A DCOP Approach to the Economic Dispatch with Demand Response

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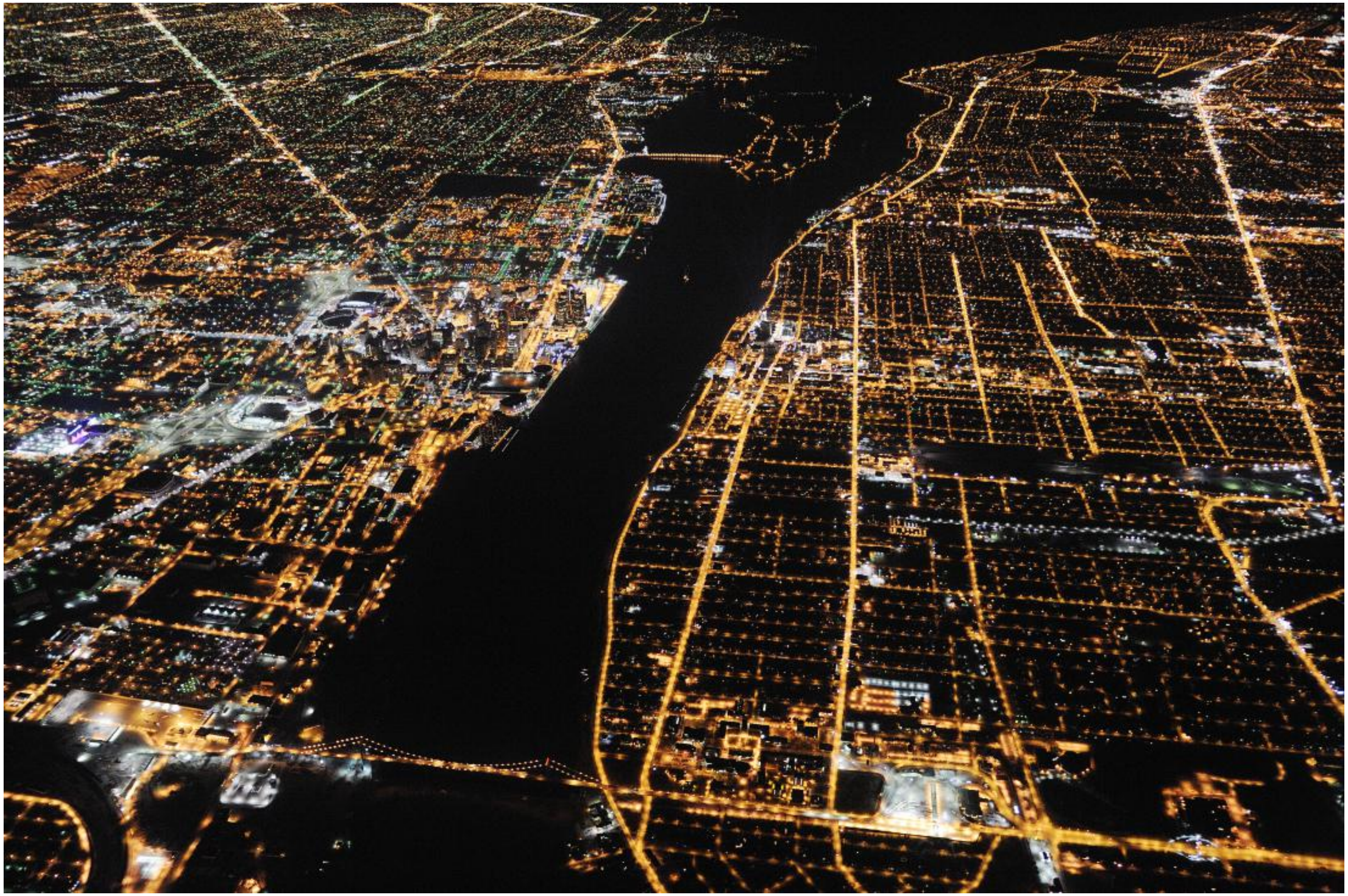
Power Grid

