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A Study on Feasibility Evaluation for Prognosis Systems based on an Empirical Model in Nuclear Power Plants

Soo Ill Lee*

Central Research Institute, Korea Hydro and Nuclear Power co., (KHNP), Daejeon 305-343, Korea

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Abstract : This paper introduces a feasibility evaluation method for prognosis systems based on an empirical model in nuclear power plants. By exploiting the dynamical signature characterized by abnormal phenomena, the prognosis technique can be applied to detect the plant abnormal states prior to an unexpected plant trip. Early operator°Øs awareness can extend available time for operation action; therefore, unexpected plant trip and time-consuming maintenance can be reduced. For the practical application in nuclear power plant, it is important not only to enhance the advantages of prognosis systems, but also to quantify the negative impact in prognosis, e.g., uncertainty. In order to apply these prognosis systems to real nuclear power plants, it is necessary to conduct a feasibility evaluation; the evaluation consists of 4 steps (: the development of an evaluation method, the development of selection criteria for the abnormal state, acquisition and signal processing, and an evaluation experiment). In this paper, we introduce the feasibility evaluation method and propose further study points for applying prognosis systems from KHNP's experiences in testing some prognosis technologies available in the market.

Key words : prognosis, early fault diagnosis, feasibility evaluation, empirical model, nuclear power plant

1. Introduction

On-line monitoring (OLM) systems have been widely researched to enhance the safety and human reliability in nuclear power plants (NPPs). As new NPPs are applying an advanced digital main control room (MCR) and I&C systems, advanced man machine interface (MMI) has been widely researched. Recently, the prognosis technique, which is a kind of advanced computerized operator support system (COSS) beyond the conventional diagnosis technique which is related only to past states, be regarded as a solution to reduce time-consuming, unnecessary maintenance and unexpected downtime [1-2]. The reason why empirical modeling techniques have been widely studied is to difficult to depict a complex system like an NPP by mathematical modeling based on a differential equation; however, some of these techniques have already been installed in NPPs. On the other hand, NPPs in Korea have mainly employed deterministic diagnosis systems based on first principle modeling (e.g., design-based modeling, physics-based modeling) because it is difficult to solve the negative impact of unexpected outcomes or failures from the uncertainty of empirical modeling [3]. Fig. 1 shows that the prognosis concept of an abnormal state is effective not only in reducing the unexpected plant downtime by extending the operator's available action time, but also in avoiding time-consuming, expensive and unnecessary maintenance by enacting plans based on the prognosis result in advance.

Most studies based on the empirical model for NPPs

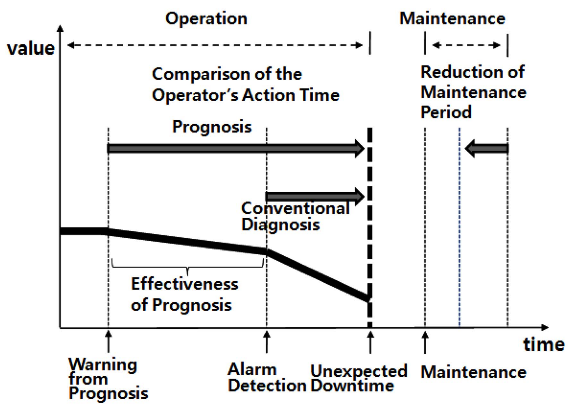


Fig. 1. Prognosis concept.

*Corresponding author: kangta1@khnp.co.kr

have concentrated on the area of signal validation (SV) and event identification (EI). In this paper, we propose a feasibility evaluation method that can be used for feasibility evaluation in the both case of SV and EI. The proposed method consists of the development of an evaluation measure, the selection criteria of abnormal states, acquisition and signal processing, and an evaluation experiment.

2. Related Work

NPPs in Korea mainly still rely on the conventional diagnosis systems based on first principle modeling and have tried to employ the empirical models to real NPPs, but several problems remain with the empirical model as outlined below:

- Solution and quantification of the uncertainty from the empirical model,
- Appropriate method to nuclear regulatory guide for the safety
- Human confusion and an increased workload by incorrect information from empirical modeling,
- Specific environment issues, i.e., noise, distortion, and aging,
- Dependency on human knowledge for modeling,

We surveyed recent prognosis studies, which are discussed below, related to NPPs to solve those problems by a proposed method. Most applications of the prognosis concept in NPPs have concentrated on the area of SV at the sensor level, and EI at the process level. In the area of EI, we reviewed four applications: Aladdin, EPI* Center, PHI (Plant Health Index) system, and ADIOS (Alarm and Diagnosis-Integrated Operator Support System). The OECD HRP (Halden Reactor Project) developed Aladdin on the basis of a recurrent neural network [4]. EPI* Center, supplied by Smart Signal Co., employs similarity based modeling as its nonparametric empirical model [5-6]. EPI* Center has been regarded as an application in practical use in technical reports. For the PHI system and ADIOS, developed in Korea, feasibility evaluations have been conducted [3].

