

Multi-Model Based Incident Prediction and Risk Assessment in Dynamic Cybersecurity Protection for Industrial Control Systems

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Hello everyone, my name is Zhang Qi, and I am the Ph.D student of Professor Zhou Chun-jie. I am very glad to be invited by Professor Yang Shuanghuang to make a presentation about my recent research.

My research interests are related to risk assessment and decision-making for industrial control systems. The title of my presentation is “Multi-Model Based Incident Prediction and Risk Assessment in Dynamic Cybersecurity Protection for Industrial Control Systems”.

Outlines

- Introduction
- Architecture
- Hazardous Incident Prediction
 - The Bayesian Network Based Knowledge Modeling
 - Incident Prediction
- Dynamic Risk Assessment
 - Decouple of Incident Consequences
 - Classification of Incident Consequences
 - Quantification of Incident Consequences
 - Calculation of Dynamic Risk
- Simulation
 - Simulation Platform
 - Simulation and Result Analysis
- Conclusion and Prospect
 - Conclusion
 - Prospect

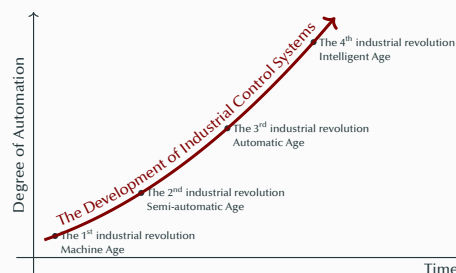
My presentation is separated into six parts:

- Firstly, I will introduce the background and the problems of risk assessment for industrial control systems.
- Secondly, I will give the architecture of our risk assessment solution for industrial control systems.
- Thirdly, I will elaborate the detail of our method.
- Then, I will show you the effectiveness of our approach by using a numerical simulation.
- At last, I will discuss the problems of our approach and introduce the future works.

Introduction

Background

Driven by computer technology, communication technology and intellectual technology, Industrial Control Systems (ICSs) develop towards the direction of intellectualization and network.



In this part, I will introduce the development history and the cybersecurity issues of industrial control systems. And, I will compare the cybersecurity issues of industrial control systems and traditional IT systems.

There are four great changes in the development of industrial control systems:

- Machine Age
- Semi-automatic Age
- Automatic Age
- Intelligent Age

The figure shows that with the development of industrial control systems...

Background

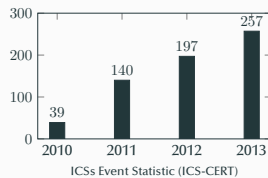
- ICSs have been widely applied in various industry of the national economy and people's livelihood, and gradually become the brain and central nervous of critical infrastructure and all kinds of industrial production.
- Once abnormal situation appears in ICSs, serious accidents may be happen, which may cause damage to property, people or a wide range of environment.



3

Background

- In 2010, Stuxnet attacked Iran's nuclear power plants and ruined almost one-fifth of Iran's nuclear centrifuges.
- In 2013, Israel Haifa highway control system was attacked by hackers, which caused massive traffic congestion in the city which lead great loss and serious subsequent problems.
- In 2014, Havex malware infects many industrial control system in European and caused the leakage of large amounts of data.



4

Problems – Timeliness and Availability

ICSs have rigorous requirements on timeliness and availability. The cybersecurity risks of ICSs are primarily from the potential loss caused by the cyber-attacks which demolish the timeliness and availability of the control system.

In order to achieve the destructive purpose, attackers generally need to follow part or all of these three steps:

1. infiltrate into the field network,
2. invalidate the system functions,
3. cause the hazardous incidents.

Therefore, the cybersecurity risk assessment of ICSs needs a novel and targeted risk model to analyze the risk propagation.

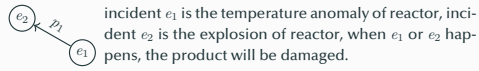
5

Problems – Overlapping amongst Consequences

The majority of existing quantitative risk assessment approaches used the following definition to calculate the risk \mathcal{R} .

$$\mathcal{R} = \sum_i S(e_i)P(e_i)$$

However, the overlapping amongst different consequences may cause the error of risk value. For example,



Assume that $P(e_1) = 1$, so $P(e_2) = p_1$, then

$$\mathcal{R} = S(e_1) + p_1 S(e_2) = S(e_1) + p_1 S(e_1) = (1 + p_1)S(e_1) \geq S(e_1).$$

