Evaluating RMS based continuous S-Transform with deep learning for detecting and classifying voltage sag and swell

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Abstract. Voltage sag and swell can cause serious problems like instability, short lifetime, and data errors in power quality. The objective of this paper is to present the detection and classification of voltage sag and swell. S-Transform is used as a base to detect the triggering point of disturbances using Root Mean Square (RMS) method. This paper also presents the type of sags and swells by applying the features into Extreme Learning Machine (ELM) neural network approach in MATLAB. In addition, ELM method is compared with Support Vector Machine (SVM) and Decision Tree method to observe the best classification between these three methods. The accuracy of the classifications was displayed in percentages. It was verified that the detection using RMS and classification using ELM are possible because the results are clearly showing the advantages of the RMS in detecting and ELM for classifying the power quality problems.

KEYWORDS: Root Mean Square (RMS), power quality (PQ), deep learning, s-transform, PQ disturbances.

1. Introduction
Electric power is the crucial type of energy as it requires continuous flow and cannot be conveniently stored. Power quality disturbances such as transient, harmonic, interruption voltage sag, and swell have negative impacts on a power supply based on the research studies [1][2]. To assure the quality of power is not an easy task. Therefore, it is necessary to know the root of disturbances based on detecting and classifying the power disturbance to maintain the quality of the power system.

Voltage sag and swell is an essential subject in Power Quality analysis and reason for the deterioration of power quality [3]. In [4][5], described that voltage sag happens when decreases in RMS occur within 0.5 cycles to 1 min voltage at power frequency. In fact, voltage sag is a short duration on the reduction of rms voltage. This is because voltage sag is measured from a reduction of rms voltage from below 0.1p.u. to above 0.9 p.u. of nominal voltage.

Meanwhile, voltage swell happens reversely from voltage sag. At the duration of 1.5 cycles to 1 min, increase in RMS voltage in between 1.1 p.u. to 1.8 p.u. nominal voltage. Voltage swell normally
associate with the system fault condition. Energizing a large capacitor bank contributes to the presence of voltage swells based on the studies done by [6].

1.1 S-Transform

In previous research papers carried out by the [3][7][8], the Wavelet Transform (WT) was used as a signal processing in detecting the voltage sag and swell. WT can identify the locations containing the frequency domain. The problem arises as WT is complicated to compute, and the process is not accurate because the information of frequency disappeared at a certain time. Delay processing can also happen in WT. Therefore, WT is not suitable for extraction features.

To solve this problem, S-Transform was presented to overcome the imperfection of WT. S-Transform is an extension of WT and Short Time Fourier Transform (STFT). ST also is known as a Stockwell's transform, and ST has a better technique in Power Signal Processing. [3] Describes ST is based on moving and scalable localizing Gaussian windows. It has the benefit of transforming signal from time domain to two-dimensional frequencies following a similar Fourier frequency domain.

Based on previous research by [3], feature extraction of disturbance signals was extracted based on ST and produce S-matrix.

There are various methods of achieving the final equation of S-Transform. Based on the paper [9], the equations related to ST are as follow:

The Continuous Wavelet Transform (CWT), $W(\tau,d)$ of a function $h(t)$ is defined as [9]:

$$W(\tau,d) = \int_{-\infty}^{\infty} h(t)w(t-\tau,d)dt$$

Equation (1) determine the expansion factor of $d$, which inverse from frequency $f$. The expansion determines the width of the wavelet.

ST is obtained by multiplying CWT with a phase factor as defined by [9]:

$$(\tau, f) = e^{i2\pi f}W(\tau,d)$$

(2)

Where the mother wavelet is defined as

$$W(\tau,d) = \frac{f}{\sqrt{2\pi}} e^{-\frac{(t-\tau)^2}{2}} e^{-i2\pi f}\tag{3}$$

Thus, the final form of the continuous ST is obtained as

$$S(\tau,d) = \int_{-\infty}^{\infty} h(t)\frac{f}{\sqrt{2\pi}} e^{-\frac{(t-\tau)^2}{2}} e^{-i2\pi f} dt$$

(4)
And the width of the Gaussian window is

\[ \sigma(f) = T = \frac{1}{f} \]  \hspace{1cm} (5)

S-Transform of a discrete series of data creates a complex matrix (ST-matrix) in which the row corresponds to the frequency and the column corresponds to the time [7][10].

