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A comprehensive overview of the ADALINE method applied to rapid voltage sags detection in multi-motors drive systems

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ABSTRACT

Several strategies have been developed for identifying power quality issues, monitoring them, and compensating for relevant disturbances. In this field, online estimate of amplitudes and phase angles of network voltages and currents is commonly used. The adaptive linear neuron (ADALINE)-based voltage sag detection algorithm with least mean square (LMS) adaptation allows for rapid convergence of estimate techniques based on artificial neural networks (ANN). This approach has the advantage of being straightforward to implement on hardware and based on simple calculations (essentially multiply and accumulate "MAC"). This paper gives a comparison of the performance of two ADALINE approaches ("with" and "without" error supervision) for detecting and estimating voltage dips. The described techniques and models of a two-coupled motor system were implemented in MATLAB/Simulink/SimPowerSystems to run simulations under various fault scenarios in order to create the three-phase voltage sag alarm signal. The simulation outcomes are presented and debated.

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1. INTRODUCTION

Voltage sag is defined as a momentary reduction in the "RMS" value of the nominal voltage for a duration ranging from 0.5 cycles to one minute [1], [2]. Voltage dips are mainly caused by power line faults such as short circuits and large induction motors starting [3]. Voltage sags are the main cause of disturbances in variable speed drives, computers, and industrial process controllers [4], [5]. Research by Wagner *et al.* [6], a case study on the monitoring of disturbances related to power quality revealed that 68% of recorded disturbances are voltage sags and that they represent the main cause of production shutdowns and losses. The above problems, as well as the increasing incidence of misdiagnosed faulty conditions in industrial robots (service requests based on incorrect logging of a disturbance source), are presented in a study on the influence of voltage dips on the continuity of operation and the life span of single-phase industrial robots [7]. In fact, as technology has improved and more power electronics devices have been used, the equipment used in industrial systems has become more sensitive to these kinds of things [8].

Several methods have been developed to detect power supply quality disturbances. Available commercial power quality analyzer instruments are based on point-by-point comparison of two adjacent power cycles [9]. When a certain threshold is reached, the disturbance is recognized. This method has many drawbacks. Firstly, it is insensitive to steady-state power quality phenomena, such as harmonics. Secondly, this method is sensitive to the chosen threshold value, which means that a low threshold value will make fake disturbance detection and a high threshold value may overlook many serious disturbances. Another method has been widely used for harmonics estimation: the wavelet transforms. This method was successfully used to estimate the "RMS" values of voltage, current, and power quality disturbance detection as the high frequencies associated with power quality disturbance could be distinguished and localized in time using low scale levels [10], [11]. This technique, however, suffers from being dependent on the basis wavelet used for detection [12].

Other methods for detecting voltage dips include the Fourier transform, peak voltage detection, and the missing voltage method. The problem with these methods is that they use windowing techniques and, as a result, can be too slow when used to detect and mitigate voltage sags and swells because they use historical data. Nowadays, with the development of artificial intelligence techniques, artificial neural networks (ANN) have been used to analyse the power quality [13], [14]. Based on adaptive linear neural network (ADALINE) [15]-[17], a method of power quality analysis by time location is brought forward in this paper. This approach uses an adaptive neural network with N inputs and one output. The output is a linear combination of the N inputs. The ADALINE was first used as an adaptive method to estimate the amplitude and phase of the fundamental and harmonics of a distorted signal [18], [19]. The simplicity of this method is due to its simple calculations (essentially multiply and accumulate "MAC" calculations), which facilitate its implementation. ADALINE is fast because of its simple construction. This is an important argument when it comes to choosing a viable and fast method for detecting voltage sags.

This paper is organized as follows: the theory of ADALINE applied to the detection and estimation of voltage dips is discussed in section 2. Algorithm examples as well as the performance of this method are applied to the fast detection of voltage dips and presented in section 3. Finally, section 4 concludes the paper.

2. ADALINE ARCHITECTURE

The problem of detecting voltage sags lies in the estimation of the amplitude of the line voltage. ADALINE have been successfully used to estimate the amplitude and phase of the fundamental and harmonics of a signal, and therefore became an interesting avenue to explore. In the case of voltage sags, only the amplitude and phase of the fundamental are of interest to us.

