

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

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# Outlines

Introduction

Architecture

Hazardous Incident Prediction

- The Bayesian Network Based Knowledge Modeling

- Incident Prediction

Dynamic Risk Assessment

- Classification of Incident Consequences

- Quantification of Incident Consequences

- Calculation of Dynamic Risk

Simulation

- Knowledge Modeling and Simulation Platform

- Simulation and Result Analysis

# Introduction

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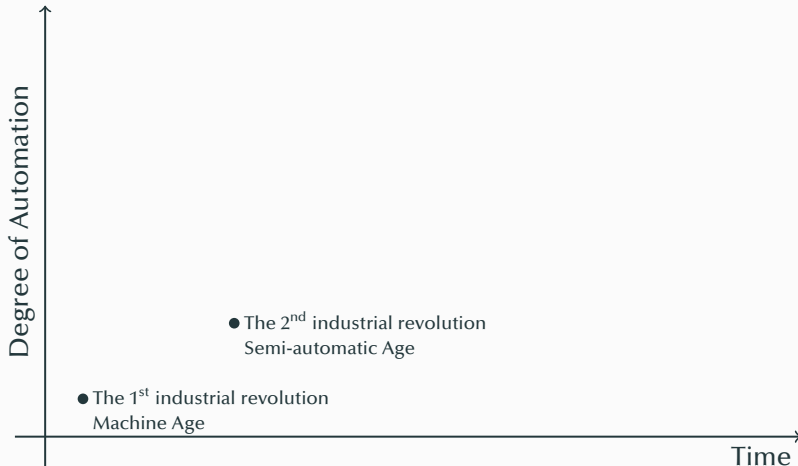
# Background

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



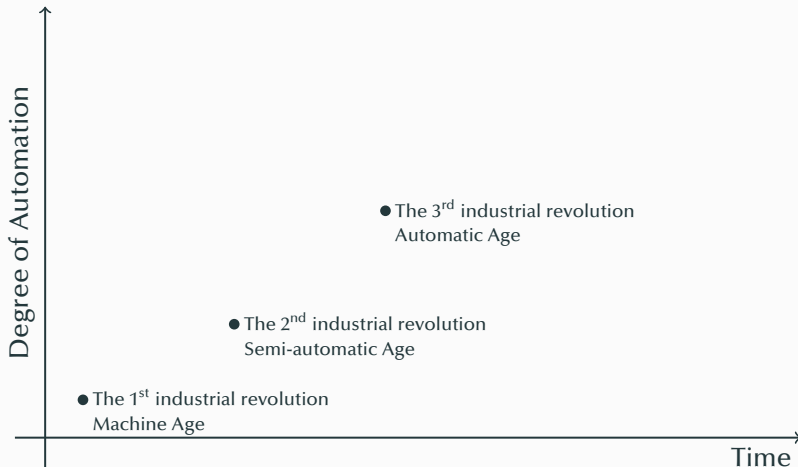
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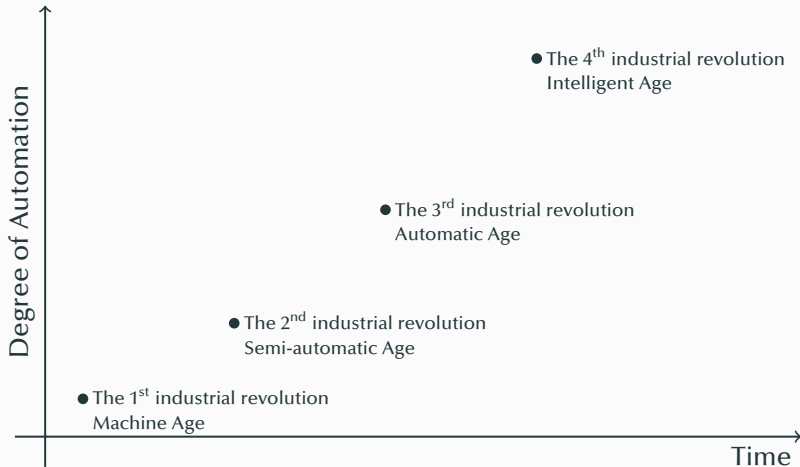
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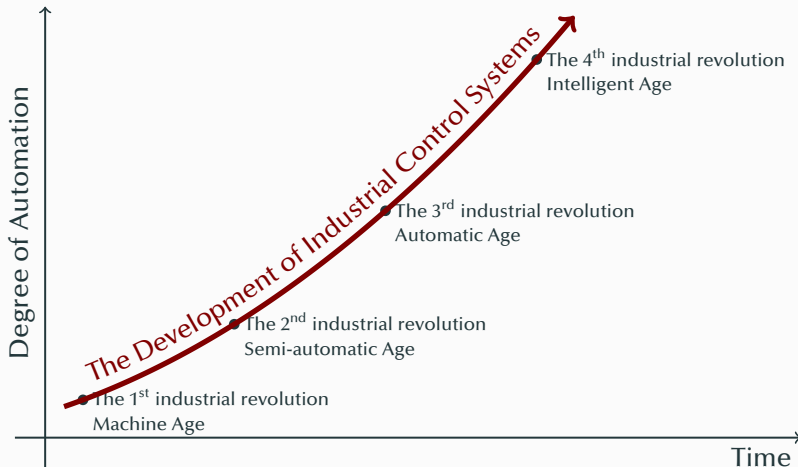
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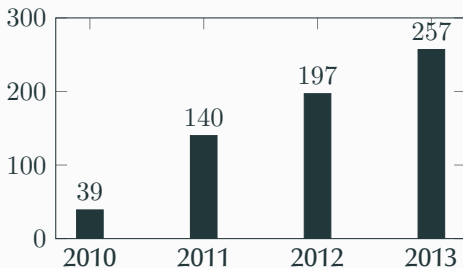
# Background

