Incorporating Minimum Frobenius Norm Models in Direct Search[*]

A. L. Custódio[†] H. Rocha[‡] L. N. Vicente[§]

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Abstract

The goal of this paper is to show that the use of minimum Frobenius norm quadratic models can improve the performance of direct-search methods. The approach taken here is to maintain the structure of directional direct-search methods, organized around a search and a poll step, and to use the set of previously evaluated points generated during a direct-search run to build the models. The minimization of the models within a trust region provides an enhanced search step. Our numerical results show that such a procedure can lead to a significant improvement of direct search for smooth, piecewise smooth, and stochastic and nonstochastic noisy problems.

1 Introduction

Direct-search methods are a very popular class of methods for derivative-free optimization whose distinctive feature is to guide the new algorithmic actions solely based on simple comparison rules of objective function values, without any attempt to approximate derivatives or build models. With some exceptions, like the Nelder-Mead methods, most of the direct-search methods are relatively inefficient since no attempt is made to explore curvature. Direct-search methods of directional type (coordinate search, generalized pattern

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[†] CMA-UNL, Department of Mathematics, FCT-UNL, Quinta da Torre, 2829-516 Caparica, Portugal (alcustodio@fct.unl.pt).

[‡] Catholic University, Pólo de Viseu, 3504-505 Viseu, Portugal (hrocha@mat.uc.pt).

[§] CMUC, Department of Mathematics, University of Coimbra, 3001-454 Coimbra, Portugal (lnv@mat.uc.pt).

search, generating set search, mesh adaptive direct search) exhibit interesting convergence properties, in particular for nonsmooth problems, and are relatively easy to code and to parallelize.

Model-based methods, in particular interpolation-based trust-region methods, have been shown to be more efficient and robust than direct search on a relatively well-representative test suit of unconstrained optimization problems [10]. Although this has been known among researchers who have tested both classes of methods, these recent results for piecewise smooth and noisy problems are nevertheless relatively surprising. One of the key ingredients of these model-based implementations is the use of quadratic models computed in an underdetermined form (using fewer points than the number of basis components) but enforcing the Frobenius norm of the Hessian (or of the variation in the Hessian) of the models to be as small as possible.

It is therefore natural to ask for a combination of both techniques. In this paper we describe and test what might be considered as a natural way to accomplish such a task. We form minimum Frobenius norm (MFN) models based on sample points for which the objective function has already been evaluated during the course of direct search. It is expected then that the minimization of these MFN models speeds up the direct-search run. There are, however, a number of variants in which this simple idea can be implemented. We will report the various possibilities and describe the one which we found to be the most successful. The final numerical results show a significant improvement in efficiency for all types of problems, although the modified direct-search method is still inferior than model-based methods for smooth and nonstochastic noisy problems. Focusing on unconstrained optimization, the best version we identified considers opportunistic polling and builds the MFN models by minimizing the Hessian norm rather than its variation. The resulting hybrid algorithm is competitive for all the different classes of problems.

The paper is organized in the following way. In Section 2 we provide a short summary of MFN models. Then, in Section 3, we show how to incorporate these models into a directional direct-search framework. Section 4 reports our numerical experiments and conclusions. We point out that all norms in this paper are Euclidean.

2 Minimum Frobenius norm models

Given a sample set $Y = \{y^0, y^1, \ldots, y^p\}$, a polynomial basis

$$\phi = \{\phi_0(x), \phi_1(x), \ldots, \phi_q(x)\},$$

and a polynomial model $m(y) = \alpha^\top \phi(y)$, the conditions for polynomial interpolation can be written as a system of linear equations:

$$M(\phi, Y)\alpha \; = \; f(Y), \tag{1}$$

where

$$M(\phi, Y) = \begin{bmatrix} \phi_0(y^0) & \phi_1(y^0) & \cdots & \phi_q(y^0) \\ \phi_0(y^1) & \phi_1(y^1) & \cdots & \phi_q(y^1) \\ \vdots & \vdots & \vdots & \vdots \\ \phi_0(y^p) & \phi_1(y^p) & \cdots & \phi_q(y^p) \end{bmatrix} \text{ and } f(Y) = \begin{bmatrix} f(y^0) \\ f(y^1) \\ \vdots \\ f(y^p) \end{bmatrix}.$$

In this paper we use the natural basis of monomials which appears in Taylor models (in two dimensions we have $\phi = \{1, x_1, x_2, x_1^2/2, x_2^2/2, x_1 x_2\}$). The system (1) is determined when $p = q$, overdetermined when $p > q$, or underdetermined when $p < q$. In this later case, we can select a solution by computing the one with the minimum ℓ_2-norm, or the one with the minimum Frobenius norm if only the size of the quadratic coefficients is considered.

