Cost-aware Defense for Parallel Server Systems against Reliability and Security Failures

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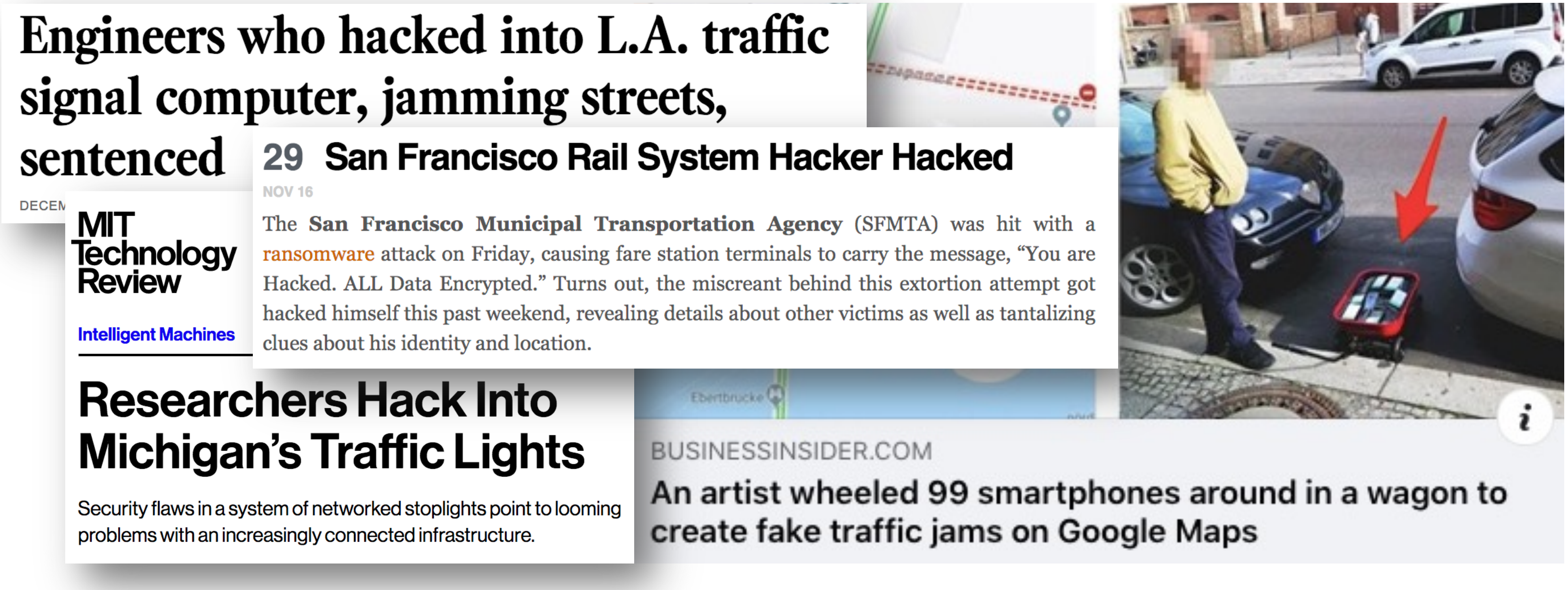
Joint work with Jiayi Wang and Li Jin, mostly done at NYU

Security risks in network systems

- Network systems rely on data collection and transmission
  - Intelligent transportation systems (ITSs)
  - Manufacturing systems (production lines)
  - Communication networks
- Cyber components susceptible to data loss and data errors
  - E.g., traffic sensors and traffic lights can be intruded and manipulated
  - Need secure-by-design features



Engineers who hacked into L.A. traffic signal computer, jamming streets, sentenced

DECEM

29 San Francisco Rail System Hacker Hacked

NOV 16

The **San Francisco Municipal Transportation Agency** (SFMTA) was hit with a ransomware attack on Friday, causing fare station terminals to carry the message, "You are Hacked. ALL Data Encrypted." Turns out, the miscreant behind this extortion attempt got hacked himself this past weekend, revealing details about other victims as well as tantalizing clues about his identity and location.

