Autonomous Algorithm for Safety Function State of Nuclear Power Plant by Using LSTM

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Abstract: With the improvement of computer performance and the emergence of cutting-edge artificial intelligence (AI) algorithms, the autonomous operation based on AI is being applied to many industries. An autonomous algorithm is a higher level of concept than conventional automatic operation in nuclear power plants. In order to achieve an autonomous operation, the autonomous algorithm needs to include the superior function level to monitor, control and diagnose automated subsystems, and AI algorithms need to be suitable to make these superior functions. The artificial neural network (ANN), which is one of the AI approaches, can solve problems about the dynamic system that include the non-linear input and output values. Safety systems of nuclear power plants (NPPs) have non-linear values, and are controlled through a combination between the automation systems based on conventional controller and the manual control by operator. It means that the automation level of current NPPs corresponds to the shared control that is not autonomous control. This study aims at improving the safety system of automation level from the shared control to the autonomous control. This study suggests a model of safety systems in NPPs by using function based hierarchical framework, and autonomous algorithm to control and diagnose the safety function state by using the Long Short Term Memory (LSTM) that is one of the recurrent neural network (RNN) methods.
Keyword: NPP, Safety system, Autonomous algorithm, AI, LSTM

1 Introduction

An autonomous system is one that has the power and ability for self-governance in the performance of functions [1]. An autonomous system consists of hardware and software which can perform the necessary control function, without external intervention over extended time periods. According to the Billing's definition about the level of automation, the autonomous control, which is a high level of automation, can be defined as the system in which human operators have no role in operation or are minimally involved in the operation, e.g., critical decision.

One way to achieve autonomy, in some applications, is to utilize high level decision making techniques, i.e., "intelligent" methods, in the autonomous controller. The field of artificial intelligence (AI) offers some of tools to add the higher level decision making abilities [1]. Traditionally, AI must fundamentally understand the world around us, and this can be achieved if a learner can identify and disentangle the underlying explanatory factors hidden in the observed milieu of low-level sensory data [2]. In the early days of artificial intelligence, the field rapidly tackled and solved problems that are intellectually di□cult for human beings but relatively straight-forward for computers problems that can be described by a list of formal, mathematical rules [3]. AI has embraced classical control theory, neural network, fuzzy logic and genetic algorithm. Recently, the performance of AI has explosively grown due to develop the hardware, multiprocessor graphics cards or graphics processing units (GPUs), and new AI algorithms (e.g., Deep Learning).

Nuclear power plants (NPPs) is one of highly automated systems. NPPs are controlled through the collaboration between personnel and plant automation, including the responsibilities of the crew for monitoring, interacting, and overriding automatic systems [4]. Generally, automated systems in current NPPs, which has a low level of automation, require the operator's intervention more extensively than in autonomous systems. According to Billings' proposed level of automation, the level of automation at nuclear power plants corresponds to the shared control [5].

There is an increased use of automation in the design for new plants compared with currently operating ones. For example, GE-Hitachi stated that "The control systems for the ESBWR have a high level of automation. All systems are automated unless regulation or human factor engineering analysis results dictate otherwise" [6]. Similarly, commenting on the concept of operation for the U.S. Evolutionary Power Reactor (US-EPR), AREVA stated that "Because of the levels of automation inherent in the I&C architecture, only one licensed operator will be required to be at the controls during normal, at power operations". Furthermore, "…the initial MCR staffing level is established based on experience with previous four loop PWR plants and takes into account the increased levels of automation…". Looking to future Generation IV NPP operations, two to four operators may manage up to a dozen modular plants [7].

Along with this increased interest in the automation, the application of autonomous control is also becomes highlighted in NPPs. Some studies have designed autonomous control systems for spacecraft nuclear power plants using PID controller [8]. Some applications of autonomous control to the system level in NPPs have been attempted using intelligent controllers (e.g., fuzzy, neural networks, and genetic algorithms) [9],[10].