- 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.

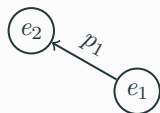
Therefore, the cybersecurity risk assessment of ICSs needs a novel and targeted risk model to analyze the risk propagation.

# 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

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# Architecture of Cybersecurity Risk Assessment for ICSs

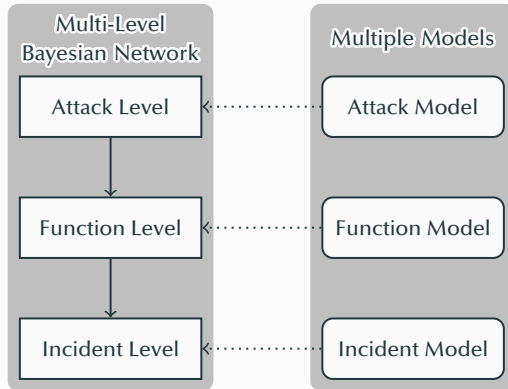
Multiple Models

Attack Model

Function Model

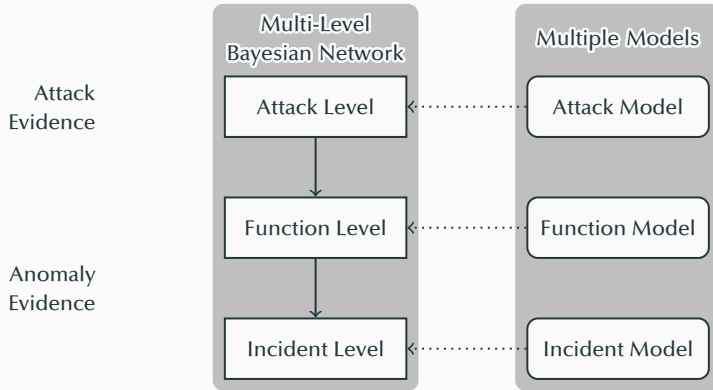
Incident Model

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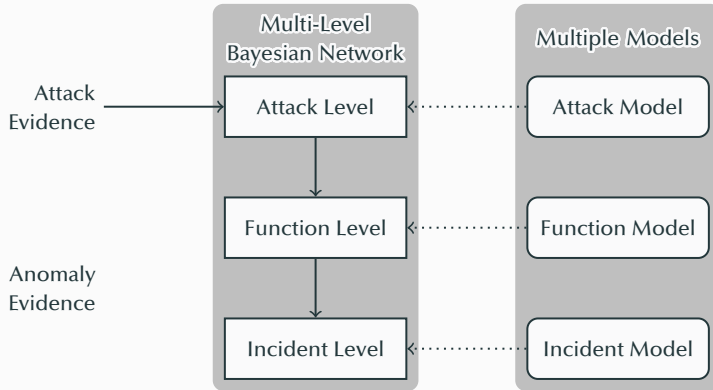




