

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

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Hello everyone, my name is Zhang Qi, and I am the Ph.D student of Professor Zhou Chunjie. 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 topic of my presentation is “Multi-Model Based Incident Prediction and Risk Assessment in Dynamic Cybersecurity Protection for Industrial Control Systems”.

The purpose of my presentation is to introduce my research, and I hope I can get your good advices.

I shall take about 20 minutes of your time. If you have any questions, please feel free to interrupt.

Outlines

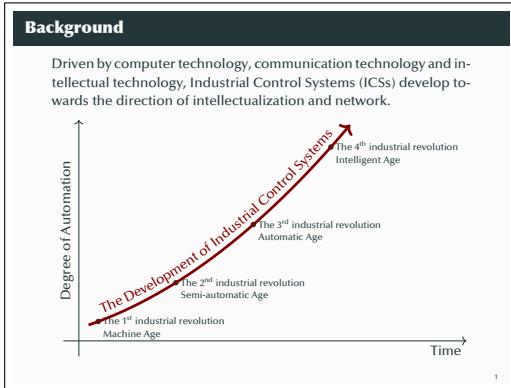
- Introduction
- Architecture
- Hazardous Incident Prediction
- Dynamic Risk Assessment
- Simulation
- Conclusion and Prospect

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

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:

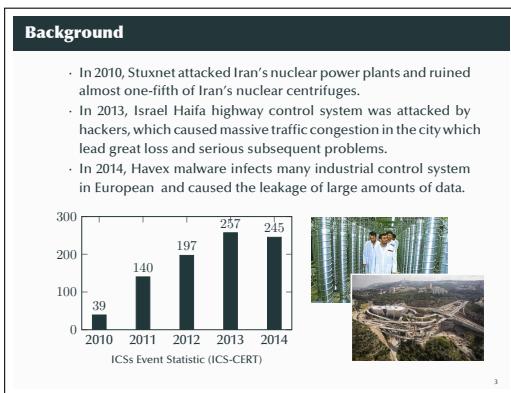
- Machine Age
- Semi-automatic Age
- Automatic Age
- Intelligent Age

From this figure, we can see that with the development of industrial control systems, the degree of automation is increasing. Intelligence and networking are the development trend of industrial control systems.



Nowadays, the industrial control systems have been widely applied in various industry, and they are becoming more and more important for the national economy and our life.

As mentioned before, the industrial control systems are evolving towards intelligence and networking. The rapid development of the industrial control systems reduce the difficulty of the development and the cost of construction, on the other hand, it has also introduced the cybersecurity issues into the industrial control systems.



For example, in 2010, the 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.

According to the statistical data from “Year in Review 2014” published by the ICS-CERT which is short for “Industrial Control Systems Cyber Emergency Response Team”, the number of attacks for industrial control systems increases year by year. In 2010, there were

only 39 security incidents of industrial control systems, but in 2014, this number has grown to 245.

Unlike traditional IT systems, the security incidents of industrial control systems can cause irreparable harm to the physical systems being controlled and to the people dependent on them. Basically, protecting industrial control systems against cyber-attacks is vital to both the economy and stability of a nation. Therefore, the cybersecurity issue of industrial control systems must be taken seriously and solved as soon as possible.

Problems – Timeliness and Availability

ICCs have rigorous requirements on timeliness and availability. The cybersecurity risks of ICCs 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 ICCs needs a novel and targeted risk model to analyze the risk propagation.

In recent years, considerable researches have been undertaken to study cybersecurity risk assessment methods. However, the cybersecurity risk assessment in the IT domain is not entirely applicable to industrial control systems because industrial control systems are relatively different from traditional IT systems in some aspects.

Firstly, the cybersecurity objectives are different. Traditional IT systems first require an ensuring of confidentiality, then integrity, and finally availability. For industrial control systems, in contrast, the priorities of

these three security objectives are first availability, then integrity, and finally confidentiality, because the timeliness and availability are the primary concerns. The malicious attacks induce the cybersecurity risk to industrial control systems by demolishing the timeliness and availability. Therefore, the risk assessment of industrial control systems needs a novel risk propagation analysis approach.

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 difference consequences may cause the error of risk value. For example,



incident e_1 is the temperature anomaly of reactor, incident e_2 is the explosion of reactor, when e_1 or e_2 happens, the product will be damaged.

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

$$\mathcal{R} = S(e_1) + p_1S(e_2) = S(e_1) + p_1S(e_1) = (1 + p_1)S(e_1) \geq S(e_1).$$

The majority of existing quantitative risk assessment approaches used this definition to calculate the risk, where $S(e_i)$ is the severity of the incident e_i and $P(e_i)$ is the probability of the incident e_i .

It is also worth noting that there is a problem when this definition is used in industrial control systems risk assessment. This is due to the fact that, for industrial control systems, different hazardous incidents may cause the same consequence; whereby, using this definition to assess risk will cause the severity of the same consequence to be accumulated multiple times. As a

result, there is an error in the risk assessment, which cannot be ignored. Even worse, the decision-making may generate a wrong policy with this inaccurate risk value.

For example, incident e_1 is the temperature anomaly of reactor, incident e_2 is the explosion of reactor, when e_1 or e_2 happens, the product will be damaged. Assume that $P(e_1) = 1$, so $P(e_2) = p_1$, then

$$\mathcal{R} = S(e_1) + p_1S(e_2) = S(e_1) + p_1S(e_1) = (1 + p_1)S(e_1) \geq S(e_1).^1$$

It is obviously wrong, because the risk of system can't be larger than the total value of all assets.

