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Optimal Energy Procurement for Geo-distributed Data Centers in Multi-timescale Markets

IFIP WG 7.3 Performance 2017

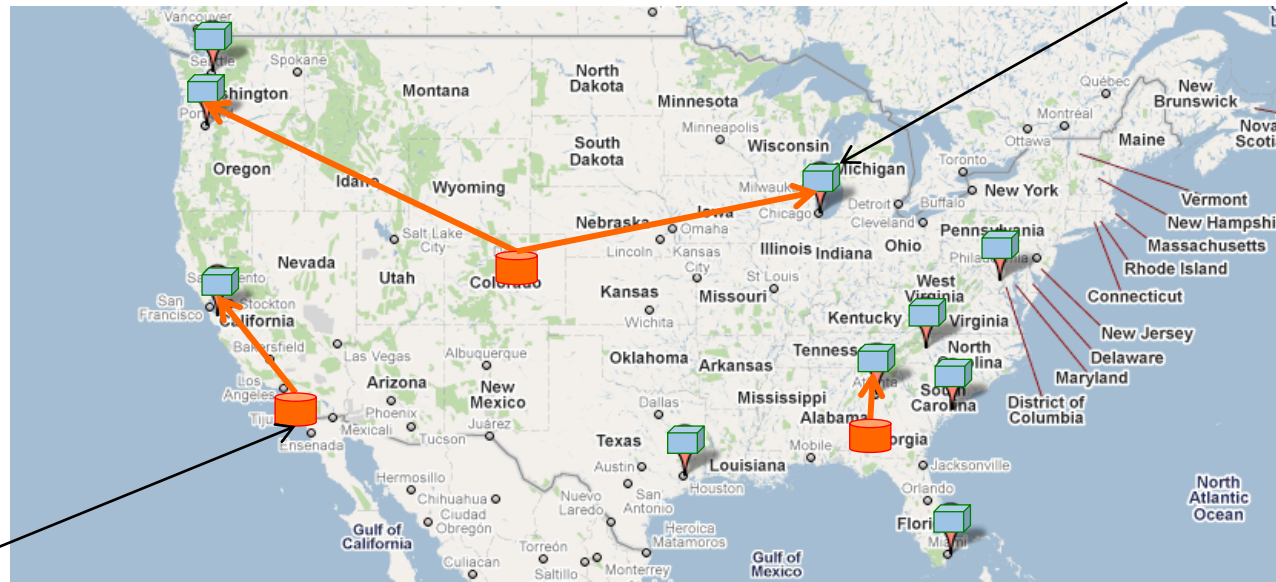
New York, USA - Nov. 16

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Ramesh K. Sitaraman, Jayakrishnan Nair, and Bong Jun Choi

Geographical Load Balancing (GLB)

Google data center



Data sources

- + Minimize network delay
- + Increase reliability
- Network latency
- Energy

All are time varying and location dependent

Energy procurement in multi-timescale markets

2 data centers in TX & NY:

TX: \$0.03 kWh (*long-term*) & \$? kWh (*real-time*)

NY: \$0.05 kWh (*long-term*) & \$? kWh (*real-time*)

In real-time, renewables & electricity prices are uncertain



→ Over or under procurement

Long-term



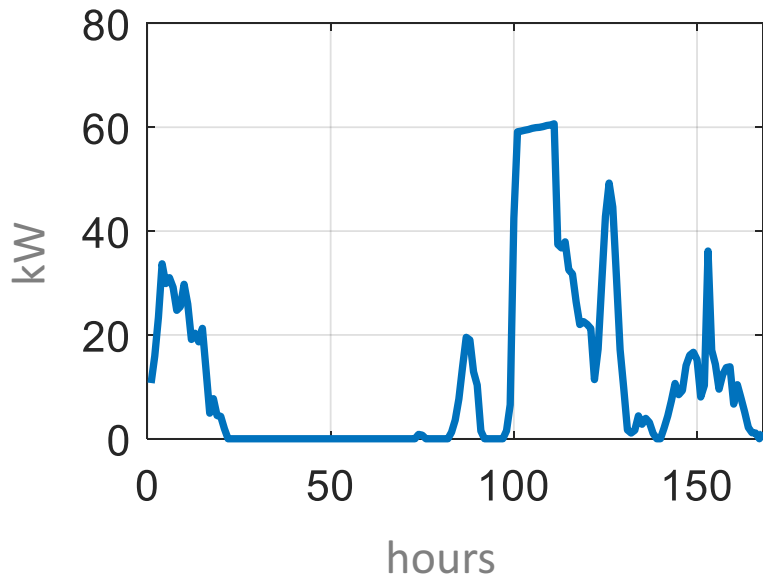
→ expensive

Real-time

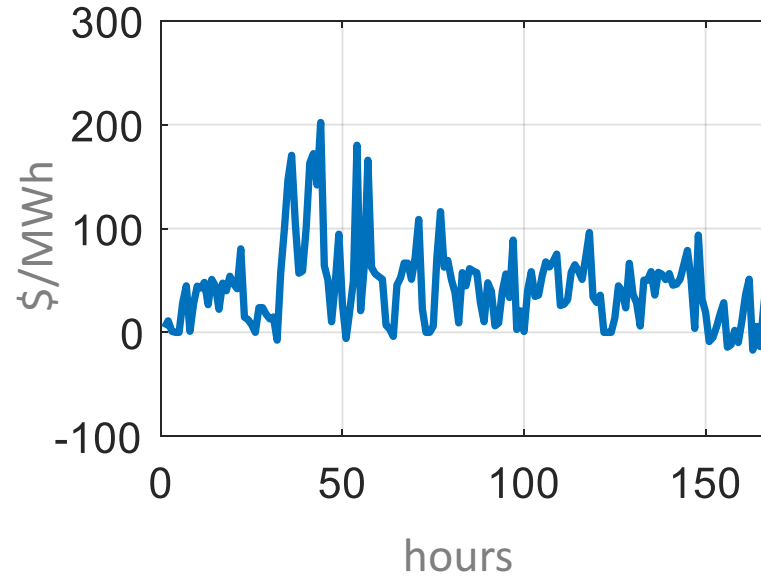
Time

How much electricity should we purchase in long-term for each data center?

