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# Hybrid Neural Network-Based Fault Diagnosis and Fault-Tolerance Design with Application in Electro-Hydraulic Servovalve

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**Abstract:** In this study, to cope with the needs of the predictive maintenance for complex systems, a hybrid dynamic Artificial Neural Network (ANN) based fault and degradation diagnosis and tolerance method is designed. The multi-layer feed forward ANN and recurrent ANN are combined, so as to be able to form a dynamic identification model for the nonlinear time-varying system. It has three work modes, and can perform the fault and degradation diagnosis and tolerance by using these modes alternately. The result of its application in an Electro-Hydraulic Servovalve of a Hydroelectric Generation Unit shows that it is effective and feasible, has the advantages of the simple and fast algorithms, working online, and no disturbance signals importing to the system.

## 1. INTRODUCTION

Today, the goal of service and maintenance is not only the after-the-event repair, but also elimination of the downtime of the machines and cutting down the maintenance cost for the user. As the modern machines are becoming more and more complex, the costs of the service and maintenance have account for a big part of their whole life cycle cost, up to 15%~40%, and about one third of which is caused by unnecessary and inaccurate maintenance activities due to the scheduled or corrective maintenance strategies [1]. So, the advanced method should be implemented to improve the accuracy of maintenance, to apply right maintenance action at right time in right place, i.e. to realize the predictive maintenance [2].

One key problem of the predictive maintenance is how to detect the failure and degradation, so as to provide timely maintenance before the failures become serious. Model-based diagnosis is one kind of the important method for fault or degradation detection and tolerance [3, 4], but the precondition of its implementation is the accurate model of the plant [5, 6]. Most complex industrial processes are nonlinear and time-varying system, it's very hard to get an accurate model. To overcome these obstacles, many artificial intelligence based fault diagnosis methods are developed [7-9]. As the Artificial Neural Network (ANN) is a nonlinear system, and has the ability of self-learning and self-organising, it has been widely adopted to solve the problems of control and fault diagnosis of the complex system [10, 11].

In the paper, an ANN-based fault and degradation diagnosis and tolerance method is designed for the purpose of the predictive maintenance of a Hydroelectric Generation Unit (HGU). It can carry out the diagnosis of the abrupt failures and gradually formed faults, and achieve the fault tolerant control of an Electro-Hydraulic Servovalve (EHS). In section 2, some key points of the predictive maintenance are discussed. In section 3, a hybrid ANN-based fault diagnosis and tolerance method is designed. In section 4, the application of this method in an EHS of the water-turbine governing system in a HGU is introduced.

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## 2. THE PREDICTIVE MAINTENANCE AND THE FEATURE VALUES OF THE FAULT

Normally, the faults of a plant can be classified into two types. One is the gradually formed failure; another is the abrupt failure [12].

The abrupt failure, as there are rare symptoms before the failure emerges, is hardly to be forecasted, but should be detected and isolated as quickly as possible. In fact, most faults of machines do not occur instantaneously but are gradually formed. There are usually some kinds of degradation state between the normal condition and the failure, and the symptoms will emerge as the degradation is becoming serious. If these symptoms can be monitored during the degradation process, the appropriate maintenance actions can be scheduled and implemented before the failure, that is, to replace "post-mortem" and "blind" maintenance with "just in time" and "accurate" maintenance. This is the main target of the predictive maintenance. The methods introduced in the paper try to carry out the diagnosis of these two kinds of failure, and achieve the fault tolerant control while some kinds of faults occur.

Three key abilities are essential for the predictive maintenance, i.e. monitoring and forecasting, diagnosis and prognosis, and maintenance decision-making [13]. To assess the healthy state of a plant, or to incarnate the symptoms of the fault, a suitable set of parameters, which are called the fault's feature values (FFVs) and can denote the healthy state of the plant, should be defined carefully, as well as the thresholds for classifying the state of the plant. In most cases, the FFVs are not measurable directly. The way to get these FFVs is one key problem of the fault and degradation diagnosis and maintenance decision making.

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## 3. THE ANN-BASED FAULT DIAGNOSIS AND TOLERANCE (ANN-FDT) METHOD

### 3.1. The Principle of the ANN-FDT Method

To get the immeasurable FFVs, a simple way is to feed the system with some special selected excitation signals, and calculate the FFVs from the responses of the system. But when is executed online, the pattern and strength of the excitation signal are limited in order to avoid serious detraction of the system. When this is executed offline, the plant should be stopped, and this is usually impossible for the industrial process.