MIT Technology Review

Intelligent Machines

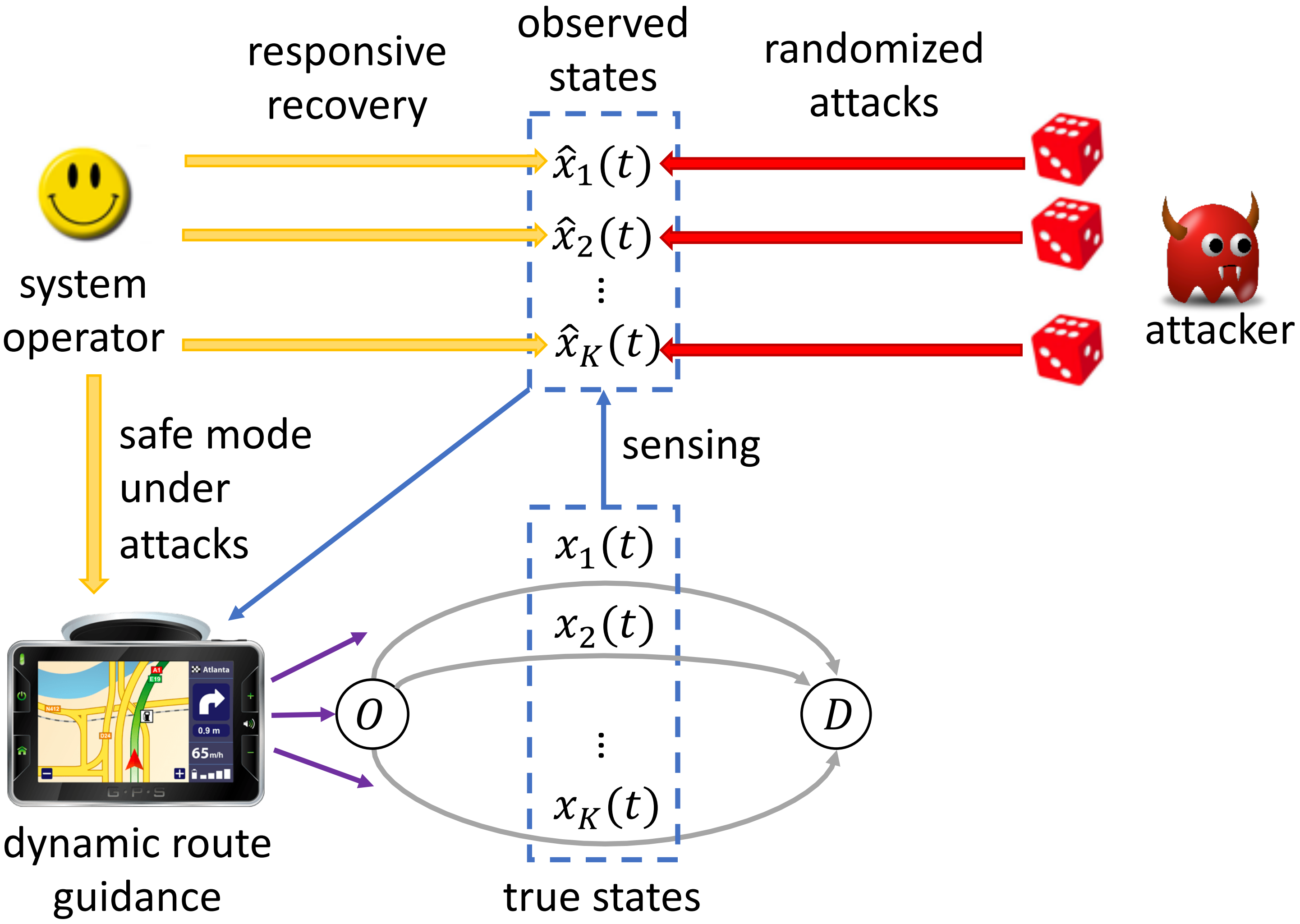
Researchers Hack Into Michigan's Traffic Lights

Security flaws in a system of networked stoplights point to looming problems with an increasingly connected infrastructure.

BUSINESSINSIDER.COM

An artist wheeled 99 smartphones around in a wagon to create fake traffic jams on Google Maps

Example: dynamic routing in ITSs



responsive recovery

observed states

randomized attacks

$\hat{x}_1(t)$

$\hat{x}_2(t)$

$\vdots$

$\hat{x}_K(t)$

system operator

attacker

safe mode under attacks

sensing

$x_1(t)$

$x_2(t)$

O

D

$\vdots$

$x_K(t)$

dynamic route guidance

true states

Research questions

Modeling & analysis

- How to model stochastic & recurrent faults/attacks?
- How to quantify attacker’s incentive?
- How to quantify the impact due to faults/attacks?
- How to evaluate various security risks?

Resource allocation

- How to allocate limited/costly security resources, including redundant components, diagnosis mechanisms, etc.?