1.2 RMS Method

A previous study by [3][4][11] describes the power quality disturbance has a wide range of frequency, magnitude, and duration. There are various ways to detect power disturbances. One of the methods used was Fast Fourier Transform (FFT). The performance using FFT for detection was carried out using MATLAB Simulink and generation code. Based on the results noticed, the FFT could detect the magnitude frequency components, but the duration information cannot be provided by FFT. The problem in this section is that to detect sag and swell the time information is important to distinguish for the data used in classification. FFT is not suitable for detecting sag and swell, but it is more convenient to detect the Harmonic disturbance. Therefore, RMS method is presented in this research paper to overcome the problem and conduct the detection of voltage sag and swell.

Other than that, RMS method was used in this research paper because RMS is the best technique to detect short and long-duration variation disturbances. The detection method is based on the calculation of rms value stated in the article [6][12]. This method is one of the most broadly applied in detecting a disturbance in the power system because of its simplicity, speed in calculation, and less memory requirement. The RMS value is defined as:

\[ V_{RMS} = \left( \frac{1}{N} \sum_{i=1}^{N} v_i^2 \right)^{1/2} \]  \hspace{1cm} (6)

Where N is the sample per cycle, \( v_i \) is the nth sample of the recorded voltage waveform.

1.3 Deep Learning Classifier

Research conducted by [13], the classification of power quality disturbance using deep learning approach for image file classification. The researchers used image files of the three-phase PQ and instead of using the sampled data PQ event. Even though the result classification was useful, but the processing time is prolonged.

This paper proposed Extreme Learning Machine (ELM) in classifies the data power disturbance sag and swell. ELM is also known as a single Feed-Forward Neural Network. According to [14], ELM’s structure consists of 3 essential layers: the input layer, single hidden layer, and output layer. In fact, [14] mentions the weights that connect hidden nodes to outputs can be trained very fast because in ELM method, input weights are generated randomly. In contrast, analytical methods are used to calculate the output weights, causing the learning process to become extremely fast. Other advantages are ELM has excellent results in generalization compared to feed-forward networks with the traditional back-propagation learning algorithm. Research carried out by [15] stated the link that connects the hidden layer to the output could be customizable. Further analysis was carried out to study different types of deep learning to identify which method produces the best accuracy in classification signals.
2. Methodology
The methodology was proposed to ensure the reliability and validity of the result obtained.

2.1 Flowchart of proposal Method

![Flowchart of proposed method.](image)

Figure 1. Flowchart of proposed method.

Figure 1 shows the methods to analyze the voltage sag and swell. A method analysis is fully carried out via programming by using MATLAB m-files. The system diagram consists of two stages, which are detection and classification.

2.2 Detection using RMS method based on S-Transform
First, sag (7) and swell (8) signals algorithm is written in MATLAB m-files based on their respective equation shown below:

\[
y = (1-\alpha * ((\text{Heaviside}(t-t1)-\text{Heaviside}(t-t2))) * \sin((2\pi(50)*t) + w));
\]

(7)

Where:
- \( \alpha \) = decrease level of rms voltage ranged from 0.1 p.u. to 0.9 p.u.,
- \( t = 0:0.0001:0.4 \),
- \( t1 \) = sag initiation,
- \( t2 \) = sag recovery or clearance,
- \( \text{Heaviside} \) = unit step function in MATLAB
- \( w \) = phase angle jump 50°, 100°, 170°
\[ y = (1+\alpha \times ((\text{Heaviside}(t-t_1)-\text{Heaviside}(t-t_2)))\times\sin((2\times\pi\times(50)\times t) + \omega)); \]  

(8)

Where:
- \( \alpha \) = increase level of rms voltage ranged from 0.1 p.u. to 0.8 p.u.,
- \( t = 0:0.0001:0.4, \)
- \( t_1 = \text{swell initiation}, \)
- \( t_2 = \text{swell recovery or clearance}, \)
- \( \text{Heaviside} = \text{unit step function in MATLAB} \)
- \( w = \text{phase angle jump 60°, 126°, 160°} \)

Then, RMS method was applied to the m-files and the proper value of RMS was set before ST can process the input data. After that, the ST was applied to the m-files as a base for signal processing. ST extracts the features from the disturbance signals and produces S-matrix that contains data of standard deviation, variances, and mean. These data were collected and arranged in Excel toward the classification process later. The main reason to extract the features is to simplify the complexity of the data. The data of standard deviation contain real and imaginary. Therefore, by removing the standard deviation, the only real part will be highlighted and used as an input for the classification process.

