		**eigmaxc_type2**		**eigmaxc_type3**		**sensitive**	
SNOPT	Y	20	Y	95	N	?[3]	Y	12	Y	25	Y	11
FILTER	Y	16(15)	Y	2(1)	Y	0(0)	Y	8(7)	Y	7(6)	Y	12(7)
KNITRO/ACT.	Y	18	Y	26	Y	3	Y	7	Y	16	Y	21
KNITRO/CG	N	2590	N	10000	Y	5478	Y	258	Y	200	N	10000
KNITRO/DIR.	N	648	N	43	Y	13	N	22	Y	575	Y	10
IPOPT	Y	35	Y	81	Y	19	Y	18	Y	32	Y	22
LANCELOT	N	1000	N	1000	Y	118	Y	35	Y	20	Y	41
MINOS	Y	482	N	73	Y	100	Y	417	Y	464	Y	31

[1] Execution failure without displaying an error message
[2] For this problem, AMPL option `presolve` was set to zero
[3] Exit with `INFO=53 from snOptB`, no Jacobian evaluations reported

well thanks to a carefully designed feasibility restoration phase. The strong performance of KNITRO/ACTIVE was somewhat unexpected since the design of that algorithm was not guided by infeasibility considerations [4]. However, an analysis of the equality constrained phase in KNITRO/ACTIVE shows that it is able to adapt itself so that the iteration gives sufficient emphasis to feasibility improvement, when needed.

The performance of the interior point methods KNITRO/DIRECT and KNITRO/CG are quite poor, which may not be surprising since these two algorithms do not contain *any* features for handling infeasibility. IPOPT contains a feasibility restoration phase, but its performance is not consistently successful. The main motivation for this paper stems from the desire to build effective feasibility detection capabilities for interior point methods.

3 Infeasibility Certificates

The goal of this section is to describe a mechanism for determining whether the optimization algorithm should be in main (or optimality) mode or in feasibility mode. Our strategy is to rely on information provided by the normal component in a step decomposition method.

The nonlinear programming problem under consideration is stated as

$$\begin{aligned} \min_x \quad & f(x) \\ \text{s.t} \quad & g(x) \le 0 \\ & h(x) = 0, \end{aligned} \tag{3.1}$$

where $f : \mathbb{R}^n \to \mathbb{R}$, $g : \mathbb{R}^n \to \mathbb{R}^m$, and $h : \mathbb{R}^n \to \mathbb{R}^t$ are smooth functions. We define

$$w(x) = \begin{bmatrix} g(x)^+ \\ h(x) \end{bmatrix}, \qquad \text{with} \qquad g(x)^+ = \max\{g(x), 0\}, \tag{3.2}$$

so that $\|w\|$ can serve as an infeasibility measure.

At an infeasible stationary point x of problem (3.1) we have that

$$\|w(x)\| > 0 \quad \text{and} \quad \theta(x) = \left(\|w(x)\| - \min_{\|d\| \le \Delta} \left\| \begin{bmatrix} [g(x) + A_g(x)d]^+ \\ h(x) + A_h(x)d \end{bmatrix} \right\| \right) = 0, \tag{3.3}$$

for any $\Delta > 0$, where $A_g(x)$ and $A_h(x)$ denote the Jacobian matrices of $g(x)$ and $h(x)$, respectively. Therefore, we may suspect that the iterates of a nonlinear optimization algorithm approach an infeasible stationary point if the sequence $\|w(x_k)\|$ remains bounded away from zero, while $\theta(x_k)$ approaches zero. These two conditions can be encapsulated in an inequality of the form

$$\theta(x_k) \le \delta \|w(x_k)\|, \quad \text{for} \ \ \delta > 0.$$

We base our switching mechanisms between main and feasibility modes on a condition of this form, translated to the interior point framework that includes slacks.

As we discuss in the next section, a step-decomposition method provides an estimate of $\theta(x)$ at every iteration. This is not the case, however, in standard line search primal-dual interior point methods, since they do not solve a trust region problem of the type given in (3.3). Instead, these algorithms compute a search direction d that satisfies the constraint linearizations, but since the step along d may be significantly shortened due to the fraction to the boundary rule or the line search, it is difficult to measure the reduction in the constraints that can be achieved, to first order. In other words, it is difficult to employ a certificate of infeasibility such as (3.3) in a line search primal-dual method.

4 A Trust Region Interior Point Algorithm

In this section, we describe the interior point algorithm with infeasibility detection capabilities. As already mentioned, the algorithm contains a main mode whose goal is to satisfy the optimality conditions of the nonlinear program (3.1), and a feasibility mode that aims exclusively at improving feasibility. In order to make use of the infeasibility certificates described in the previous section, we employ a step-decomposition trust region interior point method of the type proposed in [5,3,1,22,9, 21]. Specifically, we follow the algorithm described in [5,3], which is implemented in the KNITRO/CG option of the KNITRO package [7]. We now give a brief overview of this method.

Introducing slacks, the nonlinear program (3.1) is transformed into

$$\begin{aligned} \min_{x,s} \ & f(x) \\ \text{s.t} \ & g(x) + s = 0 \\ & h(x) = 0 \\ & s \ge 0. \end{aligned} \tag{4.1}$$

A solution to this problem is obtained by solving a series of barrier problems of the form

$$\begin{aligned} \min_{x,s} \ & \varphi(x,s) \stackrel{\text{def}}{=} f(x) - \mu \sum_{i=1}^{m} \ln s^{(i)} \\ \text{s.t} \ & g(x) + s = 0, \\ & h(x) = 0, \end{aligned} \tag{4.2}$$

with $\mu \to 0$.

The step-decomposition approach is as follows. Given an iterate (x_k, s_k) and a trust region radius Δ_k, the algorithm first computes a normal step[1] $v = (v_x, v_s)$ by solving the subproblem

$$\begin{aligned} \min_v \quad & \|g(x_k) + s_k + A_g(x_k)v_x + v_s\|^2 + \|h(x_k) + A_h(x_k)v_x\|^2 \\ \text{s.t.} \quad & \|(v_x, S_k^{-1}v_s)\| \le \xi\Delta_k \\ & v_s \ge -\xi\kappa s, \end{aligned} \tag{4.3}$$

where $S_k = \text{diag}\{s_k^i\}$ is a scaling matrix for the slacks, the scalar $\xi \in (0,1)$ is a trust region contraction parameter and $\kappa \in (0,1)$ determines the fraction to the boundary rule; see [5]. (Typical values for these parameters are $\xi = 0.8, \kappa = 0.005$.) The total step $d = (d_x, d_s)$ of the algorithm is obtained by solving the subproblem

$$\begin{aligned} \min_d \quad & \nabla\varphi(x_k, s_k)^T d + \tfrac{1}{2} d^T W_k d \\ \text{s.t.} \quad & A_g(x_k)d_x + d_s = A_g(x_k)v_x + v_s \\ & A_h(x_k)d_x = A_h(x_k)v_x \\ & \|(d_x, S^{-1}d_s)\| \le \Delta_k \\ & d_s \ge -\kappa s, \end{aligned} \tag{4.4}$$

where W_k is a Hessian approximation; see [5]. The subproblems (4.3), (4.4) can be solved inexactly as stipulated in [3]. The new iterate is given by

$$(x_{k+1}, s_{k+1}) = (x_k, s_k) + d, \tag{4.5}$$

provided it yields sufficient reduction in the merit function ϕ; otherwise the step d is rejected, the trust region radius Δ_k is decreased and a new step is computed. We define the merit function as

$$\phi(x, s; \nu) = \varphi(x, s) + \nu\|c(x, s)\|, \tag{4.6}$$

where $\nu > 0$ is a penalty parameter, and

$$c(x, s) \stackrel{\text{def}}{=} \begin{bmatrix} g(x) + s \\ h(x) \end{bmatrix}. \tag{4.7}$$

After the new iterate (4.5) is computed, the algorithm applies the slack reset

$$s_{k+1} \leftarrow \max\{s_{k+1}, -g(x_k)^+\},$$

which ensures that, at every iteration,

$$g(x_{k+1}) + s_{k+1} \ge 0. \tag{4.8}$$

The Lagrange multipliers $\lambda_{k+1} = (\lambda_g, \lambda_h)$ are defined through a least squares approach. We refer to [5] for other details of the algorithm, such as the procedure for updating the penalty parameter ν in (4.6) and the trust region radius Δ_k.

The main mode of the proposed algorithm employs the step-decomposition interior point method just outlined; the feasibility mode, which we describe next, can employ any interior point algorithm.

[1] To save space, we write

$$v = \begin{pmatrix} v_x \\ v_s \end{pmatrix} = (v_x, v_s),$$

and similarly for other vectors containing x and s-components.

4.1 The Feasibility Phase

In the feasibility phase, the algorithm disregards the objective function f and aims exclusively at improving feasibility. This goal is achieved by applying an interior point algorithm to the problem

$$\min_{x} \|w(x)\|_1, \tag{4.9}$$

where $w(x)$ is the vector of constraint violations defined in (3.2). We reformulate (4.9) as a smooth problem by introducing relaxation variables $r_g \in \mathbb{R}^m$, $r_h^+, r_h^- \in \mathbb{R}^t$, as follows:

$$\begin{aligned} \min_{x,r} \quad & r^T \mathbf{1} \\ \text{s.t.} \quad & g(x) - r_g \leq 0 \\ & h(x) - r_h^+ + r_h^- = 0 \\ & r \geq 0, \end{aligned} \qquad \text{with} \quad r = \begin{bmatrix} r_g \\ r_h^+ \\ r_h^- \end{bmatrix}. \tag{4.10}$$

The corresponding barrier problem is given by

$$\begin{aligned} \min_{x,r,\bar{s}} \quad & \tilde{\varphi}(x,r,\bar{s}) \stackrel{\text{def}}{=} r^T \mathbf{1} - \bar{\mu} \sum_{i=1}^{2m+2t} \ln \bar{s}^{(i)} \\ \text{s.t.} \quad & g(x) - r_g + \bar{s}_g = 0 \\ & h(x) - r_h^+ + r_h^- = 0 \\ & -r + \bar{s}_r = 0 \end{aligned} \qquad \text{with} \qquad \bar{s} = \begin{bmatrix} \bar{s}_g \\ \bar{s}_r \end{bmatrix}, \tag{4.11}$$

where $\bar{s}_g \in \mathbb{R}^m$ and $\bar{s}_r \in \mathbb{R}^{m+2t}$ are the feasibility mode slacks, and $\bar{\mu} \in \mathbb{R}_+$ is the feasibility mode barrier parameter.

The Lagrangian for this problem is

$$\begin{aligned} \mathcal{L}(x,r,\bar{s},\bar{\lambda}) = r^T \mathbf{1} - \bar{\mu} \sum_{i=1}^{2m+2t} \ln \bar{s}^{(i)} + \bar{\lambda}_g^T \left(g(x) - r_g + \bar{s}_g\right) + \bar{\lambda}_h^T \left(h(x) - r_h^+ + r_h^-\right) \\ + \bar{\lambda}_r^T \left(-r + \bar{s}_r\right), \end{aligned}$$

with feasibility mode Lagrange multipliers $\bar{\lambda}_g \in \mathbb{R}^m$, $\bar{\lambda}_h \in \mathbb{R}^t$, and $\bar{\lambda}_r \in \mathbb{R}^{m+2t}$.

The first order optimality conditions for the barrier problem(4.11) are given by

$$F^{\bar{\mu}}(x,r,\bar{s},\bar{\lambda}) = \begin{pmatrix} A_g(x)^T \bar{\lambda}_g + A_h(x)^T \bar{\lambda}_h \\ \mathbf{1} - \bar{\lambda} - \bar{\lambda}_r \\ \bar{S}_g \bar{\lambda}_g - \bar{\mu}\mathbf{1} \\ \bar{S}_r \bar{\lambda}_r - \bar{\mu}\mathbf{1} \\ g(x) - r_g + \bar{s}_g \\ h(x) - r_h^+ + r_h^- \\ -r + \bar{s}_r \end{pmatrix} = 0, \tag{4.12}$$

where

$$\begin{aligned} \bar{S}_g &= \operatorname{diag}(\bar{s}_g^{(1)}, \cdots, \bar{s}_g^{(m)}), \\ \bar{S}_r &= \operatorname{diag}(\bar{s}_r^{(1)}, \cdots, \bar{s}_r^{(m+2t)}), \end{aligned} \qquad \text{and} \qquad \bar{\lambda} = \begin{bmatrix} \bar{\lambda}_g \\ \bar{\lambda}_h \\ -\bar{\lambda}_h \end{bmatrix}.$$

As mentioned previously, any interior point algorithm can be applied in the feasibility phase. In our implementation, we employ the same step-decomposition method as in main mode. In order to describe this method, it is convenient to introduce the following notation:

$$\begin{aligned}
&\tilde f(x,r) = r^T\mathbf{1} \\
&\tilde g(x,r) = \begin{bmatrix} g(x) - r_g \\ -r \end{bmatrix}, \qquad \tilde h(x,r) = h(x) + r_h^+ - r_h^- .
\end{aligned} \tag{4.13}$$

This allows us to write the barrier problem (4.11) in the same form as (4.2),

$$\begin{aligned}
\min_{x,r,\bar s} \ & \tilde f(x,r) - \bar\mu \sum_{i=1}^{2m+2t} \ln \bar s^{(i)} \\
\text{s.t} \ & \tilde g(x,r) + \bar s = 0 \\
& \tilde h(x,r) = 0,
\end{aligned} \tag{4.14}$$

and the application of the step-decomposition approach to (4.14) follows the discussion in the first part of this section.

4.2 Switching Conditions

We now describe in detail the conditions for determining when the algorithm is to be in main mode or feasibility mode. These conditions are motivated by the discussion in Section 3 and depend on two constants, $\bar\delta > \delta > 0$, that are pre-selected. We recall that the constraint function $c(x,s)$ is defined in (4.7).

Principal Switching Conditions

[*Main* $\rightarrow$ *Feasible*] Suppose that at a point (x,s) the algorithm is in main mode and has computed a step $d = (d_x, d_s)$, and suppose that $s \geq -g(x)$ (see (4.8)).

$$\textbf{If} \quad ||g(x) + s + A_g(x)d_x + d_s|| + \|h(x) + A_h(x)d_x\| \geq \delta\|c(x,s)\|, \tag{4.15}$$

then start feasibility mode.

[*Feasible* $\rightarrow$ *Main*] Suppose that the algorithm is in feasibility mode and that it has computed a step $d = (d_x, d_r, d_s)$.

$$\textbf{If} \quad ||g(x) + s + A_g(x)d_x + d_s|| + \|h(x) + A_h(x)d_x\| \leq \bar\delta\|c(x,s)\|, \tag{4.16}$$

then return to main mode.

In our implementation, we choose $\delta = 0.9$ and $\bar\delta = 0.1$. To make the algorithm less dependent on the choice of these two constants, our implementation includes additional conditions that are designed to avoid unnecessary cycling between the two phases; we describe these conditions in Section 4.5.

4.3 The Complete Algorithm

We describe the trust region interior point method through the pseudo-code given in the next pages. Algorithm 1 is the driver that controls the outer iterations, while Algorithms 2 and 3 describe inner iterations performed in the main phase (mode M) and the feasibility phase (mode F), respectively.

