International Review of Electrical Engineering (I.R.E.E.), Vol. 18, N. 3
ISSN 1827- 6660 May – June 2023

Voltage Event Classification Method Based on Symmetrical Components Models for Extended ABC Classification Criterion

Ignacio Carugati[1], Carlos M. Orallo[2], Jorge L. Strack[3],
Patricio G. Donato[1], Marcos A. Funes[1]

Abstract – *The identification, analysis and mitigation of voltage events are relevant research areas in the context of smart grids. The analysis can be conducted by using predefined models that are representative of certain grid faults. One of the criteria that represents the largest number of fault types is the extended ABC, which is used as the basis of this paper. Some of the algorithms proposed in the specific bibliography that use this classification criterion have an acceptable performance under ideal conditions, but are affected by different disturbances related to the same fault or the power grid itself. Present work proposes a new algorithm that improves the classification performance evaluating the mean squared error of each event type using two different symmetrical components estimations. The algorithm is compared with different proposals reported on the bibliography and evaluated with several types of common electrical network disturbances by simulation. Results show a significant reduction of classification errors.*

***Keywords**: Voltage Dip, Voltage Swell, Event Classification, Power Quality Meter, Disturbances*

Nomenclature

ADC	Analog to Digital Converter
AECA	ABC Extended Classification Algorithm
APAR	Asymmetrical Phase Angle Rotation
ASA	Absolute Sequences Algorithm
CB	Circuit Breaker
CIGRE	International Council on Large Electric Systems
DPV	Deviation of Pre-fault Voltage related to nominal voltage
E	Average pre-fault voltage between the three-phase voltages
EHV	Extra High Voltage
h	Voltage event depth
MSE	Mean Squared Error
PAJF	Phase Angle Jumps due to Faults
PAJN	Phase Angle Jumps due to Network
PCC	Point of Common Coupling
PMU	Phasor Measurement Unit
PQM	Power Quality Meter
RMS	Root Mean Square
SCA	Symmetrical Components Algorithm
SPAR	Symmetrical Phase Angle Rotation
SPA	Six-Phase Algorithm
SVA	Space Vector Algorithm
TACS	Transient Analysis of Control Systems
TRV	Transient Recovery Voltage
V_a, V_b, V_c	RMS voltages of a three-phase system
V_{ab}, V_{bc}, V_{ca}	RMS three line voltages
Z_f	Impedance between PCC and the fault point
Z_F	Impedance between the fault point and ground
Z_l	Impedance between the fault point and the load
Z_s	Impedance between PCC and the source

I. Introduction

In recent years, electricity distribution companies and regulatory agencies have increased their efforts on the monitoring, evaluation and improvement of power quality. Many of these efforts have been driven by the deployment of smart grids, which are characterized, among other features, by the improvement and control of power quality [1], [2].

Among the different electric phenomena included in the general field of power quality, voltage events have a high interest for residential, commercial and industrial customers. Essentially, voltage events comprehend electrical disturbances such as voltage dips, swells and interruptions, that is, sudden variations in voltage with a defined start and end time. They are caused by abnormal increments of current, that results in voltage variations at the Point of Common Coupling (PCC), where the customer affected by the event is located (Fig. 1). These voltage events have different origins including line faults [3], induction motors starts [4], transformer energization [5], [6], etc. They can be characterized as transients or non-stationary phenomena, unlike other disturbances, which have a quasi-stationary behavior (frequency, voltage fluctuations, etc.).

https://doi.org/10.15866/iree.v18i3.23672

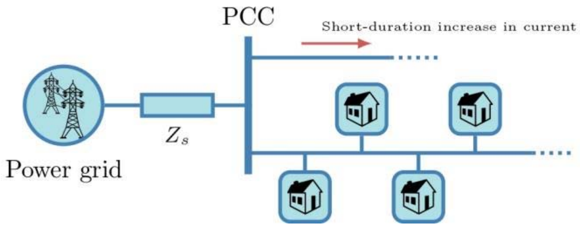


Fig. 1. A sharp current variation causes a voltage drop in the PCC due to the source impedance (Z_s), and the customers experience a voltage event (dip/swell)

In order to evaluate, quantify, characterize and mitigate voltage events, it is necessary to detect and classify them in an automated way, in the shortest time and with the greatest possible accuracy [7], [8]. The classification of a voltage event consists on the event identification among a set of predefined event models. To accomplish this, it is reasonable to use models that represent the types of faults that are most commonly found, or that are most representative of the grid status. There are different ways of approaching this issue, but the two more cited in the specific bibliography are the symmetrical components and ABC criteria [9]. This last is adopted in the present work since it is more complete than symmetrical components criterion. In particular, is used the extended ABC criterion [10], which includes swells. However, many of the concepts developed here can be easily extrapolated from ABC to symmetrical components criterion [11]. The automatic classification of voltage events can be performed through different algorithms, based on classification criterion models, which must operate with real-time measured voltage values [11]. These algorithms have some deficiencies due to the presence of disturbances in the grid that may lead to a wrong classification. These disturbances have been analyzed in a previous work [11], showing that the same voltage event can be identified in different ways depending on the parameters of the grid. The same work also evaluated and quantified the classification errors of different algorithms operating under similar conditions of disturbances. The tests showed that, in certain conditions, the errors could easily exceed 50% of the analyzed cases. To address this drawback, the authors proposed an algorithm based on the comparison between predefined models and real measurements, denominated Absolute Sequences Algorithm (ASA) [12]. ASA has demonstrated advantages over other methods reported in the specific bibliography, although, it does not eliminate classification errors completely. This paper proposes a new algorithm, based on the previous experience with ASA, leading to a significant reduction of the classification errors under the influence of different disturbances. The reduction of classification errors is achieved by using the amplitude and phase information of the symmetrical components of the three-phase voltage in the PCC. The performance of the proposal is evaluated by testing all possible combinations of disturbances for voltage event model of the ABC criterion. The theoretical background of voltage event analysis is extensive, making it impossible to summarize in few pages. For this reason, the work is organized as follows. In Section II is presented a brief overview of voltage event classification criteria and some reference classification algorithms. Also a brief description of disturbances that can be found in a real electrical network is included. Section III describes the proposal, which focuses on addressing the error sources identified in the previous section. The analysis of the performance and classification errors is shown in Section IV. Finally, Section V summarizes the contributions of this work.

