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이 논문을 공학 석사학위신청 논문으로 제출함

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최근 컴퓨터 성능의 증가와 새로운 인공지능 알고리즘의 등장으로 인공지능 기술에 기반한 높은 자동화 수준을 가진 자율 운전 시스템이 많은 산업분야에 적용되었다. 자율 운전 알고리즘은 원자력 발전소 시스템의 기존에 전통적인 자동화 알고리즘보다 더 높은 수준의 개념을 가지고 있다. 자율 운전 시스템을 개발하기 위해서는 이미 기존에 자동된 하위 시스템들을 모니터링, 제어 및 진단할 수 있는 기능을 포함해야 한다. 따라서 본 논문에서는 기능 기반 계층 프레임워크(FHF)와 장기-단기 기억장치(LSTM)를 사용하는 NPP 안전 시스템에 대한 자율 운전 알고리즘을 제시한다. FHF는 NPP의 안전 목표, 기능, 시스템 및 구성 요소를 계층적으로 모델링을 하였다. 모델링된 안전 기능 시스템의 계층 프레임워크는 재귀 신경망 네트워크(RNN)의 진화 버전인 LSTM 네트워크로 변환됩니다. 이 접근법은 Westinghouse 930 MWe 3루프 가압경수로를 참고 모델로 설계된 Compact Nuclear Simulator를 사용하여 네트워크의 훈련 및 검증을 하였다. 본 논문에서는 LSTM 네트워크의 자율 운전과 기존의 운전 전략의 비교를 통하여 LSTM 네트워크의 성능을 검증하였다. 알고리즘의 검증 결과에 따르면 자율운전 알고리즘은 발전소의 안전 기능에 목표를 현재 자동화 및 운영자의 수동 제어보다 더 잘 관리할 수 있는 것을 확인하였다.

Abstract

Autonomous Operation Algorithm for Safety Function Systems of NPPs by Using LSTM and FHF

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With the improvement of computer performance and the emergence of cutting-edge artificial intelligence (AI) algorithms, an autonomous operation based on AI is being applied to many industries. An autonomous algorithm is a higher-level concept than conventional automatic operation in nuclear power plants (NPPs). In order to achieve autonomous operation, the autonomous algorithm needs to include superior functions to monitor, control and diagnose automated subsystems. This study suggests an autonomous operation algorithm for NPP safety systems using a function-based hierarchical framework (FHF) and a long short-term memory (LSTM). The FHF hierarchically models the safety goals, functions, systems, and components in the NPP. Then, the hierarchical structure is transformed into an LSTM network that is an evolutionary version of a recurrent neural network. This approach is applied to a reference NPP, a Westinghouse 930 MWe, three-loop pressurized water reactor. This LSTM network has been trained and validated using a compact nuclear simulator. In this paper, the performance of the LSTM network was verified by comparing the autonomous operation of the LSTM network with the current operational strategy. The algorithm has

demonstrated the effectiveness. The validation results showed that the autonomous operation algorithm could manage the plant safety better than the current automation and operator’s manual control.

I. Introduction

An autonomous system is a system that has the power and capability in performing functions for self-governance [1]. Autonomous systems can perform control of a given environment over a long period of time without external intervention, in order to perform this function, autonomous systems have highly automated hardware and software. Autonomous control has a high level of automation. It can be operated without the human operators that have no role in operation strategy or are minimally involved in the operation [2].

For designing the system that has autonomy, the system, in some applications, has used intelligent controller to utilize the high-level decision-making techniques as the autonomous controller. The limitations of a classical control system in the past are difficult to adapt to changing circumstances and cannot exclude human decision-making processes. On the other hand, artificial intelligence (AI) fields provide a useful methodology for making the higher-level decision making [1].

Traditionally, AI must fundamentally understand principles and patterns within a given environment. In order to achieve understanding of the given problem, a learner need to identify and isolate basic descriptive elements hidden in the observed environment of low-level sensory data. [3]. In the early days, AI has quickly addressed problems that were repetitive processes for humans. The problem also could be described by a mathematical rules, list of formal [4]. In oder to solve the problems, AI has traditionally used the classical control theory (e.g., If-then logic), fuzzy logic, neural networks and genetic algorithms.

In particular, an artificial neural network method has shown significant improvement in performance in AI field. Behind this growth is an explosion in the performance of artificial neural network methods due to the increased speed of AI training through new AI algorithms (e.g., deep learning) and computer hardware design, multiprocessor graphics cards or graphics processing units (GPUs).

Improved performance of computer software and hardware also improved the performance of the automated system based on it. Nuclear power plants have been able to increase the efficiency and safety of systems and reduce the burden of operators by using automated systems. Current NPPs are generally operated through a collaboration between the operators and the plant automatic system, including the responsibilities of the operators for interacting, monitoring and overriding automatic systems [5]. Based on Billing’s definition of automation level [2], automated systems with a low level of aumation in current NPPs require more operator intervention than autonomous systems. The current automation level of a nuclear power plant can be considered as shared control by the definition of Billing.

When designing a new NPP compared to the current NPPs in operation, it is increasing the automation level of the system. For example, GE-Hitachi stated that "the control systems for the Economic Simplified Boiling Water Reactor (ESBWR) have a high level of automation. All systems are automated unless regulation or human factor engineering analysis results dictate otherwise" [6]. Similarly, remarking on the conceptual design about the control for the U.S. Evolutionary Power Reactor (US-EPR), it was 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." In addition, for future Generation IV reactors, two to four operators may operate up to a twelve modular plants due to the increased automation level [7].

Along with the trend of automation systems being applied to NPPs, interest in the application of the autonomous operation in NPPs has increased for the same purpose as the automation system. Upadhyaya et al. used a proportional-integral-derivative (PID) controller for designing an autonomous operation system in a space reactor system [8]. Oak Ridge National Laboratory suggested an autonomous operation decision-making framework for small and modular reactors [9]. However, those studies focused on the level of the component or controller in system. In order to apply to the extended operational scope of the NPPs, the autonomous control system or even functions need to be studied.

The purpose of this study is to suggest an autonomous algorithm for safety systems by using a long short-term memory (LSTM) network and a function-based hierarchical framework (FHF). The safety goal, functions, systems and components of the NPP were modelled hierarchically using the FHF. Then, the modeled structure was transformed into the LSTM network that is an improved model of a recurrent neural network (RNN). To test and validate the model, this study was used on a simulator called a compact nuclear simulator (CNS) where the reference NPPs is Westinghouse three-loop pressurized water (PWR) and 930 MWe. To train the LSTM network, the train and validation data was collected in this simulator. This paper is organized as follows. Section 2 introduces the FHF and LSTM briefly. In Section 3, the safety systems and functions based on the reference plant are modeled by using the FHF. Then, the process of designing a modeled structure into an LSTM network is shown in Section 4. The data set (training and testing data) are described in Section 5. The discussion and conclusion describes this work in Sections 6 and 7.

II. Methodology

A. Function-based Hierarchical Framework (FHF)

In this study, FHF is sugested for modeling safety systems in NPP. For NPP safety systems, it is designed to include functions at preventing core damage and keeping the plant safe. The FHF modeled the functions required in the design of safety systems as a hierarchical structure.

Analyzing complex systems requires understanding the parent to child system relationships. One way to analyze the system is to break down the parent system into child systems through "authoritative relationships" between tiers and further disassemble those child systems until they reach the lowest level [11]. In general, hierarchical frame work provides a process of describing complex systems in terms of the ability to break down abstract system functions into practical components. These hierarchical controls are also desirable in designing autonomous controls that require the architecture of sophisticated systems [12]. Applying hierarchical framework to the NPP's safety systems helps the system systematically to identify and understand the interactions between the child and parent system.

The FHF begins with a high level safety objective of the NPP and is subdivided into the functions necessary to achieve the goal. The FHF is divided into goal, function and system levels, as shown in Fig 1, and subdivided into the functions necessary to achieve the goal, starting with the safety goals of the NPPs.

The goal level defines ultimately achievement by the entire system for ensuring the health and the public safety by preventing or mitigating the result of postulated accidents. The goal of nuclear safety in the system can be primarily defined as the damage prevention of the core. Core damage can cause radiation from outside the NPP. In addition, the released radiation has a negative impact on the health (such as long-term cancers or short-term injuries) of humans and soil pollution around the NPPs. Thus, in this study, the goal level of NPP safety systems is defined as damage prevention of the core.