The algorithm starts in mode M, assuming that the nonlinear program has a feasible solution. In subsequent outer iterations, the algorithm updates the barrier parameter and proceeds to solve the next barrier problem of the current mode – M or F (see Algorithm 1). The iterations of Algorithms 2 and 3, solve the barrier problems (4.2) and (4.11), respectively, and generate the inner iterates, denoted by x_k. We use counter l for the outer iterations of the algorithm, and denote the subsequence of major iterates with $\{x_{k_l}\} \subseteq \{x_k\}$. The mode changes occur in Algorithms 2 and 3.

As stated in Algorithm 1, the overall algorithm terminates in three cases:

1. Convergence to a stationary point of the nonlinear program (3.1). This is measured by the KKT error for (3.1), which can be stated as

$$F^M(x_k, \lambda_k) = \begin{pmatrix} \nabla f_k + (\lambda_g)_k^T A_g(x_k) + (\lambda_h)_k^T A_h(x_k) \\ g(x_k)^T(\lambda_g)_k \\ g(x_k)^+ \\ h(x_k) \end{pmatrix}$$

   where $(\lambda_g)_k \geq 0 \in \mathbb{R}^m$ and $(\lambda_h)_k \in \mathbb{R}^t$ are the Lagrange multipliers at iteration k.
2. Convergence to a stationary point of the feasibility problem (4.10). This decision is based on the KKT error for (4.10), which is given by

$$F^F(x_k, \bar{\lambda}_k, r_k) = \begin{pmatrix} (\bar{\lambda}_g)_k^T A_g(x_k) + (\bar{\lambda}_h)_k^T A_h(x_k) \\ (g(x_k) - (r_g)_k)^T (\bar{\lambda}_g)_k \\ (g(x_k) - (r_g)_k)^+ \\ h(x_k) - (r_h^-)_k + (r_h^+)_k \\ r_k^T(\bar{\lambda}_r)_k \\ (-r_k)^+ \\ \mathbf{1} - \bar{\lambda}_k - (\bar{\lambda}_r)_k \end{pmatrix}$$

   Here, $\bar{\lambda}_k, r_k \geq 0$ are the Lagrange multipliers and the relaxation variables of (4.10) at iteration k, respectively. $\bar{\lambda}$ and $\bar{\lambda}_r$ are as defined in Section 4.1. When $\|w(x)\| > 0$ at a stationary point of (4.10), we accept this as a certificate of local infeasibility and terminate.
3. The overall algorithm may converge to a point where the constraints of (3.1) do not satisfy the linear independence constraint qualification (LICQ); see Theorem 3 in [3]. This is the third case when the algorithm terminates.

The termination criteria in Algorithms 2 and 3 correspond to the stationarity conditions of (4.2) and (4.11), respectively. In Algorithm 2, $vpred(v)$ denotes the model prediction for the decrease in $\|c(x, s)\|$ provided by the normal step v. Similarly, $pred(d)$ stands for the model prediction for the decrease in the merit function (4.6) provided by the total step d. In Algorithm 3, they denote the corresponding quantities for the feasibility phase problem (4.14).

Algorithm 1: Solve_NLP

Input: (x_0, s_0), $\mu_1 > 0$, $\gamma \in (0, 1)$, $\{\epsilon_l\}_{l \geq 1} \to 0$, $\tau \approx 0$
$l = 1$, $k_0 = 0$, $(x_{k_0}, s_{k_0}) = (x_0, s_0)$;
mode $= M$;
while *resource limits are not exceeded* **do**
  if $\|F^M(x_{k_l}, \lambda_{k_l})\| < \tau$ **then**
    Convergence to a KKT point of the nonlinear program (3.1);
    `Exit`;
  else if $\|F^F(x_{k_l}, \bar{\lambda}_{k_l}, r_{k_l})\| < \tau$ *and* $\|w(x_k)\| > \tau$ **then**
    Convergence to an infeasible stationary point;
    `Exit`;
  else
    */*not a stationary point, solve the next barrier subproblem*/*
    if *mode* $= M$ **then**
      $(x_{k_l}, s_{k_l}, mode) =$ `Solve_Main`$((x_{k_{l-1}}, s_{k_{l-1}}), \mu_l, \epsilon_l)$ (see Algorithm 2);
    else if *mode* $= F$ **then**
      $(x_{k_l}, \bar{s}_{k_l}, mode) =$ `Solve_Feas`$((x_{k_{l-1}}, \bar{s}_{k_{l-1}}), \bar{\mu}_l, \epsilon_l)$ (see Algorithm 3);
  */*upon return, mode has been set to M or F*/*
  if *mode* $= M$ **then**
    if $||(\nabla f_{k_l} + (\lambda_g)_{k_l}^T A_g(x_{k_l}) + (\lambda_h)_{k_l}^T A_h(x_{k_l})\ ,\ S_{k_l}(\lambda_g)_{k_l} - \mu_l \mathbf{1})|| \geq \epsilon_l$ **then**
      Convergence to a point failing to satisfy LICQ;
      `Exit`;
    Set $\mu_{l+1} \in (0, \gamma\mu_l)$;
  else if *mode* $= F$ **then**
    Set $\bar{\mu}_{l+1} \in (0, \gamma\bar{\mu}_l)$;
  $l = l + 1$;

4.4 Initialization of the Two Phases

In order to keep the description of Algorithms 2 and 3 brief, we did not state how various parameters and variables are initialized as the algorithm switches from one mode to the other. It is well known that interior point methods are very sensitive to the initialization of some of these parameters and that it is difficult to find settings that work well on all problems. The following initialization rules have performed well in our experiments.

Feasibility Phase. Every time the feasibility phase is invoked, we perform the following initialization.

(a) The barrier parameter $\bar{\mu}$ is set to the most recent main mode value, i.e., $\bar{\mu} \leftarrow \mu$.
(b) The initial trust region radius is initialized to $\bar{\Delta} \leftarrow \Delta\sqrt{n + m + 2t}/\sqrt{n}$, where Δ is the trust region from the main mode, m is the number of inequality constraints, t is the number of equality constraints, and the scaling $\sqrt{n + m + 2t}/\sqrt{n}$ accounts for the fact that there are more variables in feasibility mode than in main mode and that we employ the ℓ_2 norm in the trust region constraint.
(c) The penalty parameter is initialized as $\bar{\nu} \leftarrow \nu$.
(d) The slacks $\bar{s}$ and relaxation variables r are initialized to make the barrier constraints for the feasibility mode initially feasible, while also decreasing the barrier objective as much as possible for the current x_k. This involves an appropriate initialization of the auxiliary variables r and a reset of the slacks s.

Algorithm 2: Solve_Barrier_Main

Input: (x_0, s_0), $\mu > 0$, $\epsilon > 0$, λ_0, $\Delta_0 > 0$, $\eta, \rho, \beta \in (0, 1)$, $\nu_{-1} > 0$, $\delta > 0$
while *resource limits are not exceeded* **do**
  if $||F^{\mu}(x_k, s_k, \lambda_k)|| < \epsilon$ **then**
    `Return`;
  Compute normal step, $v = (v_x, v_s)$ by solving problem (4.3);
  / If linearized constraint reduction is insufficient, switch to restoration mode*/*
  if *condition* (4.15) *holds* **then**
    $mode = F$;
    Set restoration mode slacks $\bar{s}$, multipliers $\bar{\lambda}$, and parameters $\bar{\mu}, \bar{\Delta}$;
    `Solve_Barrier_Feas`$((x_k, \bar{s}), \bar{\mu}, \epsilon)$;
  Compute total step, $d = (d_x, d_s)$ by solving problem (4.4);
  Update penalty parameter, $\nu_k \geq \nu_{k-1}$ so that $pred_k(d) \geq \rho \nu_k vpred_k(v)$;
  if $\phi(x_k, s_k; \nu_k) - \phi(x_k + d_x, s_k + d_s; \nu_k) < \eta pred_k(d)$ **then**
    $\Delta_k = \beta \Delta_k$;
  else
    $x_{k+1} = x_k + d_x$;
    $s_{k+1} = \max(s_k + d_s, -g_{k+1})$;
    Compute λ_{k+1};
    Set $\Delta_{k+1} \geq \Delta_k$;
    $k = k + 1$;

Algorithm 3: Solve_Barrier_Feas

Input: $(x_0, \bar{s}_0)$, $\bar{\mu} > 0$, $\epsilon > 0$, $\bar{\lambda}_0$, $\bar{\Delta}_0 > 0$, $\eta, \rho, \beta \in (0, 1)$, $\bar{\nu}_{-1} > 0$
while *resource limits are not exceeded* **do**
  if $||F^{\bar{\mu}}(x_k, r_k, \bar{s}_k, \bar{\lambda}_k)|| < \epsilon$ **then**
    `Return`;
  Compute total step, $d = (d_x, d_r, d_{\bar{s}})$ by using an interior point procedure ;
  if *condition* (4.16) *holds* **then**
    $mode = M$;
    Adjust ν_{-1} if necessary, reset Δ;
    Reset main mode slacks s, and multipliers λ;
    `Solve_Barrier_Main`$((x_k, s), \mu, \epsilon)$;
  Update penalty parameter, $\bar{\nu}_k \geq \bar{\nu}_{k-1}$: $pred_k(d) \geq \rho \bar{\nu}_k vpred_k(v)$;
  if $\tilde{\phi}(x_k, r_k, \bar{s}_k) - \tilde{\phi}(x_k + d_x, r_k + d_r, \bar{s}_k + d_{\bar{s}}) < \eta pred_k(d)$ **then**
    $\bar{\Delta}_k = \beta \bar{\Delta}_k$;
  else
    $x_{k+1} = x_k + d_x$, $r_{k+1} = r_k + d_r$;
    $\bar{s}_{k+1} = \max(\bar{s}_k + d_{\bar{s}}, -\tilde{g}_{k+1})$;
    Compute $\bar{\lambda}_{k+1}$;
    Set $\bar{\Delta}_{k+1} \geq \bar{\Delta}_k$;
    $k = k + 1$;

(e) $\bar{\lambda} = (\bar{\lambda}_g, \bar{\lambda}_h, \bar{\lambda}_r)$, is computed as a least squares multiplier estimate; see [5, page 7].

Main Phase. When the algorithm returns from feasibility mode, the following initializations are performed:

(a) The barrier parameter μ is set to its previous value in main mode, when the feasible mode was last invoked.
(b) $\Delta \leftarrow \bar{\Delta}$, $\nu \leftarrow \bar{\nu}$, $s \leftarrow \bar{s}$, i.e., these parameters inherit their values from the feasible mode.
(c) $\lambda = (\lambda_g, \lambda_h)$ is initialized via least squares approximation.

4.5 Additional Switching Conditions

The switching conditions described in section 4.2 have a solid theoretical underpinning, as they are based on the stationarity conditions (3.3). Nevertheless, they can be sensitive to the choice of the constants $\delta, \bar{\delta}$ in (4.15), (4.16). In order to make our switching conditions effective over a wide range of feasible and infeasible problems, we have found it useful to enhance them with the following rules.

[*Main* $\rightarrow$ *Feasible*] The algorithm reverts to feasibility mode only if *all* the following conditions are satisfied, in addition to (4.15):

1. At the current iterate (x_k, s_k) we have $\|w_k\| \geq \zeta \|w_{k-1}\|$ with $\zeta \in (0,1)$ (we use $\zeta = 0.99$). This condition ensures that we do not switch as long as we are making some minimal progress in reducing the overall infeasibility.
2. At least 3 iterations have been performed in main mode.
3. The Principal Switching Conditions (4.15), (4.16), plus the conditions above, hold for two consecutive iterations. This safeguards against unnecessary switching as a result of one single unproductive iteration.

[*Feasible* $\rightarrow$ *Main*]

1. Suppose that the feasibility phase was triggered at iteration j; then, we allow termination of the feasibility phase at iteration k only if condition (4.16) and

$$\|w(x_k)\| \leq (1-\sigma)\|w(x_j)\|, \quad \text{with } \sigma \in (0,1)$$

are satisfied. This condition enforces that once we switch to feasibility phase, we do not return to the optimization phase until we have achieved some predetermined decrease in the overall infeasibility measure.

We have found that these additional switching rules prevent the algorithm from switching modes too rapidly, and also make it unnecessary to try to adjust the values of the constants $\delta, \bar{\delta}$ (see (4.15), (4.16)) during the progression of the algorithm.

5 Numerical Experiments

Algorithm 1 has been implemented in the KNITRO/CG code, and has been tested on feasible and infeasible problems.

In Table 4, we report the results for the infeasible problems listed in Table 1. The column under the header KNITRO/CG gives the results with the earlier version of the code, specifically version 8.0 of the KNITRO package with the options `alg=2`, `presolve=0`, `maxiter=3000`, `maxtime_real=500`, and `bar_switchrule=1`. KNITRO/CG/NEW denotes the new version endowed with infeasibility detection capabilities (i.e., Algorithm 1), using the same option settings, except for `bar_switchrule=2`. The columns '`inf`', '`F`', '`itr`', '`# switch`', and '`sw.itr`' report whether the algorithm was successful at detecting infeasibility (yes/no), the final value of the objective function, the total number of iterations, the number of times the feasibility mode was started, and the iteration(s) at which the feasibility mode was started, respectively. It is clear that the new algorithm has much improved feasibility detection capabilities.

Table 4 Results on Infeasible Problems

			KNITRO/CG			KNITRO/CG/NEW				
problem	n	m	inf	F	itr	inf	F	itr	# switch	sw.itr
balls	67	285	Y	6.01	1331	Y	75.81	72	1	23
eigmaxc_type2	22	23	Y	-1.00	481	Y	-1.00	25	1	13
isolated	2	4	N	0.00	3000	Y	0.00	14	1	10
nactive	2	3	Y	-0.20	317	Y	0.00	16	1	12
powellbs_modified	4	8	N	0.03	3000	Y	0.67	41	2	15,29
sosqp1_modified	200	201	N	1.94	3000	Y	0.00	21	1	13
batch	39	49	Y	255,187.40	122	Y	388,222.89	44	1	21
coverage	10	45	N	16.12	3000	Y	16.11	112	1	69
eigmaxc_type3	22	23	Y	-1.52	371	Y	-1.26	19	1	9
mccormck_modified	251	3	Y	-118.34	103	Y	433.88	18	1	10
portfolio	30	31	Y	0.00	1009	Y	0.00	71	1	6
robot_mod	7	3	Y	4.76	37	Y	5.77	16	1	5
unique	2	2	N	0.77	3000	Y	1.00	12	1	7
sensitive	2	4	N	-391.57	3000	Y	-367.79	16	1	7
locate	20	110	N	0.00	3000	Y	0.00	62	1	25
peigen	28	28	N	0.01	255	Y	0.03	22	1	11
degen	2	4	N	6.81	3000	Y	1.00	31	1	11

Next, we consider the performance of the new algorithm on feasible problems. We tested all the constrained problems in the CUTEr set [17] using KNITRO/CG and KNITRO/CG/NEW, with the same option settings as above. The test set includes a total of 430 problems, and the results are given in Appendix A. Termination diagnostics are reported in Table 5, in order to observe if the infeasibility detection mechanism has a detrimental effect when the algorithm is applied to feasible problems, and in particular whether the new algorithm might converge more often than warranted to infeasible stationary points. Table 5 indicates that this is not the case; in fact, out of the 430 problems, only once did the new algorithm report infeasibility while the old algorithm converged to an optimal solution. These result suggest that, overall, there is no loss of robustness when the new algorithm is applied to feasible problems.

