Development of Evaluation Method for Startup Operation of Nuclear Power Plants

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1. Introduction

Autonomous operation has been one of the main concerns due to the advantage of excluding human error in industrial fields. In the case of nuclear power plants (NPPs), there are some automated systems to assist operators for safety. Such a system is mainly composed of algorithms to maintain specific variables during power operation or to automatically activate safety functions in case of an emergency situation. However, the overall operation flow must be performed by humans, which has resulted in an increased operator workload in startup and shutdown operations where temperature and pressure change dynamically. In case of startup operation, operating tasks are conducted by human operators manually, taking more than 20 hours to finish.

In the previous work, the framework to develop autonomous system for startup and shutdown operation was suggested [1]. In this paper, evaluation method for startup operation of NPPs is suggested by quantifying operation performance. As an application, artificial intelligence (AI) model was implemented to two operating blocks and a plant parameter prediction model.

Since the action was selected through the exploited method for the convergence of reinforcement learning (RL) in the training stage, the evaluation of the suboptimal action is not learned as detailed as the best action. Nevertheless, in a complex multi-agent environment, the influence between agents cannot be ignored. This is why the evaluation method is needed regardless of RL training.

2. Framework of autonomous operation

2.1 Autonomous system: operating modules

Figure 1 is a framework proposed for autonomous operation of nuclear power plants. In a given state, the AI will play the role of selecting and performing an action based on the operation policy. At this time, since the actions received from the operation block may conflict, the supervisory operation module goes through the action selection process so that the actions can be prioritized.

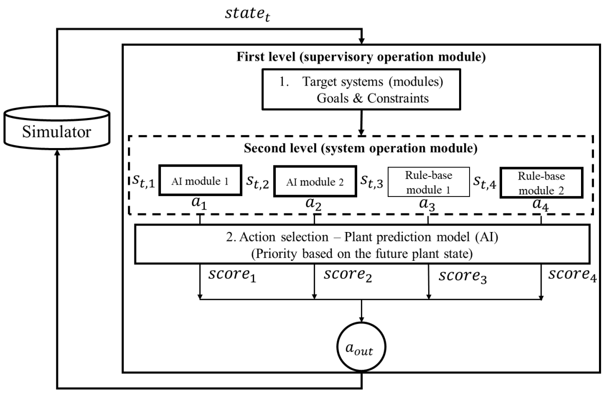


Fig 1. Framework of autonomous operation for NPPs.

The autonomous system consists of two levels: supervisory and system operating modules. Supervisory operating module manages the overall operational flow. System operating module includes operating blocks that perform small operation units that operating tasks subdividing operating tasks into. The concept of operating block was introduced by analyzing general operating procedure. Each block has an entry condition and a terminal condition, so if the conditions are satisfied, they can parallelly perform their own operation. RL is a field of machine learning, in which agents learn better behavior by receiving feedback on their behavior from an environment [2]. Operating blocks implements RL to obtain optimal policy to achieve their tasks.

2.2 Plant parameter prediction

In training stage, local agents received relatively limited information about state and reward out of global ones because a huge facility such as an NPP need to be divided into small units to apply autonomous system. Therefore, it is necessary to perform operation in a multi-agent environment. For example, a water level control operation block will be rewarded based on the target water level.

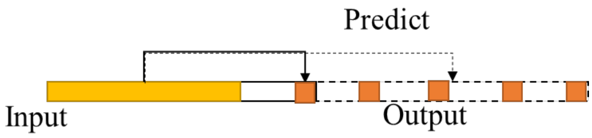


Fig 2. A plant parameter prediction model is trained by supervised learning with input data and chosen action

In a multi-agent environment where individually trained local agents output each action, it is important to set priorities among the actions. Figure 2 illustrates prediction model takes input data to predict future state of the parameters. According to the change of the variables related to the limiting conditions for operation (LCO), it is determined whether the operation is proceeding in a good direction or not.

The algorithm to be used for prediction is selected as a regression model that predicts data at a future point in time based on the data accumulated for a given time.

3. Application

A compact nuclear simulator (CNS) provided training data and a simulating environment. The CNS models three loops Westinghouse PWR, 993MWe, developed by Korea Atomic Energy Research Institute (KAERI) [3]. Soft actor-critic algorithm was implemented to control a pressurizer (PZR) pressure and level during startup operation [4]. The LSTM algorithm is used to predict the variable of an NPP, and the change of the variable up to the future after 9 minutes is predicted [5].

