A Bayesian Inference Algorithm to Identify Types of Accidents in Nuclear Power Plants

Kyung Min Kang and Moosung Jae*

Department of Nuclear Engineering
Hanyang University, Seoul, KOREA

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Purposes

- Develop An Accident Diagnosis Algorithm
  - Based on accident symptoms, components status and EOPs (Emergency Operating Procedure)
  - Contribution to reduce human errors during accident diagnosis using EOPs

Methods

- Modeling EOPs using Bayesian Theorem of Influence Diagrams
  - Use of EOPs & FSAR (Final Safety Analysis Report)
  - Collection of 13 symptoms

- Accident Scenarios
  - SLOCA
  - SGTRs

Methods

❑ Symptoms of SLOCA

- Pressurizer level and pressure decrease
- Containment pressure, temperature, radiation and moisture increase
- RDT level, temperature and pressure increase
- SIAS, CIAS
- MSIS, AFAS, RAS

Methods

- Symptoms of SGTRs
  - Pressurizer level and pressure decrease
  - S/G level increase
  - Main steam line radiation increase
  - AFAS

Influence Diagrams Modeling

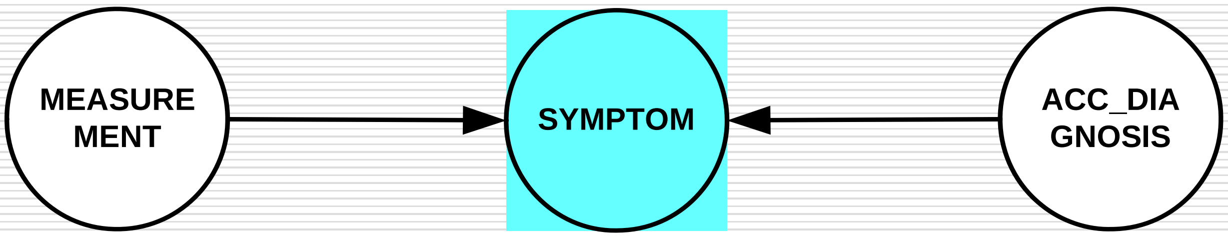
❑ Definition of Influence Diagrams

- Compact Graphical and mathematical representation for complicated probabilistic relations

