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Identification of Disturbance Affecting the Efficiency in Power System using Feed forward Neural Network

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Abstract

At present, there are various sources and unsolved reasons causing potential disturbances that are significantly detrimental towards efficiency of various individual component operations in power system. We reviewed existing approaches toward detection mechanism of disturbances to find that there is potential tradeoff in the techniques that leads to non-uniform growth in higher detection accuracy and lower computational efficiency. Therefore, the present manuscript introduces a simple framework that retains a balance between higher accuracy in detection of disturbances as well as also maintains an effective computational performance for large number of the power signals. The proposed technique uses orthogonal transforms for feature extraction and uses feed forward algorithm for optimizing the search towards elite result of convergence. The study outcome shows proposed system to excel better with respect to accuracy in identification in comparison to existing approaches.

Keyword: Classification; Disturbance; Identification; Power Quality; Power System.

1. Introduction

There has been increasing level of interest for evolving up with different approaches and techniques towards analyzing the performance of power quality [1]. The prime reason behind this interest is increasing level of sensitivity of advanced electrical components along with associated issues pertaining to the existence of non-regulatory modeling as well as non-uniform supply of power [2]. Such forms of devices offer exponential increase in non-linear loads that significantly degrade the level of power system [3]. Hence the current signals as well as voltage are significantly affected.

These are the ongoing issues that cost the hours of production for the users which leads to surfacing of electrical component that performs consistent monitoring of power system in present era [4]. Basically, the essential performance parameter for assessing superiority of the system is called as Power Quality Indices which is responsible for characterizing the system's performance being influenced by the various forms of power disturbances. The existing forms of disturbances are fluctuation in supply voltage, harmonics, transient voltage, deviation in power frequency, flickers, etc [5]. There are already some sort of performance parameters to assess such impact e.g. crest factor, power factor, peak values, total harmonic distortion, etc. However, new performance factors are also consistently arrived from research-based literatures. Majority of the existing research techniques extracts the performance factor from spectrum of signal frequency. There are also existence of standard that uses frequency domain for offering better sustenance level while performing consistent monitoring of electrical parameters e.g. Chirp Z Transform, Fast Fourier Transform, Welch algorithm, etc. Unfortunately, such technique is not capable of considering all the relevant information required for performing identification of essential disturbances. At the same time, there are various categories of electrical disturbances in power systems that are standardized by IEEE 1159 standard [6]. Such standard significantly assists in carrying out trustworthy and involuntary identification of disturbances. Such forms of research techniques can be utilized as a mechanism for assessing the influence of loads as well as understanding the origination point of such critical disturbances [7]. Such forms of mechanism are normally constructed for performing involuntary identification of disturbances along with their time of occurrences. At present, there are various design methodologies existing in the literatures meant for studying the current and voltage signals with an aid of both frequency as well as time based transforms [8][9]. Such methodology potentially assists in extracting the discrete characteristics of the signals, which are categorized as per the valuation of the data as well as time period that are already chalked out by their standards. There are various research-based methodologies evolved up in recent time that are found to use fuzzy logic, decision tree, machine learning algorithm, etc. All these techniques were claimed to be effective towards framing up the research model resulting in effective classification of the power quality-based disturbance. However, a closer look into all the existing techniques are found to conclude that existing system doesn't offer widespread outcome that could be possibly applied in practical environment on power line network. Moreover, the prime problem is associated with computational complexity that is hardly found to be seen in existing system towards performing classification of disturbances. Therefore, the present paper introduces a model that uses feedforward network for applying learning methods and orthogonal transforms of extracting potential coefficient of power signal targeting towards detection of disturbances. Section 1.1 discusses about the existing literatures where different techniques are discussed for detection schemes used in power transmission lines followed by discussion of research problems in Section 1.2 and proposed solution in 1.3. Section 2 discusses about algorithm implementation followed by discussion of result analysis in Section 3. Finally, the conclusive remarks are provided in Section 4.

