



iJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 5

Issue: XII

Month of publication: December 2017

DOI:

www.ijraset.com

Call: ☎ 08813907089

E-mail ID: ijraset@gmail.com

A Soft Computing Technique for Characterization of Power Quality Events

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Abstract: *The Power quality disturbances in the signal are unpredictable interruptions of pure sine wave. The magnitude of voltage and frequency deviates from normal value leading to economic loss. To make protection against the equipments on consumer side as well as generation, transmission and distribution side a fast, accurate detection and classification are required. In this paper, a digital signal processing technique is used to Hybrid Hilbert Transform and Discrete Wavelet Transform (HT-DWT) for tracking the signal disturbance and characterization of Instantaneous voltage variations are presented. The Hilbert Transform estimates the magnitude of the voltage signal as envelope and discrete wavelet transform detects the time duration of disturbance in the signal. A fuzzy logic controller recognize the type of voltage variation, a rule-based method for the final identification and decision making according to IEEE Std 1159-2009. The techniques presented in the literature for tracking voltage variations such as Fourier transform, Fast Fourier transform and short time Fourier transform and neural network techniques increase the computational burden and time of tracking. The new methodology does not require training stage. Therefore, its development is easier and its efficiency does not depend on a data training set. The Performance of the methodology is validated and tested using synthetic signals.*

Keywords: Fuzzy logic controller (FLC), Hilbert transform (HT), Discrete Wavelet transform (DWT), Power Quality (PQ).

I. INTRODUCTION

With the increasing usage of electronic gadgets, solid state devices lead to nonlinear loads. Such electrical equipments are susceptible to the variation in power supply lines and hence Power quality (PQ) assessments have become a very important task and interesting topic for many researchers globally [1]–[4]. Among the different disturbances that harmfully affect the PQ are Short duration variations (voltage sags, voltage swells and interruptions), usually associated with removal/inclusion of load, motor initiation, energisation of transformer, and network failures are the most important variations in voltage supply [5]–[8].

For the past two decades, researchers have developed some techniques, Algorithm and methodologies to monitor the magnitude of voltage variations [9]–[11]. To perform control tasks and to activate protection in time, it is necessary to quantify the severity of voltage variation. An effective and accurate measurement of such voltage variations is mandatory. According to IEEE Std 1159-2009 [12], the detection and classification of voltage variations using Root Mean Square (RMS) is the emblematic frame based method. Hence, the predicted RMS value is calculated on a time-window basis, which partially compromises the time resolution with a delay of one cycle [13].

The Discrete Fourier Transform is another frame-based technique used to calculate the magnitude of the fundamental component for stationary signals within time window. However, the PQ signals are non stationary and unique characteristics. The time resolution can be improved by overlapping the time window, which prominently increases the computational Burden [14]. To overcome the above-mentioned drawbacks, several advanced techniques, such as STFT [6], adaptive filtering [8], adaptive linear network (ADALINE) [15], and DWT [16], have been proposed. Even though there are powerful techniques for tracking voltage variations, a number of issues remain unanswered. Usually an algorithm is required to track down the changes in signal. In this case, the selection and performance of the algorithm becomes a primary objective in order to ensure the minimum computation and convergence time. Besides that, the tracking is achieved by adjusting the parameters of a specific harmonic based model. Therefore, an appropriate model has to be chosen based on an accurate assessment of its tracking capabilities [17]. Actually this is not a straightforward procedure for a continuous time-variant signal. In this regard, previous research efforts have presented very complex models. They represent continuous time-variant signals using neural network which increases the computational time [14]. From this point of view, the development and application of new tracking methods of voltage variations that result in a more effective, efficient and reliable monitoring is still a hot topic of research.

The organization of this paper is as follows. In Section II, a brief theoretical background is introduced. The description of the methodology is presented in Section III. Section IV shows the case study which is used to evaluate the performance of the proposal. Finally, the conclusions are presented in Section V.