6

Problems – Unknown Attacks

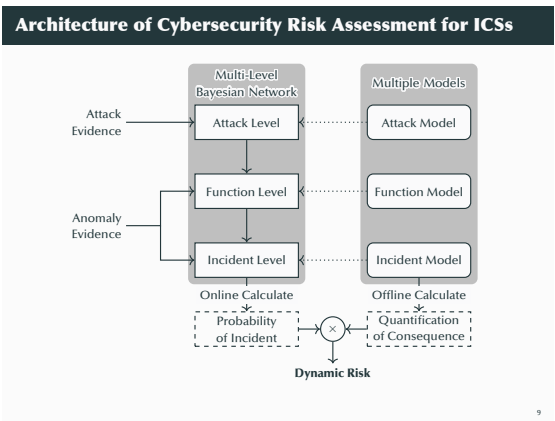
Many ICSs run 24/7/365, and therefore the updates must be planned and scheduled days or weeks in advance. After the updates, exhaustive testing is necessary to ensure the high availability of the ICS.

This leads to inability of the attack knowledge of ICSs to be updated in time. Several attack knowledge-based risk assessments cannot work well on ICSs.

Therefore, the risk assessment should have the ability of assessing the risk caused by unknown attacks without the corresponding attack knowledge.

7

Architecture



Hazardous Incident Prediction

Attack Level

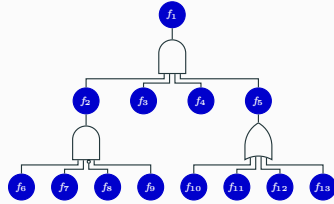
In this paper, the Bayesian network is used to model the relationship between attacks and resources.

The Bayesian network diagram shows four attack nodes (a_1, a_2, a_3, a_4) and three resource nodes (r_1, r_2, r_3). The nodes are arranged in a hierarchical structure. a_1 and a_2 are at the bottom, r_1, r_2, r_3 are in the middle, and a_3 and a_4 are at the top. Arrows indicate dependencies: a_1 and a_2 depend on r_1 and r_2 ; r_1 and r_2 depend on r_3 ; a_3 depends on a_1 and a_2 ; a_4 depends on a_2 and r_3 .

$O(r_1)$	T	T	F	F
$O(r_2)$	T	F	T	F
$L(a_1)$	$\ell_{a_1,1}$	$\ell_{a_1,2}$	$\ell_{a_1,3}$	$\ell_{a_1,4}$
$\bar{L}(a_1)$	$1 - \ell_{a_1,1}$	$1 - \ell_{a_1,2}$	$1 - \ell_{a_1,3}$	$1 - \ell_{a_1,4}$
$L(a_2)$	T	T	F	F
$\bar{L}(a_2)$	T	F	T	F
$O(r_3)$	$\phi_{r_3,1}$	$\phi_{r_3,2}$	$\phi_{r_3,3}$	$\phi_{r_3,4}$
$\bar{O}(r_3)$	$1 - \phi_{r_3,1}$	$1 - \phi_{r_3,2}$	$1 - \phi_{r_3,3}$	$1 - \phi_{r_3,4}$

Function Level

Function Tree Analysis is widely used to analyze the stability of control system, a typical function tree is shown in following figure.

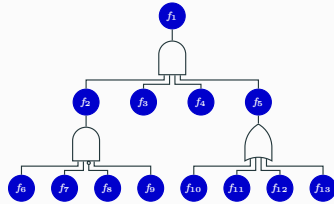


$$F_1 = F_2 F_3 F_4 F_5$$

12

Function Level

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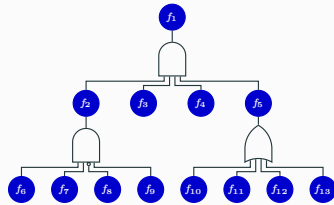


$$F_2 = F_6 F_7 \overline{F_8} F_9$$

12

Function Level

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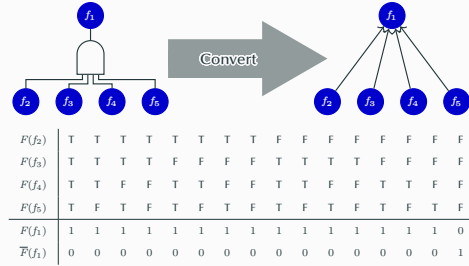


$$F_5 = F_{10} + F_{11} + F_{12} + F_{13}$$

12

Function Level

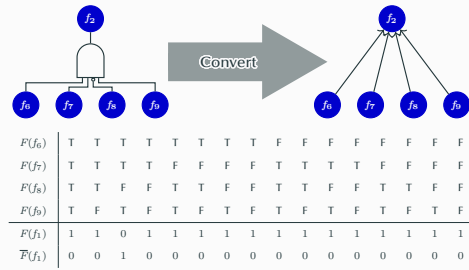
To simplify the inference, the function tree is converted into Bayesian network, which is shown in following figure.



