

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

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- Calculation of Dynamic Risk

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- Conclusion

Introduction

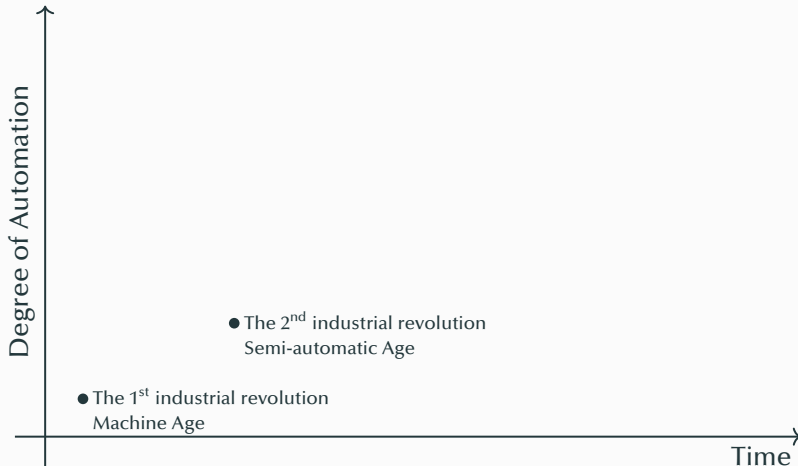
Background

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



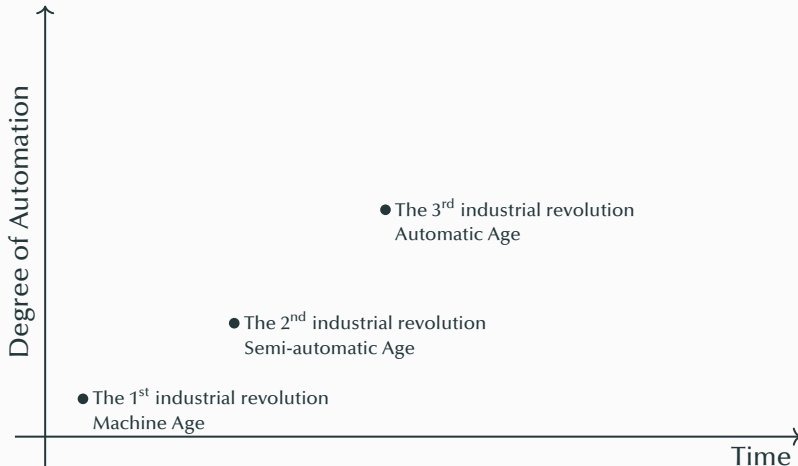
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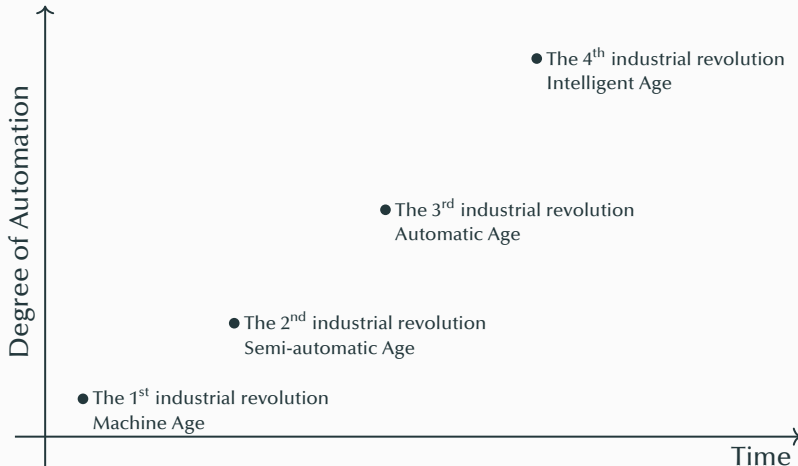
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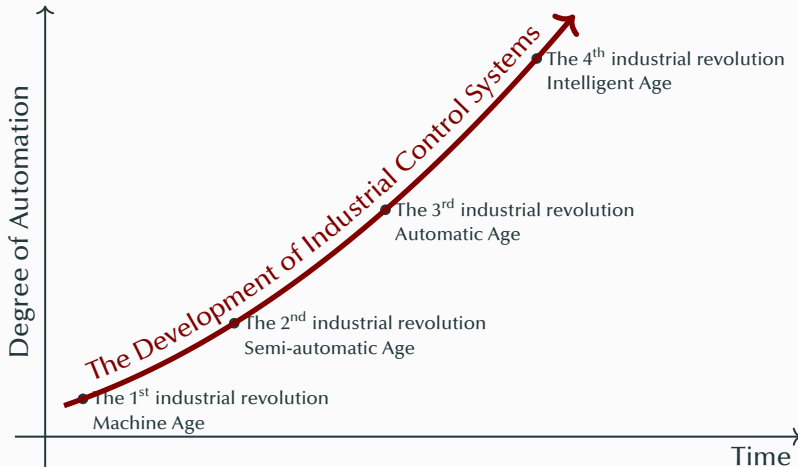
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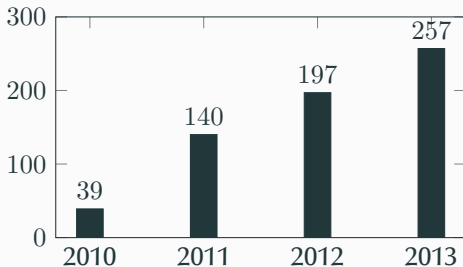
Background

- 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.



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.



ICSs Event Statistic (ICS-CERT)



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.

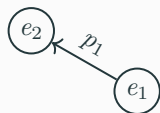
Therefore, the cybersecurity risk assessment of ICSs needs a novel and targeted risk model to analyze the risk propagation.

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

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

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.