2.1. Principle of the ADALINE method

ADALINE belongs to the family of Perceptron's. It has a single neuron with a linear activation function and an input vector x(k). It was proposed and developed by Widrow and Walach [20]. The structure of the ADALINE network is described in Figure 1. The estimated output y(k) of the reference signal d(k) is given by the following linear [15]:

$$y(k) = W^T(k)X(k) \tag{1}$$

with,

$$W^T(k) = [W_0(k)\ W_1(k)\ W_2(k)\ \ldots\ldots W_n(k)] \tag{2}$$

and

$$X^T(k) = [1\ x_1(k)\ x_2(k)\ \ldots\ldots x_n(k)] \tag{3}$$

According to Fourier analysis, a periodic signal can be decomposed into a sum of sines and cosines. The estimated signal can be represented as:

$$y(t) = \sum_{n=1}^{N}((X_n \operatorname{Cos}(n\omega t) + (Y_n \operatorname{Sin}(n\omega t)) \tag{4}$$

where X_n and Y_n are the coefficients of the Fourier series of the signal y(t); n is the harmonic rank; X_1 and Y_1 are the Fourier coefficients of the fundamental. In matrix form, (4) can be rewritten:

$$y(k) = W^T(k)X(k) \tag{5}$$

where,

$$X^T(t) = [\operatorname{Cos}(\omega t)\ \operatorname{Sin}(\omega t) \ldots\ldots \operatorname{Cos}(N\omega t)\ \operatorname{Sin}(N\omega t)] \quad and \quad W = \begin{bmatrix} X_1 \\ Y_1 \\ . \\ . \\ . \\ X_n \\ Y_n \end{bmatrix}$$

Where W is the weight matrix that must be updated at each new sampling of the signal y(t). The amplitude and phase of the fundamental are defined as (6):

$$A_1 = \sqrt{X_1^2 + Y_1^2} = \sqrt{W(1)W(1) + W(2)W(2)} \tag{6}$$

and,

$$\psi_1 = \text{atang}\left(\frac{Y_1}{X_1}\right) = \text{atang}\left(\frac{W(2)}{W(1)}\right) \tag{7}$$

$e(k) = y_{mes}(k) - y(k)$ is the error between estimated and measured outputs.

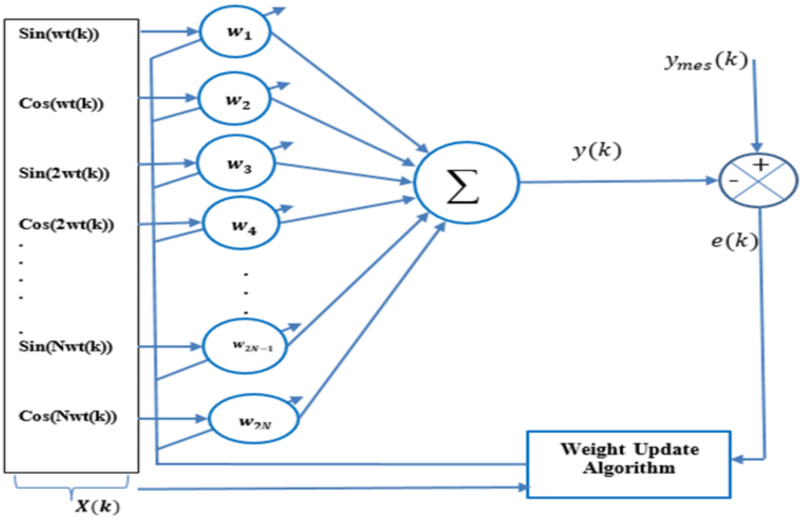


Figure 1. ADALINE network structure

For the weight adaptation algorithm, we choose the recursive least squares (RLS) algorithm [21], [22]. It is a quadratic method which consists in minimizing a quadratic function of error e(k) between the measured signal and the model. The weight matrix *W* (or the Fourier coefficient matrix) is updated by using (8).

$$W(k) = W(k-1) + K(1) \times e(k) \tag{8}$$

where:

$$K(k) = \frac{P(k-1)X(k)}{\lambda + X^T(k)P(k-1)X(k)} \tag{9}$$

$$P(k) = \left(\frac{1}{\lambda}\right)[I - K(k)X^T(k)]P(k-1) \tag{10}$$

Where K is the adaptation gains matrix of the Fourier coefficients; I is the identity matrix; P is the inverse of the autocorrelation matrix of the input vector X; λ is the forgetting factor; this forgetting factor allows to progressively forget the older samples.

This variant of the RLS algorithm allows the identification of parameters that vary slowly over time. The convergence is much faster when compared to another known algorithm such as least mean square (LMS).

2.2. ADALINE algorithm

The flow chart of the ADALINE method is shown in Figure 2. This algorithm gives results with acceptable accuracies in steady state. In transient mode, i.e., at the appearance of a voltage dip, this algorithm remains relatively slow. To improve the performance (speed and precision) of this algorithm in the presence of voltage dips, we propose a simple modification to the basic ADALINE algorithm shown in Figure 2. This modification consists in supervising the error between the measured and the estimated signals. This supervision verifies each time the calculated error (Figure 3). If the latter becomes greater than a previously fixed threshold, the inverse of the autocorrelation matrix P is reset. The flow chart of the proposed modified ADALINE method is presented in Figure 4.

2.3. Comprehensive classification of voltage sags

Electrical voltage sags are mainly characterized by their amplitude and phase, various classifications of three-phase voltage dips were presented by Bollen [1]. Voltage dips can be symmetrical or non-symmetrical in nature [23]-[25]. If the magnitudes of the individual phase voltages are equal and the phase shifts are exactly 120°, the sag is symmetrical; otherwise, the sag is non-symmetrical. Figure 5 given lists the seven major types of voltage sags, denoted by the letters A through G.