1.1 Background

Our prior study has already discussed about various research attempts toward research-based techniques on classification of power quality [10]. The work carried out by Biscaro et al. [11] have uses fuzzy ARTMAP for identifying the classified location of the fault as well as analysis of power quality. Naderian and Salemnia [12] have used Gabor transform as well as Support Vector Machine for performing identification of the power quality. Manikandan et al. [13] have formulated a hybrid dictionary where the decomposition of the sparse signal is carried out for simulatenously determining the form of disturbances in power system. Alam et al. [14] have presented a study where the voltage dips and surge have been subjected to characterization considering three-phase voltage parameters. Kumar et al. [15] have presented a technique where the symmetrical components residing in the time domain is used for identifying disturbances in power system using phase locked loop. Huang and Lin [16] have used chaos theory in order to define a novel classifier system for identifying disturbances. Rodriuguez et al. [17] have used neural network for performing the classification process. Usage of wavelets and support vector machine was seen in the work of Milchevski et al. [18]. The process of involuntary classification was carried out by Biswal et al. [19] along with implementation of Hilbert transform scheme. Krishna and Baskaran [20] have used temporal-based feature extraction process for evaluating the extent of power quality disturbances. Usage of Hilbert transform was also seen in the work of Afroni et al. [21] who have introduced an interative mechanism over non-stationary factors of power system. Ray et al. [22] have used hyperbolic-based transform for feature extraction along with claasifier constructed using decision tree and support vector machine to solve disturbance classification problem of power system. Moschitta et al. [23] have investigated about a technique that can perform identification of voltage dip using Kalman filter. Similar usage of support vector machine along with an analysis of an edge sym is presented by Jiang et al. [24] in their studies in order to perform classification of load event. Existing system also uses logistic model tree as well as wavelet transform for carrying out feature extraction that assisted in event classification by Eristi and Demir [25]. Emphasis on similar problem and reviewing their technqiues has been seen in the work of Lieberman et al. [26]. Ferreira et al. [27] have presented a study where the quality monitoring system of power was designed using statistical modeling. Adoption of discrete wavelets was again found to be adopted in the work carried out by Masoum et al.[28] where the accuracy of the presented technique was found to be 98.9%. Samantaray [29] have used fuzzy logic as well as decision tree based mechanism in order to investigate the event classification of the power system. Reaz et al. [30] have used expert system for solving classification performance using fuzzy logic and wavelet transform. Hence. there are various techniques in literature towards addressing the detection and classification problems in power system. The next section discusses about the research problems followed by brief discussion of proposed solution to address such problems.

1.2 Research Problem

The significant research problems are as follows:

- Majotity of the existing techniques have used fuzzy logic, support vector machine, genetic algorithm which is highly iterative in nature.
- There are multiple phases of power quality disturbances, whereas majority of the existing system only focuses on dips and surges.
- Inclusion of computational complexity problems has been out of scope of any existing research-based techniques towards detection of power quality disturbances event.
- Randomization of the power signals has not been considering in any modeling for which reason the applicability of existing system in practical life is highly questionable,

Therefore, the problem statement of the proposed study can be stated as "*It is highly computationally challenging task to formulate a model that can ensure higher accuracy of detection of power quality classification of disturbance event along with retention of computational efficiency.*"

1.3 Proposed Solution

The primary aim of the proposed solution in to design a generalized framework that can instantly perform identification of the type of disturbances occurring in power system. The implementation of the proposed system is carried out considering an analytical research methodology, where the emphasis is given to the extraction of the features in the form of trained data. The schematic diagram is shown as Fig.1

