제4차 산업혁명과
소듐냉각고속로 워크숍

AI-Based Monitoring and Diagnosis of Severe Accidents

May 17, 2017

Man Gyun Na

Chosun University

조선대학교
CHOSUN UNIVERSITY

Contents

조선대학교 CHOSUN UNIVERSITY

Introduction

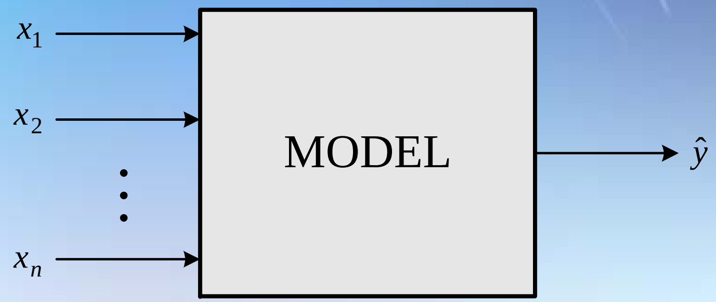
- Many AI methodologies have been proposed for identifying events, diagnosing accidents, and predicting accident scenarios, and golden time and predicting essential information.
- These methodologies include
  - Fuzzy neural networks (FNN)
  - Support vector machine (SVM)
  - Group method of data handling (GMDH)
  - Cascaded FNN and SVR
  - Etc
- These methodologies will be introduced first and then, brief application results will be presented.

Artificial Intelligence Methodologies

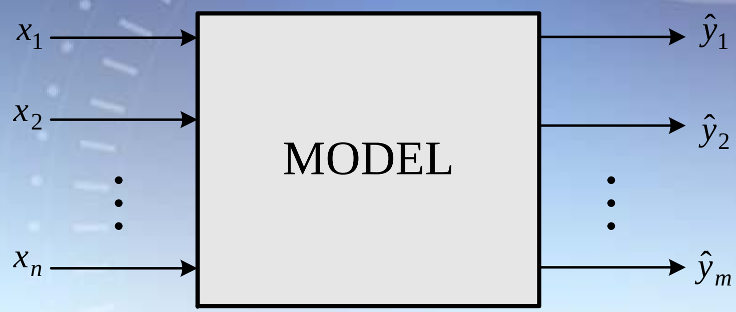
조선대학교 CHOSUN UNIVERSITY

- Redundant Methods
  - Instrumentation and Calibration Monitoring Program (ICMP)
  - Independent Component Analysis (ICA)
- Non-redundant Modeling Methods
  - Neural networks (NN)
  - Kernel regression technique (KR)
  - Multivariate state estimation technique (MSET)
  - Fuzzy neural network (FNN)
  - Group method of data handling (GMDH)
  - Support vector machines (SVM)
  - Cascaded FNN and SVR (CFNN and CSVR)

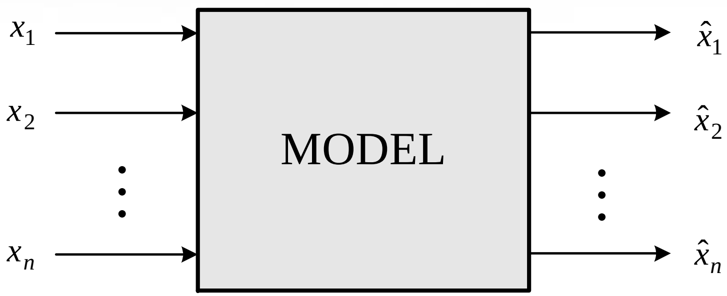
Empirical Model Classification (Inferential, Heteroassociative, Autoassociative)



<Inferential>



< Heteroassociative >



< Autoassociative>

ICMP

- Develop by EPRI in the early 1990's
- Weighted averaging algorithm
- If $\left|x_i - x_j\right| \le \delta_i + \delta_j$, then $C_i = C_i + 1$ (For example, $j = 2, 3$ for $i = 1$)

$$\hat{x} = \frac{\sum_{i=1}^{n} w_i C_i x_i}{\sum_{i=1}^{n} w_i C_i}$$

- Consistency value (C_i) : denote how much of the signal's measured value contributes to the process estimate.
- Weighting value (w_i) : apply a greater weighting to more accurate or reliable sensors.

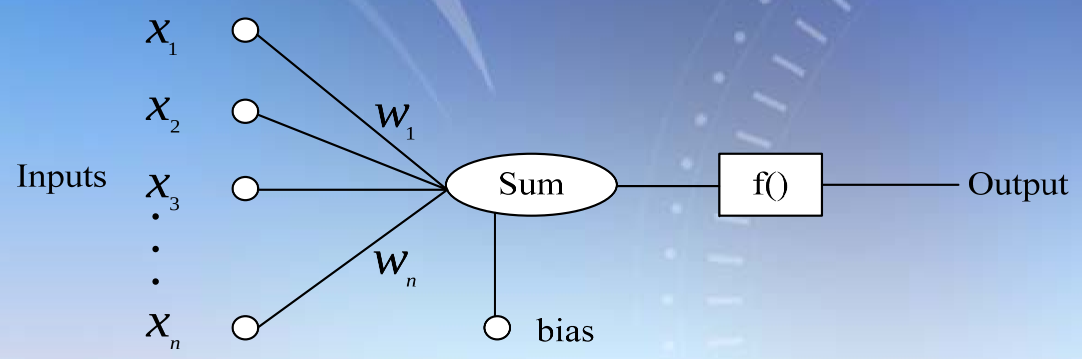
ICA

- A. J. Hyvarinen et al., Independent Component Analysis, John Wiley and Sons, 2001.
- Developed by UTK through EPRI and TVA funding
- A measured sensor value includes the true process parameter value, common noise sources, and independent instrument noise sources.

$$x_m = x_t + \delta + \varepsilon$$

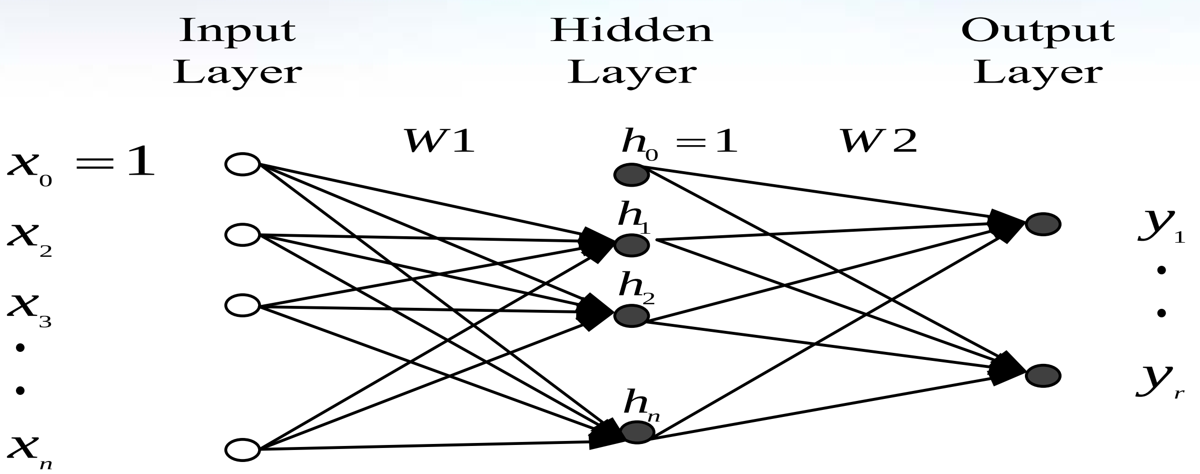
- As the sources are mixed, their combined distribution tesnds toward Gaussian.
- A method that maximizes non-Gaussianity will separate the mixed sources and be able to estimate the noise-free process parameter value.

- Neural Networks



Artificial Neuron

- Feed-forward Networks

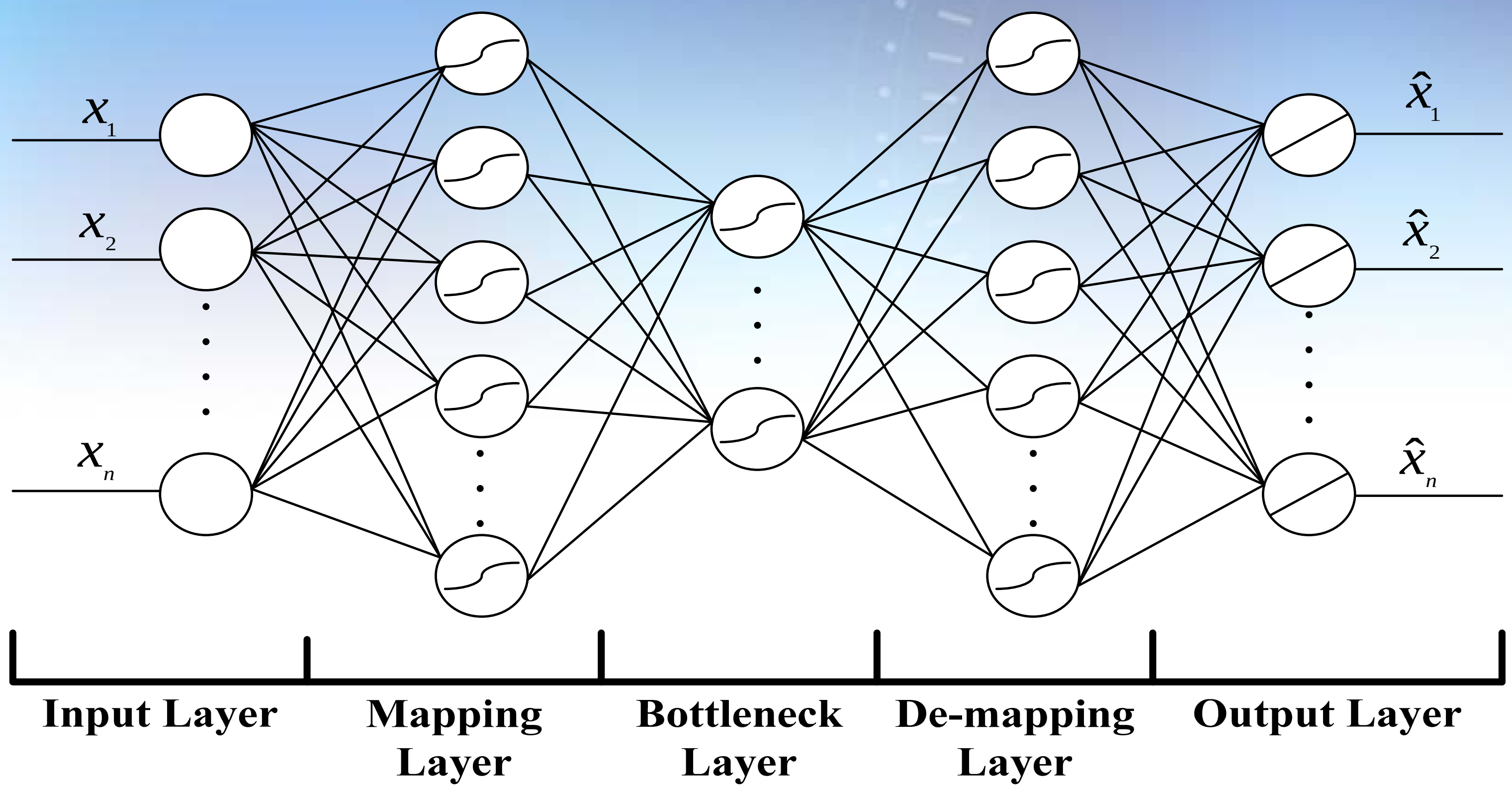


Multilayer Network

- Recurrent Networks

Neural Networks (Cont.)