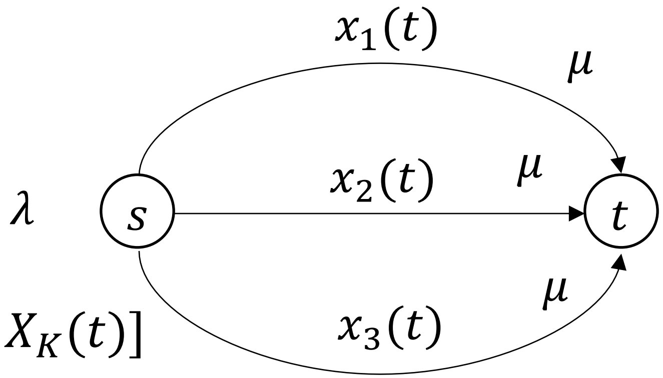
Decision making

- How to make protecting (resp. defending) decisions in the face of random faults (resp. malicious attacks)?

Parallel-queueing system

Basic model

- Poisson arrivals of rate λ
- Parallel servers with service rate μ
- State: vector of queue lengths



$$X(t) = [X_1(t), X_2(t), \dots, X_K(t)]$$

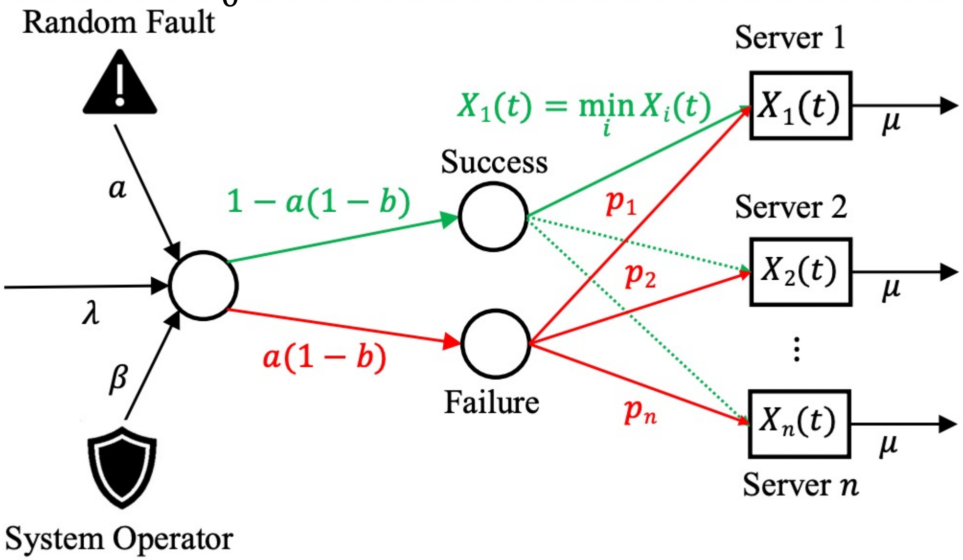
- Dynamic routing: dynamically allocate jobs (e.g., customers, vehicles, components, data packets) to servers
- Provably optimal routing policy: join-the-shortest-queue (JSQ)[1]
- Existing works based on perfect observation of system state $X(t)$ and perfect implementation of dynamic routing
- Faulty/failed closed-loop can be worse than open-loop (e.g., round robin or Bernoulli routing)
- Research gap: designing fault-tolerant dynamic routing

[1] Ephremides, Anthony, P. Varaiya, and Jean Walrand. "A simple dynamic routing problem." *IEEE transactions on Automatic Control* 25.4 (1980): 690-693.

Protection against reliability failures

- Reliability failures
  - Random malfunction: operator fails to send routing instructions
  - With constant probability a, a job joins a random queue
- Markov decision process
  - Operator protects the routing with state-dependent probability $\beta(x)$
  - Minimize expected cumulative discounted queuing cost + tech cost

$$J^*(x) = \min_\beta \mathbb{E}[\int_0^\infty e^{-\rho t}(|X(t)| + c_b \beta(X(t)))dt | X(0) = x]$$