Architecture

Architecture of Cybersecurity Risk Assessment for ICSs

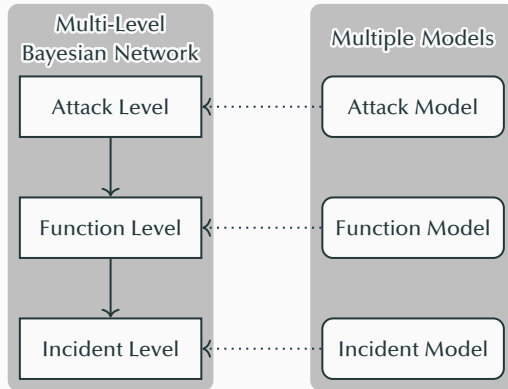
Multiple Models

Attack Model

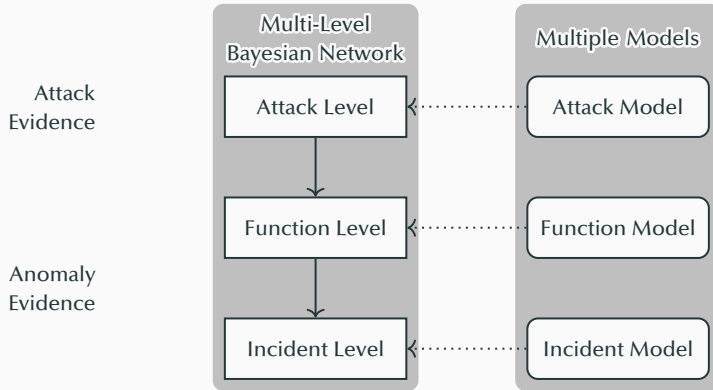
Function Model

Incident Model

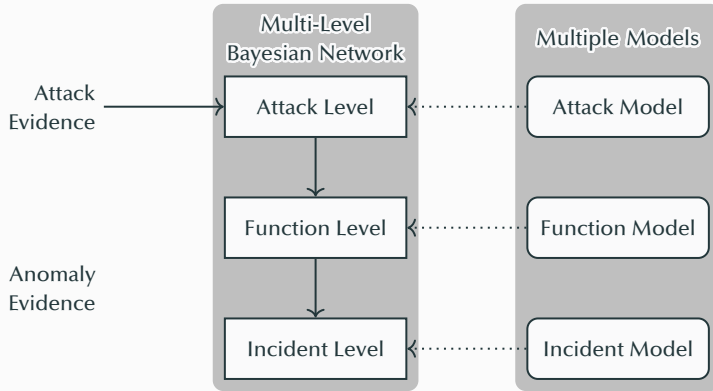
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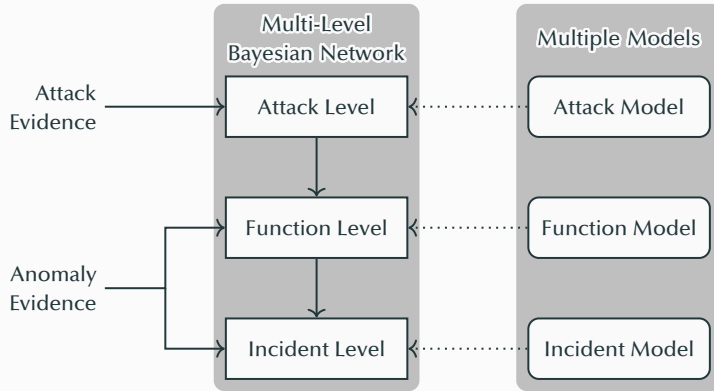
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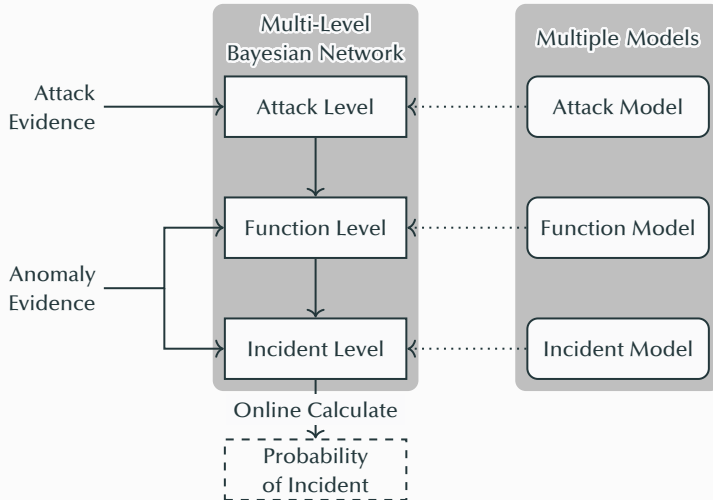
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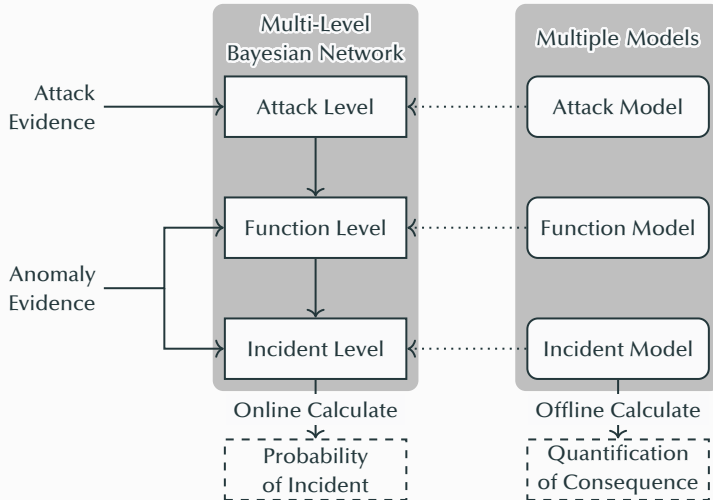
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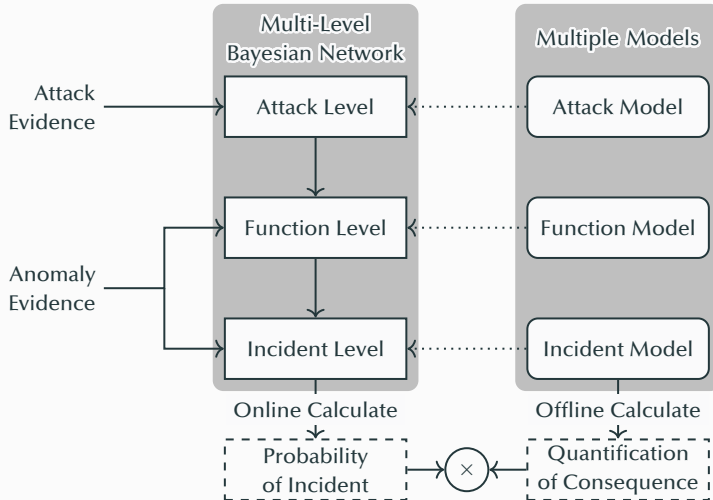
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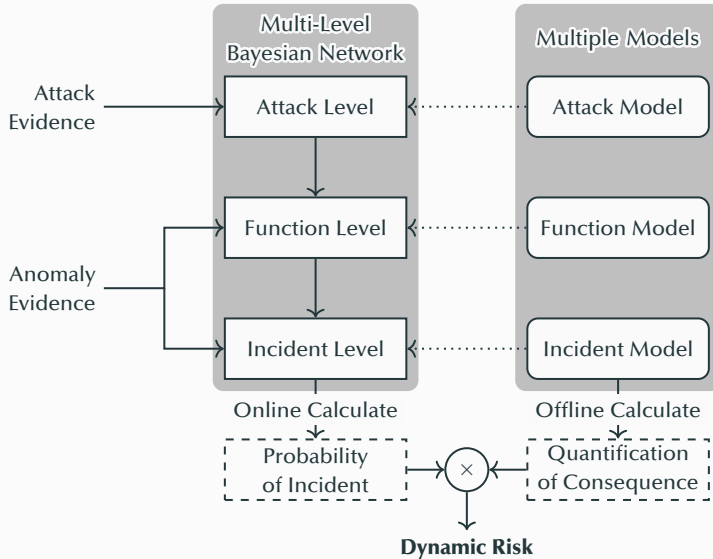
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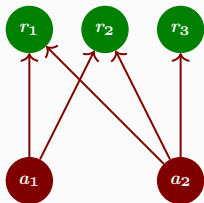
Hazardous Incident Prediction