As the first stage in the development of the operational evaluation methodology, the number of actions is consisted of a combination of two valves to simplify the problem. That is, charging water flow control valve and letdown flow control valve, FV122 and HV142 respectively appeared in the simulator, have 9 possible combination; none (00), open (01) and close (10). To distinguish them simply, they are displayed as numbers separated by 4 digits 0,1. Therefore, a total of 9 AI models are prepared.

For 17 variables listed as table 1, there are 10,000 datasets with an interval of 600 seconds. As shown in Fig. 3, the AI model has an input data up to 1 min and predicts values up to 10 min at 1-min intervals.

Table I: output variables from predicted models

No.	Description
1	PZR TEMPERATURE.
2	LETDOWN BACK PRESSURE
3	LETDOWN FLOW
4	CHARGING FLOW
5	PZR PRESSURE(NARROW RANGE)
6	LOOP 3 AVERAGE TEMP
7	LOOP 2 AVERAGE TEMP
8	LOOP 1 AVERAGE TEMP
9	PZR LEVEL
10	VOLUME CONTROL TANK LEVEL.
11	VCT PRESSURE
12	RCP SEAL INJECTION FLOW
13	RCP SEAL NO.1 DELTA PRESSURE
14	RCP SEAL NO.1 RETURN FLOW
15	S/G 3 PRESSURE
16	S/G 2 PRESSURE
17	S/G 1 PRESSURE

*VCT: Volume Control Tank, RCP: Reactor Coolant Pump, S/G: Steam Generator

A sample of dataset										
0	60 sec	120 sec	180 sec	240 sec	300 sec	360 sec	420 sec	480 sec	540 sec	600 sec
Input	Output (# of predicted points: 9)									

Fig. 3. Time and configuration per sample of data used for training and test

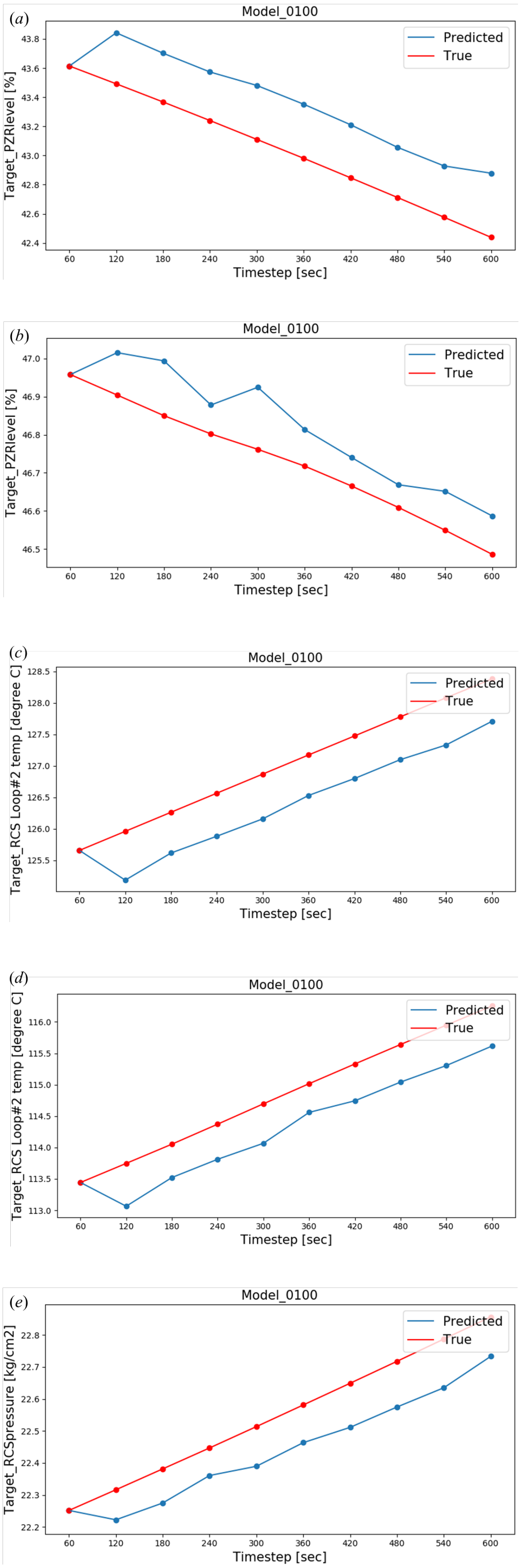
4. Result and discussion

Table 2 shows the training result of parameter prediction. The models predict given variables for the future up to 9 min at 1 min intervals. Accuracy was expressed using the root mean square error (RMSE) index using the difference from the actual value.