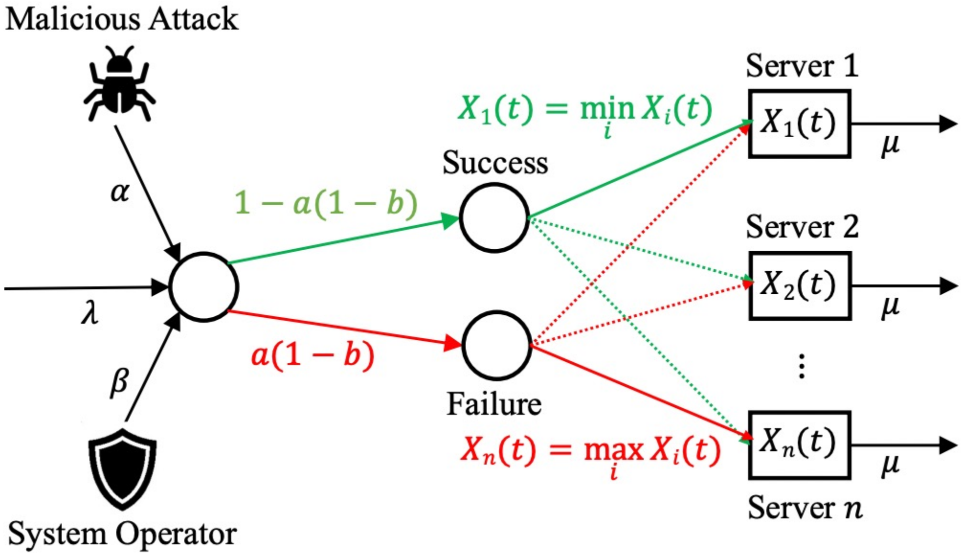


Defense against security failures

- Security failures
  - Spoofing: attacker manipulates routing (e.g., send-to-longest-queue)
- Stochastic attacker-defender game (attacker side)
  - Attacker attacks with state-dependent probability $\alpha(x)$
  - Maximize expected cumulative discounted reward

$$V_A^*(x,\beta) = \max_\alpha \mathbb{E}[\int_0^\infty e^{-\rho t} R\big(X(t)\big) dt | X(0) = x]$$

where $R(\xi) = |\xi| + c_b \beta(\xi) - c_a \alpha(\xi)$

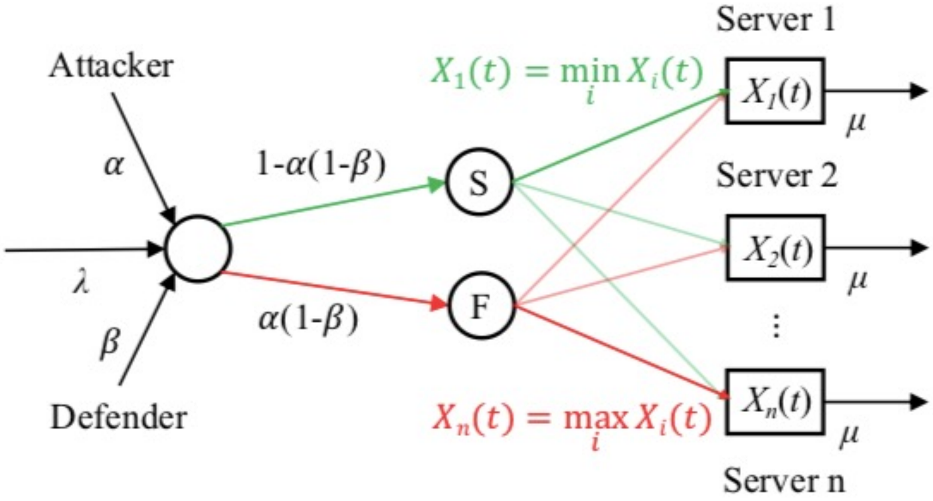


Defense against strategic attacks (cont'd)

- Security failures
  - Routing fails iff attacked and not defended (i.e., $\alpha(x) = 1$ & $\beta(x) = 0$)
- Stochastic attacker-defender game (operator side)
  - Defend the routing with state-dependent probability $\beta(x)$
  - Minimize expected cumulative discounted loss

$$V_B^*(x, \alpha) = \min_\beta \mathbb{E}[\int_0^\infty e^{-\rho t} C(X(t)) dt | X(0) = x]$$

where $C(\xi) = |\xi| + c_b \beta(\xi) - c_a \alpha(\xi)$



Stability criteria

Theorem 1. The parallel n-queue system with reliability failures is stable if for any non-diagonal vector x,

$$\beta(x) > 1 - \frac{\mu|x| - \lambda x_{min}}{a\lambda(\sum_{i=1}^{n} p_i x_i - x_{min})}.$$

Theorem 2. The parallel n-queue system with security failures is stable if for any non-diagonal vector x,

$$\alpha(x)\big(1 - \beta(x)\big) < \frac{\mu|x| - \lambda x_{min}}{\lambda(x_{max} - x_{min})}.$$