- I. the risk is equal to capital S e sub 1 plus p sub 1 multiplied by capital S e sub 2 is equal to capital S e sub 1 plus p sub 1 multiplied by capital S e sub 1 is equal to 1 plus p sub 1 multiplied by capital S e sub 1 is greater than or equal to capital S e sub 1

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.

As continuous operation systems, the industrial control systems cannot tolerate frequent software patching or updates. This causes the database of attack signatures to lag far behind the rapid development of attacks. With this defect, several intrusion detection system based misuse detections would miss the unknown attacks.

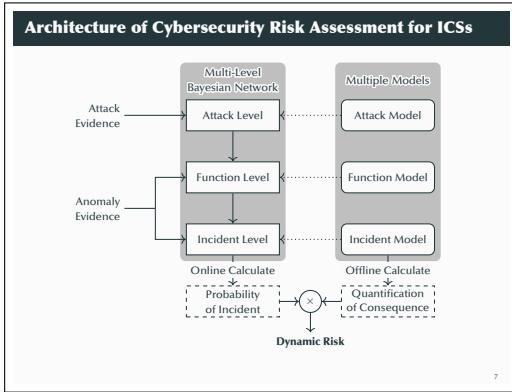
On the other hand, without the information about unknown attacks, such as purposes, consequences, and further steps, these unknown attacks and their consequences cannot be predicted accurately. As a result,

the risk assessment module will generate erroneous risk value, which may lead to a wrong decision.

Architecture

Based on the above analysis, the requirements of cybersecurity risk assessment for industrial control systems can be summarized. The risk assessment of industrial control systems needs:

- a novel and targeted risk model to analyze the risk propagation,
- a unified quantification approach to calculate the risk quantitatively without the error caused by overlapping amongst consequences,
- the ability of assessing the risk caused by unknown attacks without the corresponding attack knowledge.



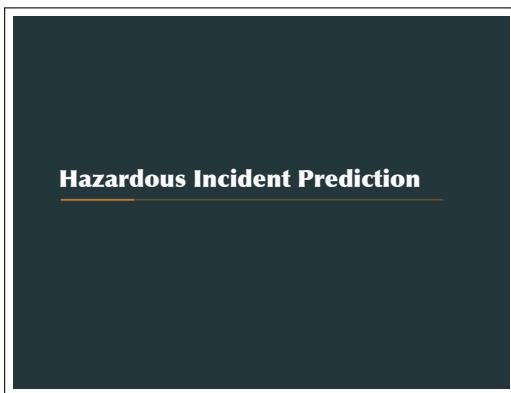
To meet the requirement of the risk assessment for industrial control systems, a dynamic cybersecurity risk assessment based on the multi-model is proposed.

To analyze the propagation of cybersecurity risk, the attack model, the function model, and the incident model are considered. Then, these three models are converted into a multi-level Bayesian network. This Bayesian network has three levels: the attack level, the function level, and the incident level.

There are two kinds of inputs for the dynamic cybersecurity risk assessment: attack evidence and anomaly

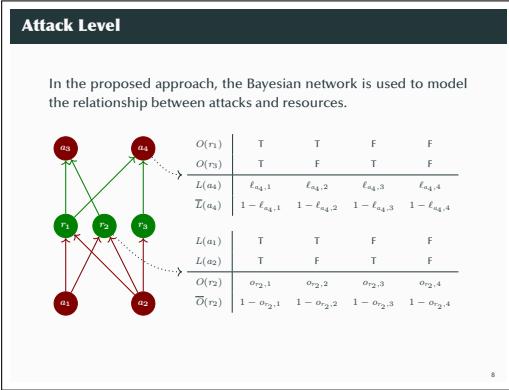
evidence. Attack evidence, which contains information about the type, target, and timestamp of the detected attack, is derived from intrusion detection system. Anomaly evidence, containing the information of the anomaly, such as the invalidation of a function, the occurrence of a hazardous incident, etc., can be obtained from the supervisor system of industrial control systems.

The dynamic cybersecurity risk assessment is divided into two phases: the hazardous incident prediction and the risk assessment. During the hazardous incident prediction phase, attack evidence and anomaly evidence are collected and marked in the multi-level Bayesian network. Then, probabilities of all the potential hazardous incidents can be calculated by analyzing the collected evidences and the multi-level Bayesian network. During the risk assessment phase, the consequences of the hazardous incidents are first classified, and then each type of consequence is quantified in the same unit. Secondly, the overlapping amongst hazardous incidents must be addressed, so the error caused by multiple accumulation of consequences can be eliminated. Finally, the probabilities and consequences of the hazardous incidents are combined into the cybersecurity risk.



Next, I will elaborate the proposed approach of risk assessment for industrial control systems from two parts:

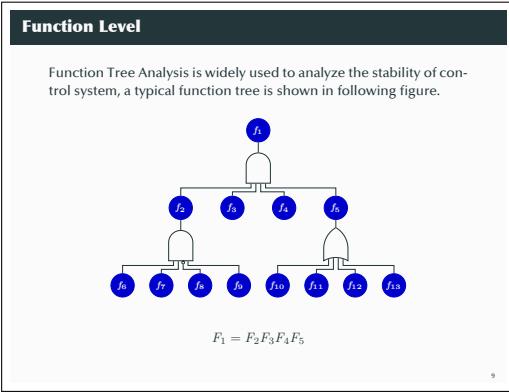
- hazardous incident prediction
- dynamic risk assessment



attack strategy may obtain another resources. So, using these two kinds of nodes, the Bayesian network can model the multi-step attack.

