Hindawi
Science and Technology of Nuclear Installations
Volume 2023, Article ID 4763033, 9 pages
https://doi.org/10.1155/2023/4763033

Research Article

Methods for Predicting the Minimum Temperature of the Outage Loop and the Maximum Power Caused by the Low-Temperature Coolant

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Received 21 March 2023; Revised 19 May 2023; Accepted 12 June 2023; Published 19 June 2023

Academic Editor: Han Zhang

When the feedwater valve at the outage loop of the floating nuclear power plant leaks, thermal stratification occurs in the steam generator. It causes lower water temperature in the outage loop. The extent of hazard of this phenomenon cannot be directly determined by the existing measurement parameters, which poses a threat to the operational safety of the reactor. Therefore, this study adopts two routes: data-driven combined with safety analysis system (DSAS) and mechanism model-driven combined with safety analysis system (MSAS), to propose the prediction methods for the minimum temperature of the outage loop and the maximum power caused by the low-temperature coolant. Then, the actual data are used to verify these methods and the prediction results under different initial conditions are analyzed. The results show that both the DSAS method and the MSAS method can predict the minimum temperature of the steam generator in the outage loop and the maximum power when the outage loop is put into operation, but the DSAS method has better performance under certain conditions. These methods can provide guidance to the operators to avoid reactivity insertion accident.

1. Introduction

When one of the two loops of the floating nuclear reactor stops operating, which is known as the outage loop, the other loop can operate normally to provide power. In this case, if a certain amount of cold water enters the steam generator of the outage loop, thermal stratification will occur, which has been proven to exist by experiment in reference [1]. It results in that the coolant temperature in steam generator became much lower than that in other locations of the primary pipe. When the outage loop is put into operation, the low-temperature coolant enters the core, and thus the reactivity insertion accident occurs [1]. Since there is no temperature measurement point in the steam generator, the fluid in the steam generator is generally considered to be in a saturated state because the feedwater is quickly heated to saturation temperature in the feed pipes and the descending channel and there is no obvious thermal stratification phenomenon in normal operation [1]. Therefore, it is difficult for the operators to determine the true temperature in the steam generator of the outage loop and to determine whether the reactivity insertion accident will occur when the outage loop is put into operation. Therefore, the methods for predicting the minimum temperature of the outage loop and the maximum power caused by it should be proposed to prevent operators from taking incorrect operational measures.

In nuclear power systems, the parameters are mainly predicted using an intelligent method based on mechanism model driven [2] and data driven [3]. Mechanistic models are more complex to build and generally require some simplification measures. Kim et al. proposed a multiphysics modeling method, which can predict and show a more realistic cladding behavior of the fuel rods [4]. Zhang et al. predicted hydrogen deflagration to detonation transition by analyzing oxygen concentration in inert diluent and verified

the feasibility and applicability of the method [5]. Wang et al. use dimensionless Reynolds number, Grashf number, and steam volume fraction to predict reverse flow characteristics, and the prediction error is within ±15% [6]. Data-driven methods require some data support. Liu et al. used a probabilistic support vector machine regression method to predict nuclear power plant system operating parameters and compared this method with the self-associative kernel regression method. The results showed that this method was better for predicting nuclear system parameters [7]. Zeng et al. combined support vector machine method with particle filter to predict unknown model parameters and reactor system state. It is with good performance [8]. Marseguerra et al. used fuzzy logic and fuzzy neural network methods to predict steam generator water level and compared the predicted value with the measured value to determine whether the measuring device is faulty [9, 10]. Liu et al. used the back propagation (BP) neural network method capable of online training for the prediction of nuclear power plant system operating parameters and compared it with the nononline prediction model. The results showed that the BP neural network method with online training function has better prediction effect but is more time consuming [11]. Wang et al. used an adaptive BP neural network model to predict the maximum temperature of the core fuel envelope based on the core power and reactor inlet flow. The average error of the prediction results did not exceed 3%, and the computational speed was 300 times faster than that of the COBRA program [12]. Chen et al. combined genetic algorithm with neural network and optimized the neural network model using genetic algorithm, which made the model function better for nonlinear system parameter prediction [13]. At present, more scholars prefer to study the application of data-driven methods in the prediction of nuclear power system parameters [14, 15] and a few scholars study the mechanism model-driven method to predict the parameters of the nuclear power system [6]. For the outage loop of the floating nuclear power plant, the temperature within the outage loop and the effects brought about by it should be obtained if the more accurate guidance is needed. Therefore, it is necessary to combine data-driven method with mechanistic model-driven method for analysis.

This paper proposes the prediction methods for the minimum temperature in the outage loop and the maximum power caused by the low-temperature coolant. The minimum temperature in the outage loop is predicted by means of a data-driven method and a mechanistic model-driven method, respectively, and then the safety analysis system based on the mechanistic model is used to further predict the maximum power.