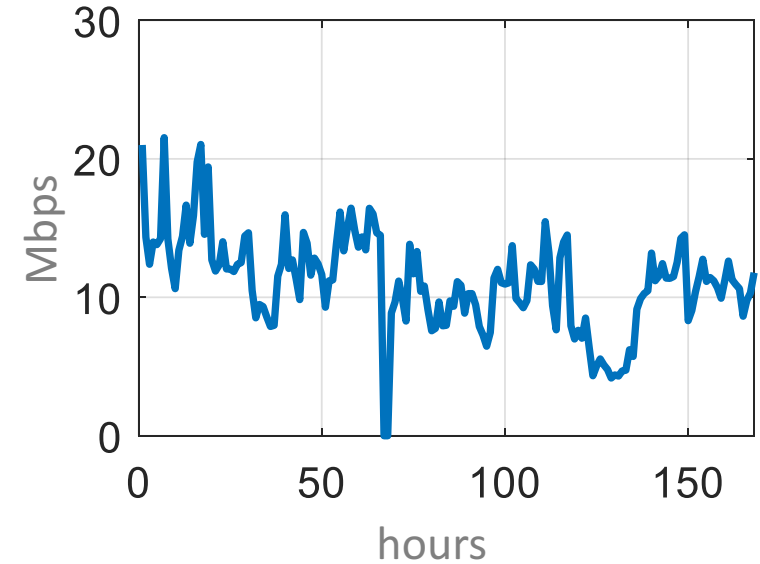
Challenges raise on the energy procurement problem



wind generation in CA
(NREL)



electricity prices
(CAISO)



workload in CA
(Akamai)

Long-term procurement and real-time GLB are coupled

- ✓ Real-time costs depend on what happens in long-term
- ✓ Long-term decision needs to consider how GLB works

Prior works

Real-time markets

Locational prices: **“Cutting the electric bill for internet-scale systems” SIGCOMM’09**

A. Qureshi, R. Weber, H. Balakrishnan, J. Gutttag, B. Maggs

“Greening geographical load balancing” SIGMETRICS’11

Z. Liu, M. Lin, A. Wierman, S. H. Low, and L. L. Andrew

Temporal prices: **“Minimizing data center SLA violations and power consumption via hybrid resource provisioning” IGCC’11**

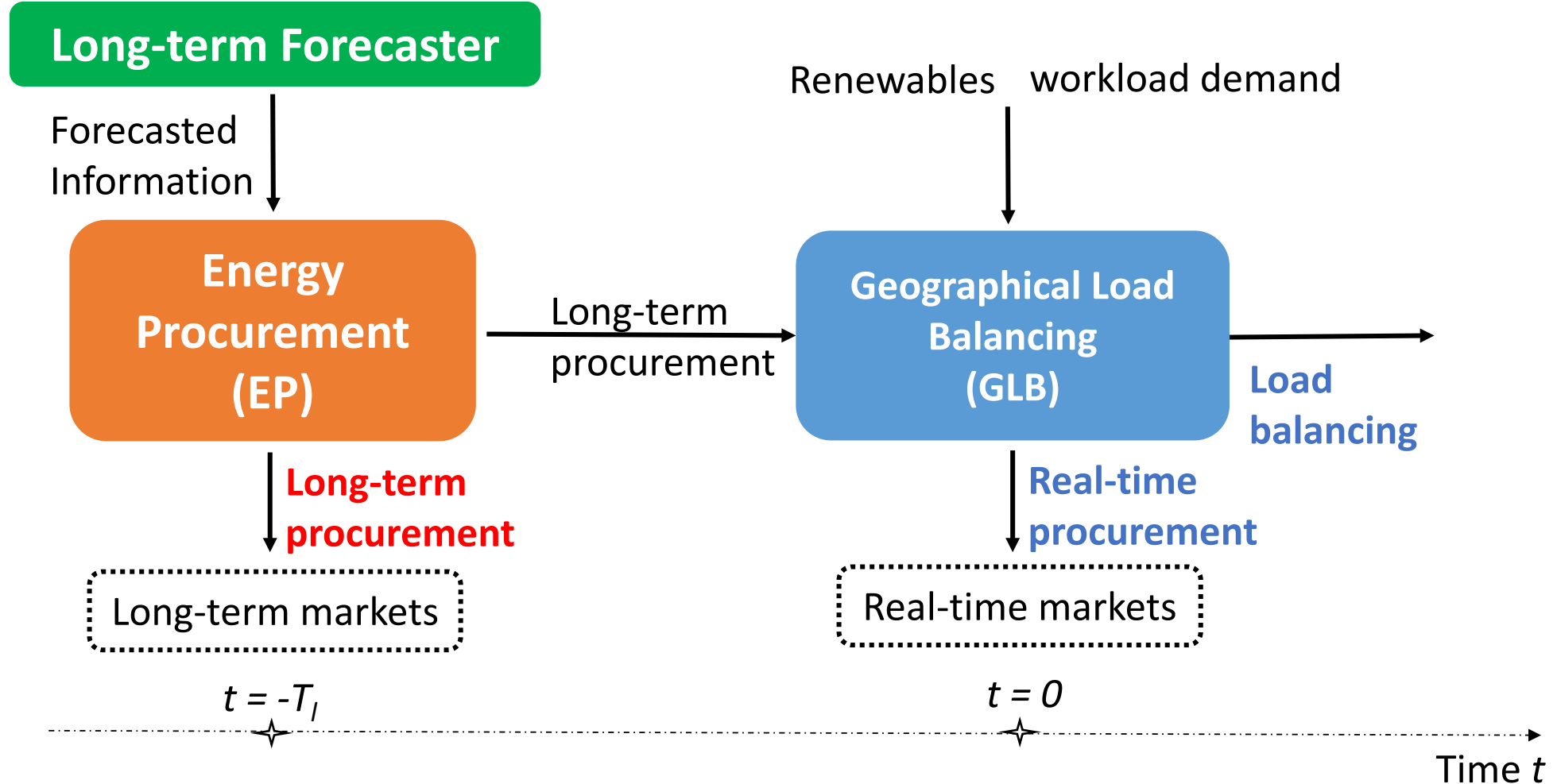
A. Gandhi, Y. Chen, D. Gmach, M. Arlitt, M. Marwah

Multi-time scale markets

“Energy portfolio optimization of data centers” Trans. Smartgrid’16

M. Ghamkhari, A. Wierman, and H. Mohsenian-Rad

Energy Procurement System



Goal: Optimize procurement in long-term markets

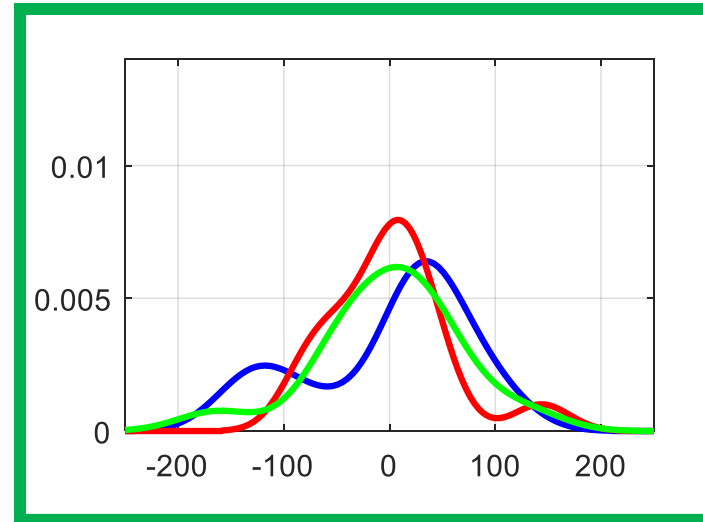
Challenges: Deal with multiple sources of uncertainty