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



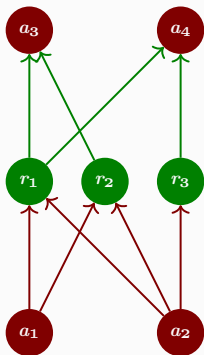
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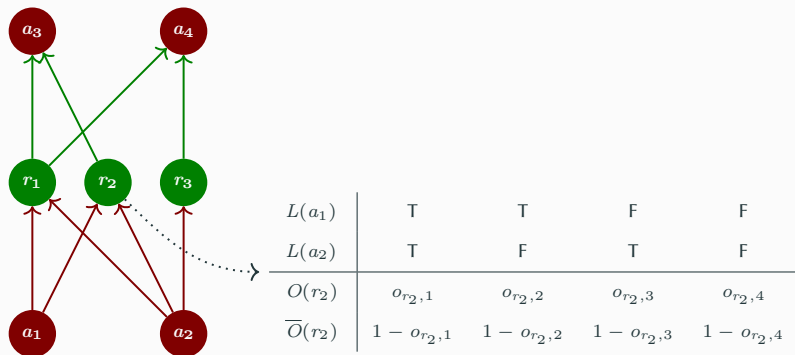
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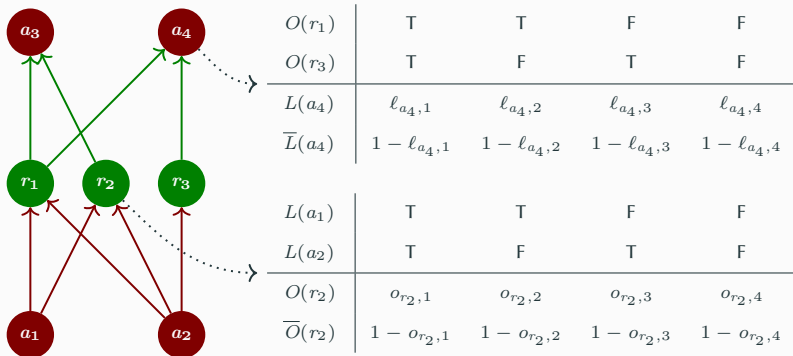
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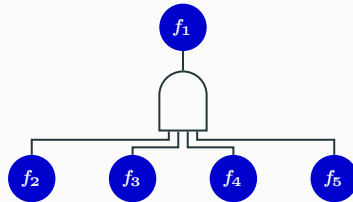
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$$F_1 = F_2 F_3 F_4 F_5$$

Function Level

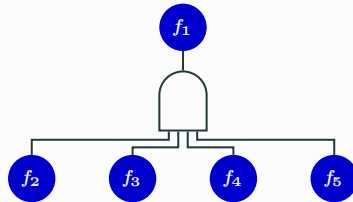
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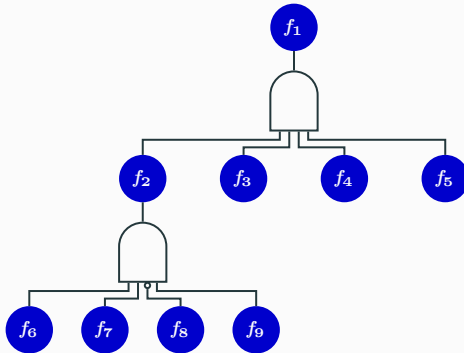
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$$F_2 = F_6 F_7 \overline{F_8} F_9$$

Function Level

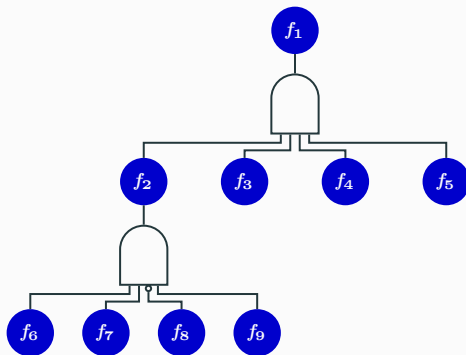
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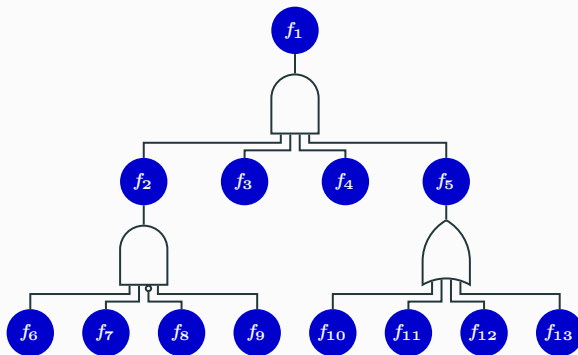
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$$F_5 = F_{10} + F_{11} + F_{12} + F_{13}$$

Function Level

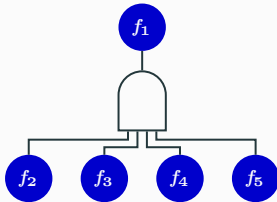
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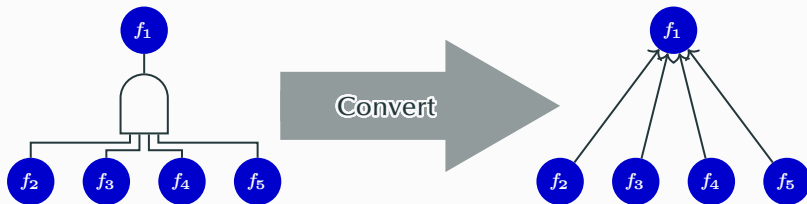
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To simplify the inference, the function tree is converted into Bayesian network, which is shown in following figure.



