A Novel Methodology For Single/Multiple Power Quality Events Prediction And Classification: A SALRNN Technique

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Abstract- *In this paper, a novel approach for the detection and classification of single and multiple power quality (PQ) events is proposed using a Sequential Ant Lion Optimizer and Recurrent Neural Network (SALRNN) technique. In the proposed method, RNN is performed in two phases for detecting and classifying the waveform of the PQ events. In the detection phase, RNN is utilized to recognize the healthy or unhealthy condition of the system signal under various situations. Then the RNN classifies the type of PQ events in the classification phase based on the detected power signal. Here, the RNN learning procedure is enhanced by using the ALO algorithm in perspective of the minimum error objective function. These techniques have been well tested on transient, sag, swell harmonics and their combinations in real-time. To test the proposed approach, the waveforms of the PQ events are executed in MATLAB/Simulink working stage. From the simulation results, it can be seen that the proposed approach is effective for the detection and classification of single and multiple PQ events and guarantees the system with lessen complexity hence the accuracy of the system is raised.*

Keywords- Power quality, single and multiple events, RNN, ALO, voltage sag and harmonic distortion

I. INTRODUCTION

The Power Quality (PQ) research is gaining more interest in recent years due to the fact that the quality of power is an important issue for electric power utilities and its customers. The power line disturbances such as voltage sag, swell, momentary interruption, flicker, notch, transients, and harmonics are the major causes which normally degrade the quality of electric power [1]. These disturbances lead to malfunctions, instabilities, reduced lifetime, and failure of electrical equipment and so on. In order to limit the PQ disturbances in the distribution system, these disturbances need to be identified before mitigating action could be taken [2]. One of the important issues in PQ analysis is to detect and classify the disturbances into different types in order to determine the sources and causes of PQ disturbances. The major requirement in PQ research is the ability to perform automatic power quality monitoring and data analysis [3]. In this regard, feature extraction and classification are the most important part of the generalized PQ event classification system where PQ event detection requires the feature extraction from the disturbances [4]. Spectral analysis using discrete Fourier transform (DFT) and fast Fourier transform (FFT) [5, 6] have been applied for this purpose, but due to the non-stationary nature of the power quality disturbances, such transforms are not effective in detecting the disturbance waveforms. In order to avoid the disadvantages of both DFT and FFT, the Wavelet transform (WT) has been widely used for analyzing the PQ problems. Wavelet transformation has the ability to analyze different power quality problems simultaneously in both time and frequency domains [7, 8]. However, it exhibits some disadvantages like excessive computation, sensitivity to noise level and the dependency of its accuracy on the chosen basis wavelet.

In most papers, fuzzy rules are used to make decisions regarding the occurrence and classification of the type of the disturbance [9–11]. In these methods, a large number of inputs to the fuzzy system increases the correct identification rate of the disturbances, but also increases the method complexity and decreases its speed. However, no attention has been paid to the detection of combined PQ disturbances. Of course, other different methods have also been presented for the detection and classification of PQ disturbances using 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]. All above-said techniques can detect PQ disturbances but a number of samples required are large and hence the complexity of the algorithm is high enough so as not to allow it to work in real-time [20]. Here, a sequential technique of RNN with ALO 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 is 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.

II. RECENT RESEARCH WORKS:A BREIF REVIEW

Numerous research works have previously existed in the literature which was based on the detection and classification of power quality in the distribution system using various techniques and various aspects. Some of the works are reviewed here.

Novel approaches to optimal feature selection have been presented by S. Khokhar *et al.* [21] for the classification of the PQDs in order to identify the sources of the disturbances. Their approach consists of the Discrete Wavelet Transform (DWT) and Probabilistic Neural Network based Artificial Bee Colony (PNN-ABC) optimal feature selection of PQDs. DWT with Multi-Resolution Analysis (MRA) was used for the feature extraction of the disturbances. The PNN classifier was used as an effective classifier for the classification of the PQDs. A.P. Kubendran *et al.* [22] have presented DWT-MSD based detection and classification of ten classes of all the single power quality events combined with different PQ events. DWT coefficients based approach for the energy contents in the different frequency zone and the coefficients at each level were used for extracting the features of various disturbances.

L. Morales-Velazquez *et al.* [23] have presented a smart sensor network that allows inspecting an electrical installation in a nonintrusive way. It delivers standard measurements but it was not limited to them, it also allows examining: PQD events in detail, interactions between lines, identify electrical equipment, correlate events between monitoring points. The presented smart sensor network was a powerful tool to evaluate an electrical system which potentially can detect failures in the system. S. Zhang *et al.* [24] have suggested an efficient classification approach based on MST and ELM for classifying PQ disturbances. The adjustable parameters were introduced in MST to improve the flexibility of the window function which was more convenient to find a tradeoff between the time and frequency resolutions. P. Kanirajan *et al.* [25] have presented a novel approach to detect and classify power quality disturbance in the power system using radial basis function neural network (RBFNN). The feature extracted through the wavelet was trained by a radial basis function neural network for the classification of events.

