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ART artificial neural networks based adaptive phase selector

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Abstract

This paper introduces a new phase selector based on adaptive resonance theory (ART). Because conventional phase selector cannot adapt dynamically to the power system operating conditions, it presents different characters under different power system conditions. To overcome the disadvantage, an adaptive phase selector, which utilizes artificial neural network based on ART, is designed. ART based neural network (ARTNN) has some advantages such as no local extremum, quickly convergence and so on. Therefore, the proposed ARTNN based phase selector has better performances compared with other neural networks based phase selector, and the new selector can adapt dynamically to the varying power system operation conditions. Furthermore, the phase selector can be trained and learned on-line. A lot of EMTP simulations and experimental field data tests have illustrated the phase selector's correctness and effectiveness.

Keywords: Adaptive resonance theory; Neural networks; Adaptive phase selection

1. Introduction

Character of conventional phase selectors varies under different power system conditions, because they cannot adapt dynamically to the power system operating conditions [1]. Pattern recognizer based on artificial neural networks (ANN) is a good classifier and adapts itself dynamically to the varying environment, which has aroused protective relay researchers' interests [1,2]. Many papers have demonstrated ANN's applications in protective relays. References [3–6] had explored Multilayer Feed forward Neural Network (MFNN) based fault direction discriminator and fault classification relay and distance protection relay, respectively. All of these facts have shown the good performance of protective relays based on ANN. Presently, most of ANN based protective relays are designed by utilizing Error Back Propagation algorithm based MFNN (BPNN). However, BPNN has some disadvantages [7] such as: low learning efficiency, local extremum and unstable weights of the network derived from all the training patterns. Unstable weights mean that the weights of the network will be retrained with all the training patterns, even if only a new pattern needs to be stored in the network. In other words, BPNN cannot get a good trade-off between weights' stability and plasticity. These questions have hindered the further applications of ANN in protective relays. In order to solve these questions, based on analyzing and comparing several neural network architectures, an adaptive phase selection relay is proposed and designed by utilizing the neural network architecture based on adaptive resonance theory (ART). Simulation results and experimental field data tests have validated the way correctness and effectiveness.

2. Basic theory

2.1. The principle of adaptive resonance theory based neural network (ARTNN)

The basic principle of ARTNN is an adaptive resonance theory introduced by Carpenter and Grossberg [8]. Compared with other neural network architectures, ARTNN could better solve the above-mentioned questions, particularly about

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the question of unstable weights that cannot be handled with other neural network architectures. A better tradeoff between stability and plasticity of weight can be attained by the cooperation of the two subsystems—attentional subsystem and orienting subsystem within ARTNN. That is to say, depending on the calculated vigilance, which denotes the extend of similarity between two patterns, the pattern, whose vigilance is above the threshold value set in advance, will be thought to be similar with a pattern stored in the network database, and be dealt with the attentional subsystem. At the same time, the pattern, whose vigilance is lower than the threshold value, is encoded and stored into the network by the orienting subsystem. It can be seen that ARTNN could learn new knowledge and avoid modifying the patterns stored in the network, which makes ARTNN obtain the ability of learning on-line. Consequently, the special character could make the phase selection relay based on ARTNN obtain better performance under different power system conditions. Moreover, learning algorithm of ARTNN is a linear iterative process, which ensures high learning efficiency and no local extremum. Architecture of ART2-A [9] shown in Fig. 1 is responsible for arbitrary sequences of analog input patterns, which has advantages of rapid category and recognition learning. It consists of attentional subsystem and orienting subsystem. The attentional subsystem consists of input representation field F_1 and category representation field F_2.

In terms of training patterns, learning strategy of BPNN is supervised, so it needs many training patterns in order to attain excellent fault-tolerance and generalization capability. Oppositely, learning strategy of ARTNN is non-supervised, so it can automatically abstract inherent characteristics of training patterns by adaptively modifying parameters of networks. According to that, ARTNN needs fewer training patterns compared with BPNN, but the training patterns should embody essential of the analyzed question as possible.

