

# ALTERNATE SEARCH FOR BLOCK-STRUCTURED NONCONVEX MINLP

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## MINLP FOR CLIMATE

## Bingo !

## decomposition methods

- combinatorics  $2^{n/2} + 2^{n/2}$
  - hybrid & recycle tools

(non)convex optimization + CO

- difference-of-convex  $y - y^2 \leq 0$
  - monotropic programming [Rockafellar'88]
  - variable splitting and alternate projection
    - e.g. *Douglas-Rachford operator, ADMM, alternate convex search*

# APPLICATIONS

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## load shifting for NL systems with storage

- unsync energy consumption/load service
- get more efficient operating points
- align consumption with energy surplus

*ex: pump scheduling in water networks  
with V. Sessa, A. Tavakoli, G. Bonvin, A. Lodi*

## traffic assignment and network design

- public infrastructures and traffic congestion

*ex: discrete network design problem  
with M. Levin, D. Rey*

## operating the power distribution grid

- stability when intermittent RES/new usages
- modulation/curtailment s.t. priority/fairness

*ex: joint chance-constr discrete AC-OPF  
with K. Syrtseva, P. Javal, W. de Oliveira*

## energy models in prospective analysis

- evaluate policies and guide political action
- long-term capacity expansion planning

*ex: Markal-TIMES (IEA-ETSAP, 1980)  
with G. Siggini, E. Assoumou, S. Selosse*

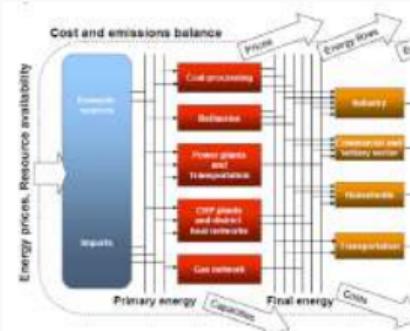
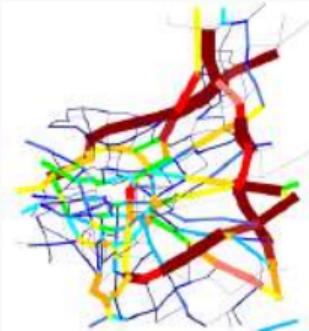
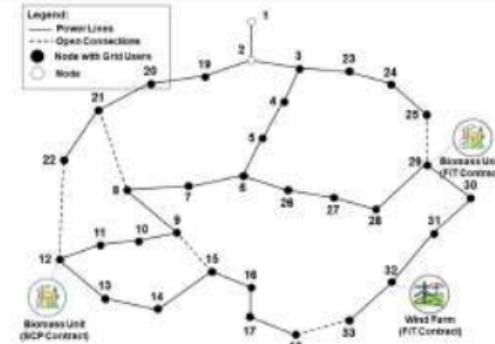
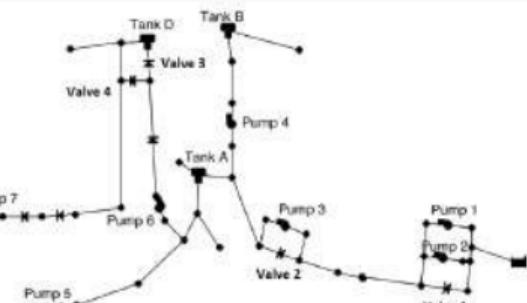
# COMMON BLOCK STRUCTURE

lower operation level: min nonlinear cost flows

single (*water, power*) or multiple (*drivers, materials*) commodities

upper decision level: network configurations with coordination

- variable topology: arc interdiction (*switch on/off a pump, road/process investment*)
- variable boundary conditions (*uncertain demand, dynamic demand/supply*)



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## interdependencies

- discrete time planning: sequence of stationary flows linked by investment decisions
- storage nodes: sequence-dependent sequence of flows
- traffic: flow-dependent individual travel times
- OPF: synchronized uncertainties and modulation

# BILEVEL MODEL, MULTIPLE FOLLOWERS

$$\begin{aligned} \min_{y,x,u} \quad & \sum_k cost(y_k, x_k) \\ \text{s.t. } & x_k \in \text{mincostflow}(y_k, u_k) \quad \forall k \\ & u_k = \text{state}(u_{\neg k}, x_{\neg k}) \quad \forall k. \end{aligned}$$

- $x$  arc flow
- $y$  binary arc interdiction/activation
- $u$  implied boundary conditions

