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

S. Jazebi, S.H. Hosseinian*, M. Jannati, B. Vahidi

Department of Electrical Engineering, Amirkabir University of Technology, 424 Hafez Avenue, 1591634311 Tehran, Iran

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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 autoreclosure 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.

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

* Corresponding author. Tel.: +98 21 64543343: fax: +98 21 66406469.
E-mail addresses: jazebi@aut.ac.ir (S. Jazebi), hosseinian@aut.ac.ir (S.H. Hosseinian), mohsen.jannati@aut.ac.ir (M. Jannati), vahidi@aut.c.ir (B. Vahidi).

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decision based on learning patterns. Combinatorial approaches have been proposed to fulfill the requirements of single phase reclosing by means of advantages of both wavelet transform and ANN (Yu and Song, 1998). The algorithm presented by Radojević and Shin (2006) is based on fundamental and third component of voltage and current waveforms to lock the reclosing equipment on permanent faults. The arc voltage has been estimated by means of the least-squares technique through spectral analysis. The technique accuracy is dependent on the arc model and parameters. The THD factor of faulty phase voltage can also be used (Radojević and Shin, 2007), considering the fact that the faulty phase voltage becomes polluted by high amplitude harmonics while secondary arc establishes. Novel signal processing methods by means of generalized multi-resolution morphology gradient (Lin et al., 2006) and close-opening-open-closing morphology gradient (Lin et al., 2007) filters have been used to extract high frequency components of the signal to improve discrimination accuracy. These methods are specially based on sampling the current of transmission line phases, because the nonlinearity of the arc can be transmitted to the currents of healthy phases by virtue of the mutual inductance of the transmission line. The proposed method by Yan and Zengping (2008) is based on the fact that the amplitude of the capacity coupling voltage is much larger in transients than in permanent faults. In EHV/UHV transmission lines with neutral shunt reactors, this capacitance is partially or totally compensated and the proposed method could not guarantee accurate operation of relays. The work presented by Dadash Zadeh et al. (2008) has widely investigated line parameters effects on secondary arc extinction and proposes some applicable rules to reduce dead time such as neutral reactors. A new yardstick based on learning error function of Adaptive Linear Neuron and voltage sampling has been applied to discriminate between transient and permanent faults (Vahidi et al., 2008). A valuable and efficient method that discriminates faults by comparison of calculated shunt reactor current and measured signal is proposed by Suonan et al. (2009). This method has overcome the drawback of shunt reactor installation. But it needs the sampling of both voltage and current of phases in addition to neutral shunt and compensating shunt reactor currents. It may also encounters problems while the CT is saturated.

A main drawback of some methods presented above is the need to determine threshold. Probabilistic classification methods such as GMM could overcome this disadvantage. The GMM has been applied specially to Speaker Identification (SI) (Xiang and Berger, 2003). It is also used for multiple limb motion classification (Huang et al., 2005), image processing and classification (Zhou and Wang, 2006; Hamouz et al., 2005), control engineering (Principe and Motter, 2007), simplification of controller design (Ruano, 2005), tracking elliptical living objects in video frames (Xiong et al., 2006), and rotating machinery fault diagnosis (Marwala et al., 2006), but recently is used in power engineering (Jazebi et al., 2009).

In this paper a time domain analyzer with a suitable criterion using the principles of GMM is introduced. A complete power system experienced an arcing fault is modeled in EMTP/ATP environment. Different aspects which can influence the reclosure responses are investigated. GMM has demonstrated the ability to discriminate between transient and permanent faults in all operating conditions.

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 $\{\Im_1,\Im_2,\ldots,\Im_S\}$ 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):

$$P(x|\Im)=\sum_{k=1}^{m}\alpha_k P(x|\theta_k) \tag{1}$$

$$\sum_{k=1}^{m}\alpha_k=1,\quad \alpha_k>0 \tag{2}$$

so the Gaussian mixture density is a combination of m Gaussian density function components, θ_k, $k=1, 2,\ldots m$. In the previous equations α_k is mixture weight for kth component, $\Im=\{\alpha_1,\ldots,\alpha_m, \mu_1,\ldots,\mu_m,\sum_1,\ldots\sum_m\}$ is the complete set of parameters to define the model and $\theta_k=\{\mu_k,\sum_k\}$ is the kth component mean and covariance, respectively (Jazebi et al., 2009). Each component density is a D-variant Gaussian function introduced by a $D\times 1$ mean vector and $D\times D$ covariance matrix. The parameters $P(x|\theta_k)$ are normal probability distributions which are defined by

$$P(x|\theta_k)=\frac{1}{(2\pi)^{D/2}|\sum|^{1/2}}e^{-(1/2)(x-\mu_k)\sum_k^{-1}(x-\mu_k)^T}. \tag{3}$$

2.2. Training process

GMM training process is identical to estimate the parameters of $\Im_g$ 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

$$P(X|\Im)=\prod_{i=1}^{n}P(x_i|\Im) \tag{4}$$

which represents the likelihood of the data X given the distribution parameters $\Im$. The goal is to find $\hat{\Im}$ that maximizes the likelihood:

$$\hat{\Im}=\arg\max_{\Im}\ P(X|\Im) \tag{5}$$

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

$$\log P(X|\Im)=\sum_{i=1}^{n}\log\sum_{k=1}^{m}\alpha_k P(x_i|\theta_k) \tag{6}$$

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, $P(X|\Im_g)$, given the data for that class. This algorithm consists of two steps.

2.2.1. E-step

In this stage the posterior probability of sample x_i in the tth step is computed through the following equation:

$$P(l|x_i,\Im^{(t)})=\frac{\alpha_l^t P(x_i|\theta_l^{(t)})}{\sum_{k=1}^{m}\alpha_k^{(t)}P(x_i|\theta_k^{(t)})}. \tag{7}$$