Using One-Class Support Vector Machine for the Fault Diagnosis of an Industrial Once-Through Benson Boiler

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Abstract

Considering that once-through Benson boiler is one of the most crucial equipment of a thermal power plant, occurrence of any fault in its different parts can lead to decrease of the performance of system, and even may cause system damage and endanger the human life. In this paper, due to the high complexity of the system's dynamic equations, we utilized data-based method for diagnosing the faults of the once-through Benson boiler. In order to enhance the fault diagnose (FD) system proficiency and also due to strong interactions between measurements, we decided to utilize six one-class support vector machine (SVM) algorithms to diagnose six major faults of once-through Benson boiler. In the proposed structure, each One-class SVM algorithm has been developed to diagnose one special fault. Finally, we carry out diverse test scenarios in different states of fault occurrence to evaluate the performance of the proposed FD system against the six major faults of the once-through Benson Boiler under conditions of noisy measurement.

Keywords: Fault Diagnose, Once-through Benson Boiler, One-Class Support Vector Machine, Data-Based

1. Introduction

In the thermal power plants, fault diagnosis technology of mechanical equipment like turbine and boiler is categorically important because the occurrence any fault in thermal power plants reduces the reliability and the performance. Since the requirement to increase reliability and decrease the possible loss of production due to occurrence of malfunctions in the underlying systems, detecting and diagnosing any kind of abnormal situation in the process is extremely necessary[1]. From this point of view, the design of FD schemes is recognized as a vital and important problem in the literature [2, 3]. Considering the issue from other point of view, fault diagnosis schemes can also be categorized as data-based or model-based schemes. In data-based schemes, mathematical model of the system is not used for fault diagnosis, while model-based schemes apply a mathematical model to diagnose the faults in the system [4, 5]. One of the important procedures of data-based methods to diagnose faults is classification or pattern recognition approach, which draw out pattern from a data set and transform it into an understandable structure for further use.

One of the most conventional source of electric power, which is widely utilized in thermal power plants, is once-through Benson boiler and it has high complexity dynamic structure. Failures in the functionality of the sensor, spraying unit, attemperators, and their related actuators are listed as the most important faults occurring in the once-through Benson boiler.

Diverse approaches have been considered for fault detection and diagnosis in thermal power plants with classification or pattern recognition methods. Principal component analysis (PCA) is utilized for leak fault detection of the boilers [6]. Self-organizing map (SOM) presents a method for fault diagnosis [7], whose classification is not precise. In order to detect and diagnose faults in turbine-boiler, a modified fuzzy min-max neural network with rule extraction ability has been presented in [8], and in the following, the detection and diagnosis of faults by Bayesian algorithms have been proposed in [9]. Recently, many research works have concentrated on fault diagnosis with adaptive neuro-fuzzy inference system (ANFIS) [10], and methods based on neural network (NN) [11].

Support Vector Machine is a relatively new powerful computational supervised learning method based on statistical learning theory and structural risk minimization principle that was originally developed for classifying data from two different classes of problems by maximizing the margin between the two opposing classes [12]. It is certified that SVM has ability in nonlinear, over-fitting, high dimensional pattern recognition problems and, opposite to most classification methods, do not need a large number of training samples [13]. SVM has been considered as one of the most efficient machine learning algorithms in many applications like the face recognition [14], time series forecasting [15], and fault diagnosing [16, 17].

In this paper our efforts have concentrated on acquiring data from a simulated power plant once-through Benson boiler to design fault diagnosis system based on the data-base approach, because satisfactory

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results in complex industrial modeling applications can be achieved with reasonable computation and time. For this purpose due to strong interaction between measurements, six one-class SVM algorithms are utilized for the diagnosis of the six major faults of once-through Benson boiler. In the face of occurrence of faults in different states under conditions of noisy measurement, testing and training data are elicited via simulation test runs at 100% boiler and turbine load of the plant operation. Subsequently, we carry out diverse test scenarios in different states of fault occurrence to evaluate the performance of the purposed FD system against the six major faults of the once-through Benson Boiler.