Power Grid: Power Generators

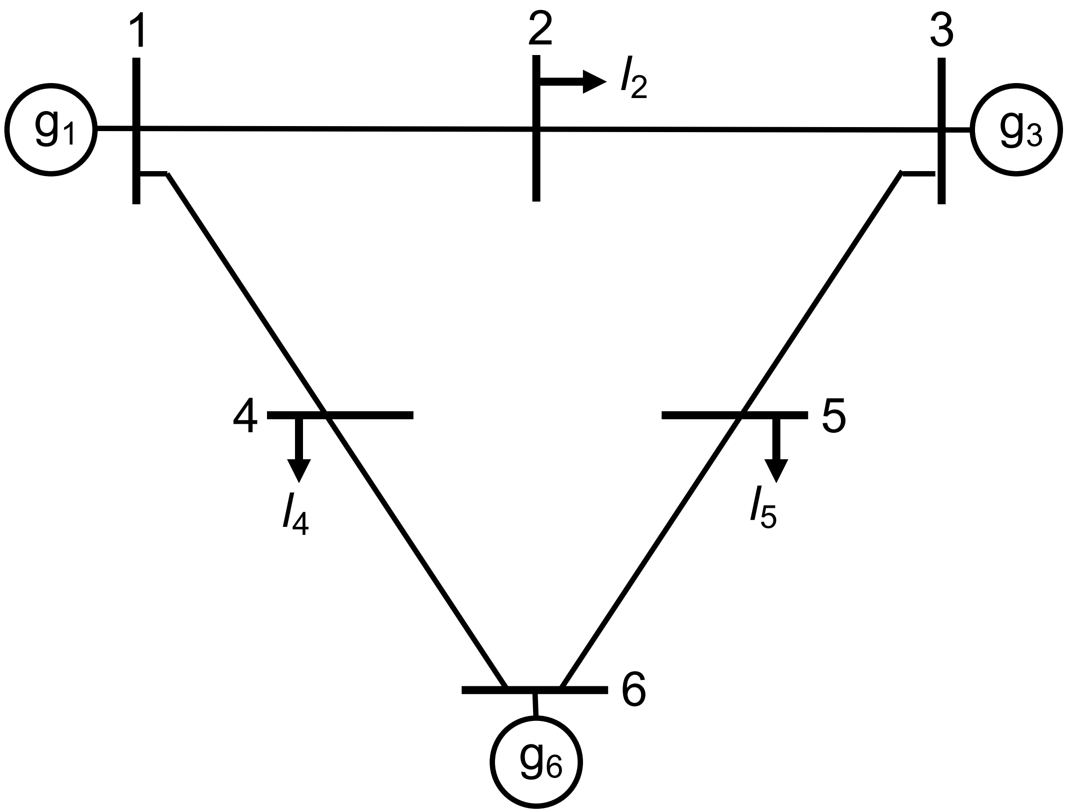
Power Grid: Power Loads



Power Grid: Distribution Cables

Power Grid: Representation

$G = (\mathcal{V}, \mathcal{E})$



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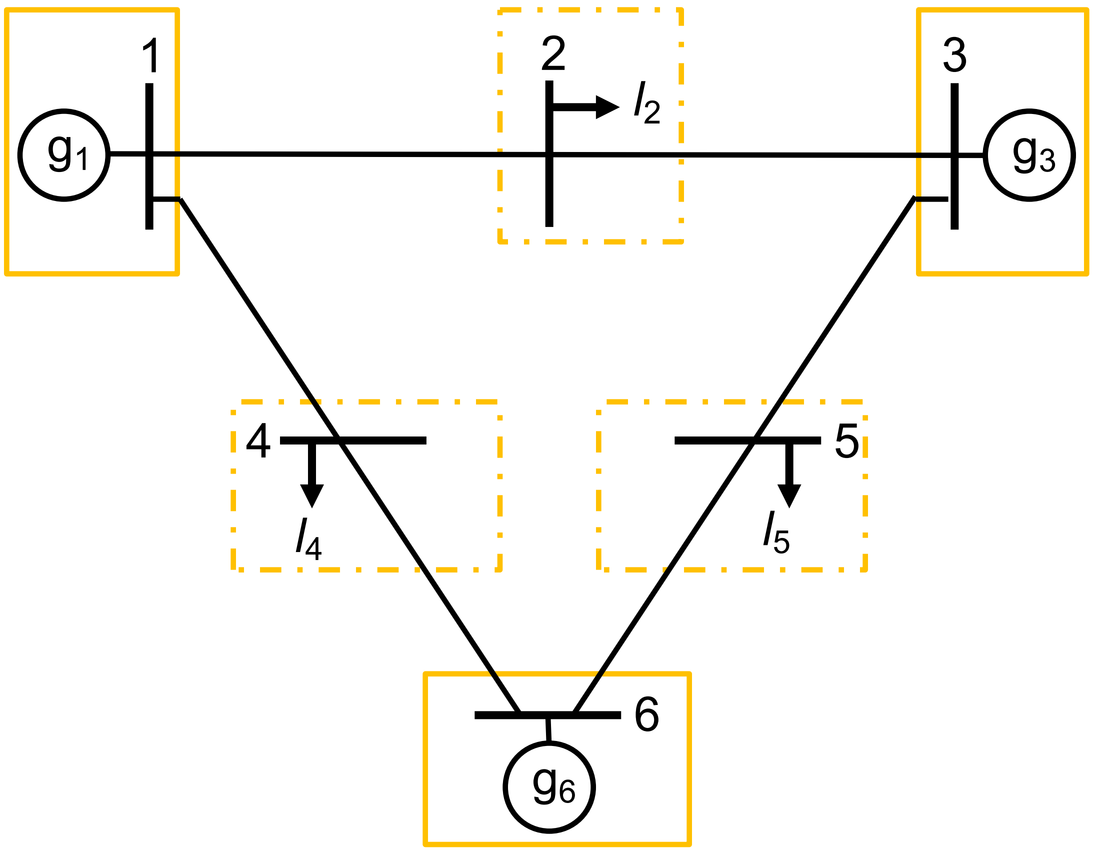

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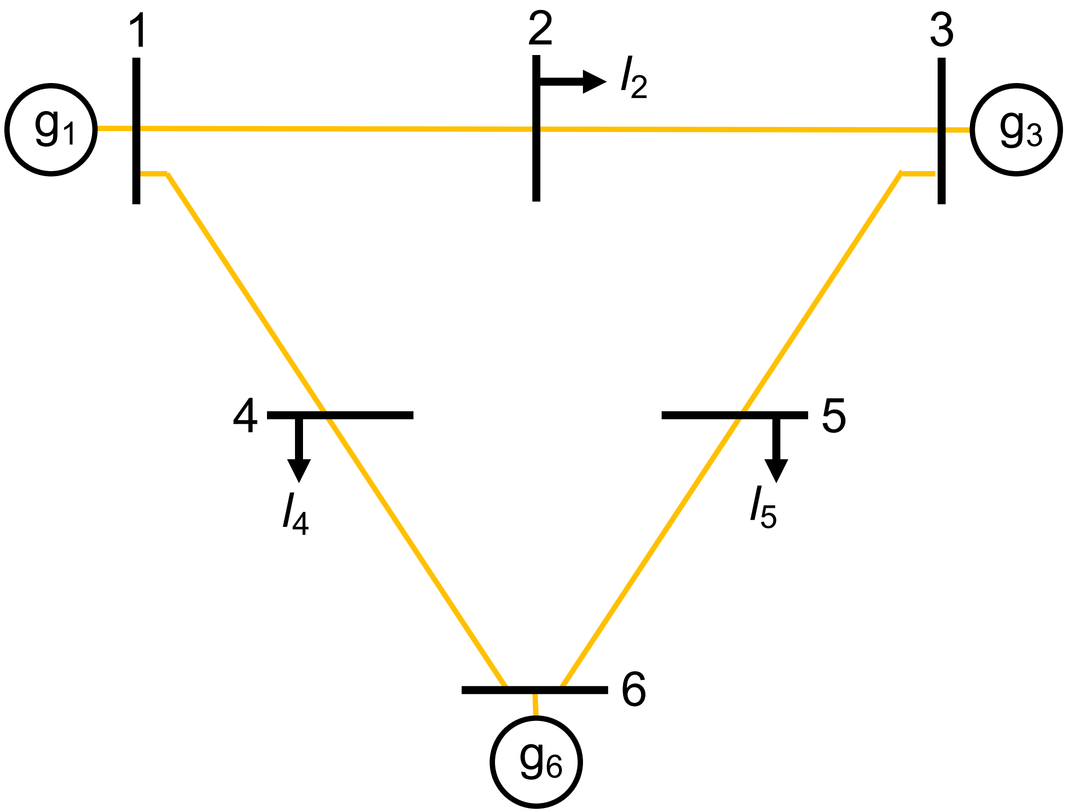
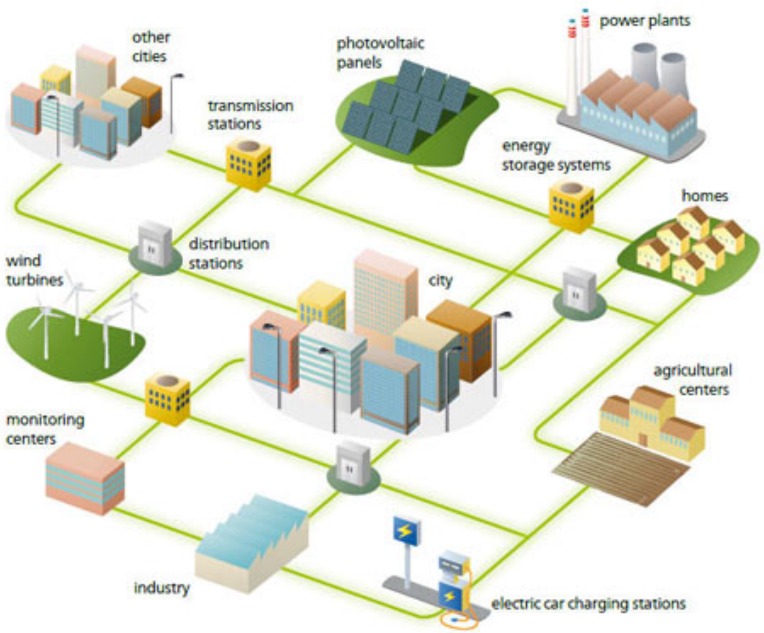


Smart Grid

- Smart Grid: is a vision of the future electricity grid.
- It adopts both electricity and information flow, to improve efficiency and reliability of the energy production and distribution.



