A Novel Algorithm for Classification of Voltage Sag Causes Using Alienation Coefficient and Power Quality Index

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ABSTRACT

This paper presents a novel algorithm for detecting and classifying voltage sags in power systems using the alienation coefficient (ACE) and Power Quality Index (PQI). Voltage sags were generated in a custom laboratory setup, with voltage and current signals recorded via an Adlink data acquisition card. The algorithm computes the alienation coefficients of voltage and current for sags caused by induction motor starting (IMS), line-to-ground (LG) faults, and resistive load-induced sag (RLIS). The PQI, derived as the product of voltage and current alienation coefficients, exhibits distinct signatures for each sag cause. In addition to analyzing the number of peak points, the algorithm incorporates the sum of peak points at the start and end of events to improve the identification of the voltage sag source. The algorithm also accurately detects the start and end of each voltage sag. By evaluating the PQI-I peak patterns and PQI-II (Psum), it distinguishes between RLIS (more peaks in the first group), IMS sags (peaks in the first group with no secondary peaks), and LG faults (more peaks in the second group). This method enhances power quality monitoring by providing reliable and accurate fault diagnosis.

Keywords: Alienation coefficient, Induction motor starting, Line-to-ground fault. Power Quality Index (PQI), Resistive load, Voltage sag Underlying Causes

1. INTRODUCTION

Voltage sags are one of the most critical power quality issues in modern electrical systems. These short-duration reductions in voltage can disrupt industrial processes, damage sensitive equipment, and lead to financial losses. The ability to detect and classify the underlying causes of voltage sags is essential for improving system reliability and enabling swift corrective actions. Among the common causes of voltage sags are induction motor starting (IMS), line-to-ground (LG) faults, and resistive load variations. Accurately identifying the cause of a voltage sag allows for targeted mitigation strategies, which ultimately enhance power system resilience.

Zhang et al. [1] proposed an auxiliary power quality monitoring system to identify the root causes of voltage sags, focusing on real-time diagnostics. While effective, their method lacked scalability for handling large-scale data from diverse power systems. Mishra and Panigrahi [2] employed signal processing techniques like the Hilbert Transform combined with Support Vector Machines (SVM) for sag classification. This approach improved accuracy but required significant computational resources, making it unsuitable for real-time environments. Kumar et al. [3] used the S-transform for identifying multi-stage disturbances in power systems. Although this method provided enhanced insights into complex events, it suffered from high computational overheads, limiting its practicality for real-time fault detection. Similarly, Kumar et al. [4] demonstrated the use of True RMS-weighted KNN for power quality disturbance recognition, showcasing the potential of simpler machine learning techniques. However, the reliance on fixed thresholds for classification reduced its adaptability to diverse operating conditions.

Advanced machine learning models have also been explored. Zheng et al. [9] introduced Bi-LSTM models for voltage sag classification, leveraging temporal dependencies in time-series data. Despite high classification accuracy, the computational intensity of this method posed challenges for real-time applications. Wu et al. [14] proposed an RMT-CNN model to improve fault detection in noisy environments. While effective, this approach required large datasets and significant processing power, which may not always be feasible.

Wavelet-based techniques have been widely adopted for voltage sag detection due to their ability to analyze signal characteristics at different resolutions. Saini et al. [11] used fractionally delayed biorthogonal wavelets for voltage sag classification, achieving high accuracy in detecting subtle signal features. However, wavelet-based methods often struggle with overlapping disturbances and require careful parameter selection. Camarillo-Peñaranda and Ramos [6] utilized voltage ellipses for fault classification, which proved computationally effi-

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cient but lacked robustness for multi-stage disturbances.

Recent studies have explored hybrid methods to enhance classification performance. Fan et al. [13] combined sparse auto-encoders with attention mechanisms, improving the resolution of sag cause recognition. However, the complexity of this model limits its implementation in real-time systems. Patnaik et al. [17] applied the S-transform with Extreme Learning Machine (ELM) for voltage sag detection, highlighting the trade-off between computational speed and classification accuracy. Several comprehensive reviews, such as Han et al. [5], provide a broader perspective on voltage sag classification techniques, including their applications and limitations. Bonde et al. [15] reviewed signal processing and machine learning approaches, emphasizing the importance of robust feature selection for accurate classification. While these studies offer valuable insights, they underline the need for methods that balance accuracy, simplicity, and real-time applicability.

