SOLAR ENERGY
TECHNOLOGIES OFFICE
U.S. Department Of Energy

Robust and Resilient Coordination of Feeders with Uncertain Energy Resources

From real-time control to long-term planning

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Solar to the Max: Innovations in Distribution Grid Planning and Operations

June 25th, 2021 (Day 2)

Orange & Rockland

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ENERGISE: how it started & how it's going

ENERGISE concept paper stage

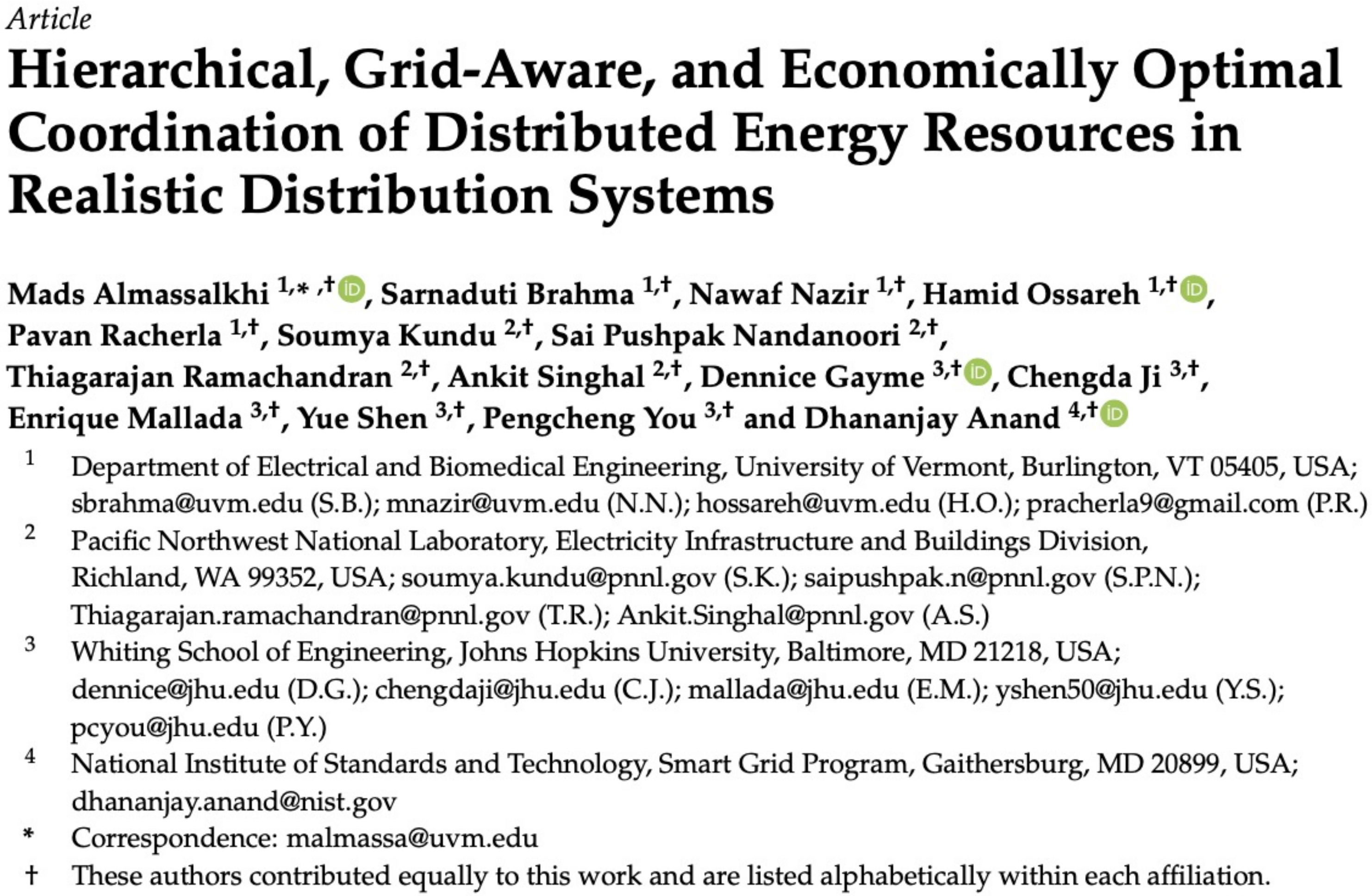
Emil born June, 2016

Concept paper submitted 1 hr later!

Post-ENERGISE

Emil in May, 2021

Team paper of 2020: human-friendly summary of FTR



Article

Hierarchical, Grid-Aware, and Economically Optimal Coordination of Distributed Energy Resources in Realistic Distribution Systems

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Optimally coordinating networked VBs at scale

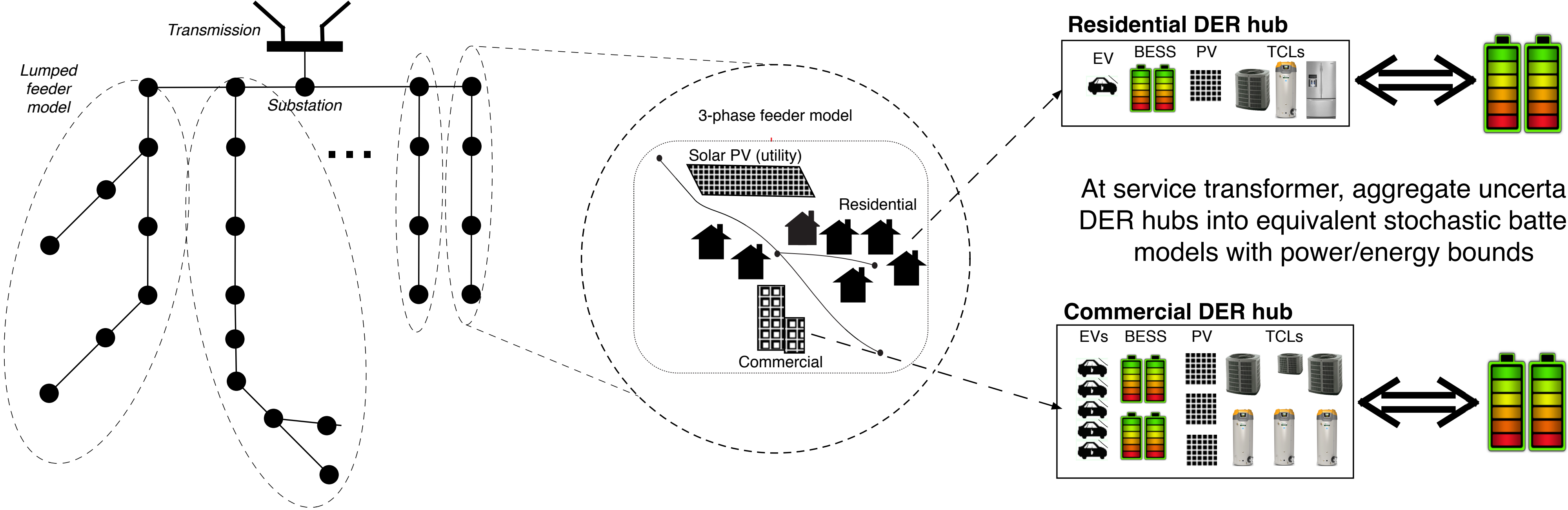
Key idea: adapt wide-area control concepts to distribution grid operations

Key challenges: grid and resources have finite power/energy constraints

Grid Market Layer
(1000 feeders & 1,000,000 DERs)

Feeder Operational Layer
(100-200 STLs per FOL)

Service Transformer Layer
(5-15 DERs per STL)



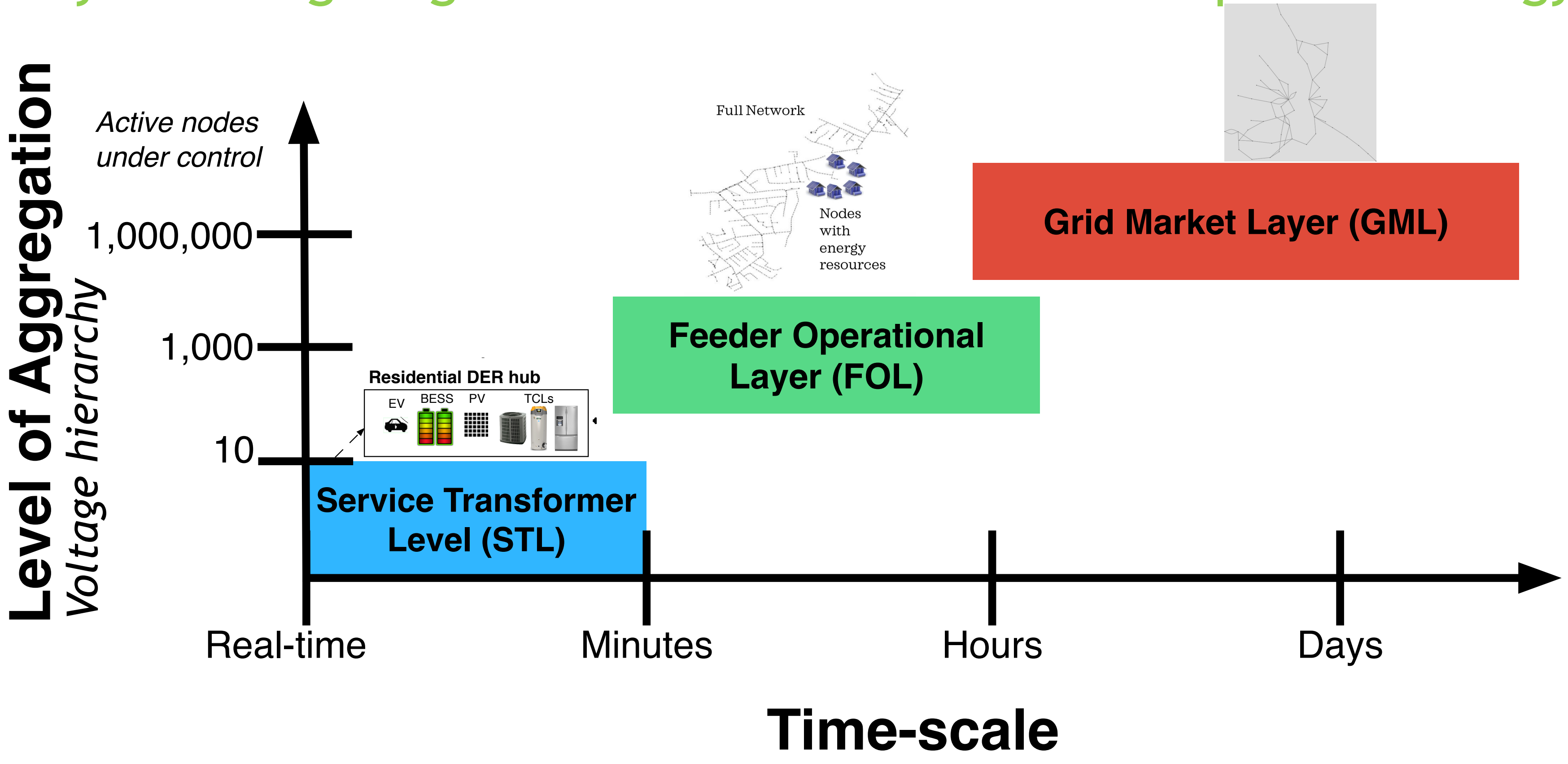
At service transformer, aggregate uncertain DER hubs into equivalent stochastic battery models with power/energy bounds

Manage resources economically *subject to 3ph grid physics* *and dynamic resource constraints*

Optimally coordinating networked VBs at scale

Key idea: adapt wide-area control concepts to distribution grid operations

Key challenges: grid and resources have finite power/energy constraints



Level of Aggregation

Voltage hierarchy

Active nodes under control

1,000,000

1,000

10

Service Transformer Level (STL)

Feeder Operational Layer (FOL)

Grid Market Layer (GML)

Real-time

Minutes

Hours

Days

Time-scale

1yr minutely PV data and intra-hour forecasts for ORU territory

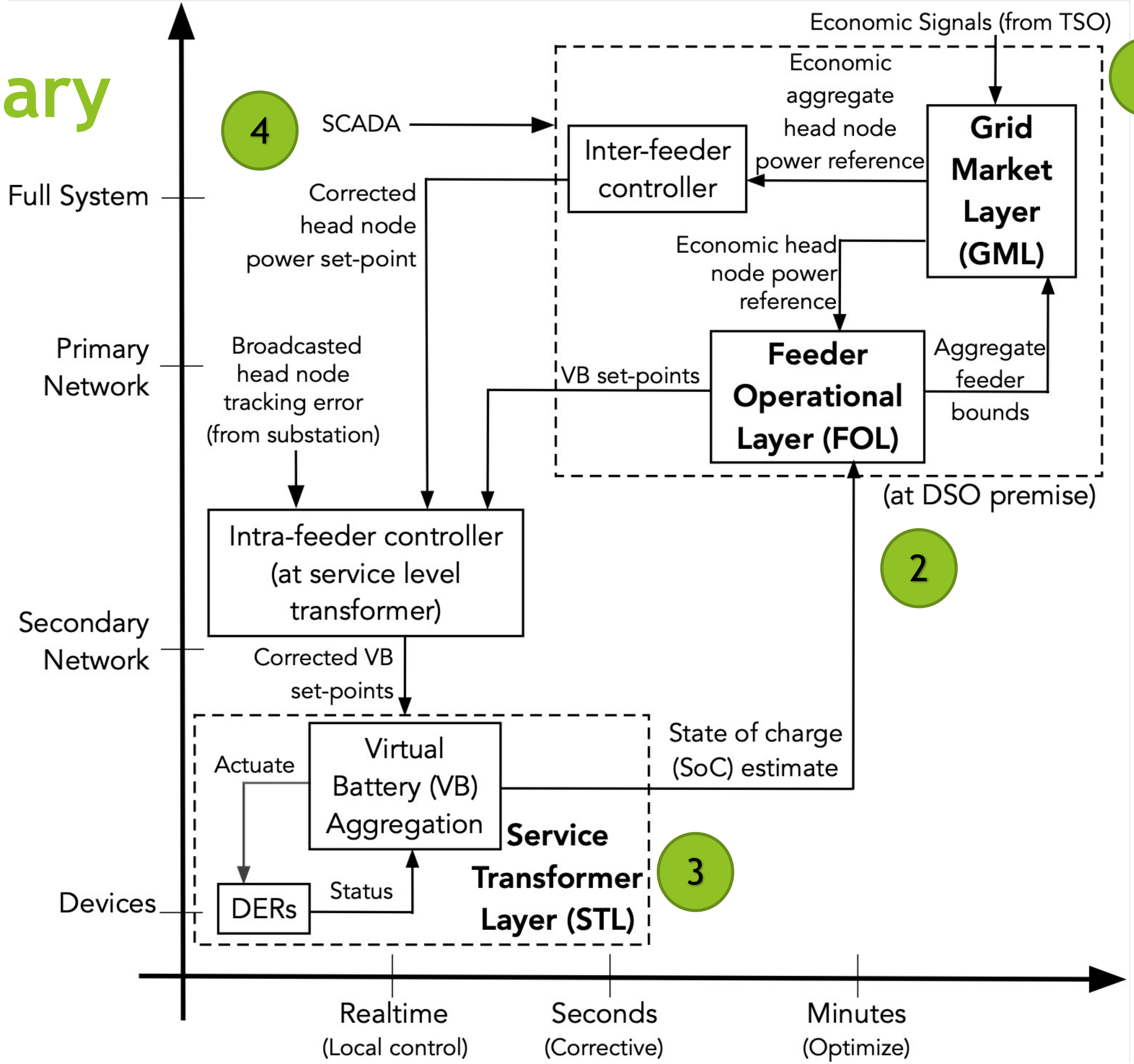
Final project summary

1+2: DSO premises have GML and FOL running via SCADA.

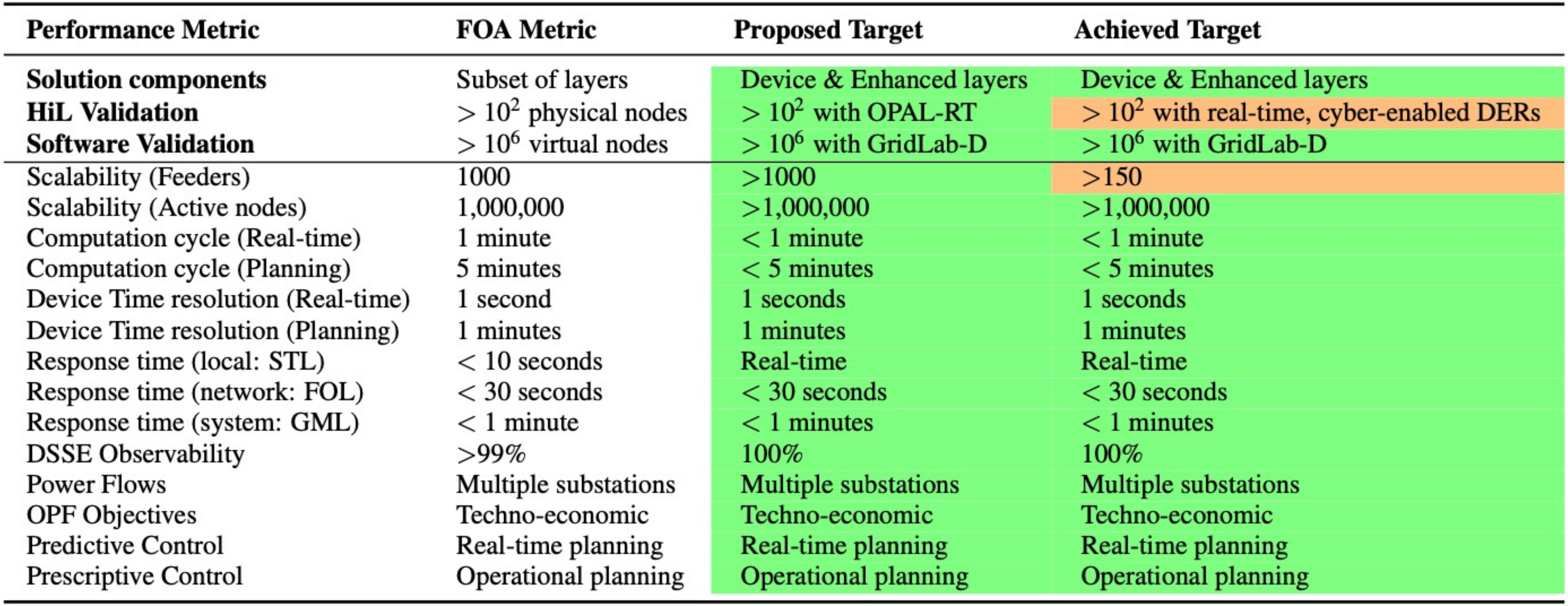
3: STL running at each *super-node* service transformer (in the field) to manage solar PV inverters and other active nodes via VB-DER interface

4: Interlayer corrective controllers improve performance in real-time

Key: all elements are advanced operational tools, but *technologically viable* across spatio-temporal scales



Project Objectives (Topic Area 2 – Year 2030)



Performance Metric	FOA Metric	Proposed Target	Achieved Target
Solution components	Subset of layers	Device & Enhanced layers	Device & Enhanced layers
HiL Validation	$> 10^2$ physical nodes	$> 10^2$ with OPAL-RT	$> 10^2$ with real-time, cyber-enabled DERs
Software Validation	$> 10^6$ virtual nodes	$> 10^6$ with GridLab-D	$> 10^6$ with GridLab-D
Scalability (Feeders)	1000	>1000	>150
Scalability (Active nodes)	1,000,000	>1,000,000	>1,000,000
Computation cycle (Real-time)	1 minute	< 1 minute	< 1 minute
Computation cycle (Planning)	5 minutes	< 5 minutes	< 5 minutes
Device Time resolution (Real-time)	1 second	1 seconds	1 seconds
Device Time resolution (Planning)	1 minutes	1 minutes	1 minutes
Response time (local: STL)	< 10 seconds	Real-time	Real-time
Response time (network: FOL)	< 30 seconds	< 30 seconds	< 30 seconds
Response time (system: GML)	< 1 minute	< 1 minutes	< 1 minutes
DSSE Observability	>99%	100%	100%
Power Flows	Multiple substations	Multiple substations	Multiple substations
OPF Objectives	Techno-economic	Techno-economic	Techno-economic
Predictive Control	Real-time planning	Real-time planning	Real-time planning
Prescriptive Control	Operational planning	Operational planning	Operational planning

Significant Accomplishments

1. The flexibility of a group of heterogeneous DERs (in the STL) has been characterized with a novel advanced methodology based on ML and the DER control method is scalable.
2. A scalable stochastic, multi-period, 3-ph AC OPF formulation (in the FOL) has been developed that incorporates diverse grid assets, DSEE, and network reduction techniques and represents an excellent contribution to power systems community.
3. Realtime Intra-feeder and Inter-feeder represent a clear, reliable, and practically implementable corrective control approach to integrate feedback control of flexible resources within a utility/DSO.
4. The market optimization (in the GML) responds to wholesale market signals by coordinating active & flexible distribution feeders in a meshed sub-transmission network and across multiple timescale services.
5. UVM’s interactive power grid analytics (iPGA) platform has developed further after being licensed and is use by utilities in the US.
6. The team has published ≥ 30 papers, including a team paper based on the final project outcomes, and co-hosted a 2-day workshop on the Future of Energy in Burlington, Vermont, with >100 people from across the US.

