

Real Time Voltage Stability Assessment, Monitoring and Control in the New Environment

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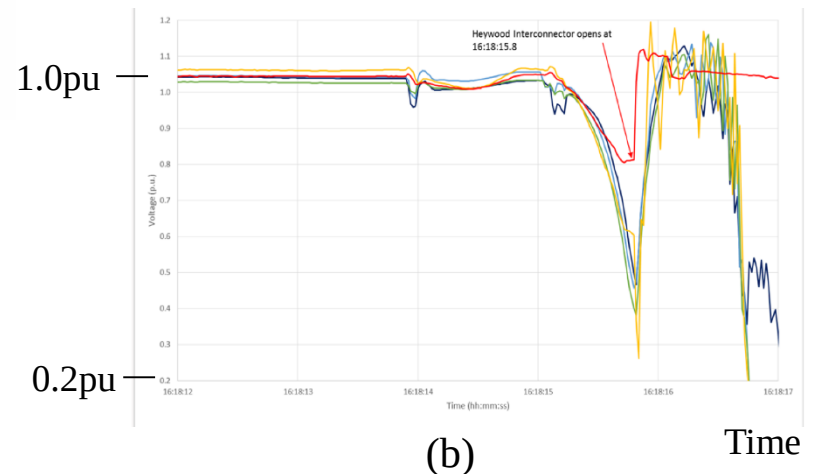
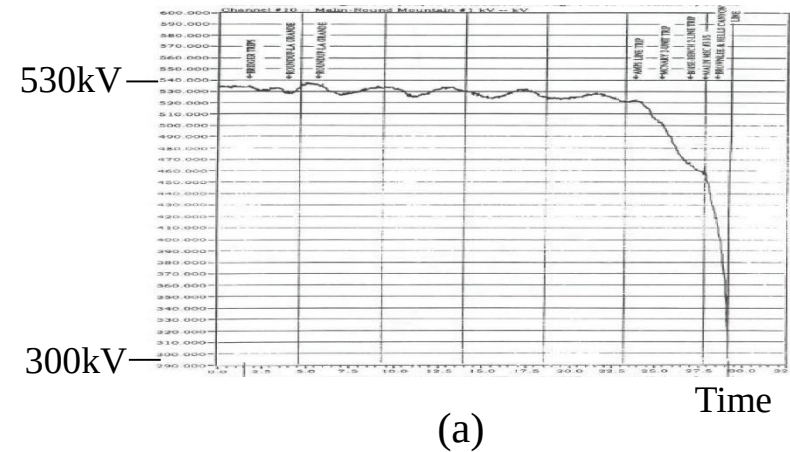
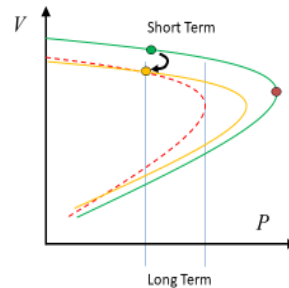
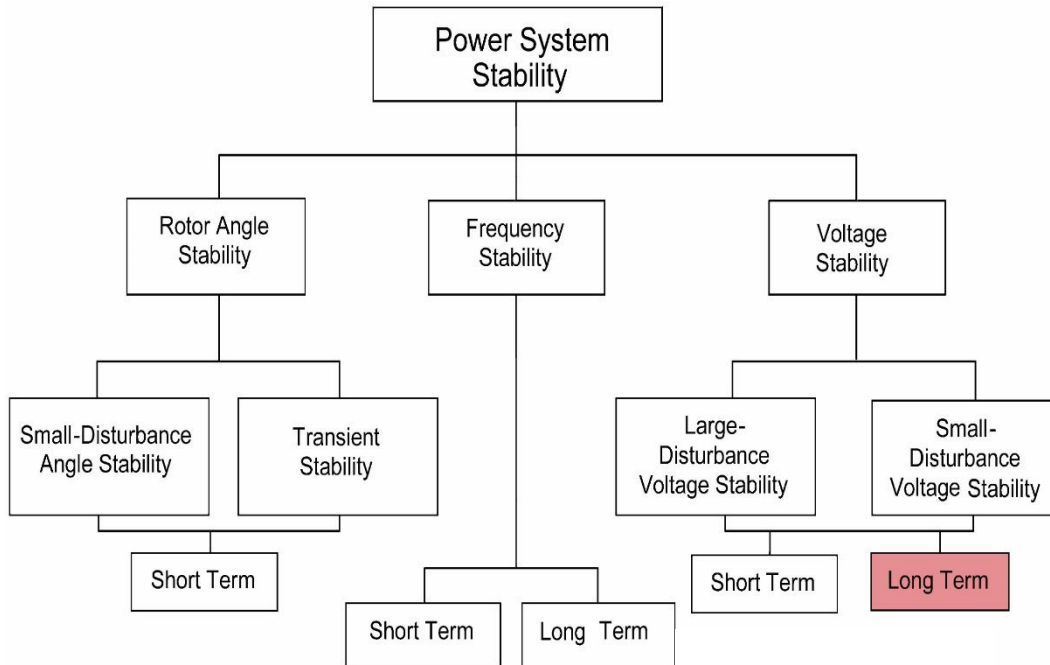


PSERC Webinar
March 6, 2018

Presentation Outline

- **Brief Introduction to Voltage Stability**
- **Real Time Voltage Stability Monitoring and Control**
 - **Long Term**
 - Reactive power reserves and voltage stability
 - Adaptive local linear regression for on line prediction and control
 - **Short term**
 - Delayed Voltage recovery
- **Cyber-Physical Real Time Test Bed**
- **The need for new tools/solutions for the future grid**
 - Distributed Energy Resources(DERs)
 - Demand Side Control
- **Overall Conclusions**

Introduction



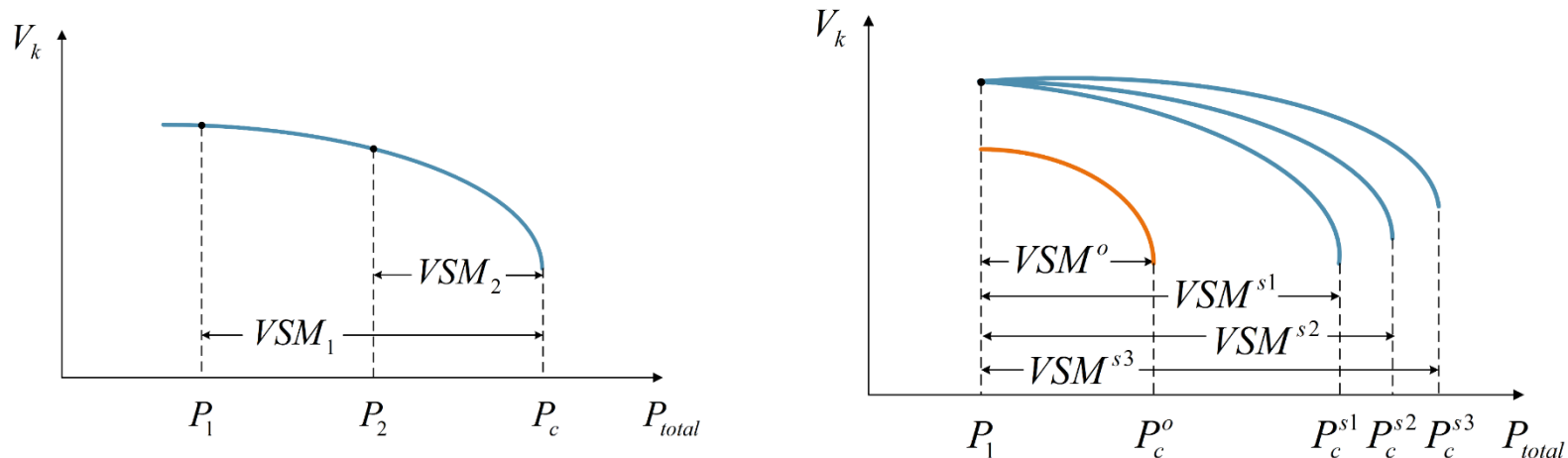
Classification of power system stability¹

1. P. Kundur, J. Paserba, V. Ajjarapu, Andersson, G.; Bose, A.; Canizares, C.; Hatziargyriou, N.; Hill, D.; Stankovic, A.; Taylor, C.; Van Cutsem, T.; Vittal, V. "Definitions and Classification of Power System Stability" IEEE/CIGRE Joint Task Force on Stability Terms and Definitions, IEEE transactions on Power Systems, Volume 19, Issue 3, pp. 1387-1401 August 2004

Voltage evolutions in blackouts.
(a) WECC, July 2, 1996. (b) Australia, 2016.

Long Term Voltage Stability

- Involves slow acting equipment:
 - Tap changing transformers
 - Thermostatically controlled loads
 - Generator current limiters
- Instability is due to the loss of long-term equilibrium
- In many cases static analysis can be used



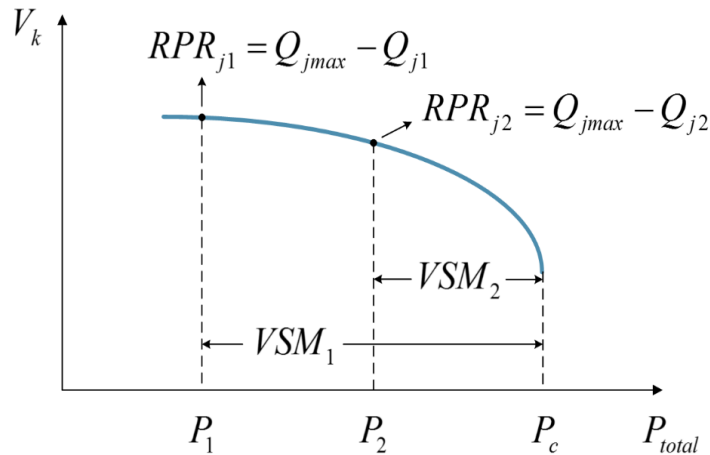
Definition of voltage stability margin (VSM)

Reactive Power Reserves and Voltage Stability

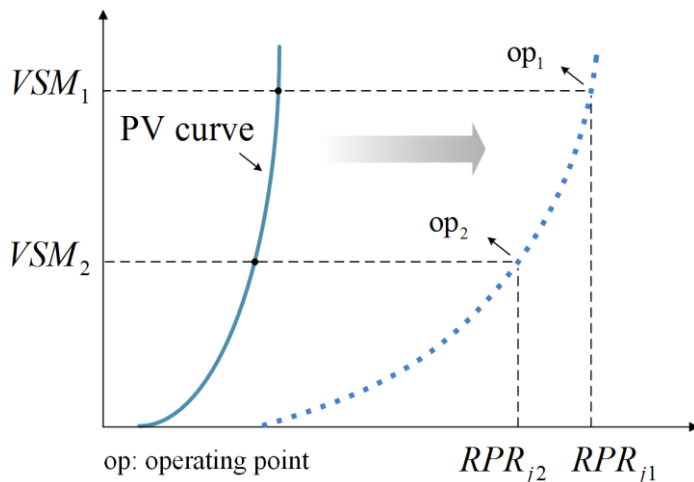
- **Reactive power reserve (RPR):** $RPR_j = Q_{j,\max} - Q_j$
- **Theoretical Connection** between voltage stability and RPR has been justified
- **NERC** (North American Electric Reliability Corporation) has issued **standards** directly related to real-time RPR monitoring and control:

*“Purpose: To ensure that voltage levels, reactive flows, and **reactive resources are monitored, controlled, and maintained** within limits **in Real-time** to protect equipment and the reliable operation of the Interconnection.”* - VAR-001-4.1, Nov. 2015
- **Utilities expect** to tap the potential of existing RPR monitoring in situational awareness

Terminology and problem statement



Definitions of VSM and RPR



Mapping from PV curve to (X, M) pairs

- Selected RPRs: $X \in \mathbb{R}^{1 \times D}$
- VSM: $M \in \mathbb{R}$
- Off-line VSA (voltage security assessment): tracing PV curves under various
 - Contingencies (gen, line, transformer outages)
 - Operating scenarios (operational configurations)
 - LIDs (load increase directions)
- Database: the set of (X, M) pairs / operating points
- Problem: design a **learning-based** approach that can **predict** M in **real time**, utilizing the **online** measurements (including X)

Multi-Linear Regression Model (MLRM) Approach²

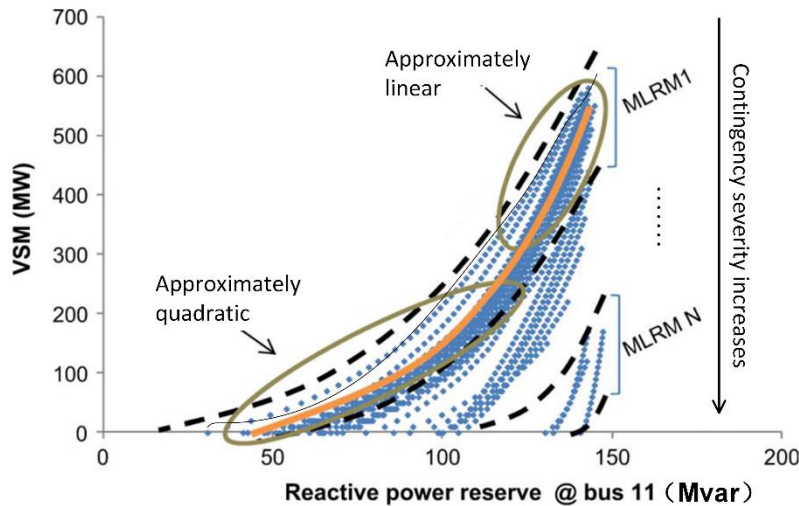


Fig. 5. MLRM approach.

- Data are partitioned into a few groups according to the VSM on base cases
- For each group, suppose the expectation of M is a low degree polynomial of X :

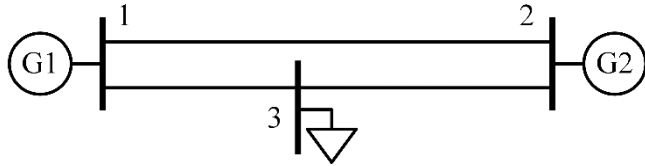
$$\hat{M} = \beta_0 + \sum_{i \geq 1} \beta_i X_i + \sum_{i,j \geq 1} \beta_{ij} X_i X_j + \dots$$

- The coefficients are estimated by ordinary least squares (OLS), or LASSO, ...

