

Mixed Monotonic Programming for Fast Global Optimization

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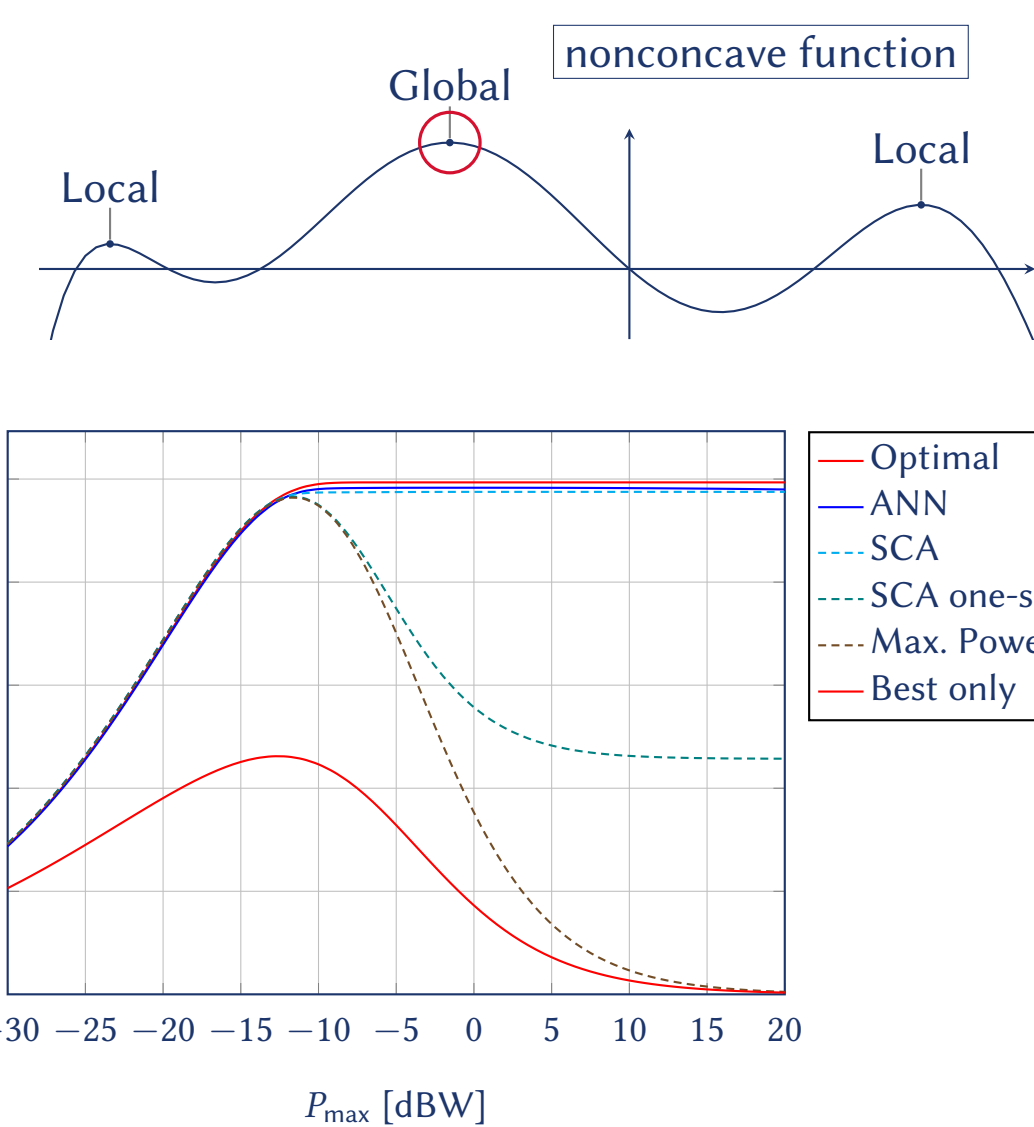
Abstract

- Global optimization framework for nonconvex optimization problems
- Exploits hidden and partial monotonicity properties
- Wide area of applications in communication systems (but not limited to this field)
- Several orders of magnitude faster than state of the art
- Published in **IEEE Transactions on Signal Processing** [1]



Global Optimization

- P-Time Algorithms: At most **local** maximum
- Convex Optimization: Local = Global
- Global Optimization: Solve multiextremal problems
- Often NP-hard → Exponential complexity



Why?