2. Methods for Predicting the Minimum Temperature of the Outage Loop and the Maximum Power Caused by the Low-Temperature Coolant

The logic for predicting the minimum temperature of the outage loop and the maximum power caused by the low-temperature coolant is shown in Figure 1. First, the minimum temperature in the steam generator of the outage loop is predicted. The data-driven prediction method is realized by the database and the data matching method, and the mechanism model-driven prediction method is realized by calculating the energy conservation equation. Then, a limiting assumption that the coolant temperature in the outage loop is all equal to the minimum temperature is made, and an interface program is written to change the corresponding parameters in the safety analysis system based on the mechanistic model and to put the outage loop into operation to predict the power variation. The detailed prediction method is described subsequently.

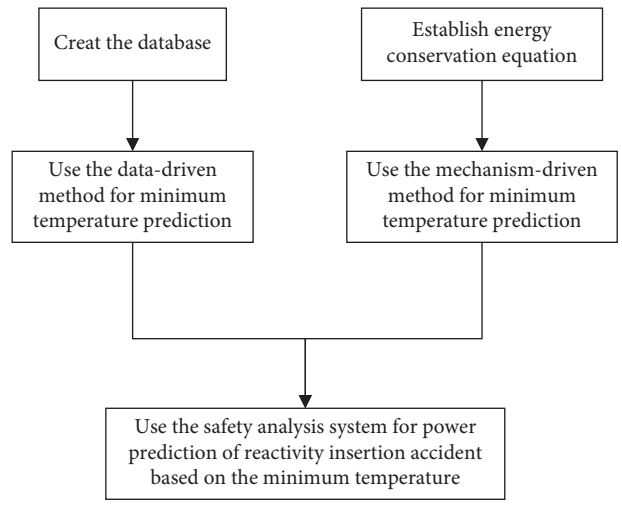

Figure 1: The logic of prediction.

2.1. Data-Driven Method for Predicting the Minimum Temperature of Steam Generators

2.1.1. Establishment of Database. A safety analysis system for floating nuclear power plants based on the mechanism model can simulate the physical, thermal, and hydraulic properties of the core and the dynamics of typical equipment under normal or abnormal operating conditions of the nuclear power system. It can be used for nuclear accident safety assessment, nuclear accident safety response protocol development, nuclear accident emergency response, and other research studies. The analysis system is able to better understand the reactor thermal safety limit parameters (including fuel center temperature, cladding temperature, and minimum burn-up ratio) and also to obtain the response characteristics of important macroscopic operating parameters in the first and second loops.

The analysis system mainly includes the core physics module, the reactor and the thermodynamic module of main coolant system, the control module of nuclear power system, and the kinetic characteristics calculation module of typical equipment. Among them, the core physics module adopts the point reactor neutron dynamics model; the reactor and main coolant system thermal-hydraulic module adopts RELAP5/MOD3.2 system analysis program; the one-dimensional thermal-hydraulic and point reactor neutron

dynamics coupling calculation model is adopted; and the control module of nuclear power system mainly includes the automatic regulation and protection module of reactor power, steam generator, pressure and the regulation and control module of water level, and the start-stop control module of main pump. The primary circuit auxiliary system mainly simulates the pressure safety system, high-pressure safety injection system, low-pressure safety injection system, etc. The second circuit adopts simplified modeling and only simulates the steam generator main feedwater system, main steam system, and steam discharge system.

This safety analysis system is capable of analyzing various operating conditions of a floating nuclear power system, so this paper is based on this system to obtain the corresponding single-loop operation data. First, the system is run to steady state, then one of the loops is shut down, and thermal stratification data (including saturation temperature and minimum temperature) in the steam generator are obtained for different steam generator initial water levels, different steam generator initial pressures, and different total leakage mass of feedwater valve in the outage loop. The variation of the temperature at different heights of the steam generator with time is shown in Figure 2, where WL_{normal} is the water level of the steam generator in normal operation. It can be seen that there is a significant thermal stratification phenomenon when cold feedwater leaks into the steam generator in the outage loop, and the temperature at the bottom of the steam generator is significantly lower than the saturation temperature.

The change in temperature for different initial conditions is shown in Figure 3, where T_{sat}, T_{min}, WL_0, P_0, P_{normal}, M, F, and F_{normal} is the saturation temperature, the lowest temperature, the initial water level, the initial pressure, the pressure in normal operation, the total leakage mass, the leakage flow, and the flow in normal operation in the steam generator of the outage loop, respectively. Through comparative analysis, it is found that the total leakage mass of feedwater valve has the greatest effect on thermal stratification, followed by the initial water level and initial pressure, and the leakage flow has less effect. Therefore, different total leakage mass of feedwater valve, different initial water level, and different initial pressure are set to calculate separately to establish the corresponding database.

