Analysis of Power Quality Variations in Distributed Generation Systems

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Received: 06.12.2018 Accepted: 06.02.2019

Abstract- The increasing use of Power Electronics along with Distributed Generation Systems (DGs) has been playing a predominant role in the efficient operation of Electric Power Systems. Thus, studies regarding identification and classification of Power Quality (PQ) events have been a subject of recent interest for researchers from the view point of initiating suitable control actions in DGs for achieving improved performance. This requires carrying out a detailed analysis of the various characteristics of real time electrical signals through a set of signal processing techniques. PQ distortions due to environmental factors, such as change in wind speed and solar irradiations are considered in this work. Signal features are extracted for various voltage sag/swell signals using S-Transform, while signal-classification is done by Least Square Support Vector Machine (LS-SVM) technique. A 17-bus test system is modeled using the open source software, Open Distribution System Simulator (OpenDSS). Smart converter control is realized with inputs received from signal classifier, so as to initiate proper grid-support functions. Controlled actions realized are Volt-VAr and Volt-Watt functions. The performance of the control functions is tested for varying levels of solar and wind penetrations. The efficacy of the results is imminent based on control actions being in line with the set reference.

Keywords

1. Introduction

In flexible Electrical Power systems (EPS), Distributed Generation systems (DGs) are considered as a subset of distributed resources connected to a system through a point of common coupling [1]. Wind, solar Photovoltaic, Diesel Generator, etc. are some of the examples for such generations. DGs provide voltage support, reduce losses and improve Power Quality (PQ) of the system. However, wind power generators and Solar Photovoltaic Systems (SPV) inject power into the grid, resulting in voltage rise/ sag/ swell/ fluctuations. Thus, it is probable that, depending on their configuration, DGs introduce disturbances that may result in reduction of PQ [2–10]. In this context, the assessment of PQ level is required for studies connected with the smart distribution systems involving DGs. The assessment can be carried out in two stages: PQ assessment before DG installation and PQ assessment after the installation of DG, requiring different tools and quantities, with the scope of these assessment methods being different. However, based on the performance of different DGs as per the various environmental operating conditions such as, solar irradiation, cell temperature, partial/full shading and variation in wind speed, it is observed that high penetration of PV and wind can cause various unpredictable Power Quality (PQ) disturbances. Hence, it is necessary to classify PQ disturbances to initialize control actions for smart converters to have grid-support functions as required.

In this context, classification of PQ events has been considered for detailed study by various researchers through different tools. Classification of PQ events is carried out using Expert Systems, Fuzzy Expert Systems, Modular Neural networks, Support Vector Machines, Least Squares Support Vector machines (LSSVM), etc.. The reasoning and connected study to extract features of the PQ events for classification purpose is carried out by signal processing techniques, such as: Fast Fourier Transform, Discrete Fourier Transform, Wavelets, modified wavelets, etc. Among the various signal processing techniques, a modified wavelet transform, known as Stockwell Transform (S-Transform) has many advantages as compared with other techniques. The S-transform provides frequency-dependent resolution while maintaining a direct relationship with the Fourier spectrum. The phase of the S-transform referenced to the time origin provides information about spectra that is not available from locally referenced phase information in the Continuous Wavelet Transform [11-17].

It is observed that the work reported in the literature in this domain have focused towards the classification of PQ problems into different classes. However, the efficacy of the classification is not verified by considering variation in different attributes/parameters in real-time. The proposed work addresses this issue by continuous verification of all the signals obtained during training stage for their effectiveness. Accordingly, novel control actions are initiated as part of realizing a proper grid support function. An algorithm is developed using MatLab software routine to keep track of all the signals. Grid support control actions are initiated until power quality variations are found to be within the acceptable limits. The control strategies adapted is intelligent Volt-VAr and Volt-Watt control. A 17-bus test system is considered and modeled using Open Distribution System Simulator (OpenDSS) [18]. The novelty of the results is found to be in the PQ analysis using intelligent algorithms corresponding to the post-DG-installation period. For all the cases of deviations observed with reference to maintenance of improved power quality, proper control actions are initiated. A machine learning algorithm based on Least Square Support Vector Machine concept has been used for facilitating the control actions.

