Electric Power Systems Research 160 (2018) 173–179

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Fault location on high voltage transmission line by applying support vector regression with fault signal amplitudes

Chunguo Fei [a,*], Guoyuan Qi [b,**], Chunxin Li [a]

[a] Department of Automation, College of Electronic Information and Automation, Civil Aviation University of China, Tianjin, China
[b] Tianjin Key Laboratory of Advanced Technology of Electrical Engineering and Energy, Tianjin Polytechnic University, Tianjin, China

ARTICLE INFO

Article history:
Received 23 September 2017
Received in revised form 6 February 2018
Accepted 8 February 2018

Keywords:
Fault location
High-voltage transmission line
Support vector regression (SVR)
Amplitudes of fault signals

ABSTRACT

This paper proposes a novel high voltage transmission line fault location scheme based on application of support vector regression (SVR). The proposed scheme just uses the amplitudes of the fault voltage waveforms, measured at a single end of the line. Various types of faults at different locations with different fault impedances and a variety of fault inception angles are studied on a 400 kV–300 km high-voltage transmission line power system. The fault voltages are obtained from 1/8 cycle post-fault signals after the noise has been eliminated using a low-pass filter. The amplitudes of the fault voltage signals are used as features to train the SVR. After training, the SVR is used in the exact location of the fault on the transmission line. When compared with other fault location schemes, the proposed scheme requires less information and a smaller time data window to estimate the fault locations. However, the proposed scheme provides more accurate estimations, irrespective of the fault types, fault inception angles and fault impedances.

1. Introduction

Faults often occur in power transmission systems and can cause supply interruptions, damage the equipment and affect the power quality. Therefore, accurate fault location estimation is very important for power transmission systems to allow faults to be cleared rapidly and ensure that the power supply is restored as soon as possible with minimum interruption. Accurate location of faults in power transmission systems can save both time and resources in the electrical utility industry.

To date, several algorithms or schemes have been proposed for fault location estimation on power transmission lines, including the line impedance algorithm [1], the traveling wave algorithm [2], and intelligent schemes. The line impedance algorithm is affected by the load conditions, high grounding resistance values, and most notably by series capacitor banks [3]. The traveling wave algorithm is based on calculation of the time taken for the line disturbance to reach the end of the transmission line. However, the travelling wave algorithm suffers from some bottlenecks [3], including a high sampling rate requirement, uncertainty in the sampling window selection process and problems distinguishing between the traveling waves that are reflected from the fault and those that are reflected from the remote end of the line. To overcome these problems, many intelligent schemes have been proposed for fault location estimation on power transmission lines. These intelligent schemes are summarized in Table 1. Intelligent schemes generally contain two steps. The first step involves obtaining features from the fault voltage signals using feature extraction processes. The second step involves training of intelligent algorithms using these features and the subsequent estimation of the fault location, called the regression process. To locate the fault, the various schemes applied different types of signals and different signal data windows, as shown in Table 1. Some of the schemes used a filter prior to the feature extraction process to eliminate any noise from the fault signals. Refs. [4–6] added low-pass filters prior to the feature extraction process, while the fault signals must pass through a band pass filter before feature extraction in Ref. [7].

All the schemes listed in Table 1 used single-end measurements to obtain the fault signals. Different feature extraction processes were used to obtain the fault features and different intelligent schemes were used to realize the fault location. Extraction of fault features means that the fault location process takes extra time. To save this time, a novel fault location scheme is proposed in this paper that eliminates this feature extraction step. The proposed scheme does not use any feature extraction process. Instead, we use the amplitude information of the signals directly, and support

* Corresponding author.
** Co-Corresponding author.
E-mail addresses: cgfei@cauc.edu.cn (C. Fei), guoyuanqisa@qq.com (G. Qi).

https://doi.org/10.1016/j.epsr.2018.02.005
0378-7796/

Table 1
Summary of the schemes for fault location on power transmission line.

Year	Reference	Feature extraction process[a]	Fault location process[b]	Signals for fault location	Data window of signals for location
2006	[8]	HS-transform	RBFNN	CS and VS	One cycle of pre-fault and one cycle of post-fault
2007	[9]	DWT	SVM and RBFNN	Current and voltage signals	One cycle of pre-fault and one cycle of post-fault
2008	[10]	DWT	BPNN	Current and voltage signals	Quarter cycle of post-fault
2008	[11]	WPD	ANN	Current and voltage signals	Half cycle of pre-fault and half cycle of post-fault
2009	[12]	WT	ERN	Current and voltage signals	Half cycle of pre-fault and half cycle of post-fault
2009	[4]	DWT	ANN	Current and voltage signals	One cycle of post-fault
2009	[13]	FT	ANFIS	Current and voltage signals	One cycle of post-fault
2010	[14]	WPT	SVM	Current signals	Half cycle of pre-fault and half cycle of post-fault
2010	[15]	WT	SVM	Current signals	Half cycle of post-fault
2011	[16]	DWT	PNN	Current signals	1/4 cycle of post-fault
2011	[5]	WPD	SVM	Current and voltage signals	Half cycle of post-fault
2012	[17]	DFT	KNN	Voltage signals	One cycle of post-fault
2012	[7]	FT and WT	CDNN	Current and voltage signals	one cycle of post-fault or one cycle of pre-fault
2014	[6]	SWT	SVM	Current and voltage signals	1/4 cycle of post-fault
2014	[18]	WPD	KNN, GRNN, RF	Voltage signals	One cycle of post-fault
2014	[19]	MPE	RBFNN	Current signals	Half cycle of pre-fault and half cycle of post-fault
2015	[20]	WT	ANN	Current and voltage signals	Half cycle of post-fault
2015	[21]	MS-transform	BPNN	Voltage signals	Half cycle of post-fault
2016	[22]	WPT	CVA	Current and voltage signals	One cycle of post-fault
2016	[23]	DWT	SVM	Current signals	One cycle of post-fault
2017	[24]	FFT	ANN	Current and voltage signals	Two cycle of post-fault