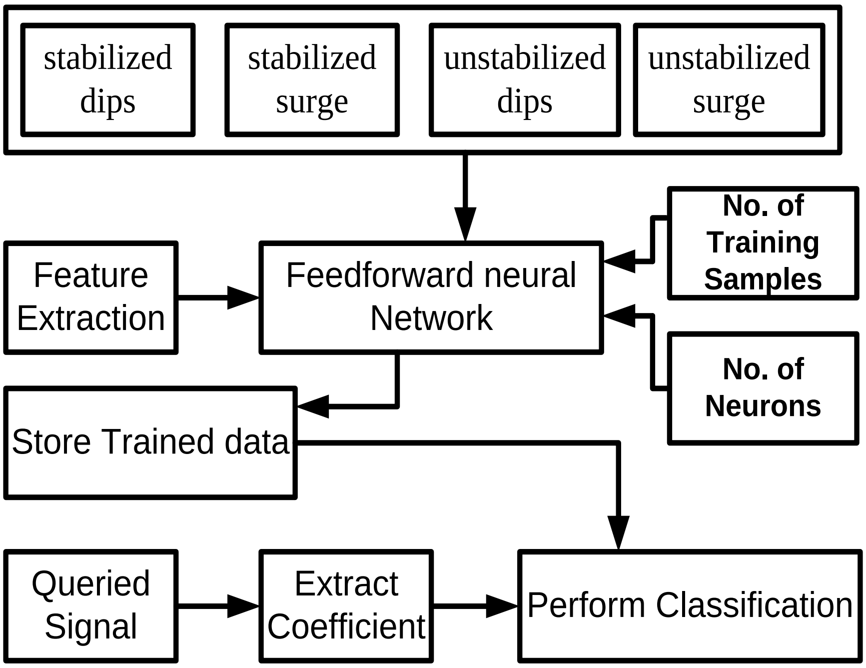


Figure 1: Schema of Methodology for 1st Objective.

The proposed solution aims to perform classification of stabilized supplyof power considering a case study of power system to asses various power quality disturbances events e.g. stabilized dips, stabilized surge, unstabilized dips, and unstabilized surge. These four forms of the disturbances are the practical forms of the disturbances that frequently occur in any form of power system. The first stage of the study will apply an orthogonal wavelet-based transformation scheme in order to extract lower and higher value of coefficients. A novel algorithm of feedforward neural network is further investigated, which has lesser processing or training time as well as higher accuracy of detection. This phase also include common feature extraction and classification stage. An extensive environment of analysis was carried out in this stage to understand the actual fluctuation in the voltage variations, if any. Finally, the study outcome of the proposed system was compared with most relevant existing system in order to measure the effectiveness of the proposed system. The contribution of the proposed study are as follows viz. i) the proposed study offers a mechanism that can perform classification of any form of disturbances in power system, ii) higher emphasis on computational efficiency is maintained by minimizing the resource dependencies and maintain the faster response time. This assists the proposed system to have higher scale of applicability in practical implementation too. The next section discusses about the algorithm implementation and its strategies involved.

2. Algorithm Implementation

The algorithm design of the proposed system basically aims for performing a better and precise classification for power quality performance with a motive to understand the level of disturbance event in better way. For this purpose, we implement feed forward neural network and performed a formulation of four different forms of disturbances e.g. i) stable dip performance, ii) stable surge performance, iii) unstable dip performance, and iv) unstable surge performance. However, the proposed technique applies a typical mechanism for performing training using feed forward algorithm. The steps of the training algorithm are as follows:

Algorithm for training using Feed forward

Input: α (No. of training Samples), β (No. of Neurons)

Output: Training with Feed forward Network (τ)

Start

1. *init* α, β

2. **For** i=1: α

3. θ=a+c.*rand*

4. y=*f*(t, θ)

5. y=y+d.rand(1, length(y))

5. δ=[L, H]→ψ(y)

6. **End**

7. Apply τ(δ)

End

The first step of the algorithm is to take the input of number of training samples and number of neurons (Line-1). The algorithm then considers the time range starting from 0 to 0.2 with a difference of 0.0001 in order to perform study of data distribution over time. Considering all the samples (Line-2), the algorithm defines a parameter θ which is controlled by external environmental coefficient e.g. *a* and *c*. The parameter is defined randomly (Line-3) and is used for constructing voltage dip pattern. The line-4 uses a function *f* that represents multiple conditions of voltage during disturbances. Following are the empirical meaning of function *f*.