13

Function Level

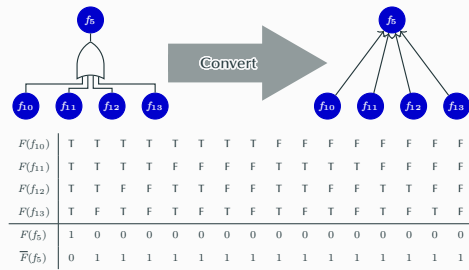
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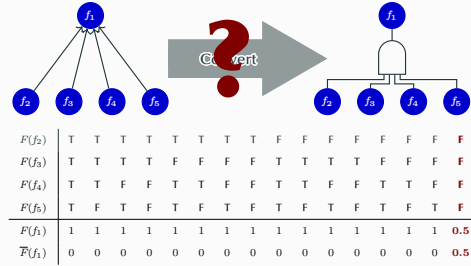
Function Level

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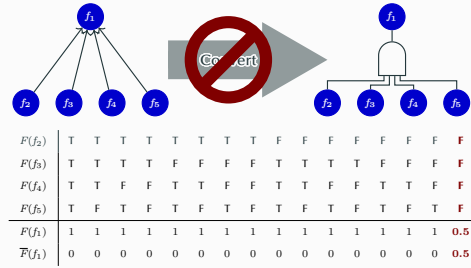
Function Level



14

Function Level

The conditional probability table of the Bayesian network contains more information than the logical gate of the fault tree.

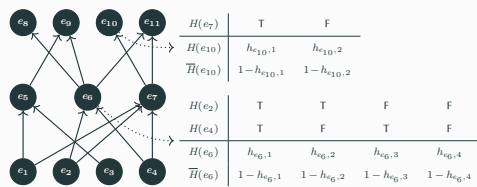


14

Incident Level

The occurrence of one incident may cause another incidents, in this paper, the Bayesian network is also used to model the causal relationship amongst the potential incidents.

A typical Bayesian network of incident is shown in following figure.

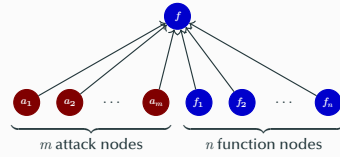


15

Information Transfer between Levels

The cyber attacks can lead to system function failures, and the function failures may cause the industrial incidents. To analyze the risk propagation, an information transfer is necessary between the three aforementioned layers.

The following figures show two kind of information transfer.

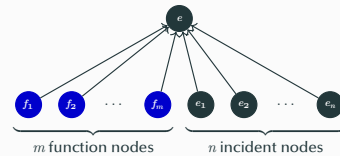


16

Information Transfer between Levels

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16

Collection of Evidence

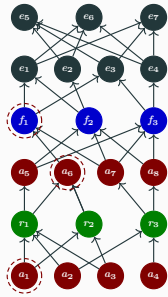
There are two kind of evidence need to be collected:

- **Attack Evidence**, contains the attack information, such as attack time, attack type, attack object, etc.
- **Anomaly Evidence**, contains the information about the anomaly, such as function failure, function restoration, incident occurrence, etc.

For each evidence, there exists a corresponding node in the multi-level Bayesian network. When the intrusion detection system or the monitoring system finds an evidence, the corresponding node will be marked in the multi-level Bayesian network.

17

Calculation of Incident Probability



The left figure shows a typical multi-level Bayesian network.

Assuming that the evidence list is

$$a_1, a_6, f_1$$

Then the nodes a_1 , a_6 , and f_1 are marked with **red** dashed circles.

Finally, the algorithm named Probability Propagation in Trees of Clusters (PPTC) can calculate the probabilities of all the hazardous incidents.

18

Dynamic Risk Assessment

Decouple of Incident Consequences – Step 1

for each incident e_i , analyze its consequence and generate a consequence set

$$c_i = (c_1, c_2, \dots, c_n).$$

The meaning of c_i is that the occurring of the incident e_i will threaten the elements in consequence set c_i .

For example, the incident e_i is an explosion of a reactor, which may cause worker casualties, air pollution, facilities damages, and products loss. The consequence set of e_i is

$$c_i = (\text{workers, air, facilities, products}).$$

20

Decouple of Incident Consequences – Step 2

21

Decouple of Incident Consequences – Step 3

For each $c'_j \in \mathcal{C}'$, generate a corresponding auxiliary node x_j . According to the **traceability** of \mathcal{C}'

$$\forall c' \in \mathcal{C}', \exists c \in \mathcal{C}, c' \subseteq c,$$

there must be a consequence set $c_i \in \mathcal{C}$, where $c'_j \subseteq c_i$. So, for each $c'_j \in \mathcal{C}'$, we can find the incident set

$$e_j = (e_{i_1}, e_{i_2}, \dots, e_{i_n}).$$

For each incident e_k of the incident set e_j , the corresponding consequence set c_k satisfies the following condition:

$$c'_j \subseteq c_k.$$

Therefore, the parent nodes of the auxiliary node x_j are incident nodes $e_{i_1}, e_{i_2}, \dots, e_{i_n}$.

22

Decouple of Incident Consequences – Step 4

For each auxiliary node x_j , generate a conditional probability table. A typical conditional probability table of auxiliary node x_j is shown as following table.

$H(e_{i_1})$	T	T	T	...	F	F	F
$H(e_{i_2})$	T	T	T	...	F	F	F
$H(e_{i_n})$	T	T	T	...	F	F	F
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
$H(e_{i_{n-2}})$	T	T	T	...	F	F	F
$H(e_{i_{n-1}})$	T	T	F	...	T	F	F
$H(e_{i_n})$	T	F	F	...	F	T	F
$H(x_j)$	1	1	1	...	1	1	0
$\bar{H}(x_j)$	0	0	0	...	0	0	1

23

Classification of Incident Consequences

In this paper, there are three main kinds of incident consequences to be considered:

- **Harm to Humans:**
 - temporary harm,
 - permanent disability,
 - fatality.
- **Environmental Pollution:**
 - air pollution,
 - soil contamination,
 - water pollution.
- **Property Loss:**
 - damage of materials,
 - damage of products,
 - damage of equipment.

24

Quantification of Incident Consequences

- **Harm to Humans Q_H :**
If the decision-maker would like to increase the cost of an investment by Δc to reduce the probability of a fatality by Δp ,

$$Q_H = \Delta c / \Delta p.$$

- **Environmental Pollution Q_E :**
The monetary loss of environmental pollution is defined as

$$Q_E = \text{Penalty} + \text{Compensation} + \text{HarnessCost}.$$

- **Property Loss Q_P :**
The cost of replacement is used to quantify the loss of property Q_P , such as the loss of materials, products, and equipment.

25

Calculation of Dynamic Risk

Due to the following two reasons:

- there is no overlapping between the consequences of any two auxiliary nodes x_i and x_j , $i \neq j$,
- the auxiliary nodes contain all the consequences of incidents,

the dynamic cybersecurity risk can be defined as

$$\mathcal{R} = \sum_{i=1}^{m'} p(x_i) q(x_i),$$

where

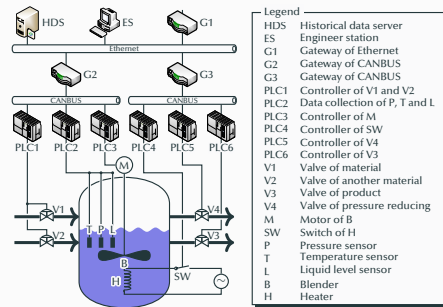
- $p(x_i)$ is the occurrence probability of the auxiliary node x_i ,
- $q(x_i)$ is the monetary loss of the auxiliary node x_i .

26

Simulation

Simulation Platform

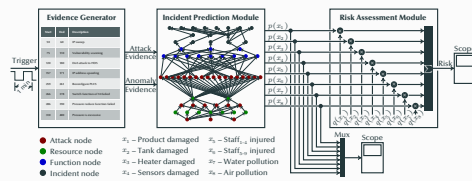
The simulation object is a chemical reactor whose control structure is shown as the following figure.



28

Simulation Platform

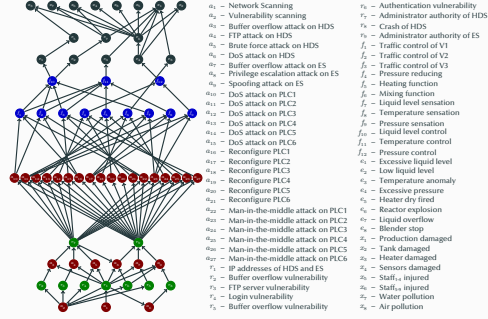
The simulation platform is implemented in Matlab, which consists of three modules: an evidence generator, an incident prediction module, and a risk assessment module.



29

Simulation Platform

The multi-level Bayesian network of the chemical reactor is shown as following figure.



30

Simulation Platform

The list of evidences is shown as following table.