The structure of the designed ANN-FDT system is shown in Fig. (**1**), in which the ANN model is the key element for the fault diagnosis and tolerance. An industrial process is usually nonlinear and time-varying, whose dynamic characteristics are variant with the change of operation conditions, or with the aging of its components. The ANN model in Fig. (**1**) acts as a representation or identifier of the plant, with the self-adaptive ability to track the changes of the plant, even in degradation situation. In the FFV extraction and fault diagnosis period, the pre-selected excitation signals are inputted directly into the ANN model instead of the plant. By this way, the excitation signals can be selected optionally, without worrying about the disturbance to the plant. From the output of the ANN model, the corresponding FFVs can be calculated. As the ANN model is ensured to have the same dynamic characteristics as the plant, the values of these FFVs can also be regarded as that of the plant. With these FFVs, the healthy state of the plant can be assessed; the fault and degradation of the plant can be diagnosed. When there is a fault within the plant, the ANN model accepts the same input as the plant and can be used as a reconstruction of the plant to achieve the fault tolerant control. The errors between the outputs of the plant and the ANN model are used to amend the ANN model, as well as monitoring the state of the plant.

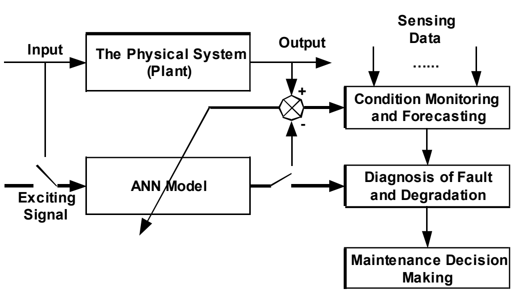


**Fig. (1).** The structure of the ANN-FDT system.

### 3.2. The FFV Extraction and State Monitoring Method Based on the Hybrid ANN

#### *3.2.1. The Structure of the Hybrid ANN-Based Identifier*

In order to simulate an industrial process, and extract the FFVs of faults, a hybrid ANN based identifier is formed, and sketched as Fig. (**2**). The multi-layer feedforward ANN (like the Back Propagation (BP) ANN) had been proved to be able to approximate any continuous finite nonlinear function [14]. But as a static ANN, it cannot describe the dynamic characteristics of the system. On the contrary, the recurrent ANN (like Hopfield ANN) utilises the historic signals of the dynamic system. It is a dynamic system, but can't ensure to be able to approximate any nonlinear system. Here, these two kinds of ANN are combined to form a dynamic identification model of the nonlinear time-varying system.

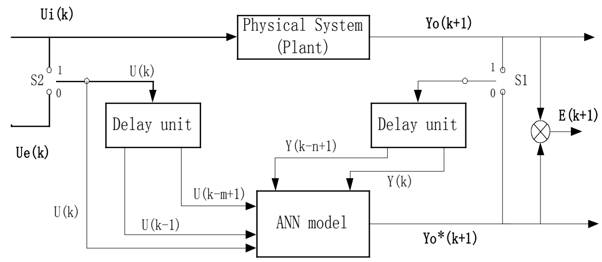


**Fig. (2).** The structure of the ANN-based dynamic identifier.

The ANN model in Fig. (**2**) is a multi-layer feedforward ANN, but its input data is combined with the present and historic data of the input and output of the plant, so as to obtain the dynamic information of the plant. The identifier has two modes according to the source of its input data. One mode is active when a part of the input data is coming from the output of the physical system, while the switch S1 in Fig. (**2**) turns to position 1. It is called the serial-parallel identification model (SPM), and is mainly used as a self-adaptive identifier to form the dynamic model that can track the change of the plant's state. Another mode is active when a part of the input data is coming from the output of the ANN model itself, while the switch S1 in Fig. (**2**) turns to position 0. It is called the parallel identification model (PM), which is mainly used as a stand-in model of the plant and is operating in parallel with the plant during the process of the FFV extraction and fault diagnosis and tolerance.

