FAULT TYPE CLASSIFICATION IN HIGH VOLTAGE POWER SYSTEMS
USING ARTIFICIAL NEURAL NETWORKS

M. Lukowicz, E. Rosolowski
Wroclaw University of Technology, Poland

ABSTRACT - The aim of this paper is to present a new approach to fault type recognition for high-speed power system protection using multilayer recurrent and feedforward Artificial Neural Networks (ANNs). Two ANNs for different purposes were trained. The first one was prepared for detection of faults in any phase of the three-phase power line and the second one for fault-to-ground recognition. The modified Marquardt-Levenberg training algorithm developed for recurrent ANN training was used. A hyperbolic tangent and linear activation functions were applied in the networks’ processing units. The results presented in this paper show that ANNs may be successfully used in digital protective relaying to discriminate the type of fault in power systems.

INTRODUCTION

The transmission lines are the most exposed elements of an electrical system due to their extensive dimensions and continuous exposure to atmospheric phenomena and accidents provoked by human activity. Automatic methods of faults detection and classification solve several significant problems involved in operation of power system. One of these problems is the inspection and maintenance of transmission lines. Because of the great length of the lines and the environment they traverse it is rather a difficult task. Automatic methods that are able to determine the location of a fault allow quick re-establishing of the power supply. Conventional methods currently employed for the detection of fault use the phase currents and voltages. They are based on:

- characteristic variations in the effective values of line voltages and currents,
- notable increase in the speed of variations of the electrical magnitudes,
- variations in the electrical magnitudes with respect to their statistics obtained under normal conditions,
- a change of the logical signals from the protection system.

Recently a new approach introducing artificial neural networks into the digital part of a relay has been proposed and analysed in some papers [3, 4]. The idea of using ANNs must be supported by an efficient software and appropriate hardware, usually including specialised chips. On the other hand, application of the pattern-recognition concept in practice requires preparation of a set of patterns covering the variety of situations to be analysed. The latter task can be done in simulative way. The patterns may be waveforms of phase currents and voltages or/calculated secondary values obtained from the simulation of the power system events to be recognised by the ANN.

The system integrity, which is necessary for continuous and economical supply of electrical power to customers, can be preserved by the use of distance-protection or time-graded methods. Classic protective relays measure the impedance of the transmission line but before measurement they need information about the type of fault which has happened. The typical structure of a protective relay is shown in Fig.1. The module “Fault Detection” signals to next
modules that a fault has occurred. “Fault (Type) Classification” module estimates which phases are affected and outputs the information on the fault type (e.g. R-to ground fault, S-T-to ground fault, etc.). In this paper our main goal is the realisation of “Fault Detection” and „Fault Classification” tasks within one unit using a set of ANNs.

MODELLED SYSTEM DESCRIPTION

Using EMTP-ATP [5] program a fragment of power system shown in Fig. 2 has been modelled. Overhead transmission line rated at 400 kV has been modelled as 3-phase continuously-transposed one. The length of the line was 310km. Its sequence parameters per unit of the length are given in the figure. The phase angle between sources U₁ and U₂ equal to 12 deg provides the power flow of about 350 MVA. All primary signals required in the relaying process were passed to the digital part of the protective relay through the analog pre-processing path comprising:

- instrument transformers,
- matching transformers,
- analog filters,

and, after sample and hold operation, were converted into digital form by an A/D converter.

SIMULATION CONDITIONS

Taking into consideration the fault parameters which influence the level and the shape of fault current and voltage waves the following conditions to be changed at each simulation run have been chosen (data for ANN training):

- systems impedances
  Four combinations of 5Ω and 25Ω values were used as impedances of the S₁ and S₂ systems. The argument of each impedance had the random value from the 80-89deg range. The $|Z_0|/|Z_1|$ ratio had random value from the 1.0-1.4 range and the $|X_0|/|X_1|$ ratio the value from the 1.0 to 1.6 range.
- type of short circuit
  a) R-G  b) S-G  c) T-G  d) R-S-T
  • fault resistance  a) 0Ω  b) 50Ω
  • fault location  a) -80km  b) 0km  c) 150km  d) 230km (sign "-" denotes backwards faults)
  • the value of the residual magnetism in the current transformer core was chosen randomly from the $<-2.8Vs ; +2.8Vs >$ range
  • fault angle  a) 0°  b) 90° (R phase voltage)