The function level includes the functions that need to design achieving the goal. The goal of NPP safety, which is the pressurized water reactors (PWRs), can be accomplished as nine safety functions. These nine safety functions are intended to contol or maintain a parameters or boundary important for preventing the release of radioactive materials, and for assuring the plant's integrity.

In the FHF, the level of system identifies the systems, components, and parameters of component's input/output that are need to satisfy the function level. For instance, in the reference NPP, the chemical and volume control system (CVCS), which control the boron concentration and RCS inventory, the safety injection system (SIS), which maintain the RCS inventory, can perform operations that satisfy the RCS inventory control function. Then, those systems can be subdivided into components. For example, in the case of SIS includes an SI tank, SI pumps and SI valves. The output and input values of the components are also defined as the system level in the FHF. These values are used for output/input variable of the LSTM network. Input values are defined as the system/component condition and the NPP physical variables. Output values are the conditions of the components considered the inputs, such as pump and valve conditions. Fig. 1 presents an FHF for the goal, safety injection systems, RCS inventory control function and related components, including the output and input values.

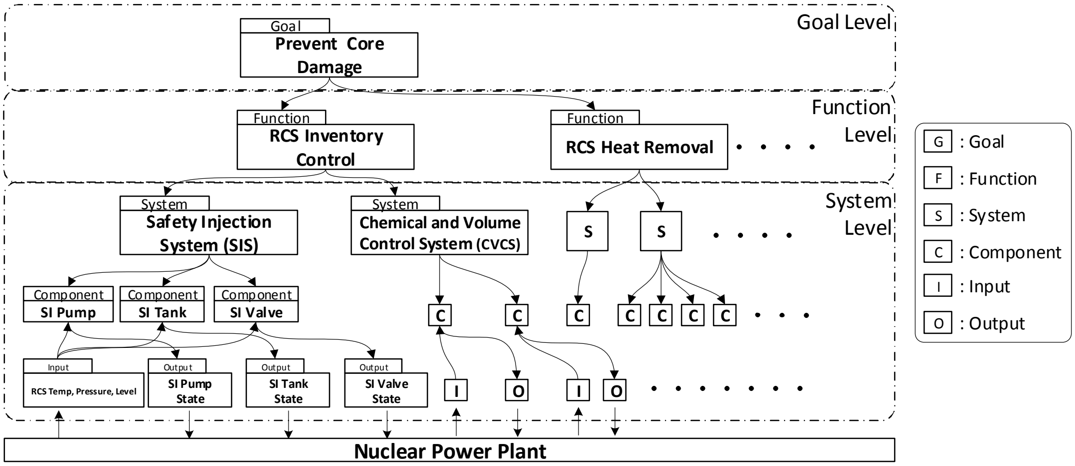


Fig. 1. Function-based Hierarchical Framework

B. Long Short-Term Memory (LSTM)

This study applied the LSTM to development the autonomous control algorithm for the NPP safety function. The FHF was converted to LSTM network that is an advanced model of an RNN.

NPPs are non-linear systems and highly complex operated and monitored by operators and automatic systems. When faced with a transient condition, such as an equipment failure, accident, or an external disturbance in the system, operators have to carry out corrective actions and diagnostic in response to a large volume of information about the NPP's parameters. Thus, the autonomous operation system, instead of the operates, may efficiently act the diagnostic and corrective actions. The operator's decision making and control is a complex logic that requires consideration of the pass operational training experience and the previous plant situation. The classic control controllers (e.g., PID controller), If-then controller, have limitation to design the fully autonomous system.

Several techniques about the non-linear pattern recognition are available in the field of AI for solving this problem. For tackling the pattern recognition problems, the artificial neural network (ANN) was used as one of the most popular tools since an ANN can search the non-linear descriptions from the input domain into the output domain, or search dependencies between several variables [13].

In scientific research, the ANN has a long history. Various neural network models have been proposed for addressing different problems in the machine learning and control fields. There has been a constant interest in the applcation of ANNs to the adaptation and identification control of practical systems that are characterized by communication constraints, uncertainty, nonlinearity and complexity [14]. In addition, the ANN is a promising approach to implement the nonlinear approximation for developing systems, such as NPPs. The LSTM method has been improved from the RNN, which is kind of ANN, by using advanced cell. The RNN has a power that can capture the dynamic behavior in the systems, represent dynamic systems, and extract the information features in hidden layer [15].

An RNN includes input nodes, output nodes, hidden nodes and delay nodes to reflect the condition of the previous system. In the case of RNN, it has delay nodes that is different of existing neural networks. The delay node is calculated from the hidden node t+1 and then from the time t, from the linear combination of input data in the input node. These structural features allow the RNN to estimate time series data. Examples of time series data application are voice recognition, video recognition, dynamic system control, handwriting recognition, and translation.

However, when there are more than five layers [16] in RNN, RNN may have problems with a gradient vanishing. The problem is that vanishes exponentially quickly to zero or gradient value becomes too large while updating the weight in hidden layers. Therefore, LSTM has been proposed to address this issue because it limits the data set for long-term memory within the RNN.

LSTM, based on the RNN model, is a neural network developed for processing long-time sequences of data. LSTM combines rapid training with efficient learning of tasks requiring sequential short-term memory for many time-steps during a trial [15]. LSTM can learn to connect more than 1000 discrete time steps by applying continuous error flow through "constant error carousels" (CECs) within a special unit called cells. [17]. An LSTM cell shows in Fig. 2. The LSTM cell consists of four main elements: the input gate, forget gate, output gate and a cell with a recurrent connection called CECs.

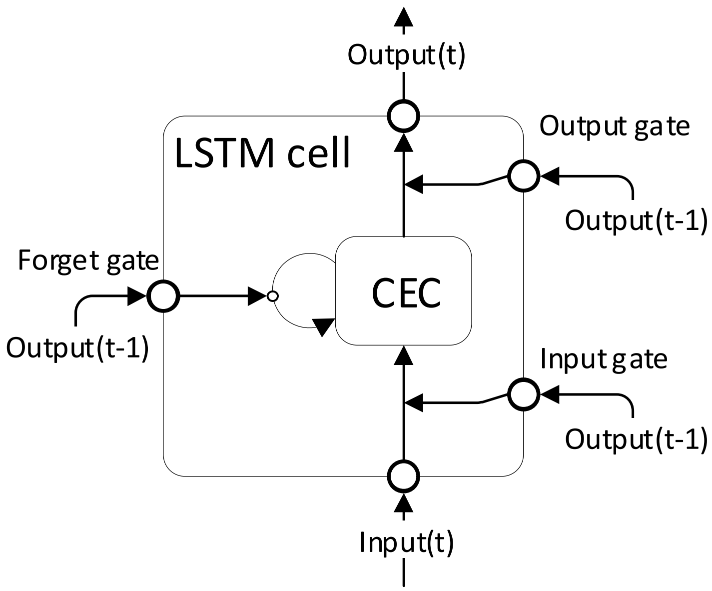


Fig. 2. LSTM structure

The LSTM cell consists of nodes that retain the condition across time-steps. The LSTM cell has three types of specialized gate nodes (output, input, and forget gates) that learn to utilize, protect, or destroy this condition appropriately. The equations below describe the memory block operation of the LSTM cell.

$$i_t = \sigma(x^t W_{xi} + h_{t-1} W_{hi} + c_{t-1} W_{ci} + b_i) \quad (1)$$

$$f_t = \sigma(x^t W_{xt} + h_{t-1} W_{hf} + c_{t-1} W_{cf} + b_f) \quad (2)$$

$$o_t = \sigma(x^t W_{xo} + h_{t-1} W_{ho} + c_t W_{co} + b_o) \quad (3)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \tanh(x^t W_{xc} + h_{t-1} W_{hc} + b_c) \quad (4)$$

$$h_t = o_t \circ \tanh(c_t) \quad (5)$$

In these equations, where x^t is the input to the LSTM block; f_t, i_t, c_t, o_t and h_t are the forget gate, input gate, cell state, output gate and output to the LSTM block, respectively, at the current time step t; W_{xi}, W_{xo} and W_{xf} are the weights between the input layer and the input gate, the input layer and the output gate, abd the input layer and the forget gate, respectively; W_{hf}, W_{ho} and W_{hi} are the weights between the hidden recurrent layer and the forget gate, the hidden recurrent layer and the output gate of the memory block, and the hidden recurrent layer and the input gate, respectively; W_{ci}, W_{co} and W_{cf} are the weights between the cell state and the input gate, the cell state and the output gate, and the cell state and the forget gate, respectively; and finally, b_i, b_o and b_f are the additive biases of the input gate, the output gate, and the forget gate, respectively. The set of activation functions includes the sigmoid function, the elementwise multiplication, i.e., the hyperbolic activation function and inner product of vector, $\circ$.

The gate updates the contents of the memory cell and provides a context-sensitive method for protecting it from interference. The gate can also protect the downstream units form subtle effects of stored information that is not yet relevant. The input gate controls which part should be allowed to alter the state in the cell and which part of the incoming information should be blocked. Meanwhile, the output gate controls some of the output signals that may affect the following cells. The forget gate modifies the recurrent connection process to decide which information it needs to remember and forget in the cell. In addition, the weight is set to 1 to prevent gradients from exploding or vanishing [17, 18].

The LSTM has several special advantages for applying to NPP safety systems. First, the LSTM is considering the ANN characteristics associated with non-linear systems. Although a system or component may have a linear data feature at the low level, but the overall NPP systems and functions can be considered as non-linear systems. Second, as mentioned previously, the operation of the safety systems are so dynamic that the LSTM are relevant for its autonomous operation. Third, the past conditions of the plant are important in the control of an NPP. The current control of systems and components in NPPs is influenced by the past conditions of these components, systems, or parameters. The LSTM uses the historical information in predicting the current output parameters, which are also considered for application to the dynamic safety system.

III. Safety System Modeling by Using the FHF

In this study, NPP safety systems are modeled by using an FHF. A Westinghouse three-loop PWR 930 MWe is used as the reference plant. The modeled safety system thorough FHF was used as an architectural framework for applying the LSTM network.

In the previous section, the main goal of NPP safety is to protect the core in the NPP and alleviate damage to the core from a severe accident. In this study, Westinghouse 900 MWe, 3-loop PWR is used as the reference plant. Safety systems of the reference plant were designed to satisfy nine safety functions. Then, each safety function includes subsystems necessary to satisfy its function, and the subsystem contains components (e.g., pumps and valves). Each component performs automatic or manual controls (e.g., for termination, actuation, and regulation).

A. Goal and Function Levels

The FHF includes three levels as shown in Fig. 3. The top layer represents the goal of NPP safety, which purpose at preventing core damage and mitigating the consequences of accidents, the release of radiation to the public, as mentioned above. Core damage has been assumed to be any condition of the core where the core is uncovered, or the fuel temperature exceeds the design limitation. Core damage can cause radiation from outside the NPP. In addition, the released radiation has a negative impact on the health (such as long-term cancers or short-term injuries) of humans and soil pollution around the NPPs.

Nine safety functions to satisfy the ultimate goal of NPP safety were identified through the reference plant. Safety functions serve for verifying the high-level safety objectives and are defined in terms of a boundary and entity important to preventing the release of radioactive materials and assuring the plant's integrity. Nine safety functions are shown in Table 1 [19] and described in Fig. 3.

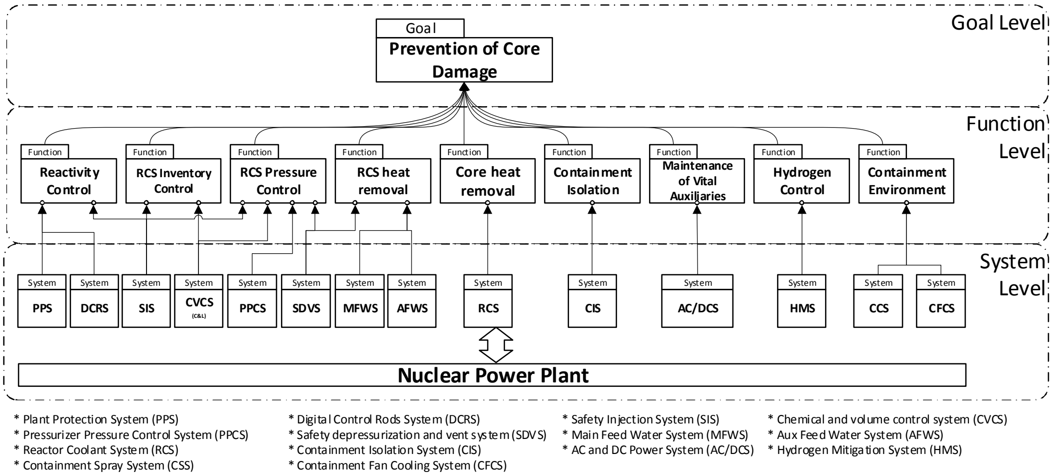


Fig. 3. An FHF structure of an NPP safety systems

Table 1. Nine safety functions

No.	Safety functions	Purpose
1	Reactivity control	Shut reactor down to reduce the heat production
2	Reactor coolant system (RCS) pressure control	Maintain pressure of the reactor coolant system
3	RCS inventory control	Maintain mass or volume of reactor coolant system
4	Core heat removal	Transfer the heat from the core to the coolant
5	RCS heat removal	Transfer heat out of the coolant system medium
6	Containment isolation	Close valves penetrating containment
7	Containment temperature and pressure control	Maintain from damaging containment
8	Maintenance of vital auxiliaries	Maintain operability of the system needed to support safety systems
9	Hydrogen control	Control hydrogen concentration

1. Reactivity control

The purpose of the reactivity control function is to monitor and control the nuclear reactions that occur within the core.

2. RCS inventory control

The RCS inventory control maintains the core covered with an coolant medium. The function monitors the actions that maintain control over either the coolant mass or volume. The RCS inventory control can control the continuous loss of coolant mass and recover from the loss of coolant inventory events, and it also prevent loss of the ability to maintain the RCS coolant inventory. To satisfaction the RCS inventory, it satisfy pressurizer water level between 17% and 92% according to the reference plant.

3. RCS pressure control

The purpose of this function is to effectively manage cooling water by keeping the RCS pressure below the designed value and the previously calculated RCS pressure boundary conditions in order to archive the goal. The reactor cooling water in the PWR should maintain the sub-cooling state to remove the heat generated from the core properly. Therefore, high RCS pressure is maintained to keep the cooling water at high temperature and to protect large boiling of the high temperature in the loops.

4. Core heat removal

The purpose of the this function is to control the heat transformation from the core to the primary cooling water for heat removal through the RCS. A loss of core heat removal capability is alerted according to high core temperatures and/or voiding in the hot leg areas and reactor vessel upper head.

5. RCS heat removal

The RCS heat removal is critical function for assuring the transfer of the stored, generated, and decay heat from RCS to a secondary side. Thus, the purpose of the RCS heat removal is to transfer the heat from RCS to the secondary side in the steam generators (SGs). The transfer of heat between the core and feed water in the SGs can be carried out by the RCS. Therefore, RCS heat removal system adjusts the level of SGs within the allowable range.

6. Containment isolation

The purpose of this function is to ensure proper isolation of the valves in the piping path when isolation signals are generated on the containment vessel to prevent radioactive releases outside the containment. Therefore, the containment isolation function provides the isolation of fluid system that passes through the containment penetration after an accident.

7. Containment pressure and temperature control

The purpose of this functions are to prevent the overstress of the containment building. The containment integrity can be maintained by controlling both containment pressure and temperature to prevent containment overpressure.

8. Hydrogen control

The purpose of the hydrogen control function is to control the concentration of hydrogen that may explode after an accident. In Loss of Coolant Accident (LOCA), hydrogen is generated due to the zirconium-water reaction of the fuel rod and water.

9. Maintenance of vital auxiliaries

Maintenance of vital auxiliaries function is required to ensure operation of the other safety functions. These systems provide the services as instrument air for closing and opening valves, electic power for operating instruments and pumps, and ultimate heat sink for transfer of RCS and core heat.

B. System Level

In system level, it is defined as the system with nine safety functions and components that make up a safety systems. Table 2 represents the systems and components modeled to satisfy safety functions. For instance, safety injection system (SIS), the plant protection system (PPS), and digital control rods system (DCRS) are modeled to control reactivity. Further, the SIS consist of components such as the safety injection (SI) tanks, SI valves, and SI pumps. The systems identified in Table 2 consists safety systems as well as non-safety systems. the CVCS and SIS can be applied in the plant for the RCS inventory control. The SIS is classified as the safety system for the reference plant, while the CVCS is classified as a non-safety system.