To examine in more detail the relative performance of KNITRO/CG and KNITRO/CG/NEW, we selected those problems from the CUTEr test set for which both methods obtained the same optimal objective value, in the sense that

$$\left| \frac{f(x_{\text{CG}}) - f(x_{\text{NEW}})}{\max\{f(x_{\text{CG}}), f(x_{\text{NEW}})\}} \right| \leq 0.01,$$

where x_{CG} and x_{NEW} denote the final solutions for each method. 391 problems satisfied this condition, and the results are given in Figure 1 using the performance plots advocated by Morales [24] (which are more informative than the Dolan-Moré performance profiles [13] when comparing only two solvers).

Table 5 Terminations

KNITRO/CG	KNITRO/CG/NEW	number of problems
optimal	infeasible	1
failure	infeasible	1
failure	optimal	4
optimal	failure	4
optimal	optimal	398
failure	failure	20
unbounded	unbounded	2
	Total	430

For each problem i, Figure 1 plots the ratio

$$R_i = \log_2 \frac{\mathrm{ITR}_{\mathrm{NEW}}}{\mathrm{ITR}_{\mathrm{CG}}}, \tag{5.1}$$

where $\mathrm{ITR}_{\mathrm{NEW}}$ and $\mathrm{ITR}_{\mathrm{CG}}$ denote the number of iterations required by the new and previous version of the algorithm, respectively. The sign of R_i therefore identifies the method with better performance. For most problems the two methods required exactly the same number of iterations, something that is clearly visible in Figure 1. For the remaining problems, the two methods appear to be equally efficient.

In conclusion, our tests indicate that the new version of the algorithm is much more efficient on infeasible problems, and is equally effective as the previous version when applied to feasible problems.

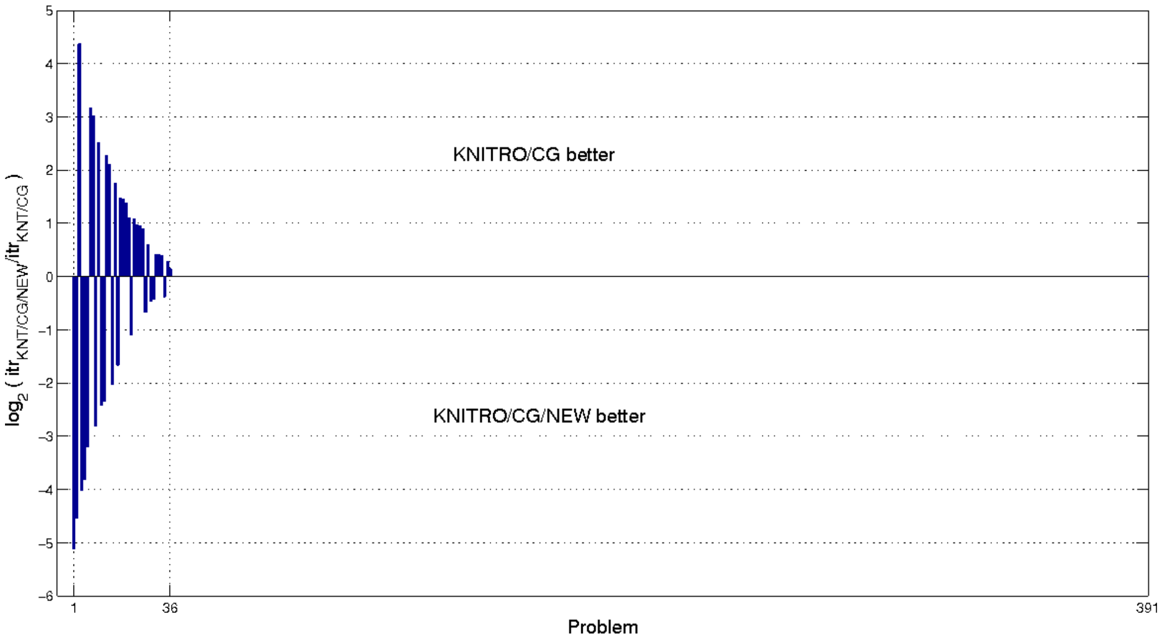

Fig. 1 Comparsion of the new and old versions of the trust region interior point algorithm (KNITRO/CG) in terms of iterations, on 391 feasible problems. Each point in the x-axis corresponds to a problem, and the y-axis plots the ratio (5.1)

6 Application to a Line Search Method

The approach for handling infeasibility presented in the previous sections is based on a trust-region method and is generally not applicable to line search primal-dual interior point methods. However, the line search algorithm implemented in KNITRO/DIRECT contains a safeguarding technique upon which our infeasibility detection mechanism can be built. In this section, we discuss how to do so, and report numerical results on the problem sets tested in the previous section.

The algorithm in KNITRO/DIRECT computes steps by solving the standard primal-dual system employed in line search interior point methods; see e.g. [26, chap.19]. However, if the step computed in this manner cannot be guaranteed to be productive, the algorithm discards it and computes the new iterate using the step-decomposition trust-region approach described in Section 4.

The decision to discard the primal-dual step is based on two criteria. First, if the steplength parameter α_k computed during the line search along the primal-dual direction is smaller than a given threshold, this may be an indication that the algorithm is approaching an infeasible stationary point, or more generally, a point of near singularity of the primal-dual system. Second, if the inertia of the primal dual system is such that the step is not guaranteed to be a descent direction for the merit function (i.e. if the Hessian of the Lagrangian is not positive definite in the tangent space of the constraints) then the primal-dual step must be modified. In these two cases, the primal-dual step is discarded and the step decomposition approach of KNITRO/CG is invoked.

This framework allows us to easily incorporate the techniques of the previous section, as follows. If KNITRO/DIRECT reverts to KNITRO/CG, we first check if the switching condition (4.15) holds for the primal-dual trial step that was just computed. If so, then we invoke the feasible mode specified in Algorithm 3; otherwise we call the main mode of KNITRO/CG and check the switching conditions after the normal step computation. A precise description is given in Algorithm 4.

To see how Algorithm 4 performs in practice, we use the same test settings as in Section 5. The results in Table 6 show that the feasibility mode greatly improves the performance of the line search algorithm on infeasible problems, whereas Table 7 and Figure 2 indicate that this mechanism does not adversely affect the performance of the new algorithm on feasible problems.

Algorithm 4: Knitro/Direct with Infeasibility Detection: Solve_Barrier_Main

Input: (x_0, s_0), $\mu > 0$, $\epsilon > 0$, λ_0, $\Delta_0 > 0$, $\eta, \rho, \beta \in (0, 1)$, $\nu_{-1} > 0$, $\delta > 0$, $\alpha_0 > 0$
while *resource limits are not exceeded* **do**
  if $||F^\mu(x_k, s_k, \lambda_k)|| < \epsilon$ **then**
    `Return`;
  `stepReady=false`;
  Factor the primal-dual system, record number of negative eigenvalues `neig`;
  if $\texttt{neig} < l + m$ **then**
    Compute step $d = (d_x, d_s, d_\lambda)$ by solving the primal-dual system;
    Initialize α_k, α_k^λ;
    while *`stepReady=false` and* $\alpha_k > \alpha_k^{min}$ **do**
      if $\phi(x_k, s_k; \nu_k) - \phi((x_k, s_k) + \alpha_k(d_x, d_s); \nu_k) \geq \eta pred_k(d)$ **then**
        $x_{k+1} = x_k + \alpha_k d_x$;
        $s_{k+1} = \max(s_k + \alpha_k d_s, -g_{k+1})$;
        $\lambda_{k+1} = \lambda_k + \alpha_k^\lambda d_\lambda$;
        `stepReady=true`;
        $k = k + 1$;
      else
        Choose smaller values of α_k, α_k^λ;
    if *`stepReady=false` and condition* (4.15) *holds* **then**
      $mode = F$;
      Set restoration mode slacks $\bar{s}$, multipliers $\bar{\lambda}$, and parameters $\bar{\mu}, \bar{\Delta}$;
      `Solve_Barrier_Feas`$((x_k, \bar{s}), \bar{\mu}, \epsilon)$;
  while *`stepReady=false`* **do**
    Compute normal step, $v = (v_x, v_s)$ by solving problem (4.3);
    if *condition* (4.15) *holds* **then**
      $mode = F$;
      Set restoration mode slacks $\bar{s}$, multipliers $\bar{\lambda}$, and parameters $\bar{\mu}, \bar{\Delta}$;
      `Solve_Barrier_Feas`$((x_k, \bar{s}), \bar{\mu}, \epsilon)$;
    Compute total step, $d = (d_x, d_s)$ by solving problem (4.4);
    Update penalty parameter, $\nu_k \geq \nu_{k-1}$ so that $pred_k(d) \geq \rho \nu_k vpred_k(v)$;
    if $\phi(x_k, s_k; \nu_k) - \phi(x_k + d_x, s_k + d_s; \nu_k) < \eta pred_k(d)$ **then**
      $\Delta_k = \beta \Delta_k$;
    else
      $x_{k+1} = x_k + d_x$;
      $s_{k+1} = \max(s_k + d_s, -g_{k+1})$;
      Compute λ_{k+1};
      Set $\Delta_{k+1} \geq \Delta_k$;
      `stepReady=true`;
      $k = k + 1$;

7 Final Remarks

Our numerical results suggest that the mechanism for endowing interior point methods with infeasibility detection capabilities presented in this paper is effective in practice. In a future study, we analyze the convergence properties of this approach, paying close attention to the effect of the switching rules between main and feasibility modes.

Table 6 Results on Infeasible Problems – Line Search Algorithm

			KNITRO/DIR			KNITRO/DIR/NEW				
problem	n	m	inf	F	itr	inf	F	itr	# switch	sw.itr
balls	67	285	N	5.92	3000	Y	135,709,295.10	102	1	45
eigmaxc_type2	22	23	N	-1.00	17	Y	-1.00	22	1	13
isolated	2	4	Y	0.00	145	Y	0.00	20	1	16
nactive	2	3	Y	-0.20	18	Y	0.00	13	1	11
powellbs_modified	4	8	Y	0.03	552	N	-427.57	35	1	20
sosqp1_modified	200	201	Y	1.94	10	Y	0.00	14	1	10
batch_mod	39	49	Y	255,185.36	291	Y	387,356.04	276	1	253
coverage	10	45	Y	15.97	63	Y	16.12	25	1	15
eigmaxc_type3	22	23	N	-1.44	3000	Y	-1.26	103	1	54
mccormck_modified	251	3	Y	-73.80	24	Y	358.92	17	1	11
portfolio	30	31	N	0.00	38	N	0.00	208	1	7
robot_mod	7	3	Y	4.79	39	Y	6.08	18	1	6
unique	2	2	Y	0.77	46	Y	1.00	29	1	25
sensitive	2	4	Y	-374.56	26	Y	-367.79	22	1	9
locate	20	110	N	0.00	3000	Y	0.00	963	1	939
peigen	28	28	N	0.00	3000	N	0.00	3000	0	-
degen	2	4	Y	5.65	15	Y	1.00	37	1	14

Table 7 Terminations–Line Search Algorithm

KNITRO/DIR	KNITRO/DIR/NEW	number of problems
optimal	infeasible	1
infeasible	optimal	1
failure	infeasible	4
failure	optimal	3
optimal	failure	3
optimal	optimal	410
failure	failure	6
unbounded	unbounded	1
infeasible	infeasible	1
	Total	430

We note, in closing, that it may be advantageous to apply a *feasible* interior point method in feasibility mode. By this we mean a method that ensures that inequality constraints that are satisfied at one iteration remain satisfied during the rest of the run. This approach eliminates the need for the relaxation variables r introduced in (4.10), and defines the objective of the feasibility phase direction in terms of the set of violated constraints. Such an algorithm would keep updating this violated set so that once a constraint is satisfied, it cannot become infeasible at a later iteration. By providing additional structure to the feasibility phase, this option could prove effective in practice.

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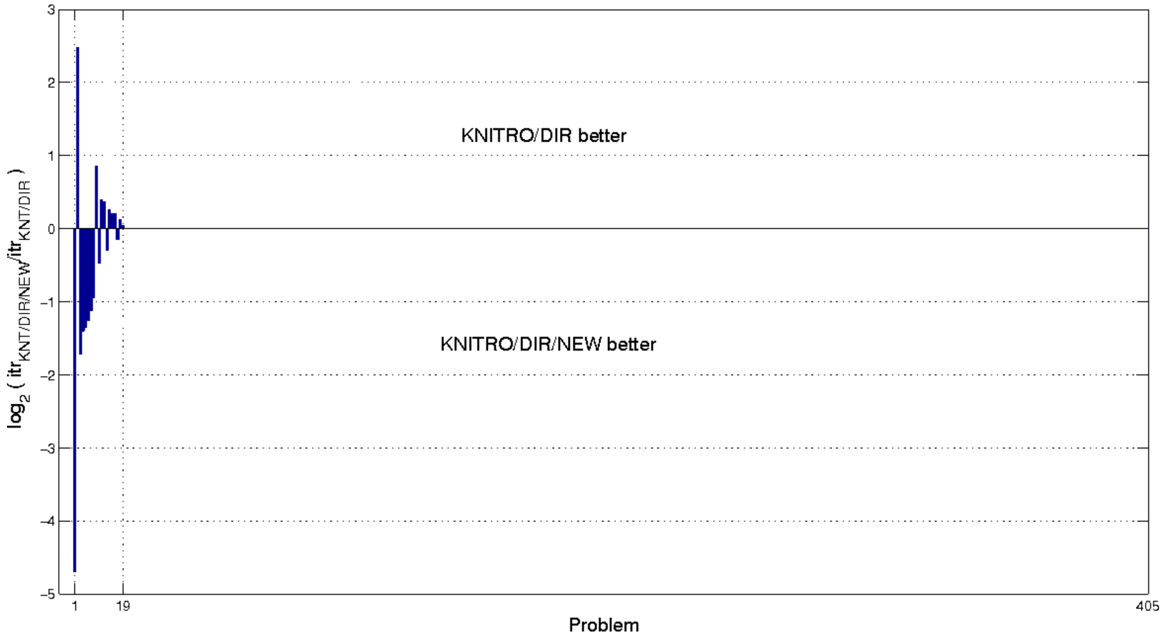

Fig. 2 Comparsion of the new and old versions of the line search interior point algorithm (KNITRO/DIRECT) in terms of iterations, on 391 feasible problems. Each point in the x-axis corresponds to a problem, and the y-axis plots the ratio (5.1)

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A Complete Output of the Tests with Constrained CUTEr Problems