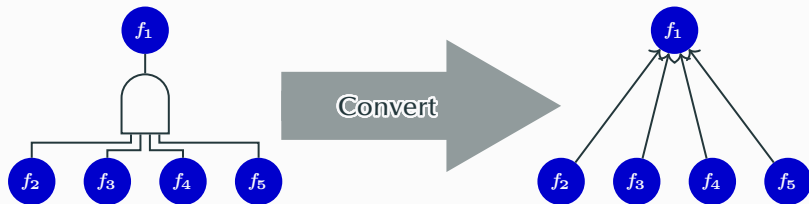
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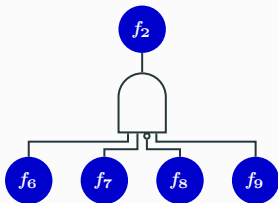
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$F(f_2)$	T	T	T	T	T	T	T	T	F	F	F	F	F	F	F	F
$F(f_3)$	T	T	T	T	F	F	F	F	T	T	T	T	F	F	F	F
$F(f_4)$	T	T	F	F	T	T	F	F	T	T	F	F	T	T	F	F
$F(f_5)$	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F
$F(f_1)$	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
$\overline{F}(f_1)$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

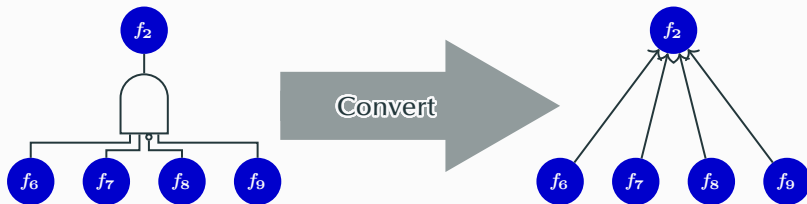
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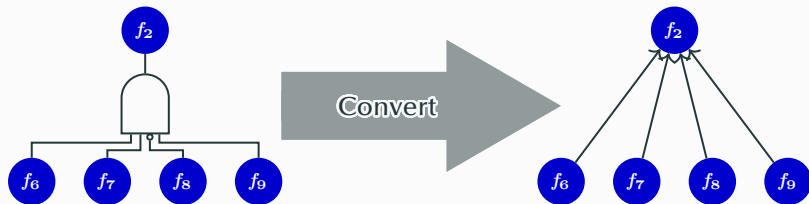
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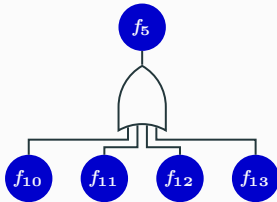
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$F(f_7)$	T	T	T	T	F	F	F	F	T	T	T	T	F	F	F	F
$F(f_8)$	T	T	F	F	T	T	F	F	T	T	F	F	T	T	F	F
$F(f_9)$	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F
$F(f_1)$	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1
$\overline{F}(f_1)$	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0

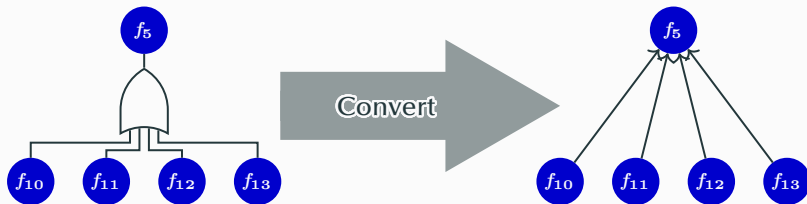
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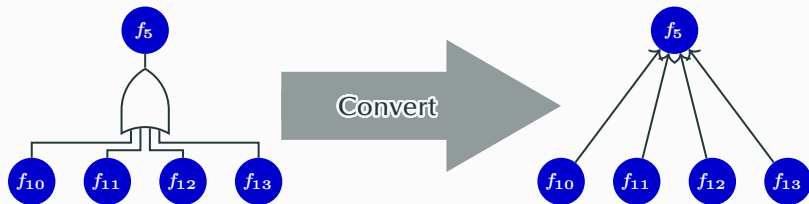
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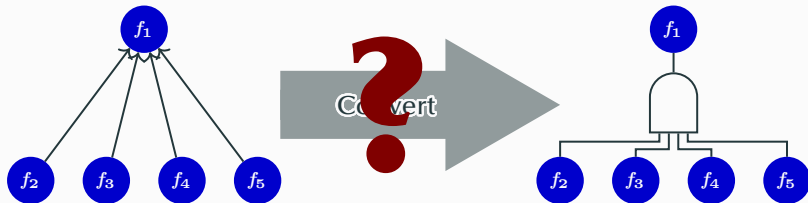
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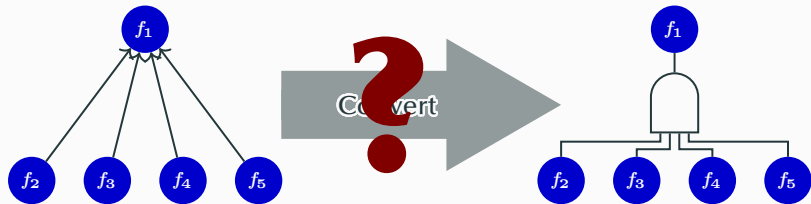


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$F(f_{11})$	T	T	T	T	F	F	F	F	T	T	T	T	F	F	F	F
$F(f_{12})$	T	T	F	F	T	T	F	F	T	T	F	F	T	T	F	F
$F(f_{13})$	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F
$F(f_5)$	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
$\overline{F}(f_5)$	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Function Level



Function Level



$F(f_2)$	T	T	T	T	T	T	T	T	F	F	F	F	F	F	F	F
$F(f_3)$	T	T	T	T	F	F	F	F	T	T	T	T	F	F	F	F
$F(f_4)$	T	T	F	F	T	T	F	F	T	T	F	F	T	T	F	F
$F(f_5)$	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F
$F(f_1)$	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.5
$\overline{F}(f_1)$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5

Function Level



$F(f_2)$	T	T	T	T	T	T	T	T	F	F	F	F	F	F	F	F
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$\overline{F}(f_1)$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5

Function Level

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



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$F(f_5)$	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F
$F(f_1)$	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.5
$\overline{F}(f_1)$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5

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.