When $p \geq n + 1$, the error bounds for polynomial interpolation typically obbey (see [4])

$$\|\nabla f(y) - \nabla m(y)\| \; \leq \; [C_p C_f \Lambda] \; \Delta \qquad \forall y \in B(x; \Delta),$$

where Y is contained in the ball $B(x; \Delta)$ centered at x and of radius Δ, C_p is a positive constant depending on p, $C_f > 0$ measures the smoothness of f (e.g., the Lipschitz constant of ∇f), and $\Lambda > 0$ is a Λ–poisedness constant related to the geometry of Y. The original definition of Λ–poisedness says that the maximum absolute value of the Lagrange polynomials in $B(x; \Delta)$ is bounded by Λ. An equivalent definition of Λ–poisedness is

$$\|M(\phi, Y_{scaled})^\dagger\| \leq \Lambda,$$

with Y_{scaled} obtained from Y such that $Y_{scaled} \subset B(0; 1)$ and one of the points in Y_{scaled} has norm one.

The underdetermined case of interest to us is quadratic polynomial interpolation, corresponding to $q = (n+1)(n+2)/2 - 1$ and $p < q$. It is convenient to write these quadratic models also in the form

$$m(y) \; = \; c + g^\top y + \frac{1}{2} y^\top H y.$$

It will be necessary to explore the partition of the matrix $M(\phi, Y)$ into linear and quadratic terms

$$M(\phi, Y) \; = \; \left[\; M(\phi_L, Y) \quad M(\phi_Q, Y) \; \right]$$

(in two dimensions this corresponds to $\phi_L = \{1, x_1, x_2\}$ and $\phi_Q = \{x_1^2/2, x_2^2/2, x_1 x_2\}$). Using this notation we also have $m(y) = \alpha_L^\top \phi_L(y) + \alpha_Q^\top \phi_Q(y)$. One can state that Y is Λ_L–poised for linear interpolation or regression when

$$\|M(\phi_L, Y_{scaled})^\dagger\| \leq \Lambda_L.$$

The following result provides a general error bound for underdetermined quadratic polynomial interpolation [4].

Theorem 2.1 *Let f be a continuously differentiable function in an open set containing the ball $B(x;\Delta)$ with Lipschitz continuous gradient in $B(x;\Delta)$ (and Lipschitz constant $C_f > 0$). If Y is Λ_L–poised for linear interpolation or regression then*

$$\|\nabla f(y) - \nabla m(y)\| \ \leq \ C_p \Lambda_L \left[C_f + \|H\|\right] \Delta \qquad \forall y \in B(x;\Delta).$$

where H is the Hessian of the model and C_p is a positive constant dependent on p.

The constant multiplying Δ in this error bound is strongly dependent on the norm of the model Hessian H. Thus, it is not surprising that the minimum Frobenius norm (MFN) models are built by minimizing the entries of the Hessian (in the Frobenius norm) subject to the interpolation conditions:

$$\begin{array}{ll} \min & \frac{1}{4}\|H\|_F^2 \\ \text{s.t.} & c + g^\top(y^i) + \frac{1}{2}(y^i)^\top H(y^i) \ = \ f(y^i), \quad i = 0, \ldots, p, \end{array} \qquad (2)$$

or, equivalently,

$$\begin{array}{ll} \min & \frac{1}{2}\|\alpha_Q\|^2 \\ \text{s.t.} & M(\phi, Y)\alpha \ = \ f(Y). \end{array}$$

The solution of this quadratic problem requires a linear solve involving the matrix

$$F(\phi, Y) \ = \ \left[\begin{array}{cc} M(\phi_Q, Y) M(\phi_Q, Y)^\top & M(\phi_L, Y) \\ M(\phi_L, Y)^\top & 0 \end{array} \right].$$

The definition of Λ_F–poisedness in the minimum Frobenius norm sense, which we used in our computational tests, is given by the condition

$$\|F(\phi, Y_{scaled})^{-1}\| \ \leq \ \Lambda_F.$$

These MFN models are used in the `DFO` code of Scheinberg [1], which implements an interpolation-based trust-region method. It is possible to show that for these models the Hessian is bounded [4]:

Theorem 2.2 *Let f be a continuously differentiable function in an open set containing the ball $B(x;\Delta)$ with Lipschitz continuous gradient in $B(x;\Delta)$ (and Lipschitz constant $C_f > 0$). If Y is Λ_F–poised in the minimum Frobenius norm sense then*

$$\|H\| \;\leq\; C_{p,q} C_f \Lambda_F,$$

where H is the Hessian of the model and $C_{p,q}$ is a positive constant depending on p and q.