- Decision-making networks consisting of nodes and arcs

Influence Diagrams Modeling

- 1st Step : Basic model

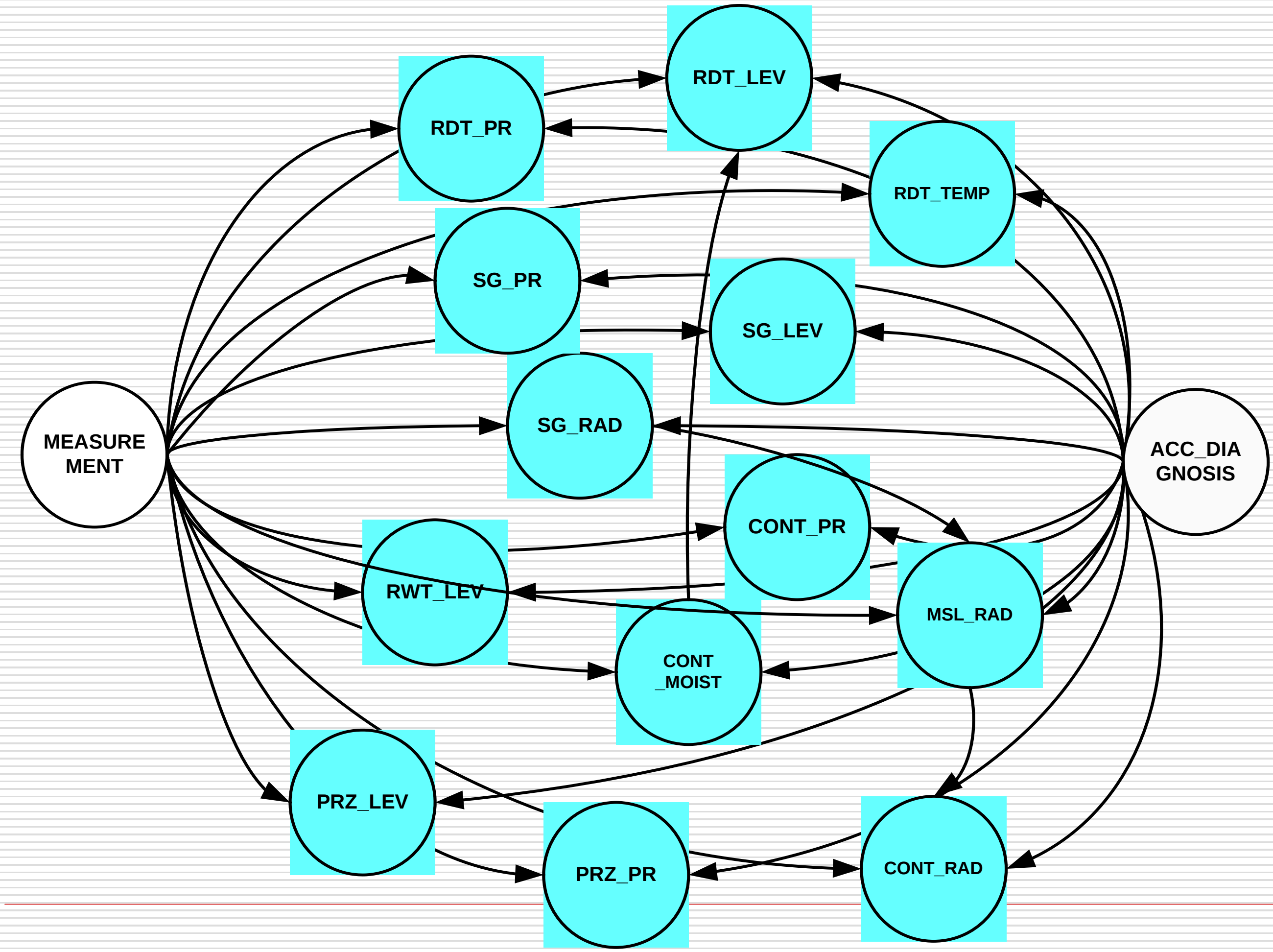


Legend

Node	Description
ACC_DIAGNOSIS	diagnosis
SYMPTOM	symptom
MEASUREMENT	measurement

Influence Diagrams Modeling

- 2nd Step : Extended model of symptoms nodes

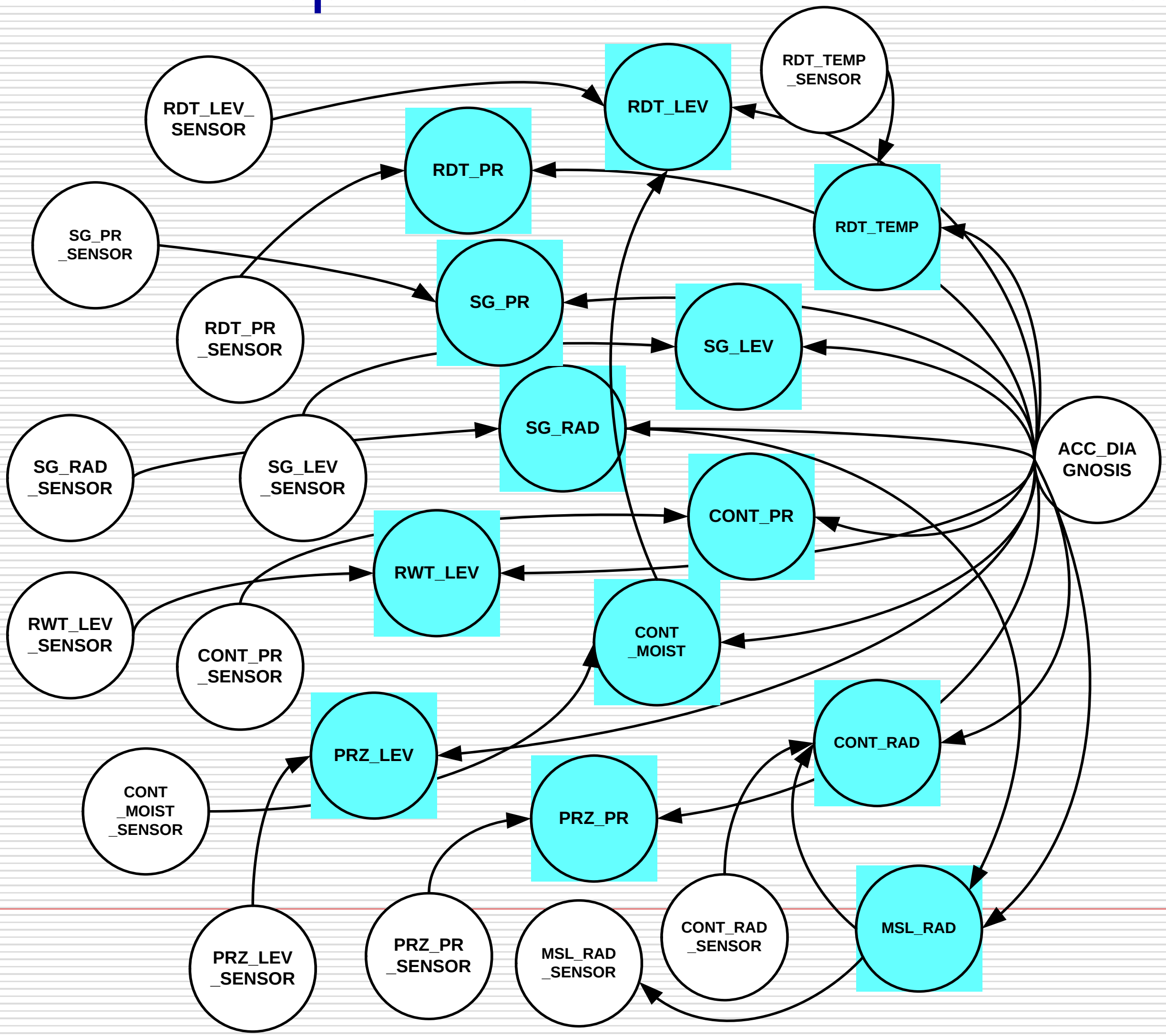


Legend

Node	Description
RDT_PR	RDT Pressure
RDT_LEV	RDT Level
RDT_TEMP	RDT Temperature
SG_PR	S/G Pressure
SG_LEV	S/G Level
SG_RAD	S/G Radiation
RWT_LEV	RWT Level
CONT_PR	Containment Pressure
CONT_MOIIST	Containment Moisture
CONT_RAD	Containment Radiation
PRZ_PR	Pressurizer Pressure
PRZ_LEV	Pressurizer Level
MSL_RAD	MSL Radiation

Influence Diagrams Modeling

- 3rd Step : Extended model of measurement nodes



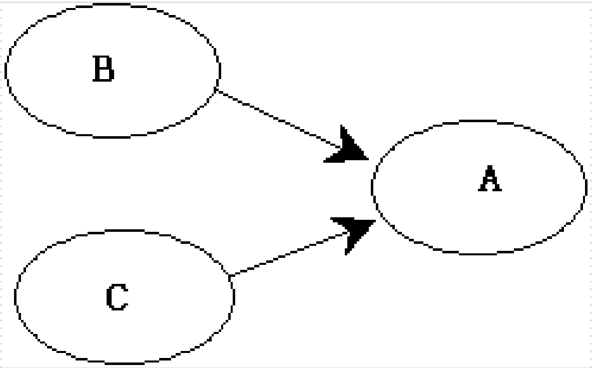
Legend

Node	Description
RDT_PR_SENSOR	RDT Pressure sensor
RDT_LEV_SENSOR	RDT Level sensor
RDT_TEMP_SENSOR	RDT Temperature sensor
SG_PR _SENSOR	S/G Pressure sensor
SG_LEV _SENSOR	S/G Level sensor