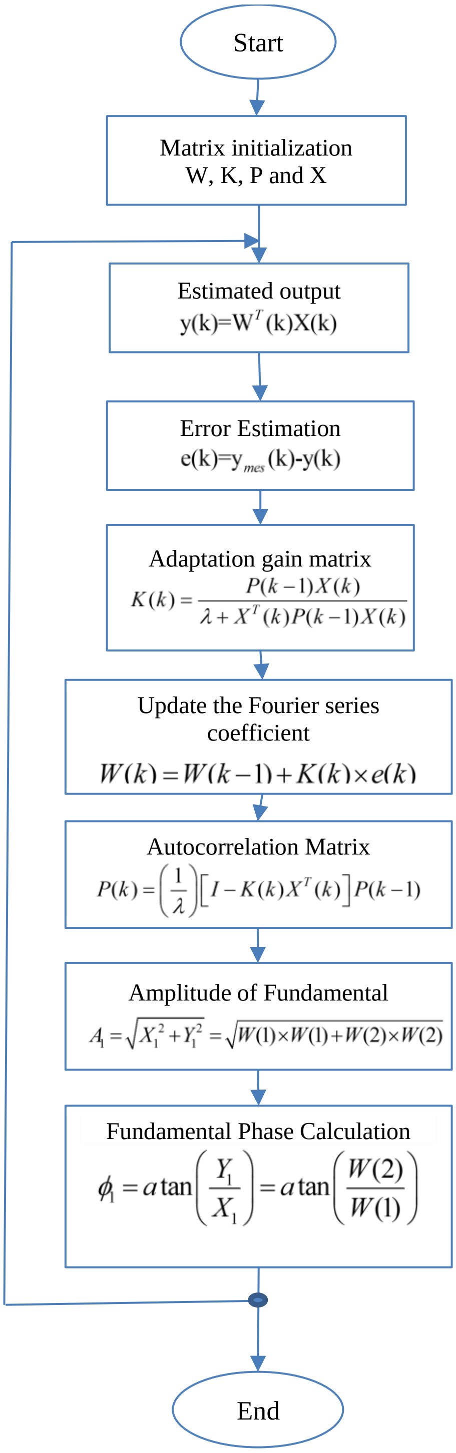


Figure 2. Flow chart of ADALINE algorithm

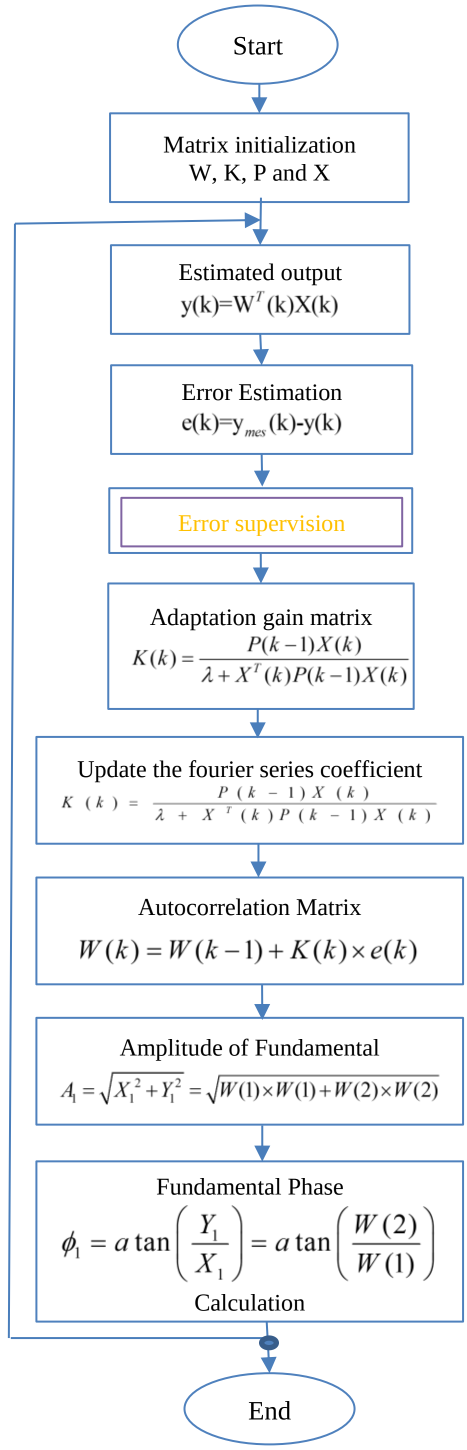


Figure 3. Flow chart of modified ADALINE algorithm with error supervision

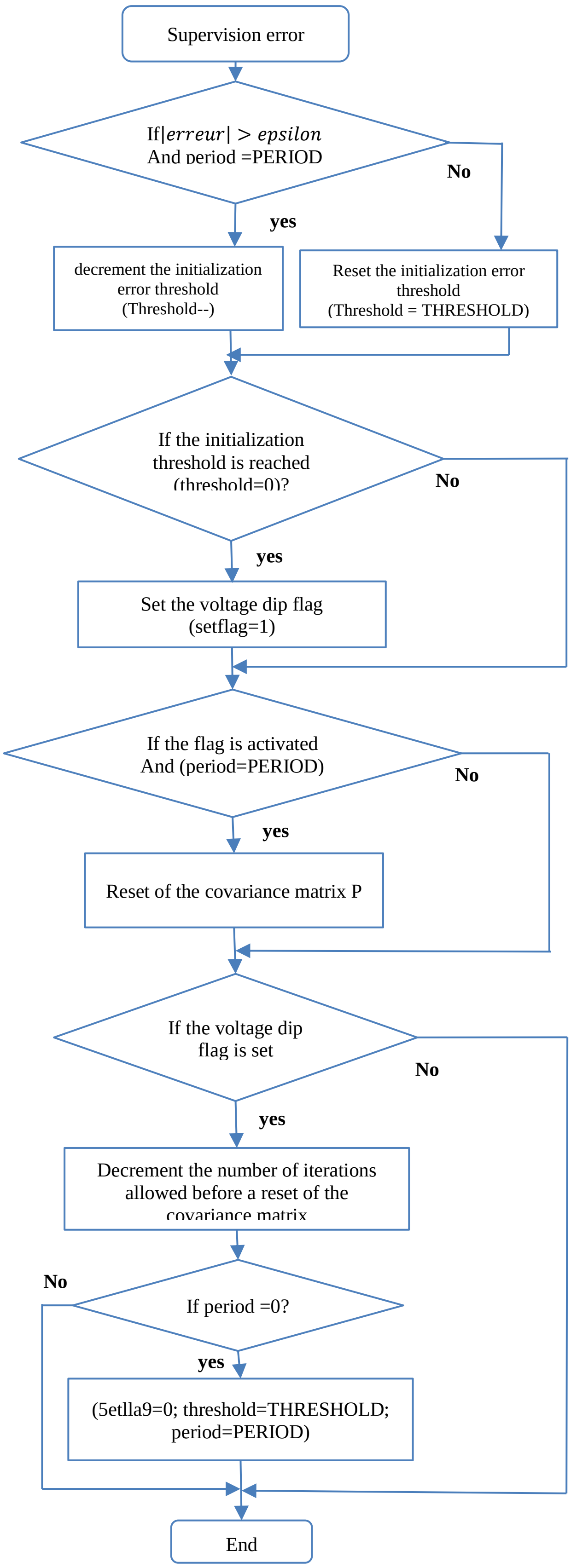


Figure 4. Flowchart of error supervision

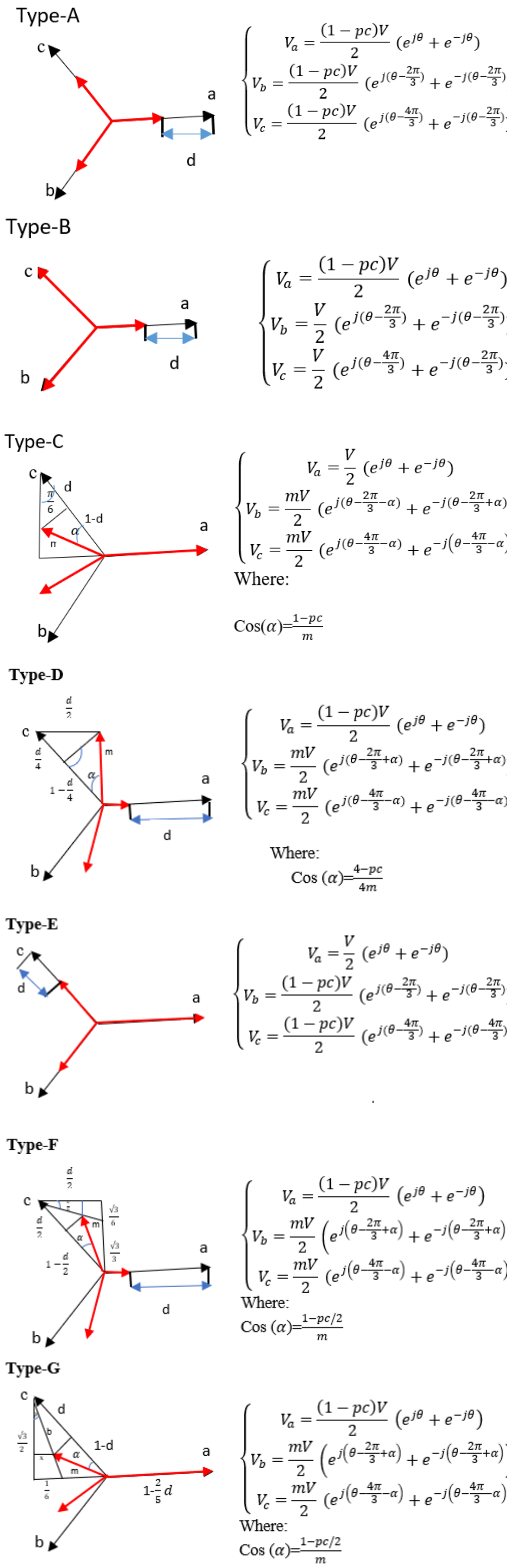


Figure 5. Voltage sag types

With: V: The maximum amplitude of an electric voltage
d: The depth of the voltage dip
m: The value of the voltage drops (type C, D, F and G)
$\boldsymbol{\alpha}$: The additional phase shift of the voltage that can be caused by the voltage dip

3. PERFORMANCE OF THE ADALINE METHOD IN RAPID DETECTION OF VOLTAGE DIPS

This section presents the performances of the two proposed ADALINE methods ("without" and "with" error supervision) for the estimation of harmonics amplitudes and phases. Simulations in MATLAB environment used a noisy voltage (synthetic signal) made of the fundamental and the 3rd, 5th, 7th and 9th rank harmonics. This signal is defined as follows:

$$y(t) = 220\sin(\omega t + 80°) + 11\sin(3\omega t + 60°) + 5.5\sin(5\omega t + 45°) + 2.64\sin(7\omega t + 36°) + 1.32\sin(9\omega t + 30°) + N(t)$$

N(t) is a random noise whose maximum value corresponds to 0.5% of the of the fundamental; and ω is the pulsation for a frequency of 50 Hz. Tables 1 and 2 allow us to verify the accuracy of the ADALINE method in steady state.

Table 1. Estimated harmonics amplitudes using ADALINE method

	Algorithm without error supervision Amplitudes			Algorithm with error supervision Amplitudes		
Harmonic rank	Actual [V]	Estimated [V]	SSE [%]	Actual[V]	Estimated [V]	SSE [%]
Fundamental	220	219,7611	0,108	220	219.8062	0,088
3	11	11,0104	0,094	11	11.0089	0,080
5	5.5	5,5676	1,229	5.5	5.5654	1,189
7	2.64	2,4964	5,439	2.64	2.4928	5,5757
9	1.3	1,2573	3,284	1.3	1.2540	3,538

Table 2. ADALINE method for estimating harmonics phase angles

	Algorithm without error supervision Phases			Algorithm with error supervision Phases		
Harmonic rank	Actual [°]	Estimated [°]	SSE [%]	Actual [°]	Estimated [°]	SSE [%]
Fundamental	80	80.0158	0,019	80	80.0114	0,014
3	60	59.4550	0,908	60	59.3675	1,054
5	45	44.9325	0,15	45	44.8792	0,268
7	36	38.1598	5,999	36	38.0598	5,721

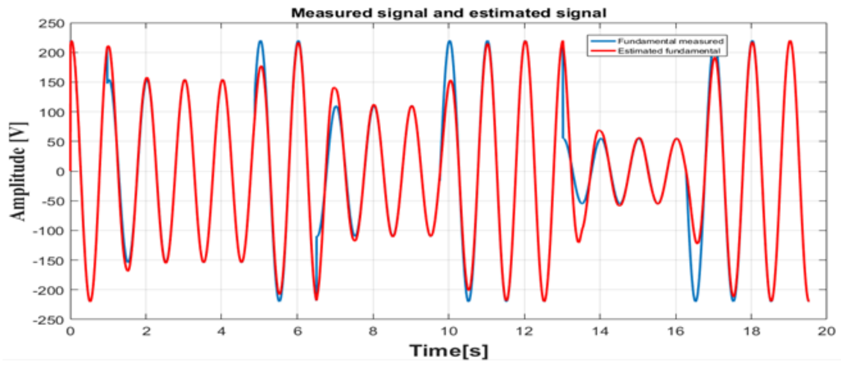
*SSE: sum squared error

Estimation of the fundamental amplitude offers the best accuracy. Still talking about the fundamental, we note that the supervision of the error contributes to improve the accuracy of the estimator even in the steady state. Figures 6(a) and (b) clearly show that error supervision method improves the speed of the algorithm for amplitude detection. Thus, error supervision will improve the dynamic response of the algorithm for detecting a voltage dip.