Prediction

Modeling

Algorithms

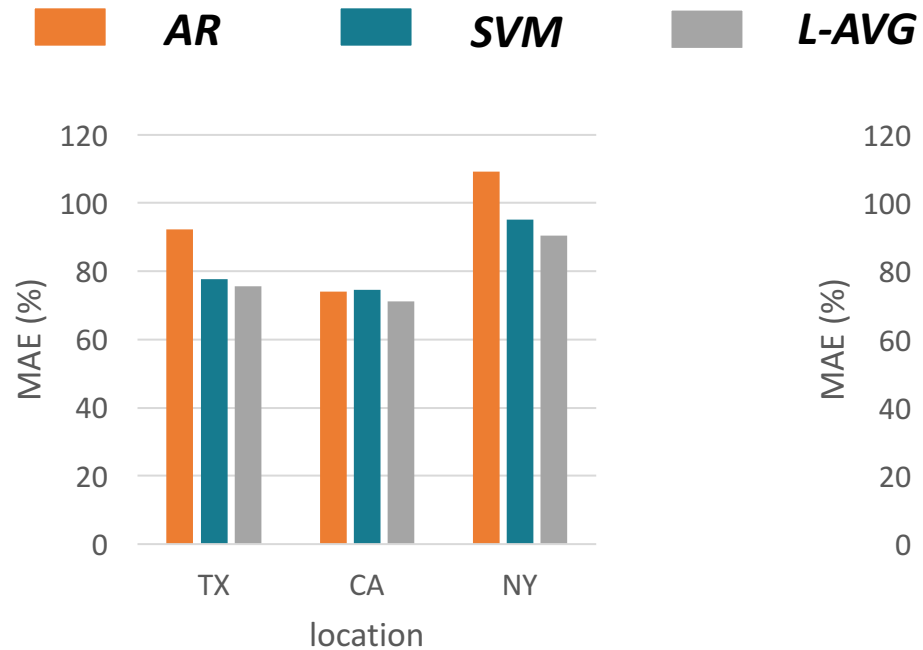
Evaluation



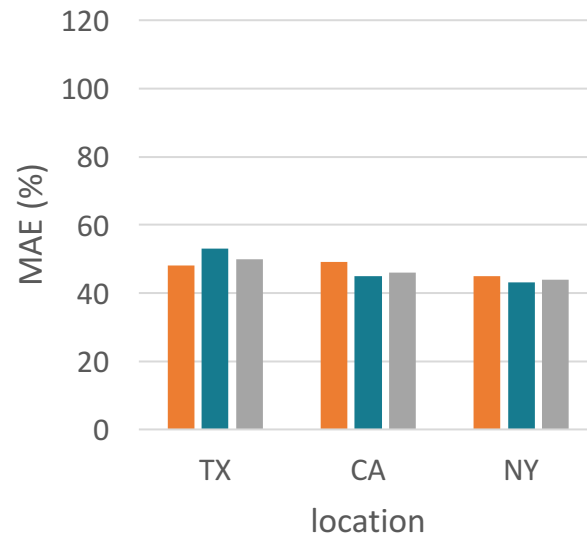
Long-term forecast

- ✓ **AR (Autoregressive model)**
captures **daily pattern**
input: historical data
- ✓ **SVM (Support Vector Machine)**
captures seasonality of data
input: hour, day, month
- ✓ **L-AVG (Long-term Average)** as a baseline
assumes data have long-term cycles
i.e., average of 30 days at the same time of previous years

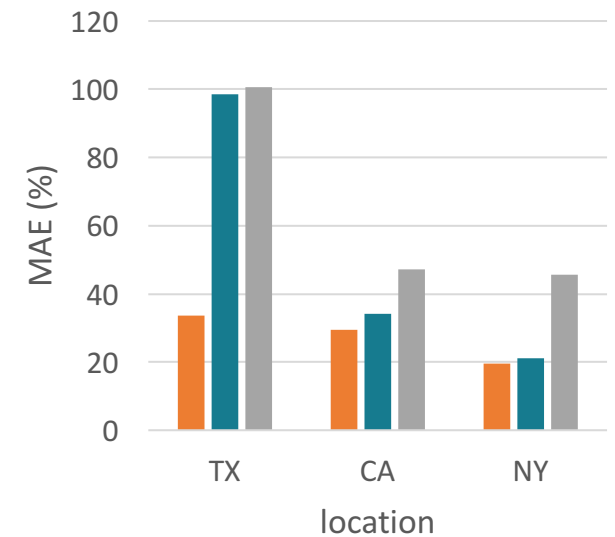
Heterogonous prediction errors based on location



Wind generation
(30-day ahead)



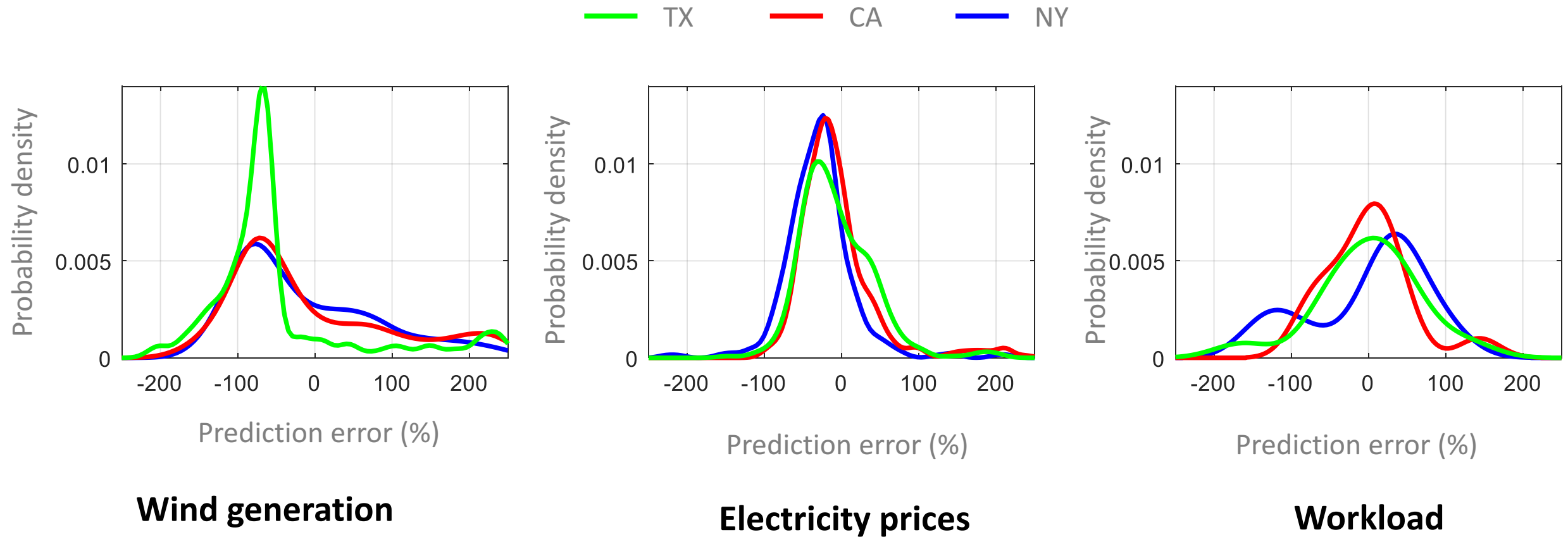
Electricity prices
(30-day ahead)