[a] HS-transform = hyperbolic S-transform, DWT = discrete wavelet transform, WPD = wavelet packet decomposition, WT = wavelet transform, FT = Fourier transform, DFT = discrete Fourier transform, SWT = stationary wavelet transform, MPE = multi-wavelet packet entropy, MS-transform = multi-resolution S-transform, WPT = wavelet packet transform, FFT = fast Fourier transform.
[b] RBFNN = radial basis function neural network, SVM = support vector machine, BPNN = back-propagation neural networks, ANN = artificial neural network, ERN = Elman recurrent network, ANFIS = adaptive neuro fuzzy inference system, PNN = probabilistic neural network, KNN = K nearest neighbor, CDNN = complex domain neural networks, GRNN = generalized regression neural network, RF = random forests, SVD = singular value decomposition, CVA = common vector approach.

vector regression (SVR) is then used as the optimization method for estimation of the fault point location. The signal amplitudes are used as the features. The SVR is used to estimate the fault location. One of the challenges in the proposed scheme is the trade-off between accuracy and the required data window size. A larger data window size will contain more information and result in more accurate fault location. However, such a scheme would also require more computation time. To balance the accuracy with the data window size, the proposed scheme uses a 1/8 cycle data window. The method is demonstrated on a power transmission system with a 400 kV–300 km transmission line. Various fault types are initiated at different locations along the transmission line using voltage signals. The fault signal amplitudes are used as the fault features. In addition, the output of the low-pass filter is applied to an SVR for fault location estimation. While there are slightly more fault features, the method can correctly and rapidly locate faults of different types with different fault inception angles and different fault impedances because no feature extraction processes are used.

2. Support vector regression (SVR)

Support vector machines (SVMs) have some related supervised learning methods that are used for classification and regression. SVMs were introduced by Vapnik and Hearst et al. [25,26] within the areas of statistical learning theory and structural risk minimization. SVMs were first developed as support vector classification (SVC) techniques to solve classification problems. SVMs can also be applied to regression problems via the introduction of an alternative loss function, i.e., to perform SVR [27]. Because the structural risk minimization principle of SVMs requires a discriminative function that has a minimal risk bound, the training sample size required can also be smaller. Therefore, SVMs are less susceptible to over-fitting of data than other classification algorithms, such as multilayer perceptron (MLP) neural network classifiers. SVMs produce global solutions because SVMs are trained in the form of a convex optimization problem. SVMs have been shown to offer an attractive and more systematic approach to learning of linear or nonlinear decision boundaries. SVR methods include both linear SVR and nonlinear SVR. In this work, linear SVR is used.

Suppose that we have a quantity of training data. x_i denotes the spaces of the input patterns, while y_i denotes the spaces of target values. The aim is to estimate a function f between the input patterns and the target values. To realize nonlinear SVR, a nonlinear mapping φ must be used to map the data into a higher-dimensional feature space where the linear SVR is performed. Consider a linear function with the mapping φ that takes the form

$$f(x) = \langle \omega, \varphi(x) \rangle + b \quad \omega \in \mathbf{R}^n, b \in \mathbf{R}, \tag{1}$$

where $\langle \cdot, \cdot \rangle$ denotes the inner product in $\mathbf{R}^n$, ω controls the flatness of the model and $\varphi(x)$ is a mapping function. The inner product plus intercept $\langle \omega, \varphi(x) \rangle + b$ is the prediction function for training data in high dimensional feature space. Therefore, the optimal regression function is given by the minimum of the following functional:

$$R(\omega, \eta, \eta^*) = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l} \left(\zeta_i(\eta_i) + \zeta_i\left(\eta_i^*\right)\right), \tag{2}$$

where C is a pre-specified value, ζ_i are loss functions, and η_i and η_i^* are slack variables. From (1) and (2), the SVR problem can be restated as determination of an optimal solution to the following quadratic programming problem [28]:

$$\begin{aligned} &\min R(\omega, b, \eta, \eta^*) = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l} \left(\zeta_i(\eta_i) + \zeta_i\left(\eta_i^*\right)\right), \\ &\text{subject to} \quad \langle \omega, \varphi(x) \rangle + b - y_i \le \eta_i + \varepsilon, \\ &\qquad y_i - \langle \omega, \varphi(x) \rangle - b \le \eta_i^* + \varepsilon, \\ &\qquad \eta_i, \eta_i^* \ge 0. \end{aligned} \tag{3}$$

To solve this quadratic programming problem, a Lagrange function is constructed based on both the objective function and the corresponding constraints by introducing the dual set of variables α_i, α_i^*. After appropriate mathematical manipulations, the solution is obtained as follows: