Discrete Optimizations for Supply Demand Matching in Smart Grids

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Outline

- Motivation and Background
- Thesis Statement
- Research Contributions
  - Optimal Curtailment Selection for Demand Response
  - Cost Optimal Supply Demand Matching
  - Discrete Supply Demand Matching Under Prediction Uncertainty
- Impact and Conclusion

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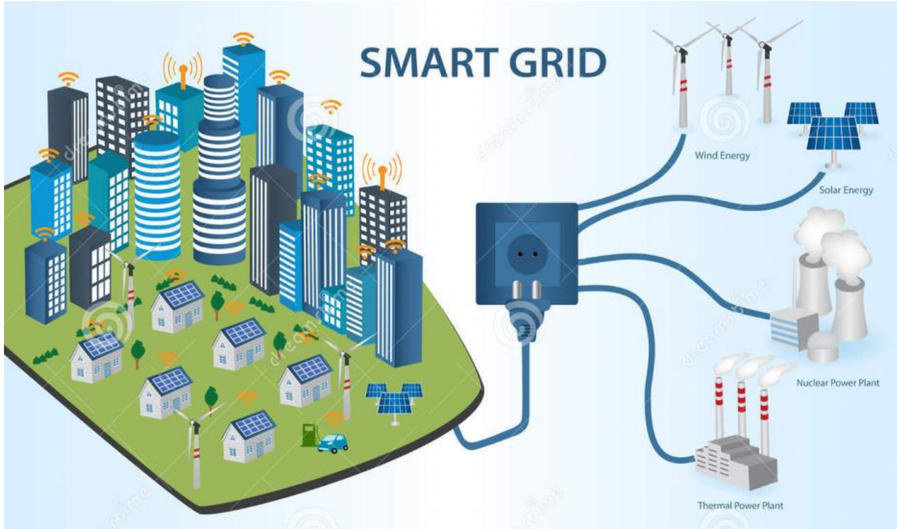
Smart Grid Overview

- Power grids with remote monitoring and control capabilities

- Trends
  - Fine grained sensing infrastructure
  - Remote control capability
  - Decentralization of generation via proliferation of Distributed Energy Resources (DER)



Our Focus – Discrete Microgrids (1)

- Example: USC Campus Microgrid

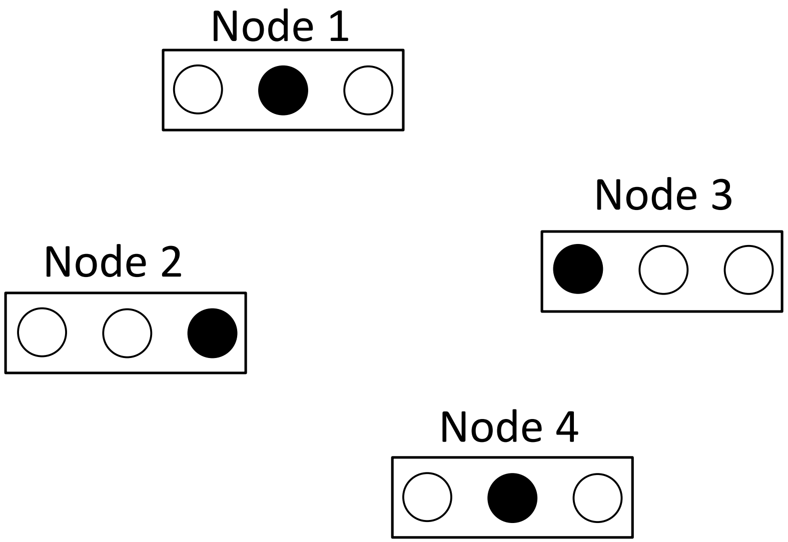
- Components
  - Centralized Controller e.g. USC FMS
  - Consumers: Buildings, athletic field, etc.
  - Producers: Photovoltaics (PV)
- Operational Values
  - Consumers: Load Values
  - Producers: Supply Values

At any given time step,
the feasible region of the operational values forms a discrete set

Our Focus – Discrete Microgrids (2)

- Load Curtailment Strategies
  - Global Temperature Reset (GTR)
  - Duty Cycling (DUTY)
  - Variable Frequency Drive (VFD)

- Solar Curtailment Strategies
  - (Dis) Connecting a subset of PV modules using micro-inverters



Supply Demand Matching (1)

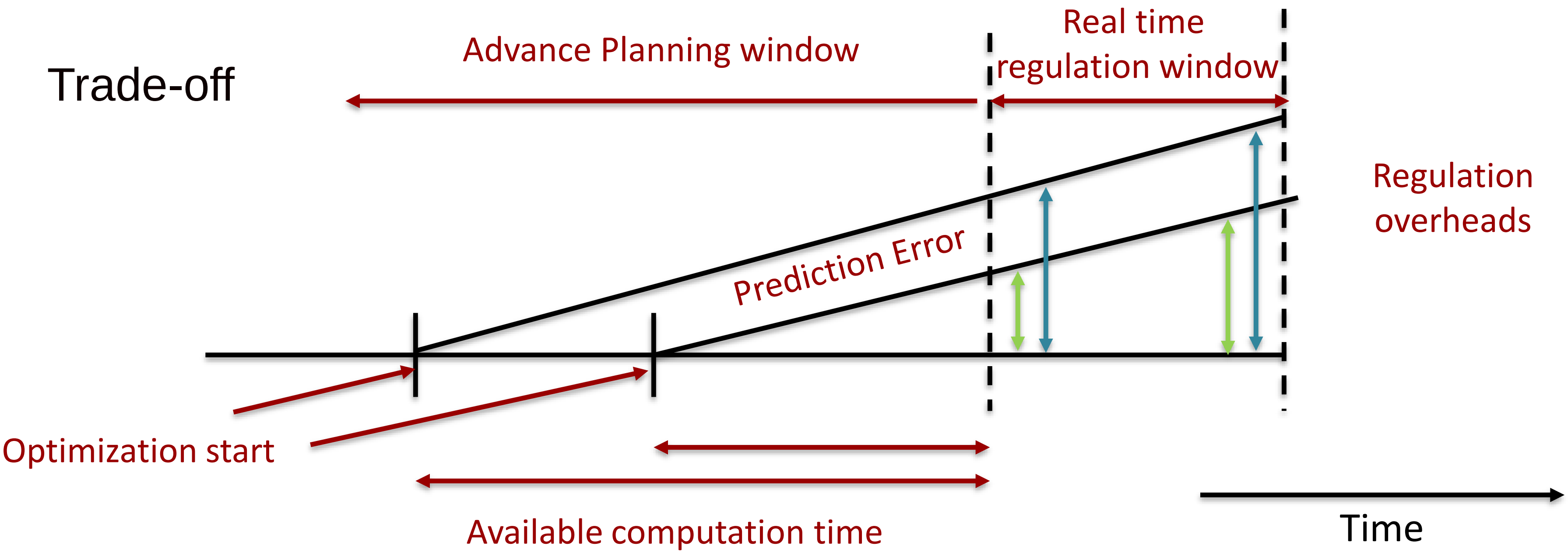
- Critical grid operation to ensure reliability

- Major steps
  - Advanced planning for dispatch of supply and demand
  - Real time regulation using low ramp up time generators (e.g. storage) to contain mismatches

- Challenges in discrete microgrid
  - **Supply variability** due to heavy influence of weather
  - **Increased** prediction errors for **longer** future horizon
  - Non convex, NP hard optimization on discrete sets

Supply Demand Matching (2)

- Trade-off



- Solution
  - **Real-time** discrete optimization and dispatch of controllable load and generation
  - Real-time: ~2.5 minutes as per CAISO real time dispatch specification

State of the Art

Supply Demand Matching in Discrete Microgrids

- Fast convex optimization solutions
  - Assume continuous operational values
  - Limitation: Unbounded errors on discrete sets

- Computationally expensive exhaustive search
  - Limitation: violates tight grid timing constraints

- Heuristics with unbounded errors
  - Limitation: compromises grid reliability

Our Contribution

- Modeling Supply Demand Matching as variants of packing problems e.g. knapsack, subset sum

- Develop **Dynamic Programming** based **approximation algorithms**

- Significant Results
  - Polynomial runtime complexity algorithm
  - Theoretical worst case bounds
    - Constraint violations
    - Objective value errors

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Thesis Statement

- **Dynamic Programming based approximation algorithms** are well suited to perform **scalable** and **bounded** supply demand matching in discrete microgrids

- Definitions
  - Scalable: In terms of runtime with respect to number of nodes
  - Bounded: Worst case guarantee on the amount of constraint violation or objective value error from the optimal solution

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Research Contributions:
Summary

- Optimal Curtailment Selection for Demand Response
  - Problem: Control demand to **reduce load** by a **targeted amount**
  - Result: **Bounded deviation** between achieved and targeted reduction

- Cost Optimal Supply Demand Matching
  - Problem: **Dispatch** supply and demand at **minimum cost**
  - Result: Minimum cost dispatch with **bounded** supply demand **imbalance**