2.1.2. Prediction Method. In the steam generator of a floating nuclear power plant, the measurement factors mainly include pressure and water level, so the initial water level, the initial pressure when the outage loop is shut down, the amount of water level change during outage, and the total outage time are selected as input parameters to predict the temperature, and the prediction method is as follows.

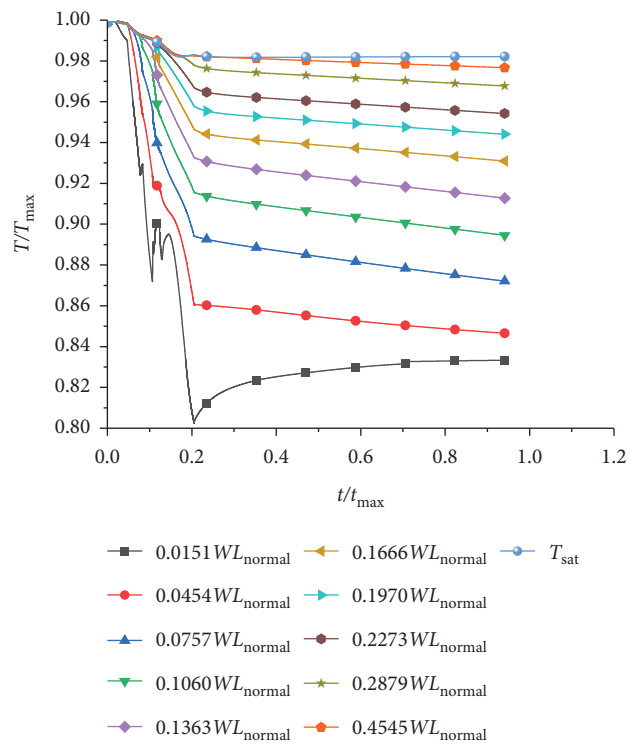

Figure 2: The variation of the temperature at different heights of the steam generator.

(1) Normalize the initial water level, initial pressure, and water level change amount in the database, and the normalization method is as follows:

$$y = \frac{x - x_{min}}{x_{max} - x_{min}}. \tag{1}$$

(2) Using the Euclidean distance method [16], the threshold value is set to 0.04, and the four parameters of initial water level WL_0, initial pressure P_0, water level change ΔWL_{actual}, and total outage time t_{actual} are selected to be matched in the database, and the matching method is as follows:

$$\begin{cases} \sqrt{a_1 (WL - WL_0)^2 + a_2 (P - P_0)^2 + a_3 (\Delta WL - \Delta WL_{actual})^2} \le 0.04, \\ |t - t_{actual}| \le 200, \end{cases} \tag{2}$$

where WL denotes the water level, P denotes the pressure, ΔWL denotes the amount of water level change, and t denotes the total outage time. Based on the results of the influence factor analysis, the coefficients a_1, a_2, and a_3 will have an impact on the prediction results of the DSAS method, which cannot be randomly selected. Therefore, the influences of the parameters corresponding to the three coefficients on the minimum temperature are analyzed. Finally, the normalized change rate of the lowest temperature

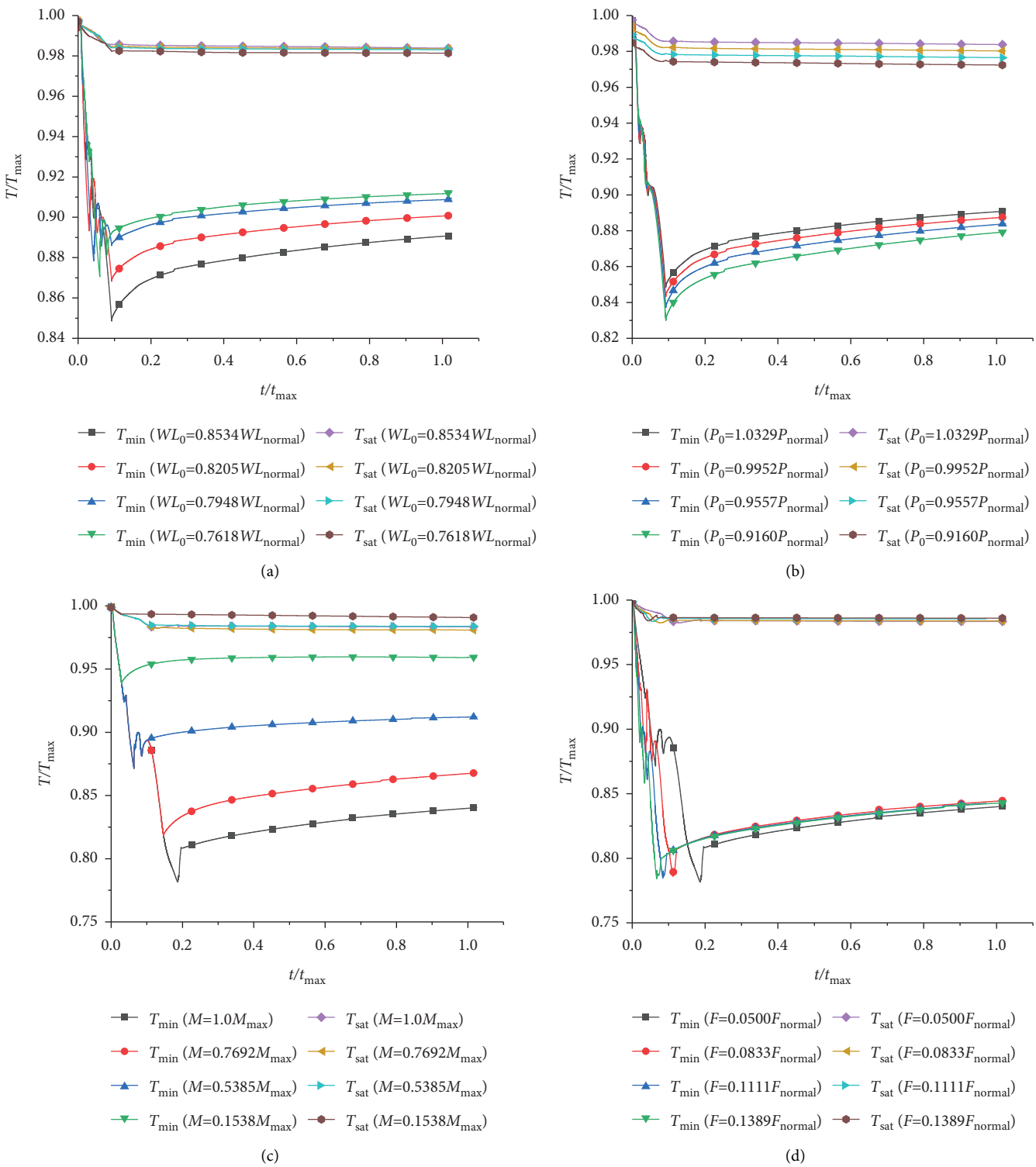

Figure 3: The change in temperature for different initial conditions.

with the three parameters is selected as the corresponding coefficient. The coefficients a_1, a_2, and a_3 are taken as 0.15, 0.15, and 0.7, respectively.

(3) The minimum temperature of the steam generator corresponding to the data matching result is selected as the prediction result.

2.2. Mechanism Model-Based Method for Predicting the Minimum Temperature of Steam Generators. After the outage loop is shut down, due to the leakage of the feedwater valve, there is a certain inflow of feedwater on the secondary side of the steam generator, and the thermal stratification is formed in the steam generator. So, it is necessary to divide the area when establishing the energy conservation equation, as shown in Figure 4.

It is assumed that there is no other fluid or energy inflow and outflow in the steam generator other than the natural cooling and the leakage feedwater, and that the mass of coolant in the U-tubes and in the lower chambers of steam generator remains constant. For conservative estimation, the initial temperature of the lower chambers is set to the saturation temperature in the steam generator, and then the energy conservation equation is as follows:

$$\begin{aligned} m_{\mathrm{FW}}u_{\mathrm{FW}} + m_{\mathrm{SG\_}g_0}u_{\mathrm{SG\_}g_0} + m_{\mathrm{SG\_l_0}}u_{\mathrm{SG\_}l_0} + m_{U_0}u_{U_0} + m_{P_0}u_{P_0} \\ = E_{\mathrm{cooling}} + m_{\mathrm{SG\_}g_1}u_{\mathrm{SG\_}g_1} + m_{\mathrm{SG\_}l_1}u_{\mathrm{SG\_}l_1} + m_{U_1}u_{U_1} \\ + m_{P_0}u_{P_1} + m_{\mathrm{SG\_}l_2}u_{\mathrm{SG\_}l_2} + m_{U_2}u_{U_2}, \end{aligned} \tag{3}$$