While these methods have significantly advanced voltage sag detection and classification, many involve complex computations or require large datasets, which can limit their real-time applicability. This paper proposes a novel, simplified algorithm based on the alienation coefficient and Power Quality Index (PQI) to detect and classify voltage sags in power systems. Voltage sags are generated in a custom laboratory environment, with voltage and current signals recorded via an ADLINK data acquisition system. The algorithm computes the alienation coefficients of voltage and current waveforms for sags caused by IMS, LG faults, and resistive loads. By analyzing the PQI derived as the product of voltage and current alienation coefficients, the proposed method identifies distinct signatures for each sag cause. The impact of the number of samples per cycle is also analyzed.

In summary, existing techniques for voltage sag detection and classification demonstrate significant advancements but are often constrained by high computational requirements, reliance on extensive training data, or limited adaptability to diverse power system conditions. This study aims to address these limitations by proposing a computationally efficient algorithm that leverages the alienation coefficient and Power Quality Index (PQI) along with machine learning techniques for robust classification of voltage sag causes. The proposed method simplifies feature extraction, reduces computational demands, and enhances real-time diagnostic capabilities, offering a practical solution to the challenges identified in the literature.

The key contributions of this paper are mentioned below:

- A novel method for voltage sag classification using the Power Quality Index derived from the Alienation Coefficient, simplifying computational requirements.
- Accurate differentiation between sag causes (IMS, LG faults, and RLIS) based on PQI peak analysis and summation (Psum).
- Validation of the algorithm on a custom laboratory setup with real-world data acquisition.
- High classification accuracy (100%) was achieved with simple machine learning techniques, demonstrating practical applicability.

2. THEORY OF ALIENATION COEFFICIENT

The **alienation coefficient** is a mathematical tool used to measure the dissimilarity or variance between two datasets, commonly applied in signal processing, especially for fault detection in power systems. In the context of electrical engineering, particularly for transmission line fault detection and classification, the alienation coefficient provides a quantitative measure of deviation between consecutive signal measurements, typically voltage or current signals. The alienation coefficient A is typically calculated using the correlation coefficient r between two data sets, x and y. The alienation coefficient is given below [16].

$$A = 1 - r^2, \tag{1}$$

where r is the correlation coefficient between the two variables x and y, which represent samples from two consecutive periods of voltage or current signals. The correlation coefficient r is computed as:

$$r = \frac{N_s(\sum xy) - (\sum x)(\sum y)}{\sqrt{\left[N_s \sum x^2 - (\sum x)^2\right]\left[N_s \sum y^2 - (\sum y)^2\right]}}, \tag{2}$$

where x and y represent the voltage or current samples at t_0 and the previous cycle, respectively, and N_s is the samples per cycle.

The alienation coefficient A ranges between 0 and 1, where A equal to zero indicates perfect correlation (no fault or disturbance).

A equals one indicates maximum alienation or dissimilarity (possible fault or disturbance). The alienation coefficient is significant because it provides a real-time and sensitive method for identifying abnormalities in power systems. The alienation technique is particularly useful for: Fault Detection: A sudden increase in the alienation coefficient indicates that a fault has occurred. Fault Classification: By analyzing the alienation coefficients of different phases, the nature of the fault (e.g., phase-to-phase, phase-to-ground) can be classified. Real-time Monitoring: The alienation coefficient is computationally efficient, allowing for real-time analysis of electrical signals, which is crucial for fast fault detection and mitigation.

2.1 Significance of the Alienation Coefficient in Recognizing the Underlying Cause of Voltage Sags

Voltage sags are temporary reductions in voltage amplitude, often caused by faults, motor starts, or sudden load changes. Identifying the underlying causes of voltage sags is essential for improving the reliability and stability of power systems. The alienation coefficient serves as a valuable mathematical tool in distinguishing the characteristics of voltage sags by quantifying the dissimilarity between voltage and current signals over time. The key role of the alienation coefficient in voltage sag analysis.

A. Quantification of voltage sags

Voltage sags can be triggered by various events such as short circuits, equipment failures, or load disturbances. The alienation coefficient allows the comparison of voltage waveforms before and during the sag event. By computing the deviation between consecutive waveform samples, the alienation coefficient provides a precise measure of how much the signal changes, helping in detecting the presence of sag. For normal conditions, the alienation coefficient is close to zero, as consecutive voltage samples are similar. During a voltage sag event, the voltage waveform changes significantly, leading to an increase in the alienation coefficient. This rise indicates the occurrence of the sag and the degree of deviation from the normal operating state.

