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Comprehensive Grid Integration of Solar Power for SDG&E

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http://solar.ucsd.edu

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Motivation

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Backdrop:

- Continued growth in solar energy installations.
- Increased interest in energy storage deployments.

Demonstration:

- Foresight improves system management.
- Feeders have a larger solar hosting capacity then previously assumed.
- Distribution feeder voltage quality can be improved by proper energy storage siting and operation.

Task Overview

- Task 2: Operational Solar Forecasting
- Task 3: Operational Feeder Net Load Forecasting

Q&A

- Task 4.1: Distribution Feeder Hotspots
- Task 4.2: Energy Storage Siting and Sizing on Distribution Feeders

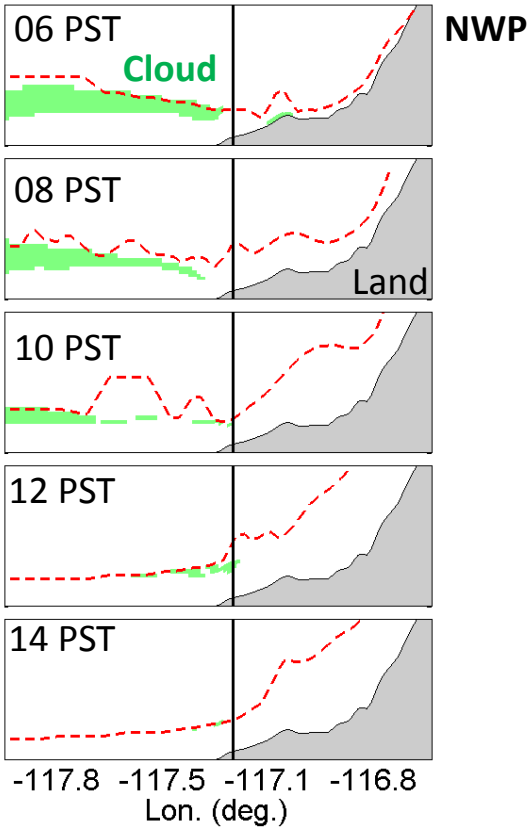
Q&A

- Task 4.3: Mitigate Grid Fluctuations

SRAF Laboratory UCSD
Solar Resource Assessment and Forecasting

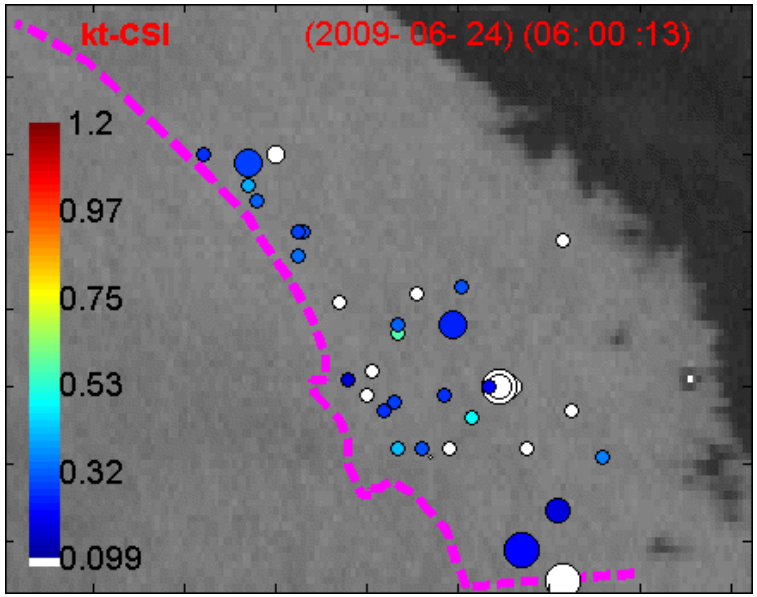
Task 2: Operational Solar Forecasting

Numerical Weather Prediction (NWP)



NWP

Satellite



- Most accurate solar forecast for >5 hours in advance
- Large scale computational physics models
  - Pressure, Geopotential, Velocity, Temperature, and Water
- Initialized by combination of observation and model output

Domain/Time Options	
Δx (km)	2.5
Vertical Pts.	75
CFL	0.3
Output Interval (m.)	15
Spin-Up Interval (hr.)	24+ (Cycling)
Initial and Boundary	12 UTC NAM

Ensemble Prediction System

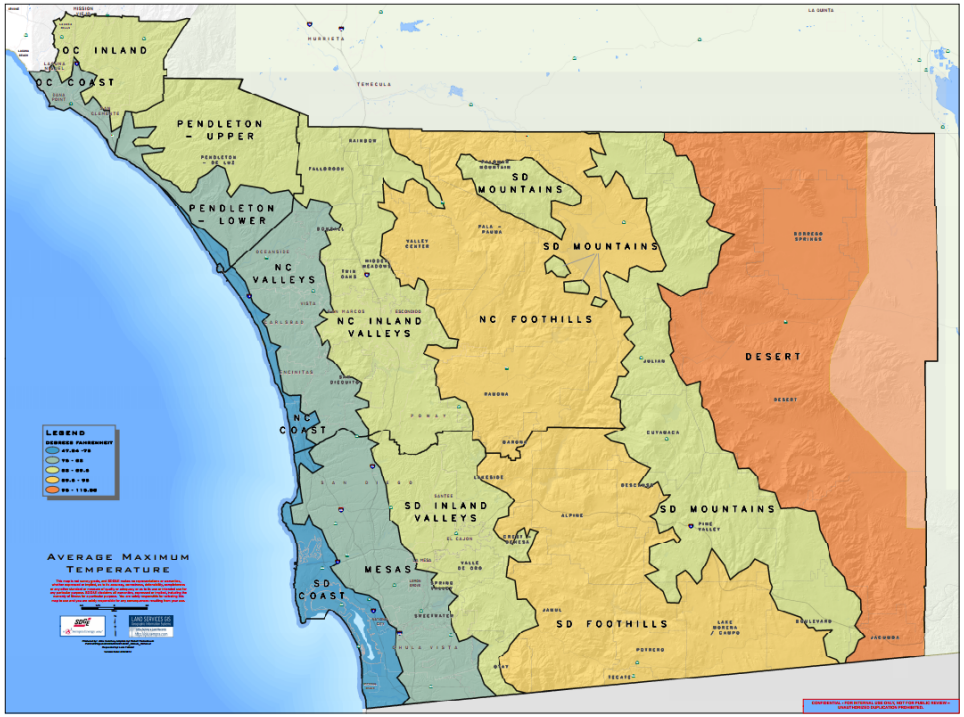
WRF (Weather Research and Forecasting) Model

- Physics chosen to promote cloud cover
- High-Density Vertical Levels
- Multi-physics ensemble prediction system

Analog Ensemble Correction

- Training period: May 2014 – Apr 2015
- Validation period: May 2014 – Apr 2015 (excluding current day and current day + 5 days)

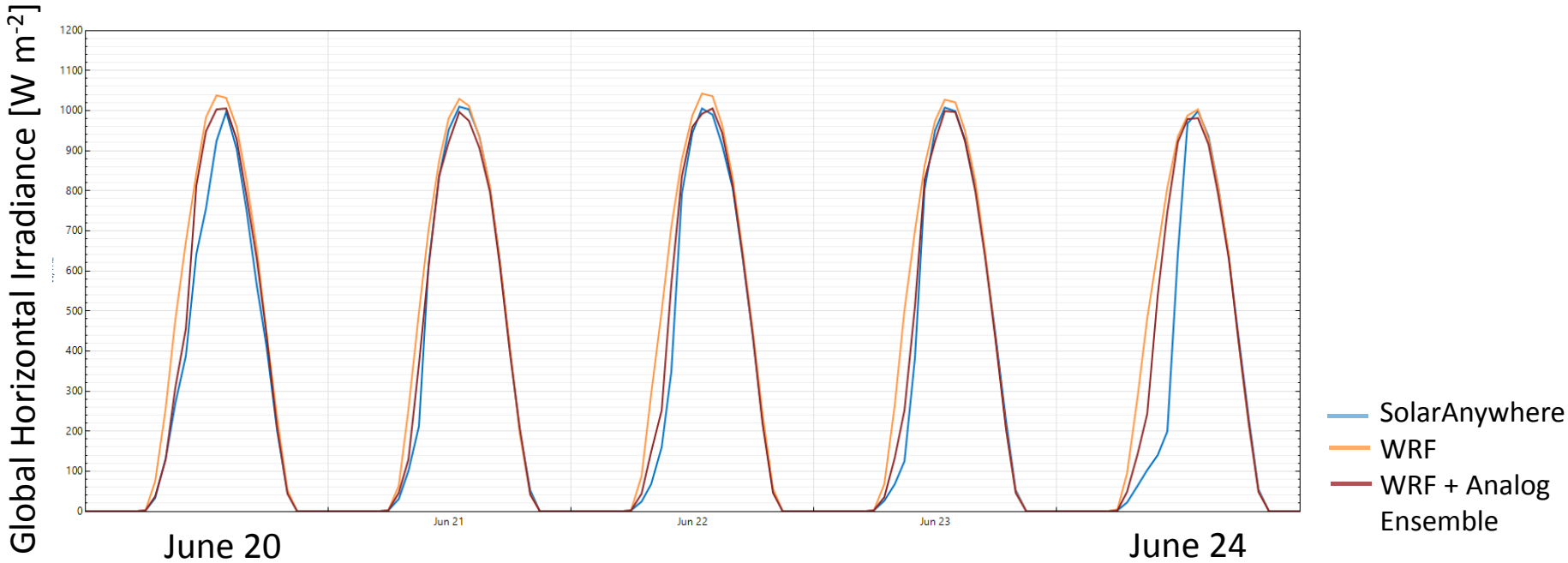
SDG&E Distributed Energy Resource Management System (DERMS)



