

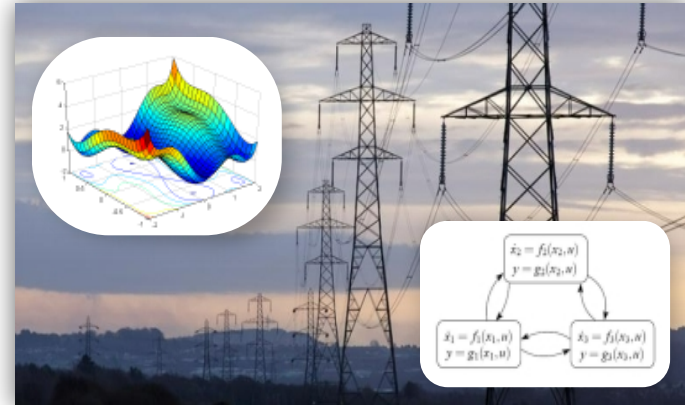
Stochastic Resilience Optimization with Grid Dynamics

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Problem

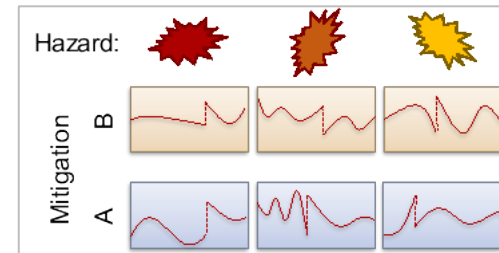
- Objective: Mitigation planning optimization for wide-area $n-k$ emergencies where multiple contingencies occur across a wide area in quick succession
- Even with mitigations in place, major dynamics and protective tripping are likely to ensue, with major implications to system stability and operability
 - Particularly want to avoid cascading, large blackouts, black start with unknown failures
- Optimization objectives are to minimize cascading, widespread blackout & permanent damage to long-lead devices, and to improve restorability.
- Decisions may include hardening, configuration, preventive & emergency control, strategic spare purchases and placement. SSTs, etc.

Key Research Challenge

- Prior resilience optimization work does not address wide-area $n-k$ events
 - Typically assumes either minor or localized hazards
 - Relies on non-dynamic impact models, which cannot detect loss of stability
 - Relies upon tight bound constraints which are likely not feasible in these emergencies (e.g., protective tripping may be unavoidable)
 - Incapable of addressing hybrid/cascading behavior due to assuming away protective devices
- We intend to incorporate both dynamic system physics *and* discrete protection in our optimization model
 - for accuracy of impact modeling and
 - to allow relaxing constraints that severely limit feasible space

Approach

- Stochastic planning optimization
 - choose from proposed hardening and mitigation measures and locations
 - optimize dynamically-assessed resilience
 - across a set of scenarios representing hazard uncertainty
- Two optimization stages:
 - mitigation decisions enacted across all hazard scenarios
 - impacts (and emergency control) assessed for each hazard scenario, using dynamic system physics and discrete protection logic
- Our phased project plan:
 1. build stochastic, continuous-dynamic optimization models
 2. add realistic hazard scenarios and appropriate discrete planning options
 3. add variables and constraints to represent discrete dynamics from protective devices, and address temporal discretization challenges



We are here



Year 1	Year 2	Year 3
Optimal control	+ optimal planning	+ hybrid dynamics
stochastic NLP	+ discrete 1 st stage vars (MINLP)	+ switching vars in 2 nd stage (time-sensitive)

Dynamic Optimization Literature

- Transient Stability Constrained
 - Optimal Power Flow (TSCOPF)
 - Emergency Control (TSEC)
- Minimize objective over contingencies, subject to DAE path constraints
 - TSCOPF: optimize initial conditions x_0 for potential contingencies
 - TSEC: optimize control inputs u for realized contingency
 - Decision variables: Generator and load real/reactive powers (or control setpoints)
 - Economic (generation cost) objectives
 - Path constraints limiting:
 - Rotor angles with respect to center-of-inertia average (approximate treatment of transient stability)
 - Line currents
 - Voltages

$\text{Min } h(x, y, u)$ objective

subject to

$$\left. \begin{aligned} \frac{d}{dt}x &= f(x, y, u) \\ 0 &= g(x, y, u) \end{aligned} \right\} \text{DAE}$$