- Benchmark** for fast algorithms
- Asses ultimate **performance limits** during system design
- Label training data for **machine learning** [2]

Methods [3, 4]

- Outer Approximation (Polyblock Algorithm [5])
- Branch-and-Bound

Branch-and-Bound (BB)

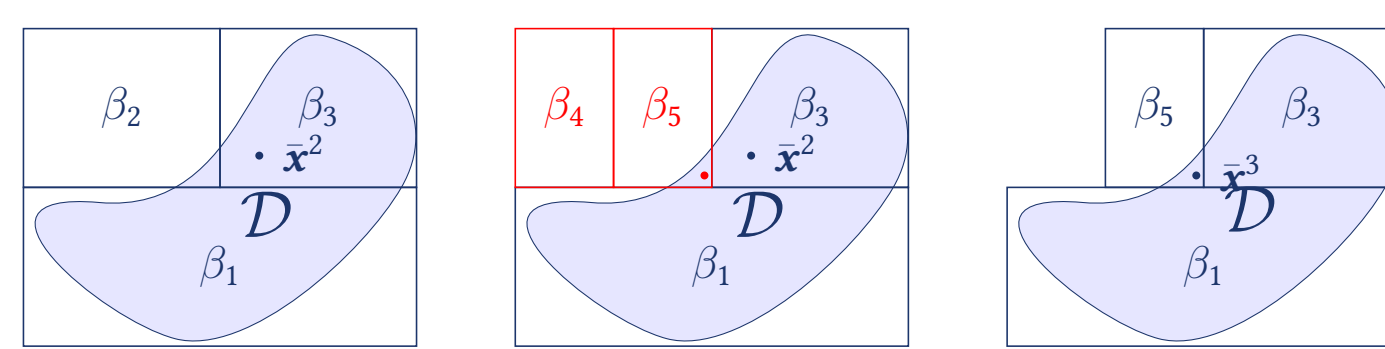
Optimization Problem (P)

$$\max_{\mathbf{x} \in \mathcal{D}} f(\mathbf{x})$$

$f: \mathcal{D} \rightarrow \mathbb{R}$ continuous
 $\mathcal{D} \subseteq \mathbb{R}^n$ compact, non-empty

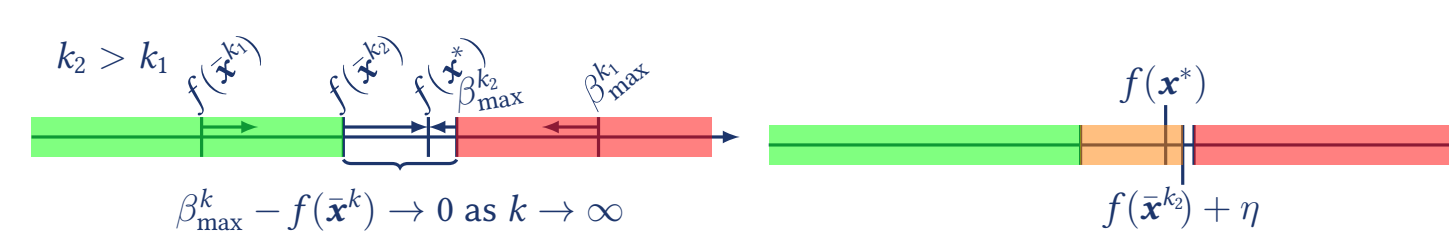
Algorithm (Prototype BB)

