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Full Length Research Paper

Support vector regression and rule based classifier comparison for power quality diagnosis

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This paper presents a comparative study for performing automated power quality diagnosis using rule base classifier (RBC) and support vector regression (SVR) to identify the causes of short duration voltage disturbances such as voltage sag and swell. In the proposed power quality diagnosis method, a time frequency analysis technique called as the S-transform was used to analyse and extract features of voltage disturbances recorded from the power quality monitoring system. The RBC and SVR which are intelligent techniques were then used to identify whether the voltage disturbances were caused by permanent, non-permanent transient or incipient faults. Test results proved that the RBC performed better than the SVR in diagnosing the causes of short duration voltage disturbances.

Key words: Power quality diagnosis, support vector regression, s-transform.

INTRODUCTION

One of the most important steps in power quality (PQ) management is to diagnose the causes of the PQ problems. The types of PQ problems frequently experienced by customers are voltage sags and momentary interruptions while the less frequent ones include harmonics, transient, flicker and noise. Voltage sags and momentary interruptions are commonly caused by faults in the power networks. Quick identification of network faults will allow more time for network operators to perform counter measure, planning and implement suitable mitigation measures. Network faults resulting in voltage sags are the most common events and can occur within the customer's plant or in the utility power system. These faults may be categorized as permanent and non-permanent faults. Permanent faults are short circuits caused by external interferences and may cause outages and PQ related disturbances such as voltage sag and voltage swell. A permanent fault normally requires some form of repair before power can be restored and its outage times range from 1 min to many hours and produces sustained interruption (IEEE 1159 2009). Examples of permanent faults are underground cable joint faults, termination cable faults and flashover at medium voltage circuit breakers. Non-permanent faults, however, occur at random moments and affect the system behavior for finite period of time. These faults comprise either of transient faults which can be caused by environmental conditions, or intermittent faults which are caused by non-environmental conditions such as loose connections and aging components. These intermittent faults are called 'incipient faults' which occur due to partial damage that progressively weakens the integrity of the network components over time and will lead to permanent insulation failure (Weeks and Steiner, 1982). These incipient faults typically last between half-cycle (10 m/s) to 3 half-cycles (30 m/s) in a 50 Hz power system. During such period, partial discharges (PD) are present in the voltage and current waveforms. The primary objectives of PQ diagnosis are to identify the sources and causes of the PQ problems. Next is to identify and implement solutions to resolve the PQ problems. From the literature, many research works have been performed in developing various methods for performing PQ diagnosis (Santoso et al., 2000; Styvaktakis et al., 2002; Schmaranz et al., 2004;

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Chunga et al., 2007; Gerek et al., 2006; Bollen et al., 2007). Santoso et al. (2000) showed that unique features which include peak amplitudes, frequency, RMS values, and wavelet transform coefficients can be used to identify causes of voltage events due to converter operation, transformer energization and capacitor energization. These features were used to build a PQ cause identification module using a rule-based expert system. However, no verification of results was made to evaluate the accuracy of this approach.

The emphasis of the study is the importance of identifying the right features for classifying the causes of the PQ events. A simpler method for identifying the causes of voltage sags using only RMS values was developed by Styvaktakis et al. (2002). The method starts with segmenting the RMS voltage series into event and transition segments in which the segmentation is based on detecting sudden changes in the voltage magnitude. Classification of voltage sag causes is done by characterizing the segments of each phase as well as comparing the corresponding segments between the phases. Seven types of causes considered are energizing of cable, non-fault interruption, fault interruption, transformer saturation, induction motor starting, voltage step change and permanent fault. It is noted that the accuracy of the voltage sag cause identification is 92%. Schmaranz et al. (2004) developed an event detector and classifier to identify the causes of voltage sags and momentary interruption due to isolation faults, broken lines, capacitor switching, motor starting, transformer energizing and turbine swinging. The features used for performing the event and cause identification are based on the RMS voltages, RMS currents, values of fundamental frequency and phase angle jumps. These features are then applied to a fuzzy expert system in which the accuracy in identifying the causes of sags and momentary interruption is 86%. Gerek et al. (2006) implemented a PQ diagnosis method by classifying two causes of short duration disturbances using a common vector classifier and wavelet transform coefficients together with spectral harmonic ratios as features. The two causes are arcing faults or high impedance fault and motor startup events. The PQ diagnosis method depends on the change in the behavior of the voltage waveform by monitoring its variance. Chunga et al. (2007) developed a PQ diagnosis system (PQDS) based on available data from an existing PQ monitoring system. The PQDS which is a GUI based software diagnosed PQ disturbance data stored in the related PQ Server in order to identify the types, sources and causes of the disturbance. From the study conducted, it is noted that the PQDS is only able to diagnose voltage sags and harmonics and not able to diagnose multiple PQ disturbances in non-stationary waveforms. In real situations, many PQ disturbances are non-stationary and occur in multiple forms. In a related study, the performance of two classification methods for diagnosing the causes of PQ disturbances was evaluated by Bollen et al. (2007). The first method based on expert system and deterministic classification is compared with the second method based on SVM and statistical classification. The list of underlying causes of disturbances being considered in this study includes energizing, non-fault interruption, fault interruption, transformer saturation due to fault, induction motor starting, transformer saturation followed by protection operation, single stage dip due to fault and multistage dip due to fault.