These two theorems together yield the following error bound for MFN models:

$$\|\nabla f(y) - \nabla m(y)\| \;\leq\; C_p \Lambda_L C_f \left[1 + C_{p,q}\Lambda_F\right] \Delta \quad \forall y \in B(x;\Delta).$$

The conclusion is that MFN models are fully linear, as defined in [4], reproducing well the accuracy of first-order Taylor models.

An alternative suggested by Powell [12] is to minimize the difference between the current and previous Hessians (in the Frobenius norm):

$$\begin{array}{ll} \min & \frac{1}{4}\|H - H^{old}\|_F^2 \\ \text{s.t.} & c + g^\top (y^i) + \frac{1}{2}(y^i)^\top H (y^i) \;=\; f(y^i), \quad i = 0,\ldots,p. \end{array} \tag{3}$$

The resulting models are called least updating MFN models and are used in Powell's `NEWUOA` interpolation-based trust-region solver [13]. Powell provided for these models the following theoretical insight [12].

Theorem 2.3 *If f is itself a quadratic function then:*

$$\|H - \nabla^2 f\| \;\leq\; \|H^{old} - \nabla^2 f\|.$$

MFN models are being used by other authors in trust-region interpolation-based methods (see, e.g., [14]) but their potential in optimization is still to be fully explored.

3 Using MFN in direct search

Direct-search methods of directional type have been extensively analyzed in the literature [4, 9]. We are interested in studying the possible positive impact of using MFN models to enhance this class of methods. As a basis for our study we selected coordinate search which has been shown to behave well for unconstrained optimization [5, 6] among other generalized pattern search methods. The poll step in coordinate search operates with the positive basis

$D_k = D_\oplus = [\,I \;\; -I\,]$ as the set of poll vectors and evaluates the objective function at the points in the poll set

$$P_k \;=\; \{x_k + \alpha_k d, \;\; d \in D_k\}.$$

Polling can be opportunistic (stopping once a decrease in the value of the objective function is found) or complete (identifying the lowest of the poll points). A search step can be applied before the poll step by considering a finite number of points in the current mesh:

$$M_k \;=\; \{x_k + \alpha_k D_k z, \;\; z \in \mathbb{Z}^{|D_k|}\}.$$

If a point in M_k is identified where the objective function is lower than $f(x_k)$, then such a point becomes the new iterate, and both the search step and the iteration are considered successful. Otherwise, a poll step is then applied. The poll step may be unsuccessful (and so is the iteration) when no point in P_k provides a function value lower than $f(x_k)$. The step size or mesh size parameter $\alpha_k > 0$ is decreased at unsuccessful iterations and increased or kept constant at successful poll or search steps.

The code `SID-PSM` is a MATLAB [2] implementation of a generalized pattern search method, developed by the authors, that uses simplex derivatives (i.e., derivatives of polynomial interpolation models) in the search and poll steps. The code handles constraints (if their derivatives are provided) but this is not treated in this paper. It also allows the selection of different ordering strategies for the poll vectors, taking as the current default ordering the one according to a negative simplex gradient. However, the search step in `SID-PSM` has been very crude and consisted of the minimization of a quadratic model with a diagonal simplex Hessian.

Our idea is to form and minimize MFN models in the search step and thus improve the performance of `SID-PSM`. The motivation is twofold. On the one hand, we know that MFN models provide very good numerical results within the `DFO` and `NEWUOA` interpolation-based trust-region codes. On the other hand, we know that direct-search methods of directional type work well for noisy/nonsmooth problems. Our goal is then to derive a hybrid method capable of being competitive with interpolation-based trust-region methods for smooth problems and perhaps better than these methods for noisy/nonsmooth problems.

The best way of incorporating MFN models into directional direct search that we found for derivative-free unconstrained optimization is as follows:

- The underlying method uses the coordinate-search directions (the coordinate vectors and their negatives) and the directions e and $-e$, where e stands for a vector of ones of dimension n.

