4-2023

Detecting Fast Frequency Events in Power System: Development and Comparison of Two Methods

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Citation Details

H. A. Alghamdi, M. A. Adham, U. Farooq and R. B. Bass, "Detecting Fast Frequency Events in Power System: Development and Comparison of Two Methods," [POST-PRINT] 2023 IEEE Conference on Technologies for Sustainability (SusTech), Portland, OR, USA, 2023, pp. 55-62,

Detecting Fast Frequency Events in Power System: Development and Comparison of Two Methods

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***Abstract*—In power systems, frequency deviation from nominal value can occur due to reasons such as loss of generation, loss of load, or major faults in the grid. Such frequency fluctuations can lead to serious subsequent outages and damages to both end-user and utility equipment. Therefore, a proper frequency deviation detection methodology must be in place to effectively identify frequency events in a timely manner. This manuscript provides a comparative analysis between two frequency deviation detection algorithms. One is based on signal processing and statistical analysis. The other is a regression-based algorithm. Both of these algorithms have multiple adjustable parameters, making them highly tunable for different Balancing Authorities.**

***Index Terms*—Frequency event, Frequency response, Frequency event detection algorithm, Least-squares linear regression, Discrete wavelet transform.**

I. INTRODUCTION

Power system operating frequency reflects the status of the balance between power supply and demand. Power imbalances occur commonly due to normal deviations between load or generation. On rare occasions, power systems can experience significant frequency deviations in the operating frequency due to sudden and large changes in load or generation. [1].

Frequency response has an essential role in power system reliability. Frequency response, also known as primary frequency control, can be defined as a quick reaction from a Balancing Authority (BA) against a frequency deviation from a nominal value, immediately after detection of the frequency event. [1]–[3].

Increased renewable energy penetration within modern power systems presents a concern of reducing power systems inertia. The amount of inertia in a system determines the system sensitivity to frequency events, the appropriate frequency response of the BA, and the Rate of Change of Frequency (ROCOF). Systems with high inertia are better able to buffer sudden deviations in frequency. In other words, the more inertia in a system, the less sensitive it is to frequency events [2].

There is no universal agreement on the definition of a frequency event due to differences in the system inertia within every BA and interconnection. Therefore, each BA must determine the characteristics of frequency events that are of concern to their balancing areas so that these events can be effectively and rapidly identified. Thus, individual BAs should adjust event detection algorithms according to their unique system characteristics [4].

Funding for this work was provided by Portland General Electric

Phasor Measurement Units (PMUs) play an essential role as data sources for grid status and as necessary tools for frequency event detection. PMU data from modern power system provide operators with valuable information that enhances power system monitoring, visibility, and reliability. Due to the valuable insights that PMUs provide, they are now widely deployed across both transmission and distribution systems. Often, PMU data exchange follows the IEEE C37.118.2 communication protocol. Consequently, PMUs are compatible with a wide range of power systems communications, control, and protection devices, including Phasor Data Concentrators, Real-time Automation Controllers, protective relays and Wide Area Measurement Systems [5]–[7].

Different methods and concepts have been used to design frequency event detection algorithms. These methods may be categorized into four main groups: signal processing-based method, statistical based method, machine learning/deep learning based methods, and hybrid methods [8].

In this paper, two different frequency event detection algorithms are presented, a newly developing algorithm, and a previously-validated algorithm. These algorithms are compared in terms of concepts, structure, and performance based on results obtained from a case study in an offline mode, using Python as an open-source programming environment. The first algorithm Least-Squares Linear Regression-Based algorithm (LSLR) is based on statistical linear regression. The second, Wavelet Transform-Based Algorithm (WTBA), is based on signal processing and statistical methods.

The paper is organized as follows: Background is stated in section II. The Frequency event detection algorithms concepts are presented in section III. Detection algorithm performance evaluation is described in section IV. In section V, the case study is presented. Discussion and comparisons are provided in section VI. Future work is stated in section VII. Section VIII concludes the paper.

II. BACKGROUND

The main goal behind developing the LSLR algorithm was to provide this research team with a detection algorithm that can reliably identify and detect frequency anomalies. LSLR serves as a baseline algorithm against which new frequency event detection algorithms may be compared. The objective of developing these algorithms is to rapidly and reliably actuate adequate online compensatory resources, such as battery-based inverter systems or aggregations of residential loads, that can provide frequency support to a balancing area.