- Discrete Supply Demand Matching Under Prediction Uncertainty
  - Problem: Dispatch supply and demand **minimizing cost** and **expected uncertainty** due to prediction errors
  - Result: Dominating solutions (Pareto frontier) with **bounded cost** and **uncertainty** deviation from the optimal

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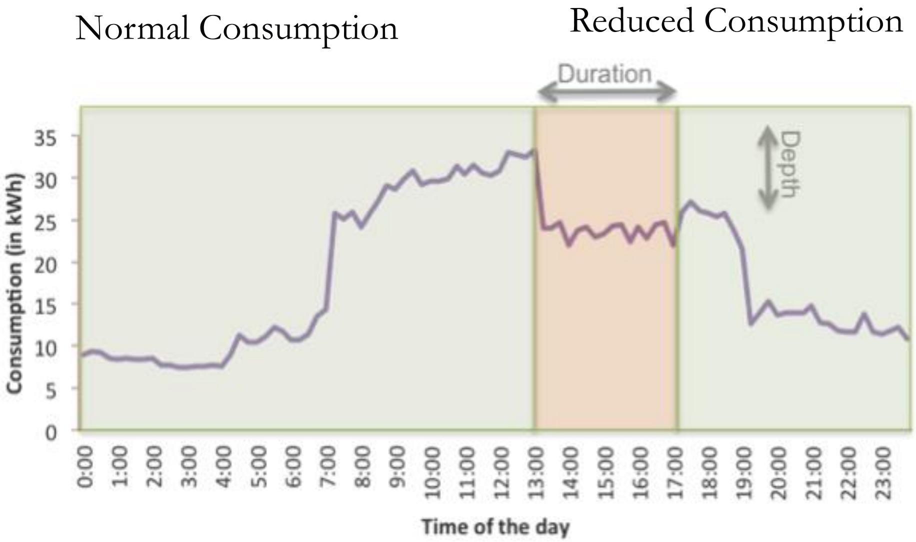
Demand Response

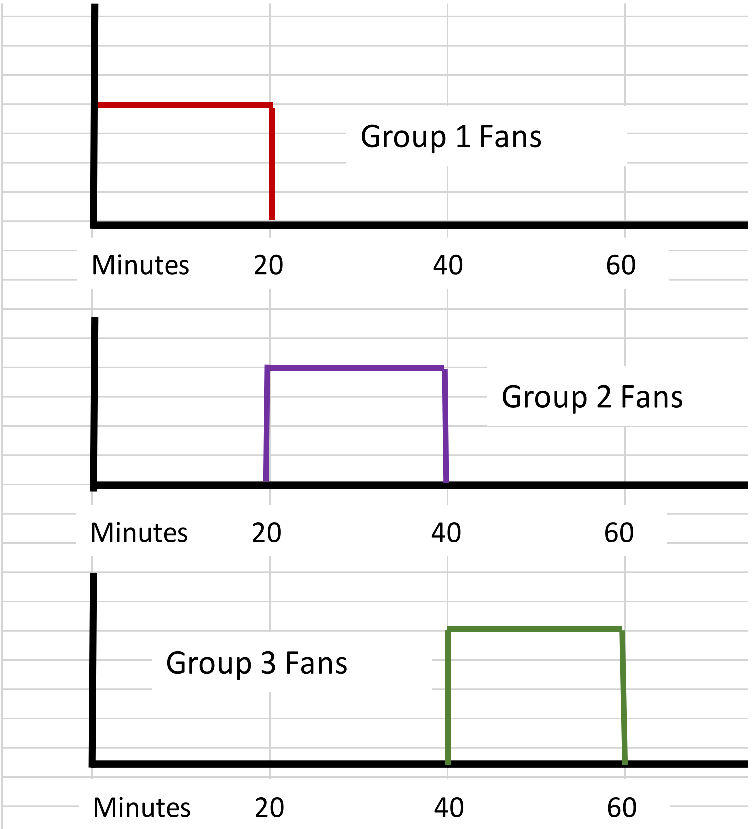
- Problem
  - Limited generation capacity
  - Supply demand imbalance during peak demand periods
- Solution: Adapt demand to supply conditions
- Demand Response: Change in electricity usage affected from the **Demand** side in **Response** to a signal from the utility



Load Curtailment Strategies

- Pre-configured strategies to reduce consumption
- Activated using control signals

- Example Strategies
  - Global Temperature Reset: Reset Air Temperature set point
  - Variable Frequency Drive: Control air flow motor speed
  - Duty Cycling: Turn on only a portion of fans at a time



Fan Duty Cycling

Problem Definition

- Given
  - M customers, with N available strategies for each customer
  - $M \times N$ time varying curtailment matrix $\gamma(t)$ with $\gamma_{bj}(t)$ denoting the curtailment value corresponding to customer b adopting strategy j at time t
  - 0-1 decision matrix: $\mathrm{X}(t)$
  - Targeted per interval curtailment value: $\Gamma(\mathrm{t})$

- Objective
  - Select customers and the strategies they should adopt to achieve per interval targeted curtailment value

- Constraints
  - Bound the number of strategy switches between intervals

Sustainable Demand Response with Strategy Overheads

- Minimize: $\sum_{t=1}^{T} \epsilon_t$
- Subject to:

$$\left|\sum_{b=1}^{M}\sum_{j=1}^{N} \boldsymbol{\gamma_{bj}(t) * x_{bj}(t) - \Gamma(t)}\right| \leq \boldsymbol{\epsilon_t}\ \forall \boldsymbol{t}$$

Per Interval Target

$$\sum_{j=1}^{N} x_{bj}(t) = 1\ \forall b$$

$$x_{bj}(t) \in \{0,1\}$$

$$S_{bj}(t) = \left|x_{bj}(t) - x_{bj}(t-1)\right|\ \forall b, j \in [N], t \in \{2 \ldots T\}$$

$$\sum_{t=2}^{T}\sum_{j=1}^{N} \boldsymbol{S_{ij}(t) \leq 2\tau}\ \forall \boldsymbol{b}$$

Bounding Number of strategy switching

Sustainable Demand Response with Strategy Overheads:
Approximation Algorithms

- Challenge
  - Intractable ILP
- Solution
  - Simplify problem and develop approximation algorithms
  - **Simplification #1**
    - **Achieve aggregated curtailment instead of per interval curtailment**
  - Simplification #2
    - Achieve per interval curtailment without strategy switching overheads
  - Simplification #3
    - Achieve aggregated curtailment without strategy switching overheads

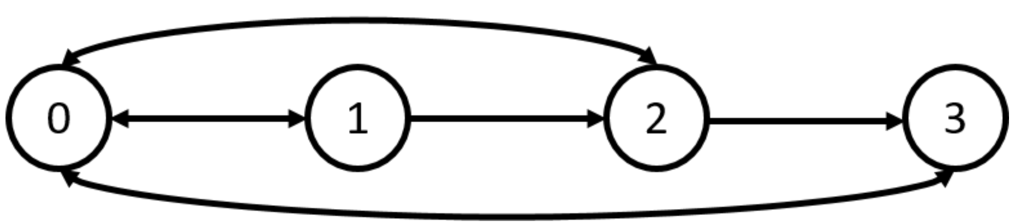
NOLESS

- Near OptimaL CurtailmEnt Strategy Selection

- Simplification
  - Achieve curtailment target for the entire interval
  - Do not enforce per interval curtailment achievement constraint

- Additional Constraints
  - $\chi_b(i, j)$: cost of switching from strategy i to j for building b
  - τ_b: Upper bound on strategy switching costs for b

$\chi_b(j, k)$



NOLESS
Problem Definition

- Minimize: ϵ
- Subject to:

$$\sum_{t=1}^{T}\sum_{b=1}^{M}\sum_{j=1}^{N}\boldsymbol{\gamma_{bj}(t) * x_{bj}(t) - \Gamma(t) \leq \epsilon}$$

Minimize aggregate error

$$\sum_{j=1}^{N} x_{bj}(t) = 1 \ \forall b$$

$$x_{bj}(t) \in \{0,1\}$$

$$S_{bij}(t) = \left|x_{bj}(t) - x_{bi}(t-1)\right| \ \forall b \in [M] \ \forall i,j, \in [N] \ t \in \{2 \ldots T\}$$

$$\sum_{t=2}^{T}\sum_{i=1}^{N}\sum_{j=1}^{N}\boldsymbol{(x_{bi}(t-1) + x_{bj}(t) - S_{bij}(t))\chi_b(i,j) \leq 2\tau_b \ \forall b}$$

Bounding strategy switching cost

NOLESS: Dynamic Programming Solution

DP#1: Boolean function Θ_{b} for each building b

$$\Theta_b(\gamma, t, S_k, q_t) = 1\ if\ \exists j \in [N]\ \Theta_{\mathrm{b}}(\gamma - \gamma_{bk}(t), t-1, S_j, q_t - \chi_b(j,k))$$