- Auto-associative Neural Networks (AANN)



Kernel Regression

- Estimate a parameter value by calculating a weighted average of historical exemplar values

$$\hat{y}(x) = \frac{\sum_{k=1}^{N} f_K\left(d_i(X_i, x)\right) \cdot Y_i}{\sum_{k=1}^{N} f_K\left(d_i(X_i, x)\right)}$$

- For Gaussian kernel

$$f_K(d) = \frac{1}{\sqrt{2\pi h^2}} e^{-d^2 / 2h^2}$$

- The bandwidth determines smoothness (Optimization required)

Multivariate State Estimation Technique (MSET)

- Nonlinear, nonparametric modeling technique developed by ANL
- Similar to multiple linear regression

$$\hat{\mathbf{y}} = \mathbf{w}^T \mathbf{Y}$$

$$\mathbf{w} = \left(\mathbf{Y}\mathbf{Y}^T\right)^{-1} \mathbf{Y}^T \mathbf{y} \quad \text{(from the ordinary least-squares solution)}$$

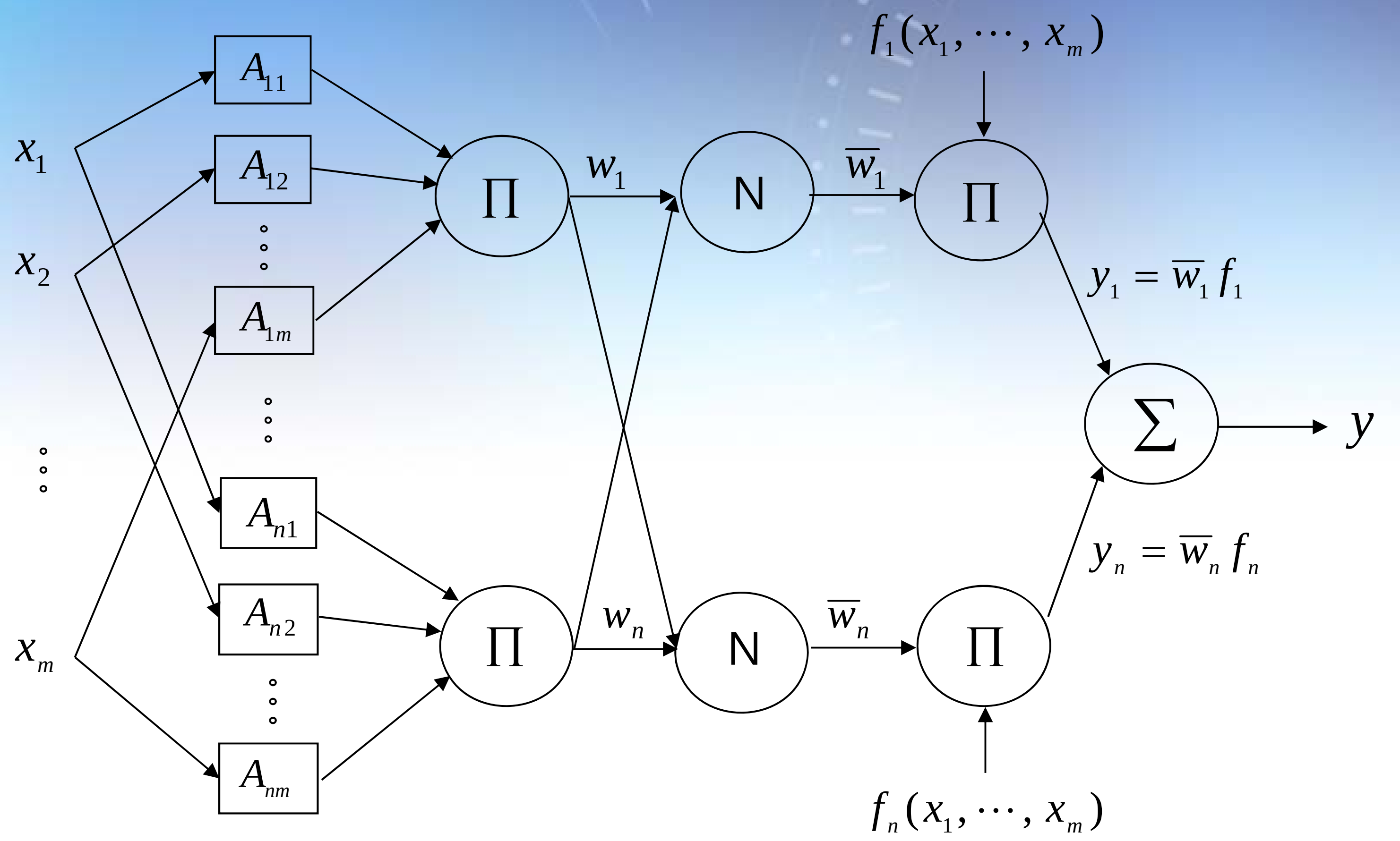
$$\hat{\mathbf{y}} = \mathbf{y}^T \mathbf{Y}\left(\mathbf{Y}\mathbf{Y}^T\right)^{-1} \mathbf{Y} \quad \text{(because of a symmetric matrix } \mathbf{Y}\mathbf{Y}^T\text{)}$$

  - **Y** : from the selected measurement vectors (memory matrix)
  - **w :** weigh vector for averaging **Y** to calculate the estimated value

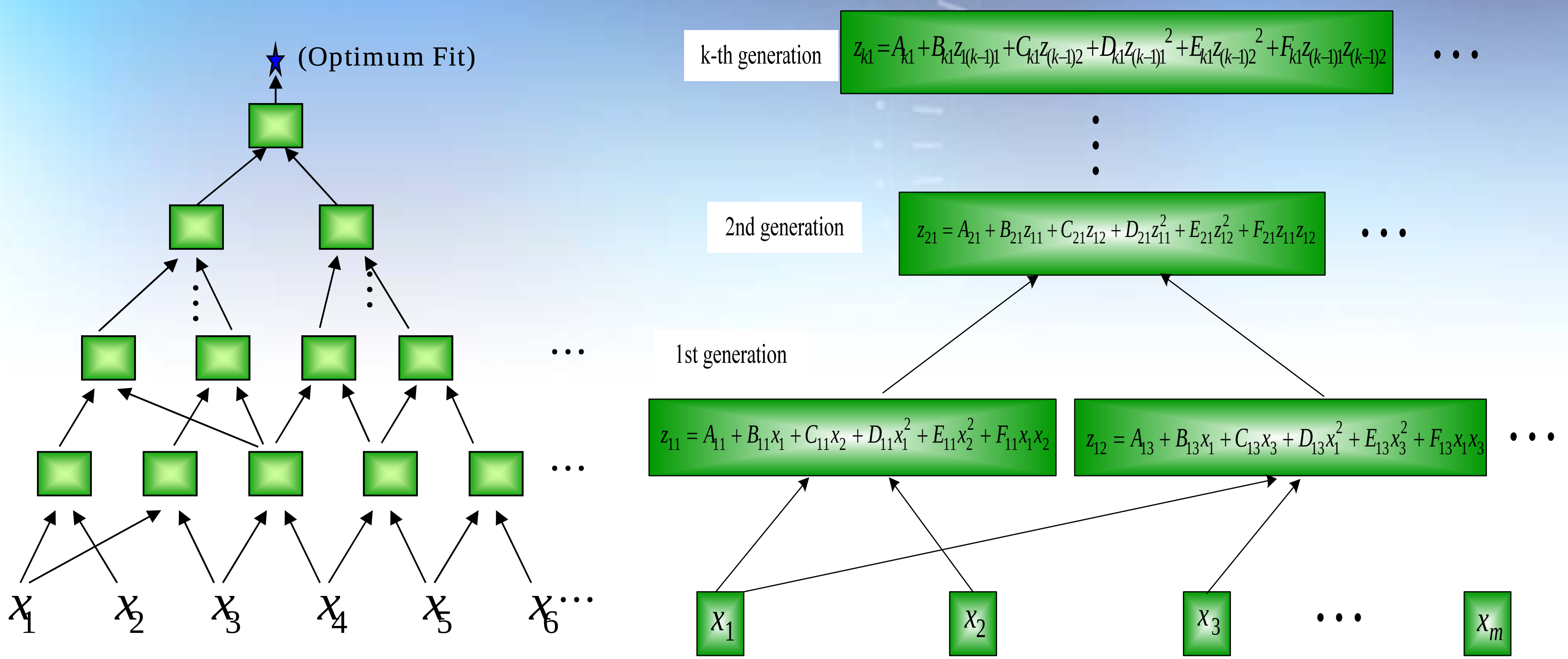
- By introducing a nonsingular operator

$$\hat{\mathbf{y}} = \left(\mathbf{y}^T \otimes \mathbf{Y}\right)\left(\mathbf{Y} \otimes \mathbf{Y}^T\right)^{-1} \mathbf{Y}$$

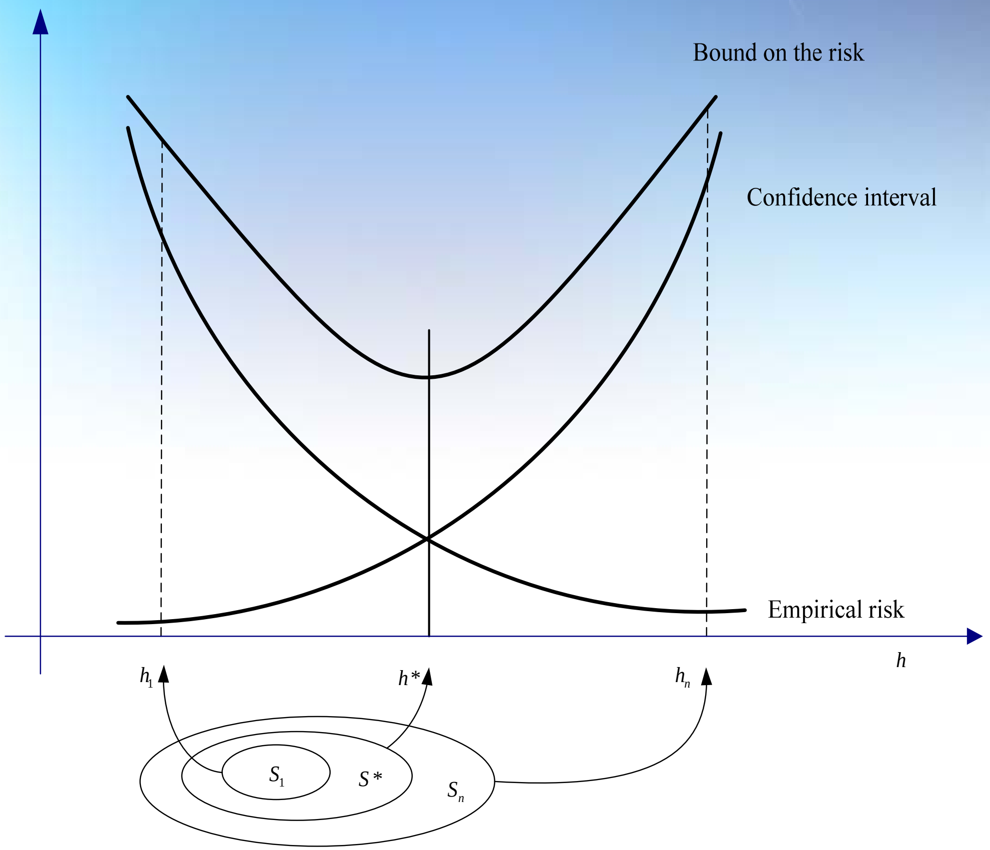
Fuzzy Neural Networks (or ANFIS)

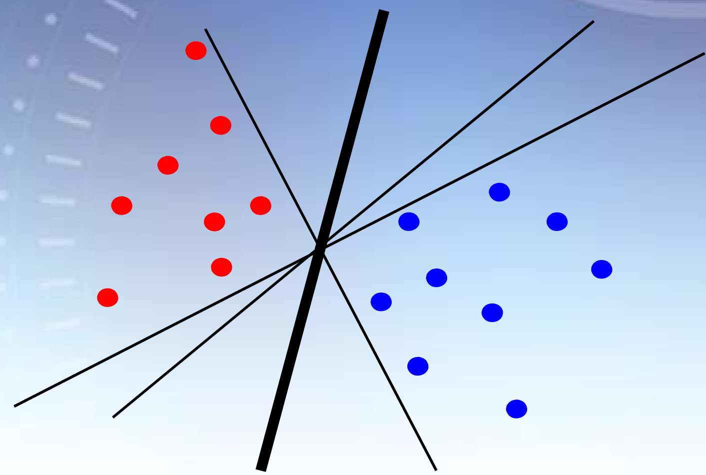


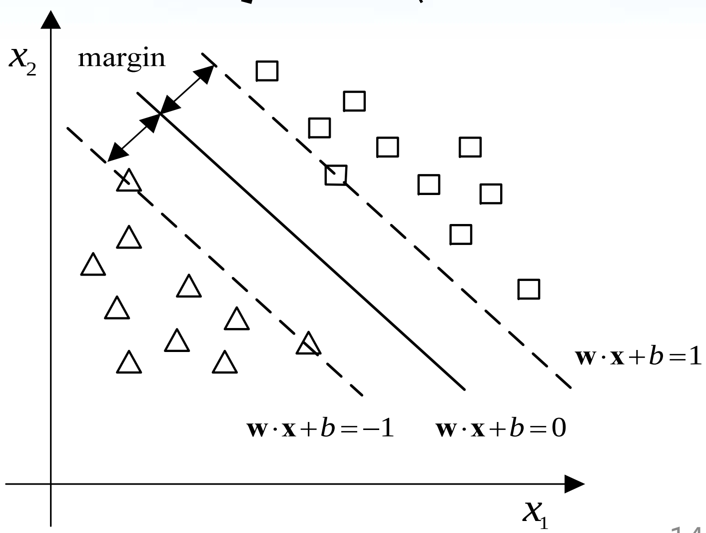
- Group Method of Data Handling (GMDH)
  - $\hat{y} = f(x_i, x_j) = A + Bx_i + Cx_j + Dx_i^2 + Ex_j^2 + Fx_i x_j$