The data generated with above parameters have been intended for ANN training. The voltage and current waveforms obtained from simulations have been used for preparation of training patterns. As the reliable ANN testing process should be carried out with use of data not presented during training, some additional simulations has been prepared with following parameters:

- system impedances
  Four combinations of 10Ω and 20Ω values have been used as impedances of the S₁ and S₂ systems. Argument of each impedance had the same values as during the testing data simulations.
- type of the short circuit
  (11 types of short circuit: R-G, R-S, R-S-T etc.)
  • fault resistance - random values from the range of 0 to 50Ω
  • fault location
    a) -64km  b) -48km  c) -32km  d) -16km  e) +46km  f) +92km  g) +138km  h) +184km
  • the value of the residual magnetism in the CT’s core was chosen randomly from the $<-2.8Vs ; +2.8Vs >$ range
  • fault angle  a) 216°  b) 306° (phase R voltage)

The sampling rate of 20 samples per cycle has been chosen for all carried out simulations.

THE NEURAL FAULT TYPE ESTIMATOR (NFTE)

The main idea of the fault type estimation is based on analysing of phase and zero-sequence voltage and current using ANNs. The NFTE consists of 4 neural networks: three recurrent nets for particular phase fault detection and the fourth feedforward one for
fault to ground recognition. The NFTE uses feature vectors formed by U and I trials. The architecture of the NFTE is sketched in Fig. 3. The ANNs are free layer networks with activation functions of both hidden layers of hyperbolic tangent type and linear functions in output neurons.

The nets work in parallel indicating faulted phases (the nets ANN-Ph) and eventually fault to ground events (the net ANN-G). Changes of outputs of particular ANN-Ph classifiers from -1 to 1 indicate fault detection in scanned phase and changes of output of fault to ground detector inform about faults as follows: R-to-G, S-to-G, T-to-G, R-S-to-G, R-T-to-G or S-T-to-G. The decision threshold in both detectors equal to 0 has been chosen.

Faults R-S-T and R-S-T-to-G are considered as the same fault type (R-S-T). Since all simulated R-S-T-to-G faults were symmetrical ones they can not be discriminated from R-S-T type faults. Such faults do not produce voltage and current zero sequence components and can not be recognised as ground faults. Moreover, value of zero sequence current in the case of faults to ground closed to symmetrical ones may be less than value of measured zero sequence current appearing during disturbances caused by CTs’ saturation.

INPUT VECTORS TO NEURAL CLASSIFIERS

The input patterns for ANN-Ph classifiers have been prepared for ANN-Ph controlling the state of phase R can be presented as:

\[ p^R(n) = [\|u^R_n\|, \|u^R_{n-1}\|, \ldots, \|u^R_{n-2*2+1}\|, \ldots, \|u^R_{n-2}\|, \ldots, \|u^R_{n-2*2+1}\|, \ldots, \|u^R_{n-9}\|, \ldots, \|u^R_{n-9}\|] \]

(1)

where:

\[ i^{ST}_n = \max(\|u^R_n\|, \ldots, \|u^R_{n-2}\|, \ldots, \|u^R_{n-2*2+1}\|, \ldots, \|u^R_{n-9}\|, \ldots, \|u^R_{n-9}\|) \]

(2)

and \( Y^R_n \) is the output of R phase state classifier at the n-th instant. Analogously, patterns for S and T phase classifiers have been prepared.

Leaving up samples with indexes n-1, n-3 etc. makes keeping to a minimum number of samples introduced to the patterns and simultaneously keeping the wide sliding window possible (when \( N_{ph} = 5 \) a half of voltage and current wave period is in the observation zone). Moreover, introducing only absolute values of voltage and current samples reduces number of different patterns to be analysed.