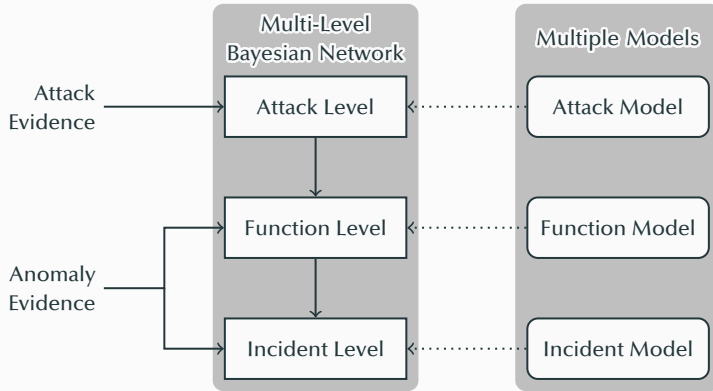
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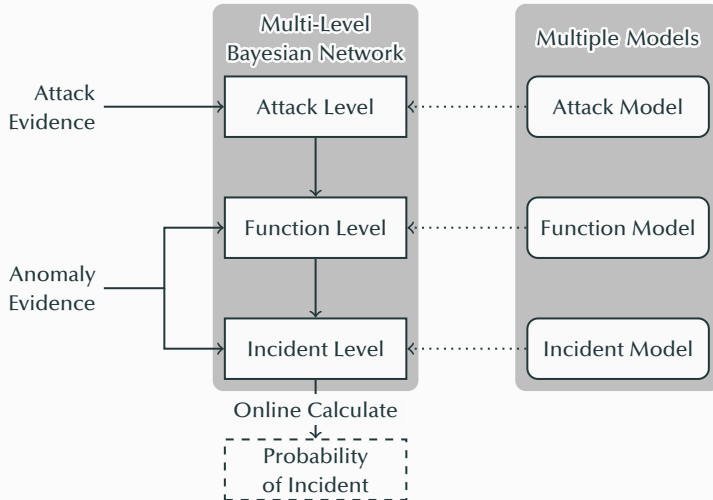
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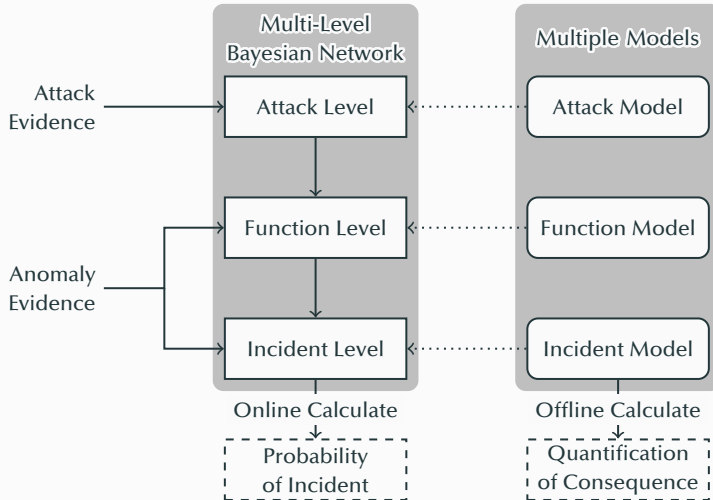
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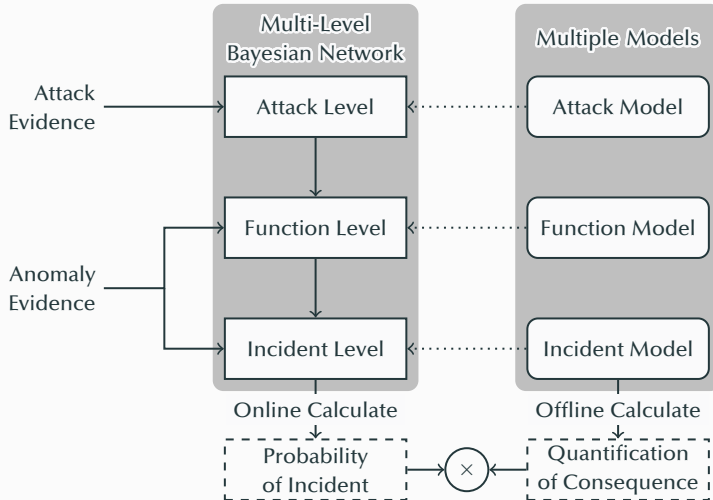
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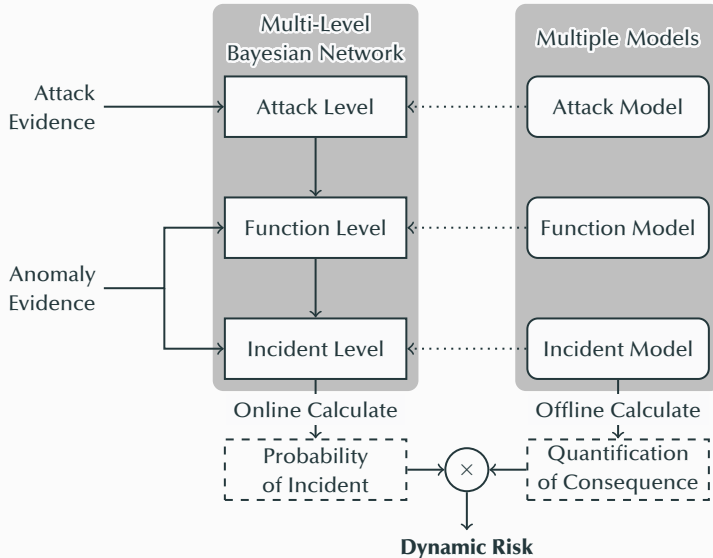
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# **Hazardous Incident Prediction**

