

Cascading Failures and Energy Landscapes for Power Systems

LANS Seminar

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Power Grid Problems

Power Grid Problems

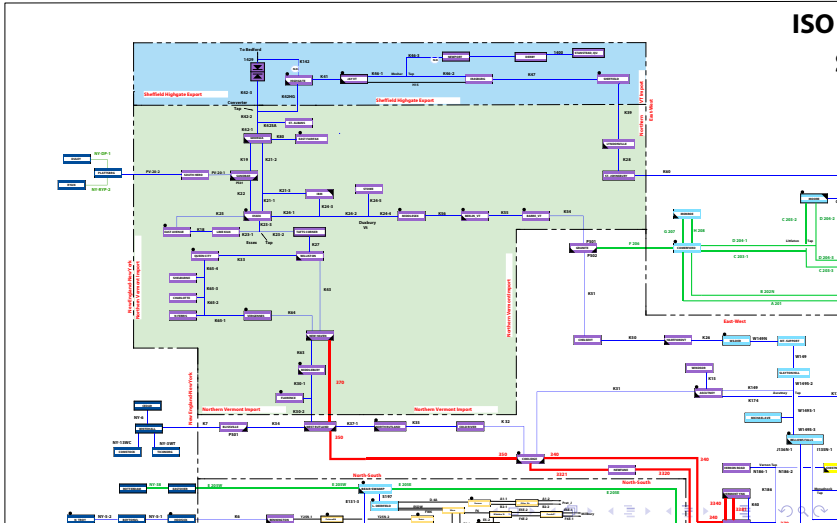
Cascad(a)-ing Failure



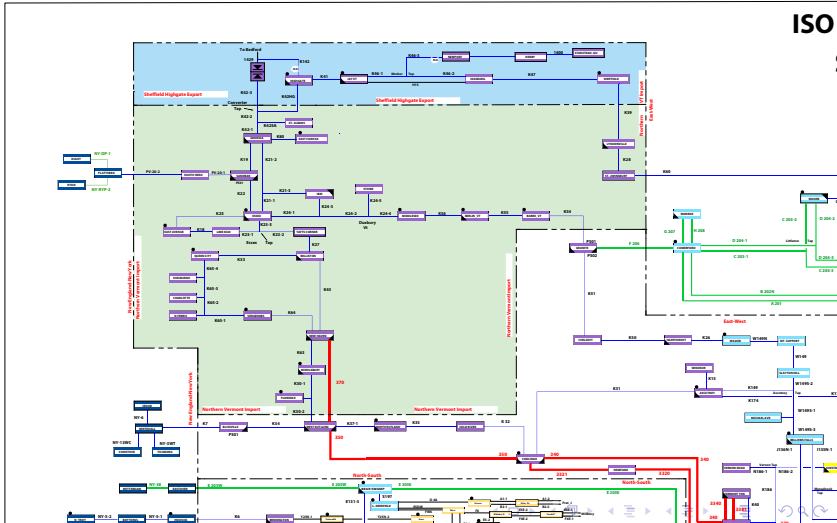
"Every time we touch, I feel the static" – Cascada¹, and also, squirrels

Every time we touch, Maggie Reilly, 1992

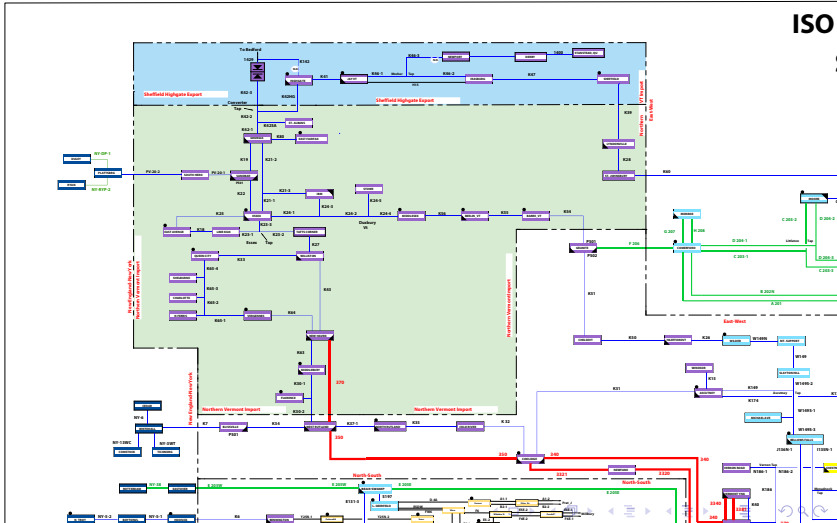
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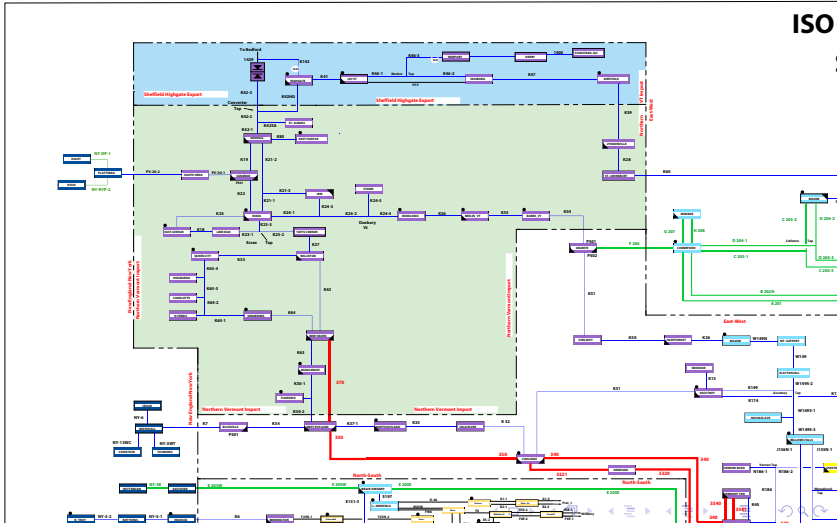
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- Metric: Line failure probability