- The number of groups is tuned to reach the accuracy requirement on validation set
- A classifier (DT, KNN, SVM, ...), called IDTool, is trained to identify the group of each input
- Voltage magnitudes and active power flows are used as the inputs of IDTool

[2] Leonardi, B.; Ajjarapu, V., "Development of Multilinear Regression Models for Online Voltage Stability Margin Estimation," *Power Systems, IEEE Transactions on*, Feb. 2011.

Limitation of Multi-Linear Regression Model (MLRM)



- The model structure may **not be flexible enough** to globally and accurately describe the discrete & nonlinear underlying relationship

Model

$$\hat{M} = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2 + \hat{\beta}_{12} X_1 X_2 + \hat{\beta}_{11} X_1^2 + \hat{\beta}_{22} X_2^2$$

- Training is purely **off-line**, based on limited operating conditions -> **cannot adapt to** the changing system or rectify bad predictions
- Need an **adaptive model**

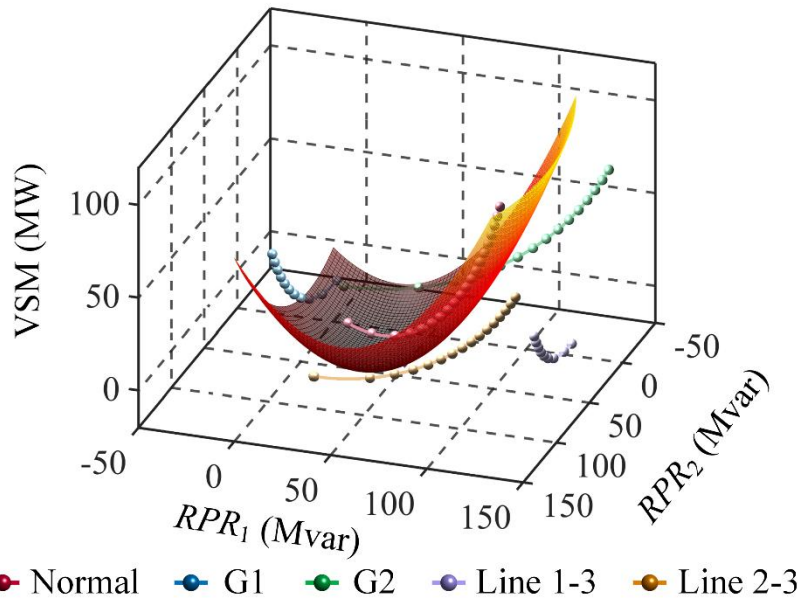


Fig. 6. The underlying RPRs-VSM relationship.

Adaptive Model Via Local Linear Regression²

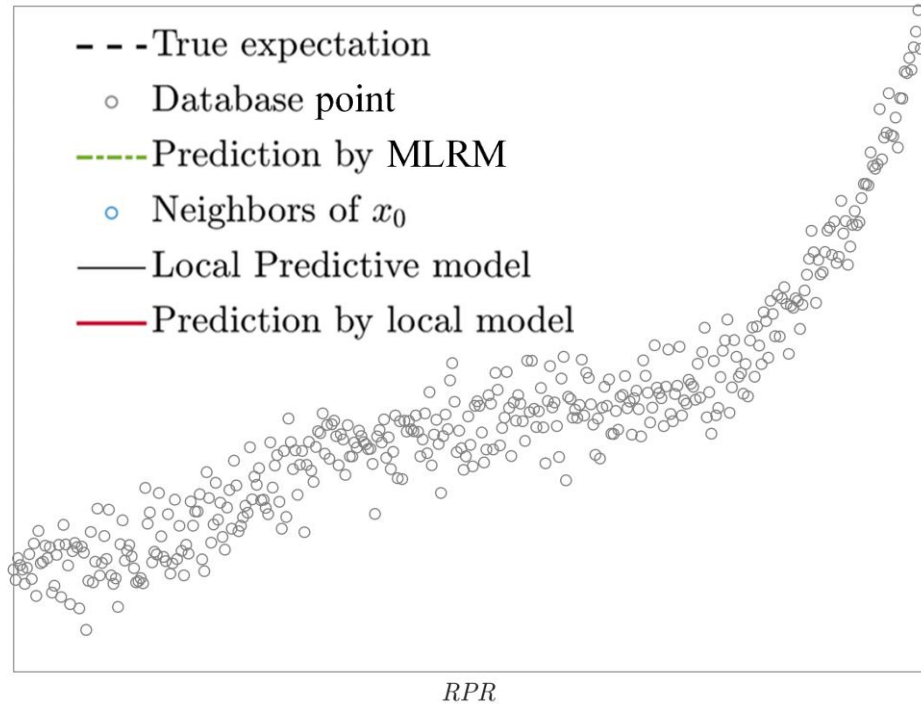
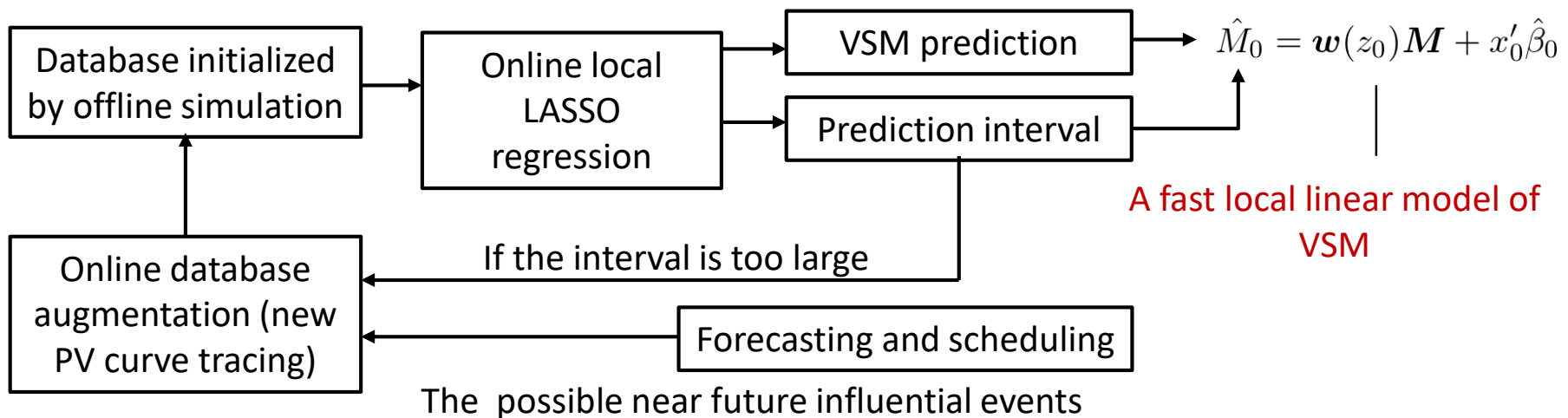


Fig. 7. Prediction on one-dimensional system via local regression

- Main idea: train a **local** model **online** exclusively for current operating point only using the data from similar operating points (neighbors)
- How to define the neighborhood:
 - Space: $Z = [X, V, P_{flow}] \cdot C$, $Z \in \mathbb{R}^{1 \times D'}$
 - C is the projection matrix to remove co-linear data and improve accuracy
 - Metric: Euclidian
 - Size or boundary (K): KNN
- Model structure: locally linear
- Regression algorithm: weighted LASSO ⁹
 - Weights: tri-cubic kernel

Overview of the Monitoring Approach^[3]

- Learning-based approaches: statistical models are trained from historical or simulated data by **supervised learning; directly maps** the online state measurements to VSM
- Proposed framework



[3] Shiyang Li and V. Ajjarapu " Adaptive Online Monitoring of Voltage Stability Margin via Local Regression, IEEE Transactions on Power Systems, Vol. 33, No.1, pp. 701-713, January 2018

Improving the prediction by data augmentation

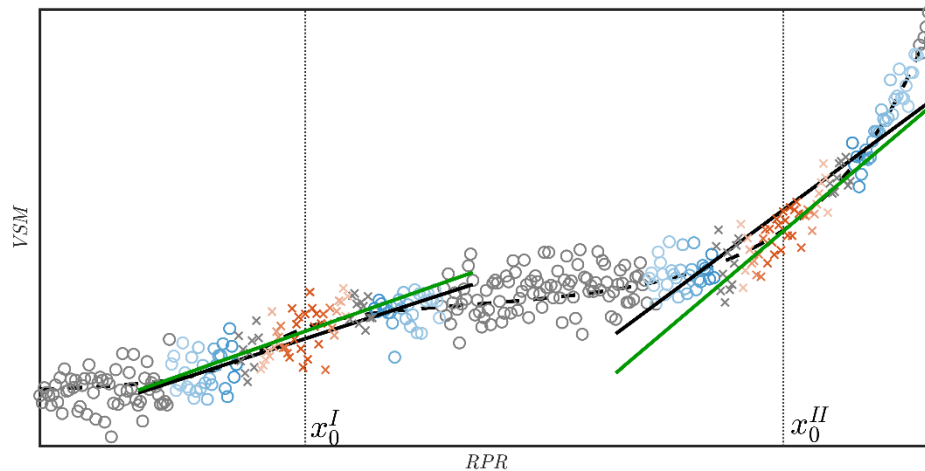


Fig. 9. Prediction is affected by the quality of the neighbors.

- Off-line data cannot cover the whole operating space with enough density everywhere
- But, predictions need “good” neighbors
- So, when the system is operating on some unfamiliar condition (inadequate data), the prediction becomes unreliable
- locally adding relevant data can improve the prediction (data augmentation as an **implicit regularizer**) [3]

[3] Shiyang Li and V. Ajjarapu” Adaptive Online Monitoring of Voltage Stability Margin via Local Regression, IEEE Transactions on Power Systems, Vol. 33, No.1, pp. 701-713, January 2018

Test Results

- Two test systems:
 - IEEE30: 30 buses
 - Practical System: > 60,000 buses

TABLE I
SUMMARY OF THE DATABASE

System	Num_Con				Num_LID	Size	Num_RPR	Num_Mes
	N-1	N-2	N-3	Sev				
IEEE30	43	259	80	0	40	206621	6	71
Utility	339	200	200	51	40	415139	85	2074

- Result: generalization error reduced by 21.84% and 16.6% respectively

Demonstration of online adaptation

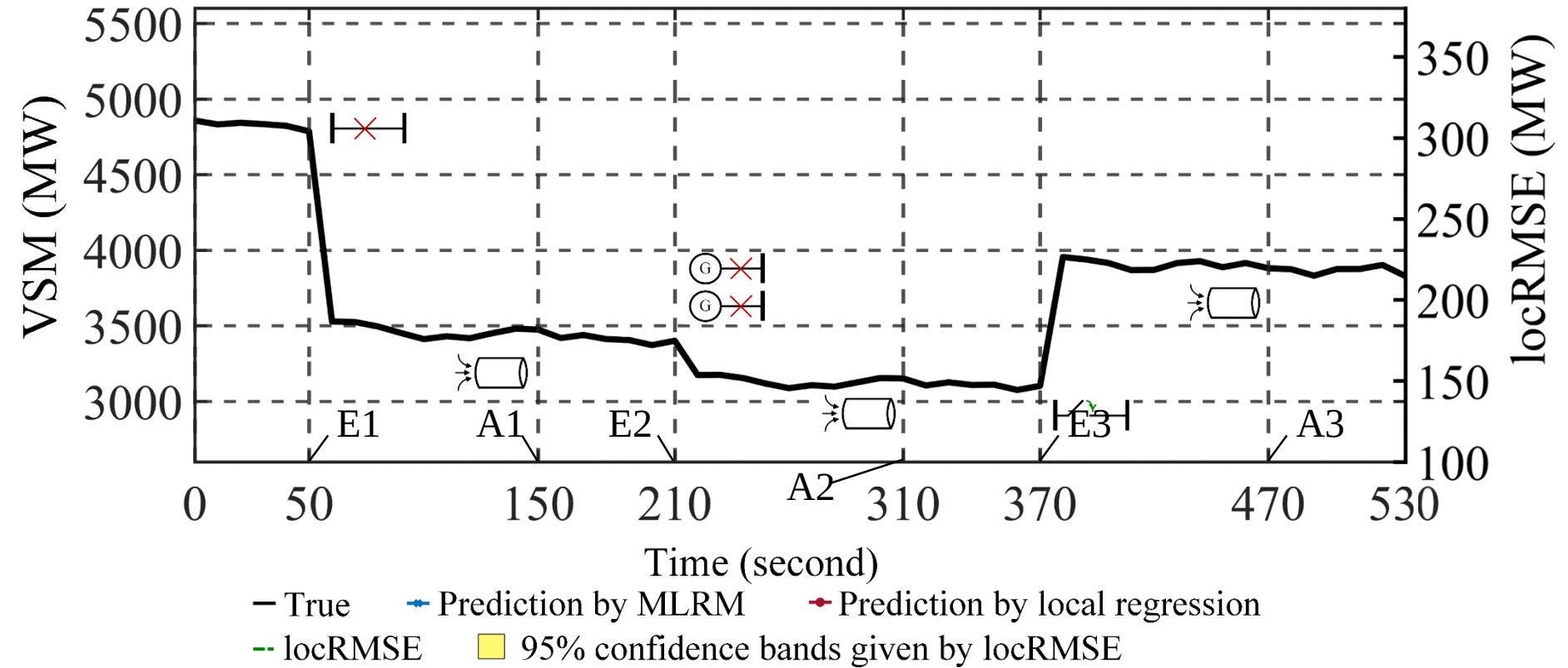


Fig. 13. Online adapt to operating condition.

Demonstration of online adaptation cont..

