TELKOMNIKA, Vol.9, No.1, April 2011, pp. 99~106
ISSN: 1693-6930
accredited by DGHE (DIKTI), Decree No: 51/Dikti/Kep/2010

Inverse S-Transform Based Decision Tree for Power System Faults Identification

Srikanth Pullabhatla, Ashwani Kumar Chandel*, Anil Naik Kanasottu
Electrical Engineering Department, National Institute of Technology Hamirpur
Himachal Pradesh 177005, India. Ph. +91-1972254534
e-mail: ashchandelin@gmail.com*

Abstrak

Pada makalah ini diusulkan sebuah identifikasi gangguan sistem daya berbasis pohon keputusan. Nilai masukan kunci terhadap pohon keputusan adalah unjuk kerja yang mengindikasikan kalkulasi nilai maksimum transformasi Stockwell invers tanpa penapis (MUNIST). Berbagai macam teknik termasuk transformasi Stockwell (ST) telah digunakan untuk mengidentifikasi gangguan sistem daya. Namun, karakteristik yang dihasilkan oleh teknik tersebut tidak unik dan kadang-kadang menyebabkan salah pennafsiran terhadap suatu gangguan. Karenanya, pohon keputusan berbasis metode transformasi Stockwell invers transformasi diusulkan dalam tulisan ini untuk mengidentifikasi gangguan sistem daya simetris dan tidak simetris secara otomatis. Metode ini dapat menentukan perubahan sinyal yang mendadak dan bertahap yang disebabkan oleh gangguan sistem daya yang berbeda. Teknik ini sangat akurat dan menghasilkan karakteristik yang unik dibandingkan dengan teknik yang sudah ada. Hasil yang diperoleh menunjukkan keberhasilan teknik yang diusulkan.

Kata kunci: *Keputusan pohon, kesalahan, identifikasi, sistem tenaga, pemrosesan sinyal*

Abstract

In this paper a decision tree based identification of power system faults has been proposed. The key input values to the decision tree are the performance indices calculated from the maximum values of unfiltered inverse Stockwell transform (MUNIST) technique. A wide range of techniques including Stockwell transform (ST) have been used for the identification of power system faults. However, the signatures produced by these techniques are not unique and sometimes lead to misinterpretation of faults. Consequently, a decision tree based on the inverse Stockwell transform method is proposed in the present paper to automatically identify both the symmetrical and unsymmetrical power system faults. The method is able to determine both sudden and gradual changes in the signal caused by different power system faults. The technique is very accurate and produces unique signatures compared to the existing techniques. The results obtained show the efficacy of the proposed technique.

Keywords*: Decision tree, faults, identification, power system, signal processing*

1. Introduction

Complexity of the power system has become manifold due to an increase in the size and power levels of the present power system. Consequently, many studies like transient stability, power quality and instability etc. have taken a center stage in the power system analysis. The faulty operation of the power system components and absence of non ideal power system design leads to transients [1], [2]. These problems have large operational effect on the power system though the time interval of the transients is negligible. The transient stability analysis can be used for analyzing such events having time periods between seconds and few minutes. With the incorporation of a large number of sensitive and critical loads into the system as well as the inclusion of deregulation and competition in the power market, utilities are now more concerned in identifying, measuring and monitoring the transient events. Also, necessary corrective actions for their reduction and elimination have now become essential.

Various types of relays have been developed to isolate the healthy circuit to be affected by the faults. However, action of the relay is same for all types of faults. This is possible if information about the type of fault is available to the system operator. However, to reduce the effect of transients exact precautionary actions are of massive importance. The information about the fault is still in need, and the utilities are also concerned about the reason behind the

Received January 19th, 2011; Revised March 12th, 2011; Accepted April 8th, 2011

transient behavior. The study of such operating conditions and periods is of intense importance. Under transient periods the circuit components are subjected to irregular stresses. Also some of the faults massively affect the customers which are near to the generating stations. Therefore, it is necessary to identify and mitigate such events before these obstruct the normal operation of the power system [3], [4].

Identification of power system faults has been dealt by various researchers using Wavelet and Stockwell transform (ST) [5]-[13]. However, it has been reported in the literature that these methods are not sufficient to predict accurately different types of faults. Though the faults analysis using time-frequency resolution (TFR) is accurate however sometimes it gives identical signatures for more than two types of faults. Hence it becomes impossible to identify what type of fault has occurred in the system. In such a case, calculation of a performance index (PI) is useful in distinguishing the type of fault. Therefore, keeping in view the concern towards fault analysis, there is still a need for the development of more accurate prediction technique which can identify various power system faults and events. Present work is a step in this direction.