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- Represent voltage $v^{(t)}$ and current $i^{(t)}$ by sinusoidals
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- Algebraic phasor manipulations (i.e., Ohm, Kirchoff, etc.) depend on a common ω and a reference δ
- Standard to use (ω - and δ -relative) voltage variables: $\tilde{v} := Ve^{i\theta} \quad (1)$
- Compute scalar (rms) power values for the real and complex components of v and i

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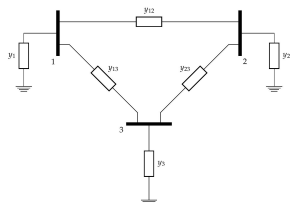
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$$S := P + iQ = \tilde{v} \odot [\tilde{Y}\tilde{v}]^*, \quad \text{partitioned as } F(V, \theta) \equiv P, \quad G(V, \theta) \equiv Q \quad (2)$$



$$Y = \begin{pmatrix} y_1 + y_{12} + y_{13} & -y_{12} & -y_{13} \\ -y_{12} & y_2 + y_{12} + y_{23} & -y_{23} \\ -y_{13} & -y_{23} & y_3 + y_{13} + y_{23} \end{pmatrix} \quad (\text{Wikipedia})$$

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DAE Model ($\mathcal{M}_{\text{generic}}$)

$$\dot{x} = d(x; y), \quad (\text{slower timescale}) \quad (4a)$$

$$0 = pfe(x; y), \quad (\text{faster timescale}) \quad (4b)$$

where d represents the generator dynamics and pfe represents the power flow equations

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DAE Model ($\mathcal{M}_{\text{classical}}$), more detail under lossless assumption

$$\dot{\theta}_i = \omega_i - \omega_S, \quad i \in \mathcal{G} \cup \mathcal{S} \quad (5a)$$

$$M_{ij}\omega_i = P_{\text{net}}^i - \sum_{j \in \mathcal{B}} V_i V_j B_{ij} \sin(\theta_i - \theta_j) - D_i(\omega_i - \omega_S), \quad i \in \mathcal{G} \cup \mathcal{S} \quad (5b)$$

$$0 = -P_{\text{net}}^i - \sum_{j \in \mathcal{B}} V_i V_j B_{ij} \sin(\theta_i - \theta_j), \quad i \in \mathcal{L} \quad (5c)$$

$$0 = Q_{\text{net}}^i - \sum_{j \in \mathcal{B}} V_i V_j B_{ij} \cos(\theta_i - \theta_j), \quad i \in \mathcal{L} \quad (5d)$$

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Failure Mechanism

For line $\ell = (i, j)$, complex current flow, line energy, and “safe” domain are:

$$\tilde{i}_\ell := (\tilde{v}_i - \tilde{v}_j) y_{ij} \quad (6a)$$

$$\Theta_\ell(x) := |\tilde{i}_\ell|^2 = \tilde{i}_\ell \tilde{i}_\ell^* = b_{ij}^2 \left(V_i^2 - 2V_i V_j \cos(\theta_i - \theta_j) + V_j^2 \right) \quad (6b)$$

$$D := \{x : \Theta_\ell(x) < \Theta_\ell^{\max}\}. \quad (6c)$$

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- Structure of DAE includes “mismatch” vectors
- “Mismatch” is central to the system’s behavior and motivates a reformulation

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DAE Model ($\mathcal{M}_{\text{Hamiltonian}}$) [?, ?]