II. THEORETICAL BACKGROUND

This section introduces a brief theoretical background on the topics addressed in this paper: the description of voltage variations according to IEEE standard 1159, HT, DWT and the FLC techniques are used for the automatic tracking of voltage variations.

A. Ieee Standard 1159-2009

This standard presents a recommended practice for monitoring the PQ of single-phase and multiphase AC power systems. With regard to voltage variations, it provides the nominal conditions of power supply as well as the deviations from those nominal conditions: typical duration and typical voltage magnitude for each category are implemented [12].The PQ synthetic signals are modelled using Table1 [28].

Class	PQ disturbance	Equation of Modelling	Value of Parameters
C1	Sinusoidal wave	$x(t) = A \sin(\omega t)$	$A=1.0$; $f=50\text{Hz}$; $\omega=2\pi f$
C2	Voltage Sag	$x(t) = A(1 - \alpha(u(t-t_1) - u(t-t_2))) \sin(\omega t)$; $t_1 < t_2, u(t) = 1, t \geq 0$	$0.1 \leq \alpha \leq 0.9$, $T \leq t_2 - t_1 \leq 8T$
C3	Voltage Swell	$x(t) = A(1 + \alpha(u(t-t_1) - u(t-t_2))) \sin(\omega t)$; $t_1 < t_2, u(t) = 1, t \geq 0$	$0.1 \leq \alpha \leq 0.8$, $T \leq t_2 - t_1 \leq 8T$
C4	Momentary Interruption	$x(t) = A(1 + \alpha(u(t-t_1) - u(t-t_2))) \sin(\omega t)$; $t_1 < t_2, u(t) = 1, t \geq 0$	$0 \leq \alpha \leq 0.09$, $T \leq t_2 - t_1 \leq 8T$

TABLE1: MODELING OF POWER QUALITY DISTURBANCE

B. Hilbert transform

The HT of a signal $x(t)$ is defined as the convolution of the signal with the function $1/t$ as follows

$$\text{HT}(x(t)) = y(t) = \int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau} d\tau \quad (1)$$

The analytic signal $xa(t)$ is obtained from coupling $x(t)$ and its HT as a complex signal as follows:

$$xa(t) = x(t) + j y(t) = A(t)e^{j\phi(t)} \quad (2)$$

$$A(t) = [x^2(t) + y^2(t)]^{1/2} \quad (3)$$

$$\phi(t) = \tan^{-1}(y(t)/x(t)) \quad (4)$$

Where $A(t)$ is the instantaneous amplitude and $\phi(t)$ is the instantaneous phase of the complex analytic signal, $A(t)$ is also known as the envelop of $x(t)$, which can be used for tracking the magnitude of voltage variations .

C. Discrete wavelet transform

The DWT consists of a set of functions namely scaling and wavelet function associated with filter banks. The continuous Wavelet Transform of a continuous time signal $x(t)$ is defined as

$$\text{CWT} \psi^{x(a,b)} = \int_{-\infty}^{+\infty} x(t) \psi_{a,b}^*(t) dt, \quad a, b \in \mathbb{R}, a \neq 0 \quad (5)$$

$$\text{Where } \psi_{a,b}^*(t) = \frac{1}{\sqrt{a}} \psi^*\left(\frac{t-b}{a}\right) \quad (6)$$

$\psi(t)$ is the mother wavelet where 'a' and 'b' are scaling and translating parameters respectively. The DWT is obtained from continuous Wavelet Transform by replacing $x(t)$ by $x(k)$ where $x(k)$ is the sampled signal. The Discrete Wavelet Transform of a time signal $x(k)$ is defined as

$$\text{DWT}_{\psi} x(m, n) = \sum_k x(k) \psi_{m,n}^*(k) \quad (7)$$

$$\text{Where } \psi_{m,n}^*(k) = \frac{1}{\sqrt{a_0}} \psi^* \left(\frac{k-n \frac{a_0^m}{a_0}}{a_0^m} \right) \quad (8)$$