- Initialize outer box $\mathcal{M}_0 \supseteq \mathcal{D}$, set best known solution \mathbf{x}^0 and value $\gamma_0 = f(\mathbf{x}^0)$
- Select box \mathcal{M}_k for branching
- Bisect \mathcal{M}_k
- Reduce new Boxes (optional)
- Compute Bound $\beta(\mathcal{M}) \geq \sup_{\mathbf{x} \in \mathcal{M}} f(\mathbf{x})$ for all new boxes \mathcal{M}
- Update best known solution \mathbf{x}^k and value $\gamma_0 = f(\mathbf{x}^k)$
- Delete infeasible ($\mathcal{M} \cap \mathcal{D} = \emptyset$) and suboptimal ($\beta(\mathcal{M}) \leq \gamma_k + \eta$) new boxes
- Terminate if no box left or $\max_M \beta(\mathcal{M}) \leq \gamma_k$: \mathbf{x}^k is global η -optimal solution



Definition (η -Optimal Solution)

$\bar{\mathbf{x}}$ is η -optimal solution of (P) if
 $\forall \mathbf{x} \in \mathcal{D} : f(\bar{\mathbf{x}}) \geq f(\mathbf{x}) - \eta$.



- Partition feasible set systematically
- On each partition element: Compute upper and lower bound on feasible objective values
- If branching is consistent: Upper – Lower → 0 as size(partition elements) → 0

SoA: Monotonic Optimization [5]

- Dominant global optimization framework for communication system design since 2009 [6, 7]
- Increasing function: $\mathbf{x} \leq \mathbf{x}' : f(\mathbf{x}) \leq f(\mathbf{x}')$
- Bounding over $\mathcal{M} = [\mathbf{r}, \mathbf{s}]$: $\max_{\mathbf{x} \in \mathcal{G} \cap \mathcal{H}} f(\mathbf{x}) - g(\mathbf{x}) \leq \max_{\mathbf{x} \in \mathcal{M}} f(\mathbf{x}) - \max_{\mathbf{x} \in \mathcal{M}} g(\mathbf{x}) = f(\mathbf{s}) - g(\mathbf{r})$
- Example: $\log\left(1 + \frac{\mathbf{a}_k^T \mathbf{p}}{\mathbf{b}_k^T \mathbf{p} + \sigma_k^2}\right) = \log\left(\frac{\mathbf{a}_k + \mathbf{b}_k}{\mathbf{b}_k} \mathbf{p} + \sigma_k^2\right) - \log(\mathbf{b}_k^T \mathbf{p} + \sigma_k^2)$

Monotonic Programming

$$\max_{\mathbf{x} \in \mathcal{G} \cap \mathcal{H}} f(\mathbf{x}) - g(\mathbf{x}) \quad f, g : \text{increasing}$$

Mixed Monotonic Programming (MMP)

Definition (MM Function)

Continuous function $F: \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}$ such that

$$F(\mathbf{x}, \mathbf{y}) \leq F(\mathbf{x}', \mathbf{y}) \quad \text{if } \mathbf{x} \leq \mathbf{x}' \quad (\text{Increasing in } \mathbf{x})$$

$$F(\mathbf{x}, \mathbf{y}) \geq F(\mathbf{x}, \mathbf{y}') \quad \text{if } \mathbf{y} \leq \mathbf{y}' \quad (\text{Decreasing in } \mathbf{y})$$

Then, F is called **Mixed Monotonic (MM) Function**.

Definition (MMP)

Consider (P). Let $\mathcal{M}_0 \supseteq \mathcal{D}$ be a box. (P) is a **mixed monotonic program** if a MM function F on \mathcal{M}_0 exists such that
 $\forall \mathbf{x} \in \mathcal{M}_0 : F(\mathbf{x}, \mathbf{x}) = f(\mathbf{x})$.

Key Observations

$$\arg \max_{\mathbf{x} \in \mathcal{M} \cap \mathcal{D}} f(\mathbf{x}) \leq \arg \max_{\mathbf{x} \in \mathcal{M}} F(\mathbf{x}, \mathbf{x}) \leq \arg \max_{\mathbf{x} \in \mathcal{M}} F(\mathbf{x}, \mathbf{y}) = F(\mathbf{s}, \mathbf{r}).$$

closed-form bound!

Composition:

Functions in \mathbb{R}

- $F_i(\mathbf{x}, \mathbf{y}) : \text{MM}$
- $g(\mathbf{x}) : \text{increasing}$
- $h(\mathbf{x}) : \text{decreasing}$

MM functions:

- $(\mathbf{x}, \mathbf{y}) \mapsto \sum_{i=1}^K F_i(\mathbf{x}, \mathbf{y})$
- $(\mathbf{x}, \mathbf{y}) \mapsto \max_{i=1, \dots, K} F_i(\mathbf{x}, \mathbf{y})$
- $(\mathbf{x}, \mathbf{y}) \mapsto \min_{i=1, \dots, K} F_i(\mathbf{x}, \mathbf{y})$
- $(\mathbf{x}, \mathbf{y}) \mapsto g(F_1(\mathbf{x}, \mathbf{y}))$
- $(\mathbf{x}, \mathbf{y}) \mapsto h(F_1(\mathbf{x}, \mathbf{y}))$

If $\forall i : F_i(\mathbf{x}, \mathbf{y}) \geq 0$

- $(\mathbf{x}, \mathbf{y}) \mapsto \prod_{i=1}^K F_i(\mathbf{x}, \mathbf{y})$ is MM

Feasibility Testing:

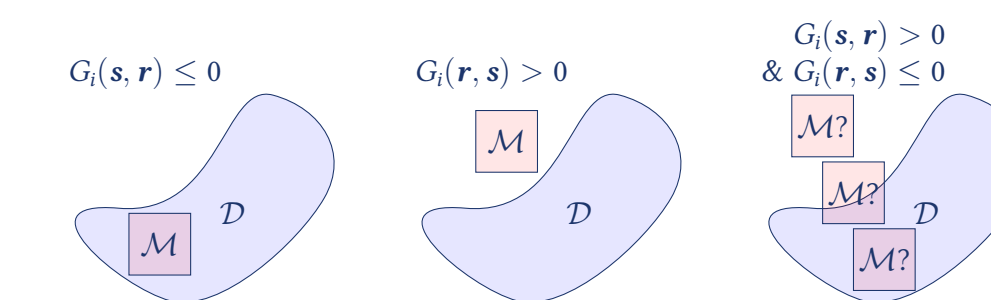
- Bounding independent of feasibility test
- Finite convergence: For all \mathcal{M}
 - Check $\mathcal{M} \cap \mathcal{D}$ conclusively
 - Find $\mathbf{x} \in \mathcal{M} \cap \mathcal{D}$

MM Program

$$\max_{\mathbf{x}} F(\mathbf{x}, \mathbf{x})$$

s. t. $G_i(\mathbf{x}, \mathbf{x}) \leq 0, i = 1, \dots, m$

- For $\mathcal{M} = [\mathbf{r}, \mathbf{s}]$:
 $\forall i : G_i(\mathbf{s}, \mathbf{r}) \leq 0 \Rightarrow \mathcal{M} \cap \mathcal{D} = \mathcal{M} \neq \emptyset$
 $\exists i : G_i(\mathbf{r}, \mathbf{s}) > 0 \Rightarrow \mathcal{M} \cap \mathcal{D} = \emptyset$.
- Inconclusive for some \mathcal{M}



Remedies:

- More Assumptions on $G_i(\mathbf{x}, \mathbf{y})$
 - Finite Convergence
 - In each dimension: Either in- or decreasing
 - Not always possible
- Modify BB Algorithm & accept infinite convergence
 - Might lead to slow algorithm
 - Most popular approach. Often works well.
- ε -Approximate Feasibility
 - Relax constraints by $\varepsilon > 0$
 - Finite Convergence
 - Numerical Issues (wrong solution!)**
- Successive Incumbent Transcending (SIT)
 - Tighten constraints by $\varepsilon > 0$
 - Solve easier "SIT dual" problem
 - MMP-SIT: [8]