Support Vector Machine

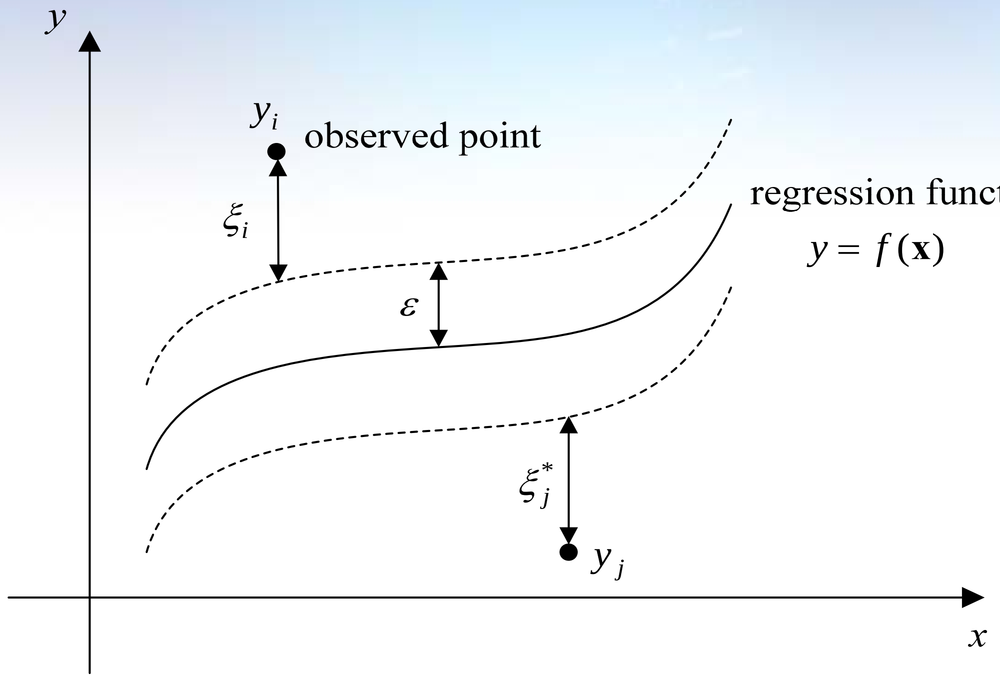




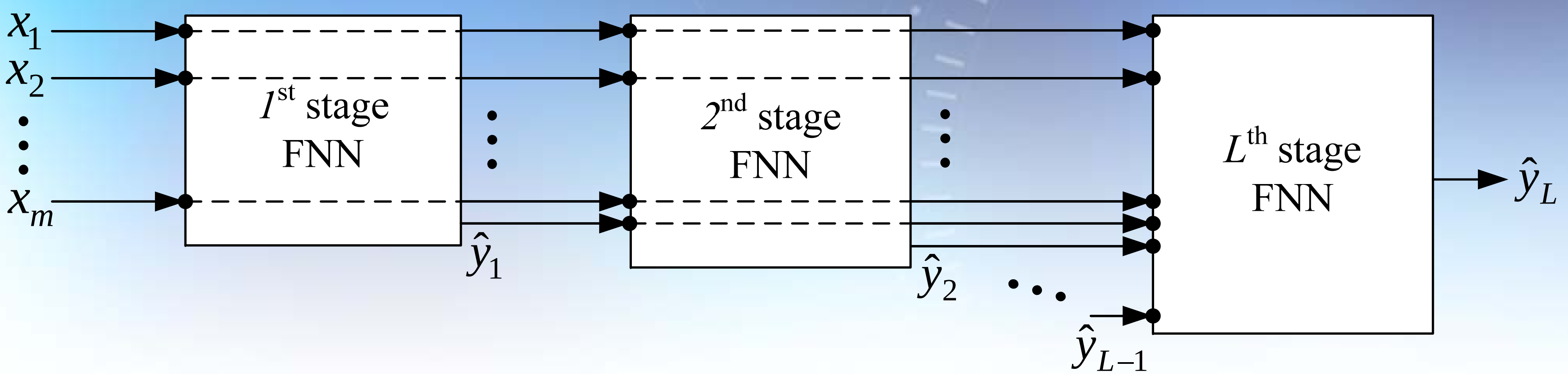


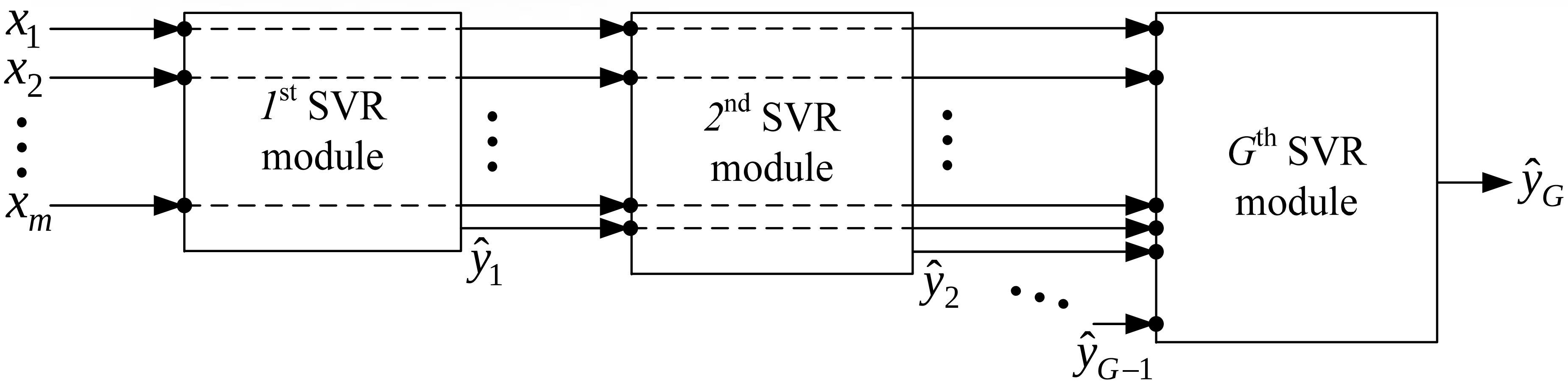
Support Vector Machine (Cont.)

$$R(\mathbf{w},\xi,\xi^*) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + \lambda\sum_{i=1}^{N}\left(\xi_i + \xi_i^*\right), \quad \text{constraints} \begin{cases} y_i - \mathbf{w}^T\boldsymbol{\varphi}(\mathbf{x}) - b \le \varepsilon + \xi_i, & i = 1, 2, \cdots, N \\ \mathbf{w}^T\boldsymbol{\varphi}(\mathbf{x}) + b - y_i \le \varepsilon + \xi_i^*, & i = 1, 2, \cdots, N \\ \xi_i,\ \xi_i^* \ge 0, & i = 1, 2, \cdots, N \end{cases}$$



- CFNN and CSVR





Performance Measure

- Accuracy : measure the ability of a model to accurately predict sensor values.

$$MSE = \frac{1}{N}\sum_{k=1}^{N}(\hat{x}_k - x_k)^2$$

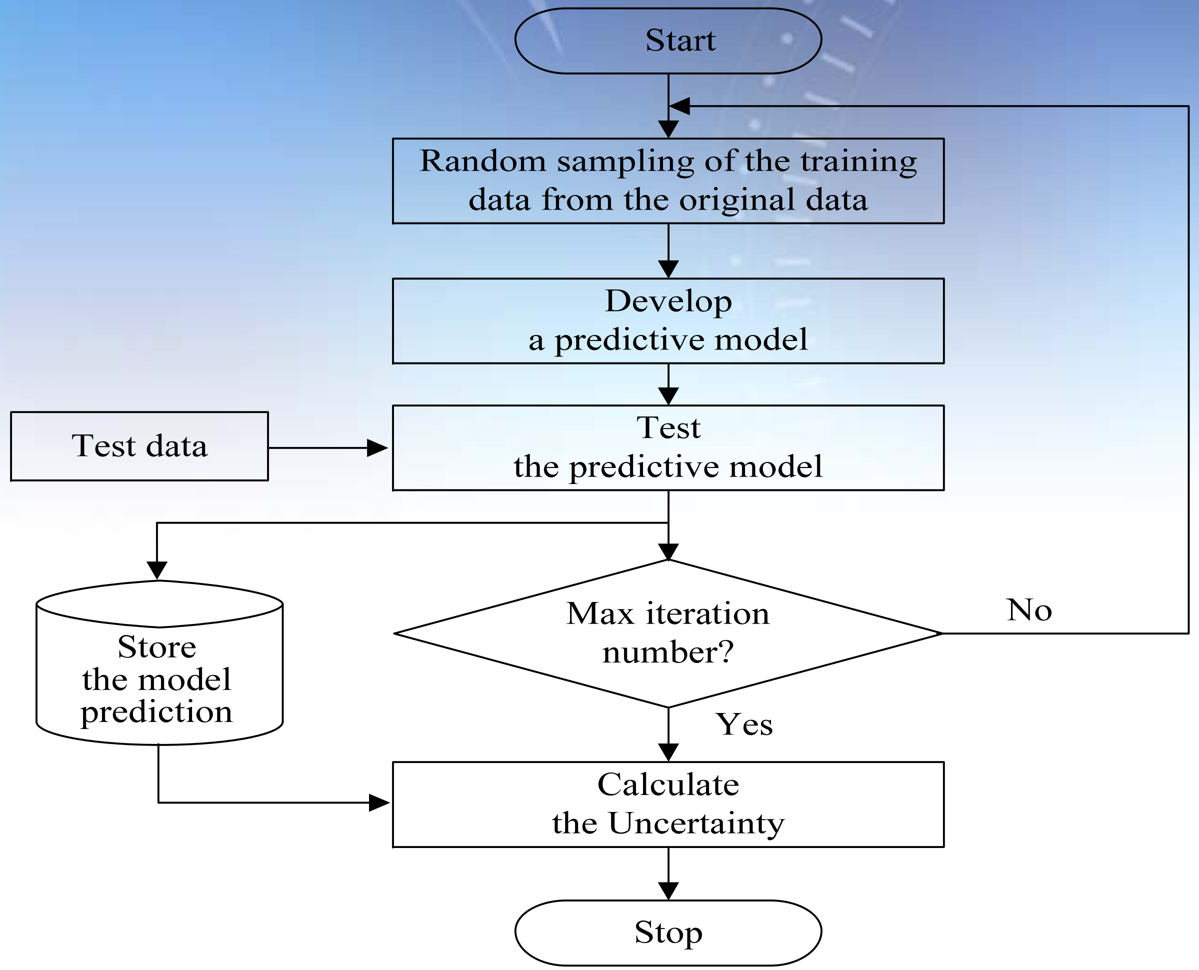
- Auto sensitivity : measure the ability of a model to make correct predictions when each measurement is incorrect due to some sort of fault.

$$S_{A,i} = \frac{1}{N}\sum_{k=1}^{N}\left|\frac{\hat{x}_{ki}^{f} - \hat{x}_{ki}}{x_{ki}^{f} - x_{ki}}\right|$$

- Cross sensitivity : measure the effect that faulty measured input has on other predictions of the model

$$S_{C,ij} = \frac{1}{N}\sum_{k=1}^{N}\left|\frac{\hat{x}_{kj}^{f} - \hat{x}_{kj}}{x_{ki}^{f} - x_{ki}}\right|, \quad i \neq j$$

❑ Uncertainty Analysis (Bootstrapping)



Applications

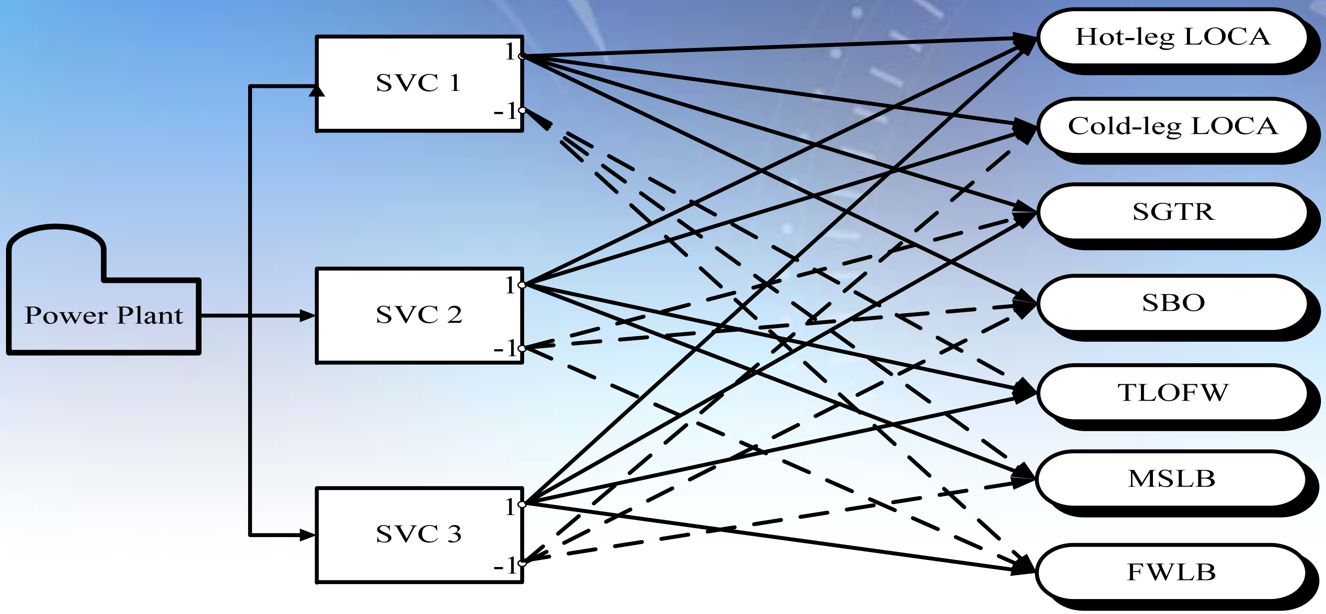
- Application of AI
  - Application to Event Identification
  - Application to Accident Diagnosis (LOCA break size)
  - Application to Accident Prediction (Scenario progression)
  - Application to Accident Countermeasure (Golden time)
  - Application to Essential Information Prediction