Where m and n are the translation and scaling parameters of discrete wavelet transform, a_0 and b_0 are integers. The Multi Resolution Analysis (MRA) consists of filter banks of low pass and high pass filters. The high pass filter gives a fine detailed version of the signal 'd1' and low pass filter gives the coarse approximate version of the signal 'a1' at the first resolution level of decomposition, whose frequency band is divided into two equal half $f_s/2$. During second resolution level the signal 'a1' is further decomposed into 'd2' and 'a2' whose frequency band is $f_s/4$. For third resolution level the frequency band is $f_s/8$ which produces the signal 'd3' and 'a3' and the process is again repeated for different resolution levels and frequency bands.

Fig.1 shows the MRA decomposition of a signal with four levels, sampled at a frequency of 15.8 kHz into four bands of frequency. 'a4' is the level of approximation with the lowest frequency band of low pass filter and 'd1','d2','d3' and 'd4' are respective details or the high frequency(scale) band of high pass filter.

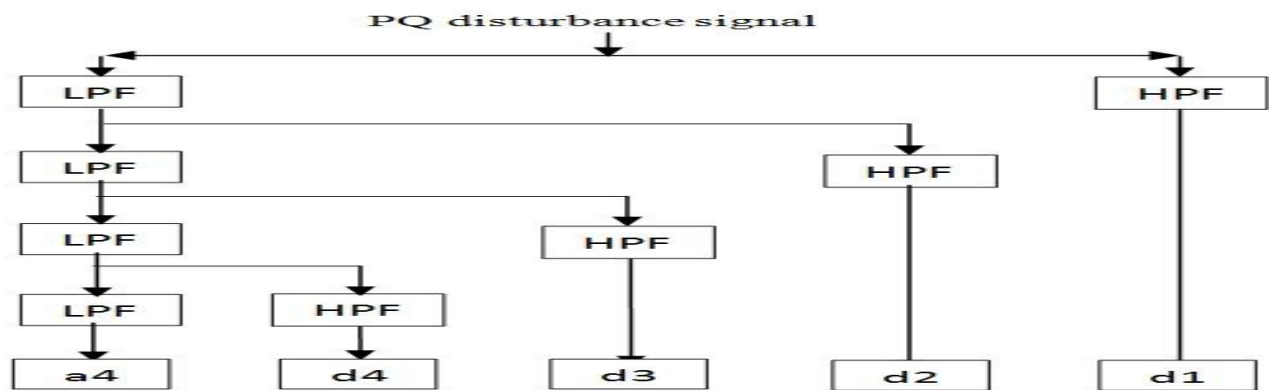


Fig.1 MRA Decomposition

D. Fuzzy logic system

FL systems represent a group of rules for reasoning under uncertainty or in an imprecise manner. They are commonly used when a physical process has to be represented by means of a mathematical model. But the model does not exist or is very complex to be implemented or evaluated in real time applications [16]. The FL system consists of four stages viz. fuzzification, inference mechanism, rule-based mechanism and defuzzification. The fuzzification stage receives information from the inputs that the inference mechanism can recognize. An inference mechanism is used to understand and perform the decision making process. The rule-based mechanism is used to achieve the goal by means of a set of if-then rules. The defuzzification stage is used to convert the output of the inference mechanism into meaningful information for the end user [20-23].

III.METHODOLOGY

The Hybrid signal processing technique for automatic detection and classification of instantaneous tracking and characterization of voltage variations is shown in Fig. 2. It consists of three stages: an initial stage for tracking the magnitude of the voltage; an identification stage, and a final classification stage. For implementing the overall methodology, the MATLAB software is used.

