Proactive Control to Minimize Impact of Extreme Events on the Power Grid

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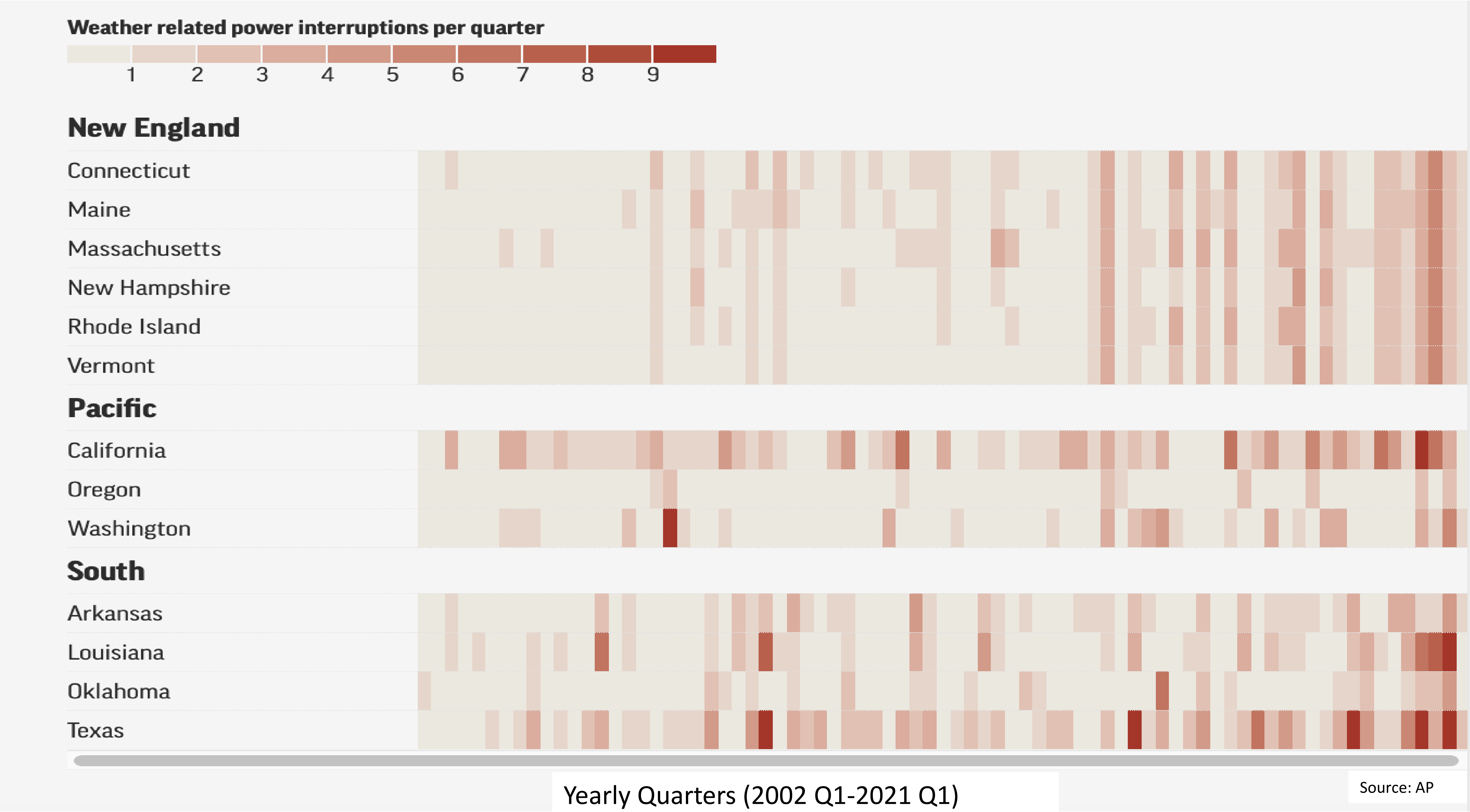
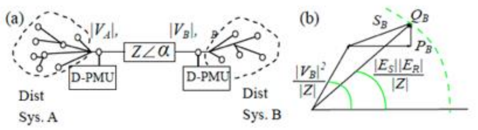
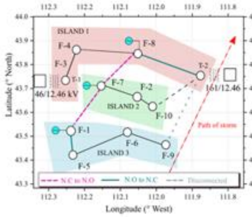
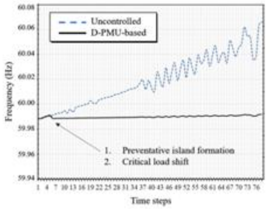

Weather related power interruptions per quarter
1
2
3
4
5
6
7
8
9
New England
Connecticut
Maine
Massachusetts
New Hampshire
Rhode Island
Vermont
Pacific
California
Oregon
Washington
South
Arkansas
Louisiana
Oklahoma
Texas
Yearly Quarters (2002 Q1-2021 Q1)
Source: AP

RTMOD Use Case 1: Data-driven Distribution System Reconfiguration with microgrid using D-PMU

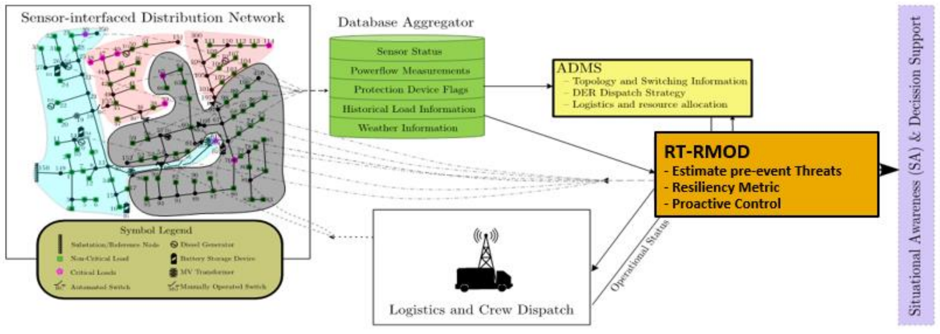


- D-PMUs can help us proactive reconfiguration of the system
- Based on the measurement we can deploy pre-event reconfiguration with controlled islanding and using shift-and-shed of loads
- *Minimize impact of expected outage by pre-event shift-and-shed of loads*





