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# Detection and localization of cyber attacks on water treatment systems: an entropy-based approach

**Key words:** Industrial cyber-physical system; Water treatment system;  
Intrusion detection; Abnormal state; Detection and localization;  
Information theory

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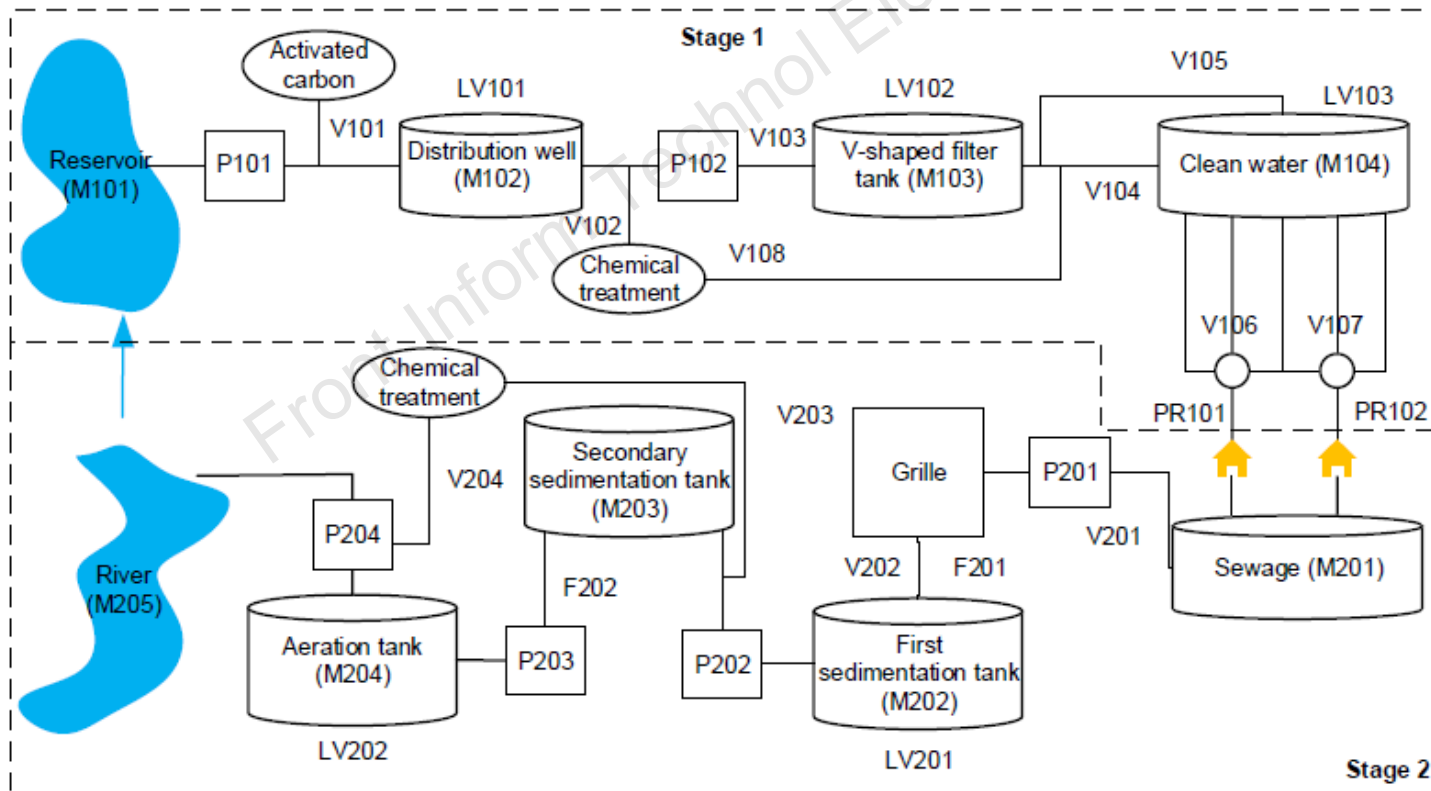
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# Motivation

- In water treatment systems (WTSs), few types of metadata are used, which limits the performance of the intrusion detection system (IDS).
- Most existing IDSs are used to locate intrusion points rather than abnormal points. However, abnormal point localization is more helpful in recovering the system than intrusion point localization.

