HANARO Secondary Cooling System Behavior Prediction based on Deep Neural Network and Data Augmentation

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1. Introduction

HANARO(High-flux Advanced Neutron Application ReactOr), which is a 30MW thermal output multi-purpose research reactor located inside the KAERI(Korea Atomic Energy Research Institute), has been operated over 100 periods from its construction in 1995. HANARO includes various research facilities such as radioisotope product facility, thermal neutron research facility(TNRF), cold neutron research facility(CNRF), and fuel test loop(FTL). It also has been utilized for various purposes including radioisotope production for medical/industrial uses and conducting neutron-based experiments.

Similar to the most of conventional nuclear power plants(NPPs), the secondary cooling system of HANARO is separated with primary cooling system to prohibit external release of radioactive materials. Cooling of secondary cooling system is conducted by cooling towers and cooling fans, and operators can adjust the cooling fans' operation mode to control the efficiency of cooling.

However, although HANARO secondary cooling system is exposed to the external atmosphere and therefore its behavior is heavily affected by atmospheric conditions, there is no existing procedure or manual that reflects such characteristic. Accordingly, operators are operating cooling fans based on their experience. It is necessary to enhance the method of operation, since current experience-based operation could decrease the efficiency of cooling process and may induce unnecessary workload to operators. As an effort for enhancing the operability of HANARO secondary cooling system, KAERI is conducting the project that aims to develop a decision support system for HANARO secondary system.

This paper presents about the deep neural network(DNN)-based models that conducts HANARO secondary cooling system behavior prediction for decision support. In section 2, characteristics of HANARO secondary cooling system are briefly introduced. In section 3, processes model development are described. In section 4, summary and conclusion is provided.

2. HANARO Secondary Cooling System

Cooling system of HANARO consists of primary cooling system, reflector cooling system, and secondary cooling for removing heat from the core, reflector, and primary cooling system, respectively. Overall configuration of cooling system is similar to the conventional pressurized water reactors(PWRs), except there are no components for steam generation and electricity generation such as steam generators, turbines, and condensers. Fig. 1. is a schematic of HANARO cooling systems.

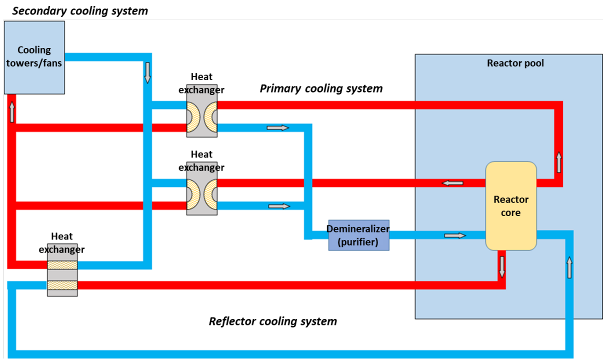

Fig. 1. Schematic of HANARO cooling systems

The secondary cooling system consists of basin, cold leg, heat exchangers(for primary cooling system and reflector cooling system), hot leg, cooling towers, cooling fans, and coolant pump. The flow path of 'cold leg – heat exchangers – hot leg – cooling towers/cooling fans – basin – cold leg' is formed with coolant pump. Among these components, cooling towers, cooling fans, and basin is exposed to the external atmosphere, and the heat of the secondary cooling system is removed from these components. Fig. 2. is a schematic of HANARO secondary cooling system.

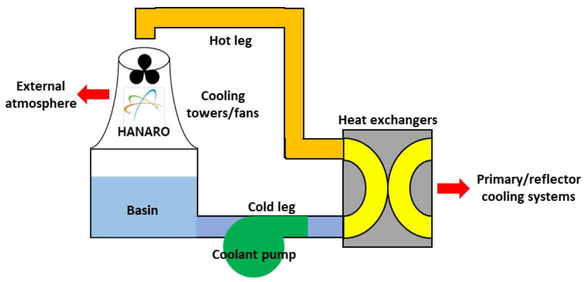

Fig. 2. Schematic of HANARO secondary cooling system

There are four cooling tower and cooling fan pairs, and each cooling fan can be operated as one of the stop, slow, and fast operation mode. Operators monitor various operation variables of HANARO, and make decisions about how to operate four cooling fans to maintain the secondary cooling system cold leg temperature(i.e. cooling tower outlet temperature) within the range of 29 and 32°C.

As part of secondary cooling system is exposed to the external atmosphere, its behavior is also affected by atmospheric conditions including atmospheric temperature and humidity. If atmospheric temperature and humidity is high, cooling efficiency of secondary cooling system is decreased(mostly in summer). In contrast, if atmospheric temperature and humidity is low, cooling efficiency is increased(mostly in winter). Therefore, it is essential to consider the atmospheric conditions for proper decision of cooling fans' operation modes. However, current manual for cooling fan operation does not consider the atmospheric conditions. Cooling fans can be operated as 'auto' mode, while it is mostly not used since the underlying logic is too simple. Accordingly, operators are operating cooling fans based on the monitoring results of various HANARO operation variables and atmospheric conditions with their empirical knowledge. Since operation based on empirical knowledge could result in decreased operation efficiency and excessive workload, decision support system or operation support system is necessary for enhanced operation performance.