## ex: pump scheduling

$$\begin{aligned} \min_{y0/1,x,u} \quad & \sum_t c_t(y_t, x_t) \\ \text{s.t. } & x_t \in \text{mincostflow}(y_t, D_t, \underline{u}_t) \quad \forall t \\ & \underline{u}_{t+1} = \underline{u}_t + \sigma^\top x_t \quad \forall t \\ & \underline{U}_t \leq \underline{u}_t \leq \overline{U}_t \quad \forall t. \end{aligned}$$

- known demand  $D_t$ , dynamic tariff  $c_t$  at each time  $t$
- flow  $x_t$  when switching pumps  $y_t$  given tank levels  $u_t$
- sequence dependency  $u_t \rightarrow x_t \rightarrow u_{t+1}$
- tank levels  $u_t$  with tight bounds  $\Rightarrow$  feasibility issue

## *mincostflow: MONOTROPIC PROGRAM*

primal (distribution):  $x$  solves

$$\mathcal{P} : \min_x \sum_a f_a(x_a) + u_R^\top E_R^\top x$$

$$s.t. E_S^\top x = D_S$$

- with  $f_a$  l.s.c; in apps:  $f_a$  (energy dissipation) smooth, strictly convex  $\Rightarrow$  unique flow  $x$

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KKT (equilibrium):  $(x, u)$  solves

$$\begin{aligned} \mathcal{E} : \mathbf{E}_S^\top \mathbf{x} = \mathbf{D}_S \\ v_a = u_i - u_j = f'_a(x_a) \quad \forall a = (i, j) \end{aligned}$$

dual (differential):  $u$  solves

$$\begin{aligned} \mathcal{D} : \min_u \quad & \sum_a f_a^*(v_a) + \mathbf{D}_S^\top \mathbf{u}_S \\ \text{s.t. } & v := -Eu \end{aligned}$$

strong duality:  $(x, u)$  solves

$$\begin{aligned} \mathcal{S} : \mathbf{E}_S^\top \mathbf{x} = \mathbf{D}_S, v := -Eu \\ \sum_a (f_a(x_a) + f_a^*(v_a)) + \mathbf{u}_R^\top \mathbf{E}_R^\top \mathbf{x} + \mathbf{D}_S^\top \mathbf{u}_S \leq 0. \end{aligned}$$

- with  $f_a$  l.s.c; in apps:  $f_a$  (energy dissipation) smooth, strictly convex  $\Rightarrow$  unique flow  $x$
- $f'_a$  resistance (potential loss),  $u_S$  potential (pressure, voltage, Wardrop's node price)
- $f_a^* = \int f_a'^{-1}$ :  $f_a^*(v_a) = -f_a(f_a'^{-1}(v_a)) + v_a f_a'^{-1}(v_a)$  convex conjugate: not polynomial

# FEASIBLE SOLUTION FOR PUMP SCHEDULING

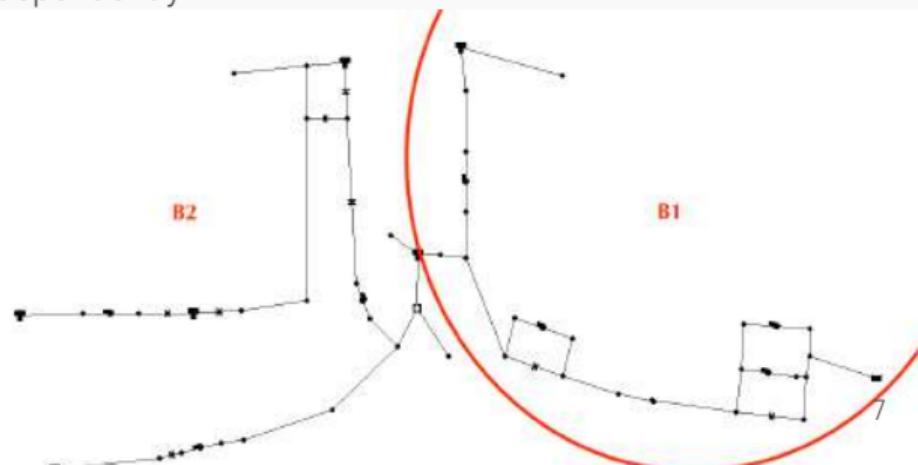
- solutions in discrete space  $y$  are sparse and scarce
- dualizing time coupling (3) in LR [Ghaddar'15] or variable copy  $u = U$  in ADMM [Ulusoy'25] does not fix  $u_t$
- dualizing (3) and fixing level variables  $u$  splits in both time and space, with few  $y_t$  variables in each component: enumerate and solve *mincostflow* independently

