Research of Fault Phase Selection based on the Energy Coefficient of Fault Current Component and PNN

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Abstract. Fault-phase selection is an important link on corrective actions of high-voltage transmission lines protection, but also an important prerequisite for accurate fault location. The traditional fault phase selection method is only applicable to simple fault, low sensitivity, and easily affected by system operation mode, fault grounding resistance etc.. On the basis of the analysis for fault component of each phase current, this paper gives a definition of fault component energy by the concept of signal energy and presents a new type of fault phase identification method based on fault component energy coefficient. This method directly uses the fault current to extract fault components and calculate the signal energy of fault component for two cycles after fault inception, and the ratio coefficient that fault component energy of each phase current accounts the total energy can be gotten. Then probabilistic neural network of fault phase selection may be established to select fault phase by fault phase identification feature vector.

Introduction

The fault-phase selection is an important link on corrective actions in the lines protection of high-voltage transmission lines. It needs immediate and accurate fault-phase selection for a new transient protection and a traveling wave protection in power system. With the number of digital substation increasing, fault phase selector could provide guarantee for automatic reclosing, also provide necessary and correct data for protective elements. The accurate fault-phase selection is important for accurate fault location. So, the immediate and accurate fault-phase selection brings remarkable economic and social benefits in power system.

For improving the traditional fault-phase selection, the paper proposes a new method for fault-phase selection. The new method extracts fault feature parameters in transmission by a fault component energy defined based on a vast amount of theoretical analysis. The new method is combined with the probabilistic neural network (PNN) to complete fault-phase selection.

Firstly, extracting fault-phase current component, half period was taken as the calculation interval, and the signal energy of fault component for two cycles was calculated after fault inception, in order to obtain four energy feature values of each fault-phase current component. Then, the method could sum three fault-phase current components in half period, at same time calculated three fault-phase current energys. The fault component energy coefficient was defined the current energys divided by the current components. The coefficient was taken as feature vector, and input PNN to recognite the fault-phase in transmission lines. Simulation results proofed that the new method could accurately select the fault-phase in various faults, and it has higher reliability.

The Energy Coefficient of Fault Current Component

When faults occur in the transmission line, the state could be considered as normal operation with fault conditions bsaed on superposition theorem. The current was normal load current under normal operation, and the fault current comes from fault electromotive force, which was defined as the fault current components. The paper proposed the energy confficient of fault current components for applying to fault-phase selection.

Fault Current Component

Such as figure 1(a) shows the simple power system with double sides supply. When the short current fault occurs in *k* point, figure 1(a) could be place of figure 1(b), which is equivalent circuit in fault operation. The voltage in *k* point is denoted by $u_{f[0]}$ before fault occurs. In figure 1(a), when the fault occurs, two voltage sources are connected in series between *k* point and the earth. The electromotive force of two voltage sources is $u_{f[0]}$, and their polarity is opposite.

Figure 1(b) shows the fault state. Basis for superposition theorem, the fault state equivalents to the sum of normal state, show in figure 1(c), and additional fault state, and shows in figure 1(d).

In figure 1(b), u_m is the full voltage, and i_m is the full current at *m* point while the fault is occuring. In figure 1(c), $u_{m[0]}$ is the operation voltage, and $i_{m[0]}$ is the operation current at *m* point while the system is normal. In figure 1(d), Δu_m is the fault voltage component, and Δi_m is the fault current component at *m* point while the fault is occuring.

In *m* point, the fault current component could be shown in following. $\Delta i_m = i_m - i_{m[0]}$ (1)

At *k* time, the fault current in *m* point component could be shown as. $\Delta i_{m(k)} = i_{m(k)} - i_{m(k-nN)}$ (2)