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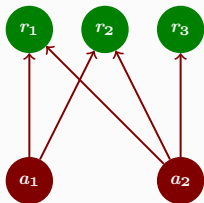


In this paper, the Bayesian network is used to model the relationship between attacks and resources.



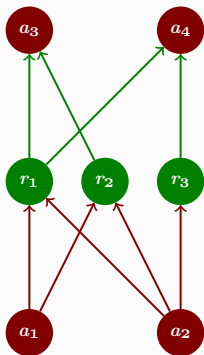
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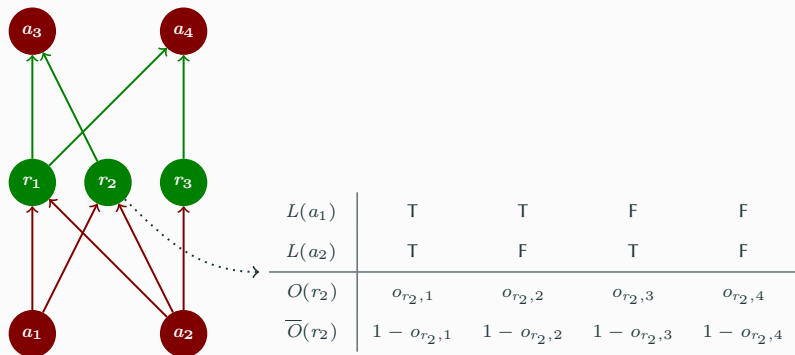
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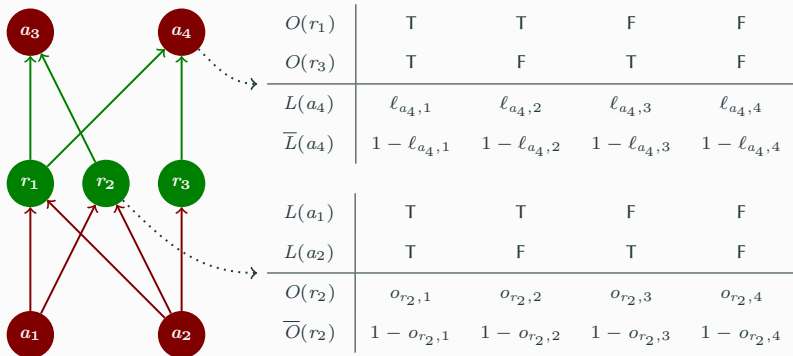
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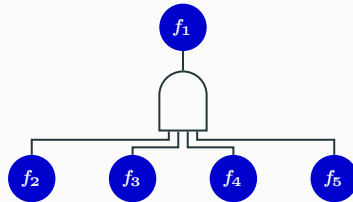


