



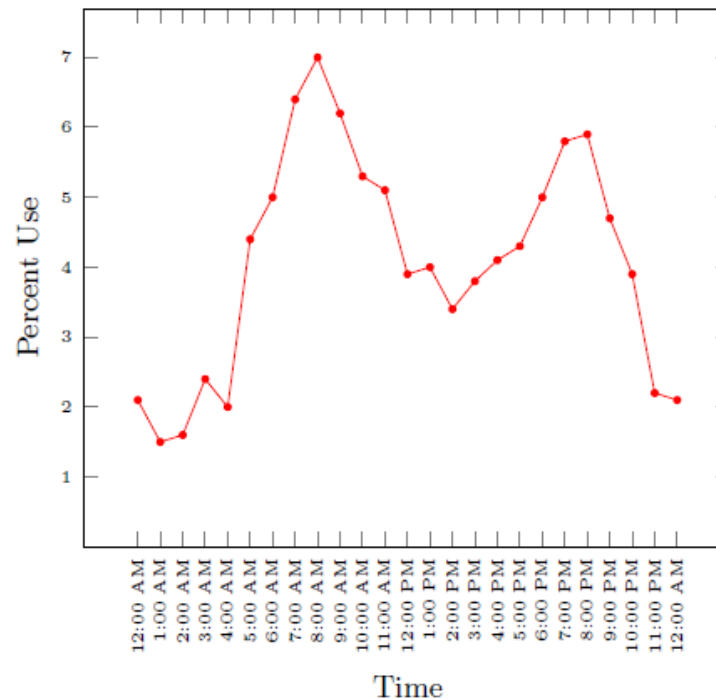
A Game-Theoretic Approach for Selecting Optimal Thresholds for Anomaly Detection in Dynamical Environments

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Example: Contamination Attack in Water Distribution System

- * Attackers may **contaminate** water in a water distribution system.
- * The expected **damage** of contamination is **high**, when **water demand** is **high**.
- * **Objective:** Design a **detection framework** that detects attacks and **minimizes damage**.



← Daily demand pattern

Anomaly Detector

1. **Predictor**: Given **previous water quality** measurements (e.g., pH, chlorine), predicts **current measurements**
2. **Statistical Test**: **Compares** prediction and observation
 - * Compute residual $r_k = ||\text{prediction} - \text{observation}||$, then:

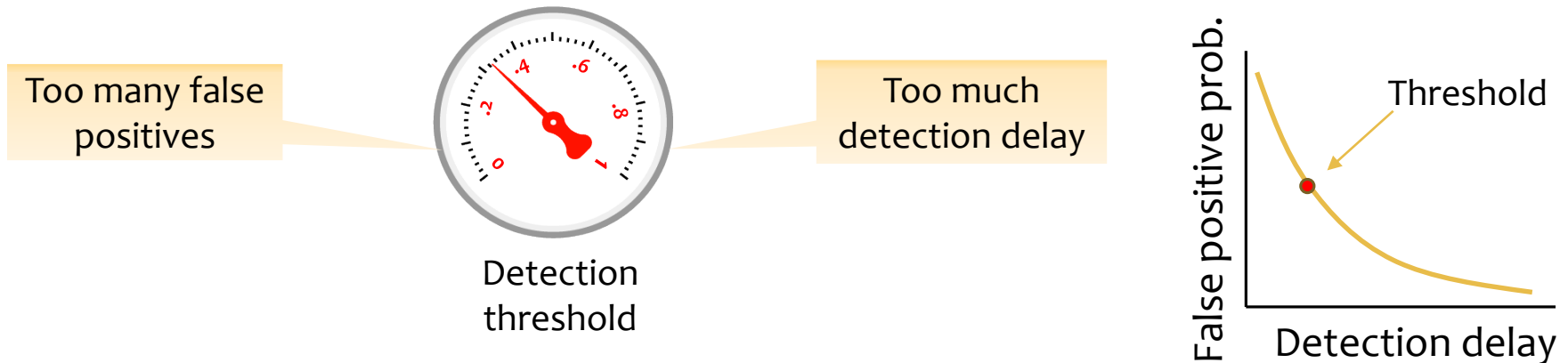
$$S(r_k) \begin{matrix} \text{Anomaly} \\ \geq \\ \text{Normal} \end{matrix} \eta_k$$

Statistics (e.g., CUSUM, EWMA, etc.)