The team's initial research and development stage successfully configured a PMU and a Real-time Automation Controller (RTAC) to automatically acquire, process, and archive PMU data directly from the local distribution system. A structured text program was developed and deployed within the RTAC. This program reads frequency data from the PMU, calculates the slew rate over a window of frequency measurements, and conducts comparisons with predetermined thresholds. If the frequency reading or slew rate is lower or higher than the thresholds, a flag is set to be true, which represents a possible under or over-frequency event. Such simple threshold-based algorithms are insufficient for reliably detecting frequency events.

A subsequent improvement was made by developing the LSLR regression-based algorithm, which can rapidly and reliably detect frequency events. LSLR has three tunable parameters: *window size*, *point separation threshold*, and *series-over threshold*. Later, a fourth parameter, *series over count*, was added to the algorithm.

The team built an Algorithm Evaluation Environment (AEE) to evaluate algorithm performance using binary classification and evaluation metrics. The AEE provides means to search for optimal algorithm parameters, in reference to industry experts' assessments. The team uses an online survey to obtain experts' assessments of historical frequency events. An optimization algorithm, Grey Wolf Optimization (GWO), is used to optimize algorithm parameters by running through the steps outlined in Figure 1 over many cycles.

This manuscript describes the development and evaluation of a new signal processing-based algorithm, the Wavelet Transform-Based Algorithm (WTBA). This manuscript compares LSLR and WTBA regarding concepts, structures, and performances.

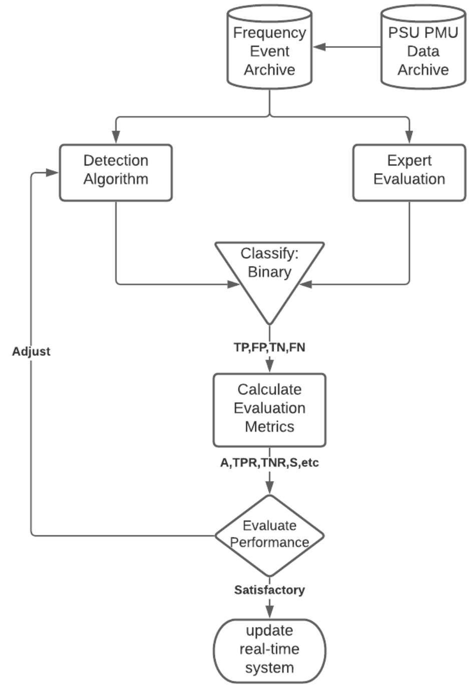

Fig. 1. Algorithm Evaluation Environment [4]

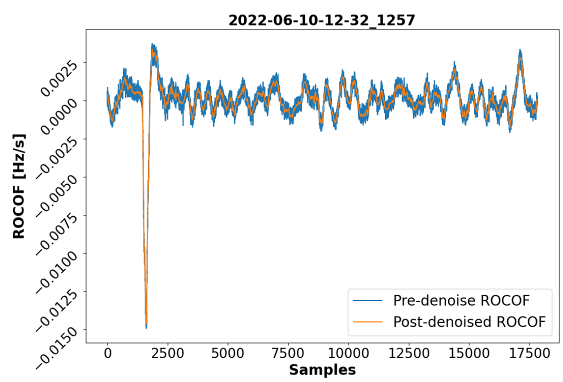

Fig. 2. Pre-denoise ROCOF VS. Post-denoise ROCOF, as produced by the Wavelet Transform-Based Algorithm

III. Frequency Event Detection Algorithms

This section explains in details the LSLR and WTBA algorithms, the methodology for each algorithm, the algorithm parameters, and the detection process steps.

A. Least-Squares Linear Regression-Based algorithm

1) Methodology: LSLR is based on the least-squares linear regression method, commonly used to interpret the relationship between an independent and dependent variable such as time, and frequency [9]. Linear regression is a statistical method used in this algorithm to detect power system frequency events. Other methods can also be adopted to detect frequency events, such as signal processing, machine learning, as well as hybrid methods [2].