Smart Grid: EDDR Model

- **Economic Dispatch (ED)**: Power allocation to generators in order to meet the power load with the lowest costs.

- **Demand Response (DR):** How consumer should change their energy usage to reduce peak power consumption.

- ED and DR are typically solved in isolation despite the clear inter-dependencies between them.

- We propose a ED DR integrated model aimed at **maximize** the benefits of customers and **minimize** the generation costs.

EDDR Model

Maximize:

$$\sum_{t=1}^{H} \alpha^t \left(\sum_{l \in \mathcal{L}} u_l(L_l^t) - \sum_{g \in \mathcal{G}} c_g(G_g^t) \right)$$

Where:

$$c_g(G_g^t) = \alpha_g G_g^t + \beta_g (G_g^t)^2 + \boxed{|\epsilon_g \sin(\phi_g (G_g^{min} - G_g^t))|}$$

$$u_l(L_l^t) = \begin{cases} \beta_l L_l^t - \frac{1}{2}\alpha_l (L_l^t)^2 & \text{if } L_l^t \leq \frac{\beta_l}{\alpha_l} \\ \frac{1}{2}\frac{(L_l^t)^2}{\beta_l} & \text{otherwise} \end{cases}$$

Rippling effect on the generator's power-cost curve caused by opening a sequence of generator steam valves.

EDDR Model

Maximize:

$$\sum_{t=1}^{H} \alpha^t \left(\sum_{l \in \mathcal{L}} u_l(L_l^t) - \sum_{g \in \mathcal{G}} c_g(G_g^t) \right)$$

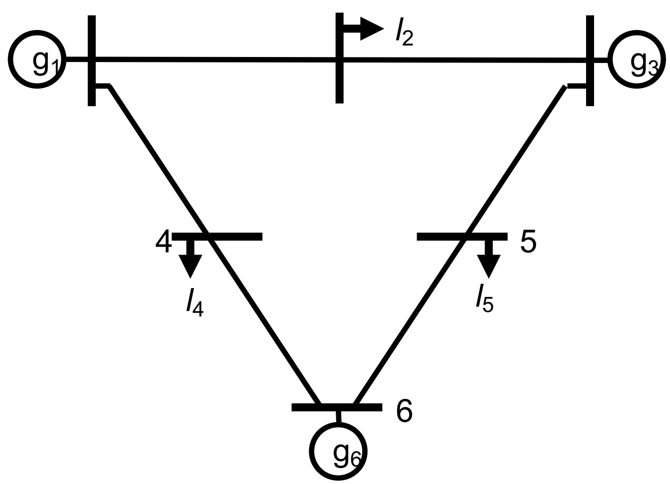
Subject to:

Constraints	Type
Generators and Loads limits	unary
Load predictions	unary
Power supply-demand balance	n-ary
DC power flow	n-ary
Transmission lines power limits	global – non monotonic
Generator ramp rate constraints	binary
Generator prohibited operating zones	unary

DCOP: Model

<***X***, ***D***, ***F***, A>:

- ***X:*** Set of variables.
- ***D:*** Set of finite domains for each variable.
- ***F:*** Set of constraints between variables.
- ***A:*** Set of agents, controlling the variables in ***X***.



x_a	x_b	U
0	0	3
0	1	$\perp$
1	0	2
1	1	5

Constraint

DCOP: Model

<***X***, ***D***, ***F***, A>:

- ***X:*** Set of variables.
- ***D:*** Set of finite domains for each variable.
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- ***A:*** Set of agents, controlling the variables in ***X***.

- GOAL: Find a utility maximal assignment.

$$
\begin{aligned}
\mathbf{x}^* &= \arg\max_{\mathbf{x}} \mathbf{F}(\mathbf{x}) \\
&= \arg\max_{\mathbf{x}} \sum_{f \in \mathbf{F}} f\left(\mathbf{x}|_{\text{scope}(f)}\right)
\end{aligned}
$$

i *i*

i

DCOP: Assumptions

- Agents coordinate an assignment for their variables.
- Agents operate distributedly.

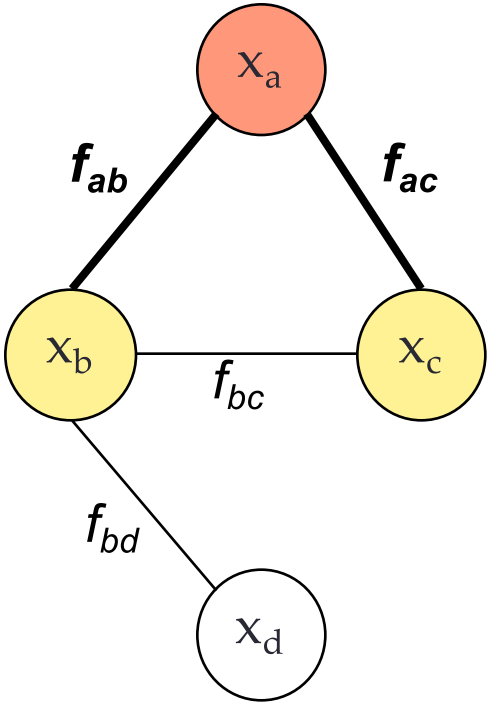
Communication:

- By exchanging messages.
- Restricted to agent's local neighbors.