Frequently occurring faults in power systems include faulty operation between any of the two phases and also all the three phases which are known as LL and LLL fault respectively. Other faults may occur between the phase and ground and are known as LG, LLG, LLLG faults. The severity level of these faults cannot be generalized and may be the same in some cases. Hence the type of fault and its consequences on the power system operation cannot be determined exactly. The difficulty in discriminating the type of fault based on its developed signature can be overcome by employing a decision tree technique which utilizes the PI values for the identification of each type power system faults [14]-[18]. The PI values used in the developed method are calculated from the inverse Stockwell transform matrix henceforth called as MUNIST. The output of the decision tree provides the exact identification of the power system faults.

The proposed technique to identify various fault conditions is explained in detail in Section 2. Application to fault type identification is discussed in Section 3. In Section 4 detail of the decision tree algorithm and identification results are presented. Finally, conclusions are drawn in Section 5.

2. Research Method

Stockwell transform (ST) is used as the base research method in the present work. ST is defined as shown in equation (1), where S is a continuous function of both time (τ) and frequency (f) [4]. The frequency f varies with the width of the Gaussian window σ with a relation shown in equation (2). Continuous ST (CST) contour plot with frequency in y-axis and time in x-axis is produced by (1).

$$S\left(\tau, f\right) = \int_{-\infty}^{+\infty} h(t)(\frac{|f|}{\sqrt{2\pi}}.\exp\left(-\frac{\left(t-\tau\right)^2 f^2}{2}\right).\exp(-\left(i2\pi ft\right)).dt \quad (1)$$

$$\sigma = \frac{1}{|f|} \quad (2)$$

2.1. Discrete S–Transform

The signal $h(t)$ can be expressed in a discrete form as $h(kT)$, where, k = 0, 1… N -1, N is the number of samples and T is the sampling time. The S-transform of a discrete time series $h(kT)$ is obtained by (letting $f \rightarrow \frac{n}{NT}$ and $\tau \rightarrow kT$). It is expressed as equation (3) [4];

$$S[kT, \frac{n}{NT}] = \sum_{k=0}^{N-1} H\left[\frac{m+n}{NT}\right].e^{\frac{-2\pi^2 m^2}{n^2}}.e^{\frac{i2\pi mk}{N}} \quad \text{for } n \neq 0 \quad (3)$$

where, k and m vary from 0 to N -1, n = 0, 1 … ($\frac{N}{2}$-1).

Each row of the ST matrix obtained from (3) displays the ST amplitude with all frequencies at the same time. Each column of the same matrix i.e. ST matrix displays the ST amplitude with time varying from 0 to N -1 in the same frequency. Discrete S- transform (DST) in magnitude-time or magnitude-frequency plot is obtained from (3). The maximum value obtained from the DST by searching through all the rows and the columns are used to determine the signature of a given signal [11]. Since power system faults are non stationary, S-transform can be effectively applied for identification purpose. However, the search technique based on DST is not unique because it gives same signatures for events like fault and transient condition. Consequently, an inverse of the ST (MUNIST) of (1) has been found to be more effective and efficient for power system faults identification which is discussed in the further section.

2.2. Proposed Methodology

The local time-frequency spectra $S(\tau, f)$ obtained with the generalized S-Transform can easily be back-transformed since the S-transform windows satisfy the condition shown in equation (4) [6], [7].

$$\int_{-\infty}^{+\infty} w(\tau - t, f).dt = 1 \tag{4}$$

This ensures that the time averaging of the S-spectrum $S(\tau, f)$ yields the spectrum $U(f)$ as in equation (5).

$$\int_{-\infty}^{+\infty} S(\tau, f) d\tau = \int_{-\infty}^{+\infty} u(t) \exp(-i2\pi ft) \int_{-\infty}^{+\infty} w(\tau - t, f) d\tau dt = U(f) \tag{5}$$

It means that the S-transform is exactly invertible with one inverse Fourier Transform and is a simple unfiltered inverse transform. Such an operation can be handled in MATLAB using the IFFT function. The result gives a matrix of the same order as that of $S(\tau, f)$. Now, if a plot between the absolute value of such a matrix and number of time samples is taken it will be a cluster of dilated and translated Gaussian windows. Subsequently, a plot with maximum value of each Gaussian window versus time samples can be obtained. This methodology has been used for identification in the present paper. As the maximum values of the Gaussian windows obtained from the unfiltered inverse ST is used it is termed as MUNIST [18].