Slew rate is used to remove noise from the PMU data, thereby producing a smoothed waveform. Figure 3 shows frequency and slew rate, processed by linear regression, as computed using Equation 1. *Slew rate* is used instead of frequency readings to avoid exposure to noise associated with the high-rate sampling of PMU data, 30 readings per second in this work. Figure 3 shows an original frequency waveform with noise above the processed smooth *slew rate* waveform [4].

$$slew\,rate = \frac{N\sum(xy) - \sum(x)\sum(y)}{N\sum(x^2) - (\sum(x))^2}, \quad (1)$$

where N is number of data points. x and y refer to the time stamp and the frequency sample, respectively.

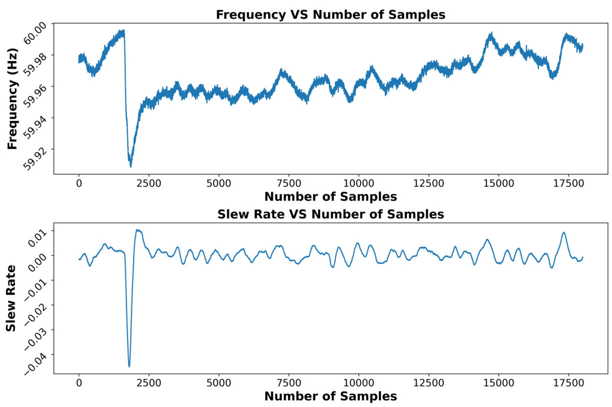

Fig. 3. Frequency and Slew rate Processed by First Algorithm

Under normal circumstances, frequency fluctuates around the nominal value of 50 or 60 Hz. However, in the case of an event caused by a large and sudden change in load or generation, a significant and rapid change in frequency will occur.

The latest version of the LSLR algorithm now uses five parameters: *Window Size (WS)*, *Point Separation (PS)*, *Standard Deviation Threshold (SDT)*, *Series Over (SO)*, and *Event Threshold (ET)*; the five parameters together are used to declare an event. The *slew rate* is computed at each time step using a sliding window. Then, consecutive *slew rate* values smoothly mimic any frequency deviations [10]. The following are the details for the five parameters in the order they appear in the algorithm:

2) Parameters: The LSLR algorithm has five tunable parameters as follows:

- WS: The algorithm uses a sliding window technique to calculate the slew rate for the frequency measurements, which presents a trade-off. A large WS value decreases the speed of detection while also reducing the noise associated with frequency measurements, and vise-versa.
- PS: Within each sliding window, a slew rate value is calculated. As more data is recorded by the PMU, the sliding window progresses, calculating a new slew rate value. Each two slew rate values are compared to one another. From experiments, it was noted that a gap between the two compared slew rate values improves the detection speed. Therefore, the gap between each slew rate is referred to as the PS.
- Slew Difference Threshold (SDTH): This parameter compares the difference between adjacent slew rates with the slew difference threshold to start the event declaration process.
- SO: This parameter is a counter for detecting how many times the slew rate threshold has been consecutively exceeded.
- ET: This parameter measures the steepness of the slew rate curve to avoid false detection for quasi-events that exhibit some frequency deviations. The event declaration occurs when both the event threshold and series over threshold have been exceeded [10].

B. Wavelet Transform-Based Algorithm

1) Methodology: WTBA has two stages in the event detection process, namely: denoising PMU data, and then computing the ROCOF and Standard Deviation (SD).

The high sampling rate of PMU data can cause marked noise in the frequency curve. Therefore, the denoising stage is crucial so the frequency signal can be used accurately. The denoise stage is conducted using a Discrete Wavelet Transform (DWT), which is used for discrete time. Generally, Wavelet Transform (WT) has an important feature in processing input signals in frequency spectral and time localization [11].

DWT is considered a desirable method in wavelet analysis because it analyzes input signals in the frequency and time domains. In addition, DWT has fewer calculations than other types of transforms, such as the Fourier Transform [12].

DWT has two stages of denoising, which starts with the decomposition of the input signal to different components in different frequency bands and time locations, followed by reconstructing the post-analyzed components again to the original signal [13]. For signal denoising purposes, Daubechies wavelet 4th order has been used widely with valid results [14]–[16]. Thus, this algorithm selects Daubechies wavelet 4th order for denoising purposes due to the validation results in other similar works. Furthermore, DWT has various wavelet families, such as Symlet Wavelet, Coiflet Wavelets, Meyer Wavelet, and Biorthogonal Wavelet. Each wavelet family has different wavelet scales and orders that produce different results when processing an input signal [11], [13]. Figure 4 shows pre-denoise frequency vs. post-denoise frequency and Figure 2 shows ROCOF with pre-denoise frequency vs post-denoise frequency.

