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Development of Nuclear Power Plant Safety Evaluation Method for the Automation Algorithm Application

Seung Geun Kim [a], Poong Hyun Seong [a*]
[a]*Department of Nuclear and Quantum Engineering, KAIST, 291, Daehak-ro, Yuseong-gu, Daejeon, 34141, Republic of Korea*
[*]*Corresponding author: phseong1@kaist.ac.kr*

1. Introduction

As the nuclear power plant (NPP) is one of the largest and most complex process control systems, human operators perform significant roles in the operation of NPPs. In this reason, deficiencies in human factors such as poor HSI (Human System Interface) design, procedure, and training, are significant contributing factors to NPPs incidents and accidents [1].

For this reason, various studies such as human reliability analysis (HRA), operation support system, and automation, have been conducted in order to reduce human errors in NPPs. Among these, automation has unique characteristic that it mainly focuses on eliminating the human error-inducing tasks to reduce human error, while others are focusing on aiding human operators during operation.

It is commonly believed that replacing human operators to the automated system would guarantee greater efficiency, lower workloads, and fewer human errors [2]. However, these beliefs are not always true in large and complex systems such as NPP, since excessive automation can generate new roles for human operators, change human operators' activities in unexpected ways, and inducing 'out-of-the-loop' (OOTL) problem [3]. Moreover, conventional machine learning techniques are considered as not capable to handle complex situations in NPP.

Due to these kinds of issues, automation is not actively adopted although human error probability drastically increases during abnormal situations in NPP due to overload of information, high workload, and short time available for diagnosis.

Recently, new machine learning techniques, which are known as 'deep learning' techniques have been actively applied to many fields, and the deep learning technique-based artificial intelligences (AIs) are showing better performance than conventional AIs. In 2015, deep Q-network (DQN) which is one of the deep learning techniques was developed and applied to train AI that automatically plays various Atari 2800 games, and this AI surpassed the human-level playing in many kind of games [4]. Also in 2016, 'Alpha-Go', which was developed by 'Google Deepmind' based on deep learning technique to play the game of Go (i.e. Baduk), was defeated Se-dol Lee who is the World Go champion with score of 4:1 [5].

Previously, most of AI applications in nuclear field were focusing on aiding human operators by rapid classification and prediction based on fixed training data sets, and capable for only limited situations. However, just like as 'Alpha-Go' wins the top-level human player although the game of Go was one of the most challenging area in machine learning field, it is expected that automation algorithm developed with these new machine learning techniques can cover more complicated situations in NPPs.

For the development of automation algorithm in NPP, it is essential to properly evaluate the status of the plant quantitatively in real-time. However, existing methodologies for NPP safety evaluation such as probabilistic safety assessment (PSA) or safety performance indicator (SPI) have some incompatibilities since they are not capable for the cases which are not included in the model, and hard to evaluate in real-time. Therefore, development of new NPP safety evaluation methodology should be preceded in order to conduct the study on NPP automation further.

In this paper, the concept of early warning score (EWS) in medical field was adopted to develop the new safety evaluation methodology for NPP. Detailed description will be provided in section 2.

2. Methods and Results

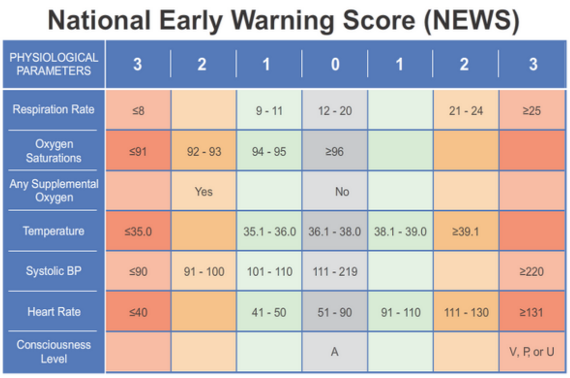
In this section, the concept of early warning score (EWS) is briefly introduced, and the method of application is described.

2.1 Early Warning Score (EWS) Concept

Early warning score (EWS) is the system which can evaluate the patients' level of seriousness in real time, with quantitative score based on various vital signs.

Most of EWS systems have been developed based on six kinds of vital signs, including respiration rate, oxygen saturations, body temperature, systolic blood pressure, heart rate, and the level of consciousness, although there are some differences in detail according to applying country, ethnicity, and other attributes.

By observation, score for each vital sign can be obtained and the final score which is the summation of each score can be also obtained. If the score gets higher, it means that the patient is in more serious state (if the total score is zero, it means that the patient is in normal state). According to the total score, corresponding action is taken to the patient.



National Early Warning Score (NEWS)

PHYSIOLOGICAL PARAMETERS	3	2	1	0	1	2	3
Respiration Rate	≤8		9 - 11	12 - 20		21 - 24	≥25
Oxygen Saturations	≤91	92 - 93	94 - 95	≥96			
Any Supplemental Oxygen		Yes		No			
Temperature	≤35.0		35.1 - 36.0	36.1 - 38.0	38.1 - 39.0	≥39.1	
Systolic BP	≤90	91 - 100	101 - 110	111 - 219			≥220
Heart Rate	≤40		41 - 50	51 - 90	91 - 110	111 - 130	≥131
Consciousness Level				A			V, P, or U

Fig. 1. EWS example: National EWS of UK [6].