- *For stable dip performance*: For stable dip performance, the function *f* empirically represents

$$f = (1-\theta(\phi(t-s).\sin(314.t))$$

In the above expression, variable ϕ represents step function and s represents statistical significance value

- *For stable surge performance*: For stable dip performance, the function *f* empirically represents

$$f = (1 + \theta(\phi(t - s).\sin(314.t))$$

In the above expression, variable ϕ represents step function and s represents statistical significance value

- *For unstable dip performance*: For unstable dip performance, the function f empirically represents,

$$f = (1 - \theta(\phi - s).\theta_3.\sum_{i=3}^{i+2} \sin(i * 3 * 314 * t))$$

$$\text{Where, } \theta_1 = \sqrt{1 - \theta_3^2 - \theta_5^2 - \theta_7^2}$$

- *For unstable surge performance*: For unstable dip performance, the function *f* empirically represents,

$$f = (1 + \theta(\phi - s).\theta_3.\sum_{i=3}^{i+2} \sin(i * 3 * 314 * t))$$

$$\text{Where, } \theta_1 = \sqrt{1 - \theta_3^2 - \theta_5^2 - \theta_7^2}$$

Although, the variable θ is same for 1st two states i.e. stable dip and stable surge, but it differs for unstable conditions for both dip and surge. For unstable dip and surge condition, we consider 3 extra parameters (e.g. θ_3, θ_5, θ_7) for θ that is empirically designed. Once the function *f* for disturbance trend is incorporated than it is followed by addition of random noises (Line-5). The signal is than subjected to discrete wavelet transform ψ in order to extract the higher value of coefficient *H* and lower value of coefficient *L*. The resultant of both the coefficient δ is then subjected to extraction of features and labels in order to make it suitable for applying feed forward network. After the above discussed process is completed, the trained data is stored in the machine so that it can be used further used in the identification phase also. The next part of the algorithm is associated with performing identification of the type of disturbance. The input to this process will call for selection of one of the form of voltage disturbance out of total 4 types as discussed above. Upon selection of one of the form of voltage disturbance parameters, the system generates signal using the similar step as discussed in Line-3 of the training algorithm. However, as the generation is carried out in random fashion, therefore, the outcome of θ will be different in every run even if the value of the other constants e.g. *a* and *c* are fixed. For effectiveness in study, we consider the value of a=0.3 and value of c=0.6. The algorithm also follows similar forms of generations of multiple value of θ for its unbalanced condition retaining the similar random functions. The next part of the identification process calls for further applying discrete wavelet transform in order to extract lower value of coefficient and higher value of coefficient. Further the saved form of the neural network is loaded in order to perform training of the newly generated signal in order to obtain the numerical value of the outcome with respect to accuracy.

The basic design principle of the proposed algorithm is as follows: The algorithm considers empirically constructing 4 different form of event associated with disturbances during power quality process. The algorithm basically carries out the sampling of the stator current very effectively and then it allows the system to perform processing when the system is found to be running over a definitive load. The complete study performs identification of disturbance type that is based on the concept that stator motor associated with the induction motor could be positively utilized. The technique also uses transform-based function for offering better extraction of coefficients. The sole objective was to extract both high and low level coefficient for better feature extraction and this extracted feature will be utilized for performing identification of the specific disturbance events. The algorithm perform sampling of the stator current considering varying range of frequencies, which is further processed using orthogonal wavelets in order to extract lower and highest value of coefficient. The next phase of implementation is about subjecting the coefficient of wavelets to the feed forward neural network, which is form of multilayered perception. From Fig.2, it can be seen that that the obtained trained data from the training phase is called in identification phase to perform precise identification of the form of power quality disturbances. Although, the computation time for using single layer perception is smaller, the proposed algorithm chooses to multilayered perception as the study considers multiple possibilities of events of disturbances. Adoption of proposed learning technique considerably assists the system to overcome the complexity associated with processing complex form of the power quality problems. The proposed algorithm also ensures that it is applicable towards considering comprehensive control and dynamic system as event of power quality classification is completely based on time factor as well as directionality of flow of information. The significant contribution of proposed algorithm is that it minimizes the uses of additional resource dependencies and works on lesser effort and time involvement for classifying power quality. It enables the accuracy of the control system to be enhanced to highest degree. The amount of resource consumption owing to implementation of feed forward-based training algorithm is considerably less as compared to other means of control system in artificial neural network. Apart from an effective resource management, the algorithm also offers significant stability during the identification of the power quality classification along with offering of faster response time.