where m_{FW} and u_{FW} is the total leakage mass of feed water and the specific internal energy of feed water, respectively. $m_{\mathrm{SG\_}g_0}$, $u_{\mathrm{SG\_}g_0}$, $m_{\mathrm{SG\_}l_0}$, and $u_{\mathrm{SG\_}l_0}$ is the mass of steam, the specific internal energy of steam, and the mass of water and the specific internal energy of water in the steam generator at initial state, respectively. m_{U_0}, u_{U_0}, m_{P_0}, and u_{P_0} is the mass of coolant in U-tubes, the specific internal energy of coolant in U-tubes, the mass of coolant in the lower chambers of the steam generator, and the specific internal energy of coolant in the lower chambers of the steam generator at initial state, respectively. E_{cooling} indicates the energy lost through natural heat dissipation on the external surface of the steam generator. $m_{\mathrm{SG\_}g_1}$, $u_{\mathrm{SG\_}g_1}$, $m_{\mathrm{SG\_}l_1}$, $u_{\mathrm{SG\_}l_1}$, $m_{\mathrm{SG\_}l_2}$, and $u_{\mathrm{SG\_}l_2}$ is the mass of steam, the specific internal energy of steam, the mass of unsaturated water, the specific internal energy of unsaturated water, the mass of saturated water, and the specific internal energy of saturated water in the steam generator at final state, respectively. m_{U_1}, u_{U_1}, m_{U_2}, u_{U_2}, and u_{P_1} are the mass of coolant in thermal stratification area of U-tubes, the specific internal energy of coolant in thermal stratification area of U-tubes, the mass of coolant in nonthermal stratification area of U-tubes, the specific internal energy of coolant in nonthermal stratification area of U-tubes, and the specific internal energy of coolant in the lower chambers of the steam generator at final state, respectively.

The energy lost through natural heat dissipation on the outer surface of the steam generator is calculated by the following equation:

$$E_{\mathrm{cooling}} = hS_{\mathrm{SG}}\left(T_{\mathrm{SG\_surface}} - T_{\mathrm{air}}\right)t_{\mathrm{actual}}, \tag{4}$$

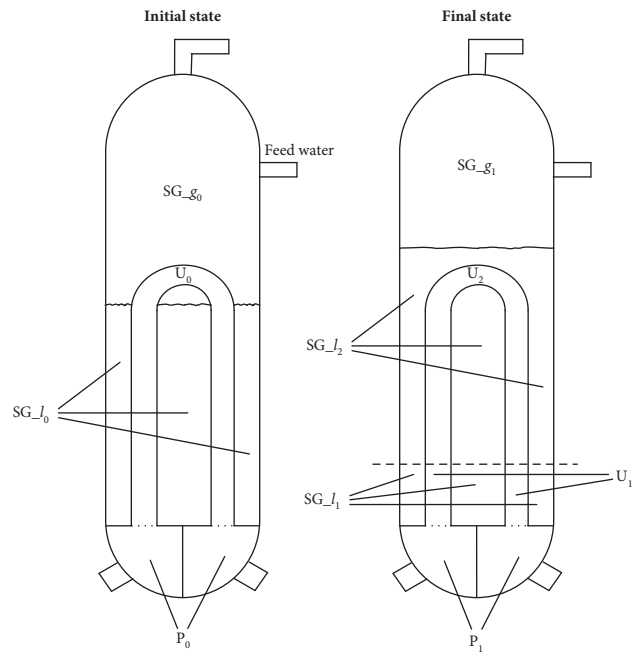

Figure 4: Area division of steam generator at the beginning and end of outage.

where h, S_{SG}, $T_{\mathrm{SG\_surface}}$, T_{air}, and t_{actual} are the heat transfer coefficient, the area of the outer surface of the steam generator, the temperature of the outer surface of the steam generator, the air temperature, and the actual outage time, respectively. It is assumed that the temperature difference between the outside surface of the steam generator and the air is constant.

The total leakage mass of feed water can be obtained by the following equation:

$$m_{\mathrm{FW}} = m_{\mathrm{SG\_}g_1} + m_{\mathrm{SG\_}l_1} + m_{\mathrm{SG\_}l_2} - m_{\mathrm{SG}_{g0}} - m_{\mathrm{SG}_{l_0}}. \tag{5}$$

The remaining fluid mass is calculated by the following equations, where ρ and V is the density and mass of the corresponding fluid, respectively.

$$\begin{aligned} m_{\mathrm{SG\_}g_0} &= \rho_{\mathrm{SG\_}g_0}V_{\mathrm{SG\_}g_0}, \\ m_{\mathrm{SG\_}l_0} &= \rho_{\mathrm{SG\_}l_0}V_{\mathrm{SG\_}l_0}, \\ m_{U_0} &= \rho_{U_0}V_{U_0}, \\ m_{P_0} &= \rho_{P_0}V_{P_0}, \\ m_{\mathrm{SG\_}g_1} &= \rho_{\mathrm{SG\_}g_1}V_{\mathrm{SG\_}g_1}, \\ m_{\mathrm{SG\_}l_2} &= \rho_{\mathrm{SG\_}l_2}V_{\mathrm{SG\_}l_2}, \\ m_{U_2} &= m_{U_0}\frac{V_{U_2}}{V_{U_1} + V_{U_2}}, \\ m_{\mathrm{SG\_}l_1} &= \rho_{\mathrm{SG\_}l_1}V_{\mathrm{SG\_}l_1}, \\ m_{U_1} &= m_{U_0}\frac{V_{U_1}}{V_{U_1} + V_{U_2}}. \end{aligned} \tag{6}$$

