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Algorithm for Fault Detection and Classification Using Wavelet Singular Value Decomposition for Wide-Area Protection

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Abstract – An algorithm for fault detection and classification method for wide-area protection in Korean transmission systems is proposed. The modeling of 345-kV and 765-kV Korean power system transmission networks using the Electro Magnetic Transient Program - Restructured Version (EMTP-RV) is presented and the algorithm for fault detection and classification in transmission lines is developed. The proposed algorithm uses the Wavelet Transform (WT) and Singular Value Decomposition (SVD). The Singular value of Approximation coefficient (*SA*) and part Sum of Detail coefficient (*SD*) are introduced. The characteristics of the *SA* and *SD* at the fault conditions are analyzed and used in the algorithm for fault detection and classification. The validation of the proposed algorithm is verified by various simulation results.

Keywords: EMTP-RV, Fault detection and classification, Transmission system, Wavelet singular value decomposition, Wide-area protection

1. Introduction

It is critical to secure transmission lines against faults to maintain stable operation of power systems. Fault detection, classification, and the location of transmission lines are very important tasks in protecting electric power systems. Fast fault detection is needed to protect the system components from the harmful effects of a fault. Fault-type classification is needed to analyse the original signal with appropriate signal processing schemes such as the Wavelet Transform (WT). The WT is a mathematical tool used in a wide variety of fields for signal and image processing applications [1]. WT is also useful in power system transient analysis, as it is based on the time and frequency domain simultaneously [2]. WT can be used on a broad frequency range rather than a specific frequency domain, which makes WT very useful for analysing the transient phenomena in a power system. For this reason, WT has been applied in protection algorithms to detect, classify, and locate faults in power systems. Although WT has good features, typically, it is not used alone in analyses of power system transients, because the transformed signals still contain a large amount of data which requires further processing.

Thus, fault-type classification has been performed with several other methods, such as traveling waves [3-4], adaptive Kalman filtering [5], discrete wavelet transform [6-7], fuzzy logic, neural networks [8], a fusion of different artificial network techniques, and combinations of wavelet and hyperbolics [9]. Neural networks have disadvantages in that they require a considerable amount of training effort to obtain good performance, especially under various operating conditions such as system-loading level, fault resistance, and source impedance. Another disadvantage of neural-based networks is that the results of training may not cover some cases, as the starting point is chosen at random and can end up in minimum times [10-13]. Wavelet Singular Entropy (WSE) using WT with Singular Value Decomposition (SVD) and Shannon's information entropy theory have been proposed [14-16]. SVD can be useful to decompose large amounts of data into small square matrices.

In this paper, an algorithm that includes fault detection and classification is proposed for wide-area protection. An algorithm for fault detection and classification is presented based on Wavelet Singular Value Decomposition (WSVD) combined with WT and SVD [17]. Singular value of Approximation coefficients (*SA*) containing low frequency components and part Sum of Detail coefficients (*SD*) containing high frequency components derived from WSVD are defined, and the mother wavelet is selected as a characteristic of WSVD. The characteristics of *SA* and *SD* are analysed in various fault conditions to detect the faults and classify between those faults. An algorithm is

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proposed based on the results of *SA* and *SD* to detect and classify various faults. The various simulation results are performed and the results are analysed. In summary, we propose an algorithm which can detect and classify faults in transmission system using WSVD for wide-area protection.

2. Modeling of Wide-Area Transmission System in Korea

The nationwide electrical power transmission network in Korea was modelled using the EMTP-RV. The system parameters used in modelling are the real system data in the PSS/E files provided by KEPCO and KPX [18].

The nominal voltages of the power transmission network in Korea are composed of 154 kV, 345 kV, and 765 kV. The target network is all the transmission lines of 345 kV and 765kV in 2008[19-22]. The transmission lines of 154 kV are treated as a load. The modelled system is operated based on the peak load condition in summer 2008. The total load is 54,647 MVA (The Active Power is 54,300 MW and the Reactive Power is 6,150 MVar). The total generation is 57,001 MVA (55,070 MW and 14,713 MVar) and the loss of transmission lines over 154 kV is about 2 %.

Fig. 1 shows the wide-area transmission system of Korea modelled by EMTP-RV [20]. Simulations are performed in steady state for 10 seconds in order to validate the performance of the modelled network. Frequencies are measured at the nine buses: Dongseoul No. 1, Sinsiheung No. 3, Asan No. 3, Sinjechun No. 3, Chungyang No. 3, Seodaegu No. 3, Uiryung No. 3, Singoangju No. 3, and Bukbusan No. 3s.

In the simulated results, the lowest frequency is 59.9931 Hz at Uiryung No. 3, and the highest frequency is 60.0002 Hz at Seodaegu No. 3. As the frequencies vary within less than 0.01 Hz, we can confirm that the modelled network operates in a stable state.

3. Characteristic Analysis of Disturbance Using Wavelet Singular Value Decomposition

3.1 Wavelet transform

The WT is able to extract time and frequency information at the same time from the original signal [23-26]. The Discrete Wavelet Transform (*DWT*) of a signal is defined as:

$$DWT(m,n) = \frac{1}{\sqrt{a_0^m}} \sum_{k=1}^{N} x[k]\psi\left[\frac{k - na_0^m b_0}{a_0^m}\right] \quad (1)$$

where $\psi[k]$ is mother wavelet, a_0^m is a scale parameter, and $na_0^m b_0$ is the time shift of $\psi[k]$ [26].

