Fault Diagnosis of Stepping Motor PLC Control Loop Based on Fuzzy ADRC

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Abstract. The method of multivariable statistical monitoring and parameter estimation based on analytic model relies too much on the model, which leads to the low accuracy of fault diagnosis of three-phase current. According to the loop fault diagnosis structure based on fuzzy ADRC, any phase of the three-phase current in the current measurement loop is taken as the analysis object to obtain the fault feature vector. Through off-line and on-line modeling and identification, the control limits of statistics at a certain confidence level are determined. Define the branch current measurement loop as the fault criterion, and design the loop fault diagnosis process. The experimental results show that the method has little difference from the actual waveform, the maximum error is 10A, and has accurate fault diagnosis results.

Keywords: Fuzzy ADRC · Step motor · PLC control · Loop fault · Diagnosis · Contribution rate

1 Introduction

Stepper motor is widely used in various motion control systems because of its high precision, small inertia and reliable operation, and it can realize high precision and quick open-loop control [1]. There is a close relationship between the PLC control loops of stepper motor. The fault of a control loop often causes chain reaction, which leads to the abnormal operation of many loops, and even causes the paralysis of the whole production process. Therefore, the reliability and safety of the control loop seem particularly important [2]. Real-time monitoring of the operation status of the control loop can quickly and accurately detect the faults in the control loop, provide accurate, necessary and timely reference information for staff, quickly deal with the faults in a short time, reduce the waste of funds and resources, and effectively reduce the occurrence of catastrophic accidents [3]. Because of the particularity of the structure of the control loop, the output signals of all kinds of equipments show a large range of uncertainty, high correlation and non-gaussian characteristics, and a large number of data show that the SNR of data collected in the production process is sometimes low, because of these

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characteristics, the work of establishing accurate mathematical model of the control loop becomes very complicated. In general working environment of stepper motor, there are strong nonlinearity, uncertainty and correlation between data, which makes it difficult for engineers to obtain a complete and accurate mathematical model, and increases the probability of misinformation. Therefore, a fault diagnosis method of stepping motor PLC control loop based on fuzzy ADRC is proposed. Firstly, the basis of loop fault diagnosis based on Fuzzy ADRC is determined. Then the fault diagnosis method of stepping motor PLC control circuit is studied from two aspects: control circuit fault identification and circuit fault diagnosis process design, and the effectiveness of the proposed method is verified by experiments.

2 Loop Fault Diagnosis Based on Fuzzy ADRC

ADRC is a kind of nonlinear robust control technology. It uses the extended state observer to transform all the unknown nonlinear uncertain objects into the series type of integrator by nonlinear state feedback, and uses the state error feedback to design the ideal controller [4, 5]. It does not depend on the precise mathematical model of the controlled plant, the algorithm is simple, and it has good control effect and strong robustness.

Its structure and principle are shown in Fig. 1:

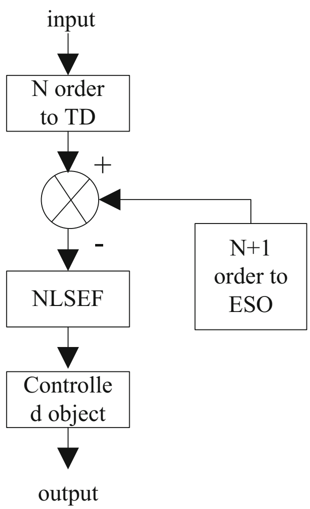


Fig. 1. Circuit fault diagnosis structure and schematic diagram based on fuzzy ADRC

In Fig. 1, the Tracking Differentiator (TD) is responsible for solving the problem of measuring signals from discontinuous or random noises [6, 7], reasonable extraction of continuous signals (given tracking) and differential signals. According to the differential output and the steepest synthesis function, the transition process of the closed-loop system can be arranged; and the extended state observer (ESO) expands the disturbances affecting the output of the controlled plant into a new state variable, and observes the expanded total disturbance signal through a special feedback mechanism [8, 9]. Through the inputs and outputs to construct the total disturbance as a state variable, the second-order system, whose extended observer reaches the third order, adds the state of the total disturbance. The total disturbances include internal disturbances and external high-frequency noise disturbances. The output of the extended state observer is the observed total disturbance of the system. The nonlinear state error feedback control law (NLSEF), based on the given signal derived from the tracking differentiator (TD) and the derivative errors of the system output and output observed by the differential and state observers of the given signal, further compensates the control and disturbance. The nonlinear control method is constructed by the fall or the fastest control synthesis function Fhan [10, 11].