The Bayesian network uses the conditional probability table to describe the reachable probability. For example, attack node a_4 has two conditions r_1 and r_3 . The first column of the conditional probability table of node a_4 shows that when the attacker obtain the resources r_1 and r_3 , the probability that he launches attack a_4 is $\ell_{a_4,1}$.^I Similarly, if he only has resource r_1 , the probability is $\ell_{a_4,2}$.^{II}

- I. the probability that he launches attack a sub 4 is I sub a sub 4 1
- II. Similarly, if he only has resource r sub 1, the probability is I sub a sub 4 2



system function f_1 .

Let's go back to the relationship amongst the functions f_1, f_2, f_3, f_4 and f_5 , if the relationship amongst the functions f_1, f_2, f_3, f_4 and f_5 is $F_1 = F_2 F_3 F_4 F_5$. The function tree uses an and-gate to describe this relationship.

- I. If the relationship amongst the functions lowercase f sub 1, f sub 2, f sub 3, f sub 4 and f sub 5 is capital F sub 1 is equal to capital F sub 2 F sub 3 F sub 4 F sub 5

In the proposed approach, the Bayesian network is used to model the relationship between attacks and resources.

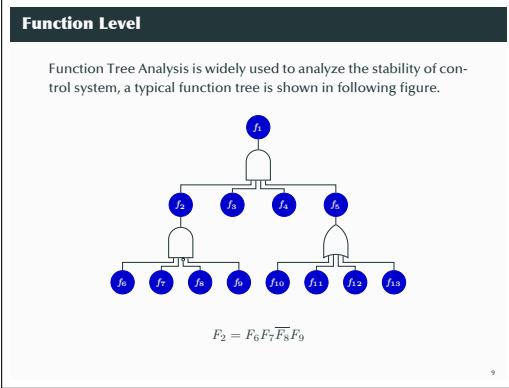
The left figure shows a typical Bayesian network of multi-step attack. In this Bayesian network, the attack nodes, which are colored red, represent attack strategies. the resource nodes, which are color green, represent resources. The enforcement of an attack strategy need some conditions. Only the conditions of an attack strategy is satisfied, may this attack strategy be launched. One the other hands, the enforcement of an

attack strategy may obtain another resources. So, using these two kinds of nodes, the Bayesian network can model the multi-step attack.

The Bayesian network uses the conditional probability table to describe the reachable probability. For example, attack node a_4 has two conditions r_1 and r_3 . The first column of the conditional probability table of node a_4 shows that when the attacker obtain the resources r_1 and r_3 , the probability that he launches attack a_4 is $\ell_{a_4,1}$.^I Similarly, if he only has resource r_1 , the probability is $\ell_{a_4,2}$.^{II}

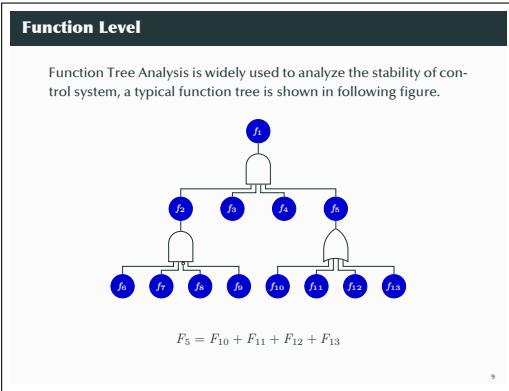
Function Tree Analysis is widely used to analyze the stability of control system, a typical function tree is shown in following figure.

If the relationship amongst the functions f_1, f_2, f_3, f_4 and f_5 is $F_1 = F_2 F_3 F_4 F_5$.^I In this slide, there are two kinds of letter F, where the lowercase f represents the system function, the capital F represents the status of system function f. For example, the F_1 is equal to True means that the corresponding system function f_1 is running normally, the F_1 is equal to False means that there is something wrong with the corresponding



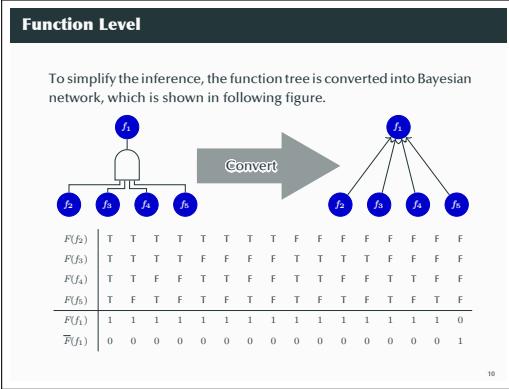
If the relationship amongst the functions f_2 , f_6 , f_7 , f_8 and f_9 is $F_2 = F_6 F_7 \bar{F}_8 F_9$.¹ The function tree will uses an appropriate logical gate to describe this kind of relationship.