SG_RAD _SENSOR	S/G Radiation sensor
RWT_LEV _SENSOR	RWT Level sensor
CONT_PR _SENSOR	Containment Pressure sensor
CONT_MOIST _SENSOR	Containment Moisture sensor
CONT_RAD _SENSOR	Containment Radiation sensor
PRZ_PR _SENSOR	Pressurizer Pressure sensor
PRZ_LEV _SENSOR	Pressurizer Level sensor
MSL_RAD_SENSOR	MSL Radiation sensor

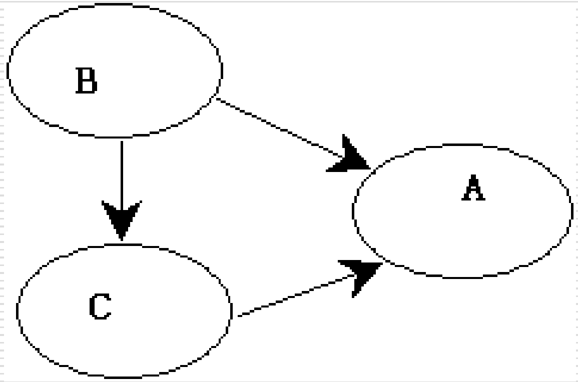
Quantifications

- Absorption of Nodes: Total Probability

(A)



(B)



Without dependency

$$P(A) = \int_{B,C} P(A,B,C)$$

$$= \int_{B,C} P(A|B,C)P(C|B)P(B)$$

$$= \int_{B,C} P(A|B,C)P(C)P(B)$$

With dependency

$$P(A) = \int_{B,C} P(A,B,C)$$

$$= \int_{B,C} P(A|B,C)P(C|B)P(B)$$

Quantifications

- Arc Reversal between Nodes: Bayesian

$$P(AE) = P(A)P(E|A) = P(E)P(A|E)$$

$$P(A|E) = P(A)\frac{P(E|A)}{P(E)}$$

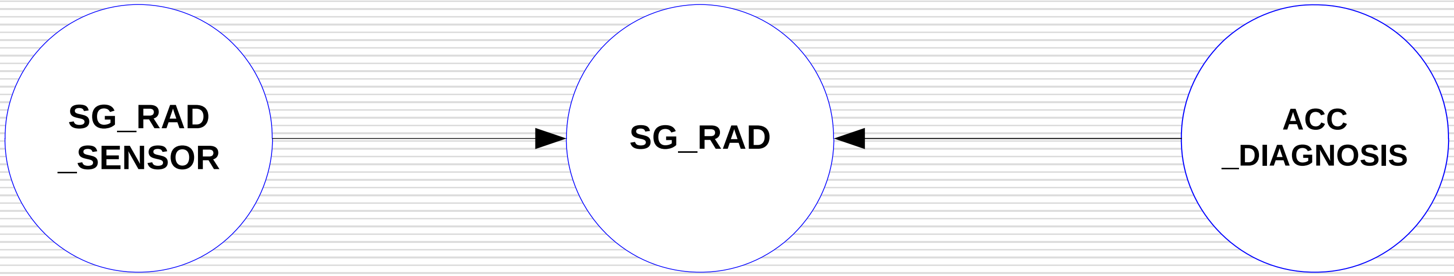
where, $\mathrm{P(A|E)}$: Posterior

$\mathrm{P(A)}$: Prior

$\frac{\mathrm{P}(E|A)}{\mathrm{Pr}(E)}$: Likelihood of Evidence

$$P(A_j | E) = \frac{P(A_j) \times L(E | A_j)}{\int_{j=1}^{N} L(E | A_j) P(A_j)}$$