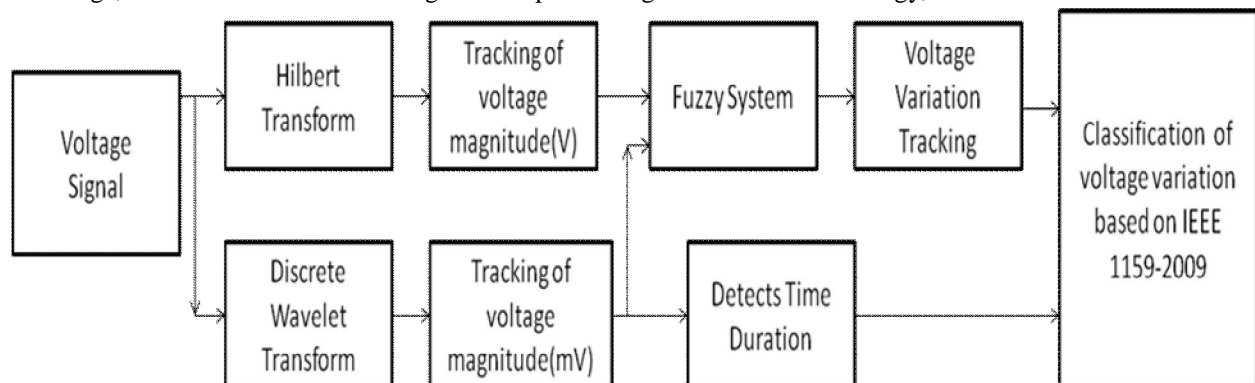


Fig.2. Block diagram for detection and classification of PQ events.

A. Voltage Magnitude tracking

The synthetic PQ signals are modeled using Table I with a sampling frequency of (F_s) 15.8 KHz. Fig. 3(a) shows a short duration variation of synthetic continuous signal with random sags, swells, and interruptions. When the signal is employed to signal processing technique, simultaneous detection of time duration and tracking of magnitude are obtained. The HT provides the information of magnitude variation of the voltage as envelope as shown in Fig. 3(b). The DWT Daubechies' fourth order is applied to the signal in order to detect the start and end point of the voltage variation of the signal. The detail1 (Db4) output is shown in Fig. 3(c) and the fuzzy logic output is shown in Fig. 3(d).