Usage of ANNs with the feedback connection makes the output signal from ANN-Ph more stable and the decision taken more reliable.

Additional explanations are necessary with regard to introduced factor (2) in pattern formula (1). Investigations shown that ANN-Ph classifiers without that input signal were often indicating phases which were not faulted. The role of that signal is to restrain the indication on healthy phase especially during close short circuits with the low level of fault resistance. There is very small probability of existence of low and high level currents at the same time in two phases during the short circuit.

Introduction of the signal (2) causes that each of the ANN-Phs makes decision based on information from
its assigned voltage and current trails and condensed information on current levels in the adjacent phases. Such a choice of input signals make possible to avoid partitioning object and separating classifiers from all three phase. The input vectors prepared for ANN-G classifier detecting faults to ground were formed of absolute values of zero sequence components of voltage and current as follows:

\[ P^U(n) = [|u_n^0|; |u_{n-2}^0|; \ldots; |u_{n-2N_G+1}^0|; \ldots; |i_n^0|; |i_{n-2}^0|; \ldots; |i_{n-2N_G+1}^0|] \tag{3} \]

where:

\[ u_n^0 = \left( u_n^+ + u_n^- + u_n^0 \right) / 3 \tag{4a} \]

\[ i_n^0 = \left( i_n^+ + i_n^- + i_n^0 \right) / 3 \tag{4b} \]

are the \( n \)-th samples of a zero-sequence component of voltage and current. \( N_G \) defines size of the input vectors of \( 2N_G \) length for ANN-G classifier.

U and I-trails of R-S-T-to-G faults have not been used for preparing \( P^U \) vectors because of low level of magnitudes of zero sequence current in some of these fault cases which may be comparable with disturbances visible in zero-sequence currents provoked by current transformer saturation [5].

### SELECTION OF PARAMETERS

Utilising the algorithm intended for real-time recurrent neural network training [1, 2] many alternative classifiers have been prepared. Parameters \( N_{Ph} \), \( N_G \) and sizes of ANNs were being changed during investigations. The goal of research was determination of the optimal parameters which would guarantee the best performance of the obtained fault type estimators.

#### Selection of optimal sizes of the ANNs and lengths of input shift registers

Table 1 and 2 show dependence of average percentage errors of incorrect classifications and average classification time on the selected network sizes. Investigations have been carried out for ANN-Ph and ANN-G networks fed from shift registers of maximum length of \( N_{Ph}=N_G=5 \). As can be seen ANN-Ph of 2-2-1 and ANN-G of 5-5-1 structure show good performance and simultaneously require small number of computation units. The value of 0% errors made for test data which had not been presented during training process proves the good generalisation feature of obtained ANN-Ph classifier.

However, the feedforward ANN used for fault-to-ground recognition needed more computational units in hidden layers than the obtained selector of faulted phase. Similarly, the minimal lengths of the input shift registers have been selected. The best performance of ANN-G has been obtained for \( N_G=3 \) and \( \text{ANN-Ph} \) for \( N_{Ph}=4 \).

#### Influence of the fault resistance and fault location on the performance of the NFTE

The dependence of performance of NFTE composed of ANN-Ph (2-2-1 \( N_{Ph}=4 \)) and ANN-G (5-5-1 \( N_G=3 \)) on the fault resistance and the fault location has been checked.

Table 3 shows quality parameters (percentage errors and classification time) evaluated based on NFTE responses to testing data obtained from simulations of different short circuits under fault resistance of \( 0 \Omega, 30 \Omega, 50 \Omega \).

Similarly, performance of NFTE has been investigated for different fault locations on considered line. Faults at both sides of current transformers mounting place have been taken into considerations (+, -).

