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

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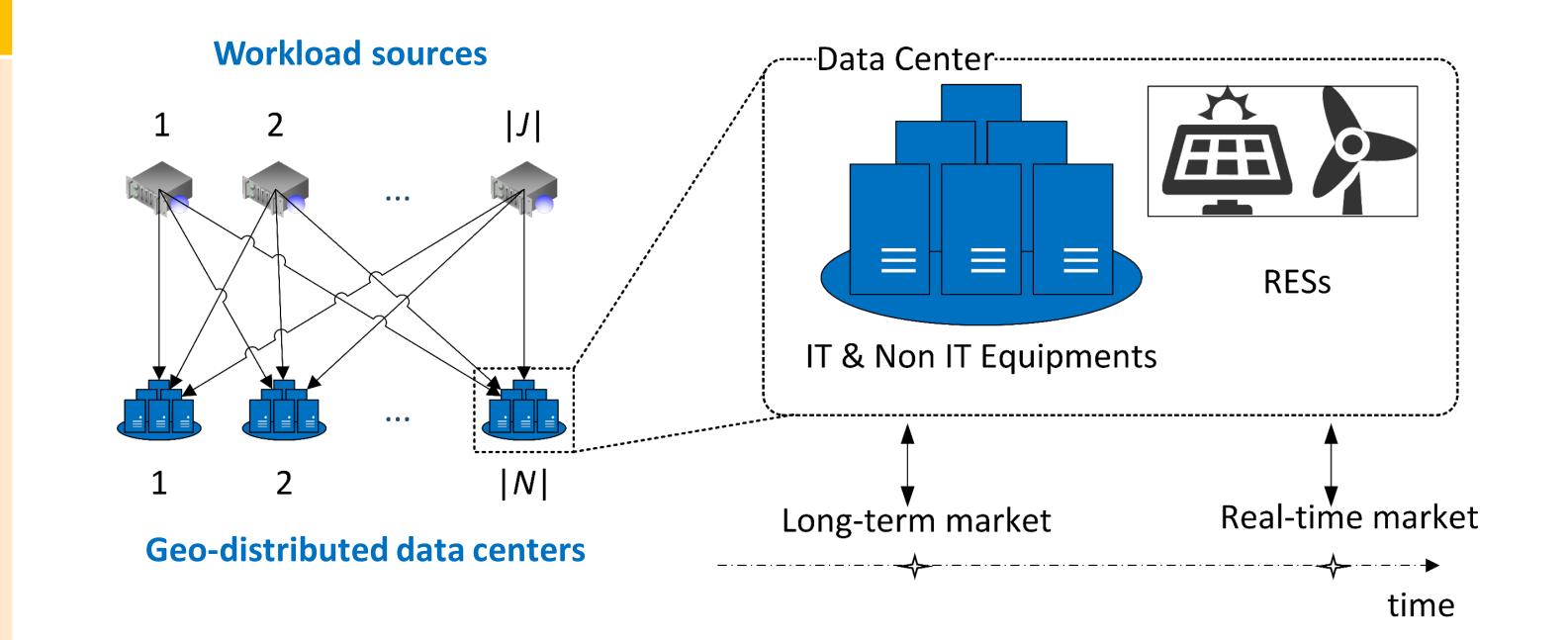
Problem & Motivation

2 data centers in TX & NY:

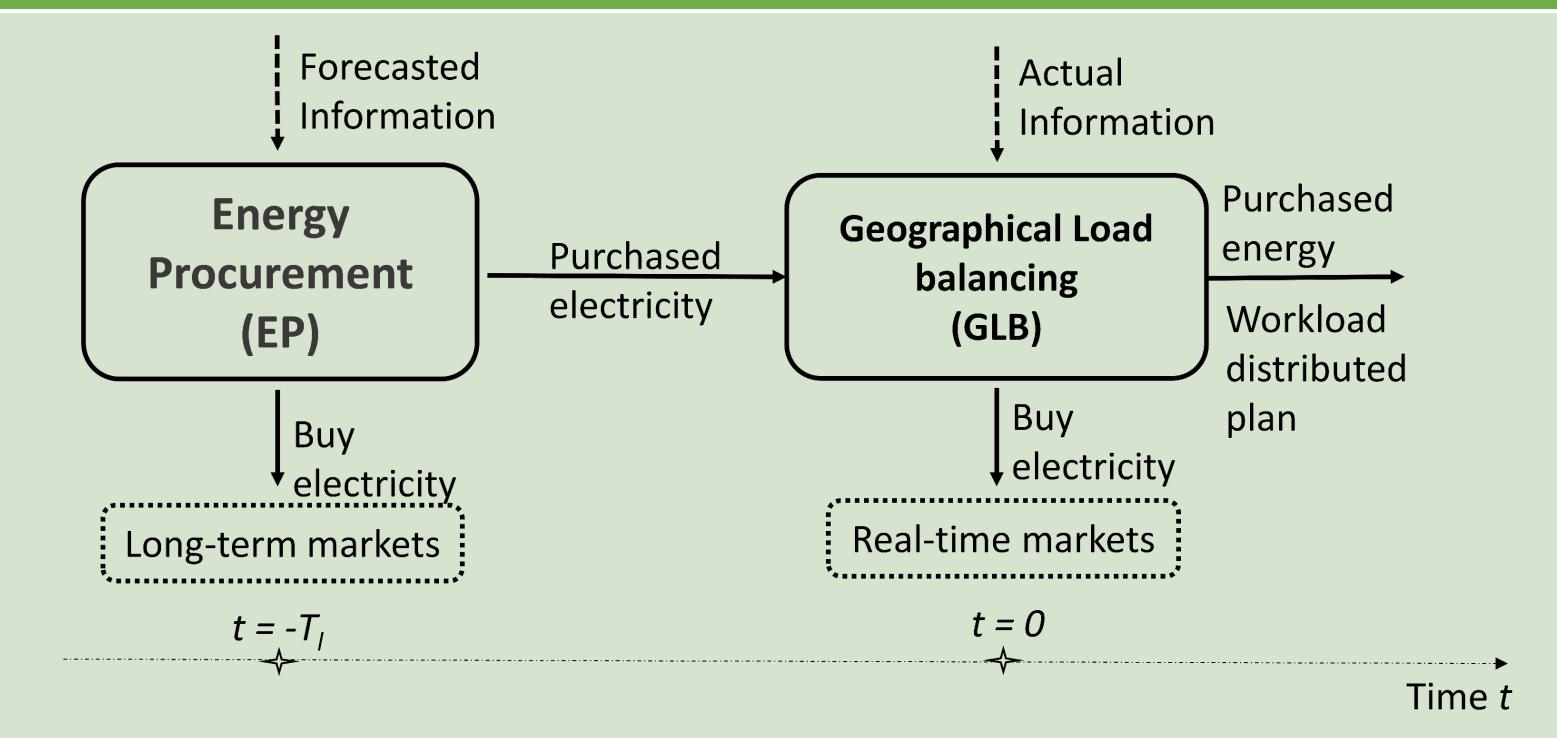
TX: \$0.03 kWh (*long-term*) \$X kWh (*real-time*) NY: \$0.05 kWh (*long-term*) \$Y kWh (*real-time*) (In real-time, renewable energy & electricity prices are uncertain.)

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

Over procurement → **waste** of energy & money **Under procurement** → **pay a lot** in real-time

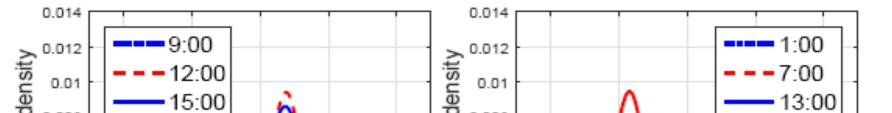


Proposed Energy Procurement System

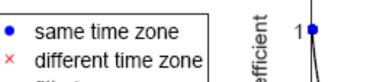


Prediction Error Analysis for the EP input

Data are collected from NREL, Akamai, ISOs in USA







same time zone

different time zone

2000 3000 4000 5000

distance (km)