To demonstrate the MUNIST a test signal as shown in Figure 1 is considered. The considered signal is sag i.e. a reduction in the amplitude of a particular signal for a short time interval. This is a common PQ problem. It is mentioned here that the parameters of the test signal i.e. voltage and frequency are 230V and 50Hz respectively. Time interval of the signal is 0.5s with sampling frequency 1 kHz. The duration of sag is considered for t = 0.20 to 0.28s. The signal is now processed using the proposed MUNIST technique and its output is shown in Figure 1(b). It is seen from Figure 1(b) that the Gaussian window behaves according to the signal amplitude. The number of Gaussian windows depends on the sampling frequency and number of samples. In the present case this number is 250, which is half of the number of samples.

Figure 1(b) is visualized that Gaussian window reduces its amplitude depending on the sag signal from interval 0.20 to 0.28s as shown between dotted lines. In case of more number of Gaussian windows obtained due to more number of samples exact and crystal clear information cannot be extracted. Hence, the plot between maximum values of the windows and the time provides a distinguishable signature and is as shown in Figure 1(c). It is mentioned here that similar signatures are also be obtained using DST however these have some disadvantages as discussed in the subsequent section.

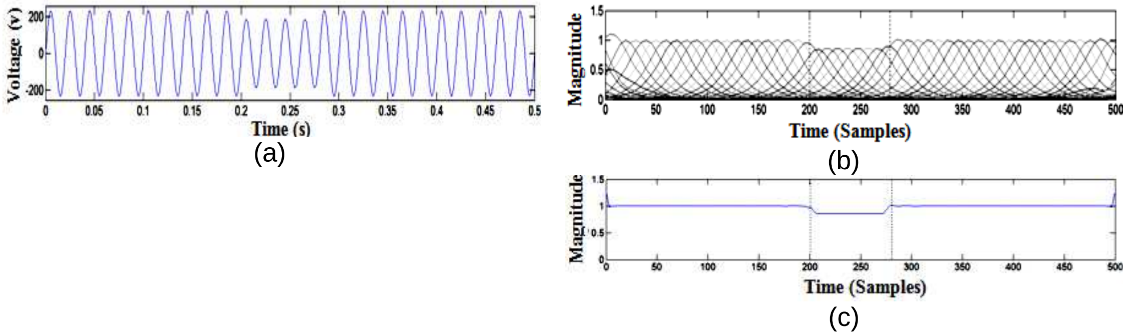

Figure 1. (a) Test signal considered, (b) Magnitude vs. time plot obtained from the inverse of ST, (c) Plot of maximum value vs. time of the Gaussian windows shown in (b)

3. Application to fault type identification

The proposed technique discussed in the section 2.2 has been tested on different fault cases. Various faults viz. LG, LLG, LL and three phase (LLL) which commonly occur in the power system are considered for identification purpose. It is mentioned here that due to lack of availability of practical data a MATLAB® model shown in Figure 2 has been used for the simulation of various types of faults. Information about the ratings of all the power system components in the model is directly accessible in MATLAB® as it is a pre-designed model. In the present study recorded voltage data at bus B1 has been utilized for fault identification. The results obtained using MUNIST technique is then compared with the existing fault identification methods based on CST and DST. Various test signals considered are nature of sinusoidal with 230V and 50Hz frequency. All the signals have the same time interval of 0.2s and the sampling frequency is set to 2.5 kHz thus giving 500 data samples as input. The magnitude of all the techniques viz. CST, DST and MUNIST are scaled to 1 to represent the variation in terms of 1p.u. Figures 3(a) to 6(a) show the various power system faults disturbances. Figures 3(b) to 6(b) are the contour plots of the test signals plotted in Figures 3(a) to 6(a) using ST.

3.1. LG Fault

LG fault is generally caused by physical contact which may be due to lightning or due to damage caused by storm. LG fault is the most common type of fault that occurs in power system [1]. This type of fault is considered in unsymmetrical analysis as all the phases are not involved during the fault. The analysis of such category of faults is a bit difficult. A signatory visualization using signal processing techniques prove more advantageous. Figure 3 shows the results obtained from all the methods for a LG fault. Figures 3(b) and 3(c) show the CST and DST signature respectively of this event which is similar to sag [8], [9]. DST which is considered for better visualization is also showing the sag signature thus giving a conflict in understanding.