The Results of *DWT* depend on the mother wavelet. One characteristic of the mother wavelet is that the mean value is zero within a certain period of time. The Daubechies 4 (db4) wavelet is usually used as a mother wavelet for transient analysis in power systems.

The WT consists of successive pairs of low-pass and high-pass filters. For each pair, the high-scale and low-frequency components are called approximation coefficients of WT, while the low-scale and high-frequency components are called detail coefficients. The approximation coefficient and detail coefficient constitute the WT-coefficient matrix [24].

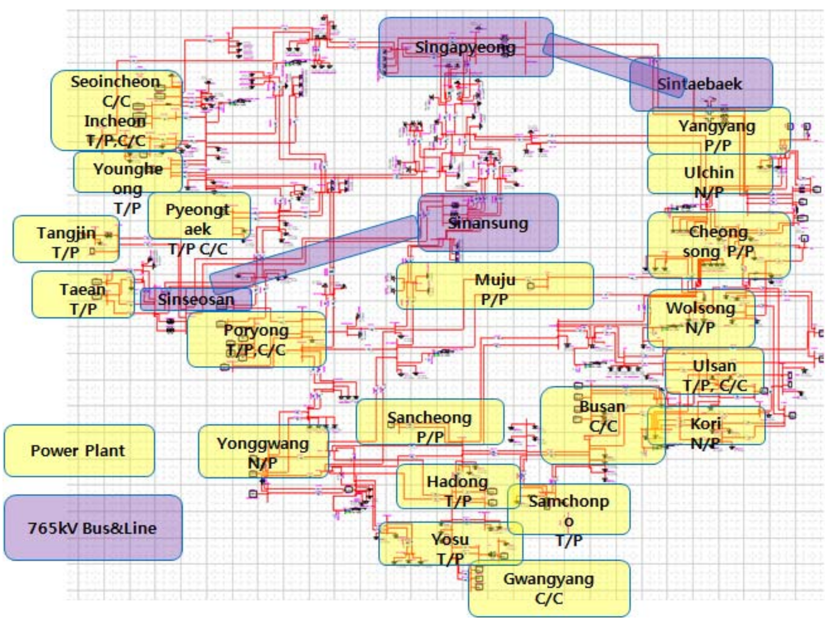


Fig. 1. Power system network modeled by EMTP-RV.

3.2 Singular value decomposition

Singular Value Decomposition (SVD) is a powerful and effective tool to extract special features in linear algebra. SVD is a factorization of the matrix. For any matrix $A \in \mathbb{R}^{m\times n}[\mathbb{C}^{m\times n}]$, matrix A can be decomposed as:

$$A = U\Sigma V^T \tag{2}$$

where U is an $m\times m$ orthonormal eigenvector matrix of AA^T, and V is an $n\times n$ orthonormal eigenvector matrix of $A^T A$. Then, Σ is an $m\times n$ matrix that can be written as:

$$\Sigma = \begin{bmatrix} \mathrm{S} & 0 \\ 0 & 0 \end{bmatrix} \tag{3}$$

Here, $\mathrm{S} = \mathrm{diag}(\sigma_1,\cdots\sigma_r)$ is a diagonal matrix by, $r\times r$ and σ is called a singular value that is calculated by SVD. SVD has information about the magnitude of the signal, which be used for analysis [26-27].

3.3 Wavelet singular value decomposition

Wavelet Singular Value Decomposition (WSVD) is a type of wavelet transform with SVD [17]. The approximation and detail coefficients *a1* and *d1* are calculated through the decomposition and reconstruction process on the level 1 DWT with the signal *x* from a moving window of size *n*. The sizes of the *x*, *a1*, and *d1* become *n* as well. The Singular value of Approximation (*SA*) is a singular value to be calculated by (4) using *a1*. The Sum of the absolute value of Detail (*SD*) is calculated by (5) and (6) using *d1*.

$$SA = SVD(a1[i,1:n]) \tag{4}$$

$$SD1[i] = \sum_{k=1+(lf-2)}^{n-(lf-2)} \left| d1[i,k] \right| \tag{5}$$

$$SD[i] = \sum_{k=i-n+1}^{i} SD1[i] \tag{6}$$

Here, i is the starting time of sampling of the moving window, and lf is the filter size according to the mother wavelet. In order to suppress the negative effect of the DWT filter caused by applying the moving window techniques, *SD1* is calculated to remove the value at both ends of *d1* during the calculation. The value of *d1* is calculated by a decomposition and reconstruction process of the level 1 DWT of the signal s[n] using Daubechies 4 (db4) as the mother wavelet based on a moving window with a size of 24 (a half cycle). In this process, assuming that the size of the filter is 8 and the high-pass filters are HD1, HD2, ···· and HD8, then *d1*[1]-*d1*[6] and *d1*[19]-*d1*[24] do not have a pattern in *d1* because of the influence of duplicated signals for convolution multiplication.