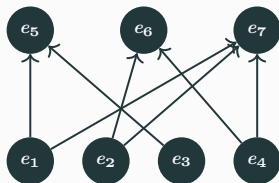
A typical Bayesian network of incident is shown in following figure.



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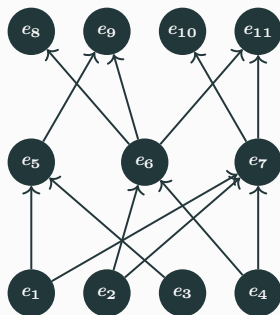
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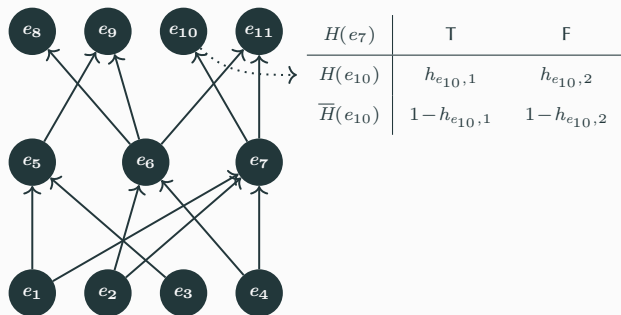
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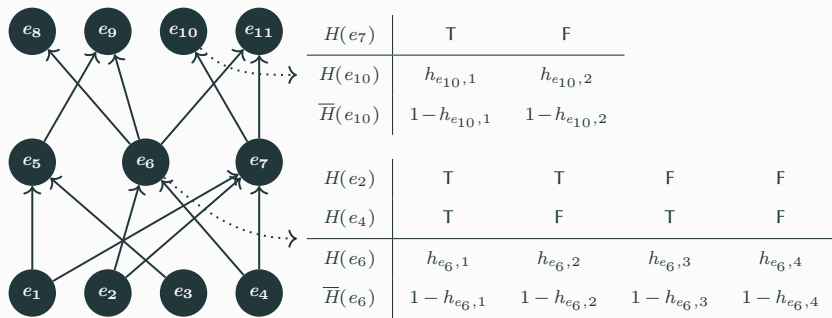
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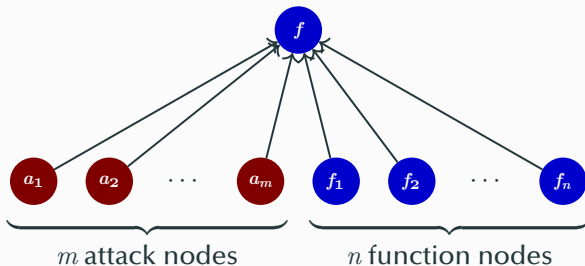
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Information Transfer between Levels

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.

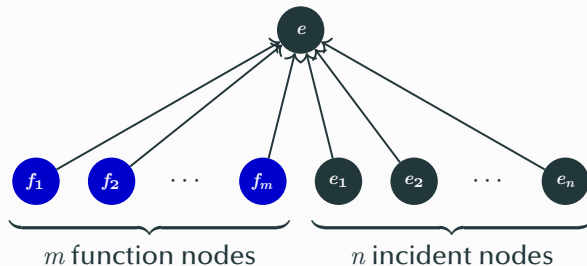
The following figures show two kind of information transfer.



Information Transfer between Levels

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The following figures show two kind of information transfer.



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.

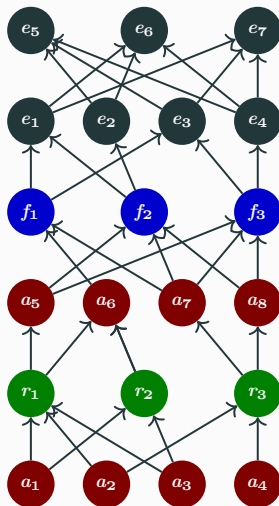
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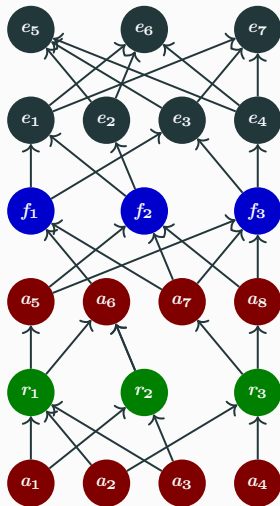
For each evidence, there exists a corresponding node in the multi-level Bayesian network. When the intrusion detection system or the monitoring system finds an evidence, the corresponding node will be marked in the multi-level Bayesian network.

Calculation of Incident Probability



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

Calculation of Incident Probability

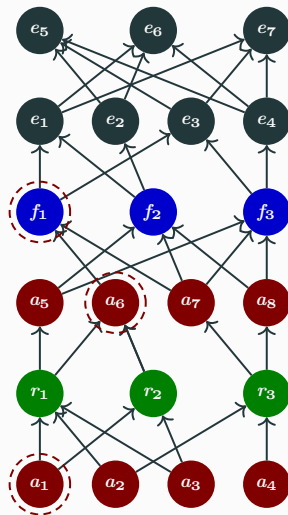


The left figure shows a typical multi-level Bayesian network.

Assuming that the evidence list is

$$a_1, a_6, f_1$$

Calculation of Incident Probability



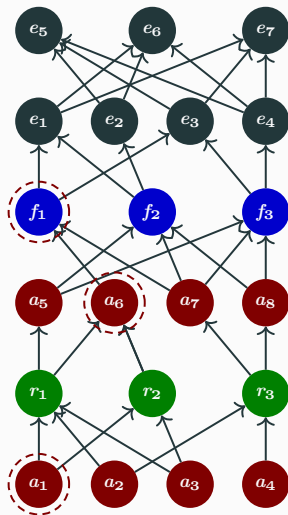
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Assuming that the evidence list is

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

Calculation of Incident Probability



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Assuming that the evidence list is

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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.

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

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

Decouple of Incident Consequences – Step 3

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

$$\forall c' \in C', \exists c \in C, c' \subseteq c,$$

there must be a consequence set $c_i \in C$, where $c'_j \subseteq c_i$.

Decouple of Incident Consequences – Step 3

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

$$\forall c' \in C', \exists c \in C, c' \subseteq c,$$

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

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

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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 $e_{i_1}, e_{i_2}, \dots, e_{i_n}$.

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

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.

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

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

- **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.