Assuming that the height of the thermal stratification area is constant, in the abovementioned equations, only the parameters $\rho_{SG\_l_1}$, $u_{SG\_l_1}$, u_{U_1}, and u_{P_1} are unknown. The average water temperature in the thermal stratification area is set as $T_{average}$. Make the equations true by constantly adjusting the value of $T_{average}$ and finding the values corresponding to the above parameters in the water properties table. Then, the final $T_{average}$ is taken as the average temperature of the water in the thermal stratification area.

It is supposed that the fluid is divided into two parts: saturated water and low-temperature water. Then, using the saturation temperature T_s and the average water temperature $T_{average}$ in the thermal stratification area, the average temperature of low-temperature water T_{ave_low} in the steam generator can be calculated by the following equation. According to the proportion of fluid in the thermal stratification area of the steam generator, the coefficients b_1 and b_2 are taken as 0.8155 and 0.1845, respectively.

$$b_1 T_{ave\_low} + b_2 T_s = T_{average}. \tag{7}$$

Finally, the minimum temperature T_{min} in the steam generator can be calculated by the following equation. The coefficient b_3 represents the rate at which the temperature rises due to weak flow in the outage loop. The coefficient b_4 represents the difference between the minimum temperature on the secondary side of the steam generator without weak flow and the mean temperature of full mixing in the low-temperature water region.

$$T_{min} = T_{ave\_low} + b_3 t_{actual} - b_4. \tag{8}$$

2.3. The Maximum Power Prediction Method When the Outage Loop Is Put into Operation. When thermal stratification exists in the steam generator, the coolant temperature on the primary side of the steam generator is much lower than the temperature at other locations of the outage loop. When the outage loop is put into operation at this time, there will be a rapid increase in reactor power and the reactivity insertion accident is prone to occur, so it is necessary to predict the change of reactor power in the presence of thermal stratification.

To simplify the calculations and to make the results more conservative, the limit assumes that the temperature in the primary pipe of the outage loop is equal to the lowest temperature in the steam generator. The power prediction process is as follows:

(1) Use the abovementioned data-driven and mechanistic model-driven prediction method to obtain the minimum temperature inside the steam generator

(2) Write an interface program to modify the input parameters of the outage loop in a nuclear power plant safety analysis system based on the prediction result of temperature and to control the outage loop into operation

(3) Run this safety analysis system to obtain the maximum power of the reactor when the outage loop is put into operation.

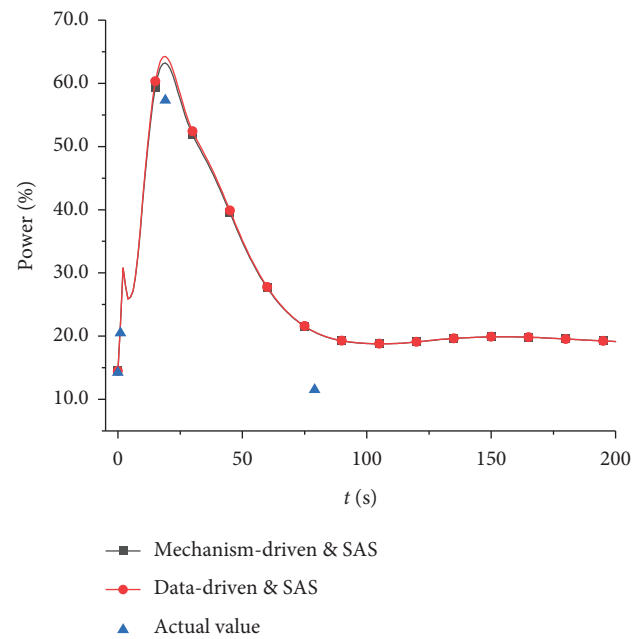

Figure 5: Comparison between predicted power and actual power.

Based on the maximum power, the operators can initially determine whether the outage loop can be put into operation directly, and if not, other disposal measures need to be taken before putting it into operation.

3. Experimental Results and Discussion

The actual data of a floating nuclear power plant are used to test the abovementioned methods, and the prediction results are shown in Figure 5. The prediction results obtained from the data-driven combined with the safety analysis system (DSAS) are similar to those obtained from the mechanism model-driven combined with the safety analysis system (MSAS), and both methods can be used for the prediction of the minimum temperature and the maximum power. These two methods can be compared with each other for verification, making the prediction results more credible. The comparison of key parameters between different prediction methods and the actual situation is shown in Table 1. The predicted powers of two methods are higher than the actual power. This is because the limit assumptions are used for power prediction, resulting in more cold water in the outage loop and higher maximum power. Besides, in the actual process of the outage loop putting into operation, the operator timely shut down the main pump to prevent further increases in power.