The results of the study showed that the expert system and the SVM gave diagnosis accuracies of 97 and 92.1%, respectively for diagnosing a total of 962 disturbance data. Ismail et al. (2009) also applied SVM to classify the causes of voltage sags. Two kernels functions were used, namely: the radial basis function (RBF) and 'polynomial function' for the SVM. Based on the result of the study, it was found that the SVM-polynomial kernel performed better compared to the SVM-RBF kernel in classifying the causes of voltage sags. In this research, a novel and practical PQ diagnosis method is proposed by classifying the causes of the short duration disturbances as either permanent or non-permanent fault. The causes due to permanent faults will be further categorized as network faults and faults in the customer's installations. The non-permanent faults will be categorized either as transient and incipient faults. These disturbance causes are considered more practical in the daily operation of distribution networks. The aim of this paper is to evaluate the accuracy of the widely used artificial intelligence techniques, namely: rule base classifier (RBC) and support vector regression (SVR) in developing this PQ diagnosis method. The RBC is the most preferred technique for performing diagnosis due to its simplicity and practicality and has been developed in Faisal et al. (2011).

MATERIALS AND METHODS

Application of S-transform for identifying and diagnosing the voltage disturbances

The S-transform (Pinnegar and Mansinha, 2003) is used to extract features for identifying the short duration voltage disturbances and causes of the disturbances which may be due to either permanent or non-permanent faults. Here, two S-transform indices, namely: the S-transform magnitude-time voltage (STMV) and the ST frequency-time voltage (STFV) (Faisal et al., 2011) are used as features to categorize the types of network faults described in Figure 1. The STMV are the maximum values of the elements present in the column of the S-matrix while the STFV are the change in values of the frequency resolutions in the S-matrix. Here, the S-matrix gives the output of the S-transform in the form of $M \times N$ matrix in which M are the rows pertain to frequency and N are the columns pertain to time (Faisal et al., 2011). Each element of the S-matrix is a complex number. The information in the S-matrix can be plotted as time-frequency contours. Features of a disturbance signal are extracted from the S-transform analysis in terms of time-frequency

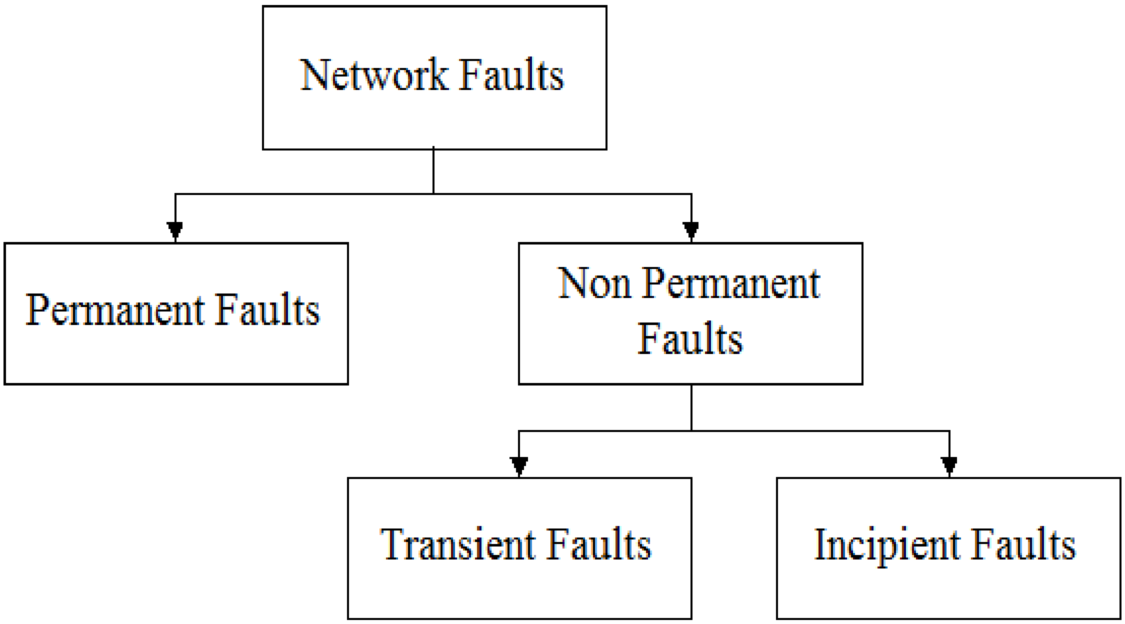

Figure 1. Categories of network faults.

representation (TFR) curve or S-transform contour that represents the energy distribution at different frequency bands over a certain period of time. The magnitude of the ST contours can be extracted from the S-matrix by isolating the maximum values of the elements present in the column of the S-matrix. These maximum values are named as the STMV features. The STMV feature for the red phase is given as:

$$\overline{S_R V_{i,j}} = \frac{|f|}{\sqrt{2\pi}} \int_{-\infty}^{\infty} v_R(t) e^{-\frac{(t-\tau)^2}{2}} e^{-i2\pi ft} dt \tag{1}$$

Where $\overline{S_R V_{i,j}}$ is the S-matrix for voltage, v_R, i = 1………N, number of columns and j = 1………M, number of rows.

The STMV for the red, yellow and blue phases which are the maximum values in all the columns of the S-matrix are given as:

$$\overline{V_{STMVR}} = \max(\overline{S_R V_i}) \tag{2}$$

$$\overline{V_{STMVY}} = \max(\overline{S_Y V_i}) \tag{3}$$

$$\overline{V_{STMVB}} = \max(\overline{S_B V_i}) \tag{4}$$

Next, the integrity of STMV is evaluated against the RMS using a scatter plot. The minimum STMV values for 215 numbers of voltage sags data are calculated and plotted on a scatter plot and are compared with the minimum values of the RMS voltage magnitudes. All the values of the voltage sags meet the definition of voltage sags based on the IEEE 1159 standard (2009) in which voltage sag values are from 10 to 90% of the nominal voltage. It was found that the range of STMV values to detect voltage sags are from 12 to 95% of the nominal STMV value. This STMV range of values is then used in detecting as well as for extracting features of voltage sags. The duration of voltage sags based on the STMV values are evaluated against the duration of voltage sags detected using the RMS technique. According to the IEEE 1159 standard (2009), the duration of voltage sag is the duration when the RMS voltage sagged below 90 to 10% of the nominal voltage and then recovers back above 90% of the nominal voltage after the cause of the sag is isolated. Using the STMV, the duration of voltage sag is the duration when the value of the STMV sagged below 95 to 12% and recovers back above 95% once the cause of the voltage sag is isolated. Therefore, the duration calculated from the STMV values are used for extracting feature of a voltage sag. To evaluate the accuracy of the STMV in detecting voltage swell, it is also compared with the RMS voltage values using a scatter plot. The minimum/maximum STMV values for 31 numbers of voltage swell data are calculated and plotted on a scatter plot and both the minimum and maximum values of the RMS voltage magnitudes are plotted in the same figure. All the values of the RMS voltage swells meet the standard voltage swell value which is above 110% of the nominal voltage. The range of the STMV values to detect voltage swell are above 117%. This STMV values is then used for detecting voltage swell.

According to the IEEE 1159 standard (2009), the duration of a voltage swell is the duration when the RMS voltage increases above 110% of its nominal voltage and recovers back when the voltage is below 110% of its nominal voltage after the cause of the voltage swell is isolated. The duration of a voltage swell is determined when the STMV value increases above 117% and recovers back when the STMV value is below 117% once the cause of the voltage swell is isolated. Therefore, the duration calculated from the STMV values are used for detecting as well as for extracting features of voltage swell. From the STMV values, four features denoted by F1, F2, F3 and F4 are selected for detecting short duration voltage disturbances such voltage sag and swell. The detailed descriptions of these features are described as shown in Table 1. The range of values for features F1 and F2 are based on the time duration of the STMV in detecting voltage sags and swells which are the values below 0.95 and above 1.17 per unit, respectively. The range of

Table 1. Description of features based on the STMV values.

Features	Description
F1	Duration (ms) of the STMV value between 0.12 to 0.95 per unit.
F2	Duration (ms) of the STMV value above 1.17 per unit.
F3	The minimum STMV values between 0.12 to 0.95 per unit.
F4	The maximum STMV values above 1.17 per unit.

values for features F3 and F4 are based on the minimum and maximum values of the STMV in detecting voltage sags and swells, respectively. Thus, voltage sags and swells are characterized based on the STMV features (F1, F2, F3 and F4) described in Table 1. The second set of features is based on the ST frequency-time voltage (STFV) plot which indicates the changes in the frequency resolutions. For extracting the features of disturbances such as transients and waveform distortions, the STFV is developed based on the values of the frequency resolutions in the S-matrix. The values of the STFV will indicate the changes in the system frequency. For the derivation of the STFV index, consider the STFV for the red phase which is given by:

$$\overline{S_R\, V_{i,j}} = \frac{|f|}{\sqrt{2\pi}} \int_{-\infty}^{\infty} v_R(t) e^{-\frac{(t-\tau)^2}{2}} e^{-i2\pi ft} dt \tag{5}$$

Where $\overline{S_R V_{i,j}}$ is the S-matrix for voltage, v_R, i = 1………N, number of columns and j = 1………M, number of rows.

Considering the vectors of the maximum value for all the rows in the S-matrix for the voltages of all the three phases, the STFV for the red, yellow and blue phases are derived as follows:

$$\overline{V_{STFVR}} = \max(\overline{S_R V_j}) \tag{6}$$

$$\overline{V_{STFVY}} = \max(\overline{S_Y V_j}) \tag{7}$$

$$\overline{V_{STFVB}} = \max(\overline{S_B V_j}) \tag{8}$$

To systematically categorize the types of network faults, two new features, F5 and F6 are derived from the STFV. Feature F5 is the sum of the standard deviations $STDV_R$, $STDV_Y$ and $STDV_B$ for the red, yellow and blue phase voltage waveforms, respectively. The equation for feature F5 is derived as follows:

$$F5 = \sqrt{\left[STDV_R^2 + STDV_Y^2 + STDV_B^2\right]} \tag{9}$$

The next feature, F6, is the difference between the maximum and minimum values of the STFV plots. The equation for feature F6 is derived as follows:

$$F6 = \sqrt{\left[MAXV_R^2 + MAXV_Y^2 + MAXV_B^2\right]} \tag{10}$$

Where $MAXV_R = \max(STFV_R) - \min(STFV_R)$,

$MAXV_Y = \max(STFV_Y) - \min(STFV_Y)$, and

$MAXV_B = \max(STFV_B) - \min(STFV_B)$

The features, F5 and F6 are used for identifying the causes of the short duration voltage disturbances such as voltage sag and swell. To extract the features, 105 numbers of data which comprised of both voltage sags and voltage swells were used. The actual causes of the voltage sags and swells were known earlier based on correlation done with the power utility reliability databases. Once the causes are known, the respective values of the features F5 and F6 were calculated and plotted on a scatter plot. From the scatter plots, the ranges for feature, F5 to differentiate between permanent faults and non-permanent faults were identified. It is noted that the feature F5 to classify permanent faults and non-permanent faults has values greater than 0.100 and less than 0.100, respectively as shown in Table 2. Later, the non-permanent fault are further classified either as transient and incipient faults. Similar methodology was applied for feature F6. The values of feature F6 for 105 numbers of short duration disturbance data were calculated and plotted on as a scatter plot. From the scatter plot, the ranges for feature F6 for classifying permanent faults and non-permanent faults are greater than 0.400 and less than 0.400, respectively as shown in Table 3. The same features, F5 and F6, developed earlier for detecting permanent and non-permanent faults are now calculated for the incipient fault waveforms. After the non-permanent faults are detected, the respective values of the features F5 and F6 are calculated and plotted on a scatter plot. From the scatter plots, the ranges for feature F5 to differentiate between transient and incipient faults are identified. The transient and incipient faults are detected such that if the features meet the specific data ranges for incipient fault, then it is considered as an incipient fault. If the data range does not meet the limits of incipient fault, then the fault is categorized as a transient fault. The summary of all the F5 ranges to detect transient and incipient fault is shown in Table 4. Similar procedure was applied for feature F6.

The range of values of feature F6 for detecting transient and incipient fault is shown in Table 5. All these feature values are used as inputs to the RBC and SVR techniques.

Power quality diagnosis using rule based classifier and support vector regression

PQ diagnosis was developed using the S-transform and applied to two artificial intelligence techniques that is, the RBC and the SVR techniques. The process flowchart for PQ diagnosis using the RBCs is shown in Figure 2 in which it begins with recording of disturbance data using the on-line PQ management system. These data are then processed using the S-transform to extract the features that characterize the short duration disturbances. These features are then applied to three RBCs in which the first RBC classifies the types of short duration voltage disturbances either as voltage sag/swell or other types of PQ disturbances, while the second RBC diagnoses the cause of sag/swell as either due to permanent or non-permanent faults. The third RBC than further classifies the non-permanent fault as either transient or incipient fault. And the final result of the RBC is the cause of

Table 2. Feature F5 for classifying permanent and non-permanent faults.

Feature	Description	Permanent fault	Non-permanent fault
F5	Square root of the sum of the standard deviations (std) for STFV.	F5>0.100.	F5<0.100.

Table 3. Feature F6 for classifying permanent and non-permanent faults.

Feature	Description	Permanent fault	Non-permanent fault
F6	Square root of the difference between the maximum and minimum values of the STFV.	F6>0.400	F6<0.400

Table 4. Feature F5 for detecting transient and incipient faults.

Feature	Description	Incipient fault	Transient fault
F5	Square root of the sum of the standard deviations (std) for STFV	0.00<F5<0.0270	0.0270<F5<0.100

Table 5. Feature F6 for detecting transient and incipient faults.

Feature	Description	Incipient fault	Transient fault
F6	Square root of the difference between the maximum and minimum values of the STFV.	0.00<F6<0.300	0.300<F6<0.400

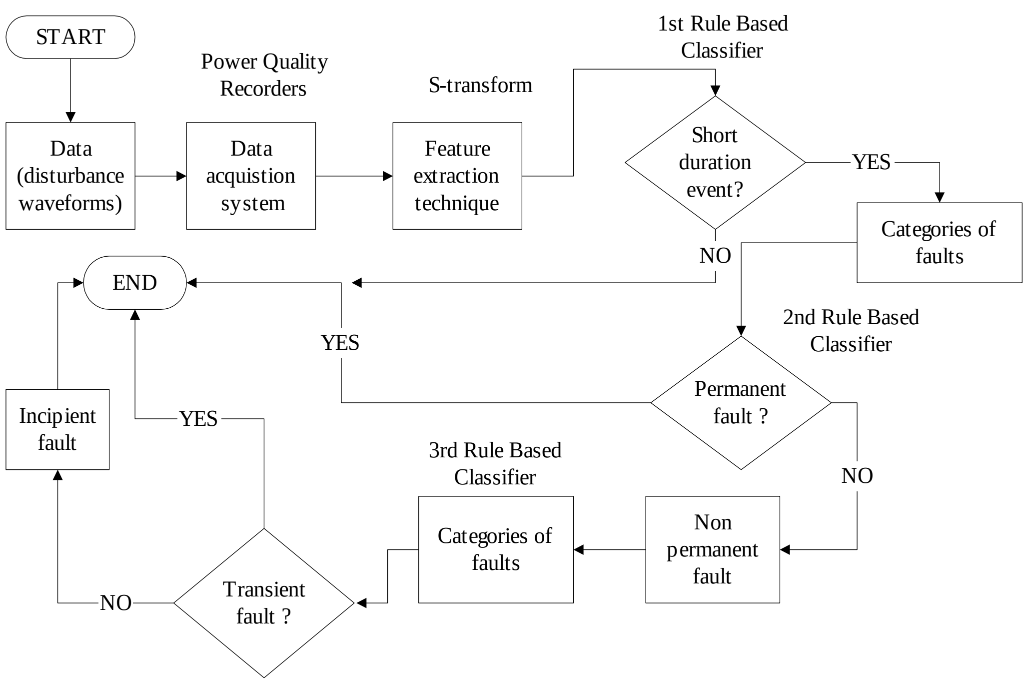

Figure 2. Flowchart for PQ diagnosis based on S-transform and RBC.

Table 6. The first level RBC for classifying short duration voltage disturbance.

Rules	Description
R1	If (F1>0) and (F3 <0.95), then the signal is detected as voltage sag.
R2	If (F2>0) and (F4 >1.17), then the signal is detected as voltage swell.
R3	If (F2>0) and (1.032 < F4 <1.17), then the signal is detected as short duration voltage disturbance due to incipient fault.

Table 7. The second level RBC for classifying permanent and non-permanent faults.

Rules	Description
R4	If (F5>0.100) and (F6>0.400), then the cause was due to a permanent fault.
R5	If (F5<0.100) and (F6<0.400), then the cause was due to a non-permanent fault.

Table 8. The third level RBC for classifying incipient and transient faults.

Rules	Description
R6	If (0.0270<F5<0.100) and (0.300<F6<0.400), then the cause was a transient fault.
R7	If (0.000<F5<0.0270) and (0.000<F6<0.300), then the cause was due to an incipient fault.

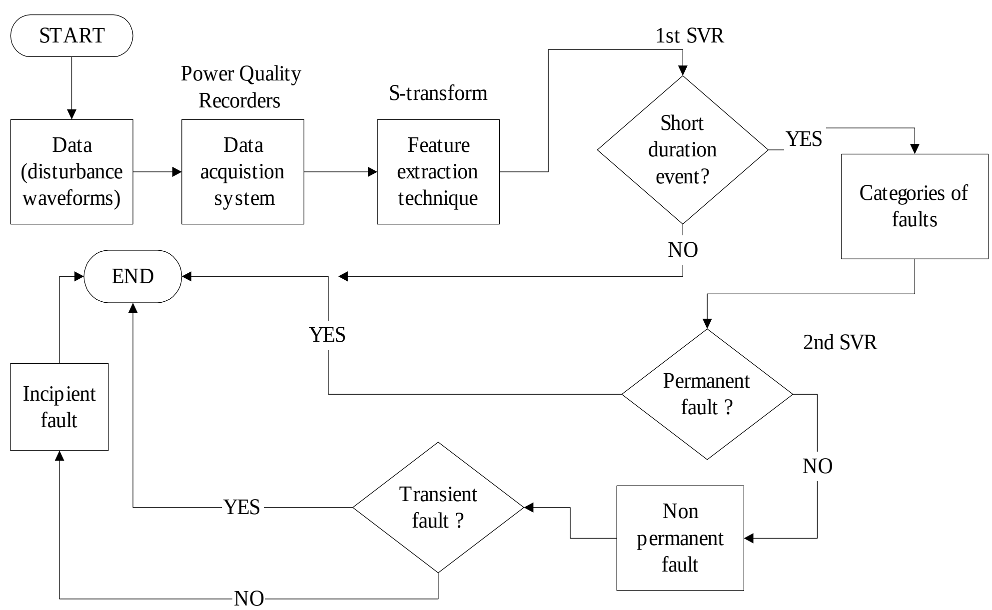

Figure 3. Flowchart for PQ diagnosis based on S-transform and SVR.

voltage sag/swell which is due to either permanent faults, transient faults or incipient faults. All the rules for the three RBCs are developed based on the features defined in Tables 1 to 5. The details of the first, second and third rules for the RBCs are explained in Tables 6, 7 and 8, respectively. The overall process flowchart for PQ diagnosis using the SVR based S-transform is shown in Figure 3 which begins with the recording of disturbance data using the on-line PQ management system (PQMS). These data are then processed using the S-transform to extract the features that characterize the short duration disturbances and these features are then applied to two SVR.

Table 9. Description and values of the parameters for the SVR.

Parameters	Descriptions	Values
γ (gam)	This is the regularization parameter, determining the trade-off between the fitting error minimization and smoothness.	10
σ^2 (sig^2)	This is the bandwidth of the RBF Kernel.	0.2

Table 10. Description of the short duration voltage disturbance data to be diagnosed.

Type of short duration voltage disturbance	Cause of voltage disturbance	Number of data sets
Voltage sag/swell	Permanent fault	121
Voltage sag/swell	Non permanent fault (transient fault)	98
Voltage swell	Non permanent fault (incipient fault)	50

Table 11. Results of the first RBC for detecting short duration voltage disturbances.

Type of short duration voltage disturbance	Number of data sets	Correct detection	Wrong detection	Accuracy in detection (%)
Voltage sag and swell	121	121	0	100.0
Voltage sags	98	98	0	100.0
Voltage swell	50	50	0	100.0

The first SVR classifies the types of short duration voltage disturbances, while the second SVR diagnoses the causes due to permanent or non-permanent faults. The second SVR then further classifies the non-permanent fault as either transient or incipient fault. The final results of the SVR will determine the causes of the short duration voltage disturbances and whether it was due to a permanent fault, transient fault or incipient fault.

The kernel selected for the SVR is the RBF kernel. In training the SVR, two extra parameters are needed in which the details and values are explained in Table 9.

RESULTS AND DISCUSSION

The proposed PQ diagnosis method developed based on the modular RBC and SVR is tested for identifying the causes of short duration voltage disturbances which may be due to either permanent or non-permanent faults. For non-permanent faults, the developed RBC and SVR are then tested for identifying the causes of short duration voltage disturbances which may be due to either transient or incipient faults. The performance of the proposed PQ diagnosis using the RBC and SVR is evaluated with 269 short duration voltage disturbance data obtained from the PQMS in Malaysia as shown in Table 10. The data comprises of 121, 98 and 50 voltage sag and swell data caused by permanent, non-permanent transient and incipient fault, respectively. The causes of the disturbance data shown in Table10 were known and validated by the existing reliability database provided by the power utility, Tenaga Nasional Berhad.

PQ diagnosis using the rule based classifier based S-transform

The results of the first RBC for detecting short duration voltage disturbances are shown in Table 11. Based on the results in Table 11, the first RBC successfully detect the various short duration voltage disturbances which are voltage sag, voltage swell and combined sag and swell with an accuracy of 100%. The results of the second and third RBC for diagnosing the causes of short duration voltage disturbances as to whether the disturbance is caused by a permanent fault and non-permanent fault categorized further as either incipient or transient fault are shown in Table 12. The results in Table 12 showed that the second and third RBCs successfully diagnosed the causes of the short duration voltage disturbances with an average accuracy of 95.8%. Overall, there are 2 errors in diagnosing permanent faults, 3 errors in diagnosing transient faults and 4 errors in diagnosing incipient faults. The errors in the diagnosis of permanent and

Table 12. Results of the second and third RBCs for diagnosing the causes of voltage disturbances.

Type of network fault	Number of data sets	Correct diagnosis	Wrong diagnosis	Accuracy in diagnosis (%)
Permanent fault	121	119	2	98.35
Non permanent fault (transient fault)	98	95	3	96.94
Non permanent fault (incipient fault)	50	46	4	92.00

Table 13. The classes of short duration voltage disturbances to be classified by the first SVR.

Types of power quality disturbances	Classes
Voltage sag	C1
Voltage swell	C2
Voltage swell due to incipient fault	C3

Table 14. The classes of faults to be classified by the second SVR.

Types of faults	Classes
Permanent fault	C4
Non-permanent fault	C5
Incipient fault	C6
Transient fault	C7

Table 15. Features arrangement for prediction of classes of PQ disturbances.

Data number	F1	F2	F3	F4	Class
Data 1	65	0	0.65147	1.00340	C1
Data 2	0	351	1.00067	1.27632	C2
Data 3	0	15	1.01241	1.04566	C3

non- permanent faults are due to the feature values which are not within the specified range of feature values. The numerical results obtained with actual PQ data recorded in a power distribution system indicated that the proposed PQ diagnosis method is effective in diagnosing the causes of the disturbances which may be due to permanent faults, non-permanent faults categorized as either incipient or transient faults.

PQ diagnosis using the support vector regression based S-transform

The performance of the SVR based S-transform is dependent on the training database which was developed based on analyses performed on 342 number of short duration voltage disturbance data with known causes. These voltage disturbance data are different from the 269 data used for testing both the RBC and SVR. The measurement data included a short pre-fault waveform (approximately 6 cycles long) followed by the actual disturbance and a post fault waveform (approximately 10 cycles). The description of the classes of the power quality disturbances and types of faults to be predicted by the SVR based S-transform are shown in Tables 13 and 14, respectively. The first step in the experiments was to extract all the six features using the S-transform for the 342 numbers of training data and to rearrange the features using the format in Table 15 in order to predict the classes of the short duration voltage disturbances. Table 16 shows examples of three PQ data that signify causes due to permanent fault (C4), non-permanent fault due to transient

Table 16. Features arrangement for prediction of causes of PQ disturbances.

Data number	F1	F2	F3	F4	F5	F6	Class
Data 1	65	0	0.65147	1.00340	0.252	0.657	C4
Data 2	0	351	1.003	1.122	0.065	0.354	C5 + C7
Data 3	0	15	1.013	1.042	0.012	0.265	C5 + C6

Table 17. Results of the first SVR for detecting short duration voltage disturbances.

Type of short duration voltage disturbance	Number of PQ data	Correct detection	Wrong detection	Accuracy in detection (%)
Voltage sag and swell	121	121	0	100.0
Voltage sags	98	98	0	100.0
Voltage swell	50	50	0	100.0

fault (C5 + C7) and non-permanent fault due to incipient fault (C5 + C6). The features for the other 339 numbers of training data would also be calculated and arranged in the same table. The results of testing the RBF SVR with 269 samples of PQ disturbance data with known causes are shown in Tables 17 and 18. The actual causes of the voltage disturbances were verified based on the correlation done with the existing PQ database provided by the Tenaga Nasional Berhad. Based on the results of the first SVR shown in Table 17 for detecting short duration voltage disturbances, the first SVR successfully detected the various classes of short duration voltage disturbances which are voltage sag, voltage swell and combined sag and swell with accuracies of 100%. From Table 18, the results of the second SVR for diagnosing the causes of voltage disturbances which may be due to permanent and non-permanent faults, give average accuracy of 95.04 and 89.43%, respectively.

There are 6, 7 and 7 errors in diagnosing the permanent, transient and incipient faults, respectively. The errors in predicting the permanent and non-permanent faults are due to the low feature values which are not within the specified range of feature values. Comparing the PQ diagnosis results of the RBC and the SVR, it is noted that the RBC performs better than the SVR with average prediction accuracy of 95.8% for RBC and 91.3% for SVR. The fact that RBC gives better accuracy than SVR may be due to the fact that RBC does not require training unlike SVR in which its accuracy depends on its training performance.

Performance comparison of the RBC and SVR in PQ diagnosis

To further evaluate the effectiveness of the PQ diagnosis method using the S-transform based RBC and the S-transform based SVR, a comparison is made with the previous methods for diagnosing the causes of voltage sags using the RMS based RBC (Styvaktakis et al., 2002) and the discrete wavelet transform (DWT) based SVM (Ismail et al., 2009). Table 19 shows a comparison on the results of the four PQ diagnosis methods in terms of percentage accuracy. The first three methods diagnose the causes of short duration voltage disturbances due to permanent and non-permanent faults while the fourth method developed by Ismail et al. (2009) focused only on diagnosing the causes due to permanent fault. From the results in Table 19, the proposed S-transform based RBC gives the most accurate PQ diagnosis with an accuracy of 96.4%, followed by the S-transform based SVR which gives diagnosis accuracy of 92.2%. The RMS based RBC and the DWT based RBC give diagnosis accuracies of 90.6 and 84.8%, respectively. The proposed S-transform based RBC and S-transform based SVR PQ diagnosis method which uses the S-transform for feature extraction accurately identified all the PQ disturbance signatures. The RMS based method averages all the values for the voltage waveforms and thus gives inaccurate diagnosis results. The DWT also cannot yield all the features accurately under noisy environment, thus gives inaccurate results. The effectiveness of the RBC in performing diagnosis is due to the fact that it is based on the well-defined rules in diagnosing the causes of voltage sags. However, the support vector machine (SVM) heavily depends on the training process, during which the support vectors are adaptively changed according to specific learning rules until a certain criterion is met.

In order for the SVM to generalize well after being trained, the training pairs used in the training process have to be chosen to be sufficiently representative.

Conclusion

A comparative study for PQ diagnosis is presented using

Table 18. Results of PQ diagnosis by the second SVR.

Causes of disturbance	No. of data	Correct prediction	Wrong prediction	Accuracy in prediction (%)
Permanent fault	121	115	6	95.04
Non-permanent fault (transient fault)	98	91	7	92.86
Non-permanent fault (incipient fault)	50	43	7	86.00

Table 19. Performance comparison of various PQ diagnosis methods.

PQ Diagnosis methods	No. of PQ data	Correct diagnosis of non-permanent fault (%)	Correct diagnosis of permanent fault (%)	Average accuracy (%)
Proposed S-transform based RBC	269	94.47	98.35	96.4
Proposed S-transform based SVR	269	89.43	95.04	92.2
RMS based RBC (Styvaktakis et al., 2002)	269	96.7	84.5	90.6
DWT based SVM (Ismail et al., 2002)	269	N/A	84.8	84.8

N/A – Not applicable.

the S-transform based RBC and S-transform based SVR techniques. The S-transform analyses the changes in the system frequency and voltage magnitudes during the occurrence of network faults and extracts features of the faults. The RBC and SVR are then used to predict the causes of short duration voltage disturbances which may be due to either permanent or non-permanent faults. The RBC and SVR are further developed to predict either transient or incipient faults. Based on the test results, the RBC gives the most accurate results in PQ diagnosis compared to SVR and therefore proven to be very effective in diagnosing the causes of short duration voltage disturbances. In addition, the S-transform gives better performance compared to the RMS and DWT techniques for extracting input features to the RBC and SVR. Such an accurate PQ diagnosis method using the S-transform based RBC can provide immediate information for utility engineers to initiate necessary corrective actions to rectify the system problem, prevent outages and reduce down times.

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