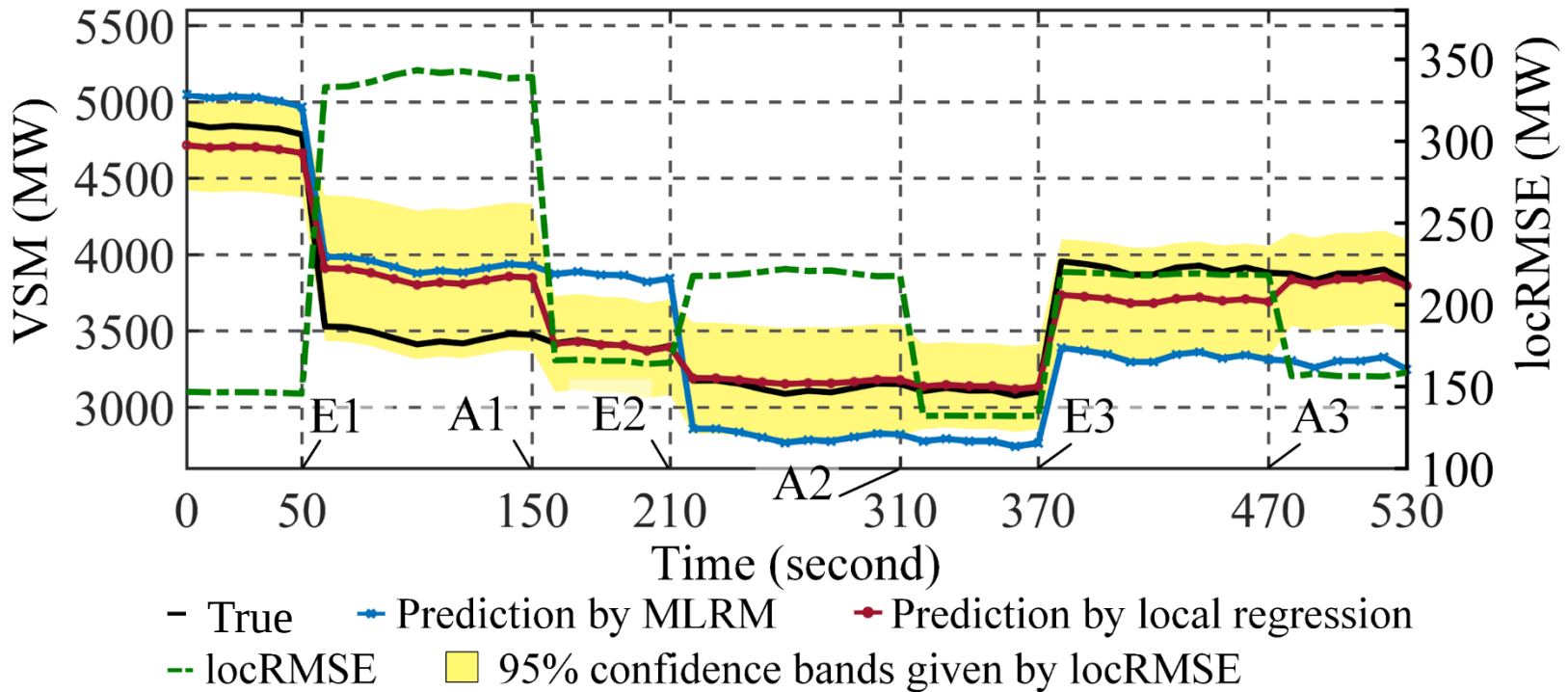


Fig. 13. Online adapt to operating condition.

- Proposed method **adapts** to the changing system condition (46% error reduction)
- Confidence band** suggest how much the operators should trust the prediction

Predictive Control Scheme

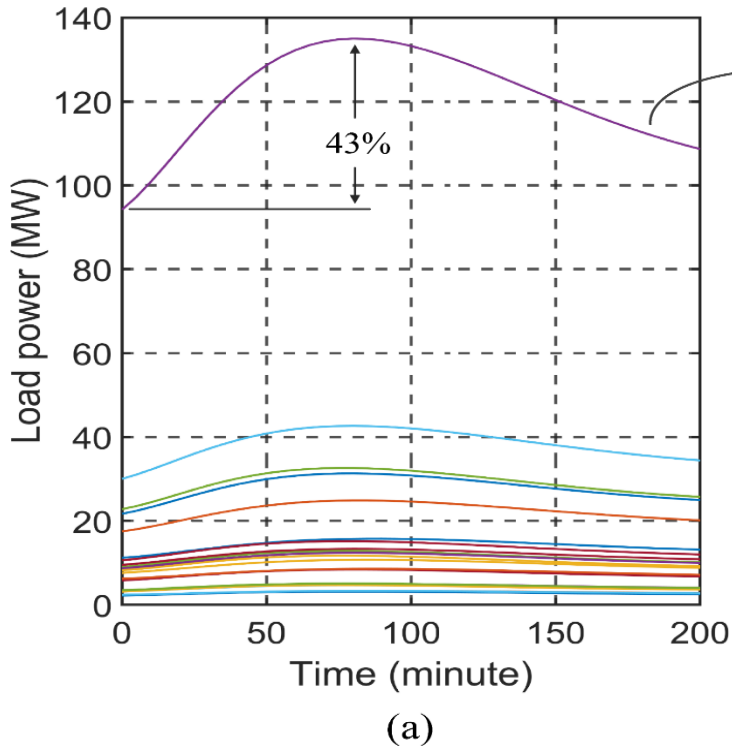
- When VSM is lower than certain threshold, **control actions** are needed to steer the system back to a secure state
 - Two technical drivers:
 1. $\hat{M}_0 = \mathbf{w}(z_0)\mathbf{M} + x'_0\hat{\beta}_0$ not only gives the current value of VSM, but also is an **explicit linear model** of VSM that can be locally **embedded** in VSM related optimization
 2. Demand response, especially **non disruptive direct load control**, can be utilized to maintain VSM^[4]
- A predictive VSM control scheme that can adapt to the changing operating conditions
 - Explicitly involves VSM constraint based on the **local predictive model(Model predictive Control)**;
 - Considers the evolvement of operating condition by **looking ahead**;
 - Engages in a more **flexible** control measure;
 - Cooperatively considers the behaviors of other controllers;
 - Fits in the time framework of **near-real-time**

[4] Ashraf Radaideh, Umesh Vaidya, and Venkataramana Ajjarapu. "Sequential Set-point Control for Heterogeneous Thermostatically Controlled Loads Through an Extended Markov Chain Abstraction." Accepted in *Smart Grid, IEEE Transactions on* , 2017

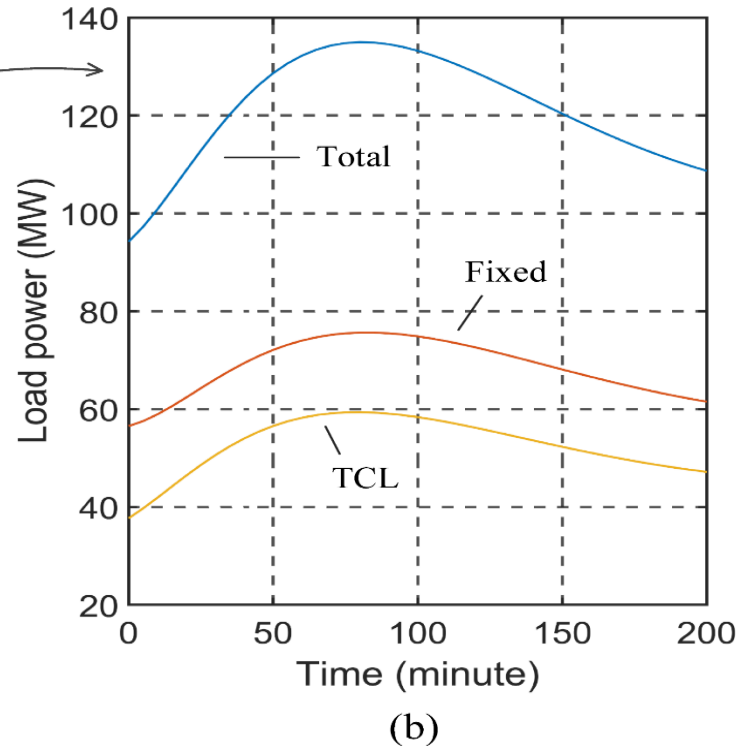
Sample result: Demand Side control

- IEEE 30-bus system: 6 RPRs, 21 loads

Case : Peak load hours + line outage

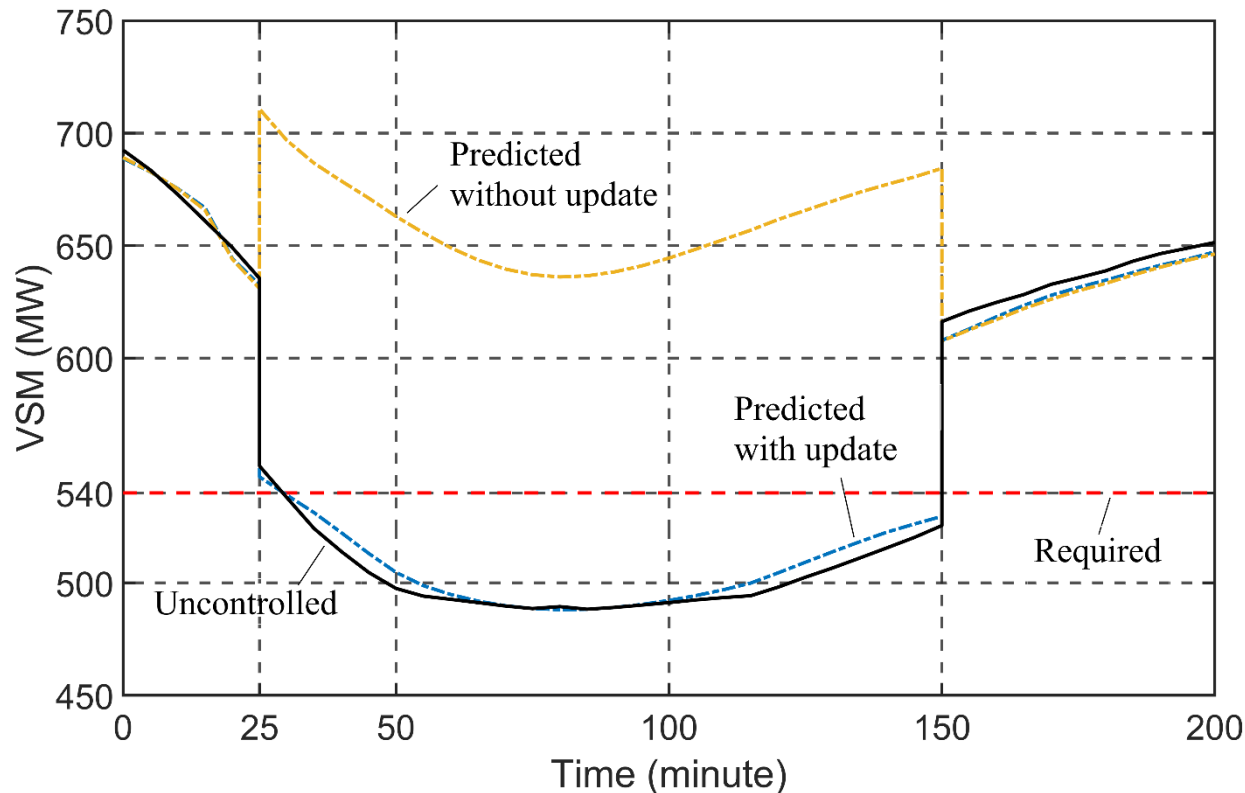


Load evolution without control



Profile of the maximum load

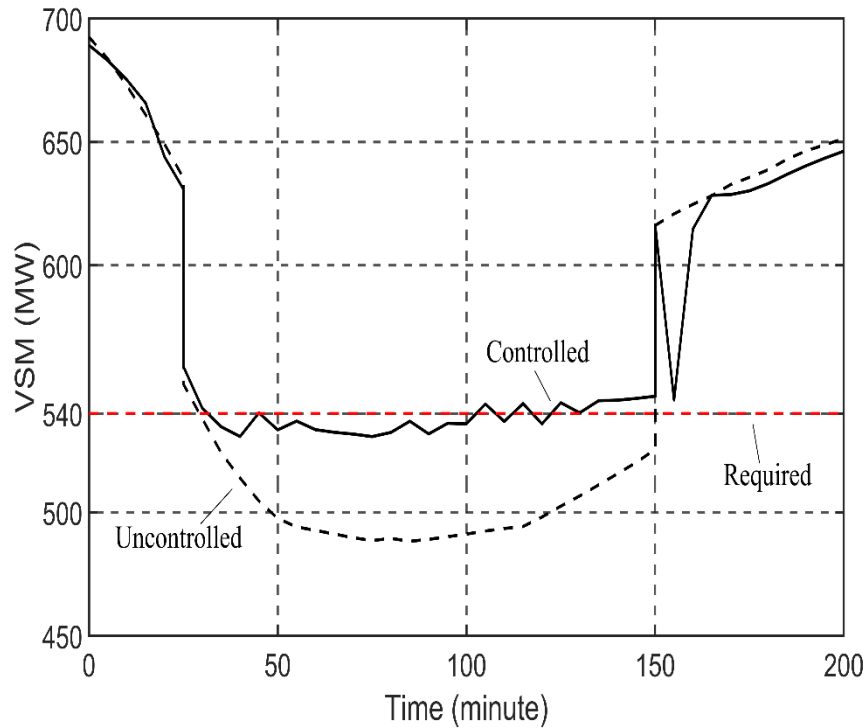
Sample result: No Control



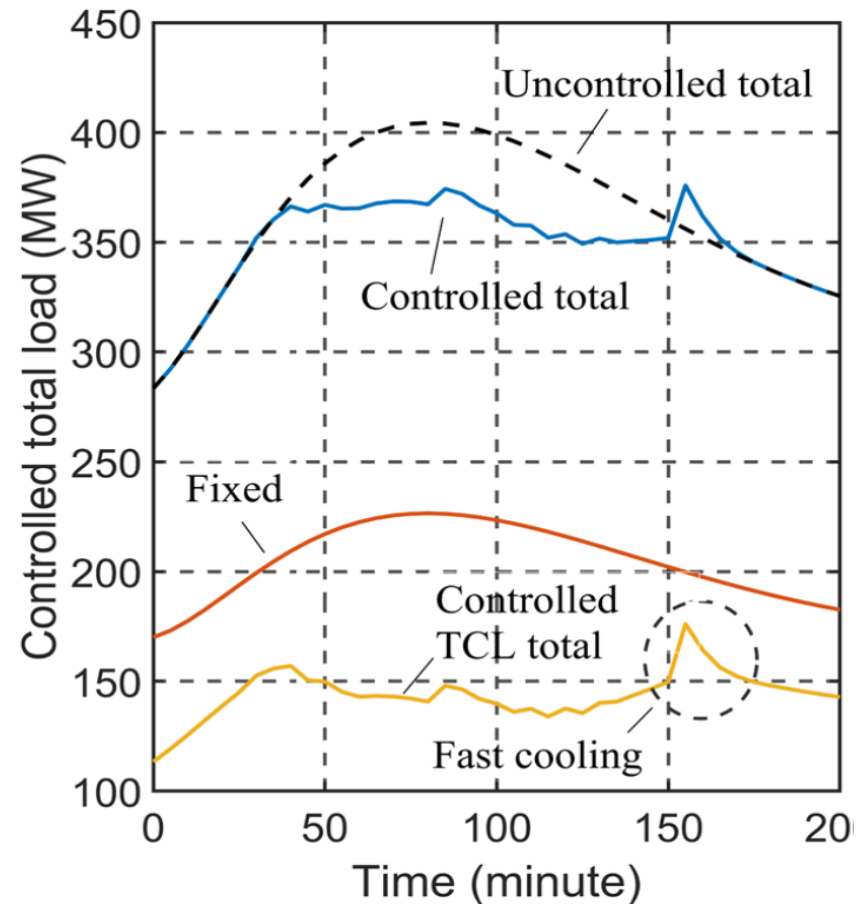
Uncontrolled VSM Profile violates requirement