Figure 4 shows 9 points of PZR level, RCS loop #2 temperature and PZR pressure from 60 sec to 600 sec predicted by the model #4 as an example. At the 60 sec, predicted and true values are the same as the starting point. The model #4, which indicates open FV122 (0100), was chosen because it has the largest RMSE among models. However, the predicted value accurately predicts the change trend over a certain period of time without much difference from the actual value.

Table II: RMSE for plant parameter prediction model

Model (action)	Train_score RMSE	Val_score RMSE
00 00	0.16440	0.16498
00 01	0.17851	0.18993
00 10	0.16424	0.16695
01 00	0.28892	0.28315
01 01	0.12891	0.12905
01 10	0.12082	0.12033
10 00	0.14195	0.14212
10 01	0.17615	0.17994
10 10	0.11743	0.11613



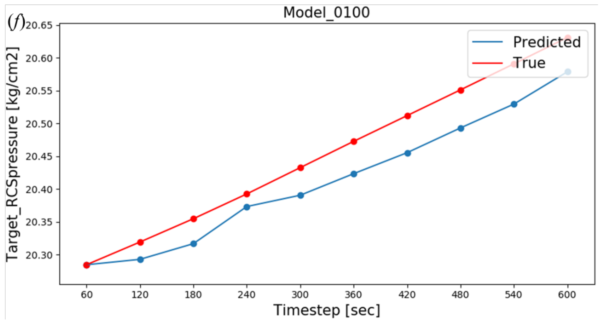


Fig 4. Prediction results of model #4, where only charging flow control valve open signal is on (True: actual value, Predicted: predicted value). (a) and (b): PZR level, (c) and (d): RCS loop#2 average temperature, (e) and (f): PZR pressure.

There is background knowledge that keeping the flow rate low is beneficial for raising the temperature. So, based on this, it has been adjusted to better score. Considering that the accuracy of the AI models converged quickly, output variables can be added in the future work for the better consideration of LCOs.

It is hoped that it will be a way to preserve the knowledge of the current generation of experts by enabling them to quantify and acquire the operation policies of current operators through future research.

5. Conclusion

This paper suggested evaluation method for startup operation for NPPs. LSTM algorithm was used to make plant parameter prediction model. With this model, autonomous system is provided with future information enabling to consider LCO with high accuracy.

The goal of this study is to implement operating tasks step by step and finally build an autonomous system that can perform entire startup operation process. While completely autonomous system is both technically and legally challenging, it is expected that research on this area will support operators who might take high workload over long periods of operating time. In addition, the knowledge acquired by current experts can be left as a quantitative indicator that can be passed on to future generations.

6. Acknowledgement

This work was supported by Korea Institute of Energy Technology Evaluation and Planning (KETEP) grant funded by the Korea government (MOTIE) (No. 20211510100020, Development of operation supporting technology based on artificial intelligence for nuclear power plant start up and shutdown operation).

REFERENCES

[1] J. M. Kim and S. J. Lee, Framework of Two-level Operation Module for Autonomous System of Nuclear Power

Plants during Startup and Shutdown Operation, Transactions of the Korean Nuclear Society Autumn Meeting, 2019.
[2] R.S. Sutton, and A.G. Barto, Reinforcement Learning: an introduction, 2nd, The MIT Press, 2018.
[3] KAERI, Advanced Compact Nuclear Simulator Textbook, Nuclear Training Center in Korea Atomic Energy Research Institute, 1990.
[4] T. Haarnoja, A. Zhou, P. Abbeel and S. Levine, Soft Actor-Critic: Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor, In International Conference on Machine Learning (ICML), 2018.
[5] S. Hochreiter and J. Schmidhuber, Long Short-Term Memory. Neural Computation, 9 (8), pp. 1735–1780, 1997.