The second stage is the ROCOF and SD computation. There are different methods for obtaining the ROCOF; either by estimation using filters such as a Kalman filter as in [14], or computed as in [17]. This work uses the latter method, Equation 2, to calculate ROCOF using the denoised frequency measurements.

The algorithm then computes the standard deviation using a sliding window over the ROCOF dataset using Equations 3, 4, and 5. The final step in the detection process is the event declaration when the SD exceeds the standard deviation threshold several consecutive times. Figure 5 shows SD of the ROCOF.

$$ROCOF = \frac{f2 - f1}{t2 - t1} \quad (2)$$

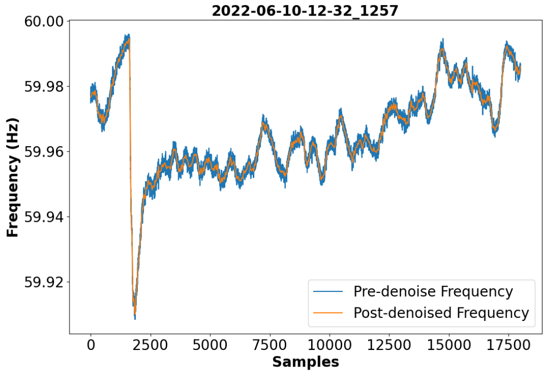

Fig. 4. Pre-denoise Frequency VS. Post-denoise Frequency, as produced by the Wavelet Transform-Based Algorithm algorithm.

where $f1$ and $f2$ are frequency measurements and $t1$ and $t2$ are the times associated with the frequency measurements $f1$ and $f2$.

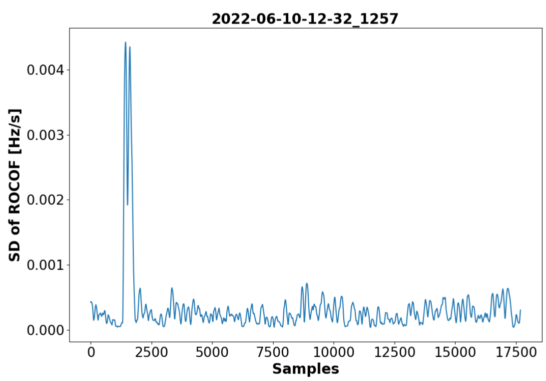

Fig. 5. Standard deviation of ROCOF, from the WTBA algorithm

$$\bar{x} = \frac{1}{n}\sum_{i=i}^{n} x_i \tag{3}$$

$$VAR = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{4}$$

$$SD = \sqrt{VAR} \tag{5}$$

where n is number of samples, and $\bar{x}$ is the samples mean, and x_i is the sample value, VAR is the Variance and SD is the standard deviation.

2) Parameters: The WTBA algorithm has four tunable parameters as follows:

- WS: This parameter affects the SD only. SD is computed within each window through the ROCOF dataset. By increasing the window size, the SD value increases accordingly.
- Frequency Measurements Difference (FMD): This parameter affects the ROCOF and SD. By increasing the FMD, the absolute value of ROCOF increases and becomes smoother.
- SDT: This parameter is considered critical because once this threshold is exceeded, a true flag is raised, and if enough consecutive flags are raised, an event can be declared. In conjunction with other parameters, an SDT value above the optimal value would increase the chance of having False Negative (FN) events. Similarly, an SDT value below the optimal value would increase the likelihood of having False Positive (FP) events.
- Consecutive Flags Threshold (CFT): This parameter generally affects the algorithm performance because it is related to having FP or FN depending on how far the CFT is from the optimal value.

IV. Detection Algorithms Performance Evaluation

This section provides an explanation of six important tools that have been used to evaluate and improve algorithm performance: frequency response test station, synchrophasor archived data, experts' evaluation, binary classification, evaluation metrics, and optimization technique.

A. Frequency Response Test Station (FRTS)

Event detection algorithms can use PMU data with a different sampling rate; the sampling rate in this work is 30 samples per second but 60, or 120 samples per second can also be used. PMU data contain several power systems quantities, including voltage, current, phasor, frequency, and timestamps. Frequency and timestamps are the only values used in this work [4].

The real-time event detection system needs several devices, equipment, and tools, such as PMU, a RTAC, a Grid Simulator (GS), a Global Positioning System (GPS) clock with an antenna, PCs, and a data archive. The assembled systems is the Frequency Response Test Station (FRTS).

The development process of the detection algorithm goes through two stages: the offline stage and then the online stage. This paper focuses on the offline stage, which requires using the PMU and data archive of the FRTS [4], [10].

B. Synchrophasor Data Archive

One of the functions of the FRTS is to continually record and archive synchrophasor measurements in the form of Comma Separated Value (CSV) files. Each file has 18,000 samples, or 10 minutes of data. The archive data has historical data for the last three years. From this archive, the team extracts examples of events, quasi-events, and non-events. Information from the local utility company about historical events in the grid is used as a reference to identify recent frequency events within the archive. [4], [10].

TABLE I
EXPERTS' EVALUATION OF 30 FILES SET

No.	File Name	Experts' Evaluation	No.	File Name	Experts' Evaluation	No.	File Name	Experts' Evaluation
1	2019-09-01-02-35_5421	FALSE	11	2021-01-07-12-12_10287	TRUE	21	2021-01-24-16-07_1762	TRUE
2	2019-09-03-12-19_6720	FALSE	12	2021-01-08-18-27_10466	TRUE	22	2021-01-25-01-45_1819	FALSE
3	2019-09-05-08-51_7722	FALSE	13	2021-01-11-10-29_10845	TRUE	23	2021-01-25-05-08_1839	FALSE
4	2019-09-10-09-20_10433	FALSE	14	2021-01-12-13-02_39	TRUE	24	2021-01-27-00-33_2096	TRUE
5	2019-09-19-08-58_866	FALSE	15	2021-01-13-14-33_190	TRUE	25	2021-01-29-11-20_91	TRUE
6	2019-10-07-05-32_6223	FALSE	16	2021-01-17-16-01_767	TRUE	26	2021-01-30-08-17_215	FALSE
7	2019-10-09-11-12_6894	FALSE	17	2021-01-18-15-20_905	FALSE	27	2021-02-04-10-34_53	TRUE
8	2019-11-13-11-57_2331	FALSE	18	2021-01-23-10-33_1587	FALSE	28	2021-02-05-15-50_147	TRUE
9	2019-11-20-02-12_4309	FALSE	19	2021-01-24-14-16_1751	FALSE	29	2021-02-06-05-21_227	TRUE
10	2019-11-26-19-43_6328	FALSE	20	2021-01-24-15-06_1756	TRUE	30	2021-02-08-16-43_20	FALSE

C. Experts' Evaluation

According to [8], [9], there is no universal definition for the frequency event because it is specific to the inertia level and flexibility in each BA. Therefore, experts in from industry and academic evaluated a diverse set of event, quasi-event, and non-event files. Table I shows the experts' evaluation of 30 files that were used to tune the algorithms, Section V. The evaluation is formulated via an online survey, which presents frequency and slew rate plots for each case. Experts rate the cases as under-frequency events, over-frequency events, or non-events. The data collected from the experts' evaluation are then compiled within a summary validation file, which is then used to evaluate algorithm performance [10].

D. Binary Classification

Binary classification is a method used in different fields to measure performance of binary outcomes. In this work, the results of processing the same files by the experts and the algorithm have been classified using binary classification, which contains the following metrics [4] [10]:

- True Positive True Positive (TP): experts' assessment and algorithm results agree that an event occurred.
- True Negative True Negative (TN): experts' assessment and algorithm results agree that an event did not occur.
- False Positive FP: algorithm wrongly declares an event while the experts' assessment did not.
- False Negative FN: algorithm did not identify an event, while the experts' assessment declares an event.