$$F_1 = F_2 F_3 F_4 F_5$$



# Function Level

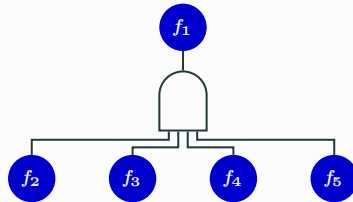
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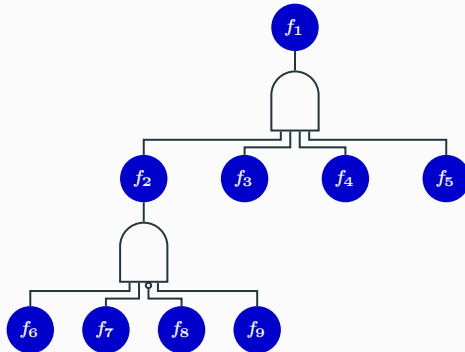
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$$F_2 = F_6 F_7 \overline{F_8} F_9$$

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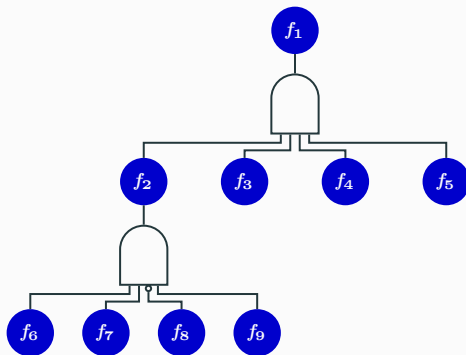
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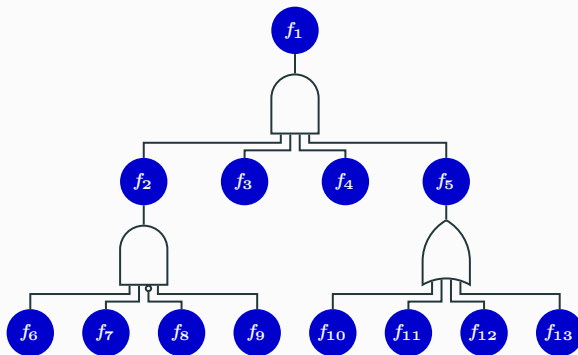
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$$F_5 = F_{10} + F_{11} + F_{12} + F_{13}$$

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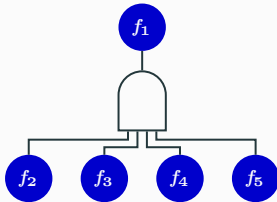
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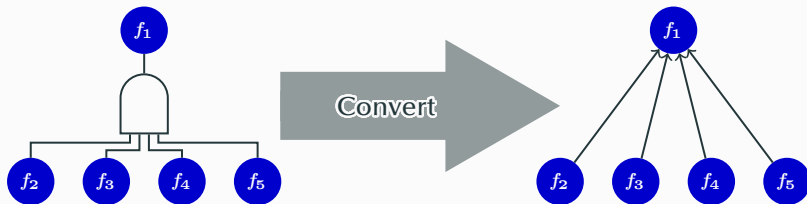
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To simplify the inference, the function tree is converted into Bayesian network, which is shown in following figure.



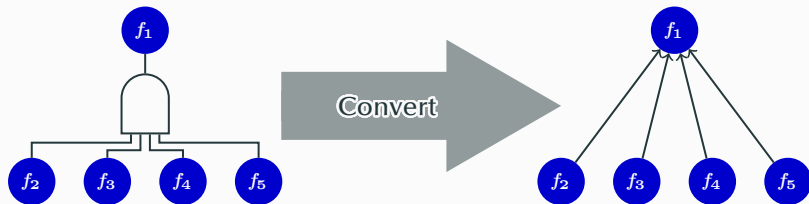
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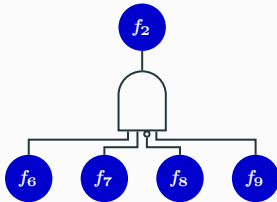


|                     |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |
|---------------------|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $F(f_2)$            | T | T | T | T | T | T | T | T | F | F | F | F | F | F | F | F |
| $F(f_3)$            | T | T | T | T | 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 |