2. Methodology

The concepts of probability for PQ study and calculation of various PQIs for PQ assessment before and after the installation of DGs have been discussed in [18]. Once the DGs are optimally placed, variations in PQ levels are to be monitored. In this section, some of the operational issues, such as, detection of voltage sag/swell, due to change in environmental conditions, load are considered and discussed. Implementation of the algorithm to arrive at improvements in PQ using Volt-VAr and Volt-Watt strategies for selected test system are presented.

2.1. PQ Detection and Classification

Power Quality analysis comprises various kinds of electrical disturbances such as voltage sag, voltage swells, harmonic distortions, flickers, imbalance, oscillatory transients and momentary interruptions etc. However, detection of sag/swell due to increase/decrease in wind speed and solar irradiation are considered in this work. Using the time frequency localization property of the S-transform, sag and swell signals are detected and classified. Following is the step-by-step procedure to extract various features and classify the signal under consideration:

i. The voltage signal is considered at the required buses of the system, for various cases of DG operations.
ii. For each of the above individual cases, signal processing is carried out using S-transform technique, to finally arrive at the S matrix. The final form of continuous S-Transform is [11-12]:

$$S(\tau,f)=\int_{-\infty}^{\infty} h(t).\left(\frac{|f|}{\sqrt{2\pi}}\right).e\left(-\frac{(\tau-t)^2f^2}{2}\right).e(-i2\pi ft)\,dt \quad (1)$$

The voltage signal Si(t) can be expressed in discrete form as $s_i(kT), k=1,2\ldots(N-1)$, where T is the sampling time. The discrete Fourier transform is obtained as:

$$S[\frac{n}{NT}]=\frac{1}{N}\sum_{k=0}^{N-1} s_i(kT).e(-\frac{i2\pi k}{N}) \quad (2)$$

Using (1), the S-transform of a discrete time series s(kT) is obtained with f→ n/NT and τ→ jT as:

$$s\left[jT,\frac{n}{NT}\right]=\sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right].G(m,n).e\left(\frac{i2\pi mj}{N}\right) \quad (3)$$

Where f is the fundamental frequency of the signal and τ is the time variable for Gaussian window

Amplitude and phase of S-matrix are obtained from (3). The rows and columns of S-matrix depict respectively the frequencies and time vectors.

iii. Following Signal Statistical Features (SSF) are extracted from S-matrix:
SSF1: Energy of the magnitude contour corresponding to maximum absolute of each column of the S-matrix
SSF2: Standard deviation of the magnitude contour corresponding to maximum absolute of each column of the S-matrix SSF3: Energy of the phase contour, SSF4: Standard deviation of the phase contour, SSF5: Mean of the magnitude contour SSF6: Mean of the

phase contour, SSF7: Skewness of the magnitude contour, SSF8: Skewness of the phase contour, SSF9: Kurtosis of the magnitude contour and SSSF10: Kurtosis of the phase contour.

iv. The Power Quality variations are detected in terms of statistical features and classified distinctly by LS-SVM. It is a popular machine learning approach which can be used for the pattern classification. The computational complexity of SVM depends on the samples used for training, higher number of training samples increases computation time. To overcome this, LS-SVM is proposed, which is improved version of SVM. LS-SVM is used to build a classifier characterized by the following optimization problem [16].

$$\min_{\omega,d,e} JLS(\omega,d,e) = \frac{1}{2}\omega T\omega + C\frac{1}{2}\sum_{k=1}^{N} e_k^2 \quad (4)$$

Subject to following constraints:

$$yk=\omega Tx+d+ek, k=1,2,\ldots\ldots\ldots,n. \quad (5)$$

The binary classifier for multiclass problem can be modeled as:

$$\min_{a,d,e} \frac{1}{2}\ \omega T\omega + C\frac{1}{2}\sum_{i=1}^{n} e_i^2 \quad (6)$$

v. Finally, the decisions are arrived at in respect of the control actions to be initiated in line with step iv. The relevant control signal is initiated, whenever a deviation from the standard pattern is observed.

The original code of S-transform developed by R. G. Stockwell [11] is modified here for feature extraction of voltage signal from OpenDSS- MatLab COM-interface. The Radial Basis Function kernel and one-vs-one multiclass classification approach are used while implementing LS-SVM in MatLab.

