RL for Mitigating Cascading Failures: Targeted Exploration via Sensitivity Factors

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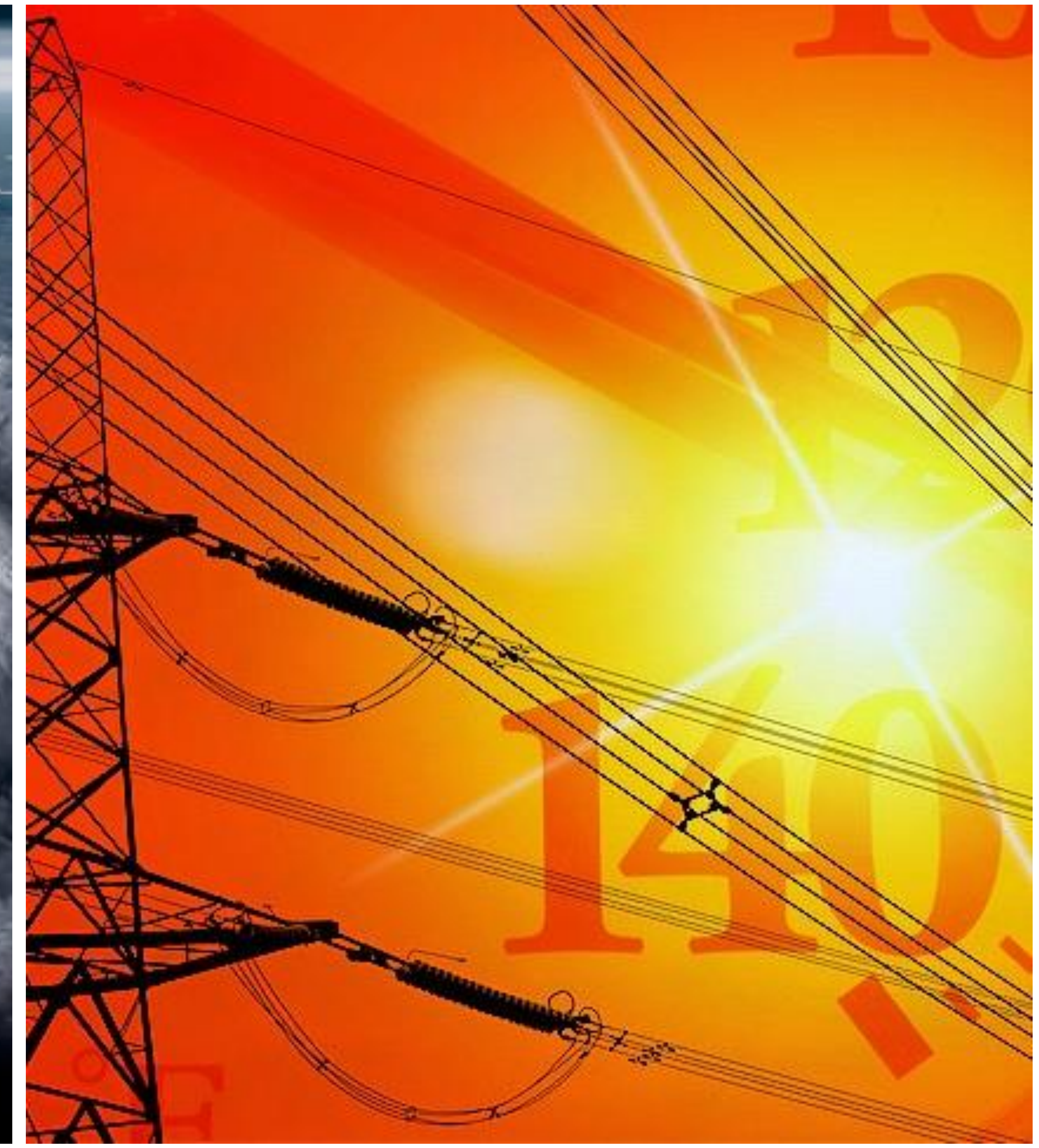
Mitigating and Adapting to Climate Change Necessitates Enhancing Grid Reliability and Resilience