In the area of SV for NPPs, we reviewed three applications: PEANO (Process Evaluation and Analysis by Neural Operators), PCSVR (Principle Component-based Auto Association Support Vector Regression) and EPRI's application which calls sensor calibration interval extension. The OECD HRP originally developed the PEANO, which employs a neural network and fuzzy-logic; this has been installed to the VC Summer NPP

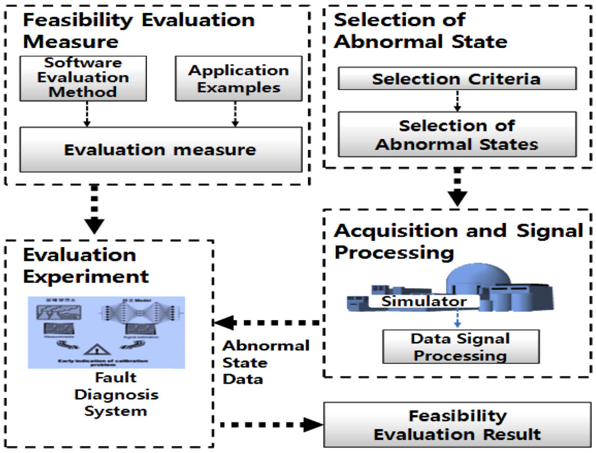


Fig. 2. Structure of the feasibility evaluation.

[7]. PCSVR, which was developed by KEPCO RI (Korea Electric Power CO., Research Institute), employs the PCA (Principle Component Analysis) and SVM (Support Vector Machine) regression methods [8]. Electric power research institute (EPRI) also developed an application that was installed at the Sizewell B NPP in 2007 [9]. U. S. nuclear regulatory commission (NRC) issued a safety evaluation report (SER) that concluded that the generic concept of OLM is acceptable and listed 14 requirements [10]. The on-line monitoring regulatory position of the U. S. NRC is in NUREG/CR-6895, which provides the technical details necessary to conduct an accurate evaluation of online instrument calibration monitoring techniques [11].

3. Feasibility Evaluation Method

The overall structure of the proposed feasibility evaluation method is shown in Fig. 2, which consists of 4 steps (: the development of an evaluation method, the development of selection criteria for the abnormal state, acquisition and signal processing, and an evaluation experiment). The analysis and simulation test of several application examples has been reviewed to develop the feasibility evaluation method.

3.1 Feasibility evaluation measure

Because it used to meet the critical software requirements when a new system is applied in an NPP, the evaluation measure has been extracted by considering the system reliability and the existing application examples of the feasibility evaluation, as shown in Table 1.

The equation (1) can be applied to the accuracy mea-

Table 1. Evaluation measure and application examples from system reliability angle

Evaluation measure	Application example
Accuracy	- Sensor Calibration Interval Extension (by EPRI) - Aladdin - PEANO - EPI* Center - PCSVR
Robustness	- Aladdin - PEANO - PCSVR

sure of the SV system.

$$A = \frac{1}{N}\sum_{i=1}^{N}(\hat{X}_i - X_i)^2 \tag{1}$$

A : Errors,
N : Number of evaluation tests,
$\hat{X}$: Predicted value on the i'th evaluation,
X_i : Real value from the process on the i'th evaluation.

On the other hand, the following probability equation (2) can be applied to the accuracy measure of the EI system.

$$A' = \frac{p}{N} \tag{2}$$

A' : Accuracy,
N : Number of evaluation test,
p : Number of well-recognition test.

For the robustness, if the quantity of a change can be measured, auto-sensitivity could be applied to the robustness measure of the early fault diagnosis technique as the following equation (3). Otherwise, the robustness result can be included in the accuracy measures (: equation (1), (2)) when the quantity of a change cannot be measured due to the complex various conditions.

$$S = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i| / |\hat{x}_i - x_i| \tag{3}$$

S : Auto-sensitivity,
N : Number of evaluation tests,
for the SV system,
$\hat{y}_i$: Predicted value on the i'th evaluation with noise or drift,
y_i : Predicted value on the i'th evaluation without noise or drift,
$\hat{x}_i$: Input value on the i'th evaluation with noise or drift,
x_i : Input value on the i'th evaluation without noise or drift.
For the EI system, When recognized successfully, $|\hat{y}_i - y_i| = 0$, otherwise, $|\hat{y}_i - y_i| = 1$.