Table 8: Results with the new algorithm for feasible models

			KNITRO/CG			KNITRO/CG/NEW		
problem	n	m	F	itr	termination	F	itr	termination
airport	84	42	4.80E+04	16	optimal	4.80E+04	16	optimal
aljazzaf	3	1	7.50E+01	56	optimal	7.50E+01	504	optimal
allinitc	3	1	3.05E+01	14	optimal	3.05E+01	14	optimal
alsotame	2	1	8.21E-02	7	optimal	8.21E-02	7	optimal
aug2d	20192	9996	1.69E+06	5	optimal	1.69E+06	5	optimal
aug2dc	20200	9996	1.82E+06	11	optimal	1.82E+06	11	optimal
aug2dcqp	20200	9996	6.50E+06	30	optimal	6.50E+06	40	optimal
aug2dqp	20192	9996	6.24E+06	29	optimal	6.24E+06	166	optimal
aug3d	3873	1000	5.54E+02	3	optimal	5.54E+02	3	optimal
aug3dc	3873	1000	7.71E+02	1	optimal	7.71E+02	1	optimal
aug3dcqp	3873	1000	9.93E+02	15	optimal	9.93E+02	15	optimal
aug3dqp	3873	1000	6.75E+02	23	optimal	6.75E+02	23	optimal
avion2	49	15	9.47E+07	19	optimal	9.47E+07	19	optimal
bigbank	1773	814	-4.21E+06	26	optimal	-4.21E+06	26	optimal
biggsc4	4	7	-2.45E+01	20	optimal	-2.45E+01	20	optimal
blockqp1	2005	1001	-9.96E+02	8	optimal	-9.96E+02	8	optimal
blockqp2	2005	1001	-9.96E+02	6	optimal	-9.96E+02	6	optimal
blockqp3	2005	1001	-4.97E+02	10	optimal	-4.97E+02	10	optimal
blockqp4	2005	1001	-4.98E+02	6	optimal	-4.98E+02	6	optimal
blockqp5	2005	1001	-4.97E+02	10	optimal	-4.97E+02	10	optimal
bloweya	2002	1002	-4.47E-02	4	optimal	-4.47E-02	4	optimal
bloweyb	2002	1002	-2.97E-02	5	optimal	-2.97E-02	5	optimal
bloweyc	2002	1002	-2.99E-02	4	optimal	-2.99E-02	4	optimal
brainpc0	6903	6898	3.82E-01	387	term feas	3.82E-01	387	term feas
brainpc1	6903	6898	1.69E+00	33	time limit	1.69E+00	33	time limit
brainpc2	13803	13798	8.50E-04	3000	itr limit	4.14E-04	183	optimal
brainpc3	6903	6898	4.14E-04	97	optimal	4.14E-04	97	optimal
brainpc4	6903	6898	4.37E-02	31	time limit	4.37E-02	31	time limit
brainpc5	6903	6898	4.23E-02	32	time limit	4.23E-02	32	time limit
brainpc6	6903	6898	1.83E-01	49	time limit	1.83E-01	49	time limit
brainpc7	6903	6898	3.62E-04	3000	itr limit	3.97E-04	396	term feas
brainpc8	6903	6898	3.76E-02	31	time limit	3.76E-02	31	time limit
brainpc9	6903	6898	4.26E-04	387	optimal	4.26E-04	387	optimal
britgas	450	360	3.84E-07	47	optimal	3.84E-07	47	optimal
bt1	2	1	-1.00E+00	7	optimal	-1.00E+00	7	optimal
bt10	2	2	-1.20E+00	3	term infeas	-1.20E+00	3	term infeas
bt11	5	3	8.25E-01	7	optimal	8.25E-01	7	optimal
bt12	5	3	6.19E+00	4	optimal	6.19E+00	4	optimal
bt13	5	1	4.00E-07	22	optimal	4.00E-07	22	optimal
bt2	3	1	3.26E-02	11	optimal	3.26E-02	11	optimal
bt3	5	3	4.09E+00	3	optimal	4.09E+00	3	optimal
bt4	3	2	-4.55E+01	5	optimal	-4.55E+01	5	optimal
bt5	3	2	9.62E+02	5	optimal	9.62E+02	5	optimal
bt6	5	2	2.77E-01	9	optimal	2.77E-01	9	optimal
bt7	5	3	3.60E+02	10	optimal	3.60E+02	10	optimal
bt8	5	2	1.00E+00	10	optimal	1.00E+00	10	optimal
bt9	4	2	-1.00E+00	17	optimal	-1.00E+00	17	optimal
byrdsphr	3	2	-4.68E+00	8	optimal	-4.68E+00	8	optimal
cantilvr	5	1	1.34E+00	12	optimal	1.34E+00	12	optimal
catena	32	11	-2.31E+04	28	optimal	-2.31E+04	28	optimal
catenary	496	166	-1.03E+09	3000	itr limit	-1.39E+08	3000	itr limit
cb2	3	3	1.95E+00	10	optimal	1.95E+00	10	optimal
cb3	3	3	2.00E+00	8	optimal	2.00E+00	8	optimal
chaconn1	3	3	1.95E+00	7	optimal	1.95E+00	7	optimal

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Table 8 -- cont'd

			KNITRO/CG			KNITRO/CG/NEW		
problem	n	m	F	itr	termination	F	itr	termination
chaconn2	3	3	2.00E+00	7	optimal	2.00E+00	7	optimal
clnlbeam	1499	1000	3.45E+02	356	optimal	3.45E+02	356	optimal
concon	15	11	-6.23E+03	9	optimal	-6.23E+03	9	optimal
congigmz	3	5	2.80E+01	24	optimal	2.80E+01	24	optimal
core1	65	50	9.11E+01	96	optimal	9.11E+01	415	optimal
core2	157	122	7.29E+01	59	optimal	7.29E+01	161	optimal
corkscrw	8997	7000	9.07E+01	412	optimal	9.07E+01	81	optimal
coshfun	61	20	-1.19E+20	43	unbounded	-1.19E+20	43	unbounded
cresc100	6	200	5.69E-01	177	optimal	5.69E-01	177	optimal
cresc132	6	2654	4.48E+00	27	term infeas	6.85E-01	1279	optimal
cresc4	6	8	8.72E-01	46	optimal	8.72E-01	46	optimal
cresc50	6	100	5.94E-01	673	optimal	5.94E-01	673	optimal
csfi1	5	4	-4.91E+01	13	optimal	-4.91E+01	13	optimal
csfi2	5	4	5.50E+01	64	optimal	5.50E+01	30	optimal
cvxqp1	1000	500	1.09E+06	9	optimal	1.09E+06	9	optimal
cvxqp2	10000	2500	8.18E+07	11	optimal	8.18E+07	11	optimal
cvxqp3	10000	7500	1.16E+08	18	optimal	1.16E+08	18	optimal
dallasl	837	598	-2.03E+05	156	optimal	-2.03E+05	156	optimal
dallasm	164	119	-4.82E+04	88	optimal	-4.82E+04	88	optimal
dallass	44	29	-3.24E+04	612	optimal	-3.24E+04	612	optimal
deconvc	51	1	2.58E-03	50	optimal	1.60E+00	64	optimal
degenlpa	20	14	3.06E+00	24	optimal	3.06E+00	32	optimal
degenlpb	20	15	-4.50E+01	58	optimal	-3.07E+01	23	optimal
demymalo	3	3	-3.00E+00	14	optimal	-3.00E+00	14	optimal
dipigri	7	4	6.81E+02	8	optimal	6.81E+02	8	optimal
disc2	28	23	1.56E+00	25	optimal	1.56E+00	25	optimal
discs	33	66	1.20E+01	449	optimal	1.20E+01	1166	optimal
dittert	327	264	-2.00E+00	170	optimal	-2.00E+00	170	optimal
dixchlng	10	5	2.47E+03	8	optimal	2.47E+03	8	optimal
dixchlnv	100	50	3.49E-13	17	optimal	3.49E-13	17	optimal
dnieper	57	24	1.87E+04	17	optimal	1.87E+04	17	optimal
dtoc1l	14985	9990	1.25E+02	9	optimal	1.25E+02	9	optimal
dtoc1na	1485	990	1.27E+01	9	optimal	1.27E+01	9	optimal
dtoc1nb	1485	990	1.59E+01	9	optimal	1.59E+01	9	optimal
dtoc1nc	1485	990	2.50E+01	16	optimal	2.50E+01	16	optimal
dtoc1nd	735	490	1.27E+01	16	optimal	1.27E+01	16	optimal
dtoc2	5994	3996	5.14E-01	249	optimal	5.14E-01	249	optimal
dtoc3	14996	9997	2.35E+02	4	optimal	2.35E+02	4	optimal
dtoc4	14996	9997	2.87E+00	3	optimal	2.87E+00	3	optimal
dtoc5	9998	4999	1.54E+00	3	optimal	1.54E+00	3	optimal
dtoc6	10000	5000	1.35E+05	12	optimal	1.35E+05	12	optimal
dual1	85	1	3.50E-02	25	optimal	3.50E-02	25	optimal
dual2	96	1	3.37E-02	15	optimal	3.37E-02	15	optimal
dual3	111	1	1.36E-01	34	optimal	1.36E-01	34	optimal
dual4	75	1	7.46E-01	14	optimal	7.46E-01	14	optimal
dualc1	9	13	6.16E+03	12	optimal	6.16E+03	12	optimal
dualc2	7	9	3.55E+03	8	optimal	3.55E+03	8	optimal
dualc5	8	1	4.27E+02	8	optimal	4.27E+02	8	optimal
dualc8	8	15	1.83E+04	13	optimal	1.83E+04	13	optimal
eg3	101	200	1.28E-01	22	optimal	1.28E-01	22	optimal
eigena2	110	55	8.25E+01	74	optimal	8.25E+01	74	optimal
eigenaco	110	55	0.00E+00	2	optimal	0.00E+00	2	optimal
eigenb2	110	55	1.60E+00	77	optimal	1.60E+00	77	optimal
eigenbco	110	55	9.00E+00	1	optimal	9.00E+00	1	optimal
eigenc2	462	231	7.72E+02	1663	term feas	7.72E+02	1663	term feas
eigencco	30	15	1.57E-16	10	optimal	1.57E-16	10	optimal
eigmaxa	101	101	-1.00E+00	8	optimal	-1.00E+00	8	optimal
eigmaxb	101	101	-2.41E-02	23	optimal	-2.41E-02	23	optimal

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Table 8 -- cont'd

			KNITRO/CG			KNITRO/CG/NEW		
problem	n	m	F	itr	termination	F	itr	termination
eigmaxc	22	22	-1.00E+00	6	optimal	-1.00E+00	6	optimal
eigmina	101	101	1.00E+00	10	optimal	1.00E+00	10	optimal
eigminb	101	101	9.67E-04	5	optimal	9.67E-04	5	optimal
eigminc	22	22	-1.13E-09	6	optimal	-1.13E-09	6	optimal
expfita	5	21	1.15E-03	15	optimal	1.15E-03	15	optimal
expfitb	5	101	5.16E-03	14	optimal	5.16E-03	14	optimal
expfitc	5	501	5.74E+01	28	optimal	5.74E+01	28	optimal
extrasim	2	1	1.00E+00	5	optimal	1.00E+00	5	optimal
fccu	19	8	1.11E+01	0	optimal	1.11E+01	0	optimal
fletcher	4	4	1.95E+01	8	optimal	1.95E+01	8	optimal
gausselm	1495	3690	-1.77E+01	113	optimal	-4.72E-01	3000	itr limit
genhs28	10	8	9.27E-01	2	optimal	9.27E-01	2	optimal
gigomez1	3	3	-3.00E+00	12	optimal	-3.00E+00	12	optimal
gilbert	1000	1	4.82E+02	30	optimal	4.82E+02	30	optimal
goffin	51	50	1.00E-06	10	optimal	1.00E-06	10	optimal
gouldqp2	699	349	1.91E-04	7	optimal	1.91E-04	7	optimal
gouldqp3	699	349	2.07E+00	11	optimal	2.07E+00	11	optimal
gpp	250	498	1.44E+04	13	optimal	1.44E+04	13	optimal
gridneta	8964	6724	3.05E+02	12	optimal	3.05E+02	12	optimal
gridnetb	13284	6724	1.43E+02	3	optimal	1.43E+02	3	optimal
gridnetc	7564	3844	1.62E+02	18	optimal	1.62E+02	18	optimal
gridnete	7565	3844	2.07E+02	5	optimal	2.07E+02	5	optimal
gridnetf	7565	3844	2.42E+02	18	optimal	2.42E+02	18	optimal
gridneth	61	36	3.96E+01	5	optimal	3.96E+01	5	optimal
gridneti	61	36	4.02E+01	9	optimal	4.02E+01	9	optimal
grouping	100	125	1.39E+01	5	optimal	1.39E+01	5	optimal
hadamard	65	256	1.00E+00	13	optimal	1.00E+00	13	optimal
hager1	10000	5000	8.81E-01	2	optimal	8.81E-01	2	optimal
hager2	10000	5000	4.32E-01	1	optimal	4.32E-01	1	optimal
hager3	10000	5000	1.41E-01	1	optimal	1.41E-01	1	optimal
hager4	10000	5000	2.79E+00	7	optimal	2.79E+00	7	optimal
haifam	85	150	-4.50E+01	11	optimal	-4.50E+01	11	optimal
haifas	7	9	-4.50E-01	17	optimal	-4.50E-01	17	optimal
haldmads	6	42	3.42E-02	58	optimal	3.42E-02	58	optimal
hanging	288	180	-6.20E+02	19	optimal	-6.20E+02	19	optimal
hatfldh	4	7	-2.45E+01	12	optimal	-2.45E+01	12	optimal
himmelbi	100	12	-1.75E+03	19	optimal	-1.75E+03	19	optimal
himmelbk	24	14	5.18E-02	20	optimal	5.18E-02	20	optimal
himmelp2	2	1	-6.21E+01	12	optimal	-6.21E+01	12	optimal
himmelp3	2	2	-5.90E+01	11	optimal	-5.90E+01	11	optimal
himmelp4	2	3	-5.90E+01	12	optimal	-5.90E+01	12	optimal
himmelp5	2	3	-5.90E+01	17	optimal	-5.90E+01	17	optimal
himmelp6	2	4	-5.90E+01	5	optimal	-5.90E+01	5	optimal
hong	4	1	1.35E+00	10	optimal	1.35E+00	10	optimal
hs006	2	1	5.98E-16	7	optimal	5.98E-16	7	optimal
hs007	2	1	-1.73E+00	27	optimal	-1.73E+00	27	optimal
hs008	2	2	-1.00E+00	5	optimal	-1.00E+00	5	optimal
hs009	2	1	-5.00E-01	6	optimal	-5.00E-01	6	optimal
hs010	2	1	-1.00E+00	11	optimal	-1.00E+00	11	optimal
hs011	2	1	-8.50E+00	6	optimal	-8.50E+00	6	optimal
hs012	2	1	-3.00E+01	7	optimal	-3.00E+01	7	optimal
hs013	2	1	9.84E-01	15	optimal	9.84E-01	15	optimal
hs014	2	2	1.39E+00	6	optimal	1.39E+00	6	optimal
hs015	2	2	3.07E+02	9	optimal	3.07E+02	9	optimal
hs016	2	2	2.50E-01	11	optimal	2.50E-01	11	optimal
hs017	2	2	1.00E+00	9	optimal	1.00E+00	9	optimal
hs018	2	2	5.00E+00	9	optimal	5.00E+00	9	optimal
hs019	2	2	-6.96E+03	14	optimal	-6.96E+03	39	optimal

