Research Needs for Co-optimization of Multi-level Integrated Electricity Systems

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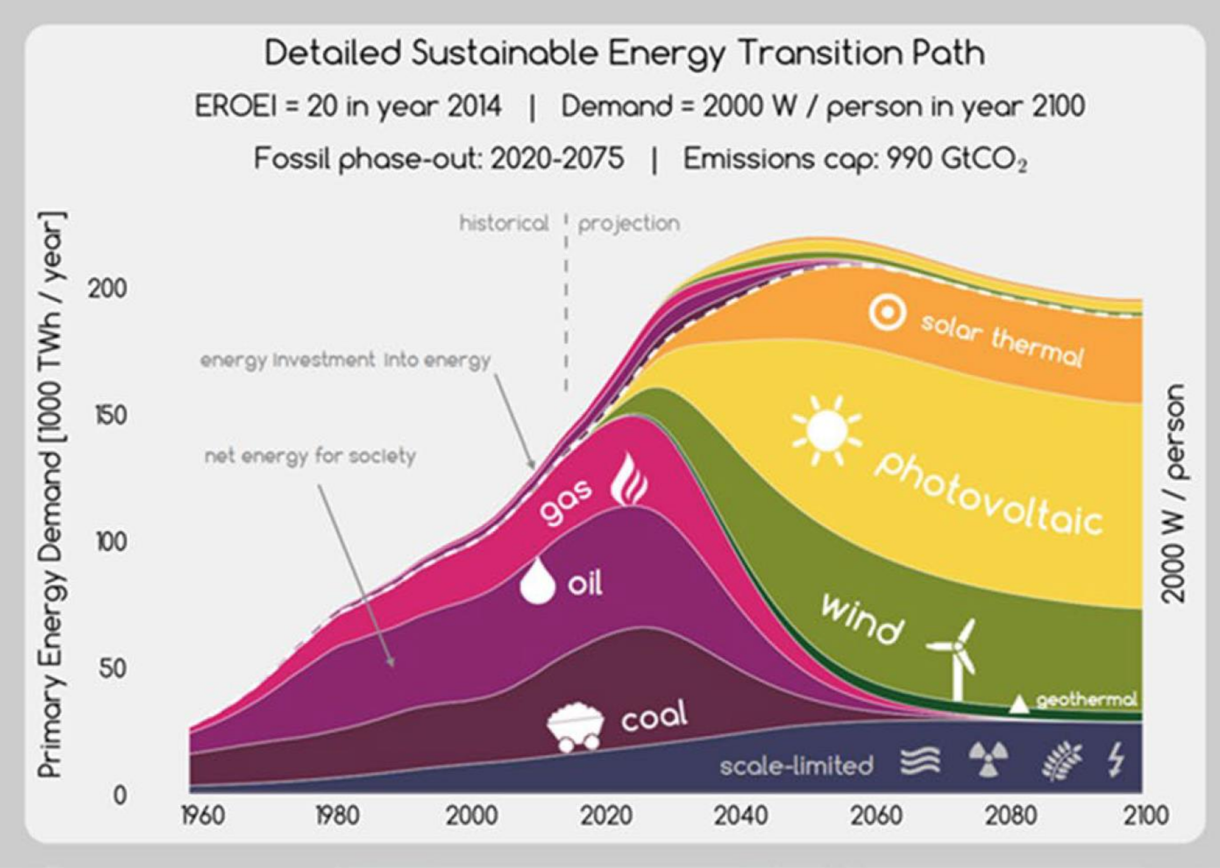
An Ambitious Future



- Estimates range from below 50% to 80% renewables by 2050
- Many reports ignore the operational issues of renewables
- Consensus that significant changes are required to address climate change

Image:Bardi & Sgouridis (2017)

Key Features of the Future

- Interconnected, renewables, **storage**, DER, and **consumer participation**
- Participating resources are split across **transmission and distribution** (or microgrids)
  - ISO including distribution system flexibility
  - Distribution flexible loads, respond to signals from ISO
- ➢ New operational models for **co-ordinated decision making**