- In the search step, one computes a MFN model when there are more than $n+1$ points (for which the objective function has been previously computed) in a ball (or trust region)

  $$B(x_k;\Delta_k) = \{x \in \mathbb{R}^n : \|x - x_k\| \leq \Delta_k\}$$

  centered at x_k with radius

  $$\Delta_k \; = \; \sigma_k \, \alpha_{k-1} \, \max_{d \in D_{k-1}} \|d\|,$$

  where D_{k-1} is the set of poll vectors considered in the last iteration and σ_k takes the value 1 if the previous iteration was unsuccessful, or 2 otherwise. When building a MFN model, the value of the trust-region radius is never allowed to be smaller than 10^{-5}.

  When there are more than $(n+1)(n+2)/2$ points in $B(x_k;\Delta_k)$, the quadratic model is built with exactly $(n+1)(n+2)/2$ points. Since the model has a local purpose, 80% of the necessary points are selected as the ones nearest to the current iterate. The last 20% are chosen as the ones further away from the current iterate, in an attempt of preserving geometry and diversifying the information used in the model computation.

  Note that we consider all the points previously evaluated (`store-all` mode in the code `SID-PSM`), meeting the conditions above, and not just those which lead to a decrease in the objective function value (`store-successful`).

- The geometry control of the sample set used for the MFN model computation is extremely loose. In fact, in the best version found we never test the condition number of the matrix $F(\phi, Y_{scaled})$. Since the search step is optional, this is an attempt to explore all model information independently of the quality of the underlying sample sets (in what resembles, in some way, the observations made in [7], in the context of the use of complete quadratic interpolation models in trust-region methods, about the use of badly poised sample sets).

  Instead of controlling the condition number of $F(\phi, Y)$, what we do is to use the singular value decomposition of this matrix and, before solving the corresponding system which computes the MFN model, replace all singular values smaller than machine precision `eps` by this threshold.

- A search step is always attempted after a first MFN model has been built, by minimizing the MFN model in $B(x_k;\Delta_k)$. If no new MFN model is formed at the current iteration, then one uses the last previously built MFN model.

- The MNF models used are those defined by (2). The least updating MFN models (3) performed worse in our context.

- Polling is opportunistic. The initial ordering of the poll vectors is the one given by $D = [\, e \;\; -e \;\; I \;\; -I \,]$. At each iteration, there is an attempt to order the poll vectors in D_k according to a negative simplex gradient. With this purpose the code tries to identify a subset of points, for which the objective function has been previously evaluated and inside the trust region considered, which satisfies a Λ–poisedness condition. (In this case there is no minimum value for the size of the trust region.) In case of failure, polling is performed cyclicly in D_k, i.e., the first polling vector at the beginning of a new poll step is chosen as the one positioned in D_k right after the last one used in the previous poll step.

In our numerical experiments we used the DGQT routine of the MINPACK2 [11] package to solve the trust-region subproblems consisting of the minimization of the MFN models in the trust regions.

The step-size parameter was maintained for successful iterations and halved when no decrease has been achieved at a given iteration.

4 Numerical experiments and conclusions

To compare our new version of SID-PSM to other algorithms we chose to work with the recently proposed data profiles [10] for derivative-free optimization. Data profiles indicate how well a solver performs, given some computational budget, to reach a specific reduction in function value, measured by

$$f(x_0) - f(x) \;\geq\; (1-\tau)[f(x_0) - f_L],$$

where x_0 is the initial iterate and f_L is the best objective value found by all solvers tested for a specific problem. The computational budget is measured in terms of the number of function evaluations.

The test suite is also the one proposed in [10], where the test problems have been divided into four classes: smooth (53 nonlinear least squares problems obtained from CUTEr functions, with $n \in [2, 12]$); nonstochastic noisy (obtained by adding oscillatory noise to the smooth ones); piecewise smooth (as in the smooth case but using ℓ_1-norms); stochastic noisy (obtained by adding random noise to the smooth ones).

We compared the results obtained for SID-PSM using MFN models against three solvers: NEWUOA [13], a trust-region code based on interpolation by MFN models; NMSMAX [3] an implementation of the Nelder-Mead simplex method; and APPSPACK [8], an implementation of an asynchronous generating set search method mainly derived for parallel computing, but considered here in the serial mode and with a random ordering of directions.