Grid Market Layer (GML)

Efficient, Stochastic Economic Optimization of DERs

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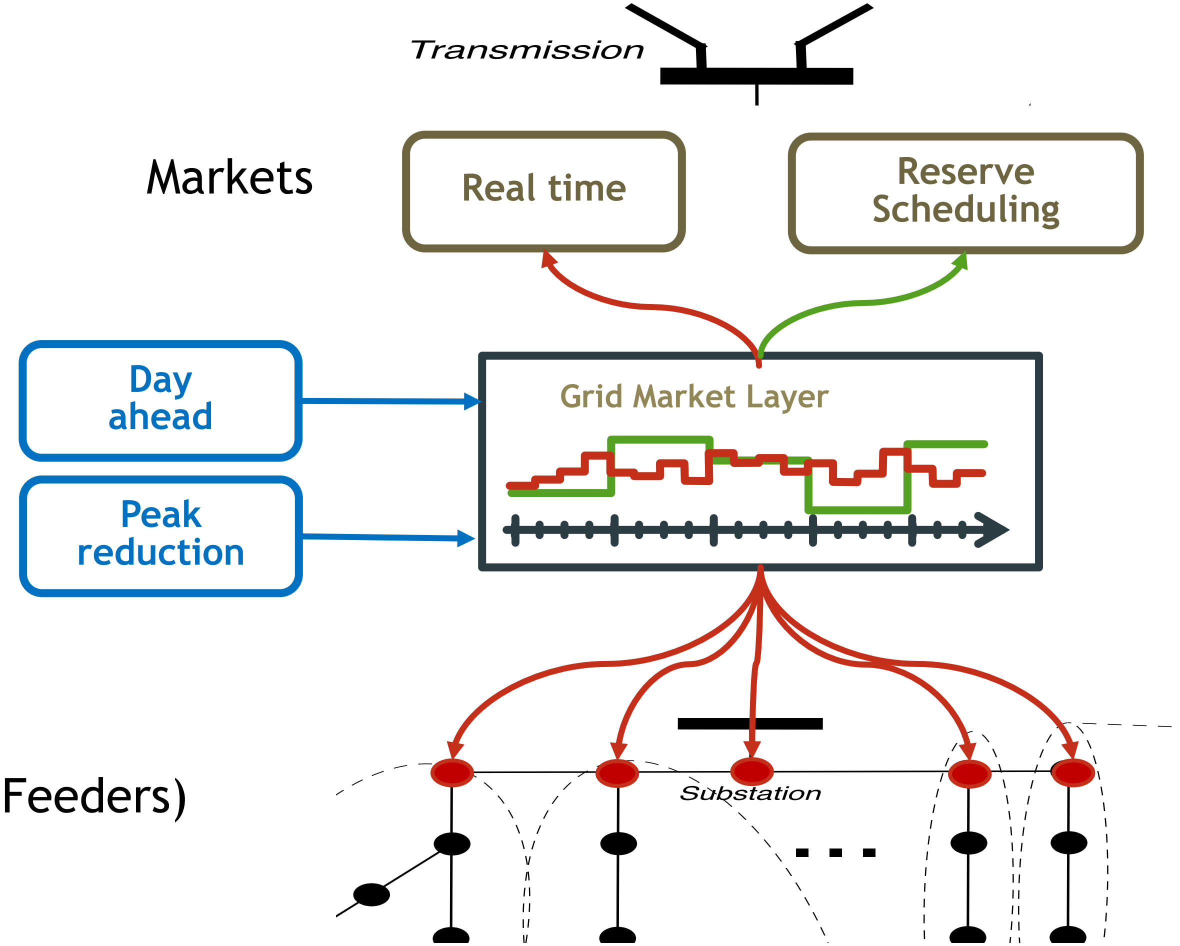
Grid Market Layer (GML) Overview

- An optimization framework that enables utilities to use flexibility in DERs to participate in **real-time, ancillary service, and day-ahead markets + peak!**



Markets

Real time

Reserve Scheduling

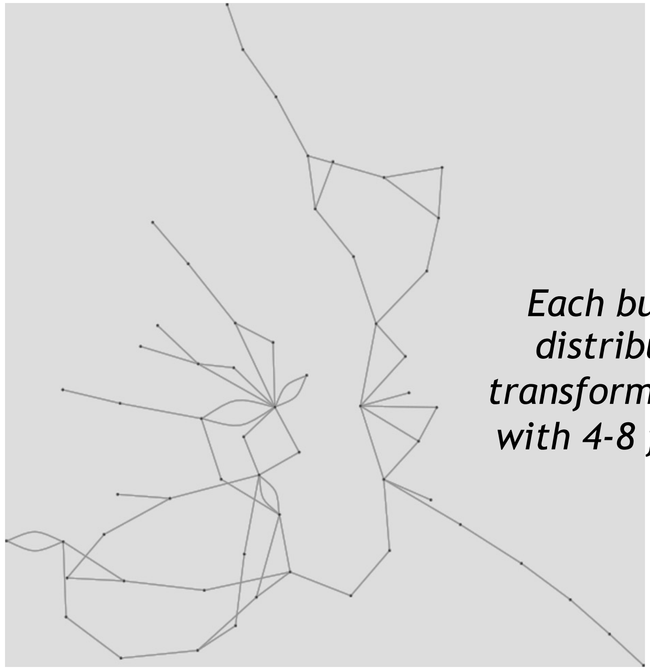
GML: Day-ahead optimization results and peak demand reduction

Day ahead

Peak reduction

FOL (Feeders)

ORU's sub-transmission system is <u>meshed network</u> and interconnects the 150-300 distribution feeders

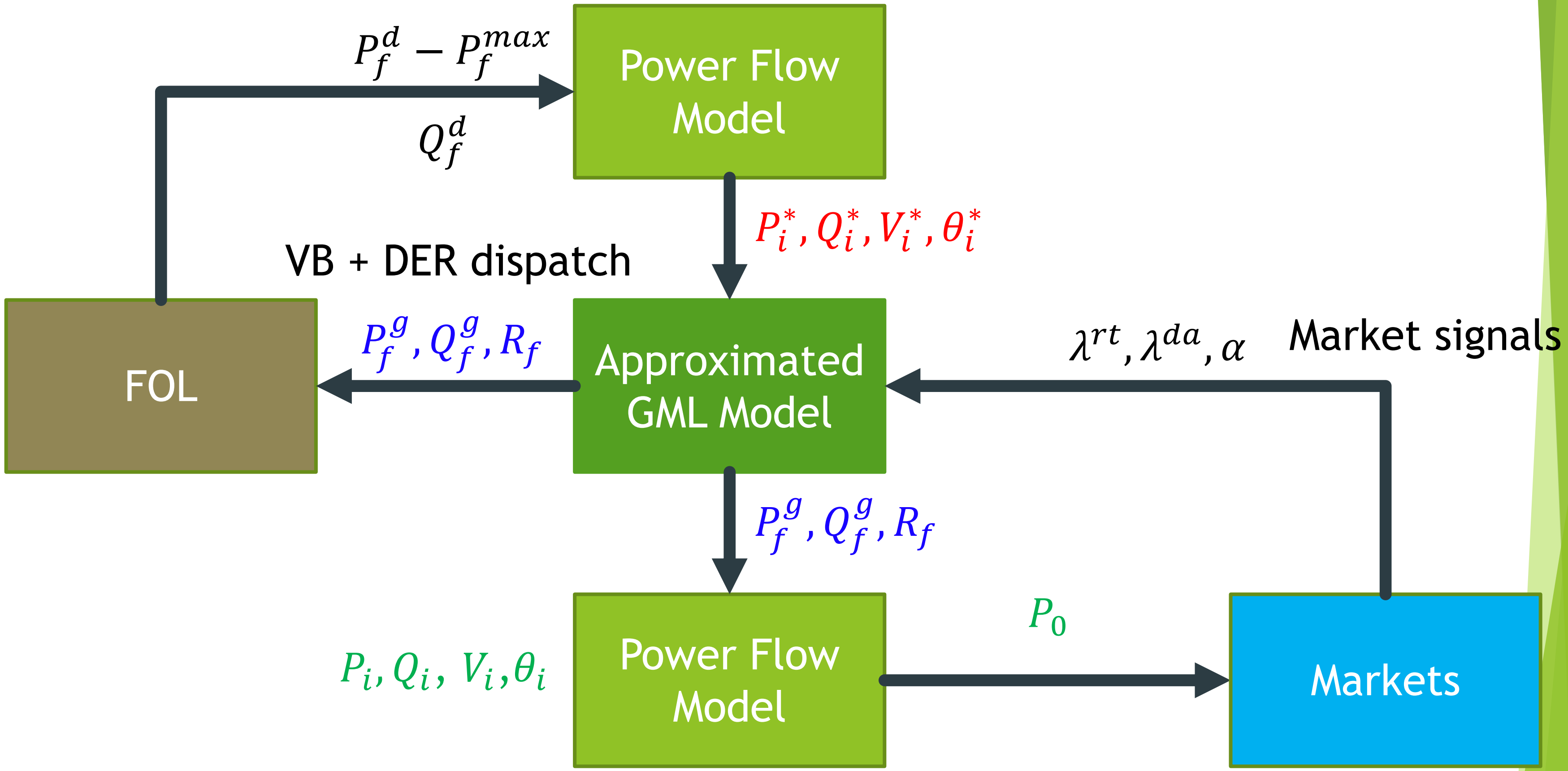


Each bus is a distribution transformer bank with 4-8 feeders

GML Overview

- A Layered approach to computationally tractable solutions for meshed networks

- Layer 1: Determine **nominal setpoints** for approximate AC power flow model
- Layer 2: Optimize **solar and virtual battery operation** based on approximate power flow model
- Layer 3: Realize **power flows** by solving power flow equations



$P_f^d - P_f^{max}$

Q_f^d

Power Flow Model

$P_i^*, Q_i^*, V_i^*, \theta_i^*$

VB + DER dispatch

FOL

P_f^g, Q_f^g, R_f

Approximated GML Model

$\lambda^{rt}, \lambda^{da}, \alpha$

Market signals

P_f^g, Q_f^g, R_f

P_i, Q_i, V_i, θ_i

Power Flow Model

P_0

Markets

GML: Market-clearing tool for flexible DSOs

peak-demand price

peak demand

$$\min \quad \sum_{t=1}^{T} \delta_t \left(\lambda^{da}(t)P^{da}(t) + \lambda^{rt}(t)\left(P_0(t) - P^{da}(t)\right) - \alpha(t)P_{rsrv}(t) + \sum_{f} f_{f,t}(P_f^g(t)) \right) + \gamma \max_t\{P_0(t)\}$$

Day-ahead cost

real-time cost

Revenue of reserve provision

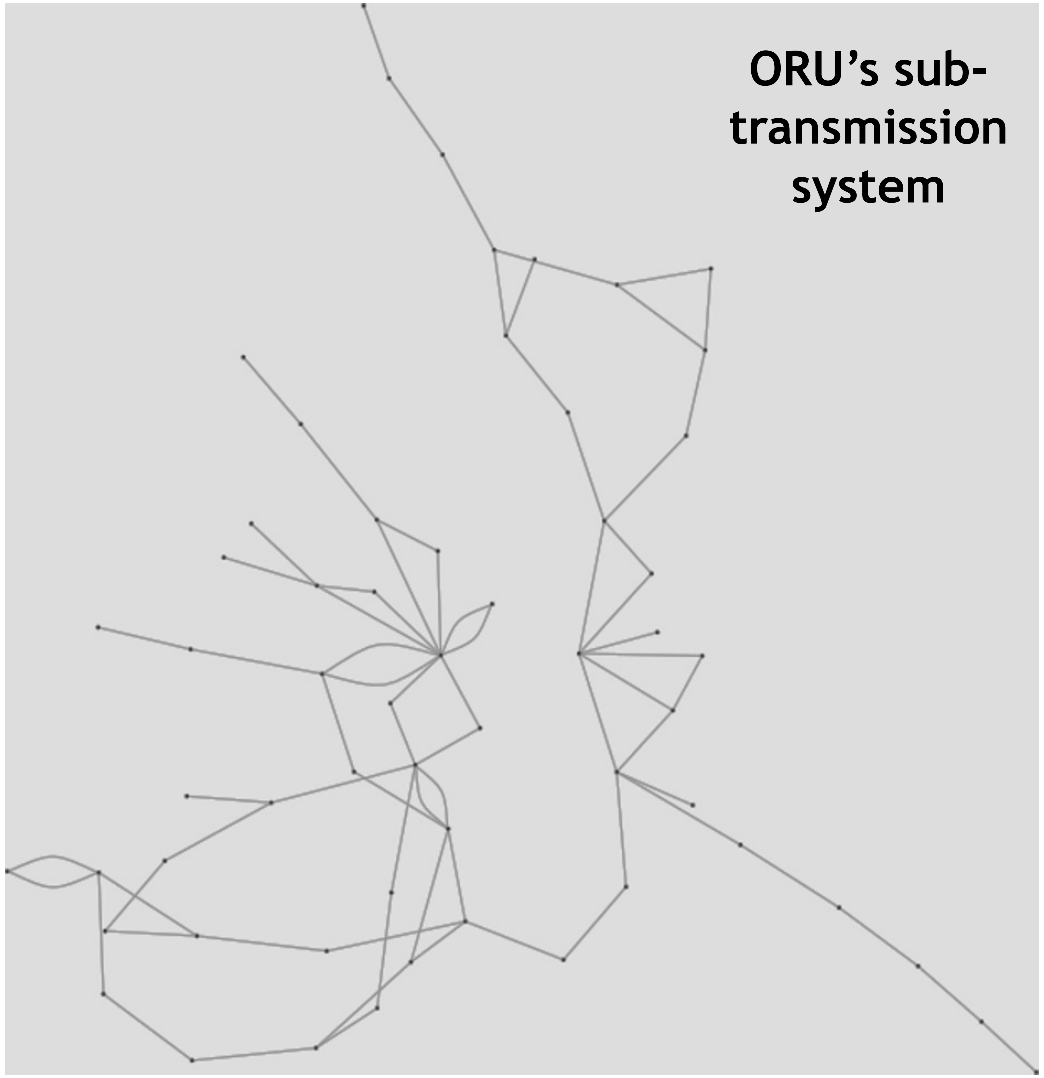
Solar curtailment cost

Peak-demand charge

- Goal: minimize operational cost + peak demand costs
  1. Arbitrage between real-time and day-ahead markets
  2. Profit from providing (ancillary) reserves
  3. Avoid solar curtailment
  4. Reduce peak demand
     - **Include a penalty on peak demand (one-time payment over a specified time horizon) , e.g., unit price $10,000/MW for monthly peak payment.**

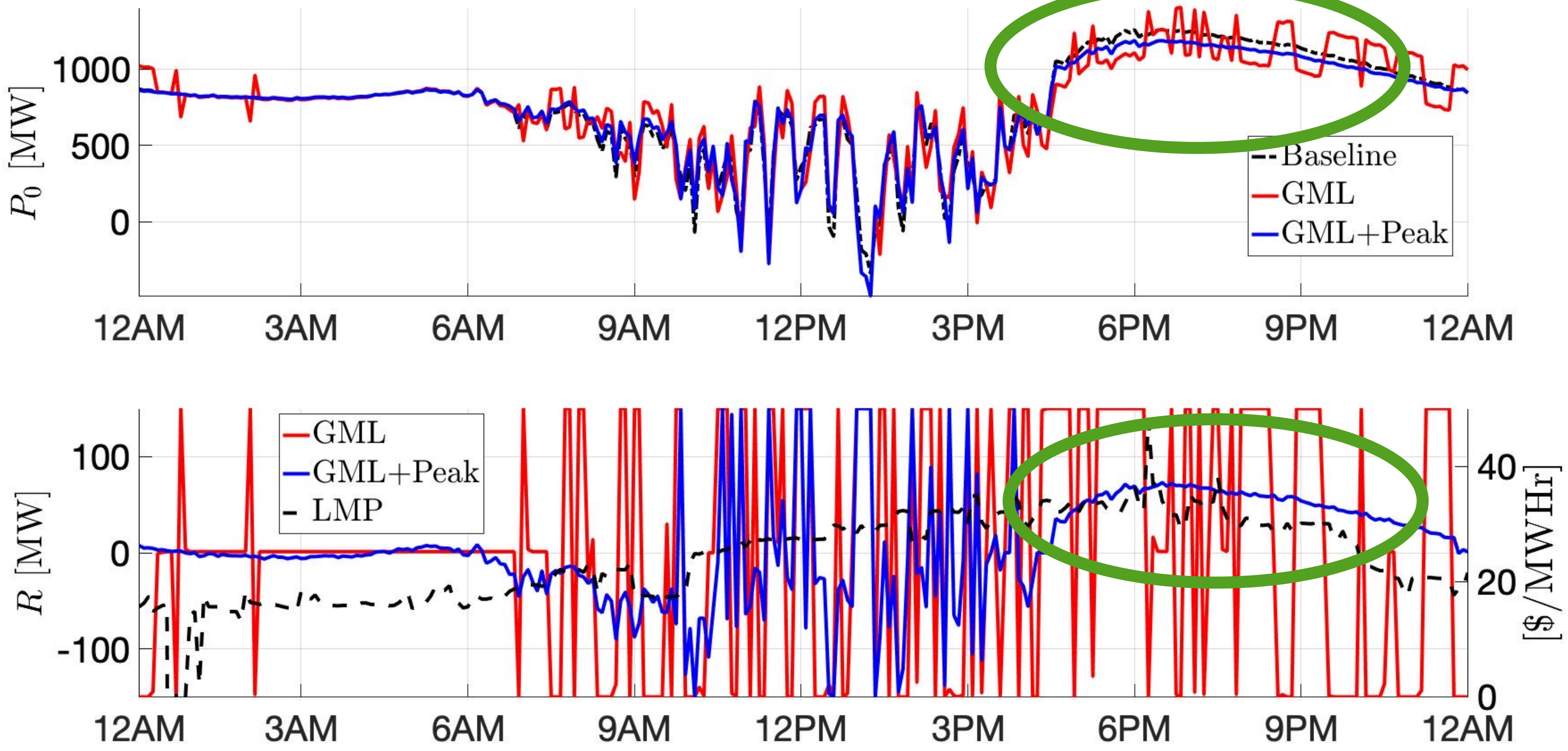
Peak-shaving demonstration

- **Setup**: New York 79-bus sub-transmission network for ORU, a typical one-day simulation runs with day-ahead and real-time trajectories of load and prices from NYISO
- Virtual battery specifications:
  - 150MW & 375 MWh
- Solar penetration rate: 25%
- Test scenarios
  - #1 Baseline: No Battery, Full solar PV
  - #2 GML Regular mode
  - #3 GML Peak-shaving mode



Dispatch Characteristics

Arbitraging RT markets with flex = power swings = bad for peaks!