II. Voltage Event Classification Overview

In this section, a brief overview of voltage event classification is presented. The theoretical basis of the three-phase voltage event analysis, disturbances that affect the event models and the classification algorithms is very extensive and exceeds the length of a normal journal article. For this reason, basic concepts and definitions will be summarized below in order to advance with the proposal. A deeper discussion about critical definitions and terminology can be found in the works of Strack et al [11], [12].

II.1. Classification Criteria

Voltage events are defined as an abnormal and temporary variation of the magnitude of the voltage supply. They are one of the most important power quality disturbances in power systems because of their frequency of occurrence and the economic impact on commercial and industrial customers. There are different ways to classify a voltage event. It can be classified by the number and magnitude of affected phases, the phase relationship between voltages, etc. The key is to be able to extract the critical information of the event, for example whether the event has a primary origin or not. In the scientific bibliography, two types of classification criteria can be found that are based on the use of predefined models of events, with particular phase and voltage characteristics, which in turn correspond to certain types of typical faults:

- *Symmetrical components classification criterion.* It is based on symmetrical components theory and distinguishes between line-to-neutral and line-to-line events [13];
- *ABC classification criterion.* It was developed as part of a stochastic prediction of voltage dips and can distinguish between 9 types of events (dips and swells). As result, it is more suitable to adequately characterize voltage events than the symmetrical components criterion, because it may discriminate between different electrical voltages. This criterion originally defined seven different voltage events (types *A* to *G*) [13], and later, it was extended with two additional events (types H and I) by Ignatova [14].

The extended ABC classification criterion is adopted in this paper because it describes the voltage events and their possible causes with more detail. Therefore it is more complete than the symmetrical components criterion.

However, it is possible to adapt the algorithms to both criteria without major difficulties.

II.2. Algorithms for Voltage Event Classification

Classification algorithms provide a methodology for criterion implementation in order to help in the identification of fault origin and possible mitigation actions. For this reason it is important to have some algorithm to classify the voltage event in an automated way by using voltage measurements as data input. The following algorithms stand out in the literature:

- *Symmetrical Components Algorithm (SCA)* uses symmetrical components representation of measured voltage during an event and the information of phase between positive and negative sequences to classify voltage dips [15].
- *Six-Phase Algorithm (SPA)* uses the line-to-neutral and line-to-line fundamental Root Mean Square (RMS) voltage, removing the zero-sequence fundamental voltage, to classify voltage dips [15].
- *Space Vector Algorithm (SVA)* is based on analysis of the space vector trajectory in the complex plane of a phasor, whose magnitude and phase angle are representative of the three-phase voltages. This method is able to discriminate between voltage dips and swells [16], [17].
- *Absolute Sequences Algorithm (ASA)* uses symmetrical components representation of measurement voltage during an event and a Mean Squared Error (MSE) estimation in order to classify voltage events. Unlike others, it make use of adaptive thresholds in the classification process. In this case the event type is determined using models that are actualized at each sample, improving classification performance [12].

In recent years, proposals for classifiers based on machine learning algorithms have been published, but most of them are focused on classification according to whether the fault amount of phases [2]. This type of algorithms has a great potential for development, but its performance is directly related to the type of training used.

This means that its performance is very good in the electrical networks where the training was done, but its results are not easily extrapolated to other places.

Additionally, the use of classifiers based on neural networks does not allow to clearly identify the classification errors when the event is disturbed by the network itself, which has not been addressed in the specific bibliography [18], [19]. Therefore, the study and comparison presented in this work are focused on algorithms based on transforms and algebraic relations, such as those previously cited.

II.3. Common Disturbances Associated with Voltage Events

Impedances between the PCC, the source and the fault can affect the detection and register of the voltage event, which derives in a wrong classification. The following list is a summarize of different disturbances that can affect classification method performance during an event:

- *Phase Angle Jumps due to Faults (PAJF).* This is a phase angle shift observed in the line-to-neutral voltage with the main voltage drop (Fig. 2). In general, it is caused by an abrupt change in the affected line impedances, generally with a resistive characteristic [3], [20];
- *Phase Angle Jumps due to Network (PAJN).* This is a phase angle shift observed in all line-to-neutral voltages (Fig. 2). It is caused by the difference in the ratio between the reactance and resistance in the impedance between fault and PCC; and PCC and the source [21], [22];
- *Symmetrical Phase Angle Rotation (SPAR).* This is an equal phase angle shift observed in all line-to-neutral voltages (balanced voltage event). Generally, this type of events is associated to the start of large three-phase loads, as induction motors [4], [23];
- *Asymmetrical Phase Angle Rotation (APAR).* This is a phase angle shift affecting all line-to-neutral voltages and it is observed when positive and negative sequence impedances between PCC and the source are different. This is the case in vicinity of rotating machines which, unlike cables and transformers, present a positive and negative sequence impedance of different magnitude and phase [11];
- *Deviation of Pre-fault Voltage related to nominal voltage (DPV).* It is a normal and expected condition in which the pre-fault voltage in the PCC differs from its nominal value. For example, this is the case when large reactive impedances are used or in electrical systems with high penetration of distributed generators.

III. ABC Extended Classification Algorithm (AECA)

This section describes the proposed event classification algorithm. The core of ABC Extended Classification Algorithm (AECA) is the comparison of measured voltages at the PCC with predefined models and the subsequent identification of the most probable event type.