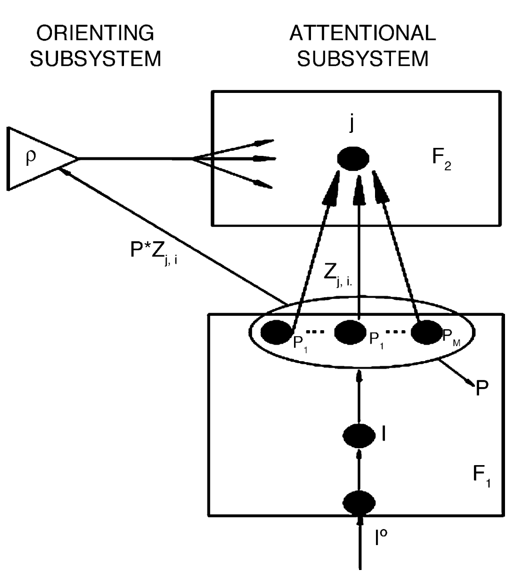

Fig. 1. Schematic diagram of ART2-A.

2.2. Simple description of ART2-A algorithm

The structure and algorithm of ART2-A are complicated and have been described and illuminated in detail in reference [9], so there only a reduced algorithm is described based on Fig. 1 as follows:

i. Importing a vector (M dimension) as input vector of network.

ii. Calculating the vectors (I, P) of the input representation field F_1.

If I^0 is an M-dimensional input vector of network, then I is the normalized vector of I^0 as follows:

$$I = \eta I^0$$

where $\eta(\cdot) = (\cdot)/\|(\cdot)\|$ and the vector P is:

$$P = \eta f I$$

$$\text{where } f(\cdot)_i = \begin{cases} (\cdot)_i, & \text{if } (\cdot)_i > \theta,\ 0 < \theta \le 1/\sqrt{M} \\ 0, & \text{otherwise} \end{cases}$$

iii. Inputted value of the output nodes (i.e. nodes of the category representation field F_2).

The inputted value of the jth output node of F_2 is given as follows:

$$Y_j = \begin{cases} 0, & \text{if the } j\text{th node is inactive} \\ P \times Z_{j,i}, & \text{if the } j\text{th node is active} \end{cases}$$

where $Z_{j,i}$ stands for the weight vector of the jth node of F_2 and P ($p_1, \ldots, p_i, \ldots, p_M$) denotes the input vector of the field F_2. Y_j is called matching value of the jth output node.

iv. Competing among output nodes and verification of matching level.

The output node, which has the biggest sum of input, is the winner among all output nodes, i.e. $Y_J = \max(Y_j)$, J is the index of winning node. ρ (named vigilance) is a set threshold in advance and is utilized to judge matching level. Depending on the relationship between Y_J and ρ, different processes are dealt with as follows:

(a) If $Y_J > \rho$, the input vector is classified to the type that the node J denotes, which has been stored in the network, then network turns into the weight learning.

(b) If $Y_J < \rho$ and there is an inactive node J' in the network, then set $Z_{J',i} = P$, where node J' denotes this new sort and the algorithm back to step i.

(c) If $Y_J < \rho$ and there are no inactive node, then the network directly back to step i.

v. Weight learning.

Equations of modifying weights are:

$$Z_{j,i} = \begin{cases} Z'_{j,i} / \left\| Z'_{j,i} \right\|, & \text{if } j = J \\ Z_{j,i}, & \text{if } j \ne J \end{cases}$$

where j stands for the index of network output nodes and $Z'_{j,i} = Z_{j,i} + \alpha \times (P - Z_{j,i})$, α is learning step.

The above five steps formed an integral algorithm, which consists of discrimination, classification and weight learning. Compared with the BPNN, its speed is quicker as the whole iterative algorithm is linear.