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

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

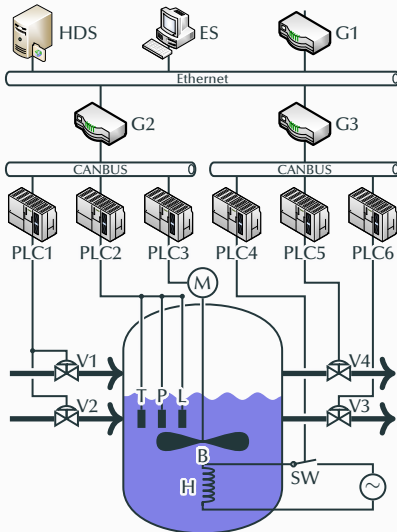
where

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

Simulation

Simulation Platform

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

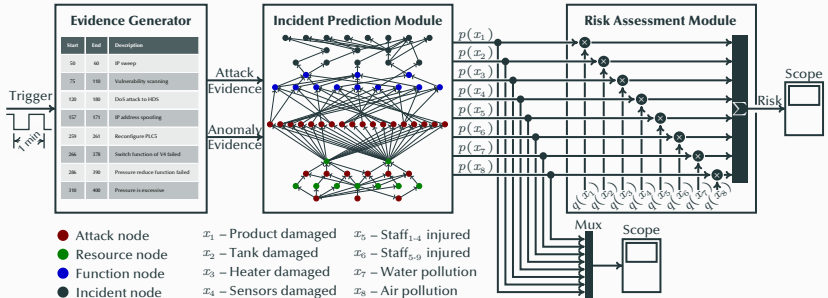


Legend

HDS	Historical data server
ES	Engineer station
G1	Gateway of Ethernet
G2	Gateway of CANBUS
G3	Gateway of CANBUS
PLC1	Controller of V1 and V2
PLC2	Data collection of P, T and L
PLC3	Controller of M
PLC4	Controller of SW
PLC5	Controller of V4
PLC6	Controller of V3
V1	Valve of material
V2	Valve of another material
V3	Valve of product
V4	Valve of pressure reducing
M	Motor of B
SW	Switch of H
P	Pressure sensor
T	Temperature sensor
L	Liquid level sensor
B	Blender
H	Heater

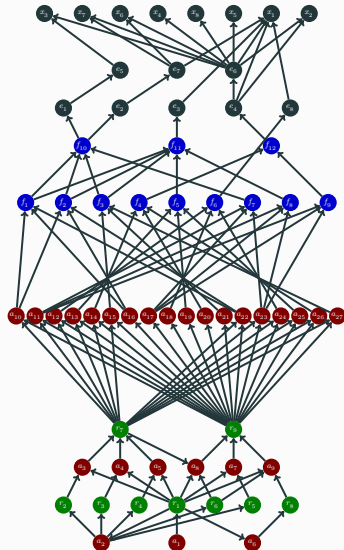
Simulation Platform

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



Simulation Platform

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



- a_1 – Network Scanning
- a_2 – Vulnerability scanning
- a_3 – Buffer overflow attack on HDS
- a_4 – FTP attack on HDS
- a_5 – Brute force attack on HDS
- a_6 – DoS attack on HDS
- a_7 – Buffer overflow attack on ES
- a_8 – Privilege escalation attack on ES
- a_9 – Spoofing attack on ES
- a_{10} – DoS attack on PLC1
- a_{11} – DoS attack on PLC2
- a_{12} – DoS attack on PLC3
- a_{13} – DoS attack on PLC4
- a_{14} – DoS attack on PLC5
- a_{15} – DoS attack on PLC6
- a_{16} – Reconfigure PLC1
- a_{17} – Reconfigure PLC2
- a_{18} – Reconfigure PLC3
- a_{19} – Reconfigure PLC4
- a_{20} – Reconfigure PLC5
- a_{21} – Reconfigure PLC6
- a_{22} – Man-in-the-middle attack on PLC1
- a_{23} – Man-in-the-middle attack on PLC2
- a_{24} – Man-in-the-middle attack on PLC3
- a_{25} – Man-in-the-middle attack on PLC4
- a_{26} – Man-in-the-middle attack on PLC5
- a_{27} – Man-in-the-middle attack on PLC6
- r_1 – IP addresses of HDS and ES
- r_2 – Buffer overflow vulnerability
- r_3 – FTP server vulnerability
- r_4 – Login vulnerability
- r_5 – Buffer overflow vulnerability

- r_6 – Authentication vulnerability
- r_7 – Administrator authority of HDS
- r_8 – Crash of HDS
- r_9 – Administrator authority of ES
- f_1 – Traffic control of V1
- f_2 – Traffic control of V2
- f_3 – Traffic control of V3
- f_4 – Pressure reducing
- f_5 – Heating function
- f_6 – Mixing function
- f_7 – Liquid level sensation
- f_8 – Temperature sensation
- f_9 – Pressure sensation
- f_{10} – Liquid level control
- f_{11} – Temperature control
- f_{12} – Pressure control
- e_1 – Excessive liquid level
- e_2 – Low liquid level
- e_3 – Temperature anomaly
- e_4 – Excessive pressure
- e_5 – Heater dry fired
- e_6 – Reactor explosion
- e_7 – Liquid overflow
- e_8 – Blender stop
- x_1 – Production damaged
- x_2 – Tank damaged
- x_3 – Heater damaged
- x_4 – Sensors damaged
- x_5 – Staff_{1,4} injured
- x_6 – Staff_{5,9} injured
- x_7 – Water pollution
- x_8 – Air pollution

Simulation Platform

The list of evidences is shown as following table.

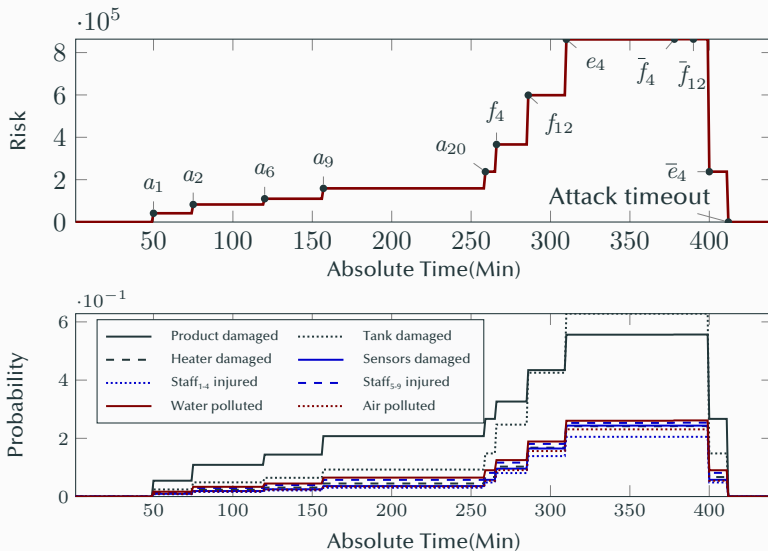
Start	End	Description	Symbol
50	60	IP sweep	$L(a_1)$
75	110	Vulnerability scanning	$L(a_2)$
120	180	DoS attack to HDS	$L(a_6)$
157	171	IP address spoofing	$L(a_9)$
259	261	Reconfigure PLC5	$L(a_{20})$
266	378	Switch function of V4 failed	$F(f_4)$
286	390	Pressure reduce function failed	$F(f_{12})$
310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

Simulation Platform

The quantification of consequences is shown as following table.