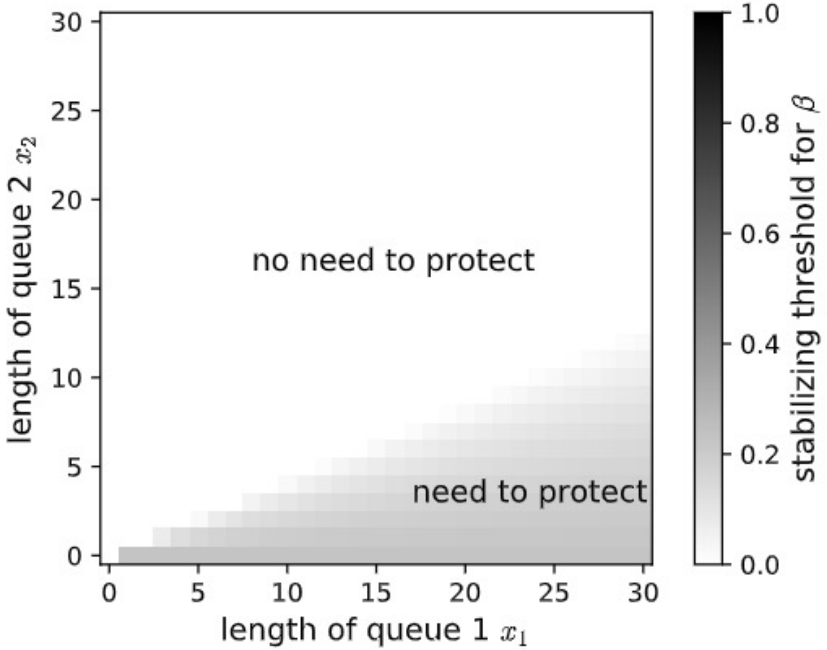
Proof sketch. Consider the quadratic Lyapunov function $V(x) = \frac{1}{2}\sum_{i=1}^{n} x_i^2$ and apply the infinitesimal generator.

Stability criteria (cont'd)

Theorem 1. The parallel n-queue system with reliability failures is stable if for any non-diagonal vector x,

$$\beta(x) > 1 - \frac{\mu|x| - \lambda x_{min}}{a\lambda(\sum_{i=1}^{n} p_i x_i - x_{min})}.$$

Characterization of the stabilizing threshold:



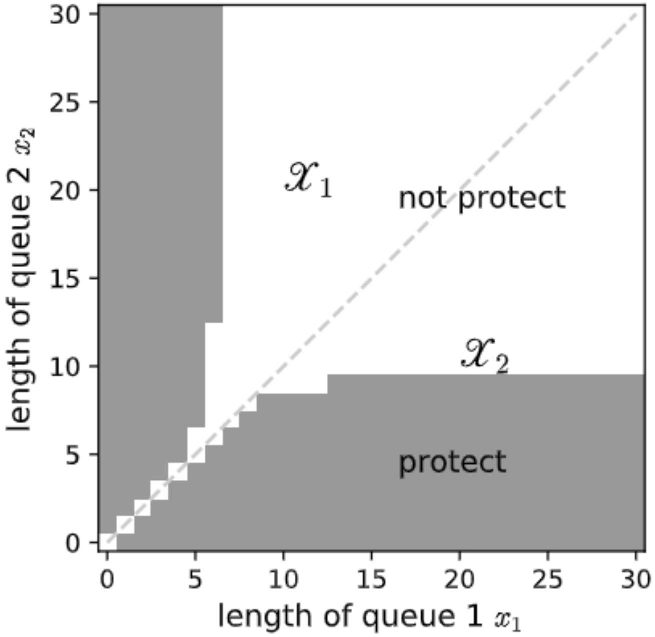
$p_1 = 0.1, p_2 = 0.9, \lambda = 1.6, \mu = 1, a = 0.9$

Optimal protecting policy

Theorem 3. Consider a parallel n-queue system with reliability failures. The optimal protecting policy $\beta^*(x)$ is threshold-based.

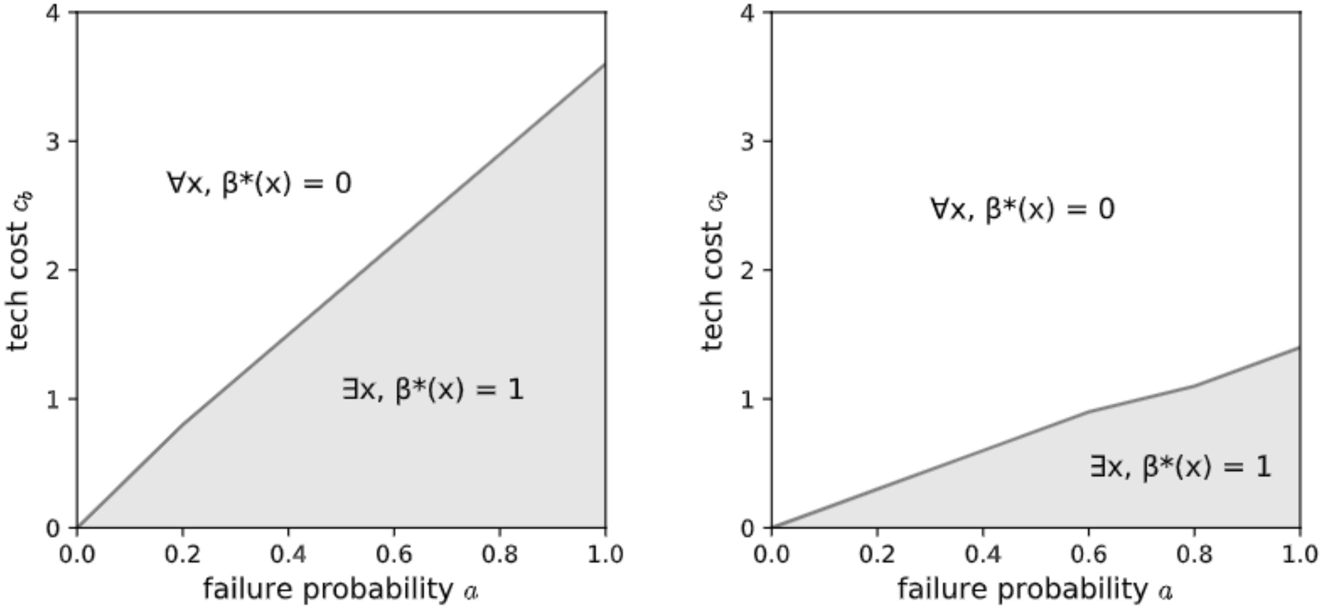
- Bang-bang control: operator either protects or does not protect (no probabilistic protection), i.e., $\beta^*(x) \in \{0,1\}$
- Operator needs to protect when 1) the queue lengths are less ‘‘balanced’’; (2) the queues are close to empty

Proof idea: HJB equation and induction on value iteration.



Numerical study

The incentive to protect is non-decreasing in the failure probability a, non-increasing in the tech cost c_b, and non-decreasing in the throughput λ (estimation of the optimal protecting policy is based on the truncated policy iteration).