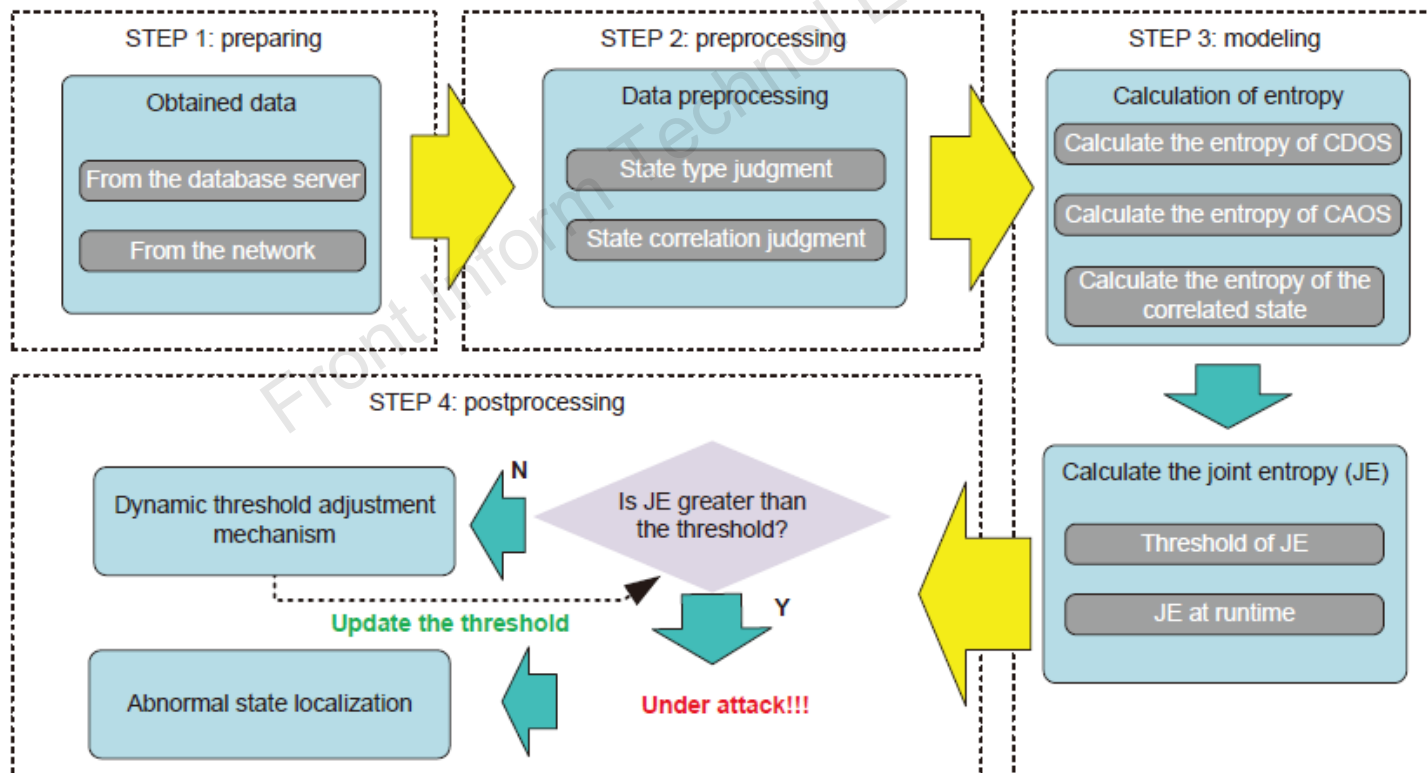
# WTS testbed

- The two-stage WTS testbed includes two programmable logic controllers (PLCs) and more than 50 measurement points



# Method overview

- Entropy-based intrusion detection method (EBID) includes mainly four steps: preparing, preprocessing, modeling, and postprocessing



# Method

- Preparing
  - Obtain the controller's output state (COS) data in two ways: exported from human-machine interface (HMI) or database, captured from the network
- Preprocessing
  - Calculate entropy for COS
    - Discrete:  $H_D(X) = - \sum_{i=1}^N P(a_i) \lg(P(a_i))$
    - Analog:  $H_A(\phi_k) = - \int_S f(x) \lg(f(x)) dx$
  - Correlation between two states
    - Calculate the information gain ratio

$$R(\phi_i, \phi_j) = \frac{I(\phi_i, \phi_j)}{\min(H(\phi_i), H(\phi_j))}$$
$$= \frac{H(\phi_i) - H(\phi_i|\phi_j)}{\min(H(\phi_i), H(\phi_j))}$$

# Method (Cont'd)

- Modeling

- Calculate the joint entropy of the system

$$H_U(\phi_1, \phi_2, \dots, \phi_M) = \sum_{k=1}^M H(\phi_k) - \sum I(\phi_i, \phi_j)$$