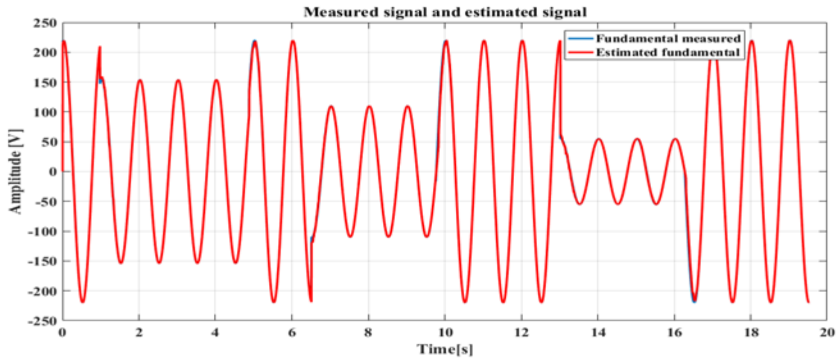
To verify the dynamic response speed of the two algorithms, we zoomed up the estimated and real amplitudes (see Figures 7(a) and (b)) and evaluated the delay and rise time during detection in critical regions; namely at the beginning and end of a voltage dip. The values obtained are given in Table 3. It can be noted that the speed of detection is not the same at the beginning and at the end of the sag. The supervision of the error largely contributes to improve the quickness of the ADALINE algorithm.

Table 3. Performance comparison of the two algorithms

Critical region	Delay in detection	
	Without error supervision (ms)	Without error supervision (ms)
Beginning of the sag	10,1	10,1
End of the sag	12,4	12,4

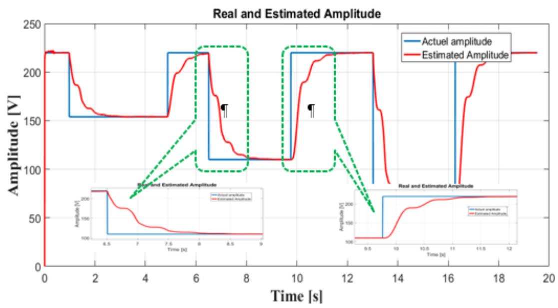


(a)

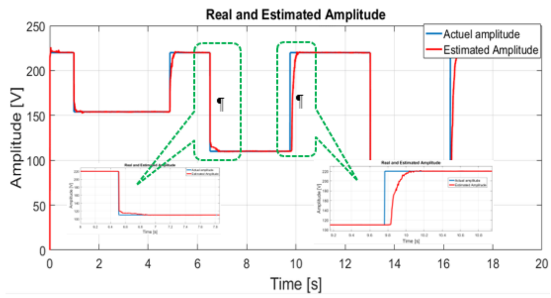


(b)

Figure 6. Waveform of the fundamental measured and estimated, (a) without error supervision and (b) with error supervision



(a)



(b)

Figure 7. Fundamental magnitude in RMS, (a) without error supervision and (b) with error supervision

4. THREE-PHASE VOLTAGE SAG DETECTION

Three dip detectors, one for each phase, are used to detect the voltage dip of a three-phase signal. The block diagram of the three-phase voltage dip detector is shown in Figure 8. In order to simulate an electrical distribution network, we first generated a three-phase voltage source, rated 230/380V-50 Hz, and then we created the different types of voltage dips using the block "fault-breaker" available in Simulink bloc libraries, which can introduce single-phase, two-phase and three-phase faults, which result in A, B, C and E type faults. Figure 9 shows the simulation scheme, which is composed of a low voltage network supplying two induction motors, a fault generator and the proposed voltage sag detector.

This simulation scheme enables us to test the proposed detection method on various types of voltage dips. The algorithm that we developed not only allows the detection of all types of voltage sags, but it also provides the depth of the sag, the phase shift of the voltages, and the affected phases.

The implementation of the estimators necessitates the creation of s-functions written in C language. An s-function allows Simulink users to design custom Simulink blocks. The “mex” command is then used to compile this model. The proposed algorithms and models of the two-motor system were implemented in MATLAB/Simulink/SimPowerSystems in order to run simulations under various operating conditions.