- I. If the relationship amongst the functions lowercase f sub 2, f sub 6, f sub 7, f sub 8 and f sub 9 is capital F sub 2 is equal to capital F sub 6 F sub 7 F sub 8 bar F sub 9



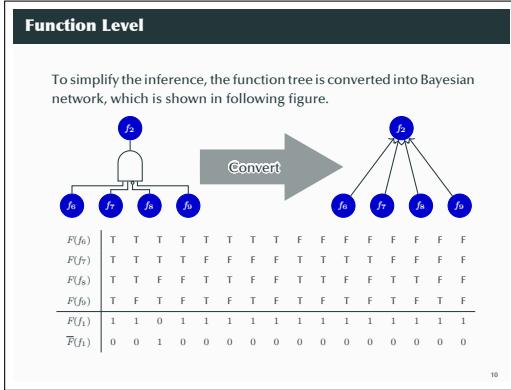
Similarly, if the relationship amongst the functions f_5 , f_{10} , f_{11} , f_{12} and f_{13} is $F_5 = F_{10} + F_{11} + F_{12} + F_{13}$.¹ The function tree will uses an or-gate to describe this kind of relationship.

- I. Similarly, if the relationship amongst the functions lowercase f sub 5, f sub 10, f sub 11, f sub 12 and f sub 13 is capital F sub 5 is equal to capital F sub 10 plus F sub 11 plus F sub 12 plus F sub 13

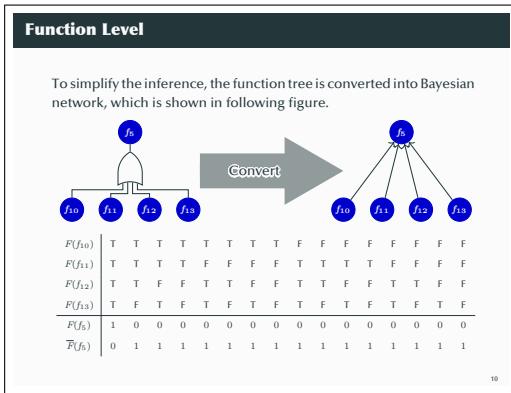


To simplify the inference, the function tree is converted into the Bayesian network, which is shown in following figure.

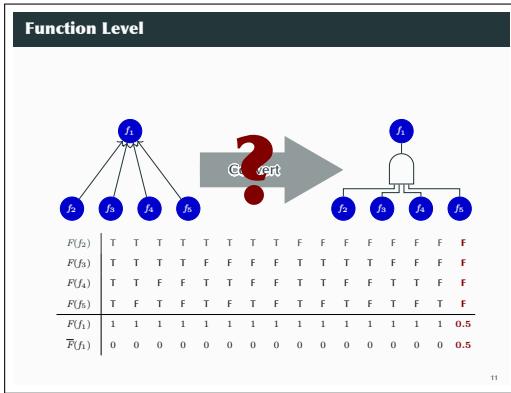
This and gate can be converted to a Bayesian network, in which f_2 , f_3 , f_4 and f_5 is the parent nodes of f_1 . Of cause, a conditional probability table is needed, too.



This kinds of gate can be also converted into a Bayesian network, but the conditional probability table is different. In fact, all kinds of logical gates can be converted into corresponding Bayesian networks.



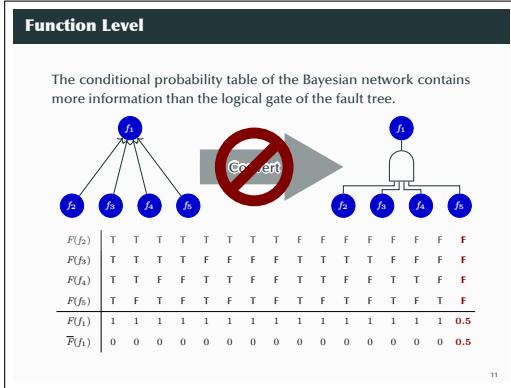
For example, the or-gate can be converted into the following Bayesian network.



Now, let me digress for a moment. There is a question: can the Bayesian network be converted into the function tree?

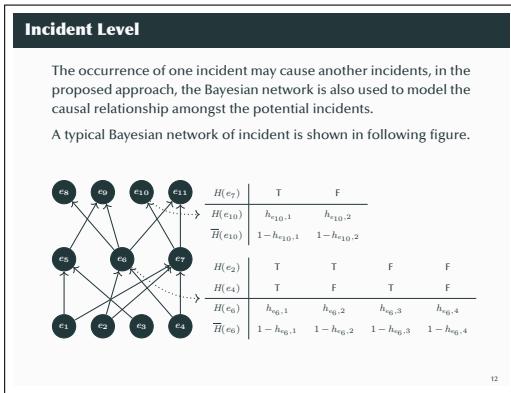
The answer is YES, but not all the Bayesian networks can be converted into the corresponding function trees.

For example, the following conditional probability table can't be converted into a function tree.



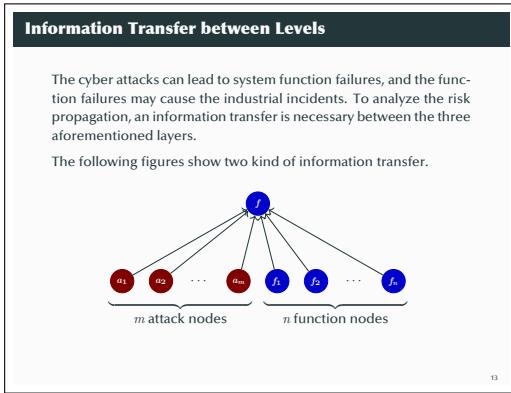
Because the conditional probability table of the Bayesian network contains more information than the logical gate of the fault tree. In other words, the logical gate cannot always accurately describe the relationship amongst functions.

the following conditional probability is an example.



The occurrence of one incident may cause another incidents, in the proposed approach, 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.

Like the attack level, the incident node also needs a conditional probability table to describe the relationship amongst it and its parent nodes.