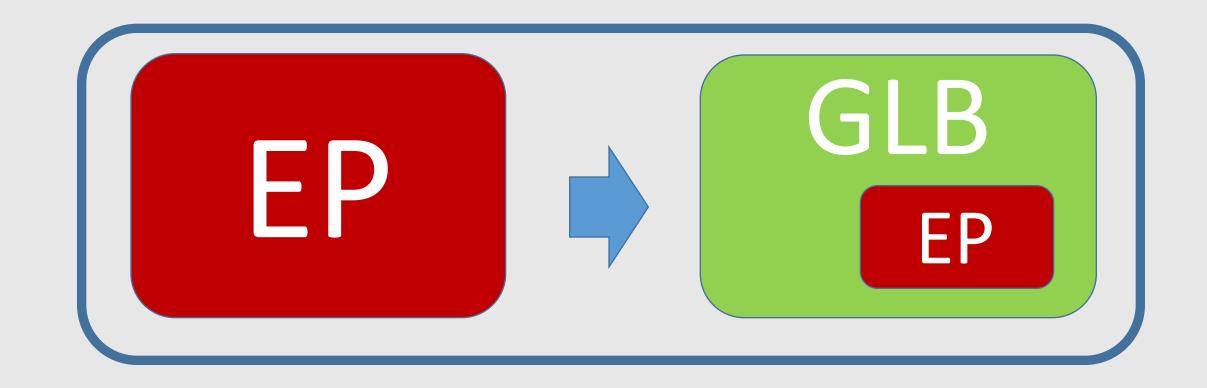
same time zone

different time zone

2000 3000 4000

distance (km)