- Line outage between $t = 25$ and $t = 150$
- Need database updating for VSM prediction after contingency

Sample result: with TCL Control



Controlled VSM



Profile of the total load

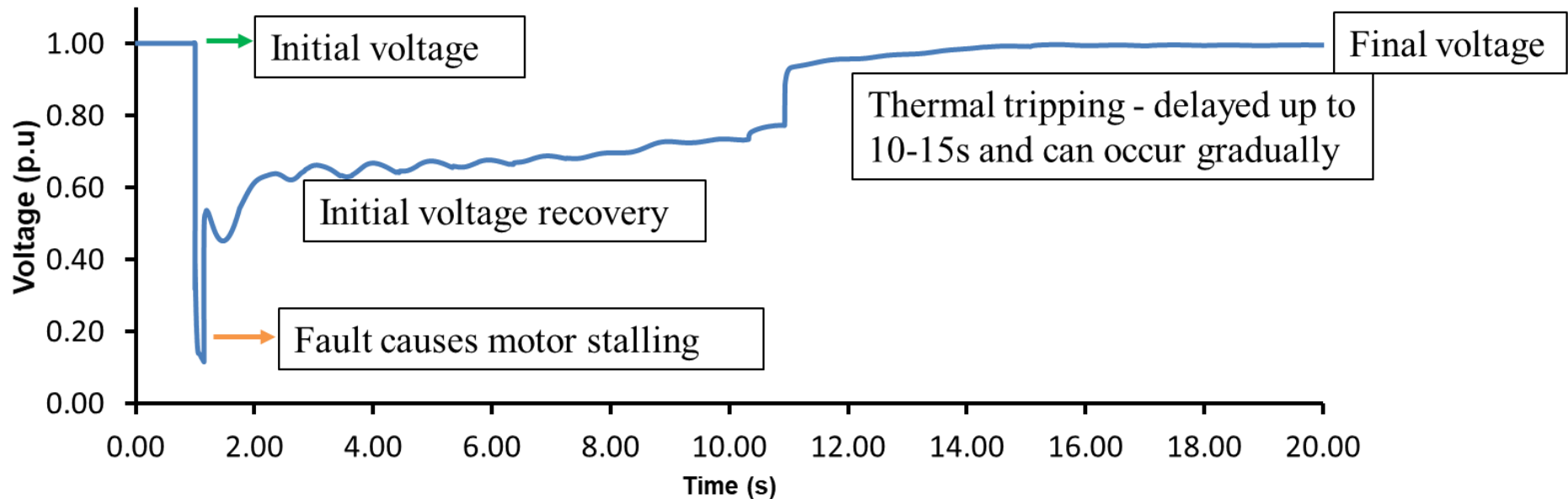
Highlights of the proposed approach^[2,3]

1. Combining the off-line and the online data, via the **adaptive regression algorithm and the adaptive data set**, to provide timely VSM prediction on the changing operating condition;
2. providing the **time-varying estimation of the confidence interval** along with the VSM prediction, so the operators can get the sense that how they can trust the current VSM prediction and where the true value VSM could be, then the closed-loop corrective adaptation can be established (bad prediction can be automatically rectified);
3. combining local linear regression and LASSO via the **relative regularization factor (γ)**, so as to achieve the sufficient scalability for large scale power systems.
4. Incorporating the demand response of the **thermostatic loads as a control** to improve the margin if the estimated margin fell below a pre-specified amount

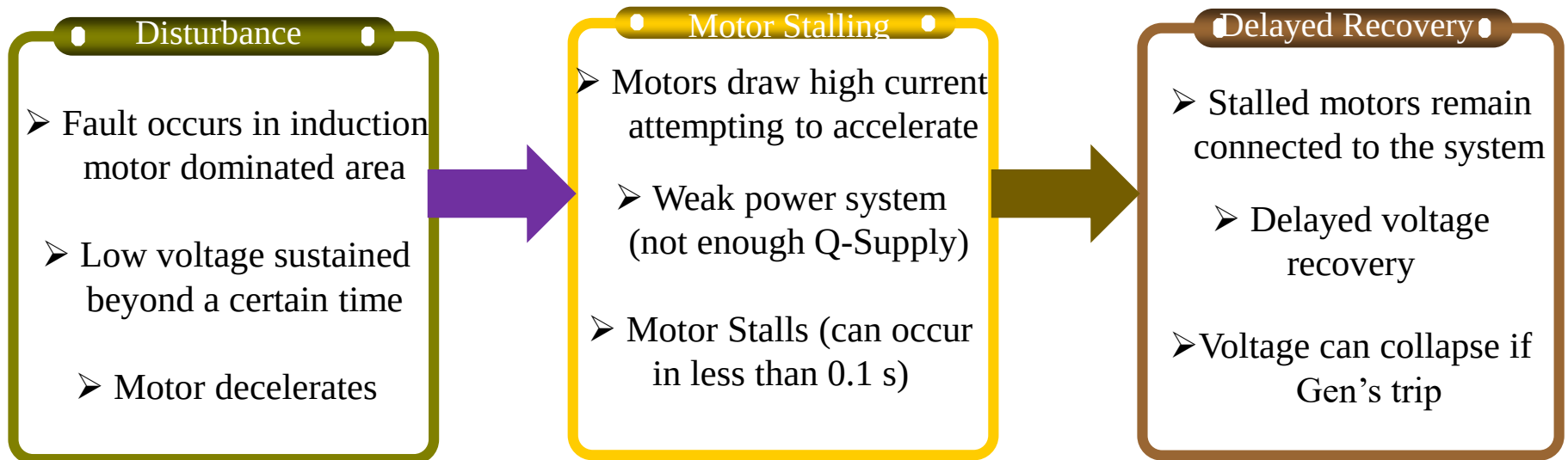
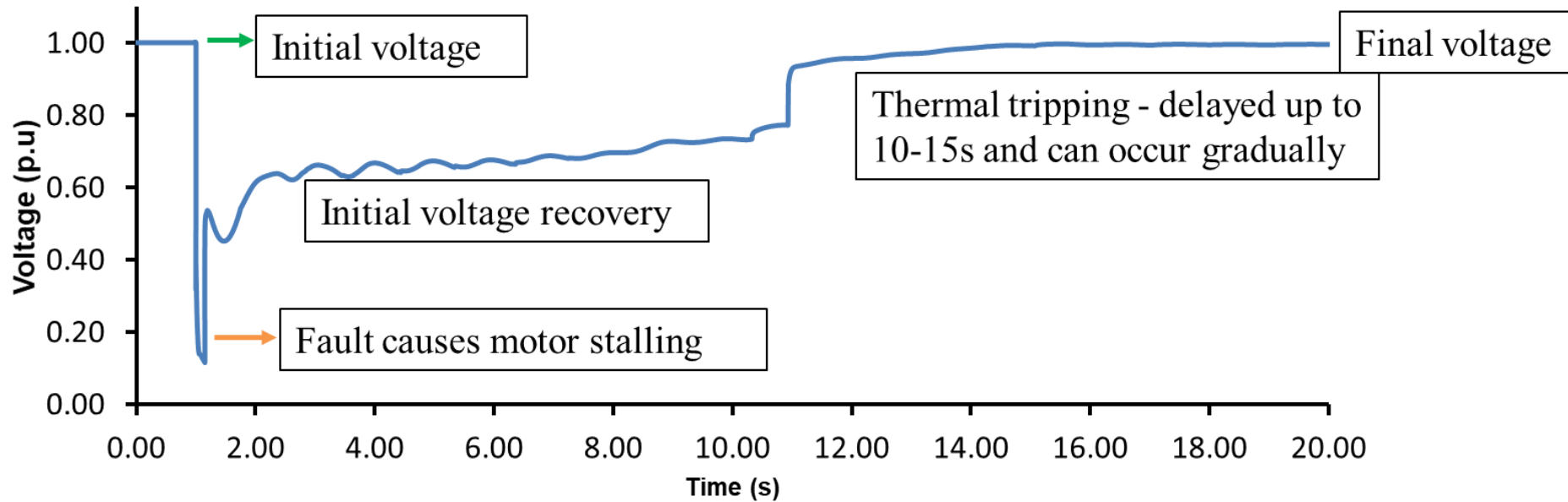
- [2] Li, Shiyang, and Venkataramana Ajjarapu. "Real-time monitoring of long-term voltage stability via local linear regression." *Power & Energy Society General Meeting*, 2015 IEEE.
- [3] Shiyang Li and V. Ajjarapu" Adaptive Online Monitoring of Voltage Stability Margin via Local Regression, IEEE Transactions on Power Systems, Vol. 33, No.1, pp. 701-713, January 2018

Short Term Voltage Stability

- Short term voltage stability deals with the behavior of the system in the few seconds after a disturbance in the power system
- A special case of interest is the Fault Induced Delayed Voltage Recovery (FIDVR) phenomenon – occurs in regions of the power grid where the Air Conditioner (AC) proportion is large ($>30\%$).
- This is a precursor to short term voltage stability due to the large number of motors being stalled



Fault Induced Delayed Voltage Recovery (FIDVR)

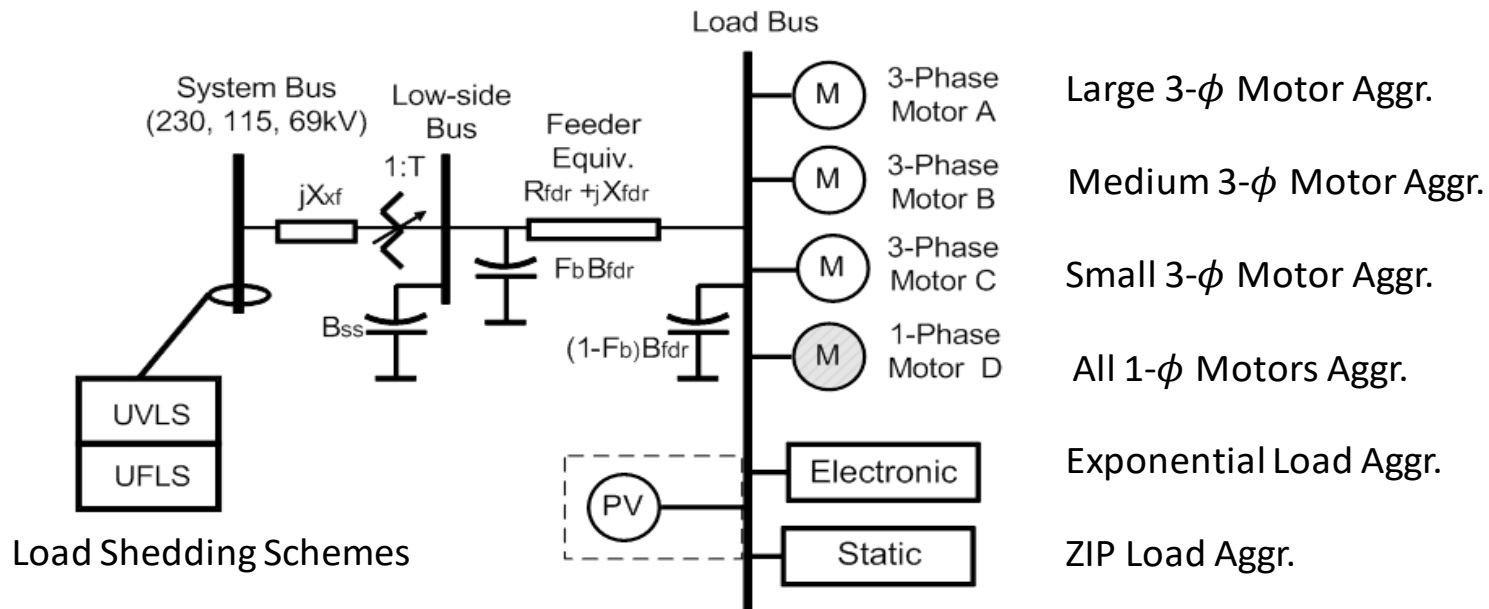


Motivation and Problem Statement

- The FIDVR phenomenon can lead to further severe phenomenon as it stresses the generator exciters and the transmission lines
- To prevent these effects, it is necessary to
 1. Detect an FIDVR event reliably
 2. Estimate the time to recover from FIDVR
 3. Determine an appropriate control if the recovery time is above a specified time
- WECC and ERCOT have various criteria for voltage recovery after a contingency and so the control should ensure the voltage recovery should satisfy these criteria. For example
 - Recovery to 0.95 p.u. in 10 sec [5]
- It is important to understand the load dynamics for this phenomenon as this is driven mainly by the load stalling

Dynamic Load Model

- To understand the dynamic behavior of the load after a fault, the Composite Load Model (CMLD) [6] is used.
- It represents an aggregation of the loads in the distribution system into various kinds of motors and static load – including the under voltage schemes