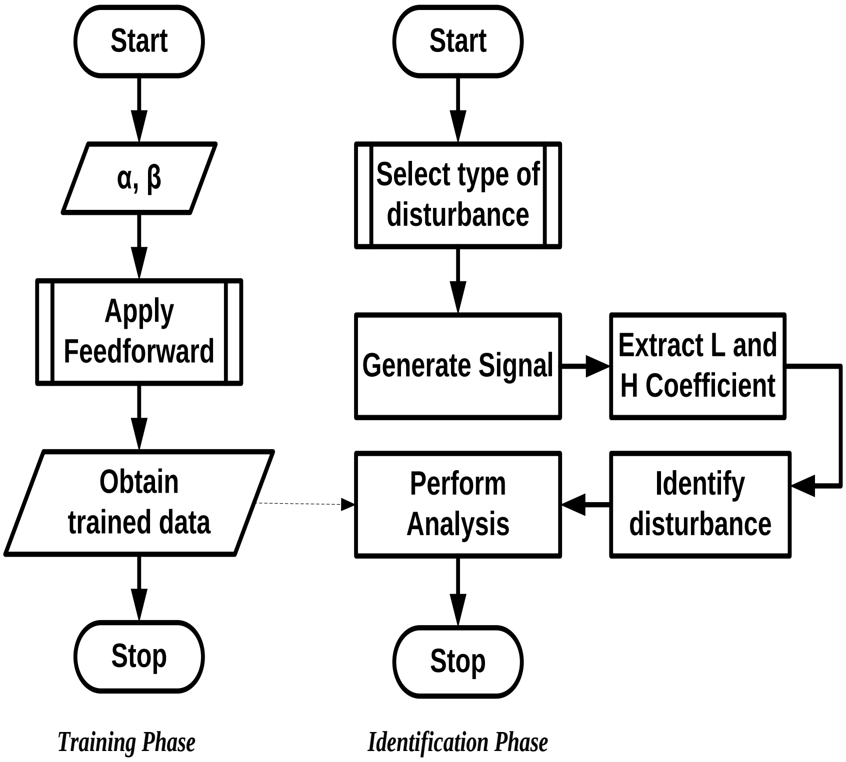


Figure 2: Operational Flow of Algorithm Implementation

3. Result Analysis

The design of the proposed system is carried out in Matlab where similar process of algorithm design discussed in prior section has been implemented. The first part of the algorithm includes training where all the 4 types of events of disturbances are subjected to feed forward neural network. The complete training is carried out in 1000 epoch with random data distribution. The performance measurement parameters for the training is mean squared error and Levenberg-Marquardt algorithm is used for optimizing the training performance. Although, 1000 iteration has been set for the training, but the proposed system obtains its convergence only in 8 iterations thereby showing the computational performance in core i5 processor. The total time required for carrying out the training is approximately 1 second.

