Artificial neural network pattern classification of transient stability and loss of excitation for synchronous generators

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Abstract

A novel artificial intelligence based neural network (ANN) global online fault detection, pattern classification, and relaying detection scheme for synchronous generators in interconnected electric utility networks is presented. The input discriminant vector comprises the fast Fourier transform (FFT) dominant frequency spectra of eighteen input variables forming the discriminant diagnostic hyperplane. The online ANN based relaying scheme classifies fault existence, fault type as either transient stability or loss of excitation, the allowable critical clearing time, and loss of excitation type as either open-circuit or short-circuit field conditions. The proposed FFT dominant-frequency based hyperplane diagnostic technique can be easily extended to multimachine electric interconnected AC systems.

Keywords: Fault detection; Fault classification; Neural networks; Synchronous generator stability; Transient stability

1. Introduction

The paper presents a novel artificial intelligence based neural network (ANN) pattern classification and online relay detection scheme for a single-machine infinite-bus system. The proposed online relay algorithm and dynamic pattern classifier utilizes specific dominant-frequency spectra of the hyperplane fast Fourier transform (FFT) discriminant vector of the machine rotor angle, speed, accelerating power, instantaneous power, voltage, and current using an ANN perceptron single-layer detection scheme for online classification and detection of fault conditions causing first-swing transient stability or loss of excitation problems. Other relay binary outputs classify fault type, condition, and allowable clearing time. The detection accuracy is improved by utilizing the cross-spectra signals of the discriminant-vector input variables.

The proposed pattern classification technique can be extended to interconnected multimachine systems by using relative rotor angles, frequency deviations, tie-line powers and their cross-spectra variables.

The synchronous-machine fault analysis, detection, and classification techniques have evolved over the past decade with the introduction of artificial intelligence techniques for online stability assessment and fault classification. The use of microcomputer and dedicated parallel processors, transputers, and neuro-fuzzy hardware promises to revolutionize fault detection and protection relaying by utilizing new techniques using accurate dynamic models of interconnected systems and machine transient parameters. These techniques will improve the detection speed and hence allow for fast online condition monitoring on interconnected AC systems.

Transient electromechanical stability of synchronous generators refers to the rotor oscillatory or unstable behavior due to shaft incremental torques, causing acceleration or deceleration of the machine rotor. Synchronous stability is essential for the integrated operation of interconnected AC systems. This synchronism condition is usually lost due to large faults, system excursions and generation–load mismatch. The severity of the fault, its location, speed of corrective action and restoration, AC control modulations, etc. all affect the stability of the system and its recovery to a final acceptable stable operating point.

Loss of excitation of synchronous machines [1–8] refers to the synchronous generator operating as either an underexcited synchronous generator or an over/underexcited synchronous motor. Loss of excitation (LOE) also refers to field short-circuit or open-circuit
conditions. LOE protection uses an impedance type relay with settings similar to conventional distance relays. Most LOE algorithms use apparent-impedance detection and the impedance trajectory movement in the equi-power circle.

To assess transient stability, many techniques [9–20] and methods are available, encompassing traditional time domain state numerical integration, Lyapunov based techniques, probabilistic methods, pattern recognition and neural networks. During the fault, the system operator needs to know as soon as possible whether the system will recover or not and approximately how long is the available critical time in which he/she has to act.

The proposed online ANN multi-output detection relay scheme provides answers to these concerns, namely:

1. system condition as either normal or faulty (bit 1);
2. fault classification as either first-swing instability or loss of excitation (bit 2);
3. classification of the allowable clearing time as either short (10–50 ms) or long (50–200 ms) to aid the operator in decision making (bit 3); and
4. classification of loss of excitation as either field short-circuit or open-circuit conditions (bit 4).

Such basic knowledge obtained by the system operator as early as possible can guide him in corrective switching and restorative actions. This is in contrast with the state and time domain based numerical-integration approach that is time consuming, where each system fault condition is treated individually and offline. The assessment of critical clearing time, T_crit, necessitates multiple iterative trial runs. New techniques [11–29] utilize ranking, dynamic programming, and pattern matching. They use adaptive hyperplane, adaptive sphere, and hyperplane type classifiers. The differences between these schemes are in the selection of the original system parameters describing the system transition state. They utilize bus voltage magnitude, active and reactive powers at each bus, and power flow on transmission lines. Other investigators use relative machine angle or angle deviations, active power losses, synchronizing powers, and individual machine kinetic energy for pattern classification. In this paper, a new approach is proposed to identify a new accurate classifier based on specific frequency FFT spectra of machine angle deviation, speed deviation, accelerating-power deviation, output power, voltage, and current.

Fig. 1 depicts the sample study single-machine infinite-bus system. Machine parameters and control settings are shown in the Appendix with the ranges of variations and fault conditions.