- Can we achieve curtailment $\boldsymbol{\gamma}$ at time $\boldsymbol{t}$ with strategy $\boldsymbol{k}$ and cost $\boldsymbol{q_t}$?
- Yes, if there exists j s.t. $\Theta_{\mathrm{b}}(\gamma - \gamma_{bk}(t), t-1, S_j, q_t - \chi_b(j,k))$

- Fill DP and create set θ_b: All possible achievable γ values satisfying constraints

$$\theta_b = \cup \{\gamma_l | \exists (S_k, q), \Theta_b(\gamma_l, T, S_k, q) = 1\ \&\ \boldsymbol{q} \leq \boldsymbol{\tau_b}\}$$

NOLESS:
Dynamic Programming Solution

DP#2: Pick exactly one element γ_b from each set θ_b

s.t. : $\sum \gamma_b = \sum_{t=1}^{T} \Gamma(t)$

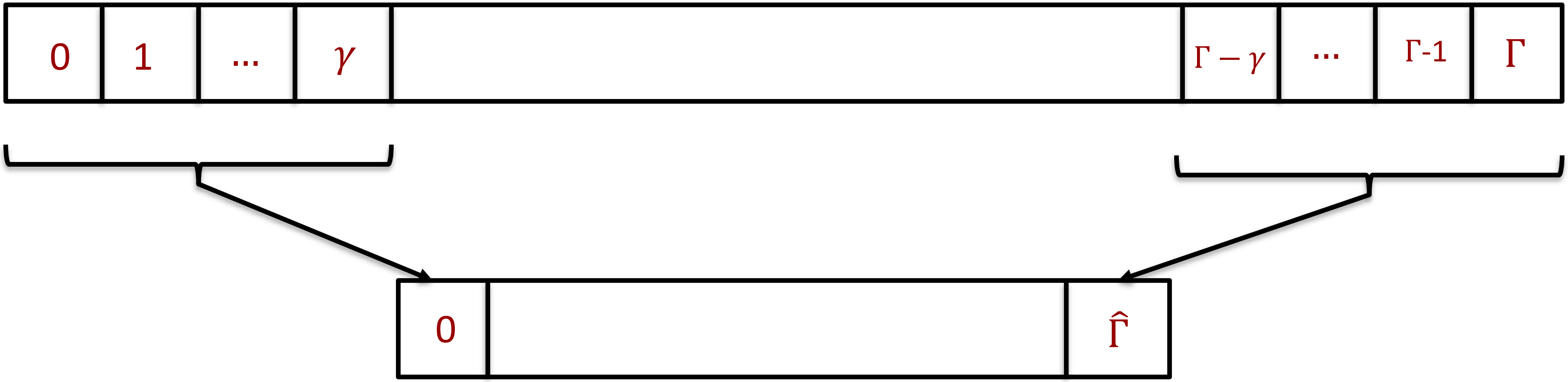
Boolean function Φ to optimize across all buildings

$$\Phi(\gamma, b) = 1 \; \exists \gamma_b, \Phi(\gamma - \gamma_b, b - 1) = 1$$

- Possible to achieve $\boldsymbol{\gamma}$ using $1, \ldots, \boldsymbol{b} \leftrightarrow$ Possible to achieve $\boldsymbol{\gamma} - \boldsymbol{\gamma_b}$ using $1, \ldots, \boldsymbol{b} - \mathbf{1}$

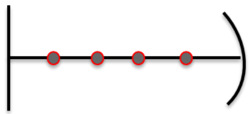
NOLESS: Rounding Approximation Technique

- Challenge
  - $O(\Gamma)$ entries in dynamic programming table
  - $\Gamma = \sum_{t=1}^{T} \Gamma(t)$
- Solution
  - Choose an accuracy parameter ϵ
  - Partition Γ into number of buckets polynomial in input size and $\frac{1}{\epsilon}$



NOLESS

- Approach
  - $\mu = \frac{\epsilon\Gamma}{TM}$
  - $\hat{\gamma} = \lfloor \frac{\gamma}{\mu} \rfloor$



Rounded down to $\lfloor \frac{\gamma}{\mu} \rfloor$

- Fill Dynamic Programming tables using rounded curtailment values

- Runtime: $O\left(\frac{T^3MN^2}{\epsilon}\right) + O(\frac{M^3T^2}{\epsilon^2})$, assuming $\tau_b = O(T)$

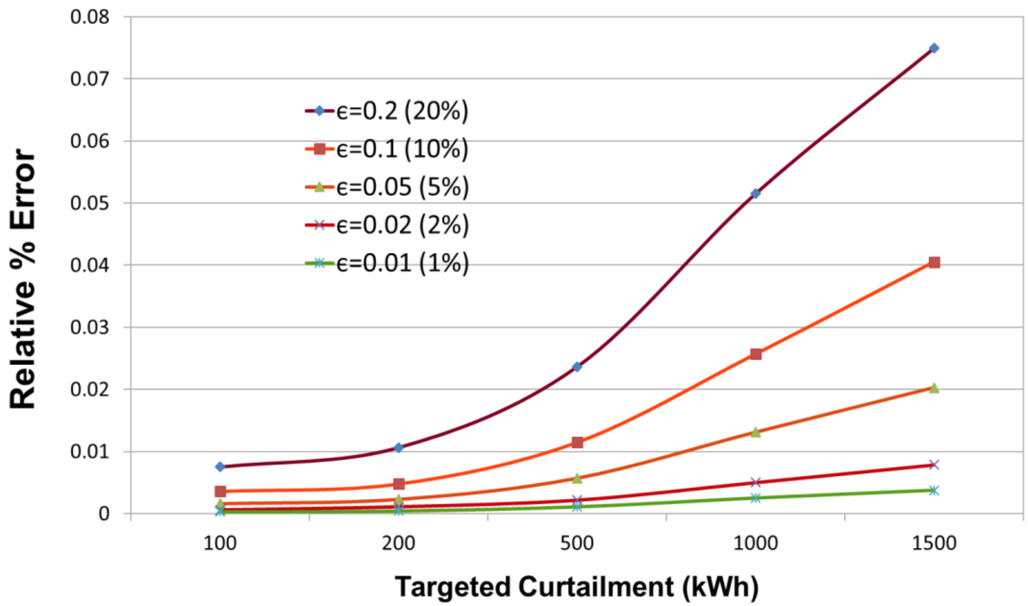
- **Result**
  - Worst case curtailment error: $\epsilon\Gamma$
  - Example: $\Gamma = 1000$ kwh, $\epsilon = 0.1$, Error = < 100 kwh

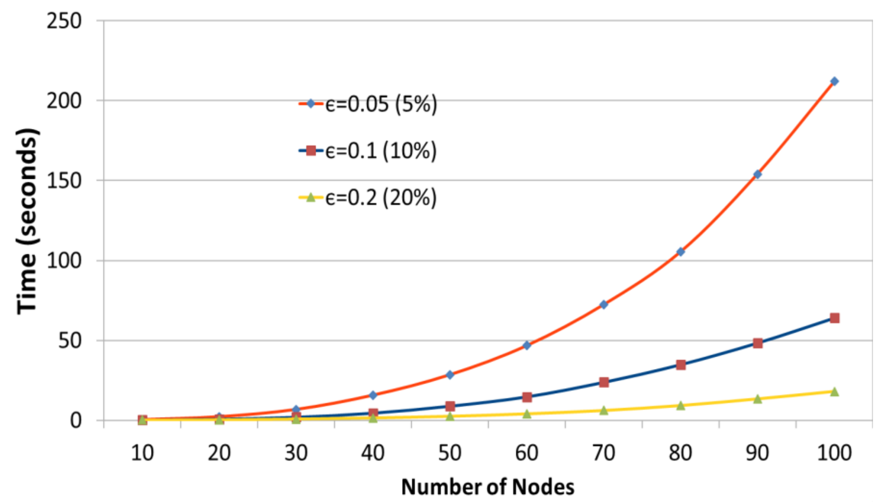
Results and Analysis

- Dataset
  - USC Smart Grid Demand Response Program
  - Number of nodes: 10-100
  - Number of strategies: 6
  - Number of time intervals: 16
  - Target Curtailment: 100-1500 kWh
- Toolkit
  - Baseline
    - IBM Cplex for ILP formulations
  - NOLESS Approximation Algorithm
    - Java
- Platform: Dell Optiplex 4-cores, 4 GB RAM

Results and Analysis

- Achieved error always less than the guarantee provided by ϵ
- Scalability
  - Quadratic in nodes and $\frac{1}{\epsilon}$





- 150 seconds
  - 90 nodes with 5% error
- Runtime of Baseline (CPLEX): a few seconds to more than an hour