Example 1: Storage Changes Operational Decisions

- All visions of the future grid include storage (utility scale, and distributed) as a key component for reliability
- Scalable algorithms for operating multiple storage units on a network are required

$$\min \left\{ \mathbb{E} \left[\sum_{t=1}^{T} c_t \left(\cdot \right) \right] \right\}$$

Subject to, for $1 \leq t \leq T$:

$$\Phi(p_t, d_t, w_t) = 0$$

$$\Theta(\theta_t, e_t) = 0$$

$$\Xi(s_t, \Delta_t) = 0$$

$$\underline{\Psi}_t \leq \Psi_t \leq \overline{\Psi}_t$$

The intertemporal nature of charge/discharge decisions make the problem more challenging, and higher dimension

Most existing research addresses a single storage unit, and/or no network constraints

Stochastic Dynamic Programming

For $t = T, T-1, \cdots, 1$:

$$F_t(s_t, p_{t-1}, w_{t-1}) = \min\left\{c_t(\cdot) + \mathbb{E}\left[F_{t+1}(s_{t+1}, p_t, \tilde{W}_t)\right]\right\}$$

$$\text{S.t.}\quad \Phi(p_t, d_t, w_t) = 0$$

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- $F_{t+1}(s_{t+1}, p_t, w_t)$, called *cost-to-go* is the cost from period $t+1$ through the end of the horizon.

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Theoretically optimal solution, but challenges in:

- *Computing the expectation*
- *Optimization at every state (s_t,p_{t-1},w_{t-1})*

- $F_{t+1}(s_{t+1}, p_t, w_t)$, called *cost-to-go* is the cost from period $t+1$ through the end of the horizon.

Approximate Stochastic Dynamic Programming

Replace $\mathbb{E}\left[F_{t+1}(s_{t+1}, p_t, \tilde{W}_t)\right]$ (assumed to be convex) with some **lower bound** $\hat{V}_{t+1}(s_{t+1}, p_t, w_t)$.

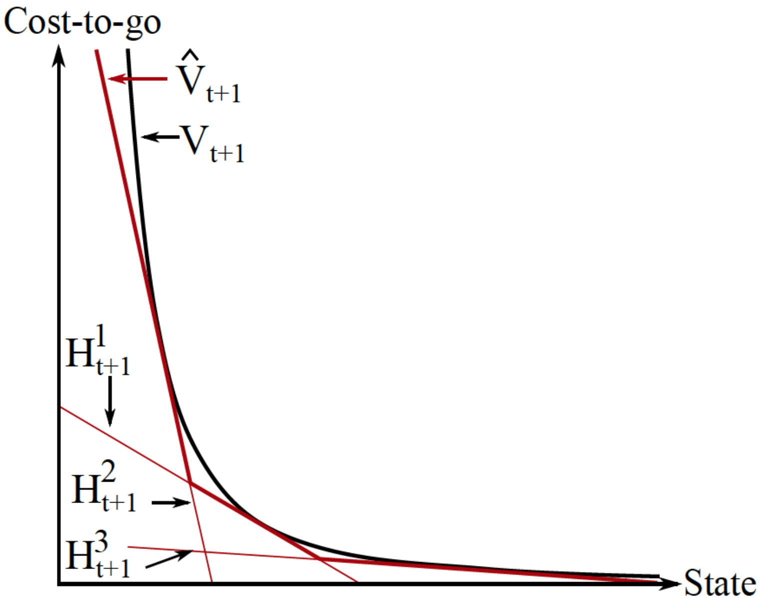


Figure: Illustration SDDP approximation

Approximate Stochastic Dynamic Programming

$$\hat{F}_t(s_t, p_{t-1}, w_{t-1}) = \min \left\{ \sum_{t=1}^{T} c_t(\cdot) + \rho_{t+1} \right\}$$

$$\begin{aligned} \text{S.t.} \quad & \Phi(p_t, d_t, w_t) = 0 \\ & \Theta(\theta_t, e_t) = 0 \\ & \Xi(s_t, \Delta_t) = 0 \\ & \underline{\Psi}_t \leq \Psi_t \leq \overline{\Psi}_t \\ & \rho_{t+1} \geq \tilde{c}^i_{t+1} + \tilde{g}_{s^i_{t+1}} s_{t+1} + \tilde{g}_{p^i_t} p_t + \tilde{g}_{w^i_t} w_t, \ 1 \leq i \leq I \end{aligned}$$

Approximate the expectation with a simpler function of the state estimators

How accurate is SDDP?