This study aims at developing an autonomous operation algorithm for safety systems in NPPs to increase the level of automation from the shared control to the autonomous control. To design the autonomous operation algorithm, two approaches have been applied, i.e., the function-based hierarchical framework to model the NPP safety systems, and Long Short-Term Memory (LSTM), which is an AI technique, to control the modeled NPP safety systems.

The Compact Nuclear Simulator (CNS) was used to obtain training data, and to verify the autonomous operation algorithm designed for the safety system. The CNS can simulate normal and emergency states based on a 930 MWe Westinghouse 3 loops plant [11].

This paper is organized as below. Section 2 describes the function-based hierarchical framework and LSTM. The safety systems of the reference plant are modelled using function-based hierarchical framework in Section 3. Then, the design of LSTM network structure is presented in Section 4. Training and test of the suggested algorithm in real time will be introduced in Section 5. Finally, Section 6 concludes this work and proposes future studies.

2 Methodology

2.1 Function-based Hierarchical Framework

This study suggests a function-based hierarchical framework to model safety systems in NPPs. One way to model a complex system is through the construction of hierarchical structures, in which it is decomposed into subsystems through some 'authority relation' and these subsystems are further decomposed until the lowest, arbitrarily chosen level is reached [12]. In general, a hierarchical framework provides a method to describe complex systems in terms of abstract entities, which can be used to represent functions and multiple components in a systems. A hierarchical control structure is also desirable to achieve an increasingly sophisticated autonomous controller [13]. Therefore, the hierarchical structure helps to systematically analyze NPP safety systems, and understand the interrelationship between lower and upper layers.

The function-based hierarchical framework is divided into three levels: goal, function, and system levels to analyze NPP safety systems as shown in Fig 1. The function-based hierarchical framework starts at the highest conceptual level with the NPP's high-level mission goal and is decomposed down to details by dividing them into the functions necessary to achieve the goal.

The goal level defines goals which have to be achieved ultimately by the entire system and to ensure the health and safety of the public by preventing or mitigating the consequences of postulated accidents. The goal of nuclear safety systems can be generally defined as the prevention of core damage. Core damage can cause radiation release to the outside of NPP, and the released radiation can induces human health bad effects (such as short-term injuries or long-term cancers) as well as land contamination around the NPP. Therefore, the goal level in NPP safety system is defined as the prevention of core damage.

The function level consists of the functions which are designed to achieve the goal. For pressurized water reactors (PWRs), the goal of NPP safety can be typically accomplished by nine safety functions. The safety functions include reactivity control, containment integrity, reactor coolant system (RCS) inventory and pressure control, RCS heat removal, core heat removal, hydrogen control and maintenance of vital auxiliaries. These safety functions are designed to maintain or control a boundary or parameter important to assuring the plant's integrity, and to preventing the release of radioactive materials.

The system level identifies systems, components, and input/output parameters of components that are designed to satisfy the safety function. For instance, safety injection system (SIS) and the chemical and volume control system (CVCS) can function to satisfy RCS inventory control function. Then, those systems can be decomposed into components. For instance, SIS contains SI pump, SI tank and SI valve. Input and output values of each component are also defined in the system level of Function-based Hierarchical Framework. These are to be used for input/output nodes of LSTM later. Input values are defined as an NPP physical variable necessary as an input for the component to operate, e.g., RCS temperature, RCS pressure, and pressurizer level. Output values are defined as a state of the component resulting from the input, such as valve and pump states.