#### *3.2.2. The Characteristics of the SPM and PM*

The SPM and PM have their special characteristics, the process of the fault diagnosis and tolerance is the procedures to use these two kinds of models respectively.

Considering a discrete dynamic system:

$$Y_o(k+1)=f\,[y_o(k),\, y_o(k-1)\ldots y_o(k-n+1);\, u_i(k) \ldots u_i(k-m+1)] \tag{1}$$

Its state equation is:

$$\begin{cases} X\ (k+1) = \phi\ [X(k), U(k)] \\ Y\ (k) = \varphi\ [X(k), U(k)] \end{cases} \tag{2}$$

where, $X(k)\in R^n$、$Y(k)\in R^p$ v $U(k)\in R^m$ are the states, outputs and inputs of the system. The system satisfies the following constraints:

C1: Let $U(k)\in\Omega\subset R^m$, then v$U(k)\in\Omega$, $X(0)\in R^n$. For a finite $K$,

$$\|X\ (K)\ \|+\|Y\ (K)\ \|<\infty$$

That is to say, the system is stable.

C2: Function $\phi$ : $R^{n+m}\rightarrow R^n$ and $\varphi$ : $R^{n+m}\rightarrow R^p$ are continuous, and satisfy Lipschitz condition, i.e. the solution of the system is exclusive.

C3: With the above two constraints, if the ANN can satisfy the constraint: for any ε>0, and any continuous function

$f$: C→$R^P$ (C⊂$R^P$ is a closed set)
there exists network parameter W, which can make the output of ANN $f^*(X,W)$ satisfying

$$\max_{X\in C} \| f^*(X,W) - f(X) \| < \varepsilon$$

In Fig. (**2**), when the switches S1 and S2 are in position 1, the identifier is in SPM formation, which can be modelled as:

$$y_o^*(k+1) = F[y_o(k), y_o(k-1), \cdots y_o(k-n+1); u_i(k), u_i(k-1), \cdots u_i(k-m+1)] \quad (3)$$

When the switch S1 is in position 0 and S2 is in position 1, the identifier is in PM formation, which can be modelled as:

$$y_o^*(k+1) = F[y_o^*(k), y_o^*(k-1), \cdots y_o^*(k-n+1); u_i(k), u_i(k-1), \cdots u_i(k-m+1)] \quad (4)$$

where, $F[\bullet]$ represents the mapping of the input of ANN to its output. $y_o(k)$ is the output of the plant and $y_o^*(k)$ is the output of the ANN model.

The hybrid ANN in SPM and PM formation has the following characteristics:

(i) The system is bounded-input and bounded-output (BIBO), all the signals used by the ANN model are bounded. This can ensure the stability of the ANN model.

(ii) When in SPM formation, the ANN has no feedback, it's possible to implement static error backward propagation (EBP) learning algorithm to train the ANN.

(iii) When the ANN is fully trained in SPM formation and can ensure that the simulating error of SPM is small enough, the PM will also get an accurate enough simulating result and can act as a representation of the physical system.

The point (iii) can be explained as follows:

Suppose the non-linear discrete dynamic system (2) satisfies the constraints C1 and C2. When the SPM is utilized, the ANN satisfies the constraint C3:

$$\begin{cases} X_s^*(k+1) = \phi^*[X(k), U(k), W_\phi] \\ Y_s^*(k) = \varphi^*[X(k), U(k), W_\varphi] \end{cases} \quad (5)$$

If $X^*(0)=X(0)=X_0\in R^n$, $U(k)\in\Omega\subset R^m$, where Ω is a closed set, for any ε, there exist network parameters $W_\phi^*$ and $W_\varphi^*$, which for any $U(k)$□Ω, the SPM has the accurate enough output approaching to the dynamic system (2), i.e.:

$$\max_{k\in[0,M]} \| Y_s^*(k) - Y(k) \| < \varepsilon_y$$

(M is a positive integer) (6)

and:

$$\max_{k\in[0,M]} \| X_s^*(k) - X(k) \| < \varepsilon_x$$

($M$ is a positive integer) (7)

In case the PM is utilized, the same ANN system can be expressed as:

$$\begin{cases} X_p^*(k+1) = \phi^*[X^*(k), U(k), W_\phi] \\ Y_p^*(k) = \varphi^*[X^*(k), U(k), W_\varphi] \end{cases} \quad (8)$$