- With the peak-shaving mode, batteries try to flatten the net demand curve to avoid higher peak demand resulting from RT arbitrage opportunities (small payout) .

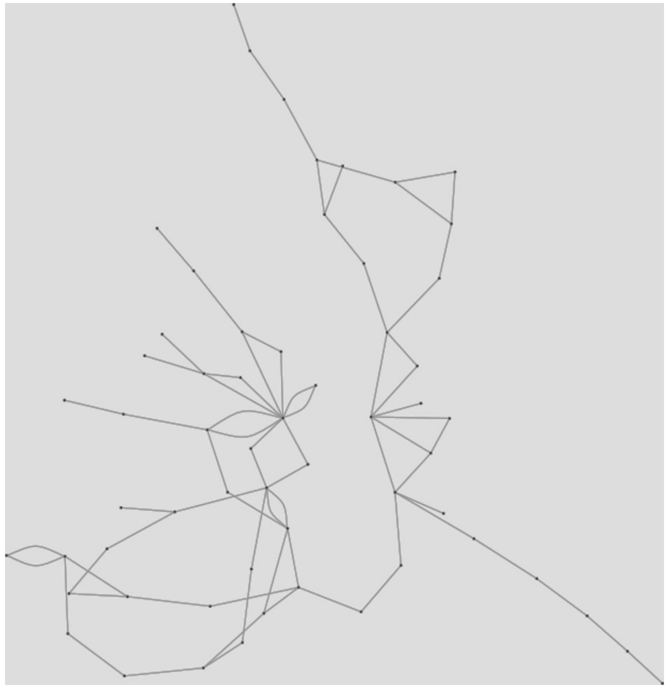
Economic Benefits Analysis

- **Background:** The economic benefits of aggregating distribution-network DERs need to be justified
- **Goal:** Demonstrate the economical benefits of our GML model on a NYISO 79-bus network
- **Outcome:**
  - Compare the peak-shaving mode and the regular mode
  - Study the economic impact of virtual battery sizes
- **Scenarios of interests:**

#1 No Flex: No Battery, Solar runs at full availability

#2 Regular: DA+arbitrage

#3 Peak-shaving: $10,000/MWpeak; 24-hr period



Costs with different battery specifications (Stochastic)

		~1500 PowerWalls		~3000 PowerWalls		100,000s ACs	
Battery	**No Flex**	**75MW & 187.7 MWh**		**150MW & 375MWh**		**375MW & 75MWh**	
Day-ahead($)	500,360	498,570		501,430		494,340	
Scenario	**Baseline**	**Regular**	**Peak-Shaving**	**Regular**	**Peak-Shaving**	**Regular**	**Peak-Shaving**
Real-time ($)	428,330	425,981	426,503	**424,322**	424,486	429,309	426,340
Solar curtailment ($)	0	0	0	0	0	0	0
Peak ($)	12,609,390	13,299,920	12,150,240	14,061,360	**11,881,330**	16,342,240	12,348,150
Total* ($)	13,037,730	13,735,901	12,576,293	14,485,682	**12,305,816**	16,771,549	12,774,490

Do nothing!

“More” is better, if incentives align!

More is less! **Duration!**

*Total cost = Real-time + solar curtailment + Peak

Deterministic vs Stochastic

- Deterministic runs outperform the stochastic runs
- Importance of sizing: Marginal savings of virtual battery sizes could decline

	Scenario	Regular	Peak-Shaving	Regular	Peak-Shaving	Regular	Peak-Shaving
Determinist	RT saving	85.39 \$/MW & 35.36 \$/MWh	/	84.07 \$/MW & 33.63 \$/MWh	/	38.34\$/MW & 191.7\$/MWh	/
	Peak saving	/	6586 \$/MW & 2634 \$/MWh	/	5092 \$/MW & 2120 \$/MWh	/	739.48 \$/MW & 3697.47 \$/MWh
Stochastic	RT saving	31.47 \$/MW & 12.59 \$/MWh	/	26.79 \$/MW & 10.72 \$/MWh	/	-2.58\$/MW & 12.91\$/MWh	/
	Peak saving	/	6122 \$/MW & 2448 \$/MWh	/	4853 \$/MW & 1941 \$/MWh	/	696.64 \$/MW & 3483.20 \$/MWh

Feeder Operational Layer (FOL)

Scalable, Stochastic Grid Optimization of DERs

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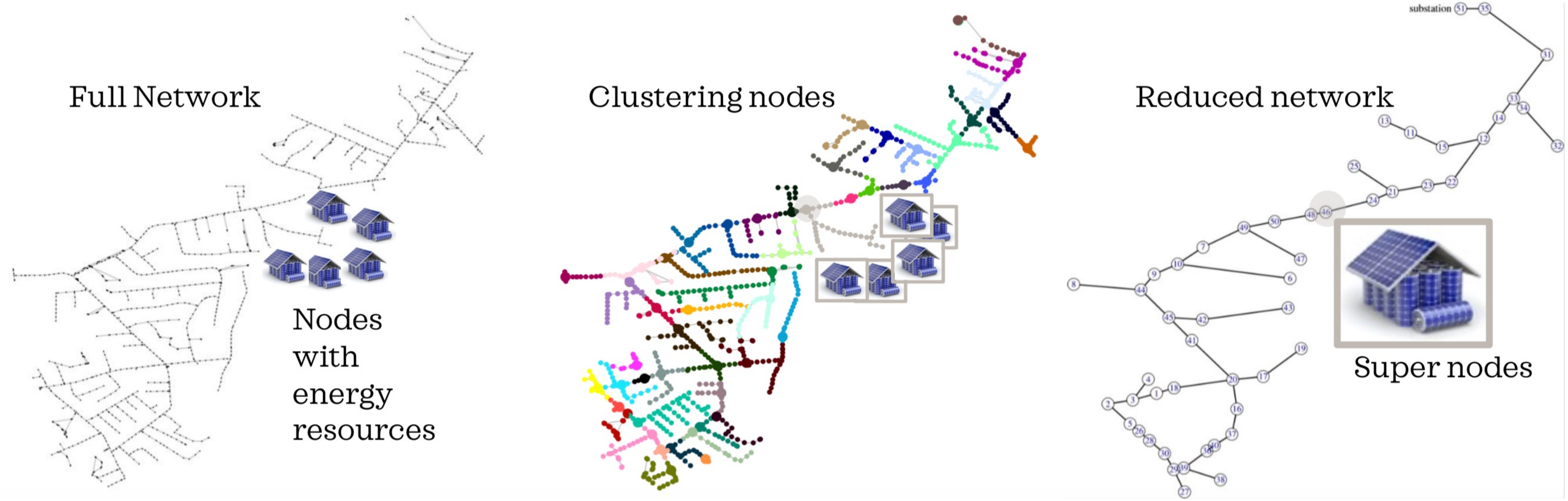
Feeder Operational Layer (FOL)

- **Aim:** To develop an optimization framework that dispatches various feeder resources (such as Transformers, capacitor banks, PV inverter, batteries, etc) in response to (P,Q) signals while ensuring satisfaction of feeder physical constraints and solve-time limits.
- **Main takeaways:**
  1. Discrete assets (such as Transformers and capacitor banks) can be effectively dispatched at a separate slower scale than the flexible continuous assets (such as solar PV inverters, connected devices, and batteries)
  2. Network reduction is useful in reducing the solve-time of large-scale feeders, while still providing satisfactory performance in the system response.
  3. Considering 3-phase nature of distribution systems is important and our 3-phase implementation of the feeder physics is shown to provide a tractable implementation capable of responding to grid signals.
  4. It is important to consider the nature of uncertainty in solar and demand, and in our formulation we develop efficient chance constraint implementation that is both scalable and robust.

Scaling up ACOPF with Kron-based network reduction



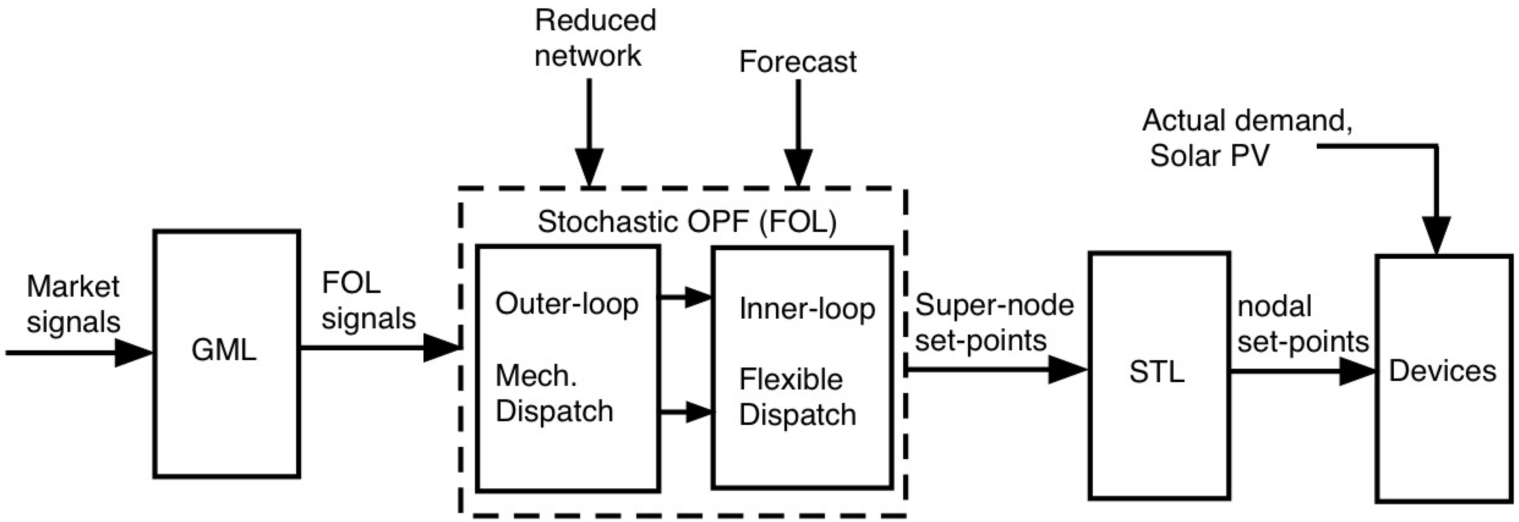
- Primary network is partitioned into clusters of physically and electrically similar nodes through Kron reduction[2]
- Voltage sensitivity to current injection is employed as the metric for partition
- A node from each sub-network is then chosen as a "super-node"

Max-APE for intra-cluster |V| is small

|V| error	Circuit 39-1-13	Circuit 39-2-13	Circuit 39-4-13
Phase-A	0.88%	1.26%	0.98%
Phase-B	0.23%	0.50%	0.43%
Phase-C	0.56%	0.78%	0.67%

[2] Dorfler, F. and Bullo, F. "Kron reduction of graphs with applications to electrical networks", IEEE Transactions on Circuits and Systems I: Regular Papers 2012

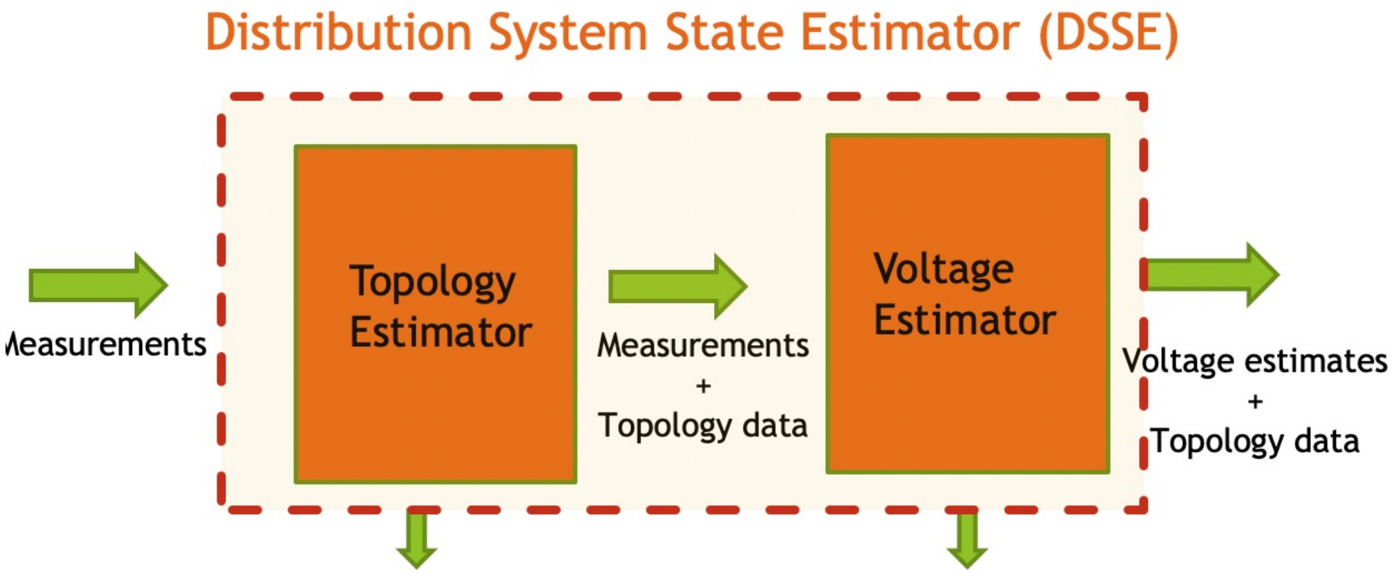
Stochastic, Multi-period, AC-feasible OPF framework



- FOL solves a stochastic, receding-horizon optimization on the reduced feeder model based on GML set-points
- The stochastic framework considers the uncertainty in solar and demand[1].
- STL disaggregates the FOL dispatch of the reduced network onto the nodes of the full-scale network.
- Through this approach feasible and fast solution to the OPF problem of a large-scale network can be obtained.

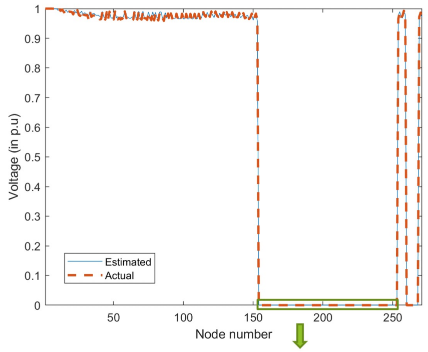
[1] Nawaf Nazir and M. Almassalkhi, “Stochastic multi-period optimal dispatch of energy storage in unbalanced distribution feeders,” in Power Systems Computation Conference, Lisbon, Portugal, 2020.

DSSE tools for state & topology estimation

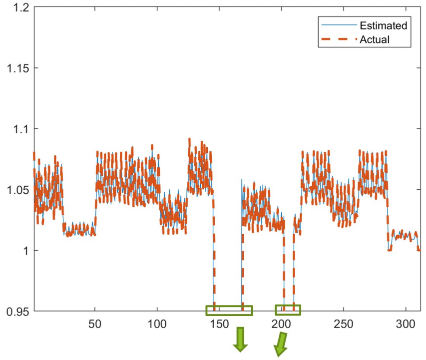


- Uses a simpler network model
- Determines the topology by estimating switch states

- Uses the full non-convex network model
- Estimates the voltages and losses

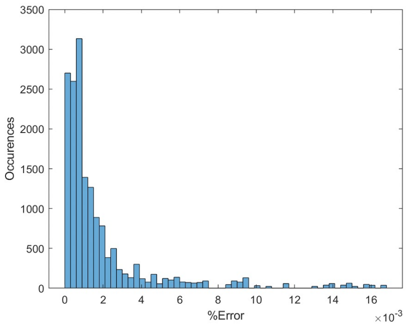


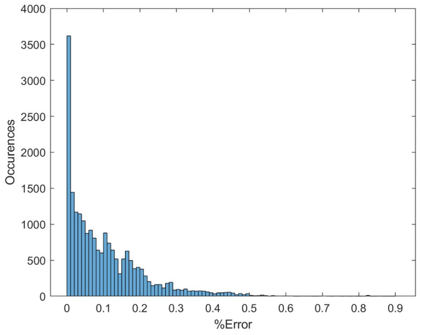
IEEE 123 bus system: Nodes 150 ~250 islanded due to SW 4 being opened