However, the MUNIST has a typical signature for such a case with the small variations which can be clearly visualized from Figure 3(d). The magnitude of MUNIST is exactly varying with the test signal leading to the signature to be very realistic.

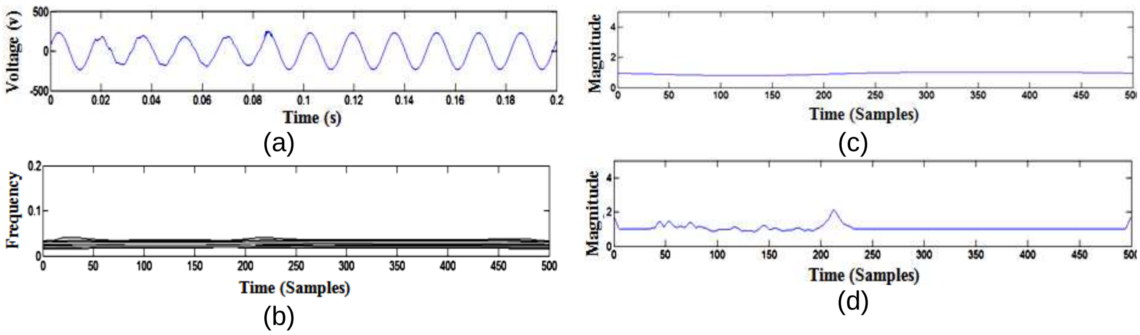

Figure 3. (a) Voltage waveform obtained due to LG fault, (b) CST of the waveform in (a), (c) DST of the waveform in (a), (d) MUNIST of the waveform in (a)

3.2. LLG Fault

A LLG fault occurs between two lines also commonly occurs due to storm damage. This type of fault is the second most commonly occurring faults. It also falls under the category of unsymmetrical faults. Consequently the severity will be higher on the power system components. The results for LLG fault are shown in Figure 4. The behavior of the CST is different in Figure 4(b) with a contour at the high frequency range. DST results are the same as that of sag and can be visualized in Figure 4(c). However, it is seen from the MUNIST signature in Figure 4(d) has become noisier and the maximum amplitude has crossed 7 thus making the signature unique, thus enabling it to be easily distinguishable.

3.3. LL Fault

A line-to-line fault is generally caused by ionization of air, or when lines come into physical contact, for example due to a broken insulator. Due to absence of involvement of all the three phases it is unsymmetrical in nature. Figure 5(a) shows the test signal of a LL fault and its analysis using various techniques in the subsequent figures. The CST in Figure 5(b) gives almost the same signature as that of Figure 4(b) and is visually confusing. DST in Figure 5(c) is again showing a signature similar to sag and is not unique. The MUNIST signature in Figure 5(d) is noisier in view and is almost as same as LLG fault but the maximum amplitude of the signature in the MUNIST plot is below 7. The maximum amplitude in each signature of LL fault and LLG fault is different. Hence depending on the maximum amplitude the type of fault is easily identified.

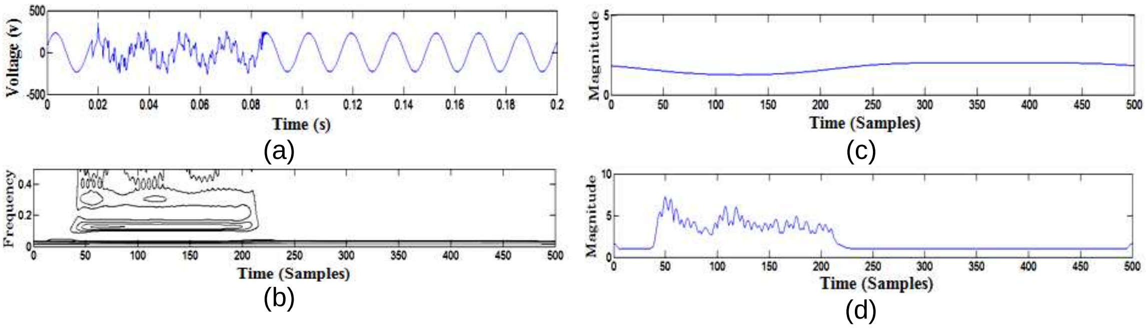

Figure 4. (a) Voltage waveform obtained due to LLG fault, (b) CST of the waveform in (a), (c) DST of the waveform in (a), (d) MUNIST of the waveform in (a)