Research Contributions: Summary

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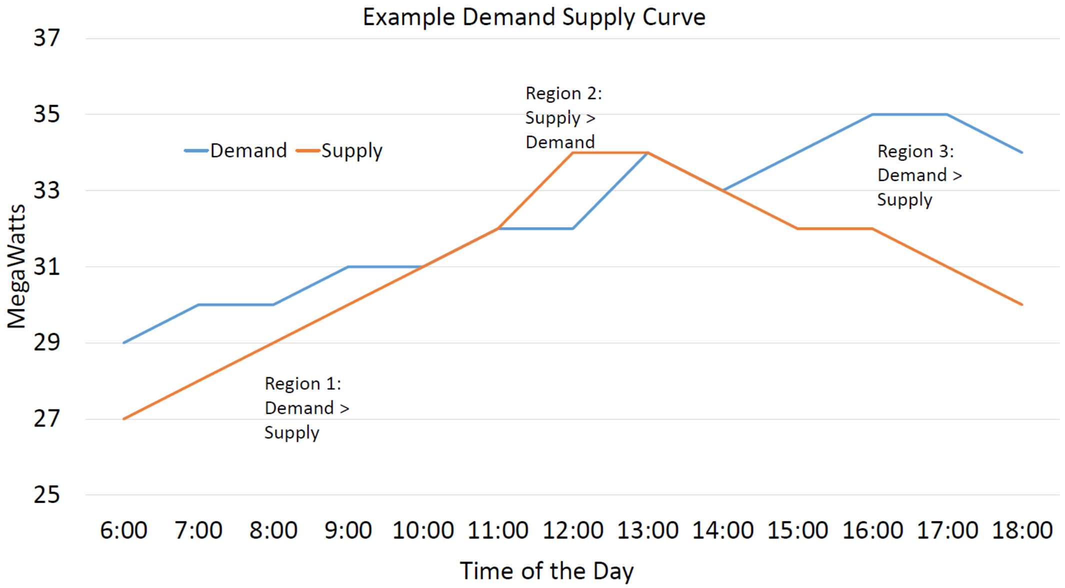
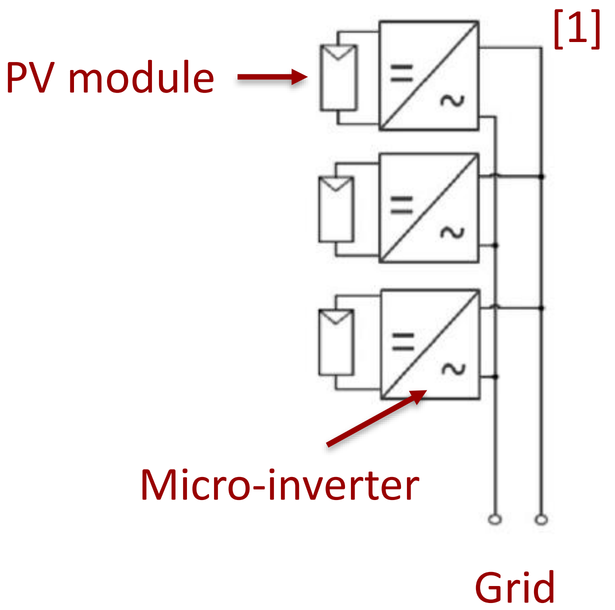
Cost Optimal Supply Demand Matching: Motivation

- Trend
  - Rapid penetration of DERs such as solar PVs
- Challenge
  - Periods with supply surplus causing over voltages
  - Load Curtailment inadequate to mitigate supply surplus
- Solution
  - Supply Curtailment



Solar Curtailment Technique

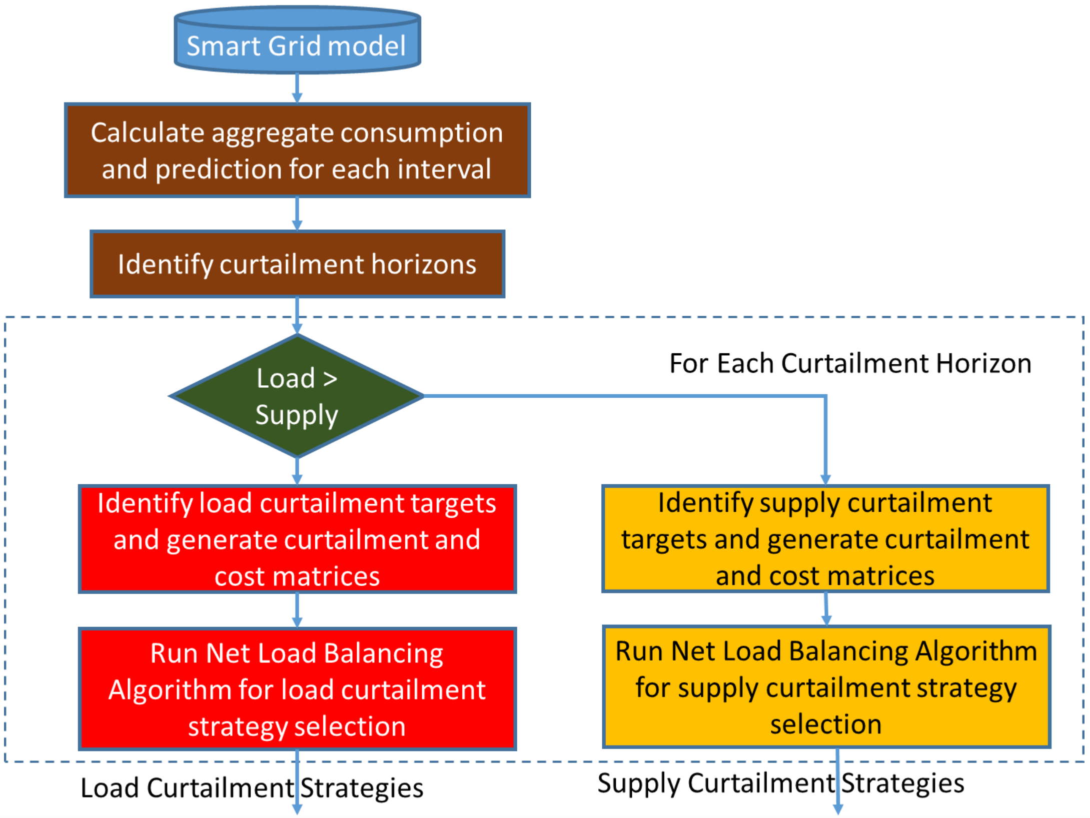
- Modern PVs installations
  - Individual PVs grid connected using single micro-inverter
- Solar curtailment
  - Turn on/off individual micro-inverter
  - Simple coarse grained control
- PV Installation Output
  - Sum of supply from grid connected PV modules (micro-inverters in on configuration)



[1] Microinverter Curtailment Strategy for Increasing Photovoltaic Penetration in Low-Voltage Networks, Gagrica et. al., IEEE Transactions on Sustainable Energy, Vol 6, No 2, April 2015

Cost Optimal Supply Demand Matching: Framework

- Unified framework that performs
  - Supply curtailment using PV micro-inverters
  - Load curtailment using DR strategies



Cost Optimal Supply Demand Matching: Problem Definition

- Model
  - M nodes, N strategies, T intervals
- $\gamma_{bj}(t)/c_{bj}(t)$: Curtailment/cost of node b following strategy j at time t
- $\boldsymbol{x_{bj}(t)}$**: 0-1** decision variable node b following strategy j at time t
- Γ_t: Curtailment target for time t
- Additional constraints
  - Fairness: No node should curtail more that its budget B_b
  - Ensures equitable curtailment burden

Cost Optimal Supply Demand Matching: ILP Formulation

$$min_x \sum_{b=1}^{M} \sum_{j=1}^{N} \sum_{t=1}^{T} c_{bj}(t) x_{bj}(t)$$

Minimize Cost

$$s.t. \sum_{b=1}^{M} \sum_{j=1}^{N} \gamma_{bj}(t) x_{bj}(t) \geq \Gamma_t \ \forall t$$

Per interval target achieved

$$\sum_{j=1}^{N} \sum_{t=1}^{T} \gamma_{bj}(t) x_{bj}(t) \leq B_b \ \forall b$$

Fairness Constraint

- Packing Integer Problem with each integer appearing in $k = 3$ constraints
- $ek + O(k) \ \rightarrow \ > 8$ - approximation factor

Cost Optimal Supply Demand Matching: Approximation Algorithms

- **Simplification #1**
  - Remove fairness constraint
  - Add upper bound on achieved curtailment $\Gamma = \sum_{b=1}^{M} B_b$
- Simplification #2
  - Assume costs proportional to curtailment
- Other Versions
  - Supply Demand matching with network constraints

MinCB: Min Cost Net Load Balancing

- Objectives
  - Γ_t achieved for each interval
  - Aggregate curtailment in T intervals is less than $\Gamma = \sum_{b=1}^{M} B_b$
  - Cost minimized

- Integer Program Formulation

$$min_x \sum_{b=1}^{M} \sum_{j=1}^{N} \sum_{t=1}^{T} c_{bj}(t) x_{bj}(t)$$

Minimize Cost

$$s.t. \sum_{b=1}^{M} \sum_{j=1}^{N} \gamma_{bj}(t) x_{bj}(t) \geq \Gamma_t \ \ \forall t$$