Then, the output error between SPM and PM is finite:

$$\max_{k\in[0,M]} \| Y_s^*(k) - Y_p^*(k) \| < \varepsilon'$$

($M$ is a positive integer) (9)

**Proof:**

With the constraints C1 and C2, for the system (2), there exist positive integers $\theta_\phi$ and $\theta_\varphi$, which for any

$$(X_1, U), (X_2, U) \in C = \{(X,U)\in R^{n+m}; \| X - X_0 \| \le d, U\in\Omega\}$$

let

$$\| \phi(X_1,U) - \phi(X_2,U) \| \le \theta_\phi \| X_1 - X_2 \| \quad (10)$$

$$\| \varphi(X_1,U) - \varphi(X_2,U) \| \le \theta_\varphi \| X_1 - X_2 \| \quad (11)$$

With the constraint C3, for the ANN model, there exist $W_\phi$ and $W_\varphi$, which let:

$$\max_{(X,U)\in C} \| \phi^*(X,U,W_\phi) - \phi(X,U) \| \le \varepsilon_x \quad (12)$$

$$\max_{(X,U)\in C} \| \varphi^*(X,U,W_\varphi) - \varphi(X,U) \| \le \varepsilon_y \quad (13)$$

Then,

$$\begin{aligned} &\| X_s^*(k) - X_p^*(k) \| = \| \phi^*[X(k-1),U(k-1),W_\phi] - \phi^*[X^*(k-1),U(k-1),W_\phi] \| \\ &= \| \phi^*[X(k-1),U(k-1),W_\phi] - \phi[X(k-1),U(k-1)] + \phi[X(k-1),U(k-1)] \\ &- \phi[X^*(k-1),U(k-1)] + \phi[X^*(k-1),U(k-1)] - \phi^*[X^*(k-1),U(k-1),W_\phi] \| \\ &\le \| \phi^*[X(k-1),U(k-1),W_\phi] - \phi[X(k-1),U(k-1)] \| + \| \phi[X(k-1),U(k-1)] \\ &- \phi[X^*(k-1),U(k-1)] \| + \| \phi[X^*(k-1),U(k-1)] - \phi^*[X^*(k-1),U(k-1),W_\phi] \| \\ &\le \varepsilon_x + \theta_\phi \| X^*(k-1) - X(k-1) \| + \varepsilon_x \le (2+\theta_\phi)\varepsilon_x \end{aligned}$$

and

,

$$\begin{aligned} &\| Y_s^*(k) - Y_p^*(k) \| = \| \varphi^*[X(k-1),U(k-1),W_\varphi] - \varphi^*[X^*(k-1),U(k-1),W_\varphi] \| \\ &= \| \varphi^*[X(k-1),U(k-1),W_\varphi] - \varphi[X(k-1),U(k-1)] + \varphi[X(k-1),U(k-1)] \\ &- \varphi[X^*(k-1),U(k-1)] + \varphi[X^*(k-1),U(k-1)] - \varphi^*[X^*(k-1),U(k-1),W_\varphi] \| \\ &\le \| \varphi^*[X(k-1),U(k-1),W_\varphi] - \varphi[X(k-1),U(k-1)] \| + \| \varphi[X(k-1),U(k-1)] \\ &- \varphi[X^*(k-1),U(k-1)] \| + \| \varphi[X^*(k-1),U(k-1)] - \varphi^*[X^*(k-1),U(k-1),W_\varphi] \| \\ &\le \varepsilon_y + \theta_\varphi \| X^*(k-1) - X(k-1) \| + \varepsilon_y \le 2\varepsilon_y + \theta_\varphi \varepsilon_x = \varepsilon' \end{aligned}$$

Thus, for the system (2), the errors between the outputs of SPM and that of PM are finite when they have the same inputs, and the error between the output of the PM and the physical system depends only on the precision of SPM. Thus, the output of the PM can be fully approached to the output of the physical system when the ANN trained in the SPM formation is accurate enough.