Optimal Energy Procurement (EP) in Long-term

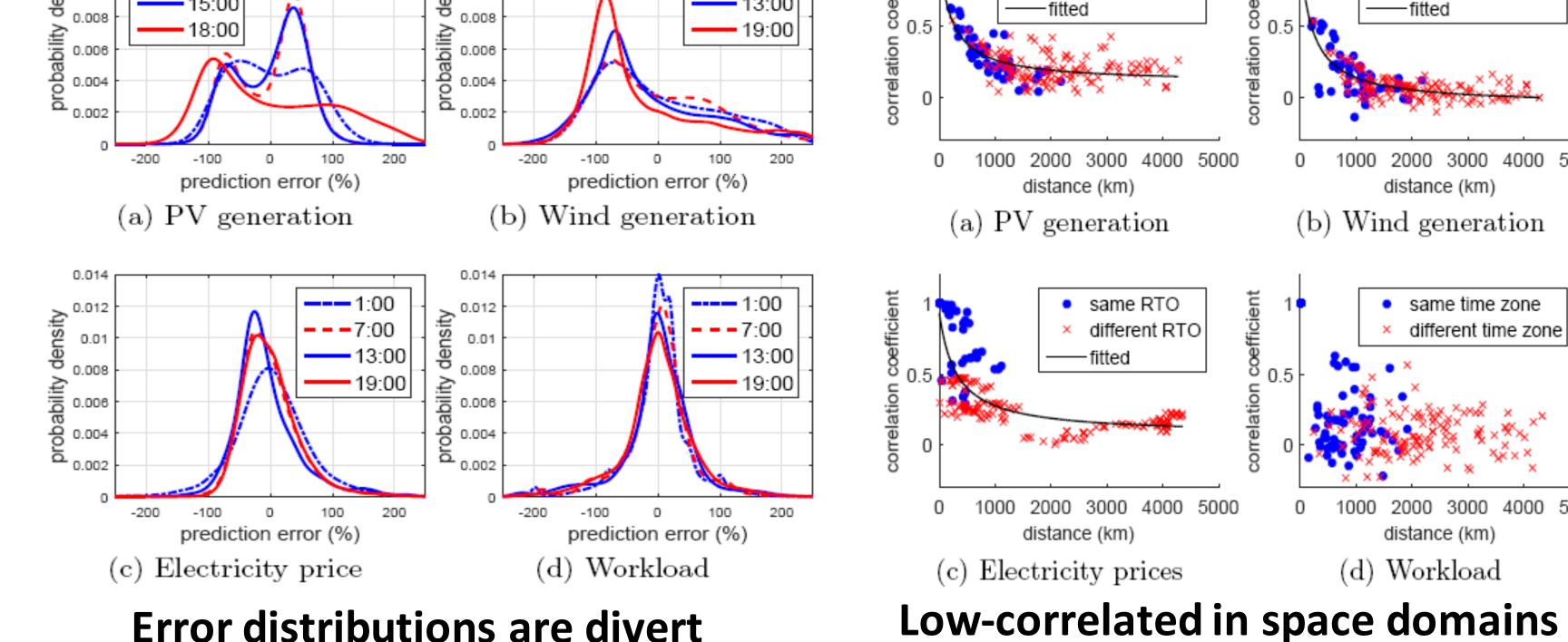


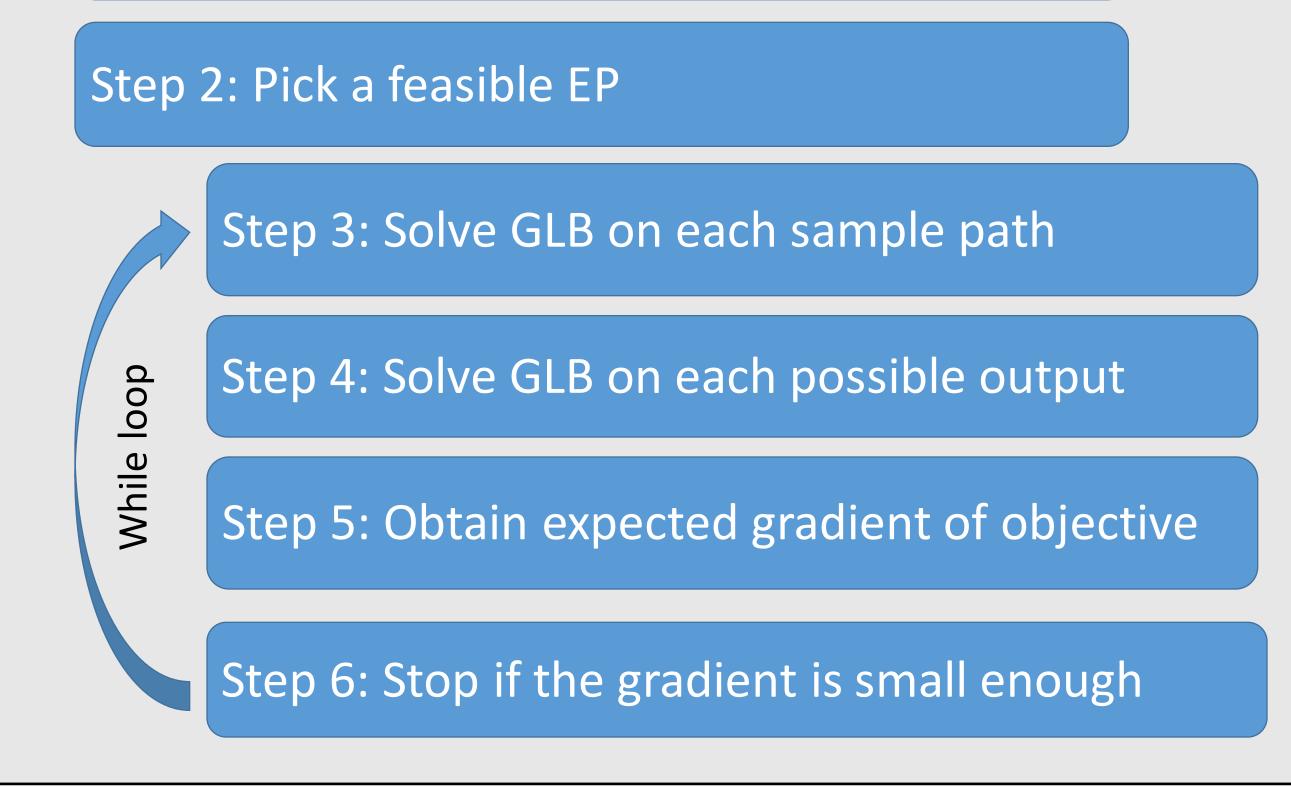
min cost(EP + GLB(EP))

Stochastic Gradient based Algorithm (SGA)