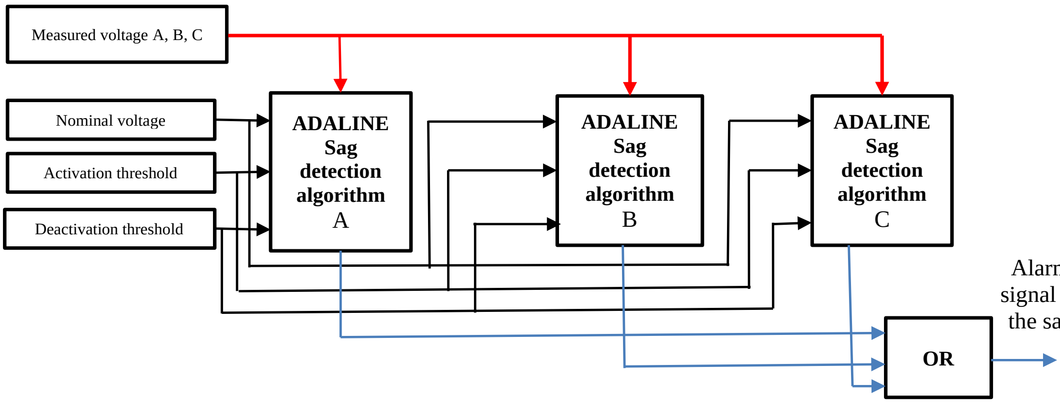


Figure 8. Voltage sag alarm signal generation using ADALINE method

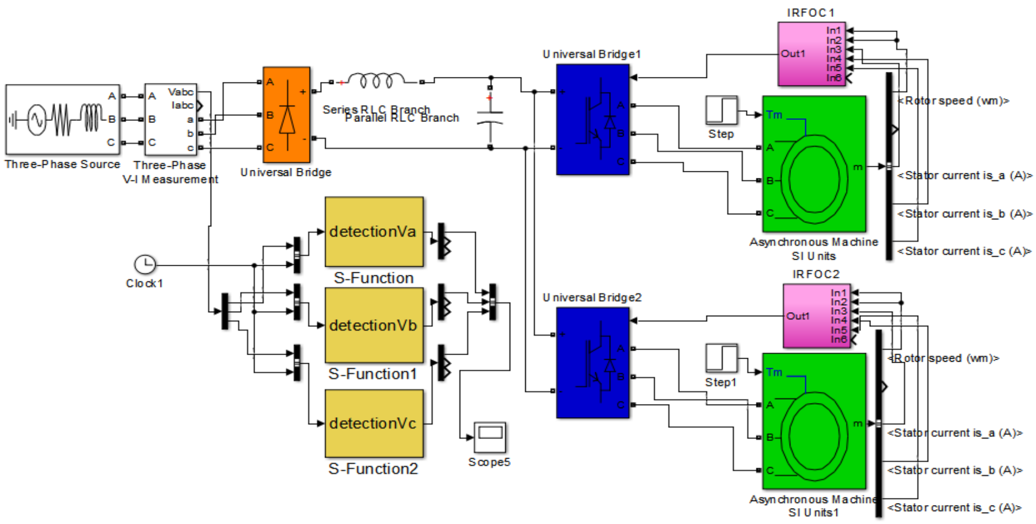


Figure 9. Simulation scheme

The case studies in this paper, are limited to the simulation of voltage sags examples that can affect multi-motor systems that use induction motors, namely:

a. Voltage sags caused by three-phase faults (type A)

Presenting voltage drops of the same depth on all three phases without any additional phase shift (Figure 10). The voltage sag is identified when the magnitude is below a specified threshold and the alarm signal is set to 1. This method can detect three phase symmetrical voltage sag in real time, and it is very accurate in determining inception and recovery instants.

b. Type B voltage dips (Figure 11)

We detect the magnitude of the voltage dips as the difference between the nominal phase voltage and the lowest actual phase voltage. A one phase to ground fault causes the line voltage to drop while the other two-phase voltages remain unchanged.

c. Dips caused by a two-phase fault (type C)

Which result from a fault due to short-circuiting two phases, while the third phase remains unchanged. Figure 12 shows the result of our method for a type C voltage dip. Our algorithm accurately calculates the voltage drop in both phases, as well as the alarm signal, which we plan to use to develop a voltage dip management strategy.

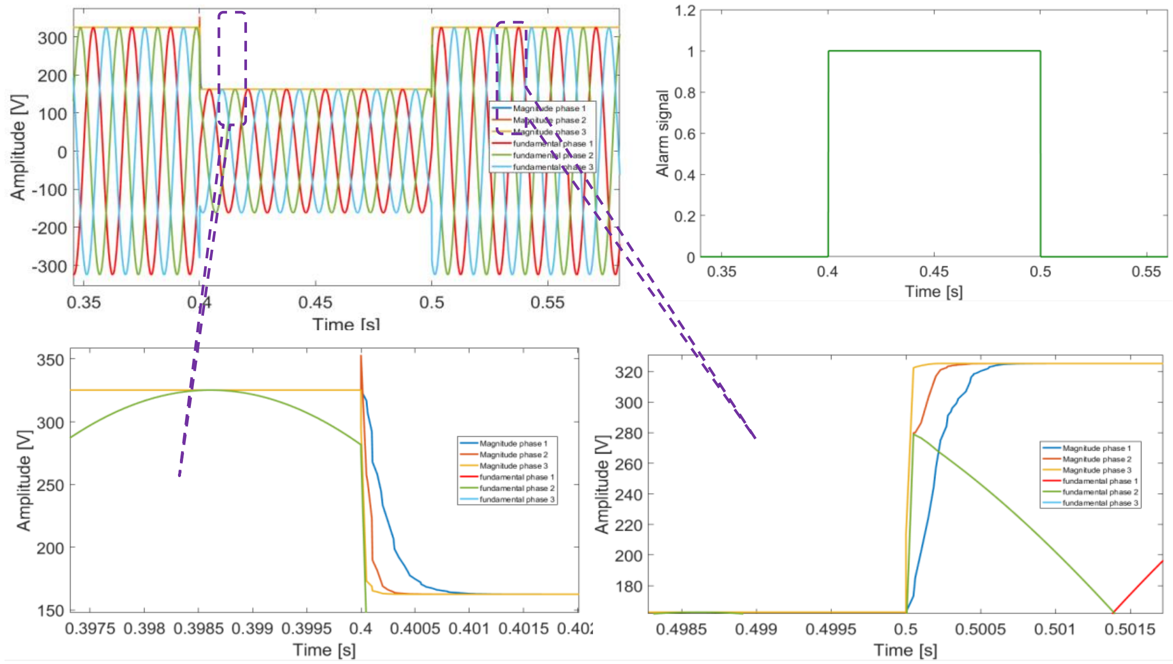


Figure 10. Three-phase fundamental voltages, magnitude and voltage sag alarm signal for symmetrical faults type A