Both, measured voltages and event models, are mathematically represented by symmetrical components theory due to the advantages that this provides in the study of unbalanced signals.

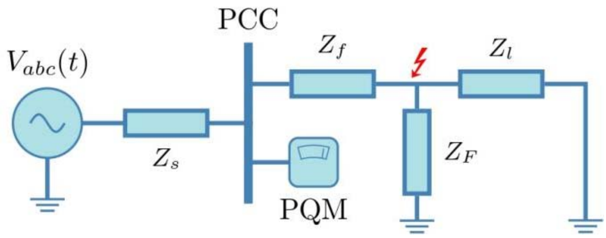


Fig. 2. Model of radial electrical network under fault situation with equivalent impedances, where PQM stand for power quality meter

Figure 3 shows a block diagram of the complete system, where it can be noted the two branches of the classification process. Each stage of the diagram will be described in the following items.

(a) *Sampling & filtering:* Before start the classification process it is necessary to acquire the PCC grid voltage magnitudes. The acquisition process includes both sampling and filtering of the voltage values by means of an Analogue to Digital Converter (ADC) and the corresponding filtering (analogue and/or digital). This process can be done in different ways and is not a part of the classification algorithm, but rather a preliminary stage to be implemented following the guidelines of the IEC 61000-4-30 standard [24]. The purpose of this processing stage is to obtain a clean signal, with no harmonic content or noise. This can be achieved using different strategies. From the sampling perspective, it can be done with a constant sampling frequency or with a synchronous sampling technique. In the first case, the acquired samples must be filtered to suppress harmonic components and noise. In the second case, which is the approach used in this work and it is the recommended strategy, the use of a synchronous sampling method has a better performance to process the signal and extract only the fundamental component of the PCC voltages [25], [26]. Voltage samples are processed in order to obtain voltage fundamental components by eliminating harmonic components and noise. The results of this process are three complex values representing the fundamental three-phase voltage at PCC ($V_i[k]$, where $i = a, b, c$);

(b) *Preprocessing:* In this block it is determined whether the current condition of the power grid requires the execution of the classification algorithm. To accomplish this, the average pre-fault voltage between the three-phase voltages (E), i.e. the voltage magnitude before the event itself occurs, and the voltage event depth (h), are calculated. The estimation of E is made according to the sliding reference voltage criterion established in the IEC 61000-4-30 standard and adopted by the IEEE 1564 standard. It is basically a first-order digital filter with a time constant of 1 minute, which is updated with the RMS voltage calculation in a window of 10/12 grid cycles [12]. The 10-cycle window is used in systems with a nominal line frequency of 50 Hz, and the 12-cycle window in systems with a nominal line frequency of 60 Hz. The magnitude of E is determined by averaging the three estimated voltages of each phase:

$$E = \frac{V_a[k]+V_b[k]+V_c[k]}{3} \tag{1}$$

where V_a, V_b and V_c are the RMS voltages estimated by the digital filter for each phase of the system. Parameter h is estimated as the quotient $h = V/E$, where V is the retained voltage in the affected phase or between the phases where a fault is detected. This can be estimated as the lowest of the six fundamental RMS voltages (three phase voltage and three line voltages) scaled by a factor according to:

$$V_{min} = \min\left\{|V_a|,|V_b|,|V_c|,\left|\frac{V_{ab}}{\sqrt{3}}\right|,\left|\frac{V_{bc}}{\sqrt{3}}\right|,\left|\frac{V_{ca}}{\sqrt{3}}\right|\right\} \tag{2}$$

Additionally, the highest of the six fundamental RMS voltages, V_{max}, which is used to detect overvoltages and triggers the classification process, is calculated as follows:

$$V_{max} = \max\left\{|V_a|,|V_b|,|V_c|,\left|\frac{V_{ab}}{\sqrt{3}}\right|,\left|\frac{V_{bc}}{\sqrt{3}}\right|,\left|\frac{V_{ca}}{\sqrt{3}}\right|\right\} \tag{3}$$

(c) *Activation:* From the calculation of the minimum and maximum values of the six fundamental RMS voltages Eqs. (2) and (3), it is decided whether the classification algorithm is executed. If V_{min} is less than 90% of the nominal value or V_{max} is greater than 110% of the nominal value, the classification algorithm is enabled. These values are based on Std. IEC 61000-4-30 [24] and Std. IEEE 1159 [27]. Otherwise, the state of the electrical network is considered normal;

(d) *Predefined models calculation:* Once the event condition is detected, predefined models for the most representative grid faults are calculated based on parameters E and h. These predefined models are summarized in Table I. Parameters were obtained by applying the Fortescue's theorem in a three-phase unbalanced system considering analytical expressions of extended ABC classification criterion [11], [16]. At the end of the predefined models calculation stage are available the magnitudes of the symmetrical components obtained from the events model. In parallel, the same symmetrical components are calculated using the Fortescue theorem, which requires a phase synchronization;

(e) *Phase synchronization:* The predefined models calculated in the previous section are obtained considering the retained voltage as $V_a[k]$ for single-phase faults or $V_b[k]-V_c[k]$ for two-phase faults. In order to reduce the classification errors and allow the comparison between PCC voltages and the predefined models, it is necessary to re-synchronize representative complex values of the three-phase voltage under fault conditions. First, the reference phase is determined from the calculation of V_{min} (Eq. (2)) and then, the angle of that phase is used to rotate the three-phase system, as shown in Fig. 4(a). This process generates a new set of complex values, where the reference voltage has a phase angle of zero degrees ($V_a^*[k]$);

(f) *Symmetrical components calculation:* This process allows representing the unbalanced three-phase voltage as the sum of three different balanced three-phase systems, known as positive sequence, negative sequence and zero sequence. The positive sequence is directly related to the energy transfer from the generator to the user, while the negative sequence is a measure of the imbalance and therefore, of the inefficiency of the system [9]. On the other hand, the zero-sequence component of the fundamental voltage is a measure of the imbalance produced during an asymmetrical fault in a network with isolated neutral;