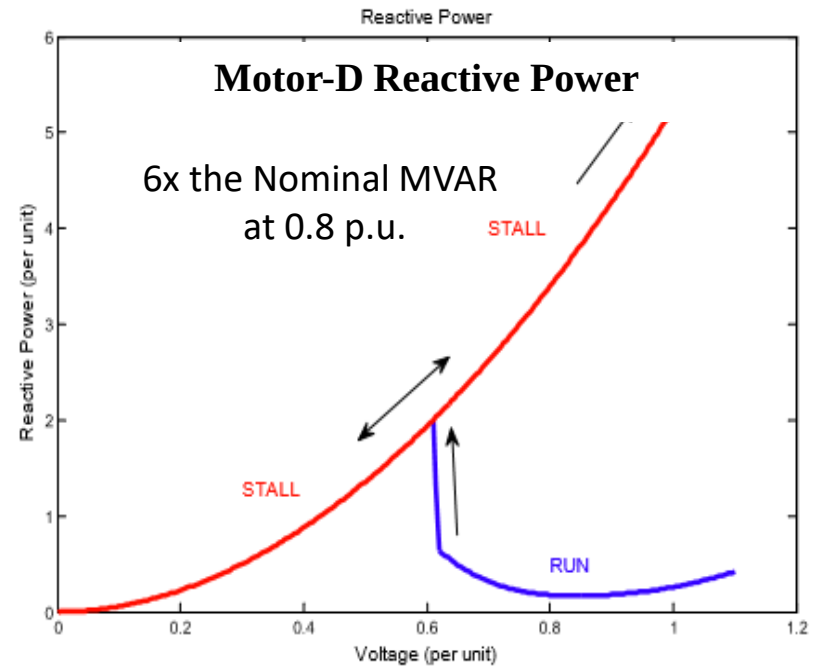
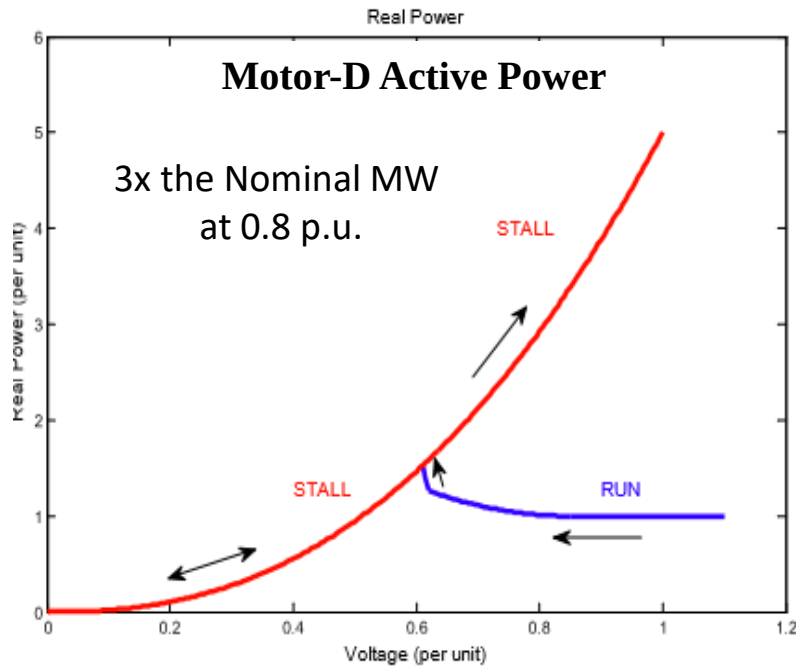


- The stalling of the Motor-D in CMLD is the reason for FIDVR

[6] Modeling and validation work group, "WECC Dynamic Composite Load Model Specifications," Western Electricity Coordinating Council, Technical Report, January 25, 2015

Reason for FIDVR

- Motor-D represents the aggregate 1- ϕ motors and includes the Air Conditioner compressor motors that are not equipped with Under Voltage Relays – causing them to stall instead of disconnecting at low voltages
- The stalled Motor-D is represented as an admittance [6] whose active and reactive power is several times the nominal - physically realistic



- MVAR of motor D increases by around 6X – reason for low voltage

Individual Component Powers during FIDVR

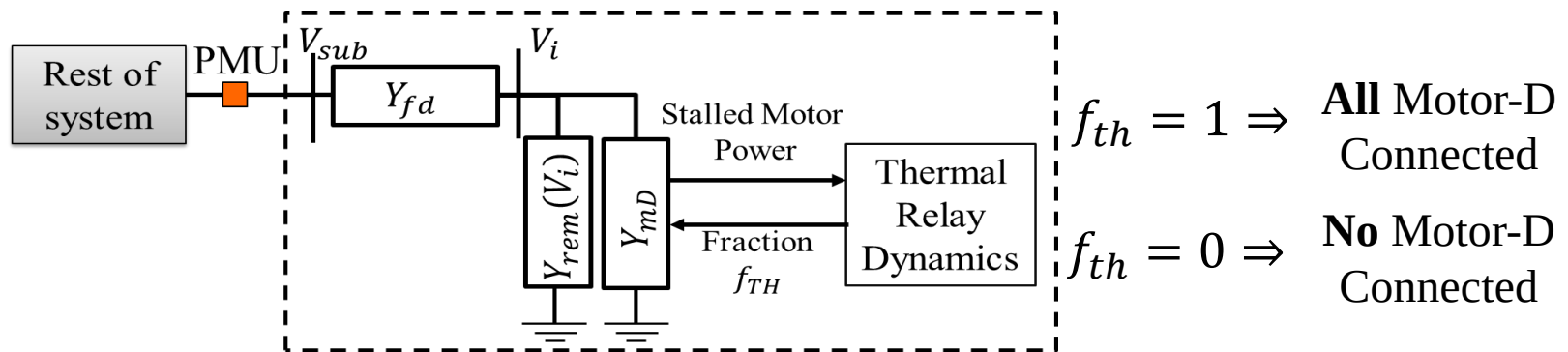
- Nominal load of 20 MW + **7.6 MVAR** becomes 26.5 MW + **20 MVAR** during FIDVR – Individual component powers in table below.

Type	fraction	Power Before FIDVR	Power in FIDVR (V=0.8)
Motor-A	$f_{mA} = 0.1$	2 MW + 1.3 MVAR	2 MW + 1.3 MVAR
Motor-B	$f_{mB} = 0.1$	2 MW + 1.3 MVAR	2 MW + 1.3 MVAR
Motor-C	$f_{mC} = 0.1$	2 MW + 1.3 MVAR	2 MW + 1.3 MVAR
Motor-D	$f_{mD} = 0.35$	7 MW + 1.7 MVAR	14 MW + 14 MVAR
Static Load	$f_{stat} = 0.10$	2 MW + 0.4 MVAR	1.5 MW + 0.5 MVAR
Elec. Load	$f_{elec} = 0.25$	5 MW + 1.6 MVAR	5 MW + 1.6 MVAR
Total Load		20 MW + 7.6 MVAR	26.5 MW + 20 MVAR

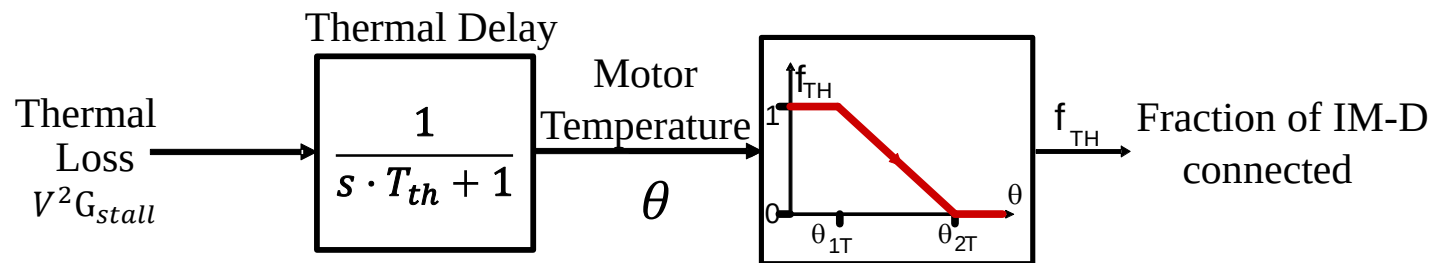
- Increase in the total MVAR demand leads to voltage reduction – due to Motor-D and so controlling Motors A,B,C or static or elec. loads don't help
- Only ways to improve time to the recovery is by
 - Injecting VARs close to the FIDVR – SVC, Gens. Condensers, etc.
 - Disconnecting Motor-D during FIDVR

Admittance based Representation of CMLD

- As the stalled motors are represented as admittance and this forms the major component of the load, let us represent the load as admittance during FIDVR
 - $Y_{rem} = Y_{mA} + Y_{mB} + Y_{mC} + Y_{static} + Y_{elec}$
 - $Y_{mD} = Y_{stall} = G_{stall} + jB_{stall}$

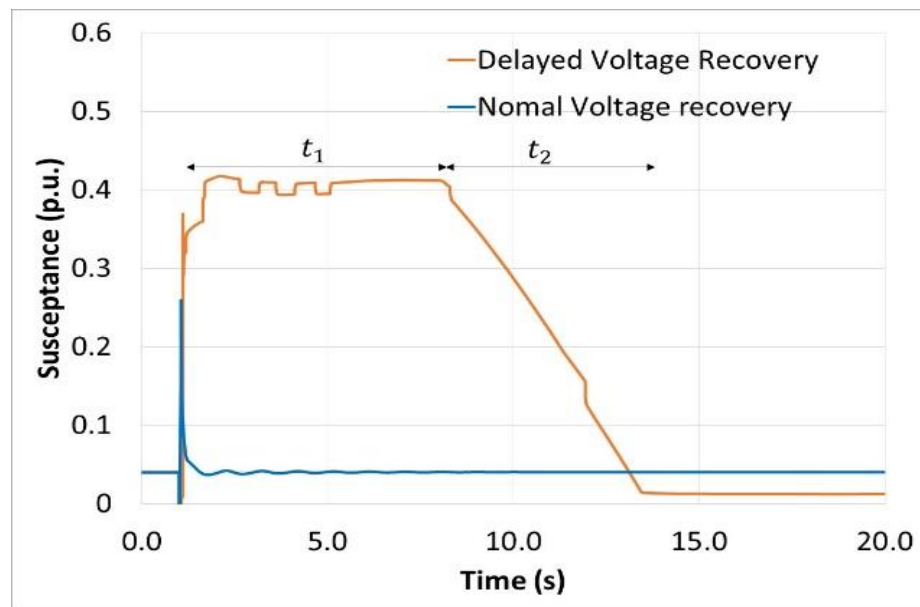
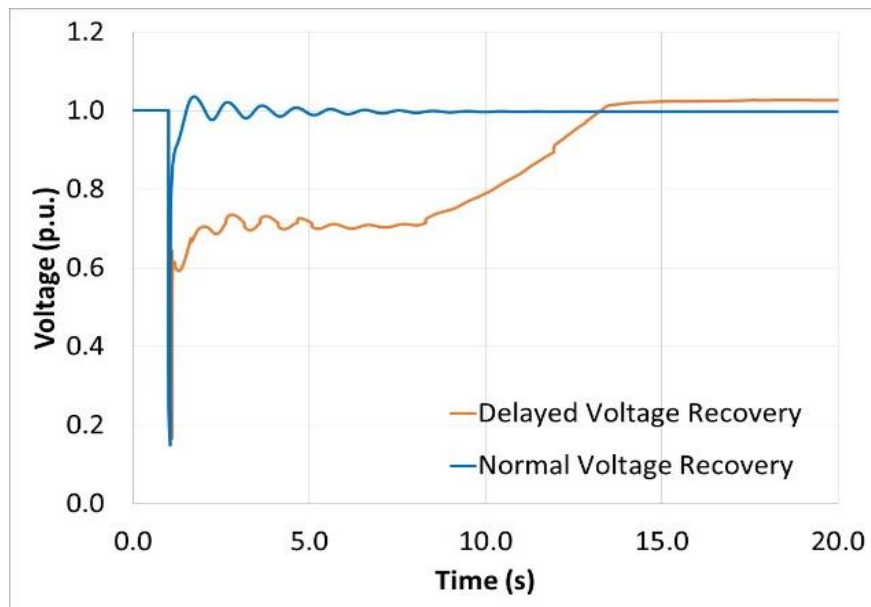


- The thermal tripping relay simulates the AC motor disconnection due to the motor temperature (θ) rise and there are 2 modes of operation
 - All AC's are connected till the temperature reaches θ_1 .
 - After this, the AC's are disconnected linearly until the temperature reaches θ_2 .



Detecting FIDVR via Susceptance

- The sudden rise in load susceptance can be used as an indicator of FIDVR
- The load susceptance can be measured from PMU measurements at substation
- Example: 162 bus system with two scenarios – one with $f_{mD} = 0$ (no FIDVR) and $f_{mD} = 0.35$ (FIDVR observed)
- The susceptance plot captures load behavior while the voltage is more nonlinear
- Susceptance plot shows two distinct sections – constant susceptance for t_1 and linear reduction for t_2 .