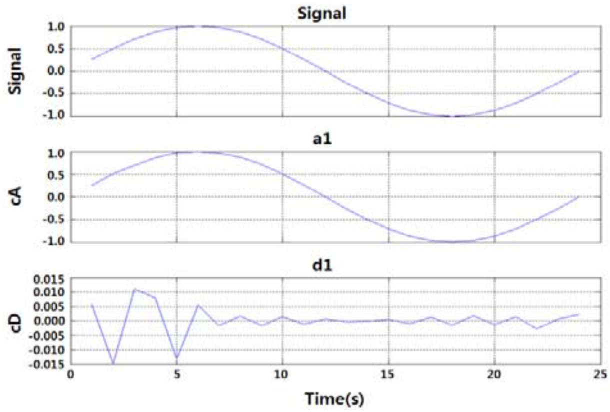


Fig. 2. *a1* and *d1* for a sinusoidal signal

However, *d1*[7]-*d1*[18] have a pattern in *d1* because they are not impacted by the signal duplication for convolution multiplication. Fig. 2 shows a sine waveform of one cycle as an original signal. *a1* and *d1* are the results of the decomposition and reconstruction process of db4 with the level 1 DWT. The *d1* curve shows fluctuation at both ends.

3.4 Analysis of fault-type characteristics based on WSVD

The various faults are simulated in the model of the 345-kV transmission system shown in Fig. 3. We model 345kV transmission system using EMTP-RV. Lines applied to the system are non-transposed constant parameter model and average parameters of ACSR 480mm^2 – 4 bundled lines, usually used in 345kV transmission system of Korea, are utilized. Fig. 3 and Table 1 indicate the transmission system model and parameters of line used, respectively.

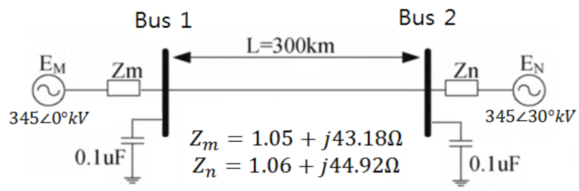


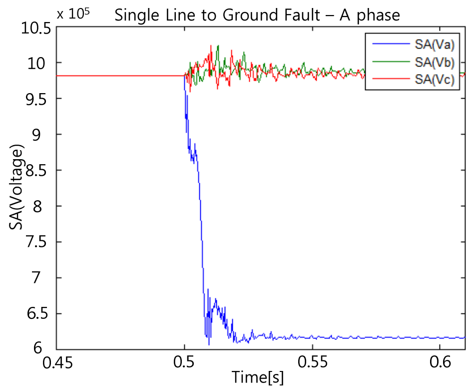
Fig. 3. 345kV transmission system model

Table 1. Line parameters

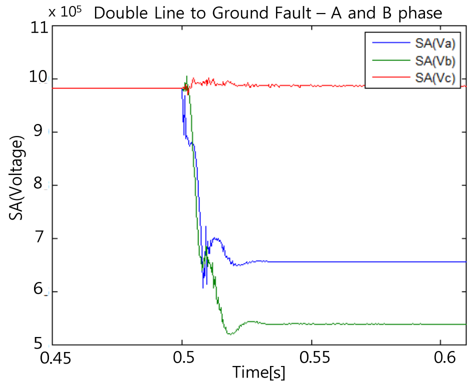
Line Parameter	Value
Positive sequence resistance, R_1	0.0208Ω/km
Zero sequence resistance, R_0	0.1148Ω/km
Positive sequence inductance, L_1	0.2821Ω/km
Zero sequence inductance, L_0	0.7186Ω/km
Positive sequence capacitance, C_1	0.0129μF/km
Zero sequence capacitance, C_0	0.0052μF/km

The simulation conditions are as follows:

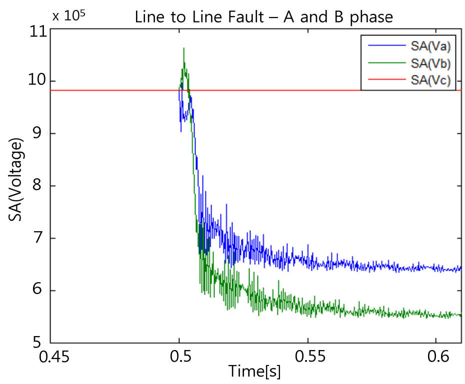
1) Fault types:
  - Single line-to-ground (SLG)
  - Double line-to-ground (DLG)