- Calculate the threshold

$$\bar{H}_U = H_U(1 + \alpha), \alpha \in [0, 1]$$

- Postprocessing

- Dynamic threshold adjustment mechanism (DTAM)

$$\bar{H}_{U_n} = \begin{cases} \bar{H}_{U_0}, & \hat{\sigma} > V \\ (1 - \varepsilon \frac{\hat{\sigma}}{V}) \bar{H}_{U_0}, & \hat{\sigma} \leq V \end{cases}$$

- Abnormal state localization

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**Algorithm 1** Abnormal state localization method

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**Input:**  $R, \gamma(\phi), I, U$

**Output:** Set of abnormal states  $\Omega$

```
1: for each state in  $\gamma(\phi)$  do
2:   Flag  $\leftarrow$  1
3:   for each substate in  $\gamma(\phi)$  do
4:     if  $R(\text{state}, \text{substate}) > \delta$  then
5:       Flag  $\leftarrow$  0
6:     end if
7:   end for
8:   if Flag == 1 and state not in  $I$  then
9:     Add state to  $\Omega$ 
10:  end if
11: end for
12: for each state1 in  $\gamma(\phi)$  do
13:   for each state2 in  $\gamma(\phi)$  do
14:     if  $R(\text{state1}, \text{state2}) > \delta$  and (state1, state2) not in
        $U$  then
15:       Add state1 and state2 to  $\Omega$ 
16:     end if
17:   end for
18: end for
```

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# Major results

- Detection rate (DR) and false positive rate (FPR)