Input: Prediction error distribution

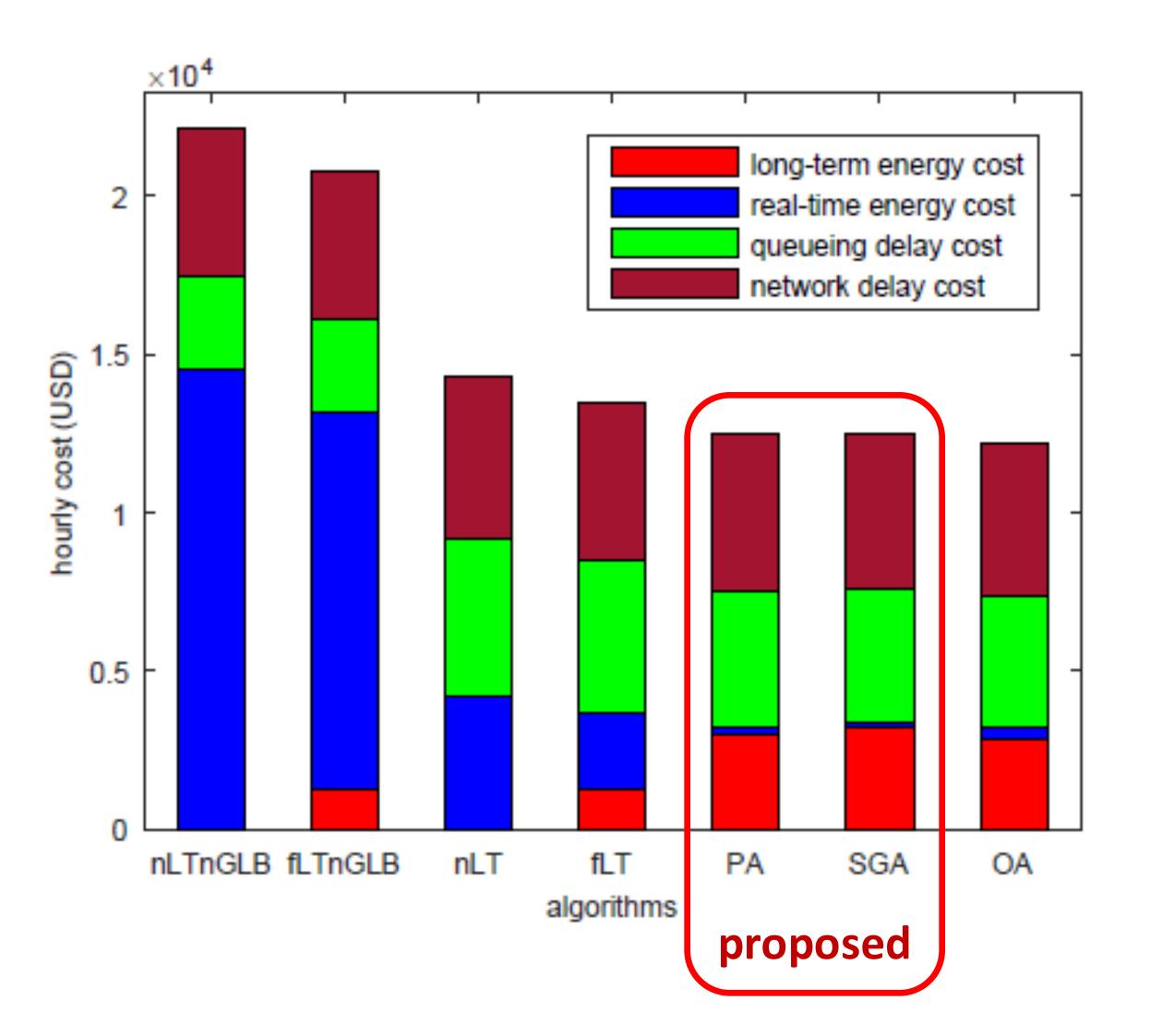
Step 1: Generate the all the possible input for GLB based prediction errors.





Experimental Setup

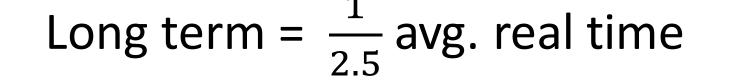
Data centers: 14 Google data centers **Renewable** penetration: 30% capacity Akamai **workload** traces: 40 sources Electricity **prices**:



Lessons learnt

Up to **50% savings** with SGA

Be **aggressive in long-term** markets thanks to GLB.



Base line methods

PA: Prediction Algorithm is proposed using predicted values

nLTnGLB: no Long Term EP & no GLB **fLTnGLB**: fixed 50% Long Term EP & no GLB **nLT**: no Long Term EP & using GLB **fLT**: fixed 50% Long Term EP & using GLB

PA & SGA are very close to optimal because of 2 reasons:

1. Long-term energy is used up to reduce the delay cost 2. GLB does a good job on distributing workload to compensate the overprocurement.