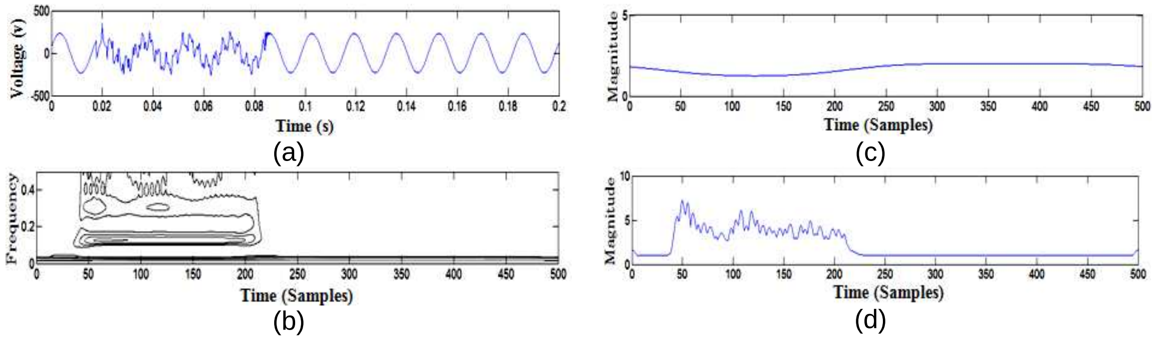

Figure 5. (a) Voltage waveform obtained due to LL fault, (b) CST of the waveform in (a), (c) DST of the waveform in (a), (d) MUNIST of the waveform in (a)

3.4. LLL Fault

A LLL fault is a symmetric fault thus affecting each of the three-phases equally. In transmission line faults, roughly 5% are symmetric. The analysis may be easy compared to the previously discussed unsymmetrical fault but they are highly severe. LLL fault case is analyzed in the similar way as the other fault cases. The results are shown in Figure 6. The CST in Figure

6(b) provides a different signature for the fault and hence predicting the LLL fault. DST signature of LLL fault in Figure 6(c) shows signature similar to sag and the signature is similar to other faults as in Figure 4(c) and 5(c). Thus, it is impossible to identify LLL fault using DST technique. However, proposed MUNIST signature shows a different signature of the LLL fault with reduced amplitude of the highest peak. Peak amplitude is below 3 in this case and hence identification of the event is easy. It is observed that the highest amplitude of the MUNIST signature varies depending on the types of faults.

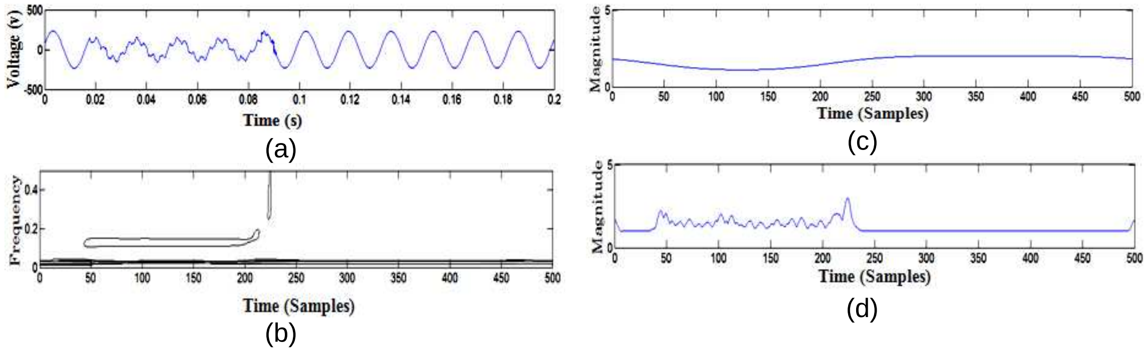

Figure 6. (a) Voltage waveform obtained due to LLL fault, (b) CST of the waveform in (a), (c) DST of the waveform in (a), (d) MUNIST of the waveform in (a)

From all the above results of various faults it is seen that the voltage waveforms are distorted. The disturbance level is high in the case of LLG and LL. Consequently, the CST plot has same signature for more than two different types of faults. DST which is considered for a better visualization is giving a signature of LLL similar to sag [9]-[13]. For both CST and DST techniques it is also not possible to define a performance index to classify various faults automatically. Though the MUNIST based fault identification also behaves in similar way as that of CST and DST techniques however the signatory part of MUNIST is better compared to CST and DST with more visualization property. However, it is visualized from Figure 4(d) and 5(d) that signatures of LLG fault and LL fault are identical. Hence, the graphical signature identification of such faults is a little bit difficult. Hence, in the present paper a decision tree algorithm as discussed below has been proposed to automatically identify even those faults which can't be identified by MUNIST based method.