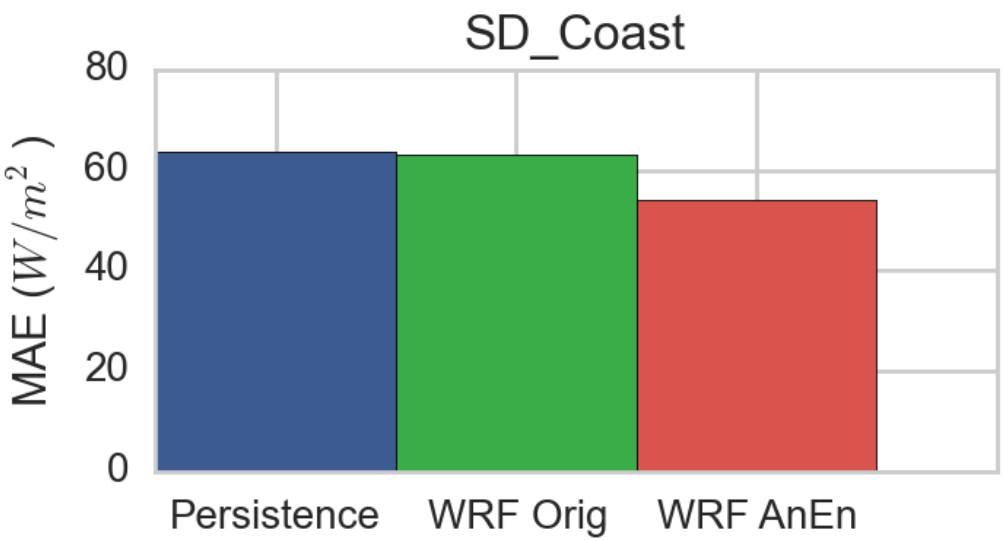
- Systemwide load flow analysis
  - Switching
  - Emergency Operations
  - Forecasts used operationally
- Solar forecast input as Solar Potential Index by Climate Zone
  - 0600 PT Delivery Time
  - Hourly for intra-day and day-ahead

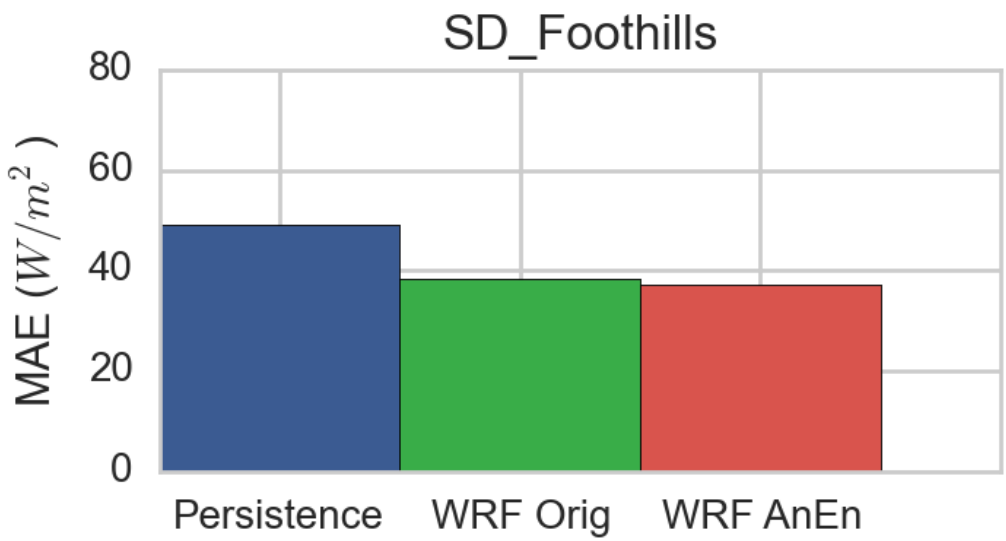
Validation

- Against SolarAnywhere satellite data and SDG&E ground stations
  - By climate zone
- Original WRF and Analog Ensemble correction



Monthly mean hourly MAE





Final product (AnEn) improves 20% over smart persistence.

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Task 3: Granular Operational Net Load Forecasting

Carlos F. M. Coimbra and Hugo T. C. Pedro

Center for Energy Research

University of California San Diego

Task description

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- Develop accurate net load forecast models for 68 SDG&E substations and feeders.
- Deploy multi-layer stochastic learning forecast engines to predict the substations and feeders net load.
- Produce intra-hour (5 to 60 min) and multiple days-ahead net load forecasts.
- Use co-located UCSD sky imagers and SDG&E solar irradiance sensors as proxy indicators of cloud cover.

Tools and data processing

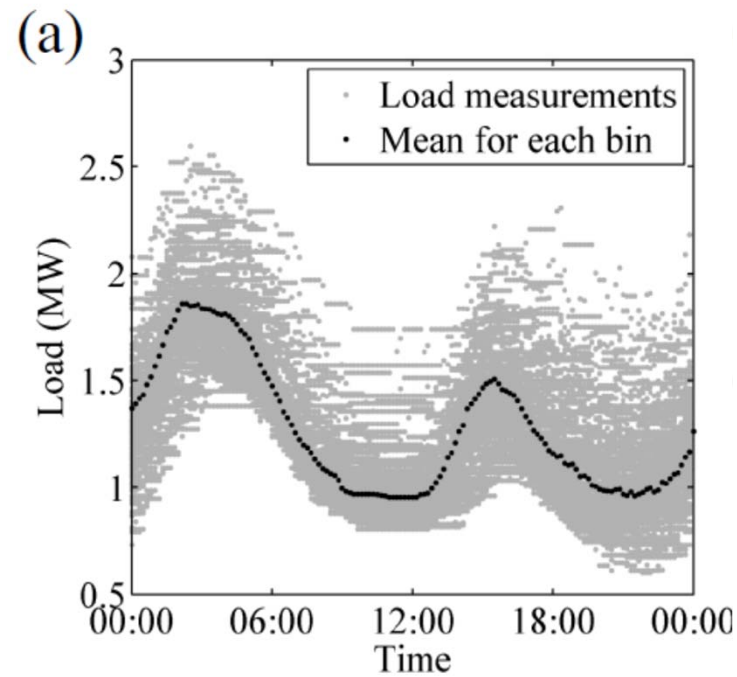
Coimbra Energy Group

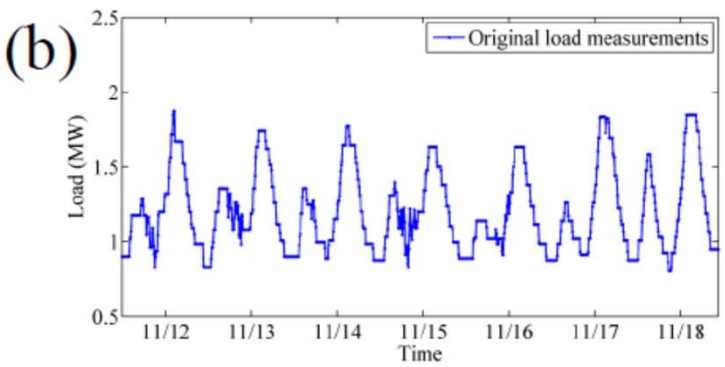
Data De-trending

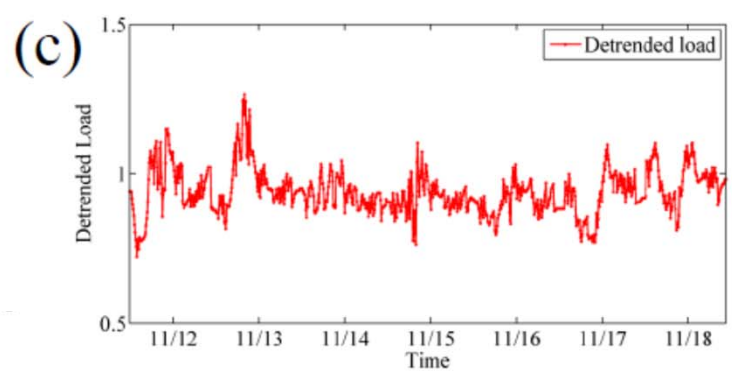
- Attempts to remove daily trend.

  Load = [De-trended Load] x [Daily Trend]

- Daily trends are computed as the mean load in 5 min bins.
- Benefits the performance of the stochastic forecasting models by removing consistent trends in the data.







Solar Forecast Data

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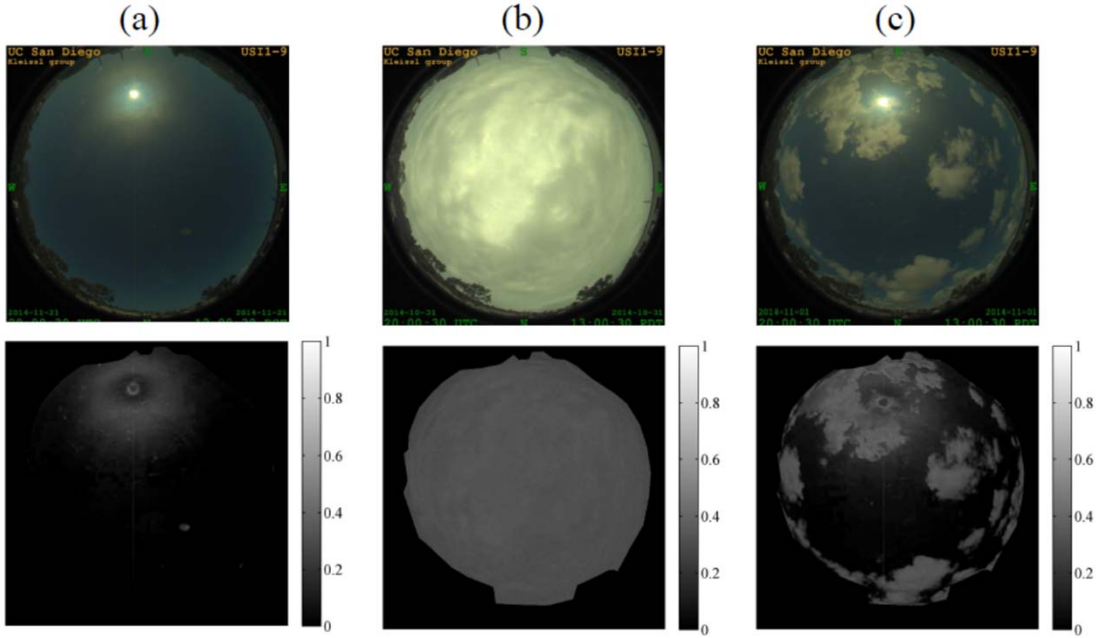
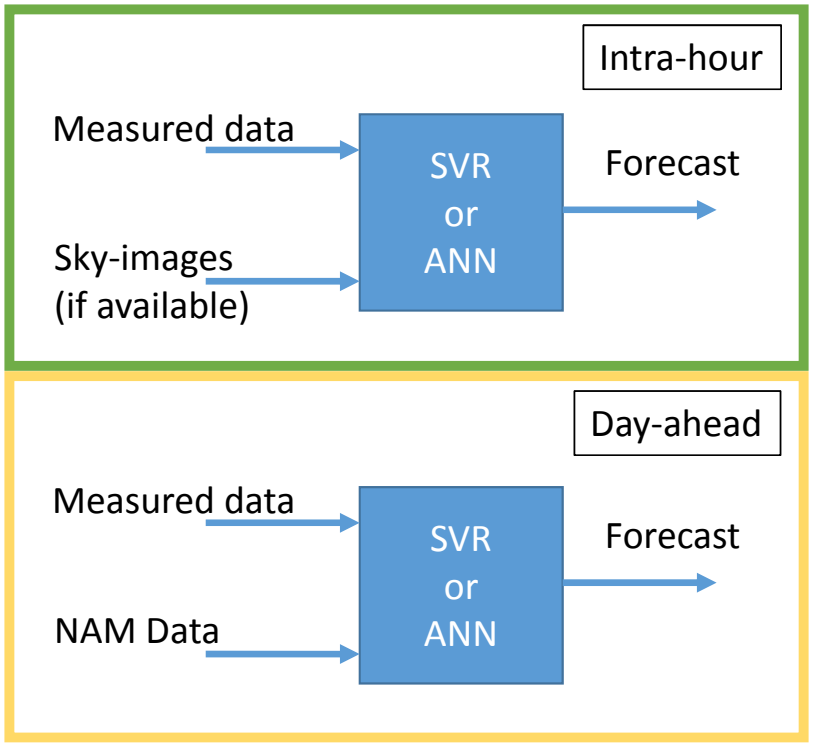
- Sky images are used as input to the intra-hour forecast models
- Normalized Red/Blue ratio (NRBR) image features are extracted .
- These features are used as input to the intra-hour forecast models
- North American Model (NAM) for day-ahead forecasts.



Top: Clear-sky, overcast and partly cloudy images.
Bottom: the resulting NRBR images.

Forecast models

- Three models are used in this work
  - Persistence model
  - Support Vector Regression (SVR)
  - Artificial Neural Networks (ANN)
- Supervised models (ANN, SVR) are trained with historical data and validated against an independent testing set.
- Validation metrics: MBE, RMSE, MAPE, etc.



Forecast Results

Coimbra Energy Group

Intra-hour forecast: Time Series

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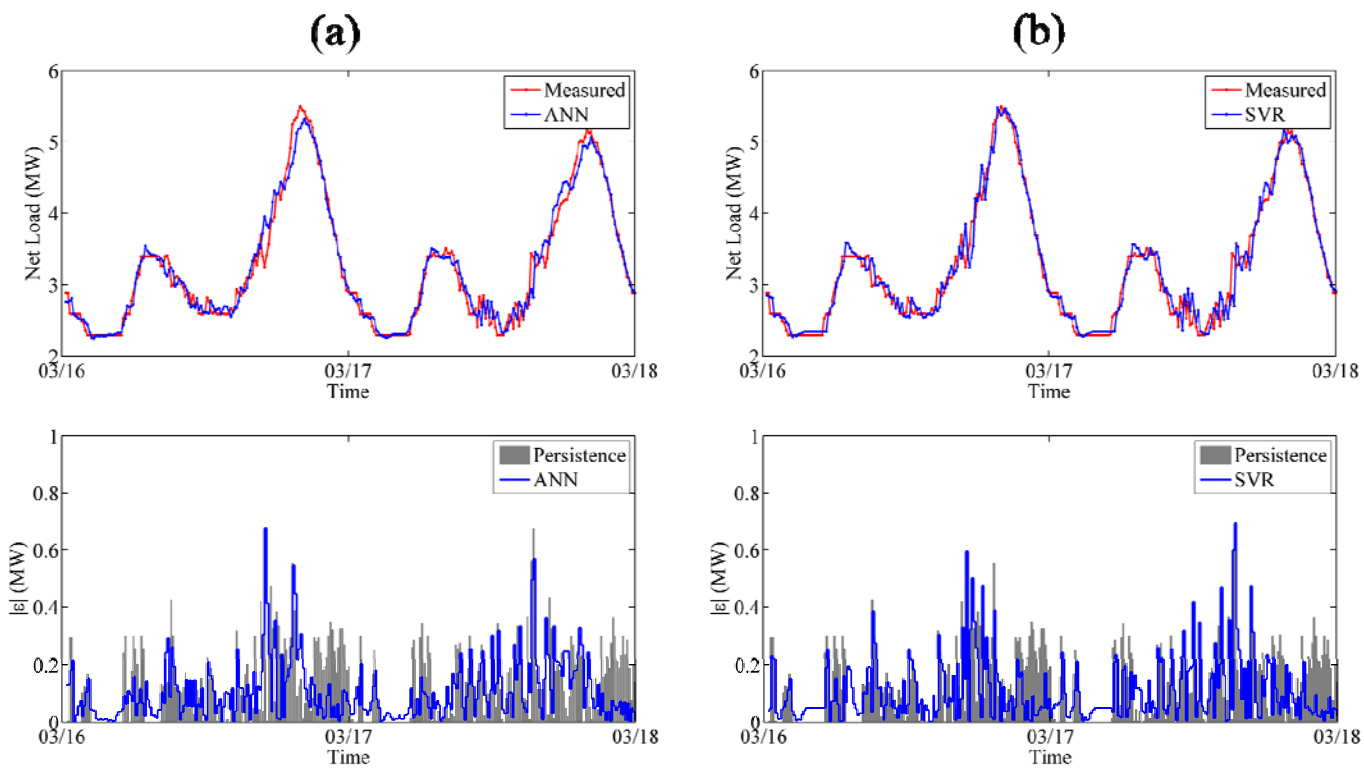

Sample time series of net load forecasts and absolute forecast errors (ε) for the Feeder B for a period of 48h using (a) ANN and (b) SVR. The timestamps indicate midnight (00:00) PDT.

Intra-hour forecast: Error metrics

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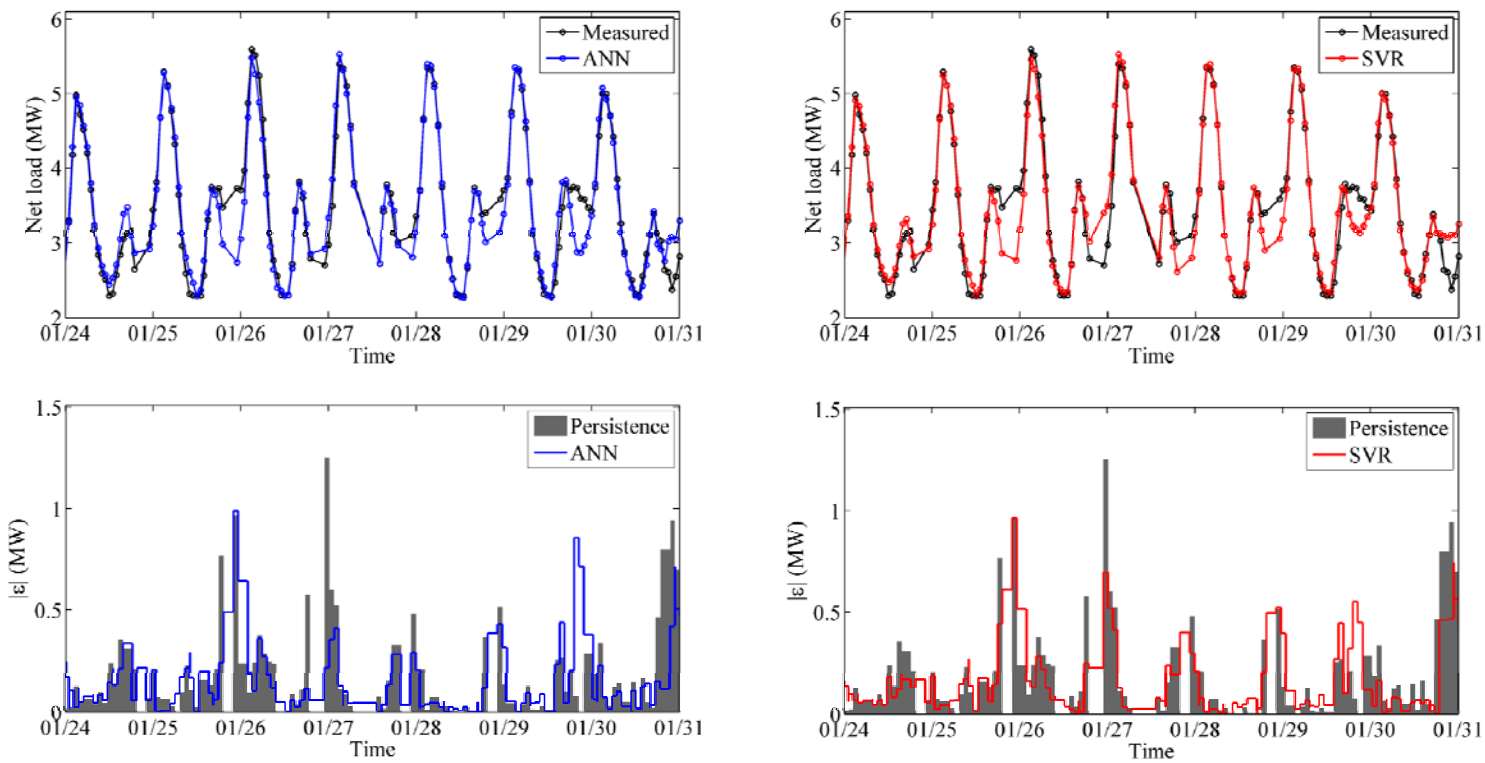
		Feeder A			Feeder B		
Forecast Horizon	[min.]	10	20	30	10	20	30
Per	MAPE	0.020	0.037	0.052	0.020	0.035	0.049
	rRMSE	0.043	0.066	0.084	0.056	0.092	0.127
ANN	MAPE	0.024	0.039	0.050	0.018	0.026	0.033
	rRMSE	0.040	0.059	0.071	0.044	0.063	0.080
ANN with Im-ex	MAPE	0.025	0.037	0.042	0.018	0.024	0.028
	rRMSE	0.040	0.056	0.064	0.044	0.059	0.073
SVR	MAPE	0.032	0.044	0.053	0.019	0.026	0.032
	rRMSE	0.044	0.060	0.072	0.045	0.063	0.079
SVR with Im-ex	MAPE	0.027	0.038	0.043	0.020	0.026	0.029
	rRMSE	0.046	0.061	0.068	0.048	0.065	0.074

