Electricity network design and operation in an era of solar and storage

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Research overview: Energy optimization, control and analysis

"Energy analysis":

- What are the benefits to strengthening international electricity transfer in the continent of Africa?
- What are the engineering and economic impacts of large scale PV penetration in distribution systems?

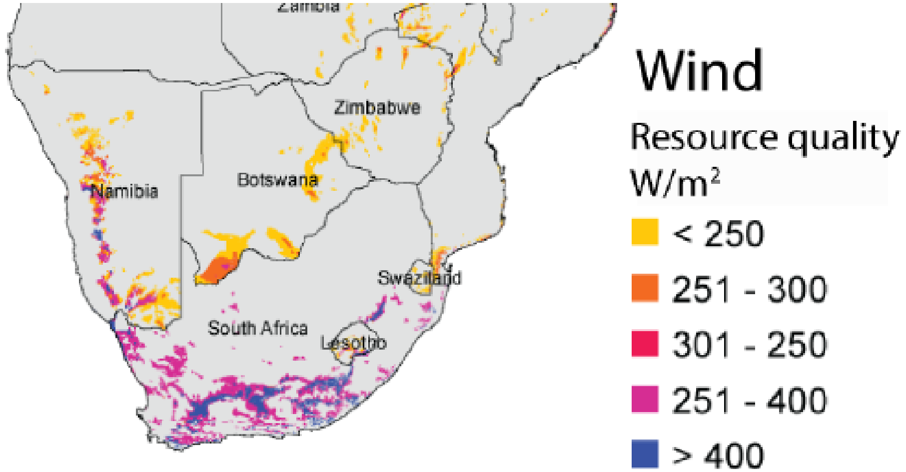


Figure: Wu, Deshmukh *et al*, PNAS (2017)

Control and optimization:

- Seeking renewables integration solutions; frequency and voltage regulation
- We develop and apply a variety of optimization and control tools
- Range of partnerships with demand response integrators, EV manufacturers, solar PV integrators.

Networks face emerging, competing pressures

- New loads, spatially diverse generation → network value increases
- New small-scale sources of generation, storage → reduces the need for the network

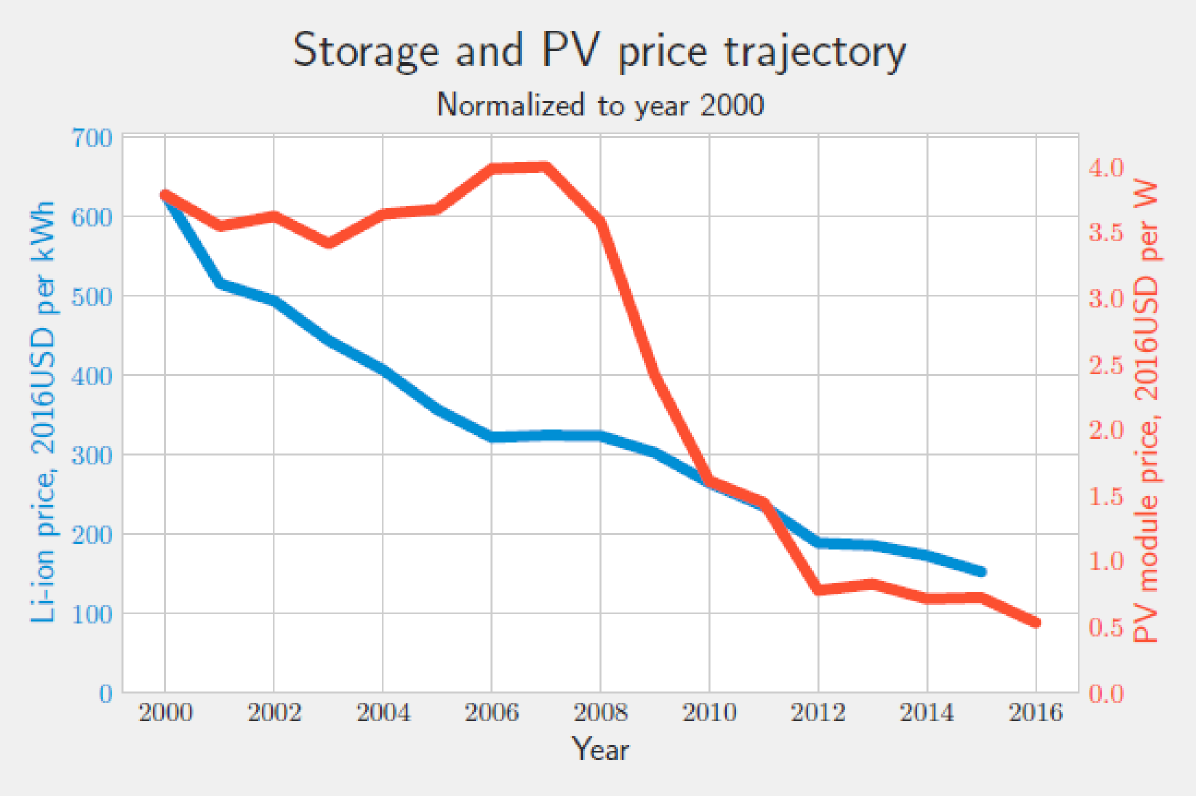
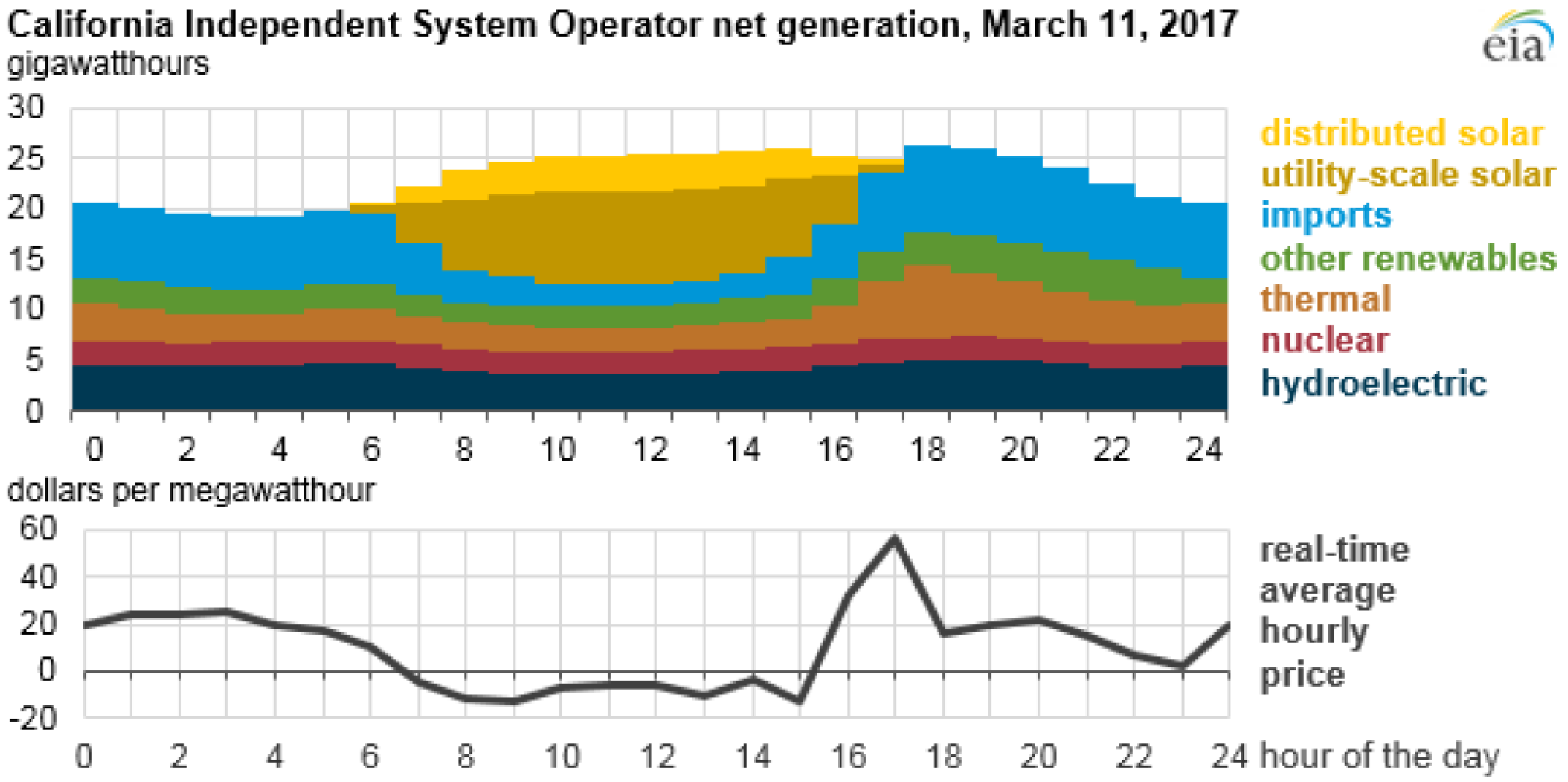


Figure: source: LBNL Tracking the Sun X (2017); Kittner *et al*, Nature Energy (2017)

Example: Solar meets EV charging...opportunity and challenge



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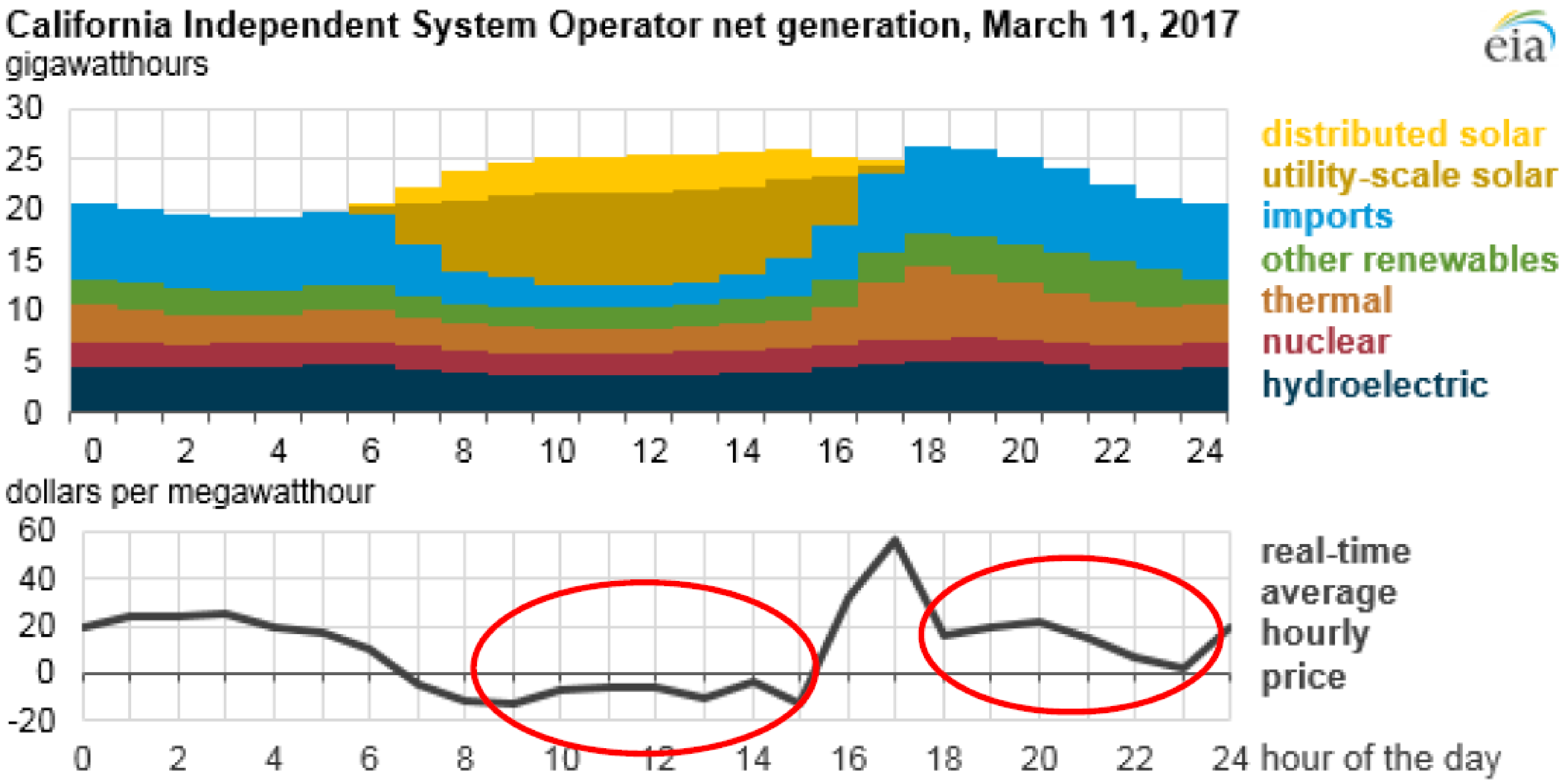
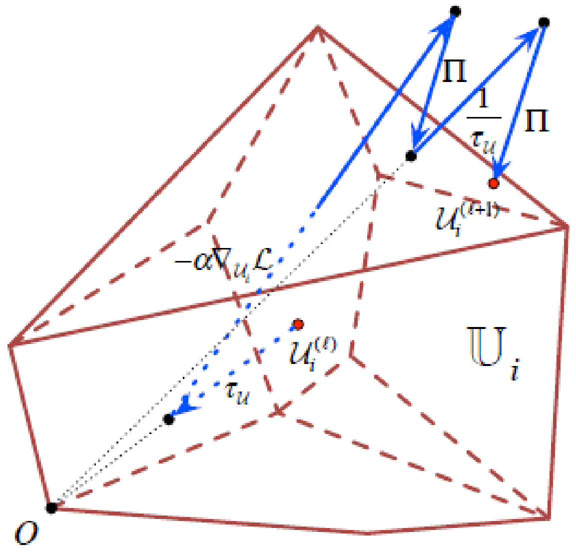


Low price hours for charging EVs, other electrified loads

Talk outline

1. Increase network utilization by coordinating distributed energy resources.
   - Decentralized control desirable, but...
   - Problem is strongly coupled
   - We modify the primal-dual subgradient method to handle this
   - Case study: EV charging



2. Decentralized *infrastructure* for electrification
   - Will storage replace wires – reliably?
   - Finding: At forecasted costs, decentralized systems need to become part of the central planning process.
   - Finding: Much of sub-Saharan Africa could see "reliability costs" of $USD 0.03 per "9" of reliability, per kWh served

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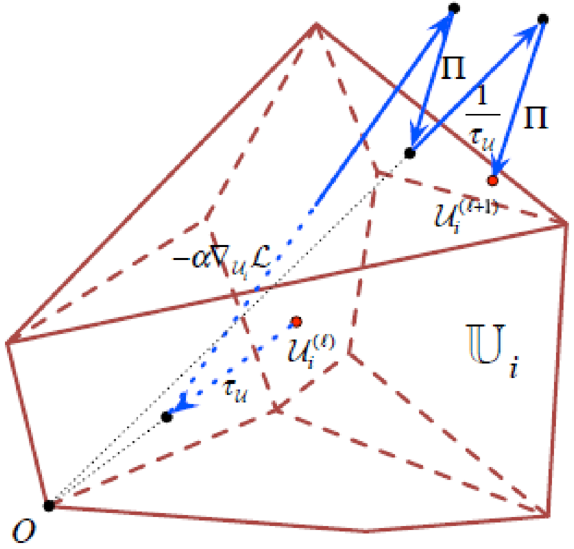

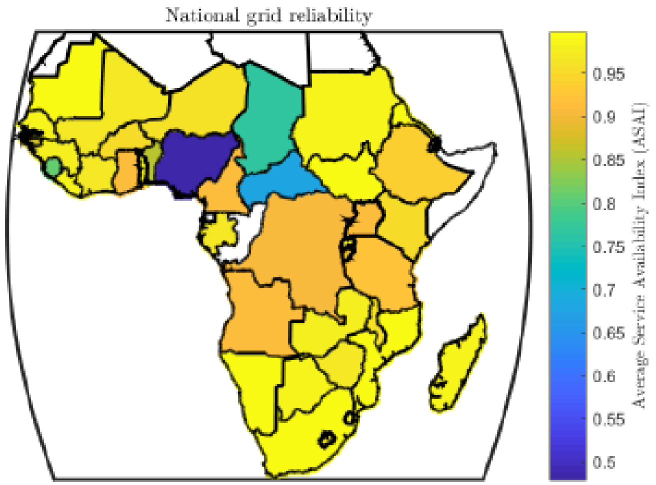

Part 1: Improving network utilization with growth in distributed energy resources

Distribution network aware battery (EV) charging

- **Objective**: Minimize some combination of:
  - Charging cost (wholesale or retail)
  - Ancillary services revenue
  - Utilization of infrastructure (e.g. “valley filling”)
  - Impact of charging on battery state of health
- **Constraints**
  - *Local*: Max / min charge rates, max / min state of charge
  - *Global*: Network thermal and voltage limits

If this is for an aggregation of resources, actions of one resource impact others in both the objective and constraints

Generic Charging Control – Mathematical Formulation

Battery charging control

$$\arg\min_{\mathcal{U}} \mathcal{F}(\mathcal{U}) \Leftarrow$$ **Convex, Coupled & Non-separable**

$$\text{s.t. } \mathcal{U}_i \in \mathbb{U}_i := \{\mathcal{U}_i | \mathbf{0} \leq \mathcal{U}_i \leq \mathbf{1}, x_i(k) + \mathcal{B}_{i,l}\mathcal{U}_i = 0\} \Leftarrow$$ **Local constraint**

$$\mathcal{Y}_{dk} + \sum_{i=1}^{n} \mathcal{D}_i \mathcal{U}_i \geq \underline{\nu}^2 \mathbf{V}_0 \Leftarrow$$ **Linearly coupled inequality constraint**

$\mathcal{U}_i$: Charging schedule of the ith device (0 to 1 charging rate)

$\mathcal{Y}_{dk} + \sum_{i=1}^{n} \mathcal{D}_i \mathcal{U}_i$: All bus voltage magnitudes during charging period

“Valley filling” Charging Control – Mathematical Formulation

Battery charging control

$$\arg\min_{\mathcal{U}} \mathcal{F}(\mathcal{U}) = \frac{1}{2}\left\|P_b + \sum_{i=1}^{n} \overline{P}_i \mathcal{U}_i\right\|_2^2 + \frac{\rho}{2}\|\mathcal{U}\|_2^2 \Leftarrow \text{Convex, Coupled \& Non-separable}$$

$$\text{s.t. } \mathcal{U}_i \in \mathbb{U}_i := \{\mathcal{U}_i | \mathbf{0} \leq \mathcal{U}_i \leq \mathbf{1}, x_i(k) + \mathcal{B}_{i,l}\mathcal{U}_i = 0\} \Leftarrow \text{Local constraint}$$

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P_b: Background load profile

Motivation for decentralized control and our aim

Centralized optimization...

- Doesn't scale well
- Requires sharing of information (conflicts with EV charging standards) and private utility functions (privacy issues)

Decentralized/distributed algorithms ...

- Must handle coupled/non-sep objective & coupled inequalities
- Introduce regularization errors or require many communication iterations (Koshal *et al* SIAM, 2011; Zhang *et al* TPS 2017).

In this work we set out to develop an algorithm that ...

- Is free of convergence error and works with relatively few communication iterations
- Does not require sharing (i) state of charge or (ii) any information with neighbors

Setup: Dual problem and projections

- Lagrangian

$$\mathcal{L}(\mathcal{U},\lambda) = \frac{1}{2}\left\|P_b + \sum_{i=1}^{n}\overline{P}_i\mathcal{U}_i\right\|_2^2 + \frac{\rho}{2}\|\mathcal{U}\|_2^2 + \lambda^\mathsf{T}\left(\mathcal{Y}_b - \sum_{i=1}^{n}\mathcal{D}_i\mathcal{U}_i\right)$$

- Projection methods can then be used to manage the local constraints with the following equilibrium condition:

$$\mathcal{U}^* = \Pi_{\mathbb{U}}\left(\mathcal{U}^* - \nabla_{\mathcal{U}}\mathcal{L}(\mathcal{U}^*,\lambda^*)\right)$$
$$\lambda^* = \Pi_{\mathbb{R}_+^{hK}}\left(\lambda^* + \nabla_{\lambda}\mathcal{L}(\mathcal{U}^*,\lambda^*)\right)$$

Finding the projected equilibrium

- **The primal-dual subgradient algorithm is simple:**

$$\mathcal{U}^{\ell+1} = \Pi_{\mathbb{U}}\left(\mathcal{U}^{\ell} - \alpha_\ell \nabla_{\mathcal{U}} \mathcal{L}(\mathcal{U}^\ell, \lambda^\ell)\right)$$
$$\lambda^{\ell+1} = \Pi_{\mathbb{R}_+^{hK}}\left(\lambda^{\ell} + \beta_\ell \nabla_{\lambda} \mathcal{L}(\mathcal{U}^\ell, \lambda^\ell)\right)$$

...but won't converge if you decentralize the control variable projection step.

- Koshal et al's solution is regularization: Convex penalties on the size of the decision variables
  - Regularization also known as a "shrinkage" methods because it drives decision variables toward zero.
  - Side effect: you're no longer solving the problem you set out to.

Could we shrink by other means and avoid the side effect?

- What if:

$$\mathcal{U}_i^{(\ell+1)} = \Pi_{\mathbb{U}_i}\left(\tau_{\mathcal{U}}\mathcal{U}_i^{(\ell)} - \alpha_{(i,\ell)}\nabla_{\mathcal{U}_i}\mathcal{L}(\mathcal{U}^{(\ell)}, \lambda^{(\ell)})\right)$$

$$\lambda^{(\ell+1)} = \Pi_{\mathbb{D}}\left(\tau_{\lambda}\lambda^{(\ell)} + \beta_{\ell}\nabla_{\lambda}\mathcal{L}(\mathcal{U}^{(\ell)}, \lambda^{(\ell)})\right)$$

...where $0 < \tau_{\mathcal{U}} < 1$ and $0 < \tau_{\lambda} < 1$?

- This shrinks the decision variables – but also moves us away from the desired solution.
- We could re-expand, but this might cause us to violate constraints again.
  - $\rightarrow$ Need to re-project
- **So, we tried an algorithm that iteratively updates:**

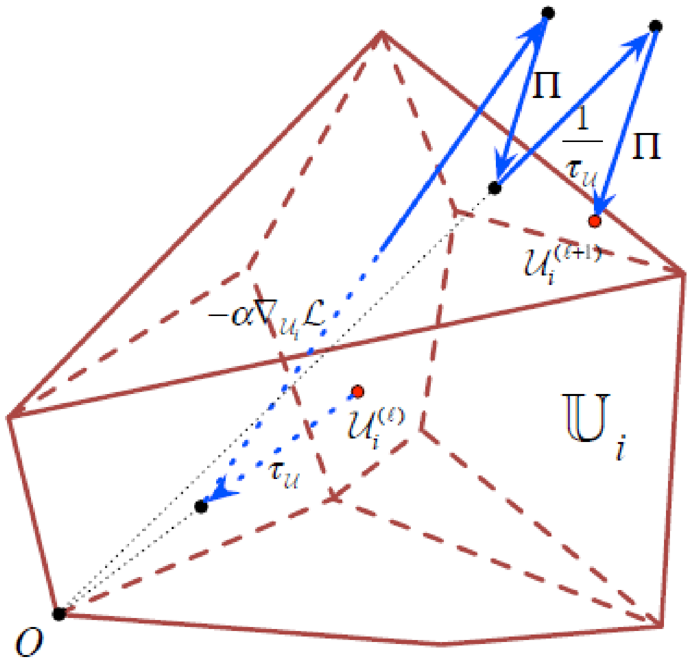
$$\mathcal{U}_i^{(\ell+1)} = \Pi_{\mathbb{U}_i}\left(\frac{1}{\tau_{\mathcal{U}}}\Pi_{\mathbb{U}_i}\left(\tau_{\mathcal{U}}\mathcal{U}_i^{(\ell)} - \alpha_{(i,\ell)}\nabla_{\mathcal{U}_i}\mathcal{L}(\mathcal{U}^{(\ell)}, \lambda^{(\ell)})\right)\right)$$

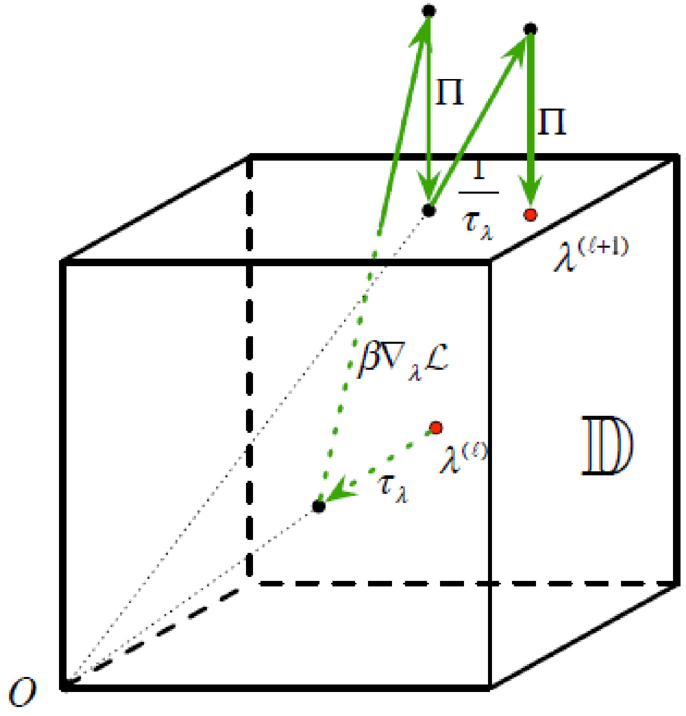
$$\lambda^{(\ell+1)} = \Pi_{\mathbb{D}}\left(\frac{1}{\tau_{\lambda}}\Pi_{\mathbb{D}}\left(\tau_{\lambda}\lambda^{(\ell)} + \beta_{\ell}\nabla_{\lambda}\mathcal{L}(\mathcal{U}^{(\ell)}, \lambda^{(\ell)})\right)\right)$$

"Shrunken Primal Dual Subgradient," or SPDS – Visualization

$$\mathcal{U}_i^{(\ell+1)} = \Pi_{\mathbb{U}_i}\left(\frac{1}{\tau_{\mathcal{U}}}\Pi_{\mathbb{U}_i}\left(\tau_{\mathcal{U}}\mathcal{U}_i^{(\ell)} - \alpha_{(i,\ell)}\nabla_{\mathcal{U}_i}\mathcal{L}(\mathcal{U}^{(\ell)}, \lambda^{(\ell)})\right)\right)$$

$$\lambda^{(\ell+1)} = \Pi_{\mathbb{D}}\left(\frac{1}{\tau_{\lambda}}\Pi_{\mathbb{D}}\left(\tau_{\lambda}\lambda^{(\ell)} + \beta_{\ell}\nabla_{\lambda}\mathcal{L}(\mathcal{U}^{(\ell)}, \lambda^{(\ell)})\right)\right)$$