Threshold

Trade-off Between Detection Delay and False Positives

- * **Detector metrics:** Detection delay, False positive probability
- * **Trade-off** between detection delay and FP that depends on **threshold**



Problem: Find **thresholds** that **minimize losses** due to **detection delay** and **false positives** considering worst-case contamination attacks.

Stackelberg Game for Optimal Thresholds

Strategic Choices:



1) Defender:
Selects **time-dependent threshold** for the detector



2) Attacker:
Selects a **start time** and an **attack type**

Defender's Loss:

Loss due to False Positive

Loss due to Threshold change

$$\mathcal{L}(\boldsymbol{\eta}, k_a, \lambda) = \sum_{k=1}^T C_f \cdot FP(\eta_k) + \sum_{k=k_a}^{\sigma(\boldsymbol{\eta}, k_a, \lambda)} \mathcal{D}(k, \lambda) + N \cdot C_d$$

Attacker's Payoff:

Loss due to Attack

$$\mathcal{P}(\boldsymbol{\eta}, k_a, \lambda) = \sum_{k=k_a}^{\sigma(\boldsymbol{\eta}, k_a, \lambda)} \mathcal{D}(k, \lambda)$$

Optimal Threshold Problem

- * **Optimal Threshold Problem:** Minimizes the defender's loss given that the attacker plays a best-response.

$$\eta^* \in \underset{\substack{\eta, \\ (k_a, \lambda) \in \text{bestResponses}(\eta)}}{\arg \min} \mathcal{L}(\eta, k_a, \lambda),$$

where $\text{bestResponses}(\eta)$ is the set of best-response attacks against a threshold and

$$\mathcal{L}(\eta, k_a, \lambda) = \sum_{k=1}^T C_f \cdot FP(\eta_k) + \sum_{k=k_a}^{\sigma(\eta, k_a, \lambda)} \mathcal{D}(k, \lambda) + N \cdot C_d$$

Algorithm for Computing Optimal Threshold

- * The algorithm consists of
 - * 1) A **dynamic-programming** algorithm for finding **minimum-cost thresholds** subject to the constraint that the damage caused by a best-response attack is at most a given **damage bound**.
 - * 2) An **exhaustive search** that finds an optimal damage bound and thereby **optimal thresholds**.
- * **Theorem:** Algorithm computes **optimal** thresholds that minimize the defender's loss.
 - * Proof) See paper.
 - * Running time: $\mathcal{O}(T^2 \cdot |\Delta|^{|\Lambda|+2} \cdot |\Lambda|^2 \cdot |E|)$

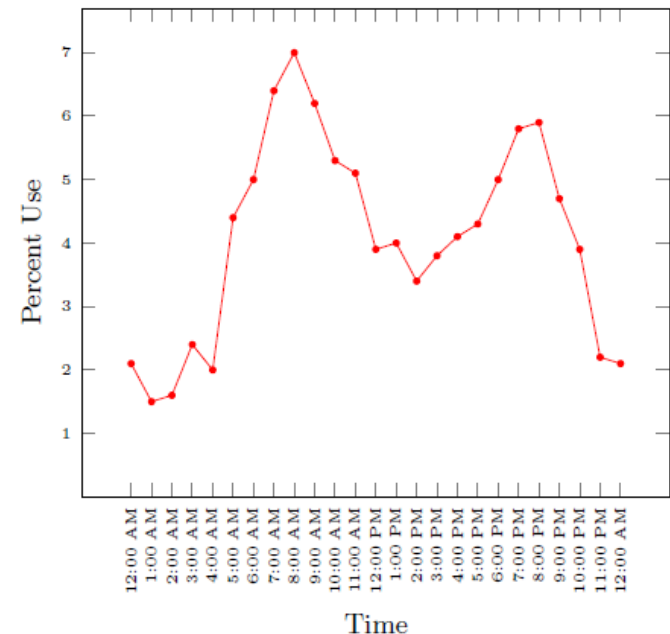
Case Study: Water Contamination

- * 6 weeks of **water quality** measurements collected by a utility in the US^[1].
- * Attacker **contaminates** water with toxic chemical types $\lambda \in \{1.5, 2, 2.5, 3, 4, 5\}$.

$$x_{\text{contaminated}} = \mathcal{F}(x_k, \lambda, \sigma_k, \mu_k)$$

- * **Damage** is a function of chemical type and demand:

$$\mathcal{D}(k, \lambda) = (\lambda - 1) \cdot d(k)$$



[1] Links, Hot. "CANARY: A Water Quality Event Detection Tool."