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Table 8 -- cont'd

			KNITRO/CG			KNITRO/CG/NEW		
problem	n	m	F	itr	termination	F	itr	termination
hs020	2	3	4.02E+01	4	optimal	4.02E+01	4	optimal
hs021	2	1	-1.00E+02	5	optimal	-1.00E+02	5	optimal
hs022	2	2	1.00E+00	6	optimal	1.00E+00	6	optimal
hs023	2	5	2.00E+00	7	optimal	2.00E+00	7	optimal
hs024	2	2	-1.00E+00	8	optimal	-1.00E+00	8	optimal
hs026	3	1	6.37E-13	17	optimal	6.37E-13	17	optimal
hs027	3	1	4.00E-02	16	optimal	4.00E-02	16	optimal
hs028	3	1	1.97E-30	2	optimal	1.97E-30	2	optimal
hs029	3	1	-2.26E+01	7	optimal	-2.26E+01	7	optimal
hs030	3	1	1.00E+00	3000	itr limit	1.00E+00	3000	itr limit
hs031	3	1	6.00E+00	4	optimal	6.00E+00	4	optimal
hs032	3	2	1.00E+00	9	optimal	1.00E+00	9	optimal
hs033	3	2	-4.59E+00	7	optimal	-4.59E+00	7	optimal
hs034	3	2	-8.34E-01	9	optimal	-8.34E-01	9	optimal
hs035	3	1	1.11E-01	8	optimal	1.11E-01	8	optimal
hs036	3	1	-3.30E+03	6	optimal	-3.30E+03	6	optimal
hs037	3	1	-3.46E+03	6	optimal	-3.46E+03	6	optimal
hs039	4	2	-1.00E+00	17	optimal	-1.00E+00	17	optimal
hs040	4	3	-2.50E-01	3	optimal	-2.50E-01	3	optimal
hs041	4	1	1.93E+00	8	optimal	1.93E+00	8	optimal
hs042	3	1	1.39E+01	3	optimal	1.39E+01	3	optimal
hs043	4	3	-4.40E+01	7	optimal	-4.40E+01	7	optimal
hs044	4	6	-1.50E+01	6	optimal	-1.50E+01	6	optimal
hs046	5	2	1.27E-11	17	optimal	1.27E-11	17	optimal
hs047	5	3	8.29E-11	16	optimal	8.29E-11	16	optimal
hs048	5	2	6.90E-31	2	optimal	6.90E-31	2	optimal
hs049	5	2	1.30E-08	15	optimal	1.30E-08	15	optimal
hs050	5	3	4.60E-25	8	optimal	4.60E-25	8	optimal
hs051	5	3	2.47E-32	2	optimal	2.47E-32	2	optimal
hs052	5	3	5.33E+00	2	optimal	5.33E+00	2	optimal
hs053	5	3	4.09E+00	4	optimal	4.09E+00	4	optimal
hs054	6	1	1.93E-01	5	optimal	1.93E-01	5	optimal
hs055	6	6	6.33E+00	4	optimal	6.33E+00	4	optimal
hs056	7	4	-3.46E+00	6	optimal	-3.46E+00	6	optimal
hs057	2	1	3.06E-02	7	optimal	3.06E-02	7	optimal
hs059	2	3	-7.80E+00	13	optimal	-7.80E+00	13	optimal
hs060	3	1	3.26E-02	7	optimal	3.26E-02	7	optimal
hs061	3	2	-1.44E+02	6	optimal	-1.44E+02	6	optimal
hs062	3	1	-2.63E+04	6	optimal	-2.63E+04	6	optimal
hs063	3	2	9.62E+02	17	optimal	9.62E+02	17	optimal
hs064	3	1	6.30E+03	14	optimal	6.30E+03	14	optimal
hs065	3	1	9.54E-01	9	optimal	9.54E-01	9	optimal
hs066	3	2	5.18E-01	9	optimal	5.18E-01	9	optimal
hs067	10	7	-1.16E+03	13	optimal	-1.16E+03	13	optimal
hs070	4	1	1.75E-01	29	optimal	1.75E-01	29	optimal
hs071	4	2	1.70E+01	8	optimal	1.70E+01	8	optimal
hs072	4	2	7.28E+02	16	optimal	7.28E+02	16	optimal
hs073	4	3	2.99E+01	7	optimal	2.99E+01	7	optimal
hs074	4	4	5.13E+03	7	optimal	5.13E+03	7	optimal
hs075	4	4	5.17E+03	9	optimal	5.17E+03	9	optimal
hs076	4	3	-4.68E+00	6	optimal	-4.68E+00	6	optimal
hs077	5	2	2.42E-01	11	optimal	2.42E-01	11	optimal
hs078	5	3	-2.92E+00	4	optimal	-2.92E+00	4	optimal
hs079	5	3	7.88E-02	4	optimal	7.88E-02	4	optimal
hs080	5	3	5.39E-02	7	optimal	5.39E-02	7	optimal
hs081	5	3	5.39E-02	7	optimal	5.39E-02	7	optimal
hs083	5	3	-3.07E+04	7	optimal	-3.07E+04	7	optimal
hs084	5	3	-5.28E+06	8	optimal	-5.28E+06	8	optimal

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Table 8 -- cont'd

			KNITRO/CG			KNITRO/CG/NEW		
problem	n	m	F	itr	termination	F	itr	termination
hs085	5	36	-1.91E+00	20	optimal	-1.91E+00	20	optimal
hs086	5	6	-3.23E+01	8	optimal	-3.23E+01	8	optimal
hs087	9	4	8.83E+03	12	optimal	8.83E+03	12	optimal
hs088	2	1	1.36E+00	37	optimal	1.36E+00	37	optimal
hs089	3	1	1.36E+00	39	optimal	1.36E+00	39	optimal
hs090	4	1	1.36E+00	2937	optimal	1.36E+00	2937	optimal
hs091	5	1	1.36E+00	51	optimal	1.36E+00	51	optimal
hs092	6	1	1.51E+00	3000	itr limit	1.36E+00	537	optimal
hs093	6	2	1.35E+02	5	optimal	1.35E+02	5	optimal
hs095	6	4	1.59E-02	21	optimal	1.59E-02	21	optimal
hs096	6	4	1.56E-02	33	optimal	1.56E-02	33	optimal
hs097	6	4	3.14E+00	22	optimal	3.14E+00	22	optimal
hs098	6	4	4.07E+00	12	optimal	4.07E+00	12	optimal
hs099	19	14	-8.31E+08	7	optimal	-8.31E+08	7	optimal
hs100	7	4	6.81E+02	8	optimal	6.81E+02	8	optimal
hs100lnp	7	2	6.81E+02	8	optimal	6.81E+02	8	optimal
hs101	7	6	1.81E+03	522	optimal	1.81E+03	57	optimal
hs102	7	6	9.12E+02	2971	optimal	9.12E+02	86	optimal
hs103	7	6	5.44E+02	200	optimal	5.44E+02	49	optimal
hs104	8	6	3.95E+00	10	optimal	3.95E+00	10	optimal
hs106	8	6	7.05E+03	33	optimal	7.05E+03	65	optimal
hs107	9	6	5.06E+03	5	optimal	5.06E+03	5	optimal
hs108	9	13	-6.75E-01	19	optimal	-6.75E-01	19	optimal
hs109	9	10	5.33E+03	794	optimal	5.33E+03	57	optimal
hs111	10	3	-4.78E+01	10	optimal	-4.78E+01	10	optimal
hs111lnp	10	3	-4.78E+01	10	optimal	-4.78E+01	10	optimal
hs112	10	3	-4.78E+01	6	optimal	-4.78E+01	6	optimal
hs112x	10	4	-4.74E+01	3000	itr limit	-4.59E+01	75	infeasible
hs113	10	8	2.43E+01	9	optimal	2.43E+01	9	optimal
hs114	10	11	-1.77E+03	20	optimal	-1.77E+03	20	optimal
hs116	13	15	9.76E+01	31	optimal	9.76E+01	31	optimal
hs117	15	5	3.23E+01	17	optimal	3.23E+01	17	optimal
hs118	15	17	6.65E+02	14	optimal	6.65E+02	14	optimal
hs119	16	8	2.45E+02	11	optimal	2.45E+02	11	optimal
hs21mod	7	1	-9.60E+01	10	optimal	-9.60E+01	10	optimal
hs268	5	5	1.56E-04	10	optimal	1.56E-04	10	optimal
hs35mod	2	1	2.50E-01	12	optimal	2.50E-01	12	optimal
hs44new	4	5	-1.50E+01	6	optimal	-1.50E+01	6	optimal
hs99exp	28	21	-1.01E+09	38	optimal	-1.01E+09	787	optimal
hubfit	2	1	1.69E-02	8	optimal	1.69E-02	8	optimal
hues-mod	10000	2	3.48E+07	48	optimal	3.48E+07	48	optimal
huestis	10000	2	3.48E+11	58	optimal	3.48E+11	469	optimal
hvycrash	201	150	-6.99E-02	138	optimal	-6.56E-02	209	infeasible
kissing	127	903	8.43E-01	66	optimal	8.47E-01	319	optimal
kiwcresc	3	2	4.00E-08	9	optimal	4.00E-08	9	optimal
ksip	20	1000	5.76E-01	19	optimal	5.76E-01	19	optimal
lakes	90	78	7.35E+11	10	term infeas	3.51E+05	1688	optimal
launch	25	29	6.31E+00	3000	itr limit	4.11E-06	429	term infeas
lch	600	1	-4.29E+00	17	optimal	-4.29E+00	17	optimal
lewispol	6	9	2.95E+00	9	optimal	2.95E+00	9	optimal
linspanh	72	32	-7.70E+01	7	optimal	-7.70E+01	7	optimal
liswet1	10002	10000	3.61E+01	18	optimal	3.61E+01	18	optimal
liswet10	10002	10000	4.95E+01	34	optimal	4.95E+01	34	optimal
liswet11	10002	10000	4.95E+01	27	optimal	4.95E+01	27	optimal
liswet12	10002	10000	-3.31E+03	314	optimal	-3.31E+03	314	optimal
liswet2	10002	10000	2.50E+01	23	optimal	2.50E+01	23	optimal
liswet3	10002	10000	2.50E+01	27	optimal	2.50E+01	27	optimal
liswet4	10002	10000	2.50E+01	27	optimal	2.50E+01	27	optimal

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Table 8 -- cont'd

			KNITRO/CG			KNITRO/CG/NEW		
problem	n	m	F	itr	termination	F	itr	termination
liswet5	10002	10000	2.50E+01	26	optimal	2.50E+01	26	optimal
liswet6	10002	10000	2.50E+01	29	optimal	2.50E+01	29	optimal
liswet7	10002	10000	4.99E+02	21	optimal	4.99E+02	21	optimal
liswet8	10002	10000	7.14E+02	123	optimal	7.14E+02	123	optimal
liswet9	10002	10000	1.96E+03	205	optimal	1.96E+03	205	optimal
loadbal	31	31	4.53E-01	10	optimal	4.53E-01	10	optimal
lootsma	3	2	1.41E+00	7	optimal	1.41E+00	7	optimal
lotschd	12	7	2.40E+03	10	optimal	2.40E+03	10	optimal
lsnnodoc	5	4	1.23E+02	9	optimal	1.23E+02	9	optimal
lsqfit	2	1	3.38E-02	7	optimal	3.38E-02	7	optimal
madsen	3	6	6.16E-01	10	optimal	6.16E-01	10	optimal
madsschj	81	158	-7.97E+02	72	optimal	-7.97E+02	153	optimal
makela1	3	2	-1.41E+00	12	optimal	-1.41E+00	12	optimal
makela2	3	3	7.20E+00	12	optimal	7.20E+00	12	optimal
makela3	21	20	7.56E-06	20	optimal	7.56E-06	20	optimal
makela4	21	40	2.27E-06	9	optimal	2.27E-06	9	optimal
manne	1094	730	-9.74E-01	164	optimal	-9.74E-01	164	optimal
maratos	2	1	-1.00E+00	3	optimal	-1.00E+00	3	optimal
matrix2	6	2	3.30E-06	13	optimal	3.30E-06	13	optimal
mconcon	15	11	-6.23E+03	9	optimal	-6.23E+03	9	optimal
mifflin1	3	2	-1.00E+00	7	optimal	-1.00E+00	7	optimal
mifflin2	3	2	-1.00E+00	11	optimal	-1.00E+00	11	optimal
minc44	303	262	2.57E-03	81	optimal	2.57E-03	81	optimal
minmaxbd	5	20	1.16E+02	100	optimal	1.16E+02	77	optimal
minmaxrb	3	4	7.98E-08	10	optimal	7.98E-08	10	optimal
minperm	1113	1033	3.64E-04	180	optimal	3.64E-04	180	optimal
mistake	9	13	-1.00E+00	24	optimal	-1.00E+00	24	optimal
model	60	32	5.74E+03	7	optimal	5.74E+03	7	optimal
mosarqp1	2500	700	-9.53E+02	10	optimal	-9.53E+02	10	optimal
mosarqp2	900	600	-1.60E+03	9	optimal	-1.60E+03	9	optimal
mwright	5	3	2.50E+01	7	optimal	2.50E+01	7	optimal
ncvxqp1	1000	500	-7.16E+07	49	optimal	-7.16E+07	49	optimal
ncvxqp2	1000	500	-5.78E+07	45	optimal	-5.78E+07	45	optimal
ncvxqp3	1000	500	-3.08E+07	58	optimal	-3.14E+07	3000	itr limit
ncvxqp4	1000	250	-9.40E+07	45	optimal	-9.40E+07	45	optimal
ncvxqp5	1000	250	-6.63E+07	47	optimal	-6.64E+07	88	optimal
ncvxqp6	1000	250	-3.46E+07	81	optimal	-3.55E+07	84	optimal
ncvxqp7	1000	750	-4.34E+07	33	optimal	-4.34E+07	33	optimal
ncvxqp8	1000	750	-3.05E+07	47	optimal	-3.05E+07	47	optimal
ncvxqp9	1000	750	-2.15E+07	44	optimal	-2.15E+07	44	optimal
ngone	97	1273	-6.37E-01	39	optimal	-6.41E-01	59	optimal
odfits	10	6	-2.38E+03	9	optimal	-2.38E+03	9	optimal
oet1	3	1002	5.38E-01	44	optimal	5.38E-01	44	optimal
oet2	3	1002	8.72E-02	40	optimal	8.72E-02	40	optimal
oet3	4	1002	4.52E-03	26	optimal	4.52E-03	26	optimal
oet7	7	1002	2.10E-03	2341	optimal	2.10E-03	441	optimal
optcdeg2	1198	799	2.30E+02	23	optimal	2.30E+02	23	optimal
optcdeg3	1198	799	4.61E+01	16	optimal	4.61E+01	16	optimal
optcntrl	28	20	5.50E+02	13	optimal	5.50E+02	13	optimal
optctrl3	118	80	2.05E+03	9	optimal	2.05E+03	9	optimal
optctrl6	118	80	2.05E+03	9	optimal	2.05E+03	9	optimal
optmass	66	55	-1.90E-01	28	optimal	-1.90E-01	37	optimal
optprloc	30	29	-1.64E+01	10	optimal	-1.64E+01	10	optimal
orthrdm2	4003	2000	1.56E+02	6	optimal	1.56E+02	6	optimal
orthrds2	203	100	3.05E+01	27	term feas	3.05E+01	27	term feas
orthrega	517	256	1.66E+03	8	optimal	1.66E+03	8	optimal
orthregb	27	6	3.35E-15	2	optimal	3.35E-15	2	optimal
orthregc	10005	5000	1.90E+02	10	optimal	1.90E+02	10	optimal