Start	End	Description	Symbol
50	60	IP sweep	$L(a_1)$
75	110	Vulnerability scanning	$L(a_2)$
120	180	DoS attack to HDS	$L(a_6)$
157	171	IP address spoofing	$L(a_9)$
259	261	Reconfigure PLC5	$L(a_{20})$
266	378	Switch function of V4 failed	$F(f_4)$
286	390	Pressure reduce function failed	$F(f_{12})$
310	400	Pressure is excessive	$H(e_4)$

31

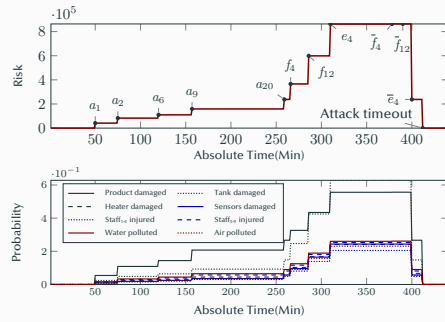
Simulation Platform

The quantification of consequences is shown as following table.

Incident Symbol	Description of Incident	Quantification of Consequence(\$)
x_1	Product damaged	50,000
x_2	Tank damaged	500,000
x_3	Heater damaged	10,000
x_4	Sensors damaged	10,000
x_5	Staff ₁₋₄ injured	800,000
x_6	Staff ₅₋₉ injured	1,000,000
x_7	Water pollution	200,000
x_8	Air pollution	200,000

32

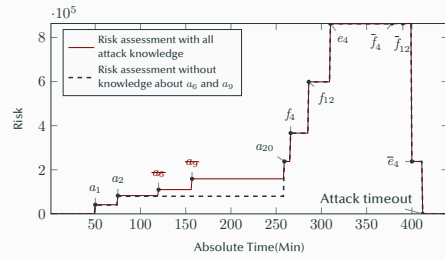
Simulation and Result Analysis



33

Simulation and Result Analysis

Then an identical multi-step attack on the system is launched to the system. The new cybersecurity risk curve is shown the dashed line in the following figure.

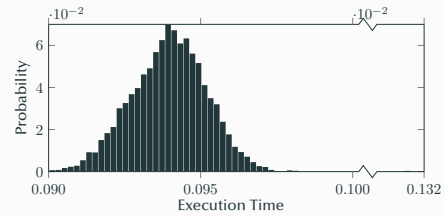


34

Simulation and Result Analysis

Some parameters of the following figure:

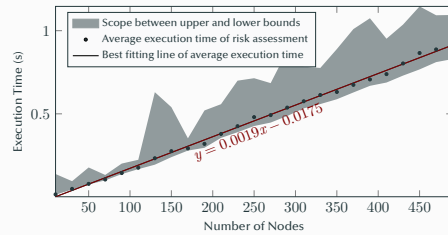
- The average execution time of a risk assessment is 94.1ms.
- The minimum execution time of a risk assessment is 89.9ms.
- The maximum execution time of a risk assessment is 131.6ms.



35

Simulation and Result Analysis

This means that the execution time of the risk assessment scales linearly with the increase of the node size of the multi-level Bayesian network.



36

Conclusion and Prospect

Conclusion

- By considering the characteristics of ICSs, a novel multi-level Bayesian network was proposed, which integrated a knowledge of attack, system function, and hazardous incident.
- The attack knowledge and system knowledge were combined to analyze the potential impact of attacks, so the proposed approach had the ability of assessing the risk caused by unknown attacks.
- A unified quantification approach for a variety of consequences of industrial accidents was introduced. Furthermore, the proposed approach could eliminate the error of risk caused by the overlapping amongst hazardous incidents.
- By using a simplified chemical reactor control system in Matlab environment, the designed dynamic risk assessment approach was verified.

38

Prospect

There are some shortcomings of the proposed risk assessment approach need to be improved.

- **Current research work has no ability for self-learning.**
- **The sub-second computation time cannot meet some hard real-time systems requirements.**

In the future, a dynamic cybersecurity risk assessment, which can automatically adjust the conditional probability and structure of the multi-level Bayesian network by analyzing the real-time data, will be researched, and several approximate inference methods will be attempted in the risk assessment.

39

Thank You!

Thank You!

You can obtain this slide from my Github:
[zqmillet@github.com:Presentation.for.Loughborough.University](https://github.com/zqmillet/Presentation.for.Loughborough.University)

And I have pushed the code of the simulation to my Github, too.
[zqmillet@github.com:Multi-level.Bayesian.Network](https://github.com/zqmillet/Multi-level.Bayesian.Network)

41

Any Questions?