M. Rodriguez-Guerrero *et al.* [26] have presented the development of a structured methodology in combination with a mathematical model, intended for describing waveforms that contain simultaneous PQ disturbances. It was broadly inclusive due to the way it can reproduce a wide number of simultaneous PQD from a single analytical expression. Fast and efficient classification method called the ELM algorithm was presented by R. Ahila *et al.* [27] for multi category power system disturbances. ELM could perform the multi category classification directly, without any modification. The presented approach aims at optimizing the performances of ELM classifiers in terms of classification accuracy by detecting the best subset of available features and solving the tricky model selection 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 prevent 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 PQ 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 PQ 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 PQ 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 PQ 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 PQ problem; the above-mentioned limitations have motivated to do this research work.

III.GENERATION OF POWER QUALITY EVENTS IN THE DISTRIBUTON SYSTEM

In this segment, different PQ events are produced in the distribution system to quantify and recognize the kind of fault and limited the fault. The PQ events are by and large named single and multiple PQ events. In the event that any one half-cycle of the modulated signal under thought has just a single kind of PQ event, at that point it is said to be a single PQ event. The modulated signal is said to be multiple PQ event, if a half cycle of a modulated signal contains voltage sag and transient. Since it would contain just sag without the transient, a similar occasion would be known as a single PQ event. Fall in the voltage waveform at the beneficiaries end for a concise interim of time alludes to the voltage sag [28]. Voltage sags are caused because of the sudden switching-on of an expansive load. A vast load implies that the device under thought draws a huge input current, because of the impedance of the line which causes an extensive voltage drop, in this way bringing about a net lessening in the voltage at the less than desirable end. The circuit which causes the event of voltage sag because of the sudden switching-on of a subjective vast load is spoken to in Fig. 1. The sudden switching operation of the switch is spoken to as S. An expansion in the voltage waveform at the beneficiaries end for a brief span of time alludes to the voltage swell. By the exchange of load from the utility source to the standby generator source, swell has been created amid the loss of utility power. If there should be an occurrence of a crisis, most facilities contain crisis generators to keep up power to basic loads. Noteworthy voltage swell is made because of sudden dismissal of loads to the generator and the critical voltage sags are made because of the sudden utilization of the loads to the generator. To get both the voltage sag and swell, they are shown in research center.

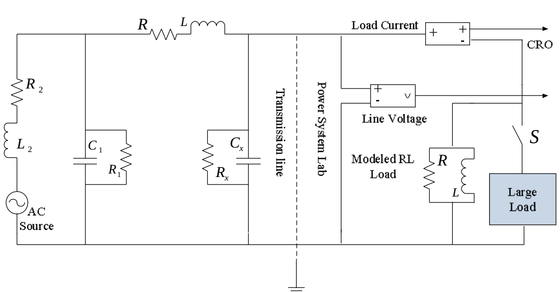

Fig. 1 Voltage sag circuit due to sudden switching-on of a large load

Since the moment of switching on and off is controlled utilizing the suitable control circuits, the thyristors go about as the controlled switches. These thyristors utilizes gate triggering circuits for the switching control. Because of the utilization of non linear loads in the distribution system, distortion additionally happens. AC voltage controllers are thyristor based devices without an adjustment in the frequency that change over settled AC voltage to variable AC. In heating devices, lightning control and speed control of motors, the semiconductor devices are utilized and they are additionally perpetually utilized as fan regulators. Fig. 2 speaks to the circuit of a single phase full wave ac voltage controller which is utilized for the speed control of a single phase induction motor. To get the desired rms voltage, the firing angles of thyristors are controlled at the input terminal of the motor. Because of the impacts of the fluorescent lamp, harmonic distortion happens, which has profoundly non-linear V–I characteristics mostly emerges because of the magnetic core inductors that are available in its stabilizer circuit. Therefore, the sinusoidal voltage application crosswise over it offers ascend to a distorted current which has an obvious substance of third, fifth and seventh harmonics.

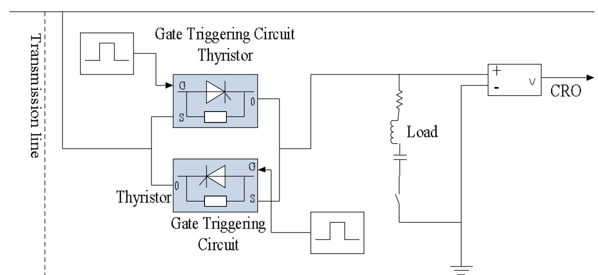

Fig. 2 Harmonic distortion circuit due to use of an AC voltage controller

In the power system research center, the age of all the PQ events has been done and the proposed algorithm has been tried on real-time to detect and classify PQ events keeping in mind the end goal to demonstrate the viability and proficiency. In the framework research facility, the algorithm displayed in this paper has been tried on such handy events. The proposed method has been utilized to achieve the errand of detection and classification of PQ events as portrayed in detail in next segment.