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Table 8 -- cont'd

			KNITRO/CG			KNITRO/CG/NEW		
problem	n	m	F	itr	termination	F	itr	termination
orthregd	10003	5000	1.52E+03	7	optimal	1.52E+03	7	optimal
orthrege	36	20	3.99E+00	32	optimal	3.99E+00	32	optimal
orthrgdm	10003	5000	1.51E+03	8	optimal	1.51E+03	8	optimal
orthrgds	10003	5000	1.77E+03	36	term feas	1.77E+03	36	term feas
pentagon	6	12	1.39E-04	13	optimal	1.39E-04	13	optimal
polak1	3	2	2.72E+00	9	optimal	2.72E+00	9	optimal
polak2	11	2	-2.05E+02	3000	itr limit	-1.50E+04	3000	itr limit
polak3	12	10	5.93E+00	39	optimal	5.93E+00	39	optimal
polak4	3	3	1.37E-07	10	optimal	1.37E-07	10	optimal
polak5	3	2	5.00E+01	19	optimal	5.00E+01	19	optimal
polak6	5	4	-4.40E+01	1067	optimal	-4.40E+01	66	optimal
portfl1	12	1	2.05E-02	9	optimal	2.05E-02	9	optimal
portfl2	12	1	2.97E-02	9	optimal	2.97E-02	9	optimal
portfl3	12	1	3.27E-02	9	optimal	3.27E-02	9	optimal
portfl4	12	1	2.63E-02	9	optimal	2.63E-02	9	optimal
portfl6	12	1	2.58E-02	8	optimal	2.58E-02	8	optimal
powell20	1000	1000	5.21E+07	434	optimal	5.21E+07	62	optimal
prodpl0	60	29	6.09E+01	13	optimal	6.09E+01	13	optimal
prodpl1	60	29	5.30E+01	12	optimal	5.30E+01	12	optimal
pt	2	501	1.78E-01	19	optimal	1.78E-01	19	optimal
qpcboei1	372	288	1.44E+07	129	optimal	1.44E+07	157	optimal
qpcboei2	143	125	8.29E+06	3000	itr limit	8.29E+06	3000	itr limit
qpcstair	385	356	6.20E+06	175	optimal	6.20E+06	130	optimal
qpnboei1	372	288	8.52E+06	189	optimal	8.46E+06	189	optimal
qpnboei2	143	125	1.27E+06	3000	itr limit	1.27E+06	3000	itr limit
qpnstair	385	356	5.15E+06	182	optimal	5.15E+06	133	optimal
reading1	10001	5000	-1.60E-01	15	optimal	-1.60E-01	15	optimal
reading2	15001	10000	-1.19E-02	6	optimal	-1.19E-02	6	optimal
robot	7	2	5.46E+00	6	optimal	5.46E+00	6	optimal
rosenmmx	5	4	-4.40E+01	13	optimal	-4.40E+01	13	optimal
s332	2	100	2.99E+01	15	optimal	2.99E+01	15	optimal
s365mod	7	5	1.51E+01	3000	itr limit	9.77E+03	3000	itr limit
sawpath	589	782	1.82E+02	176	optimal	1.82E+02	176	optimal
simpllpa	2	2	1.00E+00	6	optimal	1.00E+00	6	optimal
simpllpb	2	3	1.10E+00	11	optimal	1.10E+00	11	optimal
sinrosnb	1000	999	-9.99E+04	0	optimal	-9.99E+04	0	optimal
sipow1	2	10000	-1.00E+00	135	optimal	-1.00E+00	135	optimal
sipow1m	2	10000	-1.00E+00	131	optimal	-1.00E+00	131	optimal
sipow2	2	5000	-1.00E+00	15	optimal	-1.00E+00	15	optimal
sipow2m	2	5000	-1.00E+00	15	optimal	-1.00E+00	15	optimal
sipow3	4	9998	5.36E-01	27	optimal	5.36E-01	27	optimal
sipow4	4	10000	2.73E-01	23	optimal	2.73E-01	23	optimal
smbank	117	64	-7.13E+06	17	optimal	-7.13E+06	17	optimal
smmpsf	720	263	1.05E+06	109	optimal	7.21E+08	3000	itr limit
snake	2	2	-3.93E+03	3000	itr limit	-3.98E+03	3000	itr limit
sosqp2	20000	10001	-5.00E+03	24	optimal	-5.00E+03	24	optimal
spanhyd	72	32	2.40E+02	12	optimal	2.40E+02	12	optimal
spiral	3	2	8.00E-07	128	optimal	8.00E-07	128	optimal
sreadin3	10000	5000	-4.67E-05	1	optimal	-4.67E-05	1	optimal
sseblin	192	72	1.62E+07	130	optimal	1.62E+07	82	optimal
ssebnln	192	96	1.62E+07	302	optimal	1.62E+07	547	term feas
ssnlbeam	31	20	3.38E+02	15	optimal	3.38E+02	15	optimal
stancmin	3	2	4.25E+00	13	optimal	4.25E+00	13	optimal
static3	434	96	-2.66E+21	91	unbounded	-2.66E+21	91	unbounded
steenbra	432	108	1.70E+04	192	optimal	1.70E+04	192	optimal
steenbrb	468	108	9.08E+03	386	optimal	9.11E+03	122	optimal
steenbrc	540	126	1.84E+04	420	optimal	1.87E+04	961	optimal
steenbrd	468	108	9.04E+03	446	optimal	9.14E+03	465	optimal

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Table 8 -- cont'd

			KNITRO/CG			KNITRO/CG/NEW		
problem	n	m	F	itr	termination	F	itr	termination
steenbre	540	126	2.75E+04	959	optimal	2.97E+04	641	optimal
steenbrf	468	108	2.83E+02	89	optimal	2.83E+02	191	optimal
steenbrg	540	126	2.75E+04	1162	optimal	2.74E+04	1290	optimal
supersim	2	2	6.67E-01	1	optimal	6.67E-01	1	optimal
svanberg	5000	5000	8.36E+03	17	optimal	8.36E+03	17	optimal
swopf	82	91	6.79E-02	13	optimal	6.79E-02	13	optimal
synthes1	6	6	7.59E-01	13	optimal	7.59E-01	13	optimal
tame	2	1	1.09E-15	4	optimal	1.09E-15	4	optimal
tfi2	3	10000	6.49E-01	22	optimal	6.49E-01	22	optimal
trainf	20000	10002	3.11E+00	78	optimal	3.11E+00	152	optimal
trainh	20000	10002	1.23E+01	42	optimal	1.23E+01	42	optimal
trimloss	142	72	9.06E+00	28	optimal	9.06E+00	28	optimal
try-b	2	1	1.00E-16	9	optimal	1.00E-16	9	optimal
twirism1	343	313	-1.01E+00	366	optimal	-1.01E+00	1240	optimal
twobars	2	2	1.51E+00	7	optimal	1.51E+00	7	optimal
ubh1	17997	12000	1.12E+00	1806	optimal	1.12E+00	78	optimal
ubh5	19997	14000	7.48E-01	3000	itr limit	6.37E+01	3000	itr limit
vanderm1	100	99	3.33E-05	127	optimal	3.33E-05	127	optimal
vanderm2	100	99	3.06E-06	131	optimal	3.06E-06	131	optimal
vanderm3	100	99	2.29E-04	49	optimal	2.29E-04	49	optimal
vanderm4	9	8	1.36E-07	23	optimal	1.36E-07	23	optimal
womflet	3	3	6.05E+00	12	optimal	6.05E+00	12	optimal
yao	2000	1999	1.98E+02	71	optimal	1.98E+02	71	optimal
zecevic2	2	2	-4.12E+00	8	optimal	-4.12E+00	8	optimal
zecevic3	2	2	9.73E+01	8	optimal	9.73E+01	8	optimal
zecevic4	2	2	7.56E+00	8	optimal	7.56E+00	8	optimal
zigzag	58	50	3.16E+00	32	optimal	3.16E+00	32	optimal
zy2	3	1	2.00E+00	6	optimal	2.00E+00	6	optimal

B Complete Output of the Tests with Constrained CUTEr Problems - Line Search Algorithm

Table 9: Results with the new algorithm for feasible models - Line Search Algorithm

			KNITRO/DIR			KNITRO/DIR/NEW		
problem	n	m	F	itr	termination	F	itr	termination
airport	84	42	4.80E+04	12	optimal	4.80E+04	12	optimal
aljazzaf	3	1	7.50E+01	50	optimal	7.50E+01	26	optimal
allinitc	3	1	3.05E+01	16	optimal	3.05E+01	16	optimal
alsotame	2	1	8.21E-02	6	optimal	8.21E-02	6	optimal
aug2d	20192	9996	1.69E+06	2	optimal	1.69E+06	2	optimal
aug2dc	20200	9996	1.82E+06	9	optimal	1.82E+06	9	optimal
aug2dcqp	20200	9996	6.50E+06	16	optimal	6.50E+06	16	optimal
aug2dqp	20192	9996	6.24E+06	16	optimal	6.24E+06	16	optimal
aug3d	3873	1000	5.54E+02	2	optimal	5.54E+02	2	optimal
aug3dc	3873	1000	7.71E+02	2	optimal	7.71E+02	2	optimal
aug3dcqp	3873	1000	9.93E+02	11	optimal	9.93E+02	11	optimal
aug3dqp	3873	1000	6.75E+02	11	optimal	6.75E+02	11	optimal
avion2	49	15	9.47E+07	23	optimal	9.47E+07	23	optimal
bigbank	1773	814	-4.21E+06	25	optimal	-4.21E+06	25	optimal
biggsc4	4	7	-2.45E+01	11	optimal	-2.45E+01	11	optimal
blockqp1	2005	1001	-9.96E+02	8	optimal	-9.96E+02	8	optimal
blockqp2	2005	1001	-9.95E+02	6	optimal	-9.95E+02	6	optimal
blockqp3	2005	1001	-4.97E+02	12	optimal	-4.97E+02	12	optimal
blockqp4	2005	1001	-4.98E+02	8	optimal	-4.98E+02	8	optimal
blockqp5	2005	1001	-4.97E+02	14	optimal	-4.97E+02	14	optimal
bloweya	2002	1002	-4.55E-02	8	optimal	-4.55E-02	8	optimal
bloweyb	2002	1002	-3.05E-02	8	optimal	-3.05E-02	8	optimal
bloweyc	2002	1002	-3.04E-02	8	optimal	-3.04E-02	8	optimal
brainpc0	6903	6898	3.40E-01	32	optimal	3.40E-01	32	optimal
brainpc1	6903	6898	4.14E-04	3000	itr limit	2.62E+16	273	infeasible
brainpc2	13803	13798	4.40E-04	50	optimal	4.40E-04	50	optimal
brainpc3	6903	6898	3.83E-04	3000	itr limit	4.22E-04	222	optimal
brainpc4	6903	6898	3.66E-04	3000	itr limit	7.21E+09	3000	itr limit
brainpc5	6903	6898	3.43E-04	3000	itr limit	8.35E+10	396	infeasible
brainpc6	6903	6898	3.56E-04	3000	itr limit	2.63E+09	3000	itr limit
brainpc7	6903	6898	3.64E-04	3000	itr limit	3.95E-04	164	optimal
brainpc8	6903	6898	3.69E-04	3000	itr limit	3.59E-04	256	optimal
brainpc9	6903	6898	3.74E-04	3000	itr limit	2.11E+09	78	infeasible
britgas	450	360	2.22E-06	22	optimal	2.22E-06	22	optimal
bt1	2	1	-1.00E+00	11	optimal	-1.00E+00	11	optimal
bt10	2	2	-1.00E+00	6	optimal	-1.00E+00	6	optimal
bt11	5	3	8.25E-01	7	optimal	8.25E-01	7	optimal
bt12	5	3	6.19E+00	3	optimal	6.19E+00	3	optimal
bt13	5	1	1.00E-08	11	optimal	1.00E-08	11	optimal
bt2	3	1	3.26E-02	12	optimal	3.26E-02	12	optimal
bt3	5	3	4.09E+00	2	optimal	4.09E+00	2	optimal
bt4	3	2	-4.55E+01	5	optimal	-4.55E+01	5	optimal
bt5	3	2	9.62E+02	6	optimal	9.62E+02	6	optimal
bt6	5	2	2.77E-01	9	optimal	2.77E-01	9	optimal
bt7	5	3	3.60E+02	10	optimal	3.60E+02	10	optimal
bt8	5	2	1.00E+00	10	optimal	1.00E+00	10	optimal
bt9	4	2	-1.00E+00	23	optimal	-1.00E+00	23	optimal
byrdsphr	3	2	-4.68E+00	8	optimal	-4.68E+00	8	optimal
cantilvr	5	1	1.34E+00	12	optimal	1.34E+00	12	optimal
catena	32	11	-2.31E+04	6	optimal	-2.31E+04	6	optimal
catenary	496	166	-3.48E+05	1624	optimal	-3.48E+05	1766	optimal

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Table 9 -- cont'd

			KNITRO/DIR			KNITRO/DIR/NEW		
problem	n	m	F	itr	termination	F	itr	termination
cb2	3	3	1.95E+00	9	optimal	1.95E+00	9	optimal
cb3	3	3	2.00E+00	6	optimal	2.00E+00	6	optimal
chaconn1	3	3	1.95E+00	5	optimal	1.95E+00	5	optimal
chaconn2	3	3	2.00E+00	5	optimal	2.00E+00	5	optimal
clnlbeam	1499	1000	3.45E+02	16	optimal	3.45E+02	16	optimal
concon	15	11	-6.23E+03	6	optimal	-6.23E+03	6	optimal
congigmz	3	5	2.80E+01	21	optimal	2.80E+01	21	optimal
core1	65	50	9.11E+01	17	optimal	9.11E+01	17	optimal
core2	157	122	7.29E+01	49	optimal	7.29E+01	274	optimal
corkscrw	8997	7000	9.07E+01	380	optimal	9.07E+01	116	optimal
coshfun	61	20	-7.73E-01	28	optimal	-7.73E-01	28	optimal
cresc100	6	200	5.68E-01	365	optimal	5.69E-01	168	optimal
cresc132	6	2654	6.85E-01	798	optimal	6.23E+02	3000	itr limit
cresc4	6	8	-2.72E-01	3000	itr limit	-2.75E-02	3000	itr limit
cresc50	6	100	5.93E-01	675	optimal	5.93E-01	675	optimal
csfi1	5	4	-4.91E+01	14	optimal	-4.91E+01	14	optimal
csfi2	5	4	5.50E+01	20	optimal	5.50E+01	20	optimal
cvxqp1	1000	500	1.09E+06	10	optimal	1.09E+06	10	optimal
cvxqp2	10000	2500	8.18E+07	10	optimal	8.18E+07	10	optimal
cvxqp3	10000	7500	1.16E+08	9	optimal	1.16E+08	9	optimal
dallasl	837	598	-2.03E+05	245	optimal	-2.03E+05	245	optimal
dallasm	164	119	-4.82E+04	103	optimal	-4.82E+04	103	optimal
dallass	44	29	-3.24E+04	308	optimal	-3.24E+04	308	optimal
deconvc	51	1	2.57E-03	44	optimal	2.57E-03	44	optimal
degenlpa	20	14	2.89E+00	23	optimal	2.89E+00	23	optimal
degenlpb	20	15	-6.98E+01	14	optimal	-6.98E+01	14	optimal
demymalo	3	3	-3.00E+00	15	optimal	-3.00E+00	15	optimal
dipigri	7	4	6.81E+02	6	optimal	6.81E+02	6	optimal
disc2	28	23	1.56E+00	20	optimal	1.56E+00	20	optimal
discs	33	66	1.53E+01	275	optimal	1.20E+01	164	optimal
dittert	327	264	-2.00E+00	32	optimal	-2.00E+00	32	optimal
dixchlng	10	5	2.47E+03	9	optimal	2.47E+03	9	optimal
dixchlnv	100	50	2.71E-19	30	optimal	2.71E-19	30	optimal
dnieper	57	24	1.87E+04	32	optimal	1.87E+04	32	optimal
dtoc1l	14985	9990	1.25E+02	9	optimal	1.25E+02	9	optimal
dtoc1na	1485	990	1.27E+01	9	optimal	1.27E+01	9	optimal
dtoc1nb	1485	990	1.59E+01	11	optimal	1.59E+01	11	optimal
dtoc1nc	1485	990	2.50E+01	21	optimal	2.50E+01	21	optimal
dtoc1nd	735	490	1.26E+01	16	optimal	1.26E+01	16	optimal
dtoc2	5994	3996	5.25E-01	968	optimal	5.25E-01	968	optimal
dtoc3	14996	9997	2.35E+02	2	optimal	2.35E+02	2	optimal
dtoc4	14996	9997	2.87E+00	3	optimal	2.87E+00	3	optimal
dtoc5	9998	4999	1.54E+00	3	optimal	1.54E+00	3	optimal
dtoc6	10000	5000	1.35E+05	12	optimal	1.35E+05	12	optimal
dual1	85	1	3.50E-02	13	optimal	3.50E-02	13	optimal
dual2	96	1	3.37E-02	11	optimal	3.37E-02	11	optimal
dual3	111	1	1.36E-01	12	optimal	1.36E-01	12	optimal
dual4	75	1	7.46E-01	11	optimal	7.46E-01	11	optimal
dualc1	9	13	6.16E+03	12	optimal	6.16E+03	12	optimal
dualc2	7	9	3.55E+03	13	optimal	3.55E+03	13	optimal
dualc5	8	1	4.27E+02	7	optimal	4.27E+02	7	optimal
dualc8	8	15	1.83E+04	12	optimal	1.83E+04	12	optimal
eg3	101	200	1.28E-01	41	optimal	1.28E-01	41	optimal
eigena2	110	55	8.25E+01	36	optimal	8.25E+01	36	optimal
eigenaco	110	55	0.00E+00	3	optimal	0.00E+00	3	optimal
eigenb2	110	55	1.60E+00	78	optimal	1.60E+00	78	optimal
eigenbco	110	55	9.00E+00	1	optimal	9.00E+00	1	optimal
eigenc2	462	231	7.73E+02	1697	term feas	7.73E+02	1697	term feas