### Table 1. The performance of ANN-Ph classifiers

<table>
<thead>
<tr>
<th>Size</th>
<th>Errors [%]</th>
<th>Class. time [ms]</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-2-1</td>
<td>0</td>
<td>1.41</td>
</tr>
<tr>
<td>3-3-1</td>
<td>1.25</td>
<td>1.14</td>
</tr>
<tr>
<td>4-4-1</td>
<td>1.10</td>
<td>1.26</td>
</tr>
<tr>
<td>5-5-1</td>
<td>1.20</td>
<td>1.33</td>
</tr>
</tbody>
</table>

### Table 2. The performance of ANN-G classifiers

<table>
<thead>
<tr>
<th>Size</th>
<th>Errors [%]</th>
<th>Class. time [ms]</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-3-1</td>
<td>4.0</td>
<td>3.30</td>
</tr>
<tr>
<td>4-4-1</td>
<td>0.35</td>
<td>2.30</td>
</tr>
<tr>
<td>5-5-1</td>
<td>0</td>
<td>1.65</td>
</tr>
<tr>
<td>6-6-1</td>
<td>0</td>
<td>1.57</td>
</tr>
</tbody>
</table>

### Table 3. The influence of the fault resistance on the quality of classification

<table>
<thead>
<tr>
<th>Fault resistance [Ω]</th>
<th>Errors [%]</th>
<th>Class. time [ms]</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.00</td>
<td>3.13</td>
</tr>
<tr>
<td>30</td>
<td>3.75</td>
<td>3.12</td>
</tr>
<tr>
<td>50</td>
<td>3.75</td>
<td>3.12</td>
</tr>
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</table>

### Table 4. The influence of the fault location on the quality of classification

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Distance of the fault from the busbars [km]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-64</td>
</tr>
<tr>
<td>Errors [%]</td>
<td>0</td>
</tr>
<tr>
<td>Time [ms]</td>
<td>2.53</td>
</tr>
</tbody>
</table>
denotes forward and backward faults, respectively). The obtained results are gathered in Table 4.

CLASSIFICATION RESULTS IN THE TIME DOMAIN

Figures 4-5 show the results of fault type classification carried out for the example fault cases obtained from EMTP simulations. The case of S-to-ground backward fault via 30Ω fault resistance located 80km from bus-bars is presented in Fig. 4. It is well visible that the classification is correct despite of substantial reduction of the current magnitude. Additionally, no symptoms of the fault are visible in voltage waveshapes. Such reductions are results of the subtraction of negligible fault currents from the load current during backward distant faults caused by the large fault resistance. It is seen that ANNs responses reach a steady state after only 1ms (ANN-G) and 4ms (ANN-Ph(S)), respectively. The case of R-S-T forward metallic fault located 150km from bus-bars has been printed in Fig. 5. The presented waveshapes have been properly interpreted as well. The correct decision have been made despite of the presence of current transformer saturation in T phase and higher harmonics in phase voltages. Additionally, several simulations of phase-to-ground fault via nonlinear resistance have been carried out. Investigation showed good performance of the proposed classifier for majority of fault cases. Faults were recognised correctly despite of disturbances caused by arc resistance in voltage and current waveshapes. Voltage and current signals were filtered with used low-pass filters therefore disturbances in primary waveshapes have negligible influence on correct operation of the classifier. The average time of classification was equal to approximately 4ms. Fig. 6 shows voltages, currents and fault resistance as well as discrimination signals observed at the output of the classifier for S-G fault located -80km from bus-bars.

CONCLUSIONS

It has been shown that feedforward and recurrent neural networks combined together can be successfully used for design of reliable and fast fault type estimators intended for applications in protective relays of high voltage power systems. Despite of the introduced feedback all ANN-Ph nets worked correctly and none instability was observed. Moreover, the use of the tangent type function in output neurons may guarantee global stability of ANN-Ph nets. The networks correctly classified the waveforms irrespective of the position of the fault on the transmission line, fault angle, types of the short circuits and values of fault resistance. The NFTE provides reliable and fast fault type classification with operation time between 1 and 7ms. It seems that NFTE with its accuracy can be an excellent fault type esti-
mator when used in fault location systems. The most important inconvenience of ANNs implementation in real systems is the necessity of renewed training processes for each new considered object.

REFERENCES