This conclusion is very important and it is the foundation of the designed ANN-FDT method. For the SPM, it can utilize the output and input of the plant to train online the ANN model and make it representing accurately enough the dynamic characteristics of the plant. And for the PM, it can get accurate enough simulating outputs by utilizing the trained ANN model and doesn't need the outputs of the plant, but needs only the historical outputs of the ANN model itself. Thus, the PM can be used to extract the FFVs with any optionally selected exciting input signals, but without apprehension of detraction of the physical system. This is very important also for the fault tolerance in the case when there are some faults with the sensor of the plant's output. To perform the fault diagnosis and tolerance, these two kinds of formation (SPM and PM) are used alternately.

### 3.3. The Work Modes of the ANN-FDT System

The designed ANN-FDT system has three work modes: the state supervising and tracking work mode, the FFV extracting and state inspecting work mode and the fault isolating and tolerating work mode. The work procedure of the ANN-FDT system is sketched as the Fig. (**3**).

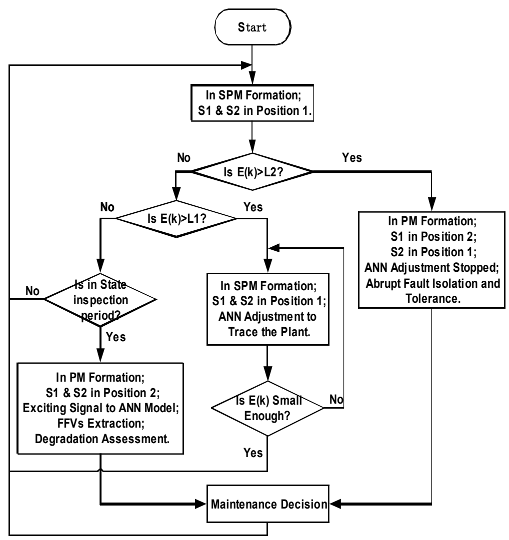


**Fig. (3).** The work procedure of the ANN-FDT system.

#### *3.3.1. The State Supervising and Tracking Work Mode*

In this work mode, SPM is adopted. The switches S1 and S2 are in position 1. The input $U_i(k)$ is given to the plant and the ANN model synchronously. When there are some changes in the plant, the error of the outputs between the plant and the ANN model is increasing. When it is bigger than a given track-trigger threshold L1, but less than the fault-level threshold L2, it is indicated that the dynamic properties of the plant is changed and the ANN model cannot simulate it accurately enough. Then the ANN model is adjusted online based on a leaning algorithm. By this way, the ANN model can adapt itself to track the change of the time-varying system, even when a degradation state occurs, and provide a representation of the plant to the following work modes.

#### *3.3.2. The FFV Extracting and State Inspecting Work Mode*

This mode is used for the detection of the gradually formed failures. In the state inspecting time windows, the system works in this mode, the ANN model is in PM formation and can be a representation of the plant. The switches S1 and S2 are in position 0, thus the input of the PM is formed by the selected exciting signal $U_e(k)$. From the excitation signal and the corresponding output of the PM, the relevant FFVs can be calculated easily. From these FFVs, the state of the plant can be assessed, as well as the presence of any faults or degradations and how serious they are at that time. By investigating the further trend of these FFVs, the future state of the plant can also be predicted for maintenance decision making.

#### *3.3.3. The Fault Isolating and Tolerating Work Mode*

If an abrupt failure appears, the output error between the ANN model and the plant will increase rapidly, and will exceed the fault-level threshold L2 (L2>L1) within a very short time. In this situation, the work mode of the ANN-FDT system will change to fault isolating and tolerating work mode. The PM formation is adopted, but maintain the input of the ANN model with the same input of the plant $U_i(k)$. That is, the switch S1 in Fig. (**1**) will turn to position 0 and S2 to position 1. The adjustment of the ANN is stopped; the ANN maintains its parameters and structure; and can be regarded as a representation of the normal state of the plant just before the abrupt failure occurred. The outputs of the ANN model can represent the outputs of the plant as if it were in normal state. The difference between the outputs of the ANN model and the plant can be used to identify the kind and the reason of the abrupt fault. If the fault is of the output feedback loop of the plant, the outputs of the ANN model can be used to replace the feedback data of the plant and keep it working normally. Thus, the fault tolerance is achieved.

## 4. THE APPLICATION OF THE ANN-DP METHOD

This method has been applied in a maintenance and technical management workstation to support the predictive maintenance of an electro-hydraulic servovalve in a water-turbine governing system.