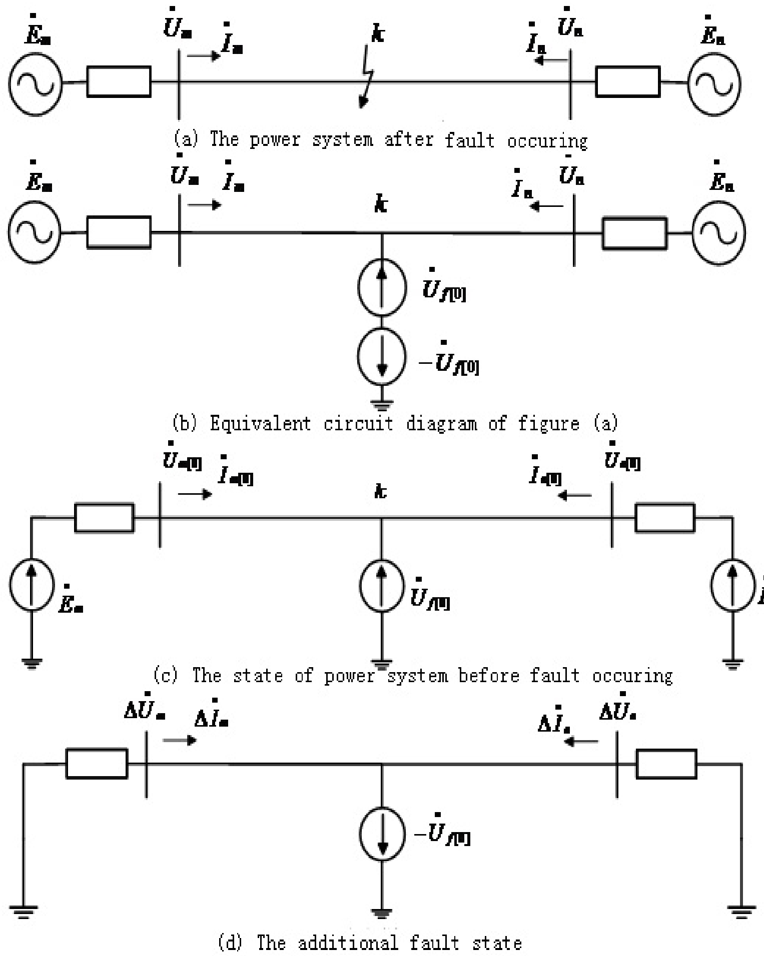

Fig.1 Electric parameters calculation at short circuit

There, *k* is the serial number of the sampling sequence, and N is number of sampling points each cycle, and n is arbitrary integer, and usually is one or two.

When transmission line operates normally, the fault current component is shown, and $\Delta i_{m(k)} = 0$. While the fault is occuring, the power system could generate the fault current component, and shown as $\Delta i_{m(k)}$. By formula (2), the fault current component could be extracted in one or two cycles at the beginning of fault.

The Energy Coefficient of Fault Current Component

The paper discusses the energy of fault current component in two cycles after the fault occurs. Basis for signal analysis theory Δi_m is used to represent the fault current component. The energy of

Δi_m is shown in time widows ($t_0 \sim t_N$). $E_i = \int_{t_0}^{t_N} \left|\Delta i_m\right|^2 dt$ (3)

The energy of Δi_m is discretized in time widows ($t_0 \sim t_N$), and it is shown. $E_i = \sum_{k=1}^{N} \left|i(t_k)\right|^2$ (4)

For accurately obtaining the fault information, the time window is chosen the half cycle while the fault is occurring in transmission lines.

By formula (4), the energy of fault current component is calculated in four half cycle after fault occurs, and they are shown as follows.

The energy of fault current component in A phase includes E_{A1}, E_{A2}, E_{A3} and E_{A4}.

The energy of fault current component in B phase includes E_{B1}, E_{B2}, E_{B3} and E_{B4}.

The energy of fault current component in C phase includes E_{C1}, E_{C2}, E_{C3} and E_{C4}.

The energy of fault current component in each half cycle are represented $E_{\Sigma 1}$, $E_{\Sigma 2}$, $E_{\Sigma 3}$, and $E_{\Sigma 4}$ in four half cycle after fault occurs. There, $E_{\Sigma p} = E_{Ap} + E_{Bp} + E_{Cp}$ （p=1,2,3,4） （5）

The energy coefficients of each phase fault current component are defined as follows.

In A phase, it shows as follows, $l_{Ai} = E_{Ai} / E_{\Sigma i}$, $(i = 1,2,3,4)$ (6)

In B phase, it shows as follows, $l_{Bi} = E_{Bi} / E_{\Sigma i}$, $(i = 1,2,3,4)$ (7)

In C phase, it shows as follows, $l_{Ci} = E_{Ci} / E_{\Sigma i}$, $(i = 1,2,3,4)$ (8)

The fault component occurs only in the phase current, while the power system operates normally, the fault current component is zero. So the energy coefficient of fault current component in the fault phase is far greater than in the normal phase.

The analysis indicates that the fault current components are obvious difference between the fault phase and the normal phase. The paper chooses energy coefficient of fault current component to structure feature vector, which is T. The energy coefficient of fault components in four half cycles structured the element of fault current feature vector.