Fig.1 shows the methodology adopted to initiate different control actions for smart converter throgh a flow diagram. It is evident from the flow diagram, that the algorithm continuously traces out the voltage signal and processes it. Various signal classes used for classification are shown in Table I. The characteristics corresponding to change in environmental conditions are modeled in OpenDSS, by using 'Loadshape objects' [20], which can be configured for daily, weekly, monthly variations in: load, wind speed, solar irradiation and temperature.

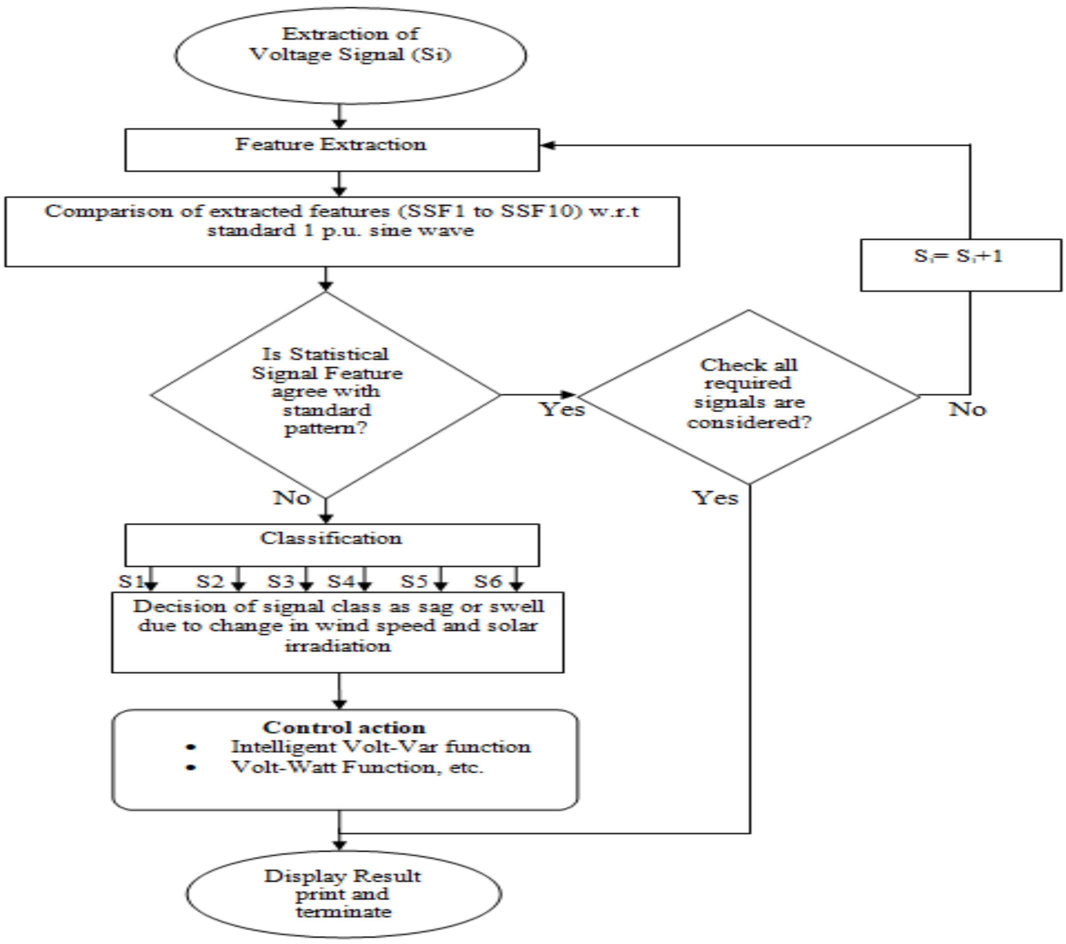

Figure 1. Flow Diagram of the method.