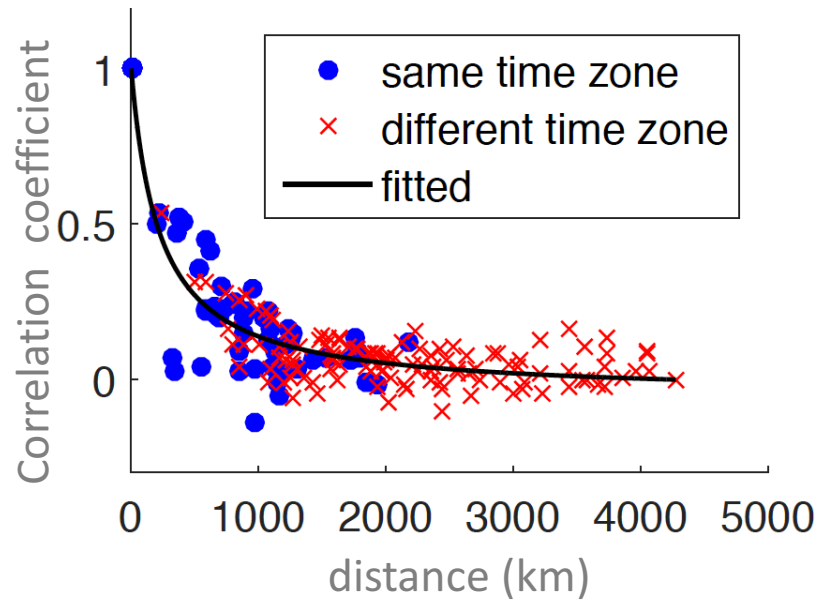
workload
(1-day ahead)

We use AR for the other results in this talk

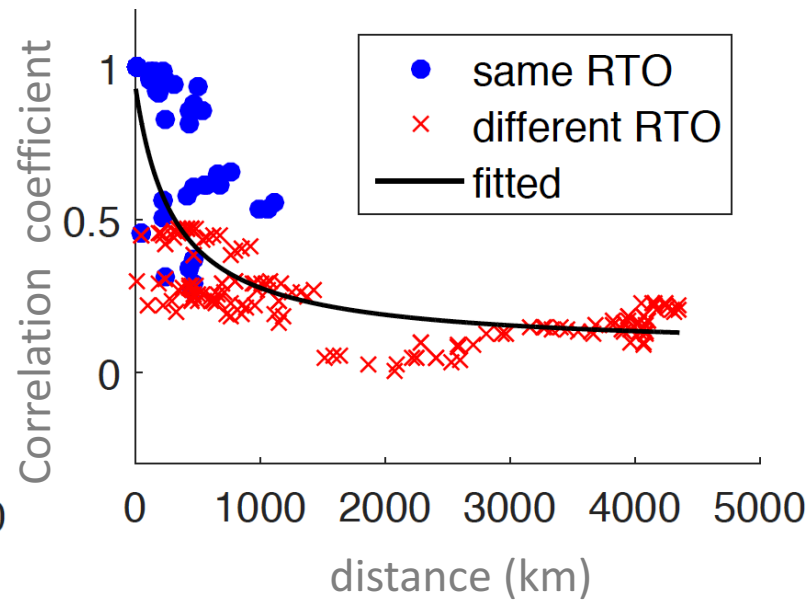
Distributions of errors are not Normal



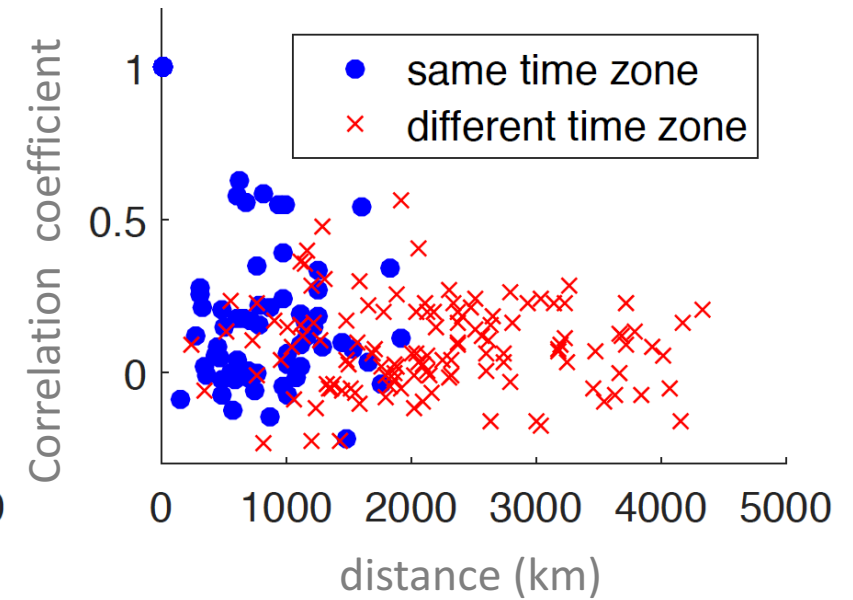
Weak correlation on long distances



Wind generation



Electricity prices



Workload

Goal: Optimize procurement in long-term markets

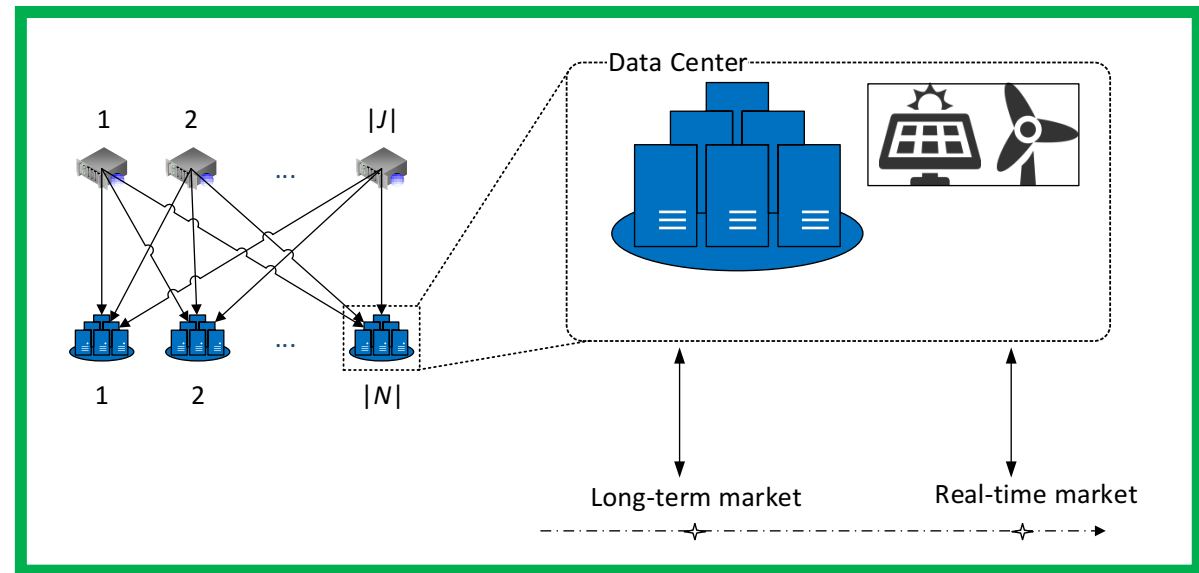
Challenges: Deal with multiple sources of uncertainty