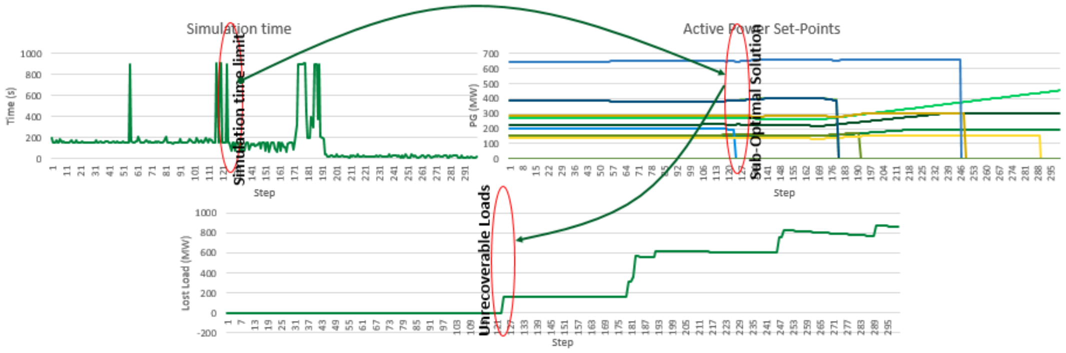
Proactive Controlled Assets Isolation



$$\max \sum_{\forall t\in T}\sum_{\forall i\in B} k_i^{CL}\alpha_i^t(2-\lambda_i)P_i^{CL,t} + k_i^{NCL}\beta_i^t(2-\lambda_i)P_i^{NCL,t}$$

RT-RMOD Use Case 2: Two Stage Proactive Control with Microgrids

- Outage of energized lines and energized generators due to expected events will cause more impact compared to unenergized lines and generators
- ***Not all* available switches available at the disposal of the operator are *remotely operable***
- When the forecast is certain, and disaster cannot be avoided, switching operations are important for resiliency improvement
- Two stage includes manually operated switch followed by automatic switches



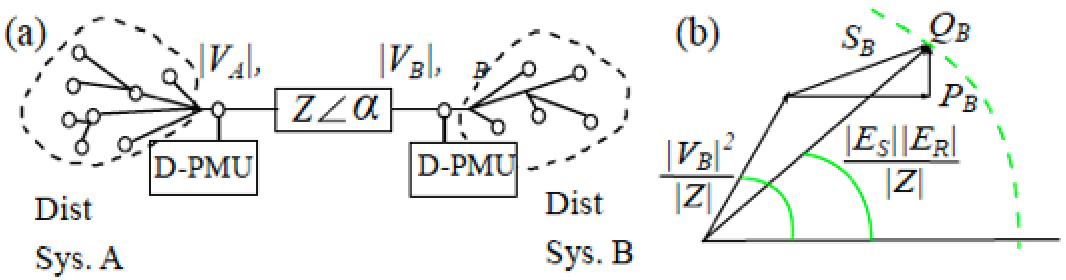
Case Scenario: Reinforcement Learning based Proactive Control for Transmission Grid Resilience

- Conventional approaches are resource intensive – especially during resiliency events
- Sub-optimal operation can be detrimental to overall operation of the grid
- ML-approaches can address some of the real-time decision-making requirements through partial operational set-points
- Conventional approach and ML-approach would go hand in hand

Summary

- During extreme weather events, situational awareness for grid operator is critical and the synergy between human operators and tools is required
- Proactive Control requires assessing expected impact of an event
- Optimization need to be solved with all the constraints, which becomes challenging for large T&D and discrete variables
- Machine learning approaches or ML assisted optimization might be helpful for faster convergence

RTMOD Use Case 1: Data-driven Distribution System Reconfiguration with microgrid using D-PMU



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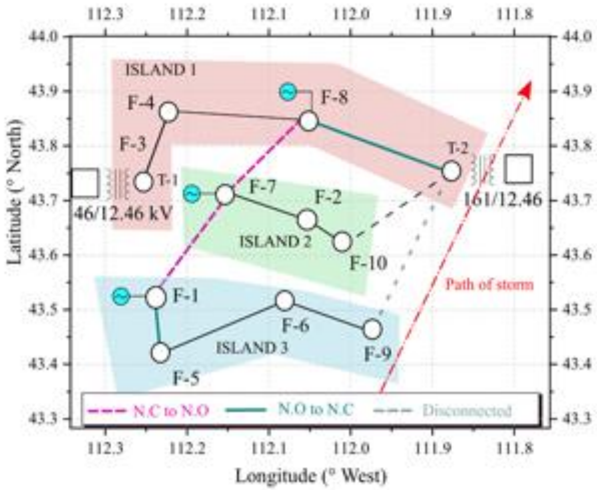
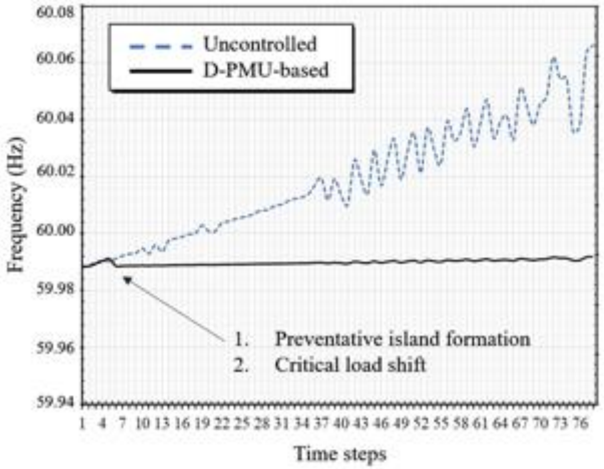




Proactive Controlled Assets Isolation

Algorithms: Distribution System Reconfiguration using D-PMU

Algorithm 1: Resilient Shift-and-Shed Proactive Control Algorithm Using D-PMU Data.