wildfires

hurricanes



heatwaves

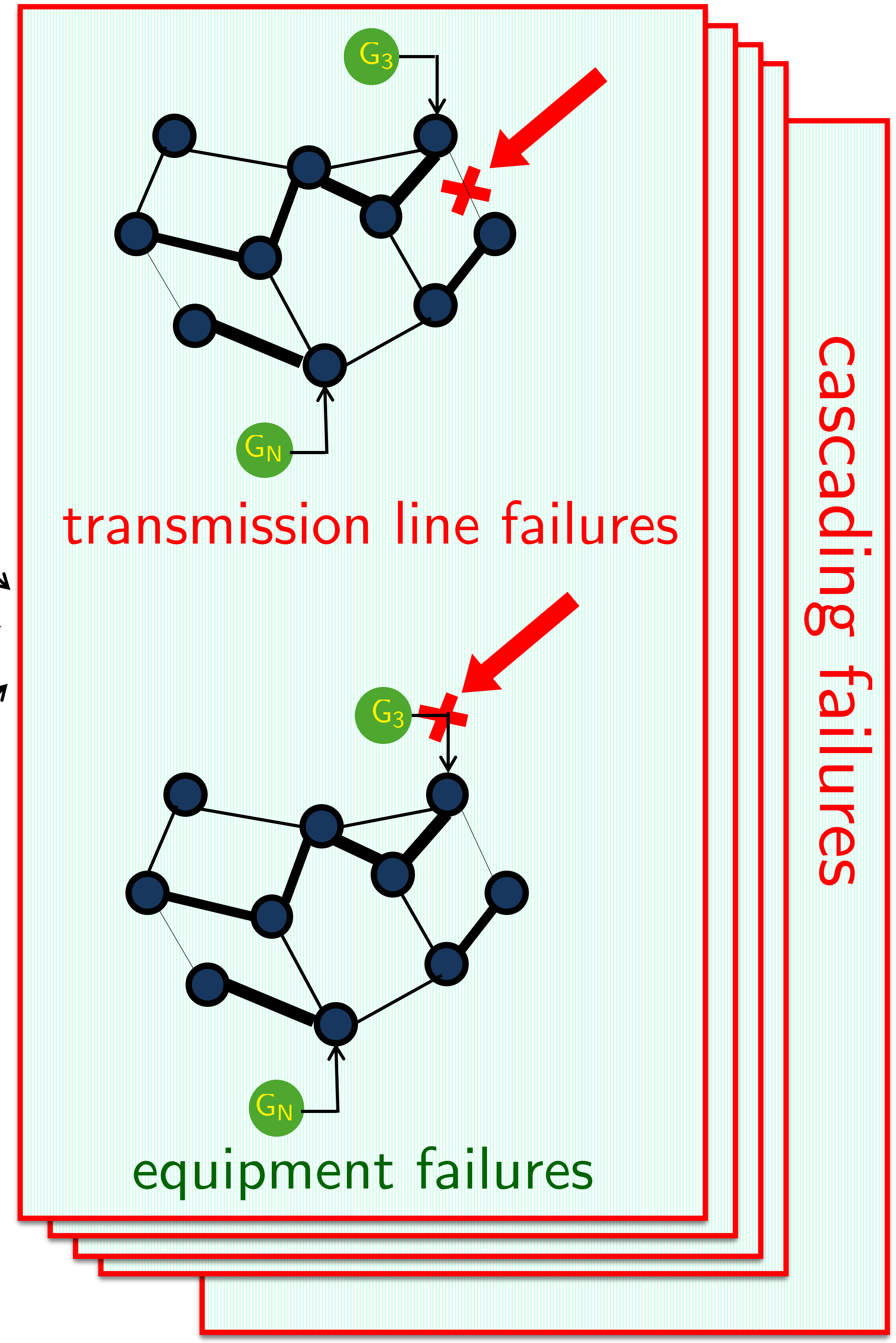
Factors Affecting Grid Reliability

extreme weather events

growing electricity demand

aging infrastructure & equipment

cyberattacks



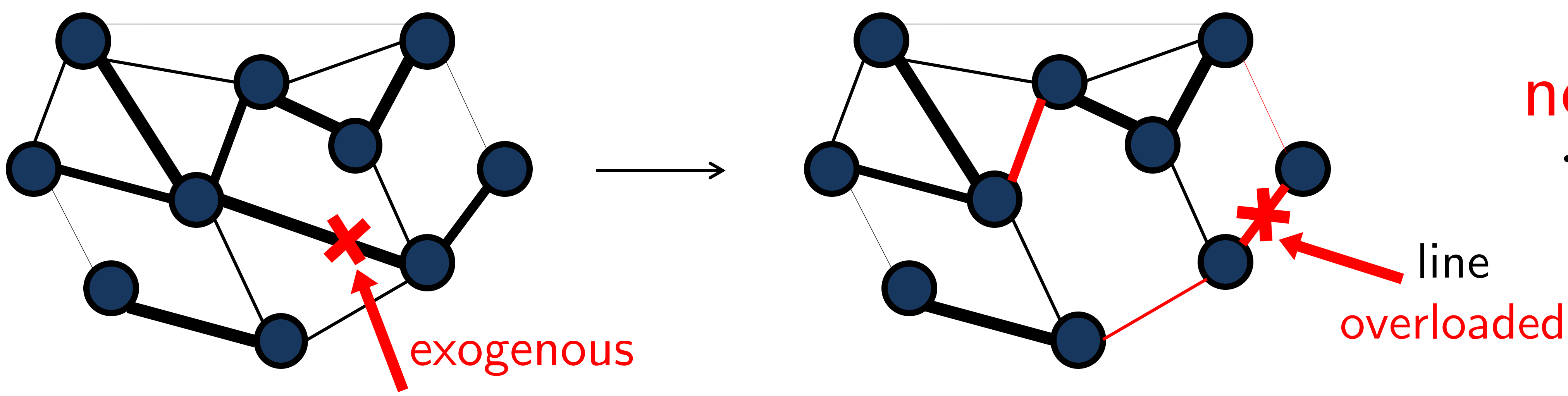
$\cdots \rightarrow$

blackouts

Focus: mitigating cascading failures

Mismanaged Line Flows: A Pathway to Cascading Failures

$n = 1$ $\qquad$ $n = 2$ $\qquad$ $n = T$



no intervention $\cdots\cdots\cdots\cdots \rightarrow$ $\sum_{\ell=1}^{L} \rho_\ell[n] \uparrow$