Prediction

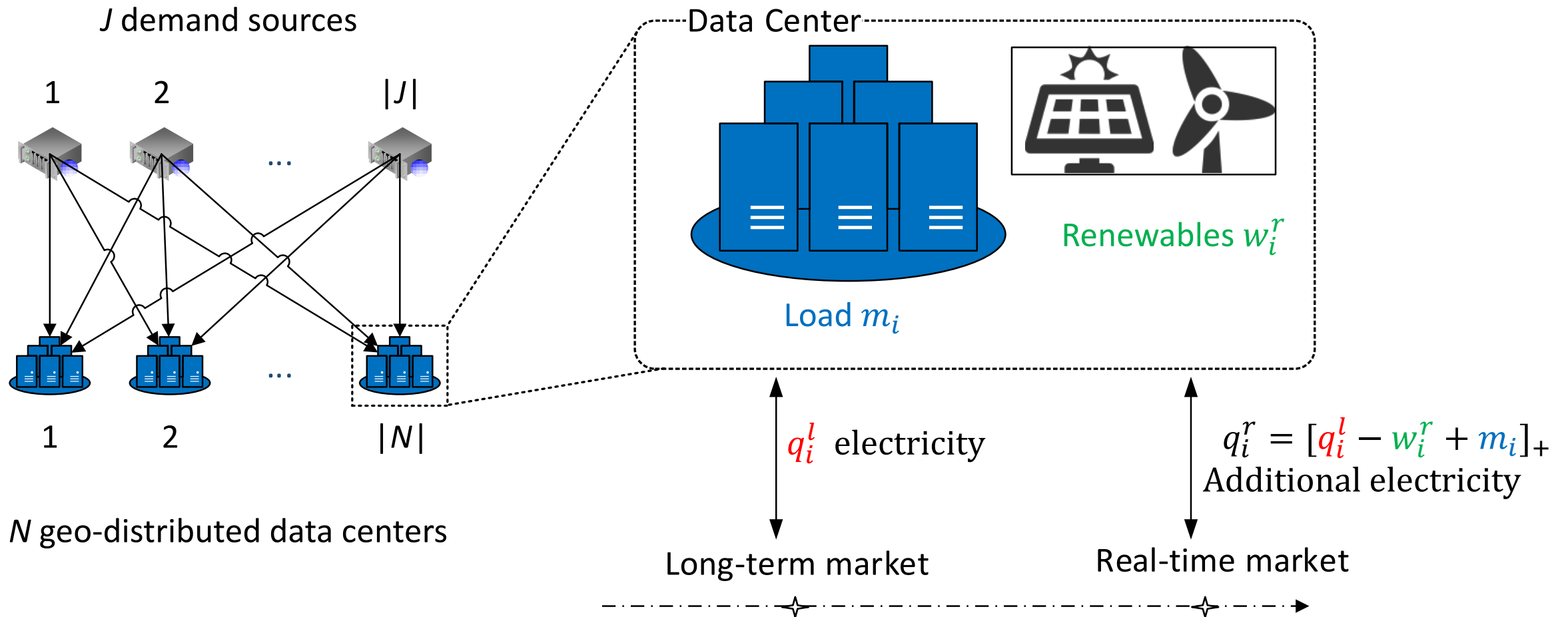
Modeling

Algorithms

Evaluation



Model: GLB in Multi-timescale Markets



How to optimally purchase the electricity in long-term markets?

Real-time geographical load balancing

$$F^{*r}(q^l, w^r, p^r, L^r) = \underset{q^r, m, \lambda}{\text{Minimize energy costs + delay costs}}$$

input

Long-term procurement q^l
Demand L
Electricity prices p^r
Renewable energy w

output

Load balancing λ
Procurement q^r
DC consumption m

Long-term optimization

Minimize long-term cost

q^l

+ expected optimal real-time cost

Long-term	Real-time
Energy cost (q^l)	$\mathbb{E}_{q^l, w^r, p^r, L^r} [\text{optimal real-time cost}]$

$$F(q^l) = \sum_{\{i \in N\}} R_i^l(q_i^l) + \mathbb{E}_{q^l, w^r, p^r, L^r} [F^{*r}(q^l, w^r, p^r, L^r)]$$

Properties of long-term optimal

Convexity of long-term optimal

The long-term objective $F(\mathbf{q}^l)$ is convex w.r.t. \mathbf{q}^l

Gradient of $F(\mathbf{q}^l)$

$$\frac{\partial F(\mathbf{q}^l)}{\partial q_i^l} = \text{long-term price} - \mathbb{E}_{\mathbf{q}^l, \mathbf{w}^r, \mathbf{p}^r, \mathbf{L}^r} [\text{gradient of real-time cost}]$$

Utilization of long-term procurement

*an optimal solution always **utilizes the long-term procurement and renewables as much as possible to reduce delay cost.***