Compare to *true optimal* for a small, solvable (for SDP) system with one storage unit.

Experiments show that

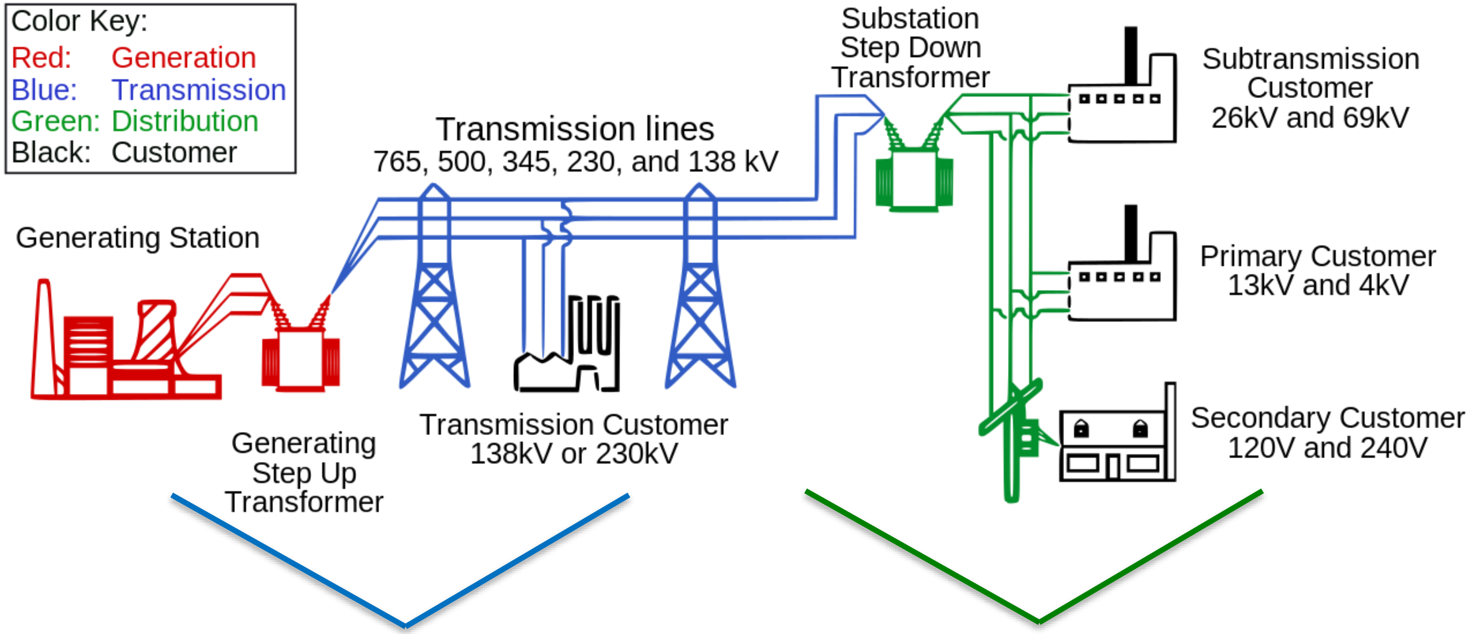
- SDDP approximates the true optimal within 0.25%
- Take less than 15% of the computation time

How scalable is SDDP?

Table: Computation time in seconds for different number of buses, storage facilities and wind farms

# buses	$\|S\|$	$\|M\|$	Time	# buses	$\|S\|$	$\|M\|$	Time
30	1	1	1 229.80	118	1	1	2 399.35
30	5	1	1 582.67	118	5	1	2 444.99
30	5	5	1 323.88	118	5	5	2 453.89
57	1	1	1 388.09	118	10	5	2 179.62
57	5	1	1 454.47	118	20	10	2 248.39
57	5	5	1 396.26	300	1	1	4 159.16
57	10	5	1 597.71	300	5	1	4 234.72
89	1	1	1 570.67	300	5	5	4 570.01
89	5	1	1 709.68	300	10	5	4 617.65
89	5	5	1 575.09	300	20	10	5 036.37
89	10	5	1 737.32				