$$\begin{bmatrix} \dot{\omega} \\ \dot{\theta} \\ 0 \end{bmatrix} = (J - S) \begin{bmatrix} \nabla_{\omega} \mathcal{H}(\omega, \theta, V; y) \\ \nabla_{\theta} \mathcal{H}(\omega, \theta, V; y) \\ \nabla_V \mathcal{H}(\omega, \theta, V; y) \end{bmatrix} \quad (7a)$$

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for a scalar function \mathcal{H}^y (parametrized by y) such that the partials are related to the mismatches:

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$$\nabla_{\theta} \mathcal{H}^y := F v_{GUL} - [P_{\text{net}}] v_{GUL} \quad (8b)$$

$$\nabla_V \mathcal{H}^y := V^{-1}(G v_L - [P_{\text{net}}] v_L) \quad (8c)$$

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and where J and S are appropriate skew-symmetric and diagonal “structure” matrices representing network interconnection and damping, respectively

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- DAEs are harder to simulate than ODEs
- Perhaps we can relax the power flow constraint assumption

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Relax the fast dynamics:

$$\dot{x} = A\nabla\mathcal{H} \equiv \begin{cases} \dot{\omega} &= -A_{\omega\omega}\nabla_{\omega}\mathcal{H} - A_{\omega\theta}\nabla_{\theta}\mathcal{H} \\ \dot{\theta} &= A_{\omega\theta}\nabla_{\omega}\mathcal{H} - A_{\theta\theta}\nabla_{\theta}\mathcal{H} \\ \dot{V} &= A_{VV}\nabla_V\mathcal{H} \end{cases} \quad (9a)$$

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$$A := \begin{bmatrix} -M_{\mathcal{V}_{\text{GUS}}}^{-1} D_{\mathcal{V}_{\text{GUS}}} M_{\mathcal{V}_{\text{GUS}}}^{-1} & -M_{\mathcal{V}_{\text{GUS}}}^{-1} T_1^{\text{T}} & 0 \\ M_{\mathcal{V}_{\text{GUS}}}^{-1} T_1^{\text{T}} & -T_2^{\text{T}} D_{\mathcal{V}_L} T_2^{\text{T}} & 0 \\ 0 & 0 & D_V^{-1} h_{\mathcal{V}_L} \end{bmatrix} \quad (10)$$

where T_1, T_2 are structure matrices

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Scalar Potential

Path-independent scalar potential [?, ?, ?, ?]:

$$\begin{aligned} \mathcal{H}^y(x^{(0)}, x^{(T)}) &= \frac{1}{2} (\omega^{(T)})^\top M_{\mathcal{V}_{GUS}} \omega^{(T)} + \frac{1}{2} \tilde{\nu}_{\mathcal{V}}^H B \tilde{\nu}_{\mathcal{V}} + \langle [P_{\text{net}}]_{\mathcal{V}_{GUL}}^{(0)}, \theta_{\mathcal{V}_{GUL}}^{(T)} \rangle \\ &+ \langle [Q_{\text{net}}]_{\mathcal{V}_L}^{(0)}, \log(\mathcal{V}_{\mathcal{V}_L}^{(T)}) \rangle + C \end{aligned} \quad (12)$$

Scalar Potential

- Structure of A : full-rank, negative-semidefinite ($\nabla\mathcal{H}(\bar{x})^\top A \nabla\mathcal{H}(\bar{x}) \leq 0$ along any solution trajectory \bar{x})
- Equilibrium points can be characterized by $\nabla\mathcal{H}(x) = 0$
- LasSalle's theorem for $\nabla^2\mathcal{H} \succ 0$ hints at Lyapunov function

First Integral

Path integral from equilibrium $x^{(0)} = \bar{x}$ to time T :

$$\mathcal{H}^y(x^{(0)}, x^{(T)}) := \int_{(0, \theta_{\mathcal{V}_{GUL}}^0, \mathcal{V}_{\mathcal{V}_L}^0)}^{(\omega_{\mathcal{V}_{GUS}}^{(T)}, \theta_{\mathcal{V}_{GUL}}^{(T)}, \mathcal{V}_{\mathcal{V}_L}^{(T)})} \left\langle \begin{bmatrix} \nabla_{\omega} \mathcal{H}^y \\ \nabla_{\theta} \mathcal{H}^y \\ \nabla_{\mathcal{V}} \mathcal{H}^y \end{bmatrix}, \begin{bmatrix} d\omega \\ d\theta \\ d\mathcal{V} \end{bmatrix} \right\rangle \quad (11)$$