Goal: Optimize procurement in long-term markets

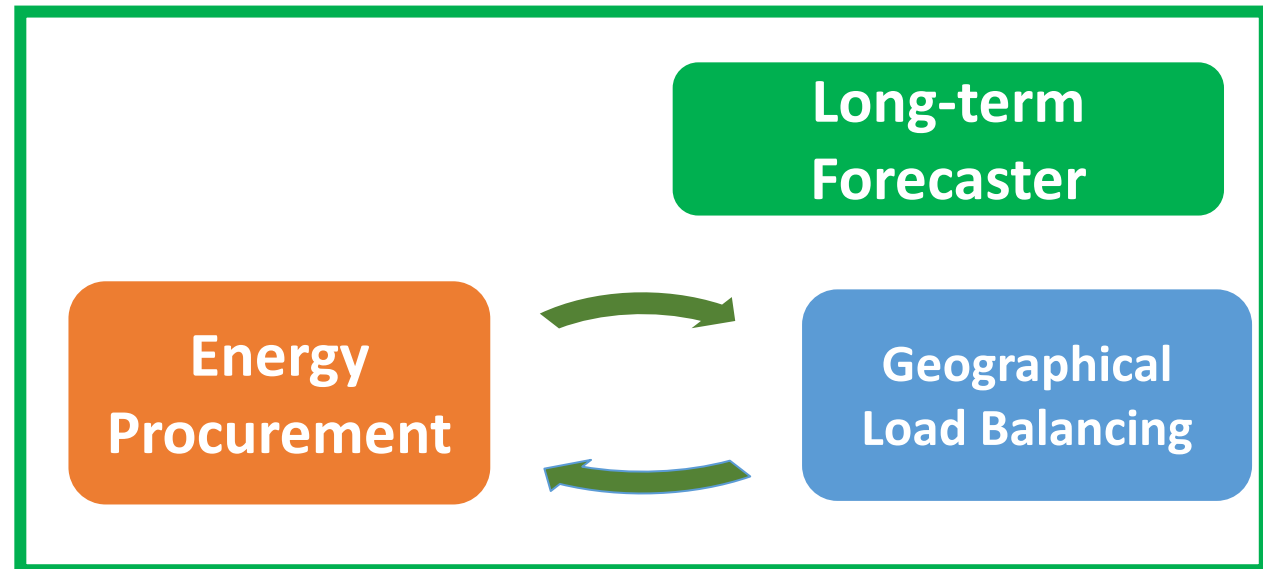
Challenges: Deal with multiple sources of uncertainty

Prediction

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Prediction based Algorithm (PA)

Obtain the *predicted values* in real-time

Demand

\hat{L}^r

Renewable generation

\hat{w}^r

Electricity prices

\hat{p}^r

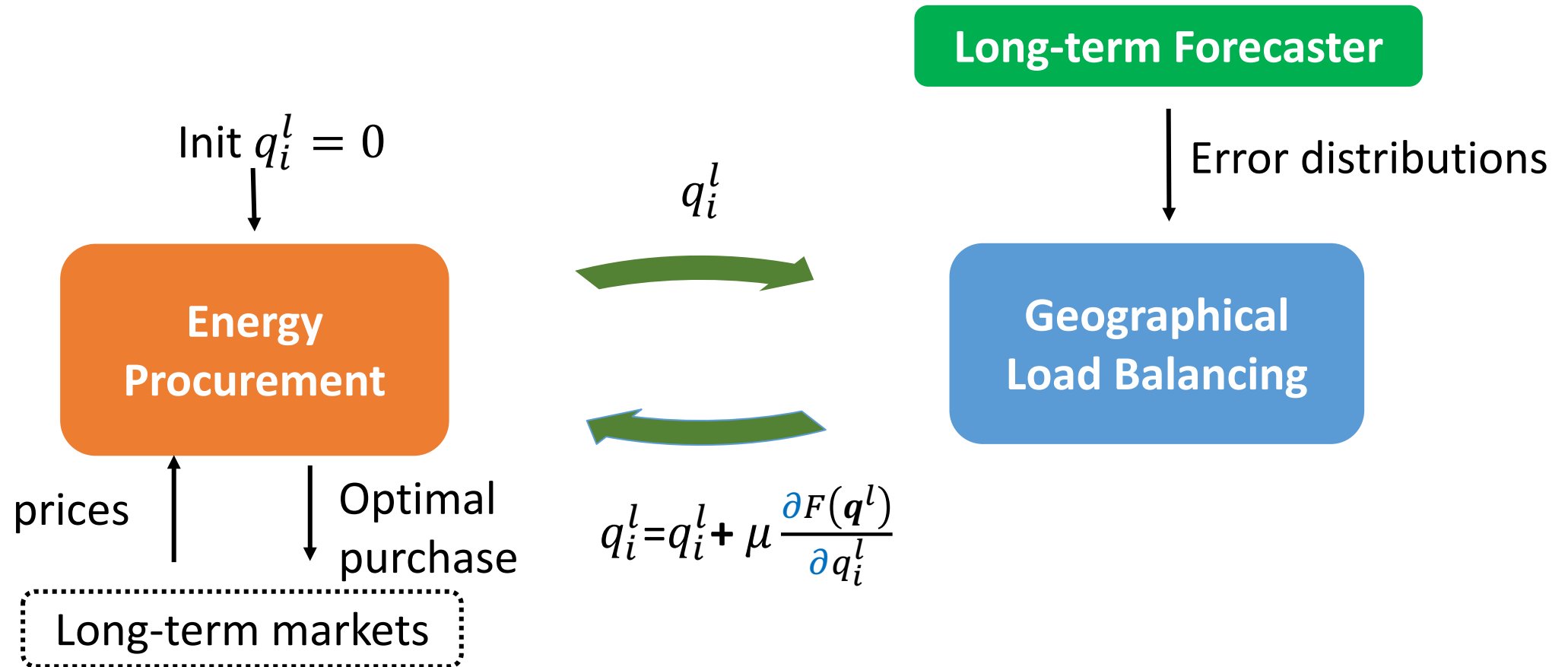
Long-term

Real-time

Energy cost (q^l)

$\mathbb{E}_{q^l, w^r, p^r, L^r}$ [optimal real-time cost]

Optimal: Stochastic Gradient based Algorithm (SGA)



Theorem. The solution of SGA converges to the set of optimal solutions under a right choice of step sizes.