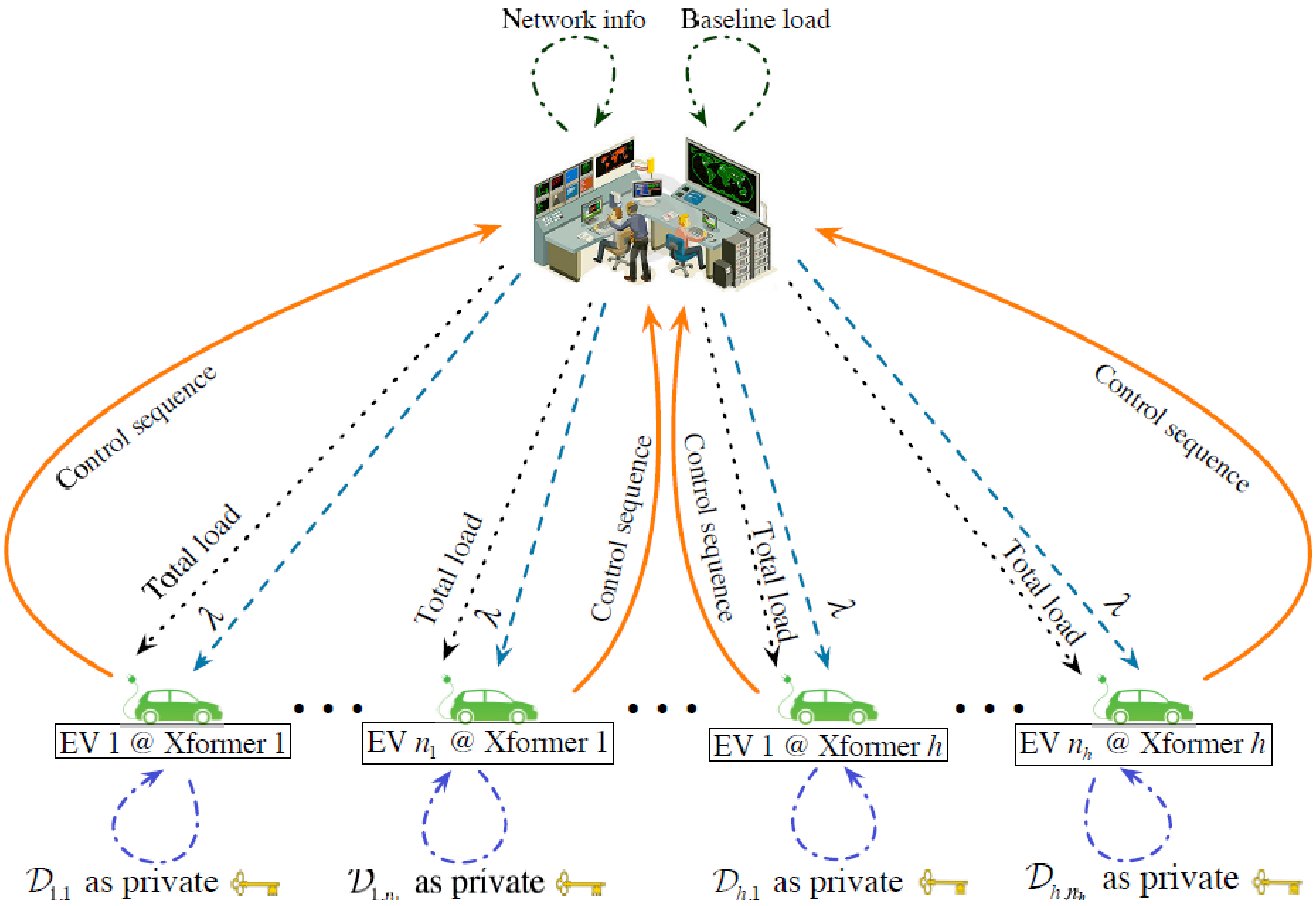




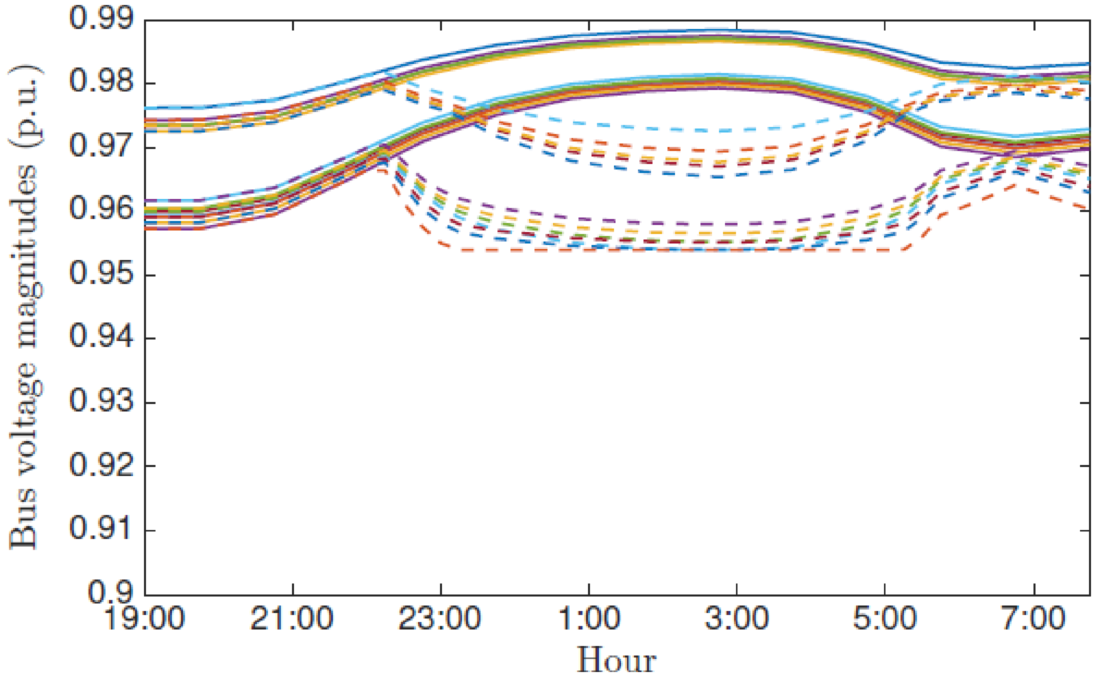
Notes on SPDS proof

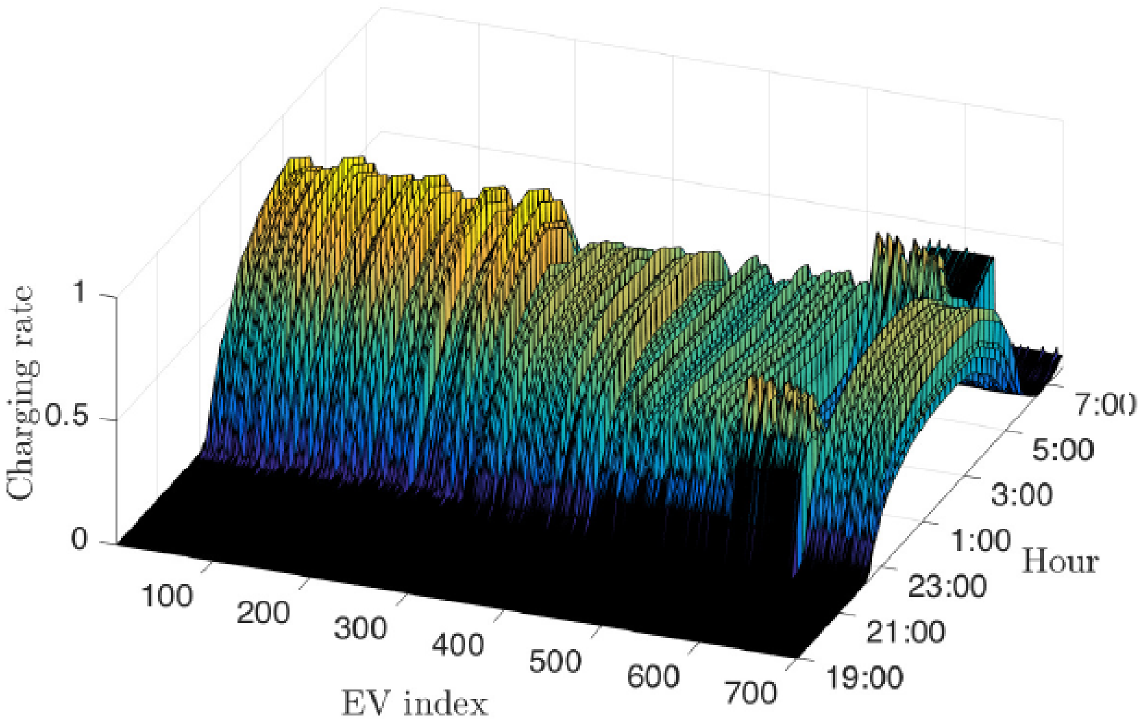
- SPDS provably convergences to the global optimum (Liu *et al.* TCST 201X)
- Proof works by guaranteeing distance to optimal point decreases monotonically.
- Places conditions on the relationship between parameters for shrinkage ($\tau_{\mathcal{U}}$, τ_λ) and step sizes (α, β)
- Future work:
  - Manual parameter tuning to reduce convergence time is tedious $\rightarrow$ results bounding iterations to convergence?
  - Another area for future work – non-constant step sizes.

A Secured Charging Control Framework

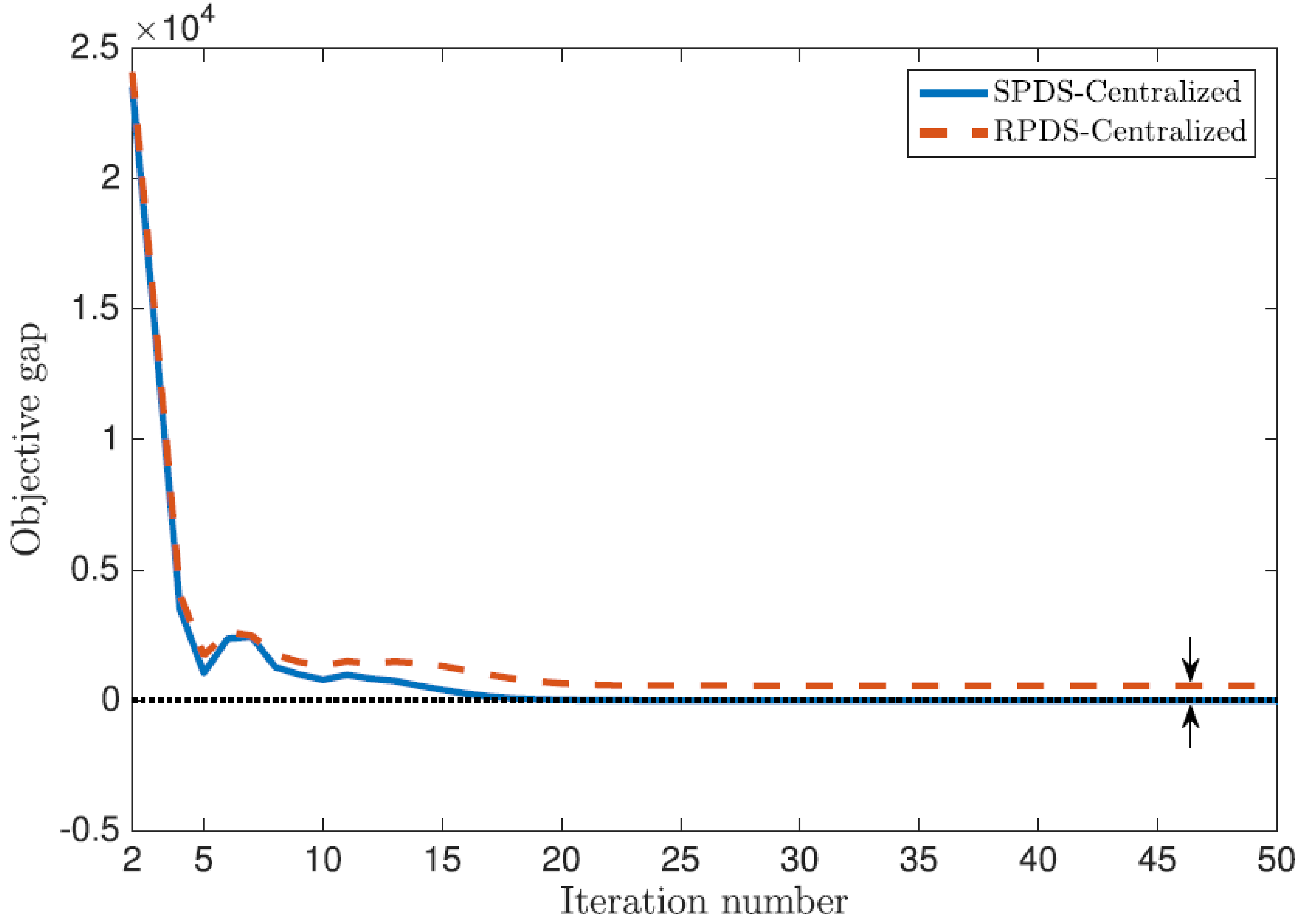


Example: Valley-Filling on IEEE 13 Node feeder





Significance



- Relatively fast convergence
- Complies w EV charging standards (ISO/IEC 15118 and SAE 2847): battery SOC information local
- Significant computations are projections, generally fast to solve.