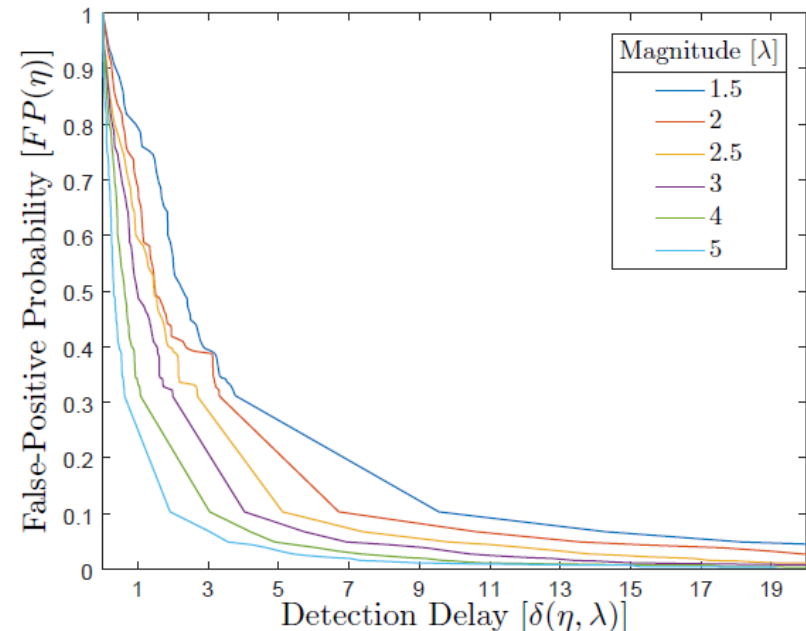
Anomaly Detector

1. Predictor

- * Feed-Forward Neural Network
- * *Input: Lagged* measurement of **target** variable and **current measurements** of other water quality parameters

2. Statistical Test (CUSUM)

- * 1,000 simulations for each threshold
- * **Trade-off curve for Chlorine**
- * Detection error decreases as attack magnitude increases