B. Classification of Sag Causes

Different causes of voltage sags, such as faults, motor starts, or load switching, produce distinct patterns in voltage and current signals. The alienation coefficient helps in distinguishing these patterns by quantifying the extent of signal deviation. Faults such as short circuits cause abrupt and significant changes in voltage, resulting in a high alienation coefficient. This sudden rise helps differentiate fault-induced sags from other types of disturbances. Induction Motor starts typically cause more gradual voltage drops compared to faults. The alienation coefficient increases, but the pattern is smoother, allowing the algorithm to classify the sag as motor-related. Voltage sags caused by load switching events tend to exhibit moderate changes in voltage signals, which can be identified by a moderate rise in the alienation coefficient.

C. Time-Sensitive Fault Detection

Voltage sags can last from a few milliseconds to several cycles. The alienation coefficient is highly time-sensitive, enabling real-time detection and classification. This characteristic is particularly beneficial in recognizing voltage sags promptly, providing the necessary information for rapid mitigation and fault location.

D. Discrimination Between Normal Variation and Abnormal events

Power systems experience normal fluctuations in voltage due to load variations, but these minor changes do not typically result in large alienation coefficient values. However, abnormal voltage sags caused by faults or disturbances will produce a noticeable spike in the alienation coefficient, making it a reliable indicator for detecting significant events that require intervention.

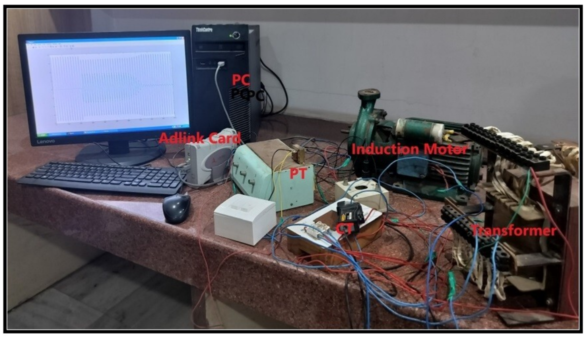

Fig. 1: *Tailor Made Experimental Setup.*

E. Integration with soft computing Technique

When combined with soft computing techniques like K-Nearest Neighbor (KNN), the alienation coefficient can enhance the classification of voltage sag events. The features extracted using the alienation coefficient can serve as inputs to classification algorithms that automatically identify the underlying cause of voltage sags based on historical data and pattern recognition. This automated approach increases the accuracy and efficiency of diagnosing sag causes.

By analyzing multiple voltage sags over time and computing the alienation coefficient for each event, the system can build a library of event signatures, allowing for the accurate recognition of sag causes based on their unique waveform characteristics. The alienation coefficient is a powerful tool for analyzing voltage sags, offering the ability to quantify deviations in voltage signals and classify the underlying causes of these sags. By computing the degree of signal dissimilarity, the alienation coefficient helps in distinguishing between different types of sags (e.g., faults, motor starts, load changes), thereby improving the diagnostic capabilities of power systems. This information is crucial for enhancing the reliability and stability of the electrical network.

3. EXPERIMENTAL SETUP FOR GENERATION VOLTAGE SAG

Fig. 1 shows the experimental setup developed in the laboratory to simulate voltage sags caused by different underlying events, such as Induction Motor Starting (IMS), Line-to-Ground Faults (LG), and Resistive Load-Induced Sags (RLIS). The setup uses an ADLINK data acquisition card to capture voltage and current signals at a sampling frequency of 1 kHz. The voltage and current are fed into the ADLINK data acquisition card via a potential transformer (PT) and current transformer (CT), as illustrated in Fig.1

To generate a voltage sag of sufficient Maharashtra State Electricity Board (MSEB) supply is first connected to an autotransformer and then to the primary winding of an isolation transformer (230 V/230 V). A single-phase induction motor (IM) is connected to the secondary of the isolation transformer through a bell push-type switch. Voltage and current are measured at the secondary terminals of the transformer. When the switch is closed, the motor starts, drawing a heavy inrush current, which causes a voltage dip at the transformer's secondary terminal, as observed on the monitor screen. Similarly, to generate RLIS, the induction motor is replaced by a resistive load bank, while the LG fault is simulated by connecting one terminal of the load to ground via a switch. This setup allows for real-time analysis of various voltage sag scenarios by capturing and processing the signals effectively.

4. METHODOLOGY FOR IDENTIFICATION OF UNDERLYING CAUSES

To identify the causes of voltage sags using the methodology based on the alienation coefficient and Power Quality Index (PQI), follow these steps:

Step 1: Read the voltage and current signal data of different underlying causes

Step 2: Compute Alienation Coefficients.

