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Application of Root Mean Square and Adaptive Neuro-FuzzyInference Systemfor Power Quality Events Classification Using Electricaland Electronics Home Appliances as Case Study

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Abstract:*The proliferation of sensitive equipment and non-linear loads atbothindustrial and domestic environment is extremely higher nowadays. This invariably contributes immensely topower quality issues on electric power system network and this indeed is a subject of concern among power system researchers since the world is aiming at ensuring clean, stable and quality electric power supply. This paper presents application of root mean square and adaptive neuro-fuzzy inference system for power quality events classification using electrical and electronics home appliances as case study.Three power quality events (voltage dip, voltage swell and voltage interruption) were considered in this paper. PQ events classification results obtained by the proposed approach were compared with the classification with FLUKE 435. Based on the analysis, obtained classification rateforelectric blender, laptop, television and electric fan was found to be 100% while that obtained forrefrigerator, vacuum cleaner and washing machine was found to be 80%. The estimatedoverall performanceaccuracy of RMS-ANFIS was found to be 91.42%. The proposed approach showed greater suitability for detection and classification of PQ events.*

Keywords;*Adaptive Neuro-Fuzzy Inference System, Fluke 435, Interruption, Power Quality,Root Mean Square, Voltage Dip, Voltage Swell*

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I. Introduction

Advancement in the field of power electronics has enhanced modern power systems and it as well led to ample availability and wide usage of several power electronicsdevices in many homes around the world.However, the increasing application/usageof power electronics devices alongside with sensitive and fast control schemes on modern electrical power networks has a degradation effect on the quality of clean electric powersupply[1, 2]. The induced disturbances caused by the integration of these devices on the electric power grid manifest inform of power quality problems such as transient (impulsive and oscillatory), short duration variations (interruption, dip and swell), power frequency variations, long duration variations (sustained under-voltages and over-voltages)and steady state variations (harmonics, notch, flicker etc.) [3,4] with an estimated manifestation time scale ranging from tens of nanoseconds to steady sate [3].

Generally, the main factors causing PQ problems among others include the use of sensitive electronic loads, proximity of disturbance-producing equipment and source of supply [5]. A critical evaluation of these factors depict that PQ problems is an issue that has come to stay; hence the needtoaddressitpromptly is highly imperative, if the dream of clean, stable and quality electric power supply and equipment serving for a relative long life span is to be attained.It is worthwhile to note that before any appropriate mitigating action can be taken, reliable and fast detection of these disturbances in addition to the root cause of disturbances must be known[6]. Early identification of PQ disturbances assists in data compression, costs reduction and as well as attenuation of its adverse effects in the field of control and monitoring system [7].The three basic fundamental steps in PQ disturbance recognition scheme entailed feature extraction (signal processing), disturbance classification (via conventional or artificial intelligenceapproaches)and decision making process (category to which a particulardisturbance belongs) [3, 8].

Features to be extracted for classification can be obtained from root mean square (RMS) values, Fourier, wavelet, short-term Fourier transform (STFT) and S-transform or alternatively from the parameters of signal models such as Kalman filter (KF) and auto-regressive (AR) models [9]. It needs to be stressed that RMS voltage supply magnitude is used in the power quality standards for detection and classification of voltage events [3, 10]. Features extraction techniques are Discrete Fourier Transform (DFT) and Short-Time Fourier Transform (STFT), Wavelet Transform (WT), S-Transform, Multi-wavelet Transform, Hilbert and Clarke transform, Sliding-Window ESPIRIT methods, Hyperbolic S-Transform, Multi-way Principal Component Analysis (MW-PCA), TT transform, and Hidden Markov model among others [11-14]. The extracted features can be classified using neural network [15], support vector machine[16], rule-based expert systems[17], fuzzy expert system [18], Genetic algorithm[19], and adaptive neuro-fuzzy inference system (ANFIS) [20]. A combination of artificial neutral network (ANN) learning skills and outstanding information representation in addition to inference capabilities of fuzzy logic produced ANFIS [21-23].Researcher [8] pointed it out that ANFIS had proven track record as an effective tool capable of tuning the membership functions of fuzzy inference systems.This paper presents application of root mean square and adaptive neuro-fuzzy inference system for power quality events classification using electrical and electronics home appliances as case study.