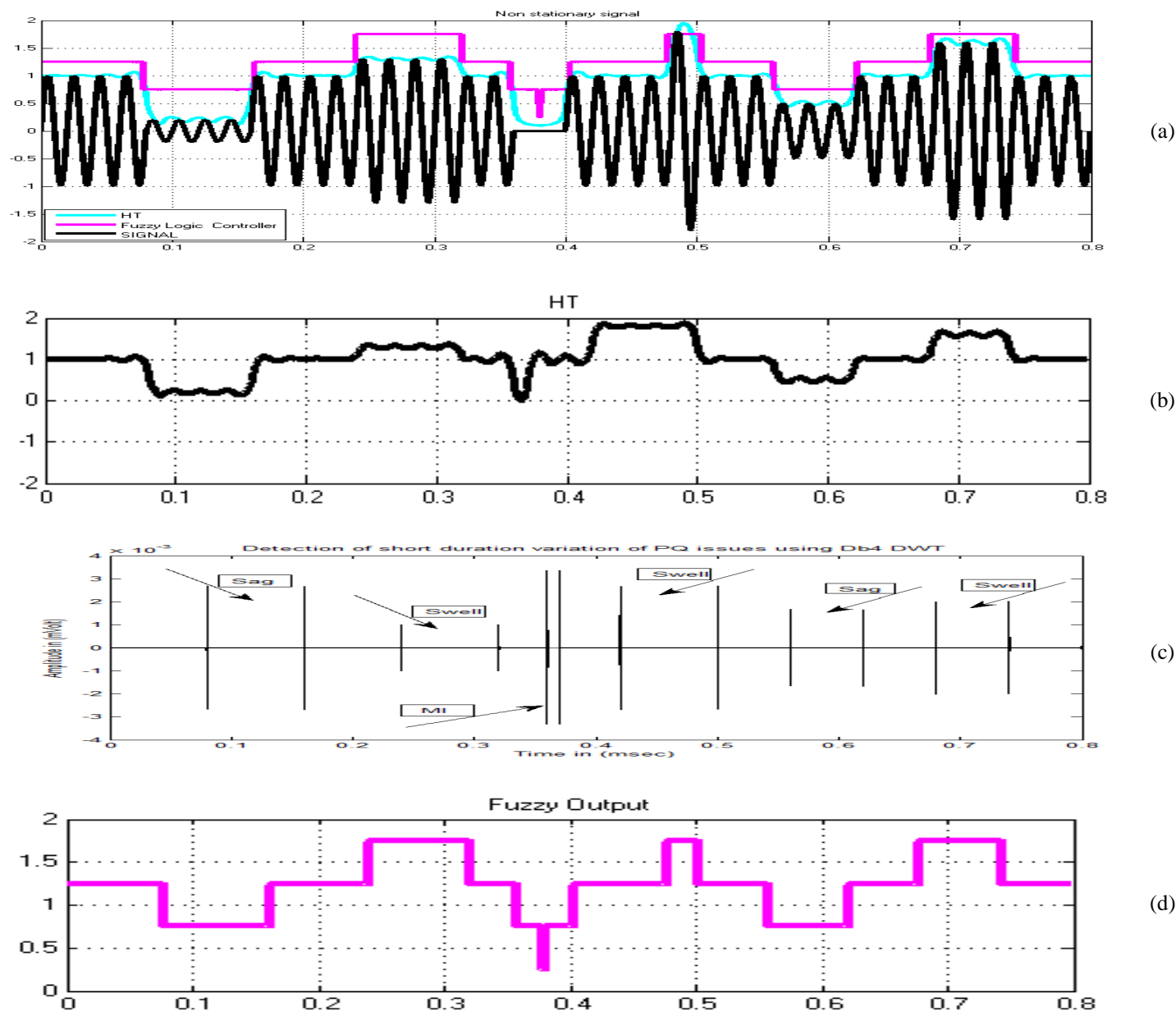


Fig. 3. Detection of voltage variation. (a) Signal with random sags, swells, and interruption. (b) Time duration output of DWT. (c) Envelope output of HT. (d) Fuzzy output.

B. Voltage variation tracking

To validate the results of the technique, an automatic Artificial Intelligence Fuzzy logic technique is adopted. The FL system tracks the voltage variation instantaneously (sample to sample). The Mamdani fuzzy inference type system with two inputs, one output, and 12 rules are used to detect the voltage variations. The inputs are the voltage magnitude of (signal's envelope) HT and DWT,

while the output is an instantaneous voltage variation. For fuzzification, the voltage magnitude input is partitioned into four trapezoidal membership functions, as shown in Fig. 4(a), which are labeled as follows: very low magnitude (VLM), low magnitude (LM), normal magnitude (NM), and high magnitude (HM). The second input is partitioned into three trapezoidal inputs, as shown in Fig. 4(b), which are labeled as follows: negative DWT (ND), zero DWT (normal ZD), and positive DWT (PD), while the output is divided into four trapezoidal membership functions, labeled as interruption, sag, normal, and swell as shown in Fig. 4(c). The FL system performs least amount composition for quantifying the output of the rules. The parameter of membership function lies between 0.5 and 4.5, with the knowledge of authors [23]. In this view, the fuzzy inference mechanism has the following rules [26].

- 1) If (HT envelope is VLM) and (DWT is negative), then (output is interruption).
- 2) If (HT envelope is VLM) and (DWT is normal), then (output is interruption).
- 3) If (HT envelope is VLM) and (DWT is positive), then (output is sag)
- 4) If (HT envelope is LM) and (DWT is negative), then (output is sag).
- 5) If (HT envelope is LM) and (DWT is normal), then (output is sag).
- 6) If (HT envelope is LM) and (DWT is positive), then (output is normal).
- 7) If (HT envelope is NM) and (DWT is negative), then (output is normal).
- 8) If (HT envelope is NM) and (DWT is normal), then (output is normal).
- 9) If (HT envelope is NM) and (DWT is positive), then (output is normal).
- 10) If (HT envelope is HM) and (DWT is negative), then (output is normal).
- 11) If (HT envelope is HM) and (DWT is normal), then (output is swell).
- 12) If (HT envelope is HM) and (DWT is positive), then (output is swell).