TABLE I. Sag/swell signal description

Signal class	Signal Description
S1	Sag due to decrease in wind speed
S2	Sag due to decrease in solar radiation
S3	Sag due to increase in load
S4	Swell due to increase in wind speed
S5	Swell due to increase in solar radiation
S6	Swell due to decrease in load

2. 2 Volt-VAr & Volt-Watt Control

A volt-VAr curve for a smart converter is shown in Fig. 2. This can be utilized to maintain the voltage at the terminal of the PV system to be within internationally acceptable standards for different circumstances. If the voltage exceeds the predetermined boundary, then absorption of reactive power (inductive VArs) is initiated. Similarly, reactive power can be injected (capacitive VArs) to maintain the voltage profile. Under some critical circumstances, where high DG output and low-load causing the feeder voltage to rise too high can be addressed by adopting Volt-Watt curve. Fig. 3 shows a typical Volt-Watt curve.

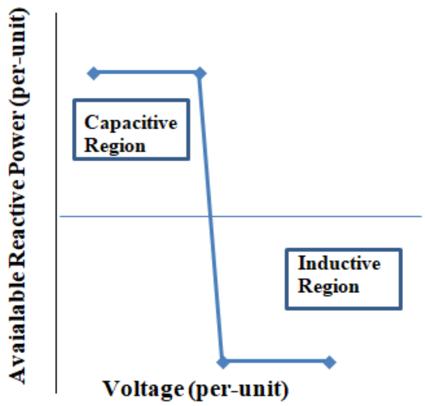

Figure 2: Typical Volt-VAr curve.

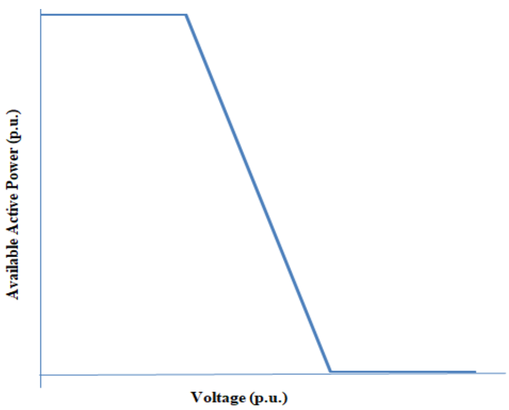

Figure 3. Typical Volt-Watt curve

2. 3 Implementation

An example distribution system including DGs, as shown in Fig. 4 is considered for analysis. Highest improvements in terms of PQ are observed at bus 17 [18] Hence it is considered as installation bus. The operation of the system in this work is presented for two DGs as: 4.95 MW Doubly fed Induction Generator and 4.95 MW SPV bus-17. This system is simulated using OpenDSS.

The objective is to realize an overall improvement in system PQ. Till such time, a series of machine learning based control actions are initiated by the operator through a decision manger, as depicted in the flow diagram of Fig. 1. These control actions are initiated based on processing of signals by using S-Transform, extracting the features and then feeding to the machine learning algorithm. Suitable time-domain to frequency-domain and vice-versa analysis have been carried out while extracting the data from the monitors, processing them and initiating control actions.

3. Results & Discussion

The proposed algorithm is tested for its effectiveness to detect PQ disturbances during variation in wind speed, voltage and load, also the required control actions are realized. This section presents the results obtained for different cases.

3.1. PQ Detection and Classification

A sample test system shown in Fig. 4 is modeled through OpenDSS. The S-transform gives the Time Frequency Representation (TFR) of the signal. Fig. 5 shows the TFR of a pure sinusoid of 1 p.u. The sections (a)-(d) respectively depict the signal under consideration, its TFR, the voltage profile, and its 3D image.

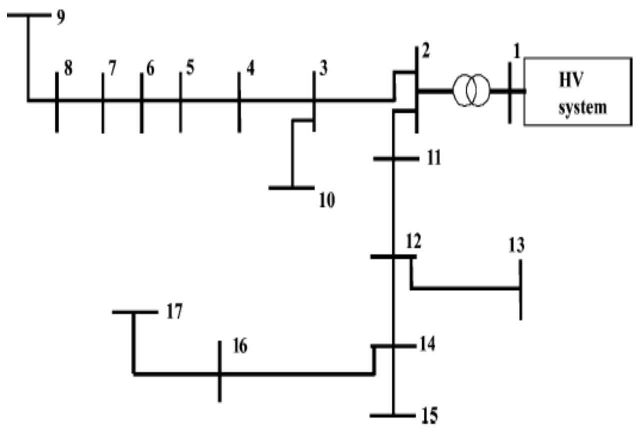

Figure 4. Sample test System.

