

# Study on Reactor Operation Automation System with AI based Program Application

Sanghoon Bae<sup>a\*</sup>, Seop Hur<sup>a</sup>, Seoryong Koo<sup>a</sup>

<sup>a</sup>Advanced Control Research Lab. Korea Atomic Energy Research Institute, Youseong-gu Daedeokdaero 989 Daejeon

\*Corresponding author: shbae@kaeri.re.kr

## 1. Introduction

The nuclear power plant start-up & shut-down operation requires very demanding manual works like checking process parameters and status of control equipment. This leads to high chance of operator's mistakes and errors. The designed automation system for reactor operation is a tool that dramatically reduces the possibility of error occurrence by automating such intensive process. Based on the operation procedures which of the existing power plants are analyzed and regularized, with as technical guidelines or OLC (operation limiting conditions) such things theoretically enable to turn manual operation into automation. However, the operator-friendly and super-convenient automation system is found hard to go through and lots of calls to deal with from the perspective of licensing. Therefore, the truly critical license issues are discussed herein and some alternatives are offered to move forward.

## 2. Methods and Results

The developed operation automation system has this key function of automatic execution of startup and shutdown process, automatic control of main parameters, and providing plant status with operation information. The system requirement for this is largely similar with one of normal plants and both its hardware and software are classified into a non-safety-related system, which it means, should not affect the soundness and functional performance of the existing safety-related system. The overall structure of operation automation system can be shown in Fig. 1. overall

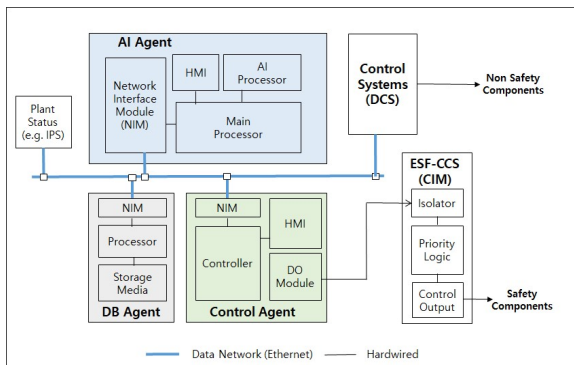


Fig. 1. Generic structure of operation automation system

In order to prove the justification of not affecting safety system, the following requirements should be verified.

- Physical independence from safety systems
- Electrical independence from safety systems
- Independence of data interface with safety systems
- Functional independence of safety system

This automation system executes only in normal operation mode and abnormal plant status whereas it is not allowed to interject in emergency operation of the plant. However, it should be evaluated whether there are any factors that would prevent or delay entry into the emergency operation procedure due to incorrect decision of the system.

### 2.1 Structure of Developed Automation System

The main function of start/stop automation system has been verified through the APR-1400 simulator. As for the early stage, it is reasonable to assume that the similar environment test stage of TRL (Technical Readiness Level) five to six has been completed. As shown in Fig.1, this system consists of AI agent, control agent, and DB agent, respectively, like a functioning group.

For automatic execution of operation procedure, AI agent receives operating data from IPS (Information Process System) of the plant and this is conducted by rule-based expert system. The Control agent comprises each DCS (Distributed Control System) for local control panels and after receiving the control demand signal from AI agent which calculate the control algorithm, it leads to control local equipment by this process. For operation trend, DB agent has function of collecting, storing real-time data from plants and historical data of automation system.

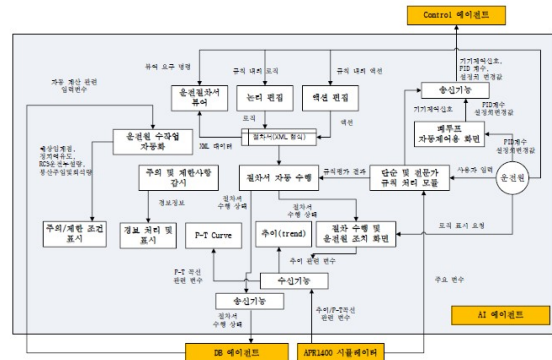


Fig. 2. Functional diagram of AI control agent

## 2.2 Pending Issues related to Safety Requirement

In order to apply this automation system to the site, extra evaluation and verification step for site adaptability should be thoroughly carried out with in-site testing. The pending issues related to license such as operation of safety grade devices should be also considered. The following things are likely close to remained key issues of license; 1) automation of safety class equipment, 2) a design plan for the application of start-up/shutdown automation system, 3) validation of prototype of this automation system, 4) field application evaluation of this system.