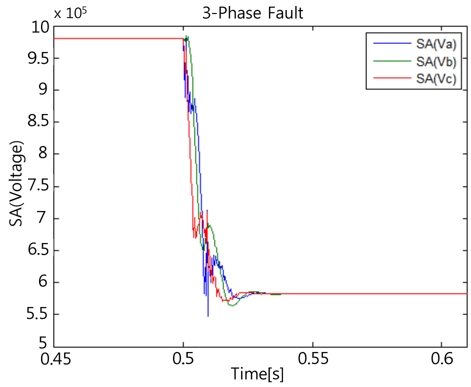
(a) SLG



(c) DLG

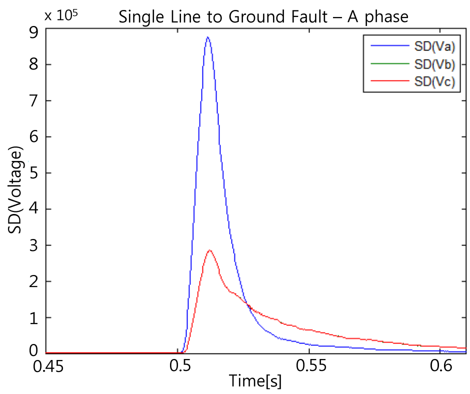


(b) DLL

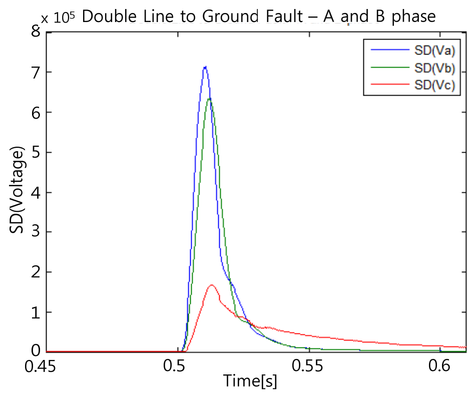


(d) 3Φ Fault

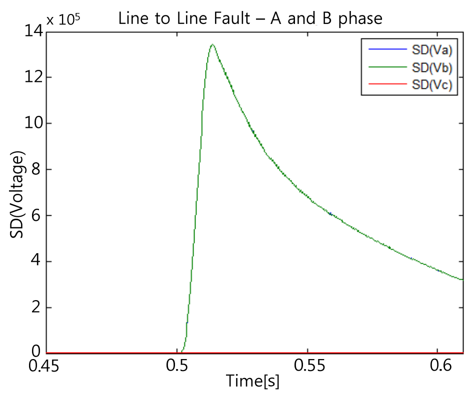
Fig. 4. Variation of the *SA* by fault type



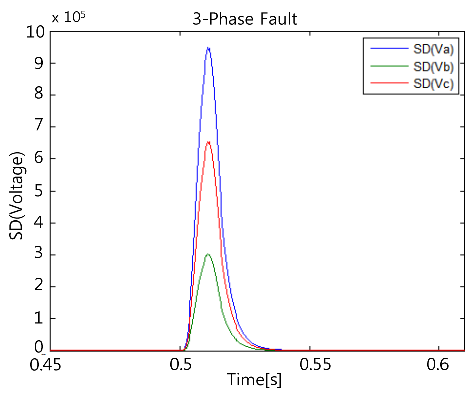
(a) SLG



(c) DLG



(b) DLL



(d) 3Φ Fault

Fig. 5. Variation of the *SD* by fault type

- Line-to-line short circuit (DLL)
- Three-phase fault (3Φ)

2) Distances of faulting position from bus 1 [km]
- 5, 10, 15, 20, 40, 60, 80, 100, 120, 140, 160, 180, 200, 220, 240, 260, 280, 285, 290, 295

3) Fault inception angles [°]
- 0, 30, 45, 60, 90, 120, 135, 150, 180

4) Fault resistances [Ω]
- Line-to-ground fault: 20, 50, 100
- Line-to-line fault: 0, 50, 100
- Three-phase line-to-line fault: 0

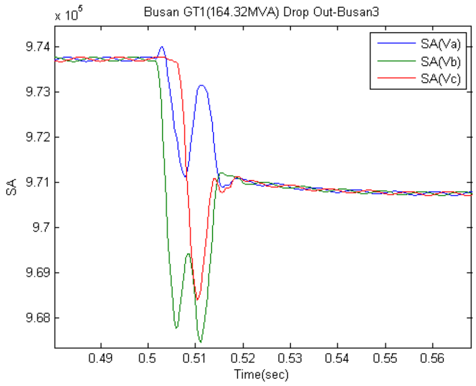
The measured original signals are each phase voltage measured at bus 1 or bus 2 after the faults. The sampling frequency is 2.88 kHz, the size of a moving window is 24 (half cycle), and the mother wavelet is db4, which is generally used for analysing transience in electrical power systems [26-28]. Figs. 4 and 5 show the *SA* and *SD* of each simulated fault. In Figs. 4 and 5, (a) shows SLG, (b) shows DLL, (c) shows DLG, and (d) shows three-phase fault (3Φ).

In the case of SLG, the variations of *SA* have the same trend as the original voltage signal. The voltage of the faulty phase is decreased, while that of the healthy phases is increased. The difference value between the faulty and the healthy phase is almost double compared with the normal conditions, as shown in Fig. 4(a). The magnitude of *SD* at the faulty phase is generally higher than that of the healthy phase. In the case of DLL, the magnitudes of the original voltages at the faulty phases are smaller than that in the healthy phase. The magnitude of *SD* at the fault phases increase rapidly, as shown in Fig. 5(b). As shown in Fig. 4(c), the result of DLG is very similar to that of DLL, but the magnitude of the healthy phase in case of DLG experiences small variance caused by the faulty phase. In the case of a 3Φ fault, the original voltage magnitude of the faulty phases is decreased rapidly, but the results are relatively low. The magnitudes are shown according to the fault resistance and the fault inception angle. The variation of *SA* is shown in Fig. 4(d), and the *SD* is shown in Fig. 5(d).