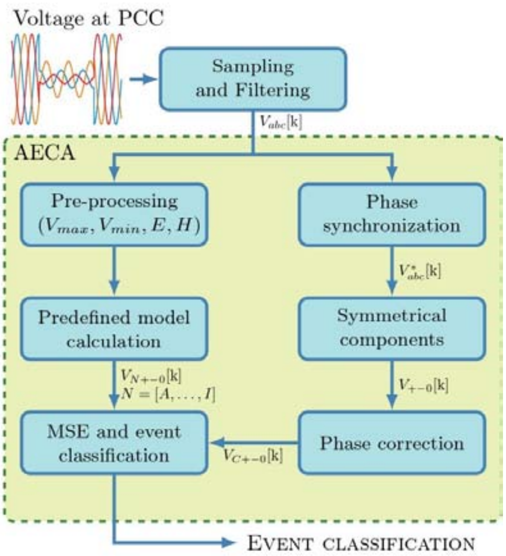
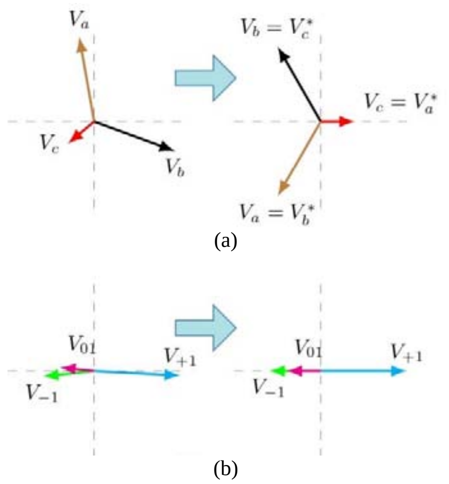


Fig. 3. Block diagram of the proposed AECA



Figs. 4. Example of (a) the phase synchronization previous the symmetrical components calculation and (b) phase compensation after the same calculation

TABLE I
TYPE OF EVENT AND SYMMETRICAL COMPONENTS REPRESENTATION

Type	V_{N0}	V_{N+}	V_{N-}
A	0	Eh	0
B	$E(1-h)/3$	$E(2+h)/3$	$E(1-h)/3$
C	0	$E(1+h)/2$	$E(1-h)/2$
D	0	$E(2+h)/2$	$E(1-h)/2$
E	$E(1-h)/3$	$E(1+2h)/3$	$E(1-h)/3$
F	0	$E(1+2h)/3$	$E(h-1)/3$
G	0	$E(1+2h)/3$	$E(1-h)/3$
H	$E(h-1)$	E	0
I*	$2E(1-h)$	E	0
I**	$E/2$	$E(1+2h)/3$	$E(1-2h)/3$

Note: type I event is defined as I** when h ≤ 0.75 or I* when h > 0.75

(g) *Phase compensation:* As mentioned in Section II.3, voltages at the PCC during a grid fault may be affected by phase jumps and phase rotations. For this reason, the positive, negative and zero sequences obtained in the previous step may present phase angles different from 0° and/or 180°, unlike what happens with the predefined models. As result, the following phase correction is implemented:

$$V_{Ci} = \begin{cases} |V_i|, & \text{if} \quad -90° \le \phi_i \le 90° \\ -|V_i|, & \text{if} \quad -90° > \phi_i > 90° \end{cases} \tag{4}$$

where i=+,−,0 are the corrected positive, negative and zero sequence respectively and φ_i is the phase of original sequence (Fig. 4(b) example). As result, corrected sequences are always in phase or phase opposition to the system reference (0°). This approach may cause some errors in the classification, but only in the case of very high phase jumps and phase rotations, which are statistically rare. Next section shows that this correction significantly reduces errors introduced by the classification algorithm;

(h) *Calculation of the mean square error and event classification:* Once the symmetric components of both, predefined models and PCC voltages, have been computed, the MSE is calculated for each type of event defined according to the extended ABC criterion. The most probable event type is determined as the one with the lowest error between the model and the measurements:

$$e^2 = \left(V_{C0} - V_{N0}\right)^2 + \left(V_{C+} - V_{N+}\right)^2 + \left(V_{C-} - V_{N-}\right)^2 \tag{5}$$

IV. Performance of AECA

The performance of the proposed AECA was evaluated through a series of exhaustive computational tests. For this purpose, different magnitudes of each disturbance (Section II.3) and all predefined models in extended ABC classification criterion (type *A* to *I*) were considered.

Voltage dips from 10% to 90% of the nominal voltage were analysed, using simulation steps of 1%. All voltage events were simulated considering phase angles between −90° and +90°, with simulation steps of 1°, and pre-fault voltage variations (DPV) from 90% to 110%, with simulation steps of 1%. Therefore, all possible combinations of the disturbances discussed in Section II.3 were considered. In this way, each type of voltage event was simulated with 16200 different combinations of voltage dip depth and phase disturbance (PAJF, PAJN, SPAR and APAR) and with 1800 combinations of voltage dip depths and pre-fault voltage variations. The results of this set of simulations for the AECA are shown in Fig. 5.

The horizontal axis of each figure is the residual voltage during the event (V) and the vertical axis is the phase angle introduced by each of the disturbances mentioned in Section II.3 (SPAR, APAR, PAJN, PAJF) or the pre-fault voltage (DPV).