C. Classification stage

Fig. 3(a) shows the synthetic signal with occurrence of multiple PQ issues in a continuous signal at different period of time. Fig. 3(b) shows the output of HT which tracks the magnitude of envelope at appropriate time. Fig. 3(c) shows the output of DWT which detects the duration of time accurately. The FL outputs for the signal in Fig. 3(d) tracks and classifies the voltage variation which the observer can monitor over a time (sample to sample). It is an advantage since it does not require a batch of data to give a result as the case of other classifiers such as neural networks. Even though the magnitude (scales) of DWT output is very low in magnitude, it acts as an input to the FL system, to detect the starting and ending time of the voltage variations of the overall methodology. The recognition of the voltage variation is carried out using an expert fuzzy based system which is simple, more effective and efficient method to categorize the hypothetical conditions.

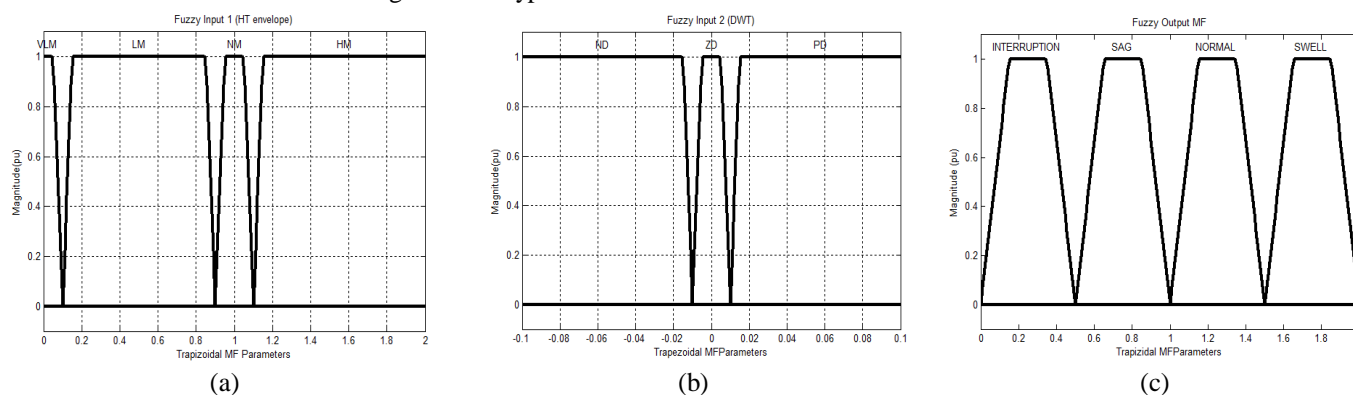


Fig. 4. Membership functions (a) (envelope) HT Fuzzy input 1, (b) DWT Fuzzy input 2, and (c) Fuzzy output.