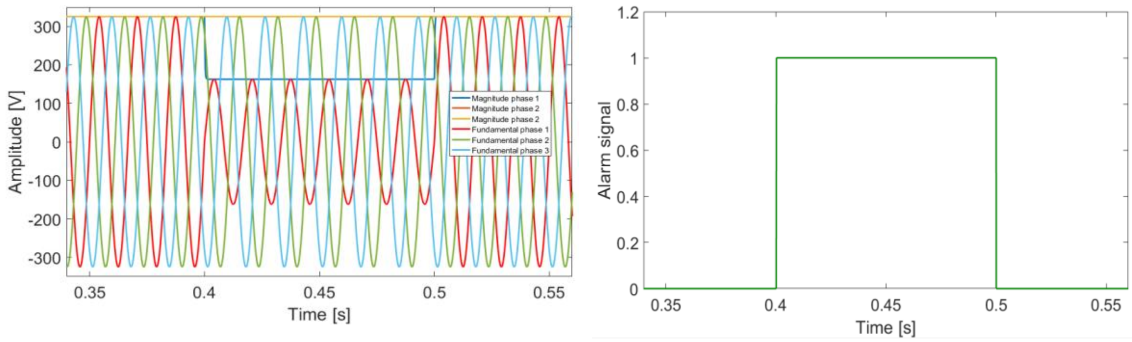


Figure 11. Three-phase fundamental, magnitude and voltage sag alarm signal for asymmetrical faults type B

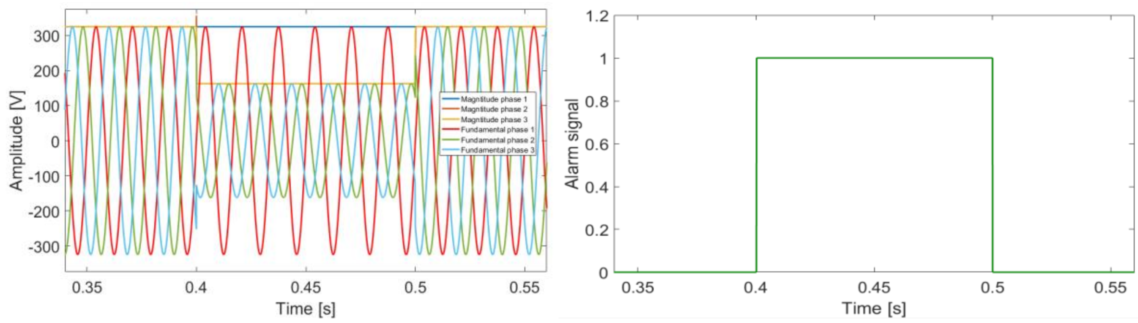


Figure 12. Three-phase fundamental, magnitude and voltage sag alarm signal for asymmetrical faults type C

5. CONCLUSION

The theory of the ADALINE approach, which is used to detect and estimate voltage amplitude, has been presented and studied using simulation. Two algorithms, "with" and "without" error supervision, were explored and compared. In steady state, the accuracy of these algorithms in calculating the amplitude of a voltage line's fundamental and harmonics has been demonstrated. The error supervision version does increase the basic amplitude estimate accuracy. The dynamic performance (reaction time) of the two algorithms was examined in critical zones (the beginning and end of a voltage dip). It should be noticed that the response time is not the same at the start and conclusion of the sag. The initial ADALINE algorithm's efficiency was considerably enhanced via error supervision. The simulation also examined the speed of three-phase voltage dips detection by the ADALINE technique (with error supervision) for type A, type B, and type C dips. The identification of the dip was accomplished with a time delay of less than 0.001s in all three case studies, and fault signals were generated. It is critical for connected multi-motor systems to identify many occurrences of voltage sags over long time intervals and to implement voltage dip management solutions. This will be the focus of future research. It is vital to note that they can continue to function prior to, during, and after the voltage decrease.

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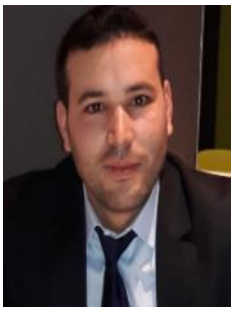
BIOGRAPHIES OF AUTHORS



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