The computational budget consisted of 1500 function evaluations, as we are primarily interested in the behavior of the algorithms for budgets applicable to problems of expensive objective function evaluation. Figures 1, 2, 3, and 4 report the data profiles obtained for the four test sets, considering the two different levels of accuracy $\tau = 10^{-3}$ and $\tau = 10^{-7}$ (Figure 1: smooth problems; Figure 2: nonstochastic noisy problems; Figure 3: piecewise smooth problems; Figure 4: stochastic noisy problems).

In general, independently of the level of accuracy required and of the class of problems considered, the best performance is obtained for NEWUOA. Our implementation, SID-PSM, takes advantage over NEWUOA only for piecewise smooth and stochastic noisy problems and for larger budgets of function evaluations. In these cases, SID-PSM is the best of the four solvers tested.

For an accuracy level of $\tau = 10^{-7}$, SID-PSM is clearly the best among the three direct-search solvers. For a lower level of accuracy ($\tau = 10^{-3}$), it is hard to establish a comparison among these three solvers.

At the highest precision level, the gap between the SID-PSM and NEWUOA data profiles reduces, essentially due to the application of the MFN search steps.

Our conclusion is that the incorporation of MFN models in direct-search methods of directional type is advantageous, resulting in a superior method when compared to Nelder-Mead methods or basic directional direct-search methods. However, our implementation took also into consideration other relevant issues like the selection of poll vectors and its ordering for polling, which had a mild but non-negligible impact in the improvement of the numerical results. Based on the data profiles presented and on the test problems selected, we claim that SID-PSM (using MFN models) is a competitive direct-search approach for unconstrained optimization, which outperforms NEWUOA ability to solve piecewise-smooth and stochastic noisy problems for larger budgets of functions evaluations. The SID-PSM website is located at http://www.mat.uc.pt/sid-psm.

