Fault location in a series compensated transmission line based on wavelet packet decomposition and support vector regression

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**Article info**

Article history:
Received 22 August 2010
Received in revised form 5 December 2010
Accepted 21 December 2010
Available online 11 April 2011

Keywords:
Fault location
Wavelets packet decomposition
Support vector machine
Support vector regression

**Abstract**

This paper proposes a novel transmission line fault location scheme, combining wavelet packet decomposition (WPD) and support vector regression (SVR). Various types of faults at different locations, fault resistance and fault inception angles on a series compensated 400 kV–285.65 km power system transmission line are investigated. The system only utilizes a single-end measurement. WPD is used to extract distinctive fault features from 1/2 cycle of post fault signals after noises have been eliminated by a low pass filter, and SVR is trained with features obtained from WPD. After training, SVR was then used in precise location of fault on the transmission line. The result shows that fault location on transmission line can be determined rapidly and correctly irrespective of fault impedance.

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**1. Introduction**

Faults often occur in power transmission system, which cause supply interruptions, damages to equipments and affect the power quality. Therefore, accurate fault location estimation is very important in power transmission system in order to restore power supply as soon as possible with minimum interruption. In addition it is imperative that faults on electric power transmission lines are quickly located and cleared, in order to improve the return on investment of power utilities. Accurate location of faults on power transmission systems can save time and resources for the electric utility industry.

In general, transmission line fault location techniques could be divide into two broad categories based on the number of terminal data used, namely single end/terminal\textsuperscript{1–6} and multi-terminals techniques\textsuperscript{7–10}. Each of these categories could still be subdivided further depending on the type measurements used in various algorithms, impedance estimation technique,\textsuperscript{11–16,6} traveling wave based technique\textsuperscript{5} and statistical or computational intelligence techniques\textsuperscript{17,2,18}. Impedance based algorithms usually use both voltage and current measurements, while other algorithms like traveling wave methods and intelligent or pattern recognition methods can use either current or voltage measurement\textsuperscript{19} to reduce the complexity and volume of data needed in fault location estimation. Some schemes use different combinations of some of the afore mentioned methods\textsuperscript{20,21}

The line impedance method is realized by comparing the impedance obtained from the line model, considering possible faults in each node of the network with the equivalent impedance of the system. This method could be grossly affected by load conditions, high grounding resistance, and most notably the presence of series capacitor banks. Fault location based on traveling wave method is accomplished by precisely time-tagging of wave fronts as they cross a known point, typically at substations. Although, traveling wave methods have been reported to be accurate compared to Impedance based techniques, however, traveling wave method has some major challenges\textsuperscript{17}: the requirement of high sampling rate, the associated computational burden of processing comparatively large data, and the possibility of misidentification of faults due to excessive attenuation of signals, especially for remote faults or close in faults have been a concern.

Generally, most computational intelligent methods have basically two stages in tandem. The first stage is used for signal pre-processing and features extraction. It is used for obtaining fault signature from measurements taken at the terminals of transmission lines. The second part involves classifiers or regressor algorithm schemes. Fault signatures obtained from the first stage is usually used in training intelligent schemes of the second stage. Consequently, fault classification and fault location are achieved. Many intelligent methods have been proposed. Joorabian et al.\textsuperscript{22} used discrete Fourier transform (DFT) to extract features and used the radial basis function neural network (RBFNN) to estimate fault
location. Samantaray et al. [23] applied hyperbolic S-transform (HS-transform) to yield the change in energy and standard deviation at the appropriate window variation and applied the RBFNN to find out fault location. Samantaray et al. [24] employed discrete wavelet transform to yield change in energy and standard deviation which are used to train and test the RBFNN to provide fault location from the relaying point accurately. Chunju et al. [25] applied DWT and wavelet fuzzy neural network to estimate fault location. DWT is applied to extract fault characteristics from the fault signals and the wavelet fuzzy neural network is used to find out fault location. Ekici et al. [27] proposed an intelligent method by combining the DWT and the Elman tm s recurrent networks. Ekici et al. [27] applied wavelet packet transform (WPT) as extraction algorithm and BP neural network as fault locator. Both current and voltage signals were used in [22–26]. One cycle pre-fault and one cycle post-fault were considered in [23–25], half cycle of pre-fault and half cycle of post-fault in [27,26], and one cycle in [22].