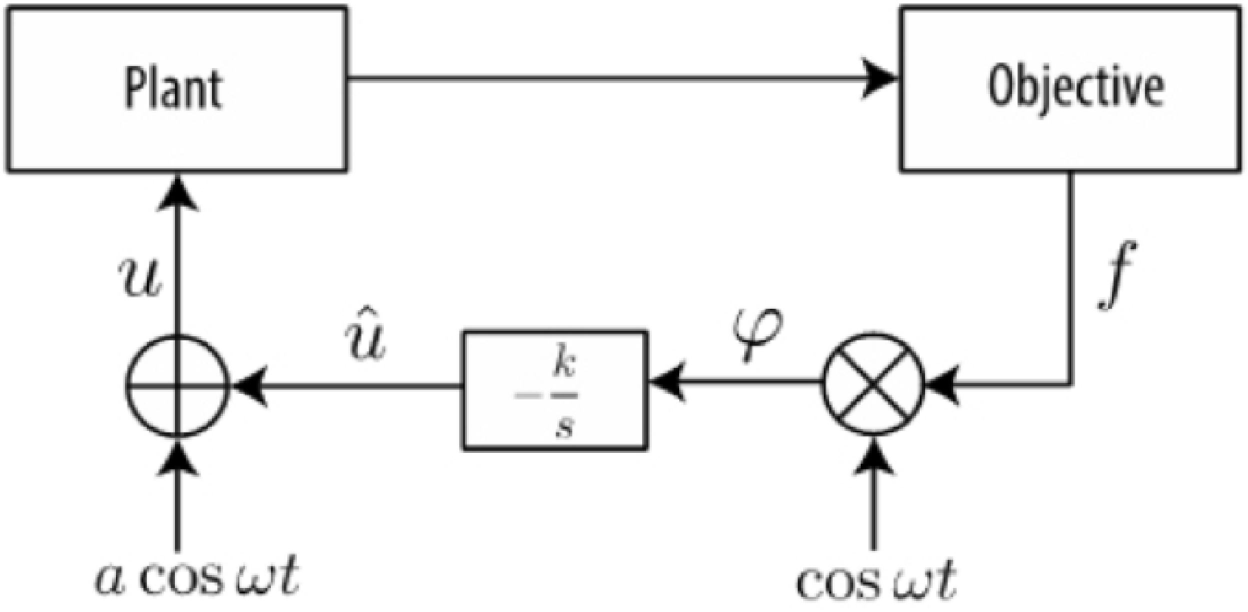
Some extensions, next steps and caveats)

- Charging decisions made locally $\rightarrow$ each agent can solve its own optimization problem.
  - Local objectives could be time to charge, battery degradation
- Secondary transformer temperature dynamics can also be incorporated into the problem (Liu *et al* PSCC 2018)
- Next step – microgrid developer New Sun Road partnering on DOE proposal to explore this approach

Caveat: Requires network model and all injections and extractions

Can we do network optimization with less information?

- Extremum seeking control (ES)
- Basic form: modulation signal (probing signal) is injected into plant dynamics: $u = \hat{u} + acos\omega t$
  - Each controller uses different frequency



$\Rightarrow$ Scheme is a form of gradient search; identifies local extremum to objective.

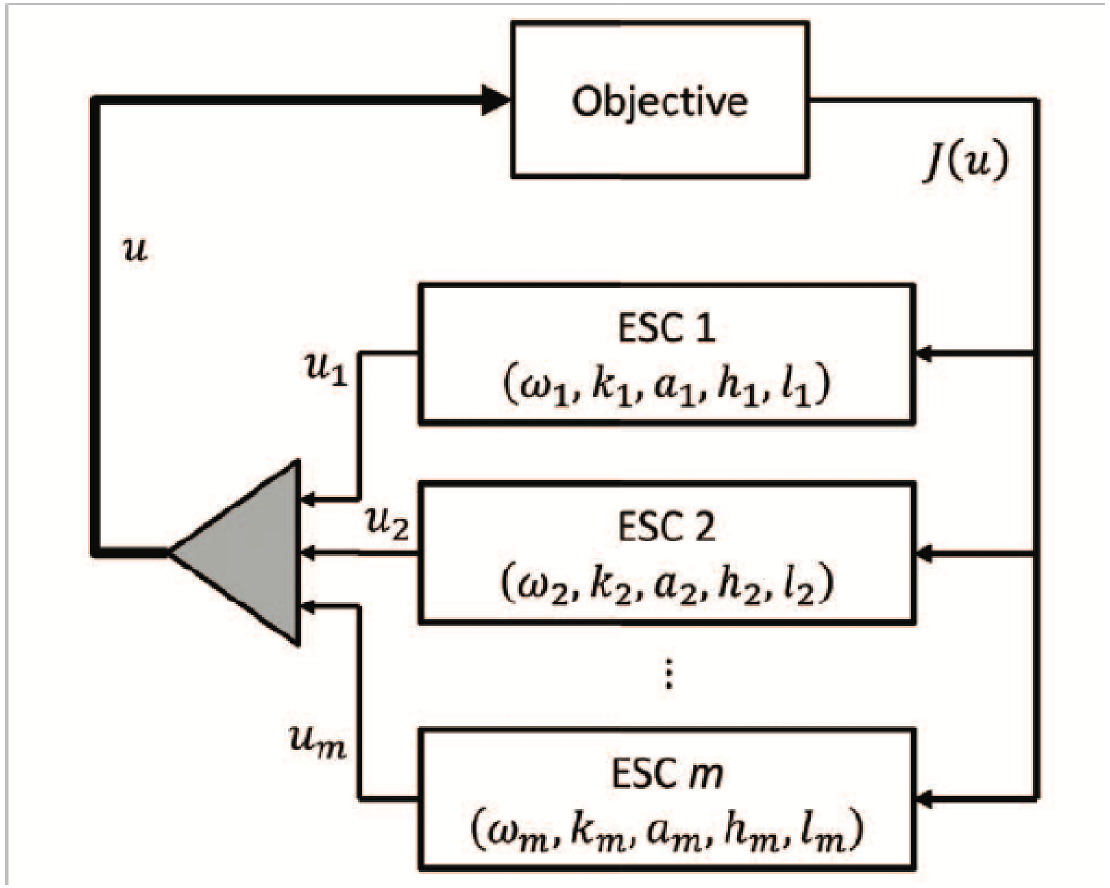
ES applied to network optimization: Basic example Arnold *et al*, TPWRS (2016)

Control: Use PV & battery inverters and EV chargers to inject real and reactive power at different nodes on a feeder

Sensors:

- Measure real power at feeder head
- Measure voltage at points of concern

Example device-level objective: Minimize feeder head real power (captures resistive losses and voltage dependency of loads) plus voltage penalty terms



Some issues you might be thinking about

First the downside:

- If you have state constraints, they need to appear in penalty functions
- Filter parameters, probing frequency and integrator gain all need to be tuned.
- Problem needs to be convex for global optimality

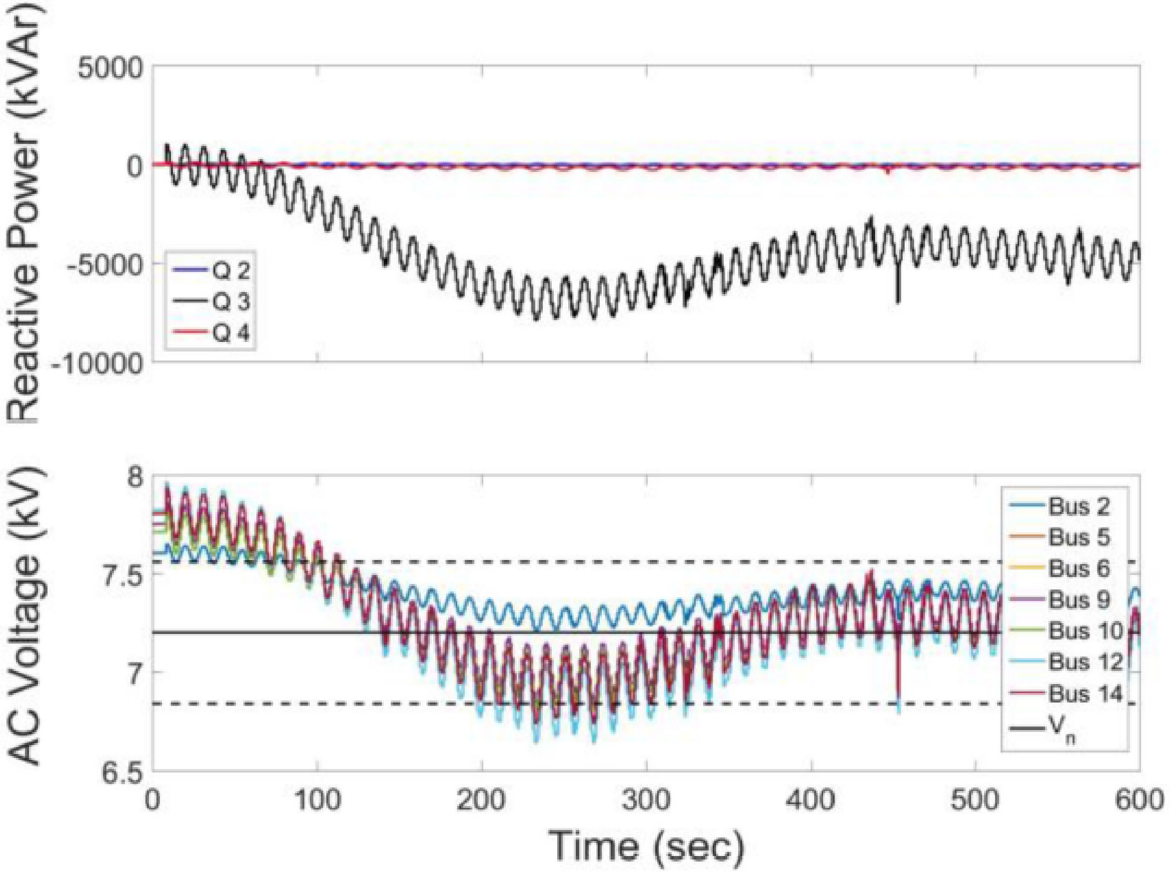
But, the upside:

- Filters and demodulation steps allow multiple controllers to coexist
- We don't need a model of the system to make this work.
- We don't need to know electricity consumption and production
- Provable optimality (convexity) and convergence for generous conditions (e.g. power flowing out at feeder rated capacity; Arnold *et al* TPWRS 2016, 2018)

Hardware in the loop proof of concept

- 3kW PV system interface with OPAL-RT network simulator via Ametek power amplifier
- Reduced-form model of network in Albuquerque
- Objective:

$$J = \sum_i C_i [V_i(u) - V_n]^2 + \sum_j \alpha \hat{u}_j^2$$



(Johnson *et al* IEEE JPV (2018))