unbounded increase in cumulative risk margins

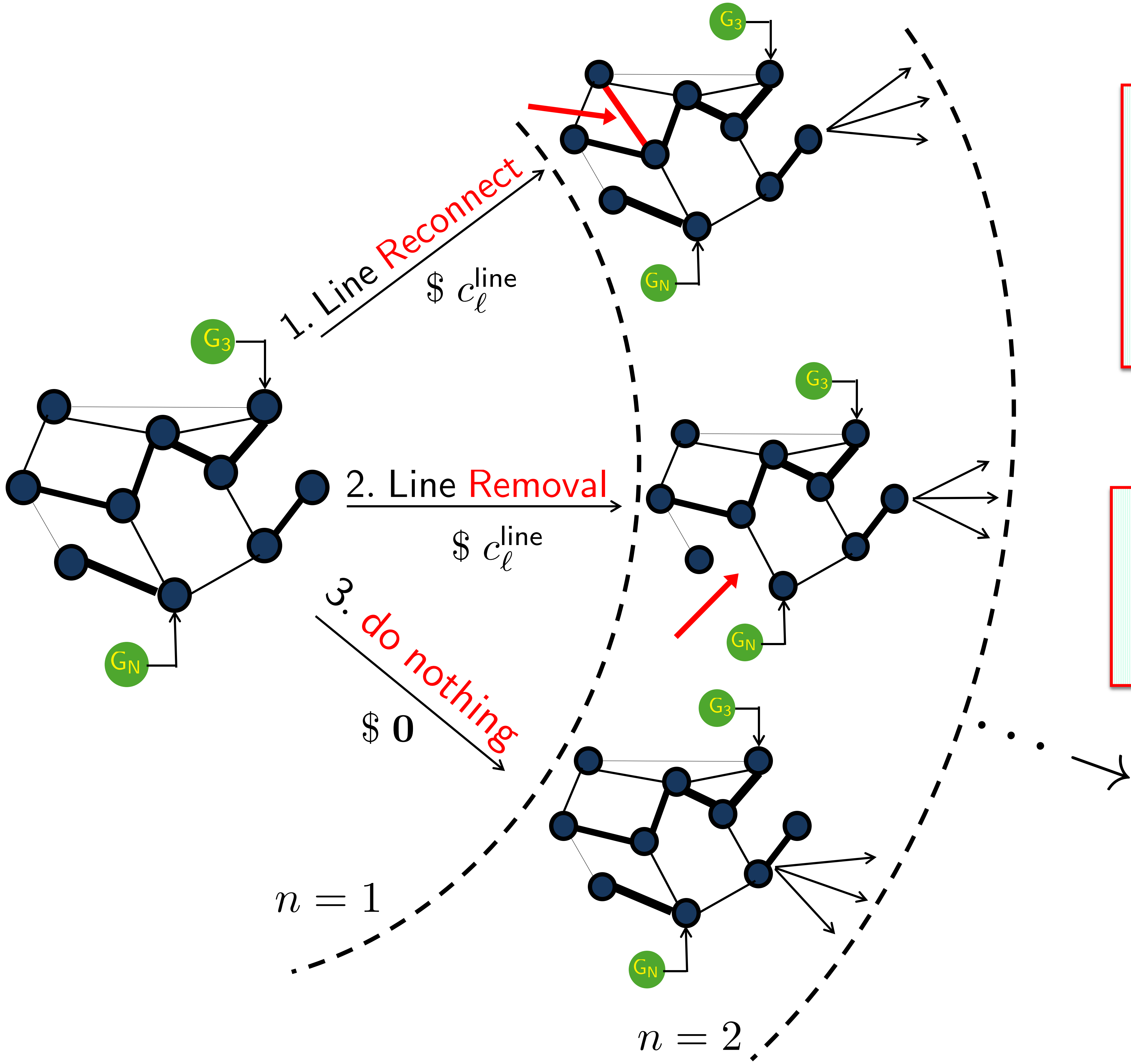
current flow in line $\ell \Rightarrow \begin{pmatrix} A_1[n] \\ A_2[n] \\ \vdots \\ A_\ell[n] \\ \vdots \\ A_L[n] \end{pmatrix}$

risk margins $\Rightarrow \rho_\ell[n] = \frac{A_\ell[n]}{A_\ell^{\text{max}}}$

$\rho_\ell[n] \geq 1 \Rightarrow$ line overloaded

$\rho_\ell[n] < 1 \Rightarrow$ within limits

Controlling Line Flows via Topology Control Actions



$$\mathcal{P} : \begin{cases} \min\limits_{\text{Control Actions}} & \sum_{n=1}^{T} \sum_{\ell=1}^{L} \rho_\ell[n] \\ \text{s.t.} & \text{Cost Constraints} \\ & \text{Operational Constraints} \end{cases}$$

Goal: Identify a sequence of control actions at each time n that *minimize* cumulative risk margins subjected to constraints

maximizing system survival time (ST)

Cascading Failure Mitigation via MDPs and Model-Free RL

State Space $\mathcal{S}$: $\mathbf{S}[n] \triangleq [\mathbf{X}[n-(\kappa-1)], \ldots, \mathbf{X}[n]]^\top \cdots \rightarrow$ sliding window of size κ of past power-grid features