In this paper, a new fault location scheme for power transmission line that uses a wavelet packet decomposition (WPD) for feature extraction and a support vector regression (SVR) for fault location is presented. One of the challenges in fault location scheme is the trade-off between the accuracy and data window size. Unlike other schemes that were highlighted earlier, which used a minimum of 1 cycle data window, the proposed scheme uses 1/2 a cycle data window. The method is demonstrated on a power transmission system with 400 kV–285.65 km transmission line. Various types of faults are initiated at different locations along the transmission line at various inception angles. The pre-fault and post-fault phase data collected at line buses are first passed through a low pass filter to reduce the effect of noise. WPT was then used to extract fault signatures from 1/2 cycle post fault data; a support vector regression scheme then used the fault features to estimate the fault location. The results obtained were subjected to error analysis, which indicated that the proposed method can correctly and rapidly locate the faults with different fault type and different fault inceptions.

This paper is organized into six (6) sections, the first section is an introduction. In the Section 2 we discuss features extraction using wavelet packet decomposition and in Section 3 application of support vector regression machine was discussed. The new scheme and simulations are described in Section 4, while result and discussion is presented in Section 6. Finally, Section 7 is the conclusion.

2. Feature extraction based on wavelet packet decomposition

Feature extraction algorithms are valuable tools, which transform high dimensional data to a lower one with an equivalent information content. Hence, feature extraction is always used to reduce the dimensionality of data, which consequently reduce the complexity of classification or regression scheme.

Discrete wavelet transform (DWT) and wavelet packet decomposition are powerful tools that have been applied in various fields, data compression, signal denoising, feature extraction just to mention just a few. They are orthogonal wavelet decomposition procedure where a signal is passed through several filters. However, in WPD the number of processing filters is more than what is used for DWT. Fig. 1 shows the splitting of a signal using DWT into approximation and detail coefficients. The information lost between two successive approximations is captured in the detail coefficients, the successive details are never reanalyzed. For an n-level decomposition, there are n + 1 possible ways to decompose or encode a signal.

Unlike DWT, in the WPD, both the detail and approximation coefficients are decomposed as shown in Fig. 2. For n levels of decomposition the WPD produces 2n different sets of coefficients (or nodes). WPD is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis.

Corresponding to the wavelet, are two finite impulse filters, a low-pass filter h(k) and a high-pass filter g(k). Using these two filters, the following sequence of recursive functions can be defined.

\[ W_{2n}(x) = \sqrt{2} \sum_{k=0}^{2N-1} h(k)W_n(2x - k) \] (1)

\[ W_{2n+1}(x) = \sqrt{2} \sum_{k=0}^{2N-1} g(k)W_n(2x - k) \] (2)

where \( W_0 = \phi(x) \) is the scaling function and \( W_1 = \psi(x) \) is the wavelet function. A wavelet packet function, is in form of

\[ W_{j,n,k}(x) = 2^{-j/2}W^n(2^{-j}x - k) \] (3)

To measure a specific time–frequency information in a signal, we simply take the inner product of the signal and that particular function. The wavelet packet coefficients of a function \( f \) can be computed by

\[ W_{j,n,k} = \langle f, W_{j,n,k} \rangle = \int f(x)W_{j,n,k}(x)dx \] (4)

Computing the full WPD of a discrete time signal involves applying both filters to the discrete time signal and then recursively to each intermediate signals. WPD decomposes the signal utilizing both low-frequency components and the high-frequency components. This flexibility of a rich collection of abundant information with arbitrary time–frequency resolution allows extraction of features that combine non-stationary and stationary characteristics.

Each coefficient of WPD measures a specific sub-band frequency content in a signal indexed by the scale parameters \( j \) and modulation parameter \( n \). These coefficients are feature representations of the original signal in different wavelet packet bases. The sub-band energies of WPD nodes can be used to represent certain features of signals [28]. WPD sub-band energies is defined as the sum of square of coefficients of wavelet packet node.

\[ e_{j,n} = \sum_{k} W_{j,n,k}^2(x) \] (5)

3. Support vector regression

Support vector machines (SVMs) were first developed as a support vector classification (SVC) to solve classification problems, within the area of statistical learning theory and structural risk minimization [29–31]. Although SVMs have been used for fault classification, and transmission lines parameter estimation for fault locations, it can also be applied to regression problems [32] by an alternative loss function. These SVMs are called support vector regression.
SVR uses structural minimization principles to choose discriminative functions that have minimal risk bound, the necessary training sample size is smaller. Therefore SVRs are less likely to over-fitting data, than other classification algorithms such as multilayer perceptron (MLP) neural network classifiers. SVR results in a global solution because they are trained as a convex optimization problem. They have been shown to be an attractive and more systematic approach to learn linear or non-linear decision boundaries. SVR includes linear SVR and nonlinear SVR. In this paper, nonlinear SVR is used for estimating fault locations.

Suppose we have a training data \((x_1, y_1), (x_2, y_2), \ldots (x_i, y_i)x_i \in \mathbb{R}^n, y_i \in \mathbb{R}\). \(x_i\) denotes the input patterns, while \(y_i\) denotes the target values. In order to realize the non-linear SVR, a nonlinear mapping \(\phi\) must be used to map the data into a high dimensional feature space where linear SVR is performed. Consider a linear function with mapping \(\phi\), taking the form

\[
f(x) = \langle \omega, \phi(x) \rangle + b \quad \omega \in \mathbb{R}^n, \quad b \in \mathbb{R}
\]

where \(<,>\) denotes the dot product in \(\mathbb{R}^n\). The optimal regression function is given by the minimum of the functional

\[
R(\omega, b, \eta, \eta^*) = \frac{1}{2} ||\omega||^2 + C \sum_i \left( \zeta_i(\eta_i) + \zeta_i(\eta_i^*) \right)
\]

where \(C\) is a pre-specified value, \(\zeta_i\) are loss functions, \(\eta_i\) are slack variables. From (6) and (7), the SVR problem can be restated as finding an optimal solution to the following quadratic programming problem [33]:

\[
\min R(\omega, b, \eta, \eta^*) = \frac{1}{2} ||\omega||^2 + C \sum_i \left( \zeta_i(\eta_i) + \zeta_i(\eta_i^*) \right) \langle \omega, \phi(x) \rangle + b - y_i \leq \eta_i + \epsilon
\]

subject to \( y_i - \langle \omega, \phi(x) \rangle + b - y_i \leq \eta_i + \epsilon \eta_i, \eta_i^* \leq 0 \)

To solve the quadratic programming problem, a Lagrange-like function is constructed from both the objective function and the corresponding constraints, by introducing a dual set of variables \(\alpha_i, \alpha_i^*\).

With a few mathematical manipulations, it is easily shown that,

\[
\max W(\alpha, \alpha^*, \eta, \eta^*) = \frac{1}{2} \sum_{i,j=1}^l (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) \langle \phi(x_i), \phi(x_j) \rangle + \sum_i (\alpha_i^* - \alpha_i) y_i - \frac{1}{2} \sum_i (\alpha_i - \alpha_i^*)^2 + C \sum_i \left( \zeta_i(\eta_i) + \zeta_i(\eta_i^*) \right) - \eta_i \frac{d}{d\eta_i} \zeta_i(\eta_i) - \eta_i^* \frac{d}{d\eta_i^*} \zeta_i(\eta_i^*)
\]

In this paper, we choose quadratic loss function \(\zeta(\eta) = \eta^2\) as \(\zeta\) and use RBF kernel function (10) to realize the nonlinear mapping into feature space.

\[
K(x, x_i) = \exp \left[ -\frac{|x-x_i|^2}{2\sigma^2} \right]
\]

Thereby changing, the optimization problem for SVR to

\[
\begin{align*}
\max & \quad W(\alpha, \alpha^*) = \frac{1}{2} \sum_{i,j=1}^l (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) K(x_i, x_j) + \sum_i (\alpha_i^* - \alpha_i) y_i - \frac{1}{2} \sum_i (\alpha_i^* - \alpha_i)^2 \\
\text{subject to} & \quad \sum_i (\alpha_i^* - \alpha_i) = 0, \quad \alpha_i, \alpha_i^* \in [0, C]
\end{align*}
\]

4. System simulation

In order to test our scheme, we used a part of ESKOM transmission network as the study case (Arnot–Maputo). ESKOM is a power utility company in South Africa. The configuration is as shown in Fig. 3. The system is modeled as a two machine system, connected by a series compensated, 285.65 km transmission line with a voltage rating of 400 kV. A Pi model of long transmission line is used in modelling the network. The whole line is divided into 6 pi sections, which ease modelling and improve accuracy.