Application to Event Identification

- In case of NPP event occurrences, these were identified using a support vector classification method.
- The data were acquired by simulating a variety of postulated events for OPR1000 using MAAP4 code.
- 620 computer simulations (7 events)
  - 200 cold-leg LOCAs, 200 hot-leg LOCAs, 200 SGTRs
  - 3 SBO
  - 3 TLOFW
  - 7 MSLB
  - 7 FWLB
- The input variables to SVC and SVR models are the time-integrated values of 13 simulated sensor signals.
  - $x_j = \int_{t_s}^{t_s+\Delta t} g(t)dt$

Application to Event Identification

- Event identification using the SVC model



SVC Mode	Hot-leg LOCA	Cold-leg LOCA	SGTR	SBO	TLOFW	MSLB	FWLB
SVC1	1	1	1	1	-1	-1	-1
SVC2	1	1	-1	-1	1	1	-1
SVC3	1	-1	1	-1	1	-1	1

Application to Event Identification

조선대학교 CHOSUN UNIVERSITY

- Result of the classified transients using the SVC and PNN models without measurement error

Performance result	Integrating time (sec)	No. of Misclassification	No. of Don't know classification
SVC	3	0	0
	5	0	0
	10	0	0
	20	0	0
PNN	3	1	0
	5	1	0
	10	1	0
	20	1	0

Application to Event Identification

조선대학교 CHOSUN UNIVERSITY

- Classification results using the SVC model with measurement errors

SVC performance result	Integrating time (sec)	-3%	3%	-5%	5%	Random (below 3%)	Random (below 5%)
No. of Misclassification	3	0	1	1	2	1	1
	5	1	1	1	2	0	1
	10	2	4	4	7	0	0
	20	3	10	7	18	0	0
No. of Don't Know classification	3	0	0	0	0	0	0
	5	0	0	0	0	0	0
	10	0	0	0	0	0	0
	20	0	0	0	0	0	0

Application to Event Identification

- Classification results using each model with safety system actuation

Performance result	Integrating time (sec)	No. of Misclassification	No. of Don't know classification
SVC	3	1	0
	5	0	0
	10	0	0
	20	0	0
PNN	3	1	0
	5	1	0
	10	1	0
	20	1	0

Application to Accident Diagnosis

- LOCA break size was estimated at the three break positions of hot leg LOCA, cold leg LOCA, and SGTR.

- The cascaded SVR (CSVR) was applied.

- The input variables to the CSVR model is the time-integrated values of 13 simulated sensor signals as follows :
  - $x_j = \int_{t_s}^{t_s+\Delta t} g(t)\,dt$

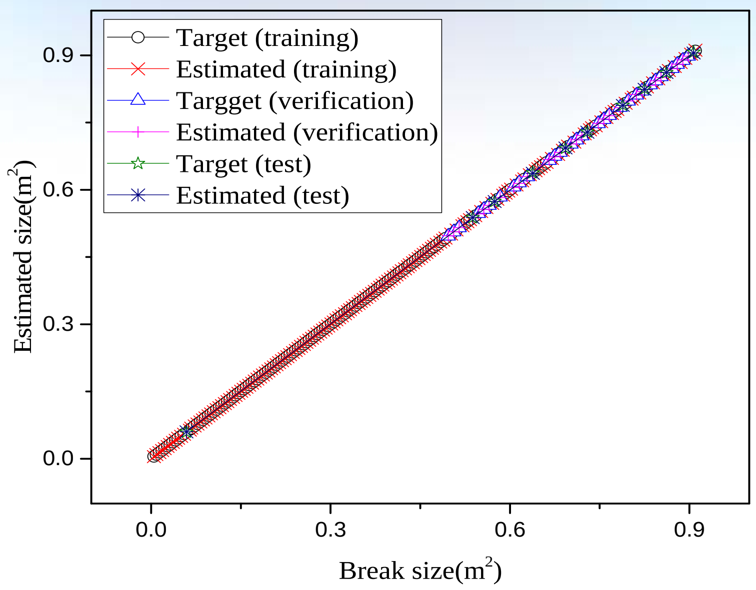
- Some of the 13 time-integrated values were selected using correlation analysis.

- Among a total of 200 simulations for each break position, the accident simulation data were divided into both 160 training data, 30 verification data, and 10 test data.

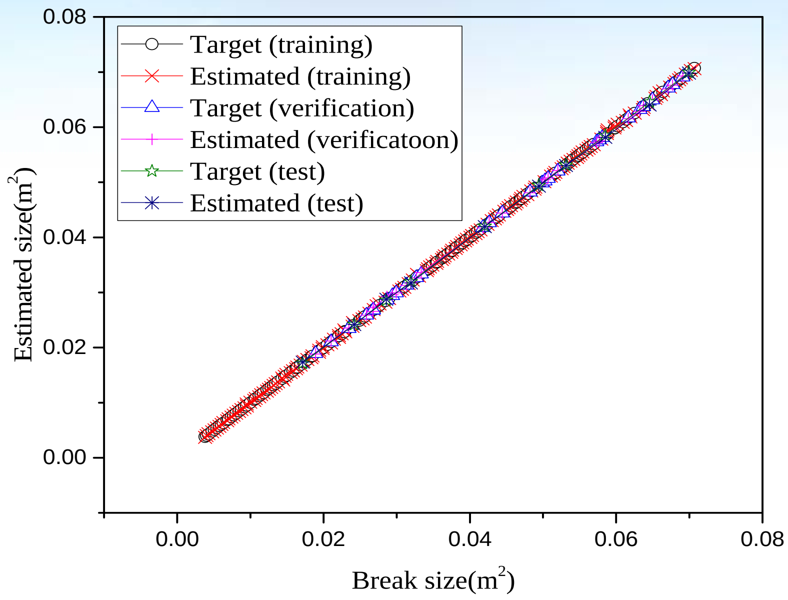
Application to Accident Diagnosis

- Performance of the CSVR model (without instrument error)

Break position	Number of SV	Development data		Test data	
		RMS error (%)	Max error (%)	RMS error (%)	Max error (%)
Hot-leg	3	0.44	0.38	0.38	0.80
Cold-leg	11	0.22	1.59	0.32	0.98
SGTR	2	0.66	2.34	0.58	1.13



<Estimated break size (Cold-leg LOCA)>



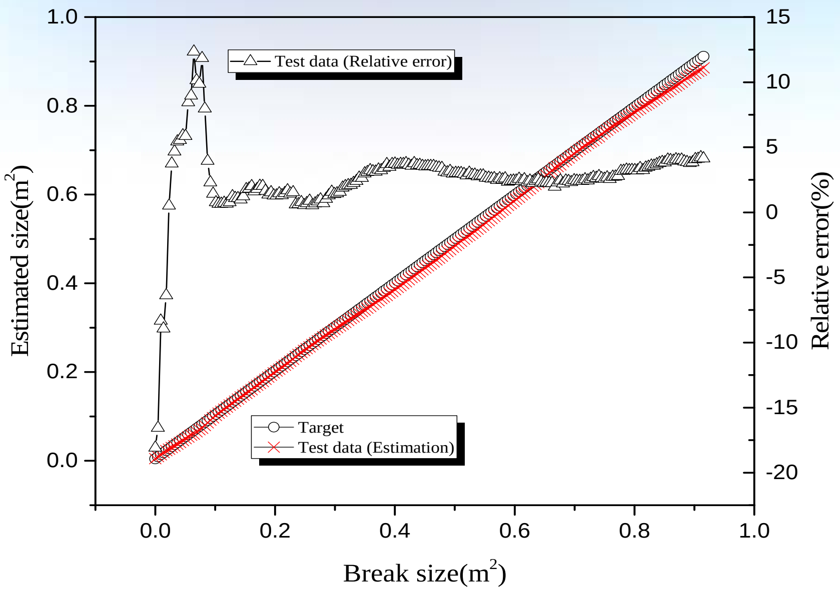
<Estimated break size (SGTR)>

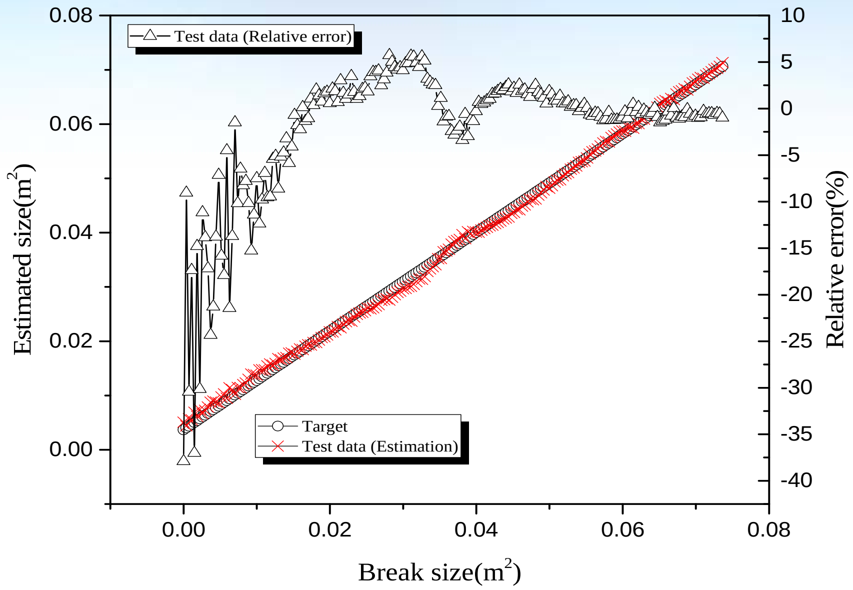
Application to Accident Diagnosis

CHOSUN UNIVERSITY 조선대학교

- Performance of the CSVR model (instrument error 5%)

Break position	Number of SV	Test data	
		RMS error (%)	Max error (%)
Hot-leg	3	3.41	11.75
Cold-leg	11	3.89	18.08
SGTR	2	7.28	37.90





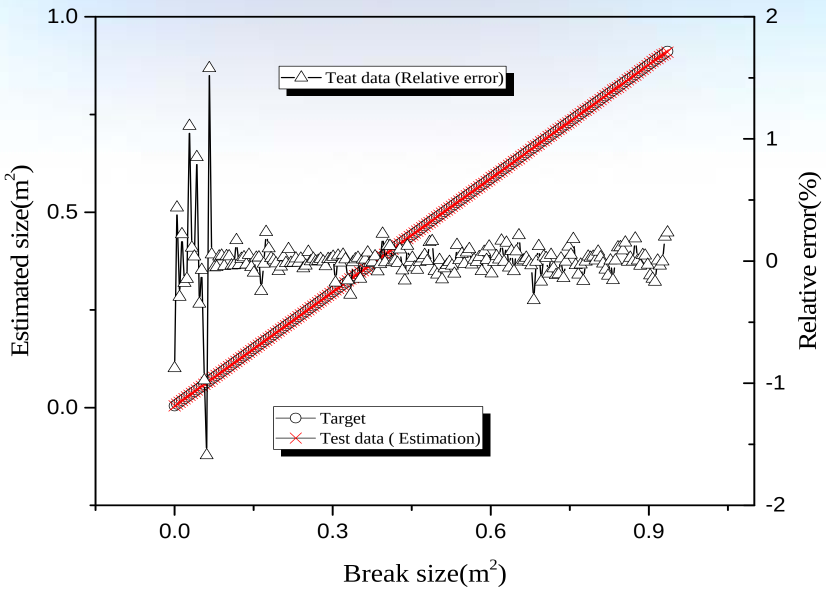
<Estimated break size and relative error (Cold-leg LOCA>

<Estimated break size and relative error (SGTR)>

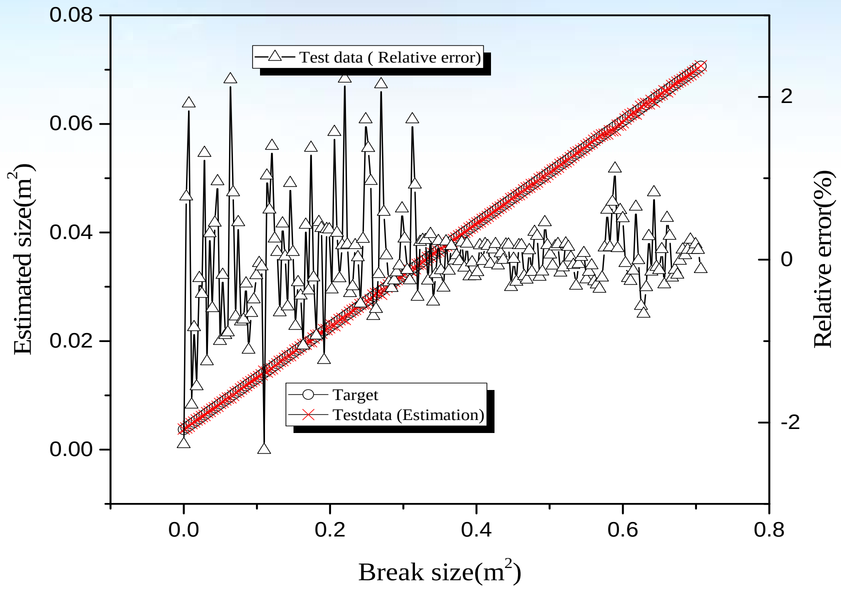
Application to Accident Diagnosis

- Performance of the CSVR model (safety system actuation)

Break position	Number of SV	Test data	
		RMS error (%)	Max error (%)
Hot-leg	3	0.44	3.38
Cold-leg	11	0.23	1.59
SGTR	2	0.65	2.34



<Estimated break size and relative error (Cold-leg LOCA>



<Estimated break size and relative error (SGTR)>

Application to Accident Prediction

- In case critical safety systems fail, it is important for operators to be informed of major timings such as core uncover, RV failure, containment failure and so forth.