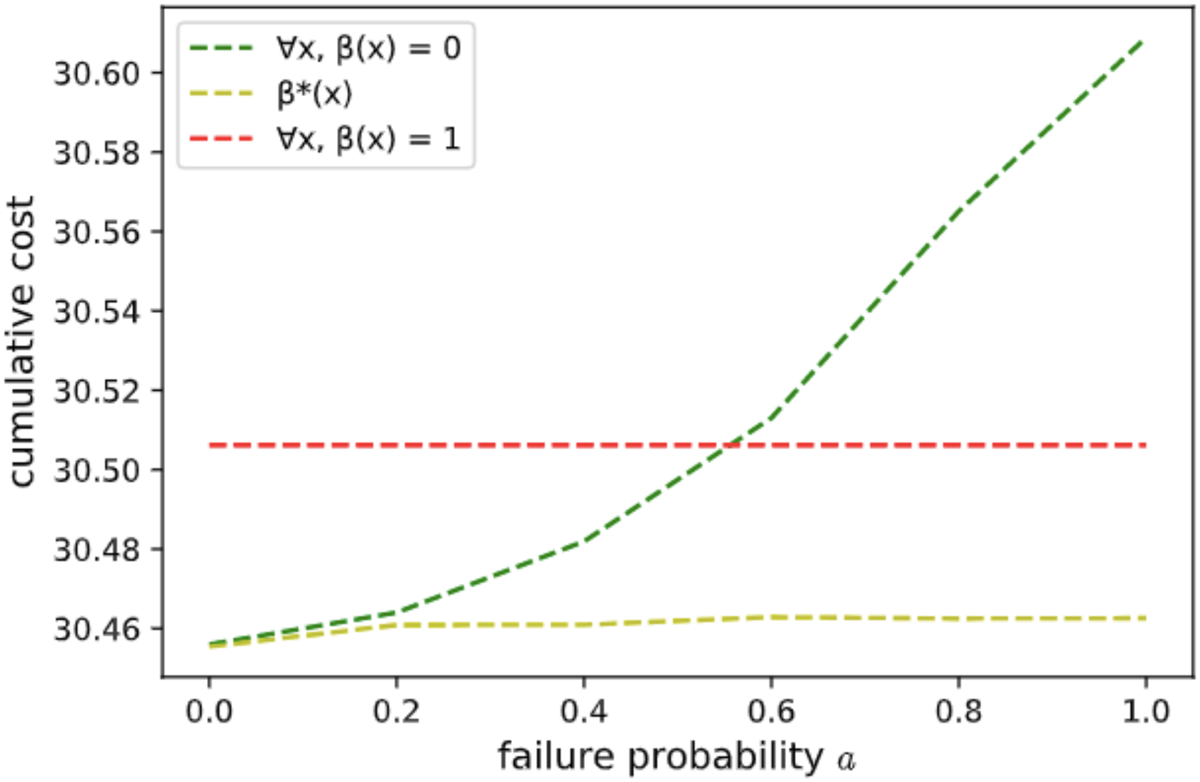
(a) $\rho = 1.6$

(b) $\rho = 0.4$

Tipping points when the operator starts to protect “riskier states”

Numerical study (cont'd)

Simulation result: the optimal closed-loop protecting policy β^* performs better in terms of the cumulative cost, compared to the open-loop policies (benchmark) never defend and always defend.



Attacker-defender game

Definition. The equilibrium Markovian attacking (resp. defending) strategy α^* (resp. β^*) satisfies that for any state $x \in \mathbb{Z}_{\geq 0}^n$,

$$\alpha^*(x) = \mathrm{argmax}_\alpha\, V_A^*(x, \beta^*),$$
$$\beta^*(x) = \mathrm{argmin}_\beta\, V_B^*(x, \alpha^*).$$

Attacker's (resp. defender's) is $V_A^*(x, \beta^*)$ (resp. $V_B^*(x, \alpha^*)$). In particular, (α^*, β^*) is a Markovian perfect equilibrium (MPE).

Remark. According to Shapley's extension on minimax theorem,

$$V_A^*(x, \beta^*) = V_B^*(x, \alpha^*) = V^*(x)$$

Proof idea. Induction on value iteration.

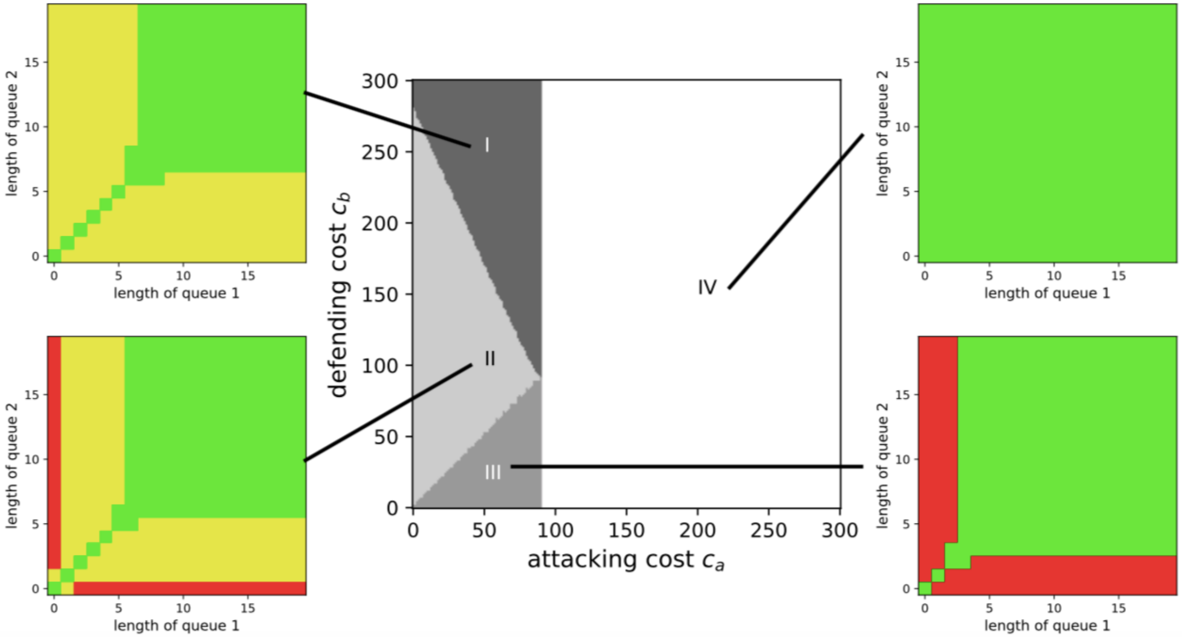
Question. Existence of MPE? - Countable infinite state space!