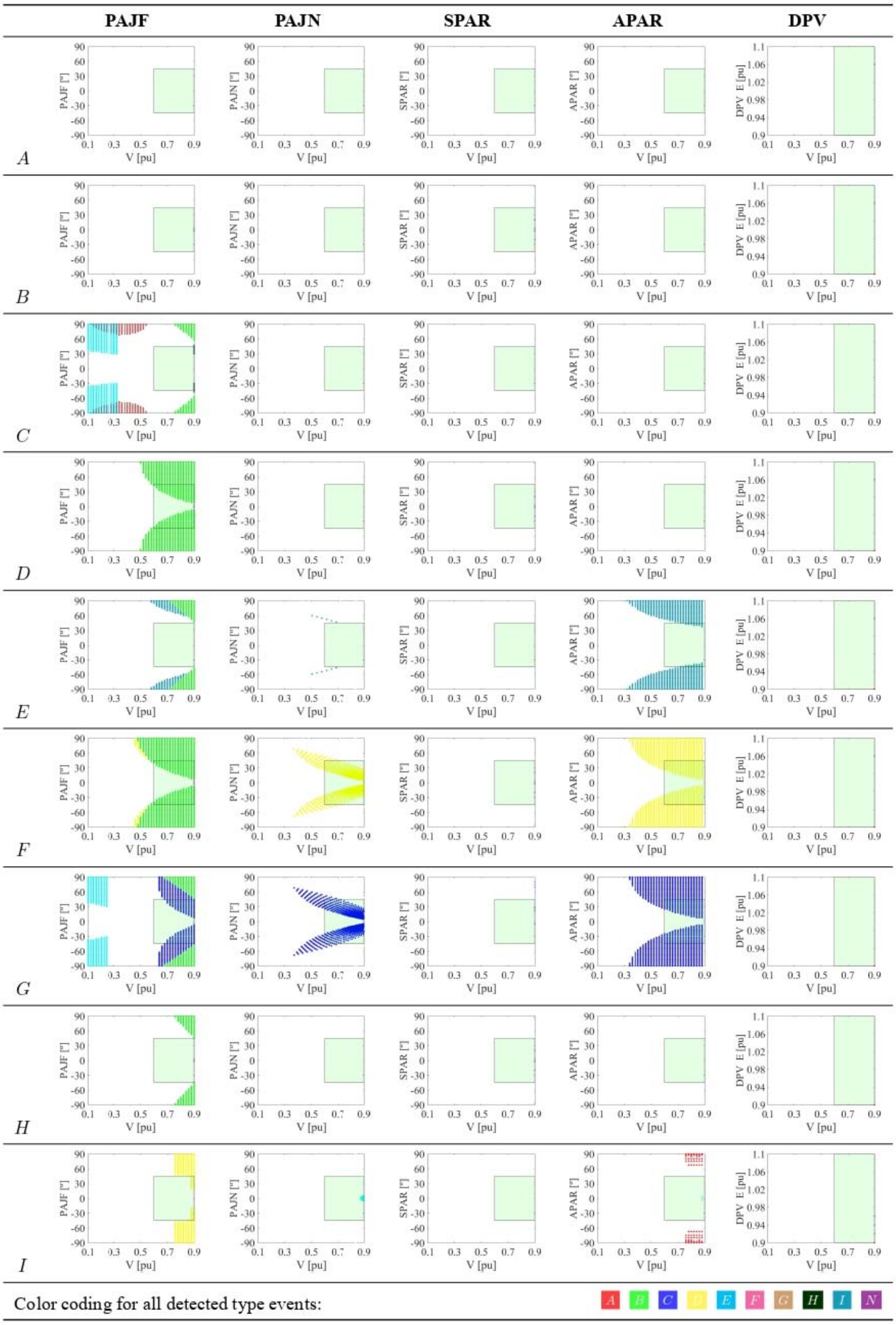


Fig. 5. AECA performance considering all types of disturbances and voltage events

Dots indicate the conditions where the algorithm fails in the event classification and the color indicates which type of event is detected in that case. However, there are extreme operation conditions that hardly ever happen in the real world (phase shifts near 90° or pre-fault voltages lower than 60% of the nominal voltage). The registers of the EPRI DPQ Statistical Summary Report [28] shown that 74.79% of the voltage dips present a minimum effective voltage between 60% and 90%, with phase jumps between −45° and 45°. For this reason, a green colored area was added to Fig. 5, to identify the region where can be found almost 75% of the voltage dips. As it can be seen in Fig. 5, proposal shows a very good performance for event classification. Events type *A, B, I* and *H*, show an error lower than 3.2% of all analyzed cases. Events type *C* and *D* only show error regions for PAJF while events type *E*, *F* and *G* show error regions for PAJF, PAJN and APAR. However, only a maximum error of 21.3% was computed considering high severity of disturbances under study.

Additionally, the algorithm is almost completely immune to SPAR and DPV disturbances in all the cases. All these items represent a significant improvement in comparison with other proposals and also, it is important to note, that some errors are difficult to solve with the classification algorithm since they are inherent to classification criteria [11]. For comparison purposes, Tables II and III report relative classification errors of AECA and the others algorithms presented in Section II.2 for all tests.

These errors were obtained by averaging the classification errors produced by all the disturbances defined in Section II.3.

In Table II, each of these errors were calculated as the number of misclassified events (dots area of figures) over the total area of the figure while, in Table III, it was considered only the area in green color to compute the percentage error. Values related to methods SCA, SPA, SVA and ASA were extracted from the tests of the work of Strack et al [12]. It can be seen that in these conditions AECA is the algorithm with the lowest error levels in all the cases. It can be shown that the error reduction of AECA with regard to the best of the previous methods (ASA) is from a 44% in the case of voltage event type *G* to more than 98% in the case of voltage events type *C*. The analysis of the data corresponding to the green area (most probable cases, Table III) shows that the classification error is reduced in relation to the other algorithms, but it also increases with respect to the general case (Table II) in the cases of events *B*, *D*, *F* , *G* and *H*.