Standards for each vital signs and total EWS score are usually established by expert consultation [6] or statistical methods [7]. Statistically, positive correlation between EWS score (specifically, a score of five or more) and likelihood of death or admission to an intensive care unit is observed [8].

2.2 Method of Application

In order to apply the concept of EWS in NPP, two major steps are needed. The first step is to select the parameters which represent the safety state of NPP, as vital signs represent the patient's condition in medical field. The second step is to set the proper scoring system for each selected parameter.

The first step can be conducted by enumerating all safety-related parameters and eliminating the parameters which have 'strong correlations' (either positive or negative) between parameters. In this study, various procedures and safety analysis reports were investigated and parameters that appeared in these documents were enumerated. Correlation analyses between listed parameters were conducted in order to eliminate parameters that have strong correlations.

Regarding the second step, it is more complicated since in medical field, it is possible to select statistical approach based on plenty samples (i.e. patients) while similar approach is not feasible due to lack of samples (i.e. incidents or accidents in NPPs) in nuclear field. Alternatively, it is expected that setting of proper scoring system is possible by conducting the simulation analysis about NPP components and systems.

2.3 Example of Application

Since this study is in the conceptual stage, brief explanations about how the results of this study that can be applied to automation of NPPs are addressed instead of detailed results.

Consider that developed EWS for NPP involves three kinds of safety parameters (X, Y, and Z). The individual score for each parameter can be evaluated as 0 to 3, or newly added 'C' score (see Table I). Score C is added in order to cover the special situations in NPPs that require immediate mitigation actions.

Table I. Simple example of EWS for NPP

Parameters	C.	3	2	1	0	1	2	3	C.
X									
Y									
Z									

The method for total score evaluation is similar with conventional EWS system (i.e. summing up the score for each parameter), while the number of parameters that have the score of C is counted separately. Automation algorithm will select most feasible action for current state based on the total score, that involves numerical total score and the number of C (i.e. an action which can mostly decreases the total score). In this process, the number of C is preferentially considered than the numerical total score.

For example, if the current state is evaluated as 2 for parameter X, C for Y, and 1 for Z, then the total score for corresponding state is '3 with 1 C'. Assume that there are only two possible actions, action A and B.

When the action A is implemented, the expected state is 0 for parameter X, C for Y, and 0 for Z (totally 0 with 1 C). For the action B, the expected state is 3 for parameter X, 3 for Y, and 3 for Z (totally 9 with 0 C). In this case, properly trained automation algorithm should select the action B although numerical score of the expected state is higher, since the number of C is preferentially considered.

Obviously, the state which is evaluated as '0 with 0 C' is most feasible for the safety of NPP. Thus, automation algorithm will continue to search and implement the most feasible action if there is any deviation between the current state and the most feasible state (state of 0 with 0 C),

3. Conclusions

By the effort for reducing human error in NPPs, the ultimate goal of this study is the development of automation algorithm which can cover various situations in NPPs. As the first part, quantitative and real-time NPP safety evaluation method is being developed in order to provide the training criteria for automation algorithm. For that, EWS concept of medical field was adopted, and the applicability is investigated in this paper.

Practically, the application of full automation (i.e. fully replaces human operators) may requires much more time for the validation and investigation of side-effects after the development of automation algorithm, and so the adoption in the form of full automation will take long time.

Still, automation algorithm can be properly applied for the development of operation support system which can cover even highly complex situations in NPPs. As many other applications of deep learning techniques have been proven to have good performance, it is expected that the operation support system developed by using the technique could work just like human operators, or better.

REFERENCES

[1] J. S. HA, et al., "Development of Human Performance Measures for Human Factors Validation in the Advanced MCR of APR-1400," IEEE Transactions on Nuclear Science, Vol. 54, No. 6, p. 2687-2700 (2007)

[2] D. D. WOODS, *Automation: apparent simplicity, real complexity*, p. 1-7, M. MOULOUA, R. PARASURAMAN, Ed., Lawrence Erlbaum Associates, Hillsdale, New Jersey (1994).

[3] S. M. LEE, et al., "Optimization of automation: II. Estimation method of ostracism rate based on the loss of situation awareness of human operators in nuclear power plants," Annals of Nuclear Energy, Vol. 79, p. 93-100 (2015).

[4] V. MNIH, et al., "Human-level control through deep reinforcement learning," Nature, Vol. 518, p. 529-533 (2015).

[5] D. SILVER, et al., "Mastering the game of Go with deep neural networks and tree search," Nature, Vol. 529, p. 484-489 (2016).

[6] B. WILLIAMS, et al., "National Early Warning Score (NEWS): Standardising the assessment of acute-illness severity in the NHS," London:RCP-2012, The Royal College of Physicians (2012)

[7] J. GARDNER-THORPE, et al., "The value of Modified Early Warning Score (MEWS) in surgical in-patients: a prospective observational study," Annals of the Royal College of Surgeons of England, Vol. 88, p. 571-575 (2006).

[8] C. P. SUBBE, et al., "Validation of a modified Early Warning Score in medical admissions," Quarterly Journal of Medicine, Vol. 94, p. 521-526 (2001).