Quantification process for a Basic node model



STATES

1. Normal
2. Fail High
3. Stuck at Steady State
4. Fail Low

STATES

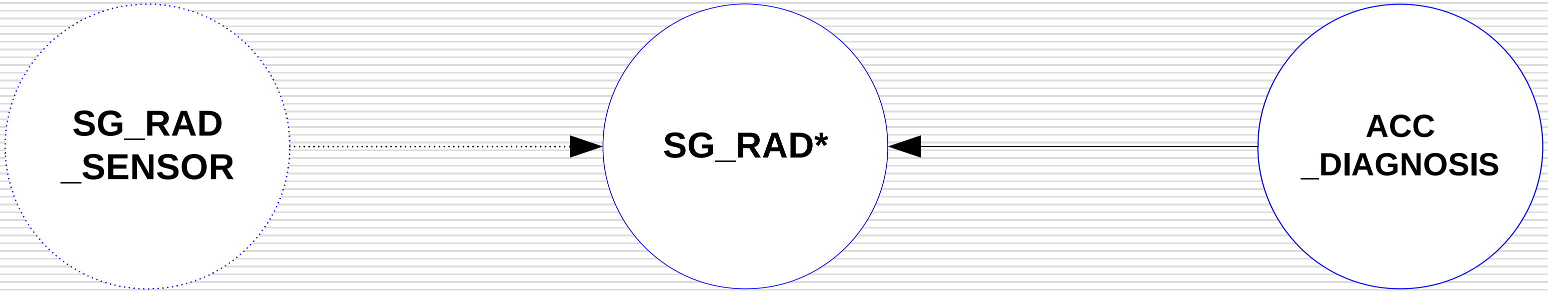
1. Increasing
2. No change
3. Decreasing

STATES

1. Normal Opreation
2. LOCA
3. SGTR

$$P\left(ACC\_DIAGNOSIS \middle| SG\_RAD, SG\_RAD\_SENSOR\right) = ?$$

Node Removal



$$P\left(SG\_RAD*\right) = \sum_i P(SG\_RAD | SG\_RAD\_SENSOR_i)$$

Arc Reversal

$$P(ACC\_DIAGNOSIS \mid SG\_RAD*) = \frac{P(SG\_RAD* \mid ACC\_DIAGNOSIS)\,P(ACC\_DIAGNOSIS)}{P(SG\_RAD*)}$$

Data Analysis

❑ Accident Diagnosis Node

- PSA Data

  - Accident frequency : 1.19×10^{-1}/yr
  - SLOCA frequency : 3.40×10^{-4}/yr
  - SGTR frequency : 4.50×10^{-3} /yr

- Vague Information

❑ Measurement Node from Tech. Spec., PSA, IEEE

$$q_{av} = \frac{1}{2}\lambda\tau$$

q_{av} : average unavailability

τ : failure rate

λ : operating time

Unavailability of SG_LEV_SENSOR : 3.59×10^{-3}

❑ Deterministic Symptom Node

- RDT_PR : 1 (Increasing at SLOCA) /Discrete RVs

Component Data

	States	λ	q_{av}
RDT_PR _SENSOR	Fail high	3.0×10^{-5}	1.08×10^{-2}
	Stuck at steady state	4.8×10^{-5}	1.73×10^{-2}
	Fail low	3.0×10^{-5}	1.08×10^{-2}
RDT_LEV _SENSOR	Fail high	5.1×10^{-5}	1.84×10^{-2}
	Stuck at steady state	1.0×10^{-5}	3.60×10^{-3}
	Fail low	5.1×10^{-5}	1.84×10^{-2}
RDT_TEMP _SENSOR	Fail high	1.9×10^{-5}	6.84×10^{-3}
	Stuck at steady state	3.5×10^{-5}	1.26×10^{-2}
	Fail low	1.9×10^{-5}	6.84×10^{-3}