The rest of the paper is organized as follows. In section 2 a brief description of the plant is provided. It is composed of a brief view of the once-through Benson boiler and its subsystems, then the inputs and outputs to the subsystems are characterized. Section 3 introduces the proposed FD system. Section 4 describes a set of fault scenarios to illustrate the effectiveness of the proposed FD system and explain the motivation of using one-class SVM to diagnose fault of once-through Benson boiler. Several simulated tests and results are demonstrated in Section 5. The last section contains the conclusion.

2. System Description

Thermal power plant due to their efficiency and costs are the mainstay of electricity production worldwide and once-through Benson boiler and steam turbine are important equipment of the thermal power plant. The main motivational investigations into dynamic analysis of power plants, to design more reliable control systems, are the growing need for more and safer power generation and facing immense request for electricity. So to design appropriate controllers, having adequate information about the system dynamics, is indispensable. Because once-through Benson boiler has highly nonlinear dynamic with numerous uncertainties, due to parametric uncertainties for such a complicated physical process cannot exactly characterize the mathematical model and there will ever be modeling errors. But for thermodynamics state conversion and heat transfer based on the basic laws of physics such as mass conservation, semi-empirical energy laws and momentum can be adjusted the analytical plant model. To construct such analytical models it is essential to describe their parameters by paying attention to boundaries, inputs, and outputs.

The model utilized in this paper is a reliable simulation of a once-through Benson boiler and steam turbine, which is provided by Chaibakhsh and Ghaffari [18, 19]. In this model, for subsystems of a once-through Benson boiler, first based on the energy balance and thermodynamics principles, they developed the mathematical models; then, by applying genetic algorithm (GA) techniques on the experimental data, specified the related parameters [20]. Fig.1 illustrates the simulated once-through Benson boiler with steam turbine in Matlab Simulink environment.