Input: $F_i = [|V_i|, \theta_i, P_i, Q_i]$, for $i = 1 \ldots n_s$, δ_{ij} (Eq. 15)
Output: Breaker status switching sequence
Phasor aggregation at DMS
1: Data filtration
2: Initialize array P_ij containing line flow data
3: **for** $i = 1$ to n_s **do**
4:   Compute line flows between nodes i and j ($j \neq i$) (Eq. 13)
5:   Compute $\frac{\Delta\delta_i}{\Delta t}$ (Eq. 14)
6:   **if** $(\frac{\Delta\delta_i}{\Delta t} \geq \delta_{threshold})$ **then**
7:     Append i to F^{risk}
8:     Change CLOSED switch to OPEN at bus i
9:     Change N.O. switch to CLOSED, between buses i and j
10:     **if** $\delta_{ijnew} < \delta_{ijprev}$ and $\delta_{ijnew} \to 0$ **then**
11:       Continue
12:     **else**
13:       Return to Line 4
14:     **end if**
15:   **else**
16:     Append i to F^{normal}
17:   **end if**
18: **end for**
19: **return** F^{risk}, F^{normal}, δ_i, P_ij

Algorithm 2: Resiliency-Driven Reconfiguration.

Input: Feeder at risk of being islanded due to storm, f_j^{normal}, δ_{t-1}
Output: R_i, Switch-on, switch status
1: Determine load transfer required
2: Predict δ_t (Eq. 15)
3: Choose the feeder edge with lowest line-flow (from Algorithm 1)
4: Compute $\frac{\Delta\delta_i}{\Delta t}$ (Eq. 14)
5: **if** $\frac{\Delta\delta_i}{\Delta t} \leq \delta_{threshold}$ **then**
6:   Compute switching sequence, available paths $(p(i,j))$ using M.S.T.
7:   **if** $n(p(i,j)) > 1$ **then**
8:     Determine R_i for each p
9:     Sort all R_i by magnitude
10:     Check for power flow convergence
11:     **if** convergence is true **then**
12:       **return** Switching sequence (i.e. path) that yielded highest R_i
13:     **else if** convergence is false **then**
14:       Choose next highest R_i path
15:       Go to Line 10
16:     **else**
17:       Shed non-critical load
18:     **end if**
19:   **else**
20:     Check for power flow convergence of only path p
21:     **if** convergence is true **then**
22:       **return** Switching sequence of path p
23:     **else**
24:       Shed non-critical load
25:     **end if**
26:   **end if**
27: **else**
28:   Shed non-critical load
29: **end if**
30: Repeat iteration until all critical loads are restored

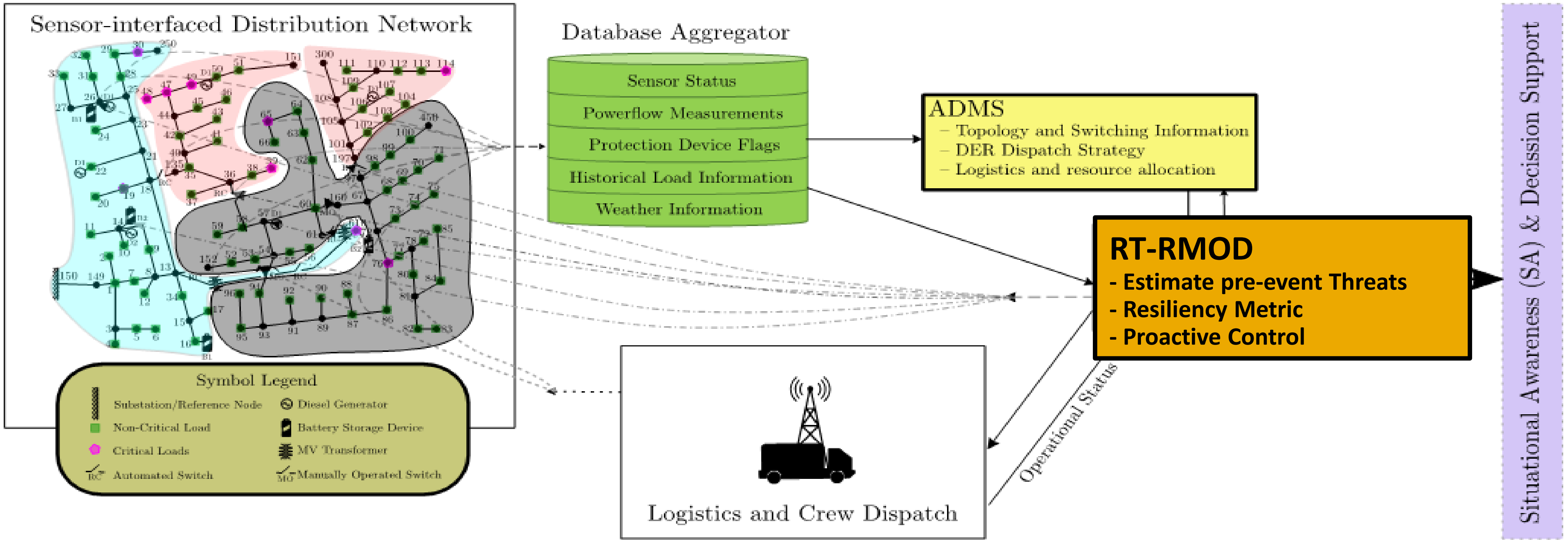
Proactive Reconfiguration for Distribution System with Microgrids using D-PMU

Resiliency Indices Comparison: Networked Microgrids

Resiliency Resource	Algorithm 1 and 2 used	Loss (kW)	Critical Load Loss (kW)	Resiliency [26]	Resiliency (AHP-based)
DG 1	No	1200	500	0.00083	0.16725
DG 1	Yes	1200	500	0.00083	0.20000
DG 2	No	1300	1000	0.00077	0.12500
DG 2	Yes	1100	500	0.00091	0.22500
DG 1, DG 2	No	1100	500	0.00091	0.27250
DG 1, DG 2	Yes	800	500	0.00125	0.32650
DG 1, DG 2, Solar	No	1100	500	0.00091	0.27250
DG 1, DG 2, Solar	Yes	400	0	0.00250	0.42125