2. Dynamic simulation, training, and validation data

To generate the training and validation data sets, the ERA technology ERACS and MATLAB software packages were utilized. A total of 25 test cases were conducted including different faults and under different variations of machine loadings, control settings, etc. to ensure a balanced sample set for training and validation input/output vectors. Table 1 lists the 25 offline simulation data used in the study. The base-case parameters are given in the Appendix.

Table 1
The 25 study cases

<table>
<thead>
<tr>
<th>Loading level</th>
<th>Fault location</th>
<th>Fault type</th>
<th>Control setting</th>
<th>Clearing time</th>
<th>T/V</th>
</tr>
</thead>
<tbody>
<tr>
<td>V. light</td>
<td>none</td>
<td>none</td>
<td>base</td>
<td>none</td>
<td>T</td>
</tr>
<tr>
<td>Medium</td>
<td>none</td>
<td>none</td>
<td>base</td>
<td>none</td>
<td>T</td>
</tr>
<tr>
<td>V. heavy</td>
<td>none</td>
<td>none</td>
<td>base</td>
<td>none</td>
<td>T</td>
</tr>
<tr>
<td>Light</td>
<td>none</td>
<td>none</td>
<td>base</td>
<td>none</td>
<td>V</td>
</tr>
<tr>
<td>Heavy</td>
<td>none</td>
<td>none</td>
<td>base</td>
<td>none</td>
<td>V</td>
</tr>
<tr>
<td>Medium 10%</td>
<td>3-d bolted</td>
<td>base</td>
<td>long</td>
<td>V</td>
<td></td>
</tr>
<tr>
<td>Heavy 10%</td>
<td>3-d bolted</td>
<td>base</td>
<td>long</td>
<td>V</td>
<td></td>
</tr>
<tr>
<td>Light 10%</td>
<td>3-d bolted</td>
<td>base</td>
<td>long</td>
<td>V</td>
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<td>Medium 10%</td>
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</tr>
<tr>
<td>Medium 10%</td>
<td>3-d bolted</td>
<td>base</td>
<td>long</td>
<td>T</td>
<td></td>
</tr>
<tr>
<td>V. light</td>
<td>none</td>
<td>loss of exc.</td>
<td>cont. 1</td>
<td>none</td>
<td>T</td>
</tr>
<tr>
<td>Light</td>
<td>none</td>
<td>loss of exc.</td>
<td>cont. 1</td>
<td>none</td>
<td>T</td>
</tr>
<tr>
<td>Medium</td>
<td>none</td>
<td>loss of exc.</td>
<td>cont. 1</td>
<td>none</td>
<td>T</td>
</tr>
<tr>
<td>V. heavy</td>
<td>none</td>
<td>loss of exc.</td>
<td>cont. 1</td>
<td>none</td>
<td>V</td>
</tr>
<tr>
<td>V. light</td>
<td>none</td>
<td>loss of exc.</td>
<td>cont. 2</td>
<td>none</td>
<td>V</td>
</tr>
<tr>
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<td>none</td>
<td>loss of exc.</td>
<td>cont. 2</td>
<td>none</td>
<td>V</td>
</tr>
<tr>
<td>Medium</td>
<td>none</td>
<td>loss of exc.</td>
<td>cont. 2</td>
<td>none</td>
<td>V</td>
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<td>cont. 2</td>
<td>none</td>
<td>V</td>
</tr>
</tbody>
</table>

T = cases used for training; V = cases used for validation.
Fig. 2. Online ANN based global detection and fault classification scheme.

The detection scheme shown in Fig. 2 utilizes the FFT dominant-frequency spectra of the machine rotor angle change $\Delta \delta$, speed deviation $\Delta \omega$, accelerating power $\Delta P_a$, as well as machine current $I_g$, voltage $V_g$, output power $P_g$, and apparent outward observed current/voltage ratio $y_g$. Cross spectra and other synthesized signals were added to enhance diagnosis.

The input FFT hyperplane discriminative vector (magnitudes only) $X_F$ is defined as follows, where $S$ stands for cross spectra:

$$X_F = [\Delta \delta F, \Delta \omega F, \Delta P_a F, I_g F, V_g F, P_g F, Y_g F,\]

$$S_{\delta P_a}, S_{\omega P_a}, S_{\delta I_g}, S_{\delta V_g}, S_{\omega I_g}, S_{\omega V_g},\]

$$x_1, x_2, x_3, S_{x_1 x_2}, S_{x_2 x_3}, S_{x_1 x_3}].$$

$x_1$, $x_2$, and $x_3$ are additional synthesized FFT signals defined as follows:

$$x_1 = \Delta \delta \Delta P_a, \quad x_2 = \Delta \delta \Delta \omega, \quad x_3 = \Delta \omega \Delta P_a$$

for the selected subset $(i)$ of dominant-frequency orders $i = 0, 1, 2, 3, 4, 123, 124, 125, 126, 127$. Only these dominant-frequency orders are used in the identification and pattern classification.