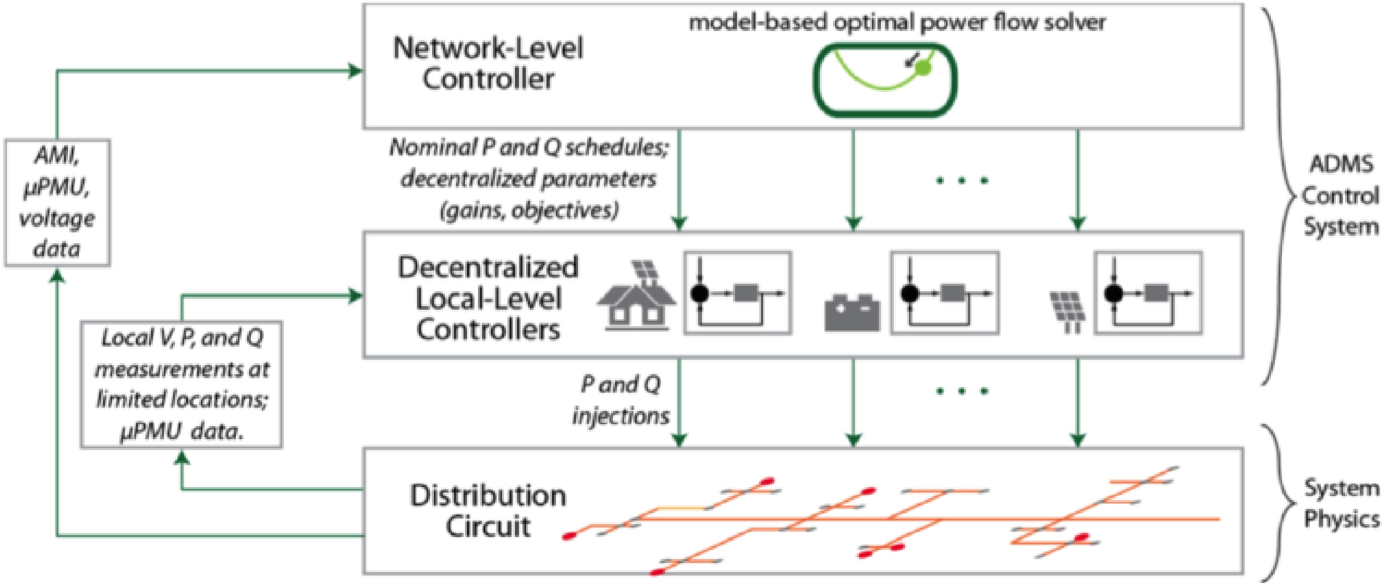
Significance and next steps

Significance

- Network optimization without models or state information
- Load buses as controllable as generators? Arnold *et al*, TPWRS (2018)

Some open questions

- How small can we make the probe amplitude?
- How fast can we probe (simulations 1-0.1 Hz)?
- Would manufacturers and utilities do it?



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NREL NATIONAL RENEWABLE ENERGY LABORATORY
BERKELEY LAB

Part 2: If we were building the grid all over again, what would it look like?

UN SDG and reliability

United Nations' Sustainable Development Goal #7

"Ensure access to affordable, reliable, sustainable, and modern energy for all."

1.1 billion people lack access to electricity

- 600 million in Sub-Saharan Africa alone
- Those with access often use an inferior product.

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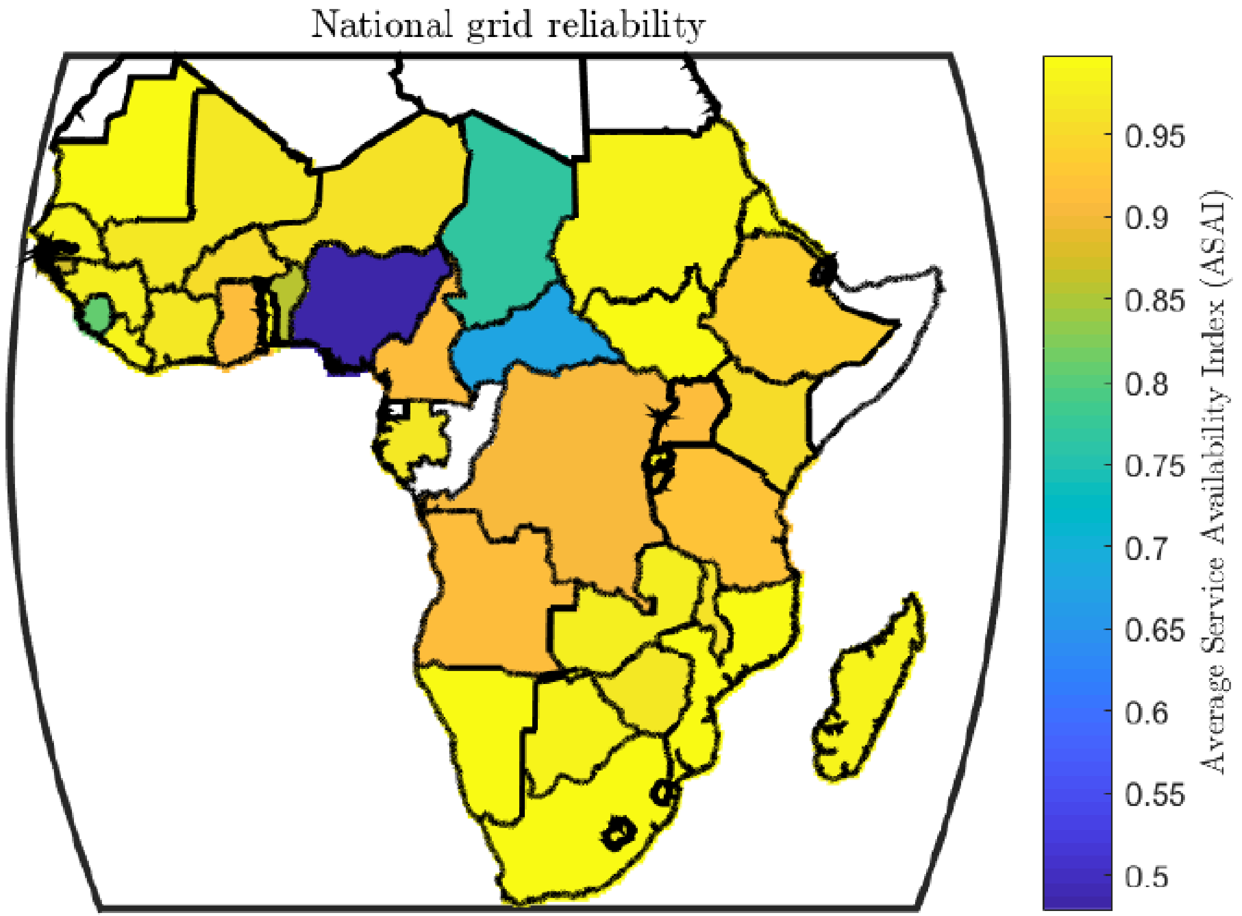
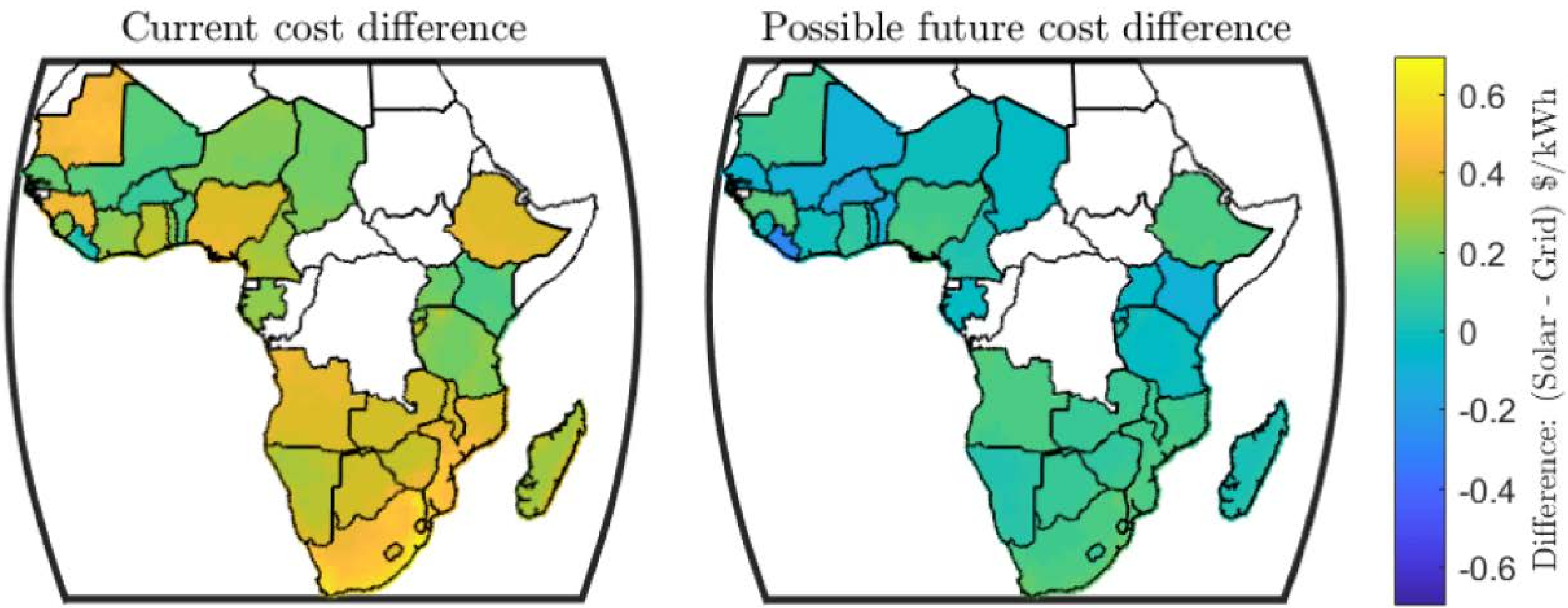
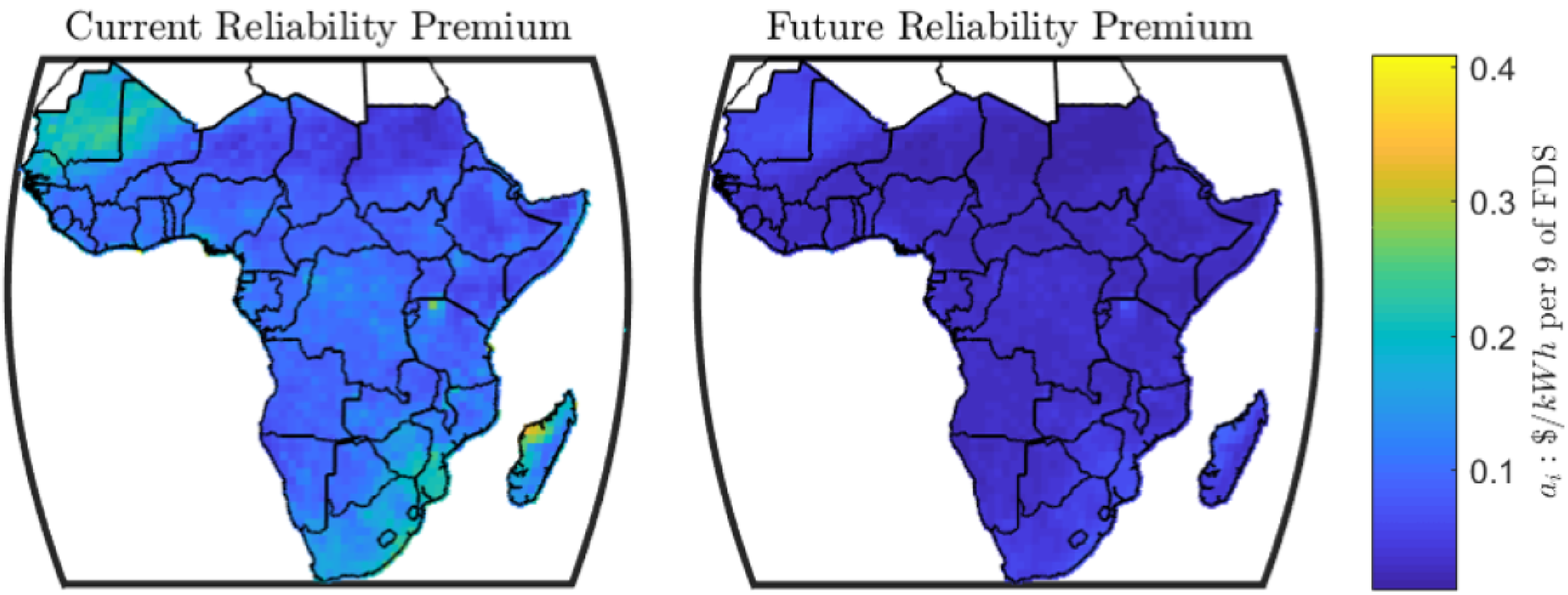


What is the potential for standalone battery-storage?



(Lee and Callaway, Nature Energy 2018)

Spatial distribution of the reliability premium



- Much of the continent around USD 0.1/kWh per “9” now
- In the future this drops to USD 0.03/kWh per “9”

Summary

In effect, we are reaching a point where batteries are becoming cheaper than wires. Added benefits:

- Fast to deploy
- Aligned incentives

Decentralized systems: credible alternative to networked systems

- Not only for systems that deliver lighting
- But for systems that deliver all but the highest power demand services
- See `emac.berkeley.edu/reliability` to set your own assumptions

New Sun Road system in Kitobo, UG

Do we need the grid?

Keep the network for

- High capacity systems, where diversity benefits you get from wires are large
- For existing reliable grids.
- In places where the solar resource isn't any good (climate; shading)
  - What will happen in the US?
- In places where there is no access to area for solar modules (urban)

But as solar and storage prices fall, the situations where these conditions hold will grow smaller...

Contact and Acknowledgements

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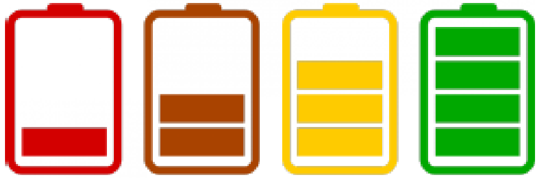
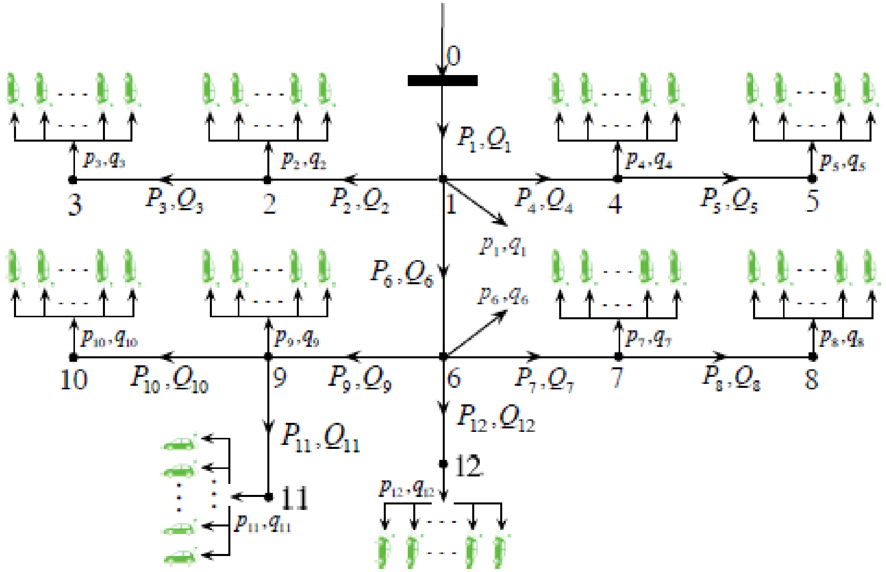
Funding:

EV Charging Control – Modeling



$$
\begin{cases}
x_i(k+1) = x_i(k) - \eta_i \Delta t \overline{P}_i u_i(k), \\
\mathcal{U}_i(k) = \begin{bmatrix} u_i(k|k) \\ u_i(k+1|k) \\ \vdots \\ u_i(k+K-1|k) \end{bmatrix}.
\end{cases}
$$



$$
\begin{cases}
\boldsymbol{V}(k) = \boldsymbol{V}_0 - 2\boldsymbol{R}p(k) - 2\boldsymbol{X}q(k), \\
\boldsymbol{R} \in \mathbb{R}^{h \times h}, \ \boldsymbol{R}_{\imath\jmath} = \sum_{(\hat{\imath},\hat{\jmath}) \in \mathbb{E}_\imath \cap \mathbb{E}_\jmath} r_{\hat{\imath}\hat{\jmath}}, \\
\boldsymbol{X} \in \mathbb{R}^{h \times h}, \ \boldsymbol{X}_{\imath\jmath} = \sum_{(\hat{\imath},\hat{\jmath}) \in \mathbb{E}_\imath \cap \mathbb{E}_\jmath} x_{\hat{\imath}\hat{\jmath}}. \\
\mathcal{Y}_k = \mathcal{Y}_{dk} + \sum_{i=1}^{n} \mathcal{D}_i \mathcal{U}_i(k).
\end{cases}
$$

Comparisons

	PD perturbation [?]	RPDS [?]	ADMM [?]	SPDS
Generic	×	✓	✓	✓
Decentralized	×	✓	✓	✓
Convergency	✓	✓	✓	✓
Optimality	✓	×	✓	✓
Iterations	Small	Small	Large	Small
Communication	Small	Small	Large	Small

Further Look – Incorporating Customers' Preferences

- Fastest charging

$$f_{\imath,\hat{\imath}}(\mathcal{U}_{\imath,\hat{\imath}}) = \tilde{\alpha}_{\imath,\hat{\imath}} \left\| \mathcal{U}_{\imath,\hat{\imath}} - \hat{\mathcal{U}}_{\imath,\hat{\imath}} \right\|_2^2$$

- Battery state-of-health protection

$$f_{\imath,\hat{\imath}}(\mathcal{U}_{\imath,\hat{\imath}}) = \tilde{\alpha}_{\imath,\hat{\imath}} \left\| \mathcal{U}_{\imath,\hat{\imath}} \right\|_2^2$$

- Designated maximum charging rates

$$\mathbb{U}_{\imath,\hat{\imath}} := \{\mathcal{U}_{\imath,\hat{\imath}} | \mathbf{0} \leq \mathcal{U}_{\imath,\hat{\imath}} \leq \bar{u}_{\imath,\hat{\imath}}\mathbf{1}, x_{\imath,\hat{\imath}}(k) + \mathcal{B}_{\imath,\hat{\imath},l}\mathcal{U}_i = 0\}$$

- Specified energy level by a specified time

$$\begin{aligned} \mathbb{U}_{\imath,\hat{\imath}} := \{\mathcal{U}_{\imath,\hat{\imath}} | \mathbf{0} \leq \mathcal{U}_{\imath,\hat{\imath}} \leq \mathbf{1},\ x_{\imath,\hat{\imath}}(k) + \mathcal{B}_{\imath,\hat{\imath},l}\mathcal{U}_{\imath,\hat{\imath}} = 0, \\ \iota_{\imath,\hat{\imath}} x_{\imath,\hat{\imath}}(k) \leq -[\underbrace{B_{\imath,\hat{\imath},c} \ \cdots \ B_{\imath,\hat{\imath},c}}_{\hat{K}_{\imath,\hat{\imath}}} \ \mathbf{0} \ \cdots \ \mathbf{0}]\mathcal{U}_{\imath,\hat{\imath}}\} \end{aligned}$$

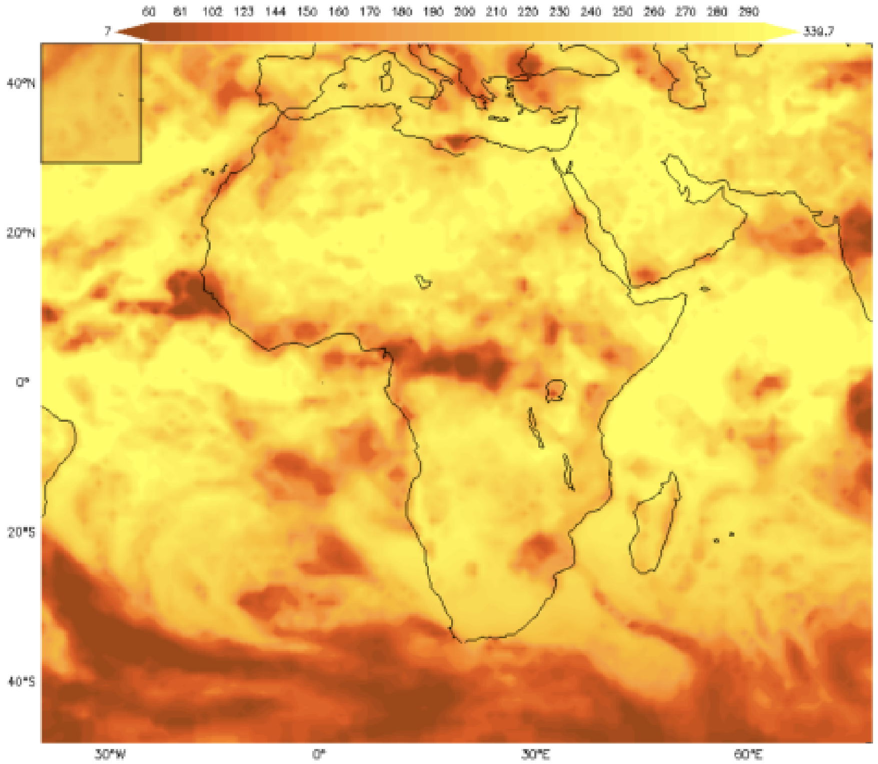
Liu, *et al.*, Power Systems Computation Conference, 2018.