Feeder Specific Resiliency Metrics

Feeder	Summer	Winter	Before Event	Without D-PMU	With D-PMU
F-1	0.78031	0.73216	0.85462	0.17819	0.58191
F-2	0.58021	0.52973	0.65232	0	0.38985
F-3	0.57223	0.56973	0.64823	0	0.26541
F-4	0.52387	0.54813	0.56648	0.19871	0.38911
F-5	0.58083	0.52364	0.60247	0	0.28192
F-6	0.46337	0.53368	0.53912	0	0.11837
F-7	0.81293	0.66107	0.72651	0.09321	0.48912
F-8	0.76938	0.68912	0.81034	0.00212	0.8103
F-9	0.64931	0.64236	0.62566	0	0.16839
F-10	0.57223	0.56981	0.64237	0	0.16892



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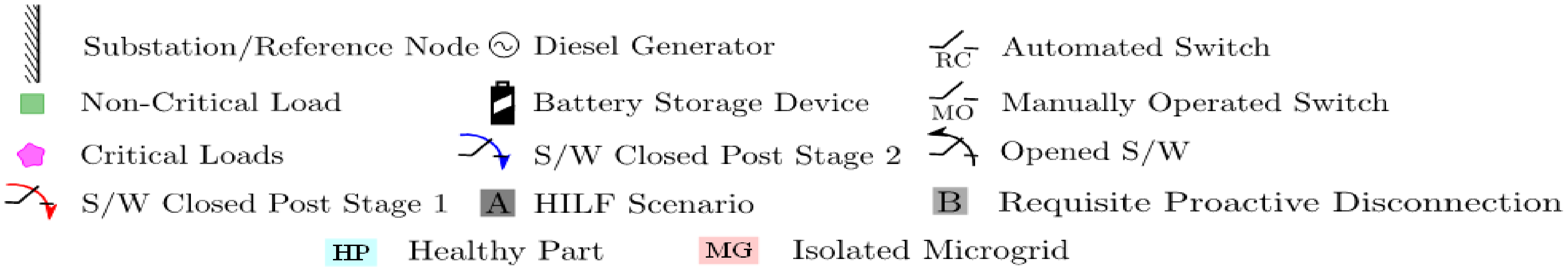
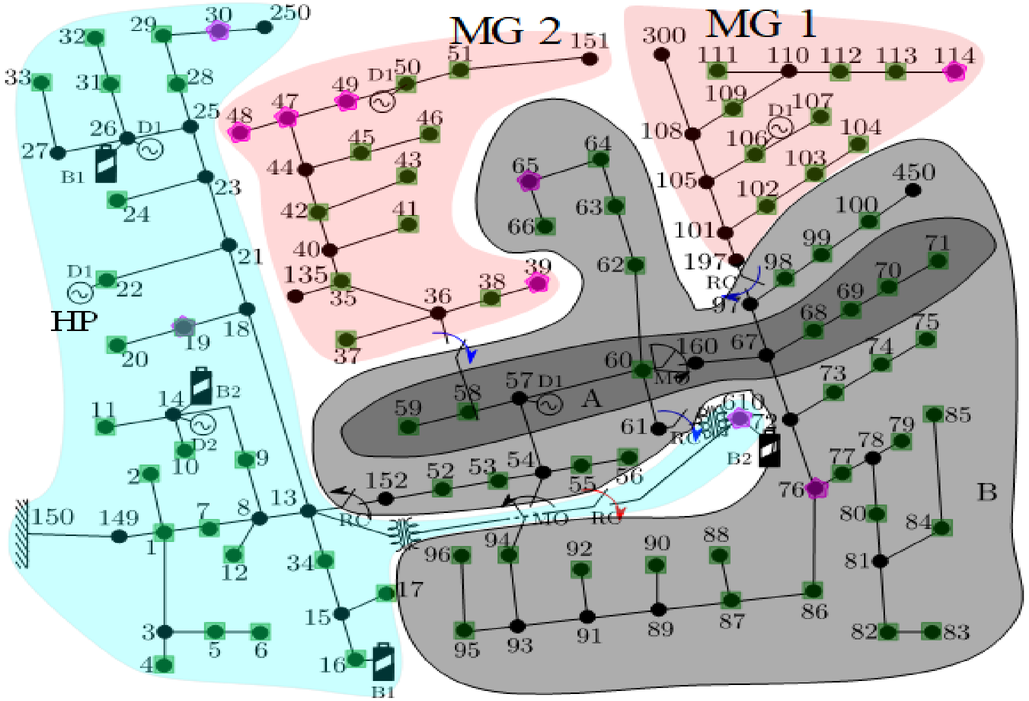
Test Systems with microgrids

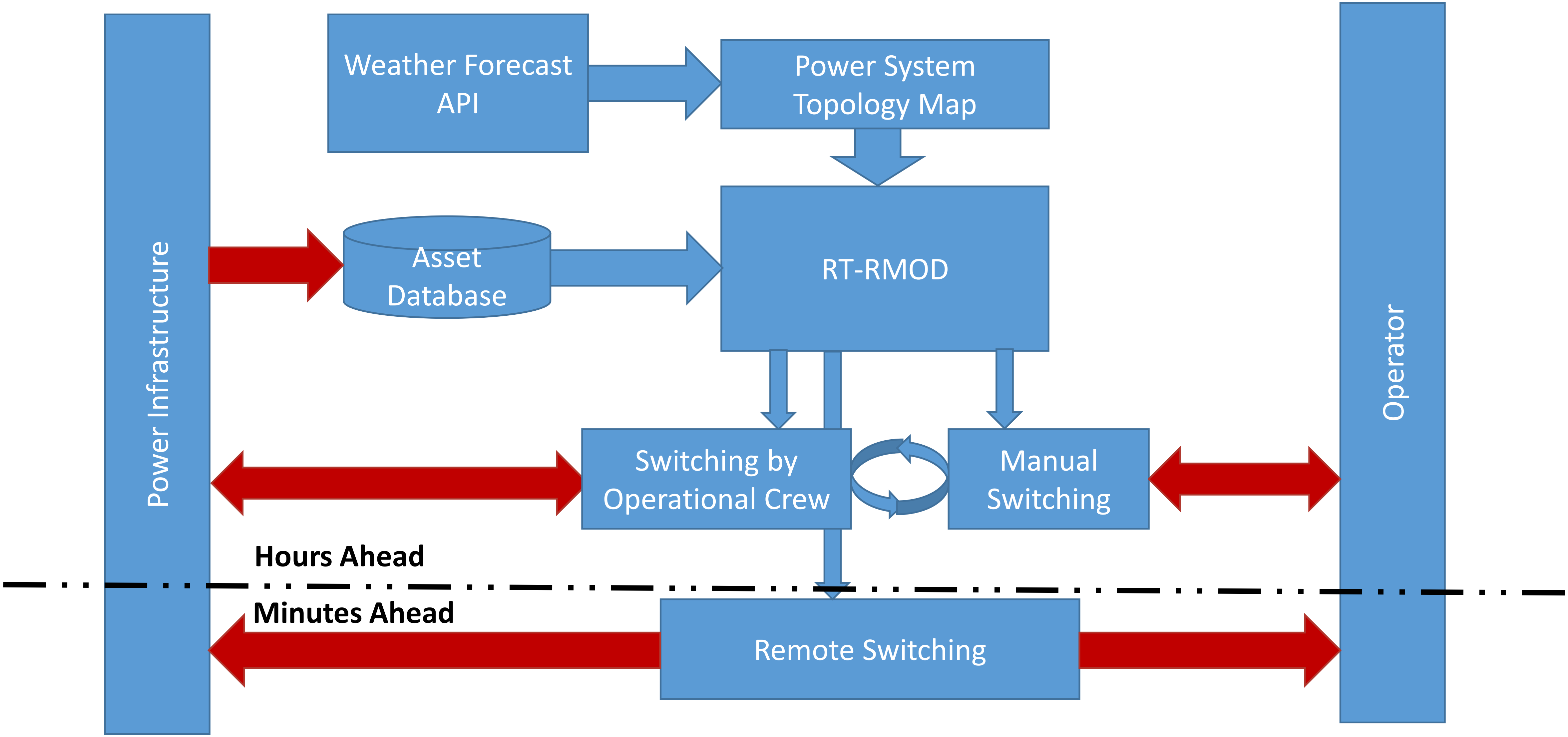


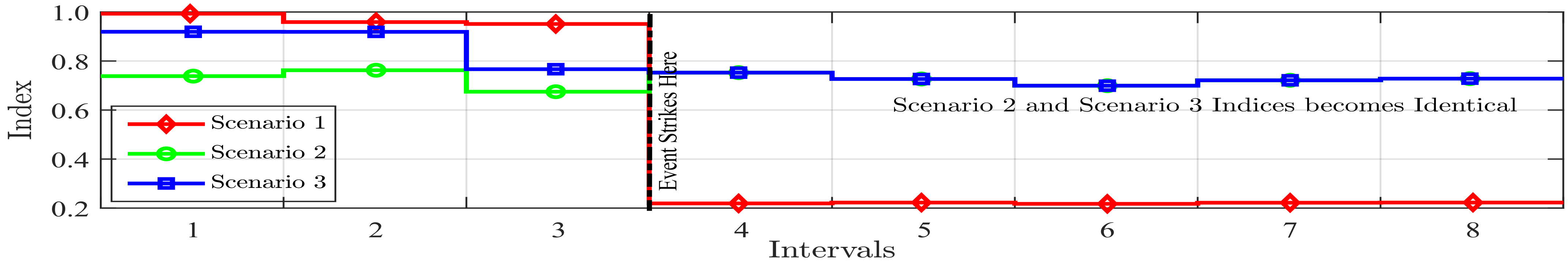


Modified IEEE 123-Bus Test System

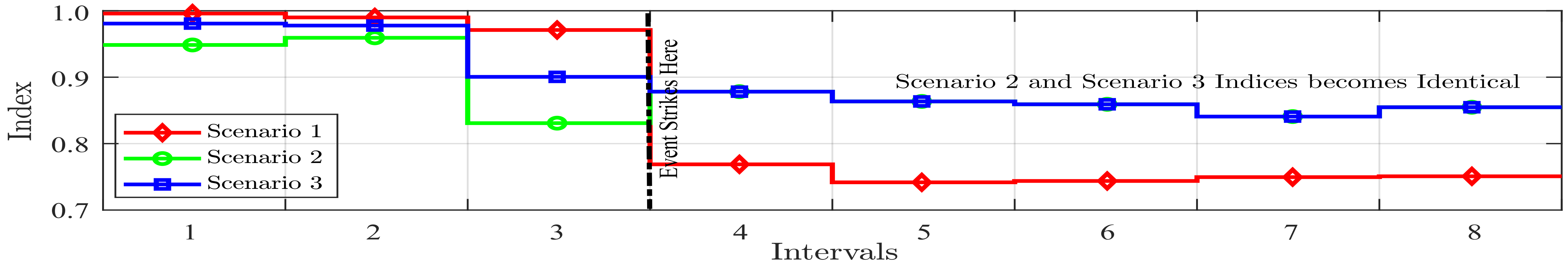
45-node CEC Islanded Microgrid System

Two Stage Proactive Control Algorithm





(a) Resiliency Indices for Modified IEEE 123-Node System

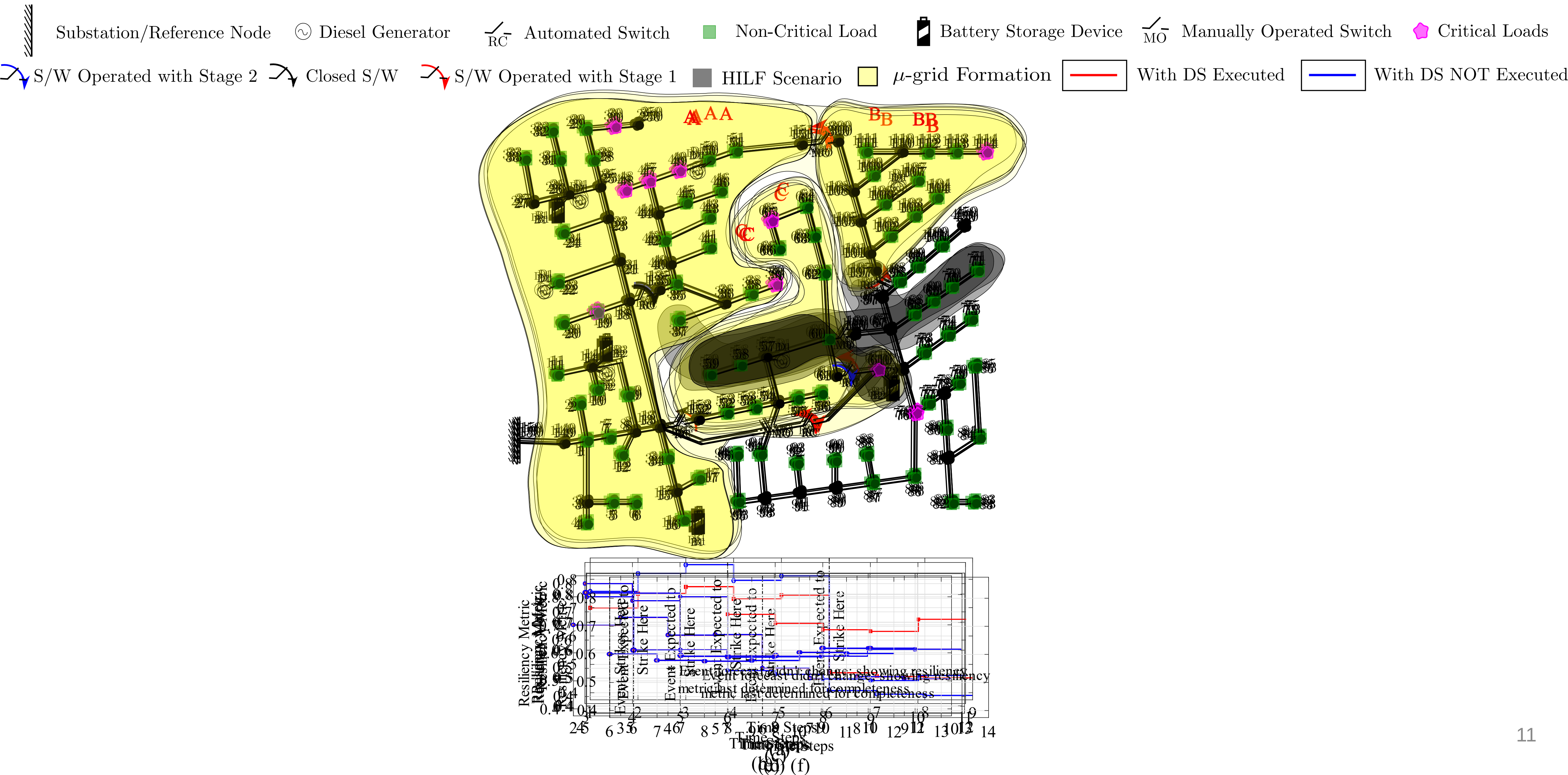