The system level is also defined as the input/output parameters and component condition to operate the components. Defined the input/output parameters in the system level are used as input/ouput data in the LSTM network. Table 3 shows an input/output parameter and component condition for the RCS inventory control funtion as an example. In the reference plant, SI valve are operated by SI signal that will be automatically actuated according to pressurizer level and RCS temperature.

Table 2. Safety systems at the system level

Nine safety function	System	Component
Reactivity control	DCRS	Control element drive mechanism
	PPS	Control element drive mechanism
	SIS	SI tanks, SI pumps, SI valves
RCS inventory control	SIS	SI tanks, SI pumps, SI valves
	Chemical and volume control system (CVCS)	Charging valve, charging pump, orifice valve, letdown valve
RCS pressure control	Pressureizer (PZR) pressure control system	PZR heater, PZR spray valve
	Safety depressurization and vent system	Power operated relief valve (PORV)
RCS heat removal	Safety depressurization and vent system	SG PORV
	Aux feedwater system	Aux feedwater pump
	Main feedwater system	Main feedwater pump
Core heat removal	Reactor coolant system	Reactor coolant pump
Containment isolation	Containment isolation system	Containment isolation valve
Containment pressure and temperature control	Containment fan cooling system	Fan cooler
	Containment spray system	Containment spray
Hydrogen control	Hydrogen mitigation system	Hydrogen ignitor
Maintenance of vital auxiliaries	DC and AC power system	Station batteries, Diesel generator

Table 3. An example of input/output for RCS inventory control

System	Component	Output parameters	Input parameters
SIS	SI tank	SI tank valve position	SI Signal SI Valve to RCS Flow SI Tank to RCS Flow RCS Hot-leg 1, 2, 3 Temperature RCS Loop 1, 2, 3 Average Temperature Pressurizer Pressure Pressurizer Delta Level Pressurizer Water Level Reactor Vessel Water Level
	SI valve	SI valve position	
	SI pump	SI pump 1,2,3 state	
CVCS	Charging valve	Charging flow control valves position	Reactor Vessel Water Level Pressurizer Pressure Pressurizer Delta Level Pressurizer Water Level
	Letdown valve	Letdown isolation valves position	
	Orifice valve	75 gpm, 60gpm. 45gpm orifice valves position	
	Charging pump	The condition of charging pump 1,2,3	

IV. Modeling the LSTM network for Autonomous Control Safety Systems

This section shows the process of changing the FHF of safety systems modeled in the previous section to the LSTM network in order to implement autonomous control. Fig. 4 illustrates the transition of SIS, which is included in the RCS inventory control function, from FHF to LSTM network. The input parameters of LSTM network uses the physical parameters required for the state and operation of components modelled in the FHF. The component states were transferred to the output parameters of LSTM network.

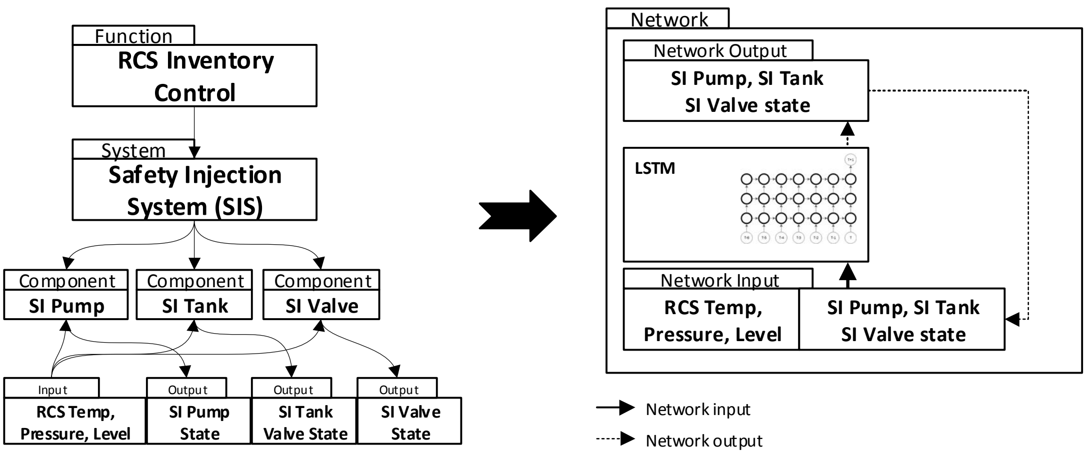


Fig. 4. Transformation from the FHF to LSTM network

The LSTM network is based primarily on the neural network (NN) model and are largely divided into input, hidden, and output layers. The input layer is used to receive prepared input data and pass it to the hidden layer, as well as to normalize the input data for training in the network. In the case of LSTM, the input layer has the data shape that include the time and the plant condition parameter to consider the data characteristic. The hidden layer serves the data communication between the output and input layer, and calculates the results of complex problems. The output layer contains the process to derive the computed content from the hidden layer into the output values.

Fig. 5 shows the structure of the autonomous operation algorithm for safety systems. The number of 168 input parameters, which includes 74 physical and 94 component condition from the NPP, were used as input values of the LSTM network. The input values are transformed to be between from 0 to 1 by using the preprocessing normalization. Then, the output processing was used to transfer the output values of LSTM according to the range of plant control variables. The elements of the LSTM algorithm are described in detail as follows.

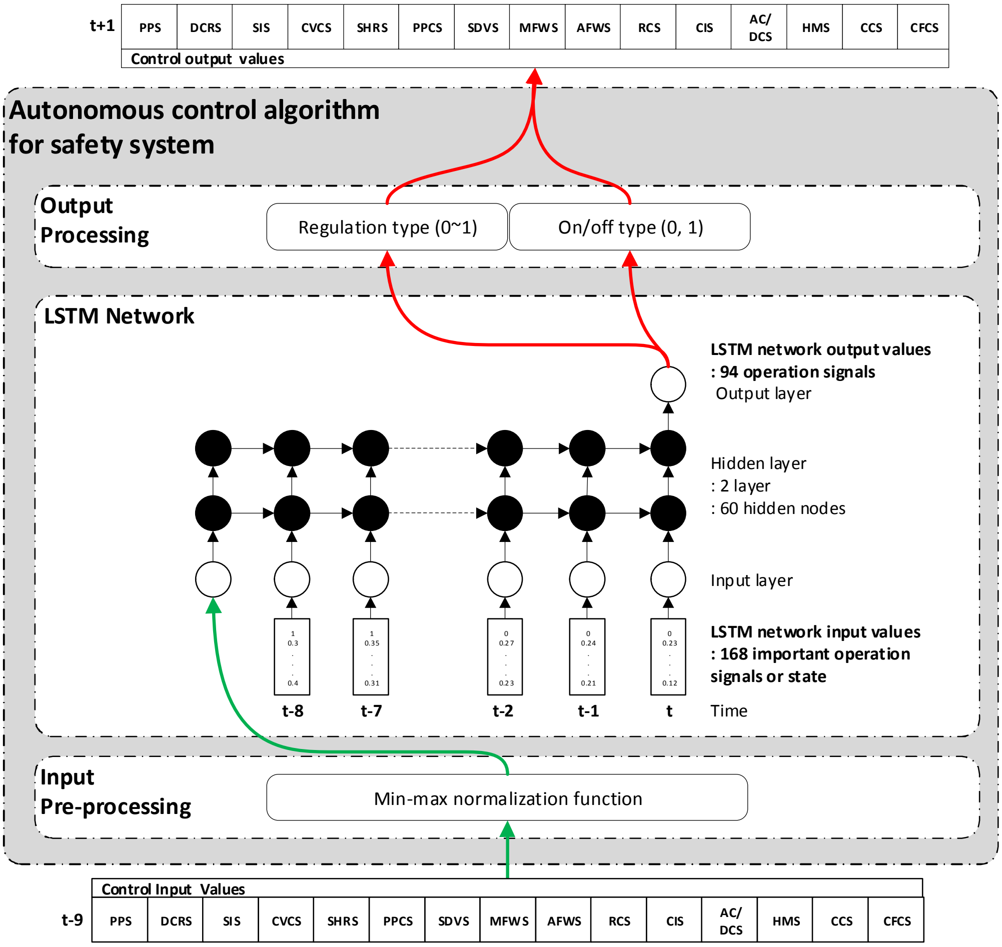


Fig. 5. Autonomous operation algorithm for the safety system

A. Preprocessing of input values

This step in LSTM network preprocessed the input values to be adapted to the LSTM input layer. It scaled the range of input values using a normalization tool. To train the LSTM network, all the parameters in the network had to be scaled from 0 to 1 to reduce the chance of getting trap in local optimization.

