

An augmented Lagrangian method on GPU for AC-SCOPF

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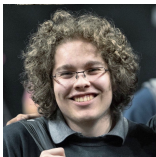
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What do we mean by SCOPF?

Corrective SCOPF

- Compute a base case solution that remains **feasible** for K given contingencies
- **Nonlinear** AC power flow formulation
- Two types of corrective actions in post-contingency state:
 1. Automatic generation control (AGC)
 2. PV/PQ switches
- We suppose contingency screening has been applied before-hand
- No structure exploiting method!

Complementarity constraints

Complementarity constraint $0 \leq a \perp b \geq 0$

We say that a complements b if

$$a \geq 0, \quad b \geq 0, \quad a \times b = 0$$

- Useful paradigm for expliciting non-convex or non-smooth structures!
- Already used by the power system community in the 2000s:
 - Rosehart W, Roman C, Schellenberg A. *Optimal power flow with complementarity constraints*. IEEE Transactions on Power Systems. 2005
 - Capitanescu F, Rosehart W, Wehenkel L. *Optimal power flow computations with constraints limiting the number of control actions*. 2009

Where do complementarity constraints appear in SCOPF?

Automatic generation control (AGC)

In contingency k , the power generations are adapted with Δ^k

$$p_g^k = \min \left(\max \left(p_g^0 + \alpha_g \Delta^k, \underline{p}_g \right), \bar{p}_g \right)$$

or, equivalently,

$$\pi_{g+}^k - \pi_{g-}^k = p_g^k - (p_g^0 + \alpha_g \Delta)$$

$$0 \leq \pi_{g-}^k \perp \bar{p}_g - p_g^k \geq 0$$

$$0 \leq \pi_{g+}^k \perp p_g^k - \underline{p}_g \geq 0$$

PV/PQ switches

If reactive power q_g reaches its bounds, the connected bus behave as a PQ node:

$$\nu_{b+}^k - \nu_{b-}^k = \nu_b^k - \nu_b^0 ,$$

$$0 \leq \nu_{b-}^k \perp \bar{q}_g - q_g^k \geq 0 ,$$

$$0 \leq \nu_{b+}^k \perp q_g^k - \underline{q}_g \geq 0 .$$

Mathematical program with complementarity constraints (MPCC)

Here, we formulate the SCOPF as a large-scale MPCC:

$$\begin{aligned} \min_{x,u} \quad & f(x_0, u_0) \\ \text{s.t.} \quad & g_0(x_0, u_0) = 0, \quad h_0(x_0, u_0) \leq 0, \\ & \forall k \in \{1, \dots, K\}: \\ & g_k(u_0, x_k, u_k) = 0, \quad h_k(x_k, u_k) \leq 0, \\ & 0 \leq G(x_k, u_k) \perp H(x_k, u_k) \geq 0, \end{aligned}$$

with

- (x_k, u_k) : state and control in contingency k
- $f(\cdot)$: objective in base case scenario
- $g_k(\cdot)$: power-flow and linear constraints
- $h_k(\cdot)$: operational constraints and line flow limits
- $G(\cdot), H(\cdot)$: complementarity left and right-hand-sides

MPCC in standard form

Reformulated as:

$$\min_{w \in \mathbb{R}^n} \phi(w) \quad \text{s.t.} \quad \begin{cases} c(w) = 0 \\ 0 \leq w_1 \perp w_2 \geq 0 \end{cases}$$

Solution methods

The MPCC reformulates as the (degenerate) nonlinear program:

$$\min_{w \in \mathbb{R}^n} \phi(w) \quad \text{s.t.} \quad \begin{cases} c(w) = 0 \\ W_1 W_2 e \leq 0 \end{cases}$$

Violate all constraint qualifications (including MFCQ)!