The proposed methodology provides a wide platform for design of a performance index (PI). The index is designed based on the magnitude of MUNIST technique. The details of the decision tree methodology are as explained below.

4. Decision Tree Based Identification

To identify various faults features are extracted from the results obtained utilizing MUNIST method explained in section 3 and depending on these features a decision tree is constructed to automatically classify all kinds of faults.

4.1. Feature Extraction and Rule Generation

A signal constitutes many features out of which only a few are useful for identification. The features considered here for the automatic identification of faults are as discussed below.

P - Maximum amplitude obtained from the plot of MUNIST magnitude and time samples. For example, in fault case of LG fault maximum amplitude is nearly 2, LLG it is above 7, for LLL it is nearly 3 and for LL it is nealy equal to 7.

MPI - It is the MUNIST performance index (MPI) defined as shown in (6);

$$MPI = V_{SINE}(MUNIST_{MAG-SINE} - MUNIST_{MAG-DIST}) \quad (6)$$

where,

V_{SINE} = voltage of apure sinusoidal wave (here it is '230V')

$MUNIST_{MAG-SINE}$ = MUNIST magnitude of a pure sine wave for all the 'T' samples (its value is '1')

$MUNIST_{MAG-fault}$ = MUNIST magnitude of a faulted sine wave for all the 'T' samples (as obtained from Figure 3(d)-6(d))

Now, based on the above defined factors the identification is carried out and decision tree is designed. The typical values of the above mentioned factors are tabulated and presented in Table 1.

Table 1. Features Extracted from Faults Considered

Fault Event	MPI	P
LLG Fault	< -200	< 7
LL Fault		> 7
LLL Fault	-30 to -90	-
LG Fault	-10 to -30	-

4.2. Algorithm Implementation

A decision tree is generally an algorithm based on IF-ELSE conditions. This will check extracted features of a signal and provides output depending on the validation of the conditions. Figure 7 shows the structure of the decision tree proposed for automatic identification of various faults. It is seen that there are four layers in the decision tree shown in Figure 7. First layer constitutes of feeding the input to the decision box. Following the input layer the next layer is assigned for calculation of MPI. The third layer divides or classifies the values of MPI into various classes and in this stage some of the faults are identified. There may be a requirement of further divisions of layer if there is an overlapping in the calculated MPI as in the case of LL fault and LLG fault. For such a case the feature P is considered for further identification. In the case of LL fault it is greater than whereas it is lesser than 7 for LLG fault.

4.3. Decision tree results

Based on the feature extraction and decision tree design discussed in the previous sections, few results are obtained. The voltage at bus B1 has been given as input to the decision tree for automatic identification of faults. The model has been simulated for 25 times for each type of fault to test the robustness of the technique for repeated applications. The average MPI values of the types of faults are calculated for 25 simulations.

All the calculated values and decisions obtained are presented in Table 2. It is seen that for an average of 25 simulations of each fault type the faults are automatically identified at accuracy of 100%. Thus the proposed technique is robust and accurate for fault identification.

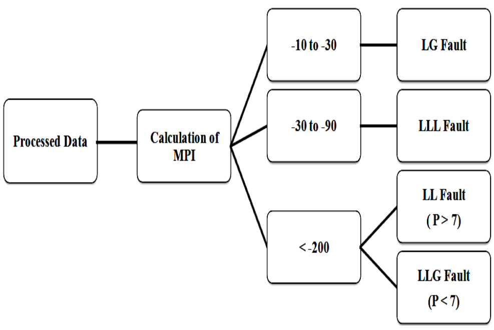

Figure 7. Decision tree from the extracted features for identification of the faults

Table 2. Calculated MPI values and decision tree output

Fault Event	MPI (Average)	P (Average)	Count of correct decisions for 25 simulations	Accuracy (%)
LLG Fault	-263.5	6.8	25	100
LL Fault	-257.8	7.21	25	100
LLL Fault	-53.2	-	25	100
LG Fault	-11.5	-	25	100