Example 2: Demand side participation changes operations



Utility scale renewables create uncertainty

Responsive loads, storage, other distributed resources

Co-ordinated decision making example

- Consider placement of a responsive DSO on a transmission system model
- Select candidate location for the responsive node based on congestion studies
- Explore impact of import/export pricing strategies on transmission congestion conditions
- Stochastic UC at transmission, with distribution flexibility via new pricing scheme

Distribution Impacts on Transmission

Investigations detailed in [Liu et al., 2016] illustrate the benefits of transmission/distribution co-operation

Case \ t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
No MG	3.91	3.87	3.86	3.84	3.85	3.85	3.88	3.96	4.04	4.41	5.80	5.40	6.26	6.86	6.56	7.01	6.16	4.69	4.20
MG @ bus 6	3.91	3.87	3.86	3.84	3.85	3.85	3.88	3.96	4.07	4.56	6.10	5.75	6.59	7.16	6.63	7.01	6.16	4.69	4.20
MG @ bus 17	3.91	3.87	3.86	3.84	3.85	3.85	3.88	3.96	4.05	4.46	5.93	5.54	6.39	6.98	6.59	7.01	6.16	4.69	4.20
MG @ bus 8	3.91	3.87	3.86	3.84	3.85	3.85	3.88	3.96	4.00	4.01	4.03	4.01	4.03	4.05	4.05	4.06	4.29	4.02	4.02

11	12	13	14	15	16	17	18	19
5.80	5.40	6.26	6.86	6.56	7.01	6.16	4.69	4.20
6.10	5.75	6.59	7.16	6.63	7.01	6.16	4.69	4.20
5.93	5.54	6.39	6.98	6.59	7.01	6.16	4.69	4.20
4.03	4.01	4.03	4.05	4.05	4.06	4.29	4.02	4.02

Distribution Impacts on Transmission

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Frequency of Transmission Congestion by hour

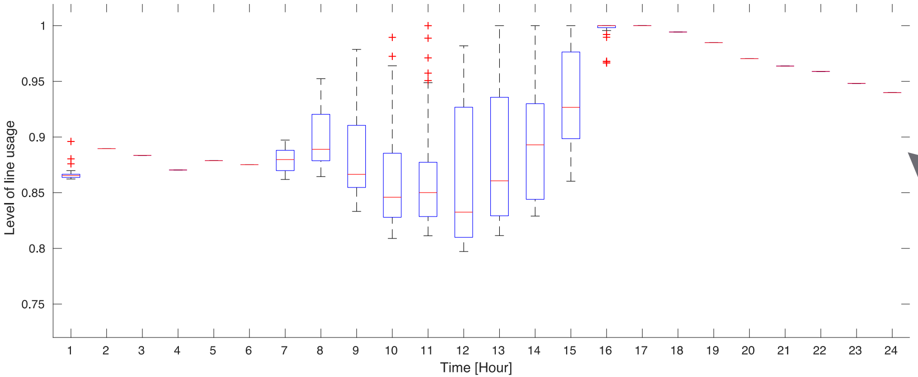
t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
PWL	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0
FLMP	0	0	0	0	0	0	0	8	6	0	0	9	0	0	0	0	6	8	22	0	0	0	0	0
HLMP	0	0	0	0	0	0	0	0	0	0	1	0	4	4	4	23	31	0	0	0	0	0	0	0

Alternative pricing schemes for transactions between microgrid and transmission system