The series compensation reactance SC is 44.24Ω and it is located at the midpoint of the line. In order to get a reliable input signals of the fault location for the proposed scheme, the over voltage protection of the series compensator is implemented by an MOV, and this
1.2 1.4 1.6 1.8 2 2.2 2.4
\times 10^5

-1 -0.5 0 0.5 1 1.5

\text{voltage in p.u.}

1 1.2 1.4 1.6 1.8 2 2.2 2.4
\times 10^5

-5 -2 0 2 5

\text{current in p.u.}

\text{time}

Fig. 4. Obtained from DFR at Arnot: Phase A–G fault at 79.7 km.

1.83 1.84 1.85 1.86 1.87 1.88 1.89 1.9 1.91

-1 -0.5 0 0.5 1

\text{voltage in p.u.}

1.83 1.84 1.85 1.86 1.87 1.88 1.89 1.9 1.91

-5 -2 0 2 5

\text{current in p.u.}

\text{time}

Fig. 5. Simulation: Phase A–G fault at 79.7 km without a low pass filter.
is taken into account during modelling and simulation. The MOV was modelled as a surge arrester with 60 C based on a reference current $I_{ref}$ of 500 A, and the protection level was set to 312.82 kV, based on 2.5 times the nominal voltage across the capacitor when the normal current of 2.0 kA is flowing through it. The MOV block configuration for MATLAB/SIMULINK simulation is shown in Fig. 8 and the details of parameters used are given in Appendix A.

The model is setup in MATLAB/Simulink. MATLAB has a power system simulation toolbox called simPowerSystems, our simulation was done in simPowerSystems environment for the ease of simulation and integration with our SVR implementation is MATLAB. The simulation could have also been done in DigSilent Power Factory or PSCAD, without any appreciable difference. All the eleven (11) types of short circuit faults are investigated. The system parameters used for the simulation are given in Table 1, and other details are given in Appendix A.

The record of various kind of faults that occured on the line between the year 2005 and 2007 were collected from ESKOM digital fault recorders (DFRs). As the data was in a propriety format (OSCOP), we first converted the data to an IEEE COMTRADE format, so that we could use a common interface for both the simulated result and the real-life data obtained from the DFRs. Fig. 4 shows the current and voltage waveforms of Phase A to ground fault at 79.7 km obtained from a DFR at Arnot substation.

Most of the faults recorded are phase to ground and a few are phases to phase faults, since we do not have control over the type of faults and the location of occurrence of faults in real-life, we used the locations that were estimated by DFRs diagnostics from the utility as fault location points in our simulation. However, we then varied the fault incident angles at an interval of 30° between 0° and 90°, and the fault resistance is also varied in the range of 0.1–300Ω at locations predicted by ESKOM diagnostics. Figs. 5 and 6 show the current and voltage waveforms of Phase A to ground fault at 79.7 km obtained from the simulation at Arnot substation. Fig. 5 shows the case when a low pass filter is not used, while Fig. 6 shows the case when, a low pass filter is used.

In order to get a sizable instances for training and testing the SVR, fault location is also varied in step of 10 km. The simulated data was then mixed with the real-life data obtained from DFRs, to form fault location pattern which is used in training and testing an SVR.
5. A novel fault location scheme based on WPD and SVR

The scheme uses regression to map WPD sub-band energies of various type of faults to fault locations on the modeled transmission line. Since energy functions are nonlinear, we expect that the relationship between the sub-band energies and fault locations is nonlinear. On this basis, we expect that a SVR with a nonlinear kernel function should give a good result of a fault location. This scheme requires only a single end measurements, and the logical sequence of data processing is as shown in Fig. 7.

Since most ESKOM DFRs use the sampling frequency of 12.8 kHz, measurements taken at one end of the transmission line in our simulation are sampled at sampling frequency of 12.8 kHz, and passed through a low pass 4th order Butterworth filter whose cutoff frequency is 250 Hz. WPD was then used to extract fault signatures from a 1/2 cycle post fault measurements. A three-level WPD was performed on each of the phase data using db1 as mother wavelet. Sub-band energies of WPD level-nodes are used as fault features, giving an 8 element feature vector per phase per measurement. A three phase system has $3 \times 8$ fault features vector each for voltage and current measurements. The fault features were then used in training and testing the SVR scheme.