IV. DETECTON AND CLASSIFICATON OF PQ EVENTS

The point of this area is to present the proposed methodology which measure and distinguish the PQ events in the distribution system. Here, sequential ant lion optimizer and recurrent neural network (SALRNN) technique are used for detecting and classifying the PQ events in the distribution system. In the proposed approach, RNN is used in two phases with the ultimate objective of detection and classification of the PQ events. The first phase of standard RNN is used to perceive the system signal healthy or unhealthy condition under different circumstances. The second phase of the RNN plays out the classification of the unhealthy signals to recognize the right PQ event. Here, the second phase of the RNN learning procedure is upgraded by utilizing the ALO algorithm in context of the minimum error objective function.

The detection and classification method of RNN is clarified in two phases and it is portrayed in the accompanying area.

A. RNN: Phase I (Detection Stage)

The point of planning phase I is to recognize single and multiple PQ events utilizing RNN. The RNN system is predominance in nonlinear structures due completed the way that can interpose and extrapolate the subjective information with high precision. It takes a shot at the establishment of a machine learning technique that speaks to a human brain and contains a whole number of synthetic neurons. The realistic neurons include the interior affiliations and every neuron in RNN acquires whole number of inputs, depending on the foundation assignment of the RNN results in the output phase of the neuron [29]. Cross-Correlation Function (XCF) has been utilized to achieve the point. XCF can gauge the degree of likeness between two power signals. Here, the input layer comprises of a modulated signal at a sampling rate of 256samples/sec. The event is ascertained in the normal mode before the estimation of the voltage and current and in view of this signals RNN appraises the output. The output objective layer is the sort out control signal which is to create for acquiring the optimal control pulses. The modulating signal may have high frequency components in order to identify them RNN has been executed. The RNN decides the overwhelming frequency segments introduce in the modulated signals and the dataset so produced is given to phase II of RNN, which classifies the PQ event display in the modulated signal.

B. RNN: Phase II (Classification Stage)

In the classification stage, the phase I output signals is connected as input to phase II of RNN. The output of the classification stage is to recognize the right PQ event. For taking in the RNN, ant lion optimization algorithm (ALO) is utilized. The ALO is a meta-heuristic optimization algorithm, which awakened by the pursuing segment of ant lions in nature [30]. Here, the RNN learning procedure is upgraded by utilizing the ALO algorithm in context of the minimum error objective function. For the time of the training technique the hidden layer gets the mass at the exact time delay from the setting layer. The proposed detection and classification structure of RNN is uncovered in fig. 3 and the training technique is cleared up in the ensuing section.

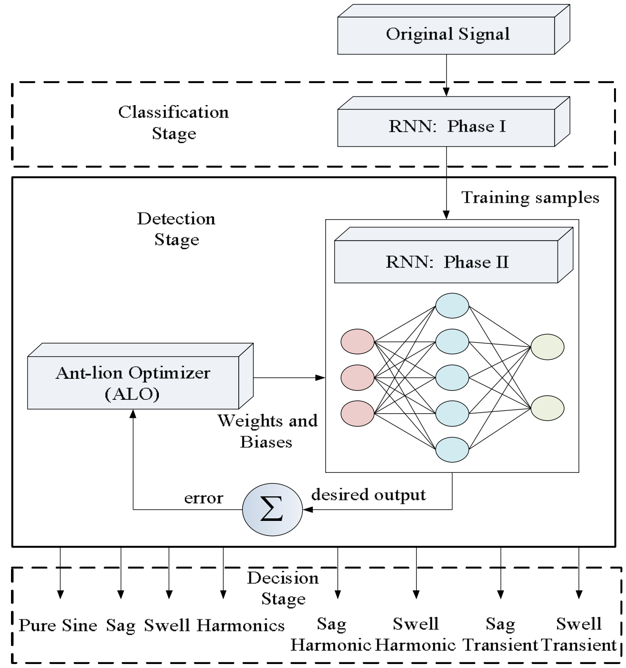

Fig. 3 Detection and classification structure of proposed algorithm

a) Training process of Ant Lion Optimization (ALO)

In the ALO algorithm, ants are search agents which meander over the search space and ant lions dive pits in the ground to trap and expend the ants [31]. The objective function of the proposed algorithm is to accomplish the highest classification rate and the lowest error rate to mirror the hunting ability of the ant lion. There are mostly five operations in ALO algorithm to be specific random movement of ants, construction of trap, trapping of ants in traps, catching preys and re-construction of traps. The critical strides in ALO algorithm is depicted as takes after,

Step 1: Initialization

Initialize the population of Ant-Lions and randomly generate the population of ants in solution space. The input to the algorithm is the weights and biases which is used to be optimized and it is represented as,

$$X = \{W_1, W_2, W_3, \ldots W_n\} \tag{1}$$

Where, n represents the number of inputs, W representsthe weight of the connection between the nodes.

Step 2: Evaluation

The objective function of the proposed algorithm is to achieve the highest classification rate at both training and testing samples. To evaluate the output of RNN, the Mean Square Error (MSE) was used where the MSE calculates the difference between the desired output and the actual output of the RNN. In other words, MSE is used to measure how the value of desired output is deviated from the value of the actual output as follows,

$$MSE = \sum_{i=1}^{m} (y_i^a - y_i^d)^2 \tag{2}$$

Where, m represents the number of outputs, y_i^a and y_i^d represents the actual and desired output respectively.