3. Design of ARTNN based phase selection relay

Learning of ARTNN is non-supervised, so training pattern of ARTNN should try to embody nature of research question. It is impractical that directly utilizing phase currents and voltages of transmission line as input vectors of ARTNN based phase selection relay, because these quantities have no evident features so that there will form too many classification nodes. It seems that by decreasing the value of vigilance ρ, the number of classification nodes could be reduced. However, it will result in sorting different kind of patterns into the same note.

When a fault occurs in the electric power system, it leads to a dynamic transition from the normal system condition to a fault system condition. This case can be analyzed by superposition theorem. The superposition theorem is one of the fundamental tools in circuit analysis. It allows considering the measured currents and voltages as the sum of all sources in the power system and a fictitious source at the fault location. The fictitious source is equal in magnitude and opposite in polarity to the prefault voltage at the fault location. This fictitious source is applied to the system at the fault inception time. It results in changes in the magnitude and phase of the measured currents and voltages. The changes in the measured currents and voltages are directly related to the fault type [10]. That is to say, the components generated by fault could better reveal the nature of the fault types. Therefore, this paper selects fault components as input vectors of network in order to reduce output nodes and not to debase precision of classification at the same time. Input vectors of ARTNN based phase selection relay are shown as follows:

(a) $\Delta I_{\mathrm{r}} = \text{postfault } I_{\mathrm{r}} - \text{prefault } I_{\mathrm{r}}$
$\Delta U_{\mathrm{r}} = \text{postfault } U_{\mathrm{r}} - \text{prefault } U_{\mathrm{r}}$

(b) $\Delta I_{\mathrm{s}} = \text{postfault } I_{\mathrm{s}} - \text{prefault } I_{\mathrm{s}}$
$\Delta U_{\mathrm{s}} = \text{postfault } U_{\mathrm{s}} - \text{prefault } U_{\mathrm{s}}$

(c) $\Delta I_{\mathrm{AB}} = \Delta I_{\mathrm{A}} - \Delta I_{\mathrm{B}},\quad \Delta I_{\mathrm{BC}} = \Delta I_{\mathrm{B}} - \Delta I_{\mathrm{C}},\quad \Delta I_{\mathrm{CA}} = \Delta I_{\mathrm{C}} - \Delta I_{\mathrm{A}}$
$\Delta U_{\mathrm{AB}} = \Delta U_{\mathrm{A}} - \Delta U_{\mathrm{B}},\quad \Delta U_{\mathrm{BC}} = \Delta U_{\mathrm{B}} - \Delta U_{\mathrm{C}},\quad \Delta U_{\mathrm{CA}} = \Delta U_{\mathrm{C}} - \Delta U_{\mathrm{A}}$

(d) $\Delta \varphi_{\mathrm{r}} = \text{postfault } \varphi_{\mathrm{r}} - \text{prefault } \varphi_{\mathrm{r}}$

(e) $\Delta \varphi_{\mathrm{p}} = \text{postfault } \varphi_{\mathrm{p}} - \text{prefault } \varphi_{\mathrm{p}}$

where I and U represent amplitude of current and voltage, respectively, and φ represents the angle between the phase of voltage and current, the subscript 'r' represents a phase (A, B and C), 's' a sequence component (positive, negative and zero sequences) and 'p' represents positive and negative sequences.

Therefore, there are 23 input vectors. Selecting fault component as input vector ensures that ARTNN based phase selection relay has fewer output classification nodes and enables network to attain stable classification ability with little training patterns.

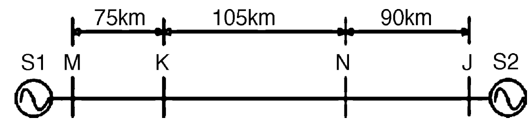

Fig. 2. A single line diagram of the power system used for simulation testing.

3.1. Simulation model of power system

The three phases power system, shown in Fig. 2, is chosen for simulation testing. Phase selection relay is located at the point K in KN line. The details of the sample power system are given in Appendix A.