Estimating Time to Recovery

- As the load dynamics are dominating in this phenomenon and are on longer time scales, we assume that the dynamics of the generator have decayed as a simple approximation.
- The time to recovery can be analytically derived for a two bus system [7] - it is observed that the times t_1 and t_2 are proportional to the load susceptance.
- The same trend is true for a multi-bus system and so we propose that the times t_1 & t_2 are related to the load susceptance as follows

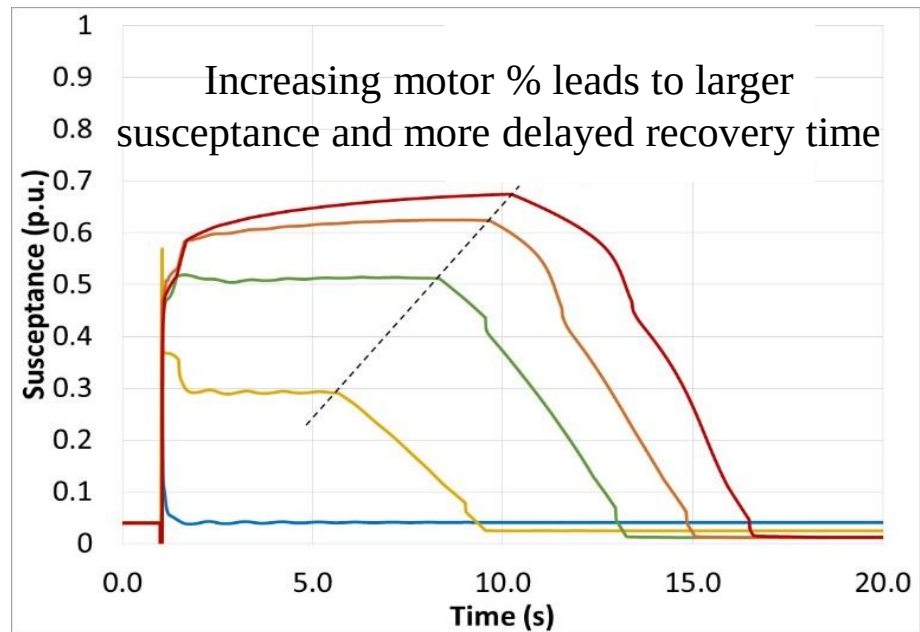
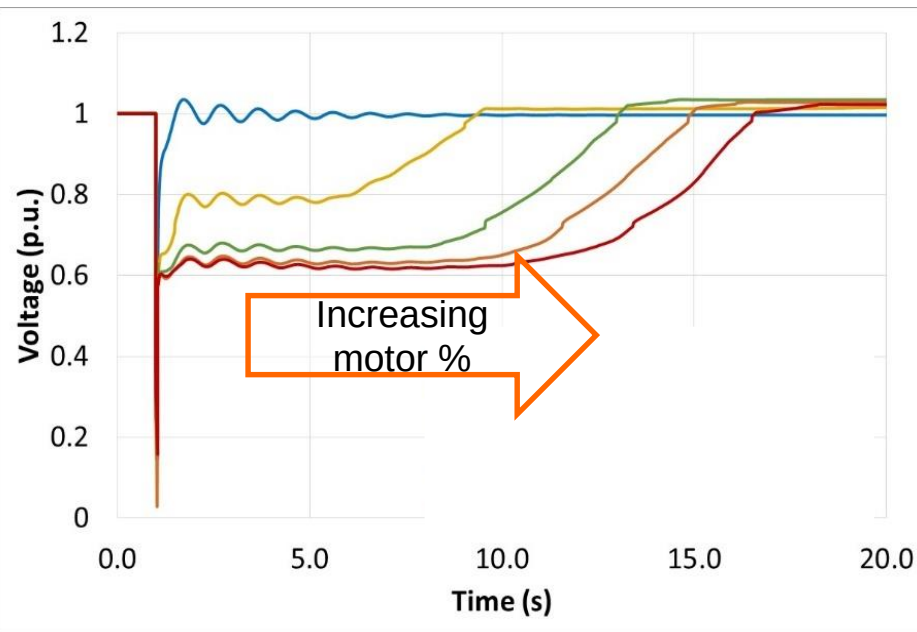
$$t_1 \approx \alpha_0 \cdot B_{load} + \alpha_1; t_2 \approx \beta_0 \cdot B_{load} + \beta_1$$

- Total time to recovery is $(t_1 + t_2)$ and needs to be estimated soon after FIDVR is detected
- The values of the coefficients $(\alpha_0, \alpha_1, \beta_0, \beta_1)$ in the above expressions are determined from offline simulations with different load fractions $f_{mA}, f_{mB}, f_{mC}, f_{mD}$ & f_{elec} and load levels

[7] PSERC S-65 Report titled “Real Time Synchrophasor Measurements Based Voltage Stability Monitoring and Control”, available online at <https://pserc.wisc.edu/home.aspx>

Results for Estimating Recovery Time

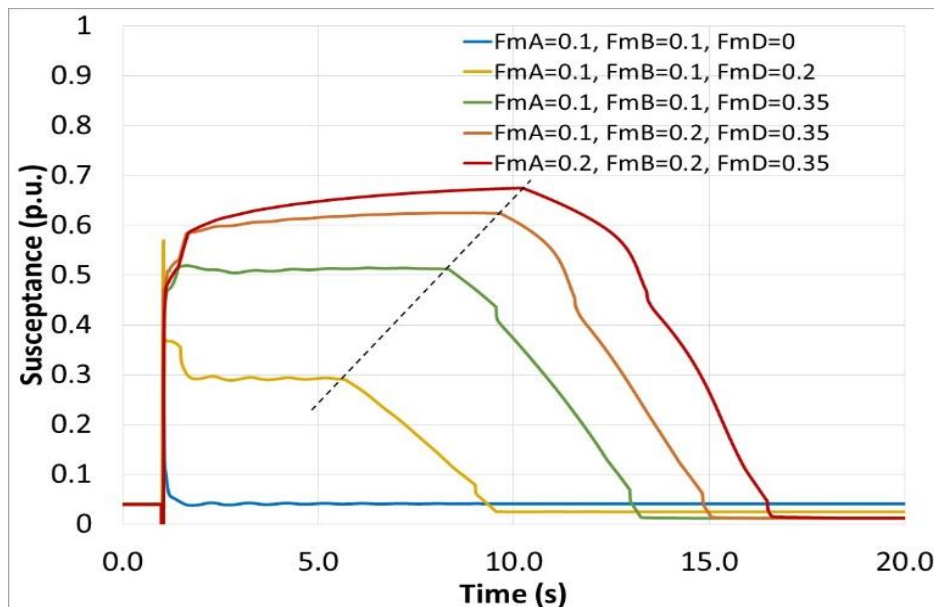
- Offline studies conducted on the IEEE 162 bus system with CMLD load models using various proportion of Motors A,B,C,D – 4 example plots shown
- Increasing motor % leads to larger susceptance and recovery time
- Easier to estimate the instant when the AC thermal disconnection begins using susceptance as the transition is sharp – not the case using voltage
- Oscillations are minimal in the load susceptance making it easier for prediction



Results for Estimating Recovery Time

- From the offline studies, the times t_1 & t_2 are related to the B_{load} as follows

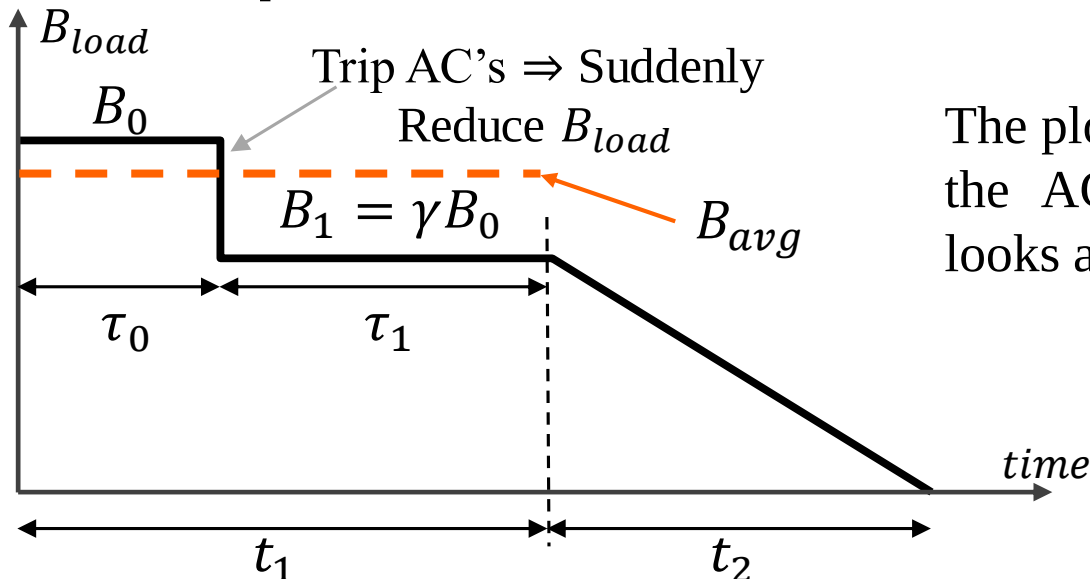
$$t_1 \approx 14.8 \cdot B_{load}; t_2 \approx 5 \cdot B_{load} + 3.3$$
- Can be used to predict the t_1 and t_2 by measuring susceptance a few seconds after the fault is cleared (B_{load})
- For the dynamics of the A,B,C motors to stabilize, it takes around 1s-2s and so using the value of the B_{load} after this time period is appropriate
- The error is usually in the range of 5% and this rises up to 8% in situations where $(f_{mA} + f_{mB} + f_{mC} \geq f_{mD})$



	Actual ($t_1 + t_2$)	Estimated ($t_1 + t_2$)	Error %
Scenario 1	8.4 sec	8.08 sec	-3.8 %
Scenario 2	12.7 sec	12.14 sec	0.5 %
Scenario 3	13.8 sec	14.16 sec	2.6 %
Scenario 4	15.5 sec	16.44 sec	6.4 %

Susceptance based FIDVR control

- Now that the time to recovery is estimated soon after fault is cleared, the decision if any mitigation is necessary can be taken
- We can communicate to the smart thermostats in the distribution grid to disconnect AC's if the substation is experiencing FIDVR
- Only a small proportion of the AC's have the smart thermostats
- Utilizing the relationship between B_{load} , t_1 & t_2 , the % of AC to disconnect at a time τ_0 can be estimated depending on specified recovery time [7]
- t_{sp} is the specified time to recover, τ_0 is time when trip signal is sent – Quadratic equation solved to estimate the amount of trip

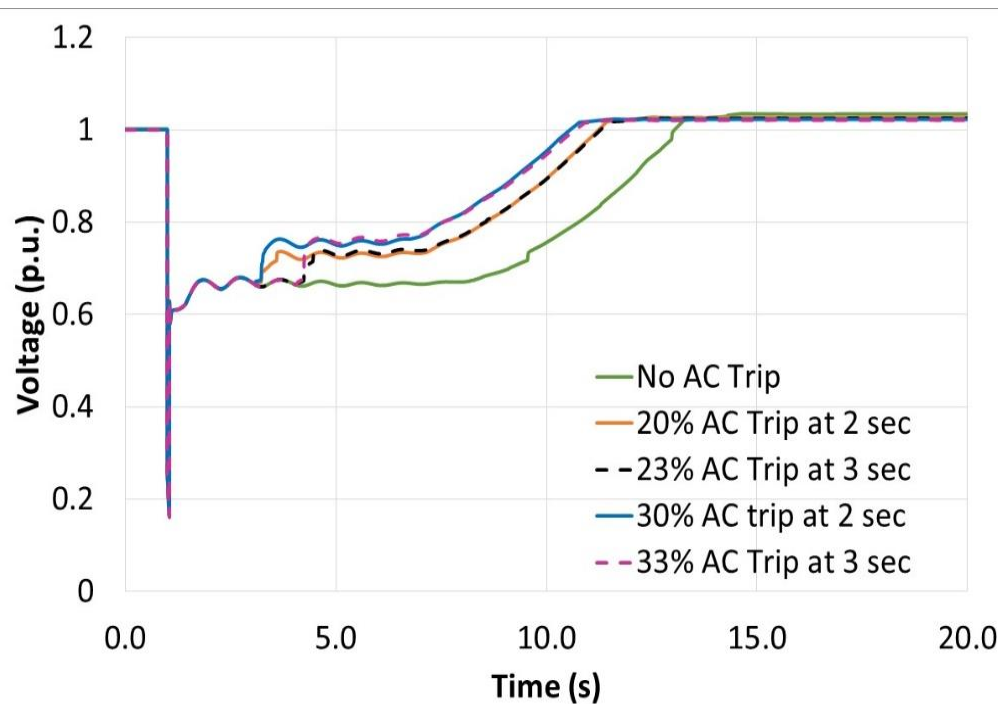


The plot of the load susceptance after the AC disconnection conceptually looks as the figure

[7] PSERC S-65 Report titled “Real Time Synchrophasor Measurements Based Voltage Stability Monitoring and Control”, available online at <https://pserc.wisc.edu/home.aspx>

Results for FIDVR control

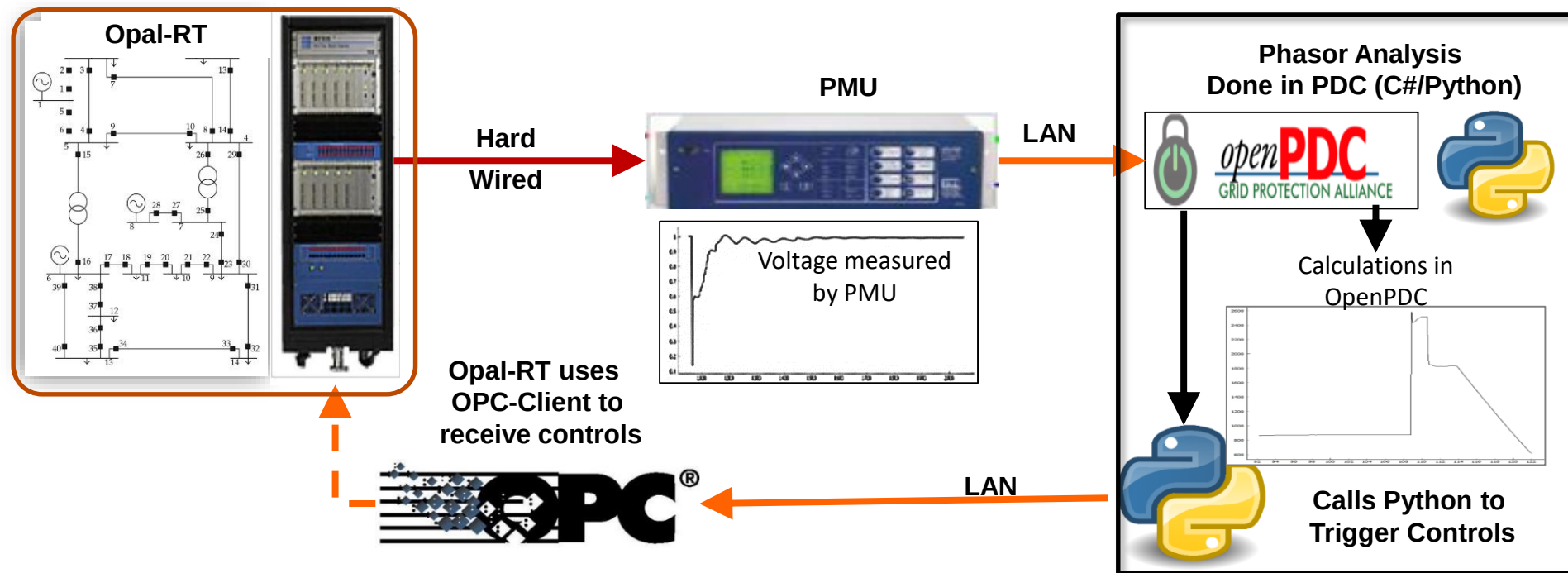
- For an example case in the IEEE 162 bus system, the recovery time is 12.7 sec
- The amounts of AC disconnection necessary for recovery in 11s and 10s were determined with control signal sent at 2s and 3s
- The actual time to recovery was 10.5s and 9.8s respectively, demonstrating that the estimated AC disconnection % is sufficient to ensure expected recovery
- This scheme can be combined with the injection of VARs to reduce AC disconnection % - future work



t_{sp}	τ_0	% AC Discon.	Actual ($t_1 + t_2$)
11 sec	2 sec	20 %	10.5 sec
11 sec	3 sec	23 %	10.5 sec
10 sec	2 sec	30 %	9.8 sec
10 sec	3 sec	33 %	9.9 sec