$$\min_{y_{0/1}, x, u} \sum_t c_t(y_t, x_t) \quad (1)$$

$$s.t. x_t \in \text{mincostflow}(y_t, D_t, \mathbf{u}_t) \quad \forall t \quad (2)$$

$$\mathbf{u}_{t+1} = \mathbf{u}_t + \sigma^\top x_t \quad \forall t \quad (3)$$

$$\underline{U}_t \leq \mathbf{u}_t \leq \overline{U}_t \quad \forall t. \quad (4)$$



# SEARCH THE $u$ -SPACE

$$\begin{aligned} \min_{u \in U} z(u) &= \min_{y \in \{0,1\}, x} \sum_t c_t(y_t, x_t) + \mu_t(u_{t+1} - u_t - \sigma^\top x_t) \\ s.t. x_t &\in \text{mincostflow}(y_t, D_t, \underline{u}_t) \quad \forall t. \end{aligned}$$

- $z$ : first-order information, smoothness, convexity ?
- alternate convex search:
  - 1/  $P(u^j)$ : fix  $u = u^j$  get  $(y^j, x^j)$
  - 2/  $P(y^j, x^j)$ : fix  $(y, x) = (y^j, x^j)$  get  $u^{j+1}$
  - 3/ (update  $\mu$ )

## partial split

- **keep**  $\text{mincostflow}$  (2) in  $P(u)$  as a constraint but **drop it** from  $P(y, x)$
- start from a (learned) trial point  $u^0$ , **repair** feasibility by alternate search
- penalty/multipliers update policy: **ADMM** [Boyd'00] or **PADM** [Geißler'17]

# OPTION 1: PARTIAL SPLIT AND PADM-LIKE

given penalty vector  $\mu$ , increase  $\mu$  when  $\|u^j - u^{j+1}\|_\infty \leq \epsilon$ ,

**1: fix levels  $u$ , then compute  $(y, x)$**

$$P(u) : \min_{(y,x)} \sum_t c_t(y_t, x_t) + \mu_t^\top \|u_{t+1} - u_t - \sigma^\top x_t\|_1$$
$$s.t. : x_t \in \text{mincostflow}(y_t, D_t, u_t) \forall t.$$

solve  $\text{mincostflow}_t$  independently on any graph component  $b$ , 0/1 vector  $y_{tb}$

$\downarrow$        $\uparrow$       stop when  $\|u_{t+1} - u_t - \sigma^\top x_t\|_\infty < \epsilon$

**2: fix command  $(y, x)$ , then compute  $u$**

$$P(y, x) : \min_u \sum_t c_t(x_t, y_t) + \mu_t^\top \|u_{t+1} - u_t - \sigma^\top x_t\|_1 : u \in [\underline{U}, \overline{U}]$$

## OPTION 2: PARTIAL SPLIT AND ADMM-LIKE

Given multipliers  $\mu$  and penalty  $\rho$ :

**1: fix levels  $u$ , then compute  $(y, x)$**

$$P(u) : \min_{(y,x)} \sum_t c_t(y_t, x_t) + \mu_t^\top (u_{t+1} - u_t - \sigma^\top x_t) + \frac{\rho}{2} \|u_{t+1} - u_t - \sigma^\top x_t\|_2^2$$

$$\text{s.t. : } x_t \in \text{mincostflow}(y_t, D_t, u_t) \forall t \forall b.$$