E. Evaluation Metrics

Researchers use evaluation metrics to measure performance, making it easier to conduct analysis and comparative studies in different cases [18]. Evaluation metrics are used in this work to evaluate the performance of the detection algorithms according to experts' assessments, as derived from the binary classification results. The evaluation metrics are:

- *Accuracy* quantifies the algorithm performance in correctly classifying events and non-events in relation to the set size.

$$Accuracy = \frac{TP + TN}{SetSize} \times 100\% \tag{6}$$

- *Sensitivity* quantifies the algorithm capability to classify TP events correctly.

$$Sensitivity = \frac{TP}{TP + FN} \times 100\% \tag{7}$$

- *Precision* quantifies the ability of the algorithm to identify TP events in relation to all positive identifications.

$$Precision = \frac{TP}{TP + FP} \times 100\% \tag{8}$$

- *Specificity* quantifies the ability of the algorithm to identify TN events correctly.

$$Specificity = \frac{TN}{TN + FP} \times 100\% \tag{9}$$

- *False Discovery Rate* (FDR) quantifies the likelihood of incorrectly identifying an event. FDR is the converse of Precision

$$FDR = \frac{FP}{FP + TP} \times 100\% \tag{10}$$

The ideal value for accuracy, sensitivity, precision, and specificity is 100. For FDR, the ideal value is 0 [4], [10].

F. Optimization

In this work, the GWO technique is used for algorithm parameter optimization. The Optimization process starts with modeling the problem mathematically in the form of an objective function. The objective function either needs to be maximized or minimized depending on the nature of the problem. In our case, the goal is to maximize the evaluation metrics: accuracy, sensitivity, precision, and specificity. Table II shows GWO settings that were used in the optimization process [10] and Figure 6 shows GWO convergence curve. The objective function then can be stated and formulated as: Max (accuracy + sensitivity + precision + specificity) and can be expressed as:

$$Fitness\,score = 100 + 100 + 100 + 100 = 400 \tag{11}$$

where the ideal value of each metric is 100. 400 is the ideal fitness score.

TABLE II
OPTIMIZATION RESULTS OBTAINED FOR 30 SAMPLES SET

	Iteration	Fitness	Search agents	Sample set size	No. of events	No. of non-events	Processing time (min)
GWO	50	400	10	30	13	17	50

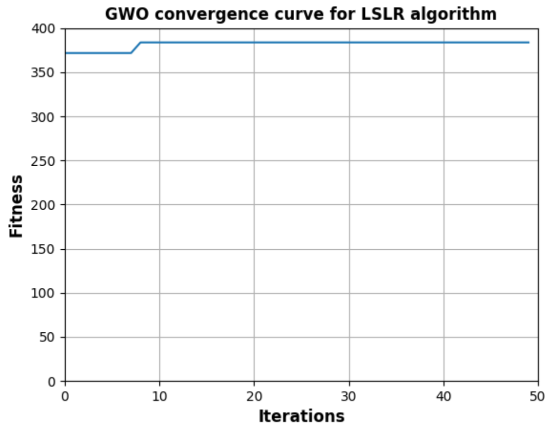

Fig. 6. GWO convergence curve for LSLR algorithm

V. Case study

A collection of 30 frequency files was extracted from the PMU archive data. These samples were used to test and evaluate the performance of the detection algorithms. This set of files contains frequency events, non-events, and quasi-events, as determined by experts [8], [10].

The detection algorithm output and experts' evaluations were assessed against each other. Binary classification and evaluation metrics were then calculated to compare the detection algorithm results and experts' opinions.

Using GWO, each parameter in the LSLR algorithm was optimized to ensure the highest detection performance possible. The WTBA parameters were estimated. The purpose of only optimizing the LSLR algorithm parameters was to clarify the importance of using an optimization method on the algorithm's performance by comparing both algorithms' detection performance. In addition to the performance, concepts and structures are compared as well.

VI. Discussion and comparison

This section discusses and compares concepts, structures, and performances of both algorithms:

A. Concept:

Starting with LSLR, linear regression represents the relationship between a dependent and an independent variables. Assuming that ***Y*** is the independent variable and ***X*** is the dependent variable, then the definition of the linear relationship between these two variables can be formulated as the line equation:

$$Y = a + Xb \tag{12}$$

Where: b is the Slope of the line as the first coefficient. a is the intercept of the line as the second coefficient. Using these coefficients, a Y value can be predicted for any given value of X.