Features extracted from the TFR of pure sinusoid of 1 p.u are set as reference for classification, e.g. SSF2= 0.149, with 2.5 kHz sampling frequency, obtained by running the algorithm on a Pentium IV, 3.2 GHz computer, under MatLab environment (This is in close proximity to the set reference of 0.1507 [12] with sampling frequency of 2.5 kHz). Various other signals are considered in sequence as per the flow diagram of Fig. 1, to extract their statistical features as stated in section II. For instance, a generated voltage waveform of 0.5 p.u. (sag) and its TFR depicting the variations in contour lines are shown in Fig. 6. Here, the sections (a)-(d) respectively depict the signal under consideration, its TFR, the voltage profile, and its 3D image. The variations are visible in these waveforms as compared to those depicted for a normal case in Fig. 5. Similarly, a generated voltage waveform of 1.5 p.u. (swell) and its TFR depicting the variations in contour lines are shown in Fig.7. With the features extracted, by using the LS-SVM, the signals are classified into the classes of sag/swell as per Table I, with the further grouping of sag into S1,S2 and S3, being shown in **Fig. 8.** The boundary plot obtained by LS-SVM gives three separate regions for three different classes of PQ variations. The hype-planes distinctly separate the PQ variations from each other.

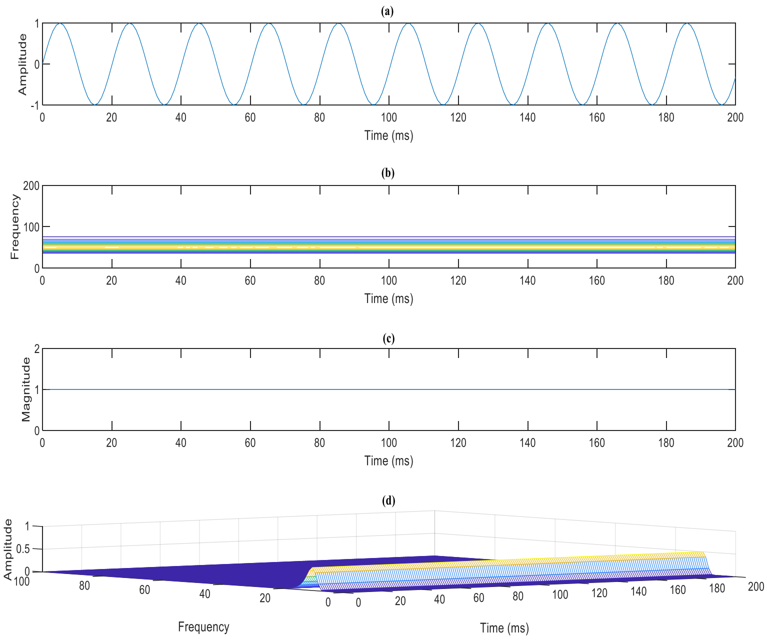

Figure 5. TFR of 1 p.u. sinusoid obtained through S-transform.

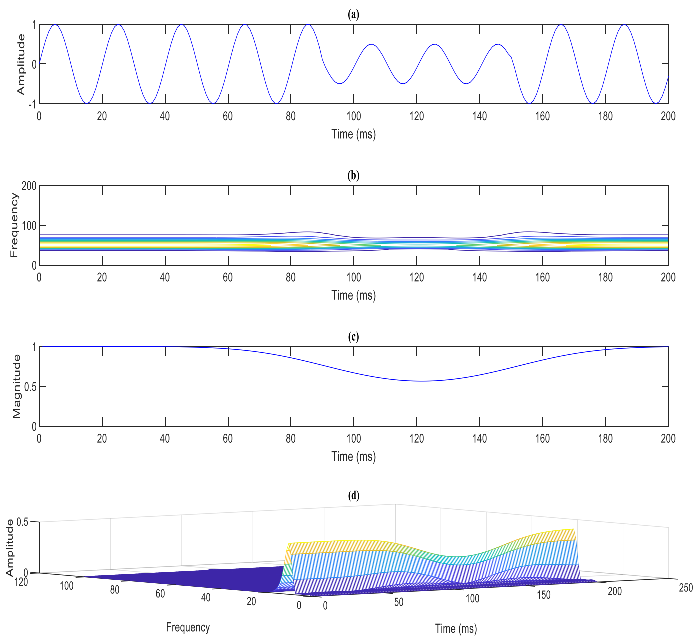

Figure 6. TFR of sag waveform obtained through S-transform.