The minimum temperatures predicted by the two methods for different initial conditions are shown in the Figure 6. As shown in Figure 6(a), the minimum temperature increases with the initial pressure, because the higher the initial pressure, the higher the saturation temperature before the outage loop is put into operation at the same total leakage mass of feedwater and then the higher the predicted minimum temperature. There is a big difference between the two methods when the initial pressure is low. This is because

Table 1: Comparison of minimum temperature and maximum power.

Parameters	Minimum temperature	Maximum power (%)	Relative error of maximum power
Actual value	—	57.3	—
DSAS	0.8406	64.25	+12.13%
MSAS	0.8422	63.23	+10.35%

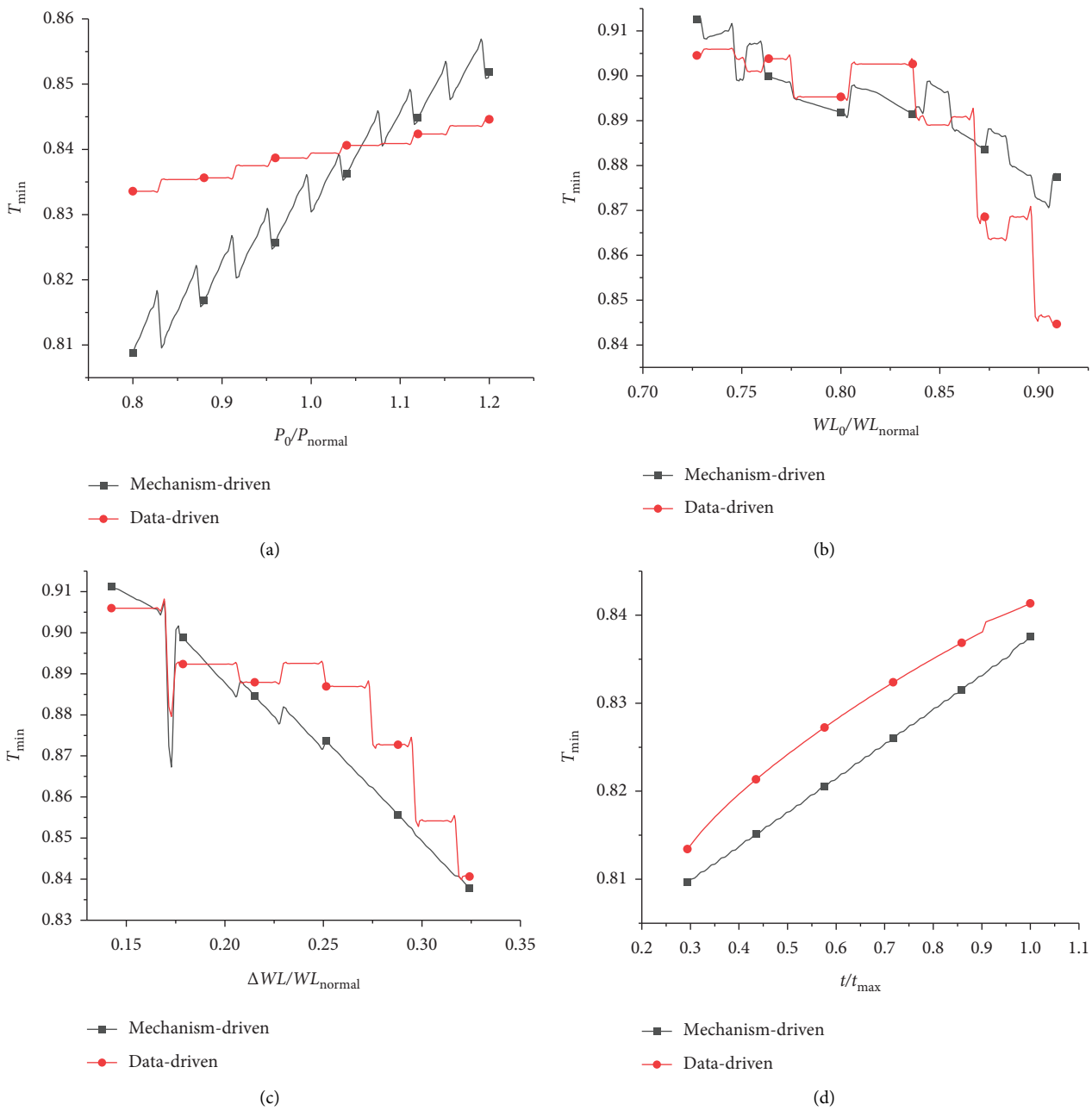

Figure 6: Prediction results of different initial conditions.

the lower the initial pressure, the lower the saturation temperature and the smaller the temperature difference between the saturation temperature and the feedwater temperature and then the more difficult it is to form the thermal stratification. However, the thermal stratification height is a constant in the mechanism model-driven method, which causes the predicted minimum temperature to be lower than that of the data-driven method.