Daytime errors for reference persistence forecasts, endogenous forecasts (just measured data used as input), and forecasts with image data for 10-, 20-, and 30- minute horizons. The red boxes identify the best model as a function of the relative RMSE.

Day-ahead forecast: Time Series



Sample time series of 2-day ahead net load forecasts (top row) and absolute forecast errors (bottom row) for the Feeder B for a period of 1-week using ANN (left column) and SVR (right column). Persistence forecast errors are shown for reference in grey. Timestamps are in UTC.

Day-ahead forecast: Error metrics

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		1 day ahead			2 days ahead		
		Persistence	**ANN**	**SVR**	**Persistence**	**ANN**	**SVR**
MAPE	Feeder A	0.103	0.1	0.095	0.119	0.11	0.098
	Feeder B	0.054	0.053	0.052	0.066	0.062	0.06
	Feeder C	0.079	0.087	0.08	0.104	0.103	0.101
	Feeder D	0.094	0.086	0.087	0.118	0.102	0.106
rRMSE	Feeder A	0.473	0.442	0.421	0.522	0.505	0.428
	Feeder B	0.267	0.253	0.249	0.33	0.308	0.293
	Feeder C	0.156	0.165	0.158	0.207	0.197	0.202
	Feeder D	0.178	0.16	0.166	0.225	0.196	0.204

Net load forecasting results for 1 and 2 days forecast horizon for four feeders. The red boxes identify the best model as a function of the relative RMSE and MAPE.

Conclusions – Net Load Forecasting

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- Intra-hour and multiple day-ahead forecasts were successfully developed for the 68 SDG&E substations.
- The models were assembled into forecasting engines that are ready to be deployed in real time.
- Very small latency allows for operational forecasts if real-time telemetry data is made available.
- Data de-trending and image processing algorithms were implemented to improve the performance of all forecasts

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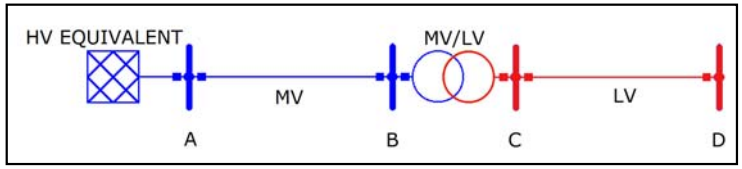
Q&A #1

Task 4.1: Distribution Feeder Hotspots

Voltage Rise due to PV

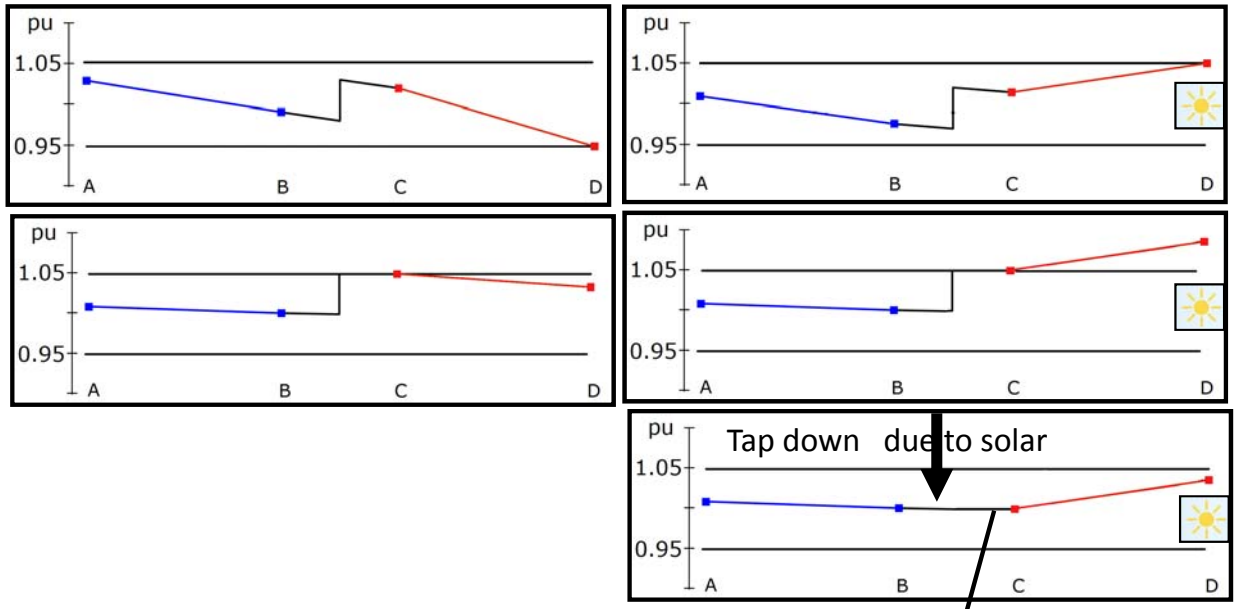
Simplified power system



base case | **with PV**

Max. Load

Min. Load



On-Load Tap Changer

[1]: IEA, Report IEA-PVPS T5-10, 2002

14 SDG&E Distribution Feeders

Circuit ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Feeder Type	urban	urban	urban	Urban	urban	urban	urban	urban	urban	urban	urban	rural	rural	rural
Total Feeder length (km)	53	58	41	45	52	55	49	56	45	51	40	35	52	**115**
# Supply Transformers	298	312	285	243	416	324	212	139	260	376	322	281	276	**649**
Peak Load (MVA)	8.0	9.7	9.5	5.9	10.8	13.2	9.8	8.8	8.0	**13.6**	8.4	4.9	3.9	6.3
# Capacitors / Rated Reactive Power (MVar)	1/ 1.2	1/ 1.2	3/ 1.2, 0.8, 1.2	1/ 1.2	1/ 1.2	1/ 1.2	(3)*/ 1.2, 1.2, 1.2	2/ 1.2, 1.2	1/ 1.2	**4**/ 1.2, 1.2, 1.2, 1.2	(2)*/ 1.2, 1.2	(2)*/ 1.2, 1.2	(1)*/ 1.2	(1)*/ 1.2
# Substation Transformers and Voltage Regulators	1	1	1	1	1	1	1	1	1	1	1	**2**	**2**	**2**
# PV systems	180	105	106	83	95	62	69	147	66	71	340	**364**	104	387
Peak PV output (MW_{AC})	1.9	1.1	0.7	0.8	0.9	0.8	0.8	1.9	1.1	1.3	**5.1**	1.3	2.7	2.4
2015 PV Penetration Level (%)	24	12	7	13	8	6	8	22	14	9	60	51	**71**	38
Substation set-point voltage (pu)	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.01	0.98	0.99	1.01

Hotspot Criteria

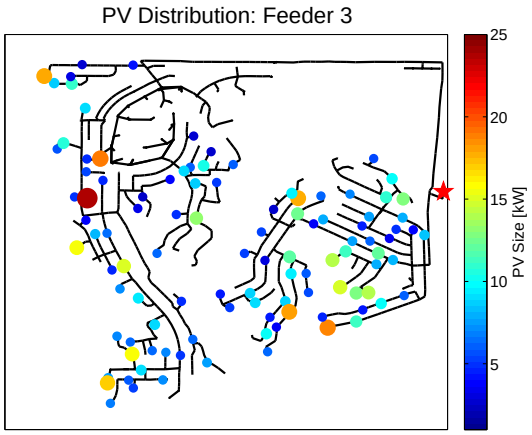
PV penetration (installed PV capacity / load peak) from 0 to 300%.
Hotspots consist of:

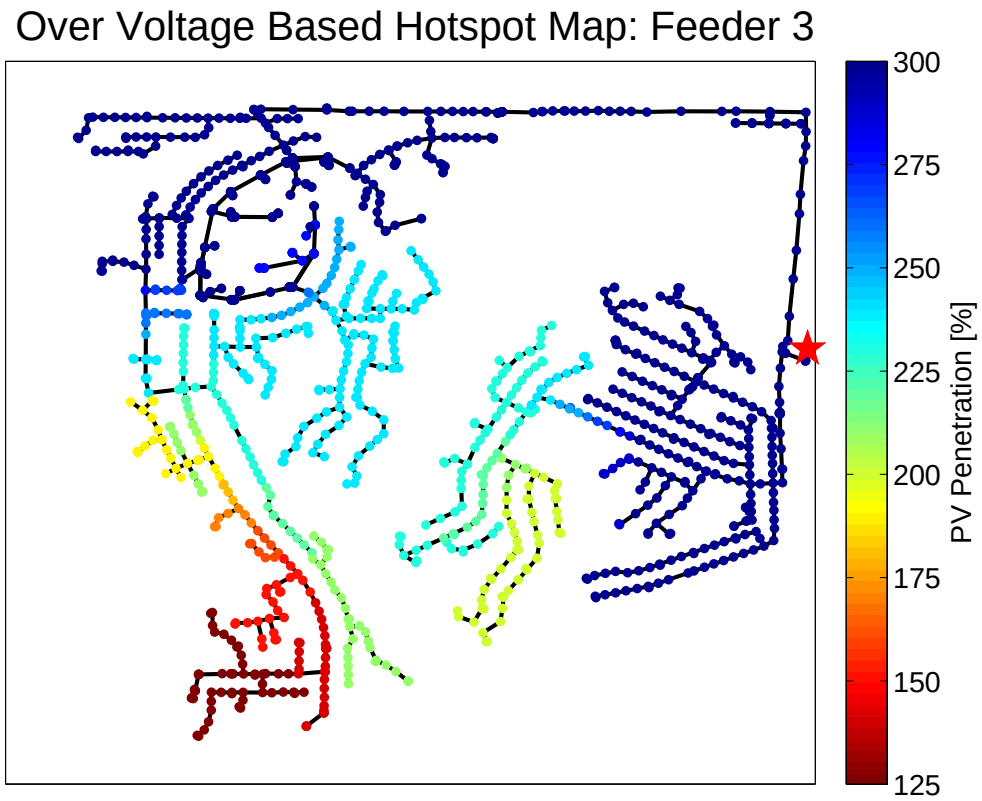
- Over- or under-voltage at a node that exceeds ±5% of a nominal 12 kV
- Steady-state power flow that exceeds the thermal rating of the conductor

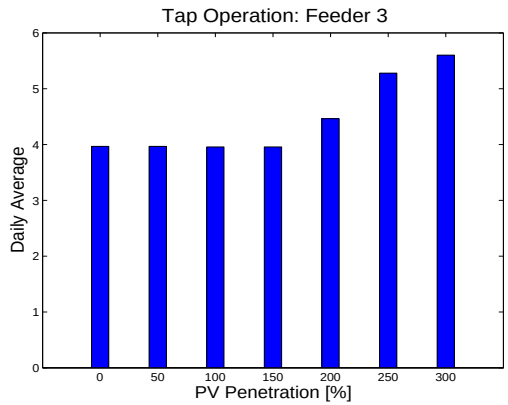
Also quantified:

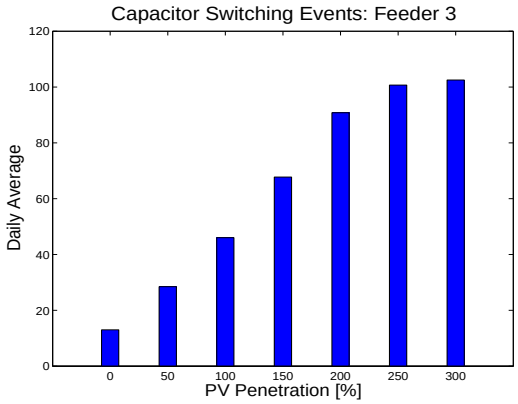
- On-Load Tap Changer (OLTC) operations
- Capacitor switches
- Voltage variability (step changes in voltage)

Sample Results for Feeder 3









All feeders

Feeder ID	Existing PV Pene-tration	Lowest PV Penetration Coinciding with a Hotspot	Max Voltage Variability at Lowest PV Penetration Coinciding with a Hotspot	Transformer Tap Changes at 0% PV [/day]	Tap Changes at 300% PV Penetration [/day]	Rating of conductor/s creating a feeder hotspot at lowest PV penetration	Trunk Section Rating
1	24%	280%	2.0%	3.7	3.7	130 A	700 A
2	12%	250%	4.2%	4.5	4.5	500 A	580 A
3	7%	125%	3.0%	4.0	5.6	180 A	700 A
4	13%	200%	2.2%	1.6	2.8	180 A	770 A
5	8%	150%	2.4%	4.7	4.2	130 A	770 A
6	6%	125%	3.2%	6.0	8.0	115 A	700 A
7	8%	125%	2.4%	1.0	11	180 A	580 A
8	22%	150%	3.2%	11	9.0	130 A	700 A
9	14%	100%	1.7%	2.7	2.2	130 A	770 A
10	9%	100%	4.7%	9.2	9.7	180 A	580 A
11	60%	100%	2.6%	2.0	9.5	15 A	520 A
12	51%	260%	1.5%	3.5	10	180 A	520 A
13	71%	250%	3.0%	18	44	130 A	520 A
14	38%	100%	5.2%	31	78	180 A	770 A

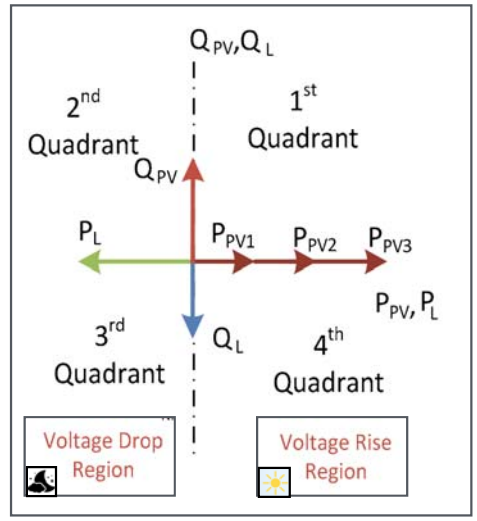
Conclusions – Feeder Hotspots

- Most feeders have a hosting capacity far exceeding 15%
  - Many feeder sections show no issues even at 300% penetration
- Most hotpots arise on feeder branches.
- Some short-term voltage variability issues.
- Tap operations:
  - On 6 feeders no change from 0 to 300%
  - Large increase on some other feeders

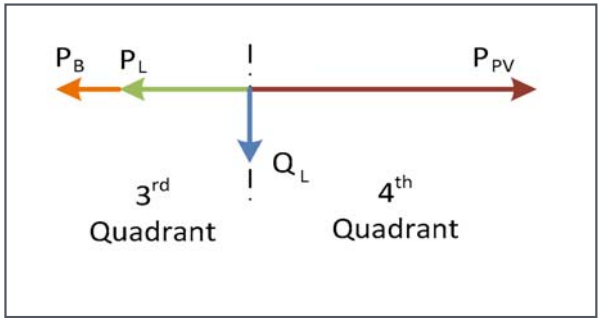
Task 4.2: Energy Storage Siting and Sizing

How to cope with solar PV adoption?