The fault of relay protection current measurement loop is characterized by the abnormality of generalized ratio of variation caused by the increase of comprehensive error. Although this error may vary with ambient temperature and operation over time, it may be considered constant for a short monitoring period of time, so the monitoring of abnormal or faulty current measurement loops may translate into a mathematical approach to the solution of the generalized ratio of variances for each relay protection loop [12].

The current conversion ratio of each link of the measurement loop is defined as a variable to identify, and the dynamic change of the ratio is identified to diagnose whether the measurement loop is abnormal. The primary current, the secondary current and the GVR are constrained by each other, and the secondary current is known. Therefore, it is only necessary to solve the GVR to know the primary current, i. e. only 1 variable needs to be solved. The primary current must satisfy the Kirchhoff's law at the bus node of substation, so the variables can be solved by the constraint equation of Kirchhoff's law. So it is not necessary to get the primary current directly, and the generalized ratio of variation can be solved by using the constraint equation of primary current.

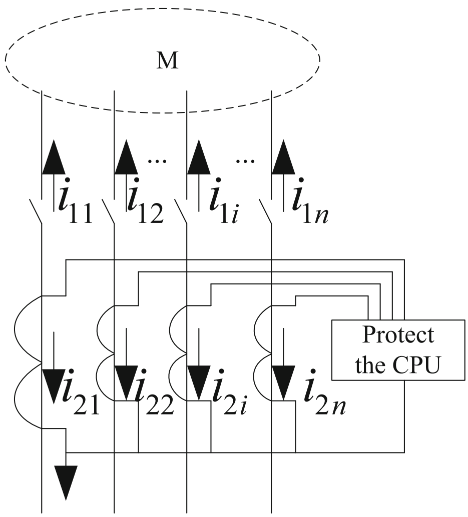


Fig. 2. Protection system for the current comparison principle

With any phase of the three-phase current in the current measurement loop as the analysis object, the protection system of the current comparison principle is shown in Fig. 2.

As shown in Fig. 2, $i_{11}, i_{12}, \cdots, i_{1i}, \cdots i_{1n}$ is a primary current flowing through a certain phase of node M, which is converted into a corresponding protective secondary sampling current which is converted through a current measurement loop to a corresponding protective secondary sampling current $i_{21}, i_{22}, \cdots, i_{2i}, \cdots i_{2n}$, according to the definition of generalized ratio of variation:

$$i_{1i} = N_{gi} \cdot i_{2i} \tag{1}$$

In formula (1), N_{gi} is the generalized ratio of variation of the current measurement loop of the i branch; i_{1i} is the primary current at the time of i; i_{2i} is the secondary current sampling value protected at the time of i [13, 14].

Set the monitoring time period of the measurement loop as $t_1 \sim t_m$, in which the protection CPU calculation value of section j branch of i. time period is $i_{2j}^{(i)}$, and the calculation value of each group shall satisfy the formula (1), then the calculation value of $m(m > n)$ hours may be listed as follows:

$$\mathbf{A} = \begin{bmatrix} i_{21}^{(1)} & i_{22}^{(1)} & \cdots & i_{2n}^{(1)} \\ i_{21}^{(2)} & i_{22}^{(2)} & \cdots & i_{2n}^{(2)} \\ \vdots & \vdots & \vdots & \vdots \\ i_{21}^{(m)} & i_{22}^{(m)} & \cdots & i_{2n}^{(m)} \end{bmatrix} \tag{2}$$

If the number of equations in formula (2) is greater than the number of unknown quantities, A may be decomposed into:

$$\mathrm{A} = \mathrm{SVD} \tag{3}$$

In formula (3), S and D are orthogonal matrices of order $m \times m$ and $n \times n$, respectively; V is diagonal matrix, whose diagonal elements are singular values of A and arranged in descending order [15, 16].

In practical calculation, the sampling group m is much larger than the current measurement loop n, and the column vector of A is linearly correlated. When m is large enough, $\mathrm{rank}(A) = n - 1$ can be obtained. At this time, there is only one basic solution system for the over determined homogeneous equations. In order to eliminate the zero solution, the constraint condition $\|n_v\| = 1$ is added. Substitution of type (3) into type (2) may be converted as follows:

$$A^{\mathrm{T}} A n_{\mathrm{g}} = (SVD)^{\mathrm{T}} (SVD) n_{\mathrm{g}} = D^{\mathrm{T}} \left(V^{\mathrm{T}} V \right) D \mathbf{n}_{\mathrm{g}} = 0 \tag{4}$$

In formula (4), D^{T} represents the orthogonal invertible matrix of unit; D is the orthogonal matrix; and $D\mathbf{n_g} = (0, 0, \cdots, 0, 1)^{\mathrm{T}}$; the eigenvector corresponding to the minimum eigenvalue of $A^{\mathrm{T}} A$.