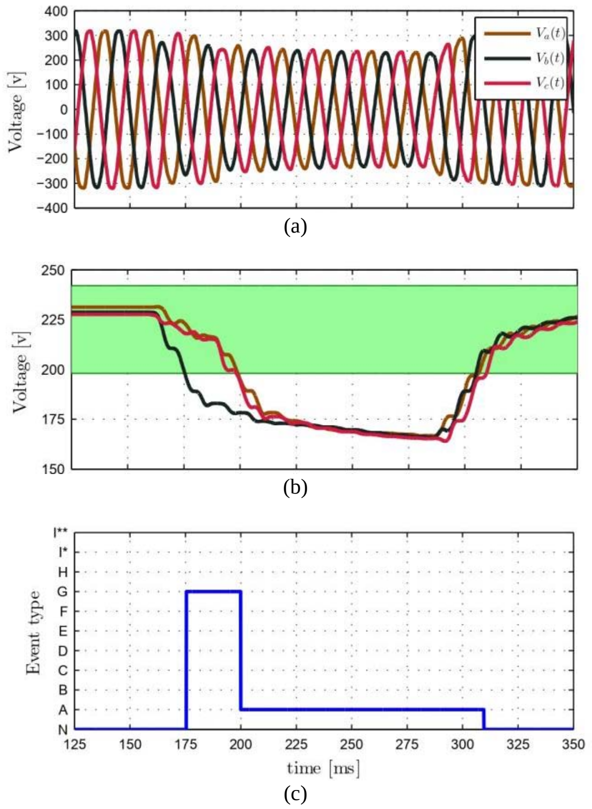
This is the result of the form in which this error percentage is being calculated. The percentage classification error comprises the sum of all error produced by different disturbances (SPAR, APAR, PAJN, PAJF and DPV). By reducing the area of analysis, constraining the phase angles and residual voltage, the ratio of properly classified cases to those that are not is modified. In the event types mentioned above, a significant proportion of errors is present in the area of interest, so the error rate increases. Even so, the final classification is more accurate than the one obtained with other algorithms, which have a lower performance. The performance of AECA operation was evaluated with real data acquired at the PCC of Engineering Faculty of the National University of Mar del Plata.

TABLE II
CLASSIFICATION ERROR OF EACH ALGORITHM, OBTAINED BY AVERAGING THE RESULTS OF THE FIVE TESTS PERFORMED

Alg.	e%	e_B%	e_C%	e_D%	e_E%	e_F %	e_G%	e_H%	e_I%
SCA	0	42.08	59.90	57.62	39.04	60.02	62.01	-	-
SPA	0	34.45	42.95	40.67	52.45	56.08	58.04	-	-
SVA	0	33.69	47.23	45.17	45.50	67.33	69.39	41.53	40.01
ASA	0	25.74	32.75	27.29	27.23	49.52	53.48	13.89	10.29
AECA	0	0.14	5.88	7.09	8.14	21.30	21.10	1.22	3.23

TABLE III
CLASSIFICATION ERROR OF EACH ALGORITHM, OBTAINED BY AVERAGING THE RESULTS OF THE FIVE TESTS PERFORMED TAKING INTO ACCOUNT ONLY THE GREEN COLORED AREA OF MOST LIKELY EVENTS

Alg.	e_A%	e_B%	e_C%	e_D%	e_E%	e_F %	e_G%	e_H%	e_I%
SCA	0	38.69	54.92	53.95	51.86	72.41	73.05	-	-
SPA	0	48.86	51.08	50.13	60.59	62.00	62.53	-	-
SVA	0	50.46	53.23	52.55	57.36	78.10	78.89	53.51	62.24
ASA	0	3.57	41.57	40.28	8.95	55.33	56.16	17.17	27.16
AECA	0	0.45	0.61	12.63	1.75	35.72	31.76	0.40	2.99



Figs. 6. Classification of a voltage event acquired from the grid: (a) acquired instantaneous voltages, (b) estimated fundamental components and (c) automatic classification generated by the AECA

Figures 6 show the results of processing a fault condition occurred on November 23, 2021, at 9:15 a.m.

The fault starts as an asymmetrical voltage dip with main voltage drop in phase b, and a lower voltage drop in phases a and c (which it may corresponds to a *B* or *G* event). Initially, the classification algorithm determines that the voltage grid is in normal state (*N*), since RMS voltages are between 90% and 110% of nominal voltage.

After the event is detected, it is classified as a type *G* event. In general, type *G* events are result of the power transformers propagation of events originated at other voltage levels. It may be the result of a type *E* event propagated through transformers that eliminate the zero sequence components. After almost one cycle of the mains voltage, voltage dip evolves to a symmetrical event and AECA changes the classification to a voltage event type *A*, resulting in an event segmentation. The maximum depth of the event is h = 0.77, after that the voltage grid normalizes the magnitude and the grid returns to the normal state (*N*). It is important to note that the algorithm is executed with each new sample of the three-phase voltage and classification dynamic depends on the filtering technique and symmetrical components estimation method used.

V. Discussion

The proposed algorithm shows a significant improvement in comparison with the methods mentioned in Section II.2. Although errors are not completely removed, since some of them are inherent to the classification criterion, and therefore impossible to mitigate, the classification errors for all performed tests were from 2 to 50 times lower than the obtained with other methods. Also, the algorithm provides total immunity to Symmetrical Phase Angle Rotations (SPAR) and Deviation of Pre-fault Voltage related to nominal voltage (DPV). One of the most important things to highlight about the proposed algorithm is that the classification can be done using a standard criterion, such as ABC, based on predefined models and performing simple mathematical calculations. Although the AECA is slightly more complex than those proposed by other authors, the results obtained are much better without having to resort to more complex approaches such as machine learning. This is a point worth highlighting, since the whole process is based on linear transformations and algebraic calculations, which makes the results independent of historical data, and there is no need to train on previous data. As far as the classification errors of the AECA are concerned, they could be reduced by adding more information about the voltage event in question. Taking into account that classification errors are mainly due to the differences in impedance between the physical location of the electrical fault and the point where the measurement is made, or due to the differences between resistance and reactance, among others, it could reduce the percentage of errors by adding information from other points in the network. One way to do it would be by measuring the voltages at different points of the grid or by adding topological information about the network.