$c(x, y, u) < 0$ constraints

$x(0) = x_0,$
 $y(0) = y_0$ initial conditions

Dynamic Power Systems Modeling

- In major emergencies, dynamics play important role in system stability
- Generator dynamics (Sauer, Pai, Chow)
 - Angular acceleration = mechanical power in, minus electrical power out
 - We use the 4th order flux-decay model commonly used in stability studies
 - An additional term (turbine with no reheating) models torque response delay
- Network power balance
- Load dynamics
 - Play an important role in stability studies*
 - Exponential recovery model (Karlsson & Hill) captures load responses to voltage fluctuations
- Combined, these pose a system of differential algebraic equations (DAE)

$$\frac{2H}{\omega_0} \frac{d^2 \delta}{dt^2} = P_m - P_e$$

$$0 = V e^{i\theta} \odot (Y V e^{i\theta})^* - S_{net}$$

*R. Zhang, Y. Xu, W. Zhang, Z. Y. Dong, and Y. Zheng (2016), *Impact of dynamic models on transient stability-constrained optimal power flow*, 2016 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC), pp. 18–23

System Stability Penalty Objectives

- In severe emergencies, bound constraints may be temporarily exceeded
- Our goal is to position the system as far within bounds as quickly as possible
 - Provide safety margin against further events
- In addition to path constraints, we penalize approaching or exceeding certain limits in the objective function
 - Example: Transient stability

$$\bar{\delta}_i = \left| \delta_i - \frac{\sum_{k=1}^{ng} H_k \delta_k}{\sum_{k=1}^{ng} H_k} \right|$$

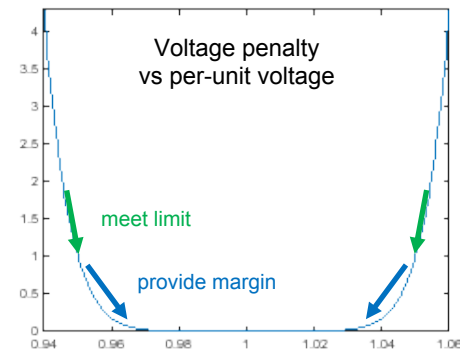
(want <100 degrees)

- Example metrics which can be penalized for deviating from nominal:

- Voltage
- Frequency
- Transient stability
- Line currents

- Decision variables

- Mechanical torque
- Exciter voltage reference
- Load shed
- (more to be added)



Stochastic Model



- A two-stage stochastic programming model is structured as follows:

$$\min_{x, y_\psi} c(x) + E[d(y_\psi)]$$

s.t.

$$f(x) \leq b$$

$$g_\psi(y_\psi) \leq f_\psi$$

$$h(x) + k(y_\psi) \leq g_\psi$$

$$\forall \psi \in \Psi$$

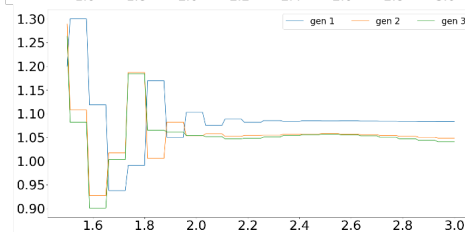
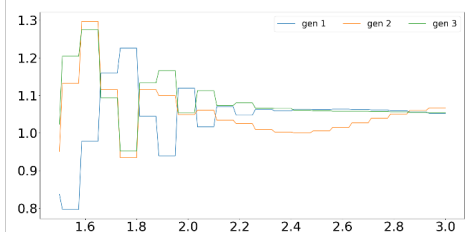
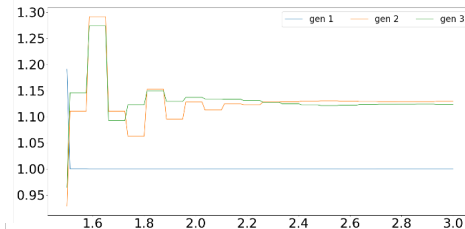
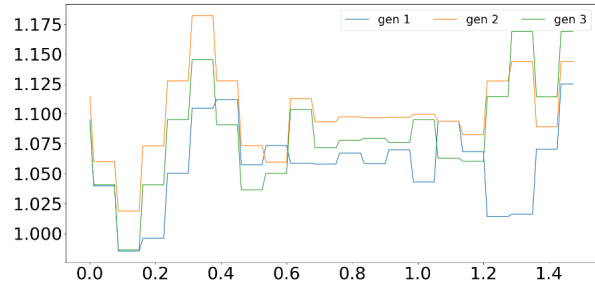
$$\forall \psi \in \Psi$$

Set of scenarios
representing
hazard uncertainty

- In the following example,
 - Variables x and y are pre- and post-contingency versions, respectively, of our control variables (P_{ref} and V_{ref})
 - Objectives $c(x)$ and $d(y)$ are pre- and post-contingency sums of penalty metrics mentioned earlier
 - Dynamics are included in constraints to assess control effects and scenario impacts

