A NEW PROTECTION PATTERN FOR DISTRIBUTION SYSTEM POWER QUALITY TRAILS PREDICTION AND CLASSIFICATION

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Abstract: *This paper displays a novel protection scheme of salp swam optimization (SSO) and artificial neural network (ANN) for distribution system power quality (PQ) events prediction and classification. In the proposed approach, ANN is utilized in two phases with the ultimate objective of prediction and classification of the PQ events. In first phase, ANN is utilized for perceive the system signal healthy or unhealthy condition under different circumstances. In second phase, ANN plays out the classification of the unhealthy signals to recognize the right PQ event for assurance. Here, the second phase ANN learning method is upgraded by utilizing the SSO in context of the minimum error objective function. These proposed methods play an assessment procedure to ensure the system and arrange the correct PQ event which occurs in the distribution system. At that point, the proposed work is completed in the MATLAB/Simulink platform and the execution is evaluated by using the examination, at different systems like SSA-ANN, MUSIC-ANN, GA-ANN. This method gets a handle on that the joined execution of ANN-SSO is more achievable in power quality events prediction and classification.*

Keywords: *Protection scheme, ANN, SSO, XCF, distribution system, power quality events, Feature extraction, prediction, classification*

1. INTRODUCTION

The power quality (PQ) is a vital factor for electric power utilities and its clients thus the exploration on protection scheme is increasing more enthusiasm for late years. Voltage sag, swell, momentary interruption, flicker, notch, transients, and harmonics are a portion of the power line events. These events are the real causes which debase the quality of electric power in the system [1]. These events may likewise prompts malfunctions, instabilities, reduced lifetime, failure of electrical equipment and so on. These events are expected to distinguish before the protection move could be made to restrict the PQ events [2]. So as to decide the sources and reasons for events, the PQ events are recognized and characterized into various kinds which are the vital issue in the protection scheme inquire about. The real prerequisite in assurance plot inquire about is the capacity to perform programmed PQ monitoring and data analysis [3]. In such manner, the most vital piece of the summed up PQ event classification system is the feature extraction and classification in which the PQ occasion forecast requires the feature extraction from the disturbances [4]. For this reason, spectral analysis using discrete fourier transform (DFT) and fast fourier transform (FFT) [5, 6] have been connected. Be that as it may, due to the non-stationary nature of the PQ occasions, such transforms are not powerful in distinguishing the disturbance waveforms. To beat the drawbacks of both DFT and FFT, the wavelet transform (WT) has been broadly utilized. Since the wavelet transformation can dissect the distinctive PQ Problems at the same time in both time and frequency domains [7, 8]. Be that as it may, it shows a few burdens like excessive computation, sensitivity to noise level and the dependency of its accuracy on the picked premise wavelet.

With respect to event and characterization of the sort of the aggravation [9–11], in many papers fuzzy rules are utilized to decide. In such techniques, an extensive number of contributions to the fuzzy system increment the right distinguishing proof rate of the aggravations. In any case, the disadvantage is that it likewise builds the strategy unpredictability and reductions its speed. Be that as it may, for the forecast of multiple PQ events no consideration has been paid. Obviously, the diverse strategies, for example, S-transform [12], discrete wavelet transform and artificial neural network with fuzzy logic [13], Hilbert and Clarke transform [14], S-transform and TT-transform [15], multi wavelet transform based neural network [16], S-transform and fuzzy expert system [17], modified S-transform and particle swarm optimization [18], wavelet packet transform [19] have been introduced for the for the prediction and classification of PQ events. All the previously mentioned systems can distinguish the PQ occasions however it requires expansive number of samples and henceforth the unpredictability of the algorithm is sufficient [20]. In this paper, a novel protection scheme of ANN with SSO is used to identify and order the single and multiple PQ events in the distribution system. In this paper, a novel protection scheme of ANN with SSO is utilized to detect and classify the single and multiple PQ events in the distribution system. The proposed technique is clearly described in detail. The remainder of this article is organized as follows; the recent research work and the background of the research work are discussed in Section 2. The proposed technique thorough explanation is explained in Section 3 and 4. The suggested technique achievement results and the related discussions are given in Section 5 and the paper is concluded in Section 6.

2. RECENT RESEARCH WORKS: A BRIEF REVIEW

Various research works have already existed in the literature which depended on the prediction and classification of power quality in the distribution system utilizing different methods and different viewpoints. A portion of the works is looked into here.

S. Khokhar *et al.* [21] have displayed a novel ways to deal with optimal feature selection for the classification of the PQDs keeping in mind the end goal to recognize the wellsprings of the unsettling influences. For the optimal feature selection, their approach comprises of the discrete wavelet transform (DWT) and probabilistic neural network based artificial bee colony (PNN-ABC). The feature is extracted from the disturbances utilizing DWT with multi-resolution analysis (MRA). For the classification of the PQDs, the PNN classifier was utilized. DWT-MSD based prediction and classification of ten classes of all the single power quality events joined with various PQ events has been displayed by A.P. Kubendran *et al.* [22]. For extracting the features of different disturbances, the DWT coefficients based approach for the energy contents in the diverse frequency zone and the coefficients at each level were utilized.

A smart sensor network was exhibited by L. Spirits Velazquez *et al.* [23] that permits reviewing an electrical installation non-intrusively. It conveys standard estimations and permits inspecting: PQD occasions in detail, interactions between lines, identify electrical equipment, correlate events between monitoring points. To assess an electrical system, the exhibited smart sensor network was a capable device which conceivably can identify disappointments in the SYSTEM. A productive classification approach in view of MST and ELM has been recommended by S. Zhang *et al.* [24] for classifying PQ disturbances. To enhance the adaptability of the window function, the customizable parameters were presented in MST which was more helpful to discover a tradeoff between the time and frequency resolutions. To identify and arrange control quality unsettling influence in the power framework, P. Kanirajan *et al.* [25] have displayed a novel approach utilizing radial basis function neural network (RBFNN). For the characterization of occasions, the feature extracted through the wavelet was prepared by a RBFNN.

The improvement of an organized procedure in mix with a mathematical model was introduced by M. Rodriguez-Guerrero *et al.* [26], proposed for portraying waveforms that contain synchronous PQ disturbances. It was comprehensively comprehensive because of the way it can repeat a wide number of synchronous PQD from a solitary explanatory articulation. R. Ahila *et al.* [27] have introduced a quick and productive classification strategy called the ELM algorithm for multi class power system disturbances. With no alteration, ELM could play out the multi category classification straightforwardly. The execution of ELM classifiers is enhanced by the displayed approach as far as classification accuracy by recognizing the best subset of accessible features and unravels the precarious model determination issue.

A. Background of the Research work

The review of the recent research work shows that the quality of electrical power is an important contributing factor in the distribution system and this can be achieved through continuous power quality monitoring which helps to detect, record and to protect power quality problems. However, the power line disturbances such as voltage sag, swell, harmonic distortion, notch, flicker, and transients are some of the most dominating power quality problems in the distribution system. Voltage swell and sag occur due to electrical drives starting, nearby circuit faults, or accidents which can lead to power interruptions. Use of nonlinear loads, arc furnaces, capacitor switching and lightning strikes are also the causes of power quality disturbances. These disturbances result in malfunctions, reduced life time and failure of electrical equipment. However, there are many techniques have been implemented for the detection and classification of the power quality events such as Fourier Transform, S-transform, Hilbert Huang transform, wavelet transform and so on. Fourier Transform has been applied for detecting the feature extraction but due to the non-stationary nature of the power quality disturbances, such transforms are not effective in detecting the disturbance waveforms. Wavelet transform has the capability to extract features from the signal in both time and frequency domain simultaneously. But it exhibits limitations like excessive computation, sensitivity to noise level and less accuracy. Although the above techniques are used for detecting the power quality disturbances, the complexity of the algorithm is very high due to increased number of samples required. To overcome these challenges, optimal detecting using advanced technology is required. In related works, few control techniques are presented to solve the power quality problem; the above-mentioned limitations have motivated to do this research work.

3. Proposed Protection Scheme for Distribution System from Single and Multiple PQ Events

Fig. 1 displays the proposed protection scheme of power quality events prediction and classification in the distribution system. In the proposed structure, the input power signal from the distribution system is dissected for prediction. At first, in the pre-processing phase, the normalization and segmentation processes are completed in light of the single (or) three phase event data. The recognized data is passed to the feature extraction stage which distinguishes the distinctive features of an event signal. In this phase, artificial neural network (ANN) is utilized for prediction of PQ events in view of the extracted features. Here, the single and multiple events are recognized in light of the cross correlation function (XCF). The recognized PQ events are dissected in the second phase of ANN for classification. Here, the amplitude demodulation has been utilized to recognize the envelope of single and multiple PQ events. The modulating signal may have high frequency parts so to identify high frequency segments salp swarm optimization (SSO) calculation is used. All the data so got forms the knowledge base of heuristic ANN classifier, which Classifies PQ events show in the modulated signal.

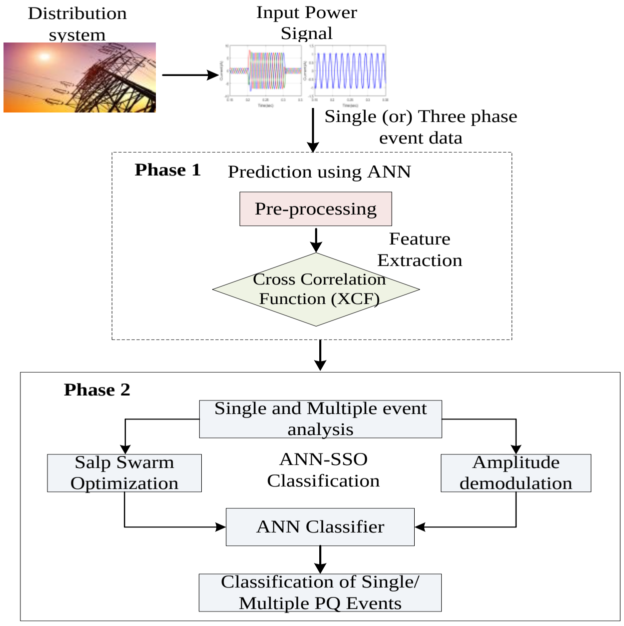

Fig. 1 Proposed protection scheme for single and multiple PQ Events

A. Generation of Single & Multiple PQ Events

In distribution system, the PQ events can be considered as single and multiple PQ events [28-30]. The single PQ event implies that it has just a single sort of PQ event in the modulated signal sag, swell, harmonics, notch, noise and so on.,. These events principally caused because of the automatic separation of load, tripping of protection devices, insulation failure, lightning and insulator flashover. Then again, multiple PQ events implies that it has in excess of one kind of PQ event, for example, sag with harmonics, swell with harmonics, sag with transient, swell with harmonics and so forth., These events are caused due to the non-linear loads, oscillations, additional energy losses and overheating. Some unsafe impacts of poor PQ events are overheating of lines, untimely maturing of equipment and appliances, mal-activity of protective equipment, motor disappointments, mistaken metering and interference with communication circuits. These are the events created in the distribution system. To detect and classify the PQ events, the proposed algorithm has been tried on real-time to demonstrate the viability. The prediction and classification assignment of PQ events by the proposed technique is depicted in detail in the accompanying area.

4. Prediction and Classification of PQ Events Based on ANN

In the proposed approach, ANN is utilized in two phases with the true objective of prediction and classification of the PQ events. In phase 1, the standard ANN is used to perceive the system signal healthy or unhealthy condition under different circumstances. In stage 2, the ANN plays out the classification of the unhealthy signals to recognize the right power quality event for protection. Here, the second phase ANN learning procedure is upgraded by utilizing the SSO algorithm in context of the minimum error objective function. The proposed protection scheme plays an assessment procedure to secure the system and classify the correct power quality event which occurs in the distribution system.

A. Phase 1: ANN Prediction

In the prediction phase, the information power signal is pre-processed which includes normalization and segmentation of single (or) three phase PQ disturbances. In the normalization procedure, all the PQ event data at various voltage levels are scaled to the per unit (p.u.) values by isolating the instant voltage values amid the event with the maximum voltage value. The segmentation process is done to build the classification accuracy of the proposed system. In the segmentation procedure, the three phase PQ events are isolated into 3 single phase PQ events at first. At that point, the section of the event signal is extracted with the end goal that the beginning of the event, span of event and end of the event are caught. The distinguished data is passed to the feature extraction stage which recognizes the distinctive features of an event signal. Here, the feature is extracted from the ANN in view of the cross correlation coefficient (XCF).

1) Modeling of Artificial Neural Network: The feed forward NN is natural for its learning and perceiving capacity, which comprises of an interconnected gathering of artificial neurons [31-33]. It is trained to play out a specific capacity by changing the estimations of connections (weights and biases) between the neurons of various layers. The ANN utilized as a part of this work comprises of input layer, hidden layer and output layer. The input layer has nodes which speak to the normalized features extracted from the deliberate event signals. In the hidden layer and in the output layer, the activation functions of sigmoid were utilized. The objective estimations of two output nodes can have the binary levels speaking to 'Healthy' (H) AND 'Fault' (F) conditions. Here, the ANN was made, prepared and actualized utilizing MATLAB/Simulink platform. The ANN was trained iteratively by limiting the execution capacity of mean square error (MSE) between the network output and the corresponding target values. The MSE work is communicated as,

$$MSE = \min \sum_{i=1}^{n} (\delta_t - \delta_o)^2 \qquad (1)$$

Where, $i = 1 \ldots n$ represents the training set index, δ_t is the target output value, δ_o is the network output of ANN. At every iteration, the gradient of execution work was utilized to alter the network weights and biases. The training would stop if any of these conditions are met. The initial weights and biases of the network were produced consequently by the program.

B. Phase 2: ANN-SSO Classification

The aim of designing phase 2 is to recognize the single and multiple PQ events show in the distribution system. To accomplish this point, XCF is utilized which ready to quantify the degree of similarity between two power signal. The kind of PQ events has been distinguished in light of the threshold value. The value of XCF coefficients so acquired has been contrasted and a present threshold value. This correlation chooses and orders whether the modulated signal at input contains a single or multiple PQ events. Keeping in mind the end goal to classify the correct PQ event, the investigation is completed between the single and multiple events. To identify the single and multiple PQ events, the amplitude demodulation is utilized. There might be a shot of high frequency components in the modulated signal. To distinguish these segments ANN second phase have been executed with demodulation techniques. In the ANN second phase, the salp swarm optimization (SSO) algorithm is utilized to upgrade the learning procedure of ANN in context of the minimum error objective function. The SSO calculation finds the high frequency components in the modulated signals. At long last, the identified events can be ordered utilizing ANN classifier which classifies the single and multiple PQ events introduce in the modulated signal.

1) Salp Swarm Optimization for Accurate Classification: The SSO is a novel algorithm for unraveling single and multi objective optimization issue proposed by S. Mirjalili [34, 35] in 2017. The fundamental inspiration of SSO is the swarming behavior of slaps when navigating and foraging in oceans. The SSO has an adaptive mechanism to abstain from stalling out into a nearby minima (or) maxima. Amid optimization process, SSO at last produces an exact optimal (or) even close to optimal arrangements. At the beginning period of optimization process, the SSO investigates the search space and after that exploits it to keep up the harmony between the exploration and exploitation.

Step 1: Initialization

In the first step of SSO, the positions of the salps are randomly initialized similar to other competing optimization techniques which is expressed as,

$$P_i = rand * (U_i - L_i) + L_i \qquad i = 1,2,\ldots..n \qquad (2)$$

Where, P_i defines the initial position of the salps, U_i and L_i represents the upper and lower bounds respectively. $rand$ represents the random numbers uniformly generated in the range of [0, 1].

Step 2: Evaluation

In this step, the objective function is evaluated based on calculating the accuracy for each classification. The accuracy is calculated as,

$$Accuracy\,(\%) = \frac{T_p + T_N}{T_p + F_N + F_P + T_N} \times 100 \qquad (3)$$

Where, T_p and T_N represents the number of correct predictions with actual class as true and false respectively. F_N and F_p represents the number of incorrect predictions with the actual class as true and false respectively.

Step 3: Updating Leader Position

The position of the leader salps is updated with respect to the food source based on the accompanying formula,

$$Pl_i = \begin{cases} F_j + R_1\left[(U_j - L_j)R_2 + L_j\right] & R_3 < 0.5 \\ F_j - R_1\left[(U_j - L_j)R_2 + L_j\right] & else \end{cases}$$

(4)

Where, Pl_i represents the position of the leader salp, F_j is the position of the food source in *jth* dimension and $R_1 - R_3$ are the uniform random numbers.

Step 4: Exploration and Exploitation

The most effective parameter in the SSO algorithm is the initial random number which makes the exploration and exploitation phases in the balanced state and it is expressed as,

$$R_1 = 2 \cdot \exp\left[-\left(\frac{4m}{I_{\max}} \right)^2 \right] \tag{5}$$

Where, m represents the current iteration and $I_{\max}$ represents the maximum number of iterations.

Step 5: Updating Follower Position

The position of the followers salp are updated based on the Newton's law of motion which is revealed as,

$$Pf_j^i = \frac{t}{2}(at + v_o) \quad \forall \geq 2 \tag{6}$$

Where, Pf_j^i represents the position of the *ith* follower salp in *jth* dimension, t is the time and v_o is the initial velocity which is assumed as zero. The time of optimization process is represented as iteration and the difference between the iterations equals 1. Then, the above eqn is formulated as,

$$Pf_j^i = \frac{1}{2}\left(Pf_j^i - Pf_j^{i-1}\right) \quad \forall i \geq 2 \tag{7}$$

From the above conditions, it is watched that exclusive two control parameters, for example, number of search salps and maximum iteration are expected to tune the qualities of the SSO algorithm. The general technique of the SSO algorithm is appeared as the flowchart in fig. 2.

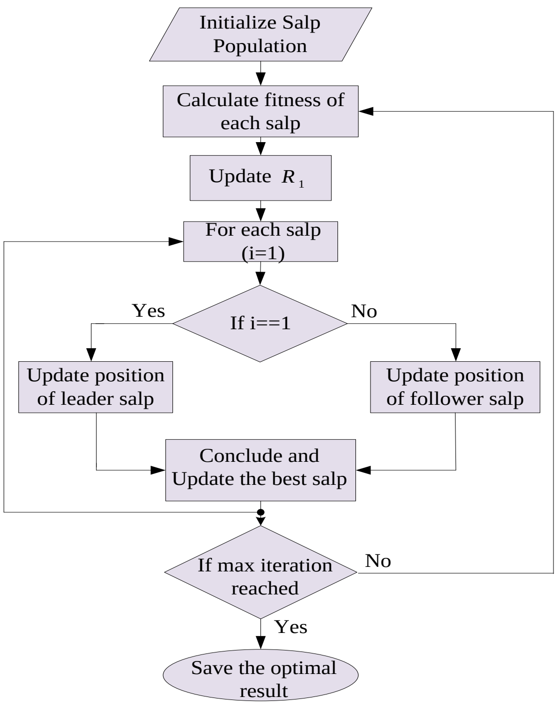

Fig. 2 Flowchart of SSO Algorithm

5. Results and Discussion

In this paper, the proposed strategy is presented for the prediction and classification of single and multiple PQ events in the distribution system. The proposed methodology is realized in MATLAB/Simulink working stage. The PQ event is broke down in both the single and three phase distribution lines and the event data is gathered. Two test cases of single and three phases are utilized with the goal that the execution of the proposed procedure is illustrated. Here, the proposed technique detects and classify the PQ events in light of the XCF of power signal. The XCF separates the power signal in light of the threshold value [28]. The choice has been taken for single and various PQ occasions in light of the limit esteem appeared in Table 1.

Table: 1 Threshold values of XCFs

XCF range	PQ event types	Threshold value
≥ 0.95	None	0.95
$\in (0.95, 0.5)$	Single	0.49
$\in (0.55, 0.10)$	Multiple	0.10
$\in (0.10, 0.01)$	Interruption	0.01

On the off chance that the threshold value is equivalent to 0.95 and the XCF is more prominent than or equivalent to 0.95, there is no event is predicted in the cycle. Here, the XCF is ascertained for the specific cycle, the event is ordered as the single or multiple events. On the off chance that the estimation of XCF is more prominent than 0.5, it is ordered as single event and it is examined. Correspondingly, if the estimation of XCF lies in the vicinity of 0.1 and 0.5, the cycle has been sorted as a multiple PQ event. Additionally, any estimation of XCF is in the vicinity of 0.1 and 0.01; the cycle has been classified as an interruption and if the estimation of cycle is under 0.01, at that point the cycle has been ordered as an outage PQ event. The proposed calculation fundamentally engaged to recognize the correct events i.e., regardless of whether it is sag, swell, sag with swell, and so on, present in the power signal.

A. Test Case 1

In this test case, the single and multiple events of single phase distribution system is broke down and assessed. The single events of the single phase current and voltage are broke down and delineated in fig. 3. The examination between the 10% sag current and voltage are showed up in Fig 3(a). Here, the sag condition is showed up in time of 0.15 to 0.2 sec and 0.3 to 0.35 sec. Likewise in voltage waveform, the sag shows up at 0.2 to 0.3 sec of time interval. After this time, the voltage goes to the typical position with no sag condition.

The correlation between the harmonic current and voltage is showed up in Fig 3(b). Here, the harmonic state of current extents from 0 to 0.03 sec. likewise, in harmonic condition of voltage ranges from 0 to 0.02 sec. After the vanishing of harmonics, the framework goes to typical operating condition. The correlation between the sag current and voltage is showed up in Fig 3(c). At the point when the system begins at heavy loads, the sag condition of current effects from 0.15 to 0.2 and 0.3 to 0.35sec. Likewise in voltage waveform, because of the heavy loads, the sag condition of voltage influences from 0.2 to 0.25sec. The correlation demonstrates that the swell current and swell voltage is showed up in Fig 3(d). Because of the short circuit in the system, the swell state of current effects from 0.2 to 0.3 sec. Likewise, the swell state of voltage fluctuates from 0.15 to 0.2sec and 0.3 to 0.35sec.

The multiple events of the single phase current and voltage is broke down and shown in fig. 4. The correlation between the 10% sag-harmonic current and voltage is showed up in Fig 4(a). Here, the sag-harmonic current is showed up in time of 0.15 to 0.2sec and 0.3 to 0.35sec. Furthermore, the sag-harmonic voltage is showed up in time of 0.2 to 0.35sec. Fig 4(b) demonstrates the correlation between the 90% sag-harmonic current and voltage. In 90% SAG-harmonic current differs from 0.15 to 0.2sec and 0.3 to 0.35sec and 90% sag-harmonic voltage ranges from 0.2 to 0.35sec. The correlation between the sag-harmonic current and voltage are showed up in Fig 4(c). Here, the sag-harmonic current extents from 0.15 to 0.2sec and 0.3 to 0.35sec. Additionally the sag-harmonic voltage shifts from 0.2 to 0.35sec. The correlation between the swell-harmonic current and voltage are showed up in Fig 4(d). Here, the present waveform begins at ordinary condition. After the sudden load diminishes, there is a disturbance in the waveform ranges from 0.2 to 0.3sec. Additionally in voltage waveform, the waveform disturbed in the scope of 0.15 to 0.25sec and 0.3 to 0.35sec. The correlation between the swell-transient current and voltage are showed up in Fig 4(e). Here, the current waveform changes from 0.2 to 0.3sec. Additionally the voltage waveform ranges from 0.15 to 0.25 and 0.3 to 0.35sec.

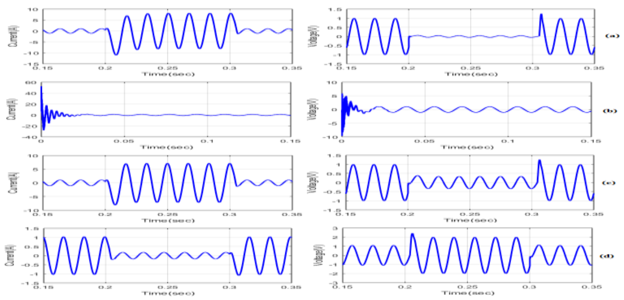

Fig. 3 Single event analysis of Single phase system (a) 10% sag current and voltage (b) Harmonic current and voltage (c) Sag current and voltage (d) Swell current and voltage.

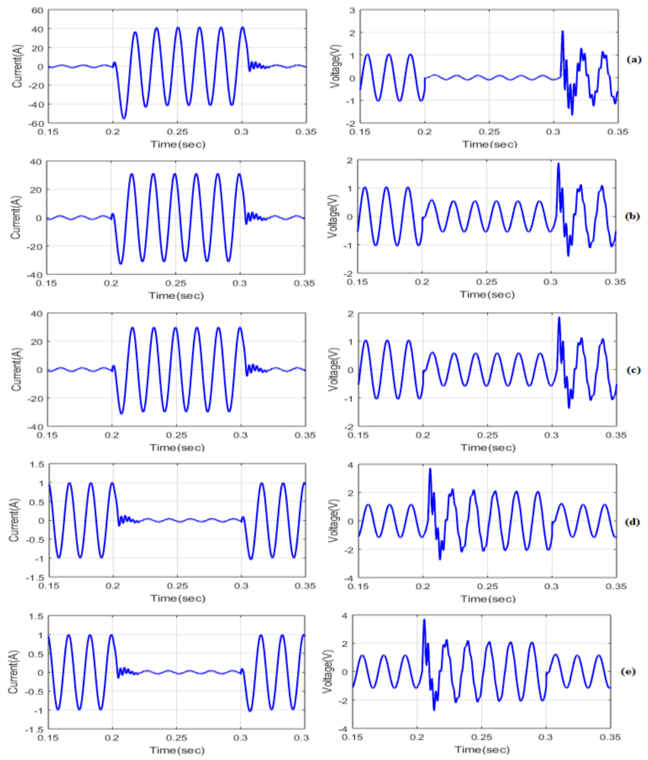

Fig. 4 Multiple event analysis of Single phase system (a) 10% sag-harmonic current and voltage (b) 90% sag-harmonic current and voltage (c) Sag-harmonic current and voltage (d) Swell-harmonic current and voltage and (e) Swell-transient current and voltage.

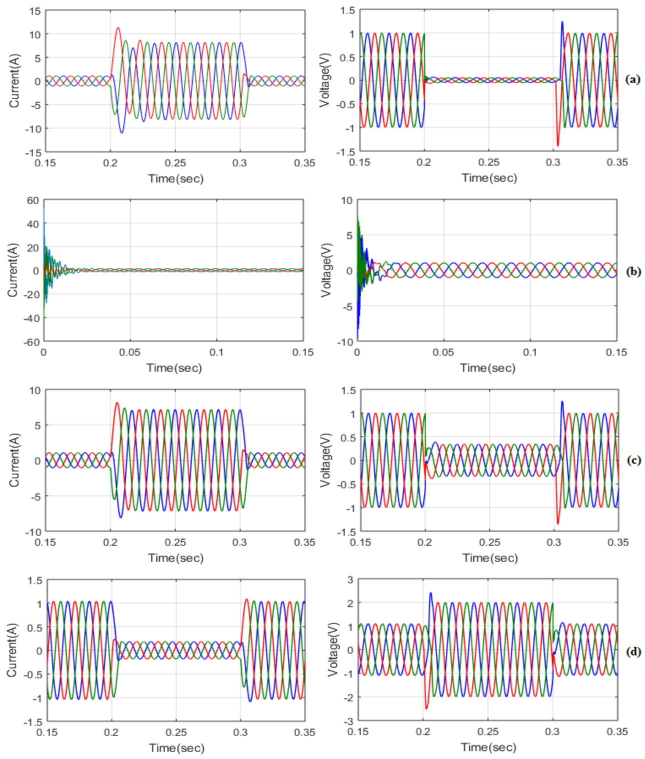

Fig. 5 Single event analysis of Three phase system (a) 10% sag current and voltage (b) Harmonic current and voltage (c) Sag current and voltage (d) Swell current and voltage.

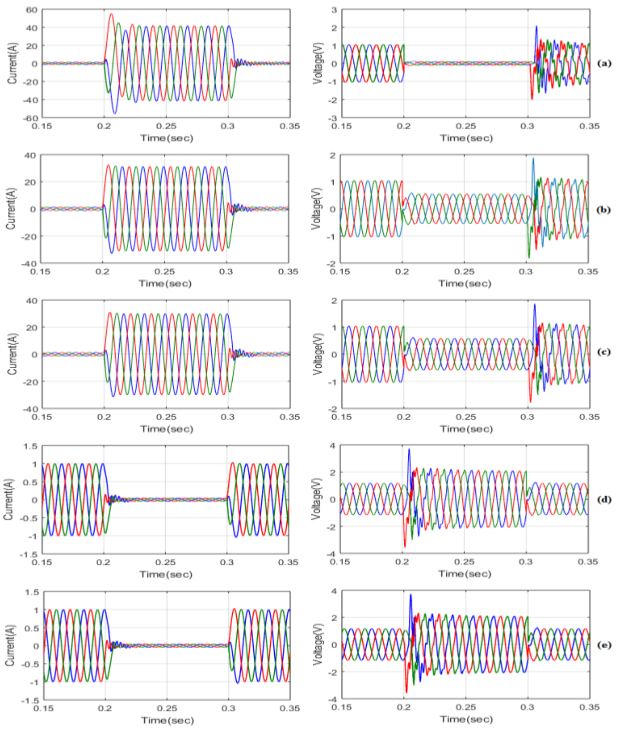

Fig. 6 Multiple event analysis of Three phase system (a) 10% sag-harmonic current and voltage (b) 90% sag-harmonic current and voltage (c) Sag-harmonic current and voltage (d) Swell-harmonic current and voltage and (e) Swell-transient current and voltage.

B. Test Case 2

In this test case, the single and multiple events of three phase distribution system is dissected and assessed. The single events of the three phase current and voltage is investigated and shown in fig. 5. The correlation between the 10% sag current and voltage are showed up in Fig 5(a). Here, the current waveform shifts from 0.15 to 0.22sec and 0.3 to 0.35sec. Additionally the voltage waveform ranges from 0.2 to 0.32sec. The examination between the harmonic current and voltage are showed up in Fig 5(b). Here, the current waveform shifts from 0.01 to 0.15sec. Likewise the voltage waveform shifts from 0.02 to 0.15sec. The examination between the sag current and voltage are showed up in Fig 5(c). Here, the sag condition for the current waveform ranges from 0.15 to 0.2sec and 0.3 to 0.35sec and the sag condition for the voltage waveform ranges from 0.2 to 0.31sec. The examination between the swell current and voltage are appeared in Fig 5(d). Here, the swell condition for the current waveform changes from 0.2 to 0.3sec. Additionally, the voltage waveform shifts from 0.15 to 0.2sec and 0.3 to 0.35sec.

The multiple events of the three phase current and voltage is dissected and represented in fig. 6. The examination between the 10% sag-harmonic current and voltage are showed up in Fig 6(a). Here, the sag-harmonic state of current waveform ranges from 0.15 to 0.2sec and 0.3 to 0.35sec. Additionally, the sag-harmonic state of voltage waveform ranges from 0.2 to 0.31sec. The examination between 90% sag-harmonic current and voltage are showed up in Fig 6(b). Here, the sag harmonic condition of current waveform fluctuates from 0.15 to 0.2sec and 0.3 to 0.35sec likewise the sag harmonic condition for voltage waveform shifts from 0.2 to 0.31sec. The correlation between sag-harmonic current and voltage are showed up in Fig 6(c). Here, the SAG harmonic condition for the current waveform ranges from 0.15 to 0.2sec and 0.3 to 0.35sec and furthermore the sag harmonic condition for the voltage waveform changes from 0.2 to 0.3sec. The correlation between the swell-harmonic current and voltage are showed up in Fig 6(d). The swell condition for the current waveform ranges from 0.2 to 0.3sec and the swell condition for the voltage waveform differ from 0.15 to 0.23sec and 0.3 to 0.35sec. The correlation between the swell-transient current and voltage are showed up in Fig 6(e). The swell transient condition for the current waveform ranges from 0.2 to 0.3sec and the swell transient condition for the voltage waveform differ from 0.15 to 0.23sec and 0.3 to 0.35sec.

The XCF of the single event voltage is dissected and delineated in fig. 7. The correlation between the 10% sag voltage is showed up in Fig 7(a). Here, the sag condition for the voltage waveform changes in the scope of 20 to 30 tests and the amplitude of waveform is 0.1 to - 0.1. The correlation between the harmonic voltage is showed up in Fig 7(b). Here, the harmonic condition for the voltage waveform ranges from 2 to 50 samples and the amplitude of waveform is 1 to - 1. The examination between the sag voltage is showed up in Fig 7(c). Here, the sag condition for voltage ranges from 20 to 30 samples and the amplitude scope of waveform is 0.4 to - 0.4. The correlation between the swell voltage is showed up in Fig 7(d). SWELL state of the voltage waveform goes is 0 to 20 tests and 31 to 50 tests and the amplitude esteem from 1.2 to - 1.2.

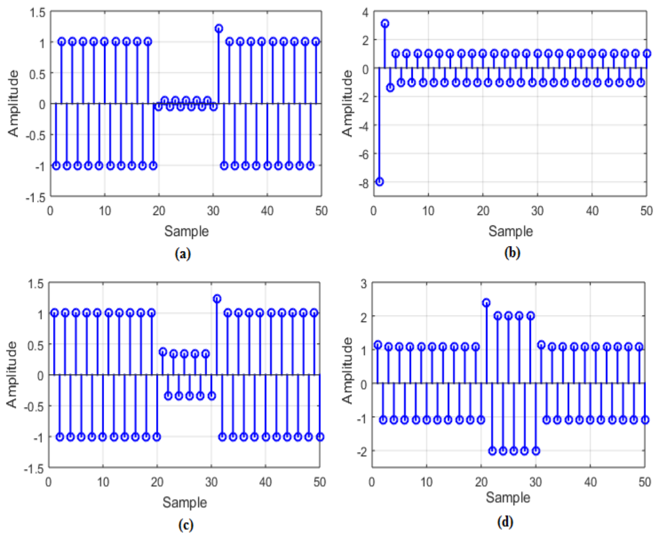

Fig. 7 XCF of single event analysis (a) 10% sag voltage (b) Harmonic voltage (c) Sag voltage (d) Swell voltage

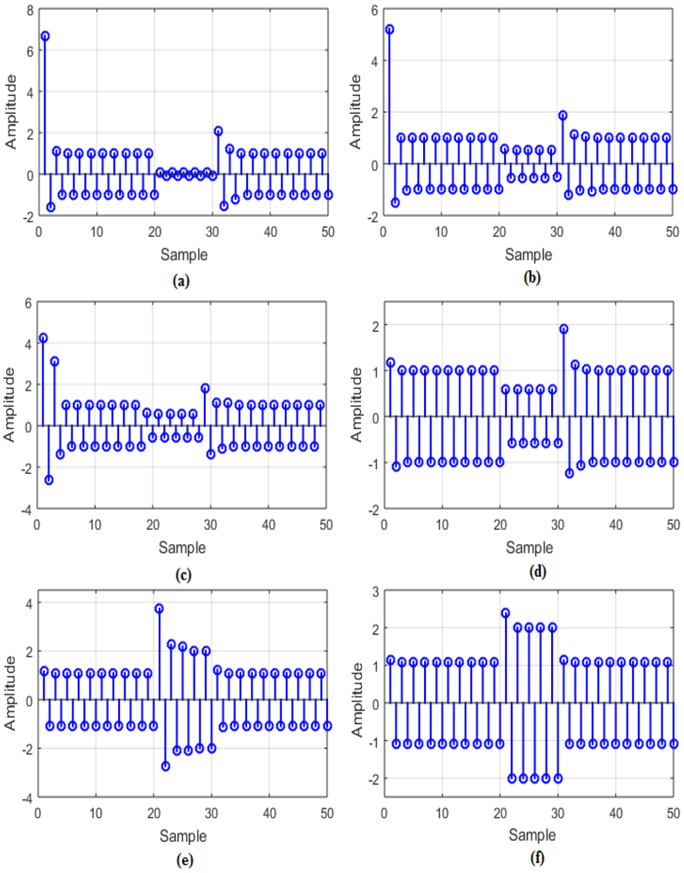

Fig. 8 XCF of Multiple event analysis (a) 10% sag-harmonic voltage (b) 90% sag-harmonic voltage (c) Sag-harmonic voltage (d) Sag-transient voltage (e) Swell-harmonic voltage (f) Swell-transient voltage

The XCF of the multiple event voltage is examined and shown in fig. 8. The examination between the 10% sag-harmonic voltage is showed up in Fig 8(a). Here, the sag harmonic state of voltage ranges from 2 to 50 samples and the amplitude esteem from 0.2 to - 0.2 and 1 to - 1. The examination between the 90% sag-harmonic voltage are showed up in Fig 8(b). Here, the sag-harmonic condition of voltage waveform ranges from 5 to 50 samples. The amplitude estimation of waveform is 1 to - 1. The examination between the sag-harmonic voltage is showed up in Fig 8(c). Here, the sag harmonic condition for voltage waveform ranges from 5 to 50 samples and the amplitude esteem from 3 to - 3 and 1 to - 1. The correlation between the sag-transient voltage is showed up in Fig 8(d). Here, the sag-transient condition for voltage waveform ranges from 0 to 30 samples and 32 to 50 and the amplitude value ranges from 0.5 to - 0.5 and 1 to - 1. The correlation between the swell-harmonic voltage is showed up in Fig 8(e). Here, the swell harmonic condition for the voltage waveform ranges from 0-20 samples and 24 to 50 SAMPLES and the amplitude value ranges from 1 to - 1 and 2 to - 2. The examination between the swell-transient voltage is showed up in Fig 8(f). Here, the swell transient condition for the voltage waveform ranges from 0-20 samples and 32 to 50 samples and the amplitude value ranges from 1 to - 1.

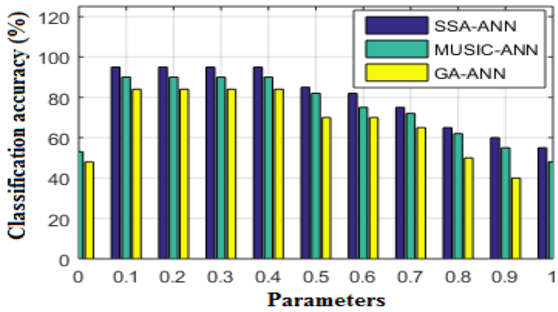

Fig. 9 Classification accuracy comparison of Proposed with Existing techniques

With a specific end goal to enhance the viability of the proposed methodology, different algorithms are presented for examination. The classification accuracy and the parameters of the proposed system are differentiated and the present techniques like MUSIC-ANN, GA-ANN is showed up in Fig. 9. When contrasting the proposed procedure with the current techniques, at that point the accuracy of the algorithm is organized in the request of SSA-ANN > MUSIC-ANN > GA-ANN. Thus, the viability of the proposed technique is demonstrated in the above request. Accordingly, the proposed algorithm brings about preferred economic impacts over the existing algorithms. In addition, it prompts top quality solution than different systems.

6. Conclusion

In this paper, a novel approach is proposed for power quality events prediction and classification which updates the protection scheme in the distribution system. In the proposed approach, ANN is used to perceive the system signal healthy or unhealthy condition in the principal phase. The second phase of the ANN is utilized for the classification of the unhealthy signals and amid this stage ANN learning procedure is upgraded by utilizing the SSO calculation. At that point, the proposed show is actualized in MATLAB/Simulink organize for exhibiting and diversions in prediction and classification of PQ event. The pervasiveness and arrangement nature of the proposed system is tried by standing out from the diverse methodologies. The simulation result shows that the proposed strategy is effective in protecting the distribution system power quality events with high precision. Likewise, the proposed method ensures the system with diminish complexity for the prediction and classification of the PQ occasion and subsequently the accuracy of the system is raised.

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