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Table 9 -- cont'd

			KNITRO/DIR			KNITRO/DIR/NEW		
problem	n	m	F	itr	termination	F	itr	termination
eigencco	30	15	3.89E-13	9	optimal	3.89E-13	9	optimal
eigmaxa	101	101	-1.00E+00	21	optimal	-1.00E+00	21	optimal
eigmaxb	101	101	-4.72E-02	11	optimal	-4.72E-02	11	optimal
eigmaxc	22	22	-1.00E+00	6	optimal	-1.00E+00	6	optimal
eigmina	101	101	1.00E+00	20	optimal	1.00E+00	24	optimal
eigminb	101	101	9.67E-04	6	optimal	9.67E-04	6	optimal
eigminc	22	22	1.39E-17	7	optimal	1.39E-17	7	optimal
expfita	5	21	1.14E-03	16	optimal	1.14E-03	16	optimal
expfitb	5	101	5.02E-03	17	optimal	5.02E-03	17	optimal
expfitc	5	501	2.33E-02	14	optimal	2.33E-02	14	optimal
extrasim	2	1	1.00E+00	4	optimal	1.00E+00	4	optimal
fccu	19	8	1.11E+01	0	optimal	1.11E+01	0	optimal
fletcher	4	4	1.95E+01	9	optimal	1.95E+01	9	optimal
gausselm	1495	3690	-1.72E+01	545	optimal	-1.72E+01	545	optimal
genhs28	10	8	9.27E-01	2	optimal	9.27E-01	2	optimal
gigomez1	3	3	-3.00E+00	17	optimal	-3.00E+00	17	optimal
gilbert	1000	1	4.82E+02	29	optimal	4.82E+02	29	optimal
goffin	51	50	5.23E-07	6	optimal	5.23E-07	6	optimal
gouldqp2	699	349	1.89E-04	9	optimal	1.89E-04	9	optimal
gouldqp3	699	349	2.07E+00	9	optimal	2.07E+00	9	optimal
gpp	250	498	1.44E+04	11	optimal	1.44E+04	11	optimal
gridneta	8964	6724	3.05E+02	12	optimal	3.05E+02	12	optimal
gridnetb	13284	6724	1.43E+02	2	optimal	1.43E+02	2	optimal
gridnetc	7564	3844	1.62E+02	16	optimal	1.62E+02	16	optimal
gridnete	7565	3844	2.07E+02	4	optimal	2.07E+02	4	optimal
gridnetf	7565	3844	2.42E+02	17	optimal	2.42E+02	17	optimal
gridneth	61	36	3.96E+01	3	optimal	3.96E+01	3	optimal
gridneti	61	36	4.02E+01	5	optimal	4.02E+01	5	optimal
grouping	100	125	5.17E+00	86	optimal	1.21E+01	56	optimal
hadamard	65	256	1.00E+00	3	optimal	1.00E+00	3	optimal
hager1	10000	5000	8.81E-01	2	optimal	8.81E-01	2	optimal
hager2	10000	5000	4.32E-01	2	optimal	4.32E-01	2	optimal
hager3	10000	5000	1.41E-01	3	optimal	1.41E-01	3	optimal
hager4	10000	5000	2.79E+00	7	optimal	2.79E+00	7	optimal
haifam	85	150	-4.50E+01	13	optimal	-4.50E+01	13	optimal
haifas	7	9	-4.50E-01	24	optimal	-4.50E-01	24	optimal
haldmads	6	42	1.22E-04	16	optimal	1.22E-04	16	optimal
hanging	288	180	-6.20E+02	19	optimal	-6.20E+02	19	optimal
hatfldh	4	7	-2.45E+01	7	optimal	-2.45E+01	7	optimal
himmelbi	100	12	-1.75E+03	18	optimal	-1.75E+03	18	optimal
himmelbk	24	14	5.18E-02	9	optimal	5.18E-02	9	optimal
himmelp2	2	1	-6.21E+01	10	optimal	-6.21E+01	10	optimal
himmelp3	2	2	-5.90E+01	7	optimal	-5.90E+01	7	optimal
himmelp4	2	3	-5.90E+01	9	optimal	-5.90E+01	9	optimal
himmelp5	2	3	-5.90E+01	12	optimal	-5.90E+01	12	optimal
himmelp6	2	4	-5.90E+01	4	optimal	-5.90E+01	4	optimal
hong	4	1	1.35E+00	8	optimal	1.35E+00	8	optimal
hs006	2	1	0.00E+00	5	optimal	0.00E+00	5	optimal
hs007	2	1	-1.73E+00	8	optimal	-1.73E+00	8	optimal
hs008	2	2	-1.00E+00	6	optimal	-1.00E+00	6	optimal
hs009	2	1	-5.00E-01	6	optimal	-5.00E-01	6	optimal
hs010	2	1	-1.00E+00	9	optimal	-1.00E+00	9	optimal
hs011	2	1	-8.50E+00	5	optimal	-8.50E+00	5	optimal
hs012	2	1	-3.00E+01	7	optimal	-3.00E+01	7	optimal
hs013	2	1	1.00E+00	30	optimal	1.00E+00	30	optimal
hs014	2	2	1.39E+00	5	optimal	1.39E+00	5	optimal
hs015	2	2	3.60E+02	18	optimal	3.60E+02	18	optimal
hs016	2	2	2.50E-01	7	optimal	2.50E-01	7	optimal

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Table 9 -- cont'd

			KNITRO/DIR			KNITRO/DIR/NEW		
problem	n	m	F	itr	termination	F	itr	termination
hs017	2	2	1.00E+00	6	optimal	1.00E+00	6	optimal
hs018	2	2	5.00E+00	8	optimal	5.00E+00	8	optimal
hs019	2	2	-6.96E+03	13	optimal	-6.96E+03	13	optimal
hs020	2	3	4.02E+01	5	optimal	4.02E+01	5	optimal
hs021	2	1	-1.00E+02	6	optimal	-1.00E+02	6	optimal
hs022	2	2	1.00E+00	4	optimal	1.00E+00	4	optimal
hs023	2	5	2.00E+00	7	optimal	2.00E+00	7	optimal
hs024	2	2	-1.00E+00	4	optimal	-1.00E+00	4	optimal
hs026	3	1	2.17E-12	19	optimal	2.17E-12	19	optimal
hs027	3	1	4.00E-02	18	optimal	4.00E-02	18	optimal
hs028	3	1	1.11E-31	2	optimal	1.11E-31	2	optimal
hs029	3	1	-2.26E+01	6	optimal	-2.26E+01	6	optimal
hs030	3	1	1.00E+00	6	optimal	1.00E+00	6	optimal
hs031	3	1	6.00E+00	4	optimal	6.00E+00	4	optimal
hs032	3	2	1.00E+00	5	optimal	1.00E+00	5	optimal
hs033	3	2	-4.59E+00	6	optimal	-4.59E+00	6	optimal
hs034	3	2	-8.34E-01	5	optimal	-8.34E-01	5	optimal
hs035	3	1	1.11E-01	6	optimal	1.11E-01	6	optimal
hs036	3	1	-3.30E+03	7	optimal	-3.30E+03	7	optimal
hs037	3	1	-3.46E+03	6	optimal	-3.46E+03	6	optimal
hs039	4	2	-1.00E+00	23	optimal	-1.00E+00	23	optimal
hs040	4	3	-2.50E-01	3	optimal	-2.50E-01	3	optimal
hs041	4	1	1.93E+00	4	optimal	1.93E+00	4	optimal
hs042	3	1	1.39E+01	3	optimal	1.39E+01	3	optimal
hs043	4	3	-4.40E+01	7	optimal	-4.40E+01	7	optimal
hs044	4	6	-1.50E+01	5	optimal	-1.50E+01	5	optimal
hs046	5	2	1.85E-09	10	optimal	1.85E-09	10	optimal
hs047	5	3	2.57E-11	17	optimal	2.57E-11	17	optimal
hs048	5	2	9.86E-31	2	optimal	9.86E-31	2	optimal
hs049	5	2	1.38E-09	16	optimal	1.38E-09	16	optimal
hs050	5	3	6.38E-13	8	optimal	6.38E-13	8	optimal
hs051	5	3	1.05E-30	2	optimal	1.05E-30	2	optimal
hs052	5	3	5.33E+00	2	optimal	5.33E+00	2	optimal
hs053	5	3	4.09E+00	4	optimal	4.09E+00	4	optimal
hs054	6	1	1.93E-01	6	optimal	1.93E-01	6	optimal
hs055	6	6	6.33E+00	4	optimal	6.33E+00	4	optimal
hs056	7	4	-3.46E+00	5	optimal	-3.46E+00	5	optimal
hs057	2	1	3.06E-02	28	optimal	3.06E-02	28	optimal
hs059	2	3	-6.75E+00	10	optimal	-6.75E+00	10	optimal
hs060	3	1	3.26E-02	7	optimal	3.26E-02	7	optimal
hs061	3	2	-1.44E+02	7	optimal	-1.44E+02	7	optimal
hs062	3	1	-2.63E+04	6	optimal	-2.63E+04	6	optimal
hs063	3	2	9.62E+02	5	optimal	9.62E+02	5	optimal
hs064	3	1	6.30E+03	15	optimal	6.30E+03	15	optimal
hs065	3	1	9.54E-01	7	optimal	9.54E-01	7	optimal
hs066	3	2	5.18E-01	5	optimal	5.18E-01	5	optimal
hs067	10	7	-1.16E+03	9	optimal	-1.16E+03	9	optimal
hs070	4	1	1.75E-01	22	optimal	1.75E-01	22	optimal
hs071	4	2	1.70E+01	6	optimal	1.70E+01	6	optimal
hs072	4	2	7.28E+02	19	optimal	7.28E+02	19	optimal
hs073	4	3	2.99E+01	7	optimal	2.99E+01	7	optimal
hs074	4	4	5.13E+03	7	optimal	5.13E+03	7	optimal
hs075	4	4	5.17E+03	7	optimal	5.17E+03	7	optimal
hs076	4	3	-4.68E+00	6	optimal	-4.68E+00	6	optimal
hs077	5	2	2.42E-01	8	optimal	2.42E-01	8	optimal
hs078	5	3	-2.92E+00	4	optimal	-2.92E+00	4	optimal
hs079	5	3	7.88E-02	4	optimal	7.88E-02	4	optimal
hs080	5	3	5.39E-02	5	optimal	5.39E-02	5	optimal

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Table 9 -- cont'd

			KNITRO/DIR			KNITRO/DIR/NEW		
problem	n	m	F	itr	termination	F	itr	termination
hs081	5	3	5.39E-02	6	optimal	5.39E-02	6	optimal
hs083	5	3	-3.07E+04	8	optimal	-3.07E+04	8	optimal
hs084	5	3	-5.28E+06	6	optimal	-5.28E+06	6	optimal
hs085	5	36	-1.91E+00	16	optimal	-1.91E+00	16	optimal
hs086	5	6	-3.23E+01	5	optimal	-3.23E+01	5	optimal
hs087	9	4	8.83E+03	11	optimal	8.83E+03	11	optimal
hs088	2	1	1.36E+00	13	optimal	1.36E+00	13	optimal
hs089	3	1	1.28E-10	8	infeasible	1.36E+00	26	optimal
hs090	4	1	1.36E+00	60	optimal	1.36E+00	54	optimal
hs091	5	1	1.36E+00	35	optimal	1.36E+00	35	optimal
hs092	6	1	1.36E+00	38	optimal	1.36E+00	38	optimal
hs093	6	2	1.35E+02	6	optimal	1.35E+02	6	optimal
hs095	6	4	1.56E-02	19	optimal	1.56E-02	22	optimal
hs096	6	4	1.56E-02	25	optimal	1.56E-02	25	optimal
hs097	6	4	3.14E+00	21	optimal	3.14E+00	21	optimal
hs098	6	4	4.07E+00	14	optimal	4.07E+00	14	optimal
hs099	19	14	-8.31E+08	3	optimal	-8.31E+08	3	optimal
hs100	7	4	6.81E+02	6	optimal	6.81E+02	6	optimal
hs100lnp	7	2	6.81E+02	8	optimal	6.81E+02	8	optimal
hs101	7	6	1.81E+03	92	optimal	1.81E+03	36	optimal
hs102	7	6	9.12E+02	50	optimal	9.12E+02	36	optimal
hs103	7	6	5.44E+02	35	optimal	5.44E+02	36	optimal
hs104	8	6	3.95E+00	7	optimal	3.95E+00	7	optimal
hs106	8	6	7.05E+03	12	optimal	7.05E+03	12	optimal
hs107	9	6	5.06E+03	8	optimal	5.06E+03	8	optimal
hs108	9	13	-6.75E-01	12	optimal	-6.75E-01	12	optimal
hs109	9	10	5.33E+03	14	optimal	5.33E+03	14	optimal
hs111	10	3	-4.78E+01	10	optimal	-4.78E+01	10	optimal
hs111lnp	10	3	-4.78E+01	10	optimal	-4.78E+01	10	optimal
hs112	10	3	-4.78E+01	6	optimal	-4.78E+01	6	optimal
hs112x	10	4	-4.74E+01	35	optimal	-4.68E+01	37	infeasible
hs113	10	8	2.43E+01	7	optimal	2.43E+01	7	optimal
hs114	10	11	-1.77E+03	10	optimal	-1.77E+03	10	optimal
hs116	13	15	9.76E+01	22	optimal	9.76E+01	29	optimal
hs117	15	5	3.23E+01	14	optimal	3.23E+01	14	optimal
hs118	15	17	6.65E+02	14	optimal	6.65E+02	14	optimal
hs119	16	8	2.45E+02	9	optimal	2.45E+02	9	optimal
hs21mod	7	1	-9.60E+01	9	optimal	-9.60E+01	9	optimal
hs268	5	5	1.31E-04	9	optimal	1.31E-04	9	optimal
hs35mod	2	1	2.50E-01	9	optimal	2.50E-01	9	optimal
hs44new	4	5	-1.50E+01	5	optimal	-1.50E+01	5	optimal
hs99exp	28	21	-1.01E+09	16	optimal	-1.01E+09	16	optimal
hubfit	2	1	1.69E-02	4	optimal	1.69E-02	4	optimal
hues-mod	10000	2	3.48E+07	15	optimal	3.48E+07	15	optimal
huestis	10000	2	3.48E+11	13	optimal	3.48E+11	13	optimal
hvycrash	201	150	-1.31E-02	116	optimal	-1.31E-02	44	optimal
kissing	127	903	8.45E-01	75	optimal	8.45E-01	75	optimal
kiwcresc	3	2	-7.49E-09	9	optimal	-7.49E-09	9	optimal
ksip	20	1000	5.76E-01	18	optimal	5.76E-01	18	optimal
lakes	90	78	3.51E+05	13	optimal	3.51E+05	13	optimal
launch	25	29	3.31E-01	2102	term infeas	4.10E-06	2792	infeasible
lch	600	1	-4.29E+00	22	optimal	-4.29E+00	22	optimal
lewispol	6	9	2.33E+00	47	infeasible	2.40E+00	12	infeasible
linspanh	72	32	-7.70E+01	6	optimal	-7.70E+01	6	optimal
liswet1	10002	10000	4.73E+01	48	optimal	4.73E+01	48	optimal
liswet10	10002	10000	2.62E+01	165	optimal	2.62E+01	165	optimal
liswet11	10002	10000	3.49E+01	743	optimal	3.49E+01	743	optimal
liswet12	10002	10000	-4.99E+03	635	optimal	-4.99E+03	635	optimal