Step 3: Updating

In order to keep random walks of ants inside the search space, they are normalized using the following equation which is based on min–max normalization. Position of ants can be updated by,

$$X_m^t = \frac{(X_m^t - a_m)(d_m - c_m^t)}{(d_m^t - a_m)} + c_t \tag{3}$$

Where, a_m, b_m are minimum and maximum of random walk of ants. c_m^t, d_m^t represents the minimum and maximum mth variable at tth iteration.

Step 4: Trapping of ants

The mathematical expression of the trapping of the ants to the ant lion's pits is given by eqn,

$$c_m^t = Antlion_n^t + c_t \tag{4}$$

$$d_m^t = Antlion_n^t + d_t \tag{5}$$

Where, $Antlion_n^t$ is position of the selected jth ant-lion at tth iteration.

Step 5: Construction of trap

Ant-lion's hunting capability is modeled by fitness proportional roulette wheel selection. The mathematical model that describes the way how the trapped ant slides down towards ant-lion is given as follows:

$$c^t = \frac{c_t}{I} \tag{6}$$

$$d^t = \frac{d_t}{I} \tag{7}$$

Where, $I = 10^w \cdot \frac{t}{T}$ t is the current iteration, T is the maximum number of iterations, w is the constant that depends on current iteration as follows:

$$w = \begin{cases} 2\,if\ t > 0.1T \\ 3\,if\ t > 0.5T \\ 4\,if\ t > 0.7T \\ 5\,if\ t > 0.9T \\ 6\,if\ t > 0.95T \end{cases} \tag{8}$$

Step 6: Elitism

To preserve the best solution obtained at each stage, the position of the best (fittest) ant lion is saved as elite. Being the best, the elite ant lion is considered to influence the movement of each ant. For this every ant is assumed to associate with an ant lion by Roulette wheel and elite which is given by following Eq.

$$Ant^{iter} = (R_{Ant}^{iter} + R_{elite}^{iter})/2 \tag{9}$$

Where, R_{Ant}^{iter}, R_{elite}^{iter} represents the random walk around the selected ant lion and elite at tth iteration respectively and Ant^{iter} indicates the position of ant at tth iteration. The objective function of the ALO algorithm aims to minimize the MSE. Thus, the weights and biases of the RNN move to minimize average MSE in each iteration. Hence, ALO iteratively converges to a global solution that is better than random initial solutions.

VI. RESULTS AND DISCUSSIONS

A. Generation of data

To examine the RNN for detection and classification of PQ events, distinctive instances of wanted events are delivered. The PQ disturbance signal concentrated in this paper has been ordered into ten events: normal voltage, sag, swell, harmonics, sag with harmonics, swell with harmonics, sag with transients and swell with transients. These unsettling influences are produced utilizing MATLAB programming and

XCF has been ascertained after data acquisition. The proposed RNN is computing XCF esteem for every half cycle of the modulated signal and the relating half cycles of the standard sine wave. The qualities for XCFs comparing to various sorts of events are given in Table. 1.

Table: 1 Values for XCF corresponding to different types of PQ events

S. No	Events type	Description of PQ event	PQ events	XCF
1	Single event	Sag (10%)	Fig. 5a	0.4162
2	Single event	Harmonics	Fig. 5c	0.9401
3	Single event	Sag	Fig. 5e	0.4165
4	Single event	Swell	Fig. 5g	0.4127
5	Multiple event	Sagand Harmonic (10%)	Fig. 6a	0.8580
6	Multiple event	Sagand Harmonic (90%)	Fig. 6c	0.5268
7	Multiple event	Sagand Harmonic	Fig. 6e	0.8737
8	Multiple event	Sag and Transient	Fig. 6g	0.9126
9	Multiple event	Swelland Harmonic	Fig. 6i	0.8502
10	Multiple event	Swelland Transient	Fig. j	0.8520

The distinctive estimations of XCF for the diverse PQ events have been appeared in Table 1 and waveforms of single and multiple events are given in fig. 5 and 6, where the XCF measures the degree of comparability between the corrupted wave with a PQ event and standard wave. Those half-cycles of the modulated signal which have more than one kind of PQ event will have a considerably higher estimation of XCF than one which has just a single sort of PQ event. The estimations of XCF for multiple events given in the Table 1 are for a specific time instant and these qualities can be marginally unique if a similar event in later instant.

a) Detection results for single events

Keeping in mind the end goal to decide the level of right recognizable proof cases for each kind of single unsettling influence, the strategy proposed is likewise executed. The waveforms for the single event generated are appeared in fig. 5. In fig. 5, the diagrams for the XCF generated for single events at various voltage levels with various harmonic distortions have been given. It is noticed that if the estimation of XCF lies in the vicinity of 0.1 and 0.5, the half cycle has been sorted as single PQ event aside from the harmonic event since the estimations of harmonic lies over 0.5. From this, it finishes up for preparatory order of single events from each other. A definitive point of the entire algorithm is to detect and identify precisely which aggravation event is available in the power signal.