### 4.1. The EHS and the FFVs of its Faults

The function of the EHS is to convert the electric signal into the movement of the guide vane of a HGU. The EHS is a servo system and acts as a pure power amplifier [15]. It is composed of a pressure oilcan, a voltage-hydraulic pressure conversion valve, a hydraulic pressure amplifier, a connector and a position transducer, as shown in Fig. (**4**).

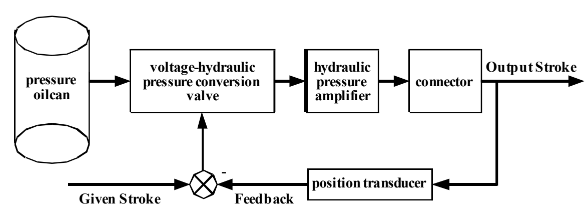


**Fig. (4).** Composition of the EHS.

When the pressure of the oilcan is supposed to be constant, the block diagram model of the EHS can be built as Fig. (**5**), in which several non-linear elements exist. The dead band (with Width ε) represent the insensibility of the output hydraulic signal to the input electric signal of the voltage-

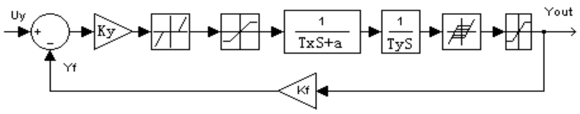


**Fig. (5).** The block diagram model of the EHS.

hydraulic pressure conversion servo valve; the first saturation element (with Bound $\psi_{l1}$ and $\psi_{h1}$) is determined by the maximum open and close speed of the guide vane; the second saturation element (with Bound $\psi_{l2}$ and $\psi_{h2}$) is determined by the maximum open and close position of the guide vane; the machinery gap (with Width $\delta$) is caused by the mechanical activation clearance of the connector. The parameters of the studied EHS are:

$Ky = Ky_0 = 10$; $Ty = Ty_0 = 0.3$; $Tx = Tx_0 = 0.015$;
$\varepsilon = \varepsilon_0 = +0.005$; $a = 3$
$\psi_{l1} = -0.1$; $\psi_{h1} = 0.1$; $\psi_{l2} = 0$; $\psi_{h2} = 1$; $\delta = \delta_0 = 0.001$;
$Kf = Kf_0 = 1$;

where the parameters with subscript 0 are their ordinary normal values.

There are several kinds of fault mode with the EHS, such as the abnormal excursion of the output, the drift of the hydraulic pressure balance, vellication of the connector, degradation of the static and dynamic performance, etc. The reasons of these faults may lay in the blockage of the oil injection hole, the lost or loose contact of the work coil or feedback coil, the error of the position sensor, too large dead band or machinery gap, etc.. Some of these faults are gradually formed, and others are abrupt.

In different fault modes, the response of the EHS is different. After a detail simulation of the EHS in different fault modes and careful analysis of the responses, the FFVs and the excitation input signals can be educed.

Consider the faults in the feedback loop of the EHS as an example. It may be the break of the feedback, which means $Kf=0$; or the error in the feedback, which means $Kf \neq Kf_0$. When the step input is 0.5, the output of the EHS with different $Kf$ is shown in Fig. (**6**), and the plot of the steady state output error versus the feedback amplification coefficient (FAC) $Kf$ is shown in Fig. (**7**). When the $Kf$ decreases with a speed of 0.01 per 3 seconds, the output of the EHS is shown in Fig. (**8**).

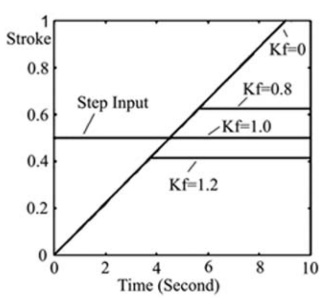


**Fig. (6).** The response of EHS with different Kf.

From these plots, it is clear that the faults in the feedback loop lead to the variety of the steady state error of the output, and the error has a fixed corresponding relationship with the FAC. Thus, to detect the faults in the feedback loop, the step