For each voltage sag event, the alienation coefficient for both voltage and current signals is calculated using equation (1). This step quantifies deviations from normal conditions, identifying significant changes during voltage sag events. Peaks are detected at both the start and end of the events, except in the case of IMS, where peaks occur only at the start of the event with none at the end. Detection flags are set by using this threshold, which is determined based on the normal (healthy) values of the alienation coefficient. In this algorithm, the threshold is set at 0.004. The flags are set at the start and end of the events. Detection flags indicate the start and end of the events accurately. This gives the quantification of the sag.

Step 3: Calculate the Power Quality Index (PQI)

Calculate the Power Quality Index (PQI) by multiplying the alienation coefficients of voltage (ACV) and current (ACI).

$$PQI = ACV \times ACI \tag{3}$$

After plotting PQI, mark the peak indices on the PQI. This product gives a measure of the disturbance in both voltage and current, reflecting the severity and type of the voltage sag.

Step 4: Analyze PQI Peaks

Analyze the number of peaks during the flag period at the start and end of the events and the pattern of PQI peak points throughout the event. These peaks occur when there is a significant deviation in the voltage and current waveforms, indicating voltage sag. Find the number of peaks during the start of the events (peaks under the first flag, i.e., Group I) and the end of the events (peaks under the second flag, if any, i.e., Group II). The distribution of peaks in these groups is critical for classifying the cause of the voltage sag. After determining the peaks, determine the second PQI, i.e., the sum of the peaks under the starting flag and ending flag of the events. It is given by

$$Psum = Psum1 + Psum2 \tag{4}$$

Step 5: Classify Voltage Sag Causes Based on Peaks and Psum Values

Classify the cause of the voltage sag based on the PQI peak values and Psum.

For Resistive Load Sags: These events show more peaks in the first group and few or no peaks in the second group, indicating a smooth return to normal.

Induction Motor Starting (IMS): These sags have peaks only in the first group, with no secondary peaks, due to the temporary large current draw when starting the motor.

Line-to-Ground (LG) Faults: These events exhibit a smaller number of peaks in the first group but more peaks in the second group, indicating a more severe and sustained disturbance.

Step 6: Sum of Peak Points for Enhanced Classification

For improved classification, sum the number of PQI peak points at both the start and end of the event. This additional feature helps further distinguish between the causes of voltage sags by identifying subtle differences in the event profiles. By following these steps, the algorithm can effectively identify the underlying cause of voltage sags, enhancing the diagnostic capabilities of power systems. The flowchart of the steps is shown in Fig.2.

5. RESULT AND DISCUSSION

A. Normal Condition

Fig. 3 shows the voltage and current waveforms along with the alienation coefficients, Power Quality Index (PQI), and detection flag following Induction Motor (IM) starting under normal conditions.

The top two plots show the steady voltage and current signals after IM startup, indicating stable operation. The middle plots depict the alienation coefficients for voltage and current, which remain small and consistent, reflecting minimal deviation from normal conditions. In the bottom plot, the PQI is overlaid with peak indices and detection flags. Peaks are scattered throughout the signal but stay below the detection threshold, ensuring no false flags for abnormal events. The threshold is set to detect significant deviations, but since the system is operating normally, no detection flags are triggered. This analysis confirms the algorithm's ability to maintain accurate detection during stable conditions by identifying minimal deviations in both voltage and current. The peak value of PQI is 1.333×10^{-6}. So in order to set the detection flag for the initiation and end of the abnormal condition, the threshold is set to 0.004.