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Constrained Minimization Problem

$$\underset{x}{\text{minimize}} \quad \mathcal{H}(x) \quad (14a)$$

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Definition (Minimizers)

$$\bar{x} := \arg \min ?? \quad (15a)$$

$$x^* := \arg \min ?? \quad (15b)$$

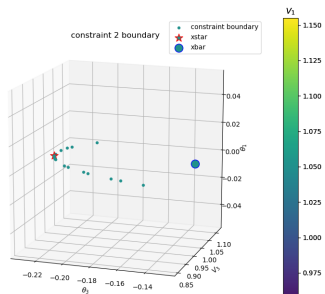
Constraint Landscape

Constraint Landscape

Phase-space constraint boundary will only involve at most four variables $V_i, V_j, \theta_i, \theta_j$:

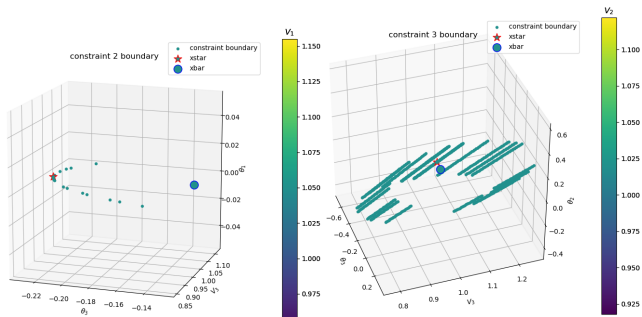
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Local energy surface, *left*: discretized constraint surface defined by line-2, *right*: line-3

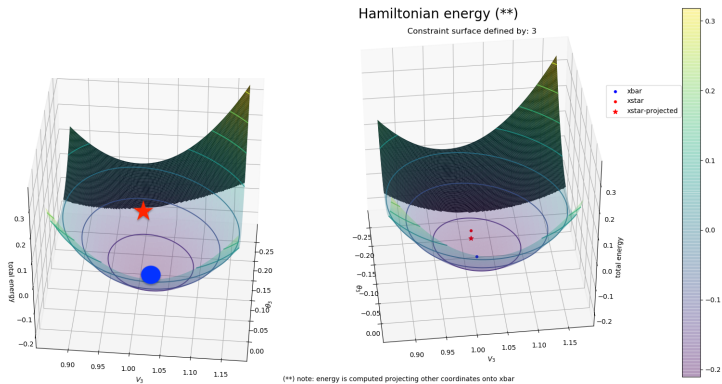
Energy Landscape

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Phase-space energy surface: [Idt](#)

Energy Landscape

Phase-space energy surface: ldt



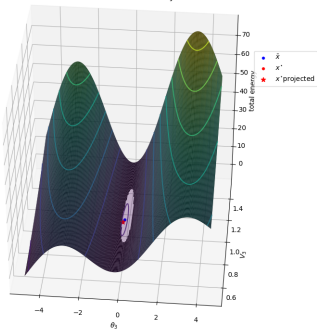
Local energy surface, *left*: energy and constraint surface (black) defined by line-2, *right*: line-3

Energy Landscape

Phase-space energy surface: Idt

Hamiltonian energy (**)

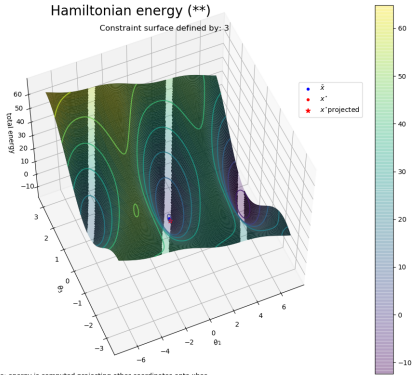
Constraint surface defined by: 2



(**) note: energy is computed projecting other coordinates onto \bar{x}

Hamiltonian energy (**)

Constraint surface defined by: 3

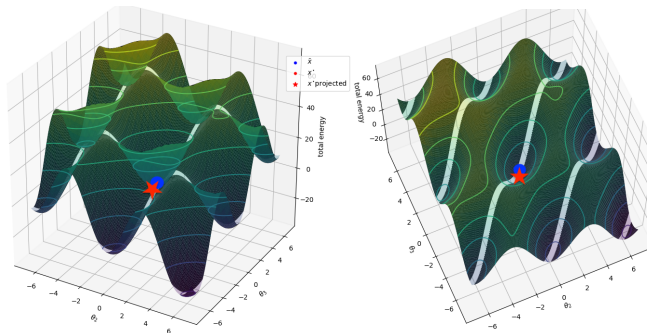


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Wider energy surface, *left*: energy and constraint surface (black) defined by line-2, *right*: line-3

Energy Landscape

Phase-space energy surface: Idt



Global energy surface, *left*: energy and constraint surface (black) defined by line-3, *right*: line-3 different view

SDE Formulation

Stochastic Perturbations [?]