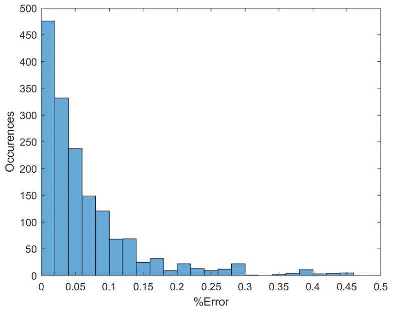


250 node system: Nodes 150~160 and 200~202 islanded due to SW 1 being opened

Three feeders



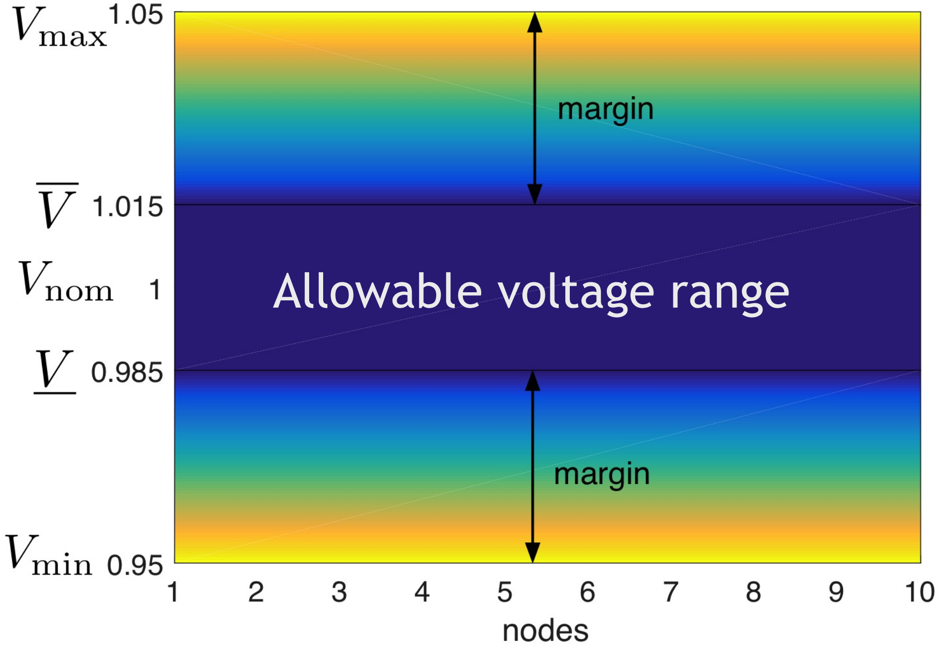




Outer Loop: Robustly schedule mechanical assets on slow time-scale

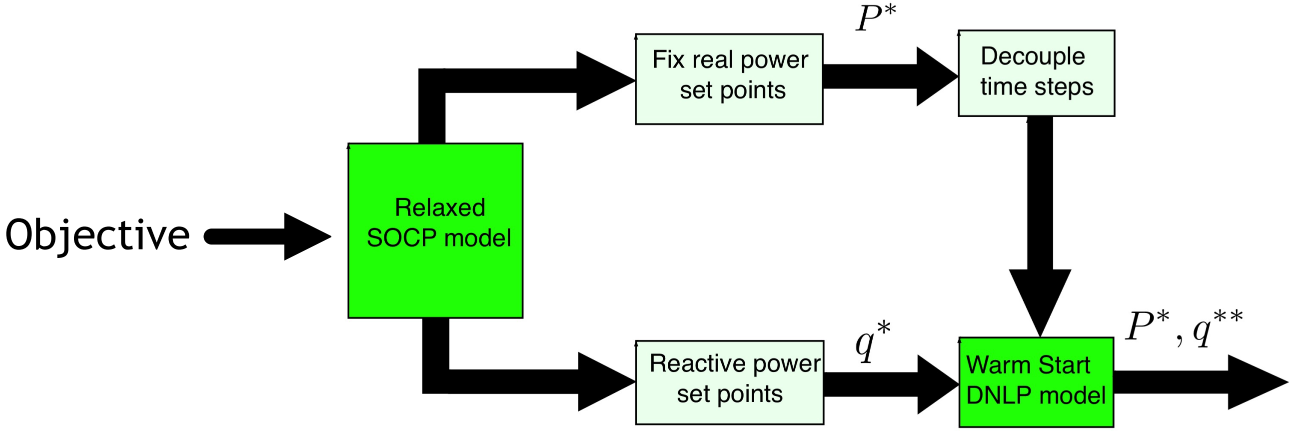
- **Aim**: Improve robustness of the voltage positioning (VP) by considering the effects of uncertainty in net-demand forecasts in the scheduling of mechanical assets (cap banks and LTCs) on hourly timescale
- **Main focus of VP:** maximize voltage margins, while minimizing the need for flexible reactive resources
  - VP introduces a co-optimization of slow mechanical assets and fast reactive power reserves.
  - Employed
  - There is fundamental trade-off between maximizing voltage margins and minimizing the use of flexible resources[3].

Voltage positioning (VP) concept



[3] Nawaf Nazir and Mads Almassalkhi, *Voltage positioning using co-optimization of controllable grid assets in radial networks*, IEEE TPWRS, 2020.

Inner Loop: Deterministic FOL dispatch



Objective

Relaxed SOCP model

Fix real power set points

P^*

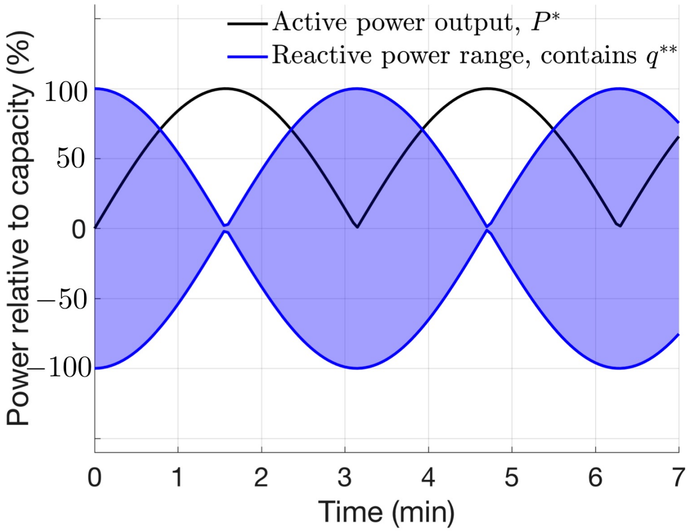
Decouple time steps

Reactive power set points

q^*

Warm Start DNLP model

P^*, q^{**}



$$SOCP_{\text{opt}} \leq NLP_{\text{opt}} \leq DNLP_{\text{opt}}$$

$$\%\text{optimality gap} \leq \frac{DNLP_{\text{opt}} - SOCP_{\text{opt}}}{DNLP_{\text{opt}}} \times 100$$

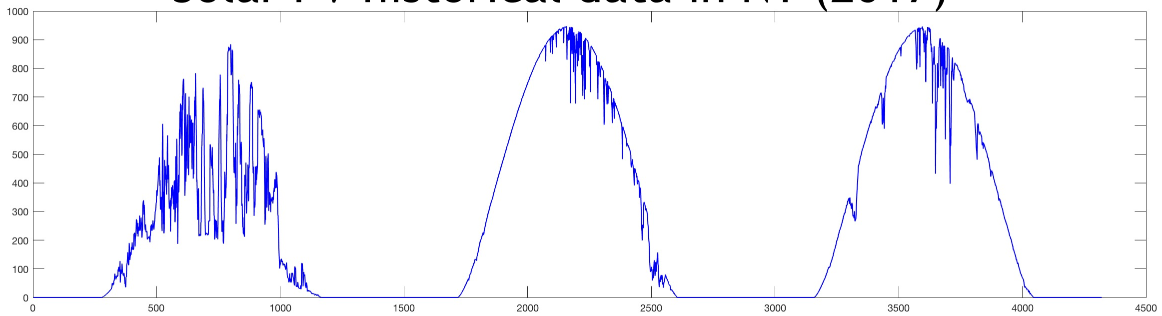
- SOCP-NLP coupled approach to turn a hard non-convex problem into a scalable solution[4]
- Optimally dispatching batteries over multiple time-steps while accounting for three-phase AC physics

[4] N. Nazir, P. Racherla, and M. Almassalkhi, “Optimal multi-period dispatch of distributed energy resources in unbalanced distribution feeders,” IEEE TPWRS, 2020

Solar PV forecast uncertainty

Clean Power Research®

Solar PV historical data in NY (2017)



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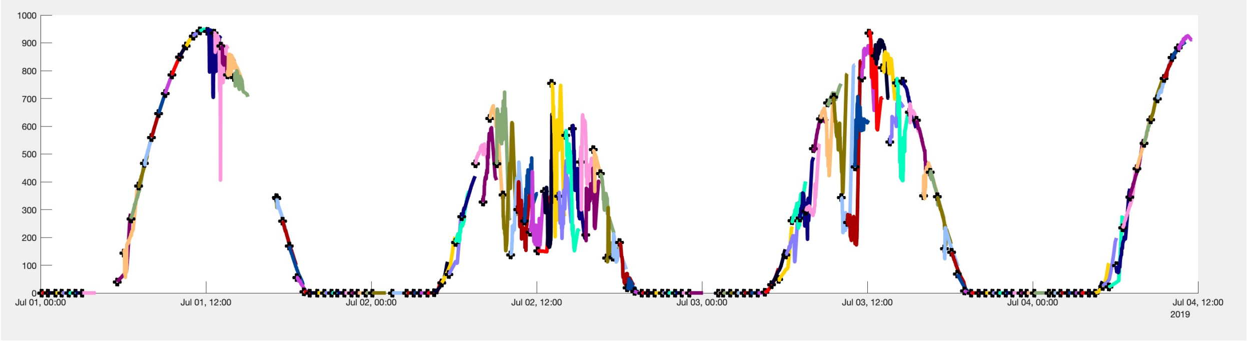
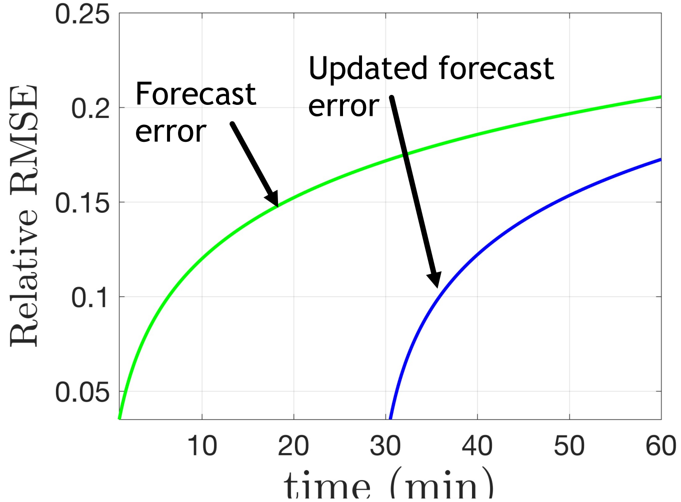
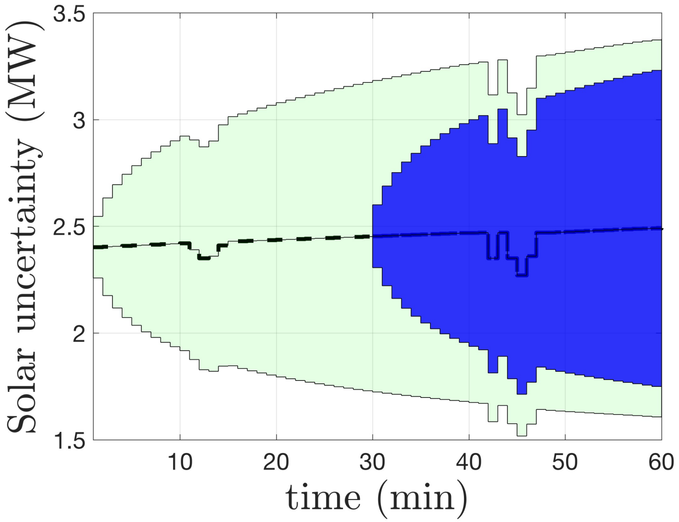
Solar PV intra-hourly forecasts in NY (2019)

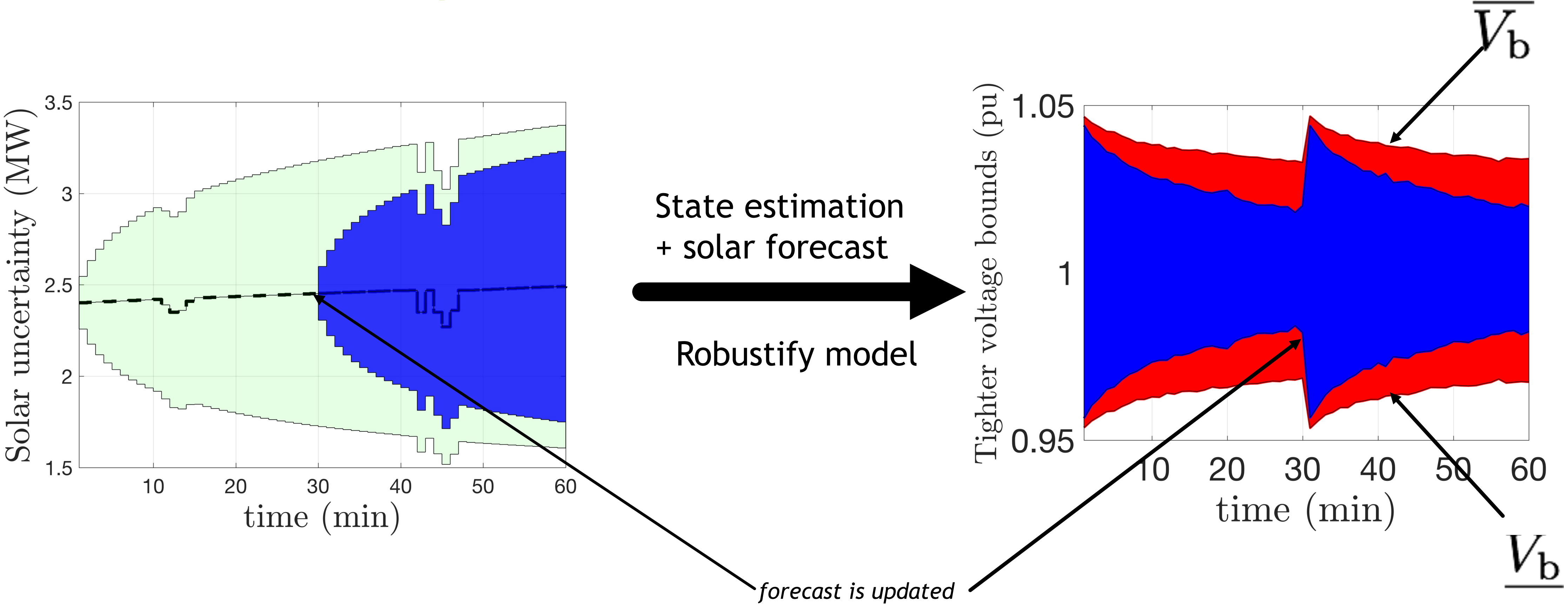


Solar PV forecast prediction error model





Robust FOL dispatch can account for solar uncertainty



State estimation
+ solar forecast

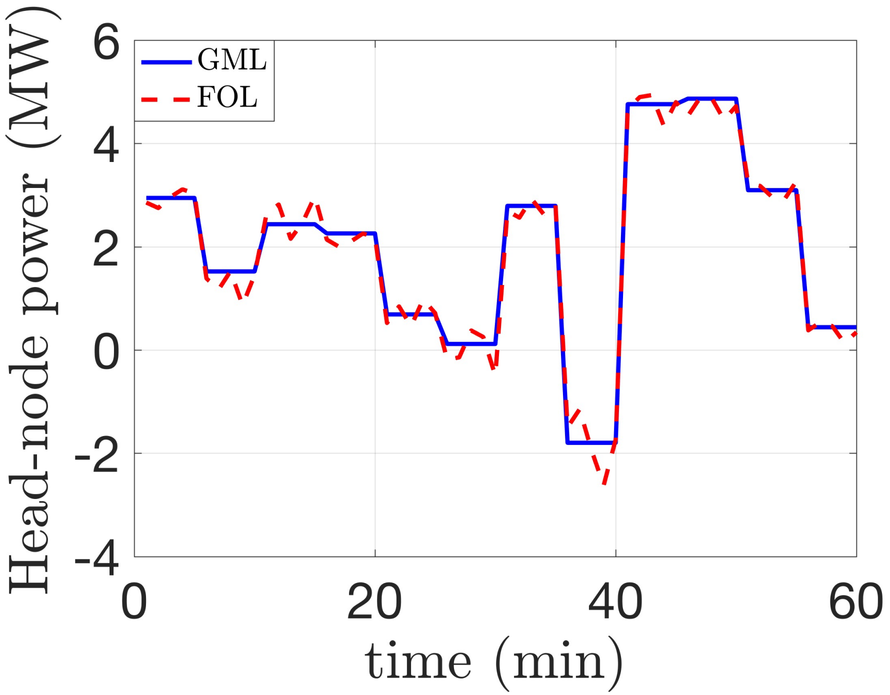
Robustify model

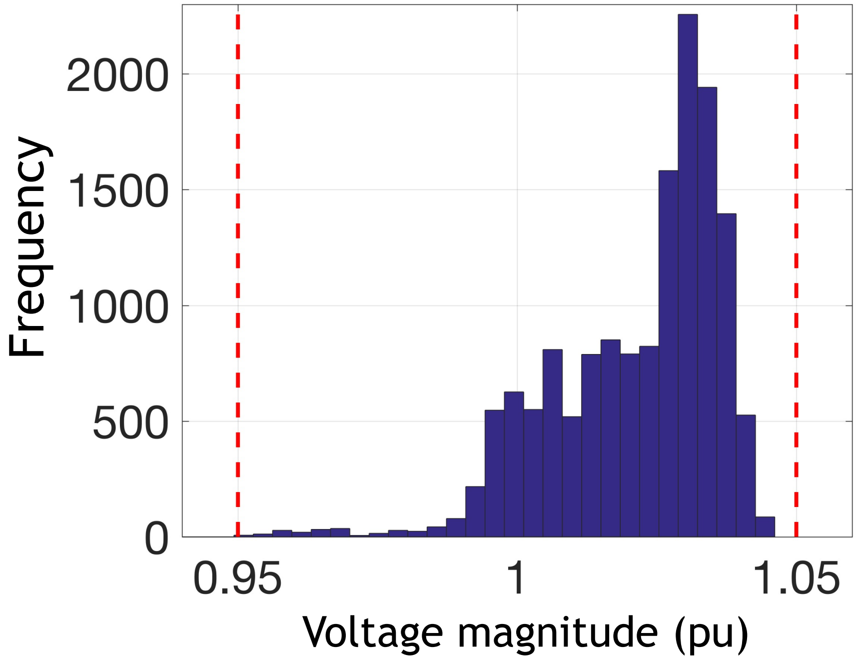
forecast is updated

- Tightening in constraint bounds is a function of forecast error
- Forecast error grows over the predictive horizon until updated
- Lower errors means less conservative responses[8]

[8] Nawaf Nazir and M. Almassalkhi, “Stochastic multi-period optimal dispatch of energy storage in unbalanced distribution feeders,” in Power Systems Computation Conference, Lisbon, Portugal, 2020.