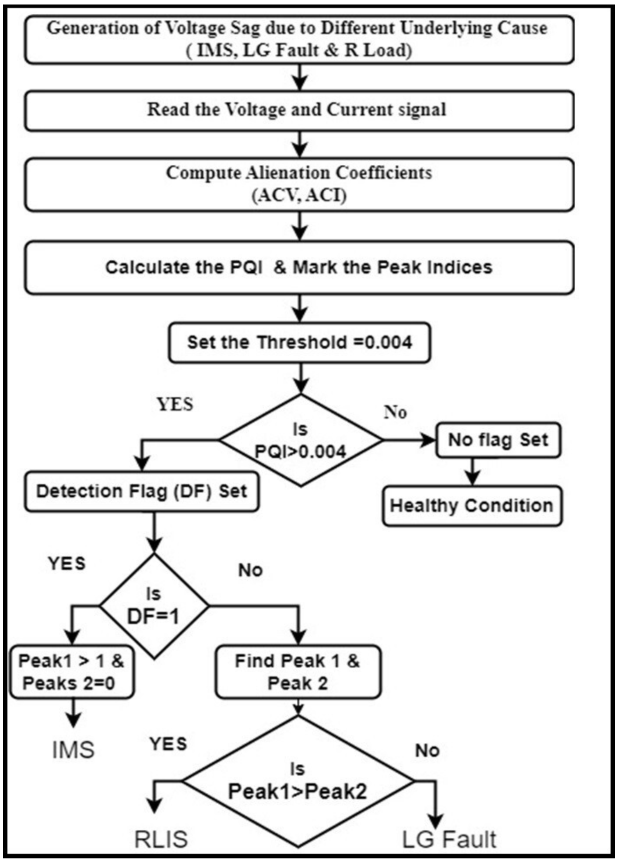

Fig. 2: *Decision Tree (Flowchart.*

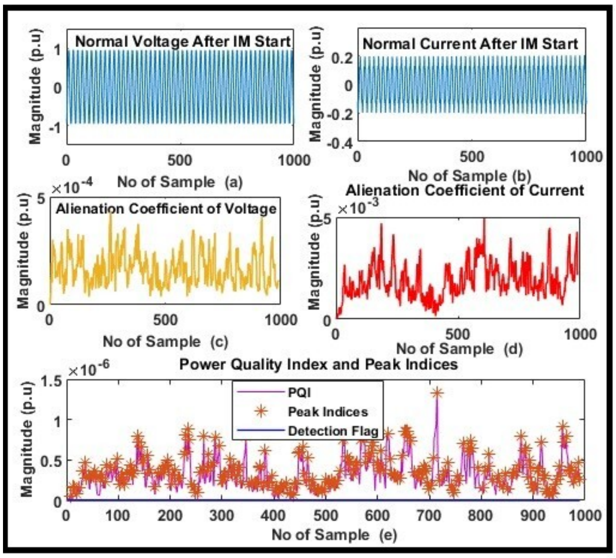

Fig. 3: *Voltage, Current, Alienation Coefficient, and Power Quality Index (PQI) Under Normal Conditions After Induction Motor (IM) Start.*

B. Induction Motor Starting (IMS)

Fig. 4 illustrates voltage sag due to induction motor starting (IMS). The voltage sag plot shows the reduction in voltage, while the current plot captures the surge as the motor starts. The alienation coefficient for both voltage and current reveals spikes that indicate the onset of the sag, with the current showing a sustained rise linked to motor inrush. The Power Quality Index (PQI) plot highlights four peak points, with a detection flag marking the sag event. Together, these elements represent critical features of the detection algorithm using the alienation coefficient and PQI. It found that only one flag is set at the time of start, and after the system resumes to normal condition, no flag is set at the end of the event.

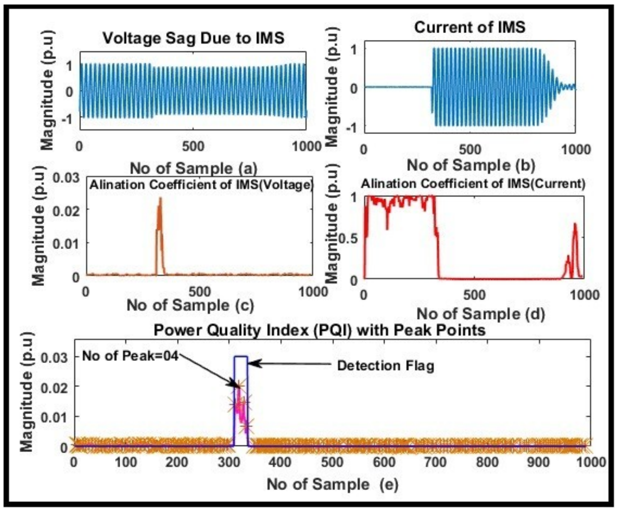

Fig. 4: *Voltage Sag Detection Due to Induction Motor Starting (IMS) Using Alienation Coefficient and Power Quality Index (PQI).*

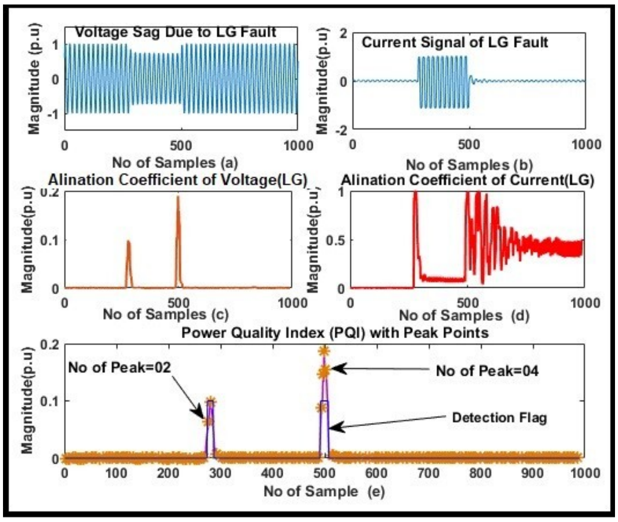

Fig. 5: *Voltage Sag Detection Due to LG fault Using Alienation Coefficient and Power Quality Index (PQI).*