3 Research on Fault Diagnosis of Stepping Motor PLC Control Loop

3.1 Control Loop Fault Identification

In the PLC control loop of stepper motor, the input and output of controller, output of control valve, output of controlled object and output of transmitter should be selected as signal observation points of fuzzy ADRC to form mixed signal matrix [17–19].

By analyzing and calculating the collected signals, the statistics can be calculated from the decomposed independent components and separation matrix, and the running state of the control loop can be monitored in real time. During the operation of the control loop, if some devices fail, their output signals will be abnormal, which will affect the fuzzy ADRC supervisory statistics calculated from the data signals. Then, the statistical value obtained from online monitoring is compared with the statistical limit. If the control limit is exceeded, the control loop is normal. If the control limit is exceeded, the control loop is abnormal or fails.

Offline Modeling Identification
In the off-line modeling, the observation data of the above five observation points in the normal operation state of the control loop are selected to form observation matrix as historical data. The main aim of the data preprocessing of the observation matrix is to remove the outliers [20]. Because some signals are disturbed instantaneously, some inaccurate measurement values may be produced. When modeling off-line, removing these erroneous data can obviously improve the parameter estimation and performance parameters of statistics, and improve the accuracy of model training. According to the fuzzy ADRC method, the independent component s(k) and separation matrix W are obtained, and two statistics are calculated by s(k) and W.

There are two ways to deal with the historical data in off-line modeling of control loop monitoring. One is that the modeling data does not contain the change of the set value. For off-line modeling without setting value change, the effect of noise of different variance in control loop on fault diagnosis is mainly studied. The data selected in the modeling are the historical data of the normal operation of the control loop under different noise forms and different variances. Because the form and variance of noise in historical data are unknown, the variance of control loop output can be calculated to replace the variance of noise. The historical data under normal conditions are divided into two groups. The mean and variance of the first group are calculated [21]. The mean and variance of the other group are subtracted by the mean and divided by the variance of the first group. The statistical control limit of the normalized fuzzy ADRC method is used.

The fault diagnosis ability of fuzzy ADRC to control loop before, after and during the change of set point is studied for off-line modeling with change of set point in modeling data [22, 23]. When modeling offline, the historical data selected shall be the same as the change of the set value of the monitored data. The selected historical data are divided into two parts, and the data pretreatment and statistic control limits are calculated according to the modeling method with the set values unchanged.

In fuzzy ADRC method, because the distribution of independent components does not conform to a common distribution law, the control limit of statistics can not be determined from the confidence interval of a specific distribution. In most statistical process monitoring, it is usually assumed that the statistics follow the Gaussian distribution, but if the two statistics are treated as Gaussian distribution, the final result is obviously inaccurate and the final monitoring effect is not credible. In view of this situation, the method of fuzzy ADRC estimation is generally adopted to estimate the fuzzy ADRC function of the statistics, and then the confidence interval of the statistics is determined by the estimated fuzzy ADRC function, which is defined as:

$$f_n(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - X_i}{h_n}\right) \tag{5}$$

In formula (5), n represents the number of samples; X_i represents the independent sample-distribution samples drawn from population X; $f(x)$ represents the density function of X; $K(\cdot)$ represents a given probability density function over the real number field, called the kernel function; and h_n represents a positive number related to the number of samples, called the smoothing parameter or window width.

Through the definition of fuzzy ADRC estimator, the performance of kernel density estimator can be greatly improved by choosing proper kernel function and window width. The key factor in the estimation is the choice of window width h, which increases the effect of randomness if the window width is too large. The choice of window width is so large that the small properties of density function are easily neglected. Usually, the principle of evaluating the minimum window width is to get the minimum mean square error, and then the control limit of the statistics is determined at a certain confidence level.

Online Modeling Identification

Firstly, the monitored data are preprocessed, then the normalized data are decomposed into fuzzy ADRC, and the statistics are calculated and compared with the control limits obtained from off-line modeling. If the statistics are not overrun, indicating that the normal operation of the system, if the statistics overrun, indicating that the system has failed, the need for fault handling. By calculating the statistical contribution diagram of the fault time, we can determine which observation variable has the problem. By looking up the fault device of the problem variable, we can work out the solution to the fault of the control loop.