Illustration of FOL





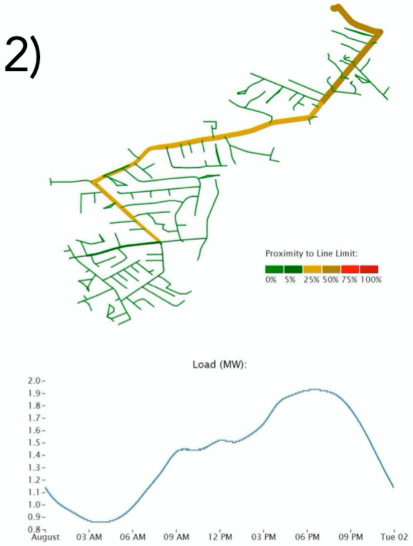
- Tracking of GML head-node power signal by 3-phase Feeder 1 (having 125 super-nodes)
- Histogram of voltages obtained in Gridlab-D through the stochastic formulation

Software: interactive Power Grid Analytics (iPGA)

Github @ teslaUVM/ENERGISE

1)

2)



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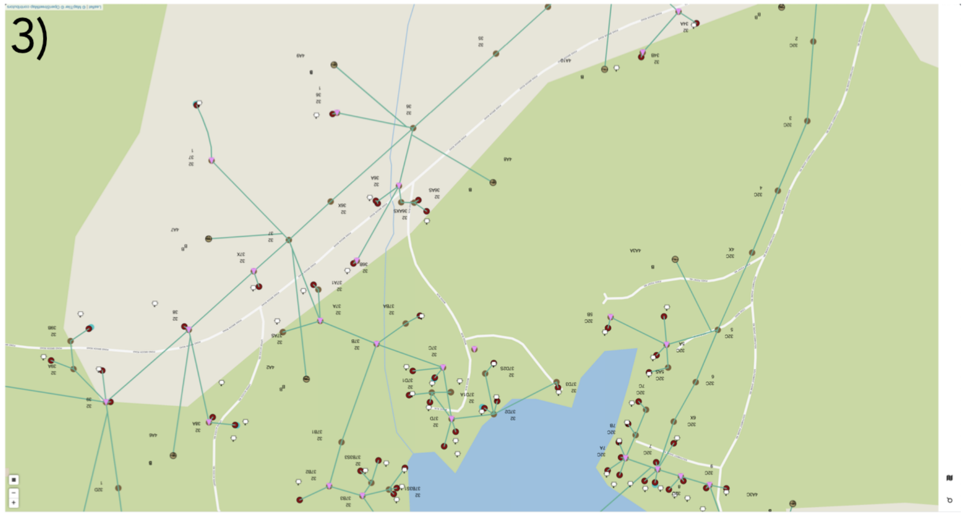
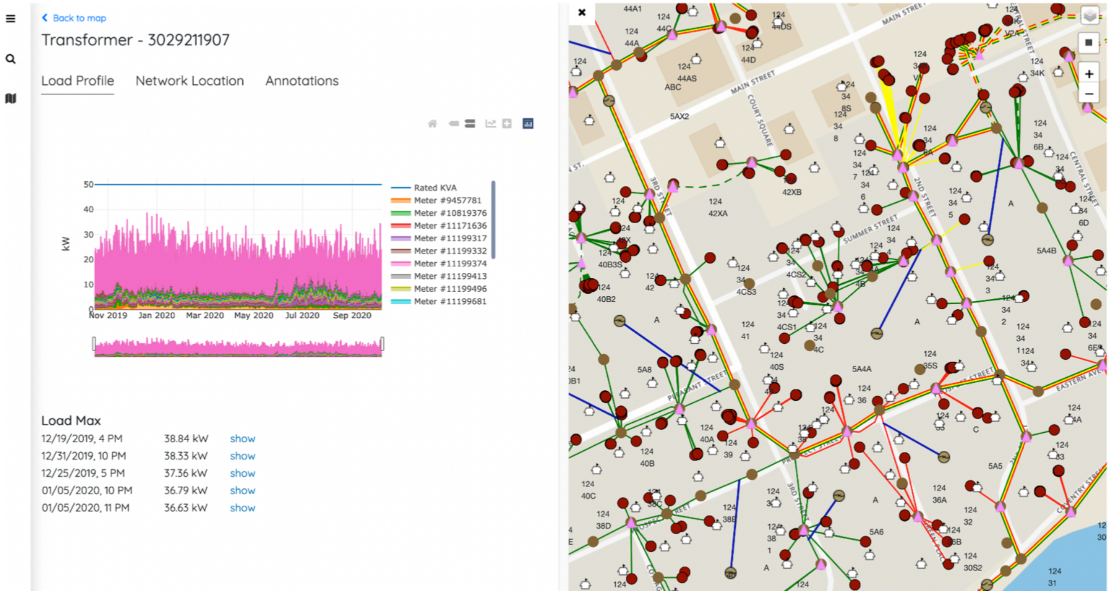


4)



Transformer - 3029211907

Load Profile Network Location Annotations

Load Max

12/19/2019, 4 PM	38.84 kW	show
12/31/2019, 10 PM	38.33 kW	show
12/25/2019, 5 PM	37.36 kW	show
01/05/2020, 10 PM	36.79 kW	show
01/05/2020, 11 PM	36.63 kW	show

iPGA has now been productized

PACKETIZED ENERGY

Service Transformer Layer (STL)

Aggregated Modeling and Control of DERs

Optimal Dispatch of DERs

- **Goal:** real-time coordination of DERs to track certain power set-points at the service transformer
  - A slightly challenging problem for switching-type devices, such as thermostatic loads – air-conditioner, electric water-heaters, etc.
- An efficient constrained *Mixed-Integer problem (MIP)* to track FOL-dispatched set-points
  - Constraints: satisfy device limitations and end-user comfort preferences
  - Objective: minimize tracking error while staying close to “normal operations”

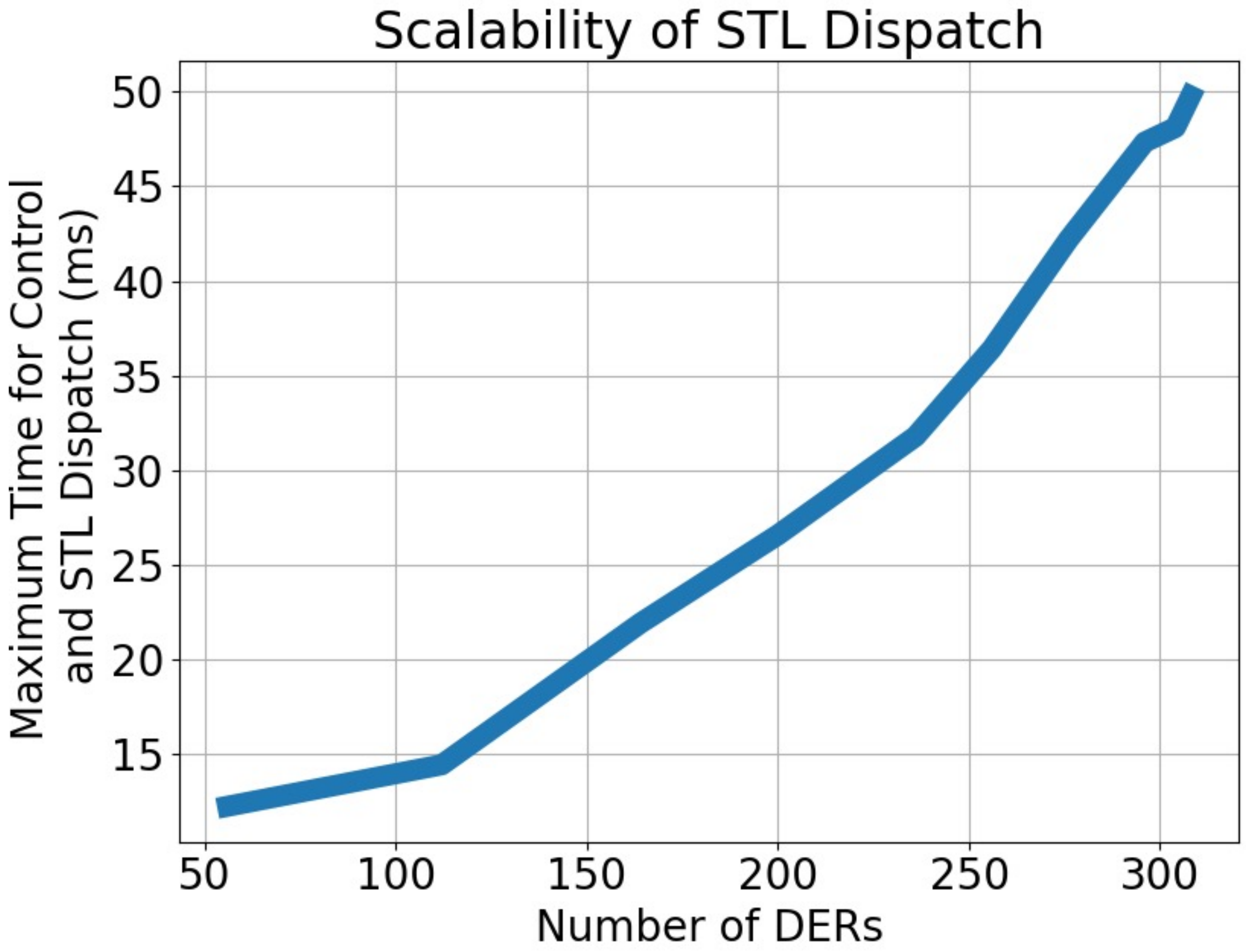
$$\forall t : \quad \underset{\varepsilon>0,\, \{p_i\}_{i=1}^{N}}{\text{minimize}} \quad w_1 \varepsilon + w_2 \sum_{i=1}^{N} \| T_i(t+1) - T_{set,i} \|_2^2$$

(tracking performance) $\left| P_{set}(t) - \sum_{i=1}^{N} p_i \right| \leq \varepsilon,$

(user comfort) $T_i(t+1) \in [T_{set,i} - \delta T_i/2,\, T_{set,i} + \delta T_i/2] \quad \forall i,$

(discrete power levels) $p_i \in \{0, P_i\} \quad \forall i,$

Scalability of DER dispatch in STL

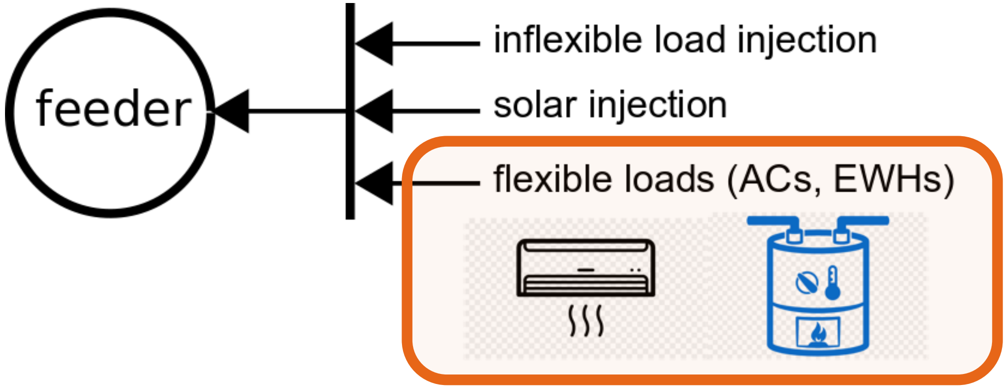


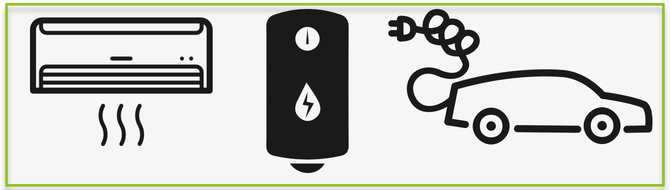
Aggregate Modeling of DERs as Virtual Battery

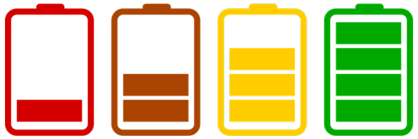
- Estimate flexibility of end-use resources in power consumption in the form of generalized battery models:

$|P| \le \varepsilon_1$	$\left|\dfrac{dP}{dt}\right| \le \varepsilon_2$	$\left|\int P\,dt\right| \le \varepsilon_3$
How much?	*How fast?*	*How long?*

- Basic idea of a virtual battery (VB) model:







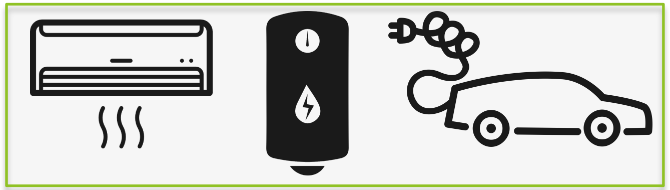
Virtual Battery (VB) Modeling

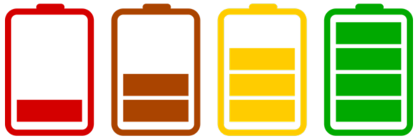
Aggregate Modeling of DERs as Virtual Battery

- Estimate flexibility of end-use resources in power consumption in the form of generalized battery models:

$|P| \leq \varepsilon_1$ | $\left|\frac{dP}{dt}\right| \leq \varepsilon_2$ | $\left|\int P\,dt\right| \leq \varepsilon_3$

How much? | *How fast?* | *How long?*





Virtual Battery (VB) Modeling

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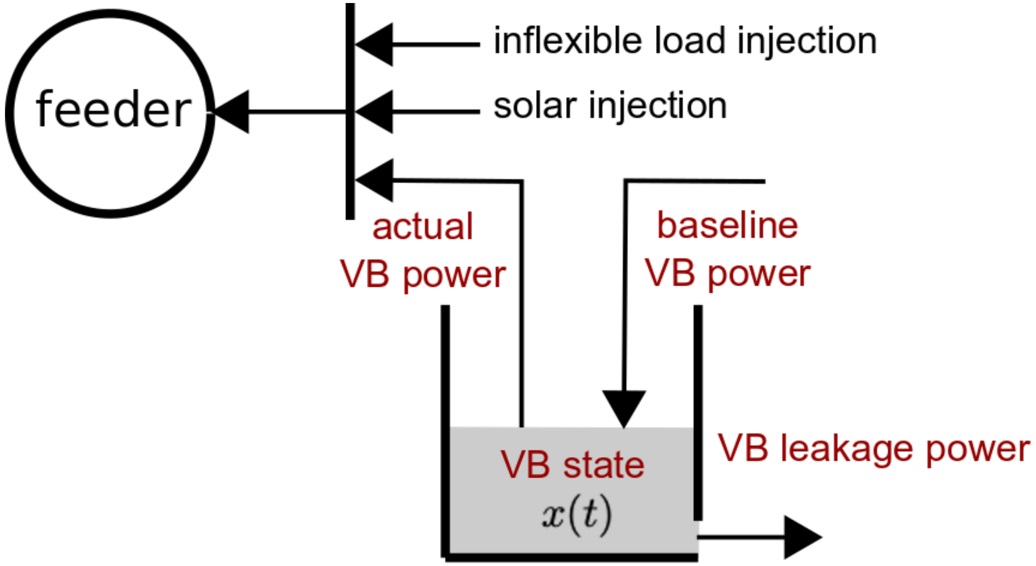


VB Dynamics:

$$\dot{x} = -\alpha x - P \quad \text{(SoC Dynamics)}$$

$$\left.\begin{aligned} x^- \leq x \leq x^+ \\ P^- \leq P \leq P^+ \end{aligned}\right\} \quad \text{(constraints)}$$

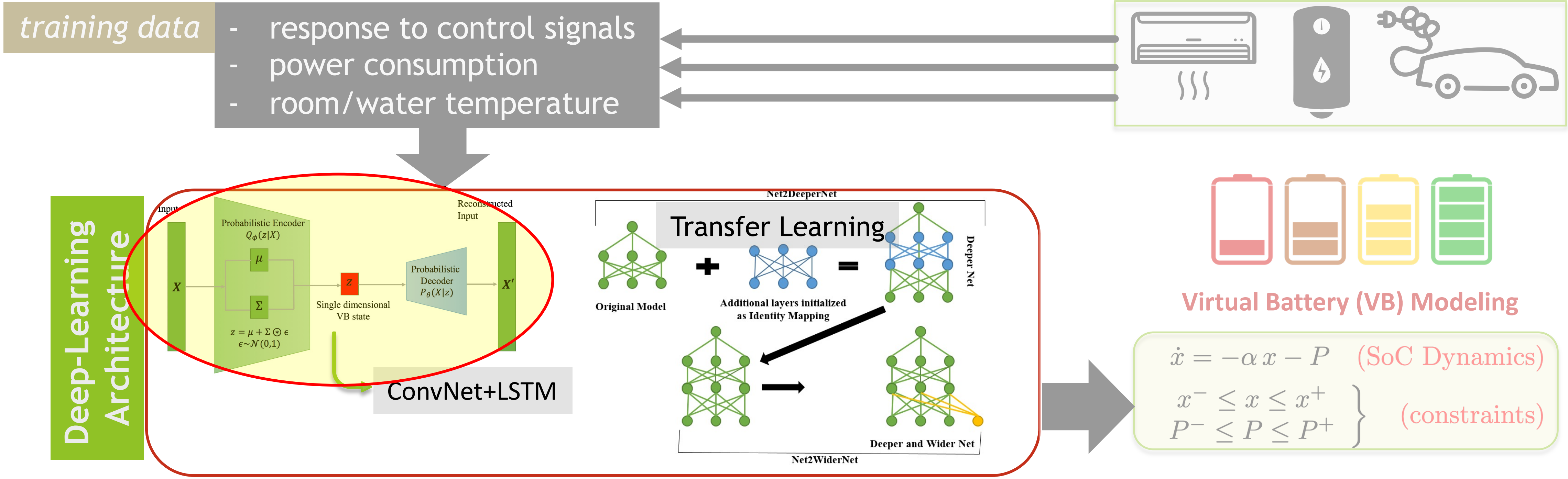
- Introduce a virtual energy state-of-charge (SoC)

- *SoC depletes if drawn power > baseline*
- *SoC increases if drawn power < baseline*

- Constraints on allowable power drawn

- Constraints on allowable SoC range

VB Modeling and Control of DERs – Key Takeaways



training data

- response to control signals
- power consumption
- room/water temperature

Deep-Learning Architecture

ConvNet+LSTM

Transfer Learning

Virtual Battery (VB) Modeling

$$\dot{x} = -\alpha\, x - P \quad \text{(SoC Dynamics)}$$

$$\left.\begin{array}{l} x^- \le x \le x^+ \\ P^- \le P \le P^+ \end{array}\right\} \quad \text{(constraints)}$$

a) **Data-driven methods to identify and validate VB models** (previously ad-hoc)
b) **Significant flexibility reserves possible from DERs, and depends on efficiency of controls**
c) **Extension of (deterministic) VB models into stochastic ones** (via *variational autoencoder*)
   - Generates distributions of VB parameters (instead of point estimates)

Real-time Inter-Layer DER Control

Leads: Sarnaduti Brahma*, Hamid Ossareh, and Mads Almassalkhi

University of Vermont

Sarnaduti is finishing up PhD this summer & is seeking R&D positions. Contact him: *sbrahma@uvm.edu*

Introduction

FOL

Objective: to track GML Head-Node Set Point

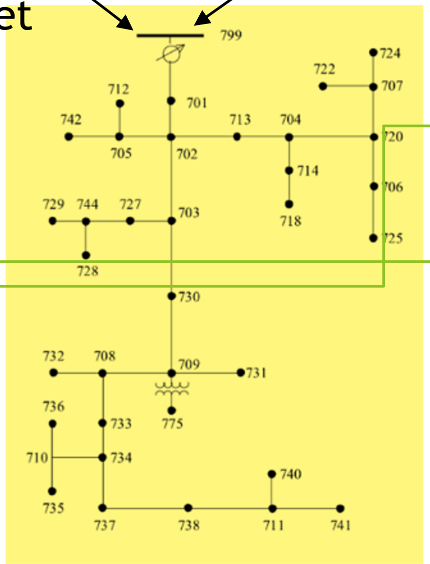
1-5 min

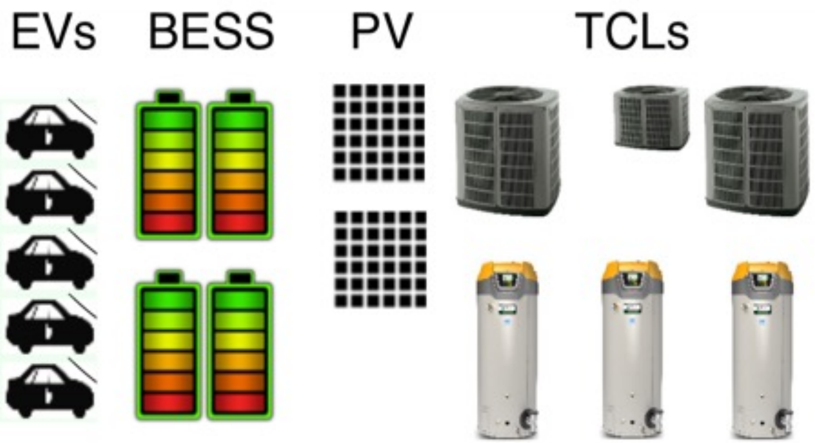
STL

ON/OFF

1-4 s

Need only Head node power





Provide real-time corrections

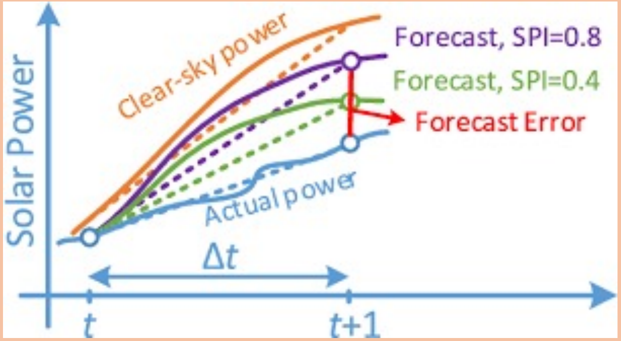
Small disturbances

Intra-feeder control (“Droop”)