- Represent load fluctuations as Gaussian perturbations

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- Guided by saddle-points and potential energy hurdle energy-landscape

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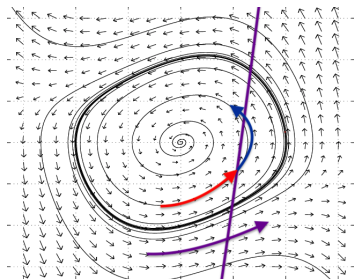
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- Reaction rate is governed by the law with:

$$\lim_{\tau \rightarrow 0^+} \tau \mathbb{E}[T_{\partial D}^{\tau}] = \min_{x \in \partial D'} V(\bar{x}, x) \quad (22)$$

Irreversible Escape Rate Approximation

Crossing Assumptions

- 1 Non-characteristic constraint boundary (correct “direction” of crossing)
- 2 $n(x)^\top S n(x) > 0$ for $x \in \partial D$ and $n(x)$ the constraint's unit normal (noise in the direction of the constraint)



Crossing events adapted to Van der Pol system portrait³

Bruzelius, 2003

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Escape Rate [?, ?]

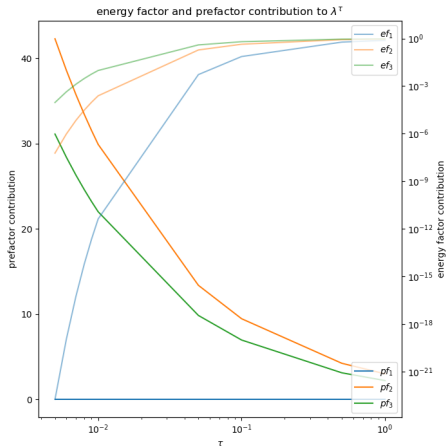
Idea is to use a Laplace approximation around the constrained minimizer:

$$\lambda^\tau = \int_{z \in \partial D} \sqrt{\frac{\det \text{Hess } \mathcal{H}(\bar{x})}{(2\pi\tau)^d}} e^{\left\{-\frac{V(\bar{x}, z)}{\tau}\right\}} \langle b^y(z), \nabla n(z) \rangle dz \quad (23)$$

$$\underset{\tau \rightarrow 0}{\approx} \gamma (\nabla_x \mathcal{H}(x^*))^\top S \nabla_x \mathcal{H}(x^*) \sqrt{\frac{\det \text{Hess } \mathcal{H}(\bar{x})}{2\pi\tau B}} \exp\left\{-\frac{\mathcal{H}(x^*) - \mathcal{H}(\bar{x})}{\tau}\right\} \quad (24)$$

where B captures curvature and volume properties at x^*

Contribution of Prefactor



Computation of λ^τ for various temperatures; split into prefactor (polynomial) and energy factor (exponential)

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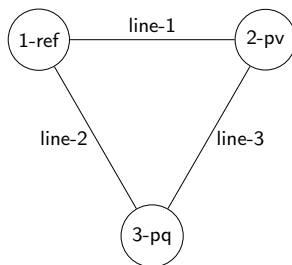
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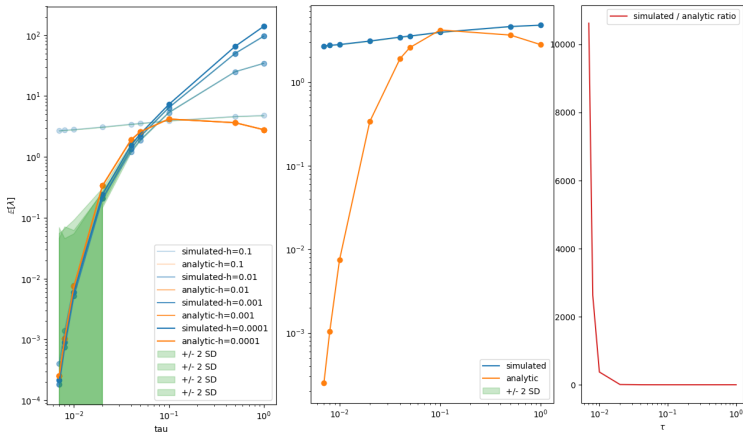
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left: 3bus structure from [?]

Integration Verification for Failure Rate

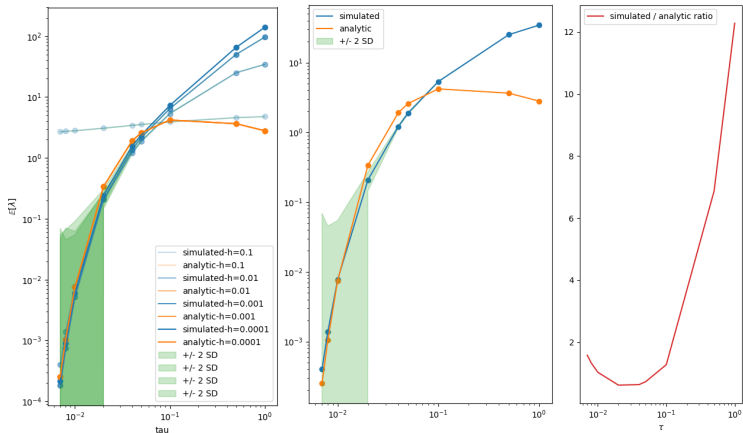
Setting integration parameters (step-size):



