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A Reactor Control Method for Flexible Operation Using Encoder-Decoder Prediction Model

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1. Introduction

In Korea, nuclear power plants (NPPs) have predominantly functioned at base load capacities without necessitating load-following operations. However, with the imminent diversification of the energy supply chain due to the incorporation of renewable energy sources into the grid, there is a paramount need for NPPs to interface synergistically with these renewables. Given this evolving energy matrix, it becomes imperative to modulate the output power of NPPs to ensure a consistent and stable energy provision. Consequent to recent technological advancements, there is an imperative for NPPs to extend their operational modalities beyond just load-following to encompass varied operational regimes, evolving towards a 'Flexible Operation' paradigm. Load-following, technically delineated, implies that the reactor core power (primary system) dynamically adapts to variations in turbine power (secondary system) [1]. We must simultaneously control the reactor and axial power distribution using CEA (Control Element Assembly) and boron concentration change to implement this.

The control method called Mode-K and Mode-P was introduced in the APR1400 nuclear power plant design phase. The method of Mode-P, an improved version of Mode-K, has been extensively demonstrated [2]. The Mode-P control method for load follow operations of APR1400 has been developed to observe the following objectives and principles [2], and Table I shows a simplified Mode-P logic [3].

- The core temperature and ASI should be properly controlled.
- CEA movement is automatically controlled.
- Measurable quantities are used as input signals.
- All the CEAs should be fully withdrawn at the full power condition if the ASI value is adequate.
- Core reactivity can be controlled by using CEAs and the boron concentration.
- Utilization of boron should be minimized.
- A predetermined dead bands for temperature and ASI control are suitably implemented.

Table I: Mode-P Logic Table [3]

Purpose	1. Keeping TM_{avg} within ref. range [Power level control] 2. Keeping ASI within ref. range [Power distribution control]
Method	1. Control Banks (PS, R5, R4) 2. Boron Concentration
Configuration	1. Mode-K RRS 1.1 input: ΔTM_{avg}, ΔASI 1.2 output: Drive requirement signal of control bank 2. CEDMCS 2.1 input: Drive requirement signal of control bank 2.2 output: Bank Driving

Input signals to the Mode-P controller are measured values: the core temperature mismatch, the ASI (Axial Shape Index), and CEA (Control Element Assembly) positions. Given the input information, the controller determines the direction of CEA movement and/or the CEA banks to be moved. The scenario of boron concentration is predetermined based on the power maneuvering strategy. The boron concentration is kept constant during power ramp-up and ramp-down and is subject to linear variations for simplicity and minimization of the waste water. It is well known that the control of ASI could be very successful if the adjustment of the boron concentration can be used as much as necessary and CEAs are introduced to control the ASI. However, the more the boron is used, the more volume of waste water. Also, the effect of the boration or dilution is very slow, and dilution of the boron concentration becomes difficult as the boron concentration decreases.

Furthermore, manual and repetitive control of the boron concentration significantly burdens the operators. Therefore, one of the primary objectives is to minimize the dependency on boron concentration control. In this study, we suggest a prediction model for CEAs and boron concentration using an Encoder-Decoder model to automate the flexible operation of the reactor.

2. Methodology

This section introduces a machine learning methodology adopted and its integration within a flexible operation framework. Additionally, we undertake a 1D core model simulation to validate the efficacy of our research in the context of flexible operation scenarios.

2.1 Definitions of Control Variables

T_{avg} refers to the average coolant temperature, which is the average of the inlet and outlet temperature. The following formula defines the Axial Shape Index (ASI):

$$ASI = \frac{P_B - P_T}{P_B + P_T} \quad (1)$$

In Eq. (1), P_B refers to the lower core power, and P_T refers to the upper core power. ASI represents the deviation in the power distribution between the upper and lower core. This factor affects the core integrity and should perform within the range specified by regulatory requirements.

The operator resorts to boron-based mitigation strategies if the established control methodologies fail to meet the specified objectives. The Reactor Regulating System (RRS) processes inputs of ΔT_{avg} and ΔASI, facilitating decisions on the selection of the control bank, as well as the insertion/withdrawal strategies and modulation of driving velocities. Subsequently, the Control Element Drive Mechanism Control System (CEDMCS) actuates the designated control bank. The parameters ΔT_{avg} and ΔASI are defined as follows:

$$\Delta T_{avg} = T_{avg} - T_{avg}^{ref} \quad (2)$$

$$\Delta ASI = ASI - ASI^{target} \quad (3)$$

T_{avg}^{ref} refers to the average moderator temperature at the target power level, while ASI^{target} refers to an equilibrium ASI at a specific reactor condition.

2.2 RNN Encoder-Decoder

We chose the Recurrent Neural Network (RNN) encoder-decoder model for developing a flexible operation technology. The encoder-decoder model consists of two RNN model and is mainly used in Natural Language Processing (NLP). The main advantage of RNNs is their ability to process sequential data due to their recurrent structure [4]. The encoder-decoder structure allows the output of a data point at a time instant of *k* to affect the output at *(k+1)* step [4]. Therefore, this structure suits the task of optimally configuring the next state based on the current state of the system. The encoder-decoder model is often called the sequence-to-sequence model because this prints the other domain sequence differently from the input sequence. Here, other domain refers to a situation where the input, which is the state of the system, and the output, which determines the operation of the system, have different formats or expressions. Fig. 1 shows the structure of the model.