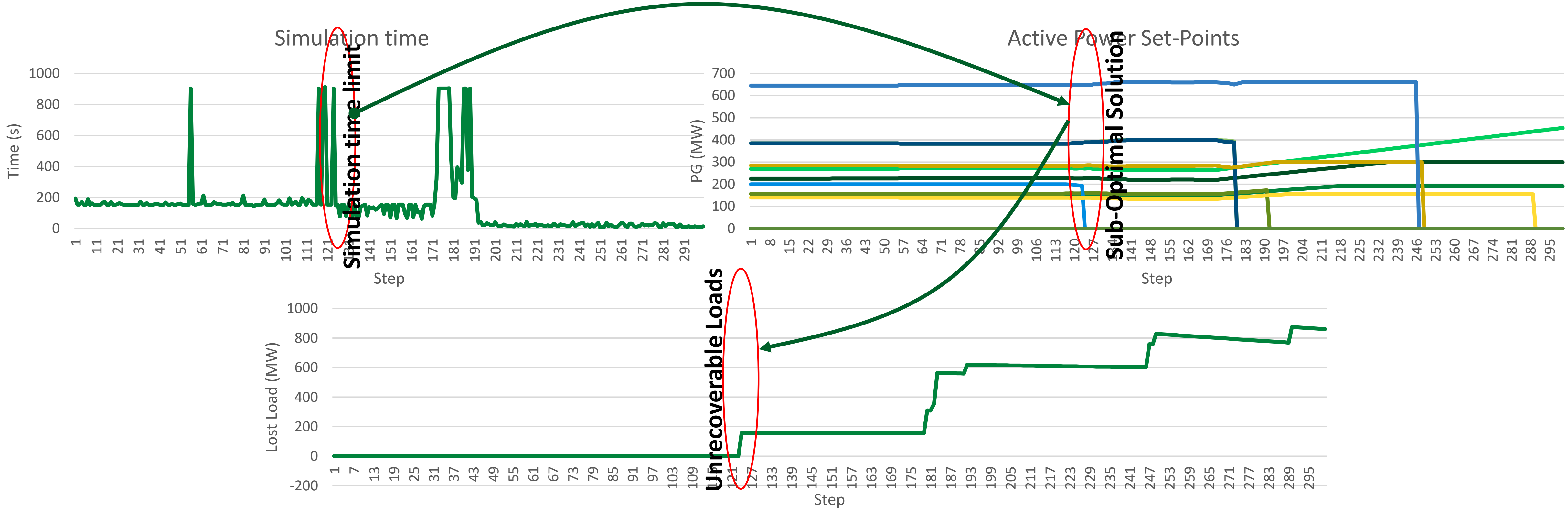
(b) Resiliency Indices for Isolated 45-Node System

Two-Stage Proactive Control: Results

- Scenario 1: Disaster strikes upon the network without prior preparation
- Scenario 2: Network is proactively reconfigured, but, to be outaged part removed apriori
- Scenario 3: Outaged part is operated through remote switches, only minutes before