As shown in Figure 6(b), the minimum temperature decreases as the initial water level increases, because the

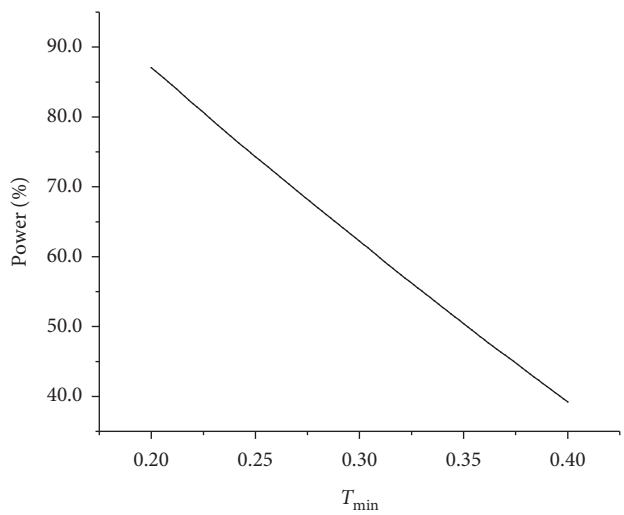

Figure 7: Power prediction results at different minimum temperatures.

higher the initial water level, the more difficult it is to transfer heat between the up and down region of the steam generator and the easier it is to form thermal stratification, which leads to a greater temperature difference between the up and down region, and a lower minimum temperature.

As shown in Figure 6(c), the minimum temperature decreases as the amount of water level change increases, because the larger the water level change, the greater the amount of feed water. The feed water temperature is much lower than the fluid temperature inside the steam generator, so the minimum temperature is lower.

As shown in Figure 6(d), the minimum temperature increases with the outage time. This is because there is a weak flow in the outage loop, which causes the primary coolant transfers heat to the secondary side of the steam generator, and then the minimum temperature increases.

The maximum power predicted by using the safety analysis system at different minimum temperatures is shown in Figure 7. The maximum power decreases with the increase of the minimum temperature, which is due to the fact that the higher the minimum temperature, the smaller the increase in reactivity caused by the cold water entering the core and the smaller the maximum power.

Through the abovementioned analysis, it was found that both the DSAS and the MSAS methods can also predict the minimum temperature of the steam generator in the outage loop and the maximum power caused by the low-temperature coolant. In most cases, the two methods predicted similar results and could be mutually verified.

The MSAS method does not rely on a database and is fast in calculation. But sometimes it has a slightly larger error because of simplifications. The DSAS method is much faster than the direct use of a safety analysis system but slower than the MSAS method because it requires matching to a database. The direct use of the safety analysis system takes approximately 1 hour to calculate, whereas both of the newly proposed methods take less than 1 second and are able to give predictions in real time. In addition, the DSAS method is capable of predicting accurate results as long as the database contains a comprehensive range of operating conditions and the calculation data is accurate.

4. Summary

This paper presents a method for predicting the minimum temperature in the outage loop of a floating nuclear power plant and the maximum power caused by the low-temperature coolant. First, the minimum temperature in the steam generator is predicted by the data-driven or mechanism model-driven method, which is used as the coolant temperature in the outage loop to predict the reactor power variation when the outage loop is put into operation by the safety analysis system. The abovementioned method is validated with actual data from a floating nuclear power plant, and the prediction results of the two methods are compared under different initial conditions.

The results show that both the data-driven and the mechanism model-driven methods can predict the minimum temperature in the steam generator, but the mechanism model-driven method has been heavily simplified, and in some cases, the prediction results are less accurate than those of the data-driven method. After predicting the minimum temperature, the maximum power can be further obtained by combining the temperature prediction results and the safety analysis system, and the maximum power decreases with the increase of the minimum temperature. Besides, the predicted maximum power is larger than the actual maximum power due to the limit assumptions, and the prediction results are more conservative and better able to avoid reactivity insertion accident.

The prediction result can assist the operator to make more accurate judgment. If the power variation is within the allowed range, the outage loop can be put into operation directly; otherwise, it is necessary to adopt the other methods to increase the temperature in the primary pipe of the outage loop before putting it into operation. This study is of great importance to the operational safety of floating nuclear power plants.

Data Availability

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy restrictions.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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