C. LG Fault

Fig. 5 illustrates the voltage sag and current disturbance caused by an LG (line-to-ground) fault. The voltage sag plot shows a clear drop in voltage magnitude, while the current plot captures the characteristic fluctuation and disruption in the current waveform during the fault. The alienation coefficient for both voltage and current

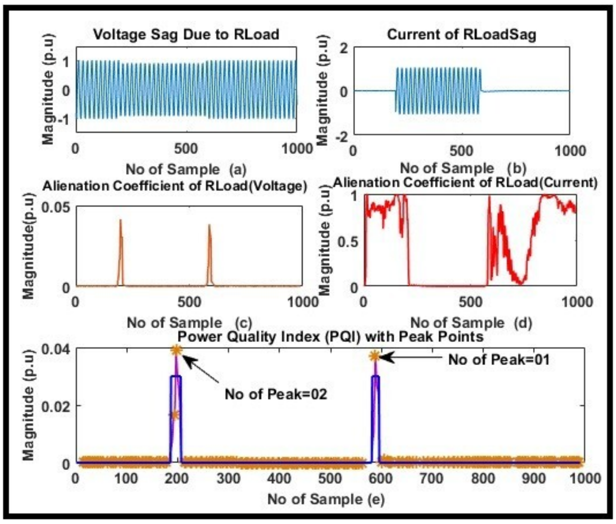

***Fig. 6**: Voltage Sag recognition Due to RLoad Induced Sag Using Alienation Coefficient and Power Quality Index (PQI).*

signals highlights distinct spikes that mark the onset and progression of the fault, with the current showing more pronounced changes as the fault persists. The detection flag goes high two times. One during the start of the event and end of the event. It is observed from the PQI plot that the first flag consists of 02 peaks and the second flag consists of 04 peaks.

D. Resistive Load Induced Sag (RLIS)

Fig. 6 represents the voltage sag and current disturbance caused by resistive load. It was observed from the PQI that the starting flag consists of 02 peaks and the ending flag has only 01 peak. The PQI I and II for various readings are tabulated in Table 1.

5.1 Comparative Analysis of Peak Detection in Voltage Sags for Induction Motor Starting (IMS),LG Fault and R Load Induced Sag (RLIS)

The data provided presents a comparative analysis of three different electrical disturbance scenarios: Induction Motor Starting (IMS), LG Fault, and RLoad Induced Sag (RLIS). The readings examine key parameters such as the number of peaks detected by the first and second detection flags and the sum of peak indices (Psum) during these events. The main observations are:

A. Induction Motor Starting (IMS)

In analyzing the detection flags for voltage sag events, it was observed that the first detection flag (Peak1) consistently identifies 4 to 5 peaks across all readings. This consistent peak detection suggests a clear pattern of disturbance during the event. However, the second detection flag (Peak2) consistently detects no peaks, remaining at 0 in all cases, implying that no additional significant activity is captured by this flag. The sum of peak indices (Psum) ranges from 0.0296 to 0.0497, indicating a relatively low level of disturbance. These observations suggest that when multiple peaks are detected by the first flag (Peak1 $\geq$ 1) and no peaks are detected by the second flag (Peak2 = 0), it signifies an event triggered by Induction Motor Starting (IMS), based on PQI-I analysis. Moreover, when the Psum value from PQI-II remains below 0.06, it further reinforces the classification of the event as IMS. This analysis aids in distinguishing IMS events from other voltage sag causes, enhancing the accuracy of power quality assessment.

B. LG Fault

The detection of an LG fault is characterized by consistent patterns in the number of peaks identified by the first and second detection flags. In all cases, the first detection flag identifies 2 peaks, while the second flag consistently detects more, with 3 or 4 peaks. This higher peak count in the second flag highlights the more prominent disturbances caused by the fault, particularly after the initial detection. The sum of peak indices (Psum) for LG faults ranges between 0.2510 and 0.3034, indicating a significant disturbance. Notably, when the Psum value exceeds 0.15, the Power Quality Index II (PQI-II) can reliably signify the occurrence of an LG fault. The consistent detection of more peaks by the second flag suggests that the fault's impact intensifies after the first detection, allowing for more precise identification of such events.