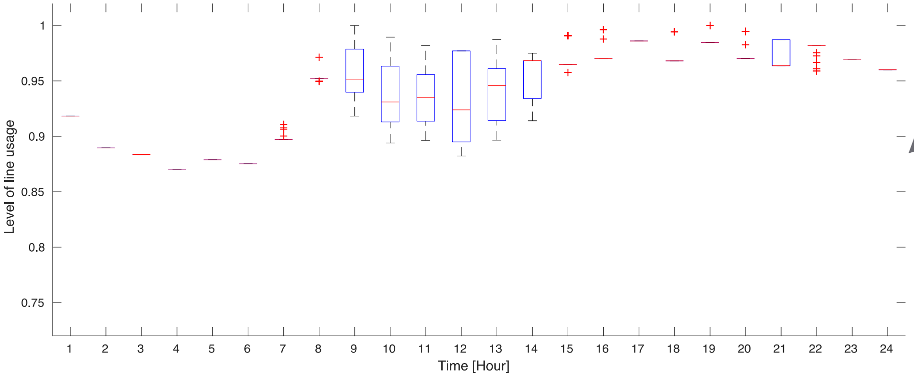
Distinct differences in congestion results

Distribution Impacts on Transmission

ISO/Distribution exchange at LMP

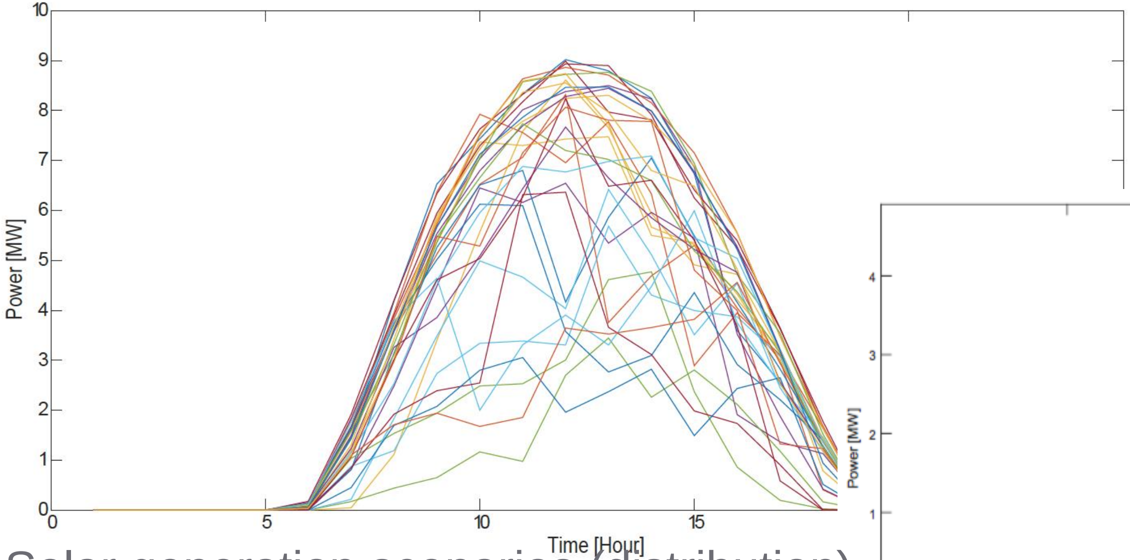


Adjusted pricing function

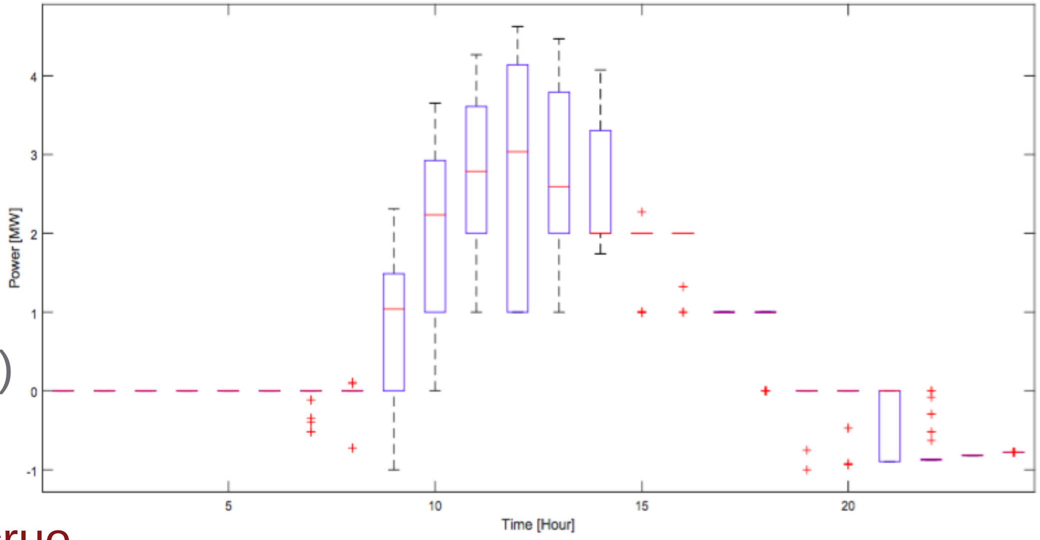


Adjusting pricing scheme also reduces LMP variability at the connected bus

Benefits to Distribution



Solar generation scenarios (distribution)



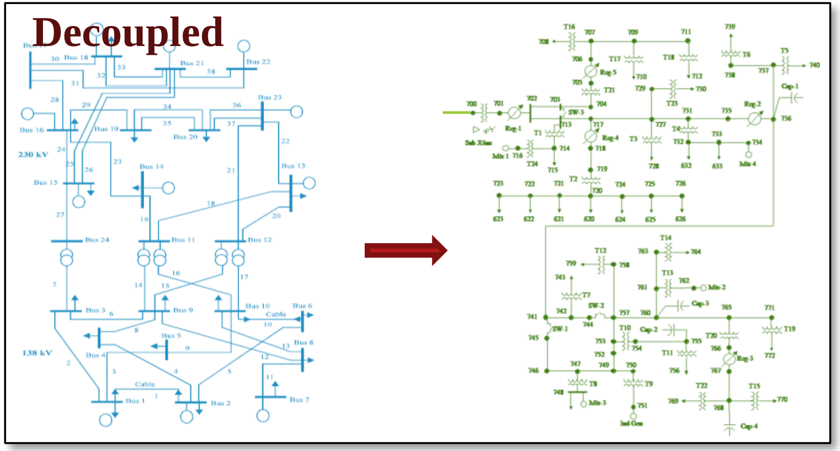
Net Export Distribution

Study indicates that both systems accrue benefits, even in simple case.

Co-optimization of T&D

The fundamental assumption is that the transmission system will provide a prescribed voltage at the substation, and the distribution system will deliver the power to the individual residential and commercial customers.

NAS (2016). Analytic Research Foundations for the Next-Generation Electric Grid.