Real Time Cyber Physical Test Bed

- The Real-Time Cyber-Physical Test Bed consists of Opal-RT, RTDS, SEL-421 PMU's, OpenPDC & Python
- The Opal-RT simulates the FIDVR and the PMU data is captured by OpenPDC which detects FIDVR, estimates time to recovery and determines the amount of the AC load to disconnect.
- The disconnect signal is sent back to Opal-RT and FIDVR is controlled in an online manner – can observe this in the simulation in real-time

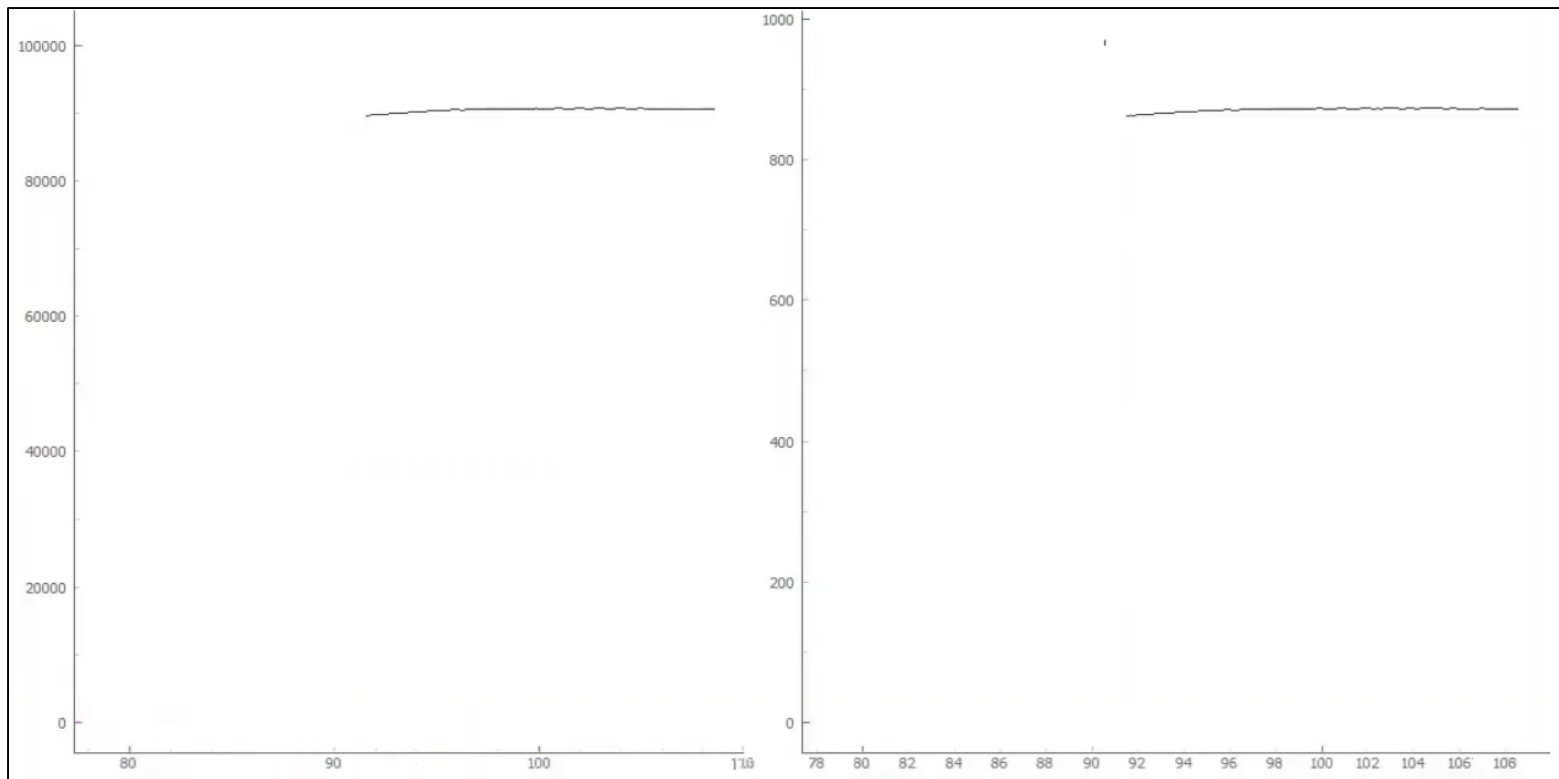


Demo Video

- The FIDVR detected from the jump of susceptance from 850 mS to 2500 mS
- Initial FIDVR(with no control) has a recovery time of 15s with voltage dipping to 0.85 p.u.
- 30% of AC load is disconnected at 2s to recover from FIDVR in 11s
- The final voltage is 1.02 p.u. after recovery (1 p.u. – 90,000V)

PMU Voltage

Load Susceptance



Summary of FIDVR Monitoring & Mitigation

- The CMLD load behavior can be properly captured using the load susceptance which can be measured in real-time by PMUs
- The time to recovery from FIDVR can be estimated using offline simulations under various conditions and using a linear function of the load susceptance
 - In the IEEE 162 Bus system, errors of $\sim 8\%$ were observed for the prediction of the recovery time
 - A wide area method that can analyze susceptances at various buses in an area will be able to handle more complicated FIDVR cases – future work
- The control scheme of AC disconnection via smart thermostats is proposed with the disconnection % estimated from the expressions for recovery time
 - A 30% disconnection within 2s of FIDVR can improve recovery time from 13s to 10s
- Another option for control is to utilize the PV smart inverters in the distribution feeders not facing FIDVR to provide VAR support – Next topic
- The monitoring and control schemes have been verified to run in real-time using the real-time cyber physical test-bed with PMUs and OpenPDC

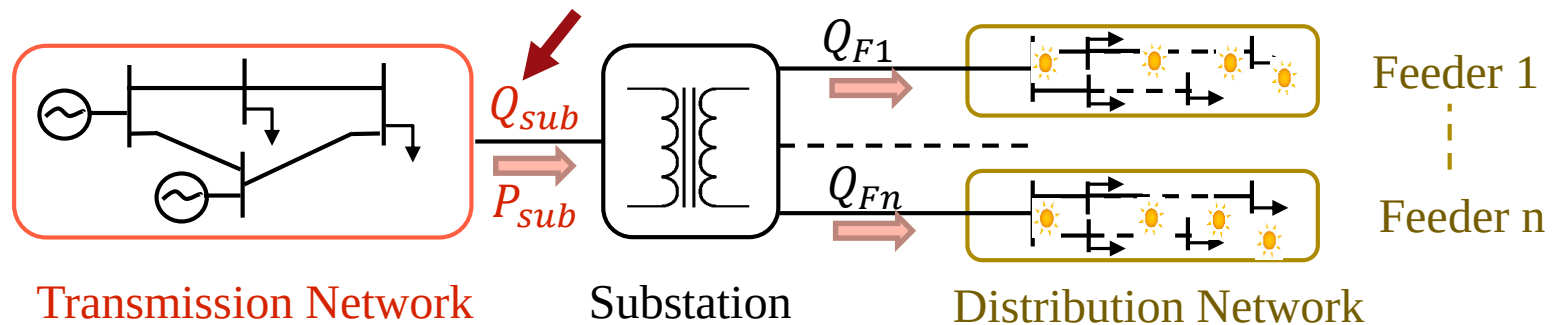
New Opportunities in the Future Grid

- The grid of the future will look and behave very differently from the existing system
- It will have a majority of power generated from renewable resources
- It will have more controllable loads in the distribution grid capable of providing support to the bulk grid
- We explored the capabilities of the following developments on the transmission grid
 1. High Solar PV Penetration in the distribution grid
 2. Demand Side Control of the Thermostatically Controlled Loads

Impact of Solar PV Inverters on Transmission

With increasing number of solar PV inverter devices in the distribution side, their **cumulative impact on transmission grid** performance can not be ignored.

Utilizing the Volt-Var Control (VVC) functionality in the solar PV inverters, they can be individually commanded to inject or absorb VARs according to a central authority – impacting the Q-substation



*Thousands of smart inverter devices can be seen as the **geographically distributed var resources (mini-SVCs)** and if controlled properly, can provide flexible volt/var support to the grid*

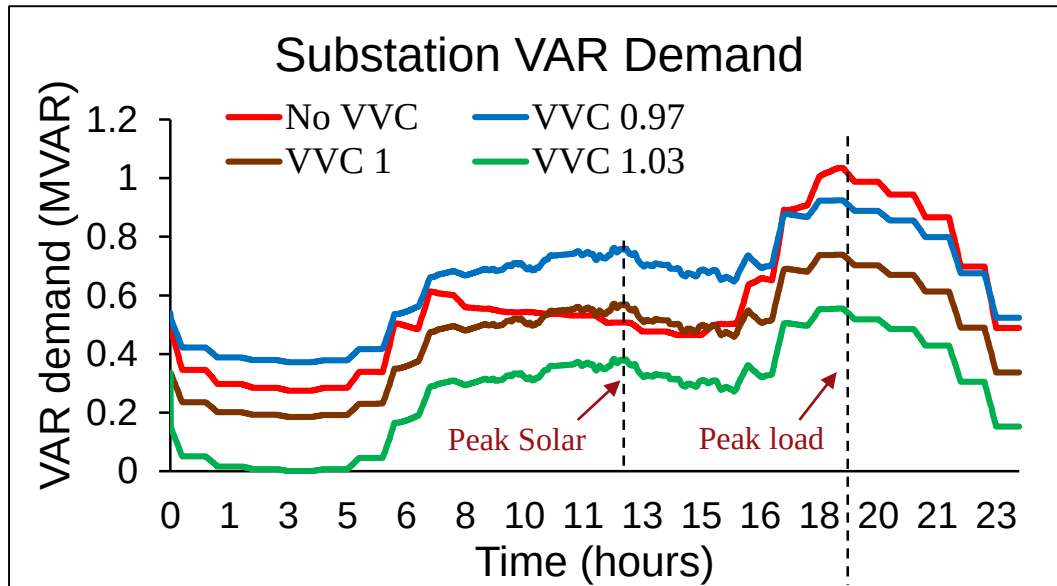
PV inverter var injection can be controlled via **VVC set-points**

Thus, net var demand/ availability at substation can be controlled

impact on voltage stability of the system – margin, etc.

Impact of VVC on Substation VAR – 60% PV

Opportunities for Transmission System



Net VAR demand at substation can be changed in desired way by appropriately choosing the set-point for the proposed VVC

Challenges in Distribution System

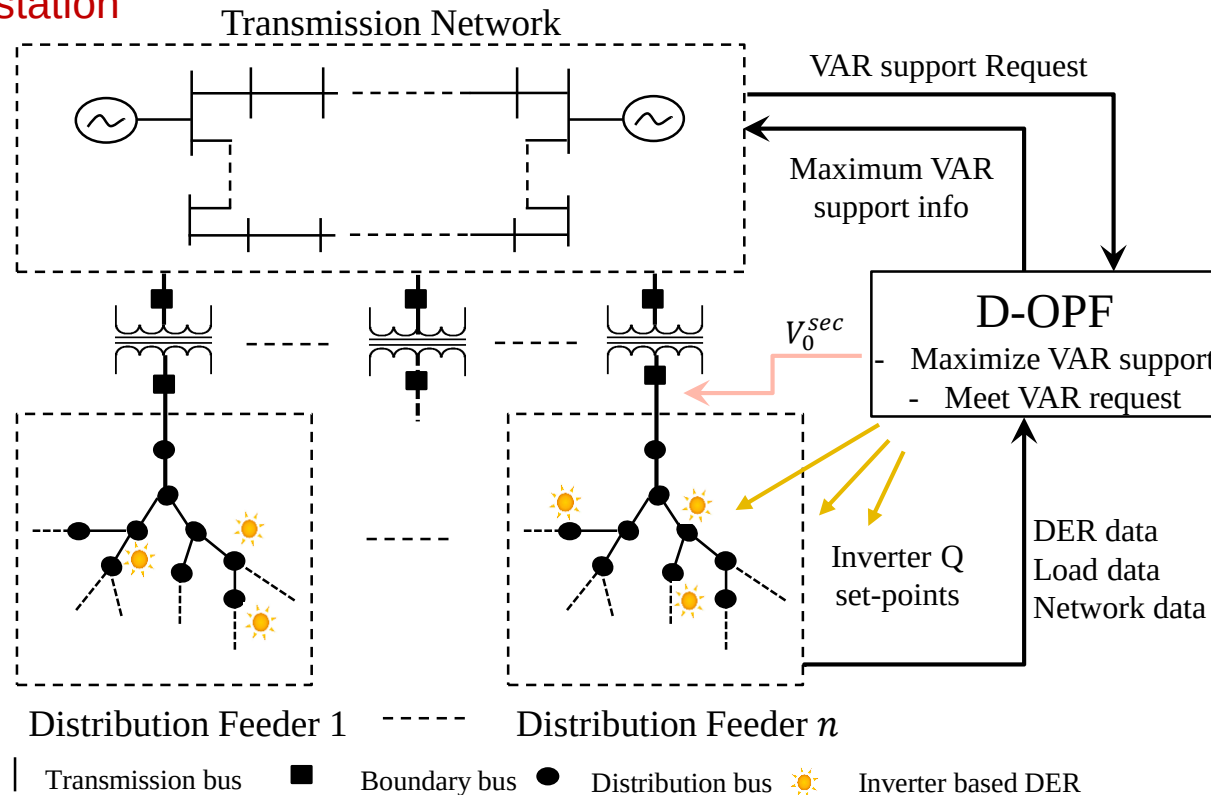
Voltage at distribution system can violate the permissible limits due to change in inverter VAR injection.