For avoiding the local optimization, this study used the min-max scaling method that can be able to scale the input parameters from the NPP for the input layers. A linear transformation was performed on the original input data from the NPP, and the input data were scaled to a range between from 0 to 1. This function is executed throught the following equation [22]. $X_{\min}$ and $X_{\max}$ are the minimum and maximum input values, respectively.

$$X_{norm} = (X - X_{\min})/(X_{\max} - X_{\min}) \tag{6}$$

B. Training the LSTM Network

In order to train the LSTM network, input/output data were collected from a CNS. The CNS was developed by the Korea Atomic Energy Research Institute (KAERI) [20]. Fig. 6 shows a snapshot of reactor coolant system in the CNS.

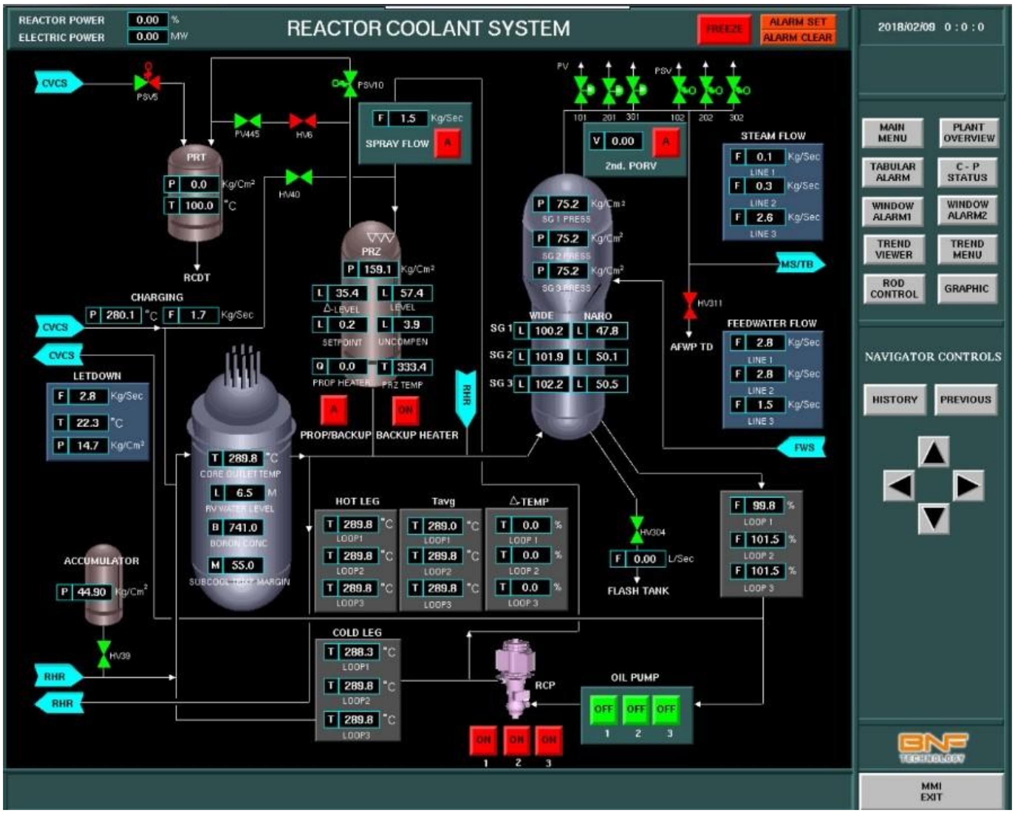


Fig. 6. CNS interface

CNS provides the parameter log file that collected with a sampling period of 1 sec. The operating data from the number of 206 scenarios were gathered by graduate students by graduate students of nuclear engineering at Chosun University. These students have knowledge about operation of the reference plant and CNS. Table 4 shows the configuration of the all collected data and the number of training sets to train data. Each scenario has a time length of 15 to 25 minutes. The training set for operation data has been sampled for 10 seconds. For example, if the scenario starts at 0 sec, the training set has been sampled from 0 to 10 sec, and the second has been sampled from 1 to 11 sec. Thus, the total number of training sets has been sampled as 244,982.

The initiating events included the typical the design basis accidents in the plant (e.g., steam generator tube rupture (SGTR) and LOCA). In addition, an additional failure of components in safety system is also included in the initiating event, e.g., failure of safety injection. All the training scenarios consists of the different failure location and break size. Each scenario included not only human action by the graduate students following operating procedures but also the automatic actuation of safety systems. As mentioned in the previous section, 168 operational parameters were collected for the input values to the LSTM network, and 94 component conditions were collected for the outputs values.

Table 4. Database used for training LSTM network

Initiating Events	Number of scenarios	Number of training sets
Loss of coolant accident (LOCA), safety injection failure	60	83,985
Loss of coolant accident (LOCA)	60	74,251
PZR safety valve failed-to-open, safety injection failure	10	13,616
PZR safety valve failed-to-open	10	13,008
Steam generator tube rupture (SGTR), safety injection valve failure	18	18,179
Steam generator tube rupture (SGTR)	18	15,128
Main steam line break (MSLB)	30	26,815
Total	206	244,982

C. Determination of optimized LSTM network structure

This section decide an optimized LSTM structure for the proposed autonomous operation algorithm. Defining the structure of the hidden layer, the time length of the input data, is the first step in designing an optimized LSTM network structure. The time length of input data is the temporal length of the previous input data that the LSTM can use to compute the output values. The structure of the hidden layers and nodes can affect the network performance, and the determination of the number of hidden layers as well as nodes according to the problem domain.

A typical way to determining the optimized parameters of the LSTM structure is via trial-and-error and experiments [21]. In this study, the trial-and-error approach is used to decide the optimal numbers of hidden nodes and layers and the optimal input length. Therefore, the length of the various input sequences and the number of hidden nodes and layers were trainband by using the data described in the previous section. With limited computing capacity, the range of trial-end-error test were limited to 2 hidden layers and 60 nodes. The LSTM network model was implemented by using Tensorflow, an open source software library based on Python code. This study used a desktop computer that includes an Intel Core i7-6850k CPU and an NVIDIA GeForce GTX 1080 Ti.

In this paper, the root-mean-square error (RMSE) is used as a basis for determining the structure of an optimized network. The network can be trained through RMSE values. The RMSE value represents the gap between the output of the network and the correct value, and having a small error means that training on the network was successful. It also means that the network architecture is suitable for current domain. Table 5 shows the RMSE of each network structure. Following equation shows the RMSE:

$$\mathrm{RMSE}(x', x) = \sqrt{\frac{1}{n}\sum_{n=1}^{N}(x'_n - x_n)^2} \tag{6}$$

The equation uses the predicted power time series x' and the measured power time series x. It is assumed that both time series have N samples. The results represented that the minimum RMSE was obtained from a 2 hidden layers, 10 input sequences and 30 nodes on each layer.

Table 5. Performance comparison between LSTM networks

# of input sequences	# of hidden layers [# of hidden nodes in each layer]	RMSE
5	1 [60]	0.0378
	2 [30, 30]	0.0276
6	1 [60]	0.0297
	2 [30, 30]	0.0270
7	1 [60]	0.0285
	2 [30, 30]	0.0265
8	1 [60]	0.0279
	2 [30, 30]	0.0263
9	1 [60]	0.0279
	2 [30, 30]	0.0258
10	1 [60]	0.0275
	2 [30, 30]	0.0255
11	1 [60]	0.0269
	2 [30, 30]	0.0255
12	1 [60]	0.0262
	2 [30, 30]	0.0256

D. Output processing

The output of the LSTM network has prediction value of the state of components to control the system of the safety functions. The control type in NPPs can be divided into the continuous and discre controls. In the case of a continuous control, it adjusts the component condition to satisfy the correct value of parameters. For example, a control valve need to adjust the its position to control the water flow. On the other hand, a discrete control has two component conditions, such as "fully open or closed" or "on or off".

The output generated by the LSTM network can be any number ranging from 0 to 1. In the case of a continuous control component, this output value can be directly converted to the component condition because the component condition can also have any value between minimum (e.g., fully closed) and maximum (e.g., fully open in a valve).

However, a discrete control component needs post-processing because the component can have one or two states, e.g., off or on, but the LSTM can generate any value between 0 and 1. Through output processing, the LSTM output is converted to a discrete control signal.