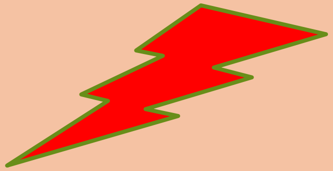
Variable nature of Solar PV

Big disturbances

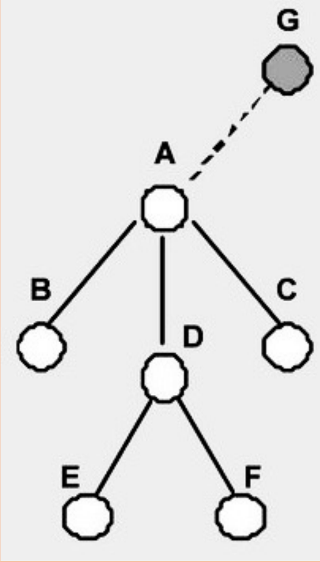
Inter-feeder control (“AGC”)



Forecast Errors to FOL

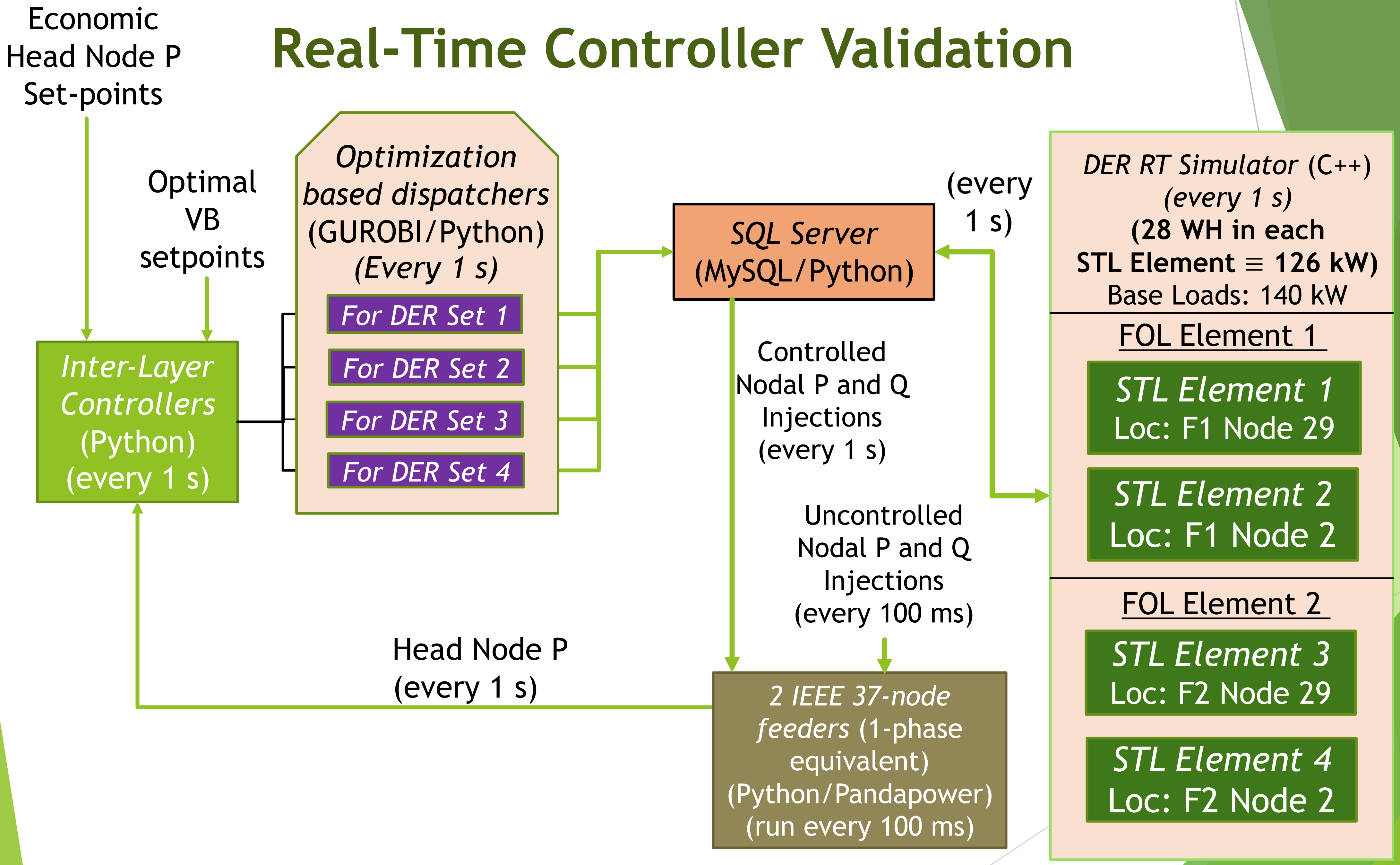


Cyber-attacks on DER Communications



Sudden Change in Network Topology

Real-Time Controller Validation



Economic Head Node P Set-points

Optimal VB setpoints

Inter-Layer Controllers (Python) (every 1 s)

Optimization based dispatchers (GUROBI/Python) *(Every 1 s)*

- *For DER Set 1*
- *For DER Set 2*
- *For DER Set 3*
- *For DER Set 4*

SQL Server (MySQL/Python)

(every 1 s)

Controlled Nodal P and Q Injections (every 1 s)

Uncontrolled Nodal P and Q Injections (every 100 ms)

Head Node P (every 1 s)

2 IEEE 37-node feeders (1-phase equivalent) (Python/Pandapower) (run every 100 ms)

DER RT Simulator (C++) *(every 1 s)*
(28 WH in each STL Element ≡ 126 kW)
Base Loads: 140 kW

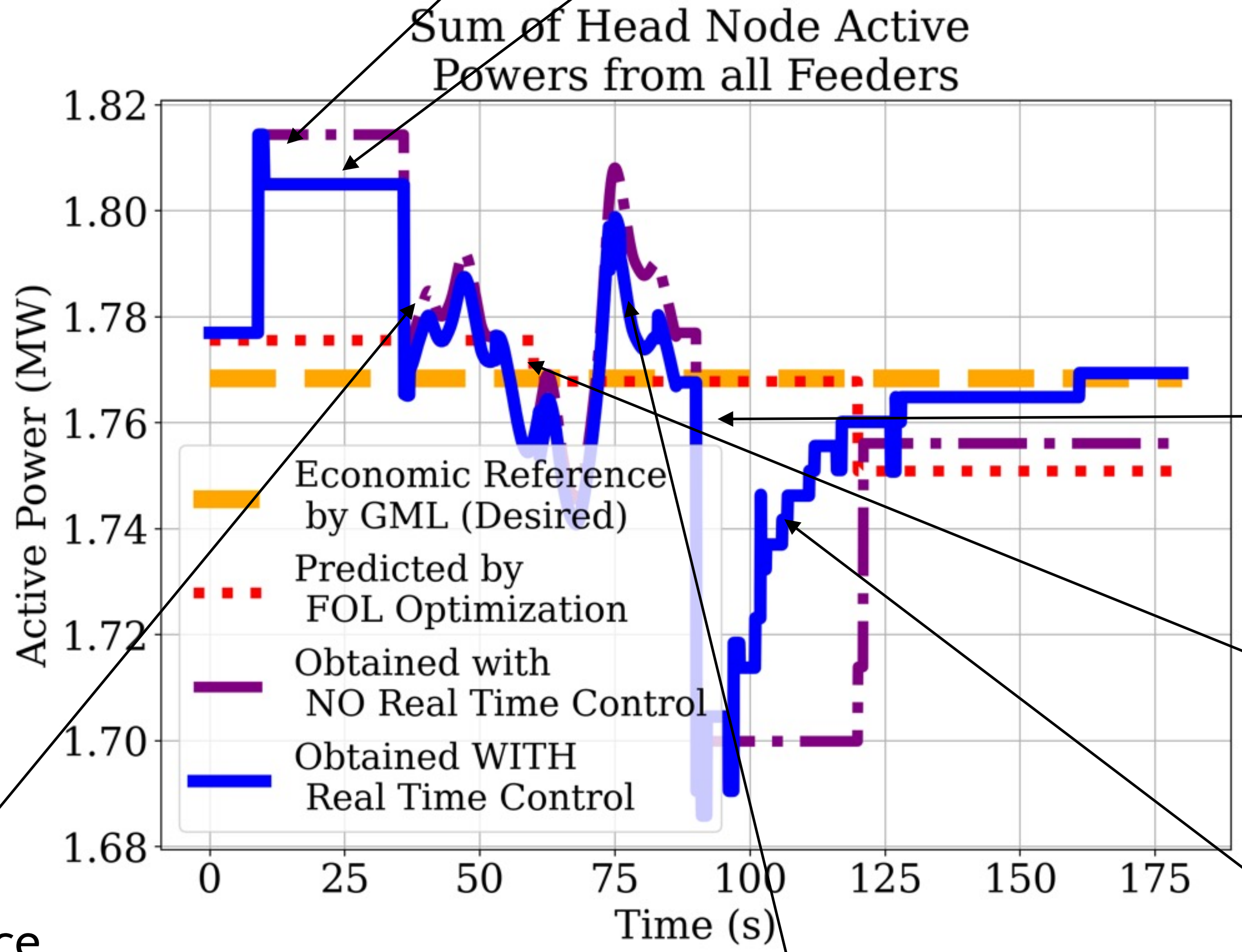
FOL Element 1

- *STL Element 1* Loc: F1 Node 29
- *STL Element 2* Loc: F1 Node 2

FOL Element 2

- *STL Element 3* Loc: F2 Node 29
- *STL Element 4* Loc: F2 Node 2

Disturbance Rejection



Step disturbance injecte **(Normal Operations)**

Better with inter-layer control
(since proportional controller, no full correction)

DER set at Node 2 of Feeder 2
(28 WH) assumed cyberattacked
To 0 power
(Contingency Operation)

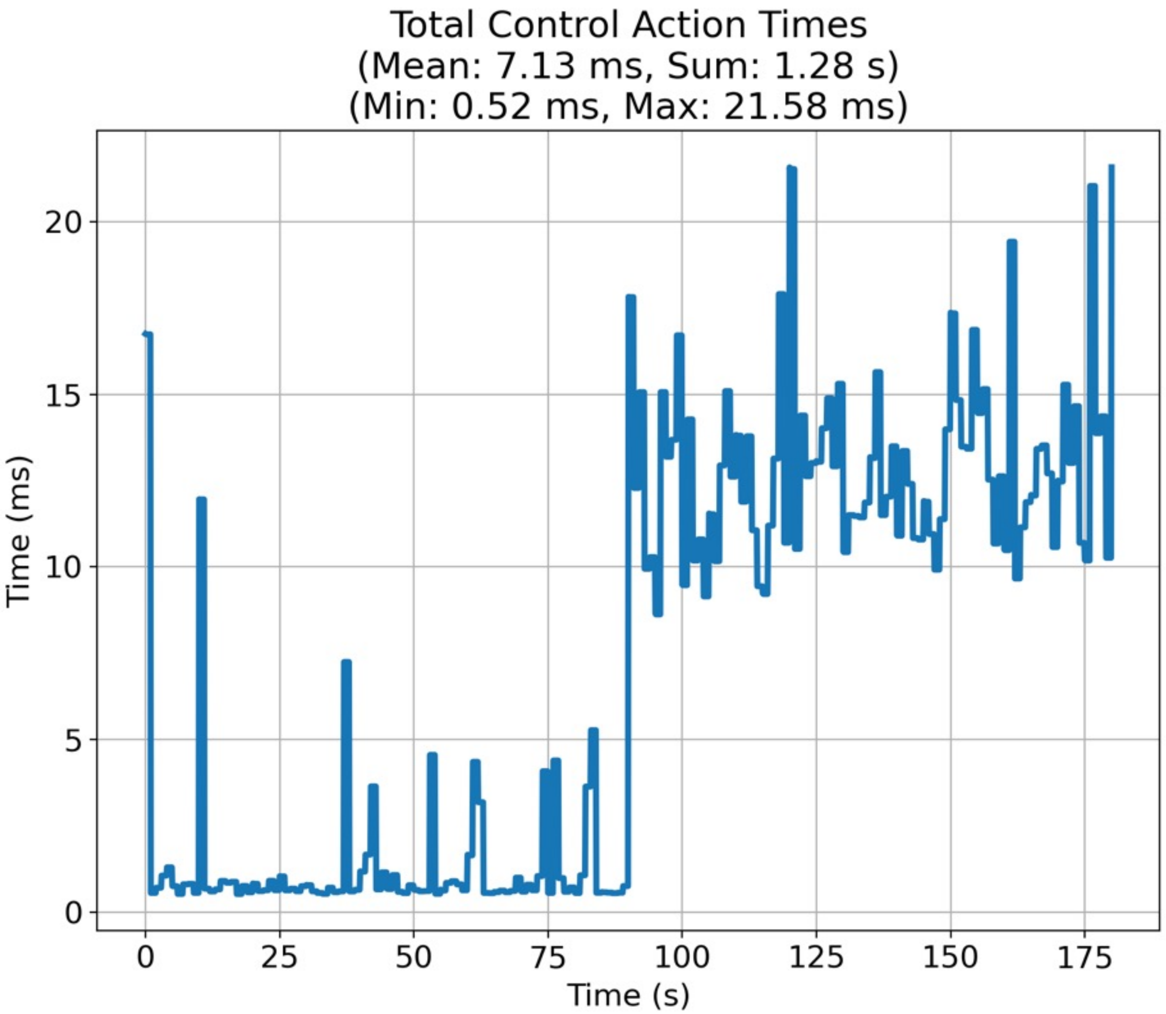
Redispatch by FOL that corrects modeling error

Random Disturbance Injected (**Normal Operation**)

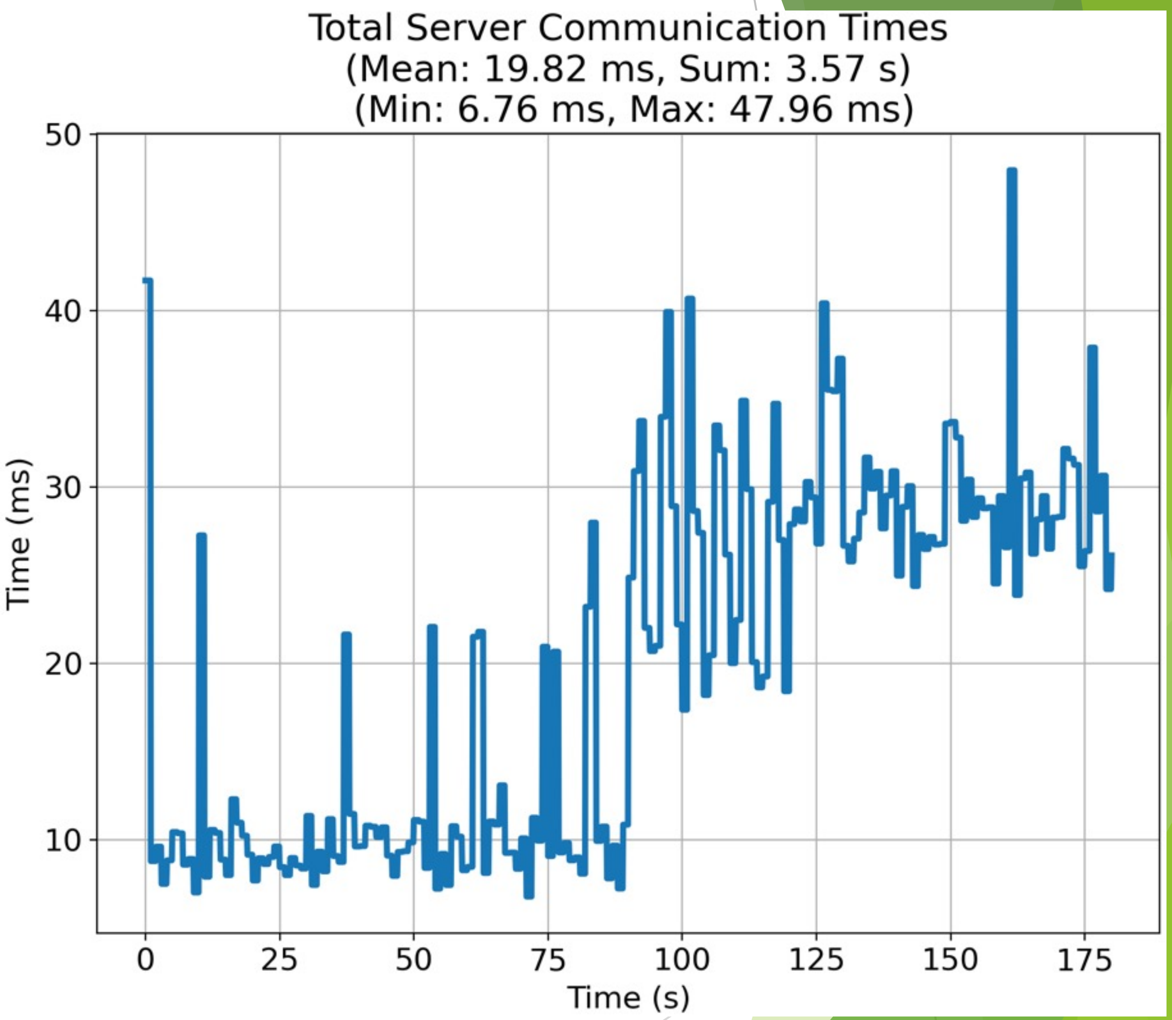
Smaller variance with inter-layer control

Better with inter-layer control (integral)

Run Times



Total Control Action Times
(Mean: 7.13 ms, Sum: 1.28 s)
(Min: 0.52 ms, Max: 21.58 ms)



Total Server Communication Times
(Mean: 19.82 ms, Sum: 3.57 s)
(Min: 6.76 ms, Max: 47.96 ms)

- **180 s simulation** ≡ 180 control actions
- ∴ For real-time, need **1 control action << 1 s**