5. Conclusions

This paper presents a new methodology based on inverse property of ST for identification of different faults. In total four types of faults viz. LL, LG, LLL, LLG, have been identified. The proposed method identifies the faults accurately and efficiently. The various test cases have been considered and the results are compared with the well researched methods utilized for identification of faults. From Figures 3 to 6 it can be seen that the proposed method for identification of faults is much more superior and accurate. A decision tree is also proposed for automatic identification of the faults and it is found to be 100% accurate in identification. It is envisaged that the exact identification of fault shall facilitate in taking up proper remedial action for their mitigation and will prove to be an effective tool for fault identification.

Acknowledgment

This work is supported in part by research and development project [22(0469)/09/EMR-II] of CSIR, Govt. of India, New Delhi awarded to A. K. Chandel.

References

[1] Greenwood A. Electrical Transients in Power Systems, 2nd ed. New York: John Wiley & Sons. 1991.
[2] Lobos T, Rezmer J, Koglin HJ. *Analysis of Power System Transients Using Wavelets and Prony Method*. Proceedings of IEEE Porto Power Tech Conference. 2001.
[3] Janicek F, Mucha M, Ostrozlık M. A New Protection Relay Based on Fault Transient Analysis Using Wavelet Transform. *Journal of Electrical Engineering.* 2007; 58(5): 271–278.
[4] Stockwell RG, Mansinha L, Lowe LP. Localization of the Complex Spectrum: The S Transform. *IEEE Transactions on Signal Processing.* 1996; 44(4): 998-1001.
[5] Stockwell RG. S-Transform Analysis of Gravity Wave Activity from a Small Scale Network. PhD Thesis. Ontario: Western Ontario University. 1999.
[6] Stockwell RG, Mansinha L, Lowe LP. Localization of the Complex Spectrum: The S Transform. *IEEE Trans. on Signal Processing.* 1996; 44(4): 998-1001.
[7] Pinnegar CR, Mansinha L. T*he S-Transform with Windows of Arbitrary and Varying Shape.* Society of Explorations Geophysicists. 2003; 68: 381-385.
[8] Ventosa S, Simon C, Schimmel M, Dañobeitia JJ, Mànuel A. The S-Transform from a Wavelet Point of View. *IEEE Transactions on Signal Processing.* 2008; *44*(7): 2771-2777.
[9] Dash PK, Panigrahi BK, Panda G. Power Quality Analysis Using S–Transform. *IEEE Transactions on Power Delivery.* 2003; 18(2): 406-411.
[10] Lee IWC, Dash PK. S-Transform-based Intelligent System for Classification of Power Quality Dsturbance Signals. *IEEE Transactions on Industrial Electronics.* 2003; 50(4): 800-805.
[11] Dash PK, Panigrahi BK, Panda G. Power Quality Analysis Using S–Transform. *IEEE Transactions on Power Delivery.* 2003; 18(2): 406-411.
[12] Zhao F, Yang R. *Power Quality Disturbance Recognition Using S-Transform*. IEEE Conference. 2006; 6: 1-7.
[13] Zhang M, Li KC, Hu WB. *Automated Classification of Power Quality Disturbances Using the S-Transform*. Proc. of the 2008 Int. Conf. on Wavelet Analysis and Pattern Recognition. 2008; 321-326.
[14] Schimmel M, Gallart J, Simon C. *An Alternative Inverse S-Transform for Filters with Time-Frequency Localization*. Proc. of the 4th International Symposium on Image and Signal Processing and Analysis. 2005; 424-429.
[15] Pei SC, Wang PW. *Modified Inverse S-Transform for Filtering in Time-Frequency Spectrum*. ICASSP. 2007; 7: 1169-1172.
[16] Pei SC, Wang PW. *New Discrete Inverse S-Transform with Least Square Filtering.* ICASSP. 2009; 7: 2989-2992.
[17] Simon C, Ventosa S, Schimmel M, Heldring A, Danobeitia JJ, Gallart J, Manuel A. The S-Transform and Its Inverses: Side Effects of Discretizing and Filtering. *IEEE Transactions on Signal Processing.* 2007; 55(10): 4928-4937.
[18] Srikanth P, Chandel AK, Naik KA. *Identification of Power Quality Events Using Inverse Properties of S Transform*. IEEE PES Power System Conference & Exposition. Phoenix, Arizona, USA. 2011.