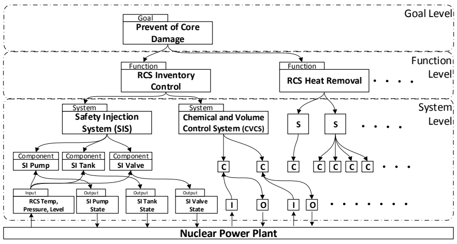

Fig.1 Function-based hierarchical framework

2.2 Long Short Term Memory (LSTM)

Artificial Neural Network (ANN), which is one approach in the AI, has a long time history in the scientific research. Various neural network structures have been proposed for solving different problems in control and machine learning fields. There has been continuously increasing interest in applying ANNs to identification and adaptive control of practical systems that are characterized by nonlinearity, uncertainty, communication constraints, and complexity [14]. The ANN is also a promising approach to implement a nonlinear approximation for developing a control system for NPPs.

This study applies the LSTM method which has been advanced from the recurrent neural network (RNN), a kind of ANNs. The RNN can naturally represent dynamic systems and can capture the dynamic behavior of a system, and it is a powerful network to extract the information feature related to the dynamic system in its hidden layer [15]. RNN has input nodes, hidden nodes, output nodes, and delay nodes to reflect the previous data. RNN contains delay nodes unlike existing NN. Delay node is calculated through the linear combination of input data in input node at time t after calculating in hidden node at time t-1.

These structural features enable the RNN to estimate time series data. Typical examples of application of time series data are speech recognition, motion picture recognition, dynamic system control, recognition of cursive writing, and translation.

However, RNN can be used only between 5 and 10 time steps due to the gradient vanishing problem [16]. The problem is that gradient value becomes too large or vanishes exponentially quickly to zero due to many layers during updating weight. Therefore, there is a restriction on the data set for long-term memory with RNN. Thus, the LSTM has been suggested to solve these problems.

LSTM was developed as a neural network architecture for processing long temporal sequences of data. LSTM, which is based on the RNN architecture, combines fast training with efficient learning on the tasks that require sequential short-term memory storage for many time-steps during a trial [15]. LSTM can learn to bridge minimal time lags in excess of 1000 discrete time steps by enforcing constant error flow through "constant error carrousels" (CECs) within special units, called cells [17]. Fig. 2 shows a structure of LSTM cell. The LSTM cell contains four main elements: input gate, output gate, forget gate and a cell with recurrent connection that is CECs.

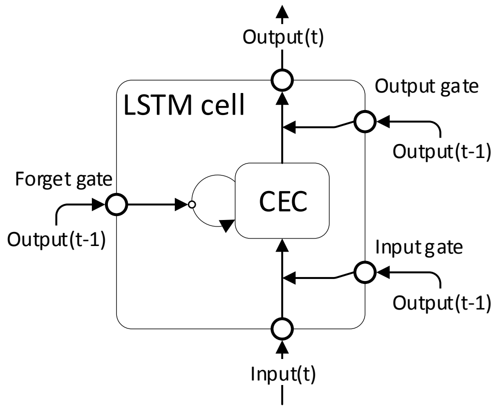

Fig.2 Structure of LSTM cell

Each LSTM cell is composed of units that retain the state across time-steps as well as three types of specialized gate units (such as input, output and forget gate) that learn to protect utilize, or destroy this stats appropriate. The gates provide a context-sensitive way to update the contents of a memory cell and protect those contents from interference. It can also protect downstream units from minor effects by stored information that has not become relevant yet. The input gate controls which part of incoming signal should be blocked, and which part should be allowed to alter the state of the cell. Meanwhile, the output gate controls which part of output signal can have effect on next neurons. The forget gate modulates the recurrent connection to decides which information the cell should remember and forget. In addition, the weight of recurrent connection is set to 1 in order to prevent gradients from vanishing or exploding [18], [19].

3. Modelling of safety system by using function-based hierarchical framework

This section introduces the development of function-based hierarchical structure to model the safety systems in NPPs. This structure will be used as an architectural platform for the LSTM algorithm.