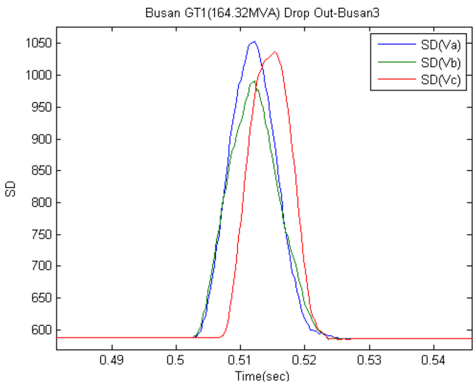
3.5 Characteristic analysis of generator loss

Simulations of generator loss are performed by tripping the Busan C/C, Ulsan C/C, Ulsan T/P, and Kori N/P. The simulation conditions include the tripping generator group, with a maximum voltage of phase and a minimum voltage of phase a, and a total of 42 simulations are conducted. Each group of selected generators is connected to the bus of each generator group, which include 8 units of Busan C/C, 6 units of Ulsan C/C, 3 units of Ulsan T/P, and 4 units of Kori N/P. The measuring point of voltage is the North Busan 3S bus, and the signals are processed with WSVD.

Fig. 6 shows the variation of *SA* and *SD* caused by generator loss. *SA* shows a similar pattern to that of DLL or 3Φ fault. *SD* shows the results to be discriminated with *SA*

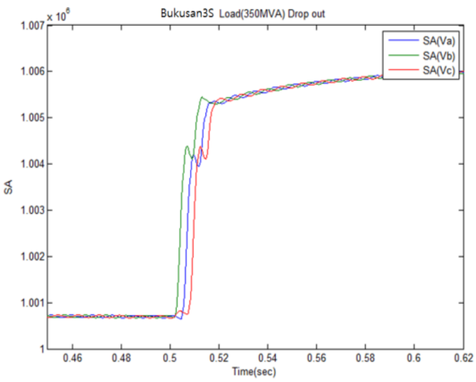


(a) *SA*

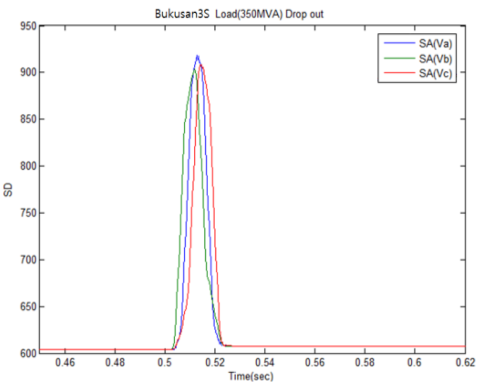


(b) *SD*

Fig. 6. Variation of *SA* and *SD* by generator loss



(a) *SA*



(b) *SD*

Fig. 7. Variation of *SA* and *SD* by load shedding

that are different from those with a 3Φ fault. However, the maximum variation rates of each phase are similar.

3.6 Characteristic analysis of load shedding

Simulations of load shedding are performed by tripping the loads at North Busan 3S and New Ulsan 3S buses from 5% to 40 % by 5% increments. A total of 32 simulations are performed, considering the magnitude of voltage at the closing point. The measuring point for the voltage signal is at North Busan 3S, and the signals are processed with WSVD.

Fig. 7 shows the variation of *SA* and *SD* by load shedding. *SA* increases by 0.01 p.u. due to the load shedding of 350 MVA. SD shows the results between DLL and 3Φ fault. The variations of SD are doubled compares to the normal state.

4. Algorithm for Fault Detection and Classification

4.1 Method of the fault detection

The characteristics of *SA* and *SD* according to the fault types were analysed in Section 3. Based on the characteristics, *SD* is selected to detect faults. This is because the variation of *SD* is more severe than that of *SA* when a fault occurs.

Fig. 8 compares the results of WSVD transformation of the 345-kV phase voltage signal and that of the same signal with SNR 100 of Additive White Gaussian Noise (AWGN). *SA* and *SD* for the signal only remain unchanged, while those for the signal with AWGN show variations. Apparently, *SD* fluctuates much more than *SA* when noise is added. Fig. 9 shows the differential value of *SD* with 1 cycle. The maximum differentiated value is 0.6. Therefore, the threshold value to detect a fault in the 345-kV transmission line, α, is set to 1 with some margin. The value can be adjusted by considering conditions of the power system and operational requirements.

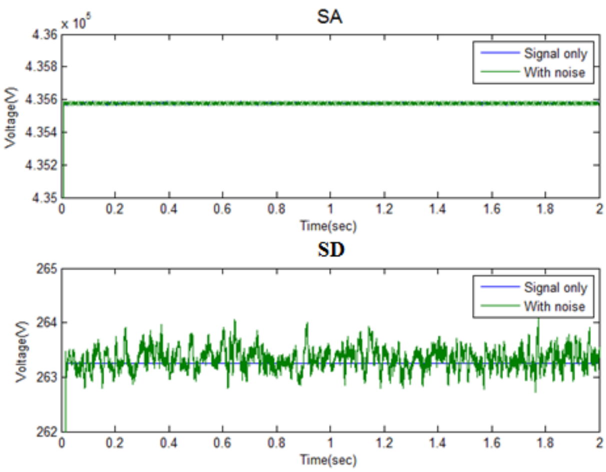


Fig. 8. WSVD signal added AWGN (Additive White Gaussian Noise)