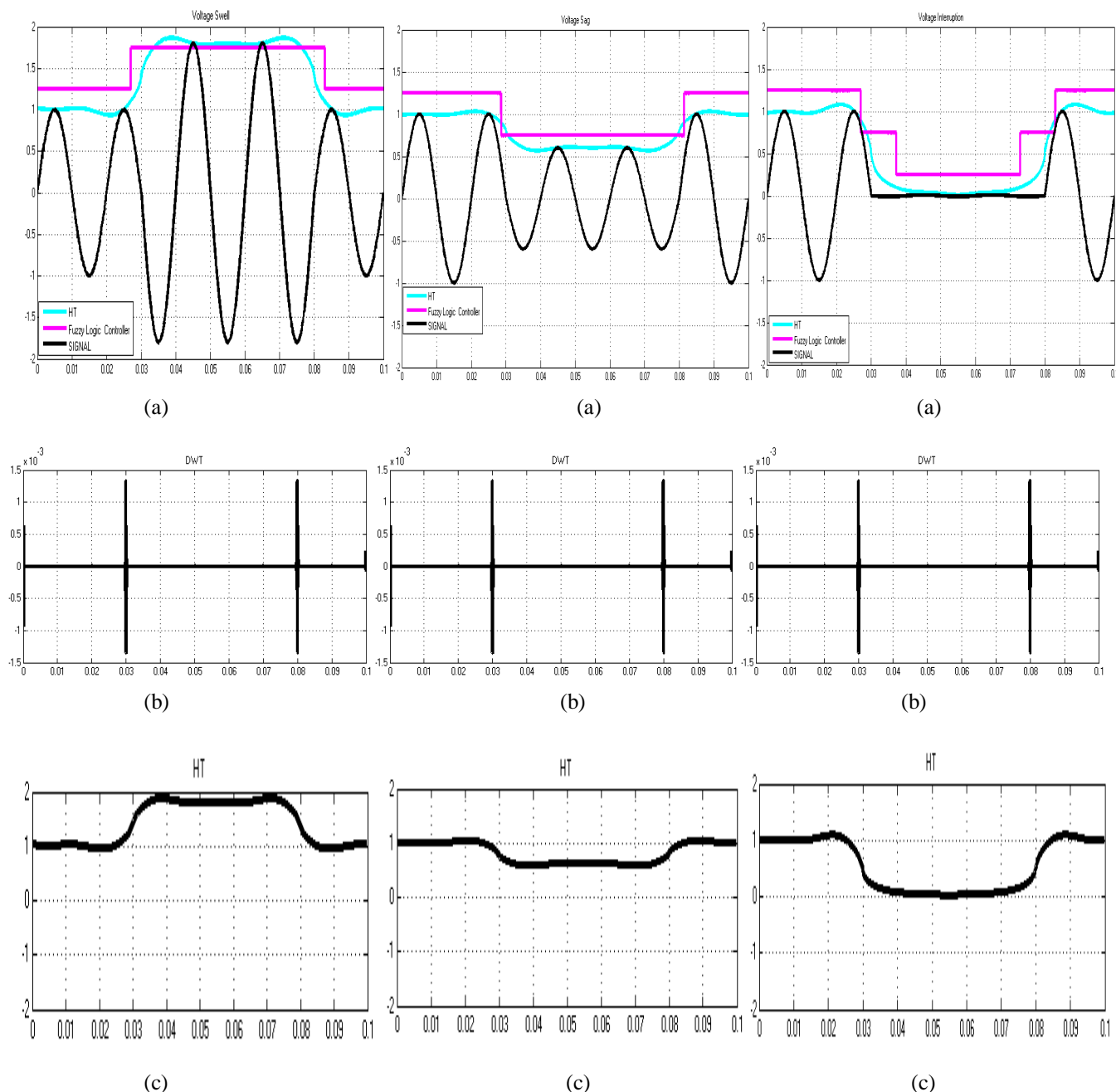
IV. CASE STUDY

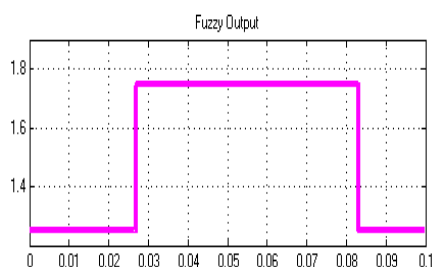
In this section, the new approach of the methodology is presented with its performance over different synthetic data conditions. In order to validate the performance of the proposal, 100 signals for each voltage variation category are generated with random values as shown in Tables I. The classifications results are shown in Table II. The efficiency of the overall methodology is calculated using equation (9). It is observed that the hybrid technique has nearly 100% of efficiency with least delay.