Per interval target achieved

$$\sum_{b=1}^{M} \sum_{j=1}^{N} \sum_{t=1}^{T} \gamma_{bj}(t) x_{bj}(t) \leq \Gamma$$

Avoid excessive curtailment

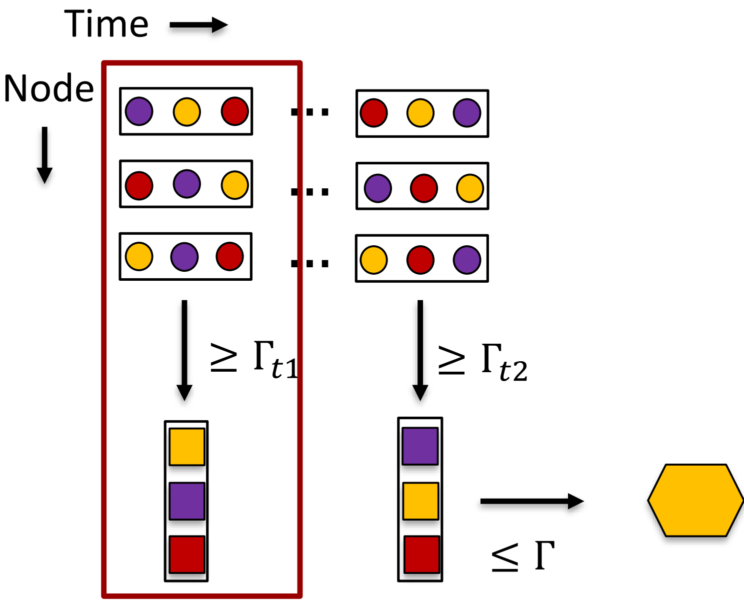
MinCB: Approximation Algorithm (1)

- Two level Dynamic Program
- First Level
  - For each time t
  - Dynamic Programming Recursion:
    - Identify minimum cost to achieve γ using $1, \ldots, b$ nodes

$$\Theta_t(\gamma, b) = \min_{j}\{\Theta_t(\gamma - \gamma_{bj}(t), b-1) + c_{bj}(t)\}$$

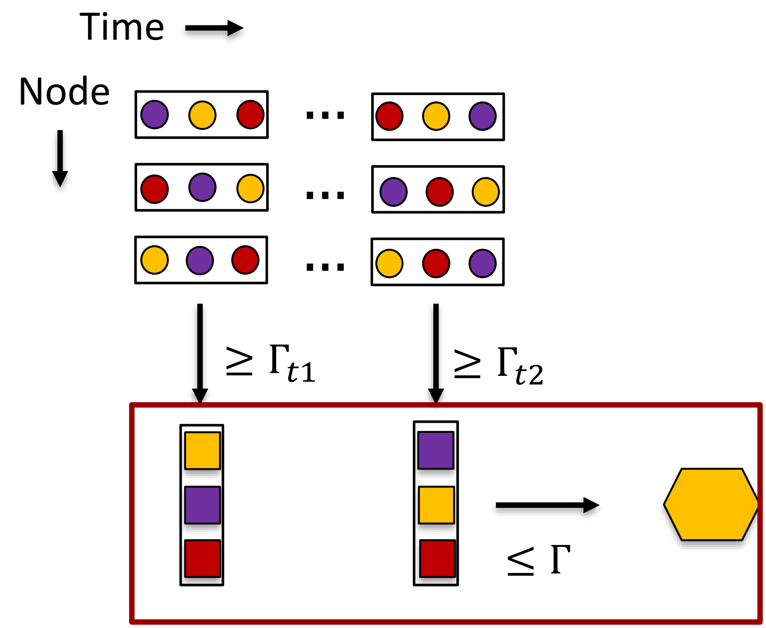
  - Select nodes strategy pairs with:
    - c: cumulative cost
    - γ: cumulative curtailment
    - And:

$$\boxed{S_t = \{(\Theta_t(\gamma, M), \gamma) | \gamma \geq \Gamma_t\}}$$



MinCB: Approximation Algorithm (2)

- Across all time intervals
  - Select exactly 1 element (c_t, γ_t) from each S_t s.t:
  - $\sum_{t=1}^{T} \gamma_t \leq \Gamma$ and $\sum_{t=1}^{T} c_t$ minimized



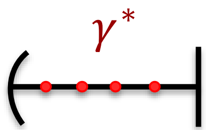
- Second Level Dynamic Program Recursion:
  - Identify minimum cost to achieve γ using $1, \ldots, t$ time intervals

$$\Phi(\gamma, t) = \min_{j \mid (c_j, \gamma_j) \in S_t} \{\Phi(\gamma - \gamma_j, t-1) + c_j\}$$

- Final result: $\min_{\gamma} \Phi(\gamma, T)$

MinCB: Approximation Algorithm (3)

- User defined accuracy parameter ϵ
- Apply rounding technique for approximation
- Result
  - Cost minimized
  - Curtailment Error Bounds
    - Aggregate Γ: $(1+\epsilon)$ factor
    - Per interval Γ_t: $(1-\epsilon)$ factor



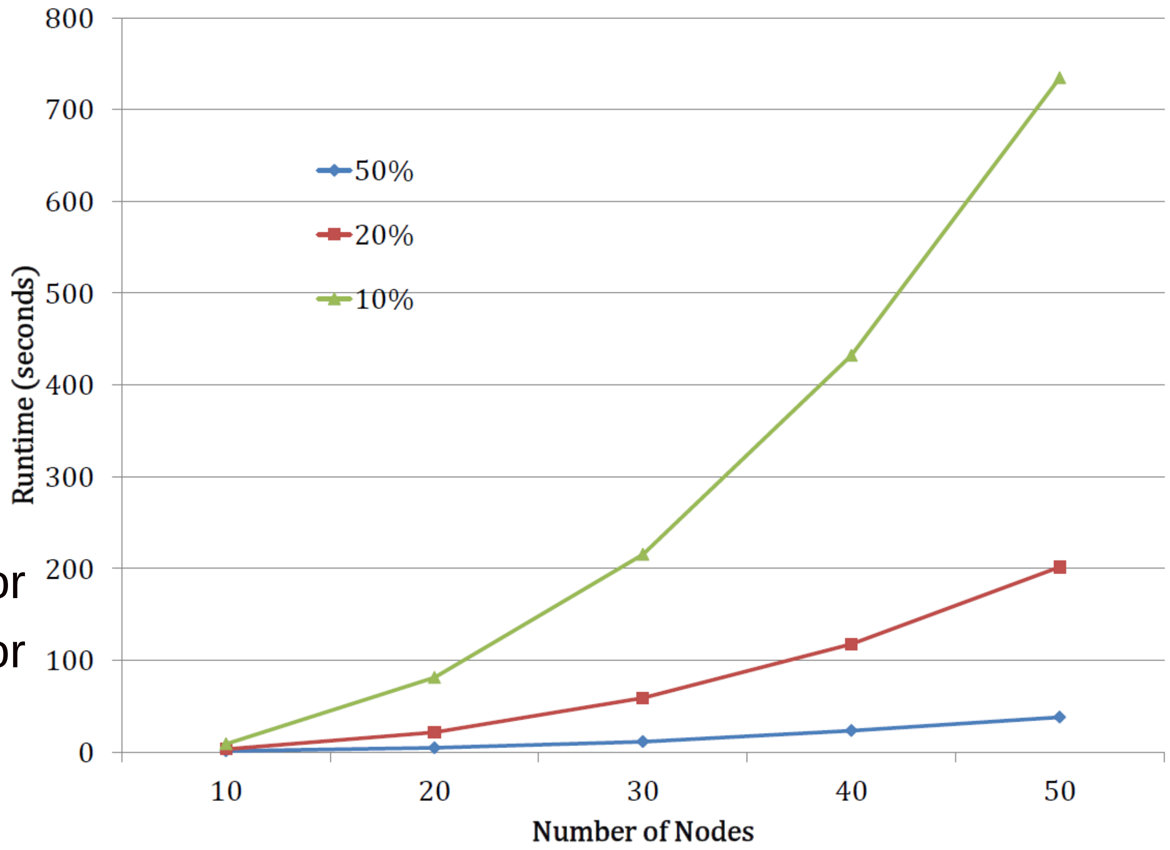
Minimum Cost solution in the vicinity of the optimal

Results and Analysis: Experimental Setup (1)

- Implementation
  - Algorithms: MATLAB
  - Integer Program/Linear Program: IBM ILOG Cplex Optimization Studio
  - Platform: Dell Optiplex 4-cores, 4 GB RAM
- Parameters
  - Horizon: 16 intervals
  - Cost: $2 \times \gamma^2$
- Dataset
  - Load Curtailment: USC Demand Response program
  - Solar Curtailment
    - Simulated Data using hourly solar radiance data for USC