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Table 9 -- cont'd

			KNITRO/DIR			KNITRO/DIR/NEW		
problem	n	m	F	itr	termination	F	itr	termination
liswet2	10002	10000	2.50E+01	20	optimal	2.50E+01	20	optimal
liswet3	10002	10000	2.50E+01	12	optimal	2.50E+01	12	optimal
liswet4	10002	10000	2.50E+01	14	optimal	2.50E+01	14	optimal
liswet5	10002	10000	2.50E+01	13	optimal	2.50E+01	13	optimal
liswet6	10002	10000	2.50E+01	14	optimal	2.50E+01	14	optimal
liswet7	10002	10000	2.86E+01	24	optimal	2.86E+01	24	optimal
liswet8	10002	10000	7.07E+02	2196	optimal	7.07E+02	2196	optimal
liswet9	10002	10000	1.15E+02	748	optimal	1.90E+03	3000	itr limit
loadbal	31	31	4.53E-01	8	optimal	4.53E-01	8	optimal
lootsma	3	2	1.41E+00	6	optimal	1.41E+00	6	optimal
lotschd	12	7	2.40E+03	10	optimal	2.40E+03	10	optimal
lsnnodoc	5	4	1.23E+02	7	optimal	1.23E+02	7	optimal
lsqfit	2	1	3.38E-02	6	optimal	3.38E-02	6	optimal
madsen	3	6	6.16E-01	9	optimal	6.16E-01	9	optimal
madsschj	81	158	-7.97E+02	24	optimal	-7.97E+02	24	optimal
makela1	3	2	-1.41E+00	12	optimal	-1.41E+00	12	optimal
makela2	3	3	7.20E+00	6	optimal	7.20E+00	6	optimal
makela3	21	20	3.85E-08	17	optimal	3.85E-08	17	optimal
makela4	21	40	5.41E-07	5	optimal	5.41E-07	5	optimal
manne	1094	730	-9.73E-01	174	optimal	-9.73E-01	174	optimal
maratos	2	1	-1.00E+00	3	optimal	-1.00E+00	3	optimal
matrix2	6	2	3.62E-08	13	optimal	3.62E-08	13	optimal
mconcon	15	11	-6.23E+03	6	optimal	-6.23E+03	6	optimal
mifflin1	3	2	-1.00E+00	5	optimal	-1.00E+00	5	optimal
mifflin2	3	2	-1.00E+00	10	optimal	-1.00E+00	10	optimal
minc44	303	262	2.57E-03	23	optimal	2.57E-03	23	optimal
minmaxbd	5	20	1.16E+02	29	optimal	1.16E+02	29	optimal
minmaxrb	3	4	3.25E-08	5	optimal	3.25E-08	5	optimal
minperm	1113	1033	3.63E-04	52	optimal	3.63E-04	67	optimal
mistake	9	13	-1.00E+00	21	optimal	-1.00E+00	21	optimal
model	60	32	5.74E+03	9	optimal	5.74E+03	9	optimal
mosarqp1	2500	700	-9.53E+02	11	optimal	-9.53E+02	11	optimal
mosarqp2	900	600	-1.60E+03	11	optimal	-1.60E+03	11	optimal
mwright	5	3	2.50E+01	7	optimal	2.50E+01	7	optimal
ncvxqp1	1000	500	-7.16E+07	36	optimal	-7.16E+07	36	optimal
ncvxqp2	1000	500	-5.78E+07	34	optimal	-5.78E+07	34	optimal
ncvxqp3	1000	500	-3.10E+07	53	optimal	-3.10E+07	53	optimal
ncvxqp4	1000	250	-9.40E+07	36	optimal	-9.40E+07	36	optimal
ncvxqp5	1000	250	-6.63E+07	37	optimal	-6.63E+07	37	optimal
ncvxqp6	1000	250	-3.47E+07	72	optimal	-3.47E+07	72	optimal
ncvxqp7	1000	750	-4.35E+07	31	optimal	-4.35E+07	31	optimal
ncvxqp8	1000	750	-3.05E+07	53	optimal	-3.05E+07	96	optimal
ncvxqp9	1000	750	-2.16E+07	52	optimal	-2.16E+07	52	optimal
ngone	97	1273	-6.41E-01	33	optimal	-6.41E-01	33	optimal
odfits	10	6	-2.38E+03	6	optimal	-2.38E+03	6	optimal
oet1	3	1002	5.38E-01	13	optimal	5.38E-01	13	optimal
oet2	3	1002	8.72E-02	11	optimal	8.72E-02	11	optimal
oet3	4	1002	4.51E-03	11	optimal	4.51E-03	11	optimal
oet7	7	1002	2.07E-03	248	optimal	8.72E-02	416	optimal
optcdeg2	1198	799	2.30E+02	26	optimal	2.30E+02	26	optimal
optcdeg3	1198	799	4.61E+01	17	optimal	4.61E+01	17	optimal
optcntrl	28	20	5.50E+02	10	optimal	5.50E+02	10	optimal
optctrl3	118	80	2.05E+03	13	optimal	2.05E+03	13	optimal
optctrl6	118	80	2.05E+03	13	optimal	2.05E+03	13	optimal
optmass	66	55	-1.90E-01	15	optimal	-1.90E-01	15	optimal
optprloc	30	29	-1.64E+01	9	optimal	-1.64E+01	9	optimal
orthrdm2	4003	2000	1.56E+02	5	optimal	1.56E+02	5	optimal
orthrds2	203	100	3.74E+01	11	optimal	3.74E+01	11	optimal

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Table 9 -- cont'd

			KNITRO/DIR			KNITRO/DIR/NEW		
problem	n	m	F	itr	termination	F	itr	termination
orthrega	517	256	1.41E+03	21	optimal	1.41E+03	21	optimal
orthregb	27	6	3.35E-15	2	optimal	3.35E-15	2	optimal
orthregc	10005	5000	1.90E+02	11	optimal	1.90E+02	11	optimal
orthregd	10003	5000	1.52E+03	6	optimal	1.52E+03	6	optimal
orthrege	36	20	1.04E+01	46	optimal	1.04E+01	46	optimal
orthrgdm	10003	5000	1.51E+03	6	optimal	1.51E+03	6	optimal
orthrgds	10003	5000	1.78E+03	41	optimal	1.78E+03	41	optimal
pentagon	6	12	1.37E-04	10	optimal	1.37E-04	10	optimal
polak1	3	2	2.72E+00	6	optimal	2.72E+00	6	optimal
polak2	11	2	5.46E+01	8	optimal	5.46E+01	8	optimal
polak3	12	10	5.93E+00	20	optimal	5.93E+00	20	optimal
polak4	3	3	-2.30E-08	3	optimal	-2.30E-08	3	optimal
polak5	3	2	5.00E+01	18	optimal	5.00E+01	18	optimal
polak6	5	4	-4.40E+01	12	optimal	-4.40E+01	12	optimal
portfl1	12	1	2.05E-02	7	optimal	2.05E-02	7	optimal
portfl2	12	1	2.97E-02	7	optimal	2.97E-02	7	optimal
portfl3	12	1	3.27E-02	8	optimal	3.27E-02	8	optimal
portfl4	12	1	2.63E-02	7	optimal	2.63E-02	7	optimal
portfl6	12	1	2.58E-02	7	optimal	2.58E-02	7	optimal
powell20	1000	1000	5.21E+07	15	optimal	5.21E+07	15	optimal
prodpl0	60	29	6.09E+01	12	optimal	6.09E+01	12	optimal
prodpl1	60	29	5.30E+01	9	optimal	5.30E+01	9	optimal
pt	2	501	1.78E-01	13	optimal	1.78E-01	13	optimal
qpcboei1	372	288	1.44E+07	22	optimal	1.44E+07	22	optimal
qpcboei2	143	125	8.29E+06	33	optimal	8.29E+06	33	optimal
qpcstair	385	356	6.20E+06	24	optimal	6.20E+06	24	optimal
qpnboei1	372	288	8.52E+06	182	optimal	8.46E+06	148	optimal
qpnboei2	143	125	1.24E+06	1226	optimal	1.41E+33	3000	itr limit
qpnstair	385	356	5.15E+06	201	optimal	5.15E+06	84	optimal
reading1	10001	5000	-1.60E-01	15	optimal	-1.60E-01	15	optimal
reading2	15001	10000	-1.14E-02	7	optimal	-1.14E-02	7	optimal
robot	7	2	5.46E+00	6	optimal	5.46E+00	6	optimal
rosenmmx	5	4	-4.40E+01	7	optimal	-4.40E+01	7	optimal
s332	2	100	2.99E+01	10	optimal	2.99E+01	10	optimal
s365mod	7	5	5.21E+01	13	optimal	5.22E+01	15	optimal
sawpath	589	782	3.91E+05	3000	itr limit	7.05E+04	3000	itr limit
simpllpa	2	2	1.00E+00	6	optimal	1.00E+00	6	optimal
simpllpb	2	3	1.10E+00	7	optimal	1.10E+00	7	optimal
sinrosnb	1000	999	-9.99E+04	0	optimal	-9.99E+04	0	optimal
sipow1	2	10000	-1.00E+00	15	optimal	-1.00E+00	15	optimal
sipow1m	2	10000	-1.00E+00	15	optimal	-1.00E+00	15	optimal
sipow2	2	5000	-1.00E+00	16	optimal	-1.00E+00	16	optimal
sipow2m	2	5000	-1.00E+00	19	optimal	-1.00E+00	19	optimal
sipow3	4	9998	5.36E-01	13	optimal	5.36E-01	13	optimal
sipow4	4	10000	2.73E-01	12	optimal	2.73E-01	12	optimal
smbank	117	64	-7.13E+06	17	optimal	-7.13E+06	17	optimal
smmpsf	720	263	1.05E+06	46	optimal	1.05E+06	46	optimal
snake	2	2	-3.51E+04	3000	itr limit	-2.32E+03	3000	itr limit
sosqp2	20000	10001	-5.00E+03	15	optimal	-5.00E+03	15	optimal
spanhyd	72	32	2.40E+02	9	optimal	2.40E+02	9	optimal
spiral	3	2	-2.91E-08	42	optimal	-2.91E-08	42	optimal
sreadin3	10000	5000	-2.55E-05	1	optimal	-2.55E-05	1	optimal
sseblin	192	72	1.62E+07	9	optimal	1.62E+07	9	optimal
ssebnln	192	96	1.62E+07	29	optimal	1.62E+07	29	optimal
ssnlbeam	31	20	3.38E+02	14	optimal	3.38E+02	14	optimal
stancmin	3	2	4.25E+00	9	optimal	4.25E+00	9	optimal
static3	434	96	-3.06E+21	99	unbounded	-3.06E+21	99	unbounded
steenbra	432	108	1.70E+04	19	optimal	1.70E+04	19	optimal

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Table 9 -- cont'd

			KNITRO/DIR			KNITRO/DIR/NEW		
problem	n	m	F	itr	termination	F	itr	termination
steenbrb	468	108	9.24E+03	65	optimal	9.24E+03	65	optimal
steenbrc	540	126	2.04E+04	127	optimal	2.04E+04	127	optimal
steenbrd	468	108	9.65E+03	98	optimal	9.65E+03	98	optimal
steenbre	540	126	2.75E+04	825	optimal	2.75E+04	825	optimal
steenbrf	468	108	7.95E+02	279	optimal	2.85E+02	121	optimal
steenbrg	540	126	2.74E+04	45	optimal	2.74E+04	45	optimal
supersim	2	2	6.67E-01	2	optimal	6.67E-01	2	optimal
svanberg	5000	5000	8.36E+03	16	optimal	8.36E+03	16	optimal
swopf	82	91	6.79E-02	9	optimal	6.79E-02	9	optimal
synthes1	6	6	7.59E-01	9	optimal	7.59E-01	9	optimal
tame	2	1	0.00E+00	5	optimal	0.00E+00	5	optimal
tfi2	3	10000	6.49E-01	9	optimal	6.49E-01	9	optimal
trainf	20000	10002	3.10E+00	30	optimal	3.10E+00	30	optimal
trainh	20000	10002	1.23E+01	53	optimal	1.23E+01	53	optimal
trimloss	142	72	9.06E+00	19	optimal	9.06E+00	19	optimal
try-b	2	1	2.50E-17	9	optimal	2.50E-17	9	optimal
twirism1	343	313	-1.00E+00	2304	optimal	-1.00E+00	89	optimal
twobars	2	2	1.51E+00	5	optimal	1.51E+00	5	optimal
ubh1	17997	12000	1.12E+00	5	optimal	1.12E+00	5	optimal
ubh5	19997	14000	1.12E+00	3	optimal	1.12E+00	3	optimal
vanderm1	100	99	3.30E-07	28	optimal	3.30E-07	28	optimal
vanderm2	100	99	3.29E-07	28	optimal	3.29E-07	28	optimal
vanderm3	100	99	3.75E-06	37	optimal	3.75E-06	37	optimal
vanderm4	9	8	2.21E-09	17	optimal	2.21E-09	17	optimal
womflet	3	3	6.05E+00	9	optimal	6.05E+00	9	optimal
yao	2000	1999	1.98E+02	36	optimal	1.98E+02	36	optimal
zecevic2	2	2	-4.12E+00	7	optimal	-4.12E+00	7	optimal
zecevic3	2	2	9.73E+01	7	optimal	9.73E+01	7	optimal
zecevic4	2	2	7.56E+00	6	optimal	7.56E+00	6	optimal
zigzag	58	50	3.16E+00	16	optimal	3.16E+00	16	optimal
zy2	3	1	2.00E+00	5	optimal	2.00E+00	5	optimal