II. Definition of Relevant Terms

The power quality issues has being a subject of interest among scholars due to extensive usage of microprocessor based devices and controllers in enormous number of complicated industrial processes and residential applications [1].Pertinent terms in this study are limited to short duration variations PQ events such asvoltageswell, voltage dip and voltage interruption.

a **Power Quality Phenomena:** This includes all possible situations in which the waveform of the supply voltage(voltage quality) or load current (current quality)deviate from the sinusoidal waveform at rated frequencywith amplitude corresponding to the rated RMS value forall three phases of a three-phase system [24].

b. **Voltage Swell:** This can be described as an increase in voltage outside normal rated tolerance for given equipment [25].

c.Voltage Dip: This is another power quality event which refers to short-term reduction in voltage of less than half a second [25].

d. **Interruption:** This can be viewed as a reduction in line-voltage or current to less than 10% of the nominal, not exceeding 60 seconds duration [26].

III. Materials and Method

A. Materials

Power quality analyzerFLUKE 435 (Fluke 2006) was used to acquire the real-time voltage signals waveform supplied at rated voltage and frequency of220 V, 50 Hz respectively to some selected home appliances. The selected electrical and electronics appliances used for this analysiswere: Blender, Laptop, Refrigerator, Television (TV), Vacuum Cleaner, Washing Machine and Electric Fan. The specification for these appliances is shown in Table A2 of Appendix A. The PQ of interest in this research is voltage swell, voltage dip and voltage interruption. Appendix B shows how theFLUKE 435was connected to obtain data needed for the analysis.

BMethodology

B1.Detection of Triggering Points

The Parseval's theorem approach was employed in this research work to obtain the energy signals. It is mathematically modelled as;

$$f(x) = \frac{1}{2}a_o + \sum_{n=1}^{\infty} a_n \cos(nx) + \sum_{n=1}^{\infty} b_n \sin(nx) \qquad (1)$$

Bessel's inequality becomes;

$$[f(x)^2 = \frac{1}{4}a_o^2 + a_o \sum_{n=1}^{\infty}[a_n \cos(nx) + b_n \sin(nx)] + \sum_{n=1}^{\infty}\sum_{n=1}^{\infty}[a_n a_m \cos(nx)\cos(mx) + a_n b_m \cos(nx)\sin(mx) + ambn\sin nx\cos mx + bnbm\sin nx\sin mx] \qquad (2)$$

By integrating equation (2), we have;

$\int_{-\pi}^{\pi}[f(x)]^2 =$

14ao2−ππdx+ao−ππn=1∞ancosnx+bnsinnxdx

+−ππn=1∞n=1∞[anamcosnxcosmx+anbmcosnxsinnxambncosmxsinnx+bnbmsinmxsin(nx)dx

(3)

$$= \frac{1}{4}a_o^2(2\pi) + a_o(0) + \sum_{n=1}^{\infty}\sum_{n=1}^{\infty}[a_m a_n \pi\delta nm + 0 + 0 + b_n b_m \pi\delta mn] \qquad (4)$$

$$= \int_{-\pi}^{\pi}[f(x)]^2 dx = \frac{1}{2\pi}a_o^2 + \sum_{n=1}^{\infty}(a_n^2 + b_n^2) \qquad (5)$$

Complex Fourier series can be represented as;

$$\frac{1}{2\pi}\int_{-\pi}^{\pi}|f(x)|^2 dx = \sum_{n=1}^{\infty}|a_o|^2 \qquad (6)$$

The features used as inputs to RMS function are calculated signal energy values since the PQ events are expected to have different energy values. The quantity of extracted features of distorted signal was reduced without losing its property hence the requirement of memory space and computing time for proper classification of PQ event type is less which solve the problem of previous research work in literature. An input voltage waveform passed into the RMS function to detect change points, upon the identification of triggering points, the waveform was segmented with each segment passed as input the created ANFIS object for classification of the event segments.

B2.Proposed Approach Flow Chart
The procedural steps for the proposed approach are as presented in the Figure 1