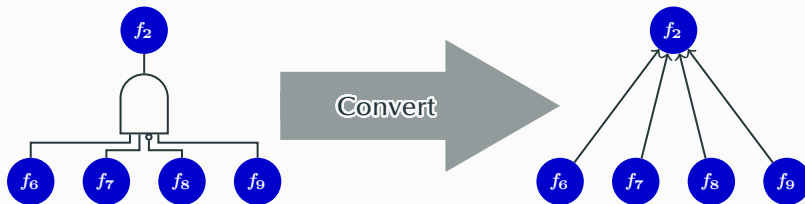
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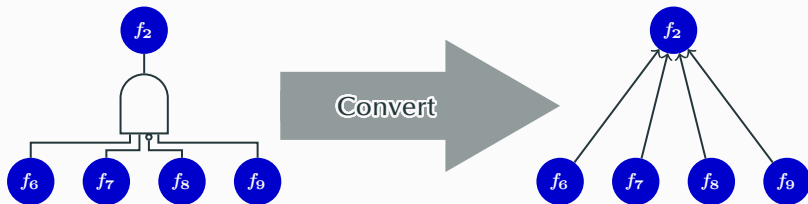
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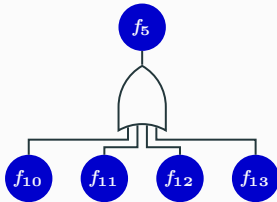
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|---------------------|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $F(f_6)$            | T | T | T | T | T | T | T | T | F | F | F | F | F | F | F | F |
| $F(f_7)$            | T | T | T | T | F | F | F | F | T | T | T | T | 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 |

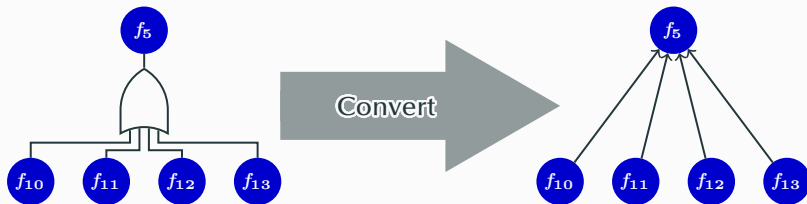
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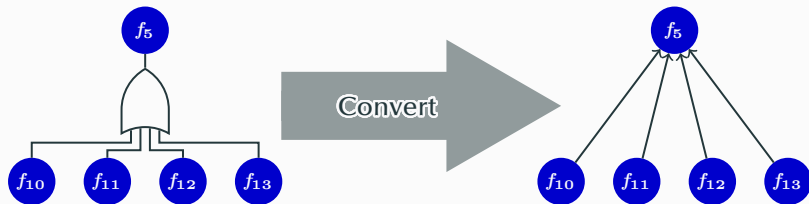
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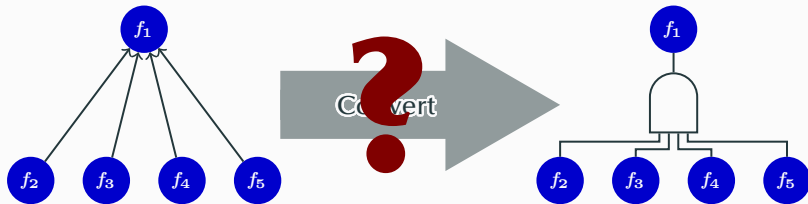
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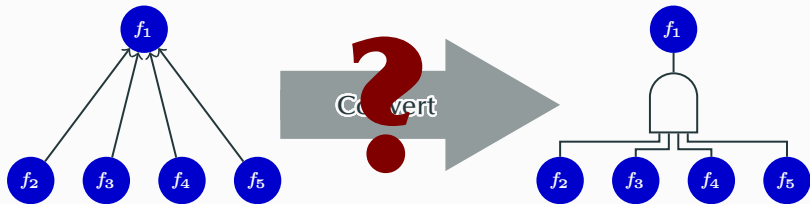


|                     |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |
|---------------------|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $F(f_{10})$         | T | T | T | T | T | T | T | T | F | F | F | F | F | F | F | F |
| $F(f_{11})$         | T | T | T | T | 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



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|                     |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |            |
|---------------------|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|------------|
| $F(f_2)$            | T | T | T | T | T | T | T | T | F | F | F | F | F | F | F | <b>F</b>   |
| $F(f_3)$            | T | T | T | T | F | F | F | F | T | T | T | T | F | F | F | <b>F</b>   |
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# Function Level



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| $\overline{F}(f_1)$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | <b>0.5</b> |

# Function Level

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



|                     |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |            |
|---------------------|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|------------|
| $F(f_2)$            | T | T | T | T | T | T | T | T | F | F | F | F | F | F | F | <b>F</b>   |
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# 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.