$\ell_2$ -regularization is separable here

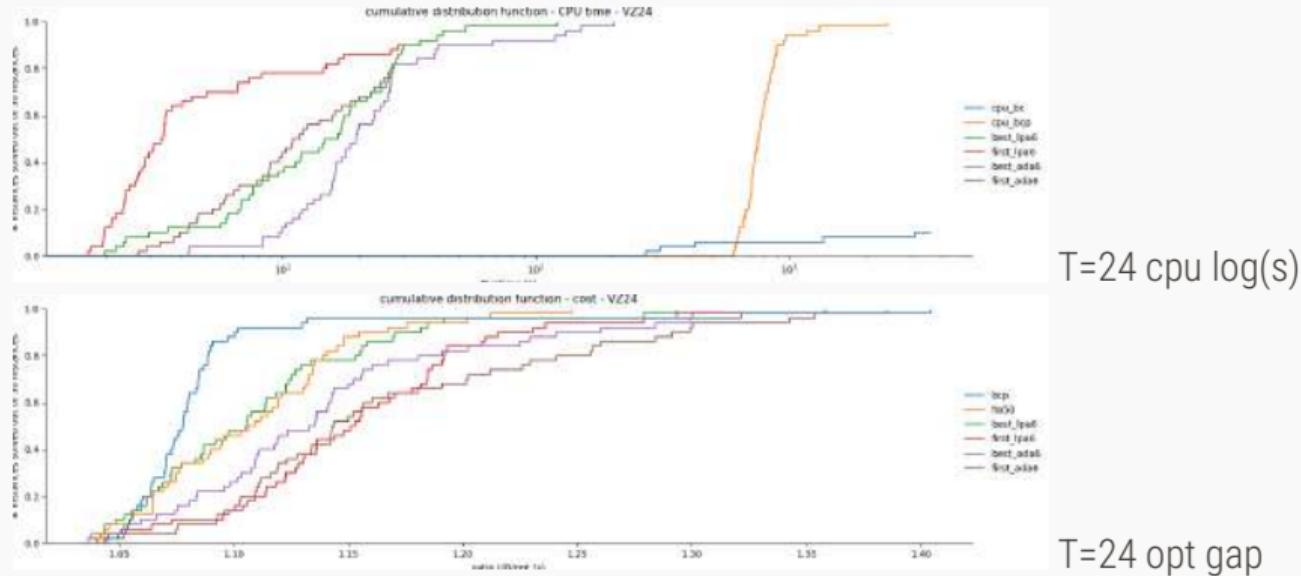
**2: fix command  $(y, x)$ , then compute  $u$**

$$P(y, x) : \min_{u \in U} \sum_t c_t(x_t, y_t) + \mu_t^\top (u_{t+1} - u_t - \sigma^\top x_t) + \frac{\rho}{2} \|u_{t+1} - u_t - \sigma^\top x_{tb}\|_2^2$$

**3: update  $\mu_t = \mu_t + \rho * (u_{t+1} - u_t - \sigma^\top x_t)$**

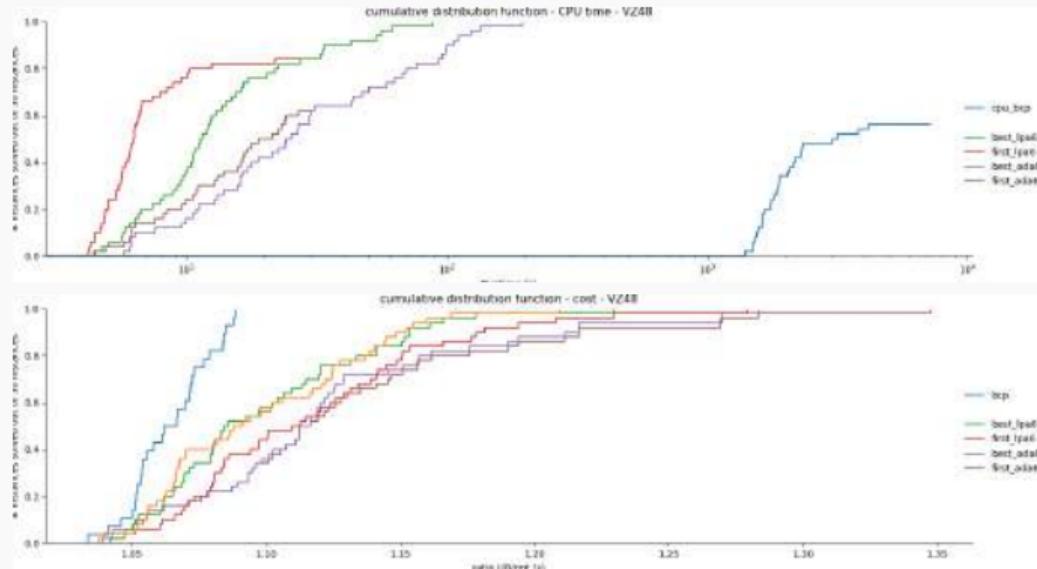
# EXPERIMENTS: LEARNED PROFILES $u$ + PARTIAL SPLIT