The main purpose of NPP safety is to protect nuclear reactor core, and to alleviate damage to the core in the event of severe accident. Safety systems in typical PWRs are designed to satisfy nine safety functions. Then, each safety function includes subsystems necessary to satisfy its function, and the subsystem contains components (e.g. pump, valve, etc.). Each component performs automatic or manual controls (e.g. activation, stop, and regulation). This study develops a function-based hierarchical structure for a Westinghouse 900 MWe, 3-loop PWR.

3.1 Goal and Function Level

The function-based hierarchical structure consists of three levels as shown in Fig. 3. The top node is the NPP safety. The NPP safety aims at preventing core damage and release of radiation the public, and mitigating the consequences of postulated accidents. Core damage has been conservatively assumed to result in any state of the core where fuel temperature exceeds the design limit, or, if the available thermal-hydraulic models cannot demonstrate successful cooling of the core. Core damage can cause radiation release to outside NPPs, and the released radiation can induces human health bad effects (such as short-term injuries or long-term cancers) as well as land contamination around the NPP.

Function level defines nine safety functions to satisfy the ultimate goal of NPP safety to prevent the core damage. Safety functions are serving to verify high-level safety objectives, and often are defined in terms of a boundary or entity important to assuring the plant's integrity, and to preventing the release of radioactive materials. Table 1 shows the nine safety functions and their purposes.

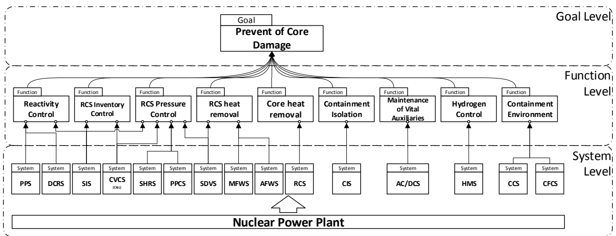

Fig.3 Overall model of NPP safety system

Table 1 Nine safety functions

No	Safety function	Purpose
1	Reactivity control	Shut reactor down to reduce heat production
2	Reactor coolant system (RCS) inventory control	Maintain a coolant of reactor coolant system
3	Reactor coolant system (RCS) pressure control	Maintain a coolant pressure of reactor coolant system
4	Reactor coolant system (RCS) heat removal	Transfer heat out of coolant system medium
5	Core heat removal	Transfer heat from core to a coolant
6	Containment isolation	Close opening in containment
7	Containment environment	Keep from damaging containment
8	Hydrogen control	Control hydrogen
9	Maintenance of vital auxiliaries	Maintain operability of systems needed to support safety systems

3.1.1 Reactivity control

The objective of the core reactivity control critical function is to control and monitor the nuclear reactions taking place within the core.

3.2.2 RCS inventory control

The RCS inventory control is to keep the core covered with an effective coolant medium. The function monitors the group of actions to maintain control over either coolant volume or mass. The RCS inventory control involves loss of the ability to control the RCS coolant inventory, and it control continuous loss of mass and recovery from loss of inventory events. The satisfaction criteria for RCS inventory control is pressurizer water level between 17% and 96%.

3.2.3 RCS pressure control

The objective of this function is to assure an effective coolant medium by maintaining the RCS pressure boundary condition, and it is to maintain the RCS pressure at the designed value in steady state in order to achieve the goal level. In Pressurized Water Reactor (PWR), the reactor coolant should keep the subcooling condition in order to deliver properly the heat generated from the reactor core. Hence, the RCS pressure should keep the highly pressure to remain the coolant at high temperatures and to prevent bulk boiling of the coolant in the loops at high temperature.

3.2.4 RCS heat removal

The RCS heat removal critical function is to assure the transfer of generated, stored, and decay heat out of the RCS to a heat sink. Thus, the purpose of RCS heat removal function is to transfer the heat from the RCS to the steam generators. The transfer of heat between the fuel in the core and the feed-water in the SG is carried out by the reactor coolant system (RCS). Therefore, the systems for the RCS heat removal control the water level of steam generator within the acceptable range.