The attack level, the function level and the incident level have been introduced. Now let's talk about the 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 amongst the three aforementioned layers.

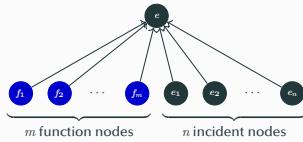
The following figures show the information transfer between attack level and function level.

We can see that the function failure can lead to another function failures, the launch of attack can also cause function failures. Therefore, we need add some parent nodes for function node f . Additional, the conditional probability table of function node f need to be extended.

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.



Similarly, the information transfer between function level and incident level is shown in the following figure.

Collection of Evidence

There are two kind of evidence need to be collected:

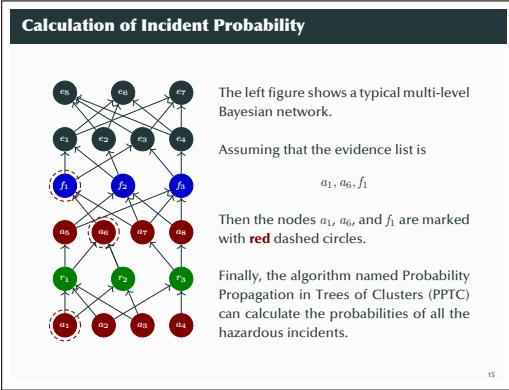
- **Attack Evidence**, contains the attack information, such as attack time, attack type, attack object, etc.
- **Anomaly Evidence**, contains the information about the anomaly, such as function failure, function restoration, incident occurrence, etc.

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.

There are two kind of evidence need to be collected attack evidence and anomaly evidence.

- The attack evidence contains the attack information, such as attack time, attack type, attack object, and so on. The attack evidence can be obtain by the intrusion detection systems.
- The anomaly evidence, contains the information about the anomaly, such as function failure, function restoration, incident occurrence, and so on. The anomaly evidence can be obtained by the monitoring systems.

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.



The right figure shows a typical multi-level Bayesian network. We can see it has three levels: attack level colored red and green, function level colored blue, and incident level colored black.

Assuming that there are three evidences which are detected. They are a_1, a_6 and 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.

Now, all the potential hazardous incidences can be calculated. So in summary, first, we collect the evidences about the systems. The evidences contains attack evidences and anomaly evidences. Then we infer what gonna happen according the evidences and their relationship. We use the Bayesian network to model the relationship amongst the evidences.



Now we have obtained the probability of all potential hazardous incidents. Let us talk about another problem, how to calculate the dynamic cybersecurity risk?

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

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

As mentioned before, there may exist overlapping amongst different incident consequences. And the overlapping will cause the error of the cybersecurity risk. So the first thing to do is the decouple of consequences.

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

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

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

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

- I. the set c sub i is equal to the set of c sub 1, c sub 2, dots, c sub n
- II. c sub i is equal to the set of workers, air, facilities and products

Decouple of Incident Consequences – Step 2

Then, generate $C' = (c'_1, c'_2, \dots, c'_{m'})$ based on $C = (c_1, c_2, \dots, c_m)$. The following conditions must be met:

Completeness: $\bigcup_{i=1}^m c_i = \bigcup_{i=1}^{m'} c'_i$

Independence: $\forall c'_i, c'_j \in C' : c'_i \cap c'_j = \emptyset$,

Traceability: $\forall c' \in C', \exists c \in C : c' \subseteq c$.

Step 2, generate $C' = (c'_1, c'_2, \dots, c'_{m'})$ based on $C = (c_1, c_2, \dots, c_m)$.^I

It is noted that all letter C is in bold type, it means that they are all sets. the lowercase c is the set of consequences, the capital C is the set of lowercase c.

When we generate the set C' , there are three conditions that set C' must be met:

First, the completeness:

$$\bigcup_{i=1}^m c_i = \bigcup_{i=1}^{m'} c'_i.^{II}$$

Second, the independence:

$$\forall c'_i, c'_j \in C' : c'_i \cap c'_j = \emptyset.^{III}$$

Third, the traceability:

$$\forall c' \in C', \exists c \in C : c' \subseteq c.^{IV}$$

- I. Step 2, generate set C prime which is equal to set c prime sub 1, set c prime sub 2, dots, set c prime sub m prime, based on set C is equal to set c sub 1, set c sub 2, dots, set c sub m

- II. First, the completeness, the union of c sub 1 to c sub m is equal to c prime sub 1 to c prime sub m prime

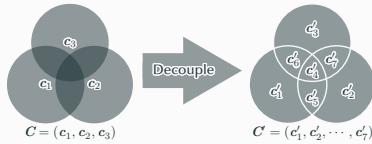
- III. Second, the independence, for each c prime i and c prime j in capital C prime, c prime i intersection c prime j is equal to empty set

- IV. Third, the traceability, for each set c prime in capital C prime, there must be a set c in capital C, which c prime is a subset of or equal to c

Decouple of Incident Consequences – Step 2

Then, generate $C' = (c'_1, c'_2, \dots, c'_{m'})$ based on $C = (c_1, c_2, \dots, c_m)$. The following conditions must be met:

- Completeness: $\bigcup_{i=1}^m c_i = \bigcup_{i=1}^{m'} c'_i$
- Independence: $\forall c'_i, c'_j \in C': c'_i \cap c'_j = \emptyset$,
- Traceability: $\forall c' \in C', \exists c \in C: c' \subseteq c$.



For example, there are three hazardous incidents e_1, e_2 , and e_3 , and their consequences are c_1, c_2 , and c_3 . From the figure we can see that there are overlapping amongst these three consequences. The decoupled consequences are shown in the right figure.

Obviously, the set C' satisfies these three conditions.

For each $c'_j \in C'$, we generate a corresponding auxiliary node x_j . According to the traceability of C' ,^I

According to the traceability of C' , there must be a consequence set $c_i \in C$, where $c'_j \subseteq c_i$. So, for each $c'_j \in C'$, we can find the incident set

So, for each $c'_j \in C'$, we can find the incident set

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

For each incident e_k of the incident set e_j , the corresponding consequence set c_k satisfies the following condition: $c'_j \subseteq c_k$.^{IV}

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

- I. For each c prime sub j in capital C prime, we can generate a corresponding auxiliary node x sub j
- II. According to the traceability of capital C prime, there must be a consequences set c sub i in capital C , where c prime sub j is a subset of or equal to c sub i .
- III. So, for each c prime sub j in capital prime, we can fine the incident set e sub j is equal to e sub i sub 1, e sub i sub 2, dots, e sub i sub n
- IV. For each incident e sub k of the incident set e sub j , the corresponding consequence set c sub k satisfies the following condition: c prime j is a subset of or equal to c sub k , where c prime sub j is an element of capital C prime
- V. Therefore, the parent nodes of the auxiliary node x sub j are incident nodes e sub i sub 1, e sub i sub 2, dots, e sub i sub n

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
$H(e_{i_3})$	T	T	T	...	F	F	F
\vdots	\vdots	\vdots	\vdots	\ddots	\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
$\overline{H}(x_j)$	0	0	0	...	0	0	1

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Classification of Incident Consequences

In the proposed approach, 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.

Next, we will talk about the quantification of incident consequences.

Before the quantification of incident consequences, the adverse effects of an incident may be classified, because different adverse effects need different quantification methods.

For industrial control systems, the adverse effects of an incident may be classified into three categories: harm to humans, environmental pollution, and property loss.

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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.

Different loss of different incident consequences need to be accumulated into the cybersecurity risk, so the loss of incident need to be quantified into same unit. In the proposed approach, we quantify the different loss into monetary loss.

For the harm to humans, if the decision-maker would like to increase the cost of an investment by Δc to reduce the probability of a fatality by Δp , in proposed approach, the quantification of harm to humans is defined as $Q_H = \Delta c / \Delta p$. ^I

The monetary loss of environmental pollution is defined as the sum of penalty, compensation, and harness cost.

- According to the environmental protection laws, if the occurrence of an incident causes environmental pollution, as the owner of industrial control system, the company must pay the penalty charge
- When environmental pollution occurs, it tends to influence the living conditions of residents near the plant, the downstream agricultural production, etc. As the relevant liable person, the company has the obligation to pay for compensation.
- To clear the polluted environment, as the polluter, the company must take action to improve the environment.

The monetary loss of property is defined as the cost of replacement.

- I. For the harm to humans, if the decision-maker would like to increase the cost of an investment by Delta c to reduce the probability of a fatality by Delta p, in proposed approach, the quantification of harm to humans is defined as Q sub H is equal Delta c over Delta p

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 .

Due to the following two reasons:

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

the dynamic cybersecurity risk can be defined as the following formula:

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

where

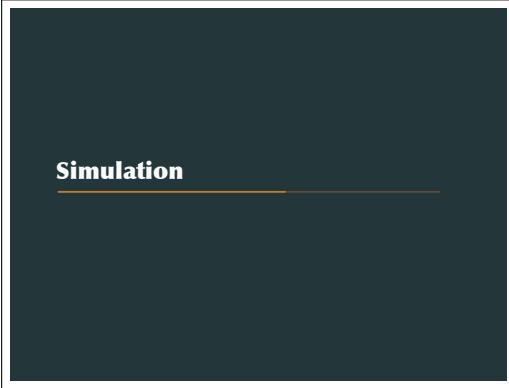
- $p(x_i)$ is the occurrence probability of the auxiliary node x_i , ^{III}
- $q(x_i)$ is the monetary loss of the auxiliary node x_i . ^{IV}

I. i is not equal to j

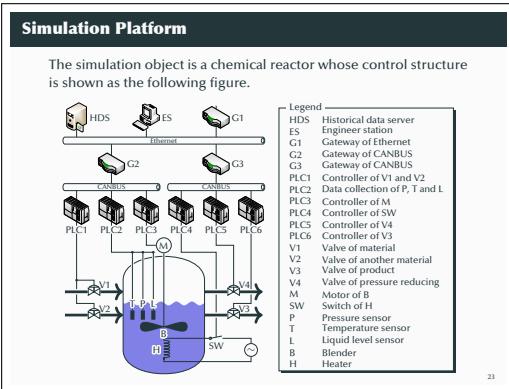
II. the risk is equal to the sum from i equals one to m prime p x sub i multiplied by q x sub i

III. p x sub i is the occurrence probability of the auxiliary node x sub i

IV. q x sub i is the monetary loss of the auxiliary node x sub i

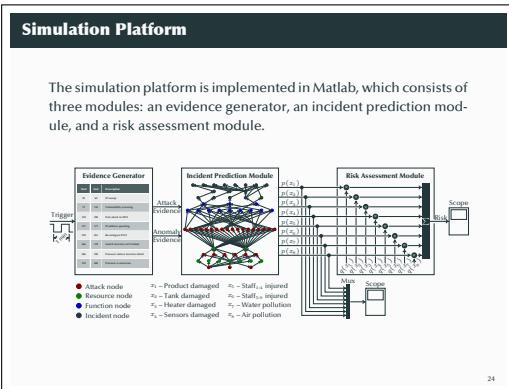


To illustrate how our approach validly calculates the cybersecurity risk in real-time, a numerical simulation is carried out.



A chemical reactor is a device for containing and controlling a chemical reaction and is widely used in the chemical industry. The representative structure of a chemical reactor control system is shown as the figure.

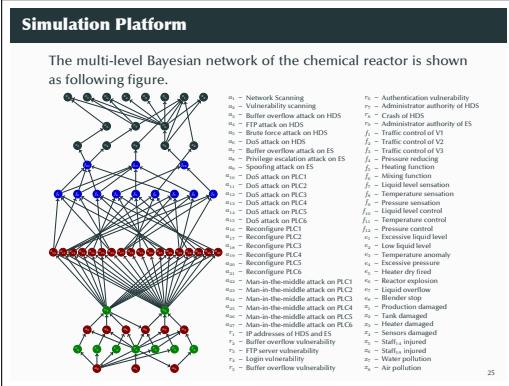
In this figure, the Ethernet connects to the enterprise network via gateway 1, which is not shown in this figure. Two CANBUS networks connect to the Ethernet via gateway 2 and gateway 3. In the Ethernet, there are an engineer station and a historical data server. The host in the enterprise network can access the historical data of the historical data server, but cannot access the engineer station. PLC1-6 are distributed into two CANBUS networks. The engineer station and the historical data server can obtain data from all of the PLCs, but only the engineer station can modify and configure PLCs.



This figure shows the structure of the 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.

The evidence generator is used to simulate the intrusion detection system and monitoring system. It uses an array to store an evidence list, which will be shown later. It has a time trigger. To the scheduled time, it will generate an evidence and send it to the incident prediction module.



This figure shows the multi-Level Bayesian network of reactor.

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	$F(f_1)$
286	390	Pressure reduce function failed	$F(f_{12})$
310	400	Pressure is excessive	$H(e_4)$

26

This table shows the evidence list of the evidence generator.

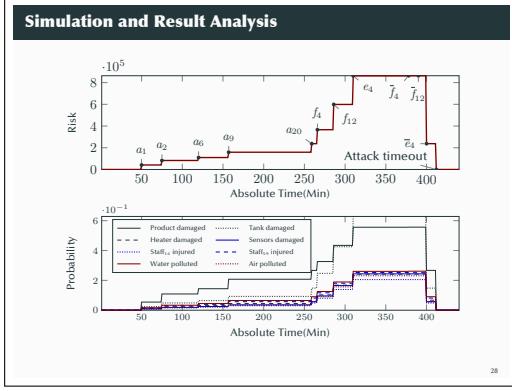
Simulation Platform

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

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This table shows the quantifications of different consequences.

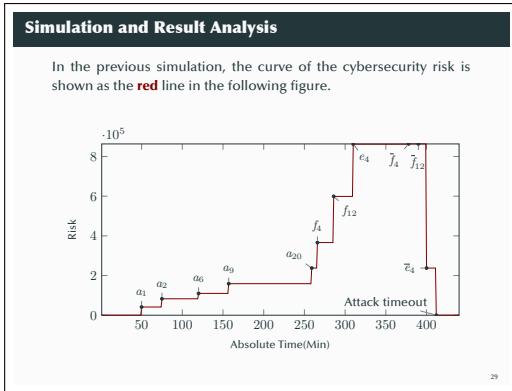


The first simulation.

A multi-step attack is launched on the chemical reactor control system. The evidences are collected and the cybersecurity risk is calculated every minute. Then the curves of the cybersecurity risk and probabilities of incidents x_1, x_2, \dots, x_8 in the multi-level Bayesian network are shown in these two figure.

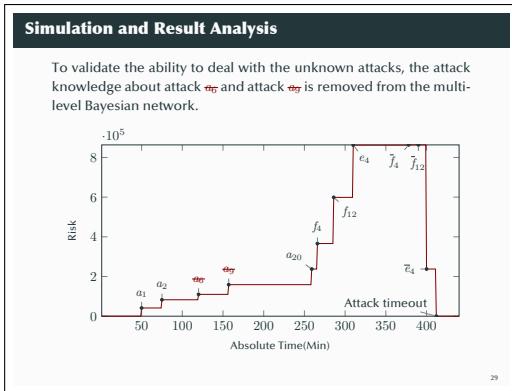
From these two figures, we can see:

- with the infiltration of multi-step attacks, the cybersecurity risk of the chemical reactor control system is increasing,
- when attack is aborted, the cybersecurity risk of the chemical reactor control system is decreasing,
- the curves of probabilities of incidents is in line with the trend of the curve of cybersecurity risk.



The second simulation.

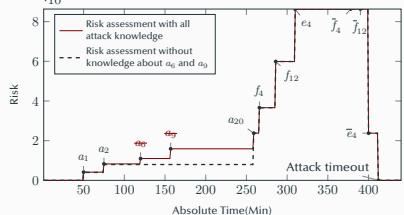
In the previous simulation, the curve of the cybersecurity risk is shown as the red line in the following figure.