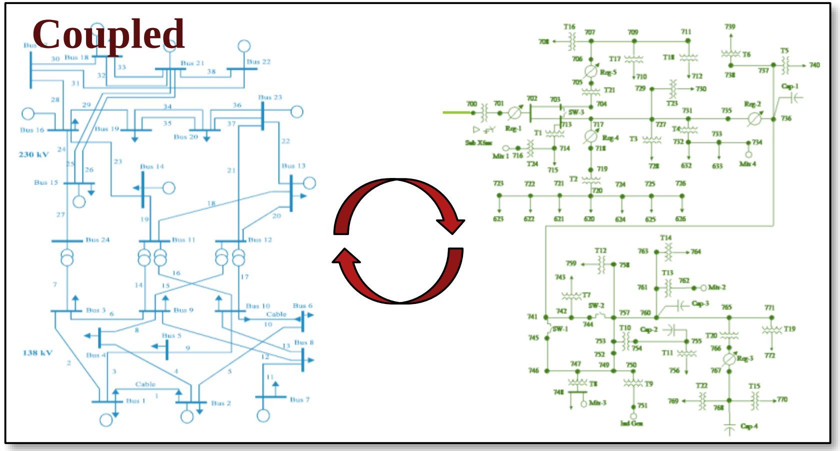
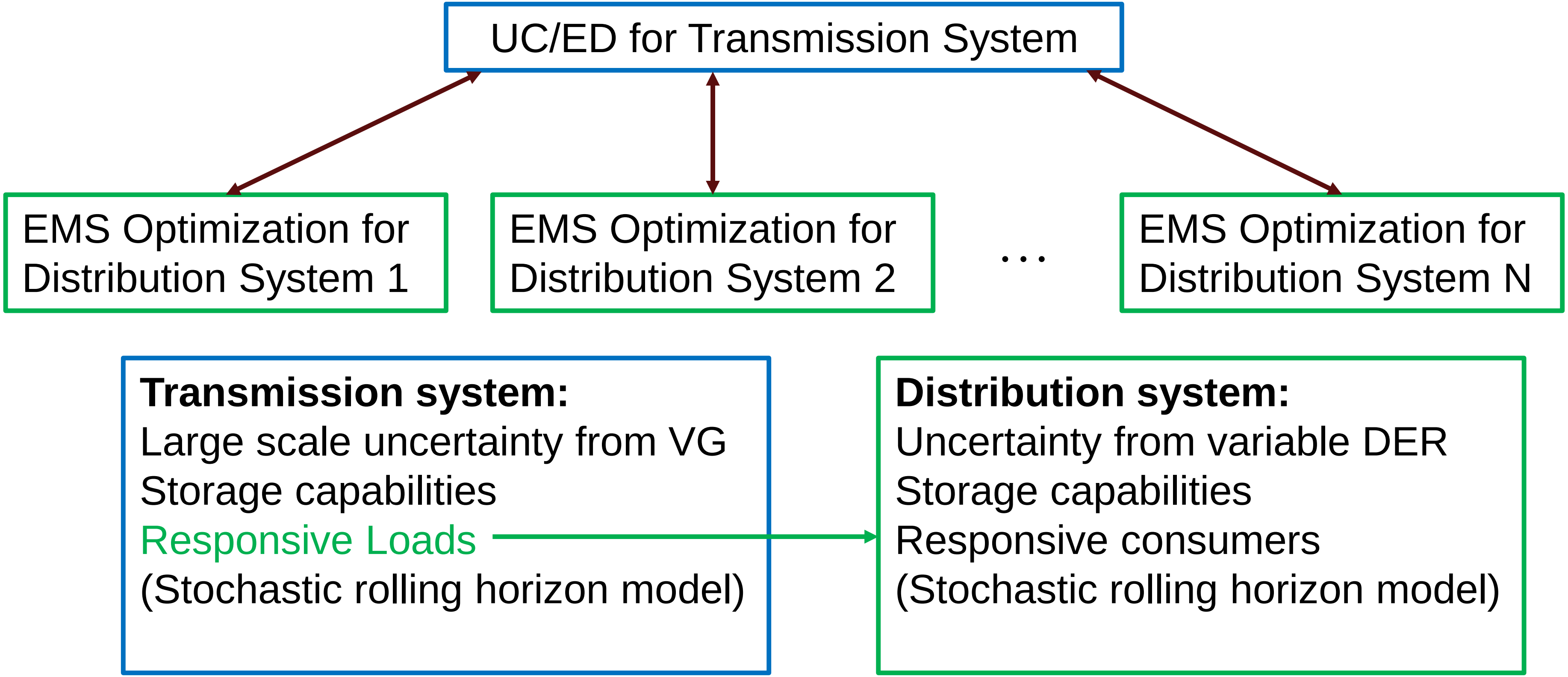