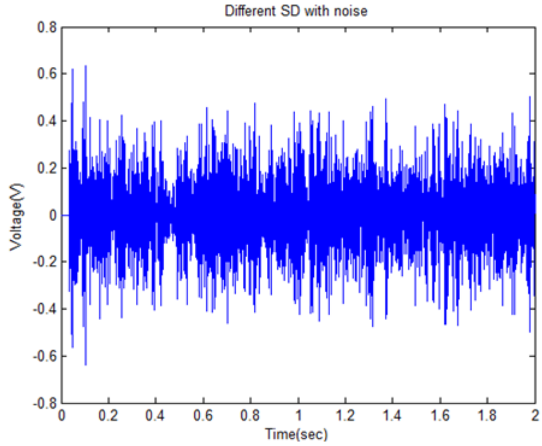


Fig. 9. Differential value of SD added AWGN

4.2 Method of fault-type classification

Several indices are defined to classify fault types based on the aforementioned characteristics of *SA* and *SD*: *NSA* (Normalized maximum *SA*; *ΔSA*), *AR* (Ranked *SA*), *NSD* (Normalized maximum *SD*; *ΔSD*), and *NSS* (Normalized Settled *SD*; *ΔSD*). The zero sequence voltage V_0 is introduced to determine whether the fault is symmetric or asymmetric.

NSA is the ratio of the absolute value of *SA* in normal conditions to that of the maximum change of *SA* for a cycle after a fault calculated in (7). The (8) calculates the last *NSA* to select the faulty phase. If the value is bigger than the threshold β, it becomes 1, but it is otherwise 0.

NSD is the ratio of the absolute value of *SD* in normal conditions to that of the maximum change of *SD* for a cycle after a fault, as shown in (9). The threshold values associated with *NSD* are $\delta = 0.001$, $\gamma = 0.5$, and $\zeta = 0.75$. The threshold value δ identifies line-to-line faults, γ double line-to-ground faults, and ζ three-phase faults from generator loss.

NSS is the ratio of the absolute value of *SD* in normal conditions to that of the maximum change of *SD* for a cycle after a fault, as shown in (10). η is the threshold value associated with *NSS*, and is set at 0.75. It identifies three-phase fault from generator trips.

β, δ, γ, ζ, and η used as threshold values that are related to the ratio values of *SA* and *SD*, and they are not directly associated with the transmission system.

$$
\begin{aligned}
NSA1 &= \left[A1_a, A1_b, A1_c\right] \\
&= \left[\frac{Max(\Delta SA_a), Max(\Delta SA_b), Max(\Delta SA_c)}{Max(\Delta SA_a, \Delta SA_b, \Delta SA_c)}\right]
\end{aligned} \tag{7}
$$

$$
\begin{aligned}
NSA &= \left[A_a, A_b, A_c\right] \\
&= \left[If(A1_a > \beta, 1, 0), If(A1_b > \beta, 1, 0), If(A1_c > \beta, 1, 0)\right]
\end{aligned} \tag{8}
$$

$$NSD = [B_a, B_b, B_c] = \left[\frac{Max(\Delta SD_a), Max(\Delta SD_b), Max(\Delta SD_c)}{Max(\Delta SD_a, \Delta SD_b, \Delta SD_c)} \right] \quad (9)$$

$$NSS = [C_a, C_b, C_c] = \left[\frac{|\Delta SD_a|, |\Delta SD_b|, |\Delta SD_c|}{Max(\Delta|SD_a|, \Delta|SD_b|, \Delta|SD_c|)} \right] \quad (10)$$

4.3 Algorithm for fault detection and fault-type classification

The proposed algorithm detects and classifies the fault using the methods described in Sections 1 and 2. 12 types of fault are numbered as shown in Table 2. Figs. 10 and 11

Table 2. The variable value of each fault type

Value	Fault Type	Value	Fault Type
0	Normal State	7	DLG-ac Phase
1	Load shedding	8	DLG-bc Phase
2	Generator loss	9	DLL-ab Phase
3	SLG-a Phase	10	DLL-ac Phase
4	SLG-b Phase	11	DLL-bc Phase
5	SLG-c Phase	12	3Φ Fault
6	DLG-ab Phase		

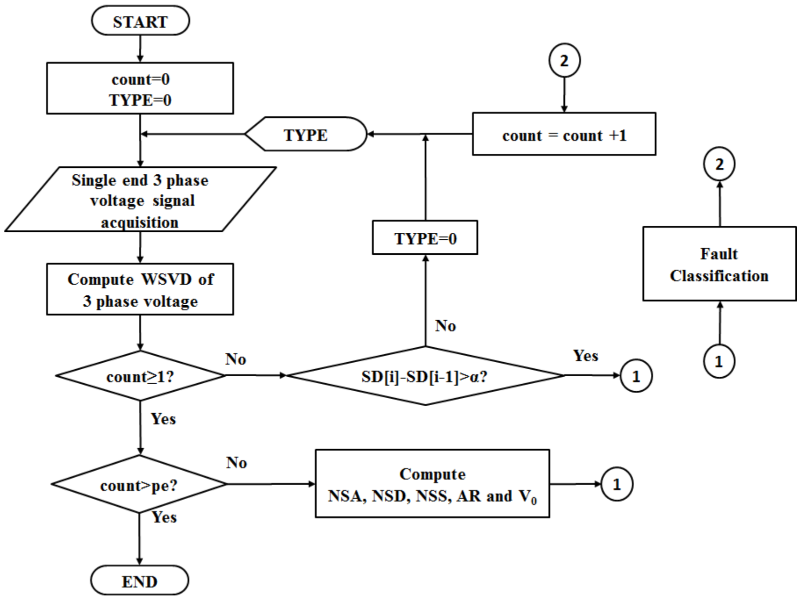


Fig. 10. Main Flow Chart of the algorithm for fault detection and fault type classification using WSVD