There is a need for co-ordination between transmission and distribution systems

DER VAR Support Framework Using D-OPF

DistFlow based Linear Distribution-OPF framework [8] is proposed to

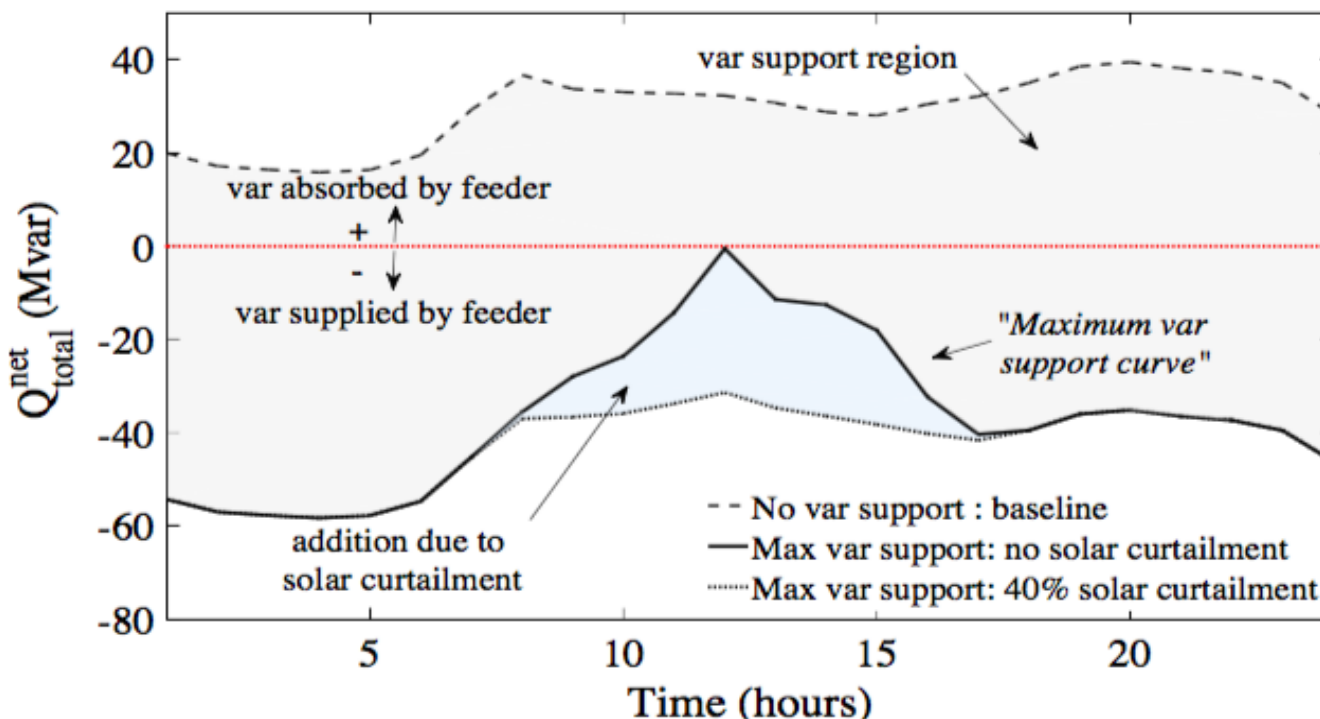
1. Send available maximum VAR support info to TSO – **Maximize VAR Support**
2. Dispatch inverter set-points to all the DERs to meet the requested VAR from the grid – **Minimize difference between VAR request and actual VAR demand at substation**



[8] Ankit Singhal, and Venkataramana Ajjaraapu, "A Framework to Utilize DERs' VAR Resources to Support the Grid in an Integrated T-D System", Accepted, PES General Meeting, 2018.

VAR Support Capability Curve

- Based on the framework proposed, a VAR support capability curve can be drawn with the minimum and maximum VAR at the substation using VVC – **depends on system load and on the solar irradiance**
- Example - IEEE 9 bus transmission + IEEE 13 bus distribution system
- Curtailing at peak solar increases the VAR injection capability



Demand Side Control

- Applications:
 - Peak Clipping, load shifting, renewable energy integration, contingency reserve requirements, voltage support and stability improvement

Thermostatically Controlled Loads (TCLs):

Examples: air conditioners, water heaters, ...

Advantages:

- Thermal energy storage
 - Abundant resources
- Minimal impacts on customers' comfort

Challenges:

- Infrastructure/ monitoring and control
- Requires participation incentives
 - Computational burdens for prediction and control

Mathematical Model of individual TCL

- The Equivalent Thermal Parameter (ETP) model

$$T_i(k+1) = e^{\frac{-h}{R_i C_i}} T_i(k) + \left(1 - e^{\frac{-h}{R_i C_i}}\right) (T_a - q_i(k) R_i S_i) + w_i(k)$$

$$q_i(k+1) = \begin{cases} 1 & T_i(k) > T_s + \frac{D}{2} \\ 0 & T_i(k) < T_s - \frac{D}{2} \\ q_i(k) & \text{Otherwise} \end{cases}$$

Variables:

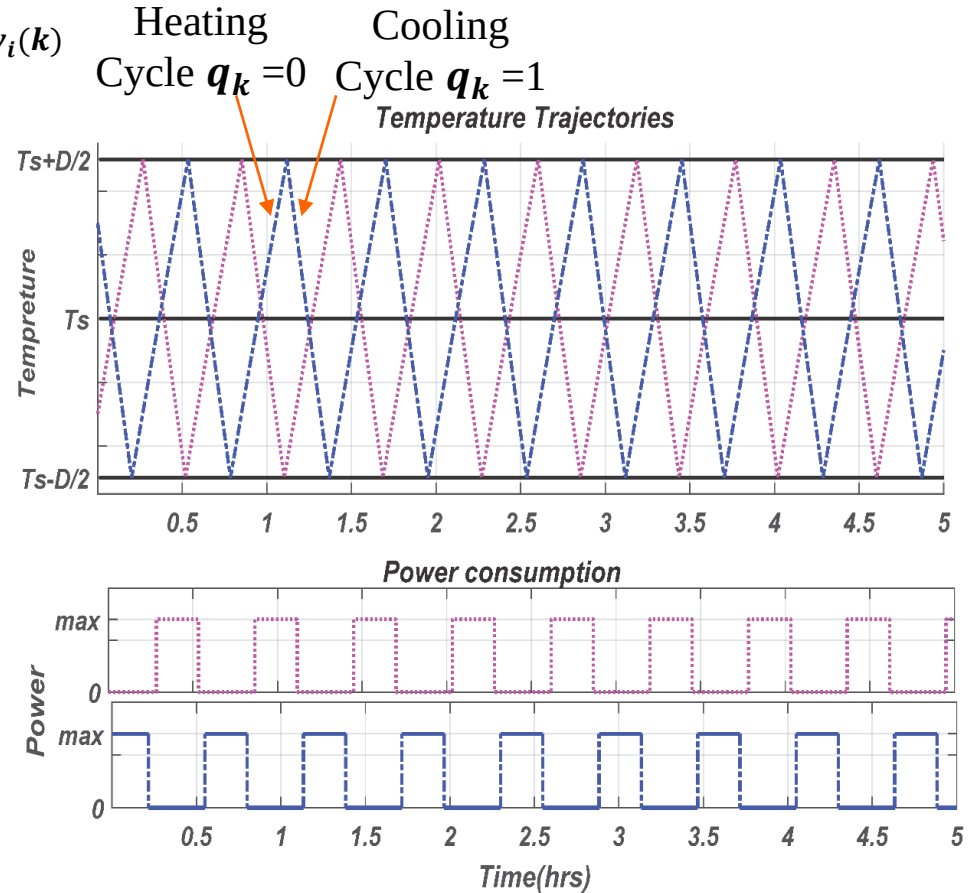
T : Temperature dynamics. ($^{\circ}\text{C}$)
 q : Device Status ON (1) or OFF (0)

Indices:

k : time index
 i : device index

Parameters:

R : Thermal Resistance ($2^{\circ}\text{C}/\text{kW}$)
 C : Thermal Capacitance ($2\text{ kWh}/^{\circ}\text{C}$)
 S : Device Power Rating (5.6 kW)
 T_s : Temperature Set-point (20°C)
 D : Device Dead Band (1°C)
 T_a : Ambient Temperature (32°C)
 h : Discretization time (10s)
 w : noise process

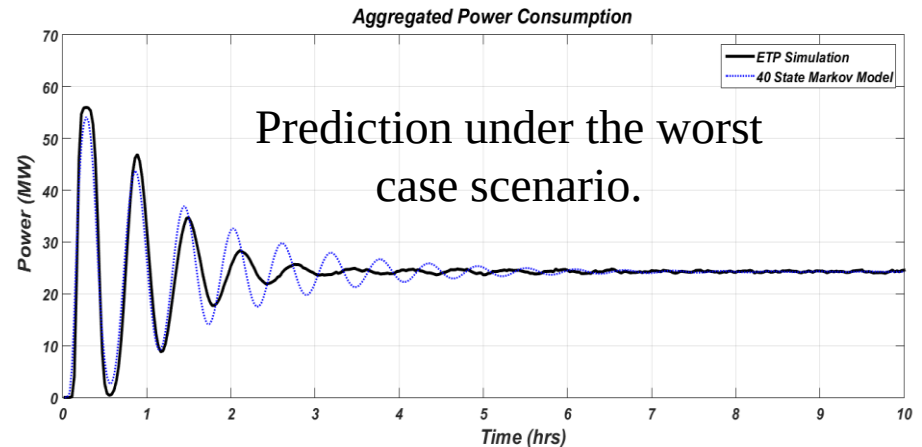


TCLs Aggregation: Markov Chain Modeling

- Probabilistic model describes the evolution of ON/OFF state devices over discrete temperature bins [9]
- Identified using statistical learning for a set of operational data sets (inside temperature trajectories and power consumption time series)

Characteristics:

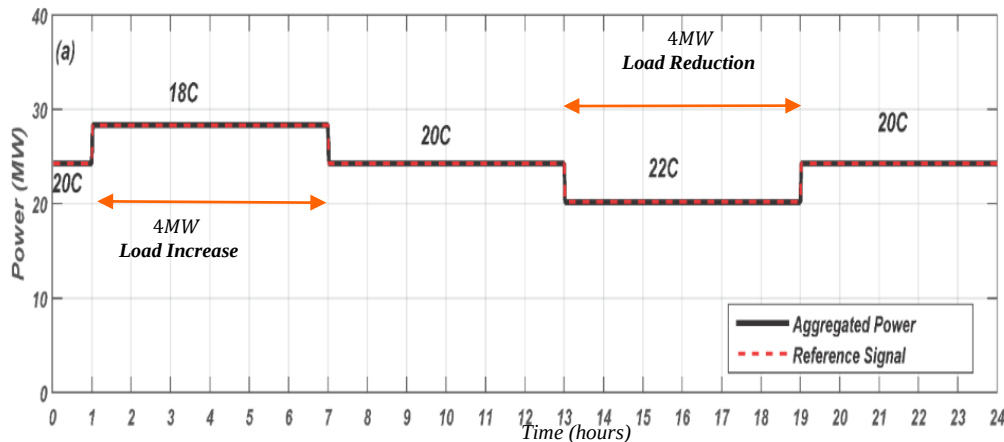
- Computationally tractable
Compared with the ETP models
- Appropriate for designing suitable control actions



[9] A. Radaideh; U. Vaidya; V. Ajjarapu. "Sensitivity Analysis on Modeling Heterogeneous Thermostatically Controlled Loads Using Markov Chain Abstraction", PES General Meeting, 2017.

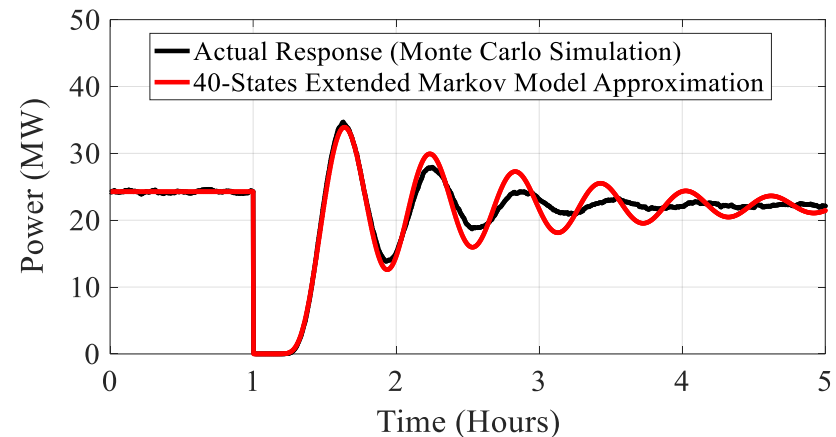
Control Examples

- Specific load increase or decrease services for relatively long time intervals



- Control Approach: Sequential set-point control & direct ON/OFF switching control using model predictive control (MPC) framework^[10]

- Fast Load Reduction for short term emergence ancillary services



- Control Approach Set-point control from 20 °C to 21 °C at t=1hr
- Need additional ON/OFF control to curb the oscillation

[10] A. Radaideh; U. Vaidya; V. Ajjarapu, "Sequential Set-point Control for Heterogeneous Thermostatically Controlled Loads Through an Extended Markov Chain Abstraction," in *IEEE Transactions on Smart Grid*, vol. PP, no.99, pp.1-1, 2017. [early access paper].

Overall Conclusions

- Voltage stability is a key issue facing the power systems and it should be monitored and controlled to enable secure operations of the grid
- For the long term voltage stability, combining the offline and the online data, via **adaptive regression and an adaptive data set**, can provide fast VSM prediction and also be used to determine control to improve from low margin
- For FIDVR, the measured load susceptance using PMUs is a good indicator for detecting FIDVR and along with offline data, it can be used for **estimating the recovery time and the control action** necessary to recover within a set criteria
- We demonstrated how a large number of PV inverters & thermostatic loads can aid the transmission system using **formulations (D-OPF & Markov Model) and tools (co-simulation)** that can effectively coordinate these devices to improve the bulk power grid performance

Questions?

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