Goal: Optimize procurement in long-term markets

Challenges: Deal with multiple sources of uncertainty

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Evaluation Setup



50% wind power

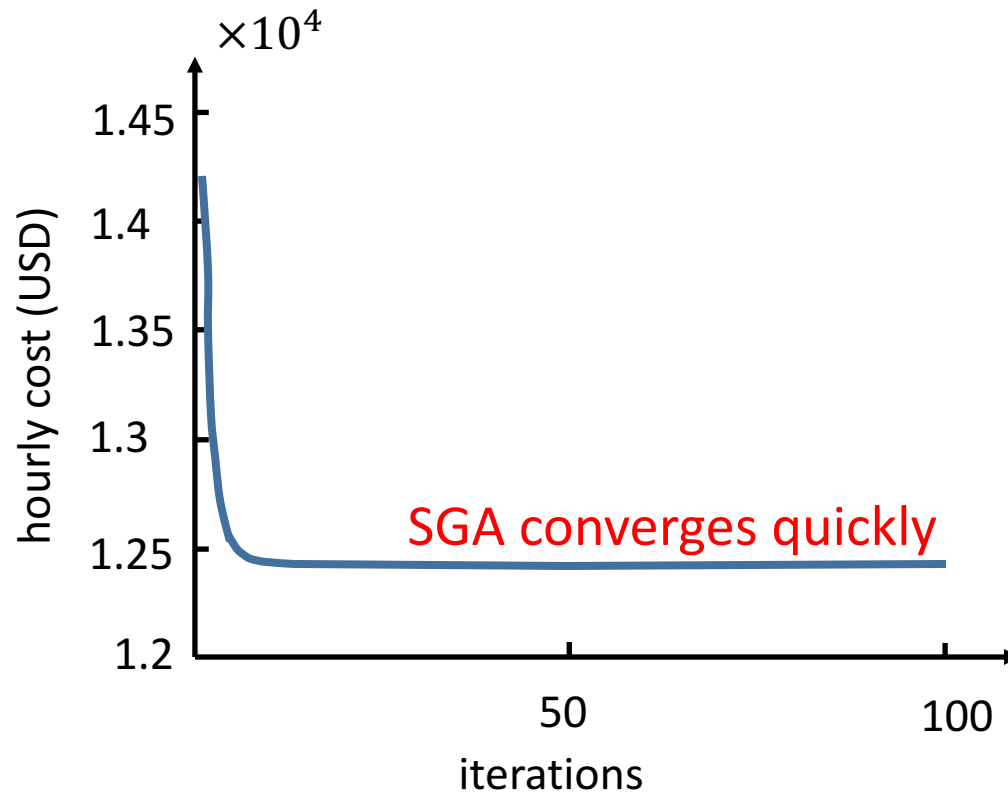


50% grid power



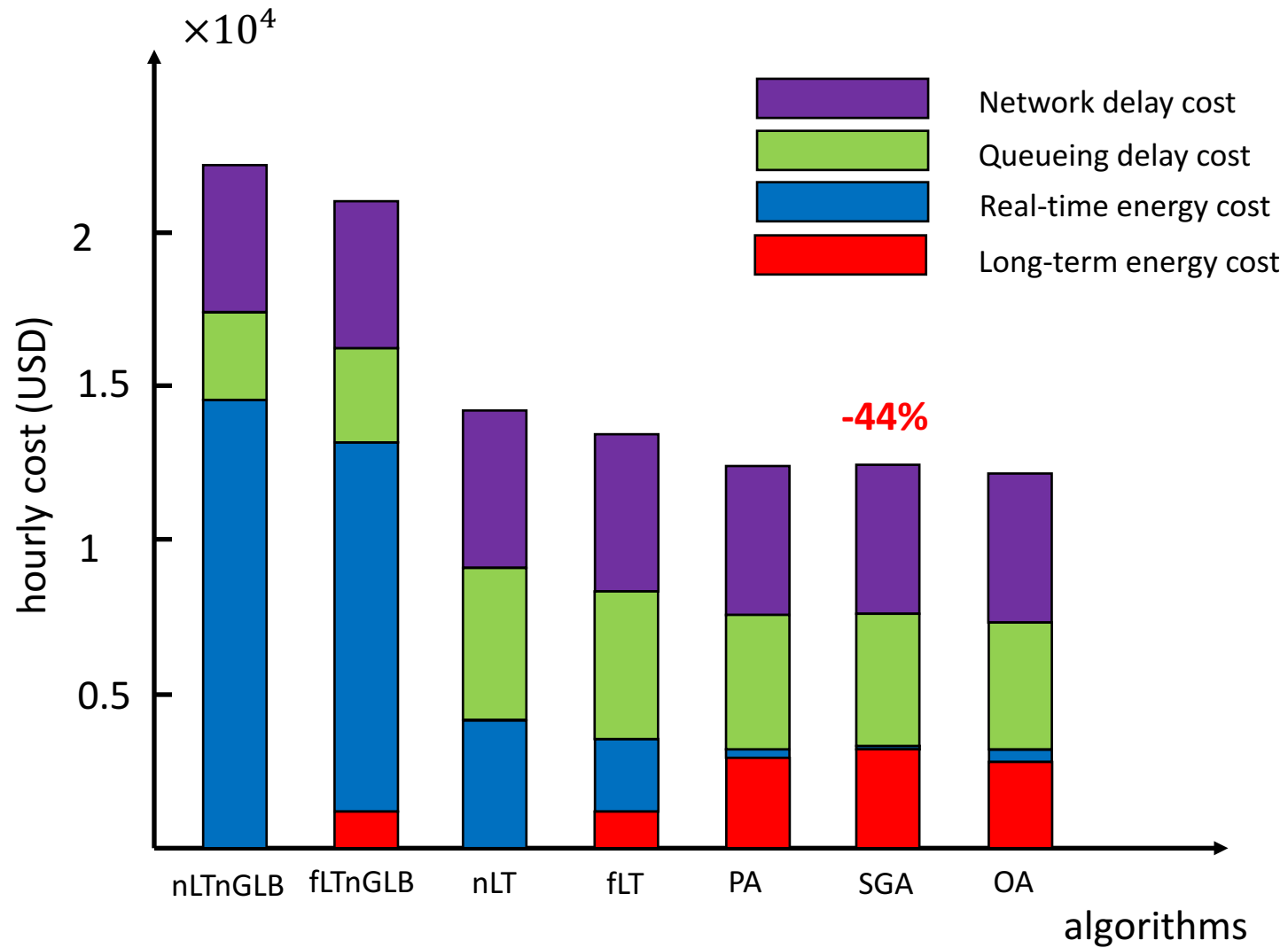
- ✓ **Workload:** Akamai data in USA
- ✓ **Electricity prices from local RTOs**
- ✓ **Prediction errors** from long-term forecaster
- ✓ **Network delay** is proportional to the distance between sources and data centers
- ✓ **Queuing delay** $M/GI/1$