Knowledge:

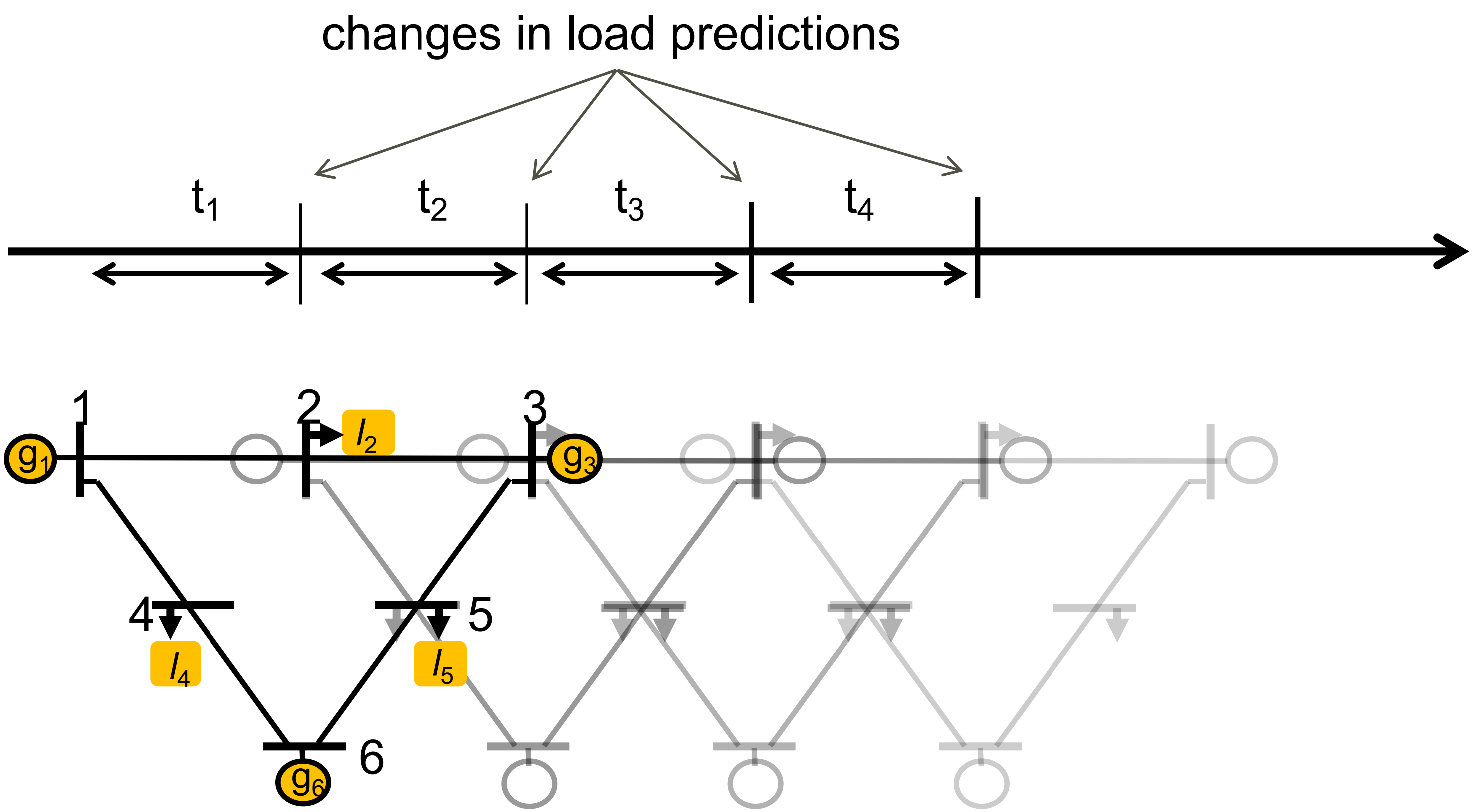
- Restricted to agent's sub-problem.

- Privacy preserving.