By relating the above explanations to this paper, the line equation reflects the regression line, ***b*** is the slope or *slew rate*, and ***a*** is the y-axis intercept. Therefore, the concept of least squares linear regression aims to either contain or exclude the data around the regression line, which are frequency measurements in this case, by minimizing the error between the data and the regression line. Linear regression provides three main benefits: denoising the frequency signal, elevating the sensitivity to outliers, and presenting an uncomplicated computational method. In addition, linear regression considers an accurate statistical method for frequency event calculation and adequate frequency response.

Regarding the second algorithm, WTBA, wavelet transform is generally used for different purposes, such as signal analysis and processing, either in continuous or discrete time. Continuous Wavelet Transform (CWT) and Wavelet Series Transform (WST) are used with continuous time, whereas for discrete-time, DWT is used. In this work, we used DWT as signal processing to denoise the frequency waveform so that frequency can be used for further calculations.

SD is a well known statistical tool to indicate the amount of data that tends to be far from the mean. In this work, SD is used to indicate the amount of data, frequency measurements, that tend to be far from the rated frequency of 60 Hz as the mean of the dataset; it is used as a threshold in the event declaration process, specifically in the SDT parameter.

B. Structure:

Another aspect is the structure of the algorithms in terms of their process flows. As shown in Figure 7, both algorithms' process stages are presented alongside each other to provide comparison clarity.

LSLR has the main stage before declaring the event, which is the calculation stage to compute the slew rate and then to find the slew rate difference. Thus, it will be possible to monitor and compare the calculated values with the specified thresholds and identify the excesses considered a frequency event.

In contrast, WTBA depends on a signal processing technique to denoise the frequency signal using a wavelet transform. Thus, the denoised frequency signal can be used to calculate the ROCOF accurately. The following step is mainly to calculate the SD using a moving window over the ROCOF data. As in the first algorithm, the SD values are monitored and compared with the SDT. An event is announced if the threshold is exceeded for several consecutive times.

Considering the above discussion, LSLR has a lower number of processing stages for calculating the *slew rate* and *slew rate difference*. In contrast, WTBA has an additional step of signal processing to denoise the frequency signal to be ready for the ROCOF and SD calculations.

C. Performance:

For the offline testing, optimization, and evaluation, Python was used to process 30 mixed files containing events, non-

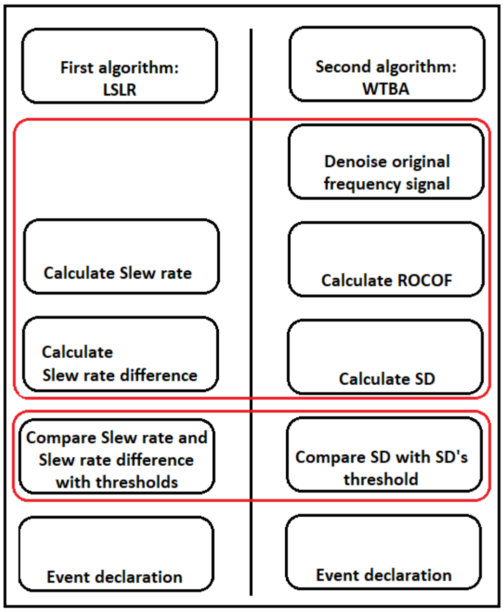

Fig. 7. Algorithms processes comparison

events, and near events, where a near event is considered a non-event samples. Therefore, the sum of the events samples is 13, and the remaining 17 are non-events, as shown in Table I. Those files were selected from the archive data system and identified by experts.

As mentioned in sections I and IV, each BA must define frequency events depending on their system tolerance to disturbances. Considering the system inertia and response capability, Table V shows the sample set and the experts' evaluations. Therefore, comparing the detection results from the two algorithms against the experts' evaluation initializes the binary classification evaluation, as shown in Table V. Thus, binary classification informs the evaluation metrics to assess the algorithm's performance, as in Table V.

In addition, another benefit of the evaluation metrics is to indicate the appropriateness of the algorithm parameters and the need to optimize, using GWO in this work, to improve the event detection performance. Both algorithms have the same window size as a standard parameter in terms of effect and functional features. However, in WTBA, the window size has an additional proportional effect on ROCOF. Another common feature of both algorithms is that they have tunable parameters that allow them to be valid as detection algorithms in different balancing authorities with varying frequency events definitions.