VI. Conclusion

In this work, a new algorithm for the classification of voltage events using the ABC criterion was proposed. The proposed algorithm shows a significant reduction of classification errors by using the phase information of positive, negative and zero sequences. It allows to distinguish among many different events that have the same absolute value of the sequence components. The algorithm also performs an error comparison between real components and those estimated from all models, classifying in a more flexible way, and eliminating some restrictions imposed in a previous proposal. A thorough evaluation of the proposal performance against different electrical network disturbances during the evolution of voltage events was presented (PAJF, PAJN, SPAR, APAR and DPV), showing a significant improvement over other methods reported in the specific bibliography (ASA, SVA, SCA and SPA). Although errors are not completely removed, since some of them are inherent to the classification criterion, and therefore impossible to mitigate, the reduction of errors in the classification for all performed tests is significant. Also, the algorithm provides a high disturbance mitigations related to Symmetrical Phase Angle Rotations (SPAR) and Deviation of Pre-fault Voltage related to nominal voltage (DPV). These are very common disturbances that affect other algorithms, independently of event type. The proposed algorithm has the potential to be further improved by incorporating additional features, such as the use of information of different sources. It is possible to develop a classification method that merges the information of all the analyzed algorithms, and that by means of a probabilistic method determines which is the most feasible event. In this way, using the information generated by the different classification algorithms and using a voting system that takes into account the response of each algorithm, it is possible to determine which is the most probable event. Another possible approach is to use Phasor Measurement Units (PMU) as a device to classify events, taking advantage of the synchronization based on a universal time clock. In this way, events could be classified from different measurement points, in order to correctly locate and identify faults.

Acknowledgements

This work was supported in part by the Universidad Nacional de Mar del Plata (UNMDP), the Consejo Nacional de Investigaciones Científicas y Tecnológicas (CONICET), Grant PUE-ICYTE 22920180100002CO, Grant PIP2643 and by the Agencia Nacional de Promoción Científica y Tecnológica (ANPCYT), Grant PICT2018-02010.

References

[1] Manish Kumar Saini and Rajiv Kapoor. Classification of power quality events – A review. In: *International Journal of Electrical Power and Energy Systems* 43.1 (Dec. 2012), pp. 11–19. doi: 10.1016/j.ijepes.2012.04. 045

[2] Rajender Kumar Beniwal et al. A Critical Analysis of Methodologies for Detection and Classification of Power Quality Events in Smart Grid. In: *IEEE Access* 9 (2021), pp. 83507–83534. doi: 10.1109/access.2021. 3087016.

[3] S. D. Kim, M. M. Morcos, and J. C. Gomez. Voltage-Sag Magnitude and Phase Jump due to Short Circuits in Distribution Systems with Variable Fault Resistance. In: *Electric Power Components and Systems* 33.5 (Mar. 2005), pp. 493–512. doi: 10.1080/15325000590504984

[4] J. C. Gomez et al. A Study of Voltage Sags Generated by Induction Motor Starting. In: *Electric Power Components and Systems* 32.6 (June 2004), pp. 645–653. doi: 10.1080/15325000490228423

[5] J. S. Peng et al. Evaluation of Transformer Inrush Induced Voltage Dips. In: *CIRED 21st International Conference on Electricity Distribution. 2011*. URL: http://www.cired.net/ publications/cired2011/part1/ papers/CIRED2011_0014_final.pdf

[6] P. Jinsheng. *Assessment of Transformer Energisation Transients and Their Impacts on Power Systems*. PhD thesis. Faculty of Engineering and Physical Sciences of the University of Manchester, 2013, p. 225. URL: https://www.research.manchester.ac.uk/portal/files/54533216/FULL_TEXT.PDF

[7] Mohammad Barghi Latran and Ahmet Teke. A novel wavelet transform based voltage sag/swell detection algorithm. In: *International Journal of Electrical Power and Energy Systems* 71 (Oct. 2015), pp. 131–139. doi: 10.1016/j.ijepes.2015.02.040

[8] Erick A. Nagata et al. Real-time voltage sag detection and classification for power quality diagnostics. In: *Measurement* 164 (Nov. 2020). doi: 10.1016/j.measurement.2020.108097

[9] Math H. J. Bollen. *Signal Processing of Power Quality Disturbances*. John Wiley and Sons, Inc., 2006. ISBN: 9780471931300.

[10] Vanya Ignatova, Pierre Granjon, and Seddik Bacha. Space Vector Method for Voltage Dips and Swells Analysis. In: *IEEE Transactions on Power Delivery* 24.4 (Oct. 2009), pp. 2054–2061. doi: 10.1109/tpwrd.2009.2028787

[11] Strack, J., Carugati, I., Orallo, C., Donato, P., Maestri, S., Carrica, D., Analysis of Drawbacks and Constraints of Classification Algorithms for Three-Phase Voltage Dips, (2018) *International Review of Electrical Engineering (IREE)*, 13 (1), pp. 23-36. doi: https://doi.org/10.15866/iree.v13i1.13391

[12] Jorge L. Strack et al. Three-phase voltage events classification algorithm based on an adaptive threshold. In: *Electric Power Systems Research* 172 (July 2019), pp. 167–176. doi: 10.1016/j. epsr.2019.03.012

[13] M. H. J. Bollen and L. D. Zhang. Different methods for classification of three-phase unbalanced voltage dips due to faults. In: *Electric Power Systems Research* 66.1 (July 2003), pp. 59–69. doi: 10.1016/s0378-7796(03)00072-5

[14] Vanya Ignatova. *Methods for analyzing the quality of electrical energy. Application to voltage sags and harmonic pollution*. PhD thesis. Universite Joseph Fourier, 2006, p. 169. URL: https://tel.archives-ouvertes.fr/tel- 00170713