Further Information

- Tutorial** @ IEEE ICASSP 2021 & IEEE ICC 2021 by Bho Matthiesen & Eduard Jorswieck
Efficient Global Optimization and its Application to Wireless Interference Networks
- Thesis "Efficient Globally Optimal Resource Allocation in Wireless Interference Networks" [9]

Example: Gaussian Interference Channel

Interference Channel:

- Model for heterogeneous dense small-cell networks
- Treating interference as noise:

$$R_i \leq \log\left(1 + \frac{\alpha_i p_i}{\sum_{j \neq i} \beta_{ij} p_j + \sigma^2}\right)$$

- Resource allocation examples

$$\max_{\mathbf{p} \in [0, P]} w_i \sum_i R_i$$

$$\max_{\mathbf{p} \in [0, P]} \sum_i \mu_i p_i + P_c$$

- An MM representation is **all it takes** to solve such an MM problem

- Weighted sum rate

$$F_{\text{WSR}}(\mathbf{x}, \mathbf{y}) = \sum_i w_i \log\left(1 + \frac{1 + \mathbf{a}_i^T \mathbf{x}}{\mathbf{b}_i^T \mathbf{y}}\right)$$

- Global energy efficiency

$$F_{\text{GEE}}(\mathbf{x}, \mathbf{y}) = \frac{F_{\text{WSR}}(\mathbf{x}, \mathbf{y})}{\mu^T \mathbf{y} + P_c}$$

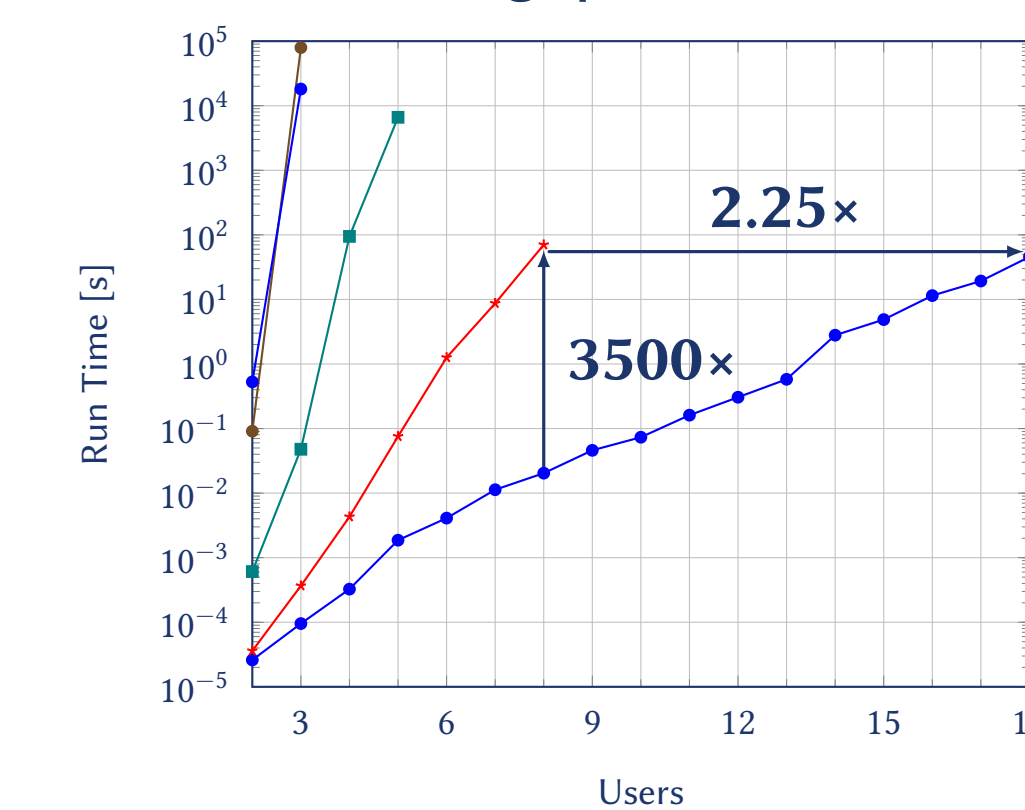
Global Energy Efficiency:

$$\max_{\mathbf{p} \in [\mathbf{r}, \mathbf{s}]} \frac{\sum_k \log\left(1 + \frac{\mathbf{b}_k^T \mathbf{p}}{\mathbf{c}_k^T \mathbf{p} + \sigma_k^2}\right)}{\phi^T \mathbf{p} + P_c} \leq \frac{\sum_k \log\left(1 + \frac{\mathbf{b}_k^T \mathbf{s}}{\mathbf{c}_k^T \mathbf{r} + \sigma_k^2}\right)}{\phi^T \mathbf{r} + P_c} = F(\mathbf{s}, \mathbf{r})$$

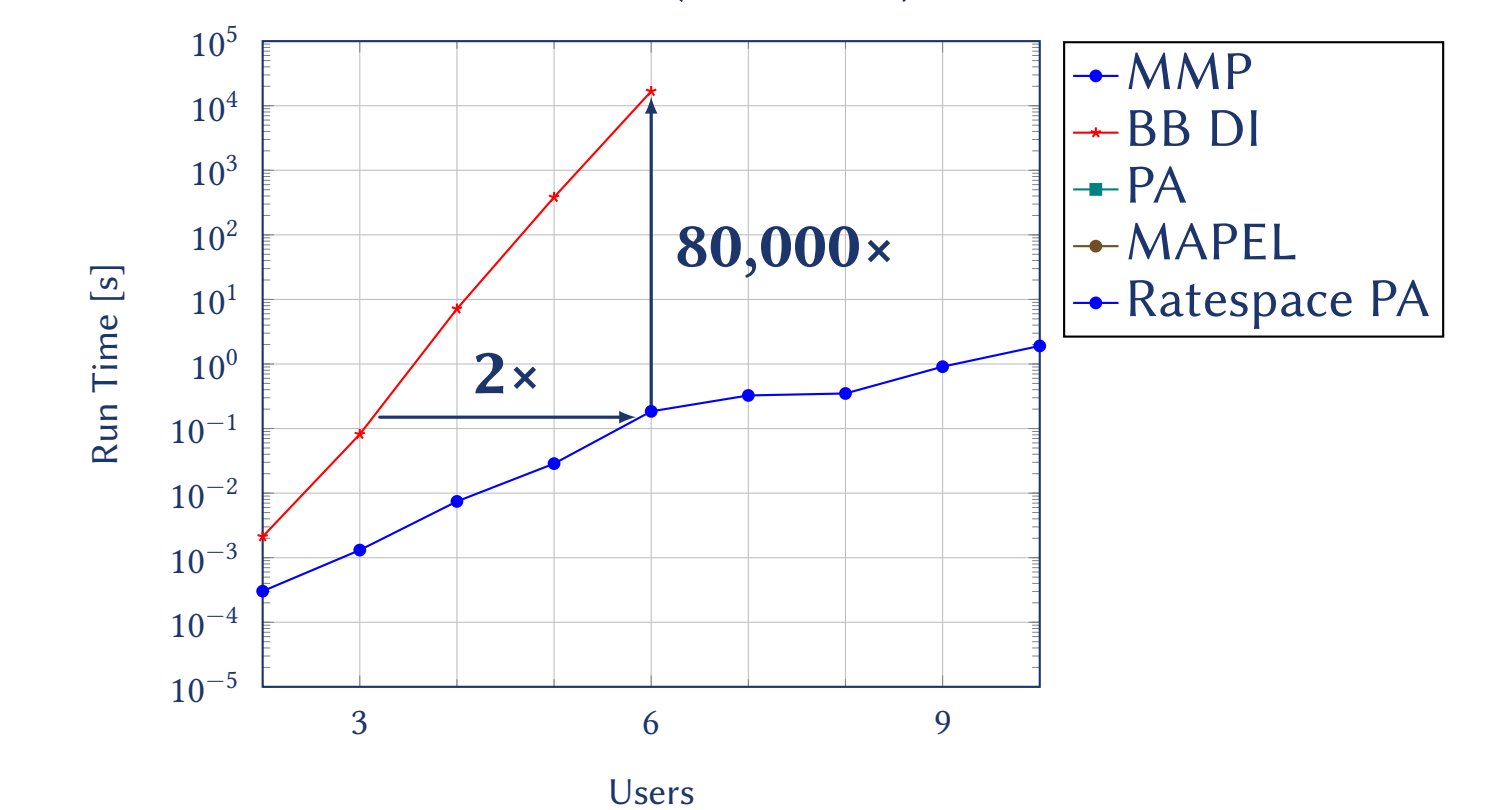
GEE Maximization with MMP (C++)

```
#include "MMP.h"
template <size_t Dim>
class GEE : public MMP<Dim> {
public:
    double alpha[Dim], Pc;
    std::array<double, Dim> beta[Dim], psi;
    GEE() : MMP<Dim>() {}
    double MMPobj(const vtype& x, const vtype& y) const override;
};
template <size_t Dim>
double GEE<Dim>::MMPobj(const vtype& x, const vtype& y) const {
    double ret = 0;
    for (size_t i = 0; i < Dim; ++i) {
        double denom = std::inner_product(y.begin(), y.end(),
            beta[i].begin(), 1.0);
        ret += std::log2(1.0 + alpha[i] * x[i] / denom);
    }
    return ret / std::inner_product(y.begin(), y.end(),
        psi.begin(), Pc);
}
```