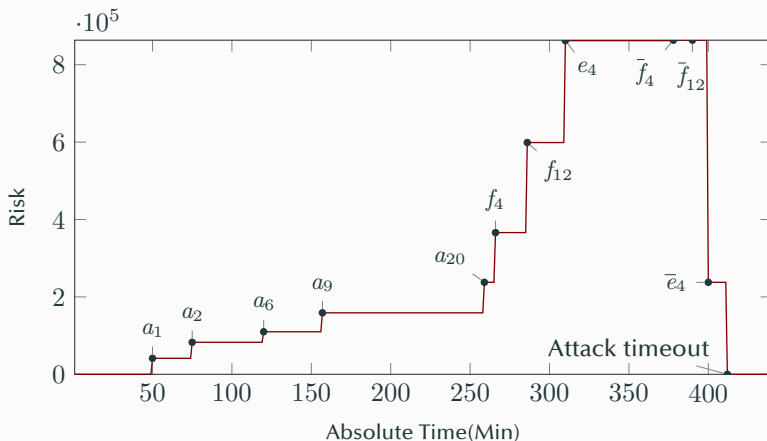
Incident Symbol	Description of Incident	Quantification of Consequence(\$)
x_1	Product damaged	50,000
x_2	Tank damaged	500,000
x_3	Heater damaged	10,000
x_4	Sensors damaged	10,000
x_5	Staff ₁₋₄ injured	800,000
x_6	Staff ₅₋₉ injured	1,000,000
x_7	Water pollution	200,000
x_8	Air pollution	200,000

Simulation and Result Analysis



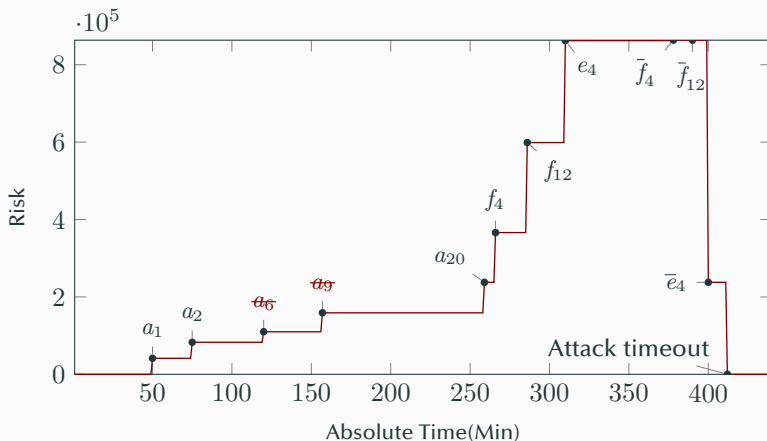
Simulation and Result Analysis

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



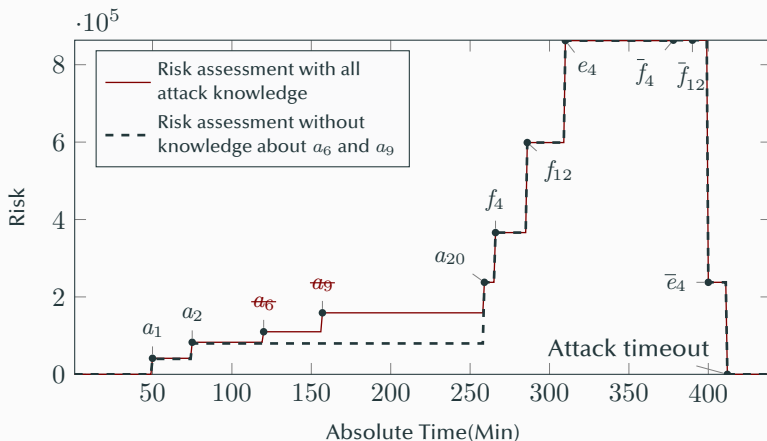
Simulation and Result Analysis

To validate the ability to deal with the unknown attacks, the attack knowledge about attack a_6 and attack a_9 is removed from the multi-level Bayesian network.



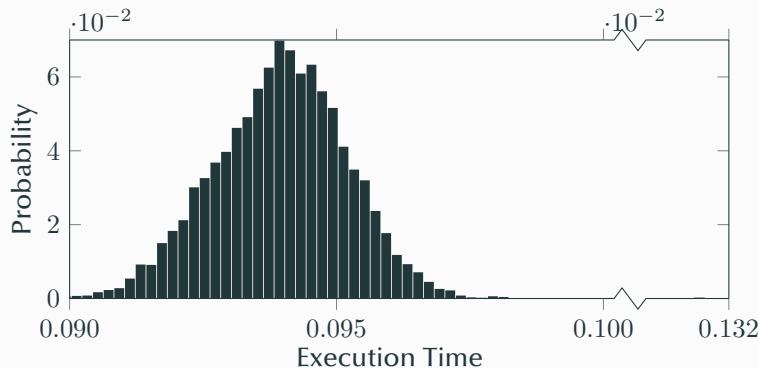
Simulation and Result Analysis

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.