3.2.5 Core hear removal

The objective of the core heat removal function is to monitor the transfer of heat from the reactor core to the primary coolant for heat removal by the RCS. A loss of core heat removal capability is alarmed by high core temperatures, and/or voiding in the reactor vessel upper head and hot leg areas. The core heat removal alarm algorithm monitors the core temperatures and other parameters indicative of RCS voiding to assure the core heat removal function is not compromised.

3.2.6 Containment isolation

The objective of this critical function is to prevent release of radioactivity through the containment by assuring that valves in piping paths penetrating containment close on appropriate isolation signals. The containment isolation function provides the means of isolating fluid systems that pass through containment penetrations such that any radioactivity that may be released into the containment following a postulated design basis accident will be confined.

3.2.7 Containment environment

This critical function is to prevent radioactivity release from the containment by preventing the overstress of the containment structure. The containment overstress is prevented by maintaining control of both containment pressure and temperature.

3.2.8 Hydrogen control

The hydrogen control is necessary because of the potential for a hydrogen explosion following an accident. The purpose of hydrogen control is to remove hydrogen that is produced by the zirconium-water reaction e.g., in case of Loss of Coolant Accident (LOCA).

3.2.9 Maintenance of vital auxiliaries

Maintenance of vital auxiliaries function is required to accomplish the other safety functions discussed previously. These auxiliary systems provide such services as instrument air for opening and closing valves, electric power for running pumps and operating instruments and ultimate heat sink to which RCS and core heat can be transferred.

3.2 System Level

The system level defines safety systems to satisfy nine safety functions as well as the components to satisfy the safety system. Table 2 shows safety systems and components designed to satisfy each safety functions. For example, Plant Protection System (PPS), Digital control Rods System (DCRS) and Safety Injection System (SIS) are designed to control NPP's reactivity. Then, the SIS includes components such as safety injection (SI) pump, SI tank and SI valve.

Table 2 Safety system of system level

Function	System	Component
Reactivity control	PPS	Control element drive mechanism
	DCRS	Control element drive mechanism
	SIS	SI pump, SI tank, SI valve
RCS inventory control	SIS	SI pump, SI tank, SI valve
	Chemical and Volume Control System	Charging valve, letdown valve
	Safety depressurization and vent system	Pilot operated safety relief valve
	RCS secondary heat removal system	Main steam safety valve, Atmospheric dump valves
	Pressurizer (PZR) pressure control system	PZR spray valve, PZR heater
RCS hear removal	Main feed water system	Main feed water pump
	Aux feed water system	Aux feed water pump
	Safety depressurization and vent system	Pilot operated safety relief valve
Core heat removal	Reactor coolant system	Reactor coolant pump
Containment isolation	Containment isolation system	Containment isolation valves

Containment environment	Containment spray system	Containment spray
	Containment fan cooling system	Fan cooler
Hydrogen control	Hydrogen mitigation system	Hydrogen ignitors
Maintenance of vital auxiliaries	AC and DC power system	Diesel generator, Station batteries

4. LSTM Network Model for Autonomous Control of Safety Systems

The safety systems' model through the function based hierarchical framework is transferred to LSTM network. For transformation, the LSTM network requires input and output values that are defined from previous modeled safety systems. Fig. 4 shows the transformation from the function based hierarchical framework of safety systems to the LSTM network as an example of SIS included in RCS inventory control function. The physical values required for operation of components and the component state values in the system are transferred to the input values of LSTM network. The component state of the framework is transferred to the output values of LSTM network.

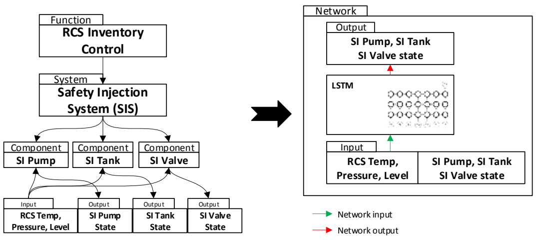

Fig.4 Transformation from function based hierarchical framework to LSTM network

The LSTM network is a network based on the NN architecture consisting of input layers, hidden layers, and output layers. The input layer is used to put in input data to network, and also prepares the normalized database to help training the network. The hidden layer connects between input layer and output layer. It can help to calculate the complex problem. The output layer shows the result of network and includes network output processing.