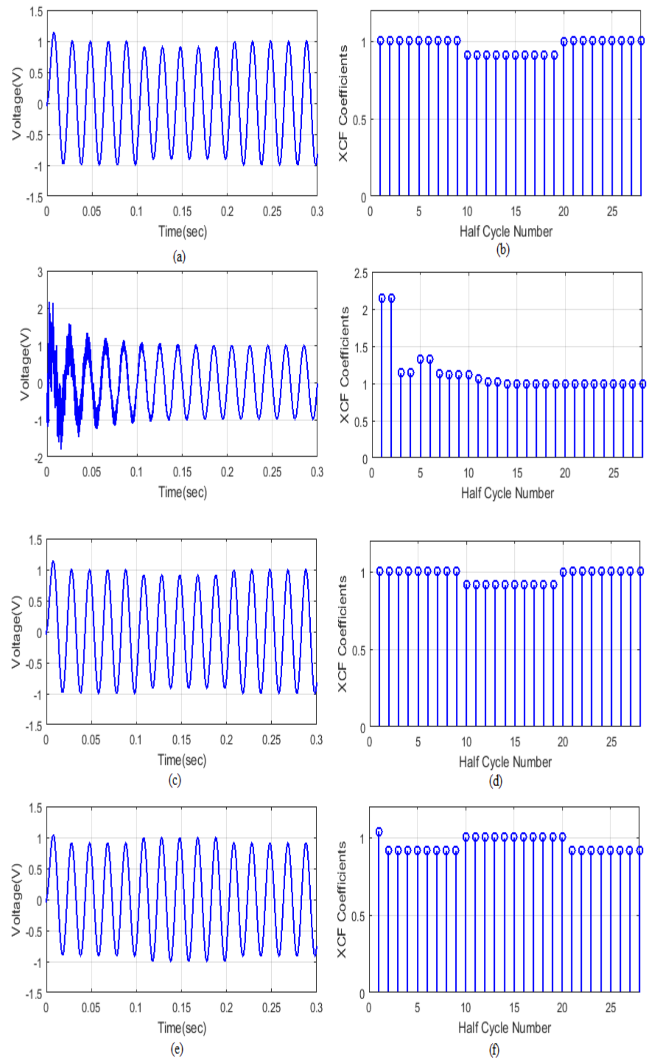

Fig. 5 Depicts XCF for single event with different distortion

b) Detection results for multiple events

With a specific end goal to decide the level of right distinguishing proof cases for each kind of multiple unsettling influences, the technique proposed is additionally executed. The waveforms for the multiple events created are appeared in fig. 6. In fig. 6, the graphs for the XCF produced for multiple events at various voltage levels with various harmonic distortions have been given. It is noticed that if the estimation of XCF is more noteworthy than 0.5, the half cycle has been arranged as multiple PQ event. From this, it finishes up for preparatory order of single events from each other. The proposed technique recognizes starting and additionally closure of unsettling influence events with and without boisterous situations and it likewise classifies different aggravations. A definitive point of the entire algorithm is to detect and identify precisely which unsettling influence event is available in the power signal.

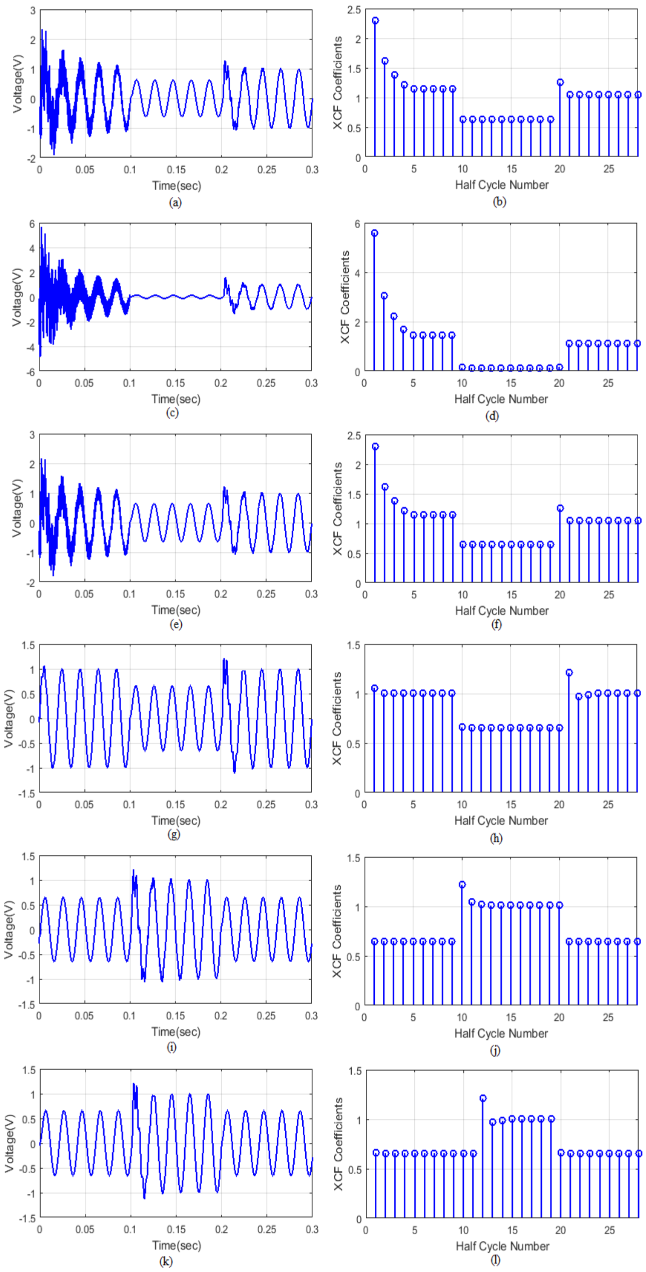

Fig. 6 Depicts XCF for multiple events with different distortion

B. Performance Analysis

In this segment, by using the proposed technique the performance measures, for example, accuracy, precision, recall and specificity have been analyzed and analyzed viably. The proposed strategy distinguishes starting and completion of unsettling influence events with and without harmonics and it likewise classifies different aggravations. The point by point correlation of results acquired for the performance measures utilizing proposed strategy is organized in Table 4. In the proposed strategy, add up to ten PQ aggravations are produced and additionally prepared utilizing two phases of RNN technique. From that point forward, the execution of the proposed system is differentiated and the present methods, for instance, ANN, RNN and Music-RNN. By then the performance parameters of the proposed technique are destitute down for 10 quantities of trials in both the single and multiple events.

Table 2: Performance comparison of proposed with existing method for 10 number of trials

Performance Measures	RNN	Music-RNN	ALO-RNN
Accuracy	0.75	0.85	0.95
Specificity	0.7	0.8	0.9
Recall	0.8	0.9	1
Precision	0.72	0.82	0.9

From the above table 2, the single and multiple events are striven for 10 number of trials and it is differentiated and the present systems for various parameters. In Table 2, the proposed methodology achieves accuracy of 0.95, specificity of 0.9, precision of 0.9 and recall of 1 than the present frameworks. The accuracy, precision, recall and specificity values are found out by using the going with condition,

Accuracy:

$$Accu = \frac{TP + TN}{TP + FP + TN + FN} \tag{9}$$

Precision:

$$\Pr ec = \frac{TP}{(TP + FP)} \tag{10}$$

Recall:

$$\text{Re}\,call = \frac{TP}{(TP + FN)} \tag{11}$$

Specificity:

$$Spec = \frac{TN}{(FP + TN)} \tag{12}$$

Where, TP is the quantity of effectively recognized samples, FN is the number of missed samples, TN is the true negative samples and FP is the quantity of noise lesions identified as samples. Fig 7 exhibits the execution examination of the proposed with existing procedures at 10 number of trials when differentiated and the present methodologies like ANN, RNN and Music-RNN strategies.

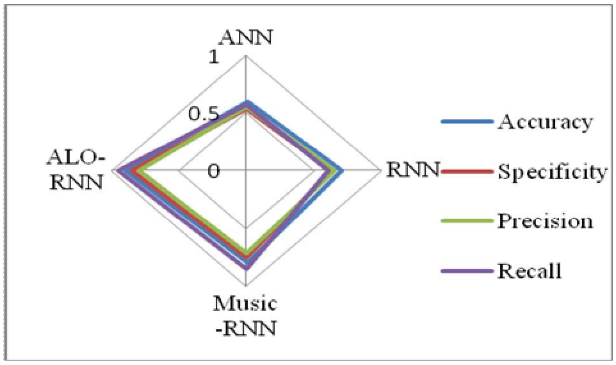

Fig 7: Performance analysis of proposed with existing method at 10 number of trials

C. Statistical Analysis

In this area, by using the proposed method the statistical measures, for example, RMSE, MAPE, MBE and consumption time have been inspected and investigated successfully. The point by point examination of results got for the statistical measures utilizing proposed strategy is arranged in Table 5. Starting now and into the foreseeable future, the execution of the proposed procedure is differentiated and the present systems, for instance, ANN, RNN and Music-RNN. By then the performance parameters of the proposed system are penniless down for 10 quantities of trials for both the single and multiple events. From the yield of proposed methodology, the event is examined as their sorts. By then, to survey the execution of the proposed ALO-RNN strategy, three sorts of errors, for example, RMSE, MBE and MAPE are figured. RMSE is a profitability pointer of the gauge strategy, MBE is a typical deviation marker and MAPE addresses a precision pointer. By then, the RMSE, MAPE, MBE and consumption time are evaluated from the testing yield of enhanced RNN system. The RMSE, MAPE, MBE and utilization time are found out using the going with condition,

$$RMSE=\sqrt{\frac{1}{z}\sum_{m=1}^{z}(I_m - I_{pm})} \quad (13)$$

$$MAPE=\frac{1}{z}\sum_{m=1}^{z}\left|\frac{I_m - I_{pm}}{I_m}\right| a \quad (14)$$

$$MBE=\frac{1}{z}\sum_{m=1}^{z} I_{pm} - I_m \quad (15)$$

Where I_m is represents the target value, I_{pm} represents the predicted value, a is represents a number of samples per leave and z is the number of samples.

Table 3: Statistical comparison of proposed with existing method for 10 number of trials

Model	RNN	Music-RNN	ALO-RNN
RMSE	18.9	23.5	10.3
MAPE	6.4	13.0	1
MBE	2.9	5.1	2.7
Consumption time	6.5	8.0	5.2

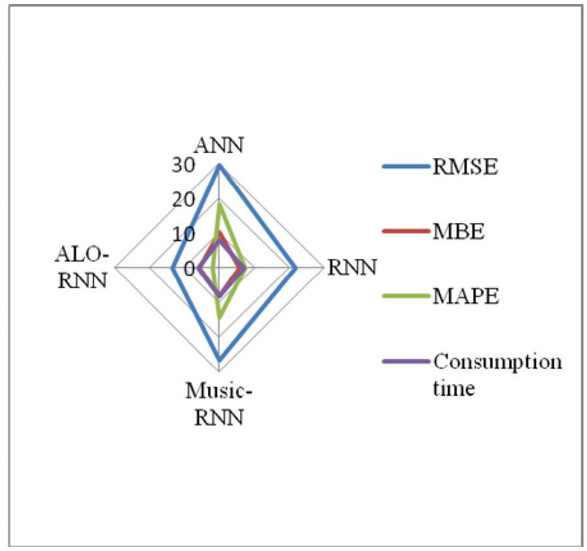

Fig 8: Statistical analysis of proposed with existing method at 10 number of trials

Table 3 shows the statistical values and time consumption of the proposed and the present techniques. In table 3, our proposed system has 10.3% RMSE, 2.7% MBE, 1 % MAPE and the consumption time is 5.2 sec. Fig 8 exhibits the statistical analysis of the proposed with existing methodologies at 10 quantities of trials amid both single and multiple PQ events. The examination comes to display the pervasiveness of the proposed method with existing systems, for instance, RNN and Music-RNN procedures to the extent RMSE, MAPE, MBE and consumption time.

VI. CONCLUSION

In the paper, a SALRNN procedure is proposed for the forecast and arrangement of single and multiple PQ events in the distribution system. Here, the proposed procedure is completed in two phases, for instance, discovery and order of single and multiple PQ events in the framework. The phase-I of RNN approach is used to perceive the healthy or unhealthy condition of system signal under different circumstances. The phase-II of the RNN plays out the arrangement of the unhealthy signals to recognize the right PQ event. Here, the phase-II RNN learning procedure is upgraded by utilizing the ALO algorithm in context of the minimum error objective function. The proposed SALRNN technique plays an assessment procedure to distinguish the fault and classify the correct PQ event which occurs in the distribution system. The proposed SALRNN method guarantees the framework with lessen complexity for the location and order of the PQ event and thus the accuracy of the system is raised. By at that point, the proposed model will be executed in MATLAB/Simulink working stage and the execution will be surveyed with the present methodology.

REFERENCES

[1] T. Jayasree, D. Devaraj and R. Sukanesh, "Power quality disturbance classification using Hilbert transform and RBF networks", Neurocomputing, vol. 73, no. 7-9, pp. 1451-1456, 2010.

[2] S. Mishra, C. Bhende and B. Panigrahi, "Detection and Classification of Power Quality Disturbances Using S-Transform and Probabilistic Neural Network", IEEE Transactions on Power Delivery, vol. 23, no. 1, pp. 280-287, 2008.

[3] U. Singh and S. Singh, "Detection and classification of power quality disturbances based on time–frequency-scale transform", IET Science, Measurement & Technology, 2017.

[4] H. Erişti and Y. Demir, "A new algorithm for automatic classification of power quality events based on wavelet transform and SVM", Expert Systems with Applications, vol. 37, no. 6, pp. 4094-4102, 2010.

[5] H. Wang, P. Wang and T. Liu, "Power Quality Disturbance Classification Using the S-Transform and Probabilistic Neural Network", Energies, vol. 10, no. 1, p. 107, 2017.

[6] P. Babu, P. Dash, S. Swain and S. Sivanagaraju, "A new fast discrete S-transform and decision tree for the classification and monitoring of power quality disturbance waveforms", International Transactions on Electrical Energy Systems, vol. 24, no. 9, pp. 1279-1300, 2013.

[7] B. Biswal and S. Mishra, "Power signal disturbance identification and classification using a modified frequency slice wavelet transform", IET Generation, Transmission & Distribution, vol. 8, no. 2, pp. 353-362, 2014.

[8] M. Masoum, S. Jamali and N. Ghaffarzadeh, "Detection and classification of power quality disturbances using discrete wavelet transform and wavelet networks", IET Science, Measurement & Technology, vol. 4, no. 4, pp. 193-205, 2010.

[9] R. Hooshmand and A. Enshaee, "Detection and classification of single and combined power quality disturbances using fuzzy systems oriented by particle swarm optimization algorithm", Electric Power Systems Research, vol. 80, no. 12, pp. 1552-1561, 2010.

[10] P. Kanirajan and V. Kumar, "Wavelet-Based Power Quality Disturbances Detection and Classification Using RBFNN and Fuzzy Logic", International Journal of Fuzzy Systems, vol. 17, no. 4, pp. 623-634, 2015.

[11] R. Kapoor and R. Gupta, "Fuzzy lattice based technique for classification of power quality disturbances", European Transactions on Electrical Power, vol. 22, no. 8, pp. 1053-1064, 2011.