Inverse of average failure time (1/sec) over 5,000 failures (25 experiments of 200 failures) for 3bus model line 2 at different step sizes; as step-size decreases, we observe low-noise asymptotic agreement between simulated and analytic approximations of $\mathbb{E}[\lambda]$

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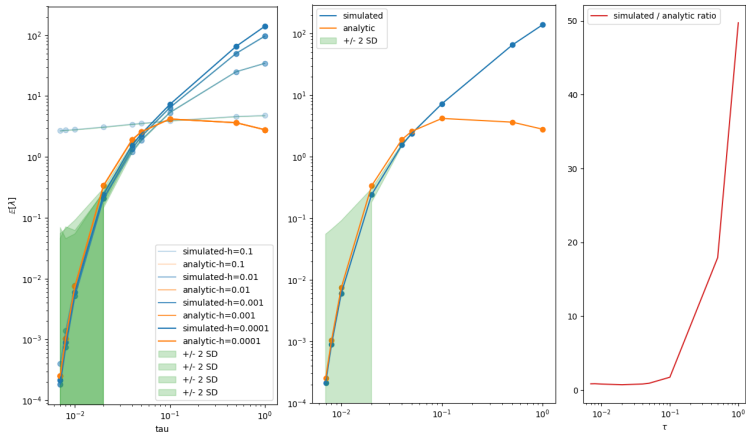
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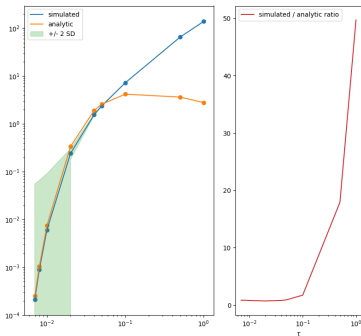
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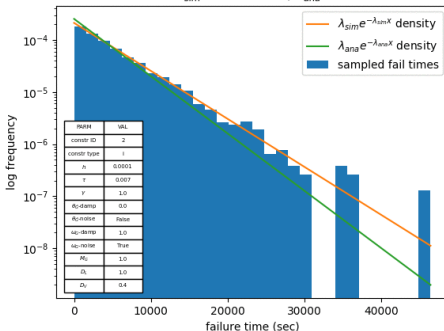


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Failures Across Lines (line-2)

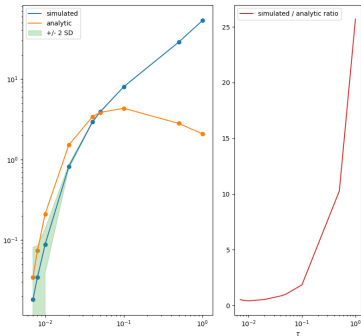


\approx exp distn of failure times, $5e+03$ (unbiased) samples
 $\tau=0.007$: $\lambda_{sim} = 2.12e-04$, $\lambda_{ana} = 2.53e-04$

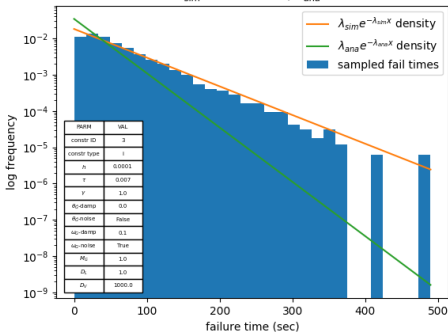


left: inverse of average failure time (1/sec) over 5,000 failures (25 experiments of 200 failures),
right: approximate exponential distribution of failure times

Failures Across Lines (line-3)

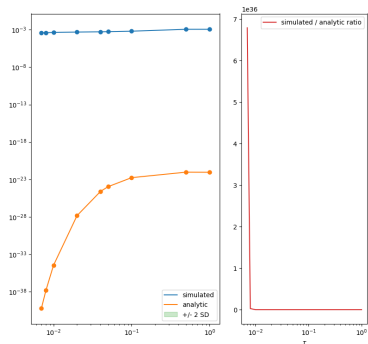


≈ exp distn of failure times, 1e+04 (unbiased) samples
 tau=0.007: $\lambda_{sim} = 1.82e-02$, $\lambda_{ana} = 3.44e-02$