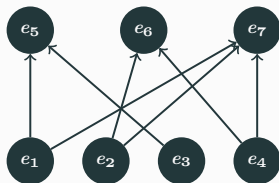
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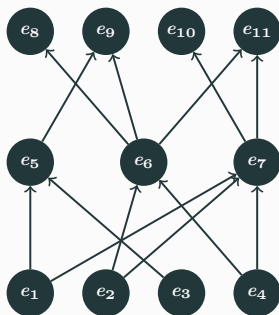
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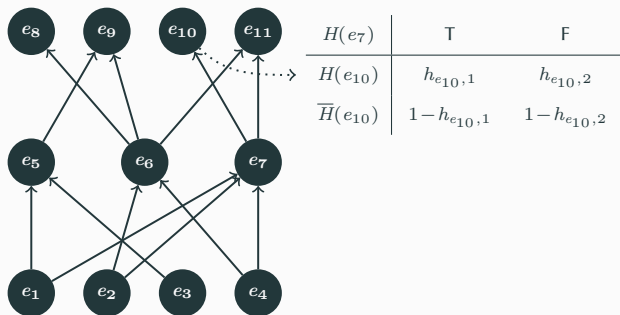
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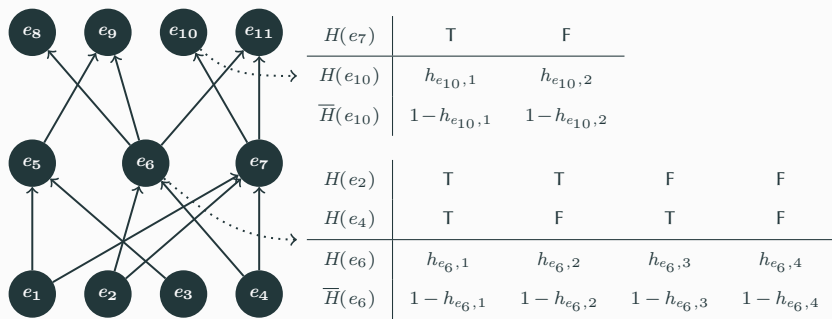
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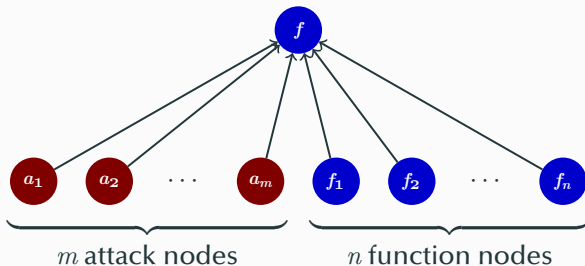
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# Information Transfer between Levels

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.

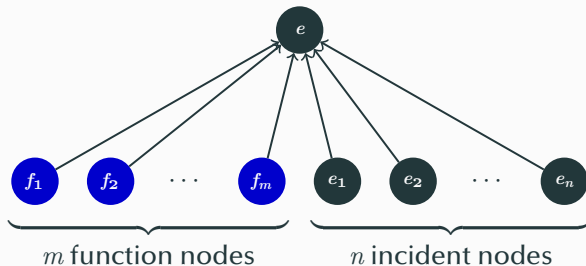




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# Collection of Evidence

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- **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 find an evidence, the corresponding node will be marked in the multi-level Bayesian network.

# Calculation of Incident Probability

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

# Dynamic Risk Assessment

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# Harm to Humans

# Environmental Pollution

# Property Loss



# Quantification of Harm to Humans

# Quantification of Environmental Pollution

# Quantification of Property Loss

# Calculation of Dynamic Risk

# Simulation

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# Knowledge Modeling and Simulation Platform

# Simulation and Result Analysis

**Questions?**