Action Space $\mathcal{A}$:

- One action for reconnecting line $\ell \in [L]$
- One action for removing line $\ell \in [L]$
- do nothing

$\cdots \rightarrow$ Total $|\mathcal{A}| = 2L+1$

Reward Dynamics $\mathcal{R}$:

$$r[n] \triangleq \sum_{\ell=1}^{L} \left(1-\rho_\ell^2[n]\right) \cdots \rightarrow \text{promotes lower risk margins}$$

$$-\,\mu_{\text{line}} \left(\sum_{\ell=1}^{L} c_\ell^{\text{line}} \cdot W_\ell[n] \right) \cdots \rightarrow \mu_{\text{line}} \text{ promotes stricter cost requirements}$$

Leverage model-free RL with function approximation to learn a remedial action policy

Exploring Topology Actions: Challenges from Repeated Simulated Blackouts

Grid topology control is sensitive to environmental changes

Algorithm 1 Canonical ϵ-greedy Exploration

Input: ϵ_1, $\mathcal{A}$, $Q(s, a)$
Output: Action a

if $\mu \sim \mathcal{U}(0, 1) < \epsilon_1$ **then**
  $a \sim \text{Uniform}(\mathcal{A})$ ▷ Random-Explore
else
  Select a based on $Q(s, a')$ ▷ Q-guided Exploit
end if

$\cdots \rightarrow$ Sequences of random topology actions quickly result in simulated blackouts

- Episodes terminate prematurely, limiting learning potential
- Restarting episodes with a random policy yields no meaningful progress

Inaccurate value function predictions for unvisited MDP states, particularly in long-horizon tasks like power-grid control

Targeted Topology Exploration via Physics-Guided RL

Targeted exploration is key for efficient exploration

Algorithm 1 Physics-Guided ϵ-greedy Exploration

Input: ϵ_1, ϵ_2, $\mathcal{A}$, $Q(s, a)$
Output: Action a

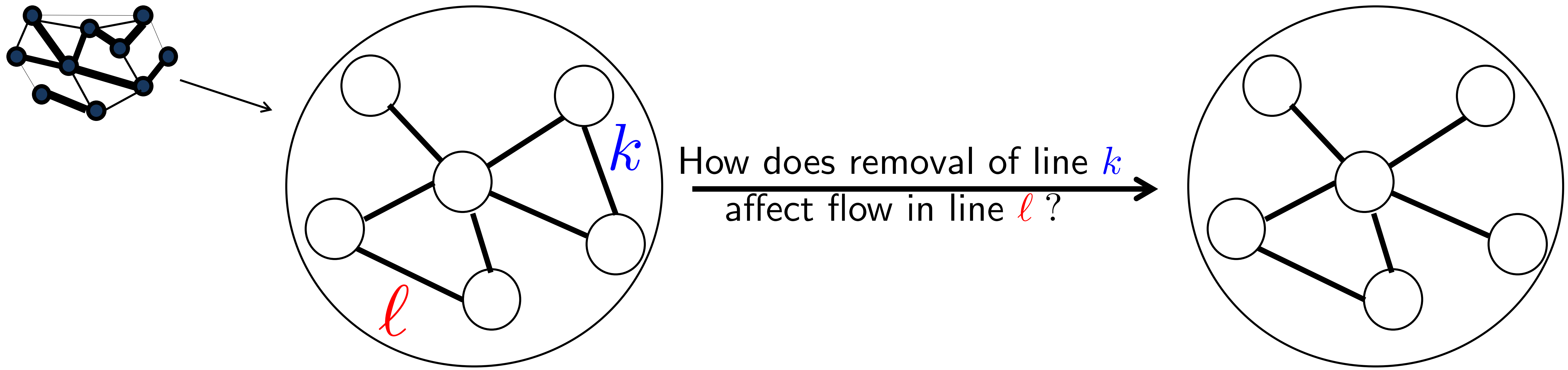
if $\mu \sim \mathcal{U}(0, 1) < \epsilon_1$ **then**
    if $\zeta \sim \mathcal{U}(0, 1) < \epsilon_2$ **then**
        $\boxed{a \sim \text{Physics-Guided}(\mathcal{A}) \ \triangleright \text{Physics-Guided Explore}}$
    else
        $a \sim \text{Uniform}(\mathcal{A})$ ▷ Random-Explore
    end if
else ▷ Q-guided Exploit
    Select a based on $Q(s, a')$
end if

$\cdots \rightarrow$ Guide exploration using grid sensitivity factors

- Help express the mapping between MDP states $\mathcal{S}$ and actions $\mathcal{A}$
- Approximate the potential impact of actions $\mathcal{A}$ on MDP reward $r \in \mathcal{R}$

Leverage sensitivity factors to search actions that reduce risk margins

Action Search using Line Outage Distribution Factors (LODF)



$$\boxed{F_{\ell}[n+1] \approx F_{\ell}[n] + \mathrm{LODF}_{\ell,k} \cdot F_{k}[n]}$$

remove line k that reduce line flow
in all other lines $\Rightarrow \sum_{\ell=1,\ell\neq k}^{L} \rho_{\ell}[n] \downarrow$ ✗ $\cdots \rightarrow$ challenging optimization problem due to grid non-linearlities

remove line k that reduce line flow
in maximally overloaded line $\Rightarrow \rho_{\ell_{\max}}[n] \downarrow$ ✓

$$F_{\ell_{\max}}[n+1] \approx F_{\ell_{\max}}[n] + \mathrm{LODF}_{\ell_{\max},k} \cdot F_{k}[n]$$

$$\ell_{\max} \triangleq \arg\max_{\ell \in L} \rho_{\ell}[n]$$

Experiments - Grid2Op 36-bus Network

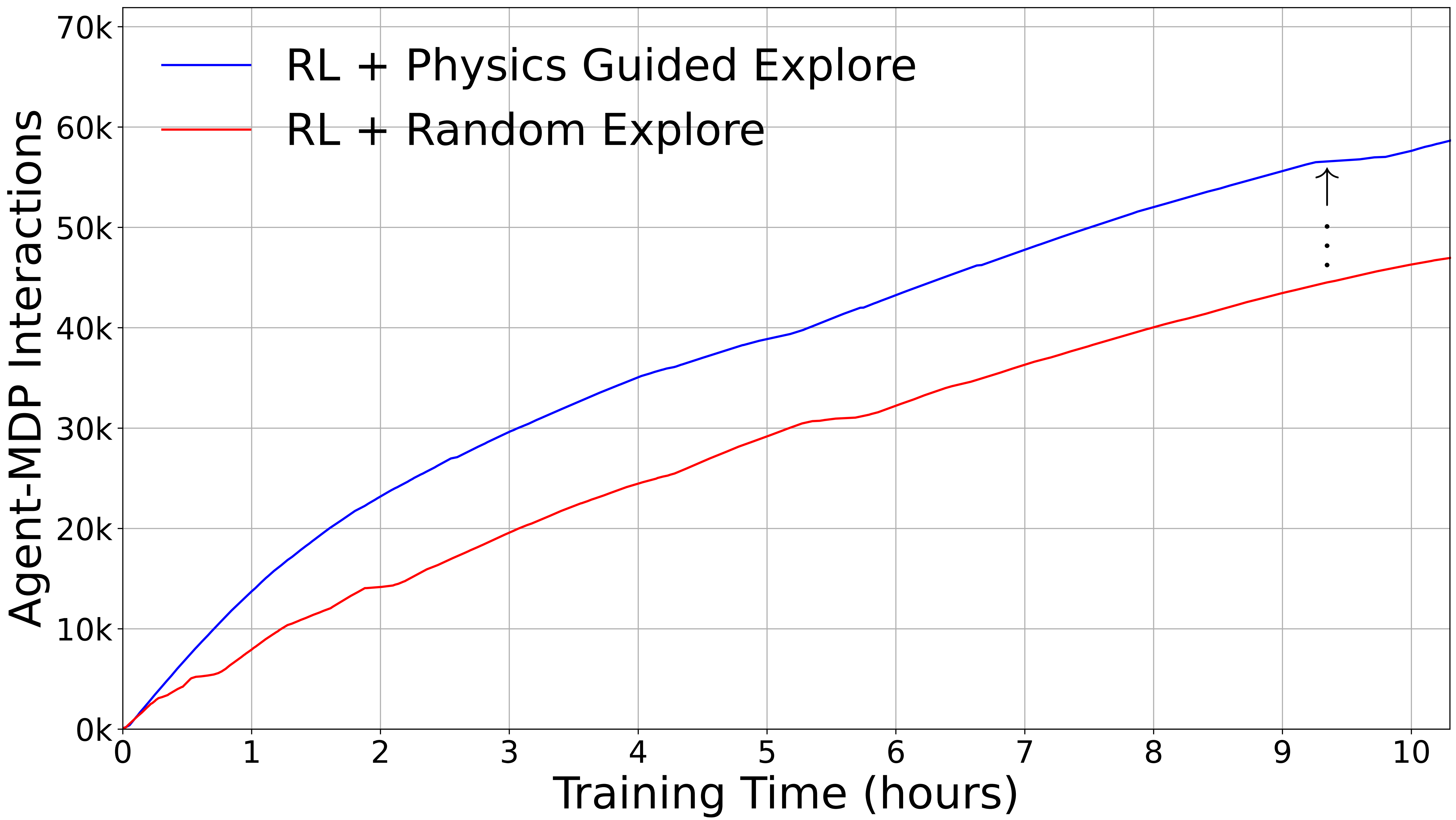
$N = 36$ buses
$L = 59$ transmission lines
$T = 8062$ episode length

$\leftarrow \cdots |\mathcal{A}_{\text{line}}| = 119 \ (2L+1)$

Action Space ($|\mathcal{A}|$)	Agent Type	Avg. ST	Avg. Action Diversity	
–	Do-Nothing	4733.96	–	$\leftarrow \cdots$ no action policy π
$\mathcal{A}_{\text{line}}$ (60)	Re-Connection	4743.87	1.093 (1.821%)	$\leftarrow \cdots$ Always reconnect line policy π
$\mathcal{A}_{\text{line}}$ (119) $\mu_{\text{line}} = 0$	$\pi_{\theta}^{\text{rand}}(0)$	5929.03	13.406 (11.265%)	$\leftarrow \cdots$ Random Exploration π_θ^{rand}
	PG-RL $[\pi_{\theta}^{\text{physics}}(0)]$	**6657.09**	**17.062 (14.337%)**	$\leftarrow \cdots$ Physics-Guided Exploration $\pi_\theta^{\text{physics}}$
$\mathcal{A}_{\text{line}}$ (119) $\mu_{\text{line}} = 1.5$	$\pi_{\theta}^{\text{rand}}(1.5)$	4916.34	3.406 (2.862%)	$\leftarrow \cdots$ Random Exploration
	PG-RL $[\pi_{\theta}^{\text{physics}}(1.5)]$	**6761.34**	**15.718 (13.208%)**	$\leftarrow \cdots$ Physics-Guided Exploration

PG-RL identifies impactful topological actions,
leading to greater action diversity resulting in better
grid-utilization along with a significant *increase* in survival time

Why is Physics-Guided Exploration More Effective?



each episode is more thoroughly explored for a given computational budget

Thank You!
See you in the Poster Session

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- Code:
  - https://github.com/anmold-07/Physics-Guided-Blackout-Mitigation
- Extended Work including Generators Adjustment Actions:
  - A. Dwivedi, S. Paternain, A. Tajer, "Blackout Mitigation via Physics-Guided RL," *IEEE Transactions in Power Systems*, DOI: 10.1109/TPWRS.2024.3472570, 2024