[15] M. H. J. Bollen. Algorithms for characterizing measured three-phase unbalanced voltage dips. In: *IEEE Transactions on Power Delivery* 18.3 (July 2003), pp. 937–944. doi: 10.1109/tpwrd.2003.813879

[16] V. Ignatova et al. Classification and characterization of three phase voltage dips by space vector methodology. In: *2005 International Conference on Future Power Systems*. IEEE, 2005. DOI: 10.1109/fps.2005.204283

[17] Azam Bagheri, Math H.J. Bollen, and Irene Y.H. Gu. Improved characterization of multi-stage voltage dips based on the space phasor model. In: *Electric Power Systems Research* 154 (Jan. 2018),pp. 319–328. doi: 10.1016/j.epsr.2017.09. 004

[18] Khalfan Al Kharusi, Abdelsalam El Haffar, and Mostefa Mesbah. Fault Detection and Classification in Transmission Lines Connected to Inverter-Based Generators Using Machine Learning. In: *Energies* 15.15 (July 2022),p. 5475. doi: 10.3390/en15155475

[19] Abdul Malek Saidina Omar et al. Fault classification on transmission line using LSTM network. In: *Indonesian Journal of Electrical Engineering and Computer Science* 20.1 (Oct. 2020), p. 231. doi: 10.11591/ijeecs.v20.i1.pp231-238

[20] Jairo Blanco Solano. Propagation of Voltage Sags: Influence of Transformers, Induction Motors and Fault Resistance. In: *Simposio Internacional sobre la Calidad de la Energí́a Eléctrica-SICEL*. Vol. 6. 2011.

[21] Elisa Espinosa Juarez and Araceli Hernandez. Stochastic Assessment of Phase-Angle Jumps Caused by Voltage Sags Applying an Analytical Method. In: *2006 International Conference on Probabilistic Methods Applied to Power Systems*. IEEE, June 2006. doi: 10.1109/pmaps.2006.360402

[22] Ying Wang et al. A quantitative comparison approach for different voltage dip characterization methods. In: *Electric Power Systems Research* 133 (Mar. 2016), pp. 182–190. doi: 10.1016/j. epsr.2015.12.032

[23] Juan Carlos Gomez and MM Morcos. Estimation of Voltage Sag Effects on Sensitive Equipment Due to Induction Motor Starting Cycles. In: *Electric Power Components and Systems* 31.7 (2003), pp. 709–716.

[24] Electromagnetic compatibility (EMC) - Part 4-30: Testing and measurement techniques - Power quality measurement methods. In:IEC61000-4-30:2015-02(Feb.2015). URL: https://webstore.iec.ch/publication/21844

[25] Ignacio Carugati et al. Three-Phase Harmonic and Sequence Components Measurement Method Based on mSDFT and Variable Sampling Period Technique. In: *IEEE Transactions on Instrumentation and Measurement* 65.8 (Aug. 2016), pp. 1761–1772. doi: 10.1109/tim.2016.2552679

[26] Carlos M. Orallo et al. Study on Single-bin Sliding DFT algorithms: Comparison, stability issues and frequency adaptivity. In: *Measurement* 69 (June 2015), pp. 9–19. DOI: 10.1016/j.measurement.2015.03.011

[27] IEEE Recommended Practice for Monitoring Electric Power Quality. In: *IEEE Std 1159-2019* (Revision of IEEE Std 1159-2009) (2019),pp. 1–98. doi: 10.1109/IEEESTD.2019.8796486

[28] DPQ Statistical Summary Report. In: Id. 1017341 (2003), p. 256. URL: https://www.epri.com/research/products/1017341

Authors' information

[1]Consejo Nacional de Investigaciones Científicas y Tecnológicas (CONICET), Instituto de investigaciones científicas y tecnológicas en electrónica (ICYTE), Universidad Nacional de Mar del Plata (UNMDP), Laboratorio de instrumentación y control (LIC).

[2]Instituto de investigaciones científicas y tecnológicas en electrónica (ICYTE), Universidad Nacional de Mar del Plata (UNMDP), Laboratorio de instrumentación y control (LIC).

[3]Universidad Nacional de Mar del Plata (UNMDP).

Ignacio Carugati was born in Argentina in 1983. He received the B.S. and Ph.D. degrees in electronics engineering from UNMDP, in 2008 and 2012 respectively. He is currently with the ICYTE of UNMDP and is a member of the CONICET. His current research interests include control systems, power quality, smart grids and digital signal processing.

Carlos M. Orallo was born in Mar del Plata, Argentina, in 1982. He was awarded his B.S. and Ph.D. degree in Electronics Engineering by the UNMDP, in 2011 and 2015 respectively. He is currently with the ICYTE of UNMDP. His research interests include power quality, smart grids and digital signal processing.

Jorge L. Strack was born in Argentina in 1989. He received the B.S. and Ph.D. degrees in electromechanical and electronics engineering from UNMDP, in 2013 and 2019 respectively. His current research interests include detection and classification of voltage events, power quality and digital signal processing.

Patricio G. Donato was born in Argentina in 1975. He received the B.S. degree in electronics engineering from Universidad Nacional de la Patagonia San Juan Bosco, in 2000, and the Ph.D. degree in electronics from Universidad de Alcalá, Alcalá de Henares (Spain), in 2005. He is currently with the ICYTE of UNMDP and is a member of the CONICET. His current research interests include digital signal processing, power quality, smart grids, machine learning and power line communications.

Marcos Funes was born in Mar del Plata, Argentina, in 1974. He received the Electronics Engineering degree and the Ph.D. degree in electronics engineering from the UNMDP, in 1999 and 2007 respectively. He is currently working in the ICYTE of UNMdP, as director of the Instrumentation and Control Laboratory. He is a researcher at the CONICET, from 2009 and associate professor of Electronic Measurements at UNMDP from 2020. His current research interests include signal processing, high-density programmable logic devices, power converters control and smart grids.