Although this feasibility evaluation method did not deal with the real-time performance and reliability, two parameters should be considered when specifying the requirements of the system at the production stage by considering the cost, application area, etc.

3.2 Selection criteria of abnormal states

Because it is difficult to consider all fault states in a diagnosis system, an operational plant model related to the fault state, categorization and features should be derived [12]. Thus, we proposed the selection criteria of abnormal states as shown in Table 1. The applicable abnormal states in the proposed selection criteria were categorized and selected on the basis of the plant AOP (Abnormal Operating Procedure).

In the feasibility evaluations in this case, for the no. 1 and no. 2 criteria in Table 1, we statistically analyzed on the basis of the AOPs the unexpected trip data which was taken from six units of the OPR1000 (Optimal Power Reactor 1000MWe) type reactor and two units of the other type of reactor as shown in Table 2

Table 2. Selection criteria for abnormal states

No.	Selection criteria	Ranking method
1	Relationship to the reactor trip	• Analysis of the past fault data
2	Probability of fault states (according to past statistical data)	• Analysis of the past fault data
3	Easy of modeling the fault diagnosis system	• Physical process • Identification of the relationship between cause and effect
4	Performance of the early fault diagnosis system(accuracy, robustness)	• Simulation
5	Easy of quantifying uncertainty	• Analysis of the empirical model, • Simulation
6	Easy of training with the model	• Simulation

Table 3. Priority ranking to cause of unexpected trip and the type of artificial malfunction in simulator

Priority	The title of AOP	Physical process	# of artificial malfunction type
1	Turbine generator trip	×	8
2	Control rod drop and misalignment	×	1
3	Closure of main steam stop valve	×	-
4	Fault of the reactor control system	×	-
5	Fault of moving power transformer	×	1
6	Abnormal state of reactor coolant pump	○	8
6	Main feed-water pump trip	×	1
6	Leakage of reactor coolant system	○	3

[12]. Because the plant AOPs include not only system processes but also physical processes, no. 3 criterion must be checked to grasp the dynamic features of the prognosis capability, specifically whether or not the AOP is related to the physical.

In addition, past experience related to Aladdin and the EPI* Center shows their effectiveness in the case of leakage of the RCP(Reactor Coolant Pump) or in the event of bearing trouble. Because the most frequent trips, which are no.1 and no.2 in Table 2, were derived from trouble with various devices, it was difficult to identify the relationship between cause and effect. Therefore, "the abnormal state of RCP," which is ranked no. 6 in the Table 3, can meet the no. 4 criterion.

For the no. 4 criterion in Table 1, we conducted simulation tests to measure the performance (e.g., accuracy, robustness) for the case of the selected abnormal states by using various developed prognosis systems (e.g., Aladdin, EPI* Center). These simulation tests used an abnormal states dataset, acquired from the APR1400 (Advanced Power Reactor 1400MWe) simulator with varying of proceeding time, slope, level, temperature and flow for the malfunctions, in an effort to measure the robustness as well as the accuracy.

3.3 Acquisition and signal processing

For the EI evaluation experiment, the data obtained from the simulation are configured for 8 types of abnormal state and 1 type of normal state related to RCP. We

Table 4. Eight abnormal states

Abnormal State	Description	Varying conditions
State #1	RCP PP01A Seal #1 Failure	proceeding time, slope
State #2	RCP PP01A Seal #2 Failure	proceeding time, slope
State #3	RCP PP01A Seal #3 Failure	proceeding time, slope
State #4	RCP #1A Trip	-
State #5	Reactor Coolant Pump PP01A Sheared Shaft	proceeding time, slope
State #6	Oil Reservoir 1A Level	level
State #7	RCP PP01A CTRL Bleed Off Temp.	temperature
State #8	RCP PP01A CTRL Bleed Off Flow	flow

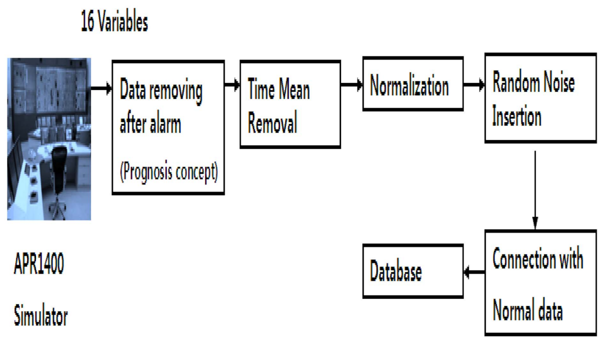


Fig. 3. Procedure of digital signal processing.

conducted five tests per each state with varying of proceeding time and slope for system malfunction, with varying of the level, temperature and flow for the component malfunction, which aims at evaluating the robustness of the prognosis systems. In order to cover the eight abnormal states as shown in Table 4, we dealt with 16 variables by using a sampling rate of 1 SPS (Sample Per Second).