3.2. Parameters of ARTNN

According to the fault types, the number of ARTNN output node is set to 10. The value of vigilance ρ is derived from training patterns. Generally, the approach based on ANN has good generalization capabilities. In this paper, by utilizing fault components, which can better reflect the characteristics of different fault types, ARTNN can further improve generalization capabilities. At the same time, the classified precision of network could still keep fine. A series of simulation tests have verified this idea. Simulation results of phase A to ground fault occurred in the line KN under various fault conditions, have been shown in Table 1. Training patterns of ARTNN are generated by phase A to ground faults occurred under the conditions: fault inceptive angles $\Phi = 0^\circ$ and 45°, fault location distance L from point K is 15 km, fault path resistance $R = 0\ \Omega$. Simulation results have indicated that fewer training patterns could achieve the training purpose of ARTNN based phase selection relay.

Parameters of ARTNN are set as follows: $\theta = 0.2$; $\rho = 0.85$; $\alpha = 0.05$. It should be noted that these parameters do not vary when conditions of power system vary, which has been verified by lots of simulation tests.

3.3. Training patterns set

Training patterns are generated by simulating single phase to ground faults, two phase or two phase to ground faults and three phase faults under different fault conditions: fault inceptive angles $\Phi = 0^\circ$ and 45°; fault location distance from location of relay $L = 1$, 10 and 40 km; fault path resistance $R = 0$, 20, 50, 80 and 100 Ω. Sampling frequency is set to 2000 Hz. In this paper, the vector of current and voltage can

Table 1
Simulation results with phase A to ground fault occurring

Patterns	Fault condition				
	$L = 90$ km, $R = 100$, $\Phi = 0°$	$L = 45$ km, $R = 10$		$L = 90$ km, $R = 100$, $\Phi = 144°$	$L = 45$ km, $R = 10$, $\Phi = 216°$
		$\Phi = 54°$	$\Phi = 90°$		
1	$N = 1$, $S = 0.9465$	$N = 1$, $S = 0.9466$	$N = 1$, $S = 0.9483$	$N = 1$, $S = 0.9500$	$N = 0$, $S = 0.8431$
2	$N = 1$, $S = 0.9442$	$N = 1$, $S = 0.9441$	$N = 1$, $S = 0.9455$	$N = 1$, $S = 0.9470$	$N = 0$, $S = 0.8418$
3	$N = 1$, $S = 0.9481$	$N = 1$, $S = 0.9482$	$N = 1$, $S = 0.9493$	$N = 1$, $S = 0.9501$	$N = 0$, $S = 0.8432$
4	$N = 1$, $S = 0.9494$	$N = 1$, $S = 0.9549$	$N = 1$, $S = 0.9568$	$N = 1$, $S = 0.9511$	$N = 0$, $S = 0.8429$
5	$N = 1$, $S = 0.9563$	$N = 1$, $S = 0.9620$	$N = 1$, $S = 0.9635$	$N = 1$, $S = 0.9576$	$N = 0$, $S = 0.8459$
6	$N = 1$, $S = 0.9601$	$N = 1$, $S = 0.9654$	$N = 1$, $S = 0.9670$	$N = 1$, $S = 0.9609$	$N = 1$, $S = 0.9614$
7	$N = 1$, $S = 0.9591$	$N = 1$, $S = 0.9642$	$N = 1$, $S = 0.9658$	$N = 1$, $S = 0.9589$	$N = 1$, $S = 0.9589$
8	$N = 1$, $S = 0.9564$	$N = 1$, $S = 0.9612$	$N = 1$, $S = 0.9629$	$N = 1$, $S = 0.9558$	$N = 1$, $S = 0.9541$
9	$N = 1$, $S = 0.9557$	$N = 1$, $S = 0.9603$	$N = 1$, $S = 0.9619$	$N = 1$, $S = 0.9552$	$N = 1$, $S = 0.9524$
10	$N = 1$, $S = 0.9569$	$N = 1$, $S = 0.9612$	$N = 1$, $S = 0.9627$	$N = 1$, $S = 0.9561$	$N = 1$, $S = 0.9529$

S: matching level of verifying pattern. N: output of verifying pattern. $N = 1$ denotes phase A to ground fault; $N = 0$ denotes no output.