Results for IEEE 123 Node System





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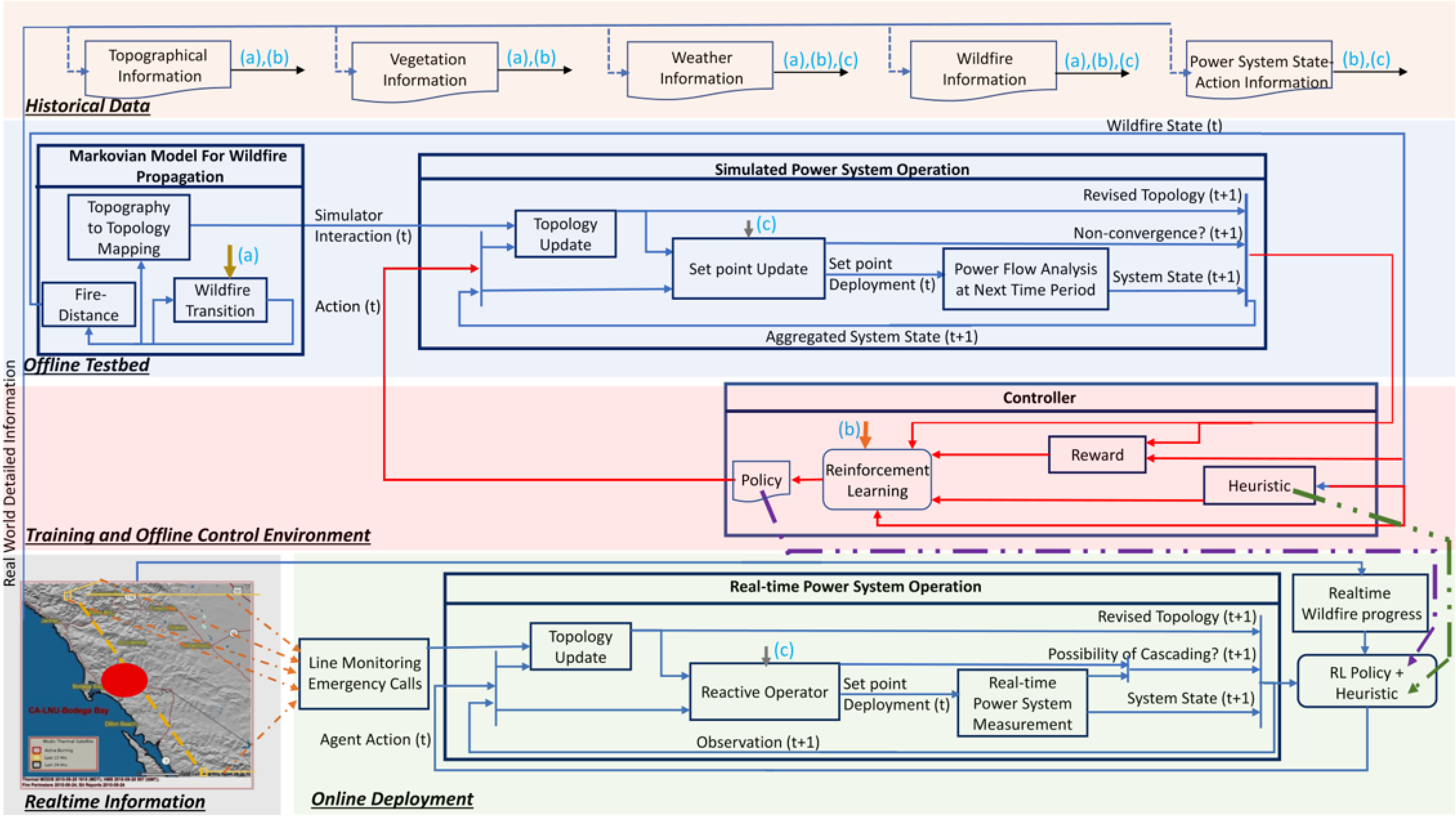
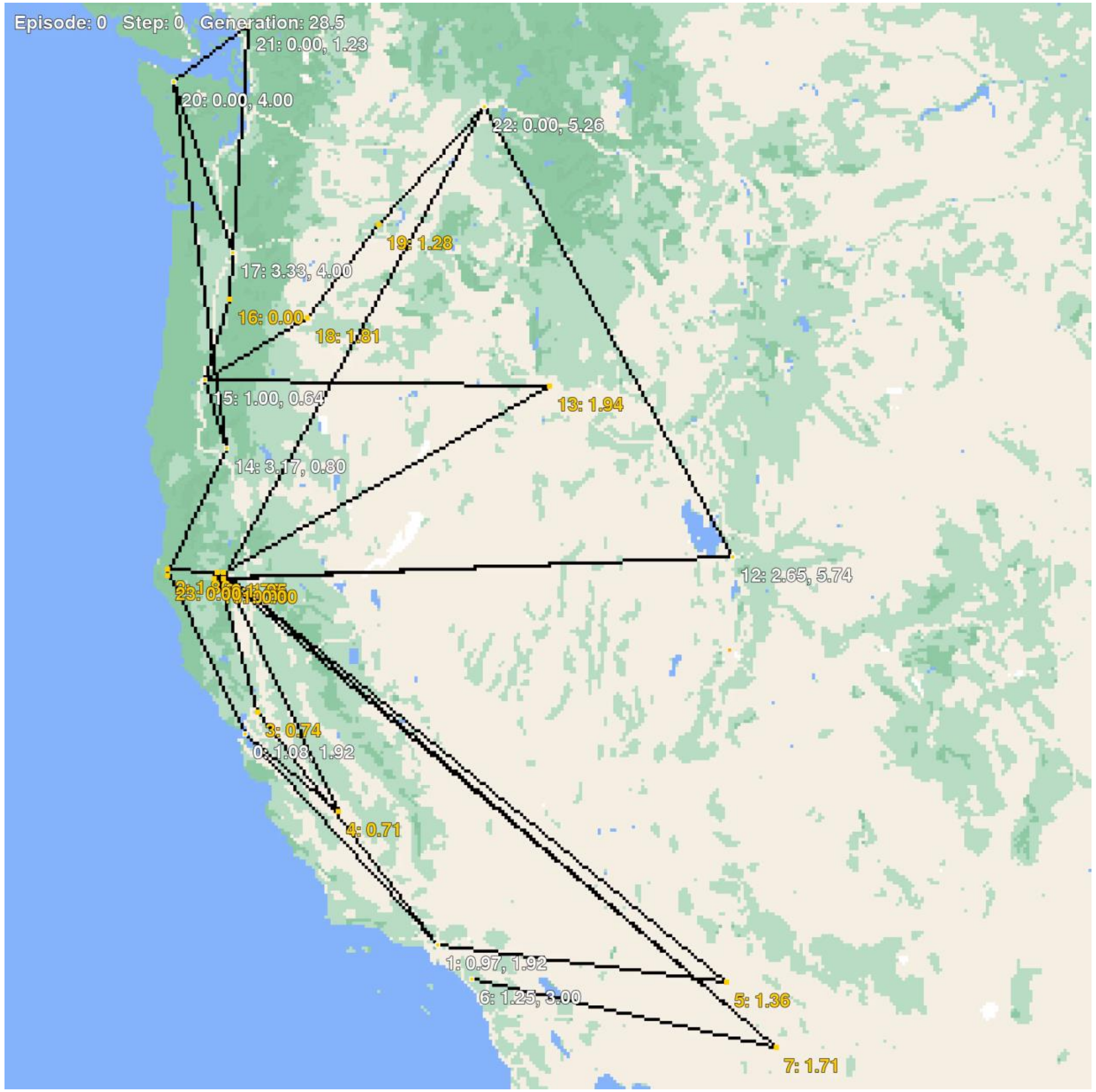
Use Case 3: RL-agent Learning for Proactive Control