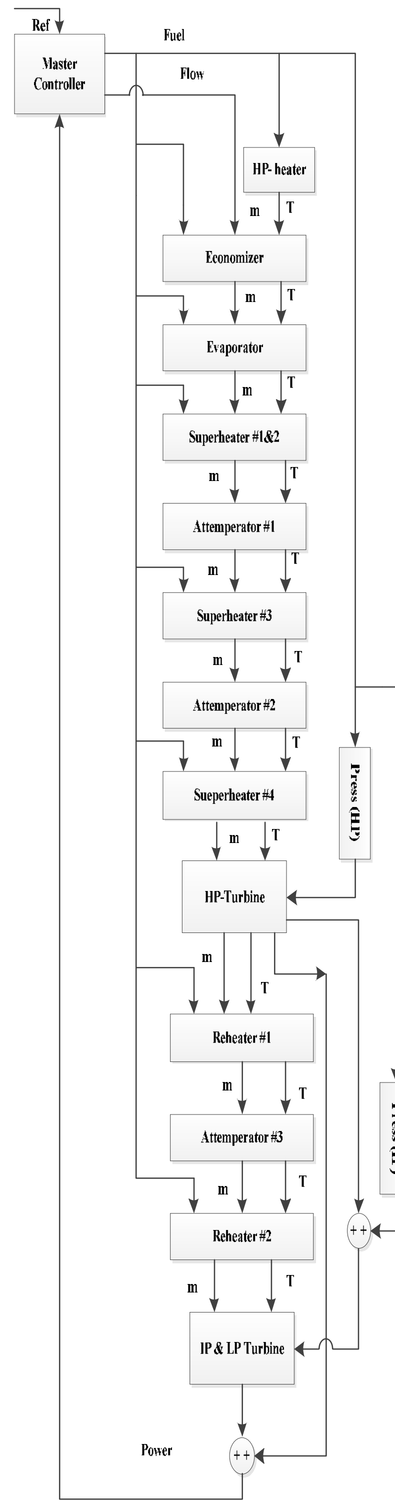

Figure 1. Overall once-through Benson boiler and steam turbine model

The intended system demonstrates an industrial 440 MW power plant which includes many sections such as evaporator, superheaters, attemperators, and steam turbine sections. In this boiler, heating all sections of the boiler utilizes 14 bottom burners with a single furnace. In the evaporator, by converting the hot water to steam and increasing the outlet temperature up to $365^{\circ}C$, the produced steam goes to the superheater#1 section. The superheater#1 heating surface is situated in the boiler walls and outlet steam goes from this part toward superheater#2 and its outlet steam temperature is not constant but at typical condition is about $407^{\circ}C$, subsequently, the steam leaving superheater#2 goes to superheater#3 and the outlet temperature of attemperator#3 should be kept constant at $470^{\circ}C$. At the end, for final superheating stage, the produced steam from superheater#3 section goes towards superheater#4 and the outlet temperature of this section should be constant at $535^{\circ}C$. Also for controlling the fast steam temperature between the each two sections of superheaters, four spray attemperators are placed. From main steam header, the superheated steam is fed towards the high pressure (HP) turbine, and in the following the outlet steam is discharged into the cold reheated header. After RH-1 the outlet reheated steam temperature should be stable at $452^{\circ}C$ and that of RH-2 should be stable at $535^{\circ}C$, also, the outlet temperature of reheater is controlled in the same manner as the superheater. The reheated steam is discharged into the intermediate pressure (IP) turbine, subsequently, the outlet steam from IP turbine is discharged into the low pressure turbine. After that, the feedwater inlet into the high pressure heaters and its temperature is increased about $80^{\circ}C$.Finally, the hot feedwater is discharged into the economizer header and the power generation cycle is iterated.

3.Support Vector Machine

Support vector machine is a supervised machine learning method based on the structural risk minimization (SRM) approach effectively applied in many machine learning applications such as pattern recognition, classification, regression, face detection, and outlier detection and first proposed in 1995 by a team lead by Vapnik, who was one of the founders of statistics learning theory and also a major inventor of SVM [12]. The main idea of SVM is that maximizing the margin between the separating hyperplane and the nearest sample points to construct the optimal separating hyperplane that minimize the upper bound of the generalization. SVM assertion advantages over other machine learning algorithms on shorter training time nonlinear and high dimensional datasets. For constructing a linear classifier in feature space, in the case of datasets which are not linearly separable, support vector machine utilizes kernel trick to map training samples from feature vector to a high-dimensional feature space. So this is equivalent to make a non-linear classifier in the original input space. There are several kernel functions, and commonly used kernel functions are as follows:

Linear kernel: $K(x, x_i) = (x^T x_i)$ (1)

Polynomial kernel: $K(x, x_i) = (\gamma(x^T x_i) + r)^d$, $\gamma > 0$ (2)

RBF Kernel: $K(x, x_i) = exp(-\gamma\|x - x_i\|^2)$, $\gamma > 0$ (3)

Sigmoid kernel: $K(x, x_i) = tanh(\gamma(x^T x_i) + r$ (4)

Where each x_i, $i = 1, \dots, n$ is an input data and γ, d, r are kernel parameters for each kernel function.

A. One -Class Support Vector Machines

One-class SVM classifier is an unsupervised learning which trains on unlabeled sample and proposed by Schölkopf [21] in 2001. One-class SVM is a variant of the original support vector machine algorithm, so the main difference between the 1-class SVM and the traditional SVM is that the former needs only the one dataset to train the model whereas the latter requires two datasets to build a classifier.

Consider a single class training dataset $\mathbf{x_i \epsilon R^m}$, $\mathbf{i = 1, \dots, n}$ and define a map $\boldsymbol{\phi}: \boldsymbol{X} \rightarrow \boldsymbol{F}$ to be the mapping of $\boldsymbol{X}$ into feature space $\boldsymbol{F}$ such that a dot product in feature space can be calculated by a kernel function, i.e. $\boldsymbol{\phi(x_i).\phi(x_j) = K(x_i, x_j)}$. The main objective here is to make a model to accept target examples and reject outlier. Samples which fall outside this model are classified as outliers. The standard one-class SVM can be formulated as the following objective function to be minimized:

$$\min \quad \frac{1}{2}\|\mathrm{w}\|^2 - \rho + \mathrm{c}\sum_{\mathrm{i}} \xi_{\mathrm{i}} \qquad (5)$$

$$subject\ to \quad w.\phi(x_i) \geq \rho - \xi_i, \quad \xi_i \geq 0, \ i = 1, \dots, n$$

Where ξ_i slack variables, $\|.\|$ indicates Euclidean norm, c is predefined coefficient that determines the fractional of outliers and $w.\phi(x_i) = \rho$ relation shows a hyperplane in feature space. To obtain the hyperplane which has the maximal distance from the origin and contains most of the training examples, one should minimize the following dual objective function:

$$\min \ \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j K(x_i, x_j), \ 0 \leq \alpha_i \leq c, \ \sum_i \alpha_i = 1 \qquad (6)$$

Where α_i indicates Lagrangian multiplier.