Component Data

	States	λ	q_{av}
SG_PR _SENSOR	Fail high	$3.3X10^{-5}$	$1.18X10^{-2}$
	Stuck at steady state	$4.8X10^{-5}$	$1.71X10^{-2}$
	Fail low	$3.3X10^{-5}$	$1.18X10^{-2}$
SG_LEV _SENSOR	Fail high	$5.1X10^{-5}$	$1.82X10^{-2}$
	Stuck at steady state	$1.0X10^{-5}$	$3.59X10^{-3}$
	Fail low	$5.1X10^{-5}$	$1.82X10^{-2}$
SG_RAD _SENSOR	Fail high	$5.1X10^{-5}$	$1.82X10^{-2}$
	Stuck at steady state	$1.0X10^{-5}$	$3.59X10^{-3}$
	Fail low	$5.1X10^{-5}$	$1.82X10^{-2}$
RWT_LEV _SENSOR	Fail high	$5.1X10^{-5}$	$1.82X10^{-2}$
	Stuck at steady state	$1.0X10^{-5}$	$3.59X10^{-3}$
	Fail low	$5.1X10^{-5}$	$1.82X10^{-2}$

Component Data

	States	λ	q_{av}
CONT_PR _SENSOR	Fail high	$3.3X10^{-5}$	$1.18X10^{-2}$
	Stuck at steady state	$4.8X10^{-5}$	$1.71X10^{-2}$
	Fail low	$3.3X10^{-5}$	$1.18X10^{-2}$
CONT _MOIST _SENSOR	Fail high	$5.1X10^{-5}$	$1.82X10^{-2}$
	Stuck at steady state	$1.0X10^{-5}$	$3.59X10^{-3}$
	Fail low	$5.1X10^{-5}$	$1.82X10^{-2}$
CONT_RAD _SENSOR	Fail high	$5.1X10^{-5}$	$1.82X10^{-2}$
	Stuck at steady state	$1.0X10^{-5}$	$3.59X10^{-3}$
	Fail low	$5.1X10^{-5}$	$1.82X10^{-2}$
PRZ_PR _SENSOR	Fail high	$3.3X10^{-5}$	$1.18X10^{-2}$
	Stuck at steady state	$4.8X10^{-5}$	$1.71X10^{-2}$
	Fail low	$3.3X10^{-5}$	$1.18X10^{-2}$

Component Data

	States	λ	q_{av}
PRZ_LEV _SENSOR	Fail high	$5.1X10^{-5}$	$1.82X10^{-2}$
	Stuck at steady state	$1.0X10^{-5}$	$3.59X10^{-3}$
	Fail low	$5.1X10^{-5}$	$1.82X10^{-2}$

Deterministic RVs of Symptom Nodes

1. RDT_LEV Node

	RDT_LEV _SENSOR	RDT_LEV		
		Increasing	No change	Decreasing
Normal operation	Normal operation	0.0	1.0	0.0
	Fail high	1.0	0.0	0.0
	Stuck at steady state	0.0	1.0	0.0
	Fail low	0.0	0.0	1.0
SLOCA	Normal operation	1.0	0.0	0
	Fail high	1.0	0.0	0.0
	Stuck at steady state	0.0	1.0	0.0
	Fail low	0.0	0.0	1.0
SGTR	Normal operation	0.0	1.0	0.0
	Fail high	1.0	0.0	0.0
	Stuck at steady state	0.0	1.0	0.0
	Fail low	0.0	0.0	1.0

Deterministic RVs of Symptom Nodes

2. MSL_RAD Node

	MSL_RAD _SENSOR	MSL_RAD		
		Increasing	No change	Decreasing
Normal operation	Normal operation	0.0	1.0	0.0
	Fail high	1.0	0.0	0.0
	Stuck at steady state	0.0	1.0	0.0
	Fail low	0.0	0.0	1.0
SLOCA	Normal operation	0.0	1.0	0.0
	Fail high	1.0	0.0	0.0
	Stuck at steady state	0.0	1.0	0.0
	Fail low	0.0	0.0	1.0
SGTR	Normal operation	1.0	0.0	0.0
	Fail high	1.0	0.0	0.0
	Stuck at steady state	0.0	1.0	0.0
	Fail low	0.0	0.0	1.0

Influence Diagrams Modeling

- Application of Influence Diagrams model

  Quantitative and probabilistic diagnosis using symptoms given after reactor trip

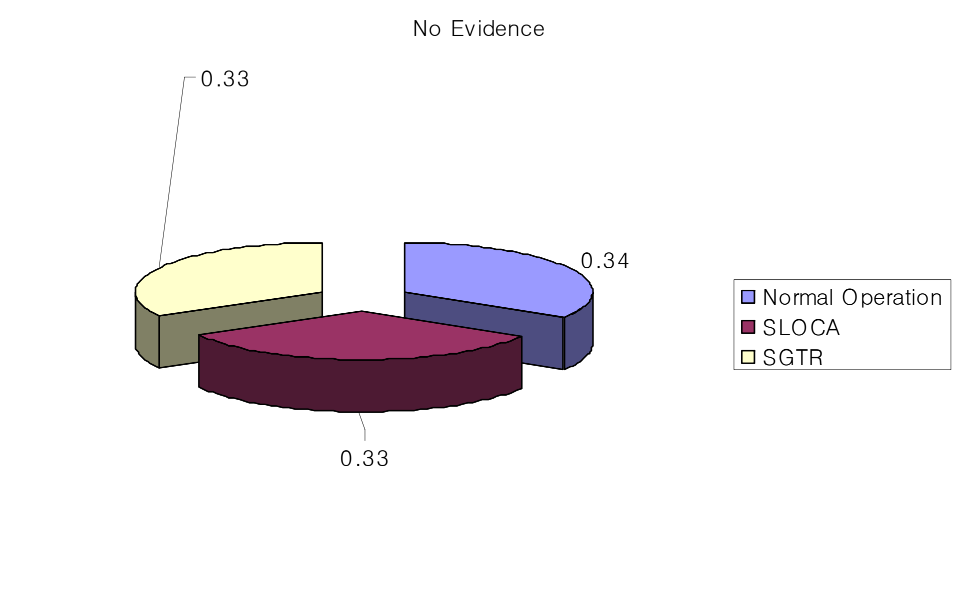
  - Accidents : SLOCA, SGTRs
  - Evidences : PRZ_PR decrease (Common symptom)