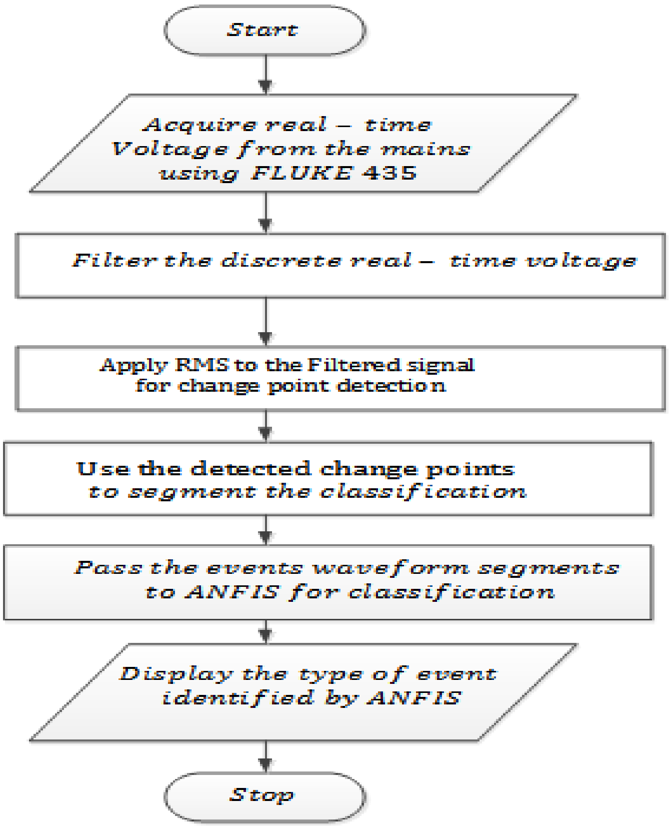

Figure 1: PQ Event Classification on Real-Time Voltage Signal

IV. Results and Discussion

The proposed approach was implemented in MATLAB (R2013a) and run on a portable computer an Intel Core 2 Duo (1.8GHz) processor, 2GB RAM memory and MS Windows 8 as an operating system. Table 1 presents the feature vector in form of energy signal for PQ event segments using RMS triggering point detection and actual triggering point detection respectively

Table 1: Feature Vector (Signal Energy) for PQ Event Segment using RMS Triggering Point Detection

Percentage of Disturbance (%)	Voltage Swell	Voltage Dip	Interruption
10	$4.4873e^7$	$3.0295e^7$	$7.7322e^5$
20	$5.3256e^7$	$2.4099e^7$	$7.7322e^5$
30	$6.2367e^7$	$1.8632e^7$	$7.7322e^5$
40	$7.2208e^7$	$1.3894e^7$	$7.7322e^5$
50	$8.2777e^7$	$9.8848e^6$	$7.7322e^5$
60	$9.4076e^7$	$6.6046e^6$	$7.7322e^5$
70	$1.0610e^8$	$4.0533e^6$	$7.7322e^5$
80	$1.1886e^8$	$2.2310e^6$	$7.7322e^5$
90	$1.3234e^8$	$1.1376e^6$	$7.7322e^5$

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It could be observed that relatively large signal energy levels were created for each PQ events so as to ensure that ANFIS objects were sufficiently trained and it was put in mind not to over-train the created ANFIS objects. The trained objects were saved and subsequently used for classification of the acquired signals.The results obtained with the proposed approach were compared to that obtained with FLUKE 435 (Fluke 2006). FLUKE 435 being an excellent power quality analyzer has capacity to classify PQ events appropriately. The results obtained areas shown in Table 2. As guide to interpreter Table 2 below; 1 indicated that PQ event was detected while 0 indicated that no PQ events weredetected.

Table 2: A Comparison of the RMS-ANFIS and FLUKE 435 Schemes for PQ Events Detection

Home Appliance	PQ Event Types	RMS-ANFIS	FLUKE 435	Percentage Efficiency of Classification rate
	Dip	1	1	
Blender	Swell	0	0	100%
	Interruption	0	0	
	Dip	1	1	
Laptop	Swell	0	0	100%
	Interruption	0	0	
	Dip	1	0	
Refrigerator	Swell	0	0	80%
	Interruption	0	0	
	Dip	1	1	
Television (TV)	Swell	0	0	100%
	Interruption	0	0	
	Dip	0	0	
Vacuum cleaner	Swell	1	0	80%
	Interruption	0	0	
	Dip	1	0	
Washing Machine	Swell	0	0	80%
	Interruption	0	0	

The results obtained with the proposed approach as compared to that obtained with FLUKE 435 indicated that the classification accuracy was excellently. Observation shows that same PQ event was detected in blender, laptop and television while that of refrigerator, vacuum cleaner and washing machine are slightly different.