Fig. 2 shows the WPD used in formulation of the feature vectors. Since level – 3 has 8 nodes $[A A A_3 \cdots D D D_3]$, the post fault measurements taken over a 1/2 is used in formulating a feature vectors $f_{ip}(x)$ and $f_{vp}(x)$ for phase currents and phase voltages respectively, where $x$ denotes the fault location and $p$ represents each of the phase $A$, $B$ or $C$. By concatenating $x$, $f_{ip}(x)$ and $f_{vp}(x)$, we have the pattern matrix $P$ for various fault locations, where $P$ is given by

$$P = [x, f_{ip}(x), f_{vp}(x)]$$

(12)

$P$ is an $m \times 49$ matrix, where $m$ is the number of instances obtained from simulations and data obtained from DFRs. The first column of $PP(:, 1)$ represents fault locations, while the rest 48 columns $PP(:, 2:49)$ represents $8$WPD features $\times$ 3phase currents and $8$WPD features $\times$ 3phase voltages. The pattern vector $P$ is then supplied as input into an SVR with an RBF kernel function as defined by (10) (Fig. 8).

6. Results and discussion

Mean square error (MSE) and absolute error (AE) are criteria generally used in assessing the quality of the fault location schemes. In order to be able to compare our result with other schemes, we also use MSE and AE as a measure of quality index. Absolute error is defined as

$$|\text{actual fault location} - \text{estimated fault location}|$$

(13)

Tables 2 and 3 show the estimated fault locations, when the fault impedances $Z_f$ are 0.1 and 0.3 kΩ respectively. It can easily be seen from both tables that the scheme is robust to varying

| Table 2 | Estimated distance for fault location at 30 km for fault impedances 1Ω. |
|---|---|---|---|---|---|
| Fault type | 30 km | 210 km |
| | $0^\circ$ | $30^\circ$ | $90^\circ$ | $0^\circ$ | $30^\circ$ | $90^\circ$ |
| LL | 29.99 | 29.99 | 30.06 | 210.00 | 209.99 | 209.95 |
| LLG | 30.00 | 30.00 | 29.99 | 210.01 | 209.98 | 209.98 |
| LLL | 30.00 | 30.00 | 29.99 | 210.02 | 209.99 | 209.99 |
| LLLG | 29.99 | 30.00 | 30.00 | 209.99 | 210.00 | 210.00 |

| Table 3 | Estimated distance for fault location at 30 km for fault impedances 0.3 kΩ. |
|---|---|---|---|---|---|
| Fault type | 30 km | 210 km |
| | $0^\circ$ | $30^\circ$ | $90^\circ$ | $0^\circ$ | $30^\circ$ | $90^\circ$ |
| LG | 29.99 | 29.94 | 29.99 | 210.02 | 209.99 | 209.98 |
| LLG | 30.00 | 29.95 | 29.98 | 210.01 | 210.00 | 210.01 |
| LLL | 29.99 | 29.99 | 29.98 | 210.01 | 210.02 | 210.01 |
| LLLG | 29.99 | 29.99 | 29.98 | 210.01 | 210.02 | 210.01 |
than what is reported in Ref. [27], however, the data window requirement for the scheme is lower, a 1/2 cycle data window compared to 1 cycle data window required in Ref. [27].

Table 4  
Effect of low pass filtering on the scheme.

<table>
<thead>
<tr>
<th>Fault type</th>
<th>Without low pass filter</th>
<th>With low pass filter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( Z_r = 0.1 \Omega )</td>
<td>( Z_r = 0.3 \Omega )</td>
</tr>
<tr>
<td></td>
<td>( 30^\circ )</td>
<td>90°</td>
</tr>
<tr>
<td>LG</td>
<td>210.19</td>
<td>212.48</td>
</tr>
<tr>
<td>LL</td>
<td>205.82</td>
<td>269.28</td>
</tr>
<tr>
<td>LLG</td>
<td>197.97</td>
<td>244.24</td>
</tr>
<tr>
<td>LLL</td>
<td>207.10</td>
<td>240.47</td>
</tr>
<tr>
<td>LLLG</td>
<td>207.81</td>
<td>240.47</td>
</tr>
</tbody>
</table>

In addition, in most schemes, the highest fault impedance used in simulation is 100 \( \Omega \). In our work the fault impedance was increased to 0.3 \( \Omega \), and we were still able to get an accurate result.