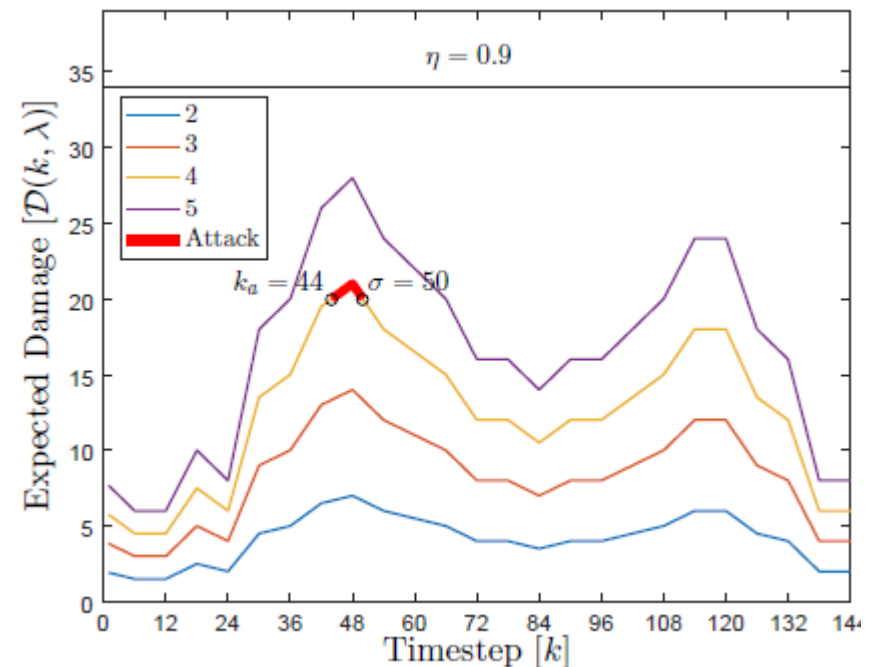
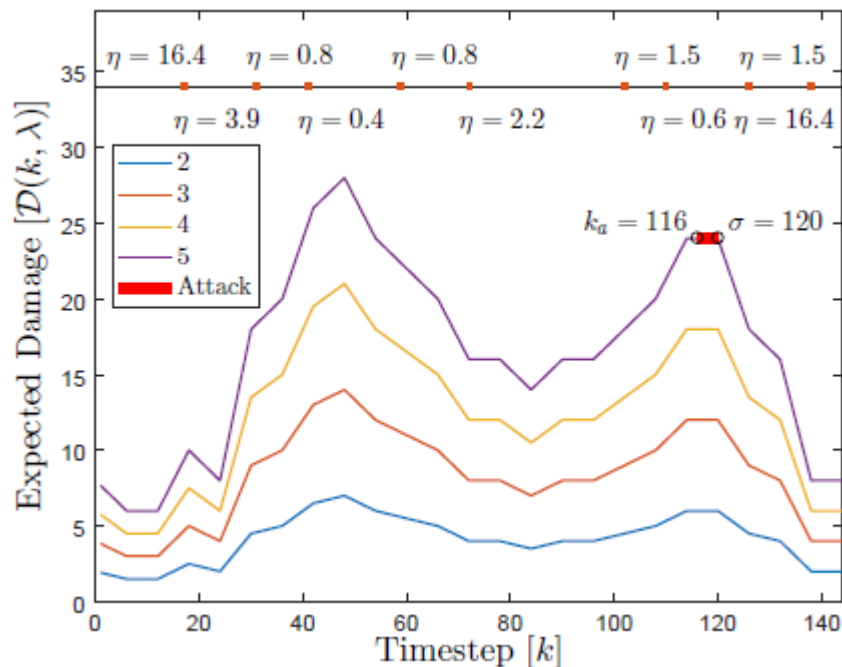
Results

Threshold **decreases** during **critical** periods and **increases** during **non-critical** periods

Fixed Threshold

$$L^* = 222.45$$

$$P^* = 144$$

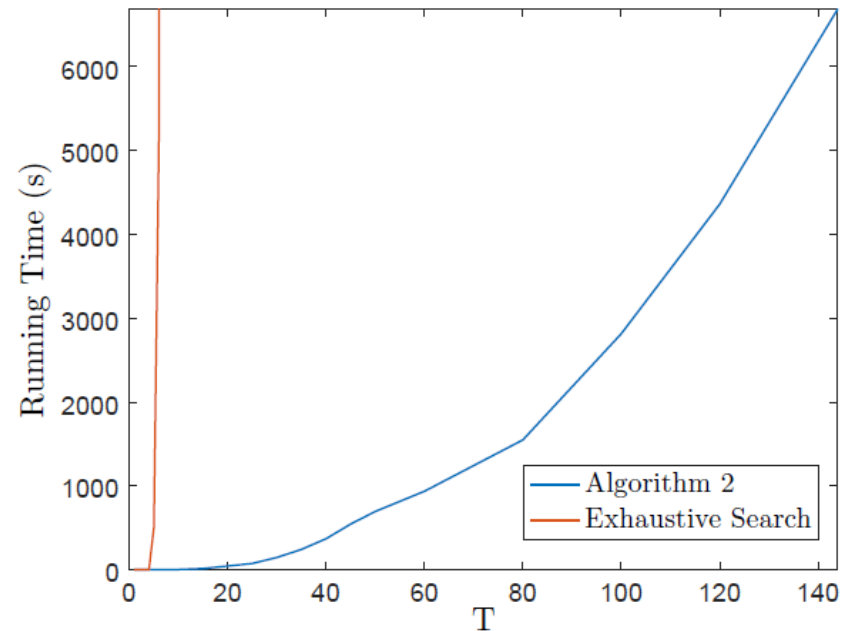


Simulation & Running Time

- * Theoretical model vs. Simulation of realistic operation (42 days)
 - * Expected: $L = 187.72$, $P = 120$
 - * Relative error between theoretical loss and actual loss: **4.26%**