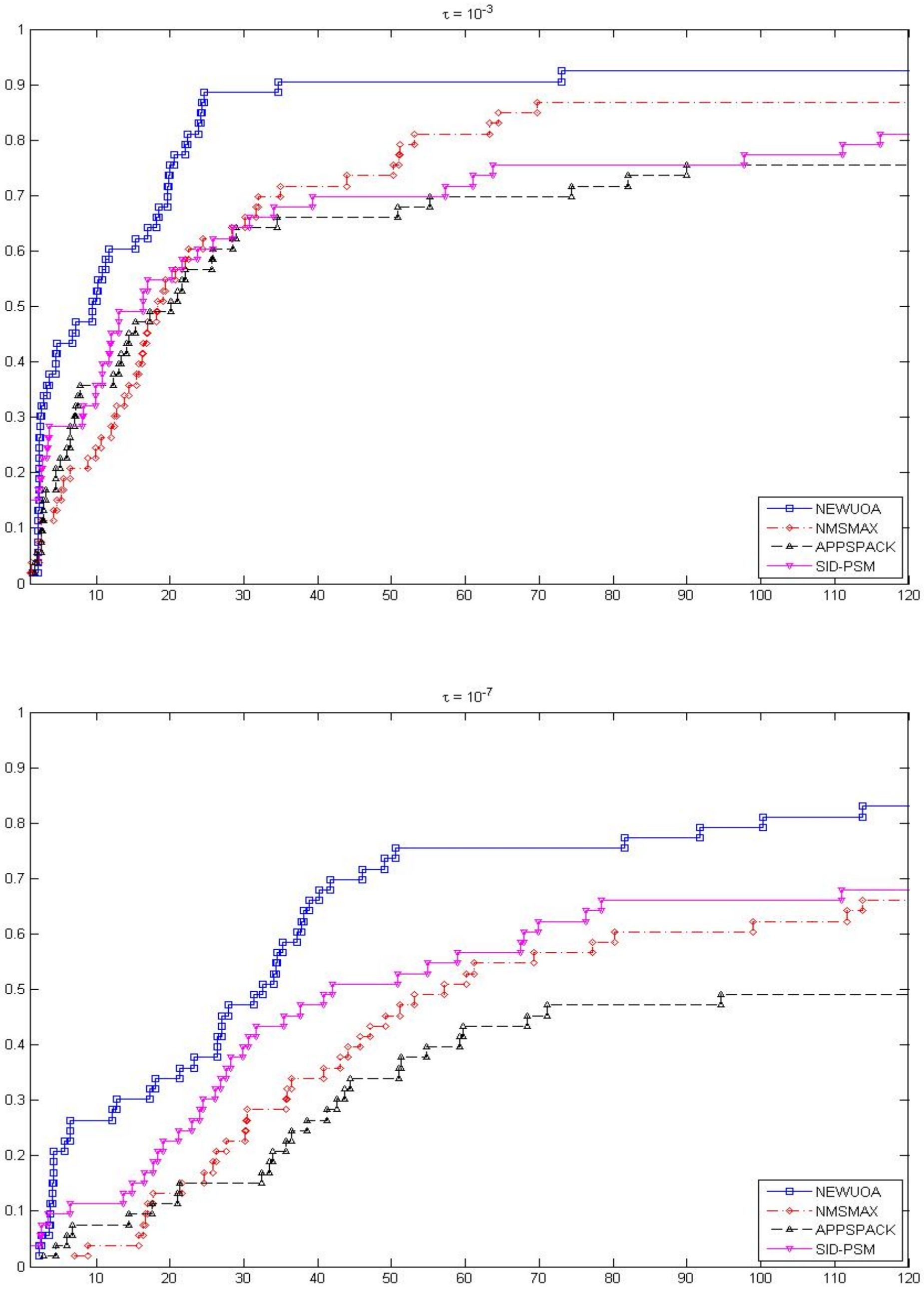
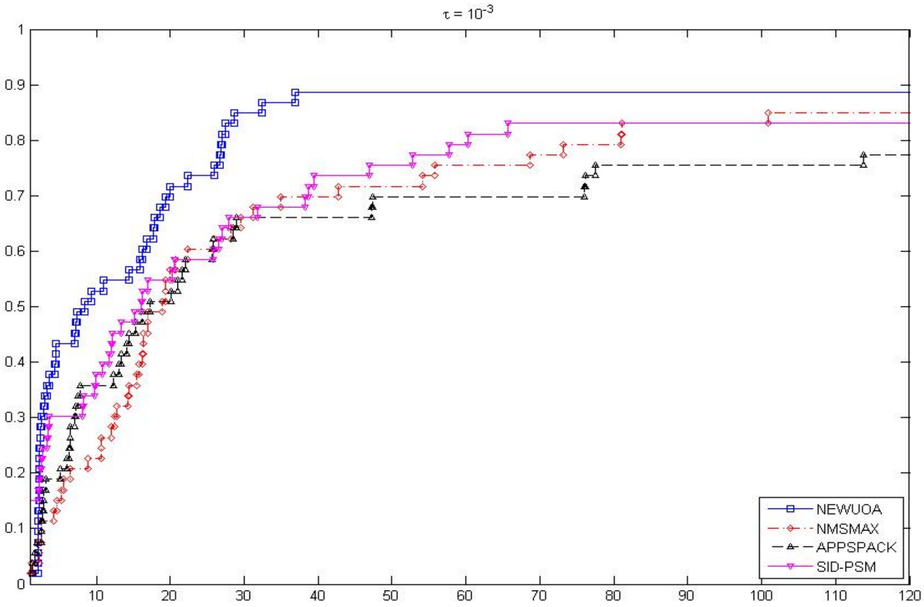


Figure 1: Data profiles computed for the set of smooth problems, considering the two levels of accuracy 10^{-3} and 10^{-7}. The profiles are plotted as a function of the budget, expressed in number of simplices of dimension n.