- Accident progression scenarios were predicted using cascaded SVR models.

- Most data are identical to the data used in predicting the LOCA break size.

Application to Accident Prediction

CHOSUN UNIVERSITY 조선대학교

❑ Used Signals

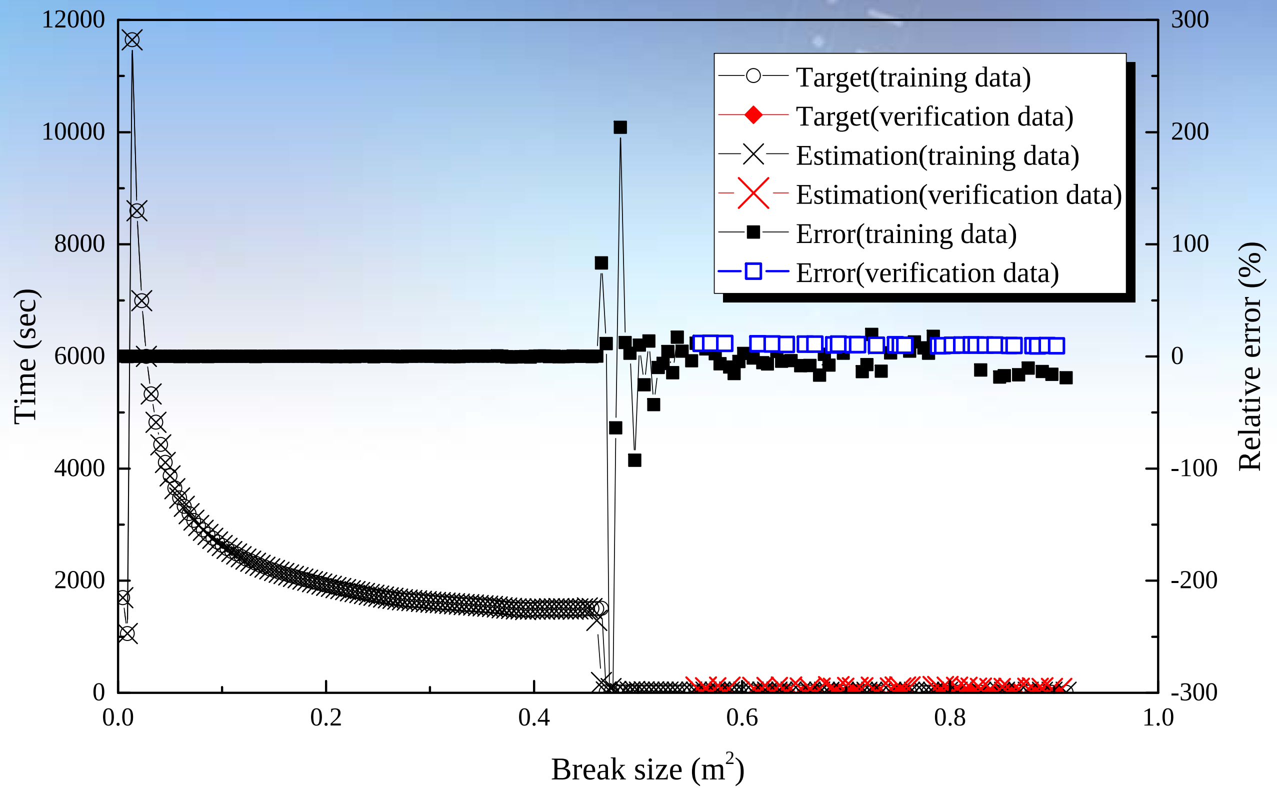
	Hot-leg LOCA		Cold-leg LOCA		SGTR	
Identification	Selected inputs	Input number	Selected inputs	Input number	Selected inputs	Input number
Core uncovery time	Containment pressure Containment temperature Pressurizer pressure Pressurizer water level Broken side S/G temperature	5	Containment pressure Containment temperature Pressurizer pressure Pressurizer water level Broken side S/G temperature	5	Containment temperature Reactor core water level Broken side S/G pressure Broken side S/G temperature Unbroken side S/G water level	5
Time that CET exceeds 1200F	Containment pressure Containment temperature Pressurizer pressure Pressurizer water level Broken side S/G temperature	5	Containment pressure Containment temperature Pressurizer pressure Pressurizer water level Broken side S/G temperature	5	Containment temperature Reactor core water level Broken side S/G pressure Broken side S/G temperature Unbroken side S/G water level	5
Reactor vessel failure time	Containment pressure Containment temperature Pressurizer pressure Pressurizer water level Broken side S/G temperature	5	Containment pressure Containment temperature Pressurizer pressure Pressurizer water level Broken side S/G temperature	5	Containment temperature Reactor core water level Broken side S/G pressure Broken side S/G temperature Unbroken side S/G water level	5
Containment failure time	Containment pressure Containment temperature Pressurizer pressure Pressurizer water level Broken side S/G temperature	5	Containment pressure Containment temperature Pressurizer pressure Pressurizer water level Broken side S/G temperature	5	Containment temperature Reactor core water level Broken side S/G pressure Broken side S/G temperature Unbroken side S/G water level	5

* 1200F : starting point of severe accident management

Application to Accident Prediction

CHOSUN UNIVERSITY 조선대학교

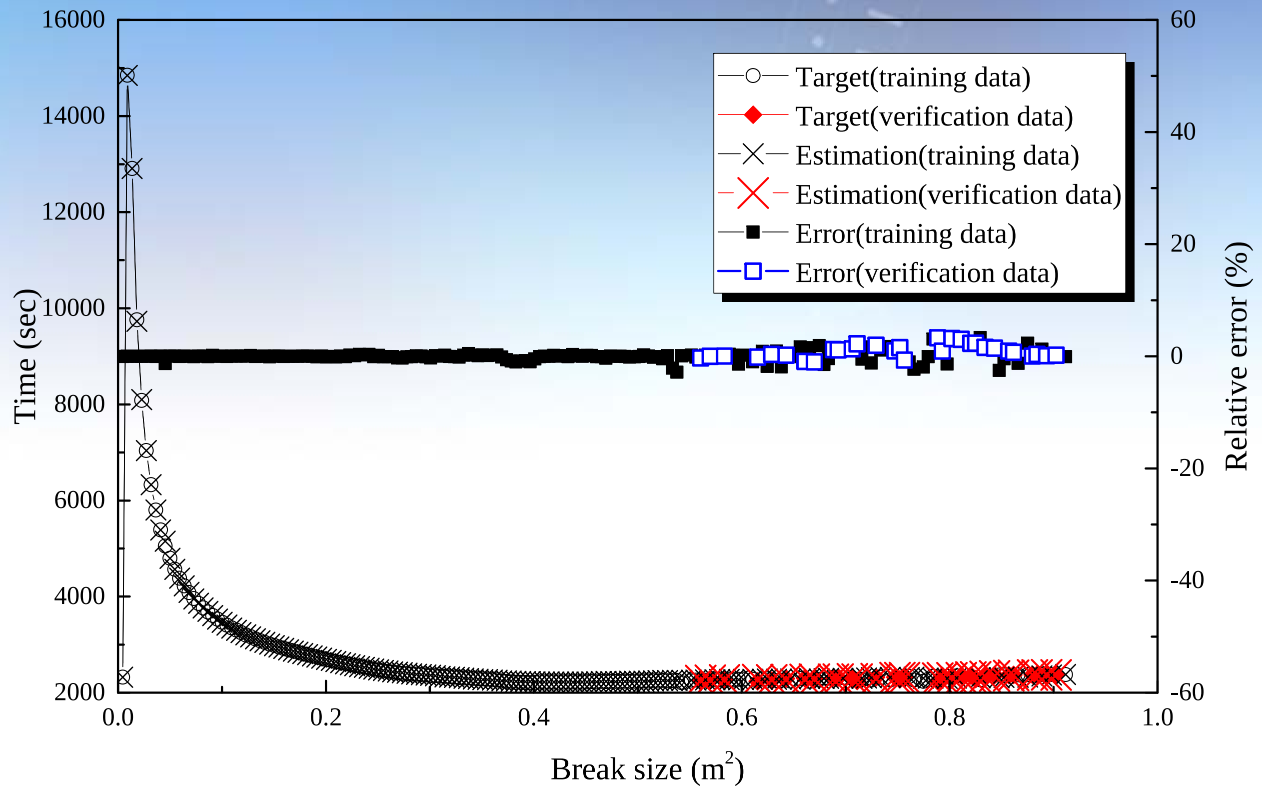
- Reactor core uncover time due to cold-leg LOCA