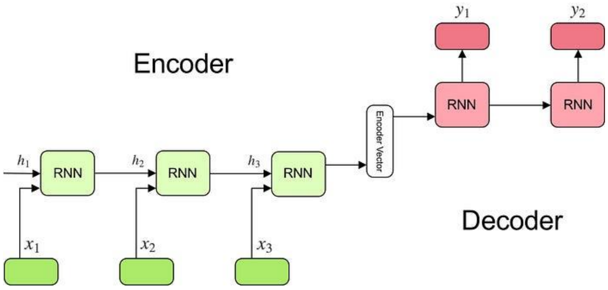

Fig. 1. Encoder-Decoder Model [5]

2.3 Simulation Code and Training

We used a 1-dimensional core model as the plant model and demonstrated the performance of the control method based on the encoder-decoder model.

The model was trained using TensorFlow 2.0 in the Python environment. This training objective is to estimate the reactor power and ASI changes for the next 120 seconds via the previous 3,600 seconds of data. We used simulated results of a neural network trained on data accumulated by a randomized control model to train the model to obtain long-term reactor operation data. Each operation data was recorded in 1-second increments, containing operation history from several hours to about a day. We allocated 10% of the total operation data to testing and validation. The remaining 80% was used as training data. Factors to be controlled are time differential, turbine load rate, boron concentration, control banks 3 and 4, turbine load, ASI, and reactor power. We observed the change in reactor power and ASI in a simulation driven by the developed model.

Fig. 2 shows the process of defining the encoder and decoder. The question marks indicate that the array size has not been explicitly specified during the model construction phase. The past: InputLayer refers to nuclear reactor operational data over the past 3600 seconds, encompassing 10 reactor factors and 2 results (ASI, reactor power). The encoder is responsible for interpreting the previous data and generating the hidden state of the decoder. The x_future: InputLayer has only 10 reactor factors over the future 120 seconds. The decoder predicts the next hidden state based on the current hidden state. The pred_nn estimates the rate of change of ASI and reactor power about the future 120 seconds based on the hidden state of the decoder. The encoder uses 1-d convolution, and the decoder uses a Gated Recurrent Unit (GRU), a type of RNN, and the pred_nn uses a Feed-Forward Neural Network (FFNN). This predictive model integrates with the simulation code to produce a module that controls turbine output and ASI in response to changes in the output target. This module receives inputs from the factors previously mentioned, representing the current reactor state at each time step of the code, and adjusts control banks and boron concentration to generate optimal ASI and turbine output values.

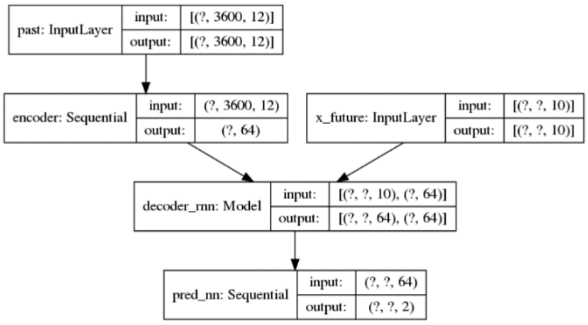

Fig. 2. Encoder-Decoder Model

3. Conclusions

We obtained the simulation results shown in Fig. 3 by using the module. In this graph, the green line corresponds to ASI, the red line represents turbine output, and the blue line signifies reactor output. During one day of operation, changing output randomly, the turbine load follows the reactor power accurately, and the control of ASI remains stable without significant oscillations. This study demonstrated the feasibility of machine learning-based nuclear reactor operation technology. Furthermore, when combined with existing technologies, commercial operation performance is expected to be improved. In addition, we can anticipate a more effective control over ASI in predefined flexible operational scenarios when output changes are determined rather than random. Finally, provided that operational data can be acquired, this methodology possesses a remarkable versatility in establishing reactor control modules for any reactor type without constraints. As a result, this research shows the potential of employing machine learning not based on logic for commercial operation by creating control modules enabling flexible operation, regardless of the reactor type.

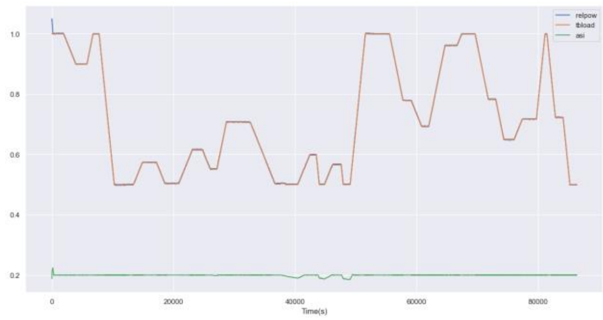

Fig. 3. Random Changing Operation Simulation based on Encoder-Decoder Model

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