Throughput (IFC TIN)



Global EE (IFC TIN)



References

- B. Matthiesen, C. Hellings, E. A. Jorswieck, and W. Utschick, "Mixed monotonic programming for fast global optimization," *IEEE Trans. Signal Process.*, vol. 68, pp. 2529–2544, Mar. 2020.
- B. Matthiesen, A. Zappone, K.-L. Besser, et al., "A globally optimal energy-efficient power control framework and its efficient implementation in wireless interference networks," *IEEE Trans. Signal Process.*, vol. 68, pp. 3887–3902, Jun. 2020.
- H. Tuy, *Convex Analysis and Global Optimization*, 2nd ed., ser. Springer Optim. Appl. New York; Berlin, Germany; Vienna, Austria: Springer-Verlag, 2016, vol. 110.
- R. Horst and H. Tuy, *Global Optimization: Deterministic Approaches*, 3rd, rev. and enl. ed. New York; Berlin, Germany; Vienna, Austria: Springer-Verlag, 1996.
- H. Tuy, "Monotonic optimization: Problems and solution approaches," *SIAM J. Optim.*, vol. 11, no. 2, pp. 464–494, Feb. 2000.
- L. P. Qian, Y. J. Zhang, and J. Huang, "MAPEL: Achieving global optimality for a non-convex wireless power control problem," *IEEE Trans. Wireless Commun.*, vol. 8, no. 3, pp. 1553–1563, 2009.
- E. A. Jorswieck and E. G. Larsson, "Monotonic optimization framework for the MISO IFC," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, Taipei, Taiwan, Apr. 2009, pp. 3633–3636.
- B. Matthiesen, E. A. Jorswieck, and P. Popovski, "Hierarchical resource allocation: Balancing throughput and energy efficiency in wireless systems," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC) Workshops*, Mar. 2021.
- B. Matthiesen, "Efficient globally optimal resource allocation in wireless interference networks," Ph.D. Thesis, Technische Universität Dresden, Dresden, Germany, Nov. 2019. [Online]. Available: <https://theses.eurasip.org/theses/853/efficient-globally-optimal-resource-allocation-in>.