The feature vector of the energy coefficient of fault current component shows as follows.

$$\mathrm{T} = [\, l_{m1} \quad l_{m2} \quad l_{m3} \quad l_{m4} \,]$$

The Fault-Phase Selection based on the Energy Coefficient and PNN

Probabilistc Neural Network

The probabilistic neural network put the Bias estimator in a feedforward neural network. The Bias decision has obtained classification result by the nonparametric estimation of probability density. According to the probability density function of Parzen-window and Bias classification theory, Specht proposes four layer model of probabilistic neural network, and it shows as follows figure 2. The network inclides input layer, model layer, sumulation layer, and decision layer.

The samples input the iuput layer, and then they are assigned to the model layer. The model layer generates the scalar product that structures the input model vector expressed X and the weight vector expressed W_j, and it represented

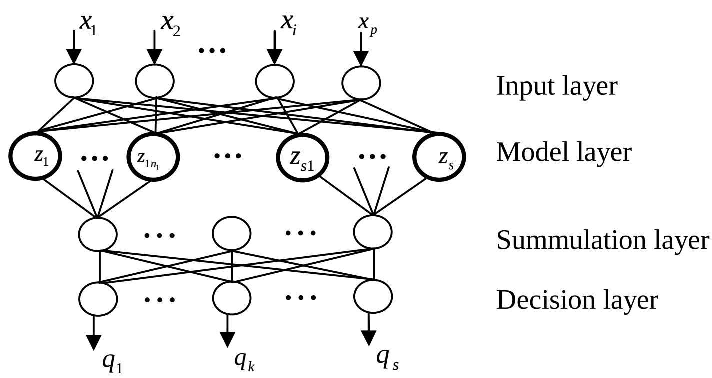

Fig.2

by $Z_j = X \bullet W_j$. Z_j is nonlinearized by the nonlinear operator expressed $\exp[(Z_i - 1)/s^2]$, and then it is transfored to summulation layer. The input data is summulated in summulation layer to obtain the maximum probability of property. The probability density function from model layer is transfored to the decision layer. The maximun probability desity from neuron expresses 1 and others express 0.

The Training Sample Matrix based on Fault-Phase Selection by PNN

For increasing the reliability of training sample matrix based on fault-phase selection, the paper chooses different energy coefficient of fault current components as the feature vctors in all kinds of fault states.

When all kinds of phase-phase fault occur, the energy coeficients of fault current component have little difference. When all kinds of single-phase earth fault occur, the energy coeficients of fault current component have little difference. When all kinds three-phase short circuit occur, the energy coeficients of fault current component have little difference. For realizing fault-phase selection, the paper selectes randomly the various feature vctors in multiple conditions.

When the phase-phase short circuit or two-phase earth fault occurs in multiple conditions, six kinds of energy coefficients of fault phase current component are chosen as feature vctors.

$a_1 = [l_{11} \quad l_{12} \quad l_{13} \quad l_{14}]$, $a_2 = [l_{21} \quad l_{22} \quad l_{23} \quad l_{24}]$, $a_3 = [l_{31} \quad l_{32} \quad l_{33} \quad l_{34}]$, $a_4 = [l_{41} \quad l_{42} \quad l_{43} \quad l_{44}]$, $a_5 = [l_{51} \quad l_{52} \quad l_{53} \quad l_{54}]$, $a_6 = [l_{61} \quad l_{62} \quad l_{63} \quad l_{64}]$

When the single-phase earth fault occurs in multiple conditions, three kinds of energy coefficients of fault phase current component are chosen as feature vctors.

$a_7 = [l_{71} \quad l_{72} \quad l_{73} \quad l_{74}]$, $a_8 = [l_{81} \quad l_{82} \quad l_{83} \quad l_{84}]$, $a_9 = [l_{91} \quad l_{92} \quad l_{93} \quad l_{94}]$

When the three-phase earth fault occurs in multiple conditions, three kinds of energy coefficients of fault phase current component are chosen as feature vctors.

$a_{10} = [l_{101} \quad l_{102} \quad l_{103} \quad l_{104}]$, $a_{11} = [l_{111} \quad l_{112} \quad l_{113} \quad l_{114}]$, $a_{12} = [l_{121} \quad l_{122} \quad l_{123} \quad l_{124}]$

For realizing non-fault-phase selection, the feature vctors of training sample are chosen as follows in PNN.