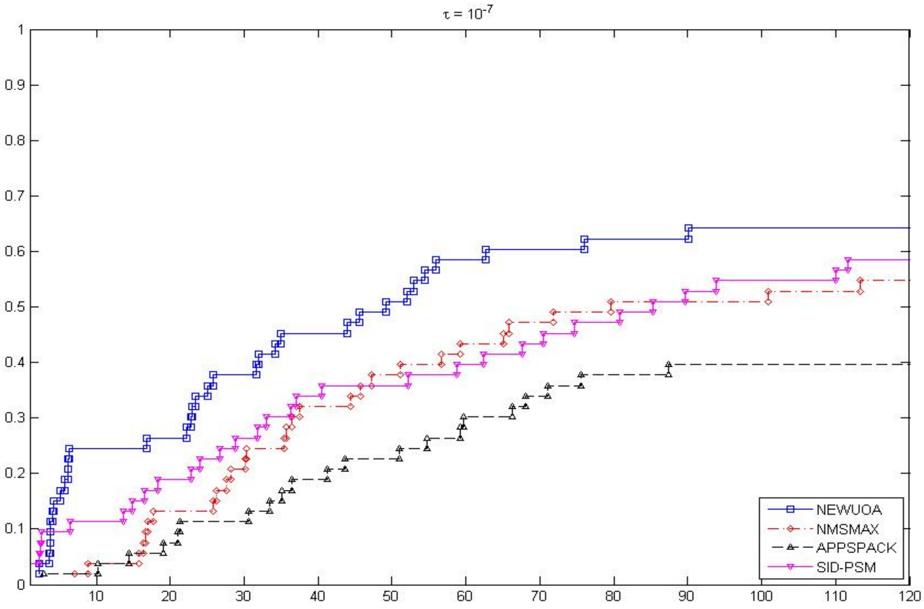


Figure 2: Data profiles computed for the set of nonstochastic noisy problems, considering the two levels of accuracy 10^{-3} and 10^{-7}. The profiles are plotted as a function of the budget, expressed in number of simplices of dimension n.

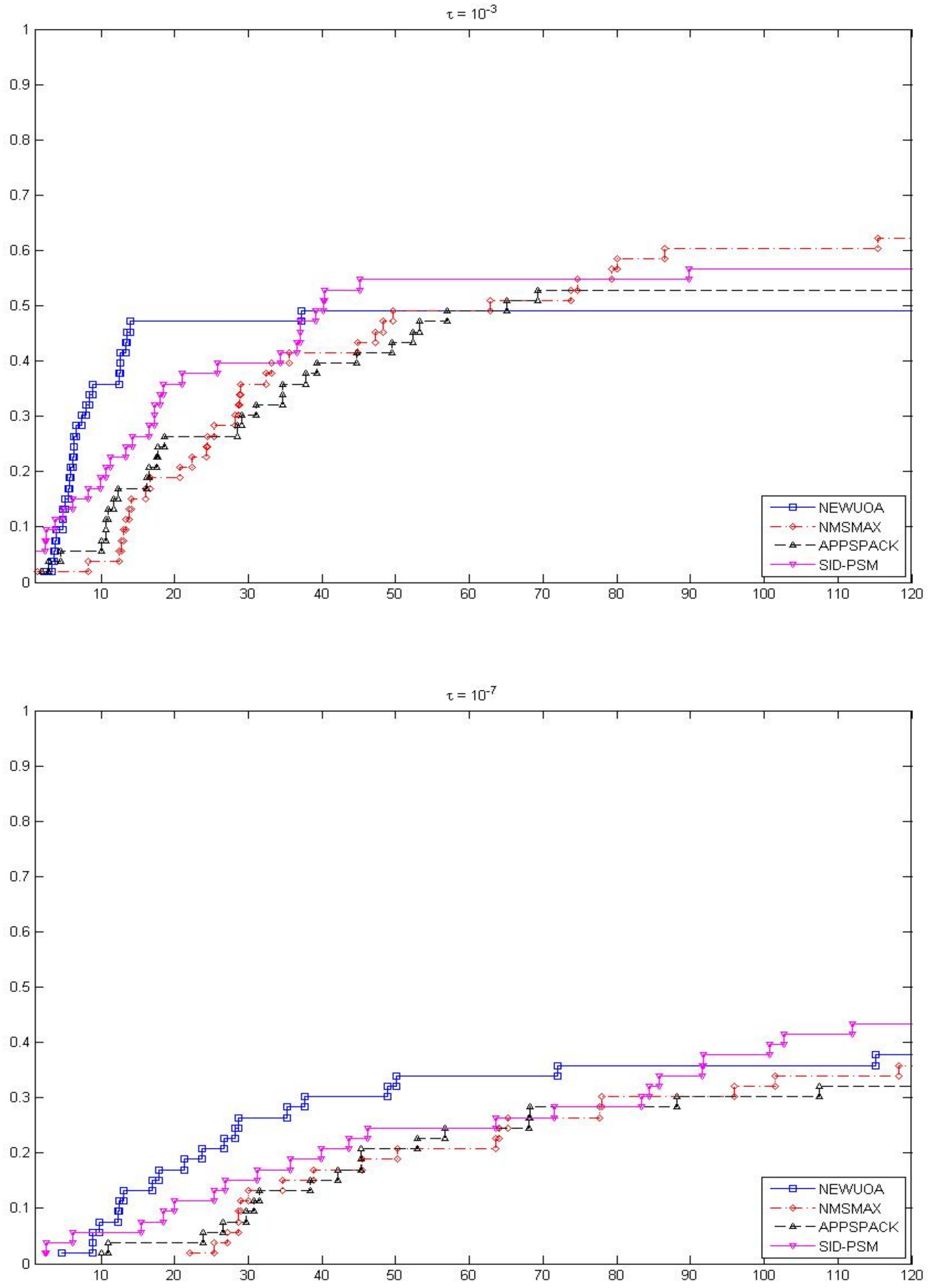


Figure 3: Data profiles computed for the set of piecewise smooth problems, considering the two levels of accuracy 10^{-3} and 10^{-7}. The profiles are plotted as a function of the budget, expressed in number of simplices of dimension n.