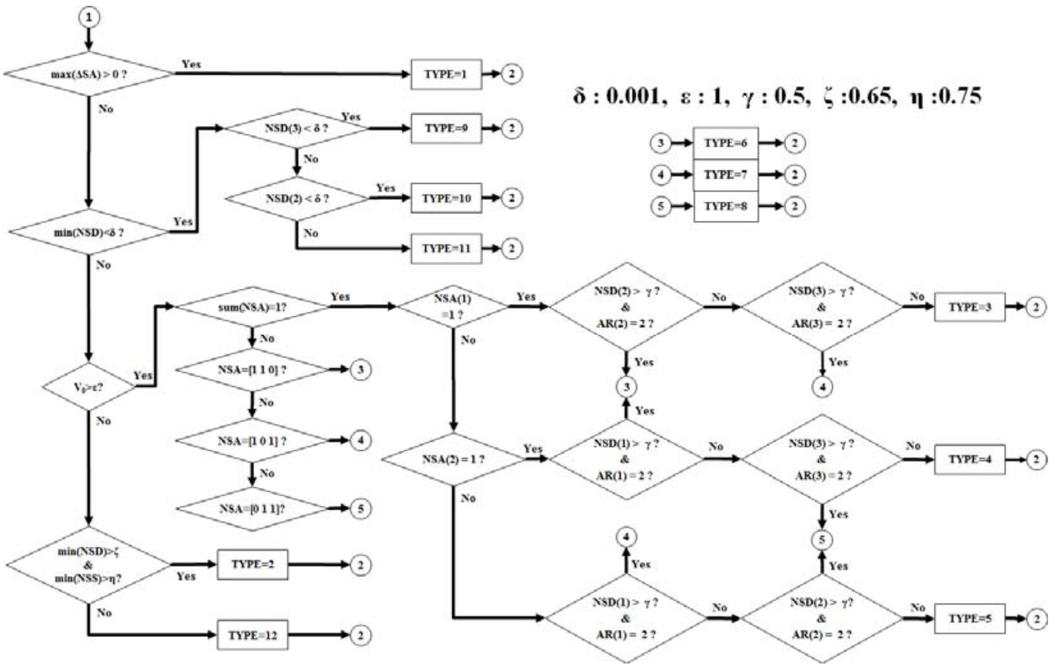


Fig. 11. Algorithm for fault detection and type classification using WSVD

describe the proposed algorithm, and pe in the figures is the sample number for one cycle.

5. Simulation and Discussions

5.1 Simulation conditions

The various faults are simulated in the 345kV transmission system presented in Fig. 3, to verify the algorithms. A total of 56,744 simulations are conducted, until the failed cases become 20 times.

Simulation conditions consist of various fault distances, fault types, fault resistances, and fault inception angles, as follows:

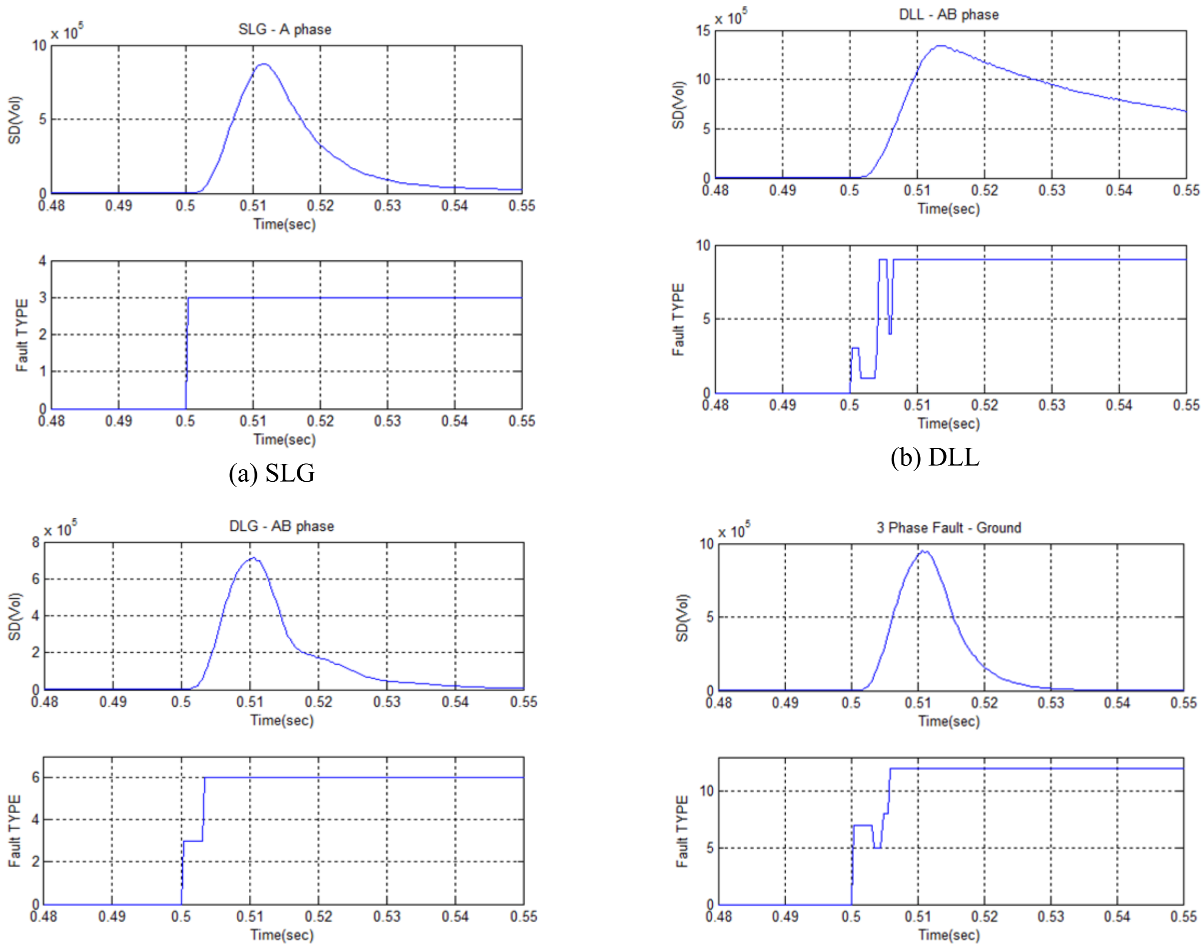
- Fault distance: randomly selected, between 1~299 km from bus 1, with a unit of 1 km
- Fault type: randomly selected
- Fault resistance: randomly selected, between 1 and 100 Ω, with a unit of 1 Ω
- Fault inception angle: randomly selected, by starting a fault at random time within 1 cycle, with a unit of 0.1 ms