Question. Estimation of MPE? - Adapted Shapley's algorithm.

MPE analysis

Theorem 4. The MPE has four regimes depending on $c_a,\ c_b$ and $\delta^*(x) = \lambda(\max_j V^*(x+e_j) - \min_j V^*(x+e_j))$. For each MPE, the state space is divided into subsets with different security risk levels:

- $S_1 = \{x|(\alpha^*(x), \beta^*(x)) = (0, 0)\}$ (low risk)
- $S_2 = \{x|(\alpha^*(x), \beta^*(x)) = (1, 0)\}$(medium risk)
- $S_3 = \{x|(\alpha^*(x), \beta^*(x)) = (\frac{c_b}{\delta^*(x)}, 1 - \frac{c_a}{\delta^*(x)})\}$ (high risk)

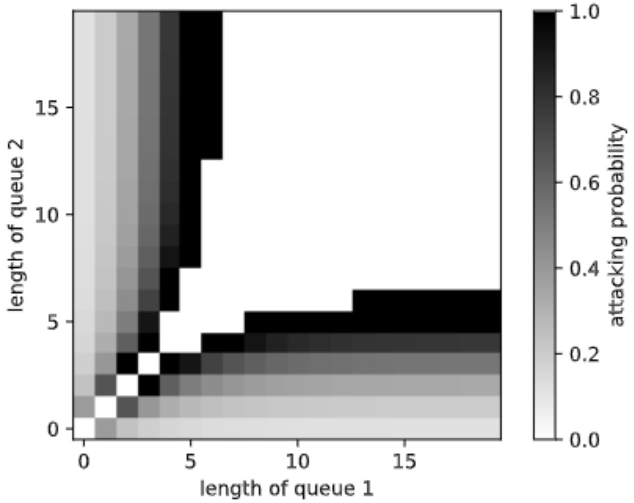


MPE analysis (cont'd)

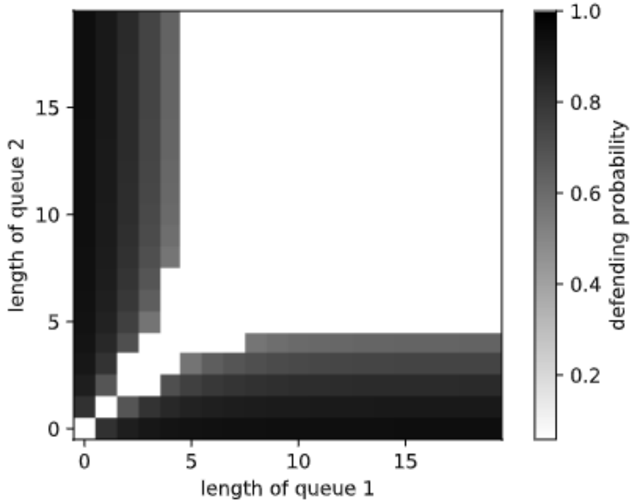
Theorem 4. The MPE has the following regimes depending on c_a, c_b and $\delta^*(x) = \lambda(\max_j V^*(x+e_j) - \min_j V^*(x+e_j))$

- $\delta^*(x) \le c_a \Rightarrow S_1 = \{x | (\alpha^*(x), \beta^*(x)) = (0,0)\}$ (low risk)
- $c_a < \delta^*(x) \le c_b \Rightarrow S_2 = \{x | (\alpha^*(x), \beta^*(x)) = (1,0)\}$(medium risk)
- $\delta^*(x) \ge \max(c_a, c_b) > 0 \Rightarrow S_3 = \{x | (\alpha^*(x), \beta^*(x)) = (\frac{c_b}{\delta^*(x)}, 1 - \frac{c_a}{\delta^*(x)})\}$ (high risk)

The equilibrium strategies α^* , β^* are both threshold-based.



α^*



β^*

Conclusion

- Without secure dynamic routing, random faults and malicious attacks can destabilize the queueing system
- The optimal protecting strategy and the equilibrium of attacker-defender game have threshold-properties
- The system operator has higher incentive to protect when
  - the failure probability is higher
  - the tech cost is lower
  - the throughput is higher
  - the queue lengths are less ‘‘balanced’’
  - the queues are close to empty
- Our proposed optimal protecting policy (closed-loop) performs better than the benchmark (open-loop)
- Optimal protecting strategy (resp. equilibrium) can be estimated by truncated policy iteration (resp. adapted Shapley’s algorithm)