The sampling frequency $f_s$ was selected at 200 Hz ($T_{\text{sampling}} = 5 \text{ ms}$) with frequencies $f_j$ for a 128-point FFT defined as follows:

$$f_j = f_s(0 - 127)/128 \quad j = 0, 1, 2, \ldots, 127$$

Figs. 3 and 4 depict the sample time domain and frequency domain frequency spectra of the discriminant vector input variables for the first-swing instability and LOE open-circuit and short-circuit conditions.

3. ANN single-layer perceptron based FFT frequency spectra detection scheme

The stability detection and neural network based relay utilizes the single-layer perceptron ANN structure [24] shown in Fig. 5. The ANN network was trained using only 15 cases, marked T, and validated using the remaining 10-case data ensemble marked V in Table 1. The global success rate for any relay output bit was as follows: bit 1, 80%; bit 2, 90%; bit 3, 80%; bit 4, 90%. The relay’s four-bit output validation status is shown in Table 2, where 1 and -1 depict false and misdiagnosis, respectively.

4. Conclusions

A novel ANN single-layer perceptron based detection scheme for transient stability, loss of excitation

Fig. 3(a). Dynamic simulation response for an unstable case: time domain.
(LOE), fault type, and allowable clearing time has been presented. The relay computational algorithm is similar to an FIR filter and is based on four perceptron hard-limit activation functions. It is simple to implement and requires minimal hardware. The relay pattern classification and detection scheme is suitable for fast online implementation on an AC power system as an operator's aid, and can be extended to large interconnected generators and power exchange areas. The scheme is based on a 128-point FFT pattern identification of the discriminant hyperplane vector \( X_v \) (magnitudes only) comprising machine rotor angle change, speed deviation, accelerating power deviation, machine current, machine voltage, instantaneous power, cross spectra, and additional synthesized signals.

In multimachine implementation, relative angles \( \delta_{ij} \), speed deviations \( \Delta \omega_i \), and tie-line powers and currents can also be utilized. The proposed relaying scheme can be retrained online to improve its adaptability and success rate. The proposed hyperplane diagnostic vector \( X_v \) can be extended, modified and customized for each electric utility system.

The scheme can also be enhanced by zooming in on a specific critical frequency band as well as enlarging...
Fig. 4(a). Dynamic simulation response for an LOE case: time domain ($K_A = \infty$).

Fig. 4(b). Dynamic simulation response for an LOE case: frequency domain ($K_A = \infty$).
Fig. 4(c). Dynamic simulation response for an LOE case: time domain ($K_A = 0$).
Fig. 4(d). Dynamic simulation response for an LOE case: frequency domain ($K_A = 0$).
Zero-sequence resistance = 0.007
Zero-sequence reactance = 0.172
Negative-sequence resistance = 0.0141
Negative-sequence reactance = 0.265
Stator resistance = 0.003
Potier reactance = 0.13
Saturation factor = 1.1
Saturation index = 1.66
Inertia = 3.5

Automatic voltage regulator information

Forward gain = 0.02
Feedback gain = 100.0
Forward time constant = 0.2
Input filter time constant = 0.01
Amplifier lead time constant = 1.0
Maximum amplifier output = 0.6 p.u.
Minimum amplifier output = 0.85 p.u.
Maximum rate of change = 9.86 p.u./s
Exciter gain = 1.0
Exciter time constant = 0.85
Maximum exciter output = 5.8 p.u.
Minimum exciter output = 0.5 p.u.
Exciter saturation constant S1 = 0.2
Exciter saturation constant S2 = 0.7

Speed governor information

Speed droop = 4.0
Speed sensor gain = 0.75
Turbine time constant = 0.2
Control valve time constant = 1.0
Control value limit rates
Increasing output = 0.5 p.u./s
Lag time constant = 0.25
Second control valve block
Decreasing output = 0.25 p.u./s
Lead time constant = 0.2
Turbine lead time constant = 4.0
Runaway speed = 1.1 p.u.

AC line and cable branch data

Positive sequence (p.u.) Zero sequence (p.u.)
$R = 0.00187$ $R = 0.00313$
$X = 0.3142$ $X = 0.10996$
$B = 0.80425$ $B = 0.50266$
MVA limit = 500.0

Variation ranges

Loading ranges: 100–500 MW, 50–350 MVAr
Fault location: 10%
Excitation control parameter:
Base case, $K_A = 200$
Contingency case 1, $K_A = 0$, open circuit
Contingency case 2, $K_A = \infty$, short-circuit

References