Stochastic Preventive-corrective Control

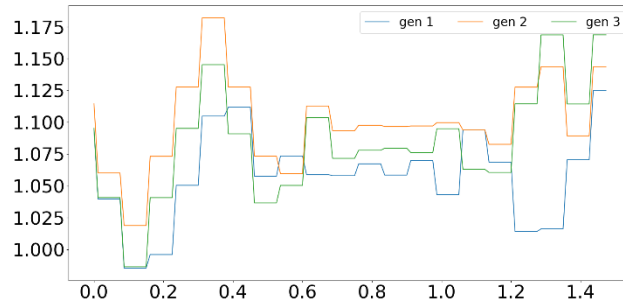
TSCOPF-like
control problem



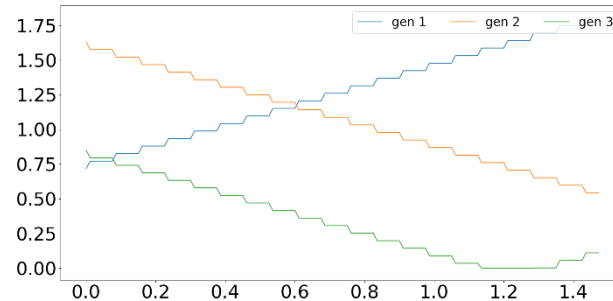
TSEC problem for each hazard scenario

Multi-scenario Case Pre-positioning

- Consider on the 9-bus test system four possible scenarios – the no-failure case, a line trip, a load trip, and a generator trip, each with probability of occurring of 0.25
- Below is first-stage pre-positioning of V_{ref} and P_{ref} to minimize first stage penalty plus average second stage penalty across all scenarios



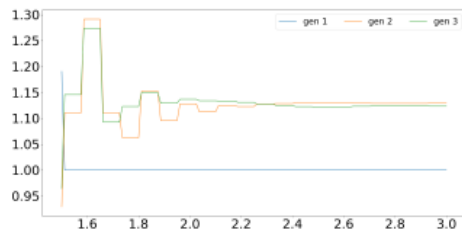
V_{ref}



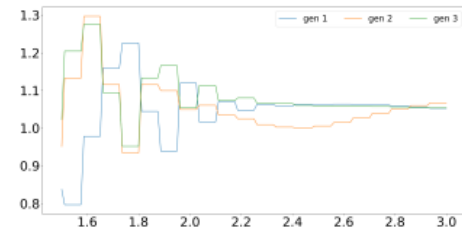
P_{ref}

(MVA – very fast ramp rates assumed for demonstration purposes)

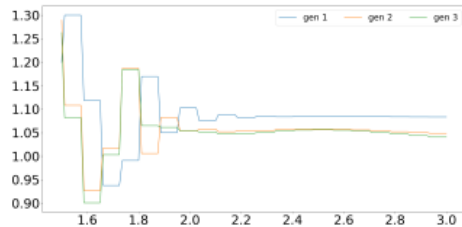
Multi-scenario Case Recourse Action



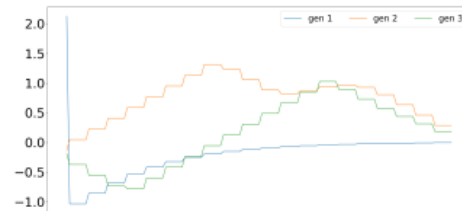
Gen
Trip



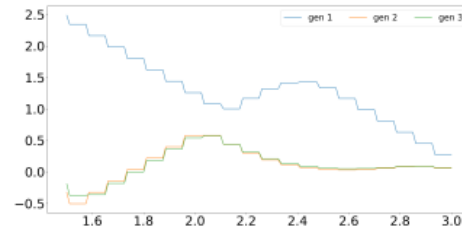
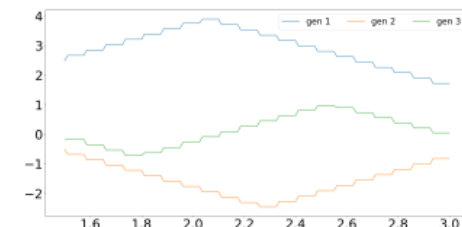
Load
Trip