Convergence of SGA

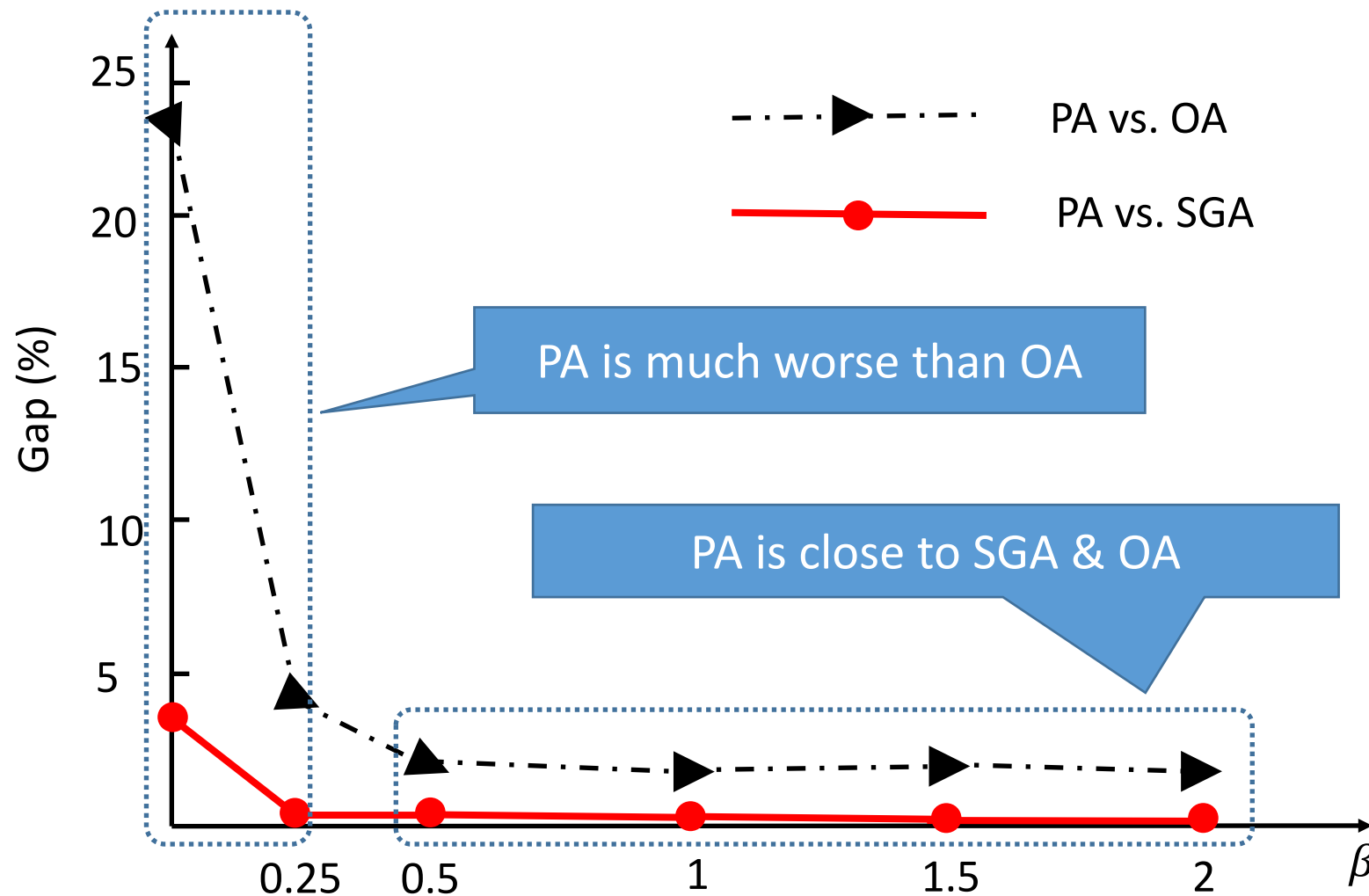


step sizes are decreasing & dynamic

How much do PA & SGA improve?



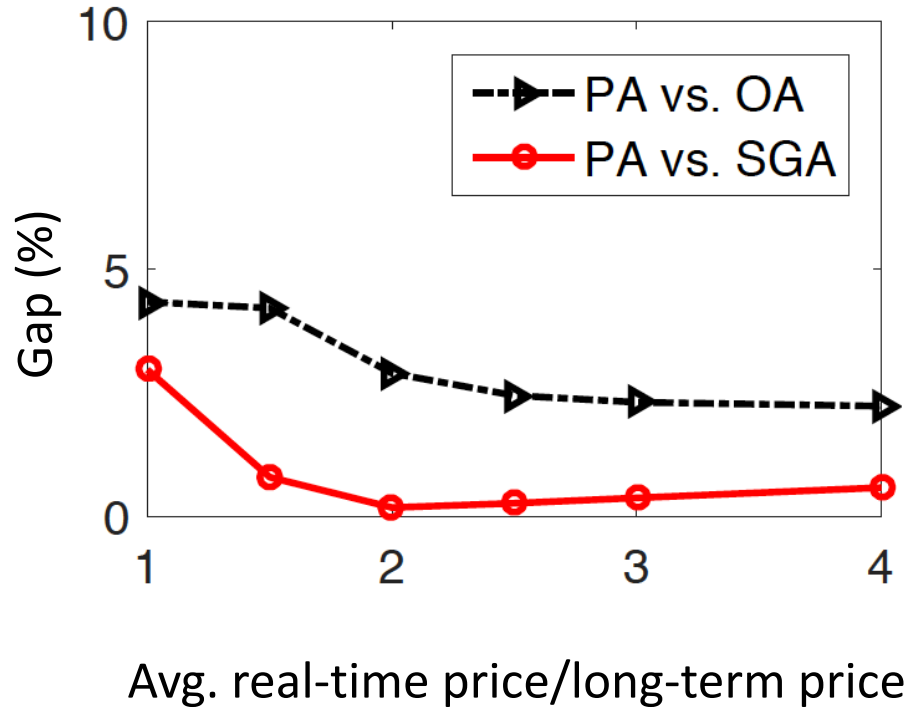
Why does PA work well?



Trade-off between energy and delay facilitates PA

β : scaled importance factor of delay

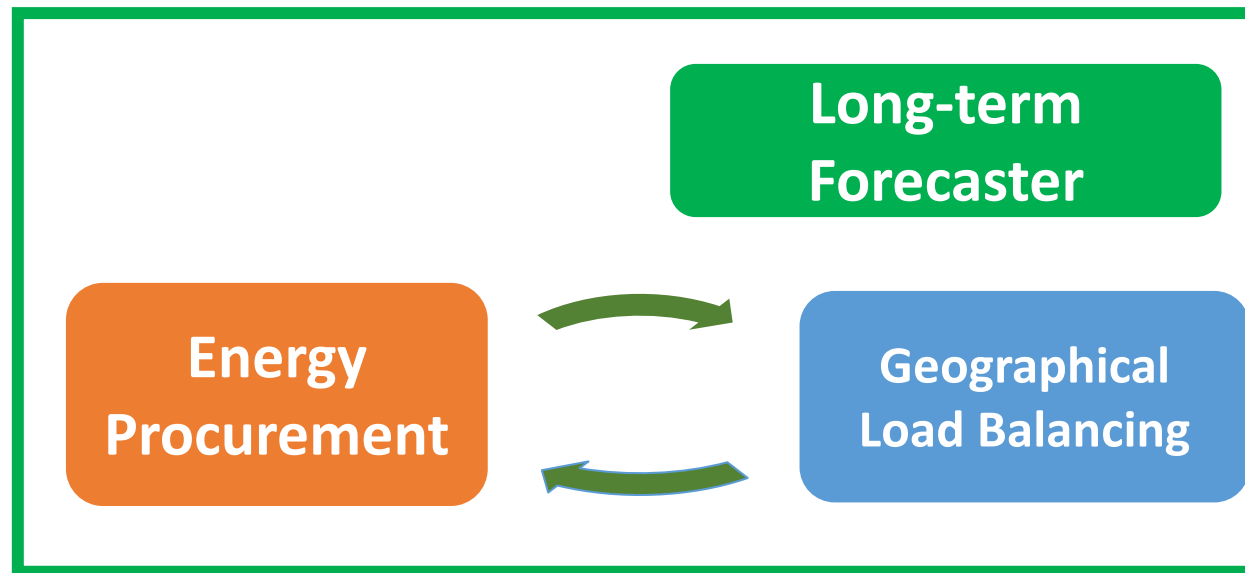
Sensitivity analysis



**SGA is more preferable to PA when
the long-term prices are high**

Goal: Optimize procurement in long-term markets

Approach: Deal with multiple sources of uncertainty



Thank you