Image credit: Visvakumar Aravinthan

Co-optimization

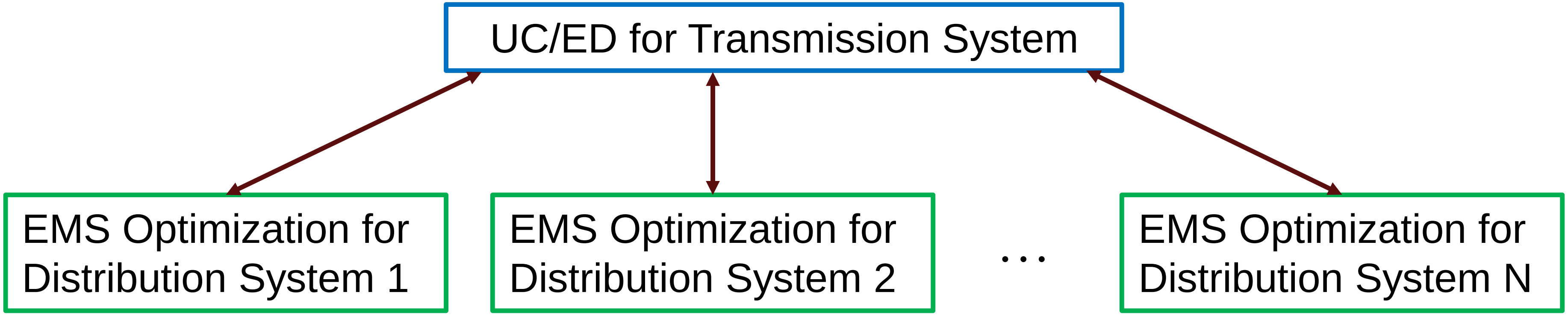


Requirement: Scalable Co-optimization Algorithms

We are currently exploring two approaches:

- Bi-level optimization: the SCUC and economic dispatch includes decision variables at distribution to maximize “social welfare”
- Distributed predictive control: relevant information can be shared between systems/subsystems, each system optimizes for individual objectives, while linking variables promote co-operation

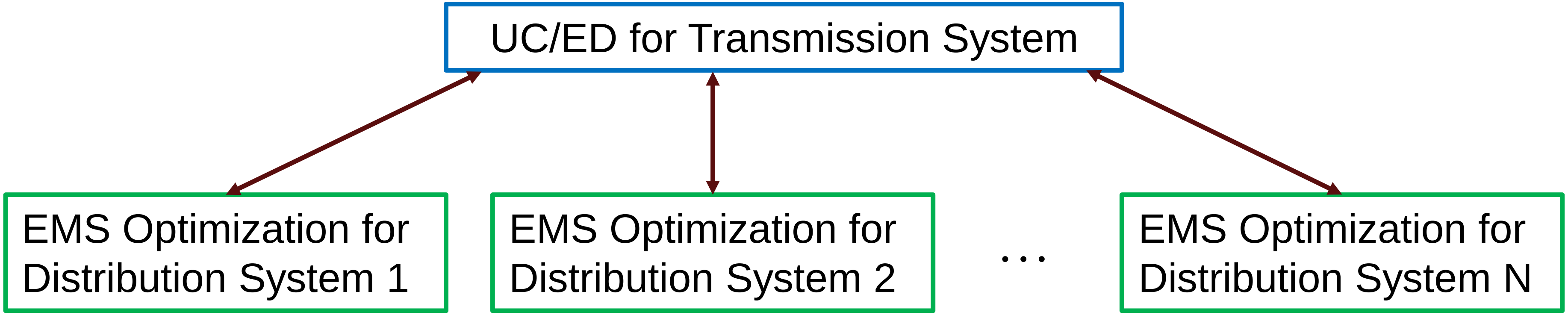
Bi-level Optimization



First approach: Formulate into extensive form, using KKT conditions to include distribution level decisions in single formulation

Challenge: Tractable for small number of distribution systems on a single network. A single distribution system does not contribute sufficient flexibility to support high penetration of renewables.

Co-optimization – decomposed, shared information



Second approach: Decompose problem, with iterative feedbacks (similar to the simple example described early)

Challenge: Tractable due to decomposition, timing of coordinating information has trade-offs.

Examples illustrate that

1. modern **approximate models** with provable convergence can provide high quality solutions more efficiently,
2. system-wide benefits are possible through **co-ordinated decision making** to facilitate responsive loads, and
3. new distributed/co-ordinated models are required that will be **scalable to high-dimension**.

These developments in power system optimization will facilitate high renewable penetration scenarios in the future grid.

National Academy of Engineering (2016) states:

These major challenges then become a combination of

(1) sufficiently accurate models relevant for computing and decision making at different layers of such complex, interconnected grids,

(2) sufficiently accurate models for capturing the interdependencies/dynamic interactions, and

(3) control theories that can accommodate adaptive and robust distributed, coordinated control.

References

J. Liu, G. Martinez, and C. L. Anderson, “Quantifying the impact of microgrid location and behavior on transmission network congestion,” Proceedings of the Winter Simulation Conference, 2016, pp. 1745–1756.

Zéphyr, L., and C L. Anderson (2018). Stochastic dynamic programming approach to managing power system uncertainty with distributed storage. *Computational Management Science*, *15*, 87–110. http://doi.org/10.1007/s10287-017-0297-2

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