To illustrate the ability to deal with unknown attacks, the attack nodes a_6 and a_9 are removed from the multi-level Bayesian network. Thus, the incident prediction module does not know that an attacker can get the administrator authority of the engineer station through a DoS attack and an IP spoofing attack. In other words, a_6 and a_9 are unknown attacks to the incident prediction module. Additionally, the conditional probability table of the resource node r_9 also needs to be modified.

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.



The same multi-step attack is launched to the chemical reactor control system again. Since there is no knowledge of attacks a_6 and a_9 , the evidences of a_6 and a_9 must be removed from the evidence list. The cybersecurity risk value is recorded every minute, the new cybersecurity risk curve is shown the dashed line in the following figure.

This figure shows that, before the 120th minute, the risk of the second simulation is slightly below that of the first simulation. The reason is that, without the knowledge of a_6 and a_9 , the probability of an attack

obtaining the resource r_9 is lower in view of the incident prediction module. After the 120th minute and before the 259th minute, there is a difference between two of the risk curves. Since there is no evidences of a_6 and a_9 , the risk of the second simulation in this range remains unchanged. After the 259th minute, we can see the risk curves of two simulations that have overlapped. This comparison shows that, without the knowledge of several atom attacks, there is no comparatively large deviation in the result of the risk assessment. Therefore, if there are a few unknown atom attacks in a multi-step attack, our approach can still generate a relatively accurate risk value.

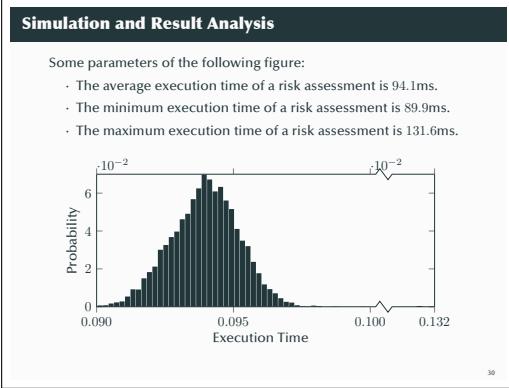
Simulation and Result Analysis

We repeat the first simulation 5,000 times, and the execution time of 5,000 calculations is recorded. This simulation is run on a machine with Intel Pentium processor G3220 (3M Cache, 3.00GHz) and 4GB DDR3 memory. The following figure shows the distribution of the 5,000 execution times.



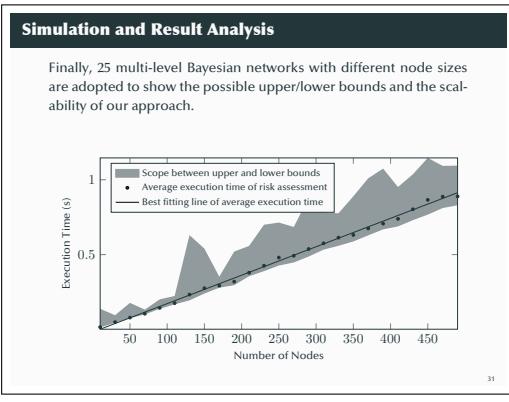
The third simulation.

We repeat the first simulation 5,000 times, and the execution time of 5,000 calculations is recorded. This simulation is run on a machine with Intel Pentium processor G3220 (3M Cache, 3.00GHz) and 4GB DDR3 memory. The following figure shows the distribution of the 5,000 execution times.



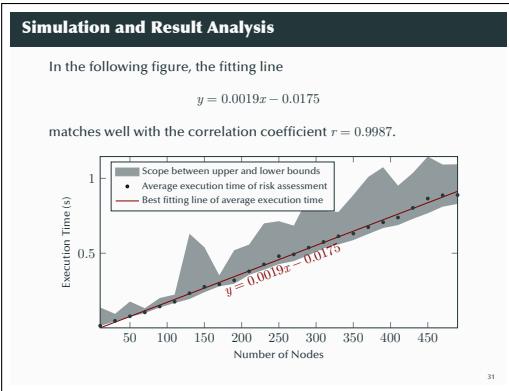
Some parameters of the following figure:

- 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.



The final simulation.

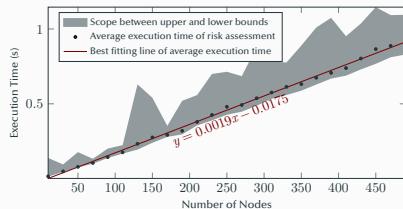
25 multi-level Bayesian networks with different node sizes are adopted to show the possible upper/lower bounds and the scalability of our approach. The minimum node size is 10, and the maximum node size is 490, which can model extremely complicated control systems. For each multi-level Bayesian network, the risk assessment is repeated 200 times and all the execution time is recorded. The following figure shows the possible upper/lower bounds and the scalability of the proposed risk assessment approach.



In this figure, a fitting line $y = 0.0019x - 0.0175$ matches well with the correlation coefficient $r = 0.9987$.

Simulation and Result Analysis

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Conclusion and prospect.

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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.

Now, let me make a conclusion for my presentation.

First, 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.

Second, 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.

Third, a unified quantification approach for a variety of consequences of industrial accidents was intro-

duced. Furthermore, the proposed approach could eliminate the error of risk caused by the overlapping amongst hazardous incidents.

At last, by using a simplified chemical reactor control system in Matlab environment, the designed dynamic risk assessment approach was verified.

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.

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Thank You!

Thank you for your listening! I hope I have made myself understood.

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If you have some questions to discuss with us, you can contact us by email.



We are very glad to welcome you to Huazhong University of Science & Technology.

Welcome to HUST!



Any questions?

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