After all the coding for detection was completed, the data was run. The value of phase angle in equation (7) and (8) applied is not the same for each sample in order to produce different sag and swell event for the comparison in the future. If the detection line does not fit the signal, the equation of RMS must be corrected to get a good result detection sag and swell signal. Along with that, the magnitude and duration of sag swell can be obtained from the waveform.

2.3 Classification using Extreme Learning Machine

Extreme learning machine is the learning algorithm used for a single-layer feed-forward network architecture useful for a single hidden layer determined by [15]. At the detection section, it had mentioned that the generated data was arranged inside Excel, and it consists of 300 inputs, which were mean, variance, and standard deviation with 1 output or target. The output or target was a binary function where output 0 is a normal signal, while 1 is a disturbance signal. These generated data were important to distinguish so that the ELM will know how to read the data. The data arrangement was saved as txt file and ready to be uploaded into the ELM. After the data was completely arranged, the data was import and loaded into the Neural Network. The hidden layer neuron number was set to 20 and the data ready to be trained.

The results classify presented in the form of a confusion matrix. Figure 2 is an example of a confusion matrix. The confusion matrix consists of three different colors. For the green box reporting, the correct classification, while red specifies misclassification and grey, determines overall accuracy. Simulation results and the comparison with the other types of neural network like SVM and Decision Tree were presented in the next section.
Figure 2. Example of the confusion matrix.

3. Result and discussions

3.1 Detection Voltage Sag and Swell using RMS based on S-Transform.

A blue line in figure 3 is specified as a detection line or mean line. The red line shows the input data.

Figure 3. Detection of sag from sample 1.

Table 1. Comparison of the starting moment detection of voltage.

| Sample | Phase angle | Sag initiation /ms | Sag recovery /ms | Duration /ms | Sag peak amplitude /pu | RMS magnitude /pu | Distance /pu |
|--------|-------------|---------------------|------------------|--------------|------------------------|-------------------|-------------|
| 1      | 50°         | 431                 | 936              | 505          | 0.6008                 | 0.9635            | 0.3627      |
| 2      | 100°        | 432                 | 932              | 500          | 0.5999                 | 0.9664            | 0.3665      |
| 3      | 170°        | 432                 | 931              | 499          | 0.6004                 | 0.8685            | 0.2681      |

Based on table 1, each sample used the same alpha value, which was 0.4 but different applied phase angle. Sample 1 had the longest duration detection refer to figure 3 and followed by sample 2 and sample 3. For the RMS line detection magnitude, sample 2 with 100° begins to detect at magnitude 0.9664 p.u., which had a long 0.3665 p.u. distance to reach the 0.5999 p.u. sag peak amplitude. Furthermore, refer to figure 3 and table 1 for the sample 1 with 50° phase angle had 0.3627 p.u. gap line detection to reach the 0.6008 p.u. of sag peak amplitude. Other than that, sample 3 with a 170°
phase angle gets to detect sag disturbance at 0.8685 p.u. magnitude, which was shorter distance 0.2681 p.u. to reach 0.6004 p.u. sag peak amplitude.

The conclusion can be made from the data collected above; the improved phase angle significantly improves the detection line. The RMS detection line was stable and faster for sample 3 compared to the other two samples. This is because sample 3 with 170° phase angle had the shorter duration detection and lower distance magnitude to reach the sag peak amplitude. For all samples, the detection line form is a straight line.

![Detection by RMS](image)

**Figure 4.** Detection of swell from sample 1.

| Sample | Phase angle (°) | Swell initiation (ms) | Swell recovery (ms) | Duration (ms) | Swell peak amplitude (p.u.) | RMS initiation detection magnitude (p.u.) | Distance (p.u.) |
|--------|----------------|-----------------------|--------------------|---------------|------------------------------|------------------------------------------|---------------|
| 1      | 60            | 431                   | 931                | 500           | 1.401                        | 1.120                                    | 0.281         |
| 2      | 126           | 433                   | 927                | 494           | 1.401                        | 1.138                                    | 0.263         |
| 3      | 160           | 431                   | 933                | 502           | 1.402                        | 1.038                                    | 0.364         |

