A novel fast power swing blocking strategy for distance relay based on ADALINE and moving window averaging technique

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Abstract
This study proposes a novel efficient strategy for identifying symmetrical faults from power swings in order to improve the performance of distance relay. This method is based on two new indices and the use of adaptive linear neuron and moving window averaging technique, which is applied to the waveforms of the current. If the proposed algorithm detects power swings, it enables power swing blocking; and if it recognizes the occurrence as a symmetrical fault, it resets the power swing blocking as quickly as possible. The efficiency of the proposed method has been tested in different conditions and compared to other methods from different points of view. Simulation results under different conditions in PSCAD and MATLAB software show that the proposed strategy is able to detect symmetrical faults from power swings with high accuracy. The high robustness of adaptive linear neuron and the moving window averaging technique has made the proposed method highly noise-resistant; and also, because of its low computational cost, the response speed of the proposed strategy is very high, and hence its practical implementation is simple.

1 | INTRODUCTION

Power grid is a dynamic network that connects the generated power to the load through power transmission lines. Power systems operate in steady-state conditions very close to their nominal frequency. Events such as power system faults, transmission line switching, generator failure, and entering and exiting large loads can cause sudden changes and disturbances in electrical power. These disturbances can cause oscillations in the rotor angle of machines, which will impose severe swings on the distribution of electrical power. Power swings (PS) can cause distance relays (DRs) to malfunction, and this can make the situation of power distribution worse, even leading to large blackouts.

The cause of the PS is the existence of at least two different frequencies in the grid. Depending on whether the two frequencies move closer or further apart over time, the PS is divided into two stable or unstable groups [1]. The phenomenon of PS affects the behaviour of the protective relays and causes their unwanted functioning. The swing of power causes the impedance trajectory to enter the protection zones of the DR and cause improper functioning. Therefore, it seems necessary that during the PS occurrence, the DR should be blocked to prevent its faulty functioning. But another challenge is to detect faults that occur during the PS. Detection of asymmetrical faults is possible due to the presence of zero or negative sequence components, but due to the symmetrical nature of the PS and the symmetrical faults, detecting symmetrical faults during the PS is still a serious challenge. To this end, researchers have suggested several different approaches. A study reviewing DR techniques under PS situations is presented in [2]. The authors in [3] introduce power difference as a solution for identifying the symmetrical faults from the PS. This method needs excessive simulations. In [4], the fault is discriminated during the PS by detecting the main frequency components of the power signal. A method utilizing the maximum rate of active and reactive power changes is presented in [5]. That method can detect the fault in 30 ms. The authors in [6] propose an algorithm based on a fuzzy-neural system in order to identify the faults at the time of PS. Although that method is fast, it has high computational cost. In [7,8], fault detection during the PS is accomplished by continuous investigation of the voltage angle in the network. This scheme is not capable of identifying symmetrical faults.
The authors in [9] identify the faults by exploring the PS centre voltage for abrupt reductions in its magnitude. The detection time in that method is near 40 ms, which shows that it is a slow scheme. In [10], an index is introduced that utilises the dynamic phasor estimation for fault discrimination during the PS. However, that method needs a threshold level to be adjusted. Literature [11] propose an approach by introducing an S transform, and using neural networks (NN). Although that method is comparatively efficient, it needs off-line training. In [12], a support vector machine (SVM) classification algorithm is proposed which controls the function of traditional DRs.

The classifier used in that method requires off-line training and should be differently adjusted for different configurations of the networks. In [13], the PRONY method and the frequency components of the current signal excluding the constant value are used to identify faults from the PS. The authors in [14] introduce an algorithm for determining the fault and PS occurrences by considering the changes of the slip frequency and the system impedance. In [15] a setting-free method based on the frequency components of three phase power is proposed to detect faults during the PS. In [16], the symmetrical components of zero and negative sequences of the current are used to detect the fault. To this end, the fuzzy system is utilised to detect the fault characteristic, while the zero and negative sequences of the protective relay are used for clearing the asymmetrical faults during the PS. That method requires a threshold level and it is not evaluated in faulty conditions with different resistances. In [17], the PS and the faults are determined by measuring the value of current at the ends of the line. That method depends on the sending end currents and receiving end currents of each phase. The authors in [18] suggest a solution based on the negative sequence of the apparent power. The rate of the energy changes of the current signal in [19] is used for the detection of PS, which is dependent on the specified threshold limit. In [20], a moving window averaging technique is employed for the detection of PS. In [21], a scheme based on the differential of the active power is presented. The method proposed in [22] uses differential power coefficient with the instantaneous voltage and the current factors that are obtained by the phasor measurement units (PMUs). The efficiency of that approach is not evaluated for different directions and resistances of the fault. In [23], a method is presented for the function of concentric power swing blocking (PSB) in the transmission lines compensated by the unified power flow controller (UPFC). This method is specific to the lines equipped with UPFC. In [24], a number of practical adjustments are proposed for the impedance-based blockers of the PS. The efficiency of that approach is not approved in the PS occurrence during the faulty conditions. The authors in [25] propose a method using a pre-processing filtering for PMU-assisted DR for zone 3 of a series-compensated wind-integrated system. The authors in [26] present a method based on the piecewise linear spline wavelet to distinguish PS from faults in compensated series transmission lines. In [27], authors present a PS detection scheme in multi-machine power systems that is based on Zubov’s stability boundaries. This scheme may need the boundaries to be updated, which can be a significant challenge. The authors in [28] suggest a method that can improve the zone-3 operation of the DR using an index based on the rate of active power changes and angle derived from synchronised PMUs. The total energy of approximate wavelet coefficients of equivalent machine angular velocity signal is utilised in [29] to discriminate stable PS from unstable situations. The need for threshold adjustment is the main drawback of that approach.