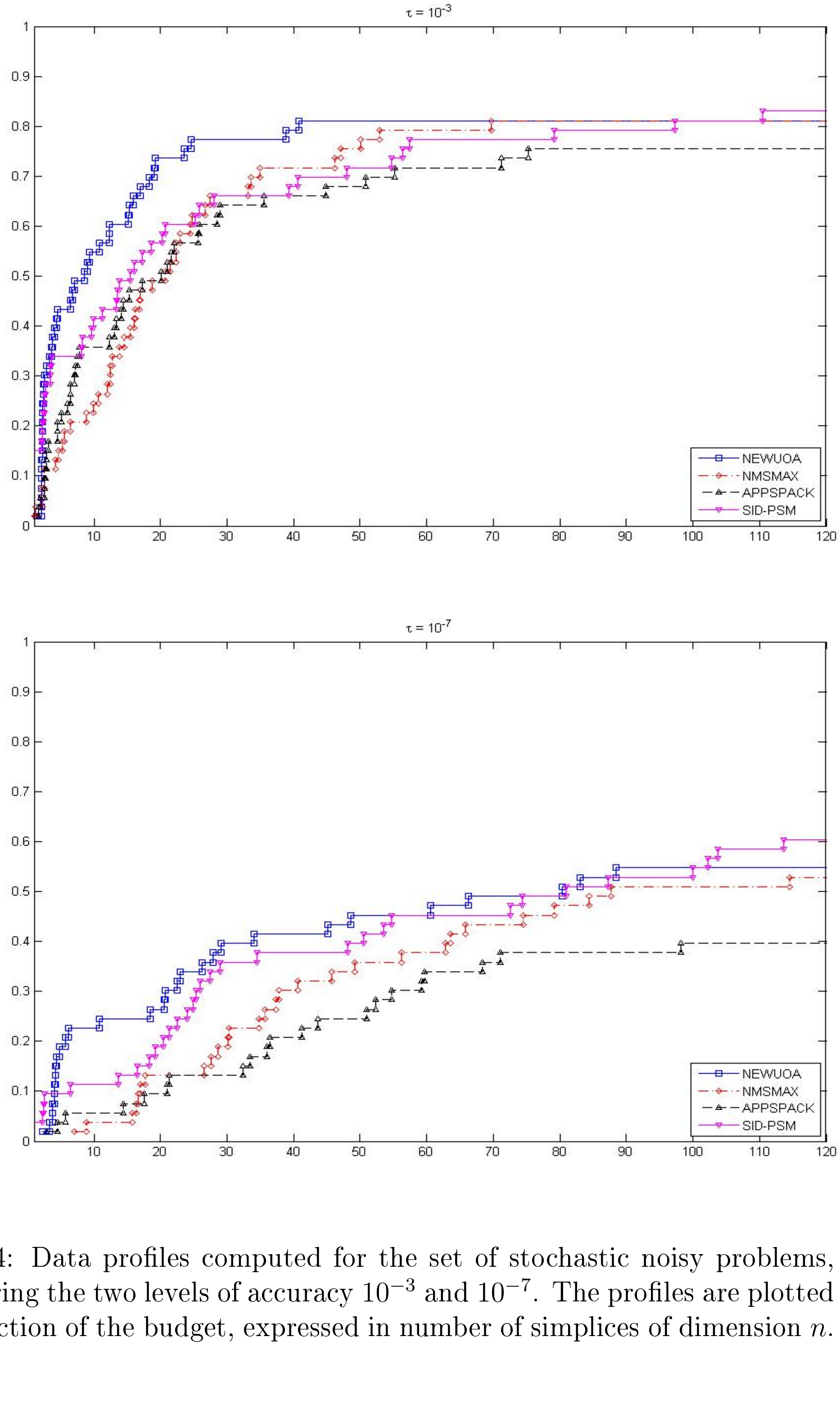


Figure 4: Data profiles computed for the set of stochastic noisy problems, considering the two levels of accuracy 10^{-3} and 10^{-7}. The profiles are plotted as a function of the budget, expressed in number of simplices of dimension n.

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