



Securing Dynamic Routing for Parallel Queues against Reliability and Security Failures

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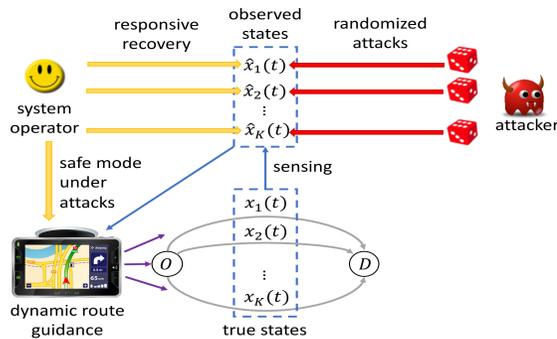
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Introduction

- 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 signals/lights can be intruded and manipulated
 - Need secure-by-design features



Example: dynamic routing in ITSs



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

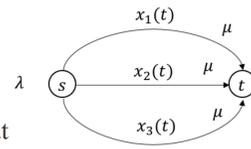
- How to allocate limited/costly security resources, including redundant components, diagnosis mechanisms?

Decision making

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

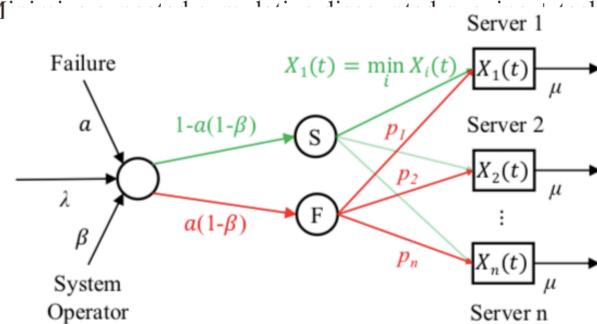
Model: Parallel-queueing system

- Poisson arrivals of rate λ
- Parallel servers with service rate μ
- State: vector of queue lengths
- Dynamic routing: dynamically allocate vehicles, components, data packets to servers
- Provably optimal routing policy: **join-the-shortest-queue (JSQ)**
- Existing works based on **perfect observation** of system state 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



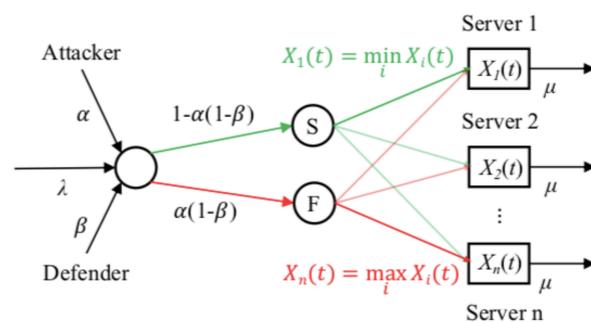
Model: Protection against reliability failures

- Random malfunction: operator fails to send routing instructions
- Denial-of-service: operator loses observation temporarily
- With **constant** probability a , a job joins a random queue
- Operator protects routing with **state-dependent** probability $\beta(x)$
- Markov decision process (MDP) with state x and cost



Model: Defense against security failures

- Spoofing: attacker compromises sensing
- Attacker manipulates routing with **state-dependent** probability $\alpha(x)$ and sends the job to the **longest** queue
- Operator defends routing with **state-dependent** probability $\beta(x)$
- Max/minimize expected cumulative discounted reward/loss



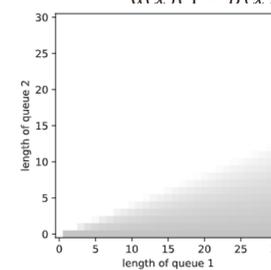
Main results

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

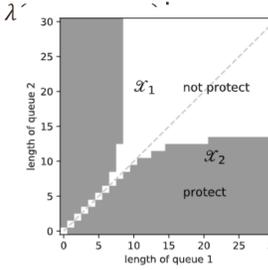
$$\beta(x) > 1 - \frac{\mu|x| - \lambda x_{\min}}{a\lambda(\sum_{i=1}^n p_i x_i - x_{\min})}$$

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

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



Characterization of the threshold



Characterization of the optimal policy

Markov decision process

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

- Operator either protects or does not protect (no probabilistic protection), i.e. $\beta^*(x) \in \{0,1\}$;
- Operator is more likely to protect when the queues are 1) less “balanced”; 2) close to empty.

Proof: HJB equation and induction on value iteration.

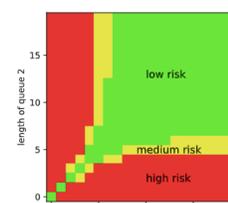
Attacker-defender stochastic game

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

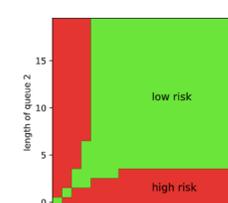
- $\delta^* < c_a \Rightarrow (0, 0)$ (low risk)
- $c_a \leq \delta^* < c_b \Rightarrow (1, 0)$ (medium risk)
- $\delta^* > \max(c_a, c_b) \Rightarrow (\frac{c_b}{\delta^*}, 1 - \frac{c_a}{\delta^*})$ (high risk)

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

Proof: Adapted Shapley's algorithm and induction.



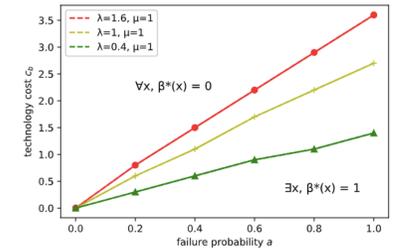
(a) $c_a = 0.1, c_b = 0.2$



(b) $c_a = 0.2, c_b = 0.1$

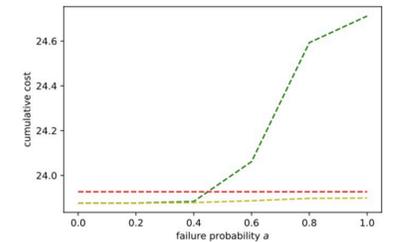
Numerical Studies

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**).



Tipping points of the operator starting to protect

The optimal **closed-loop** protecting policy β^* performs better in terms of the **simulated** cumulative discounted cost, compared to the **open-loop** policies (benchmark) never protect and always protect.



Conclusions

- 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**
- 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)

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