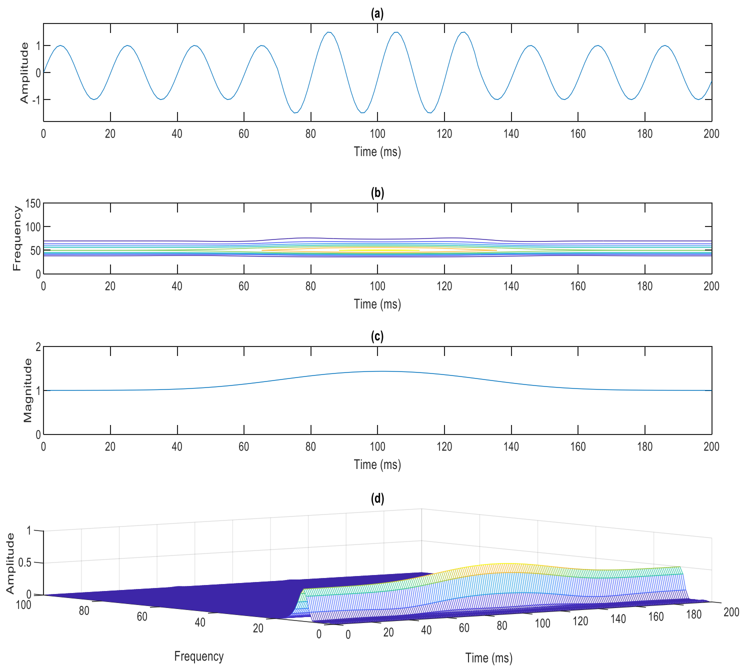

Figure 7. TFR of swell waveform obtained through S-transform.

3.2. PQ Detection and Classification

The origin for each of such sag class could be of different nature and hence, they are considered through 'Loadshape Objects' available in OpenDSS. Depending on the type of signal class identified, it is possible to initiate the control action of the inverter. As a consequence of the initiation of one of the control actions, such as Volt-VAr control, a Volt-VAr curve is shown in Fig. 9, that could be useful to regulate the voltage according to the requirement. Similarly, Volt-Watt strategy implemented is shown in Fig. 10.

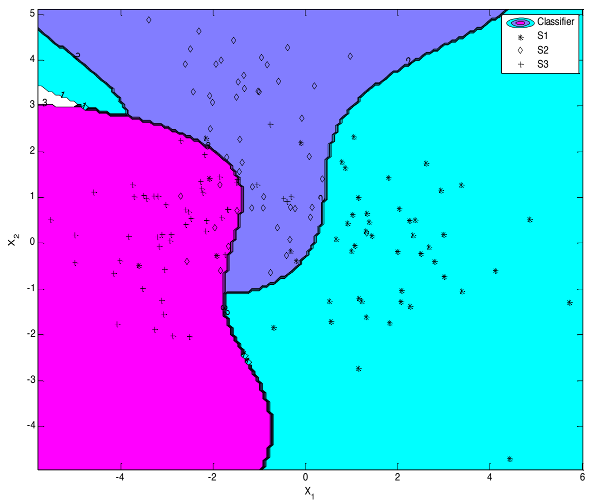

Figure 8. Boundary plot of LS-SVM for grouping of voltage Sag.

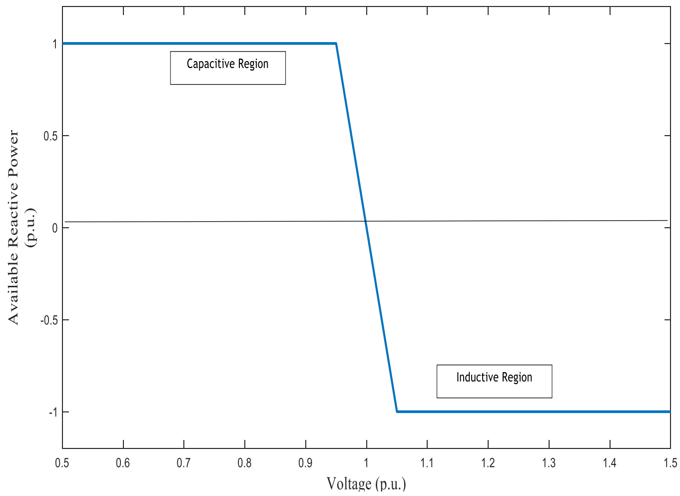

Figure 9. Typical Volt-VAr curve considered for study.