7. Conclusion

A new fault location scheme for power transmission line is proposed in this paper. The simulations show that, the scheme has a high accuracy for estimation of fault locations using 1/2 circle post fault phase voltage measurements. All the 11 types of faults at different inception angles on a 285.65 km long power transmission line system were used. Compared with other methods, the scheme in this paper needs less information and short time data window to estimate fault location. The scheme only used 1/2 cycle to accurately decide where a fault has occurred along the transmission line. It indicates that the scheme proposed in this paper can correctly and rapidly locate the faults with different fault type and different fault inceptions. We also observed that using a low pass filter, improved the accuracy of the scheme.

Appendix A.

R, L, and C line parameters:

Resistance matrix in (\( \Omega/km \)):

\[
R_{\text{matrix}} = \begin{bmatrix}
0.12 & 0.10 & 0.10 \\
0.10 & 0.12 & 0.10 \\
0.10 & 0.10 & 0.12 \\
\end{bmatrix}
\]

Inductance matrix in (H/km):

\[
L_{\text{matrix}} = \begin{bmatrix}
1.90e^{-3} & 1.03e^{-3} & 8.91e^{-4} \\
1.03e^{-3} & 1.90e^{-3} & 1.03e^{-3} \\
8.91e^{-4} & 1.03e^{-3} & 1.90e^{-3} \\
\end{bmatrix}
\]

Capacitance matrix in (F/km):

\[
C_{\text{matrix}} = \begin{bmatrix}
1.10e^{-8} & -2.09e^{-9} & -6.39e^{-10} \\
-2.09e^{-9} & 1.130e^{-8} & -2.09e^{-9} \\
-6.39e^{-10} & -2.09e^{-9} & 1.100e^{-8} \\
\end{bmatrix}
\]

Table 1–A.4.

Table A.1  
Transmission lines geometry.

<table>
<thead>
<tr>
<th>Cond. no.</th>
<th>Phases</th>
<th>X (m)</th>
<th>Ytower (m)</th>
<th>Ymin (m)</th>
<th>Cond. type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>-8.2</td>
<td>20.59</td>
<td>9.5</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>0.0</td>
<td>20.29</td>
<td>9.5</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>8.2</td>
<td>20.50</td>
<td>9.5</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>-14.5</td>
<td>29.04</td>
<td>19.5</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>14.5</td>
<td>29.04</td>
<td>19.5</td>
<td>2</td>
</tr>
</tbody>
</table>
Table A.2
Conductor and bundle characteristics.

<table>
<thead>
<tr>
<th>Type</th>
<th>Outer diam. (cm)</th>
<th>T/D ratio</th>
<th>GMR (Ω/km)</th>
<th>DC resistance (Ω)</th>
<th>No. of Conds.</th>
<th>Bundle diam. (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2.70</td>
<td>0.375</td>
<td>1.074</td>
<td>0.072</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1.35</td>
<td>0.50</td>
<td>0.526</td>
<td>3.107</td>
<td>1</td>
</tr>
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Table A.3
Substation parameters.

<table>
<thead>
<tr>
<th>Parameters short circuit</th>
<th>Arnot</th>
<th>Maputo</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level (MVA)</td>
<td>22656.07</td>
<td>6835.20</td>
</tr>
<tr>
<td>(I_{max} ) (kA)</td>
<td>30</td>
<td>9.8</td>
</tr>
<tr>
<td>X/R</td>
<td>24.98</td>
<td>11.51</td>
</tr>
</tbody>
</table>

Table A.4
MOV simulation parameters.

<table>
<thead>
<tr>
<th>Segment, i</th>
<th>(R_i ) (Ω)</th>
<th>(\alpha_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.955</td>
<td>50</td>
</tr>
<tr>
<td>2</td>
<td>1.0</td>
<td>25</td>
</tr>
<tr>
<td>3</td>
<td>0.9915</td>
<td>16.5</td>
</tr>
</tbody>
</table>

References


