

Goal: Obtaining guarantees on methods applied to $\min_x f(x) + g(Ax)$

- Automatic computation of worst-case performance of a method
- Better understanding, tuning of methods
- Selection of best method

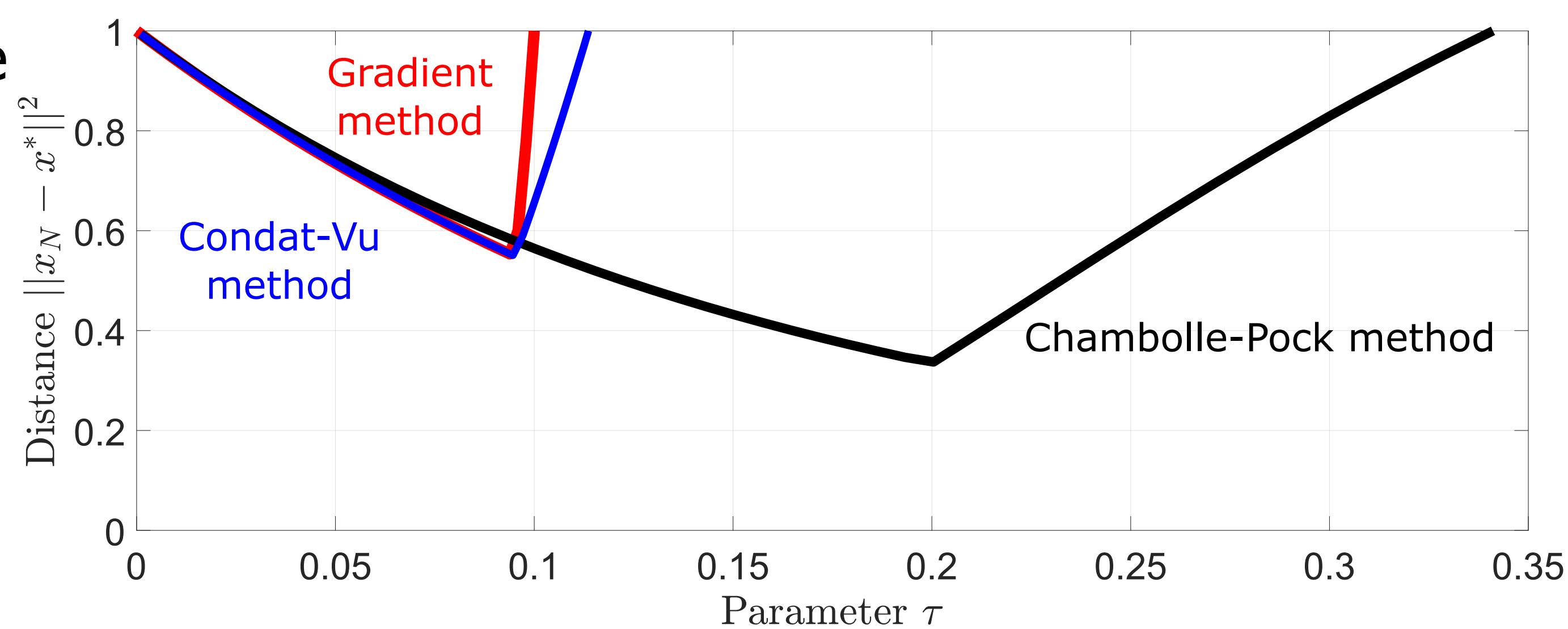


Fig. 1 Comparison by **PEP** of three methods (f and g smooth convex)

Methodology: Performance Estimation Problem

- Compute the worst-case performance as an optimization problem

$$\begin{aligned}
 & \max_{x_0, x^*, f} \text{Perf}(x_N, f) \quad \text{Performance measure (e.g. } \|x_N - x^*\|^2) \\
 & f \in \mathcal{F} \quad \text{Function class (e.g. smooth convex functions)} \\
 & x_N = \mathcal{M}(x_0, f) \quad \text{Optimization method (e.g. Gradient method, Chambolle-Pock method)} \\
 & \|\nabla f(x^*)\|^2 = 0 \quad \text{Optimality} \\
 & \|x_0 - x^*\|^2 \leq 1 \quad \text{Bounded initial distance}
 \end{aligned}$$

- **Exact convex reformulation** efficiently solvable
- Solution of (PEP) is the **worst-case performance** of **method \mathcal{M}** on **function class \mathcal{F}**
- Available in Python library (PEPit) and Matlab toolbox (PESTO)

Main requirement: Interpolation conditions

- **Discretization** of (PEP):

Continuous function $f \rightarrow$ Discrete variables $f_i, g_i : \begin{cases} f(x_i) = f_i \\ \nabla f(x_i) = g_i \end{cases}$

- **Interpolation conditions** guarantee existence of a function consistent with the variables x_i, g_i, f_i
- Example on L-smooth convex function $\mathcal{F}_{0,L}$:

Theorem: Given $(x_1, g_1, f_1), \dots, (x_N, g_N, f_N)$

$$\exists f \in \mathcal{F}_{0,L} : \begin{cases} f(x_i) = f_i \\ \nabla f(x_i) = g_i \end{cases} \Leftrightarrow f_i \geq f_j + g_j^T(x_i - x_j) + \frac{1}{2L} \|g_j - g_i\|^2 \quad \forall (i, j)$$

- Analyzing $\min_x f(x) + g(Ax)$ requires **interpolation conditions for linear operators**

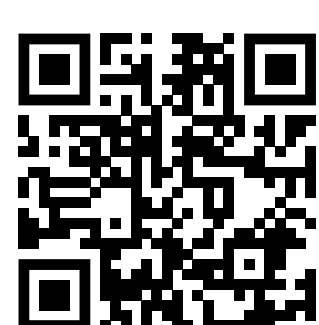
Theorem: Given $(x_1, y_1), \dots, (x_N, y_N)$

$$\exists \mu I \preceq Q \preceq LI : y_i = Qx_i \Leftrightarrow \begin{cases} X^T Y = Y^T X \\ (Y - \mu X)^T (LX - Y) \succeq 0 \end{cases}$$

where $X = (x_1 \dots x_N)$ and $Y = (y_1 \dots y_N)$

References

N. Bouselmi, J. M. Hendrickx, and F. Glineur, "Interpolation conditions for linear operators and applications to performance estimation problems" arXiv preprint arXiv:2302.08781, 2023.



Applications: Rate of convergence

- 1) Optimal step size selection of **Gradient method**:

$$x_{k+1} = x_k - \tau \nabla f(x_k)$$

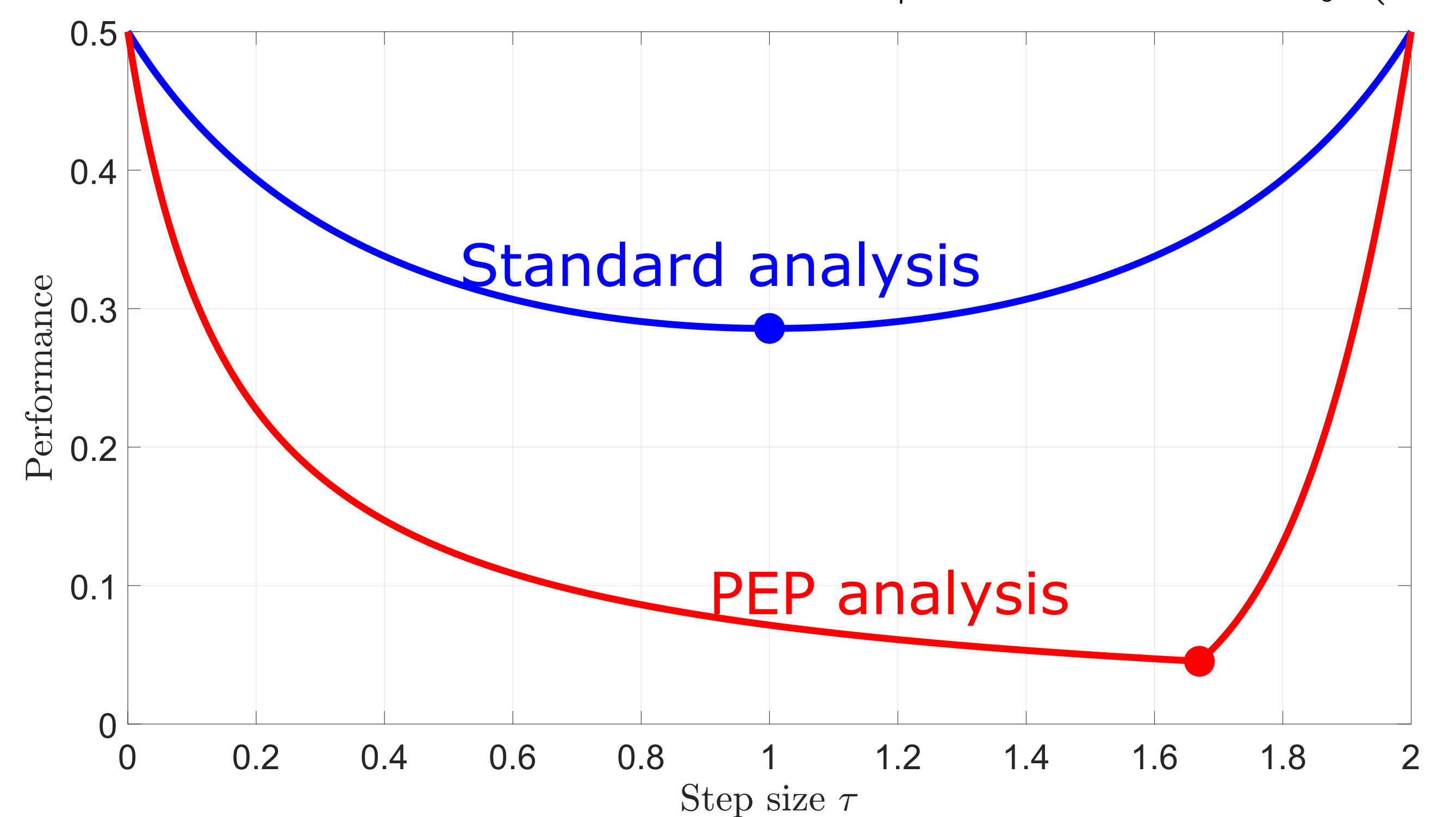


Fig. 2 Worst-case performance of 3 iterations of Gradient method on smooth convex functions: Standard analysis (blue line) and PEP analysis (red line)

- PEP provides tight worst-case performance
- Not tight standard analysis led to sub-optimal step size

- 2) Direct analysis of different performance measures of the **Chambolle-Pock method**:

$$\begin{cases} x_{k+1} = \text{prox}_{\tau f(\cdot)}(x_k - \tau A^T u_k) \\ u_{k+1} = \text{prox}_{\sigma g^*(\cdot)}(u_k + \sigma A(2x_{k+1} - x_k)) \end{cases}$$

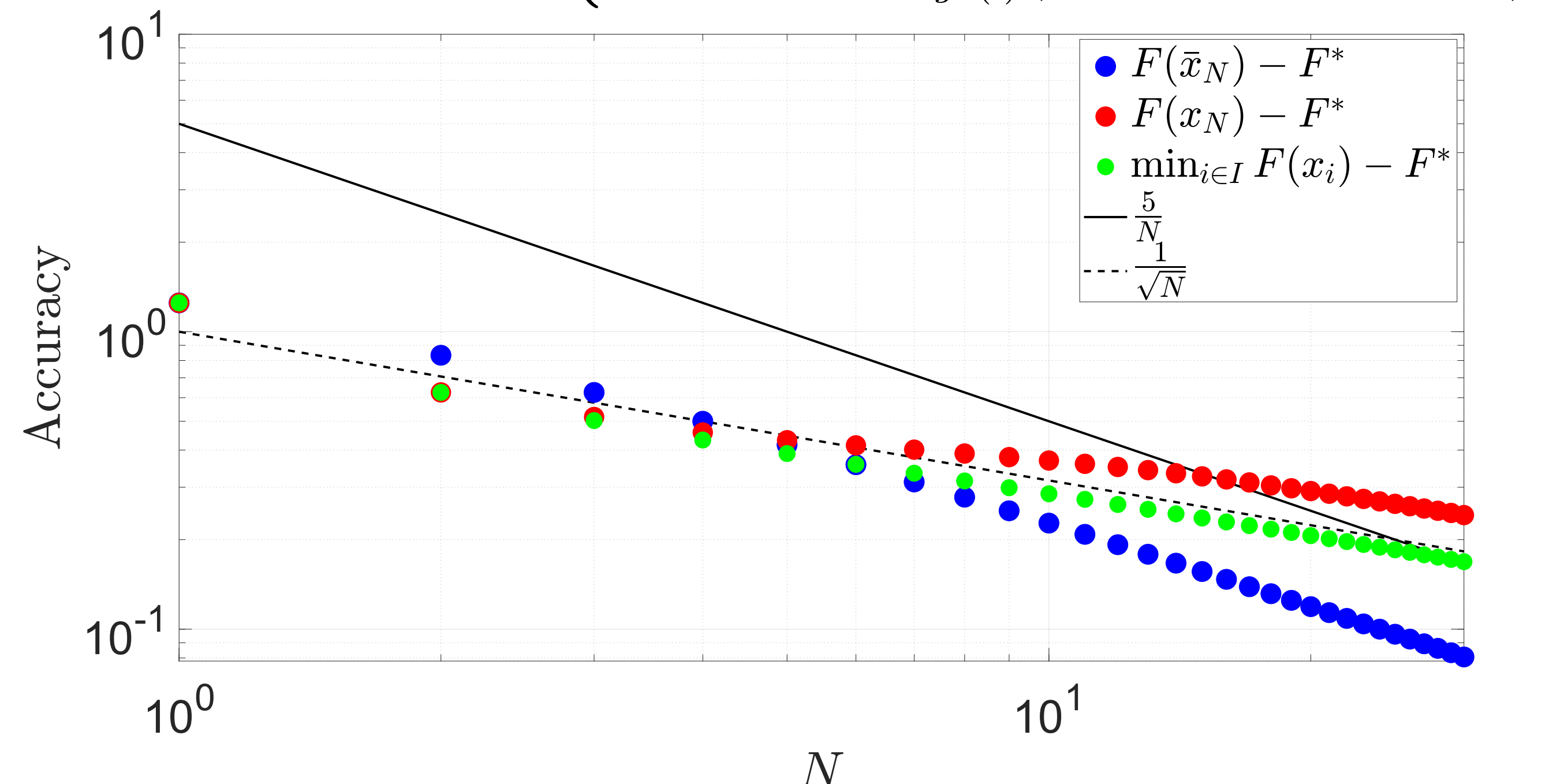


Fig. 3 Worst-case performance of Chambolle-Pock method in terms of number of iterations N for different performance measures: value accuracy of the average (blue dots), last (red dots) and best (green dots) iterations

- PEP easily unifies the analysis of different frameworks

- 3) Other methods with linear operators

- Alternating Direction Method of Multipliers (ADMM)
- Condat-Vu method
- Primal-Dual Three-Operator Splitting
- Proximal Alternating Predictor-Corrector