Scholtes method

Relax the degenerate constraint with a positive parameter $\tau > 0$:

$$\min_{w \in \mathbb{R}^n} \phi(w) \quad \text{s.t.} \quad \begin{cases} c(w) = 0 \\ W_1 W_2 e \leq \tau e \end{cases}$$

Elastic reformulation

Move the complementarity constraints to the objective:

$$\min_{w \in \mathbb{R}^n} \phi(w) + \rho w_1^\top w_2 \quad \text{s.t.} \quad c(w) = 0, \quad (w_1, w_2) \geq 0$$

Augmented Lagrangian algorithm

Lagrangian

For multipliers (λ, ξ, ν) , define

$$\mathcal{L}(w, \lambda, \xi, \nu) = \phi(w) + \lambda^\top c(w) - \xi^\top w_0 - \nu_1^\top w_1 - \nu_2^\top w_2 + \nu_0^\top W_1 W_2 e$$

Augmented Lagrangian

For multiplier estimates $(\lambda^{(n)}, \nu_0^{(n)})$ and penalty $\rho^{(n)}$, define

$$\mathcal{L}_\rho(w, \lambda^{(n)}, \nu_0^{(n)}) := \phi(w) + \frac{1}{2\rho^{(n)}} \left(\|c(w) + \lambda^{(n)}\|^2 + \|\max\{0, W_1 W_2 e + \nu_0^{(n)}\}\|^2 \right)$$

Have to handle inequality constraints!

Algorithm: At each iteration n , solve

$$\min_{(w_1, w_2) \geq 0} \mathcal{L}_\rho(w, \lambda^{(n)}, \nu_0^{(n)})$$

Update the multipliers and penalty according to threshold $\eta^{(n)}$:

- If current primal infeasibility less than $\eta^{(n)}$, update $(\lambda^{(n)}, \nu_0^{(n)})$;
- Otherwise, increase $\rho^{(n)}$.

Linear system solve

Remember that the decision variable decomposes as $w = (w_0, w_1, w_2)$

At each iteration, NCL solves a *KKT system* with the saddle-point structure

$$\begin{bmatrix} A & B^\top \\ B & -C \end{bmatrix} \begin{bmatrix} \Delta w \\ \Delta y \end{bmatrix} = \begin{bmatrix} r_1 \\ r_2 \end{bmatrix}$$

with

$$A = \begin{bmatrix} H_{00} & H_{01} & H_{02} \\ H_{10} & H_{11} & H_{12} \\ H_{20} & H_{21} & H_{22} \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ 0 & W_1^{-1} V_1 & V_0 \\ 0 & V_0 & W_2^{-1} V_2 \end{bmatrix}$$

and

$$B = \begin{bmatrix} J_0 & J_1 & J_2 \\ & W_2 & W_1 \end{bmatrix}, \quad C = \begin{bmatrix} \rho^{-1} I & \\ & \rho^{-1} I + V_0^{-1} S \end{bmatrix}$$

Observations

- The complementarity terms increase the indefiniteness in A
- If $\mathcal{I}_{00}(w) \neq \emptyset$, the matrix B is not full row-rank
- Problem with unbounded multipliers!

GPU acceleration with MadNLP

Umbrella project: madsuite.org

- The algorithm has been built on top of MadNLP
- Derivatives (Jacobian and Hessian) are evaluated in parallel using ExaModels
- Benefit directly from GPU-acceleration



MadNLP



ExaModels

Bottleneck: Factorization algorithm

- Factorize the KKT system with a LDL^T factorization
- Require slight regularization for the pivots, but allow for a solution on the GPU