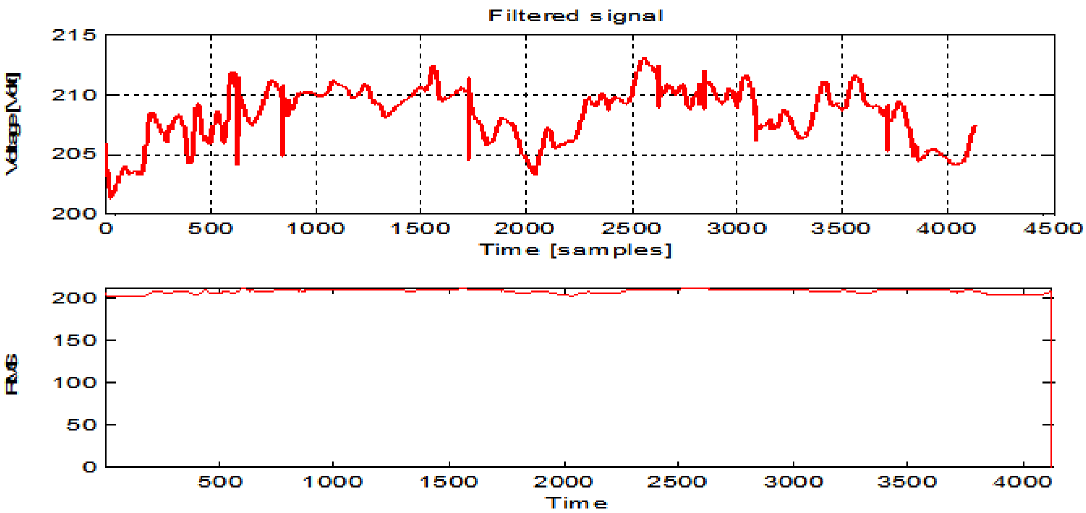

Figure 2: RMS Decomposition of Blender Signal with Voltage Dip

Figure 2 shows the real-time signal with voltage dip supplied to an electric blender. The RMS detected the change points at 530th, 1600th, 2500th and 3300th samples.

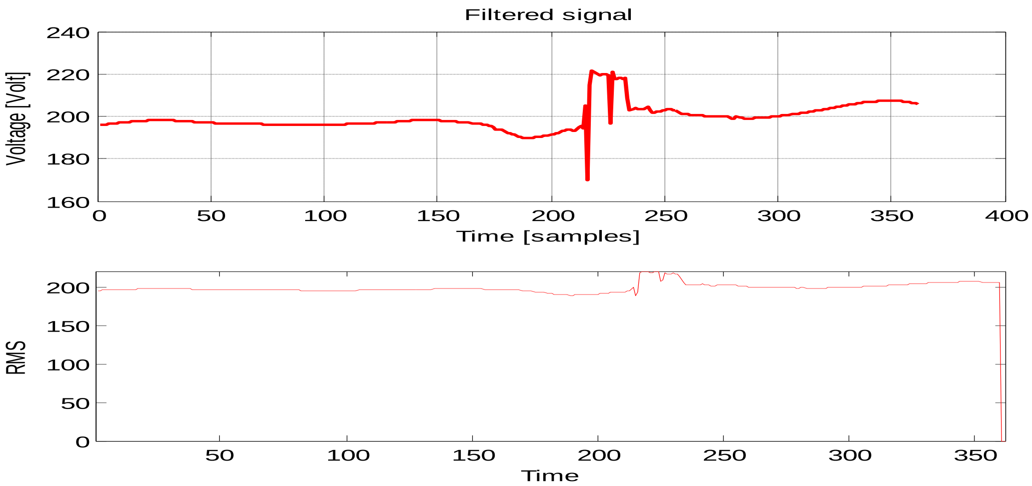

Figure 3: RMS Decomposition of Laptop Signal with Voltage Dip

Figure 3 shows the real-time signal with voltage dip supplied to a laptop; RMS was applied on the waveform and was able to detect the triggering points at 220^{th} and 230^{th} samples.