Fig. 5 shows the LSTM network developed from the function-based hierarchical structure of safety systems. The input to the LSTM network is the safety system values that are defined as NPP physical values. The output is the state values of components defined from the function-based hierarchical model in the previous section. The numbers of safety system values are 168, respectively. The safety system values include 74 variables of physical value and 94 variables of component state values.

This section introduces the modeling process of each LSTM layers according to the characteristics of each layer.

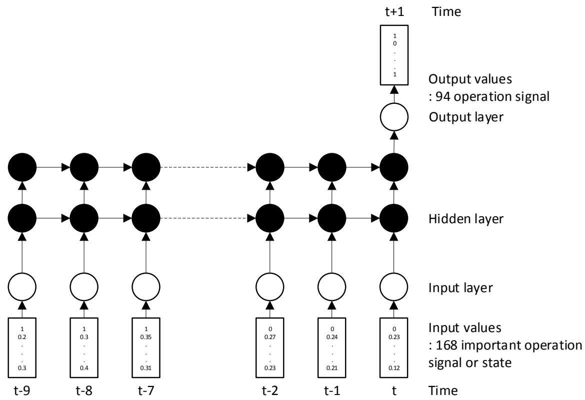

Fig.5 LSTM network

4.1 Safety system values preprocessing

This step describes the preprocessing of the input/output values to be applied to the LSTM input layer. This step rescales the range of values by using normalization tool.

In order to train the LSTM network, all the values in the network need to be scaled by using normalization on each values from the previous modeled safety systems. It can help to reduce the chance of getting stuck in local optima. In this study, the min-max scaling method is used to scale the safety system values.

Min-max normalization perform a linear transformation on the original data, and the data is scaled to fixed range from 0 to 1 [20]. This function is typically done via the following equation:

$$\mathrm{X_{norm}} = (X - X_{min})/(X_{max} - X_{min}) \qquad (1)$$

4.2 Determination of optimized LSTM network structure

In order to design the structure of LSTM network, it is necessary to determine the following two parameters:

- the number of input sequence length
- the number of hidden layers and hidden nodes

The input sequence length is the temporal length of the past data that LSTM will use to compute the output. RNN should use fewer than 10 sequence lengths. But LSTM has practically no limitation of sequence lengths. The number of hidden layers and nodes can affect the performance of network, and the selection of the number of hidden layers depends on the problem domain.

To select two parameters, the most common way in determining the number of each parameters is via experiments or trial-and-error [21]. This study applied the trial error approach to find the optimal number of hidden layers and the length of input sequence. Table 3 shows the result of determination of these parameters. Sequence lengths ranging from 6 to 10, and the number of hidden layers with one or two are tested. The test case has 60 hidden nodes. To evaluate the performance of the different shapes of networks, the root-mean-squared error (RMSE) is used with the following equation:

$$\mathrm{RMSE}(\mathrm{x}', \mathrm{x}) = \sqrt{\frac{1}{n}\sum_{n=1}^{N}(x_n' - x_n)^2} \quad (2)$$

The equation uses the measured power time series x and the predicted power time series x'. It is assumed that both time series have N samples.

As a result of the performance comparison, the optimal LSTM network structure has been determined with the 10 input sequence length, 2 layer and total 60 hidden nodes.

Table 3 Performance comparison between networks

No	Sequence	Layer	Hidden node	RMSE
1	6	1	60	0.02977
2	8	1	60	0.02797
3	10	1	60	0.02750
4	10	2	30, 30	0.02555

4.3 Network output processing

The network output processing coverts the output of LSTM to the form of simulator value. The predicted output values in the LSTM network is generated as a range value. Therefore, to be applied to control the simulator, the output values from the LSTM network should be converted to be relevant for the simulator control.