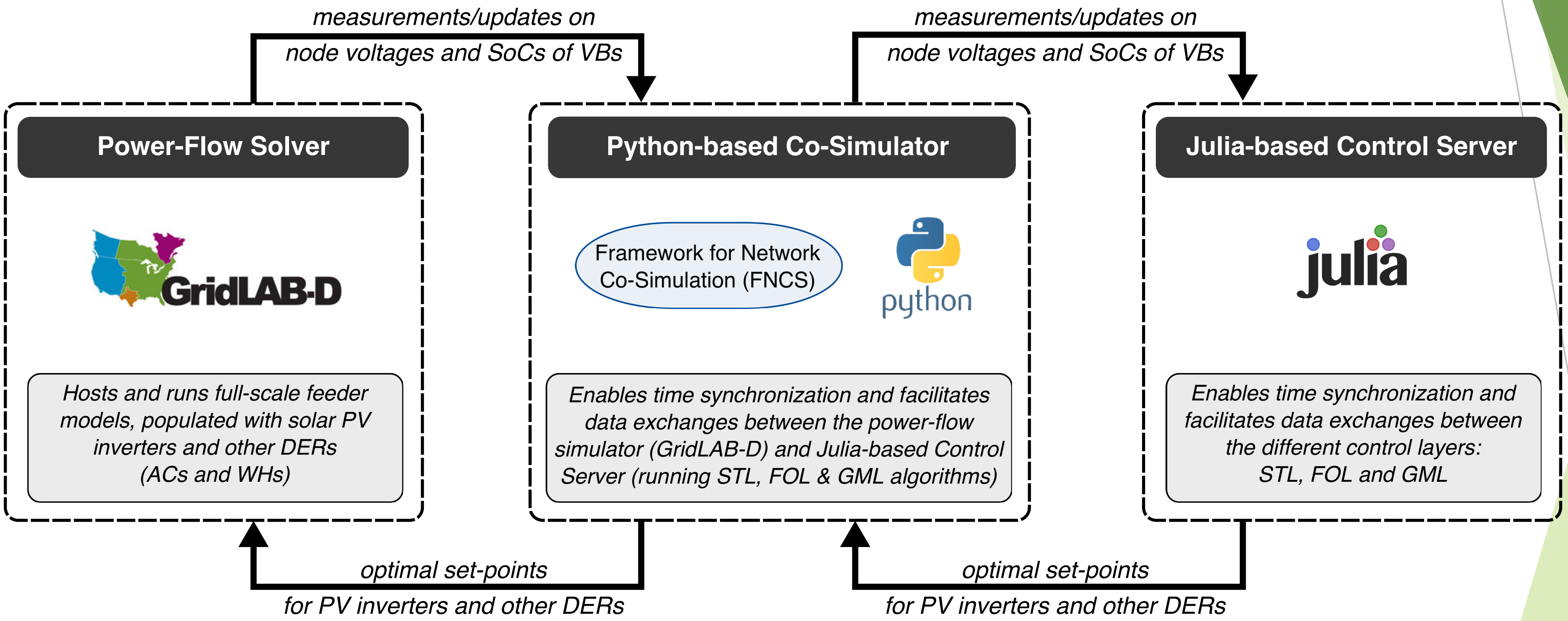
Max control action ≡ **21.58 ms << 1 s** ⇒ *Real Time Feasible*

Large-scale simulations**

Coupled Markets+Grids+DERs optimization

***Unfortunately, COVID-19 hit during the last 3 quarters of the project and the team had a key member stranded abroad for 10 months. SETO denied multiple request for NCE, which impacted research and the extent of analysis of final simulations.*

Simulation Framework: DERs+Grids+Market



measurements/updates on node voltages and SoCs of VBs

measurements/updates on node voltages and SoCs of VBs

Power-Flow Solver

GridLAB-D

Hosts and runs full-scale feeder models, populated with solar PV inverters and other DERs (ACs and WHs)

Python-based Co-Simulator

Framework for Network Co-Simulation (FNCS)

python

Enables time synchronization and facilitates data exchanges between the power-flow simulator (GridLAB-D) and Julia-based Control Server (running STL, FOL & GML algorithms)

Julia-based Control Server

julia

Enables time synchronization and facilitates data exchanges between the different control layers: STL, FOL and GML

optimal set-points for PV inverters and other DERs

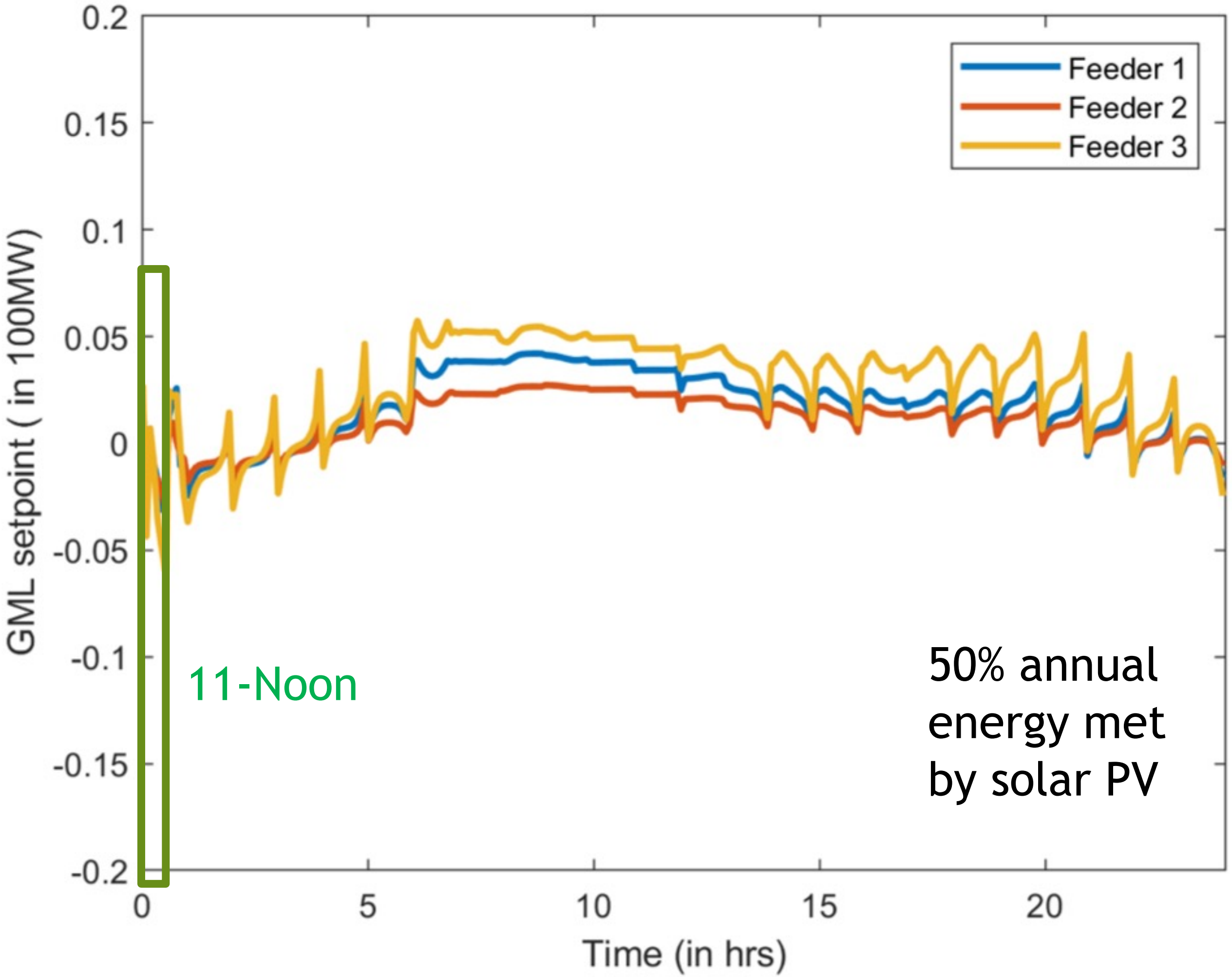
optimal set-points for PV inverters and other DERs

At each time step….

- Gridlab-D solves the power flow given the load/solar information and the FOL dispatch points and communicates the state of charge/nodal voltages to the Julia server.
- The Julia server, which hosts the DSSE/STL/FOL/GML algorithms, dispatches the virtual batteries and ACs, WHs based on the state of charge information received from Gridlab-D and the GML setpoint.
- FNCS is a co-simulaton platform used to facilitate data exchange between Julia and Gridlab-D.

Peak Reduction – GML dispatch

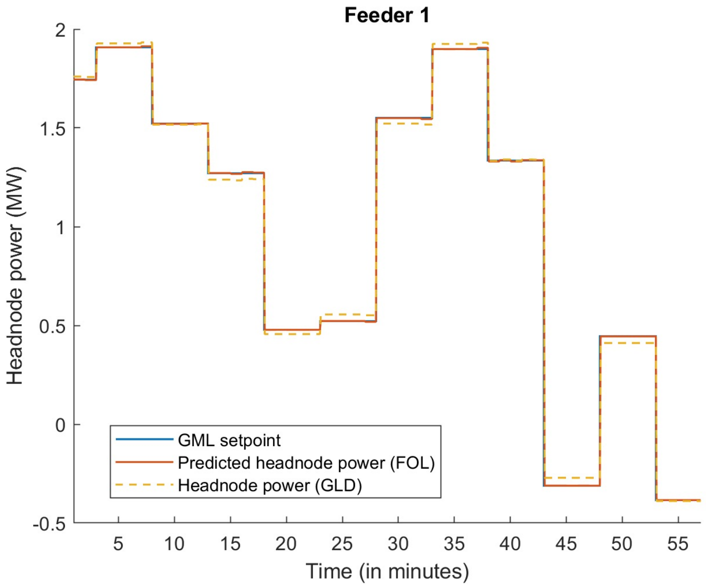
ORU network is optimized with GML for all feeders and 3 feeders are fully modeled with VBs of which 2-3 VBs are fully populated with DERs

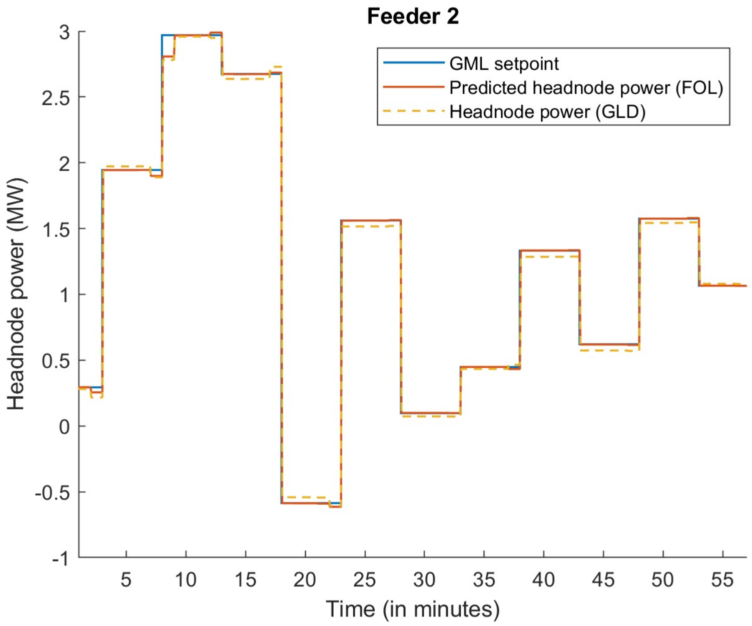


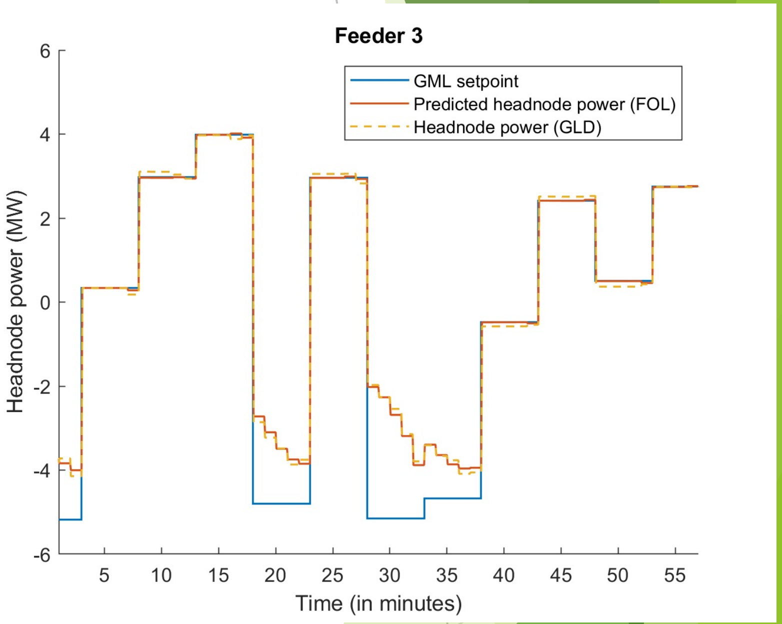
11-Noon

50% annual
energy met
by solar PV

Peak Reduction – FOL tracking performance (11:00 AM – 12:00 AM)





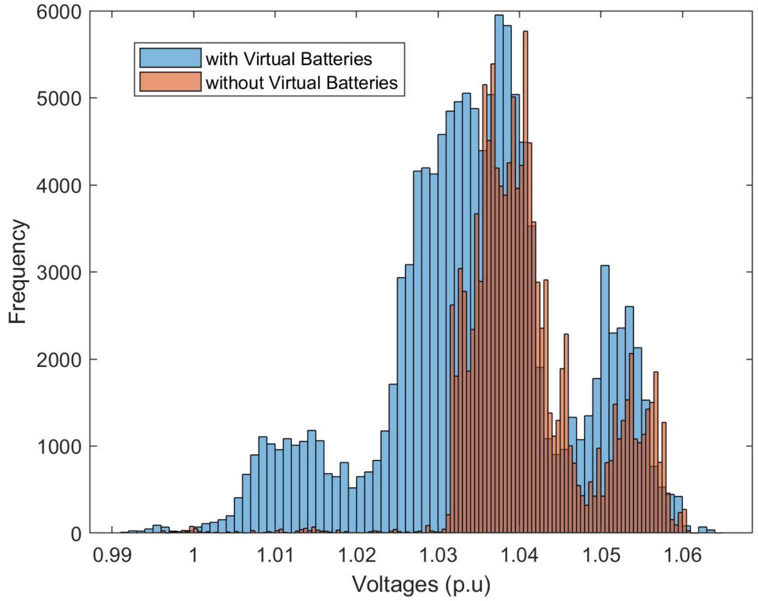


	Tracking RMSE
Feeder 1	14 kW
Feeder 2	20 kW
Feeder 3	90 kW

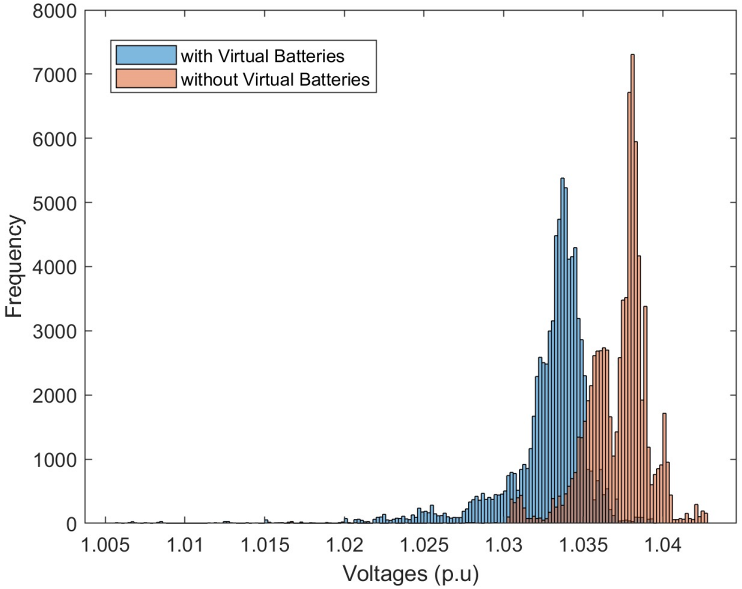
Much less solar PV than (robustly) expected causes tracking errors

Feeder Nodal Voltages

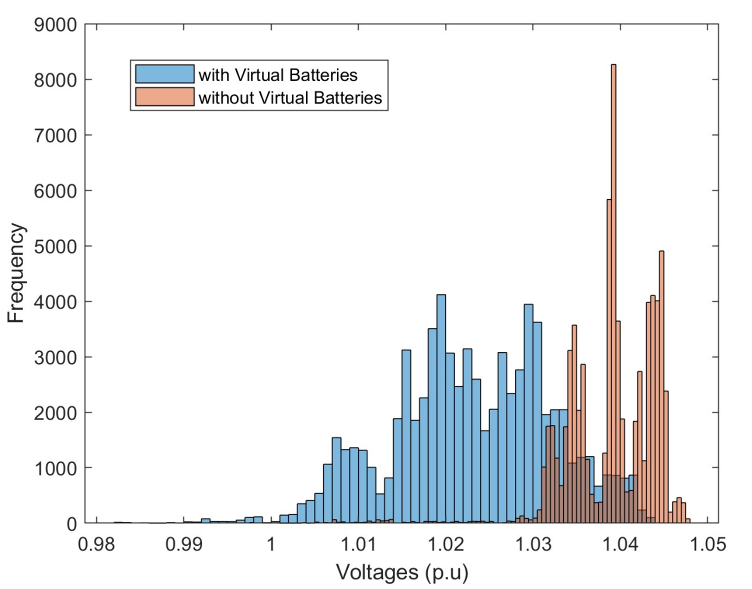
Feeder 1



Feeder 2



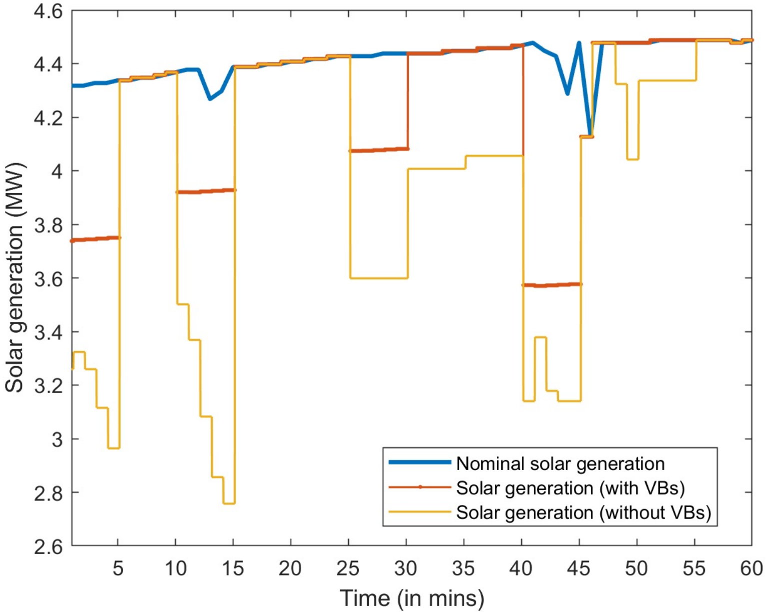
Feeder 3



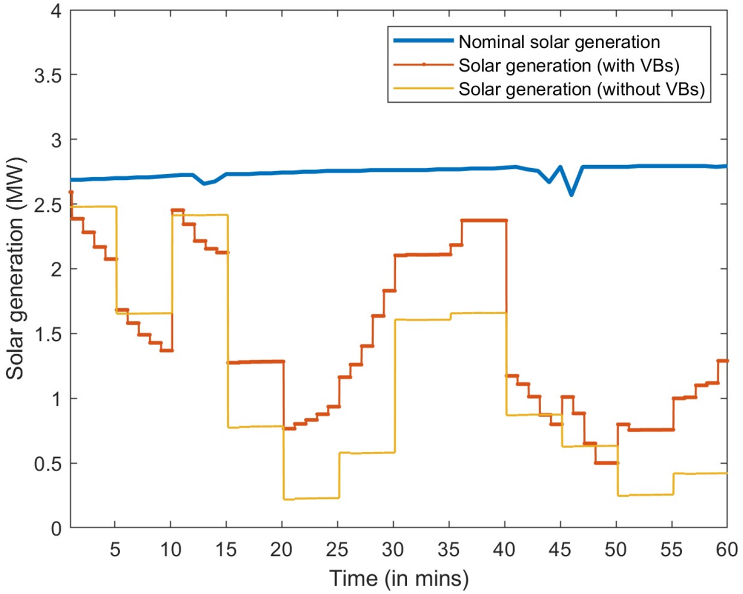
	Voltage u.b. (95th percentile without VBs)	Voltage u.b. (95th percentile with VBs)
Feeder 1	1.058	1.053
Feeder 2	1.041	1.035
Feeder 3	1.047	1.038