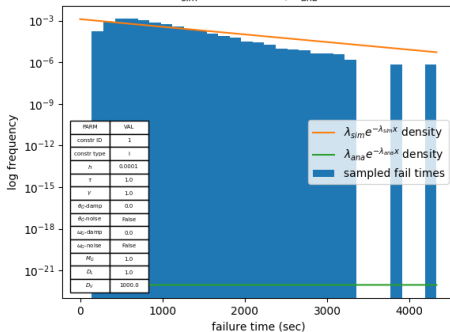


left: inverse of average failure time (1/sec) over 10,000 failures (50 experiments of 200 failures),
 right: approximate exponential distribution of failure times

Failures Across Lines (line-1)



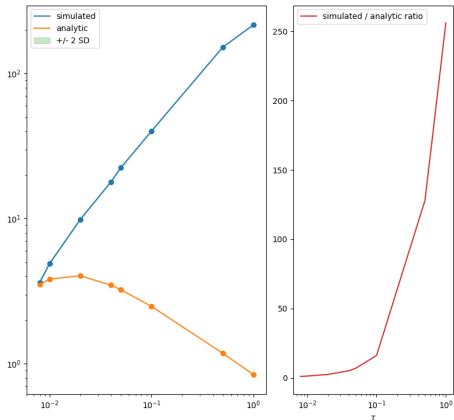
\approx exp distn of failure times, $1e+04$ (unbiased) samples
 $\tau=1.0$: $\lambda_{sim} = 1.27e-03$, $\lambda_{ana} = 9.05e-23$



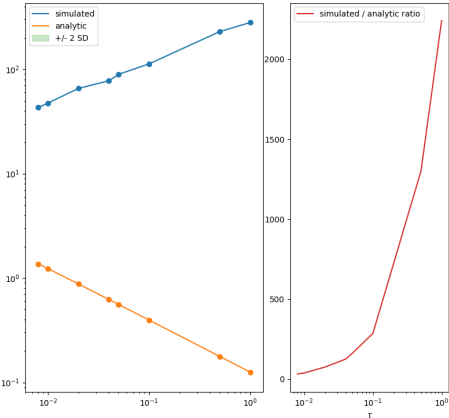
note: λ is calculated excluding the prefactor. *left*: inverse of average failure time (1/sec) over 10,000 failures (50 experiments of 200 failures), *right*: approximate exponential distribution of failure times

Failures Across Line Limits

constraint 2 fail rate across tau



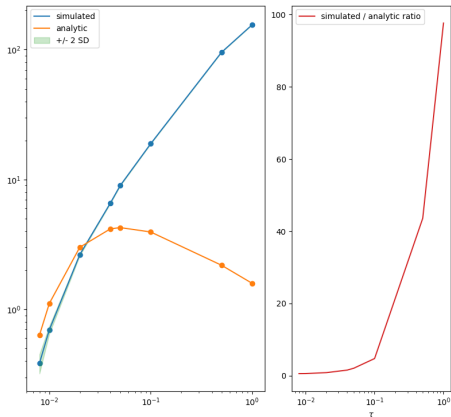
constraint 3 fail rate across tau



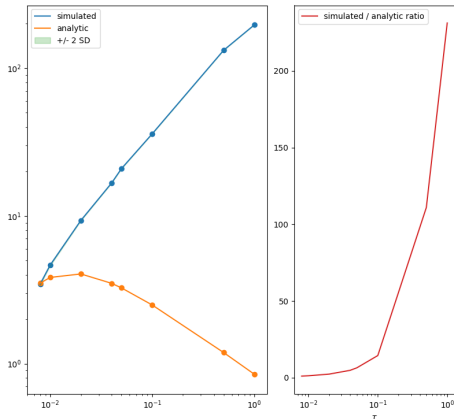
left: line-2 failure rate across line limit Θ_2^{\max} , right: line-3 failure rate across line limit Θ_3^{\max}