The achieved hyperplane $f(x)$ can be formulated as:

$$f(x) = \sum_i \alpha_i K(x, x_i) - \rho \qquad (7)$$

For adjusting the values of α_i one can utilize the traditional quadratic programming with a linear constraint, and the bias term ρ can be also determined from $f(x_s) = 0$, where x_s denotes one of the obtained support vectors. Simply to determine the sign of testing data (x), utilize $g(x)$ decision function as follows:

$$g(x) = sgn(f(x)) = sgn(\sum_i \alpha_i K(x, x_i) - \rho) \tag{8}$$

4. Slmulation Studies

In this section, we introduce the set of faults that are considered for the once-through Benson boiler and clarify the structure of the proposed FD system to diagnose malfunction circumstances which occur in once-through Benson boiler.

A. *Fault scenarios*

The suggested FD is applied to be evaluated on a subset of candidate faults with emphasis on common faults that would be difficult to detect and can lead to plant shutdown or damage of the boiler.

As illustrated in Table 1, the set of faults that we consider for boiler is taken from the diverse contributed works, which is reported in the literature [22-24]. Finally, these faults have been simulated by using ramp-type functions with a 30 percent change in their value.

Table 1. List of fault and their situations

Faults number	**Fault description**
1	Mismatching in the water spraying
2	Measurement of boiler pressure output
3	Fouling in the economizer
4	Actuator fault in the attemperator#1
5	Actuator fault in the attemperator#2
6	Actuator fault in the attemperator#3

Normally, each of the preceding faults in real industrial applications develops slowly over a period of weeks. Even so, for the purpose of this simulation study and in order to prevent extremely long time durations, the fault advancement rates have been increased. Eventually, supposed that at any time, only one fault can occur in the components of the simulated plant.

B. *Structure of the One Class SVM Classifier for Fault Diagnosis*

The main concept in this paper is using the pattern recognition capability of SVM algorithm for interpreting the combinatorial nature of the data which is difficult for a human expert to discriminate. In order to diagnose the faults, due to the strong interactions between measurements, part load operations, and subtle changes in correlations between measurements, we cannot set alarm thresholds on individual measurement devices, which are produced by the introduced faults. In the following, we will clarify the structure of the proposed FD system to efficiently specify the individual occurrences of 6 once-through boiler faults.

Table 2. Measurement used as inputs and output for the FD system

FD system type	Input of FD system type	output of FD system type
SVM#1	First input: Mismatching in the water spraying	Fault diagnosis of mismatching in the water spraying
SVM#2	Second input: Measurement of boiler pressure output	Fault diagnosis of Measurement of boiler pressure output
SVM#3	Third input: Fouling in the economizer	Fault diagnosis of fouling in the economizer
SVM#4	Forth input: Actuator fault in the attemperator#1	Fault diagnosis of actuator fault in the attemperator#1
SVM#5	Fifth input: Actuator fault in the attemperator#2	Fault diagnosis of actuator fault in the attemperator#2
SVM#6	Sixth input: Actuator fault in the attemperator#3	Fault diagnosis of actuator fault in the attemperator#3

In the case of using only one multi classifier SVM to detect and diagnose all the faults occurred in a process, the complexity of the network structure will increase and its proficiency for process monitoring will be reduced. According Fig .2, to simplify the process monitoring measures, we decided to use one-class classifier to detect and diagnose one particular fault. In the other words can claim that the number of SVM classifiers to be constructed is equal to the number of faults probable to occur in the process. Hence, fault detection and fault diagnosis can be performed simultaneously taking advantage of the proposed scheme, besides, another advantage of utilizing multiple classifiers is reducing the computational load during the training phase. According Table .2, for adjusting the required FD objectives, a method based on a distributed configuration of six one-class SVM has been presented ,whereas all measurement signals are fed as inputs of each SVM and each SVM are trained to diagnose special fault.