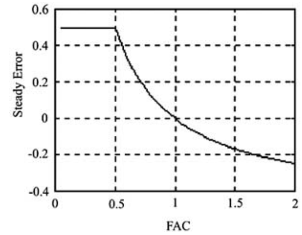


**Fig. (7).** Relationship of steady state error and FAC.

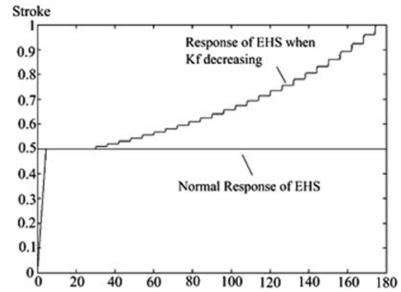


**Fig. (8).** Response of EHS when Kf is decreasing.

input can be adopted as excitation signal, with the steady state output error as the FFV of the faults.

### 4.2. The ANN Model and its Training

The ANN model used here is a $4 \times 7 \times 1$ feedforward ANN, with four inputs: previous control value $U(k-1)$, current control value $U(k)$, two latest stroke values $Y(k)$ and $Y(k-1)$ of the connector. The output of the ANN $Y^*(k+1)$ is the estimated output of the EHS. The training algorithm is based on the EBP method, combined with the learning-rate adaptation procedure based on the delta-delta learning rule [16] to speedup the training of the ANN. The method of adding the weighted term [17] is used to avoid local minimum.

The ANN is trained off-line at first with the sample data set which is composed of the pseudo-random binary sequence (PRBS) as input and the corresponding output of the plant. Fig. (**9**) shows respectively the responses of the plant, the trained ANN model, and their difference. The same input, that is, a step input with the amplitude of 0.7, followed by a slope signal with the slope of -0.1, and than a RPBS with the amplitude of 0.25 and the period of 12.75 second is used. The plots indicate that the trained ANN model can simulate the EHS accurately enough (less than 3% difference).

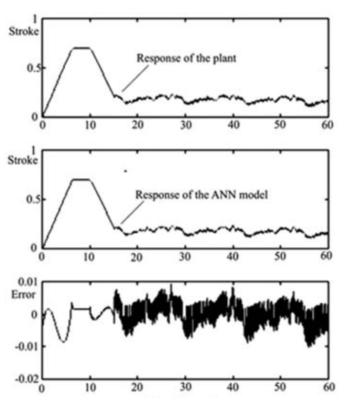


**Fig. (9).** Response of plant and the trained ANN model with given input.

### 4.3. The Online Adjustment of ANN Model to Trace the Change of the Plant

No matter in normal or in degradation state, the EHS is a non-linear and time-varying system. This may cause the error between the output of the pre-trained ANN model and EHS. When the error is bigger than L1=2.5% but less than L2=5%, the ANN model is trained online to track the change of the EHS's properties. As the bound needed to be adjusted is very small each time, the time needed to train the ANN is very short. For example, Fig. (**10**) shows for a constant input 0.5, the output of the EHS (curve 1), the ANN model (curve 2) and the error between them (curve 3) when the FAC of the EHS decreases at the rate of 0.01 per 3 seconds. The ANN model is adjusted 54 times within 180 seconds and can track the change of the EHS with an acceptable error.

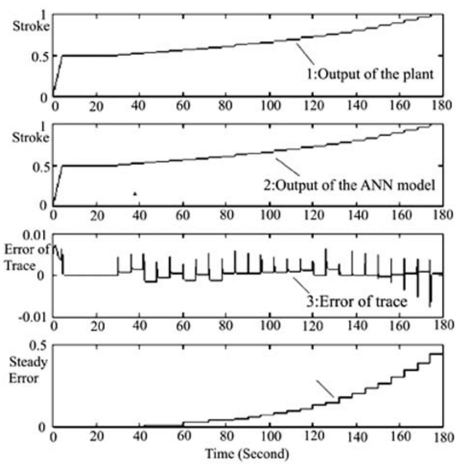


**Fig. (10).** Online adjustment result of ANN model.

### 4.4. The Extraction of the FFVs and the Diagnosis of the Gradually Formed Fault in the EHS

One of the gradually formed failures of EHS is the FAC creeping. It has an inherent relationship with the steady state error as mentioned before. Fig. (**7**) shows this relationship when the input of the EHS is fixed as 0.5. Thus the steady state error of the system with a step input can be the FFV and excitation signal respectively. To retrieve the steady state error, the ANN-FDT system works in FFV extracting and state inspecting work mode, the switches S1 and S2 are in position 0, the excitation signal of the constant 0.5 is imported into the ANN model, and the steady state output error can be calculated easily and sketched in Fig. (**10**), curve 4. The FAC creeping value can be identified by the synthesis of the results in Fig. (**7**) and Fig. (**10**), as shown in Fig. (**11**). From these plots, the fault mode is clear to be the FAC creeping, and its seriousness can be assessed.