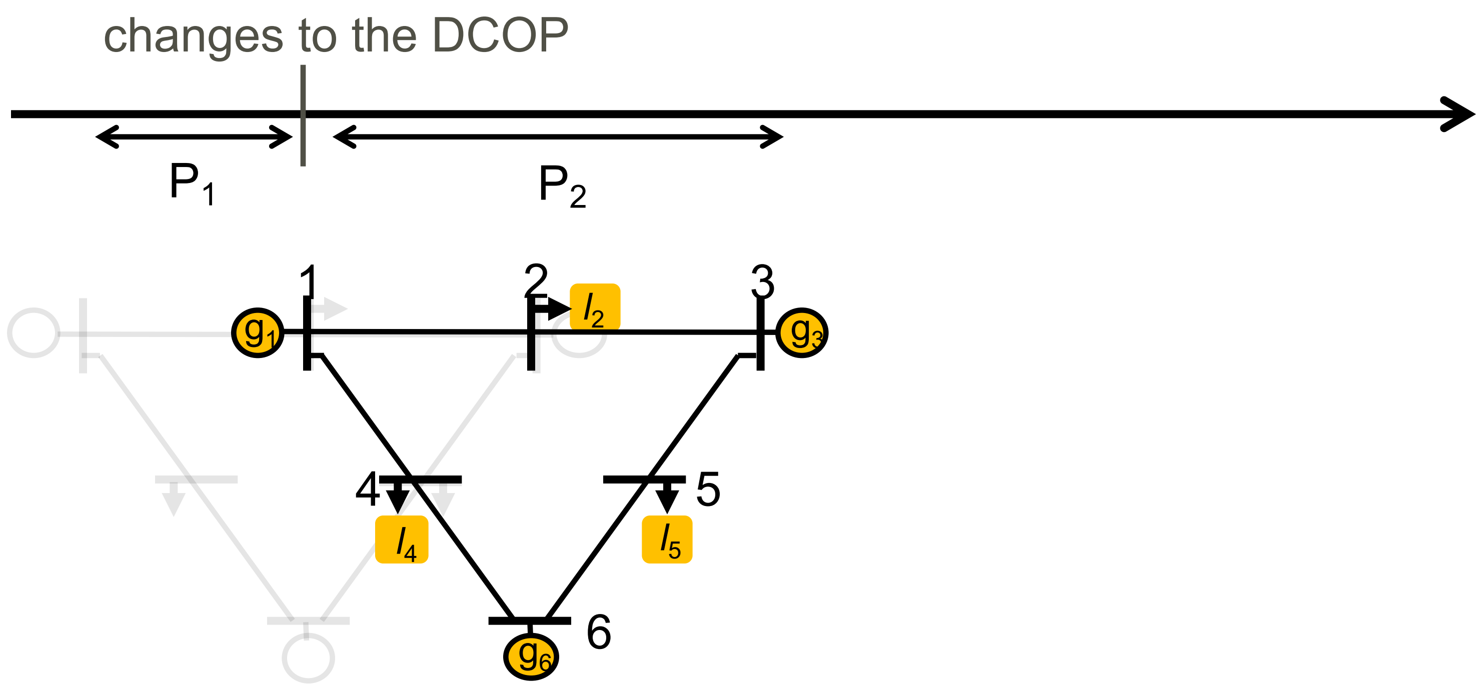
EDDR Model

- The EDDR model accommodates dynamic changes in the load predictions.



Dynamic DCOP

- Dynamic DCOP:
  - Model dynamic changes as sequence of static DCOPs $P_1, \ldots, P_H$.
  - Solve each static DCOP individually.
- **Reactive approach**.