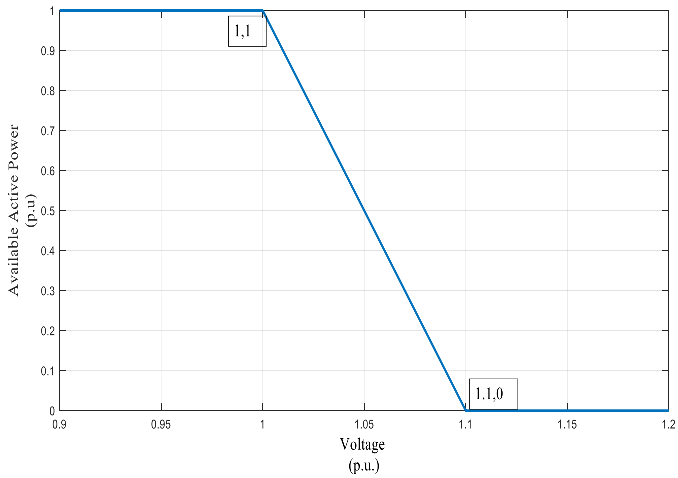

Figure 10. Typical Volt-Watt curve considered for study.

To demonstrate the ability of the algorithm, the system shown in Fig. 4 is considered with DG at bus-17 (4.95MW). The uncertainties in load are modeled using OpenDSS.

Fig. 11 shows the variations in voltage at bus-17 before initiating control actions. With the Volt- VAr and Volt-Watt control functions enabled, it is observed that voltage is restored to normal condition as depicted in Fig. 12 and Fig. 13. Further, to verify the effectiveness of the algorithm, the uncertainties in wind and SPV are modeled, the variations in the voltage are monitored. For these variations, the algorithm keeps track of these variations and initiates control actions. Voltage (sag/swell) and improvement in voltage as a consequence of Volt-VAr control action obtained is shown in Fig. 14. The obtained values as a result of control action are in close approximation to the set reference.

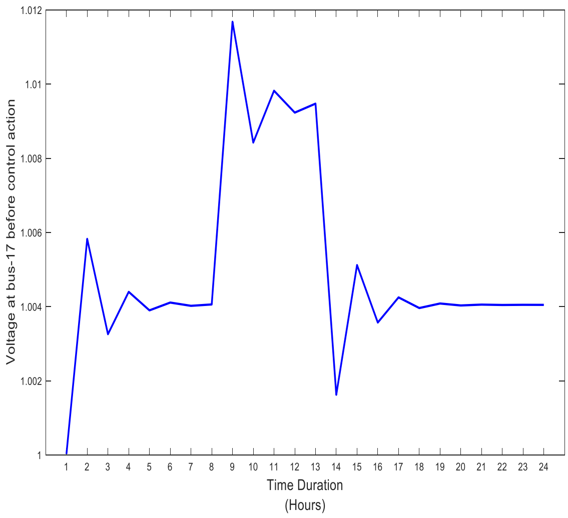

Figure 11. Voltage at bus-17 without control action.

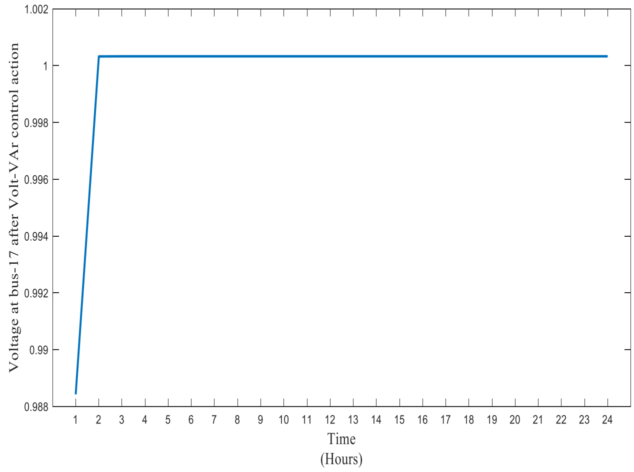

Figure 12. Voltage at bus-17 after Volt-VAr control.