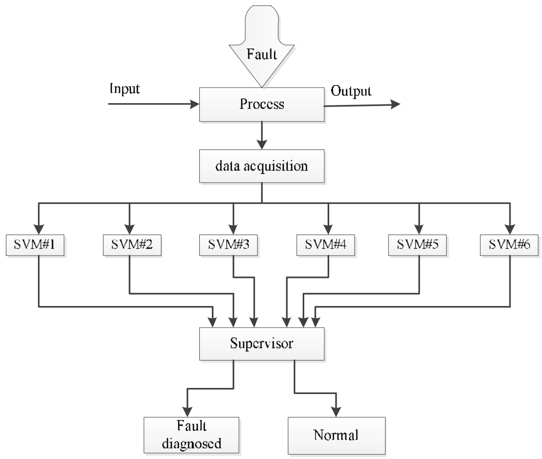

Figure 2. . Framework of the proposed fault diagnosis

5.Simulation test and result

In this section to evaluate the proposed FD system several scenarios that introduced in Table .1, have been performed. For training each SVM, we utilize six data set, whereas each data set were acquired from plant when system was affected by a special fault.

Attemperator is one of the most important and common components in once-through Benson boiler, and its failures can cause both personal and economic damage if fault cannot be detected and diagnosed well in advance. Fig .3 and 4 show the results obtained for fault number 5. Fig .3 depicts the actual attemperator#2 output, As shown, the fault number 5 due to the occurrence of the actuator fault in attemperator#2, has been introduced at t = 145 sample time instant, and simulated by using ramp-type functions. Fig. 4 verifies the prosperous operation of FD system to quickly detect and diagnose the occurred fault after 16s via SVM#5.

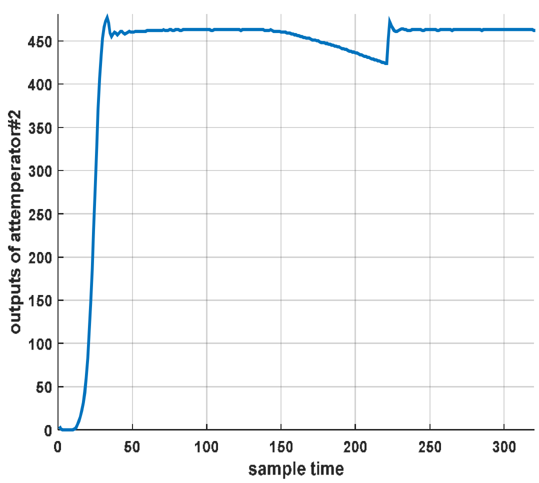

Figure 3. Output of attemperator#2

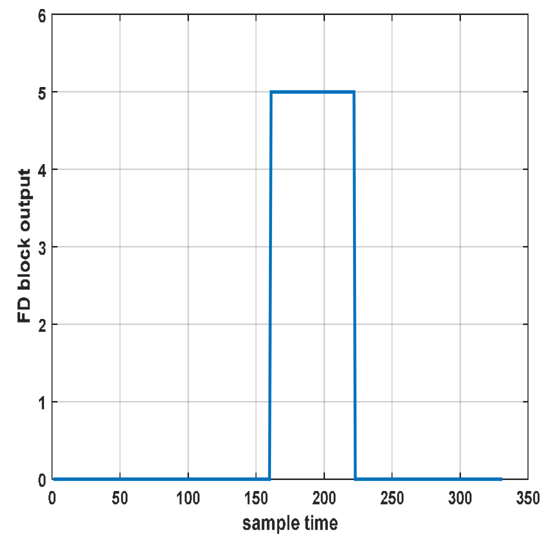

Figure 4. Fault diagnosis system output

Fig .5 and 6 represent the result of the proposed FD system output and show the pressure output of the once-through Benson boiler when the system is affected by the fault number 2. Fig .6 represents the capability of the FD systems to diagnose the type of the fault which occurred in system. According to Fig .5, at 338 sample time fault number 2 has occurred. Fig .6 demonstrates that the proposed FD system has correctly diagnosed the type of fault at 346 sample time via SVM#2.