Decentralized system costs

	2017	Future (c. 2025)
Solar costs		
Modules plus DC Balance of System	1.00	0.50
Charge controller	0.20	0.10
Total ($/W)	**1.20**	**0.60**
Battery costs		
Total ($/kWh)	**400**	**100**
Load costs		
Inverter	0.30	0.15
Soft costs plus AC Balance of System	1.00	0.50
Total ($/W)	**1.30**	**0.65**

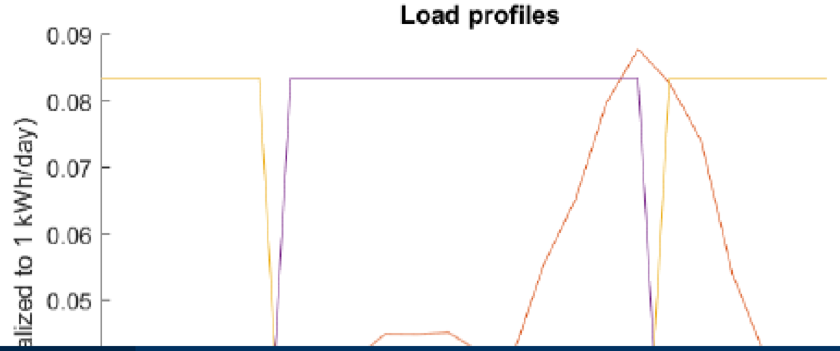
Additional economic assumptions	
O&M costs	$100/kW peak load/year
Project length	20 years; battery replacement at 10 years
Annual discount rate	10%

- Daily solar data 1995-2005 from NASA, 1 degree resolution; converted to hourly using sun angle calculations



- Four load cases:
  1. daylight hours
  2. non-daylight hours
  3. constant load
  4. re-scaled from a village in Uganda.

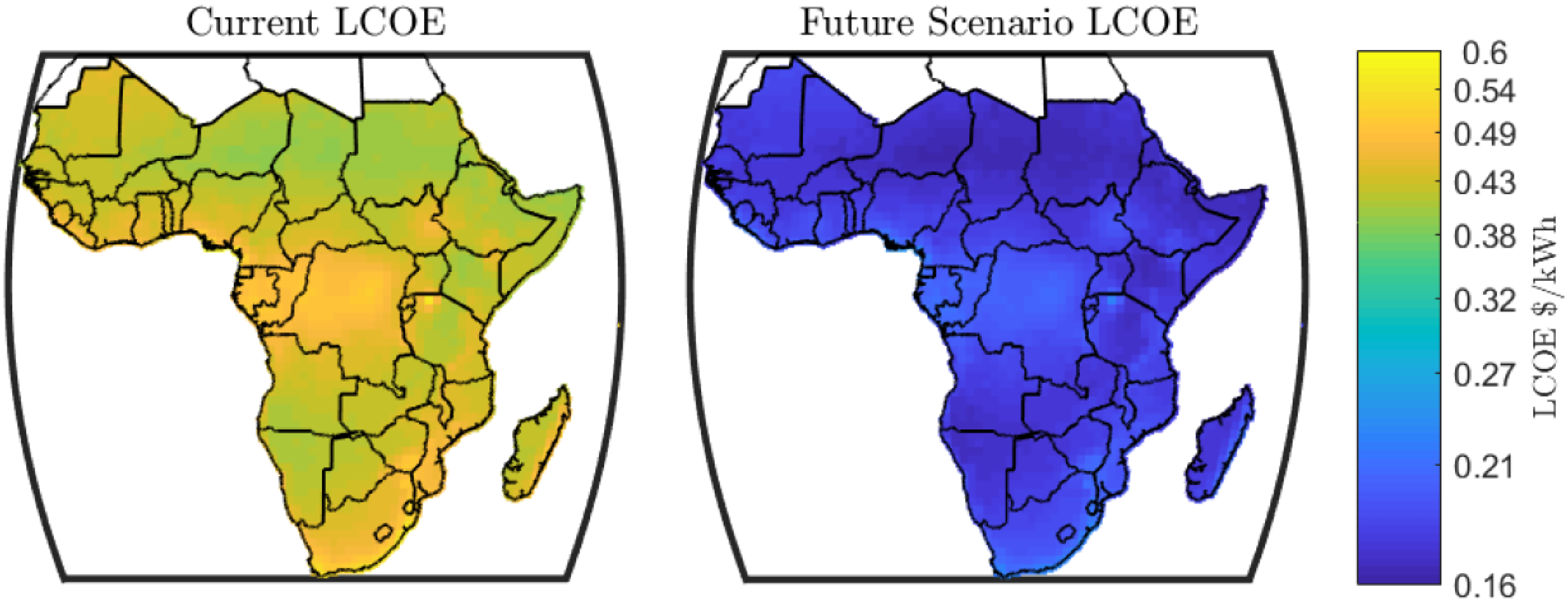
  Most results we present are independent of load case; we use constant load for simplicity.



More data and model

- **Iso-reliability curves for a given reliability *and* location:**
  - Curves for **fraction of demand served** (FDS) ranging from 0.6 (Nigeria) and 0.9999 (high-performing), for each pixel in solar data
- **Levelized cost of electricity:**
  - Present value of unit-cost of electricity over system lifetime.
  - We use 20 y life, 10% discount rate, battery replacement at 10 y.
  - **Current**: solar (USD 2.30/W) and storage (Li-ion, USD 400/kWh)
  - **Future**: 2-fold reduction in solar modules; 4-fold reduction in batteries
- For each cost and reliability, we find the optimal point on the iso-reliability curve by simple line search

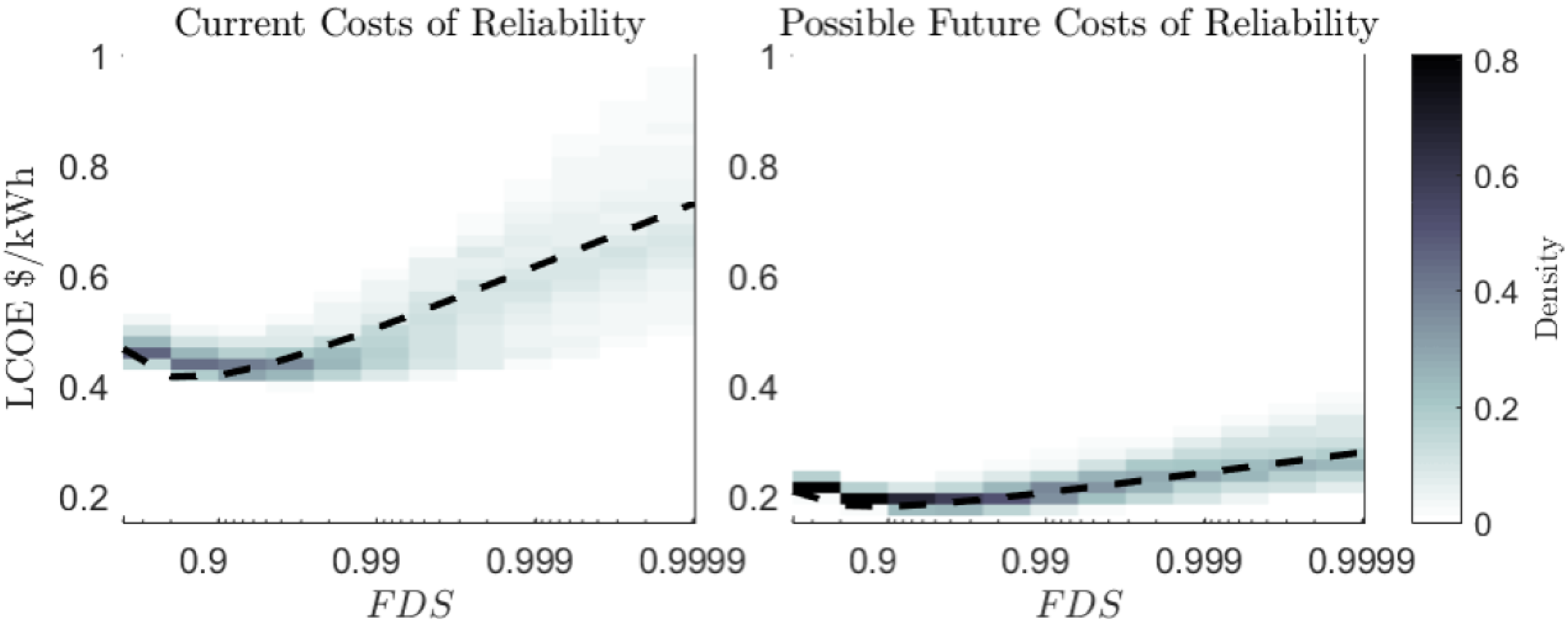
Present and future LCOE



- Figure above for systems serving 8.2 kWh/day at

Linear relationship between cost and "9"s of reliability.

Cost of reliability: LCOE $= a_i \frac{\log(1-r)}{r} + b_i \frac{1}{r} + c_i$



- R^2 here 0.6, but for individual locations 0.9-0.99.

Questions?

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