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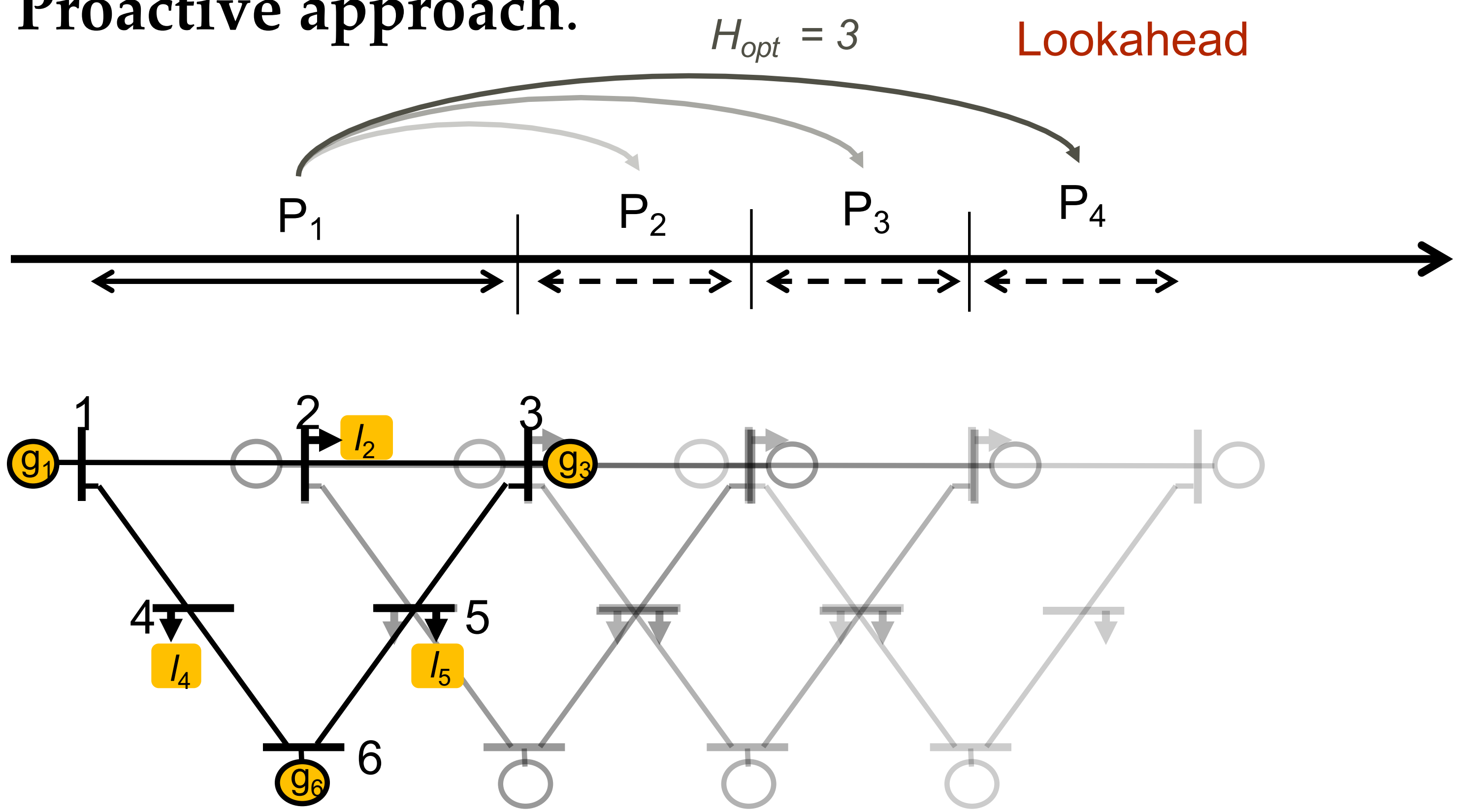

EDDR Model

- Inference-based DCOP approach.
- Problem: Transmission lines power limits.
  - Causes the messages size to increase exponentially at each step.

Maximize:

$$\sum_{t=1}^{H} \alpha^t \left(\sum_{l \in \mathcal{L}} u_l(L_l^t) - \sum_{g \in \mathcal{G}} c_g(G_g^t) \right)$$

Subject to:

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EDDR Model

- Inference-based DCOP approach.
- Problem: Transmission lines power limits.
  - Discard the global constraint.
  - Introduce a penalty term for each transmission line.

Maximize:

$$\sum_{t=1}^{H} \alpha^t \left(\sum_{l \in \mathcal{L}} u_l(L_l^t) - \sum_{g \in \mathcal{G}} c_g(G_g^t) - \boxed{\sum_{(i,j) \in \mathcal{E}} \lambda_{ij}^t} \right)$$

Subject to:

Constraints
Generators and Loads limits
Load predictions
Power supply-demand balance
DC power flow
~~Transmission lines power limits~~
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Generator prohibited operating zones

Iterative approach to attempt improving the solution quality.

EDDR: Results

- Domains (all with non-convex solution spaces):

System	# generators	# loads	# transmission lines
IEEE 5-Bus	1	5	7
IEEE 14-Bus	5	11	20
IEEE 30-Bus	6	27	41
IEEE 57-Bus	7	42	80
IEEE 118-Bus	54	91	177

- Evaluation Metric:
  - Simulated Runtime.
  - Solution Quality (Normalized Social Welfare).
  - Solution Stability (with *Matlab Simulink SimPowerSystem* simulator).

EDDR: Results

IEEE Buses	H_{opt}	Normalized Quality 1	2	3	4
	5	0.8732	0.8760	0.9569	1.00
	14	0.6766	0.8334	1.00	–
	30	0.8156	1.00	–	–
	57	0.8135	1.00	–	–
	118	1.00	–	–	–

IEEE Buses	H_{opt}	Simulated Runtime (sec) CPU Implementation 1	2	3	4
	5	0.010	0.044	3.44	127.5
	14	0.103	509.7	–	–
	30	0.575	9084	–	–
	57	4.301	–	–	–
	118	174.4	–	–	–

Settings

- 0.01PU discretization unit.
- Domain sizes = 100 – 320.
- We fix H = 12 and vary the H_{opt}.

Main Results

- All solutions reported were satisfiable within **4 iterations**.
- The solution quality increases as H_{opt} increases.
- The runtime increases as H_{opt} increases.

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EDDR: Exploiting GPU parallelism

- Each agent need to compute a large number of combinations of powers injections and withdraws.
  - Fine granularity in the domain representation (0.01 PU).
- Exploit Parallelism from *[Fioretto et al., CP'15].*

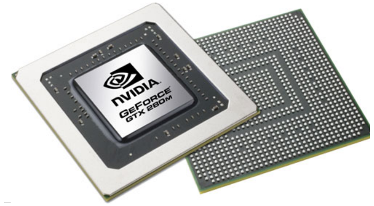
Exploit GPU parallelism

G_1^1	L_1^1	...	f_{12}^1	f_{13}^1	...	Utility
10	23	...	21.3	1.3	...	70.4
9	23	...	20.3	2.2	...	71.3
...	...	...	...	...	...	...