The variables that contribute the most to the failure graph are the main variables that cause the failure, as shown in Table 1.

3.2 Circuit Fault Diagnosis Process Design

The fault of the current measurement loop can be judged by comparing the calculated GVR L_{gi} of the current measurement loop with the ideal VR L_i of the CT. Thus, the expression of the fault criterion T_i for the current measurement loop of the branch circuit i is defined as:

$$T_i = \frac{L_{gi} - L_i}{L_i} \tag{6}$$

Table 1. Failure elements corresponding to the variables in the contribution diagram

Variable name in contribution diagram	Faulty device in control loop
Controller input	Transmitter failure or change of setting
Controller output	Controller failure
Control valve output	Control valve failure
Output of controlled object	Control object exception
Transmitter output	Transmitter failure

Under normal operation, the comprehensive error ε of the current measurement loop shall be less than 10%, and the expression of the fault criterion eigenvalue Q_i of the i branch current measurement loop shall be:

$$Q_i = \frac{-\varepsilon}{1+\varepsilon} \tag{7}$$

When the measurement loop is normal, the error is within the specified range, i.e. p; E $Q_i \in (-0.0909, 0.1111)$; when the measurement loop is abnormal, the generalized

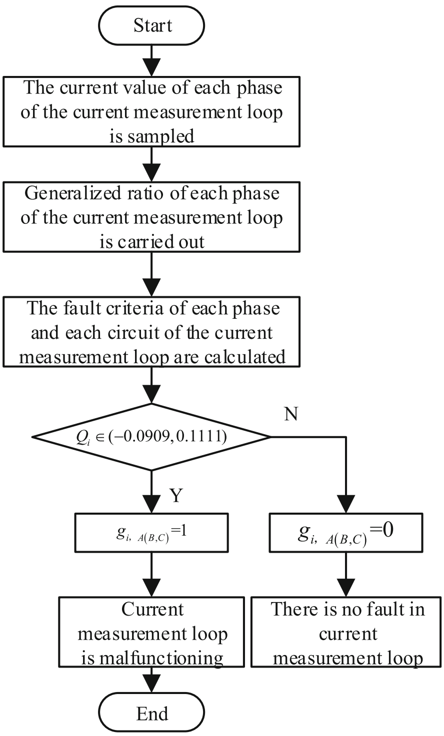


Fig. 3. Loop fault diagnosis process

variation ratio exceeds the above range. Therefore, according to the value range of Q_i, it can be judged whether there is a fault in the i-branch current measurement loop. The method is applied to the three-phase current measurement circuit of A, B and C respectively, and then the abnormity of the whole circuit can be identified by logic decision.

In order to clarify the fault criteria, the following definitions are given:

If $Q_{i,A(B,C)} \in (-0.0909, 0.1111)$, then $g_{i,A(B,C)}=1$ means that there is no fault in the A(B,C) phase measurement loop of the current protection device i; if $Q_{i,A(B,C)} \notin (-0.0909, 0.1111)$, then $g_{i,A(B,C)}= 0$ means that there is a fault in the A(B,C) phase measurement loop of the current protection device i, then the flow of fault diagnosis of the step motor PLC control loop based on fuzzy ADRC as shown in Fig. 3 can be obtained.

As can be seen from Fig. 3, the above criteria can be integrated when a bus current differential protection is installed in a substation. There are many ways to use this method in the station area and wide area protection. When a branch exits, the branch object in this method must be changed accordingly. In practice, the station and wide area protection have the function of network topology identification, so the network topology identification result can be used in the research method at the same time. However, when the number of branches changes, the identification equation variable shall be changed and the data shall be switched temporarily, but the number of branches included shall be unlimited.

4 Experiment

In order to verify the fault diagnosis method of stepping motor PLC control loop based on fuzzy ADRC, the experimental verification analysis is carried out.

4.1 Experimental Environment

A parallel fault diagnosis experimental platform of power equipment state information is established; the experimental environment includes 10 ordinary PCs with the same configuration, one as NameNode and the other as datanode. Each computer has a dual-core Interi5-2400 CPU with 4.00 GB of memory and 80 GB of hard disk. Build a parallel diagnostic test platform for power equipment status information, which includes 10 ordinary PCs with the same configuration, one for NameNode, and one for datanode. 4.00 GB of memory, 80 GB of hard disk, each computer has CPU dual-core Interi5-2400.