When the phase-phase short circuit or two-phase earth fault occurs in multiple conditions, three kinds of energy coefficients of fault phase current component are chosen as feature vctors.

$b_1 = [l'_{11} \quad l'_{12} \quad l'_{13} \quad l'_{14}]$, $b_2 = [l'_{21} \quad l'_{22} \quad l'_{23} \quad l'_{24}]$, $b_3 = [l'_{31} \quad l'_{32} \quad l'_{33} \quad l'_{34}]$

When the single-phase earth fault occurs in multiple conditions, six kinds of energy coefficients of fault phase current component are chosen as feature vctors.

$b_4 = [l'_{41} \quad l'_{42} \quad l'_{43} \quad l'_{44}]$, $b_5 = [l'_{51} \quad l'_{52} \quad l'_{53} \quad l'_{54}]$, $b_6 = [l'_{61} \quad l'_{62} \quad l'_{63} \quad l'_{64}]$, $b_7 = [l'_{71} \quad l'_{72} \quad l'_{73} \quad l'_{74}]$, $b_8 = [l'_{81} \quad l'_{82} \quad l'_{83} \quad l'_{84}]$, $b_9 = [l'_{91} \quad l'_{92} \quad l'_{93} \quad l'_{94}]$

So the training samples matrix of fault-phase selection show as follows.

$$P = \begin{bmatrix} a_1 \\ \vdots \\ a_{12} \\ b_1 \\ \vdots \\ b_9 \end{bmatrix} = \begin{bmatrix} l_{11} & l_{12} & l_{13} & l_{14} \\ \vdots & \vdots & \vdots & \vdots \\ l_{121} & l_{121} & l_{121} & l_{121} \\ l'_{11} & l'_{12} & l'_{13} & l'_{14} \\ \vdots & \vdots & \vdots & \vdots \\ l'_{91} & l'_{92} & l'_{93} & l'_{94} \end{bmatrix}$$

Realization Fault-Phase Selection in Transmission Line

The training samples matrix of fault-phase selection expressed P input the PNN of fault-phase selection. Let 1 express the fault phase, and 2 express the non-fault phase. The output vctors from the PNN show as follows. $T = [1 \ 1 \ \cdots \ 1 \ 2 \ 2 \ \cdots \ 2]^T$

The PNN is trained by the training sample matrix expressed P and T, and the fault-phase selection PNN could be trained well. If the fault occurs in transmission line, the fault current data could be collected in the protected point. Basis for the data, the paper could obtain the energy coefficients of three-phase fault current component, and structure the testing sample matrix expressed B, which shows as follows.

$$B=\begin{bmatrix} l_{A1} & l_{A2} & l_{A3} & l_{A4} \\ l_{B1} & l_{B2} & l_{B3} & l_{B4} \\ l_{C1} & l_{C2} & l_{C3} & l_{C4} \end{bmatrix}$$

The testing sample matrix is input the trained PNN, and the fault-phase selection network output the results. The output results could indicate the fault-phase and the non-fault-phase. The process of fault-phase selection shows as follows in figure 3.

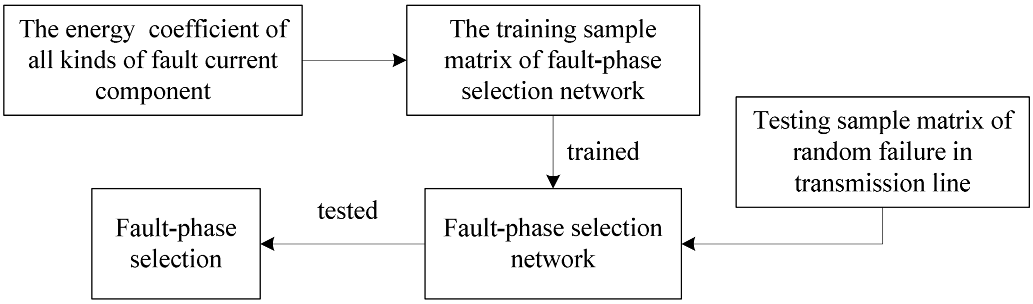

Fig.3 Fault phase selection by PNN

Conclusion

The paper proposes a new method for the fault-phase selection based on the energy coefficient of fault current component and PNN. The fault current component and the thoery of signal energy are combinated, and calculate the energy coefficient of each phase, which could accurately reflect the fault type and feature information in fault-phase or non-fault-phase. The paper applies PNN to the fault-phase selection, and it could accurate identificate the fault-phase in transmission line.

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