C. Resistive Load Induced Sag (RLIS)

The RLoad Induced Sag (RLIS) is characterized by the detection of peaks in both the first and second flags, with the first detection flag identifying between 2 and 4 peaks across different readings, while the second flag identifies fewer peaks, typically 1 or 2. This indicates that the disturbance from the RLoad sag is captured earlier, with more significant activity observed in the initial stages of the event. The sum of peak indices (Psum) for RLIS ranges from 0.0760 to 0.0926, reflecting a moderate level of disturbance. Notably, when the PQI-II value (Psum) lies within the range of $0.06 \leq Psum \leq 0.15$, it is indicative of an RLoad-induced sag Sag event. This pattern, where the first flag consistently detects more peaks than the second, distinguishes RLIS from other fault types, such as LG faults, where the second flag typically records more peaks.

These findings highlight the distinct behavior of each type of voltage sag event, based on peak detection and disturbance severity as measured by Psum. This signifies that the algorithm can effectively differentiate between various underlying causes of voltage sags based on peak detection PQI-I and the PQI-II (Psum).

The influence of the samples per cycle (Ns) on the alienation coefficients (ACE) and the power quality index (PQI) is critical for accurately assessing power quality and detecting abnormalities. From Table 2, illustrate the impact of sampling resolution on ACE and PQI measurements. The higher the value of Ns more the

***Table 1**: Comparative Analysis of Peak Detection in Voltage Sags for Induction Motor Starting (IMS), LG Fault, and RLoad Induced Sag (RLIS).*

Sr. No	Induction Motor Starting (IMS)		
	No of Peak in First Detection Flag-1 (Peak1)	No of Peak in Second Detection Flag-2 (Peak2)	Sum of Peak Indices in First and Second Flag (Psum)
IMS	04	00	0.0497
	04	00	0.0369
	04	00	0.0296
	04	00	0.0312
	05	00	0.0444
Observation	Peak 1 >= 1, Peak2 =00 & Avg Psum =0.0386		
LG Fault	02	03	0.2552
	02	03	0.2963
	02	03	0.2510
	02	04	0.2525
	02	04	0.3034
Observation	Peak 1 < Peak2 & Avg Psum =**0.27168**		
RLIS	02	01	0.0817
	02	01	0.0760
	03	02	0.0774
	03	02	0.0803
	04	02	0.0926
Observation	Peak 1 > Peak2 & Avg Psum =**0.0816**		

***Table 2**: Impact of Sampling Resolution (N_s) on Power Quality Index (PQI) Metrics and Ace.*

Types of Voltage Sag Causes	Ns=10 (Sample/Cycle)		Ns=40 (Sample/Cycle)	
	Max1 & Max2 Of PQI	No of Peak in I & II Detection Flag (Peak 1& 2)	Max1 & Max2 Of PQI	No of Peak in I & II Detection Flag (Peak 1& 2)
Induction Motor Starting (IMS)	0.0202 & 0.0093	04 & 00	0.0140 & 0.0083	05 & 00
	Peak 1 >= 1, Peak2 =00		Peak 1 >= 1, Peak2 =00	
LG Fault (LG)	0.0982 & 0.1878	03 & 04	0.0446 & 0.0760	06 & 07
	Peak 1 < Peak2		Peak 1 < Peak2	
Resistive Load Induced Sag (RLIS)	0.0378 & 0.0425	04 & 02	0.0127 & 0.0099	06 & 07
	Peak 1 > Peak2		Peak 1 > Peak2	

peak point in the PQI increases and the ACE coefficient magnitude value reduces slightly. So it suggested that you prefer the half cycle for Ns rather full cycle or more than it.

D. Comparison with Other Method

The algorithm proposed in this research is based on a decision tree. To evaluate the accuracy of this method in comparison with recent literature, the features outlined in Table 1 are utilized. Each class consists of 10 observations, resulting in a total of 30 observations across three classes. The MATLAB Classification Learner App is employed for classification, with cross-validation selected as the validation method. In this mode, the same dataset is used for both training and testing purposes. The resulting confusion matrix for testing is illustrated in Fig. 7.

Table 3 presents a comparative analysis of classification methods, including the proposed ACE-based approaches and existing techniques. The proposed methods, using various classifiers such as Coarse Gaussian SVM, Weighted KNN, Cubic KNN, and Ensemble (Bagged Trees), achieved high accuracy across all classes (IMS, LG, and RLIS), with the best results consistently reaching 100% accuracy. These methods utilize the number and sum of peaks of the PQI as features, demonstrating efficiency with low training times.