4.2 Experimental Results and Analysis

The life signal is divided into 4000 data segments, and the non-zero feature values and their corresponding feature vectors are determined as the comprehensive feature indices for the first time. Figure 4 shows the schematic diagram of fault diagnosis of stepper motor PLC control loop.

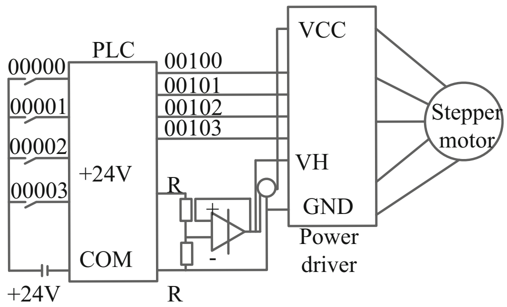
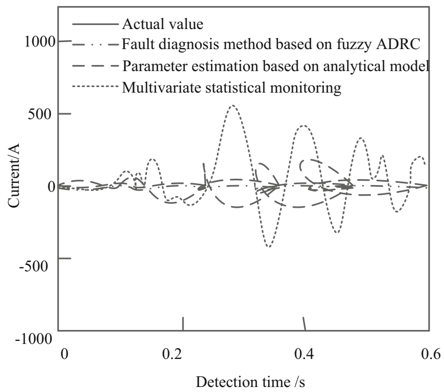


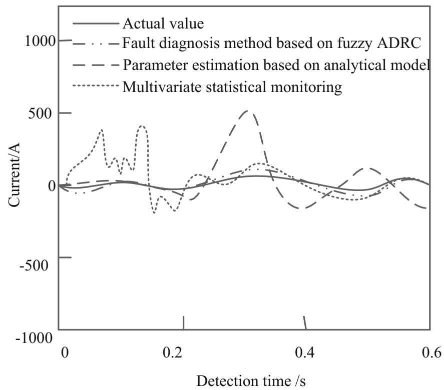
Fig. 4. Schematic diagram of fault diagnosis of stepping motor PLC control loop

According to the bearing faults shown in Fig. 4, the three-phase short circuit of the PLC control loop of the stepping motor is diagnosed by using multivariable statistical monitoring, parameter estimation based on analytical model and fault diagnosis based on fuzzy ADRC, as shown in Fig. 5.

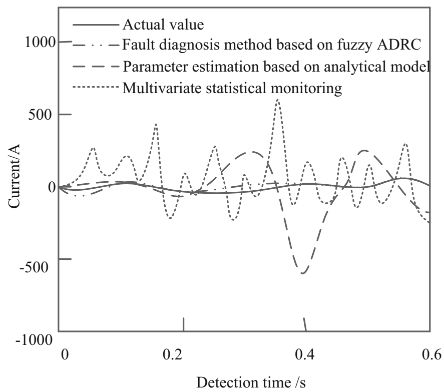
Through the comparison of the results shown in Fig. 5, it can be seen that there is little difference between the waveform of the fault diagnosis method based on fuzzy ADRC and the actual waveform after the three-phase short circuit fault occurs, and the waveform change at other time points is basically the same as the actual curve, in which the maximum error is 10A, while the waveform difference of the method based on multivariable statistical monitoring and parameter estimation based on analytical model is large.



(a) Phase A



(b) Phase B



(c) Phase C

Fig. 5. Comparative analysis of three fault diagnosis methods

5 Conclusion and Prospect

Based on fuzzy ADRC, the fault diagnosis method of PLC control loop of stepping motor is studied. The input and output of PLC controller in the loop are selected as signal observation points. When a component in the control loop fails, it can be monitored through changes in statistics. This method can fully consider the problem of signal correlation in the control loop, and can monitor all parts of the control loop at the same time, not just a single device in the control loop. Compared with multivariate statistical monitoring and fault diagnosis method based on analytic model parameter estimation, this method has the advantages of fast operation speed and strong self-learning ability. The simulation results show that the method can detect the fault accurately and locate the fault accurately.

At present, the research on fuzzy ADRC control loop fault diagnosis method is still preliminary, and many related problems need to be further studied. Fuzzy ADRC has strict restrictions on the historical data needed for monitoring the transition process when the set point is changed, but it is difficult to obtain a large number of historical data with the same set point change method in the actual continuous process. At present, the method only involves a single loop control system, and there is no research on more complicated control loops such as cascade control system and proportional control system.

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