3. Behavior Prediction Model Development

HANARO secondary cooling system behavior prediction model is a DNN-based model that predicts future trend of secondary cooling system-especially cooling tower outlet temperature-from the previous trends of multiple variables. Processes of behavior prediction model development is as follows: data acquisition and preprocessing, data augmentation, and model development and testing.

3.1 Data Acquisition and Preprocessing

Among over 100 periods(single period corresponds to 30 days of operation) of HANARO operation, data from period-65 to period-96(from year 2010 to 2014) was utilized for the development of HANARO secondary cooling system behavior prediction model. Total number of period is 36 periods as some periods between period-65 and period-96 are further separated(e.g. period-83(1) and period-83(2)).

HANARO operation variables are retrieved from the Historian database. Among various operation variables, 16 kinds of variables that are related to the operation of secondary cooling system were selected. Every variables are archived with intervals of one minute.

Additionally, to consider the effect of atmospheric conditions, meteorological data from year 2010 to 2014 was acquired from the Daejeon meteorological administration center(since HANARO is located in Daejeon)[1]. Acquired meteorological data includes 27 variables such as temperature, humidity, pressure, and wind direction, only temperature and humidity were selected for model development. Table I is a list of acquired variables, both from the HANARO operation data and meteorological data.

Table I: List of acquired variables

Category	Variables (numbers)
Core	Thermal output(2) Core inlet temp.(1) Core outlet temp.(1)
Primary cooling system	Coolant flowrate(2) Heat exchanger inlet temp.(2) Heat exchanger outlet temp.(2)
Secondary cooling system	Coolant flowrate(2) Cooling tower inlet temp.(2) Cooling tower outlet temp.(2) Cooling tower in/out temp. difference(2) Basin water level(1) Basin water temp.(1) Cooling fan operation status(1)
Reflector cooling system	Coolant flowrate(1) Heat exchanger inlet temp.(1) Heat exchanger outlet temp.(1)
Atmospheric conditions	Temperature(1) Humidity(1)

Meteorological data acquisition point and HANARO has about 5~6km distance, and it is assumed that the atmospheric conditions between these two points are almost identical. Also, it is assumed that the atmospheric condition is identical for one hour to match the time window, since acquired meteorological data has one hour intervals and HANARO data has one minute intervals.

After the data acquisition, following data preprocessing methods were applied. Some missing values are replaced to 0 or previous value. Also, minimum-maximum normalization was applied to set the values of variables between 0 and 1.

In many cases in machine learning model development, training/validation/testing data are selected randomly in specified ratio. However, in this study, training/validation/testing data were manually selected to ensure the evenly distributed seasonality and atmospheric conditions. As a result, 36 periods of data were separated into 24 periods of training data, 6 periods of validation data, and 6 periods of testing data.

To quantitatively consider the difference between cooling fan operation modes, it is necessary to digitize the difference of cooling abilities between slow mode and fast mode. In HANARO, RPM(round per minute) value of fast mode is about twice of slow mode, and corresponding cooling capacity can be differed about 1.5~2 times, according to the given conditions[2]. In this study, it is assumed that the cooling capacity of fast mode is twice of slow mode. Assuming that the cooling capacity of one A at low speed is 1 and the cooling capacity at high speed is 2, the cooling capacity of the four cooling fans ranges from at least 0 to 8.

Data sets are prepared to have 1 hour length of 18 kinds of variables(16 kinds from HANARO operation variables and 2 kinds from atmospheric conditions), and corresponding answer sets are also prepared to have 1 hour length of cooling tower outlet temperature. The goal of behavior prediction model is to predict future 1 hour trend of cooling tower outlet temperature, from the past 1 hour trend of given 18 kinds of variables and future cooling fan operation mode as a given condition.

3.2 Data Augmentation

In the process of using actual data for the study, a data imbalance problem has occurred that there is a large difference in the number of data included in each class. The most severe case is for the cooling capacity 1, as only 5,342 data among total 1,278,720 data(about 0.42%) was categorized into that class. Since severe data imbalance adversely affects the learning process of the DNN-based model, data augmentation was applied to bring the number of data included in each class to a similar level.

Data augmentation was conducted by two kinds of methods: noise addition and interpolation. For noise addition, noise values that sampled from Gaussian distribution with mean 0 and variance 1 were added with 0.005 multiplier to the original data. In this case, augmented data belongs to the same class with original data. For interpolation, augmented data was generated from the two original data that belongs to different classes. In this case, augmented data belongs to the class that corresponds to the arithmetic mean of cooling capacities of two original data. Table II presents the number of data before and after data augmentation.