Scalability: MinCB

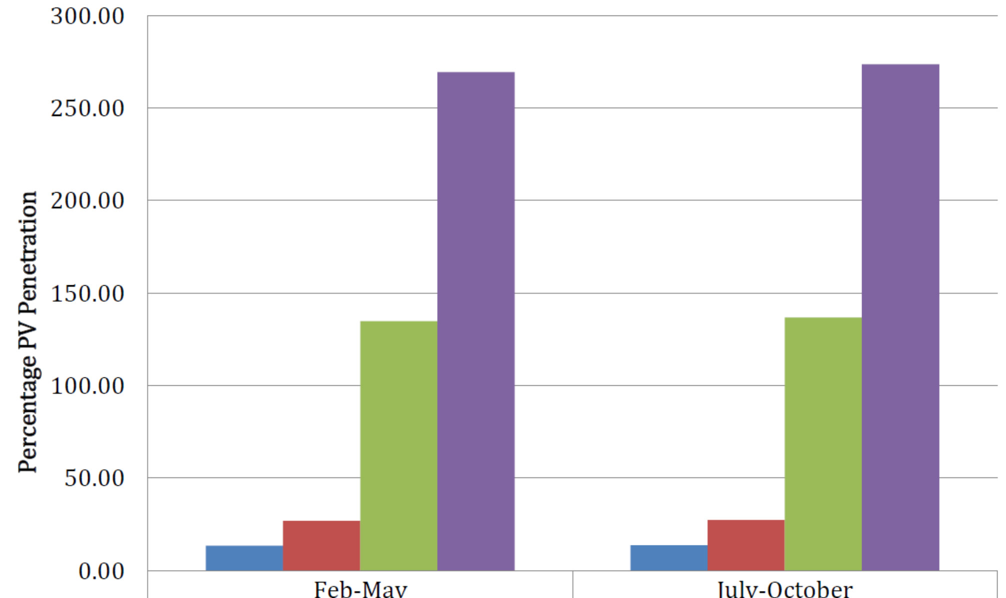
- Scalability:
  - Quadratic increase in runtime with number of nodes
  - $\frac{1}{\epsilon^2}$ dependence on accuracy parameter ϵ
- 150 seconds
  - 40 nodes with 20% error
  - 25 nodes with 10% error



Improvement in PV Penetration

- PV Penetration = $\frac{PV_{avg}}{Load_{avg}} \times 100$
- Limit on PV penetration
  - Average supply + 1 std < minimum load
- Maximum Curtailment: $1 - \epsilon$ times maximum supply
  - Supply: 100 kwh, $\epsilon = 0.1$
  - Max Curtailment: 90 kwh

- Potential PV penetration increase from ~13% to 250%



	Feb-May	July-October
No NLB	13.47	13.68
50%	26.94	27.36
10%	134.68	136.78
5%	269.36	273.56

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Supply Demand Matching with Prediction Uncertainty: Motivation

- Supply Demand Predictions for future horizon have prediction errors
- Prediction errors create uncertainty in grid operation
- Model: Two stage decision making[2]
  - Dispatch load/generation in first stage
  - Use storage to address supply demand mismatch in second stage
- Scenario:
  - Random variable X, governed by randomness ξ
  - Scenario $\varepsilon \in \xi$ corresponds to a single realization of randomness

[2] Sampling Bounds for Stochastic Optimization, Charikar, Moses, Chandra Chekuri, and Martin Pál , Approximation, Randomization and Combinatorial Optimization. Algorithms and Techniques. Springer, Berlin, Heidelberg, 2005. 257-269

Supply Demand Matching with Prediction Uncertainty (2)

- Supply side control
  - Supply Value: $\gamma_{ij} + \delta_{ij}^{\varepsilon}$
  - γ_{ij}: predicted supply value for node i strategy j
  - $\delta_{ij}^{\varepsilon}$: realization of supply uncertainty value in scenario ε

- $C(x)$: $\sum_{i=1}^{M}\sum_{j=1}^{N} c_{ij}x_{ij}$: cost of supply dispatch decision x

- $v(x, \varepsilon)$: $\sum_{i=1}^{M}\sum_{j=1}^{N} \delta_{ij}^{\varepsilon}x_{ij}$: uncertainty due to first stage dispatch decision x for scenario ε

- $X = \{x \mid \sum_{i=1}^{M}\sum_{j=1}^{N} \gamma_{ij}x_{ij} = D\}$, D being the expected demand

Supply Demand Matching with Prediction Uncertainty (3)

- Multi-Objective Optimization: Minimize the cost of dispatch in first stage and expected uncertainty in second stage

$$\min_{x} C(x), E[v(x)]$$
$$s.t. \, x \in X$$

- By linearity of expectation: $E[v(x)] = \sum_{i=1}^{M} \sum_{j=1}^{N} v_{ij} x_{ij}$
- v_{ij} $\rightarrow$ Expected uncertainty value of node i following strategy j
- Dynamic Programming Formulation

$$\Theta(\gamma, c, i) = \min_{\mathrm{j}} \{\Theta\left(\gamma - \gamma_{ij}, c - c_{ij}, i - 1\right) + v_{ij}\}$$

- Identify minimum expected uncertainty to achieve $\boldsymbol{\gamma}$ at cost $\boldsymbol{c}$ using $1, \dots, i$ nodes

Supply Demand Matching with Prediction Uncertainty (4)

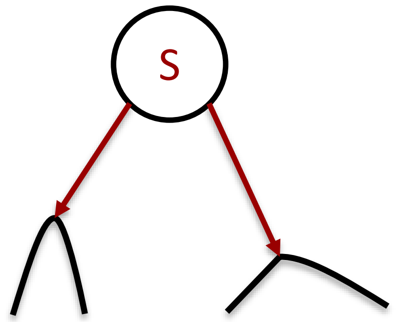
- Rounding Approximation Technique

- Find Pareto optimal solutions on the set: $\Theta(D,:,M)$
  - All cost, uncertainty pairs that achieve D in first stage using $1, \ldots, M$ nodes

- Approximation Guarantee
  - $(1+\epsilon)$ factor for cost
  - Uncertainty minimized
  - ϵD difference from first stage optimal supply

Supply Demand Matching with Prediction Uncertainty (5)

- Challenge: How to calculate v_{ij}?
  - Possibly exponential number of scenarios
  - Even tractable problem definition not possible



Latent State Model

- Solution
  - Latent state model
    - Assume a latent variable realizes all the random variables simultaneously
    - Use expectation value of uncertainty for each random variable independently
  - **Blackbox model**
    - A blackbox realizing scenarios
    - Sample scenarios using $O(1)$ operation

Supply Demand Matching with Prediction Uncertainty (6): BlackBox Model

- Assumptions
  - $0 \leq v(x, \varepsilon) \leq \lambda Z^*$, where Z^*: optimal expected uncertainty, λ problem parameter

- Implications
  - Worst case uncertainty for a given decision x for a given scenario ε is not "too large" compared to the optimal expected uncertainty

- Approximation Algorithm
  - Choose $\epsilon > 0$: accuracy parameter, $\delta > 0.5$ probability parameter
  - Sample $K = \Theta(\lambda^2 \epsilon^{-2} \log|X| \log\frac{1}{\delta})$
  - Use DP based approximation algorithm to generate dominating solutions

Supply Demand Matching with Prediction Uncertainty (7): BlackBox Model

- With probability $(1 - \delta)$
  - Approximation factor: $(2 + \epsilon)$ for uncertainty
  - Runtime: polynomial in $\lambda, \frac{1}{\delta}, \frac{1}{\epsilon}$ and input size

- Proof Sketch
  - i^{th} sample: $v^i(x)$
  - Define $Y_i = \frac{v^i(x)}{\lambda Z^*}$, $Y_i \in [0,1]$
  - Apply Chernoff's bound for $\sum Y_i - E[\sum Y_i] > \epsilon K$
  - To get bound on $\sum v^i(x) - E[v(x)]$

Results and Analysis: Experimental Setup (1)