- 30 initial trials  $u$  (deep learning + MonteCarlo dropout) + interpolation  $T = 12 \rightarrow 24$
- stop at first feasible solution, or best within 30s [D., Sessa, Tavakoli'24] (no parallelization)
- compare with first solution from SOA Branch-and-Check [Bonvin, D., Lodi'21] w/wo advanced preprocessing [Tavakoli, D., Sessa'22] on Van Zyl benchmark



# EXPERIMENTS: LEARNED PROFILES $u$ + PARTIAL SPLIT

- 30 initial trials  $u$  (deep learning + MonteCarlo dropout) + interpolation  $T = 12 \rightarrow 48$
- stop at first feasible solution, or best within 30s [D., Sessa, Tavakoli'24] (no parallelization)
- compare with first solution from SOA Branch-and-Check [Bonvin, D., Lodi'21] w/wo advanced preprocessing [Tavakoli, D., Sessa'22] on Van Zyl benchmark



T=48 cpu log(s)

T=48 opt gap

## OPTION 3: FULL SPLIT ON THE STRONG-DUALITY MODEL

step 1: fix level  $u_R$ , then compute schedule and flow  $(y, x)$

$$w(u_R) : \min_{(y,x)} \sum_t c_t(y_t, x_t) + \mu_t^\top (u_{t+1} - u_t - \sigma^\top x_{tR}) + \lambda_t SD_t(x_t, u_t) : (1 - y_t)x_t = 0, x_{tS} = D_{tS} \forall t$$

with  $SD_t(x_t, u_t) = \sum_a f_a(x_{ta}) + f_a^*(v_{ta}) + u_{tR}^\top x_{tR} + D_{tS}^\top u_{tS}$  and  $v_t = -Eu_t$

$w(u_R)$  remains separable in time and space

each is **separable in primal ( $x$ ) /dual ( $u_S$ ) parts**, corresponding each to **a follower mincostflow** augmented with leader costs  $c$  and multipliers  $\mu, \lambda$ :

**perturbed primal**

$$\begin{aligned} \mathcal{P}_t(y_t, u_{tR}) : & \min_{x_t} \lambda_t f(x_t) + (\lambda_t u_{tR} - \mu_t + c_t^1)^\top x_t \\ s.t. : & x_{tS} = D_{tS}, (1 - y_t)^\top x_t = 0. \end{aligned}$$

**perturbed dual**

$$\begin{aligned} \mathcal{D}_t(y_t, u_{tR}) : & \min_{u_{tS}} \lambda_t f^*(v_t) + \lambda_t D_t^\top u_{tS} \\ s.t. : & v_t = -Eu_t. \end{aligned}$$

# CONCLUSION

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- **fixing coupling variables vs relaxing coupling constraints:** keep structure, split deeper (time/space/primal-dual), linearize bilinear terms
- **alternative bilevel view:** (leader) implied continuous storage variables (follower) discrete decisions
- **alternative ML/MIP hybrid:** ML for optimality, MIP for feasibility
- generalization to bilevel programming and MPEC (with Antonio Sasaki and Valentina Sessa)
- convergence for partial split ?

# REFERENCES

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- **Rockafellar** on nonlinear flows, **Eckstein, Rockafellar** on monotone operators
- **Boyd** on proximal algorithms, apps of ADMM in ML, image processing, and for OPF
- biconvex optimization [Gorski,Pfeuffer,Klamroth'07]

Combinatorial Optimization:

- The feasibility pump [Fischetti,Glover,Lodi'05], PADM for MIP [Geißler,Morsi,Schewe,Schmidt'17]
- Application to gas transportation problems [Geißler,Morsi,Schewe,Schmidt'15 and '18]
- Computing feasible points of bilevel problems with PADM [Kleinert,Schmidt'20]
- Application to pump scheduling [D.,Sessa,Tavakoli'24], [Ulusoy,Stoianov'25]



- **S.D., V. Sessa, A. Tavakoli** DL and alternating direction method for discrete control with storage. ISCO 2024.
- **A. Tavakoli, V. Sessa, S. D.** Strengthening mathematical models for pump scheduling. ICAE 2022.
- **G. Bonvin, S. D., A. Lodi** Pump scheduling in water networks with an LP/NLP-based B&B. Opt&Eng 2021.
- **G. Bonvin, S. D.** Extended linear formulation of the pump scheduling problem in water networks. INOC 2019.
- papers available at <https://sofdem.github.io/> code at <https://github.com/sofdem/>