Table II: The number of data before and after augmentation

Cooling capacity	# of data (before augmentation)	# of data (after augmentation)
0	150,233	151,902
1	5,342	144,000
2	116,849	152,872
3	304,423	304,423
4	236,596	247,503
5	179,240	203,912
6	111,519	144,000
7	72,335	146,448
8	102,183	179,211
Total	1,278,720	1,674,271

After the data augmentation, about 10% of data was sampled and used for the model development and testing, to reduce the computational burden. As a result, 118,873(about 71%), 24,277(about 14%), and 24,277(about 14%) data sets were used as training data, validation data, and testing data, respectively.

3.3 Model Development and Testing

The DNN-based model that performs HANARO secondary cooling system behavior prediction was developed based on LSTM(Long Short-Term Memory)[3] architecture. The model is trained repeatedly with varying the number of hidden layers and hyperparameters including the number of nodes and learning rate. The final version of behavior prediction model with best performance consists of 1 LSTM layer and 3 FC(Fully-Connected) layers after the LSTM layer. For all layers, ReLU(Rectified Linear Unit) activation function. During the training, MSE(Mean Squared Error) was applied as loss function and Adam optimizer[4] was applied as an optimizer. Fig. 3. is a schematic of the developed HANARO secondary cooling system behavior prediction model.

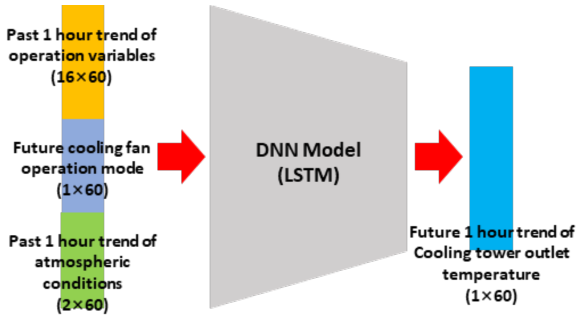

Fig. 3. Schematic of the developed behavior prediction model

The final version of behavior prediction model has shown about 0.67% MAPE(Mean Absolute Percentage Error), implying that the model can predict cooling tower outlet temperature with about 0.18°C prediction error. Since the cooling tower outlet temperature is generally maintained within the range of 29 and 32°C, the 0.18°C of mean prediction error can be regarded as acceptable level.

For the data corresponds to full-power or near-full-power operation, prediction error of the model was about 0.10°C. On the contrary, for the data corresponds to low-power operation and the data with severe temperature fluctuation, the prediction error tended to be higher, larger than 0.20°C. In particular, since the cause of the relatively high error for the low-power operation data is likely to be another data imbalance problem, it is expected that the model's prediction error could be further reduced through the application of additional data augmentation. Fig. 4. and Fig. 5. show the example of prediction with relatively low error and high error, respectively. Note that the cooling tower outlet temperature of Fig. 4.(y-axis) lies within the range of 29 and 32°C, while Fig. 5. does not.

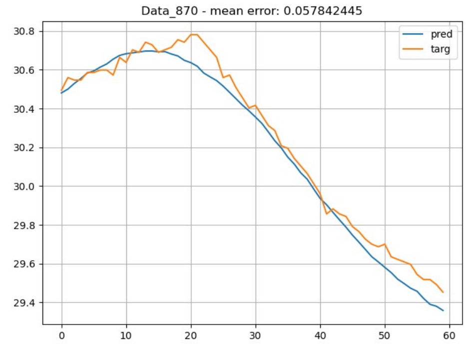

Fig. 4. Example of prediction with relatively low error (blue line: prediction value, orange line: target value)

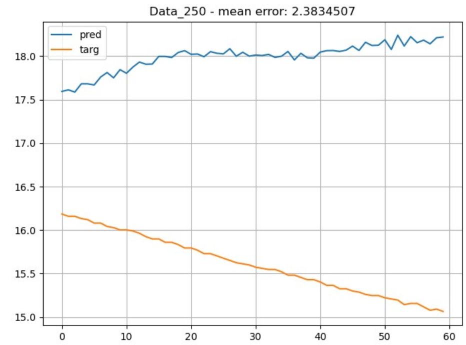

Fig. 5. Example of prediction with relatively high error (blue line: prediction value, orange line: target value)

4. Conclusion

In this study, HANARO secondary cooling system behavior prediction model was developed based on DNN. Data was acquired not only from the HANARO Historian database, but also from the Daejeon meteorological administration center, to consider the atmospheric conditions. Moreover, data augmentation was applied to alleviate the data imbalance problem. The model was developed based on LSTM architecture, and the developed model was able to predict the cooling tower outlet temperature with about 0.18℃ prediction error, which is acceptable.

Although developed model shows relatively higher prediction error for the data corresponds to low-power operation and the data with severe temperature fluctuation, it is expected that the developed behavior prediction model could be applied for aiding operators' decision for cooling fan operation, to reduce their workload and to increase the operation efficiency.

As future works, decision support system based on developed behavior prediction model should be developed and tested. In addition, the model itself should be improved via applying additional data augmentation to cover the data corresponds to low-power operation and the data with severe temperature fluctuation.

ACKNOWLEDGMENT

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