The overall procedure of digital processing, which can create the experimental environment for evaluation of the robustness and can evaluate early diagnosis performance before alarm occurs, is summarized in Fig. 3.

For the SV evaluation experiment, we used the real start-up mode data, which include 65 variables, acquired from real Kori NPP unit #3 and select the highly correlated 11 variables as shown in Table 5. We employed 3 types of the change of drift (: decrease exponentially at the range of 75%, 80%, 85%) and 3

Table 5. Eight abnormal states

No.	The name of variable
1	CorePwr
2	PZRLvl1
3	MFW1Fw1
4	TBNPwr
5	TBNSpd
6	RCCL1Tp
7	RCSPr
8	SG1Fw1
9	SG1Lvl
10	SG1Pr
11	SG1WLvl

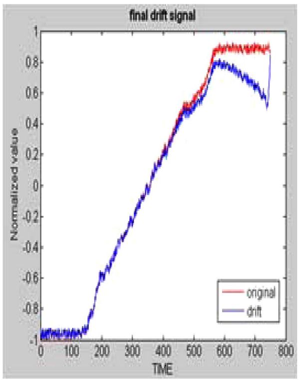


Fig. 4. Example of drifted data.

types of the maximum range of random noise(: 1%, 4%, 7%). In Fig. 4, red line means the original signal, and blue line means the drift signal which is artificially added by noise and exponential function. The total number of experiment can be 165 times(: 3 types of drift * 11 variables * 5 datasets) [12].

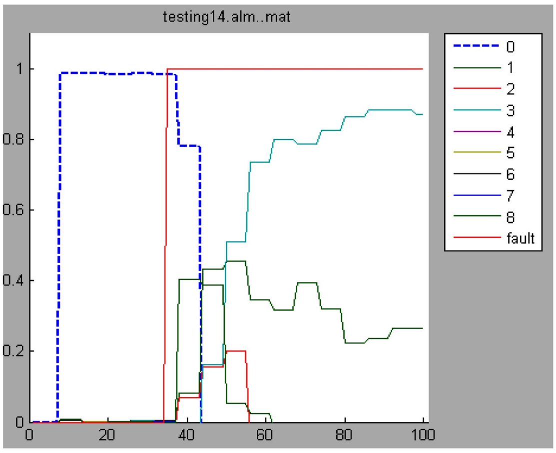
3.4 Evaluation experiment

In this paper, we used the Aladdin system and EPI* Center for the EI evaluation experiment. Because Aladdin employs the ensemble concept of recurrent neural network to solve the difficulty of training and the WOLP (Wavelet On-Line Pre-processing) [4], we conducted the experiment with various sizes of the window and ensemble. Table 6 shows the accuracy of 100% for states #4 to #8, and lower accuracy for states #1 to #3. For states #1 to #3, selected variables for the Aladdin were unable to diagnose the abnormal states accurately with quite large recognition errors.

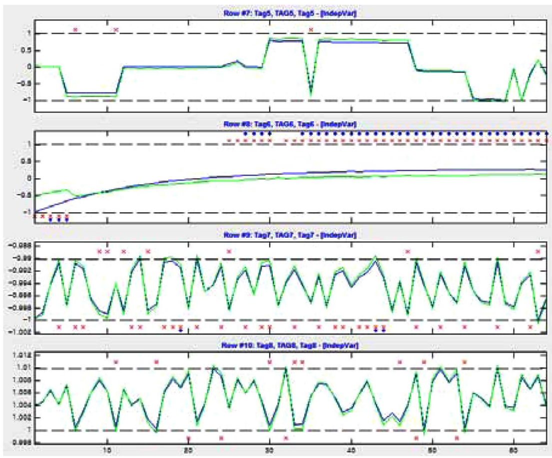
This evaluation experiment shows the accuracy of 81.1% by equation (2). However, Table 6 shows not

Table 6. Recognition performance of Aladdin (Success Number/Trial Number)

Abnormal State	Trial #1	Trial #2
State #1	0/5	0/5
State #2	1/5	3/5
State #3	5/5	4/5
State #4	5/5	5/5
State #5	5/5	5/5
State #6	5/5	5/5
State #7	5/5	5/5
State #8	5/5	5/5



(a) Misrecognized result by Aladdin



(b) Well−recognized result by EPI* Center

Fig. 5. Simulation test examples for the state#1.

only robustness but also accuracy due to the dataset obtained by the acquisition process with varying conditions (: proceeding time, slope, level, temperature and flow) and artificial insertion of random noise. As described equation 3, we did not measure the robustness independently because various conditions and random noise were employed.