G_2^1	L_2^1	...	f_{12}^1	f_{13}^1	...	Utility
5	10	...	1.6	2.2	...	10.0
6	10	...	3.2	-4.4	...	20.0
...	...	...	...	...	...	...

$\oplus$

$G_{1\,2}^1$	$L_{1\,2}^1$	...	f_{12}^1	f_{13}^1	...	Utility
15	33	...	22.9	3.5	...	80.4
16	33	...	24.5	-3.1	...	90.4
...	...	...	...	...	...	...



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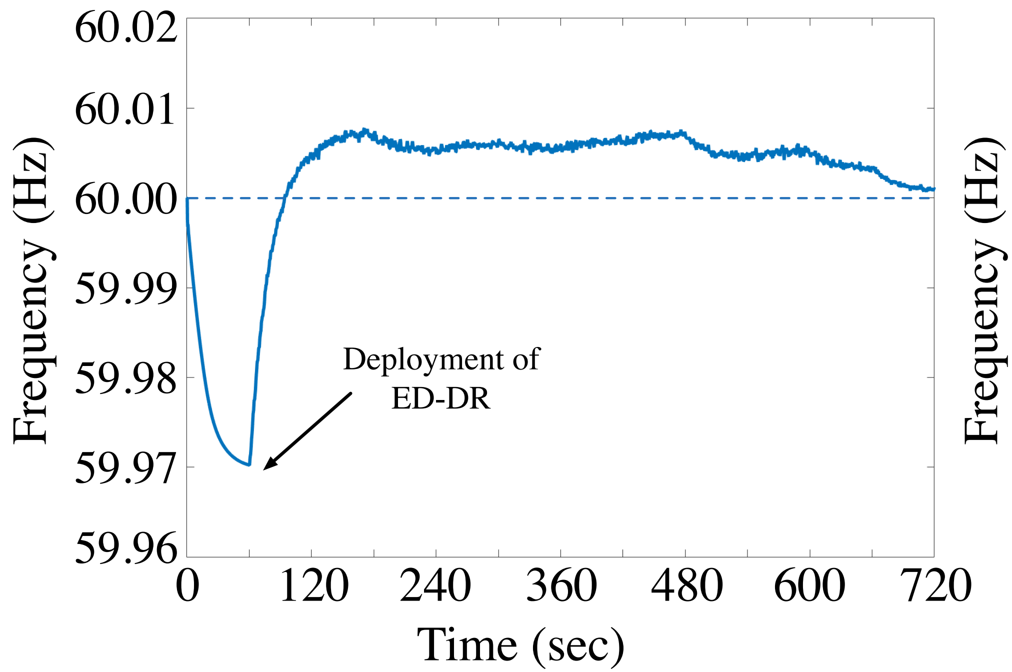
Main Results

- GPU speeds up R-Deeds up to 2 order of magnitude!
- GPU increases scalability of R-Deeds.

IEEE Buses	H_{opt}	Simulated Runtime (sec) GPU Implementation 1	2	3	4
	5	0.025 (0.4x)	0.038 (1.2x)	0.128 (26.9x)	2.12 (60.2x)
	14	0.077 (1.3x)	3.920 (130x)	61.70 (n/a)	–
	30	0.241 (2.4x)	79.51 (114x)	–	–
	57	0.676 (6.4x)	585.4 (n/a)	–	–
	118	4.971 (35.1x)	–	–	–

EDDR: Results



Settings

- Control signal are transmitted to the loads and generators every minute.
- First 60 sec. ED solutions only.

Main Results

- Frequency deviation is within 0.05 Hz (good stability).

Conclusions and Future Work

- Exciting era for multi-agent systems in smart grids!
- Distributed Economic Dispatch with Demand Response as a DCOP.
- **Deeds**: An iterative inference-based algorithm to solve the D-EDDR problem.
- GPU solution to scale to acceptable runtimes.

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- Distributed Economic Dispatch with Demand Response as a DCOP.
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Thank You!

EDDR Dynamic DCOP Model

- Time Step → Time steps of the Dynamic DCOPs $P_1, \ldots, P_H$
- Buses → DCOP Agents
  - Generators → Decision Variables.
    Domains: Power injected in MW.
  - Dispatchable Loads → Decision Variables.
    Domains: Power withdrawn in MW.
  - Flow → Environment variables.
- EDDR Constraints:
  - → DCOP hard constraints within the same DCOP P_i
  - → DCOP hard constraints across DCOPs P_i, P_{i+1}
- EDDR Objective Function:
  - → Decomposed in $|\mathcal{L} \cup \mathcal{G}|$ unary functions.