	Loss	Payoff	Delay	Number of FPs
Mean	195.83	110.29	3.71	5.60
STD	4.66	8.87	0.31	0.25
MSE	87.04	127.99	0.12	0.43

- * Running Time of time-dependent threshold algorithm vs. exhaustive search



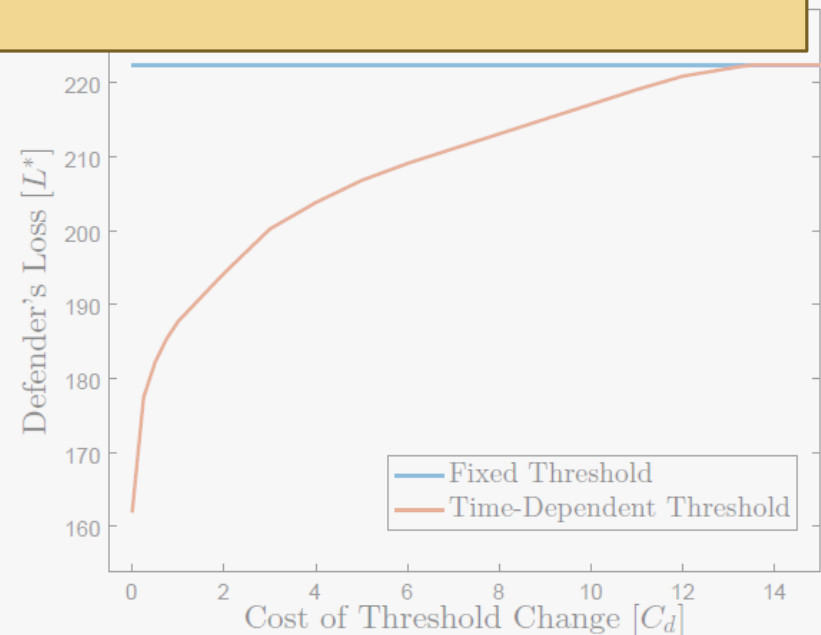
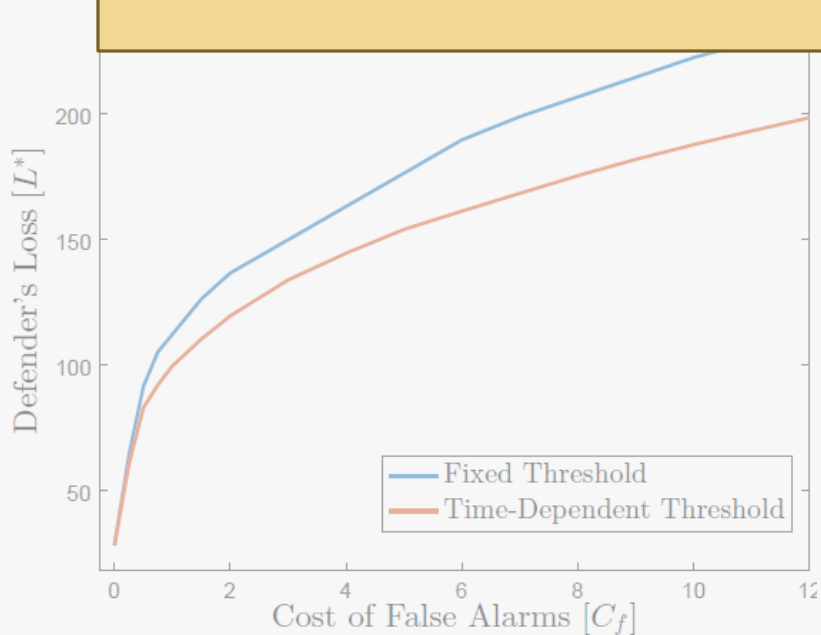
Sensitivity Analysis

- * Time-dependent threshold **reduces** the loss by **up to 30%**.
- * Improvement compared to fixed threshold:

*

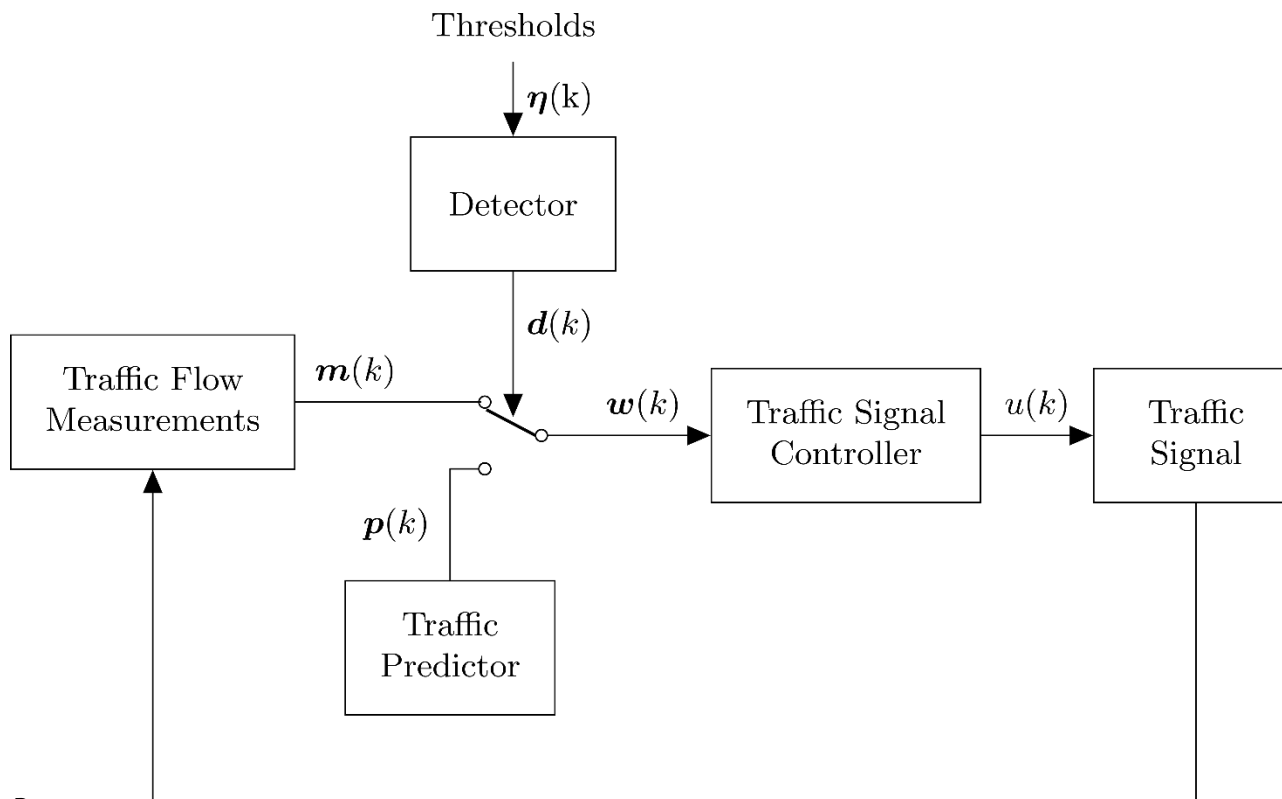
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Conclusion: By taking into account **time-varying** aspects of CPS, we can reduce **losses** due to attacks and false alarms by **~30%**.



Ongoing Work: Application-Aware Detection In Traffic Networks

- * Optimal detection can be applied to for example, **real-time control** of **traffic signals**:

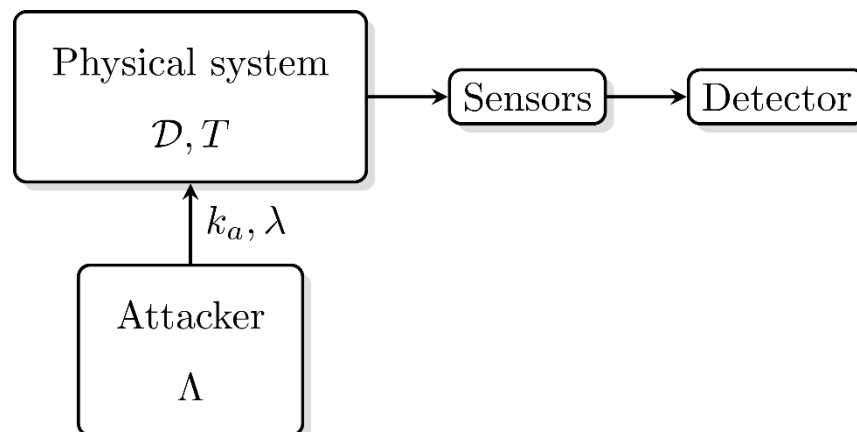




Thank you for your attention!
Questions?