Fig. 7 explains the LSTM algorithm with which the output processing changes the LSTM output to the on/off discrete control condition. The component status of the safety system changes when the predicted output value of the LSTM reaches 0.05 in the upward direction or 0.95 in the downward direction. The transition values have been based on the average error in the training data sets. The average error of on/off signals was 0.0434. According to this value, the transition values were selected to 0.95 and 0.5.

In Fig. 7, the component condition at time = 0 is "on" because the network generate an output values around "1". If the LSTM generate a number below 0.95 in the downward direction, the condition of the component will be changed to "off." From the "off" condition, the condition of the component will be changed when the LSTM generated an output values above 0.05 in the upward direction.

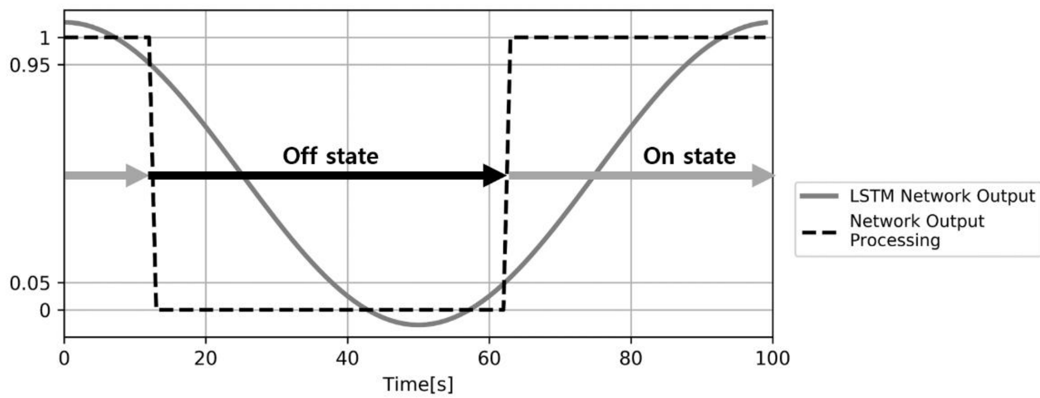


Fig. 7. The algorithm of output processing for discrete control

V. Validation

The autonomous operation algorithm with LSTM network was tested for LOCA and SGTR scenarios. The two scenarios differ in the ratio of automatic and manual control. For LOCA, automation systems perform more operations than manual operator operations. On the other hand, the SGTR required relatively many manual controls following the procedure, such as controlling the reactor coolant pumps, auxiliary feedwater valves and PORVs. The main purpose of testing against two scenarios is to compare the performance of the proposed autonomic algorithms with of the automatic and manual control systems. The scenarios, which are not included in the training, consist of an SG loop 3 SGTR scenario and a loop 2 hot-leg LOCA scenario.

A. LOCA scenario

Fig. 8 and Fig. 9 compare the autonomous operation algorithm with automation and operator's manual control at the system level through the LOCA scenario. In this scenario, the plant was tripped at 65 sec. Fig. 8 represents the charging valve position for operating the RCS inventory. While the automation and operator's manual control closed the charging valve, the autonomous operation algorithm controlled actively until the charging valve become closed. Fig. 9 shows the change of the SI valve. The autonomous operation algorithm opened the SI valve 17 seconds earlier than the automation and operator's manual control. It means that the autonomous operation algorithm supplied more water to the RCS. However, it is not possible to compare the performance of an autonomous operation algorithm and an automation and operator's manual control with only system level results. Therefore, this study shows a comparison of the performance results of the functional levels of each operation system. Fig. 10 shows the result of RCS inventory, core heat removal and RCS heat removal to compare the performance of operation system. In the RCS heat removal and RCS inventory control, SG's water level and coolant level in the reactor are more desirable for safety, while faster cooling is better for core heat elimination after a LOCA occurs. As the result, the autonomous operation performed better management of safety functions than the automation and operator's manual control.

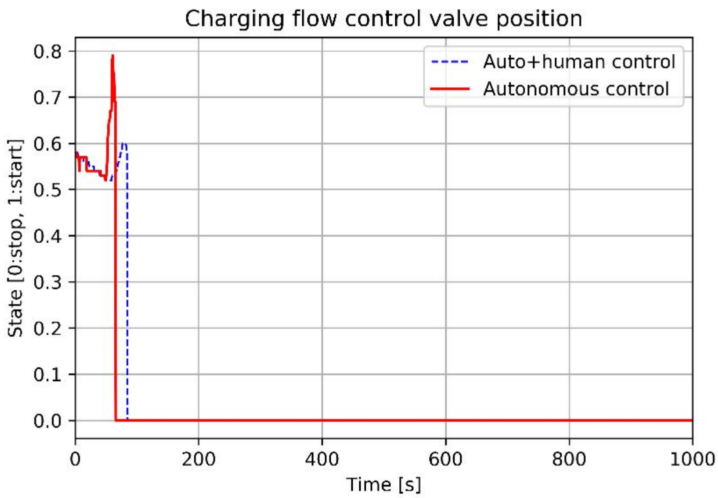


Fig. 8. Charging valve position

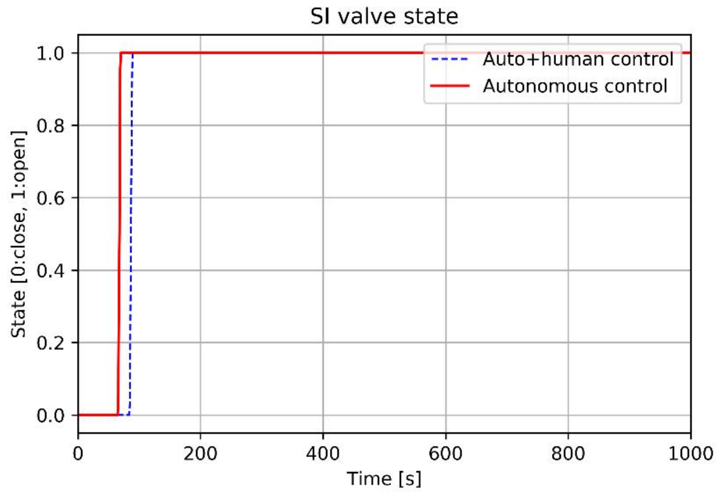
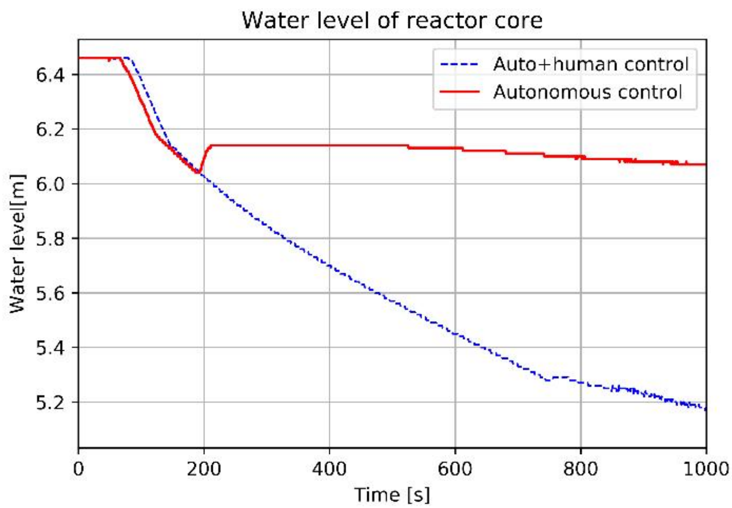
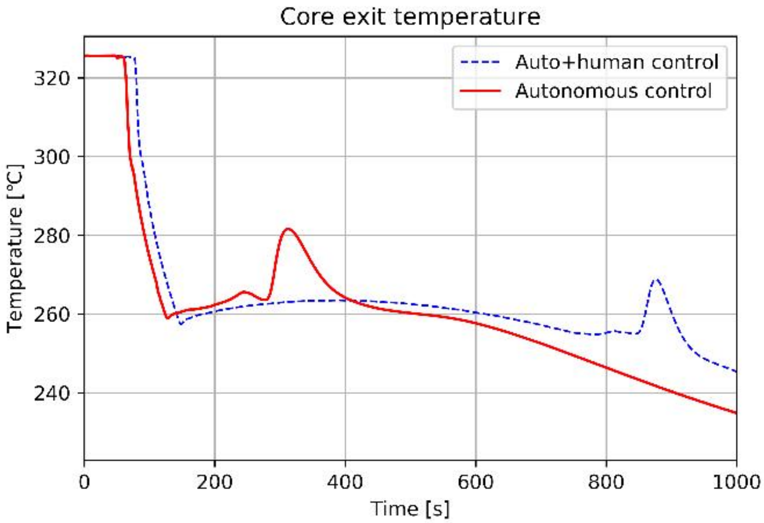