The components of simulator can be divided into two types: the regulation type and on/off type. An example of regulation type is a control valve which adjusts the position. The simulator uses a value ranging from 0 to 1. The values of 0 and 1 mean that the valve is completely closed and open, respectively. The value between them means that the valve is located in the middle according to the proportion of value. Since the LSTM always produces a value ranging from 0 to 1, the output of the LSTM can be directly used as an input to the simulator for the regulating system.

Examples of on/off type components are pumps or on/off valve which have only binary states. For this type of component, it is necessary to post-process the output values of LSTM because the LSTM generates not only 0 or 1 (e.g., binary values), but also values around them. Thus, this study applies the following rule.

- 0 to 0.1 of LSTM output converted to the closed state in the component of simulator
- 0.9 to 1 of LSTM output converted to the open state in the component of simulator

5. Training & Validation

5.1 Training the LSTM Network

The CNS has been used to train the LSTM developed in the Section 4. The CNS was originally developed by Korea Atomic Energy Research Institute (KAERI) and Studsvik Inc., and has been recently renewed by KAERI [11]. The reference plants is Westinghouse 900 MWe, 3-loop PWR.

A wide range of operational data were collected to train an LSTM. The data for total 206 scenarios were collected with a sampling period of 1 sec, as shown in Table 4. In the training scenario, the plant safety is managed by the combination of automatic control and human operator. The average running time of scenarios is about 30 minutes. The scenarios include Loss of Coolant Accident (LOCA), LOCA + safety injection (SI) valve failure, Steam Generator Tube Rupture (SGTR), Loss of All Feed-water (LOAF) and SGTR+SI valve failure. Training data include 168 important operational parameters, state of components and physical state of simulator as the inputs to the LSTM. Output parameters are 94 operational signals for controlling the safety systems and components.

Table 4 Database used for network training

Types of accident scenarios	Number
Loss of coolant accident(LOCA)	60
Loss of coolant accident(LOCA) + Safety injection fail	60
PZR safety valve fail	10
PZR safety valve fail + Safety injection fail	10
Steam generator tube rupture(SGTR)	18
Steam generator tube rupture(SGTR) + Safety injection valve fail	18
Main steam line break(MSLB)	30
Total	206

The data of accident scenario have been sliced in the length of 10 seconds for the LSTM training. Thus, the total number of training set for the LSTM is 225,538.

5.2 Validation

This study uses a LOCA scenario (loop2 hot-leg), i.e., an untrained accident scenario, to validate whether the LSTM network can manage the plant safety without any human intervention. This section compares the operation by the autonomous LSTM control with one by the combination of automatic system and human operators.

5.2.1 System level simulation result

The control signals of components between LSTM network output and the auto-human control are compared. Fig.4 shows the change of the pressurizer spray valve position. The accident occurs at 40sec. The purpose of spray valve is to control the pressurizer pressure. Fig. 6 shows that the LSTM control sprays more water to the pressurizer than the auto-human control.

Fig. 7 presents the change of reactor coolant pump 1 (RCP) state. The purpose of the RCP is to forcibly circulate the primary coolant to remove heat from the core. Figure 5 shows that the LSTM stops the RCP earlier than the auto-human the control. However, the comparison at the system and component level does not indicate which control approach shows a better performance.

Therefore, it is necessary to compare them at the function level.