Besides, human errors should be reduced through such autonomous operation for better application and a few more details should be evaluated for this purpose like job load reduction and time allowance which should be determined through job time analysis (TTA). It also should be confirmed through design testing of human system linkage (HSI). Unlike most deterministic logic-based procedure instruction, this automatic operation features the capability of detection of abnormal condition by artificial neural network-based data learning.

However, the information on this automation system may affect the operator's judgment, and in this aspect, it is difficult to say that safety is not ruled out. Therefore, verification of the information provided by AI should be proceeded for practical license to go through successfully, and the development of reasoning must be checked out like a white box. In other words, the cause of the model's learning process must be cleared and compensated.

## 2.3 Ongoing Study of Explainable AI

Explainable AI (XAI) technology refers to one of AI that can explain the actions and judgments of AI in a way that humans can understand. Since decisions can be made based on solid evidence, the reliability of support information can be secured by providing information from operation automation system.

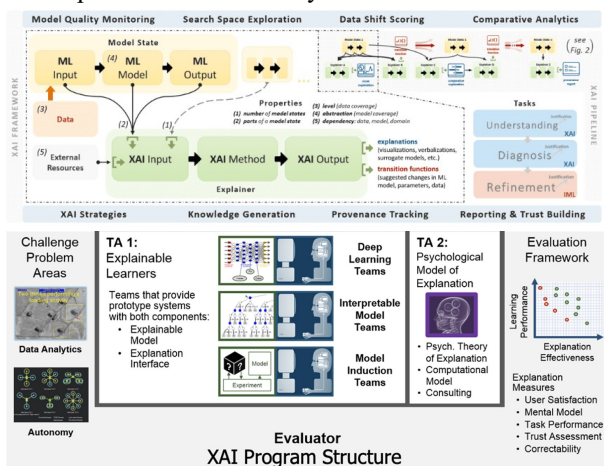


Fig. 3 XAI frameworks for general interpretation

If the process of judging an AI model is interpreted through AI and can be explained, it can also be analyzed to improve the performance of the model itself and obtain qualitatively improved results. Basically, AI application herein must be interpretable for human verification and be secured to support it in a safe and reliable manner. Necessity of explainable AI application is being discussed to compensate for lack of internal information.

The AI model for determining abnormal states used in the actual condition was learned from data produced through a simulator with a structure that receives three channels as input to a convolutional neural network. A total of nine abnormal states can be determined, and the accuracy of the final model's verification data was 98.4% and explainable AI process can be shown in Fig.4.

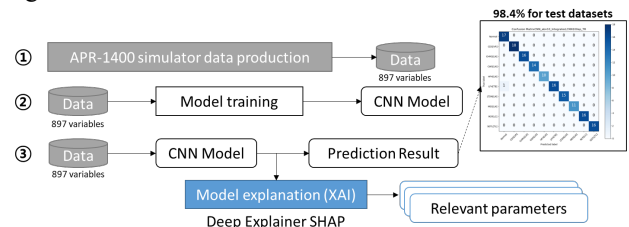


Fig. 4 Process of learning explainable AI technology applying to abnormal status judgment models.

The evaluation data for each abnormal state was input into the learned model and interpreted through Deep Explorer SHAP, a technique for explaining the results obtained. The data used for learning and testing has 897 variables, and the degree of relevance of the judgment results made by the AI model for all variables is calculated through Deep Explorer SHAP.

The selected top variables are not intended to completely match the entry conditions of the abnormal operation procedure, but represent the variables that have most contributed to the purpose of distinguishing each abnormal condition. Therefore, analyzing the results of explainable AI technology is expected to identify potential defects in operation automation system.

## 3. Conclusions

The designed automated system for reactor operation will have far-reaching impact on future autonomous operation system that has so many advantages compared to current system. Nonetheless, the scope of AI application included herein never pursue autonomous operation. It would rather say that AI technology does not directly run safety devices on behalf of operators or making big judgments affecting safety, so it still does not yet belong to the licensing category. In the long run, explainable AI research introduced herein has been conducted and it is confirmed that the performance of

the model itself can be improved in quality although it is not perfect.

#### **REFERENCES**

- [1] Seung Jun Lee, Poong Hyun Seong, Development of automated operating procedure system using fuzzy colored petri nets for nuclear power plants, *Annals of Nuclear Energy*, 2004.
- [2] Finale Doshi-Velez and Been Kim. Towards a rigorous science of interpretable machine learning. arXiv preprint, 2017.
- [3] Amina Adadi and Mohammed Berrada. Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI). *IEEE Access*, 6:52138–52160, 2018.
- [4] Information Commissioner’s Office and The Alan Turing Institute. Explaining decisions made with AI, 2020.
- [5] Timo Speith, Authors Info & Claims. A Review of Taxonomies of Explainable Artificial Intelligence (XAI) Methods, June 2022 Pages 2239–2250