System Model

- * CPS with a finite **time horizon** of interest $\{1, \dots, T\}$
- * Detector is deployed in CPS.
- * Adversaries may perform an attack of **type** $\lambda \in \Lambda$ (e.g., type of toxic chemical).
- * Attack starts at **time** k_a
- * **Damage Function**: Represents the **expected damage** $\mathcal{D}(k, \lambda)$ incurred by the system from an **attack** of type λ at time k .



ALGORITHM 1: MINIMUMCOSTTHRESHOLDS(P)

```
1  $\forall m \in \Delta^{|\Lambda|}, \eta \in E : \text{COST}(T + 1, m, \eta) \leftarrow 0$ 
2 for  $n = T, \dots, 1$  do
3   forall  $m \in \Delta^{|\Lambda|}$  do
4     forall  $\eta_{\text{prev}} \in E$  do
5       if  $\forall \lambda \in \Lambda (\sum_{k=n-m_\lambda}^n \mathcal{D}(k, \lambda) > P)$  then
6          $\text{COST}(n, m, \eta_{\text{prev}}) \leftarrow \infty$ 
7       else
8         forall  $\eta \in E$  do
9           if  $\eta_{\text{prev}} = \eta \vee n = 1$  then
10             $S(n, m, \eta_{\text{prev}}, \eta) \leftarrow \text{COST}(n + 1,$ 
11               $\langle \min\{\delta(\eta, \lambda), m_\lambda + 1\}_{\lambda \in \Lambda}, \eta \rangle + C_f \cdot \text{FP}(\eta)$ 
12            else
13               $S(n, m, \eta_{\text{prev}}, \eta) \leftarrow \text{COST}(n + 1,$ 
14                 $\langle \min\{\delta(\eta, \lambda), m_\lambda + 1\}_{\lambda \in \Lambda}, \eta \rangle + C_f \cdot \text{FP}(\eta) + C_d$ 
15              end
16            end
17             $\eta^*(n, m, \eta_{\text{prev}}) \leftarrow \arg \min_{\eta} S(n, m, \eta_{\text{prev}}, \eta)$ 
18             $\text{COST}(n, m, \eta_{\text{prev}}) \leftarrow \min_{\eta} S(n, m, \eta_{\text{prev}}, \eta)$ 
19          end
20        end
21      end
22    end
23   $m \leftarrow \langle 0, \dots, 0 \rangle, \eta_0^* \leftarrow \text{arbitrary}$ 
24  forall  $n = 1, \dots, T$  do
25     $\eta_n^* \leftarrow \eta^*(n, m, \eta_{n-1}^*)$ 
26     $m \leftarrow \langle \min\{\delta(\eta_n^*, \lambda), m_\lambda + 1\}_{\lambda \in \Lambda}$ 
27  end
28  return  $(\text{COST}(1, \langle 0, \dots, 0 \rangle, \text{arbitrary}), \eta^*)$ 
```

ALGORITHM 2: OPTIMALTHRESHOLDS

```
1  $\text{SearchSpace} \leftarrow \left\{ \sum_{k=k_a}^{k_a+\delta} \mathcal{D}(k, \lambda) \mid \exists k_a \in \{1, \dots, T-1\}, \delta \in \Delta, \lambda \in \Lambda \right\}$ 
2 forall  $P \in \text{SearchSpace}$  do
3    $(\text{TC}(P), \eta^*(P)) \leftarrow \text{MINIMUMCOSTTHRESHOLDS}(P)$ 
4 end
5  $P^* \leftarrow \arg \min_{P \in \text{SearchSpace}} \text{TC}(P)$ 
6 return  $\eta^*(P^*)$ 
```