Experiment #1: time per iteration

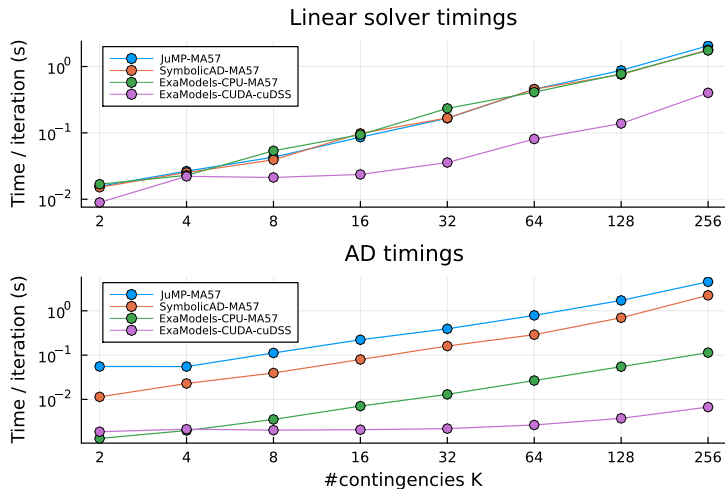


Figure: Scalability as we increase the number of contingencies K for a network with 500 buses.

Experiment #1: time per iteration

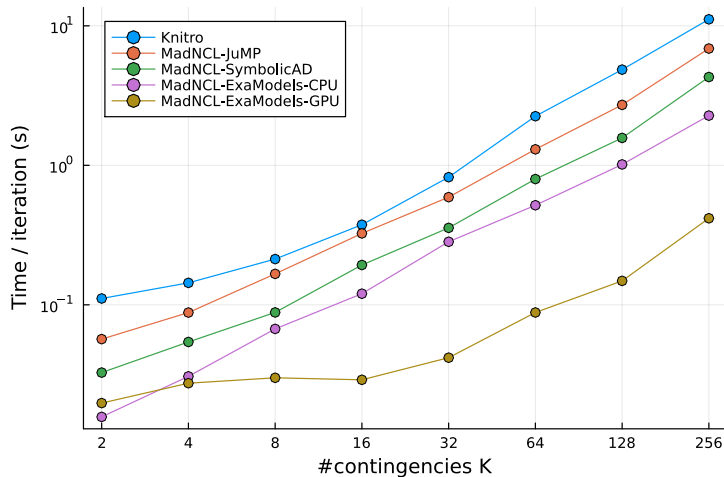


Figure: Scalability as we increase the number of contingencies K for a network with 500 buses.

Experiment #2: time to solution

Instances from the ARPAE GO competition (Challenge 1)

Name	K	nvar	Knitro (ref)				MadNCL-GPU			
			Iter	Obj.	Time (s)	Time/it (s)	Iter	Obj.	Time (s)	Time/it (s)
Network07O-122	5	111k	135	0.04	219.90	1.63	786	0.04	42.80	0.05
Network07O-122	10	203k	303	0.04	952.59	3.14	1050	0.04	100.45	0.10
Network09O-070	5	245k	46	0.05	245.72	5.34	81	0.05	12.60	0.16
Network07O-122	20	388k	257	0.04	981.03	3.82	1093	0.04	116.36	0.11
Network09O-070	10	451k	-	0.06	3600.08	8.51	101	0.05	18.66	0.18
Network12O-030	5	518k	-	10.39	3601.25	9.89	-	10.41	265.41	0.44
Network09O-070	20	861k	135	0.05	2493.12	18.47	501	0.05	152.38	0.30
Network12O-030	10	950k	-	10.39	3611.73	19.42	875	10.39	413.43	0.47
Network12O-030	20	1814k	-	12.96	3646.33	33.76	679	10.39	474.33	0.70

The symbol "-" indicates that the solver failed to find a solution.

Take-home messages

Final answer

Yes, it is now practical to solve large-scale SCOPFs on the GPU!

We are looking for challenging problems to solve!

The end of complementarity winter?

- `MathOptComplement.jl`: improve the support of complementarity in JuMP (including automatic problem's reformulation)
- `MadNCL.jl`: A robust nonlinear solver that support the solution of MPCCs
- `CCopt.jl`: A custom solver for MPCCs