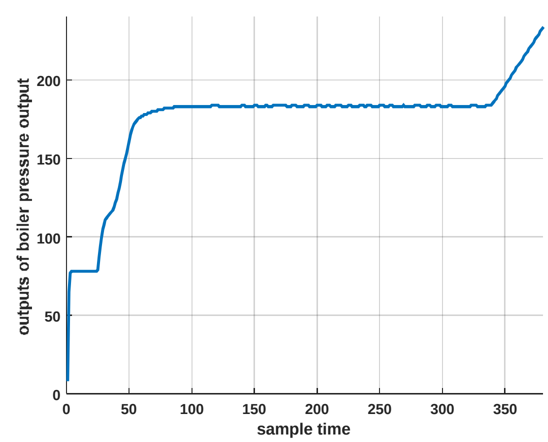

Figure 5. Output pressure of boiler

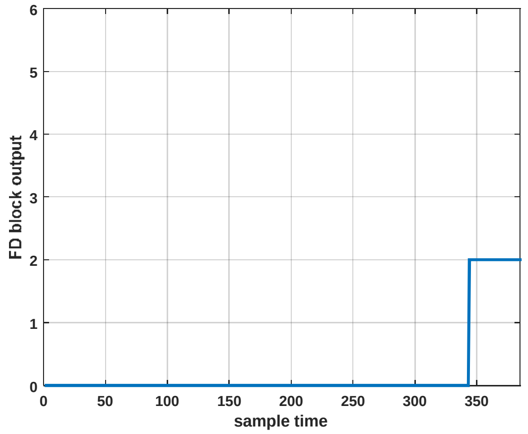

Figure 6. Fault diagnosis system output

In this part we prepared a challenging test scenario to evaluate the sensitivity performance of the proposed FD system to handle faults with a slight perturbation in their slopes. As it is illustrated in Fig. 7, for this purpose we modify the time-series pattern of fault number 5 compared to its original fault pattern recorded in Fig. 4. Nevertheless, Fig .8 demonstrates the successful diagnostic inference of the developed FD system to identify the correct nature of the fault after the short time interval.

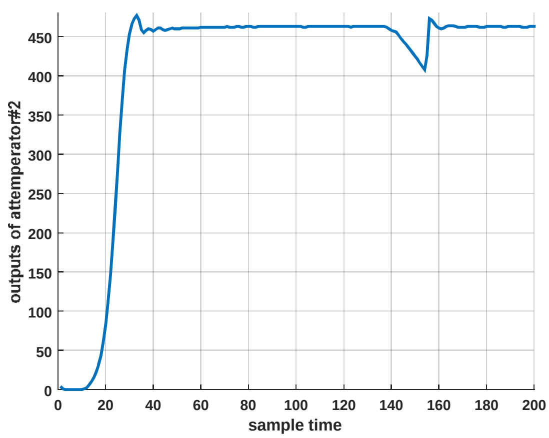

Figure 7. Output of attemperator#2

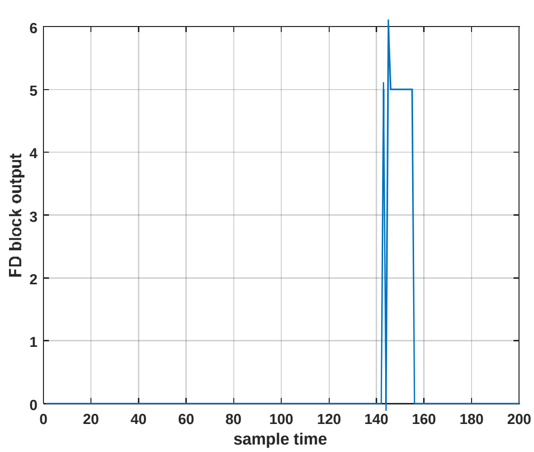

Figure 8. Fault diagnosis system output

6. **Conclusion**

This work proposed an SVM-based model for fault diagnosing of once-through Benson type boiler in an industrial 440 MW power plant with steam turbine. In order to improve the proficiency of process monitoring due to strong interaction between measurements, an FD methodology has been proposed based on six one-class SVM against 6 major faults of once-through Benson type boiler, whereas all measurement signals are fed as inputs of each SVM and each SVM is trained to diagnose special fault. The main difference between 1-class SVM and other algorithms is that it has ability in solving small sample size, nonlinear, over-fitting, and high dimensional pattern recognition, so this algorithm can generalize well to any kind of fault. The simulation result indicated that proposed FD under noisy measurement conditions has successful performance against 6 major faults of once-through boiler and experimental observations represented that the FD system is partially insensitive to perturbation in its slopes of faults, too.

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