$$\text{Efficiency} = \frac{\text{Number of events correctly characterised}}{\text{Total number of Events}} \quad (9)$$

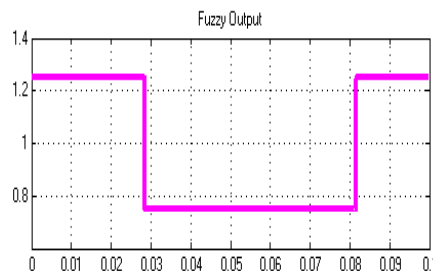
Fig.5.a shows the voltage swell of 90% with the time $t_1=0.03\text{sec}$ and $t_2=0.08\text{sec}$, and the comparison of HT and Fuzzy output are depicted, in which DWT was not included; the reason is that the output of DWT is very low magnitude (scales) which was depicted separately in Fig.5.b. The HT output shown Fig.5.c tracks the magnitude envelope in the upward direction (above the magnitude of p.u value) for voltage swell. The output of DWT, HT and Fuzzy tracks the magnitude of voltage variation and duration of starting and ending time absolutely.

Fig.6.a. shows the voltage sag of 60% with the time $t_1=0.03\text{sec}$ and $t_2=0.08\text{sec}$, with the comparison of HT and Fuzzy output. The outputs of DWT, HT and Fuzzy are depicted in Fig.6. [b-d]. The HT output shown in Fig.6.c tracks the magnitude envelope in the downward direction (below the magnitude of p.u value) for voltage sag. The output of Fuzzy tracks the magnitude of voltage variation and duration of starting and ending time precisely.

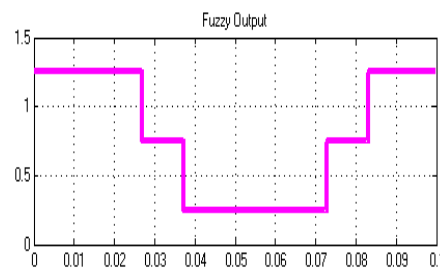




(d)
Fig. 5.



(d)
Fig. 6.



(d)
Fig. 7.

Fig.[5-7]. Detection of voltage variation (a) Signal with swell, sag, interruption (b) Time duration output of DWT. (c) Envelope output of HT. (d).Fuzzy output

Fig.7.a. shows the voltage Interruption of 100% with the time $t_1=0.03\text{sec}$ and $t_2=0.08\text{sec}$, with the comparison of HT and Fuzzy output. The outputs of DWT, HT and Fuzzy are depicted in Fig.7. [b-d]. The HT output shown in Fig.7.c. tracks the magnitude envelope at zero level for 100% loss of power for more than two cycles. When it is less than a cycle, a spike at $t=0.37\text{ sec}$ are depicted (below the magnitude of p.u value) in Fig.3.c and d.

PQ Class	C1	C2	C3	C4
C1	1	-	-	-
C2	-	99	-	1
C3	-	-	100	-
C4	-	-	-	100
Classification efficiency in %	100	99	100	100
Classification error in %	0	<1	0	0
Overall Efficiency	99.66%			

TABLE 2: Results of Classification

V. CONCLUSION

This paper documents a new methodology for automatic detection and characterization of voltage variations such as sag, swell and interruption in instantaneous time, i.e., sample to sample. The Hybrid HT and wavelet detect the magnitude of voltage variation and time duration of event occurrence simultaneously with the induction of FL system which classifies the PQ events accurately. Unlike the other neural networks that require features extraction process, training the data set which increases the complexity and computational burden. The hybrid method reduces the computation, increases the accuracy, detects and classifies the PQ issues automatically. The signals are generated using MATLAB code, and analyzed for stored data (offline processing). The same technique can be investigated with other PQ issues and explored with FPGA implementation for online and real-time monitoring of voltage variations.

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