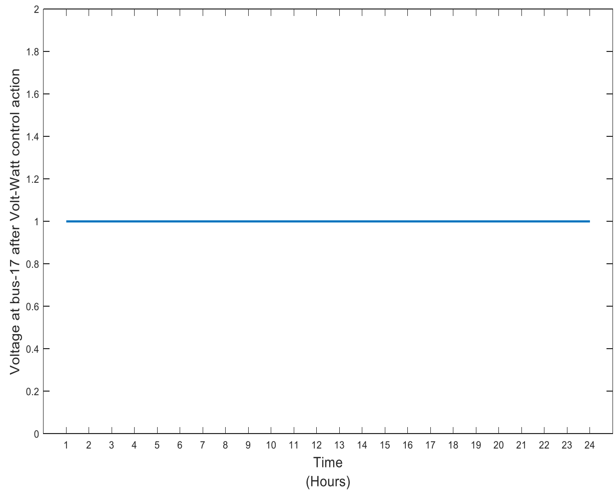

Figure 13. Voltage at bus-17 after Volt-Watt Control.

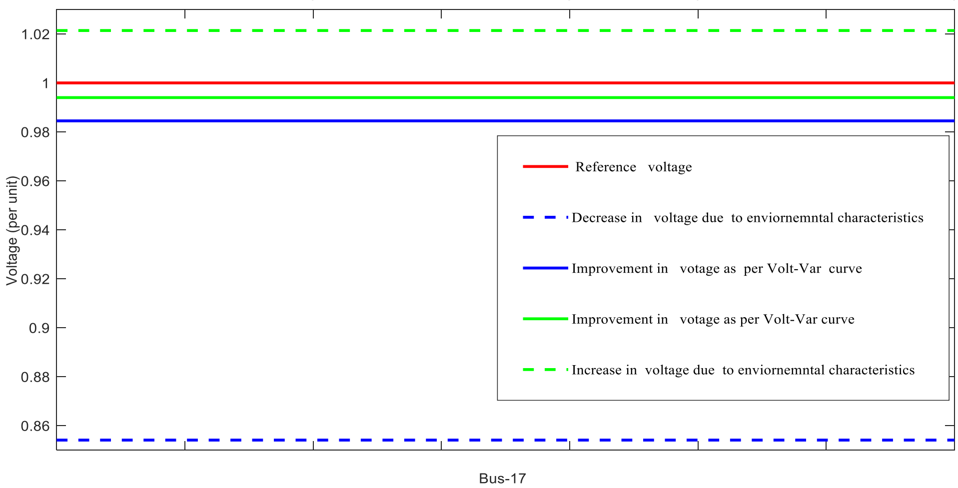

Figure 14. Voltage (sag/swell) for various cases of uncertainties and voltage after control action at bus-17.

4. Conclusions

In this work, a new methodology has been proposed to classify PQ disturbances that help to generate control signals for smart converter operations. This is more useful in grid connected renewable energy based systems interfaced through power electronic converters. The proposed algorithm is able to keep track of variations in wind speed, solar insolation and load. In this work, results for Volt-VAr control scheme are presented. Similarly Volt-Watt control scheme also can be adopted. Further, combined Volt-Var and Volt-Watt strategies can be also integrated in to the control algorithm to avail benefits of both control strategies. However it requires design of robust controller, which can handle both strategies at a time.

The novelty of the proposed work is in the fact that, the results of PQ analysis have been arrived at using the intelligent algorithms corresponding to the electrical network with Distributed Generations. It also facilitates distribution manager/operator to utilize proper hosting capacity of DGs. The future scope of the work includes investigations on complexities with respect to implementation of LSSSVM algorithm on a digital platform and there by examine the difficulties in development of a hardware prototype to implement PQ improvement.

Acknowledgement

This work is carried out at the Research Centre, Dept. of Electrical & Electronics Engineering, Malnad College of Engineering, Hassan, India, affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, under the financial assistance of World Bank - MHRD initiated TEQIP II/III program.

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