Both algorithms processed the set of 30 files to evaluate detection performance individually. The detection results for both algorithm are shown in Table V in the binary classification form, which indicates superiority of LSLR over WTBA in binary classification. LSLR outperformed WTBA in terms of FPs, with just one faulty classification sample that was evaluated as a non-event by the experts in contrast with three cases of FP for the WTBA algorithm. That leads to a significant disparity between the results in the evaluation metrics shown in Table V, especially the noticeable score of LSLR sensitivity as 100%, 93% for the rest of the metrics, and 7% in False Discovery Rate (FDR). In comparison, the highest metric score for the WTBA algorithm was sensitivity at 92% and 87%, 80%, and 82% for accuracy, precision, and specificity, respectively.

GWO was used to optimize LSLR parameters to improve the algorithm performance, while the WTBA parameters were estimated. Table III and Table IV present the optimized LSLR parameters values and the WTBA best-estimated parameters that enabled the best match to the experts' definition of events. Using LSLR with optimized parameters gave superior results compared to the un-optimized WTBA algorithm. Due to the need to shed more light on the impact on the detection performance of using different estimated sets as values of algorithm tunable parameters, two scenarios of using two sets of estimated parameter values on the WTBA algorithm have been conducted and analyzed. Table VI shows the relevant results.

TABLE III
LSLR OPTIMIZED PARAMETERS

	Parameter	Value
1	WS	158
2	PS	3
3	SDTH	0.00000385
4	SO	6
5	ET	0.0002161

TABLE IV
WTBA ESTIMATED PARAMETERS

	parameter	Value
11	WS	200
2	FMD	225
3	SDT	0.0018
4	CFT	10

TABLE V
LSLR AND WTBA OFFLINE EVALUATIONS RESULTS COMPARISON

	Least Square Linear Regression (LSLR)	Wavelet Transform-Based Algorithm (WTBA)
TP	13	12
FP	1	3
FN	0	1
TN	16	14
Total examples	30	30
Accuracy	93	87
Sensitivity	100	92
Precision	93	80
Specificity	93	82
FDR	7	20

The first and second scenarios use two sets of estimated parameters. In the first scenario, the algorithm used the first set of parameters. The results show that 13 samples were detected correctly as an event, and seven samples were incorrectly detected as an event. This detection scenario resulted in a Sensitivity of 100%. The rest of the evaluation metrics experienced degraded values.

TABLE VI
WTBA ALGORITHM OFFLINE EVALUATIONS WITH DIFFERENT PARAMETERS SETS

	Estimated Parameters Set 1	Estimated Parameters Set 2
TP	13	12
FP	7	3
FN	0	1
TN	10	14
Total examples	30	30
Accuracy	77	87
Sensitivity	100	92
Precision	65	80
Specificity	59	82
FDR	35	20

In the second scenario: by tuning just one parameter, FMD, the algorithm performance improved noticeably, with results jumped to 87%, 80%, and 82% in accuracy, precision, and specificity, respectively. A slight decline in sensitivity with notable and desirable descent from 35% to 18% in FDR were reported. Precision and specificity account for FP, so by increasing these two metrics, the chance of FP occurrence will decrease.

VII. FUTURE WORK

Implementing WTBA in real-time is the leading future target. Future work will also focus on developing WTBA using the optimization technique, GWO, to obtain optimal parameters values instead of estimating the values. Moreover, comparing the WTBA online detection speed with the offline results will be a future goal. Finally, comparing the WTBA results in both offline and online stages with the corresponding LSLR results will be conducted for further validation.

VIII. CONCLUSION

This paper presented the WTBA as a new frequency event detection algorithm compared it with the valid LSLR algorithm in terms of concept, structure, and performance.

The binary classification compared detection results from both algorithm against the experts' assessments for a set of 30 selective files. Evaluation metrics then used the binary classification results to quantify each metric value as algorithm performance evaluation.

The LSLR is based on a least-squares linear regression with five parameters, whereas the WTBA is based wavelet transform with four parameters.

Both algorithms have tunable parameters which control the algorithms' performance. Thus, GWO was utilized to optimize the LSLR algorithm parameters which improved the performance accordingly in contrast WTBA with estimated parameters values. Algorithms' concepts, structures, and performances were discussed and compared. The paper is concluded by setting up a plan to further develop and optimize the WTBA in future work and evaluate it against the LSLR in an online and offline environment.

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