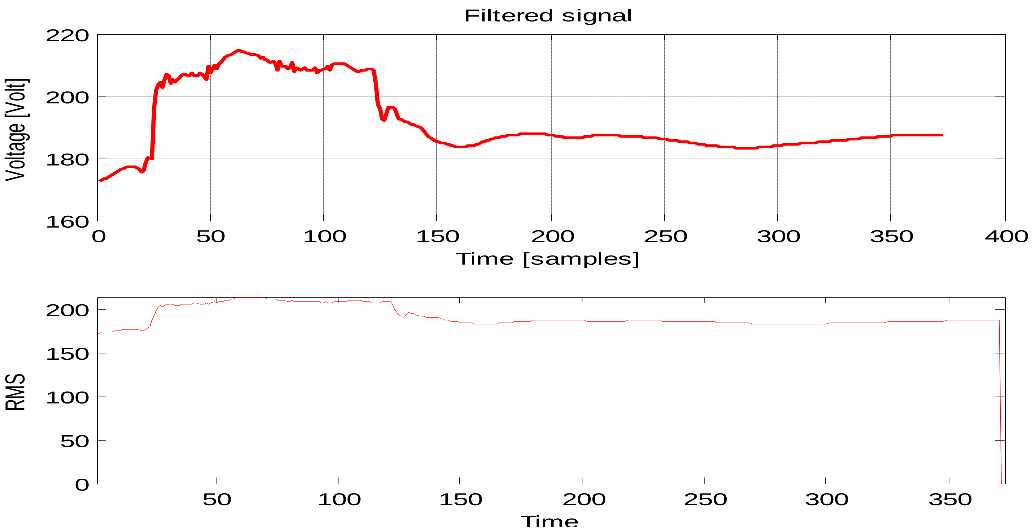

Figure 4: RMS Decomposition of TV Signal with Voltage Dip

Figure 4 shows the real-time voltage waveform containing voltage dip supplied to a TV set, the applied RMS detected the change points for dipat 400^{th} samples.

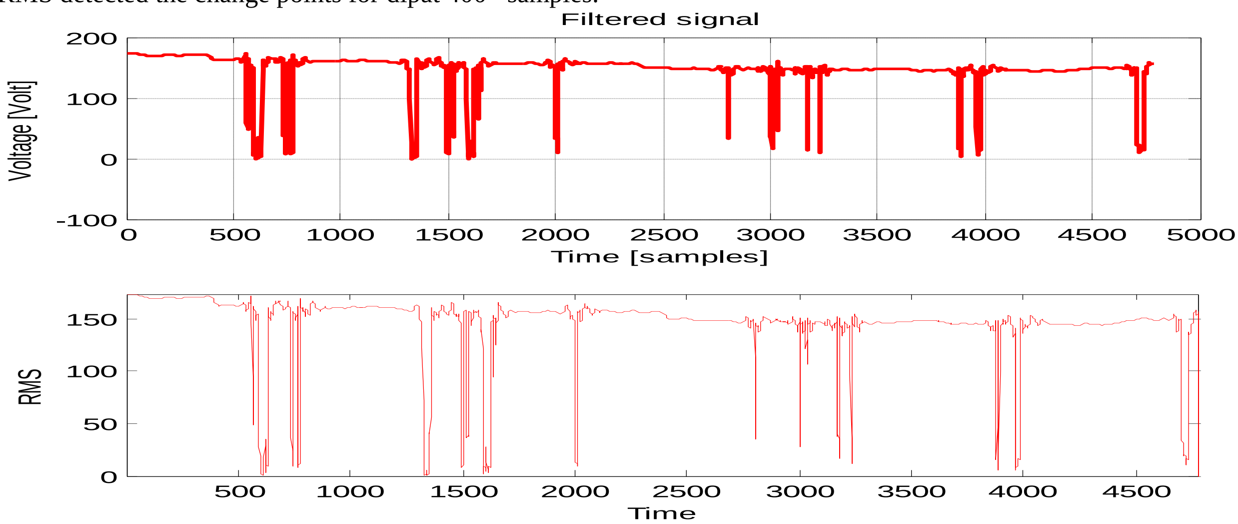

Figure 5: RMS Decomposition of Washing Machine Signal with Voltage Interruption

Figure 5 shows the real-time signal for washing machine. RMS was applied to the waveform and voltage interruption was detected at 650th, 1440th and 4830th samples.

V. Conclusion

Application of root mean square and adaptive neuro-fuzzy inference system for power quality events classification using electrical and electronics home appliances as case studyhas been presented in this paper. The technique usedwasRMS for change point detection and ANFIS for event segment classification. The proposed approach for PQ event detection and classification was experimented on real-time voltage waveforms supplied to some selected home appliances. The results obtained with the proposed approach was compared to that obtained with FLUKE 435 (which was used as benchmark), it was observed that the overall performance accuracy of the RMS-ANFIS was found to be 91.42%.Conclusively, RMS-ANFIS technique applied shows greater suitability for detection and classification of PQ events.