According to the data collected in table 2, all samples had the same value of alpha and different phase angles applied. The shape of the detection line is a straight line for those three samples. Based on table 2 and figure 4, the RMS line detection for sample 1 happens at 431ms with magnitude 1.120 p.u. The distances for the detection line to reach 1.401 p.u. swell peak amplitude is 0.281 p.u. Move to sample 2 with 126°, the distance obtained for RMS line detection to reach 1.401 p.u. peak amplitude swell is only 0.263 p.u. The duration for detection only takes 494ms, which is faster than sample 1 and sample 3 duration. For the last sample 3 with 160°, swell detection occurred at 431ms with 1.038 p.u. magnitude, and it took 0.364 p.u. distance magnitude for the detection to reach the swell peak amplitude of 1.402 p.u. From the data obtained, the improve phase angle gives better results detection. It can be verified that the sample 2 with 0.4 alpha and 126° phase angle had the best detection because the distances for line detection to reach swell peak amplitude is shorter.
3.2 Classification using deep learning

Table 3. Overall percentage accuracy on the classification of sag and swell.

| Type of disturbance | Data size | ELM | SVM | Decision Tree |
|---------------------|-----------|-----|-----|---------------|
|                     |           | Correct | Misclassified | Correct | Misclassified | Correct | Misclassified |
| sag                 | 1400      | 96.7%  | 3.3%  | 94.9%  | 5.1%  | 93.4%  | 6.6%  |
| swell               | 1400      | 97.1%  | 2.6%  | 95.7%  | 4.3%  | 95.8%  | 4.2%  |
| Average percentage  |           | 96.9%  | 3.0%  | 95.3%  | 4.7%  | 94.6%  | 2.4%  |

Table 3 and Table 4 shows the comparison of ELM, SVM, and Decision tree method in classifying the disturbances sag and swell. From table 3, ELM has the highest average percentage correct classification followed by SVM method and Decision Tree method. The correct classification for ELM method in sag is 96.7\%, with the misclassified of 3.3\%. Meanwhile, swell get 97.1\% correct and only 2.6\% is misclassified. For SVM method, the correct classification for sag and swell is 94.9\% and 95.7\%. Moreover, the correct classifications for the Decision Tree method in sag and swell can be seen that there were not so many different percentages obtained from SVM. Decision Tree had the highest average percentage of misclassification with 5.4\% compared to SVM and ELM.

Table 4. Comparison of trained time on sag and swell.

| Disturbance | Method   | Training Time/ sec |
|-------------|----------|---------------------|
|             | ELM      | SVM                 | Decision Tree |
| sag         | 0.050    | 20.313              | 17.172        |
| swell       | 0.160    | 4.959               | 25.503        |

From table 3, the average percentage accuracy for ELM, SVM, and Decision Tree was discussed, and ELM obtained the highest correct classification. However, in table 4, the given training time for the ELM was shorter than SVM and Decision Tree. Sag data that trained under ELM were only taking 0.050 sec, while SVM and Decision Tree take longer than this, which is 20.313sec and 17.172sec. The same goes for the swell training time. This gives an advantage for the ELM method in terms of computational speed.

Therefore, by comparing these three methods, it was found out that in terms of classification performances, ELM was more accurate as well in terms of training time. ELM was the fastest method to train the data. Thus, ELM had the best overall classification technique for sag and swell signal.
Figure 5. Sag classification by ELM method from sample 3.

Figure 5 explained:
- Class 1 stands for sag data, while class 0 stands for the normal signal.
- 507 out of 550 sag data, which was correctly classified. The rest is misclassified under output class 0, which carried 3.1%.
- Only 6 data out of 850 normal data was misclassified under output class 1, which carried 0.4%.
- The total correct classification for sag is 96.5%.

Figure 6. Swell classification by ELM method for sample 2.

Figure 6 explained:
- Class 1 stands for swell data, while class 0 stands for the normal signal.
- 473 out of 500 sag data, which was correctly classified. The rest is misclassified under output class 0 which carried 1.9%
- Only 20 data out of 900 normal data, which was misclassified under output class 1 which carried only 1.4%.
- The total correct classification for swell is 96.6%.
4. Conclusion and recommendation
In this paper, the extraction features were analyzed using mean, variances, and standard deviation from voltage sag and swell signals by using S-Transform. This paper also included analysis detection of voltage sag and swell using RMS method by comparing the data sample to determine which sample has the best performance. As a result, the initiation detection magnitude with lower gap magnitude to reach peak sag or swell is the best.

Besides that, it is observed that ELM correctly classifies the sag and swell class with high accuracy. The ELM is compared with the other classifying methods, which are SVM and Decision Tree. It is found out that the ELM gives the best result in terms of classification and computational time. Therefore, all objectives were achieved.

Also, to improve the analysis performance, the scope of disturbances is not just limited to the sag and swell signal only. It can be done by applying other types of disruption as well.

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