V_{ref}



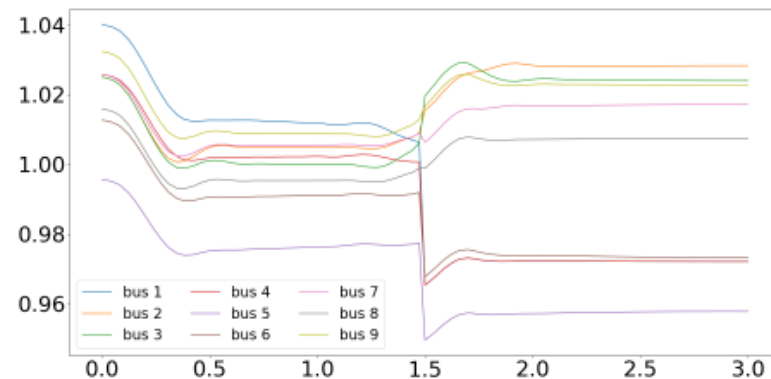
(note gen 1 values are meaningless here)



P_{ref}

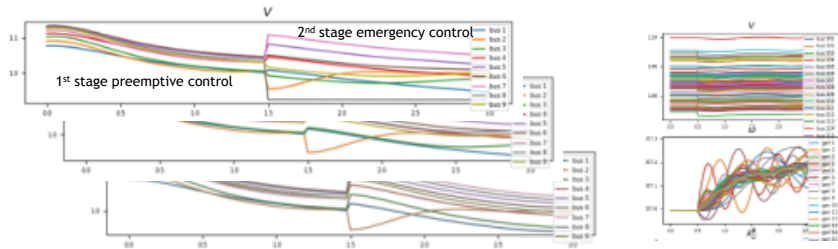
Impact of Preventive-corrective Control

- Generator trip example on 9-bus system
- Despite sudden loss of 24% of total generation, voltages are kept centered within acceptable bounds around 1.0 p.u.
- Coupling first and second-stage controls is particularly effective:
 - 65% reduction in objective value compared to pre-positioning alone
 - 61% reduction compared to recourse control alone



Project Status

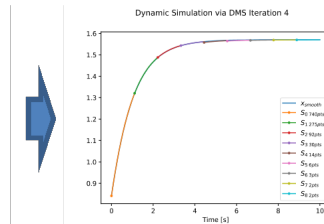
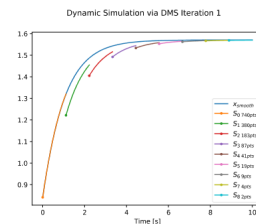
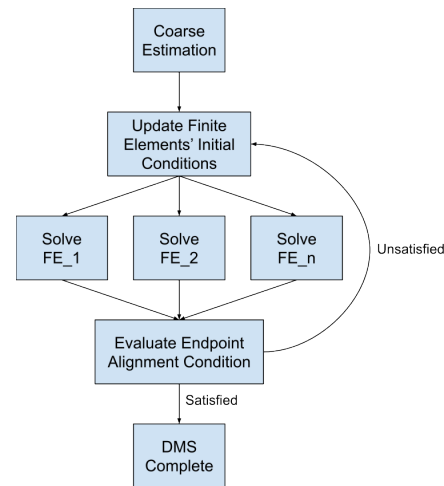
- Built 2-stage stochastic model with power system dynamics
 - Novel coupled dynamic preventive-corrective control*
 - Demonstrated on RTS-96 test system
- Research into
 - mitigation options
 - model & variable reduction
 - multiple-shooting discretization (see next slide)
- Beginning MINLP research
 - Binary variables representing component-wise failures and mitigations
 - Toy HDS model to start addressing temporal discretization challenges in year 3



*B. Arguello, N. Stewart, M. Hoffman (2021), *Stochastic Optimization of Power System Dynamics for Grid Resilience*. 54th Hawaii Int'l Conf. on System Sciences.

NMT Research

- Multiple-shooting is a hybrid of the sequential and simultaneous discretization methods
 - coarse discretization in optimization formulation, reconciled with higher-fidelity simulation between nodes
- It has been used once on dynamic power system problems*; we wish to further explore its benefits:
 - More natural inclusion of adaptive time discretization for accurate switching times
 - High-fidelity continuous-time control despite coarse discretization of optimization model
 - Computational efficiency and parallelizability



Conclusion

- In year 1, optimizing preventive-corrective control vs. uncertain hazards
 - Allows better solutions across a wider set of contingencies than otherwise possible
 - Serves as a foundation for dynamics-informed resilience planning optimization against severe threats in following years
- Remaining key challenges:
 - Improving realism and scale
 - Stochastic (MINLP) mitigation planning
 - With realistic mitigations & resilience objectives (load shed, device damage, etc.)
 - With protective tripping in dynamics (year 3)
- Relevance:
 - Hybrid dynamic physics within an optimization model addresses key gaps
 - Especially resilience planning for n-k emergencies
 - Formulation and solution methods are relevant to other infrastructures and hybrid dynamical systems
 - Insights regarding scalability, solution methods and discretization relevant to optimization community

Team

- Sandia core team
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- NMT
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