Table 1: Waveforms Generated during each Disturbance Process

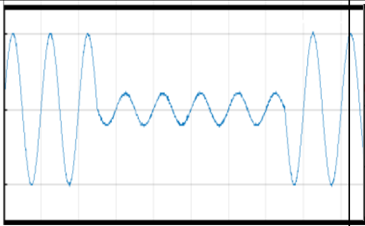
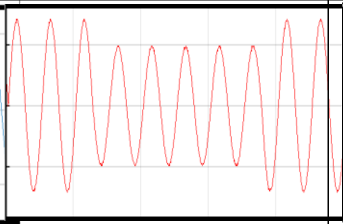
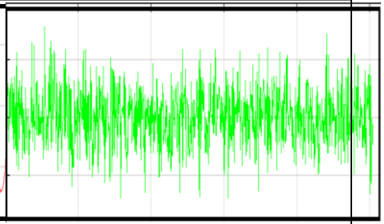
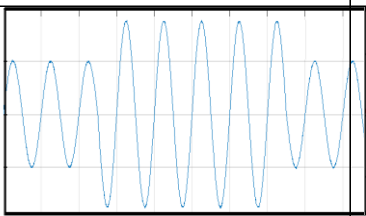
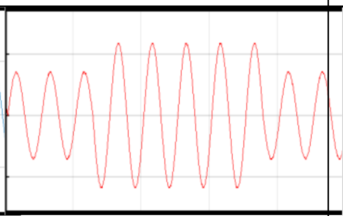
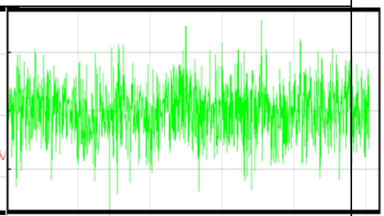
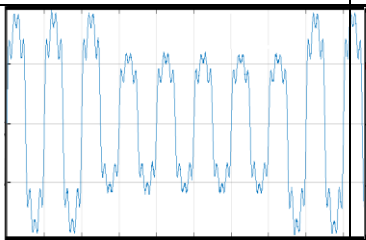
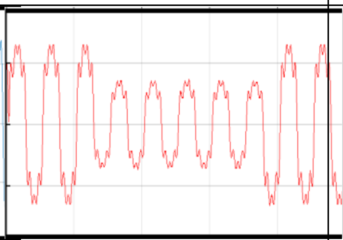
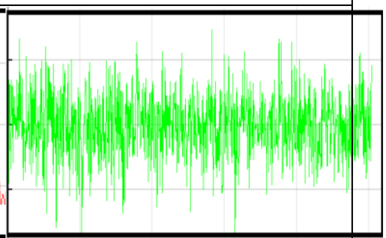
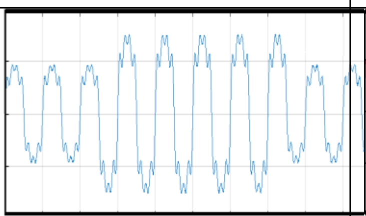
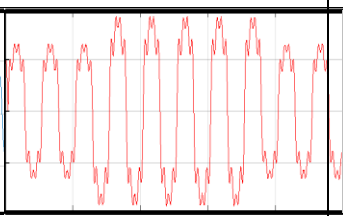
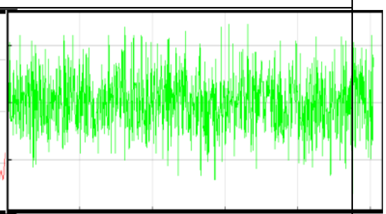
	Original Signal	Lower Coefficient	Higher Coefficient
stable dip			
Stable Surge			
Unstable dip			
Unstable surge			

Table 1 showcases the different form of the waveforms evolved during the stage of recognition phase. There are three forms of waveforms generated in the process i.e. original signal, signals bearing only lower value of coefficient, and signals bearing only higher value of coefficient. All the 4 different forms of events of disturbances i.e. stable dip; stable surge, unstable dip, and unstable surge have been verified during the process of identification of power quality disturbance. As the proposed system is testified under the random environment of data division therefore, it was seen that the functuation in the disturbances significantly exists and it is quite challenging to perform in depth analysis of it. Initially, the training of the proposed network was carried out using only 40 inputs where one input was related to stabilized factor and rest of 39 are related to allocated voltage with significant level of power quality disturbances. Theere are 115 coefficients of wavelets that were trained using 1000 iterations. Finally, there are total of 1009 inputs given to the processor where there are 6 nodes in hidden layer and 1 node in output layer. The gradient value after the training is accomplished as 57.5, while Mu value is found to be 0.00100, while there are 0 validation checks required after the successful training of the neural network.

For effective analysis of the outcome of the proposed system, we compare the outcomes of the proposed system with that of most relevant work carried out in existing system. The criteria for selection of existing work for the proposed system is mainly two i) addressing similar type of problem i.e. disturbance classification in power system and ii) adoption of optimization algorithm for learning methods. In this regard, the work carried out by Liao [31] has used radial basis function for the similar reasons. The author has evolved up with a technique where a classification algorithm using *k*-means and radial basis function has been developed. The complete work targets to perform identification of the events associated with power quality. The technique performs identification of both dips and surge performance of the voltage along with monitoring of oscillatory transient stage as well as notching state. Basically, a stochastic process has been utilized to perform modeling in this work where the accuracy in detection rate is found to be approximately 97%. Not only this, the outcome was also claimed ot be superior in comparison to existing supervised learning methods too. The comparative analysis was also carried out for the recent work being carried out by Zhou et al. [32], where basically the motive of the study was to perform prediction of stability performance of the power systems. For this purpose, the authors have used multiple supervised learning algorithms along with function fitness in neural network. However, the test-environment for both Liao [31] and Zhou et al. [32] are very different than proposed system. Therefore, in order to maintain generality in the test-platform of comparative analysis, the proposed system performs minor amendment in the existing system by retaining the core algorithm of radial basis function and function fitness neural network and overlooking other secondary parameters confidence level, support level, number of inputs, rotor angle, stator current, etc. The numerical outcome of the accuracy is showcased in Table 2.