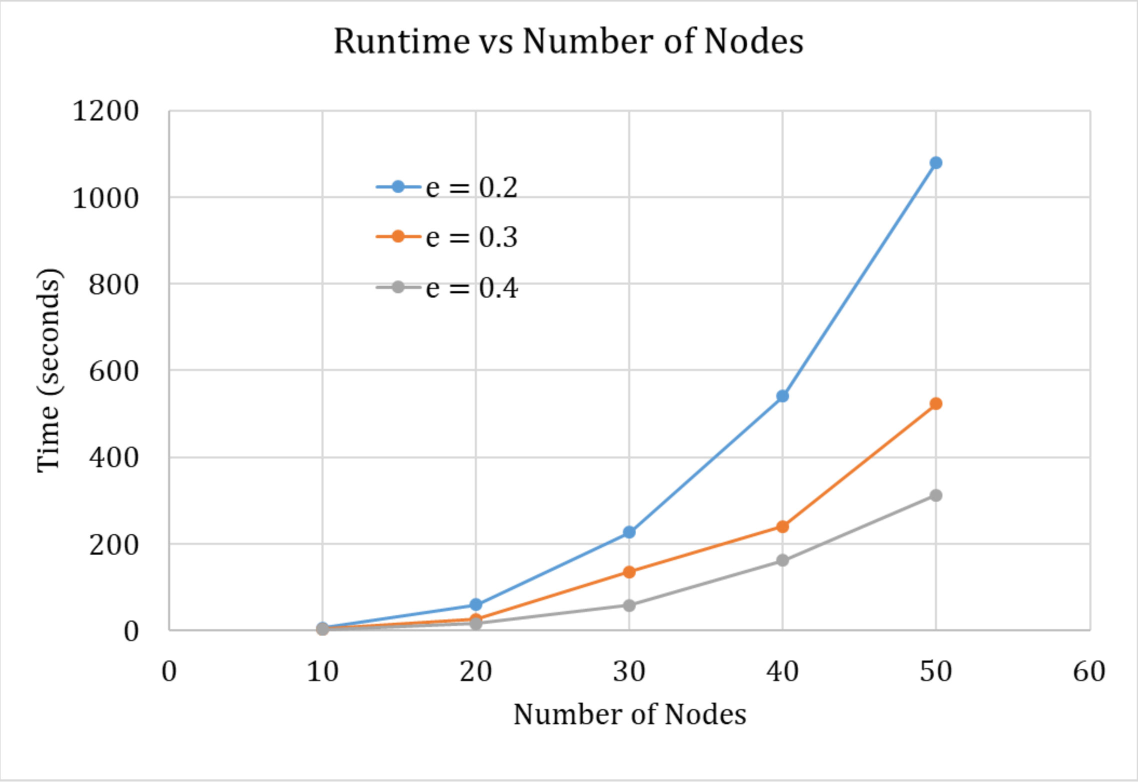
- Implementation
  - Algorithms: python
  - Platform: Dell Optiplex 4-cores, 4 GB RAM

- Parameter
  - Cost: $2\gamma^2$
  - Uncertainty: 0.5γ

- Dataset
  - Solar Generation Data
    - Simulated Data using hourly solar radiance data for USC

Scalability

- Scalability
  - Cubic increase in runtime with number of nodes
  - $\frac{1}{\log^3 1+\epsilon}$ dependence on accuracy parameter ϵ
- 150 seconds
  - 25 nodes for 20% error
  - 30 nodes for 30% error
  - 40 nodes for 40% error

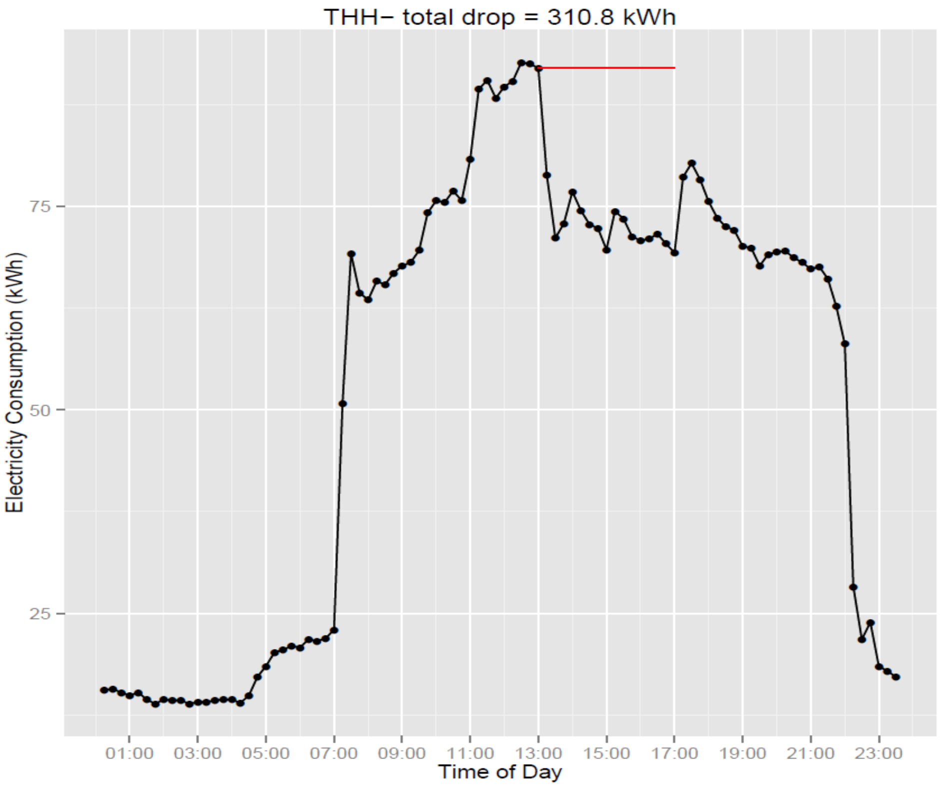


Outline

- Motivation and Background
- Thesis Statement
- Research Contributions
  - Optimal Curtailment Selection for Demand Response
  - Cost Optimal Supply Demand Matching
  - Discrete Supply Demand Matching Under Prediction Uncertainty
- Impact and Conclusion

Impact

- LA Smart Grid Demonstration Project
  - Successful implementation of Demand Response program in USC
  - As high as 1.2 MWh curtailment achieved in a single DR event
  - Knowledge Transfer to LADWP for implementation in LA
  - Patent Pending: System for Automated Dynamic Demand Response



Conclusion

- Polynomial runtime complexity supply demand matching algorithms with bounds on worst case errors

- Problems studied
  - Optimal Demand Response: Curtailment error bounded by ϵ factor of the targeted error
  - Cost Optimal Supply Demand Matching: Cost minimized with ϵ factor bound on curtailment constraint violation
  - Supply Demand Matching with Prediction Uncertainty: Dominating solutions with cost and uncertainty within $2 + \epsilon$ factor

Thank You

- Questions?

- Personal Webpage: http://sraok.space

P-group

Vidushak Indian Improv Comedy Group

Relevant Publications

- Sanmukh R. Kuppannagari, Rajgopal Kannan, and Viktor K. Prasanna Optimal Discrete Net Load Balancing in Smartgrids with High PV Penetration, (to appear in) The **ACM Transactions on Sensor Network**, Special Issue: Systems for Smart and Efficient Built Environments , Volume 1, Article 1, 2018.

- Sanmukh R. Kuppannagari, Rajgopal Kannan, Viktor K. Prasanna, Risk Aware Net Load Balancing in Micro Grids with High DER Penetration, The Ninth IEEE Conference on **Innovative Smart Grid Technology (ISGT 2018)**, February 2018.

- Sanmukh R. Kuppannagari, Rajgopal Kannan, Viktor K. Prasanna, NO-LESS: Near OptimaL CurtailmEnt Strategy Selection for Net Load Balancing in Micro Grids, The Ninth IEEE Conference on **Innovative Smart Grid Technology (ISGT 2018)**, February 2018.

Relevant Publications

- Sanmukh R. Kuppannagari, Rajgopal Kannan, and Viktor K. Prasanna Optimal Net Load Balancing in Smartgrids with High PV Penetration, The 4th ACM International Conference on **Systems for Energy-Efficient Built Environments (BuildSys 2017),** November 2017.

- Sanmukh R. Kuppannagari, Rajgopal Kannan, Charalampos Chelmis and Viktor K. Prasanna, Implementation of Learning-Based Dynamic Demand Response on a Campus Micro-grid**,** 25th **International Joint Conference on Artificial Intelligence, IJCAI-16 Demo Track**, July 2016.

Relevant Publications

- Sanmukh R. Kuppannagari, Rajgopal Kannan, Charalampos Chelmis, Arash S. Tehrani, and Viktor K. Prasanna Optimal Customer Targeting for Sustainable Demand Response in Smart Grids**, International Conference on Computational Science**, June 2016.

- Sanmukh R. Kuppannagari, Rajgopal Kannan and Viktor K. Prasanna, An ILP Based Algorithm for Optimal Customer Selection for Demand Response in Smartgrids, **International Conference on Computational Science and Computational Intelligence (CSCI '15),** December 2015.