Solar generation – Peak reduction

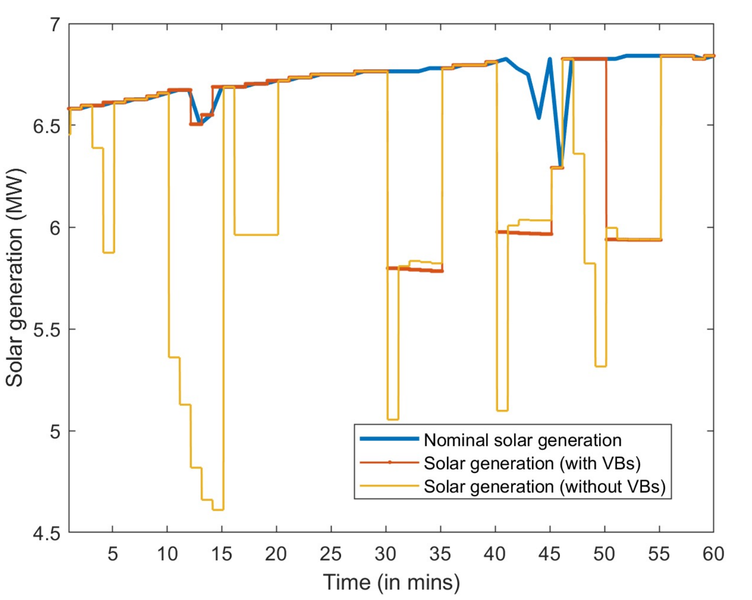
Feeder 1



Feeder 2



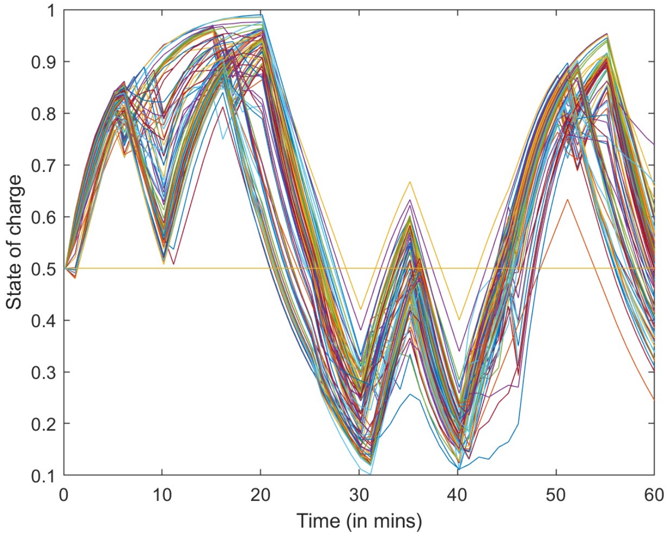
Feeder 3



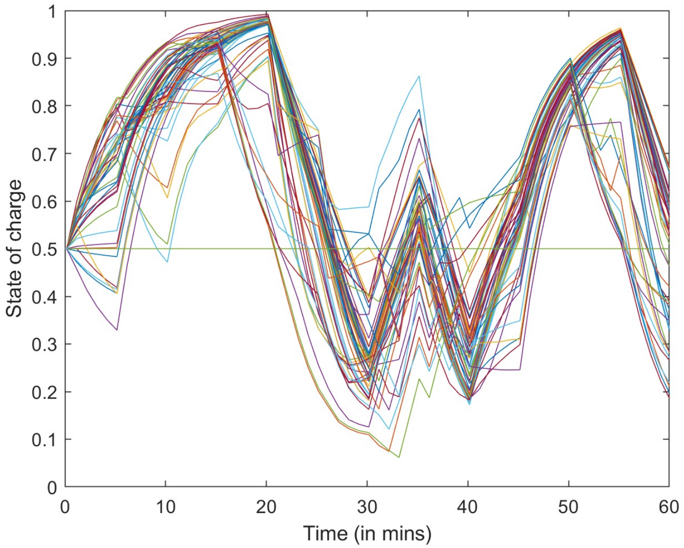
	Mean curtailment with VB	Mean curtailment without VB
Feeder 1	0.2 MW	0.5 MW
Feeder 2	1.2 MW	1.6 MW
Feeder 3	0.3 MW	0.6 MW

Equivalent feeder-level state of charge

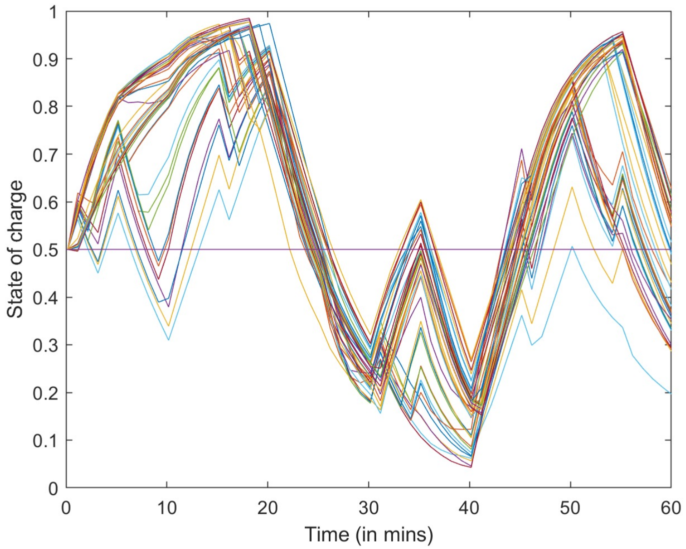
Feeder 1



Feeder 2



Feeder 3



- The evolution of the feeder’s aggregate state of charge (from gridlab-D) depends on the overall solar generation relative to the load during any given hour.

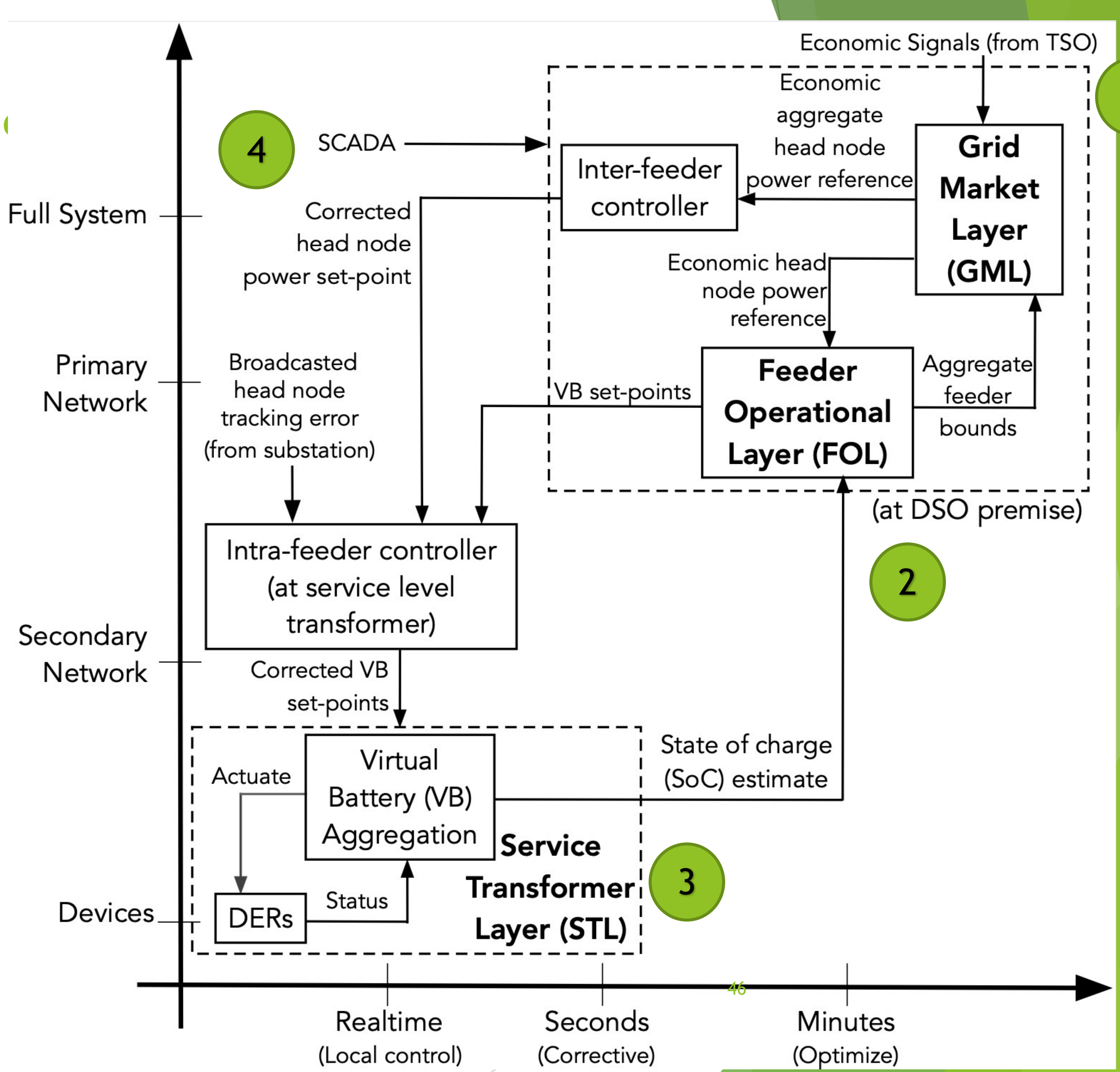
Final project summ

1+2: DSO premises have GML and FOL running via SCADA.

3: STL running at each *super-node* service transformer (in the field) to manage solar PV inverters and other active nodes via VB-DER interface

4: Interlayer corrective controllers improve performance in real-time

Key: all elements are advanced operational tools, but *technologically viable* across spatio-temporal scales



Thank you! Any questions or comments?

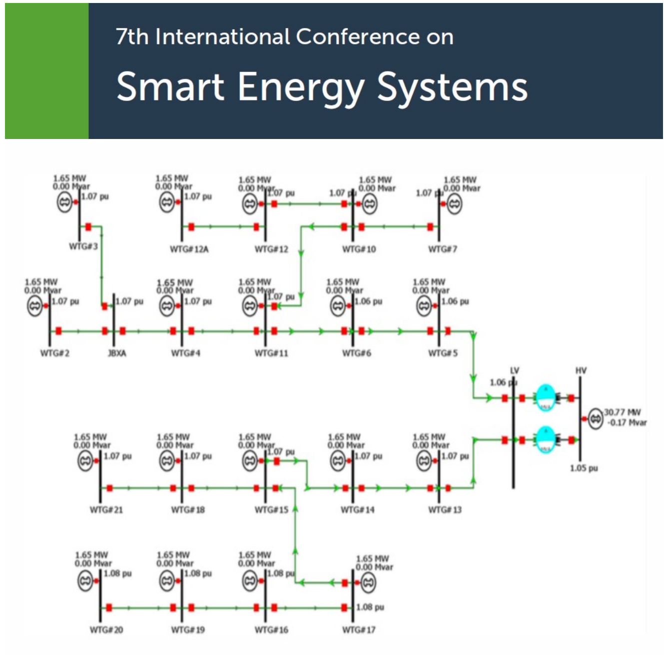
Mads Rønne Almassalkhi ✉ *malmassa@uvm.edu* *@theEnergyMads*

See you in Denmark Aug 2021- July 2022?

DTU AAU

Sabbatical

2021-22


7th International Conference on

Smart Energy Systems

Some things never run out of energy!

This material is based on work graciously supported by U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under SETO ENERGISE program (DE-EE0001495) Award Number DE-EE0008006

SOLAR ENERGY TECHNOLOGIES OFFICE
U.S. Department Of Energy

Project Team Publications

Publications

1. (Submitted) Y. Jiang, E. Cohn, P. Vorobev, and E. Mallada Storage-based frequency shaping contro IEEE Transactions on Power Systems
2. (Under review; Rev02) S. Brahma, Nazir, N, H. Ossareh, and Almassalkhi, M. Optima and resilient coordination of virtual batteries in distribution feeders IEEE Trans. o Power Systems
3. Nazir, N, Racherla, P., and Almassalkhi, M. Optimal multi-period dispatch of dis tributed energy resources in unbalanced distribution feeders IEEE Trans. on Powe Systems
4. (Under review; Rev02) Nazir, N, and Almassalkhi, M. Voltage positioning using co optimization of controllable grid assets IEEE Trans. on Power Systems
5. F. Paganini and E. Mallada Global analysis of synchronization performance for powe systems: Bridging the theory-practice gap IEEE Trans. on Automatic Control
6. (Under review; Rev01) L. S. P. Lawrence, J. W. Simpson-Porco, and E. Mallada Th optimal steady-state control problem IEEE Trans. on Automatic Control
7. (Under review; Rev01) Y. Jiang and R. Pates and E. Mallada Dynamic Droop Contro in Low-inertia Power Systems IEEE Trans. on Automatic Control
8. (To be submitted shortly) S. Brahma, and H. Ossareh Analysis of Accuracy and Nu merical Properties of Stochastic Linearization International Journal of Control
9. H. G. Oral, E. Mallada, and D. Gayme Performance of single and double-integrato networks over directed graphs IEEE Transactions on Automatic Control
10. Bahram, Alina and Hajiesmaili, Mohammad H. and Lee, Zachary and Crespi, Noel an Mallada, Enrique Online EV Scheduling Algorithms for Adaptive Charging Network with Global Peak Constraints IEEE Transactions on Sustainable Computing
11. E. Weitenberg, Y. Jiang, C. Zhao, E. Mallada, C. De Persis, and F. Dorfler Robus decentralized secondary frequency control in power systems: Merits and trade-of IEEE Transactions on Automatic Control
12. R. Pates and E. Mallada ”Robust scale free synthesis for frequency regulation in powe sys- tems” IEEE Trans, on Control of Network Systems
13. N. Nazir and M. Almassalkhi, “Grid-aware aggregation and realtime disaggregation o distributed energy resources in radial networks,” 2020, under review in IEEE Trans actions on Power Systems.
14. Nawaf Nazir, Mads Almassalkhi Receding-horizon optimization of unbalanced distr bution systems with time-scale separation for discrete and continuous control device 2018PSCCS05E Power System Computation Conference Dublin, Ireland June, 2018
15. Sarnaduti Brahma, Mads Almassalkhi, Hamid Ossareh A Stochastic Linearization Approach to Optimal Primary Control of Power Systems with Generator Saturation ThC2.1 IEEE Conference on Control Technology and Applications Copenhagen, Denmark August, 2018
16. Chakraborty I., S. Nandanoori, and S. Kundu ”Virtual Battery Parameter Identification using Transfer Learning based Stacked Autoencoder **Nominated for best paper award” 502 ICMLA Orlando, FL December, 2018
17. Nandanoori S., I. Chakraborty, T. Ramachandran, and S. Kundu Identification and Validation of Virtual Battery Model for Heterogeneous Devices PES General Meeting 2019 Atlanta, GA August, 2018
18. Ramachandran T., A. Reiman, M. Rice and S. Kundu Distribution System State Estimation in the presence of high PV penetration American Control Conference Philadelhia, PA July, 2019
19. Weiping Huang, Sarnaduti Brahma, Hamid Ossareh Quasilinear control of systems with time-delays and nonlinear actuators and sensors American Control Conference Philadelhia, PA July, 2019
20. Chengda Ji, Mohammad Hajiesmaili, Dennice F. Gayme and Enrique Mallada Coordinating Distribution System Resources for Co-optimized Participation in Energy and Ancillary Service Transmission System Markets American Control Conference Philadelhia, PA July, 2019
21. C. Avraam, J. Rines, A. Sarker, F. Paganini, and E. Mallada Voltage Collapse Stabilization in Star DC Networks American Control Conference Philadelhia, PA July, 2019
22. Sarnaduti Brahma, Hamid Ossareh Quasilinear control of feedback systems with multivariate nonlinearities ThB19.6 IEEE Conference on Decision and Control Nice, France Dec, 2019
23. P. You, D. F. Gayme, and E. Mallada The Role of Strategic Load Participants in Two-Stage Settlement Electricity Markets FrC25.2 IEEE Conference on Decision and Control Nice, France Dec, 2019
24. H. Min and E. Mallada Dynamics Concentration of Large-Scale Tightly-Connected Networks WeA21.6 IEEE Conference on Decision and Control Nice, France Dec, 2019
25. N. Nazir and M. Almassalkhi (to appear) Stochastic multi-period optimal dispatch of energy storage in unbalanced distribution feeders Power Systems Computation Conference Porto, Portugal
26. Nawaf Nazir and Mads Almassalkhi Convex inner approximation of the feeder hosting capacity limits on dispatchable demand ThC05.2 IEEE Conference on Decision and Control Nice, France
27. C. Shapiro, C. Ji, and D. F. Gayme (to appear) Real-time Energy Market Arbitrage via Aerodynamic Energy Storage in Wind Farms Proc. of the American Control Conference
28. J. Guthrie and E. Mallada Minimum-Time Charging of Energy Storage in Microgrids via Approximate Conic Relaxation IEEE European Control Conference (ECC) 2020
29. Y. Shen, M. Bichuch, and E. Mallada On the Value of Energy Storage in Generation Cost Reduction IEEE European Control Conference (ECC) 2020
30. C. Shapiro, C. Ji, and D. F. Gayme Real-time Energy Market Arbitrage via Aerodynamic Energy Storage in Wind Farms American Control Conference Denver, CO 2020

Other Results

1. The Future of Energy Workshop 09/27/18 09/28/18, Burlington, VT
2. NIST WORKSHOP ON SMART GRID TESTBEDS & COLLABORATIONS 04/23/20, Burlington, VT
3. Dennice Gayme was featured in IEEE Control System Society’s Control Magazine.

Bonus Slides

Communications

Point of coupling
Between feeders

Using
RTACs