Table 2
Simulation results of using patterns corresponding to ten sampling points before fault inception

Fault type	Verifying pattern									
	1	2	3	4	5	6	7	8	9	10
Phase A–B fault	0	0	0	0	0	0	0	0	0	0
Phase A–C–ground fault	0	0	0	0	0	0	0	0	0	0

be calculated according to the sampling point and the Fourier algorithm within half cycle. For every simulation test, six consecutive vectors after 10-ms fault duration are selected as the training patterns. So the number of simulation testing is $2 \times 3 \times 5 \times 10 = 300$, and the number of total training patterns is $2 \times 3 \times 5 \times 10 \times 6 = 1800$.

As mentioned above, the algorithm of ARTNN is a simple algebra process, so weights of ARTNN quickly achieve stable after 60–80 iterative loops. It should be noted that this training should be performed before the network is carried out, i.e. the training is off-line.

4. Verifying performance of ARTNN based phase selection relay

Verifying patterns are generated by different type faults under various system conditions, including normal and oscillation, different source impedances, etc. Parts of the relay's responses to verifying patterns are shown in Tables 2 and 3.

Table 3
Simulation results of using patterns corresponding to ten sampling points after 10-ms fault duration

Fault type	Verifying pattern									
	1	2	3	4	5	6	7	8	9	10
Phase A–B fault	0	1	1	1	1	1	1	1	1	1
Phase A–C–ground fault	1	0	1	1	1	1	1	1	1	1

0 denotes no output; 1 denotes correct output.

4.1. General condensed summary

(1) Operation speed of ARTNN based phase selection relay.
After fault occurs, at least 10 ms is necessary for fault component calculation when half-wave Fourier algorithm is utilized. For reliability, the network makes a decision by judging four points consecutively, which needs 2 ms, so the whole operation time is about 12 ms.

(2) Coping with mal-output of pattern.
In terms of theory, artificial neural network may reflect arbitrary complex function, but in practical applications, ANN based protection relays cannot be perfect, so there are always mal-operation zones of protection relays. In this case, ARTNN based phase selection relay will present good performance. For example, after a fault occurred, which is not embodied in the patterns stored in the network, the relay will have a mal-output. As mentioned in Section 2.1, ARTNN could learn fast new knowledge and simultaneously avoid modifying the patterns stored in the network, so according to the algorithm in Section 2.2, an inactive output node could be added to the network and its weight vector is set to the input vector P, which is derived from the mal-operation conditions, i.e. the added output node denotes a sort, which represents the above-mentioned conditions. Based on the described algorithm, this process is very fast and can be performed on-line. Then, the relay could be rectified and will have a correct output if later similar conditions occur.

5. Experimental and field results

The proposed algorithm has been tested in an experimental prototype. The hardware of this prototype [11] is a multi-processor system comprising a master controller and several DSP processors. The DSP card has been designed according to the low cost principle and sufficient computing ability. In this paper, TMS320F206 has been used in the relay, based on its good performance and flexibility to meet the needs

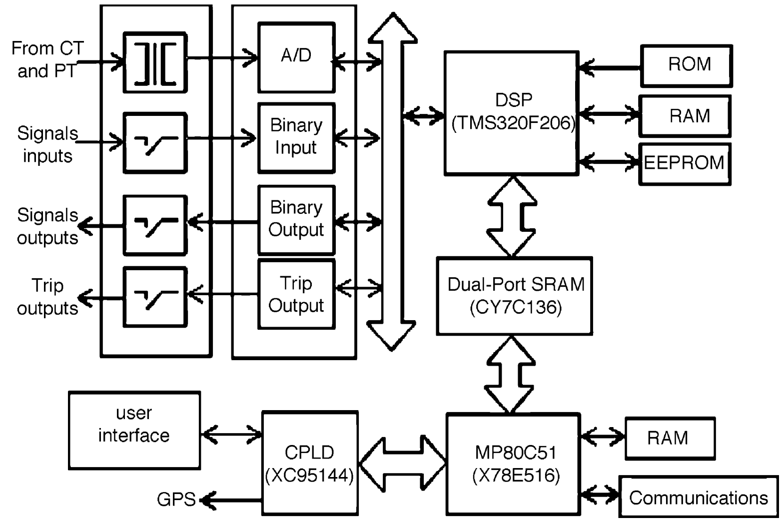

Fig. 3. Block diagram of one of typical relay hardware.