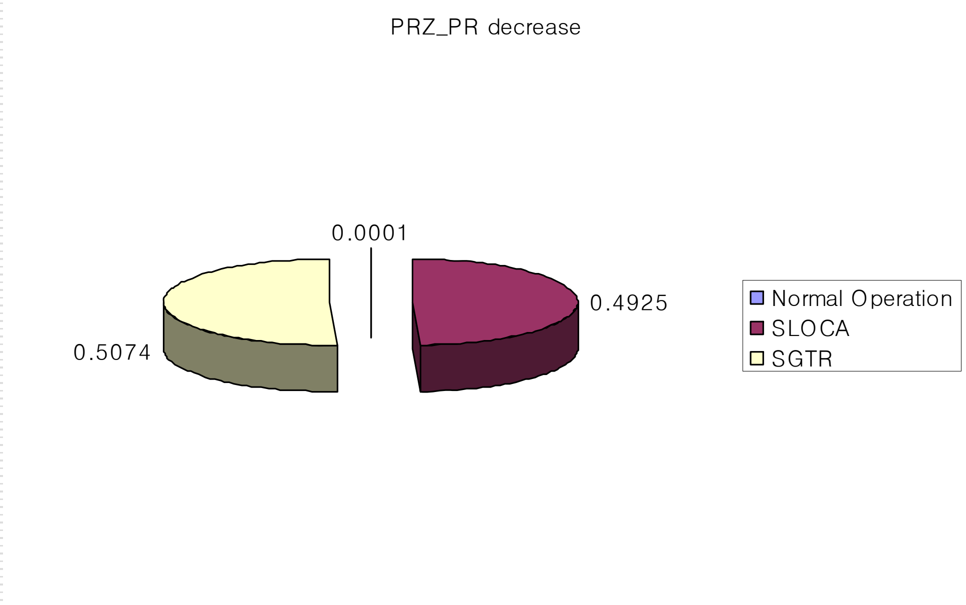
    RDT_LEV decrease (SLOCA symptom)

    MSL_RAD decrease (SGTRs symptom)

Results

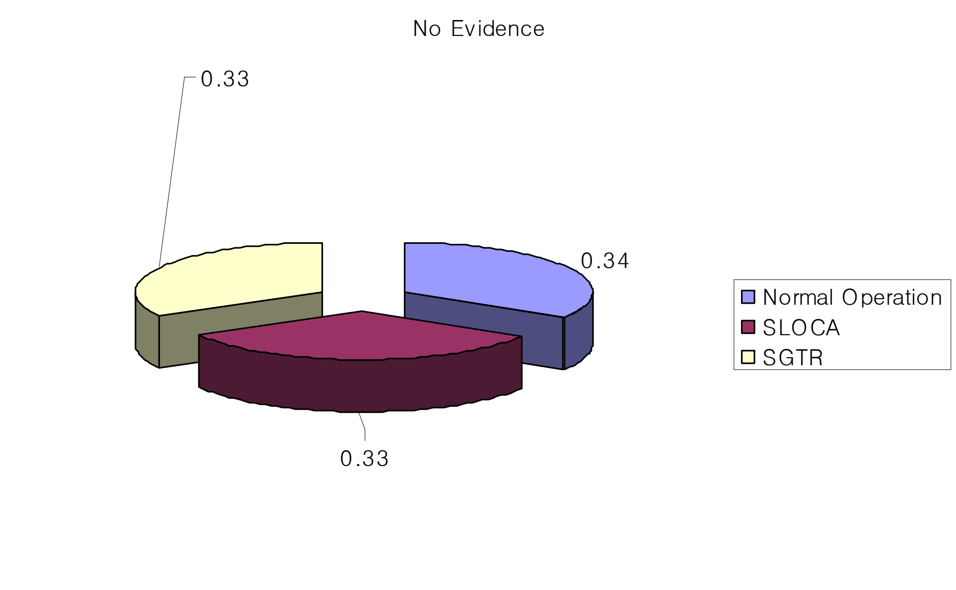
- Evidence : PRZ_PR (Pressurizer Pressure) decrease