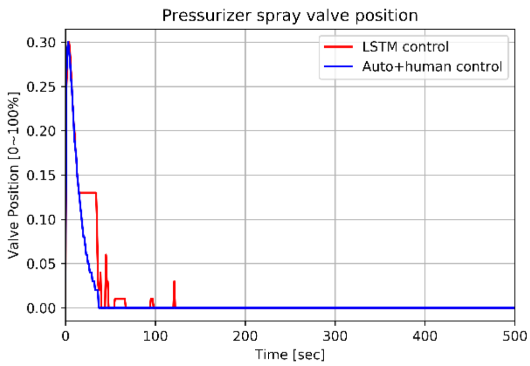

Fig.6 Pressurizer spray valve position

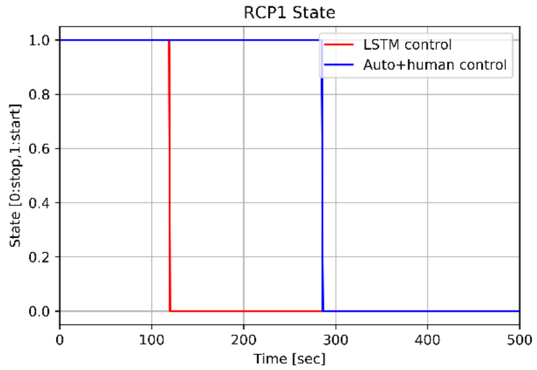

Fig.7 RCP state

5.2.2 Function level simulation result

Fig. 8 shows the water level of core for the validation scenario. The core level is related to the RCS inventory control that is one of the safety functions. As shown in the figure, the LSTM network can maintain higher water level, which is more desirable, than the auto-human control.

Fig. 9 presents the change of RCS average temperature. The decrease in RCS average temperature indicates the cooling of reactor core. The result shows that the LSTM control can cool down the reactor faster than the auto-human control.

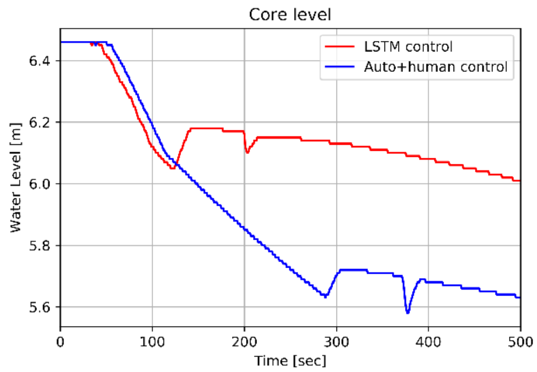

Fig.8 An example of figure.

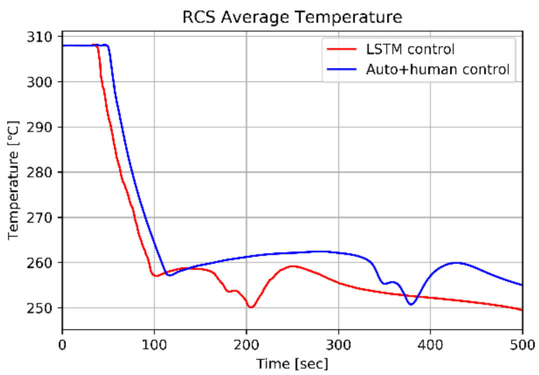

Fig.9 An example of figure.

5.2.3 Discussion on the test result

The simulation result indicates that the trained LSTM network can generate control signals without any human intervention. The LSTM network showed a better performance in managing safety functions than the auto-human control within the scope of the trained accident.

6. Conclusion

This study attempted to develop an autonomous algorithm for the safety systems of NPP by using the LSTM method. In order to define the input and output values in LSTM, the NPP safety system is modeled by using the function-based hierarchical framework. The training data, which includes automatic control and manual control in accident scenarios, are collected through the CNS. The LSTM has been trained by training data. It was also tested to demonstrate the feasibility of the approach.

The result indicated that the LSTM can capture not only the automatic control but also the manual control of operator. In addition, the LSTM control performed better than the auto-human control. This study will continue to develop a high level of autonomous control by adding more features such as monitoring, diagnostics, and prognostics.

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