Failures Across Line Limits

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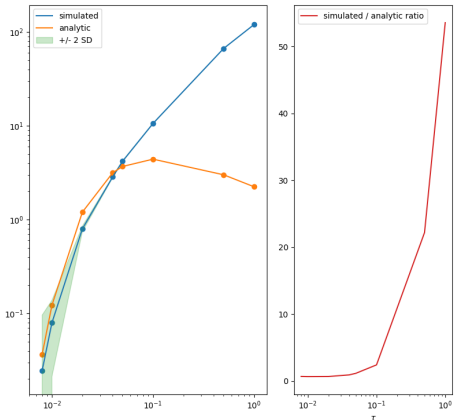
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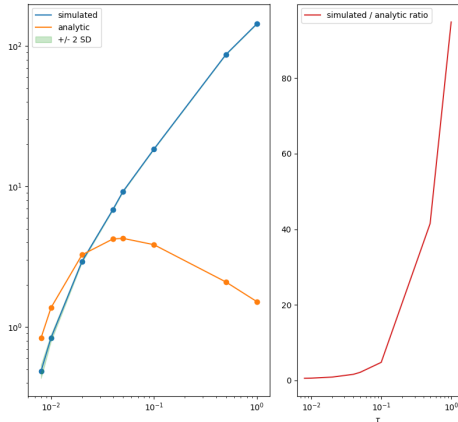
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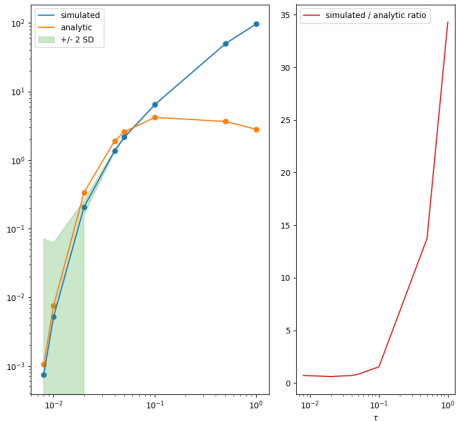
constraint 3 fail rate across tau



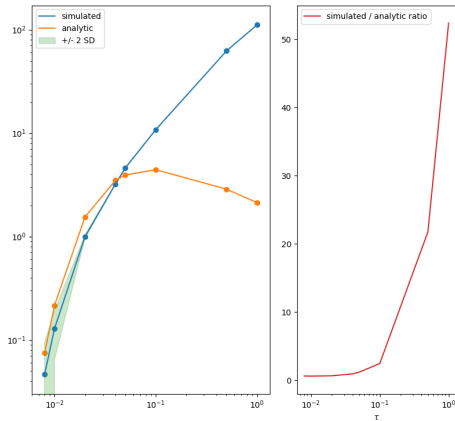
left: line-2 failure rate across line limit Θ_2^{\max} , right: line-3 failure rate across line limit Θ_3^{\max}

Failures Across Line Limits

constraint 2 fail rate across tau

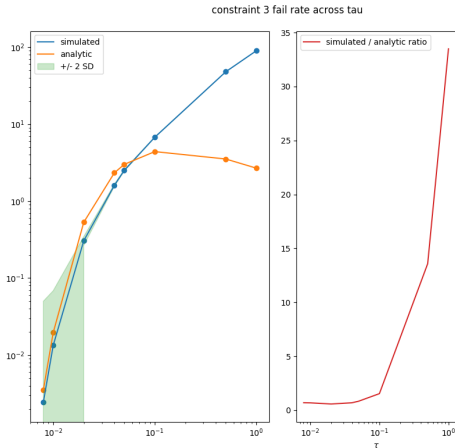


constraint 3 fail rate across tau



left: line-2 failure rate across line limit Θ_2^{\max} , right: line-3 failure rate across line limit Θ_3^{\max}

Failures Across Line Limits

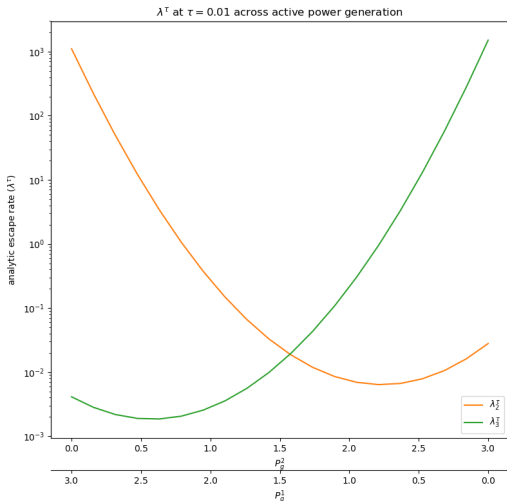


left: line-2 failure rate across line limit Θ_2^{\max} , right: line-3 failure rate across line limit Θ_3^{\max}

Animations

animations

Sensitivity to Dispatch



Line-2 and line-3 failure rate versus active power generation P_g^2

Validation Summary

Takeaways

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- Heuristic measure is when exit points cluster around x^* , not just good agreement between analytic and simulated λ
- Prefactor correction is important; escape point is not a true saddle point

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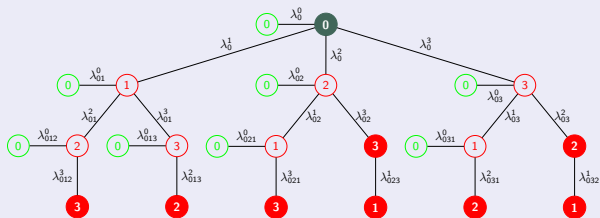
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- Difficult to know when τ is low enough; can estimate τ from data but then might need to tune γ for real network

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- Larger model (working on simulations and validation for 30-bus model)
- Failure sequences (parallelize x^* calculation) and build Markov network



References I