Time domain single-phase reclosure scheme for transmission lines based on dual-Gaussian mixture models

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A R T I C L E   I N F O

Article history:
Received 13 June 2011
Received in revised form 29 February 2012
Accepted 1 March 2012
Available online 27 March 2012

Keywords:
Adaptive single phase auto-reclosing (ASPAR)
Transient and permanent faults
Gaussian mixture models

A B S T R A C T

The basic principle of new adaptive reclosures are to first identify whether a fault is transient or permanent and consequently to determine the reclosing moment. In this paper a novel method to enhance self-adaptive single phase auto-reclosure of transmission lines is presented. Using Gaussian Mixture Models (GMM) the redundancy of setting the threshold is omitted. The proposed algorithm could prevent closing command in permanent faults and adapt dead time in temporary events. The method is derived by processing line terminal voltage around the period of dead time. The proposed scheme uses two sampled windows from the inception of the fault and two groups of GMM. Simulations performed in EMTP/ATP environment advocate the validity of the proposed algorithm convergence speed as well as fast and accurate protection scheme for reclosing relaying. The design of GMM is easy and the relative factors of the structure elements can be regulated due to the desirable effects. Since the discrimination method is done with stochastic characteristics of signals in time domain without application of any deterministic index, more reliable and accurate classification is achieved.

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1. Introduction

Customer costs due to electric supply interruptions, service restoration cost due to damages caused by mal-operation of circuit breakers and system transient stability are of great importance in deregulated power systems. Transients are one of the most common issues, which cause mal-operation of protection devices and interruptions in power delivery. The most prevalent reason for transients in power systems are lightning, transmission lines switching and jiff contact by external objects. Experiences show that almost 70% of faults are single phase faults, among which 80% are transients. In the case of self-clearing faults, the line could be re-energized by means of Single Phase Auto-Reclosing (SPAR) that enhances reliability and promotes transient stability of power system. In this case, more than half of the transmitted power transits through the two robust phases because only the faulty phase is disconnected. However reclosing of permanent faults is not only unfavorable to system stability but also harmful to generators and other electric apparatus. A main concern in auto-reclosure schemes is to reduce the risk of the second shock to the system in the case of a permanent fault. Although the conventional reclosures were simple in design and operation but the blind behavior due to adopting a fixed dead time also may cause a delay when there is a chance to reenergize the line adaptively after secondary arc extinction moment. So it is essentially important to (1) discriminate between transient and permanent faults avoiding reclosing on permanent faults and (2) distinguish the moment which the secondary arc being extinguished in order to reenergize the line as fast as possible. As the result, the adaptive-dead time based schemes would prevent long time electric power delivery interruptions. This makes the adaptive dead time methods more preferable than fixed dead time based methods. Nowadays digital protection has known to be the most common auto-reclosing control strategies.

Many sophisticated approaches have been introduced to discriminate between permanent and transient faults. For example Fast Fourier Transform (FFT) is applied to analyze current and voltage signals (Djuric and Terzija, 1995). The method proposed by (Ahn et al., 2001) simply tracks the increment of RMS value of faulty phase voltage and compares it to a predefined threshold to detect secondary arc extinction moment. A fuzzy logic based method is proposed by (Lin and Liu, 1998) where one of the shortcomings is the complexity of developing fuzzy relations. The method presented by (Elkalashy et al., 2007) uses the fundamental component of zero sequence instantaneous power and differential protection principles. This needs synchronization of line terminal communication channels signals. Some references have used wavelet transform (Sanaye-Pasand and Kadivar, 2006) and some others have used neural network (Aggarwal et al., 1994) as control logics to reclose the breakers by recognizing certain distinct features within the system signals. One of the disadvantages of neural network is the blind
2. Basic principles of GMM

A suitable classifier should be fast and accurate. It is also essential to have the capability to be optimized for the unique patterns. The flexibility to be adapted to novel patterns is required because it must satisfy the real time uncertainties of fault signals. Although not essential, it should be trained in lowest computational effort. The GMM satisfies almost all above criteria. The following describes the structure of GMM algorithm.

2.1. Definition

Mixture models are a kind of probability densities which provide greater flexibility and precision in modeling the underlying statistics of sample data such as fault signals (Jazebi et al., 2009). For an S-class pattern classifier, a set of GMMs \( \{ \mathcal{G}_1, \mathcal{G}_2, \ldots, \mathcal{G}_S \} \) stand for S classes. A random variable \( x \) with D-dimensions follows a Gaussian mixture pattern, if its probability density function can be formulated by (1) with constraints presented in (2):

\[
P(x | \mathcal{G}) = \sum_{k=1}^{m} a_k P(x | \mu_k)
\]

(1)

\[
\sum_{k=1}^{m} a_k = 1, \quad a_k > 0
\]

(2)

so the Gaussian mixture density is a combination of \( m \) Gaussian density function components, \( \mu_k, k = 1, 2, \ldots m \).

2.2. Training process

GMM training process is identical to estimate the parameters of \( \mathcal{G} \), so that the Gaussian mixture density can best match the distribution of the training feature vectors. For a set of \( n \) independent and identically distribution vectors \( X = \{ x_1, x_2, \ldots, x_n \} \), the likelihood corresponding to a mixture is

\[
P(X | \mathcal{G}) = \prod_{i=1}^{n} P(x_i | \mathcal{G})
\]

(4)

which represents the likelihood of the data \( X \) given the distribution parameters \( \mathcal{G} \). The goal is to find \( \mathcal{G} \) that maximizes the likelihood:

\[
\hat{\mathcal{G}} = \arg \max_{\mathcal{G}} P(X | \mathcal{G})
\]

(5)

This function is maximized indirectly by calculating the logarithm of the above probability:

\[
\log P(X | \mathcal{G}) = \sum_{i=1}^{n} \log \sum_{k=1}^{m} a_k P(x_i | \mu_k)
\]

(6)

This is log-likelihood function that is easier to calculate but not analytically. Expectation Maximization (EM) algorithm is widely used to estimate the parameters of GMM (Xiong et al., 2006). EM is an iterative algorithm which maximizes the likelihood probability of GMM, \( P(X | \mathcal{G}) \), given the data for this class. This algorithm consists of two steps.

2.2.1. E-step

In this stage the posterior probability of sample \( x_i \) in the \( t \)th step is computed through the following equation:

\[
P(\mathcal{G} | x_i, t) = \frac{a_1^t P(x_i | \mathcal{G}_1^t)}{\sum_{k=1}^{m} a_k^t P(x_i | \mathcal{G}_k^t)}
\]

(7)
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