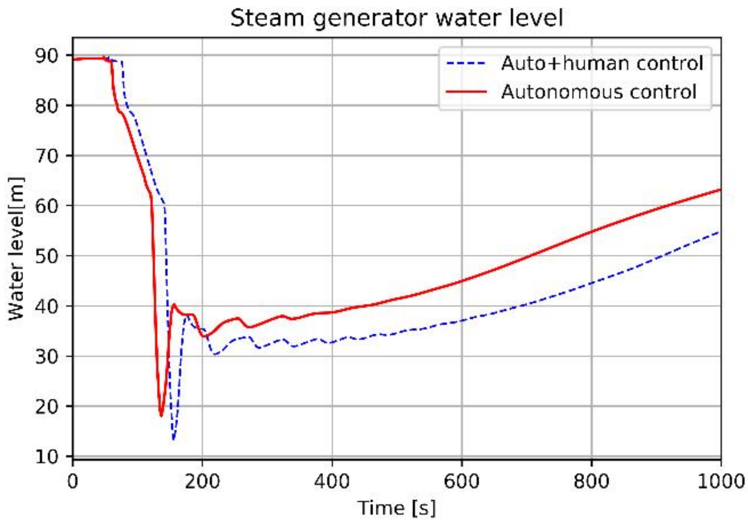
Fig. 9. The change of SI valve position



(a). RCS Inventory – the water level in reactor



(b) Core Heat Removal – the temperature of core exit



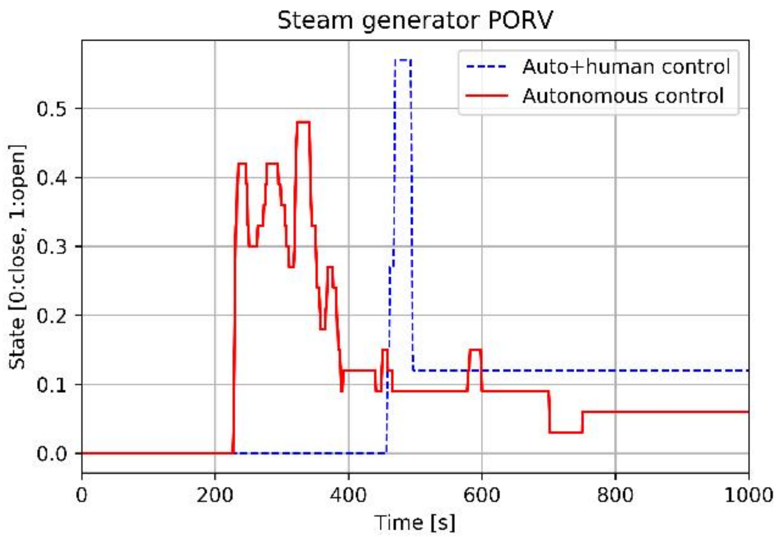
(c) RCS Heat Removal – SG water level

Fig. 10. Comparison of autonomous and automation and operator’s manual control for safety functions during a LOCA

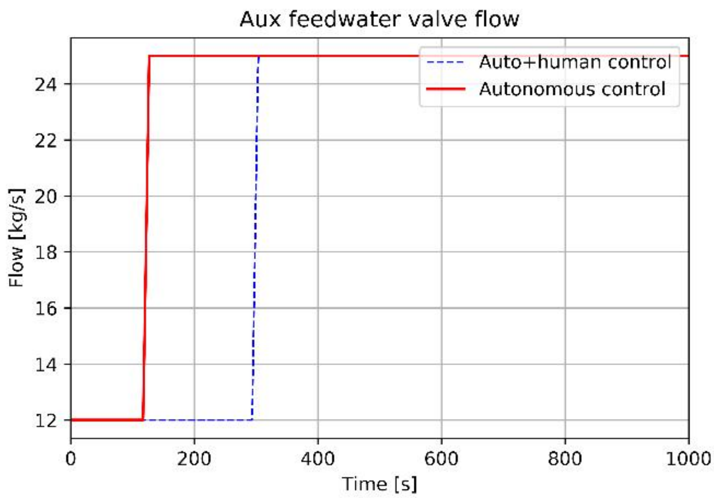
B. SGTR scenario

Fig. 11 shows the comparison of autonomous and automation and operator's manual controls at the system level for the reactor coolant pump (RCP), auxiliary feedwater valve, and SG PORV in the SGTR scenario. The initiating event occurred at 60 sec. The goal of controlling the SG PORVs is to eliminate heat from the RCS. With automation and operator's manual control, the operator choses and opens the PORVs of the intact SGs. Fig. 11 (a) shown that the autonomous operation algorithm started to open the PORV earlier and operated the positions of the PORV valves more frequently than the automation and operator's manual control. In the case of auxiliary feedwater valve, the autonomous operation algorithm started to open the valve that controls water to the SGs early. The control of the RCPs was different between two control approaches. The automation and operator's manual control maintained the operation of the RCPs while the autonomous operation algorithm stopped them after approximately 110 sec.

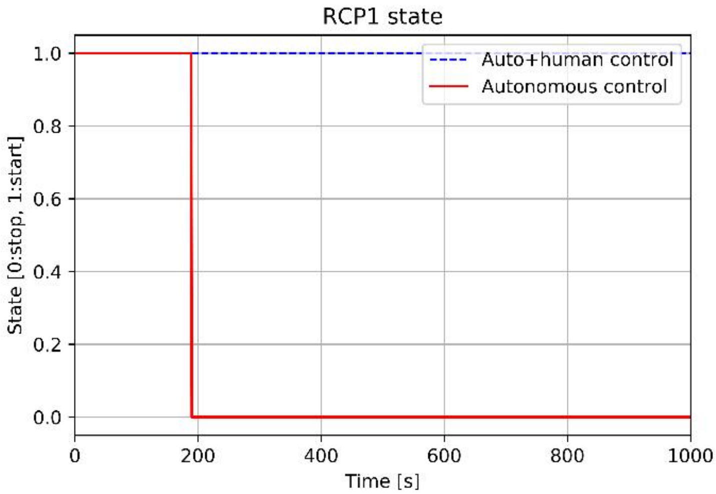
Fig. 12 compares the two control approaches at the function level. Similar to the LOCA scenario, these results show that the autonomous operation algorithm controled the accident in a safer way for three safety functions.