Backup Slides

Approximation Algorithms

- State of the art Approximate Supply Demand Matching
  - Constant Factor algorithms for peak demand reduction based on strip packing

- Other applications of approximation algorithms in smart grids
  - Placement Problems: PMU, Storage, generation using submodularity
  - Steiner tree based protection tree for cyber physical security of smart grids

Simplification #2: Sustainable Demand Response (SDR)

- Simplification: No strategy switching costs considered

- Minimize: $\sum_{t=1}^{T} \epsilon_t$
- Subject to:
  - $\left|\sum_{i=1}^{M} \sum_{j=1}^{N} \gamma_{\{ij\}}(t) * x_{\{ij\}}(t) - \Gamma(t)\right| \leq \epsilon_t \ \forall t$
  - $\sum_{j=1}^{N} x_{\{ij\}}(t) = 1 \ \forall i$
  - $x_{\{ij\}}(t) \in \{0,1\}$

Sustainable Demand Response (SDR) (2)

- Approximation Algorithm
  - Variant of Subset sum problem
- DP:

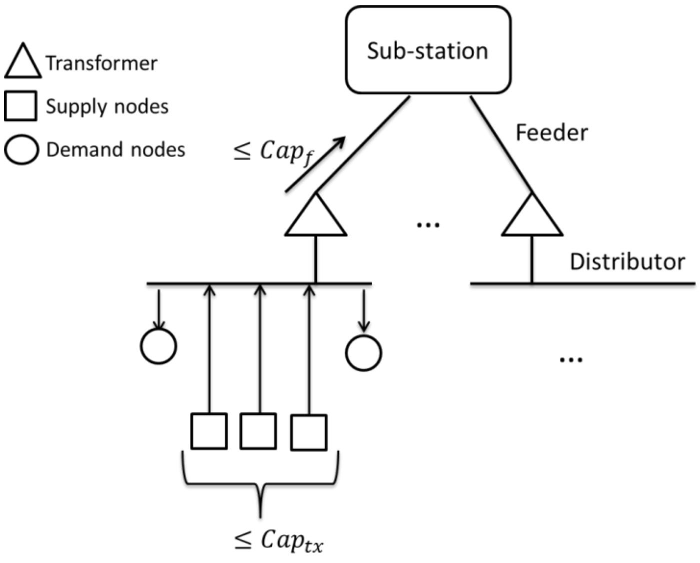
$$\Theta_t(\gamma, b) = \begin{cases} 1 & \exists j \in [N], \Theta_t(\gamma - \gamma_{bj}, b-1) = 1 \\ & 0 \end{cases}$$

- Rounding scheme: $\mu = \frac{\epsilon\Gamma}{M}$
- Runtime: $O(\frac{M^2 N}{\epsilon})$
- Worst case approximation error: $\epsilon\Gamma$

Simplification #2 and Other Problems

- Assume costs are a function of curtailment: $c = f(\gamma)$
- (2,2)-factor algorithms using LP rounding technique (linear f)

- Transform Level Supply Demand Matching
  - Distributor capacity constraints violated by at most $(1 - \epsilon)$ factor
- Smart Grid Level Supply Demand Matching with Network Capacity Constraints
  - Feeder and distributor capacity constraints violated by at most $(1 - \epsilon)$ factor
  - Required supply/demand curtailment within $(1 \pm 2\epsilon)$ of optimal



Simplification #2: MinCB with Fairness

- Assume costs are a function of curtailment: $c = \ f(\gamma)$
- Integer Program:

$$min_x \sum_{b=1}^{M} \sum_{j=1}^{N} \sum_{t=1}^{T} f(\gamma_{bj}(t))x_{bj}(t)$$

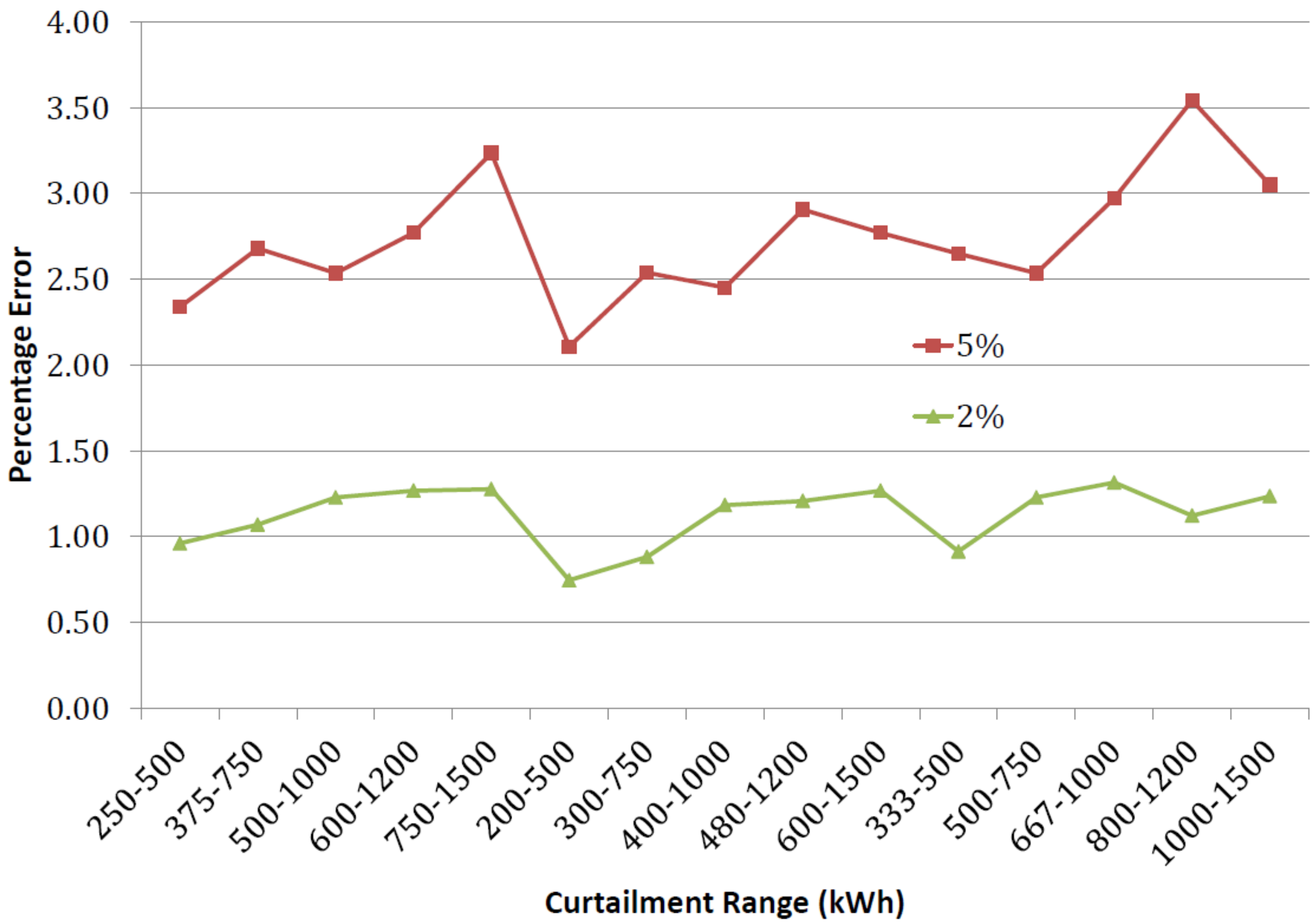
$$s.t. \sum_{b=1}^{M} \sum_{j=1}^{N} \gamma_{bj}(t)x_{bj}(t) \geq \Gamma_t \ \forall t$$

$$\sum_{j=1}^{N} \sum_{t=1}^{T} \gamma_{bj}(t)x_{bj}(t) \leq B_b \ \forall b$$

Simplification #2: Approximation Algorithm

- Relax the Integer Program to Linear Program i.e. $0 \leq x^*_{bj}(t) \leq 1 \; \forall b, t$
- $\gamma' \leftarrow \sum_{j=1}^{N} \gamma_{bj}(t) x^*_{bj}(t)$
- Round γ' to strategy i with nearest curtailment value for node b at time t: $\gamma_{bi}(t)$
- Result: For a linear cost function f, the algorithm above is a (2,2)-factor Algorithm. For quadratic cost function f, the algorithm is (4,2)-factor algorithm

MinCB: Accuracy



Future Direction #1:
Discrete Multi Phase Supply Demand Matching

- Discrete optimization considering
  - Active and reactive power
  - Phase angles
  - Control variables: p, q

$$\min_{p,q,P,Q,l,v} f(p,q,P,Q,l,v)$$

$$\left.\begin{aligned} p_j &= \sum_{k:j\to k} P_{jk} - \sum_{i:i\to j} \left(P_{ij} - r_{ij} l_{ij}\right) + g_j v_j \ \forall j \\ q_j &= \sum_{k:j\to k} Q_{jk} - \sum_{i:i\to j} \left(Q_{ij} - x_{ij} l_{ij}\right) + b_j v_j \ \forall j \end{aligned}\right\} \text{Phase angle relaxation}$$

$$v_j = v_i - 2\left(r_{ij} P_{ij} + x_{ij} Q_{ij}\right)\left(r_{ij}^2 + x_{ij}^2\right) l_{ij} \ \forall (i,j) \in E$$

$$l_{ij} \geq \frac{P_{ij}^2 + Q_{ij}^2}{v_i}$$

Equality relaxation

Future Direction #2:
Joint Optimization over Multiple Infrastructure for Smart Cities

- Discrete Operational values
  - Smart Parking: Binary variables
  - EV charging rates: Discrete values
- Example Problem
  - EV Truck to visit a set of pre-defined locations for delivery and return (TSP)
  - Possibly visit Charging/Discharging location to charge or provide grid services (Shortest path problem)
  - Objective: Minimize sum of charging costs, traveling costs minus discharging compensation
  - Constraints: Delivery deadline