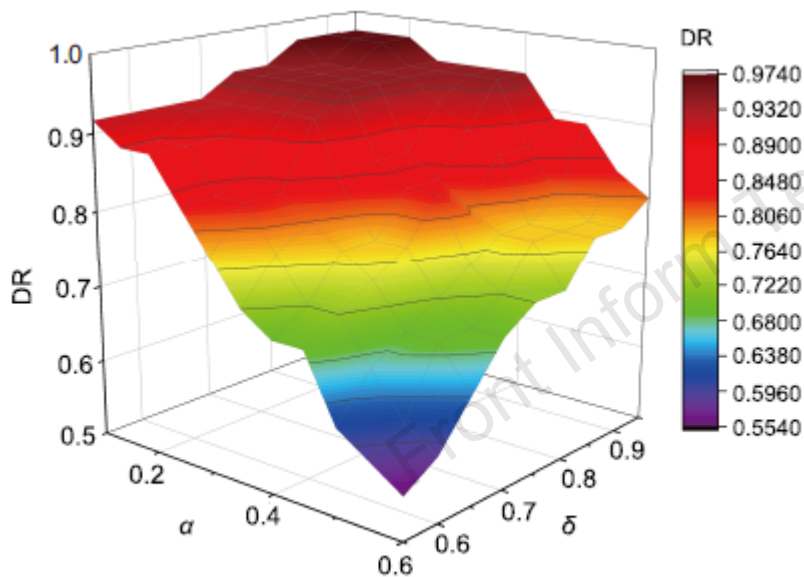


Fig. 7 Detection rate (DR) with different  $\delta$ 's and  $\alpha$ 's

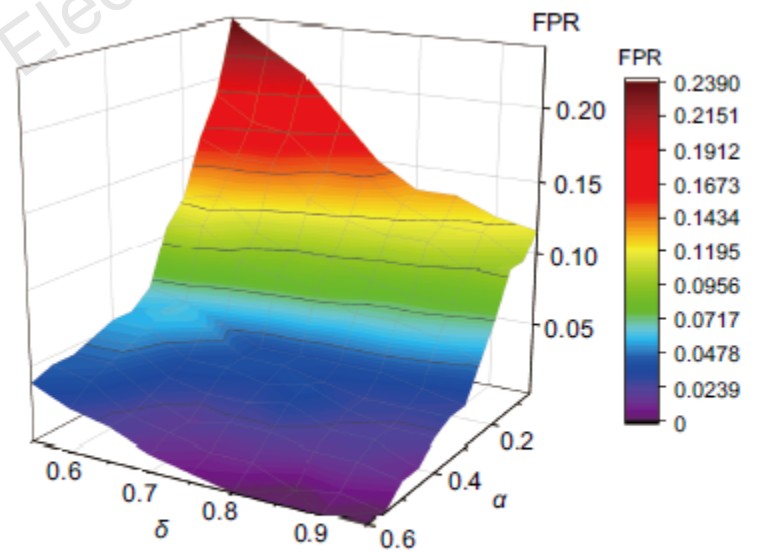


Fig. 8 False positive rate (FPR) with different  $\delta$ 's and  $\alpha$ 's

# Major results (Cont'd)

- Impact of the calculation cycle

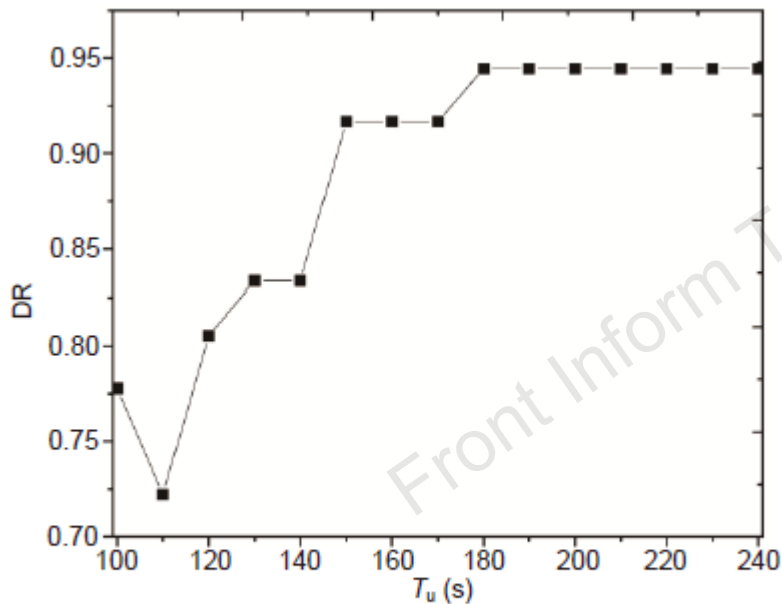


Fig. 10 The varying of the detection rate (DR) with different  $T_u$ 's

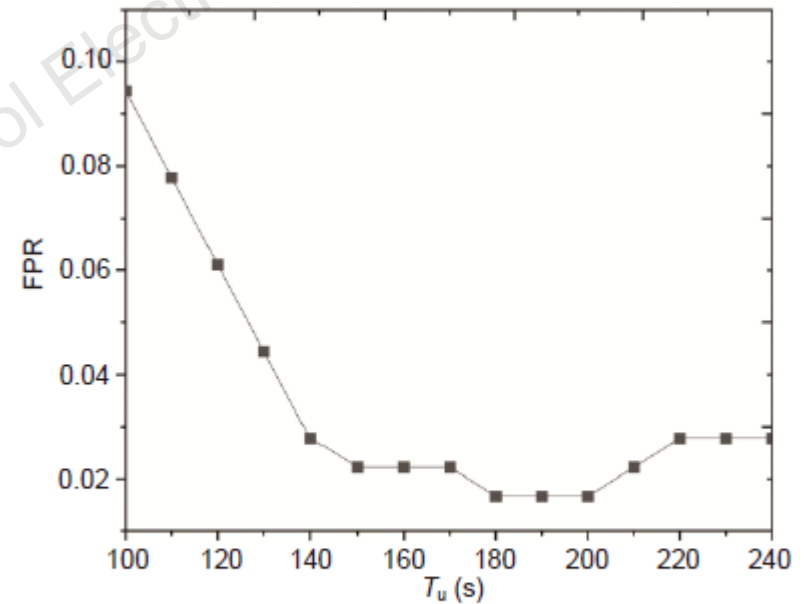


Fig. 11 The varying of the false positive rate (FPR) with different  $T_u$ 's

# Major results (Cont'd)

- Impact of the DTAM

**Table 1** The varying of the detection rate (DR) with increasing  $\varepsilon$

$\varepsilon$	DR without DTAM	DR with DTAM
0.04	94.44%	94.44%
0.08	94.44%	97.22%
0.12	94.44%	97.22%
0.16	94.44%	97.22%
0.20	94.44%	97.22%

DTAM: dynamic threshold adjustment mechanism

**Table 2** The varying of the false positive rate (FPR) with increasing  $\varepsilon$

$\varepsilon$	FPR without DTAM	FPR with DTAM
0.04	1.67%	1.67%
0.08	1.67%	1.67%
0.12	1.67%	2.22%
0.16	1.67%	3.33%
0.20	1.67%	6.11%

DTAM: dynamic threshold adjustment mechanism

# Conclusions

- In this paper, we presented a novel EBID for intrusion detection by using COSs as input from the WTS. To improve the performance of EBID, we also proposed DTAM and the abnormal state localization method.
- EBID achieved a 97.22% detection rate and 1.67% false alarm rate.
- EBID can be extended to other industrial control systems (ICSs) by adding parsers and encoders of HMI data and network protocols.



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