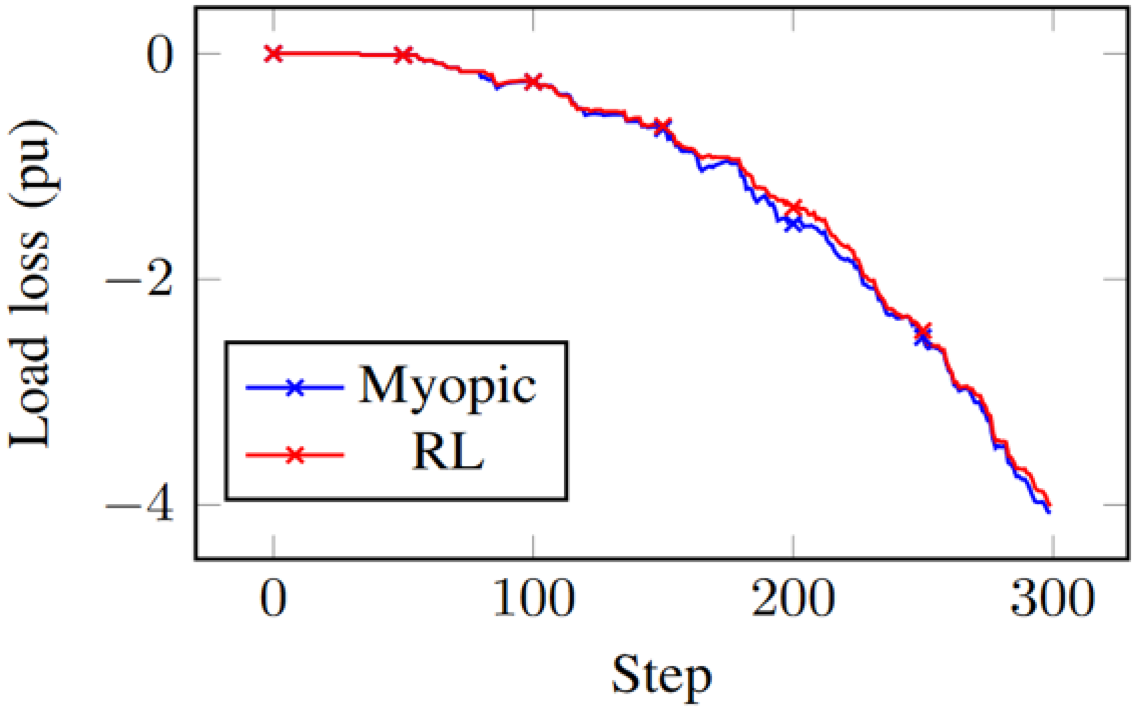


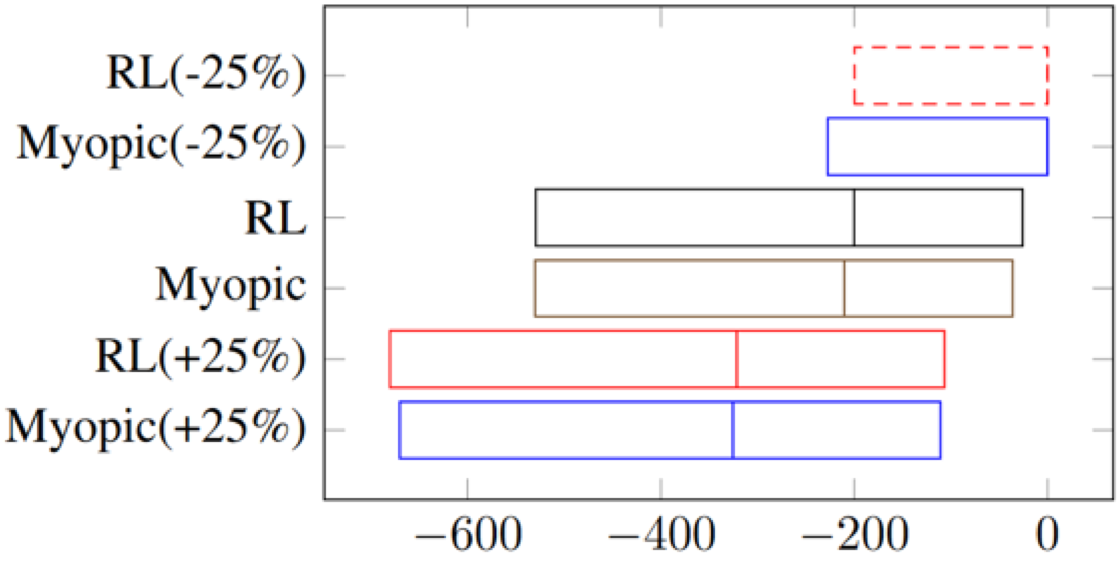
With University of Houston

Interactive agent for Wildfire



RL-agent Performance





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Thanks to my students, collaborators and funding agencies including DOE UI-ASSIST, RADIANCE and NSF to support this work.