### 4.5. The Diagnosis of the Abrupt Failure of the EHS and the Fault Tolerance

One of the abrupt failures is the break of feedback loop, which means *Kf=0*. The corresponding response of the EHS is shown in Fig. (**6**). The output stroke of EHS will increase rapidly to 100%.

If the feedback loop is broken, the error between the output of the ANN model and that of the EHS will increase rapidly, and will exceed a previously defined threshold L2 (5%) within a very short time. In this case, the ANN-FDT system will switch to the fault isolating and tolerating work mode immediately, with PM and the switch S1 in the position 0 and S2 in position 1. The parameters of the ANN model will no longer change, so that the state of the EHS before the failure is maintained by the ANN model. As explained in section 3.2.2, the ANN model can also give an accurate enough output in PM formation when the ANN is fully trained in SPM. So, the feedback value of the output of the EHS can be replaced with the output value of the ANN model. Thus, the faults in the feedback loop of the EHS are isolated. Fig. (**12**) shows the responses of the EHS with and without the replacement of the feedback value by the output of the ANN model in the case that the feedback loop breaks at 10s while the input of the EHS is 0.2. The EHS can stabilise its output at 0.205 at around 15s when its feedback signal is reconstructed by the output of the ANN model. In this case, the fault tolerance is achieved.

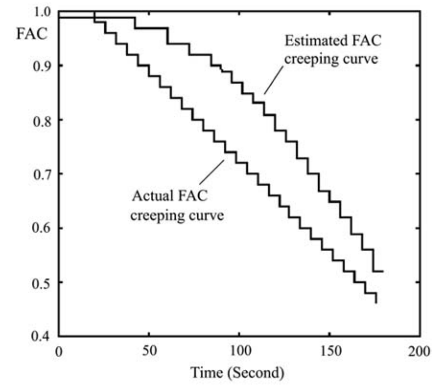


**Fig. (11).** Estimation of the FAC.

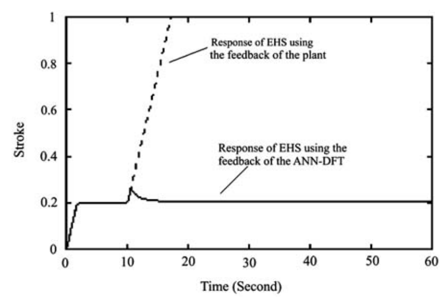


**Fig. (12).** Fault tolerance with the ANN-FDT.

## CONCLUSION

The implementation results show that the designed hybrid ANN-based fault diagnosis and tolerance method has the ability to track the change of the dynamic properties of an industrial process, to extract necessary FFVs for state assessment by utilizing the SPM and PM alternately, so as to diagnose the gradually formed failures, detect and isolate the abrupt failure, and achieve fault tolerant control. The algorithm is simple and fast enough to satisfy the requirement of real-time applications. Any kind of excitation signals can be adopted as the input of ANN model for the FFV extraction, so as to facilitate the online detection of the failures, without worrying about importing disturbance signal into the physical system. The method meets the requirement of the fault diagnosis and tolerance of the non-linear time-varying dynamic system, and support the predictive maintenance.

## NOMENCLATURE

| | | |
|---|---|---|
| ANN | = | Artificial Neural Network |
| ANN-FDT | = | ANN-Based Fault Diagnosis And Tolerance Method |
| EHS | = | Electro-Hydraulic Servovalve |
| FAC | = | feedback amplification coefficient of EHS |
| FFV | = | Fault's Feature Value |
| HGU | = | Hydroelectric Generation Unit |
| PM | = | Parallel Identification Model of the ANN-FDT |
| PRBS | = | Pseudo-Random Binary Sequence |
| SPM | = | Serial-Parallel Identification Model of the ANN-FDT |

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