Fig. 5 shows two examples of the recognition results by two kinds of prognosis applications. The X axis denotes the time and the Y axis indicates the normalized values of process variables. As shown in Fig. 5(a), the result of Aladdin contains errors, as can be recognized by state #3 for abnormal state #1. Fig. 5(b) is an example of the accurate recognition of abnormal state #1 by EPI* Center.

Although we did not deal with the no. 5 and no. 6 criteria in our feasibility evaluation, we added the two criteria to note the interaction between a human and the empirical model:

- no. 5 criterion can give the confidence of the empirical model to a human by clarifying or quantifying the uncertainty.
- no. 6 criterion can give the convenience of a human to maintain an empirical model of the prognosis system.

In this paper, we used the PCSVR system for the SV evaluation experiment. Fig. 6 shows an example of the well-predicted result by drift input signal. The X axis denotes the time and the Y axis indicates the normalized values of process variables. As shown in Fig. 6, when the difference between measured drift signal and predicted signal is bigger than the designated value, the operator can realize the abnormal state of the signal.

The total average of the error rate by equation (1) is 0.1495. As shown in Fig. 7, the change of the error rate is much affected by drift range compared to by noise weight.

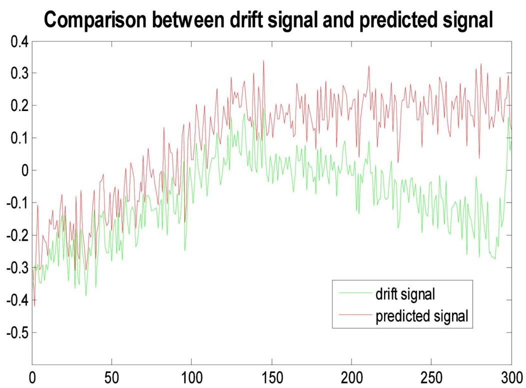
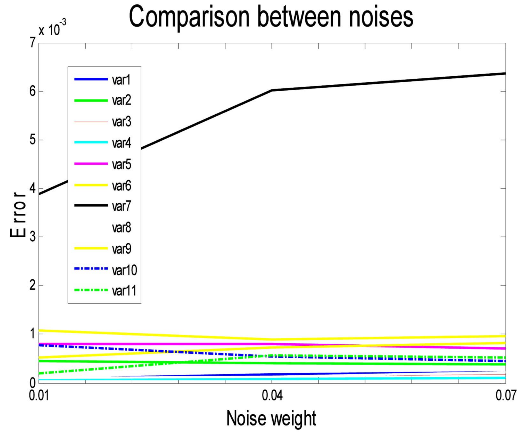
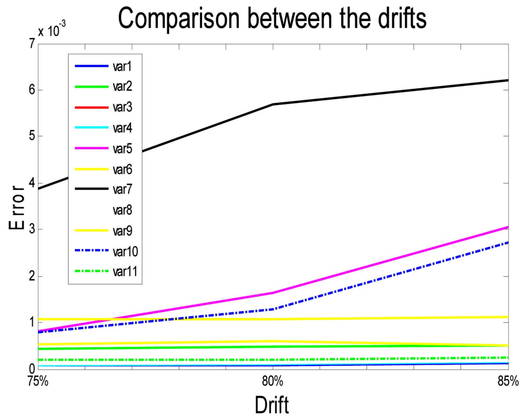


Fig. 6. Simulation test examples by SV system.



(a) Error rates by the change of noise weight



(b) Error rates by the change of drift range

Fig. 7. Robustness test by SV system.

4. Conclusion

In this paper, we introduce a feasibility evaluation experience and method that is made up of the development of an evaluation measure, the development of selection criteria for the abnormal state, acquisition and signal processing, an evaluation experiment for applying the prognosis systems to real NPPs in Korea. The result of this experiment indicates that it is somewhat feasible to apply the empirical model to real NPPs, but we have also found improvement points for a further study as summarized below.

- Comparison between the performance of the existing prognosis systems,
- Careful selection of variables and faults for finding optimized variable set,
- Development of a prognosis algorithm to make the uncertainty minimized,
- Solutions for other difficulties (e.g., environmental issues, dependency on human knowledge).

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