(a) SG PORV position

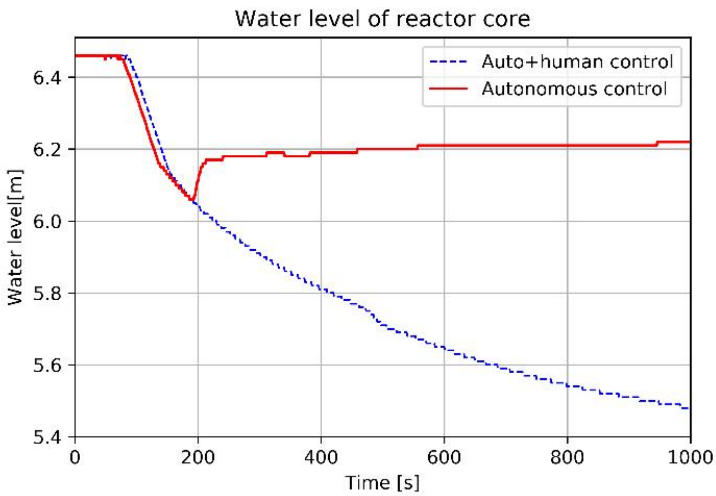


(b) Auxiliary feedwater valve position

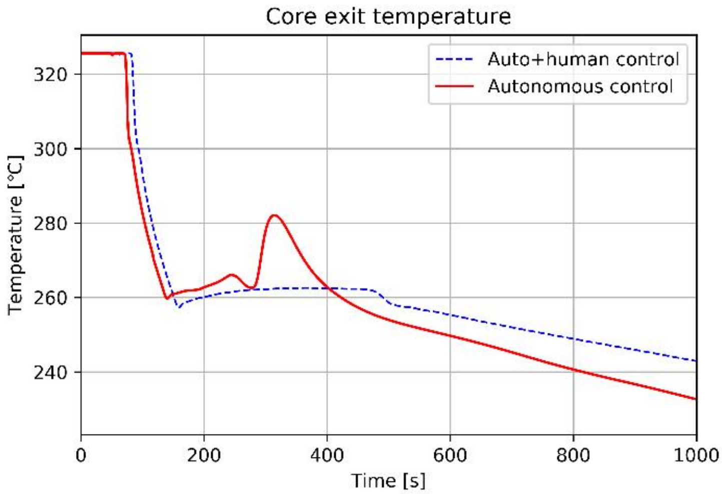


(c) RCP condition

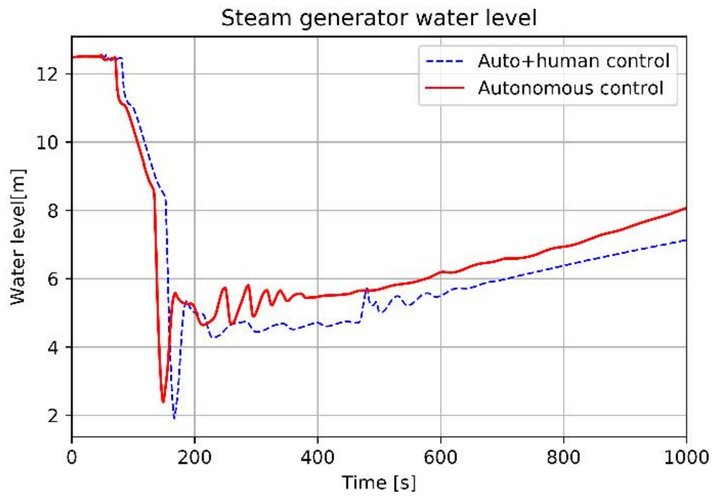
Fig. 11. Comparison of autonomous and automation and operator’s manual controls at the system level during an SGTR



(a) RCS Inventory – the water level in reactor



(b) Core Heat Removal – the temperature of core exit



(c) RCS Heat Removal – SG water level

Fig. 12. Comparison of autonomous and automation and operator’s manual control for safety functions during an SGTR

VI. Discussion

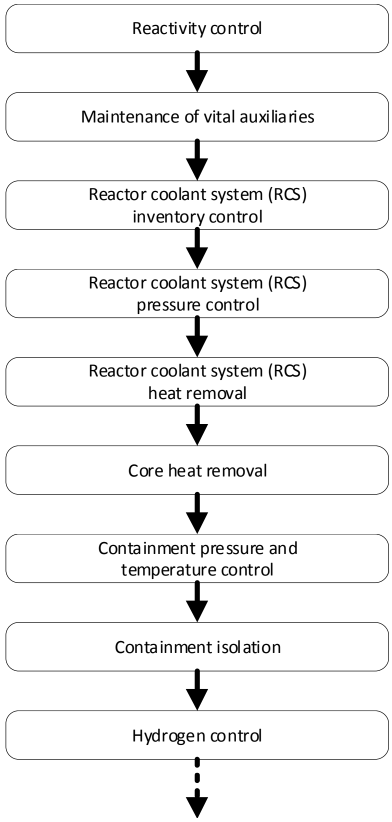
The validation results presents that the autonomous operation algorithm performed better than the autonomous operation algorithm and automation and operator's manual control in managing the safety parameters in the two scenarios. Table 6 shows a comparison of the safety functions for the two control approaches at 1000 sec. There are a couple of plausible assumptions for this performance difference. First, the LSTM predicted the component state by considering the plant condition history, while the automation and operator's manual control determined it based on the present plant condition. The LSTM generated the output control signal based on the input plant data of the previous 10 time steps. It can predict the plant condition and control the plant component earlier. In the automatic system in the reference plant, control signals were actuated according to the current set point parameters, and the operating procedure also instructs operators to carry out the actions based on the current plant values.

Second, the autonomous operation algorithm simultaneously supervised the safety functions, while the human actions in the automation and operator's manual control are performed sequentially. Fig. 13 shows the difference between the two approaches to operating safety functions during accidents. With the automation and operator's manual control, the emergency operating procedures are generally organized to instruct the operators to control one safety function. The emergency operating procedure is sequentially determined by accident urgency and importance, as shown in Fig. 13 (a). This sequential operation strategy seeks to reduce human errors due to the operator's limited capacity for addressing multiple tasks simultaneously. However, the autonomous operation algorithm has no such limitation in addressing multiple tasks because these algorithm is performed at the computer environment. The parallel processing, as shown in Fig. 13 (b), enabled the autonomous operation algorithm to respond to the accident faster than the automation and operator's manual control.

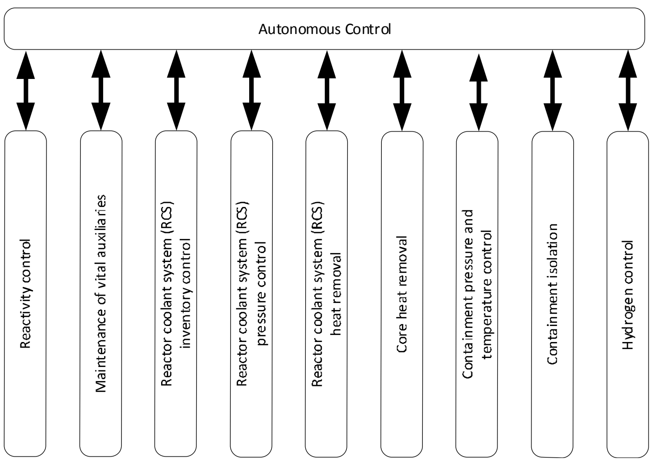
In addition, if the training data sets are obtained from the operation by actual operators, it can improve the quality of suggested autonomous operation algorithm. The quality of the LSTM network largely depends on that of training data sets. Therefore, if expertise can be included in the training data sets, the LSTM network can be trained to be better tuned and then show the better capability of mitigating the accident.

Table 6. Comparison of the four safety functions for two approaches at 1000 sec

Scenarios	Function	Parameter	Autonomous control	Auto-Human control
LOCA	Core Heat Removal	Core exit temperature	230.73℃	245.26℃
	RCS Inventory	Reactor water level	6.06m	5.18m
	RCS Heat Removal	SG level	9.35m	7.67m
	RCS Pressure	Pressurizer pressure	63.75 kg/cm^2	69.4 kg/cm^2
SGTR	Core Heat Removal	Core exit temperature	228.44℃	242.89℃
	RCS Inventory	Reactor water level	6.22m	5.48m
	RCS Heat Removal	SG level	8.64m	7.13m
	RCS Pressure	Pressurizer pressure	97.02 kg/cm^2	97.6 kg/cm^2



(a) The sequential operation of safety functions in automation and operator’s manual control



(b) The parallel operation of safety functions in autonomous operation algorithm

Fig. 13. Differences in the operation strategies of the two approaches

VII. Conclusions

This study suggested an autonomous operation algorithm for NPP safety functions by using an FHF as well as LSTM network. For analyzing the NPP safety systems, a hierarchical framework to model the NPP safety functions were suggested. According to this framework, an autonomous operation algorithm based on an LSTM network was modeled to control the safety functions. The LSTM network was trained and validated by using a CNS. The algorithm has demonstrated the effectiveness. The validation results showed that the autonomous operation algorithm could manage the plant safety better than the current automation and operator's manual control.

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그리고 업무로 인해 바쁘신 와중에도 논문에 대한 조언과 심사를 해주신 나만균 교수님, 송종순 교수님께 감사드리며, 학부 과정을 무사히 마칠 수 있도록 도움을 주신 정운관 교수님, 이경진 교수님, 김진원 교수님께 감사를 드립니다.

또한 대학원 기간 동안 같은 실험실에게 생활한 Awwal, 주영, 재민, 승헌, 경민, 수봉, 가영, 윤철에게 감사를 표합니다.

그리고 지금은 멀리 IAEA에서 일하고 있지만, 늘 곁에서 연구적으로나 사랑으로 지켜봐준 애인 이희재에게 고맙다는 말을 전하고 싶습니다. 마지막으로 저의 가장 큰 정신적 지주이며, 제가 무슨 일을 한다고 해도 묵묵히 지지해주신 아버지와 하나 뿐인 아들의 건강을 늘 걱정해주시고 사랑해주시는 어머니께 감사의 말씀을 전하고 싶습니다.