Faults are simulated using EMTP. The results from EMTP were converted to a format compatible to MATLAB, and WSVD was performed in MATLAB.

5.2 Simulation results of fault detection and classify-cation

Fig. 12 shows the simulation results of fault classify-cation for various fault types. Table 3 shows the results of the simulations. It shows the times of simulation and failure, and success rate of the fault type classification for each fault type. SLG, DLL, and 3Φ fault classified 100% correctly. However, the success rate of DLL classification was 99.88%. The total success rate of fault classification is 99.96%.

The most failed cases for the fault type classification are DLG faults with the distance of 23 km and 277 km from the bus. The three phase voltage, *SA* and *SD* of this case are shown in Fig. 13. In the cases of the DLG fault, if the distance is 23 or 277 km, it shows that the SA of the faulted phase does not rapidly decrease, hence β of the faulted phase becomes less than 1. As a result of *NSA1*, the algorithm classifies the SLG fault. However, the fault



(a) SLG (b) DLL (c) DLG (d) 3Φ Fault

Fig. 12. Results of fault classification for the various fault types

Table 3. Verification result of faults classification

Fault Type	Times of Simulation	Times of Failure	Success Rate (%)	
SLG-a Phase	5,877	0	100	100
SLG-b Phase	5,809	0	100	
SLG-c Phase	5,737	0	100	
DLG-ab Phase	5,593	7	99.87	99.88
DLG-ac Phase	5,426	9	99.83	
DLG-bc Phase	5,773	4	99.93	
DLL-ab Phase	5,853	0	100	100
DLL-ac Phase	5,560	0	100	
DLL-bc Phase	5,448	0	100	
3Φ Fault	5,668	0	100.00	
TOTAL	56,744	20	99.96	

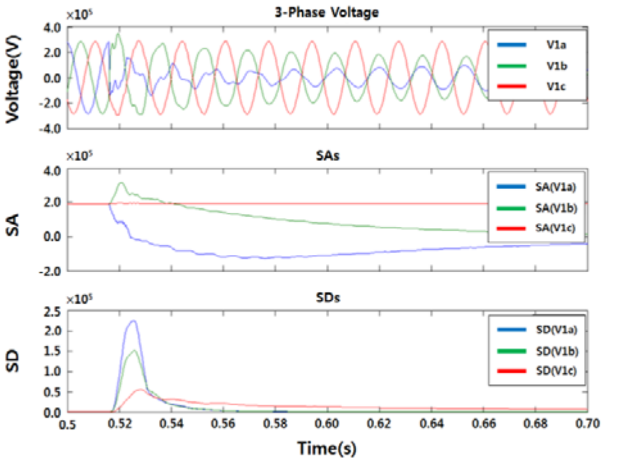


Fig. 13. The failed case of the fault type classification (DLG, Distance of fault: 23km, Fault Resistance: 54Ω)

would be detected, if the detecting period becomes 2 cycles.

6. Conclusion

Modelling of the 345-kV and 765-kV Korean nation-wide power system network in EMTP-RV has been described based on real data in PSS/E files provided by KEPCO and KPX. Based on the modelled system, an algorithm for wide-area protection in the Korean transmission system has been proposed. The proposed algorithm consists of fault detection and classification. The method for fault detection and classification using WSVD was also discussed. Various simulation conditions were performed to analyse the characteristics at each fault in the 345-kV transmission model system. The characteristics in various fault conditions using WSVD were analysed. With the analysis results, NSA, AR, NSD, and NSS were designated with proper values for fault detection and classification. All algorithms for wide area protection, including fault detection and fault type classification are validated through various simulation conditions. The algorithms of fault detection and type classification work perfectly in the simulations.

By using the proposed algorithm, national wide monitoring and supervising system can be monitoring and classifying of the faults in national wide-area transmission network as a new way redundantly with the SCADA (Supervisory Control and Data Acquisition) and EMS (Energy Management System) in order to be more reliable operation when the signal can be acquired by PMU on national wide.

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