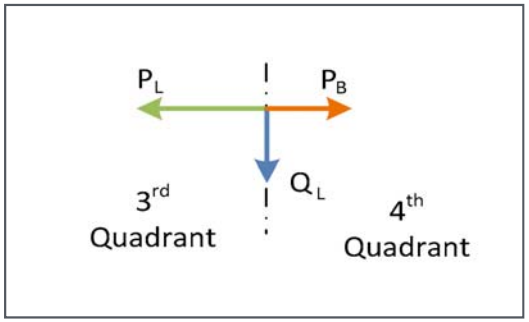
BESS: Battery Energy Storage Systems



Battery charging

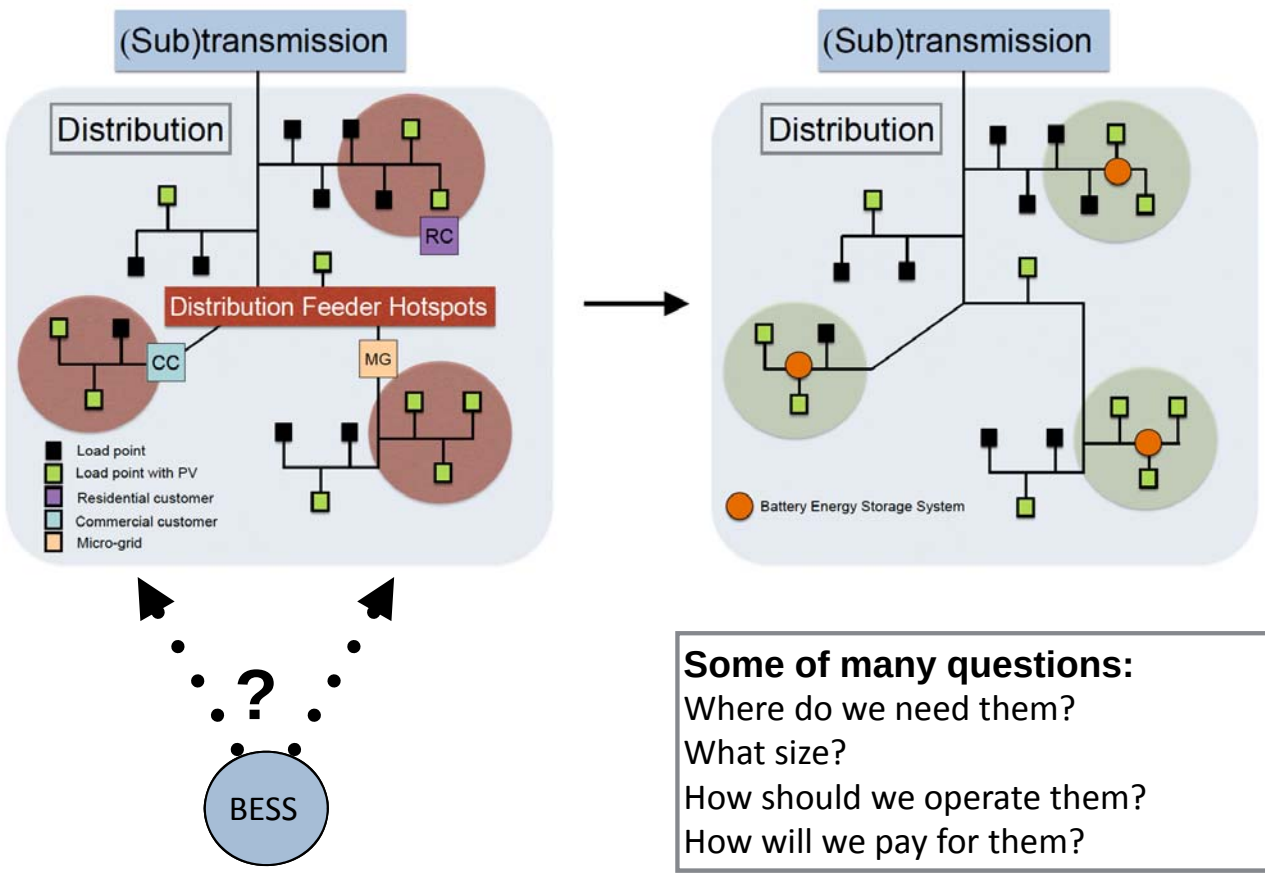


Battery discharging



[1]: Alam et al., "Distributed energy storage of mitigation of voltage-rise impact caused by rooftop solar PV"

But how to allocate batteries in the grid?



Some of many questions:
Where do we need them?
What size?
How should we operate them?
How will we pay for them?

BESS: Battery Energy Storage Systems

Problem Formulation

The goal: **What: To optimally site and size BESS(s)**
Where: Anywhere in a distribution network
Why: To mitigate voltage fluctuations caused by solar PV

$$\max \quad \lambda_{\text{cost}} \cdot \bar{V}_{\text{dev-reduction}}$$

λ_{cost} cost penalty parameter

$\bar{V}_{\text{dev-reduction}}$ voltage deviation reduction

where

$$\lambda_{\text{cost}} = f(n_s, k_s)$$

$$\bar{V}_{\text{dev-reduction}} = f(n_s, k_s)$$

$$k_s = \{k_1, \ldots, k_m\}$$

$$n_s = \{l_1, \ldots, l_m\}$$

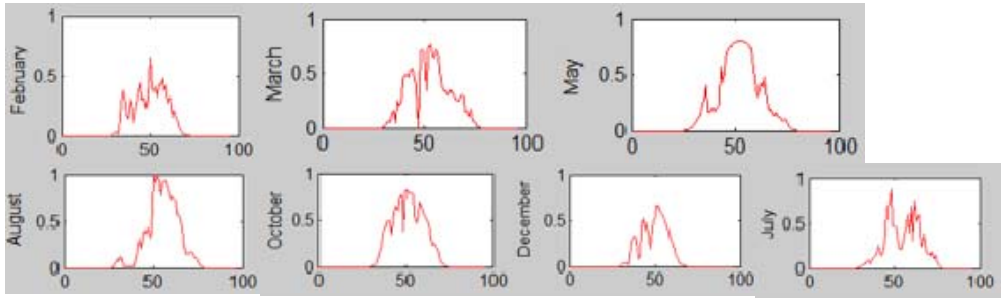
$$\{n_s, k_s\} \in C(N_{all}, K_{all})$$

n_s: system locations of a set
k_s: system capacities of a set
m: # of systems
N_{all} : permissible maximum locations
K_{all} : permissible system locations

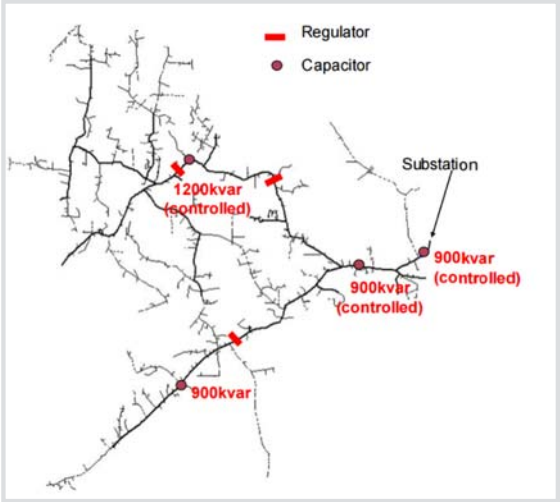
Data and Test Network

Solar Data:

15-minute solar PV output data from UC San Diego campus systems during the year 2014



IEEE8500 test feeder one-line diagram



Load Data:

15-minute synthetic data generated for San Diego region by Open Energy Information during the year 2014

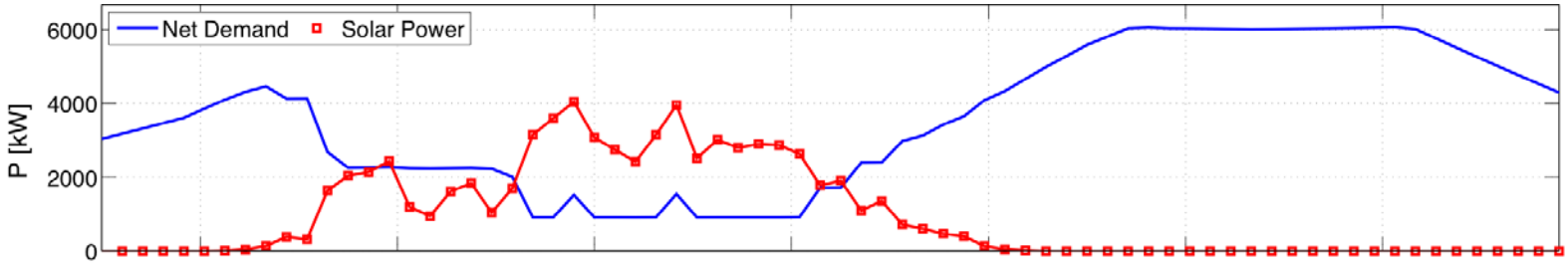
Test Network:

Radial distribution feeder with multiple feeder regulators and capacitors with balanced 120V secondary loads on the service transformers.

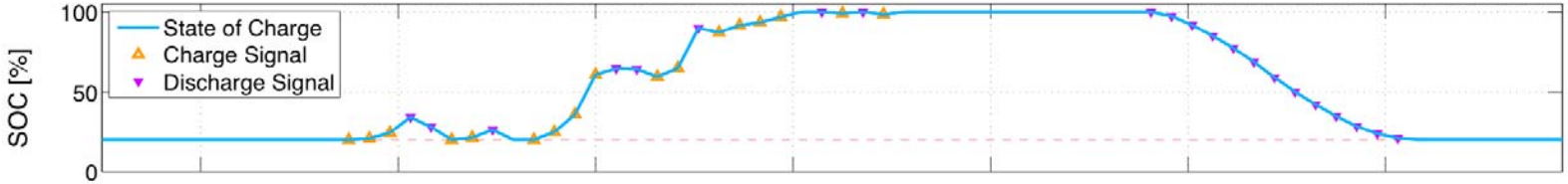
Example power-flow simulation overview

Power Flow for PV + BESS case

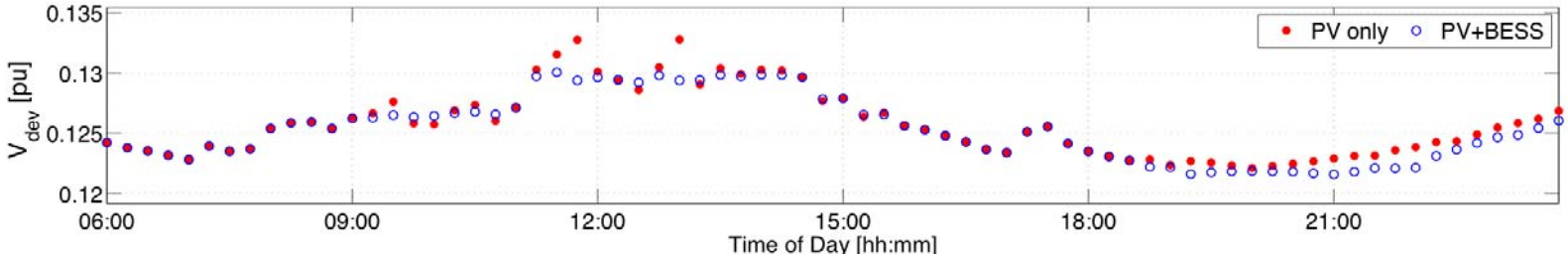
Aggregated Solar Resource and Load - PV - BESS at Substation



Operation of Batteries



Voltage Deviations in PV and PV+BESS case

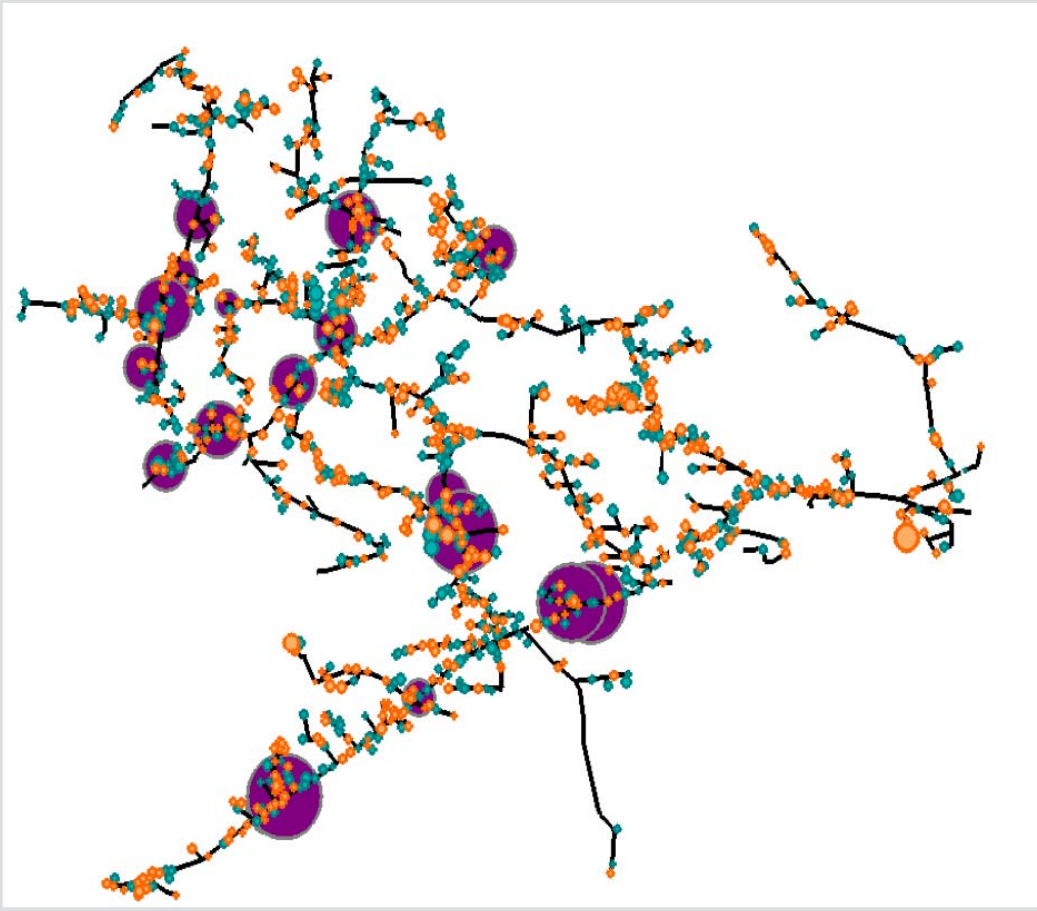


Sample results – siting and sizing

645 permissible nodes on the primary lines.

50% PV penetration for a partly cloudy day.

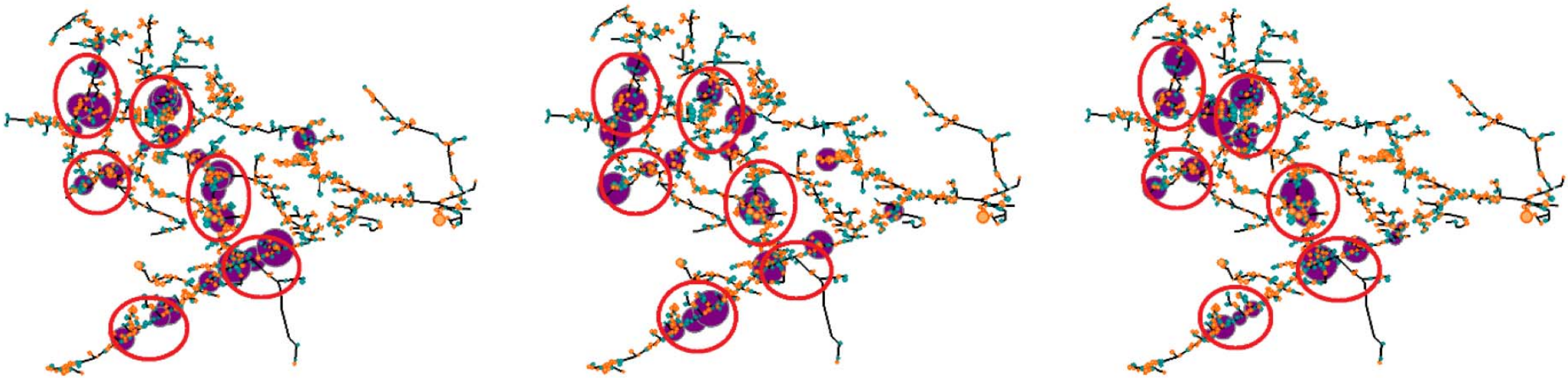
BESS units (**purple)**.
Loads with PV (**Orange**)
Loads (**turquoise**)
Each dot sized to the capacity.



Siting Convergence

- 3 different model runs with the same settings
- 6 frequently chosen node clusters shown with red circles.
- Consistent clusters emerge

IEEE8500 test feeder with 50% PV penetration for a partly cloudy day.

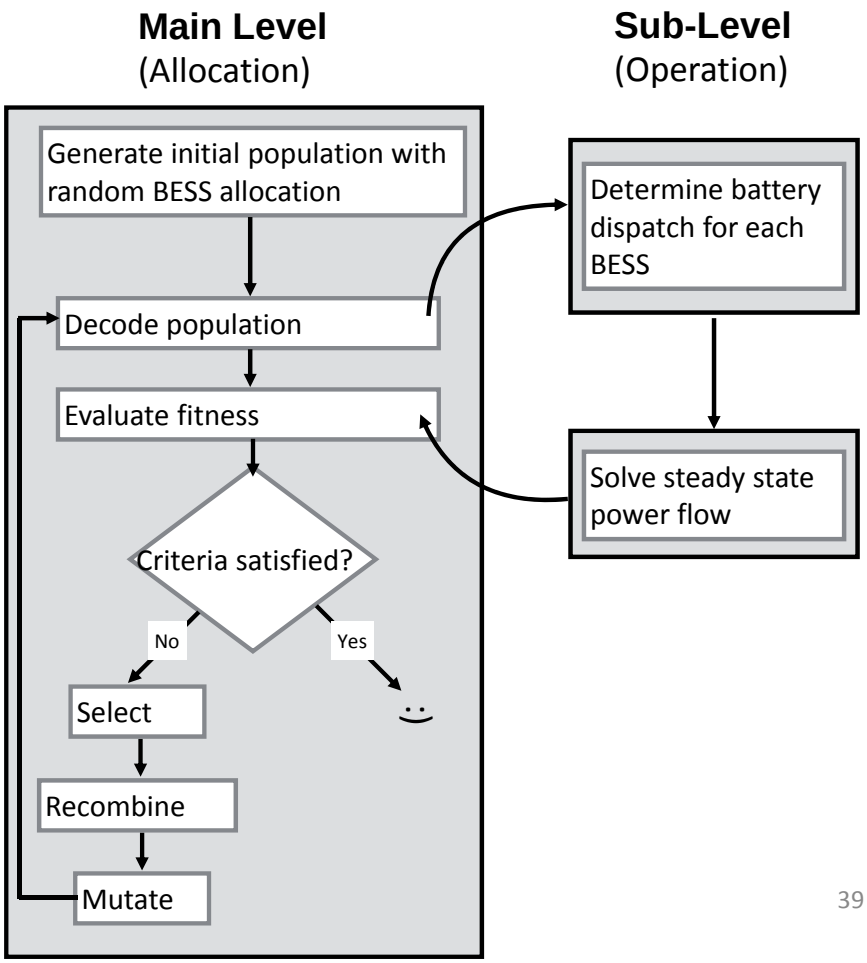


Conclusions – Battery Siting and Sizing

Novel Genetic Algorithm-based bi-level allocation optimization method

1. **Peak shaving** for aggregated customers helps voltage mitigation.

2. Proposed method has well-behaved **convergence in small siting sets.**



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Q&A #2

Task 4.3: Understanding and Counteracting Real Power Oscillations

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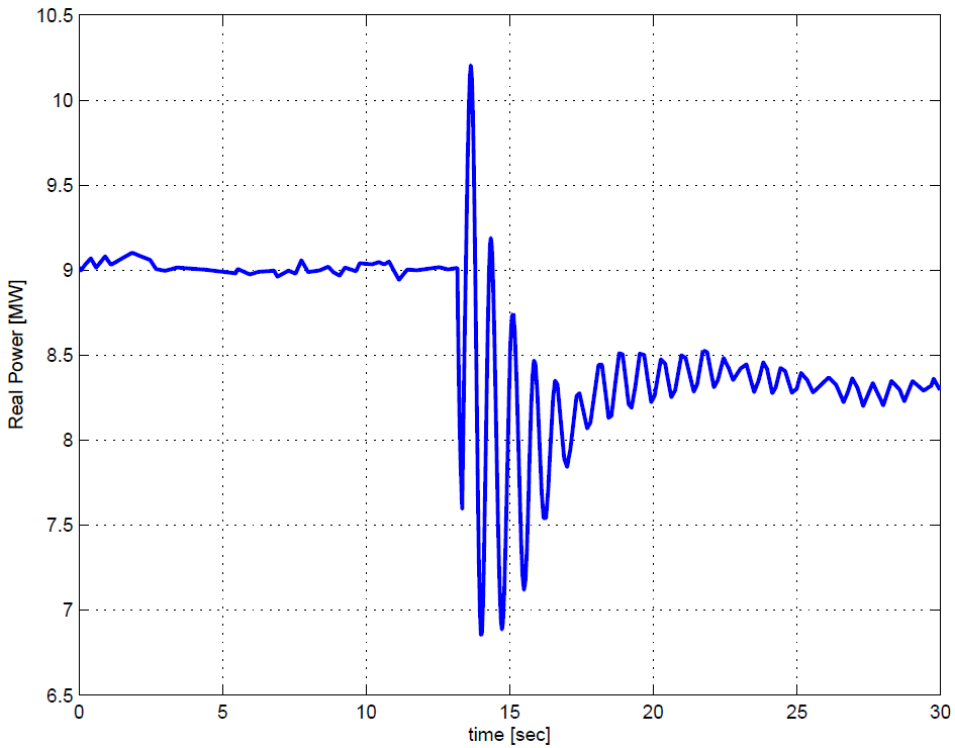
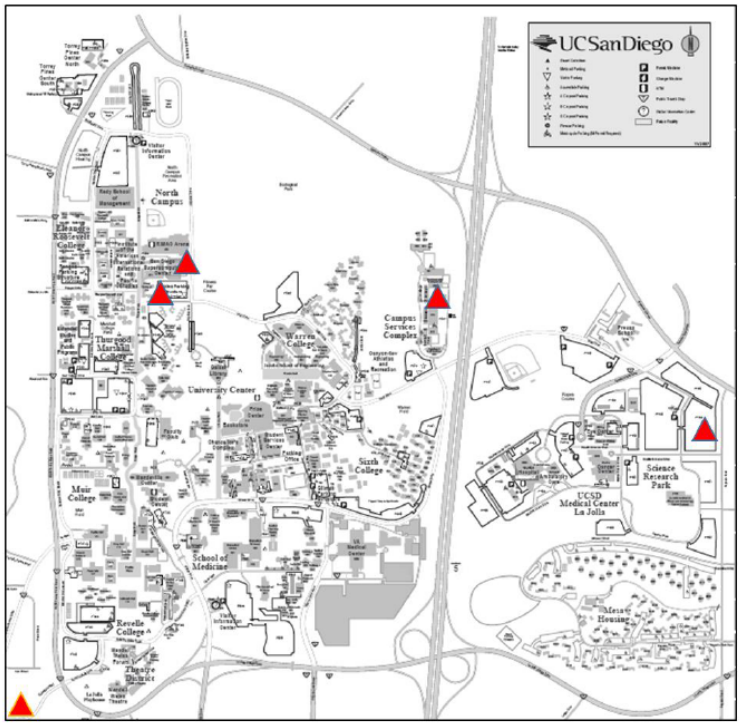
Motivation

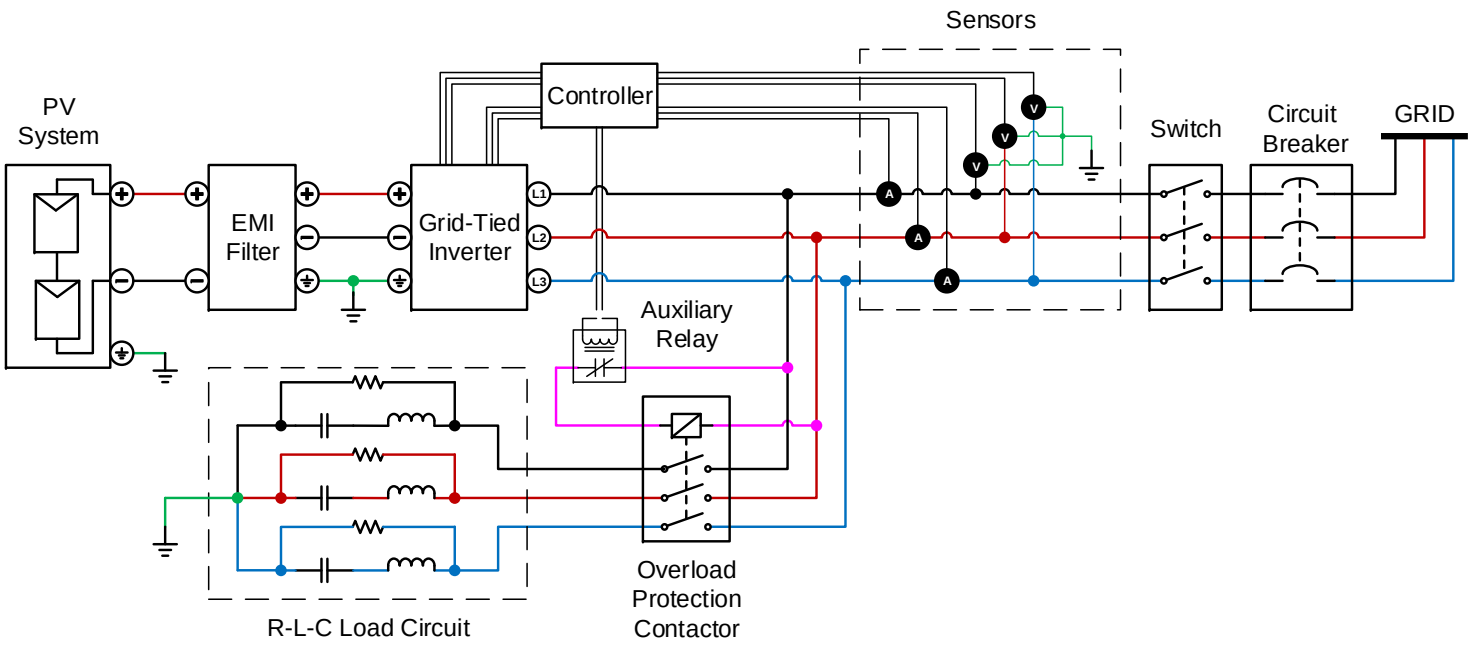
PMU measurements and real power oscillations on micro-grid





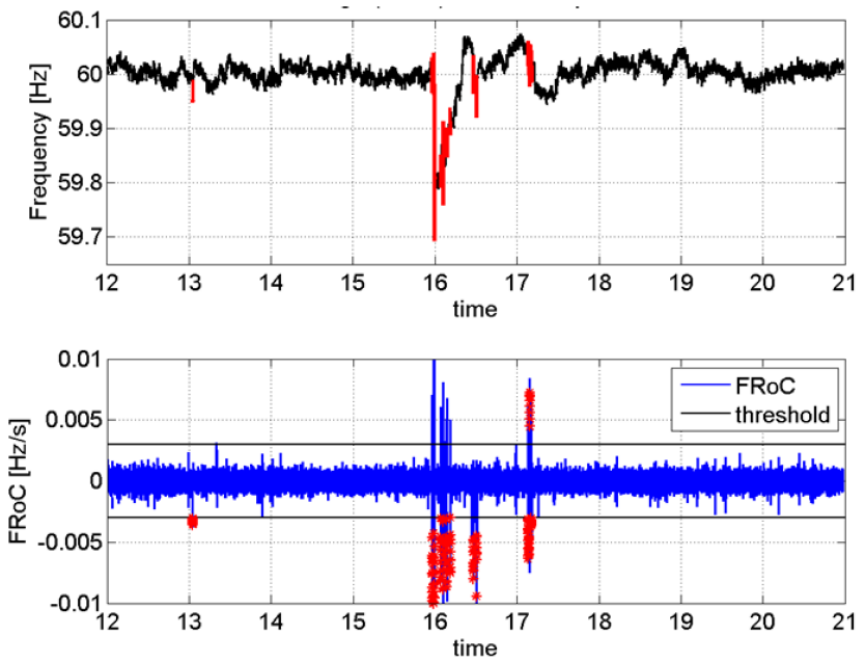
Experimental Setup

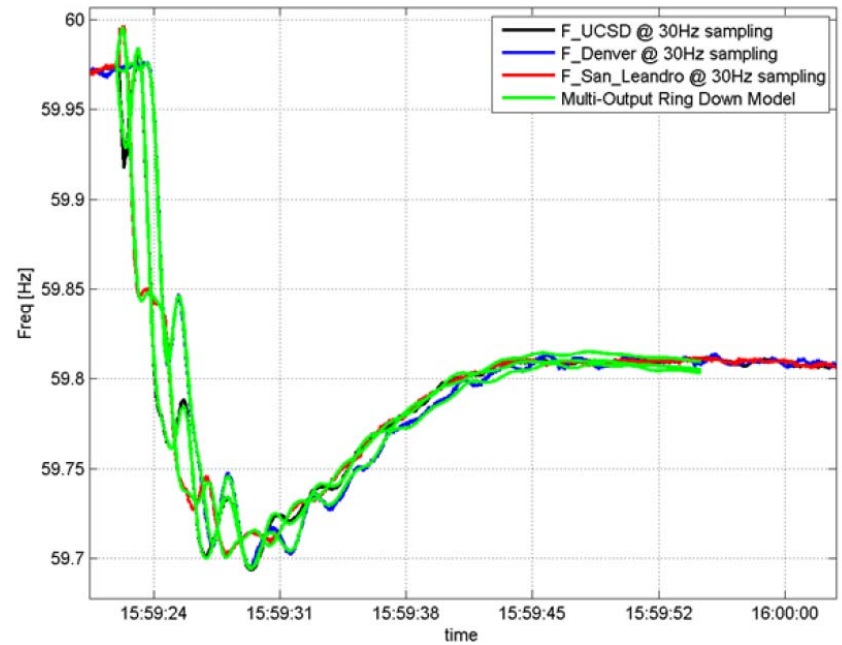
Testbed for control of AC power flow – system diagram



Event Detection and Model Fitting

- Left: Event detection based on by adaptive threshold crossing of filtered rate of change signal
- Right: Event modeling using step based realization algorithm





Conclusions – Counteracting Power Oscillations

- Real-time detection of power oscillations
- Characterized actuator and disturbance dynamics
  - Model grid events
- Actuate inverter to counteract grid oscillations

Overall Conclusions

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- All distribution feeders have large solar hosting capacity
  - Voltage issues often confined to small areas of the feeder.
  - Improved coordinated voltage regulator action will further increase hosting capacity.
  - Smart inverters will further increase hosting capacity.
- Battery storage can be sited systematically
  - Optimize benefits for grid operation.
  - Prevent outages by counteracting oscillations.
- Lower integration costs for solar photovoltaic.