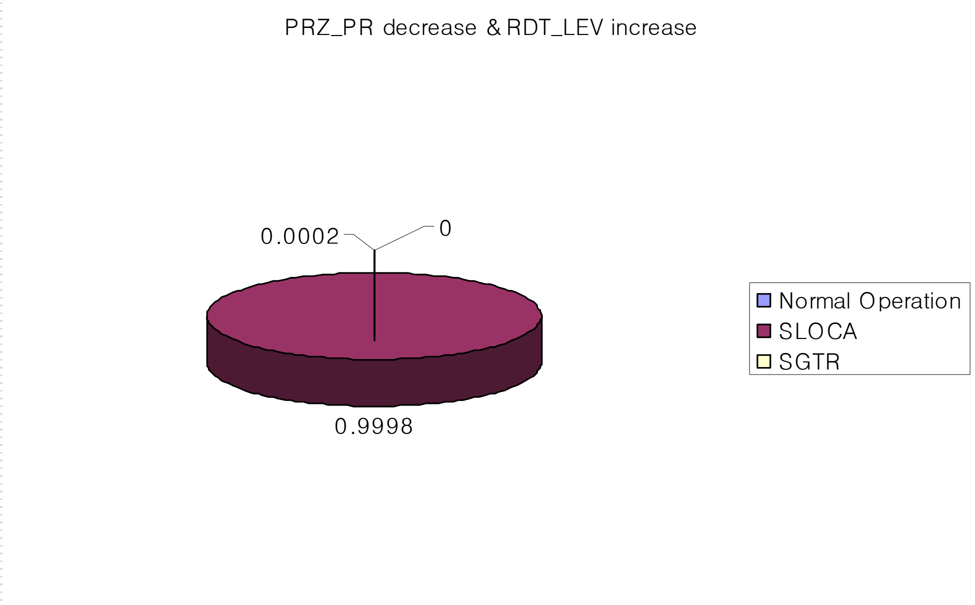




Results

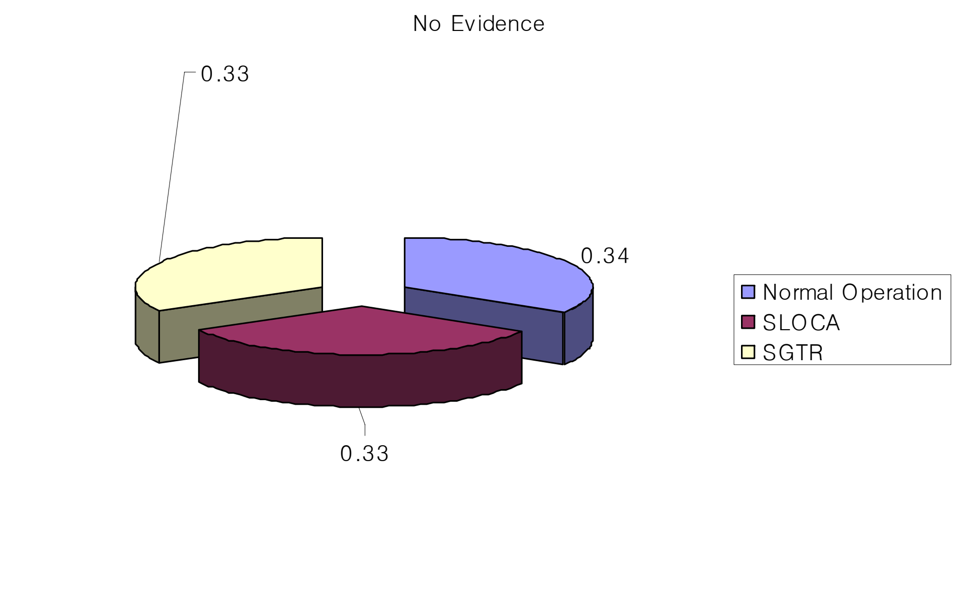
- Evidence : PRZ_PR decrease & RDT_LEV increase