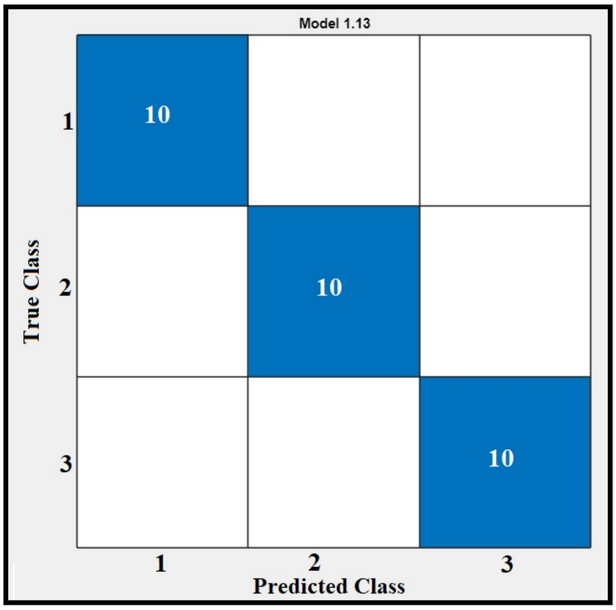

***Fig. 7**: Testing Confusion Matrix (Gaussian SVM).*

In contrast, existing methods like Stockwell Transform + ELM and HOS + SVM also achieve high accuracy but rely on more complex features such as higher-order statistics and energy-based metrics. The proposed methods provide comparable or superior accuracy with simpler and faster implementations.

***Table 3**: Performance Comparison of Proposed ACE-Based Classification Methods with Existing Techniques.*

Classification Method	IMS (%)	LG (%)	RLIS (%)	Features
Proposed Method (ACE) with Coarse Gaussian SVM	100%	100%	100%	No of Peaks and Sum of Peaks of PQI
Proposed Method (ACE) with Weighted KNN	100%	100%	100%	No of Peaks and Sum of Peaks of PQI
Proposed Method (ACE) with Cubic KNN	90%	100%	100%	No of Peaks and Sum of Peaks of PQI
Proposed Method(ACE) with Ensemble (Bagged Trees)	100%	100%	100%	No of Peaks and Sum of Peaks of PQI
[17] Stockwell Transform +ELM	100%	100%	100% (TE)	1. Energy content 2. Standard deviation of MAT 3. Standard deviation of MAF 4. Shannon Entropy of MAT 5. Kurtosis of MAT
[18] Higher Order Stastastics (HOS)+SVM	100%	99.33 %	99.33 % (TE)	2^{nd},3^{rd} &4^{th} order cumulants

E. Limitations and Future Scope

This methodology has some limitations, which can lead to false detections, and its dependence on threshold settings for accurate sag detection. It currently focuses on limited sag causes, such as IMS, LG faults, and RLIS. Additionally, the classification relies heavily on peak analysis, which can be challenging for complex or overlapping events. Further, the experimental validation is limited to controlled laboratory setups, requiring extensive real-world testing for broader applicability.

The proposed methodology can be enhanced by integrating advanced machine learning techniques like deep learning to improve classification accuracy and scalability. It holds potential for real-time deployment in large-scale power networks with optimized hardware implementations. Future work can extend this approach to other power quality disturbances, such as swells and harmonics, offering a broader application. Hybrid methods that combine this technique with wavelet transforms or other signal processing methods could further refine disturbance detection. The proposed algorithm can be applied to three-phase system events.

6. CONCLUSION

The proposed algorithm for voltage sag classification using alienation coefficients and Power Quality Index (PQI) proves to be an effective and reliable method for identifying the underlying causes of voltage sags in power systems. By analyzing the patterns of peaks detected by the first and second flags, along with the sum of peak indices (Psum), the algorithm accurately distinguishes between sags caused by Induction Motor Starting (IMS), Line-to-Ground (LG) faults, and Resistive Load-Induced Sags (RLIS). The results demonstrate that IMS events consistently exhibit multiple peaks in the first detection flag with none in the second, while LG faults show more peaks in the second flag, and RLIS events have a greater peak count in the first flag. The use of Psum further enhances classification accuracy, enabling a clear distinction between different sag events. This methodology not only simplifies voltage sag classification but also improves the real-time diagnostic capabilities of power quality monitoring systems, making it a valuable tool for enhancing the reliability and stability of power networks

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