Table 2: Comparative Summary of Accuracy in Identification

	Proposed System	**Existing System**	
		Liao [31]	**Zhou et al. [32]**
Stable Dip	100%	50%	100%
Stable Surge	100%	90%	60%
Unstable Dip	100%	100%	60%
Unstable Surge	100%	70%	100%

From the Table 1, it is quite clear that proposed system offer 100% accuracy on determining 4 exclusive forms of the power quality disturbances. Fig.2 showcase that proposed system offers a faster algorithm processing time as compared to the existing system of Liao [31] and Zhou et al. [32]. A closer look into Fig.2 shows that time consumption to identifying stable surge and unstable dip is significantly larger in existing system due to inclusion of increasing number of heuristics associated with events of power system. On the other hand, the complete system, as the proposed system extracts a large range of trained data with vast consideration of randomness in data, therefore, the identification time consumption is quite reduced to larger extent irrespective of any type, dimension, and form of data associated with power system. This causes faster rate of algorithm processing time with larger accuracy and therefore the proposed system offers increasing accuracy retaining higher computational efficiency in algorithm processing.

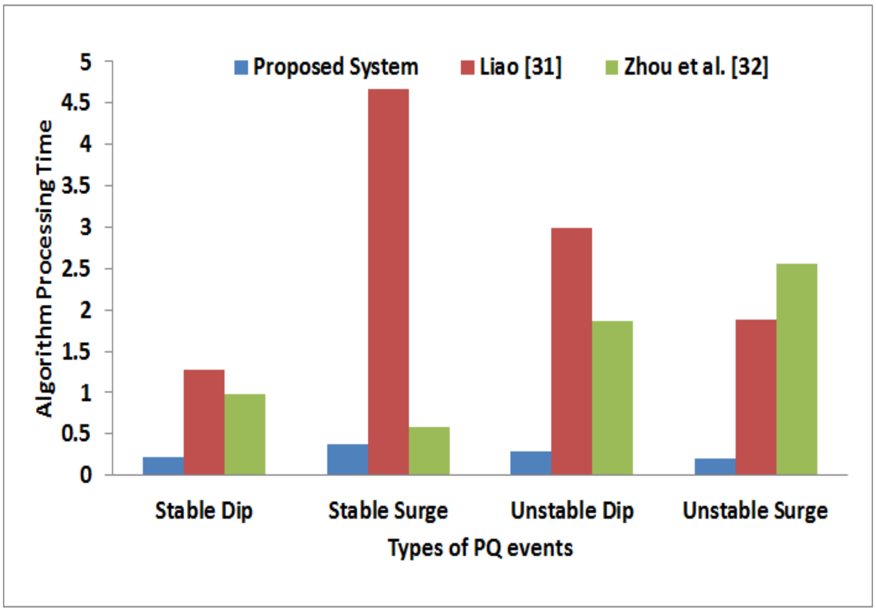


Figure 2: Comparative Analysis of Algorithm Processing Time

4. Conclusion

This paper has discussed about a novel technique where both detection as well as classification is carried out toward power quality. The proposed system introduces two significant modules i.e. training module and identification model. The training module takes the inputs of number of samples and applies machine learning using feed forward network in order to evolve up with a trained data. The recognition module takes the queried signal of power which is subjected to feature extraction using orthogonal transforms and then the trained data is applied for performing detection of the type of the disturbance. The study considers both stabilized and unstabilized version of dips and surge in power system. The study outcome shows higher accuracy in detection and classification of proposed system as compared to existing system.

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