Table 4
The field data derived from numerical fault recorders of East China Grid Company Limited

Date	Fault phase	Data file	Sampling frequency (Hz)	Length (km)
2001 4 29	5905-C	Ping4386.x 01	3840	143
2001 4 29	5905-A	Ping438a.x 01	3840	143
2001 8 8	5408-B	011882.eve	2400	138.69
2001 7 7	5407-B	012921.eve	2400	139

of signal processing and control applications in protection. One of typical relay hardware is shown in Fig. 3. A watchdog has been fitted to the master microprocessor to check its operation. According to the hardware design, digital signal processing algorithms are used to calculate the input vectors of the neural network.

Some field data derived from numerical fault recorders of East China Grid Company Limited have been shown in Table 4. The test results with those field data have been shown in Table 5.

Table 5
The experimental test results with the field data

Output	5905-A	5408-B	5407-B	5905-C
Phase A–ground	√	◎	◎	◎
Phase B–ground	◎	√	√	◎
Phase C–ground	◎	◎	◎	√

(√) A correct output of fault phase selection; (◎) no output of fault phase selection.

6. Conclusion

A new fault phase selection scheme has been proposed in this paper. Firstly, the power frequency fault components are calculated by utilizing half-wave Fourier algorithm, and then ART based neural networks are used to extract features among those fault components and discriminate between the fault phase and the non-fault phase. The new scheme has such advantages as higher flexibility, fewer training patterns and quicker training speed compared with BP neural network based protection schemes. Furthermore, this scheme can better adapt itself to varying system conditions by dynamically adding output node. Extensive simulations and experimental field data tests have validated this scheme correctness.

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Appendix A

Parameters of perfect transposition line (Clarke model):

Positive sequence impedance:

$$Z_1 = 0.86\,\text{mh/km}, \qquad R_1 = 0.027\,\Omega/\text{km},$$
$$C_1 = 0.0123\,\mu\text{F/km}$$

Zero sequence impedance:

$$Z_0 = 3.6\,\text{mh/km}, \qquad R_0 = 0.1948\,\Omega/\text{km},$$
$$C_0 = 0.0051\,\mu\text{F/km}$$

The parameter of sources is not fixed; there are two set of parameter for each source.

The first set of parameters of source 1:

$$U_{mp} = 330\,\text{kV}, \qquad f = 50\,\text{Hz}$$

Positive sequence impedance:
$Z_1 = \text{j}45.149\,\Omega$
Zero sequence impedance:
$Z_0 = \text{j}23.321\,\Omega$

The first set of parameters of source 2:

$$U_{mp} = 330\,\text{kV}, \qquad f = 50\,\text{Hz}$$

Positive sequence impedance:
$Z_1 = \text{j}45.149\,\Omega$
Zero sequence impedance:
$Z_0 = \text{j}23.321\,\Omega$

The second set of parameters of source 1:

$$U_{mp} = 330\,\text{kV}, \qquad f = 50\,\text{Hz}$$

Positive sequence impedance:
$Z_1 = \text{j}6.06\,\Omega$
Zero sequence impedance:
$Z_0 = \text{j}7.07\,\Omega$

The second set of parameters of source 2:

$$U_{mp} = 330\,\text{kV}, \qquad f = 50\,\text{Hz}$$

Positive sequence impedance:
$Z_1 = \text{j}44.1\,\Omega$
Zero sequence impedance:
$Z_0 = \text{j}79.4\,\Omega$

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