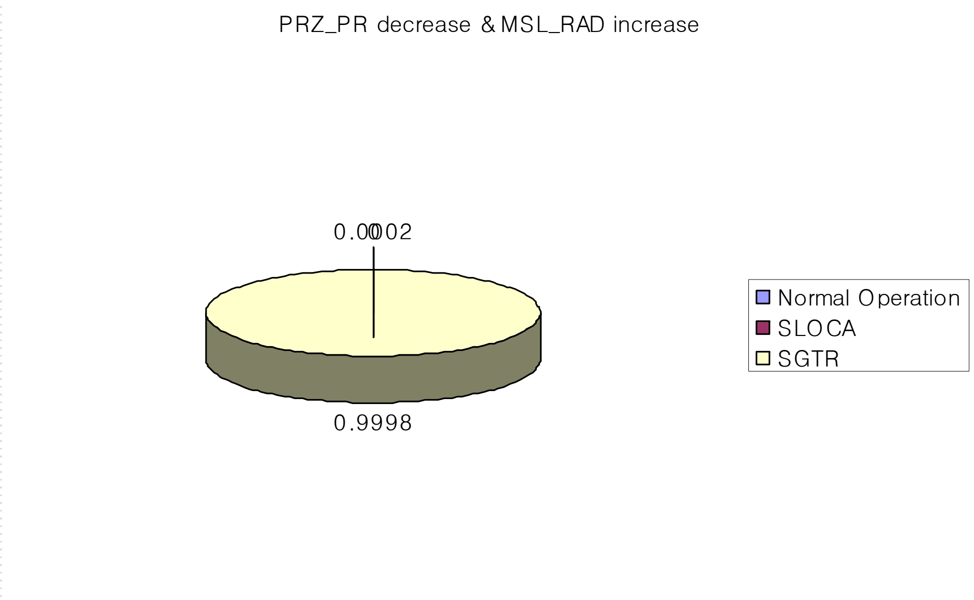




Results

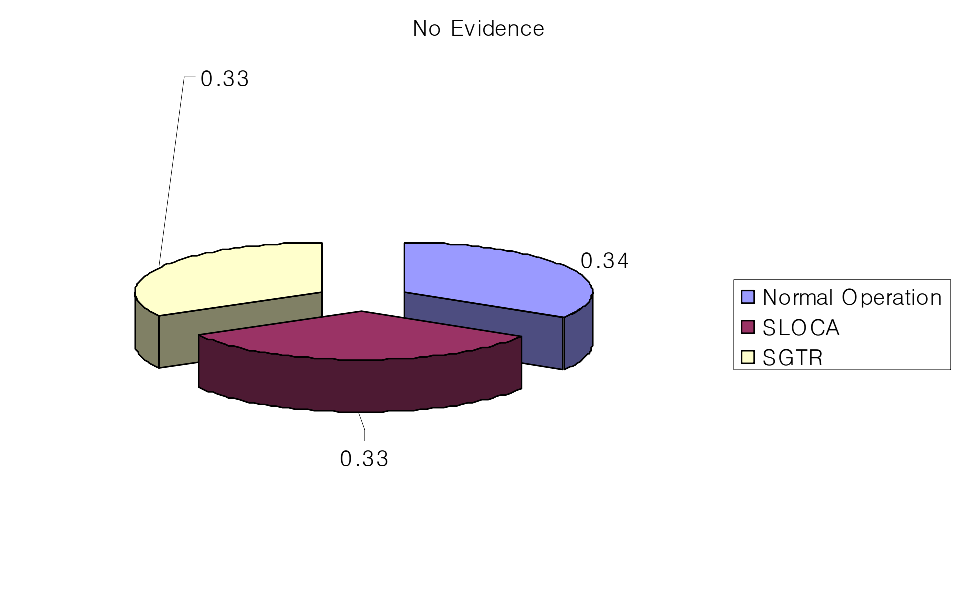
- Evidence : PRZ_PR decrease & MSL_RAD increase

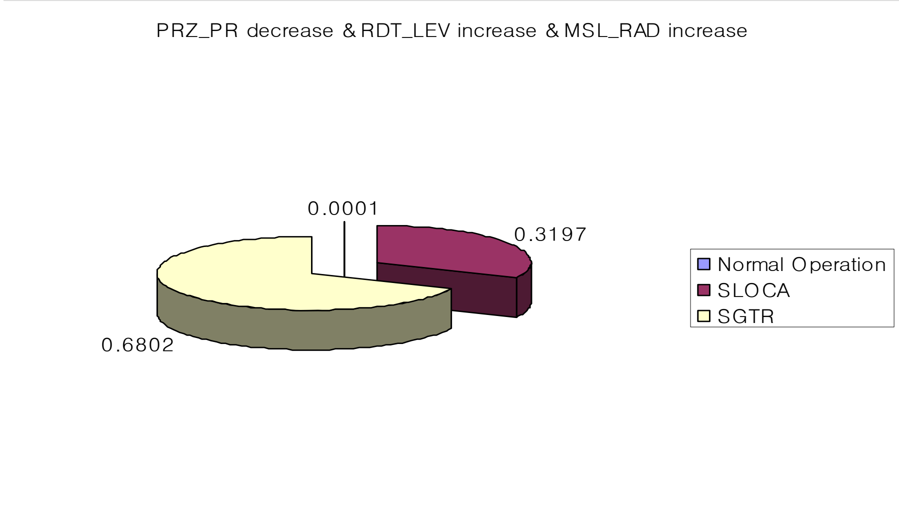




Results

- Evidence : PRZ_PR decrease & RDT_LEV increase& MSL_RAD increase





Concluding Remarks

- Based on EOPs, a quantitative diagnosis algorithm using bayesian Theorem has been developed.
- Applications to other accident diagnosis with confusing symptoms are possible.
- This work can be used for safety enhancement by reducing human errors associated with accident diagnosis.
- It is shown that bayesian theorems are useful tool to help operators diagnosis correctly in a given short time.

Thank you.