Application to Accident Prediction

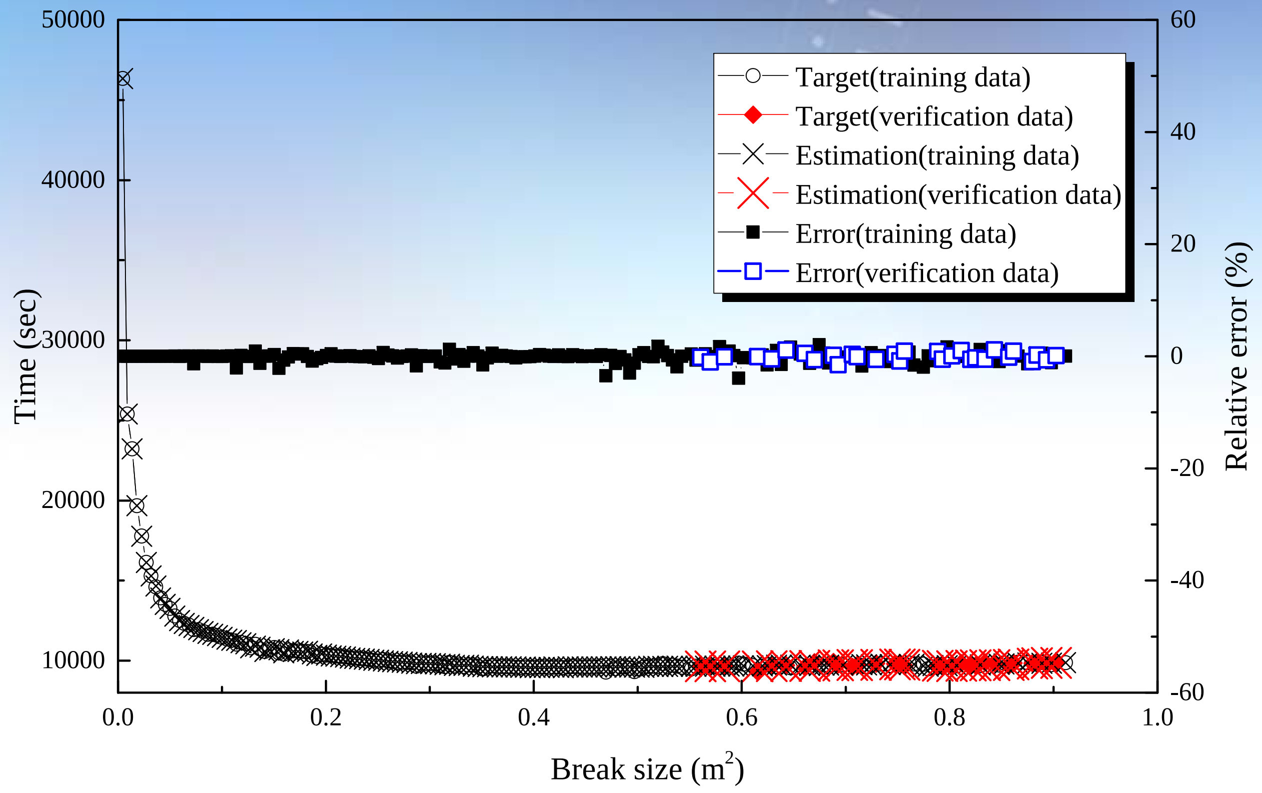
CHOSUN UNIVERSITY 조선대학교

- Time that CET exceeds 1200°F due to cold-leg LOCA



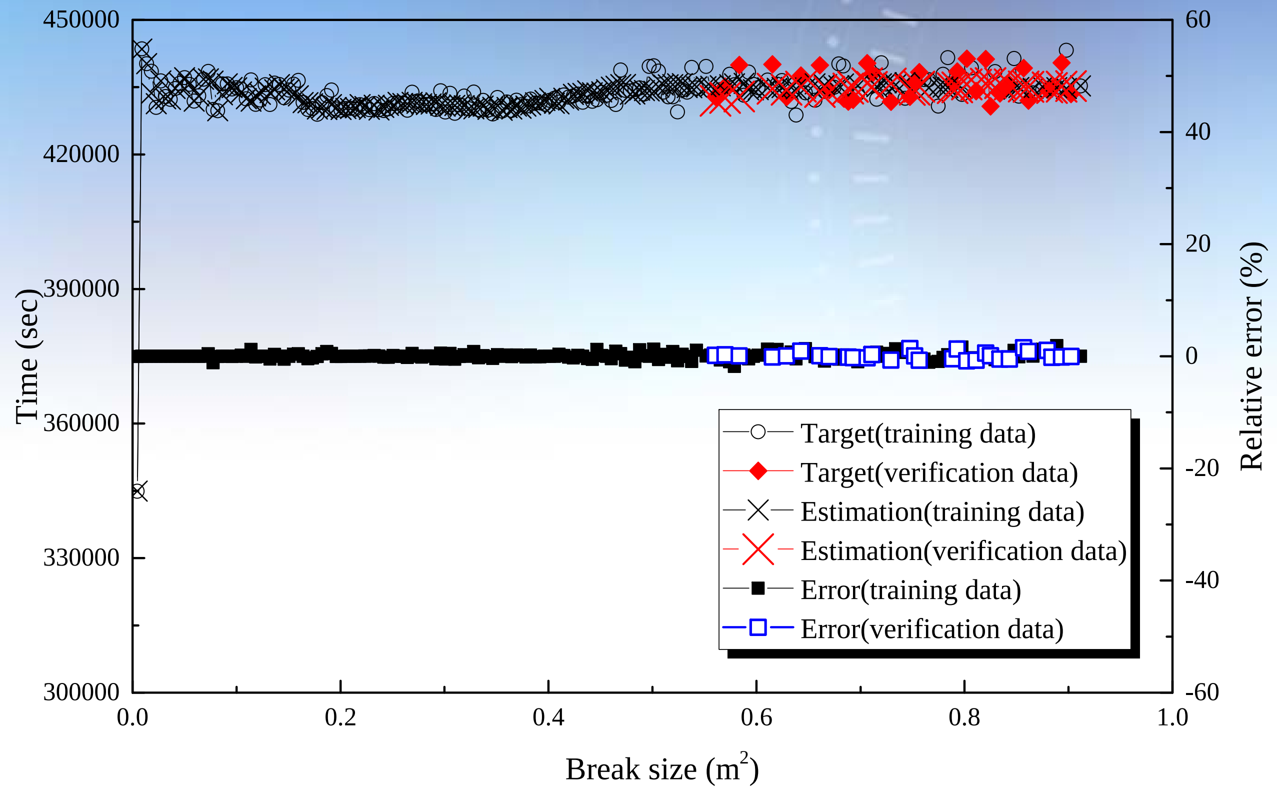
Application to Accident Prediction

- Reactor vessel failure time due to cold-leg LOCA



Application to Accident Prediction

- Containment failure time due to cold-leg LOCA



Application to Accident Prediction

CSVR performance

LOCA position	Time points	No, of SVR modules	Development data		Test data	
			RMS error (%)	Max Error (%)	RMS error (%)	Max Error (%)
Hot-leg	Core uncovery	5	0.244	0.819	0.372	0.826
	CET>1200F	6	0.401	2.410	0.492	1.379
	RV fail	6	0.223	0.970	0.328	0.772
	Containment fail	3	0.155	0.629	0.081	0.134
Cold-leg	Core uncovery	6	31.279	353.010	2.329	4.593
	CET>1200F	2	0.897	3.555	0.735	1.417
	RV fail	3	0.831	3.800	0.798	1.543
	Containment fail	2	0.570	1.880	0.561	1.337
SGTR	Core uncovery	3	3.523	25.346	1.248	1.974
	CET>1200F	6	2.734	15.619	1.965	5.869
	RV fail	1	5.665	21.806	3.017	7.284
	Containment fail	2	7.209	21.104	6.081	13.121

Application to Golden Time Prediction

조선대학교 CHOSUN UNIVERSITY

- During a loss-of-coolant accident (LOCA), failure of emergency core cooling system (ECCS) induces a very serious accident that exceeds the DBAs.

- By using a cascaded fuzzy neural network (CFNN) model, we predicted the golden time for SIS recovery that can accomplish a reactor cold-shutdown and prevent reactor core uncover or RV failure when the SIS was not operated normally by faults.

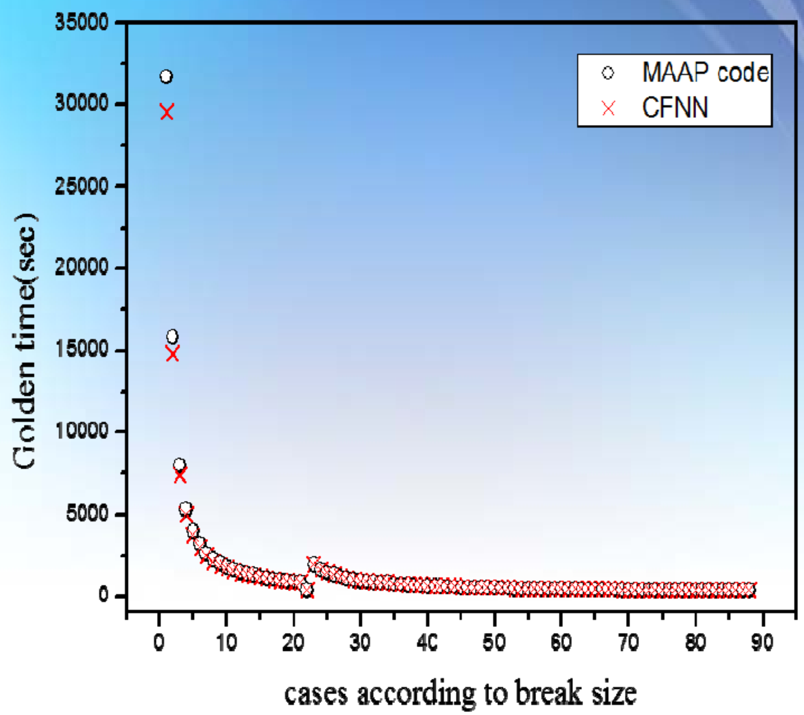
Application to Golden Time Prediction

- Actuation scenarios of safety systems

Type	Location	SIT Operation	CSS Operation	PORV	HPSI Operation	LPSI Operation
1	Hot-leg	Success	Injection & Recirculation	Close	Delay Injection & Recirculation	N/A
2				Open	N/A	Delay Injection & Recirculation
3	Cold-leg	Success	Injection & Recirculation	Close	Delay Injection & Recirculation	N/A
4				Open	N/A	Delay Injection & Recirculation

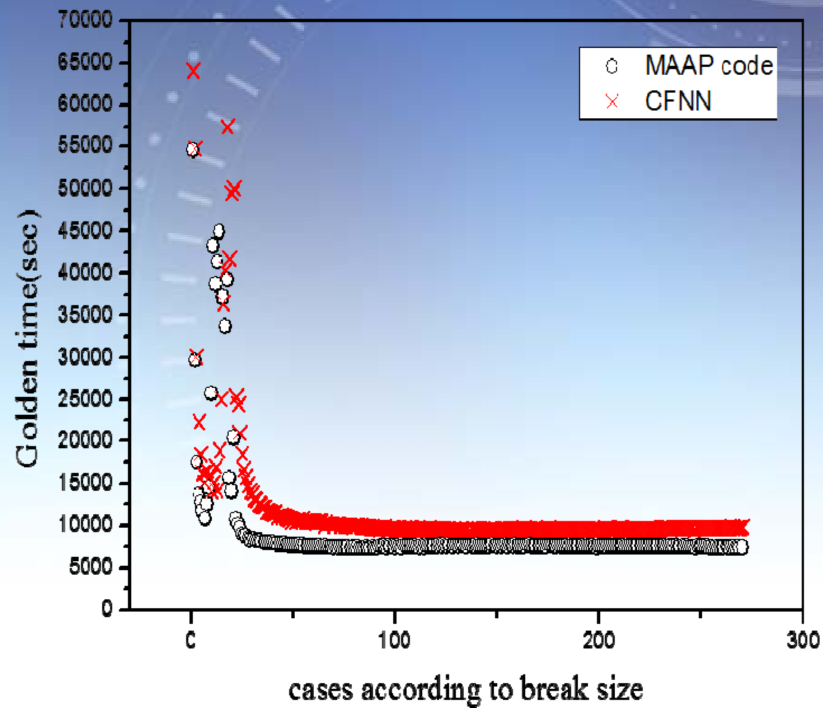
Application to Golden Time Prediction

조선대학교 CHOSUN UNIVERSITY



Golden time prediction for Type 1

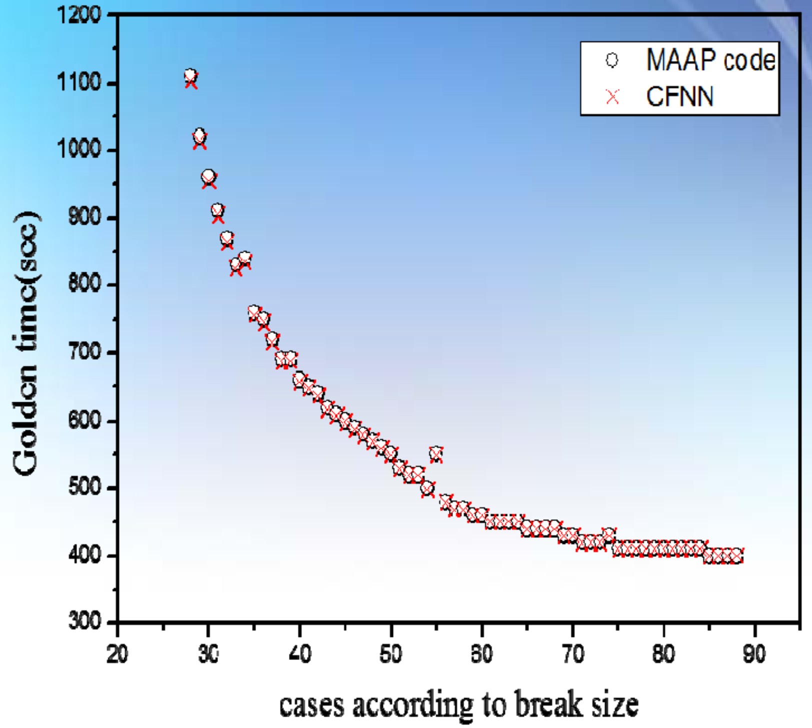
(HPSI delay, core uncovery)



Golden time prediction for Type 1

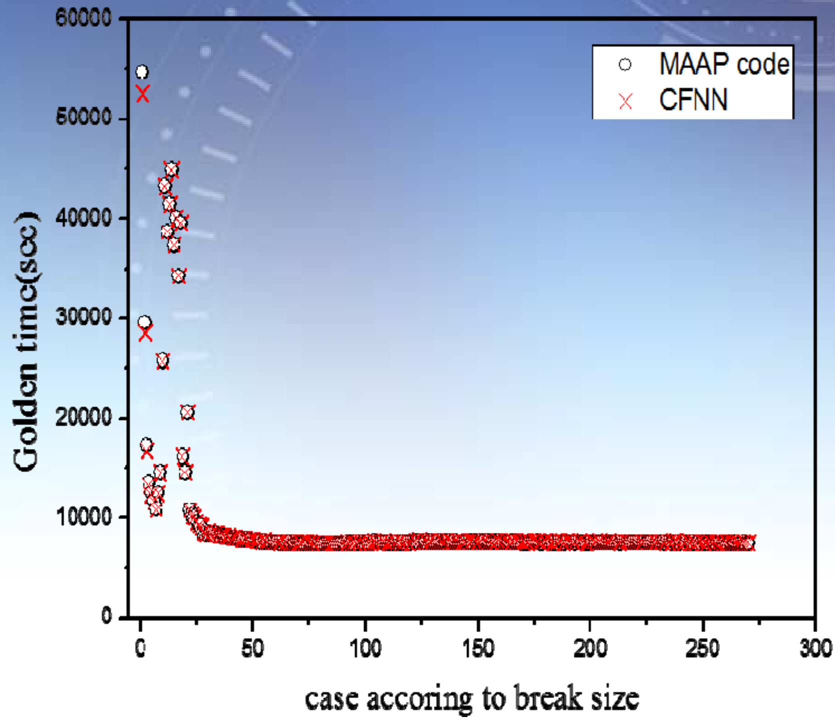
(HPSI delay, RV failure)