Simulation and Result Analysis

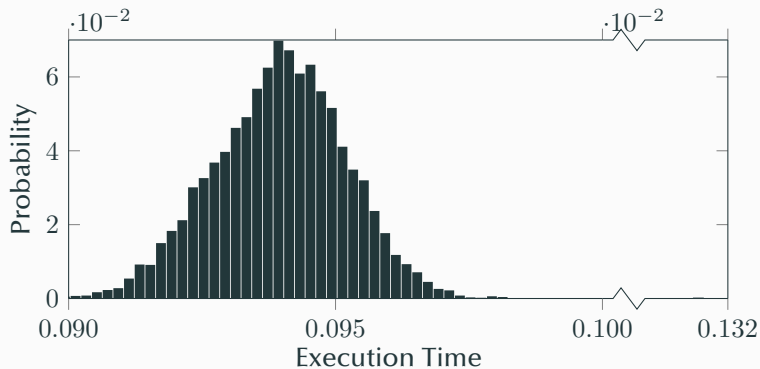
We repeat the first simulation 5,000 times, and the execution time of 5,000 calculations is recorded. This simulation is run on a machine with Intel Pentium processor G3220 (3M Cache, 3.00GHz) and 4GB DDR3 memory. The following figure shows the distribution of the 5,000 execution times.



Simulation and Result Analysis

Some parameters of the following figure:

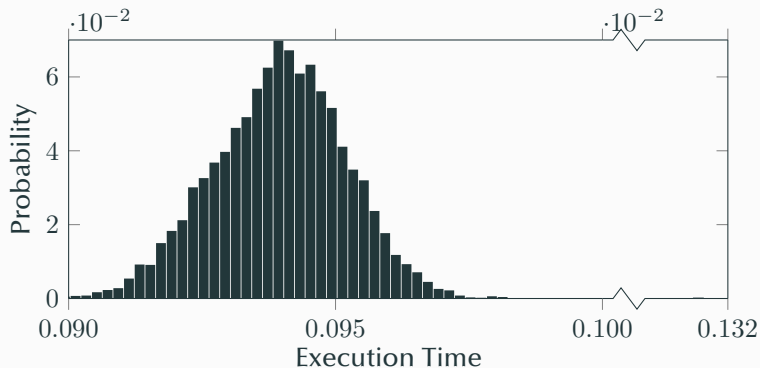
- The average execution time of a risk assessment is 94.1ms.



Simulation and Result Analysis

Some parameters of the following figure:

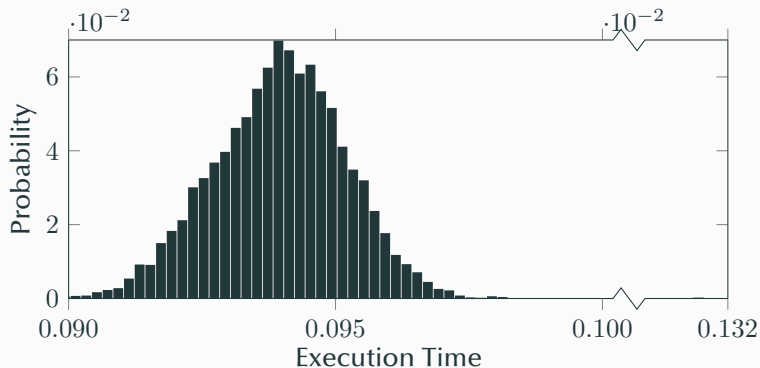
- The average execution time of a risk assessment is 94.1ms.
- The minimum execution time of a risk assessment is 89.9ms.



Simulation and Result Analysis

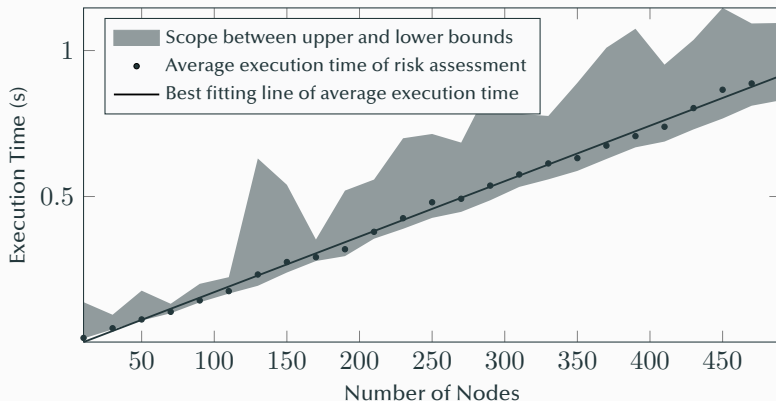
Some parameters of the following figure:

- 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.



Simulation and Result Analysis

Finally, 25 multi-level Bayesian networks with different node sizes are adopted to show the possible upper/lower bounds and the scalability of our approach.

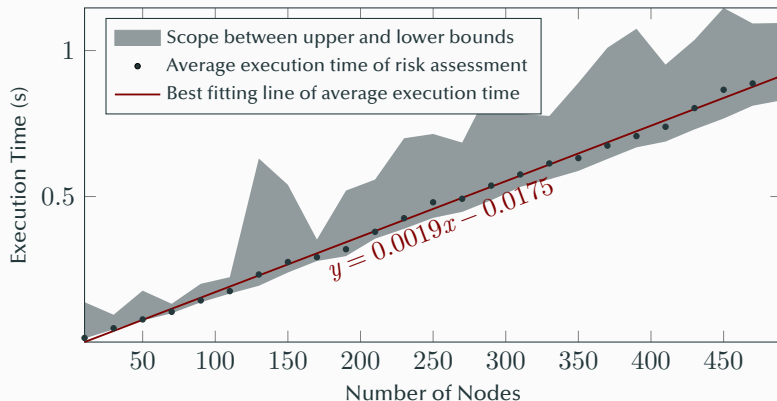


Simulation and Result Analysis

In the following figure, the fitting line

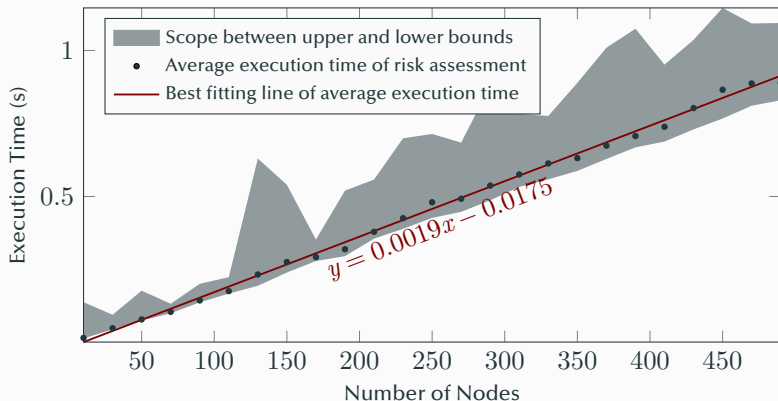
$$y = 0.0019x - 0.0175$$

matches well with the correlation coefficient $r = 0.9987$.



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.



Conclusion and Prospect

Conclusion

Questions?