[12] A. Puliyadi Kubendran and A. Loganathan, "Detection and classification of complex power quality disturbances using S-transform amplitude matrix-based decision tree for different noise levels", International Transactions on Electrical Energy Systems, vol. 27, no. 4, p. e2286, 2016.

[13] S. S, K. Rao and S. Sukrutha Jade, "Detection and Classification of Power Quality Disturbances in the Supply to Induction Motor Using Wavelet Transform and Neural Networks", Balkan Journal of Electrical and Computer Engineering, vol. 4, no. 1, 2016.

[14] T. Jayasree, D. Devaraj and R. Sukanesh, "Power quality disturbance classification using Hilbert transform and RBF networks", Neurocomputing, vol. 73, no. 7-9, pp. 1451-1456, 2010.

[15] S. Jashfar, S. Esmaeili, M. Zareian-Jahromi and M. Rahmanian, "Classification of power quality disturbances using S-transform and TT-transform based on the artificial neural network", Turkish Journal Of Electrical Engineering & Computer Sciences, vol. 21, pp. 1528-1538, 2013.

[16] Kuldeep Singh and Anand Tewari, "Classification of Power Quality Disturbances using Wavelet Transform and Neural Network", International Journal of Engineering Research and, vol. 4, no. 05, 2015.

[17] P. Sundaram and R. Neela, "Characterization and Localization of Power Quality disturbances Based on S-transform and Fuzzy Expert System", IOSR Journal of Electrical and Electronics Engineering, vol. 11, no. 04, pp. 42-53, 2016.

[18] R. Ahila, V. Sadasivam and K. Manimala, "Particle Swarm Optimization-Based Feature Selection And Parameter Optimization For Power System Disturbances Classification", Applied Artificial Intelligence, vol. 26, no. 9, pp. 832-861, 2012.

[19] Z. Liu, Y. Cui and W. Li, "Combined Power Quality Disturbances Recognition Using Wavelet Packet Entropies and S-Transform", Entropy, vol. 17, no. 8, pp. 5811-5828, 2015.

[20] R. Kapoor and M. Saini, "Hybrid demodulation concept and harmonic analysis for single/multiple power quality events detection and classification", International Journal

of Electrical Power & Energy Systems, vol. 33, no. 10, pp. 1608-1622, 2011.

[21] S. Khokhar, A. Mohd Zin, A. Memon and A. Mokhtar, "A new optimal feature selection algorithm for classification of power quality disturbances using discrete wavelet transform and probabilistic neural network", Measurement, vol. 95, pp. 246-259, 2017.

[22] A. Puliyadi Kubendran and A. Loganathan, "Detection and classification of complex power quality disturbances using S-transform amplitude matrix-based decision tree for different noise levels", International Transactions on Electrical Energy Systems, vol. 27, no. 4, p. e2286, 2016.

[23] L. Morales-Velazquez, R. Romero-Troncoso, G. Herrera-Ruiz, D. Morinigo-Sotelo and R. Osornio-Rios, "Smart sensor network for power quality monitoring in electrical installations", Measurement, vol. 103, pp. 133-142, 2017.

[24] S. Zhang, P. Li, L. Zhang, H. Li, W. Jiang and Y. Hu, "Modified S transform and ELM algorithms and their applications in power quality analysis", Neurocomputing, vol. 185, pp. 231-241, 2016.

[25] P. Kanirajan and V. Suresh Kumar, "Power quality disturbance detection and classification using wavelet and RBFNN", Applied Soft Computing, vol. 35, pp. 470-481, 2015.

[26] M. Rodriguez-Guerrero, R. Carranza-Lopez-Padilla, R. Osornio-Rios and R. de J. Romero-Troncoso, "A novel methodology for modeling waveforms for power quality disturbance analysis", Electric Power Systems Research, vol. 143, pp. 14-24, 2017.

[27] R. Ahila, V. Sadasivam and K. Manimala, "An integrated PSO for parameter determination and feature selection of ELM and its application in the classification of power system disturbances", Applied Soft Computing, vol. 32, pp. 23-37, 2015.

[28] R. Kapoor and M. Saini, "Hybrid demodulation concept and harmonic analysis for single/multiple power quality events detection and classification", International Journal of Electrical Power & Energy Systems, vol. 33, no. 10, pp. 1608-1622, 2011.

[29] R. Selva Santhose Kumar and S. Girirajkumar, "Z-Source Inverter Fed Induction Motor Drive control using Particle Swarm Optimization Recurrent Neural Network", Journal of Intelligent & Fuzzy Systems, vol. 28, no. 6, pp. 2749-2760, 2015.

[30] P. Saxena and A. Kothari, "Ant Lion Optimization algorithm to control side lobe level and null depths in linear antenna arrays", AEU - International Journal of Electronics and Communications, vol. 70, no. 9, pp. 1339-1349, 2016.

[31] M. Raju, L. Saikia and N. Sinha, "Automatic generation control of a multi-area system using ant lion optimizer algorithm based PID plus second order derivative controller", International Journal of Electrical Power & Energy Systems, vol. 80, pp. 52-63, 2016