Application to Golden Time Prediction



Golden time prediction for Type 2

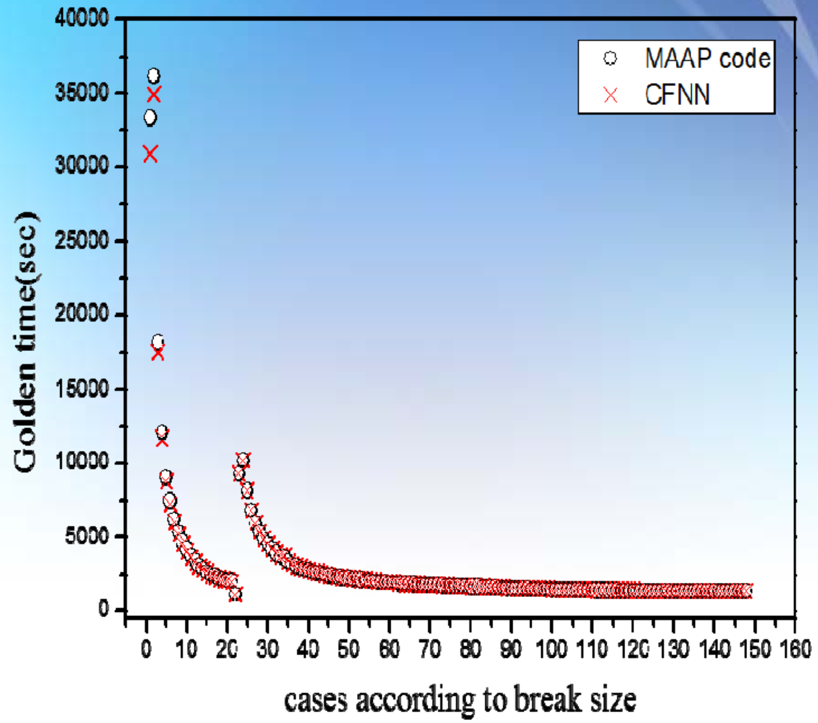
(LPSI delay, core uncovery)



Golden time prediction for Type 2

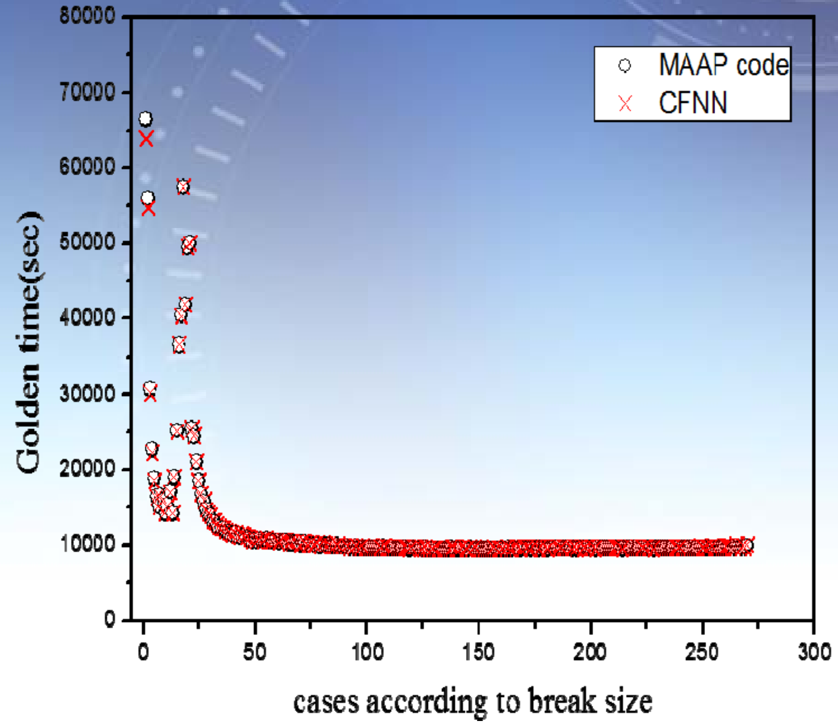
(LPSI delay, RV failure)

Application to Golden Time Prediction



Golden time prediction for Type 3

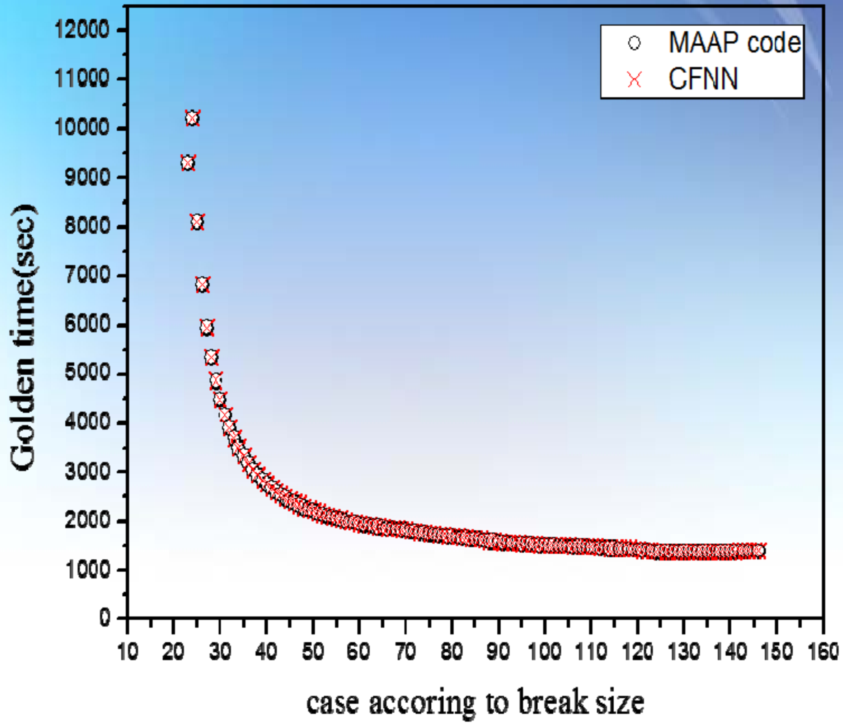
(HPSI delay, core uncovery)



Golden time prediction for Type 3

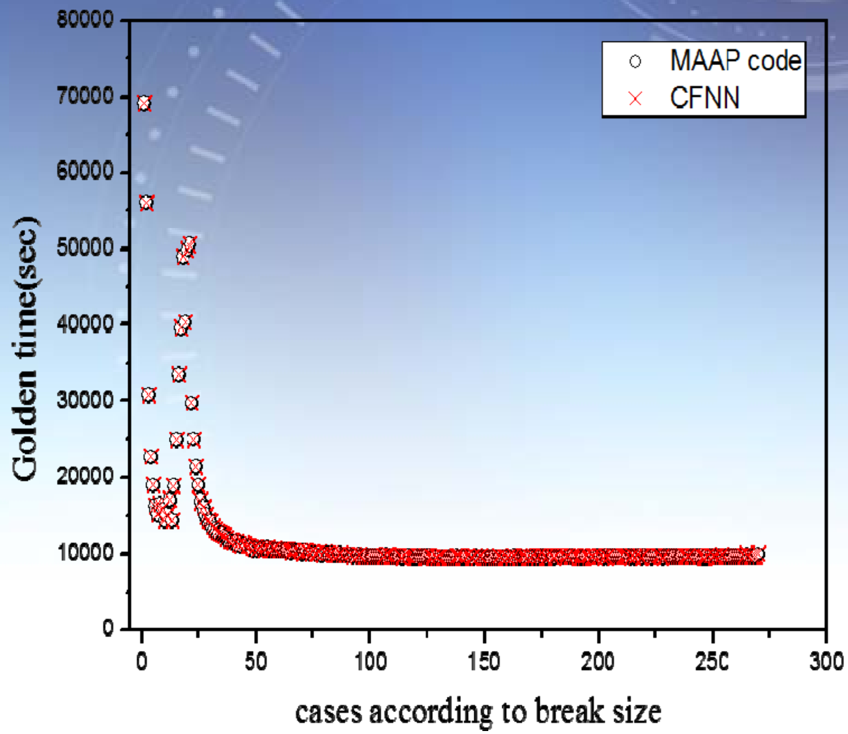
(HPSI delay, RV failure)

Application to Golden Time Prediction



Golden time prediction for Type 4

(LPSI delay, core uncovery)



Golden time prediction for Type 4

(LPSI delay, RV failure)

Application to Golden Time Prediction

조선대학교 CHOSUN UNIVERSITY

Prediction performance of CFNN (HPSI delay)

No	HPSI	No. of FNN Modules	Complexity	Training data RMS Error (%)	Test data RMS Error (%)
Hot-leg LOCA (Type 1)	Core uncovery	11	286	0.58	3.37
	RV failure	11	286	0.52	3.15
Cold-leg LOCA (Type 3)	Core uncovery	8	184	0.64	19.11
	RV failure	3	54	2.77	3.10

Prediction performance of CFNN (LPSI delay)

No	LPSI	No. of FNN Modules	Complexity	Training data RMS Error (%)	Test data RMS Error (%)
Hot-leg LOCA (Type 2)	Core uncovery	3	54	1.10	2.87
	RV failure	2	34	12.01	10.95
Cold-leg LOCA (Type 4)	Core uncovery	5	100	0.21	0.35
	RV failure	6	126	1.58	7.31

Application to Essential Information Prediction

조선대학교 CHOSUN UNIVERSITY

- Prediction of the reactor vessel water level (small LOCA)
  - Reactor vessel water level was predicted using FNN, SVR, GMDH and CFNN

No. of fuzzy rules	Hot-leg LOCA		Cold-leg LOCA		SGTR	
	RMS error(m) (Development data)	RMS error(m) (Test data)	RMS error(m) (Development data)	RMS error(m) (Test data)	RMS error(m) (Development data)	RMS error(m) (Test data)
2	0.4142	0.7726	0.4239	0.6011	0.3086	0.2147
3	0.2077	0.5911	0.1047	0.2253	0.3059	0.2222
5	0.1372	0.3218	0.1562	0.1957	0.3083	0.2206
7	0.1513	0.3587	0.1343	0.2114	0.2985	0.2106

Application to Essential Information Prediction

조선대학교 CHOSUN UNIVERSITY

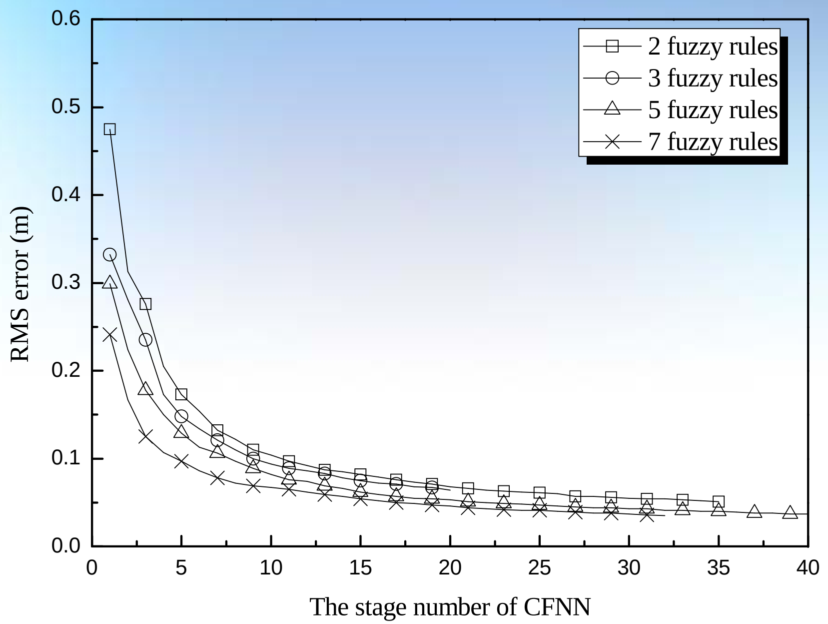
- Prediction of the reactor vessel water level (large LOCA)
  - Reactor vessel water level was predicted using FNN, SVR, GMDH and CFNN

No. of fuzzy rules	Hot-leg LOCA		Cold-leg LOCA		SGTR	
	RMS error(m) (Development data)	RMS error(m) (Test data)	RMS error(m) (Development data)	RMS error(m) (Test data)	RMS error(m) (Development data)	RMS error(m) (Test data)
2	0.0506	0.0864	0.1295	0.1921	0.3544	0.5734
3	0.0639	0.1348	0.1325	0.2881	0.3827	0.5349
5	0.0366	0.0705	0.1121	0.1488	0.3421	0.5006
7	0.0355	0.0381	0.1445	0.2812	0.3498	0.5060

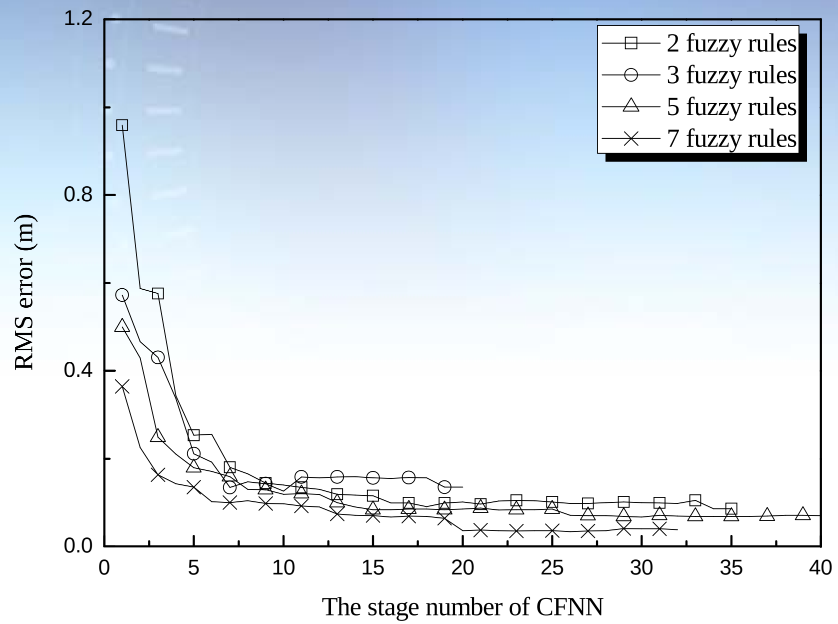
Application to Essential Information Prediction