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Appendix A

Table A1: Standard Parameters for operating the FLUKE 435 PQ Analyzer

Electrical Parameter	Value
Maximum Phase Voltage	220V
Minimum Phase Voltage	180V
Maximum Neutral Voltage	3V
Maximum Impulse Voltage	500V
Maximum Wave shape Voltage	10V
Maximum Frequency Deviation	0.02Hz
Minimum Power Factor.	0.85
Maximum Voltage T.H.D.	5%
Maximum Current T.H.D	20%
Maximum Voltage Imbalance	2%
Maximum Current Imbalance	5%

Table A2: Specifications of the Home-Based Electrical / Electronic Appliances

S/N	Home- Based Electrical / Electronics Appliances	Manufacturer	Model No	Power Rating
1	Blender	LEXUS	MG2053	230V; 50 Hz; 500W, A.C. only
2	Refrigerator	THERMOCOOL	HRF-300R	130W; 230V; 50 Hz
3	Electric Fan	LEXUS	-	220/240V, 50Hz
4	Laptop	HP	dm4-2020sn dm4-2020sn	100-240 V AC 360W; 50-60Hz
5	Vacuum cleaner	SAMSUNG	U314S14B/XE U	1400W
6	Washing machine	KMOSON	XPB38-8000	220V; 50Hz; 240W
7	Television (TV)	LG	21SBIRG-T4	110-240V, 50/60Hz, 85W

APPENDIX B: The use of FLUKE 435 for Measurement of Power Quality of Home-Based Electrical / Electronic Appliances

Plate B1: Acquisition and Analysis of Supplied Power Signal for Laptop by FLUKE 435

Plate B2: Acquisition and Analysis of Supplied Power Signal for Refrigerator by FLUKE 435

Plate B3: Acquisition and Analysis of Supplied Power Signal for Fan by FLUKE 435

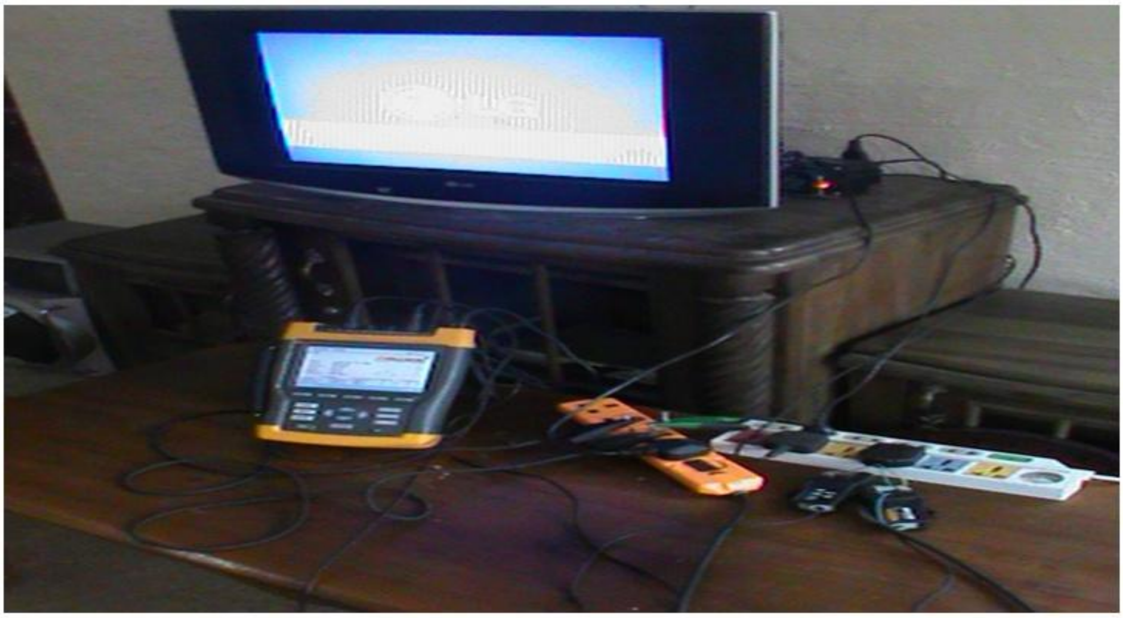

Plate B4: Acquisition and Analysis of Supplied Power Signal for TV by FLUKE 435

Plate B5: Acquisition and Analysis of Supplied Power Signal for Washing Machine by FLUKE 435

Plate B6: Acquisition and Analysis of Supplied Power Signal for Vacuum Cleaner by FLUKE 435

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