CHOSUN UNIVERSITY 조선대학교

- Prediction of the reactor vessel water level
  - Performance of the CFNN model



<Development data>



<Test data>

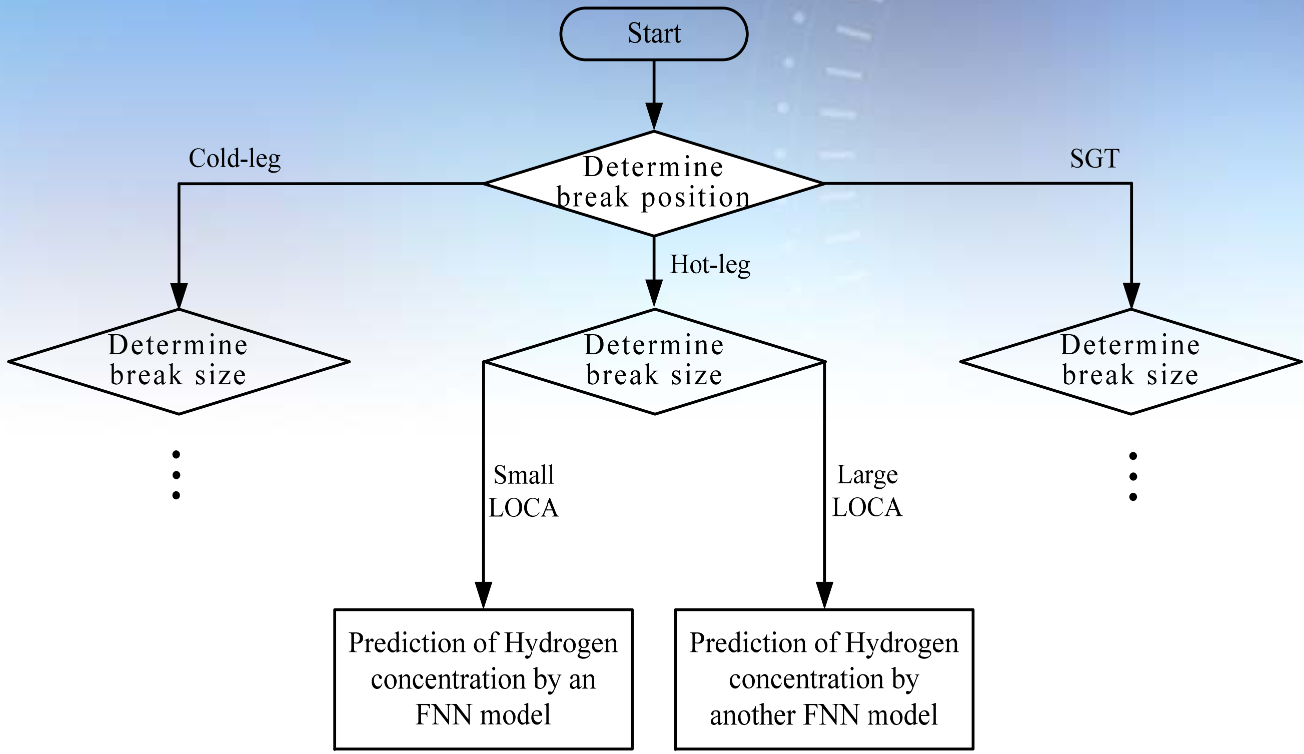
Application to Essential Information Prediction

- Prediction of the reactor vessel water level
  - Compare the results of FNN, GMDH and CFNN

Break position	CFNN model		FNN model		GMDH model	
	RMS error in small LOCA (m)	RMS error in large LOCA (m)	RMS error in small LOCA (m)	RMS error in large LOCA (m)	RMS error in small LOCA (m)	RMS error in large LOCA (m)
Hot-leg LOCA	0.3218	0.0705	0.5275	0.2295	0.78	0.32
Cold-leg LOCA	0.1957	0.1488	0.5595	0.3008	1.20	0.59
SGTR	0.2206	0.5006	0.4148	0.3950	0.43	0.37

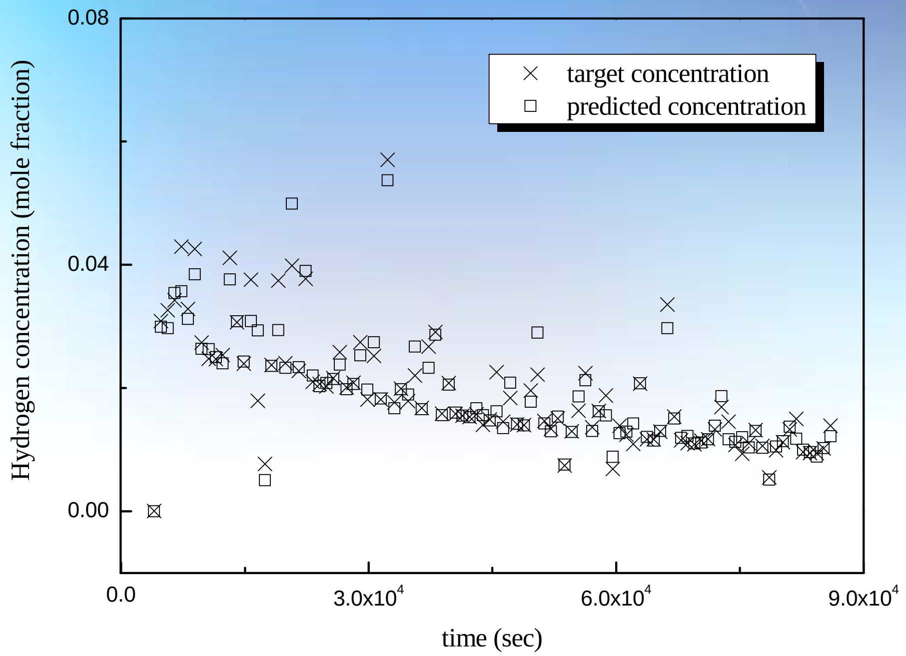
Application to Essential Information Prediction

- Prediction of hydrogen concentration in containment during severe accidents using FNN, GMDH and CFNN

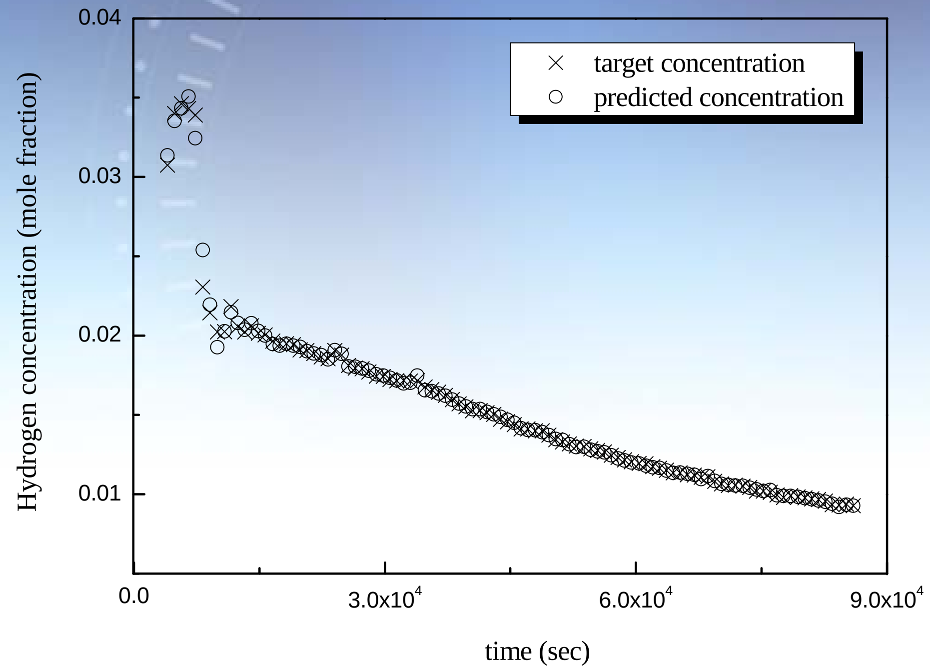


Application to Essential Information Prediction

- Prediction of hydrogen concentration in containment during severe accidents using FNN, GMDH and CFNN



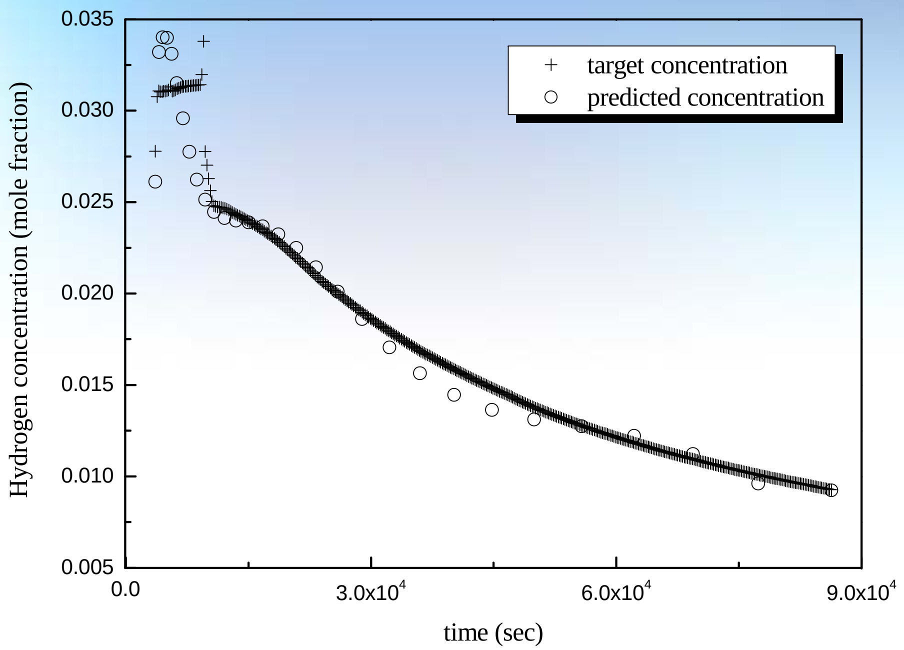
<Hot-leg small LOCA>



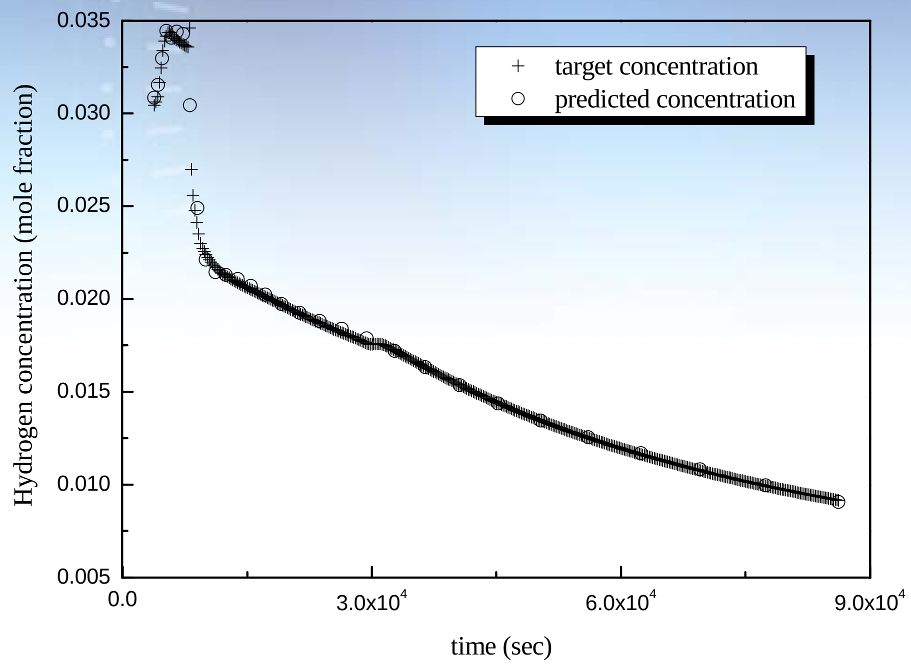
<Hot-leg large LOCA>

Application to Essential Information Prediction

- Prediction of hydrogen concentration in containment during severe accidents using FNN, GMDH and CFNN
  - Hydrogen concentration versus time at a specific LOCA break size



<Hot-leg small LOCA>



<Hot-leg large LOCA>

Summary

- Application of AI Methods to Event Identification
- Application of AI Methods to Accident Diagnosis (LOCA break size)
- Application of AI Methods to Accident Prediction (Scenario progression)
- Application of AI Methods to Accident Countermeasure (Golden time)
- Application of AI Methods to Essential Information Prediction

Thank you

조선대학교
CHOSUN UNIVERSITY