Although the proposed methods in the literature are numerous, there is still need for a solution with a higher speed, and capability for precise distinction, as well as the simplicity for practical implementation.

In this study, a novel fast strategy is presented to tackle two basic challenges of DRs during the PS, including discriminating PS events from fault events and identifying symmetrical faults during the PS, which is based on the use of adaptive linear neuron (ADALINE) and moving window averaging technique (MWAT). The proposed protection strategy uses two new indices. These new indices, which are based on ADALINE and MWAT, are well able to detect PS and symmetrical faults. The proposed scheme is also able to detect symmetrical faults with any fault resistance even under noise conditions, and unlock the PSB. Due to the low computational cost and high resistance of ADALINE and MWAT against noise, the main features of the proposed method can be summarised as follows:

- high accuracy and speed of detection;
- high robustness against noise;
- simplicity for practical online implementation; and
- no need for adjustment.

The configuration of this paper is as follows. In Section 2, the proposed algorithm, including the introduction of ADALINE, the MWAT, and the PSB operation, will be covered. Section 3 presents the simulation results under different scenarios compared with some other methods. Conclusions and references are also given in Sections 4 and 5, respectively.

## 2 | EXPLANATION OF THE PROPOSED ALGORITHM

The method presented here is based on the use of ADALINE and MWAT, which will be explained in continue.

### 2.1 | ADALINE architecture

ADALINE is a one-layer NN. According to [30], ADALINE output is equal to the linear combination of inputs. The most important advantages that make ADALINE attractive include:

- its training is online;
- its self-adapting algorithm is applicable to weight training; and
- it has an uncomplicated configuration that makes it easy to implement on hardware.

ADALINE can be used to track an arbitrary signal online. For a closer look at the aforementioned issue, an arbitrary signal,
containing the following harmonic, is considered:

\[ i(t) = A_{DC} e^{-\lambda t} + \sum_{n=1}^{N} I_n \sin(n \omega t + \varphi_n), \]  

(1)

where the first component is the transient DC and \( \lambda \) is the damping constant time. Also in second component, \( I_n \) and \( \varphi_n \) are the amplitude and phase of the \( n \)th harmonic, \( N \) is the total number of harmonics, and \( \omega \) is the main frequency. It is worth mentioning that \( \varphi \) is assumed to be a constant value in ADALINE. In order to model ADALINE properly, we need discrete time domain form of \( i(t) \) (denoted by \( i(m) \)), which can be written as

\[ i(m) = A_{DC}(1 - \lambda m T_s) + \sum_{n=1}^{N} \{A_n \sin n \omega t(m) + B_n \cos n \omega t(m)\}, \]  

(2)

where \( T_s \) equals to \( 2\pi / \omega N_s \), \( N_s \) is the sampling period, \( A_n \) equals to \( I_n \cos \varphi_n \), \( B_n \) equals to \( I_n \sin \varphi_n \), and \( \omega t(m) \) is the \( m \)th sampling time. \( Y(m) \) is the input vector defined as

\[ Y(m) = \begin{bmatrix} \sin \omega t(m) \cos \omega t(m) \\ \sin n \omega t(m) \cos n \omega t(m) \end{bmatrix} \]  

(3)

If \( \mathbf{R}(m) \) is assumed to be the weight vector of ADALINE, the output of ADALINE will be the inner product of \( \mathbf{R}(m) \) and \( Y(m) \):

\[ i_{ADA}(m) = \sum_{j=1}^{2N+2} \mathbf{R}_jY_j(m) = \mathbf{R}(m)Y^T(m). \]  

(4)

If, in the training step, the output of \( i_{ADA}(m) \) is equal to the desired signal \( \bar{i}(m) \), then the discrete Fourier transform coefficients of \( \bar{i}(m) \) become the weight vector of \( \mathbf{R}(m) \). In the training phase, weights should be chosen in a way to minimise the error between \( i_{ADA}(m) \) and \( \bar{i}(m) \). The Widrow–Hoff Learning Rule (WHLR) [31] is employed for the training of the ADALINE. Weights correction is also performed as follows:

\[ \mathbf{R}(m+1) = \mathbf{R}(m) + \mu \times \frac{e(m)Y(m)}{Y^T(m)Y(m)}. \]  

(5)

where \( e(m) \) is the error \( (e(m) = \bar{i}(m) - i_{ADA}(m)) \), and \( \mu \) is the training rate. If \( e(m) \) is less than the threshold value or is equal to zero, correct tracking of \( \bar{i}(m) \) will be achieved. If the above condition is met, \( \bar{i}(m) \) becomes

\[ \bar{i}(m) = i_{ADA}(m) = \mathbf{R}_sY^T(m), \]  

(6)

where \( \mathbf{R}_s \), the weight vector after converging to zero, equals to

\[ \mathbf{R}_s = [A_1 \quad B_1 \ldots A_N \quad B_N \quad A_{DC} \quad \lambda A_{DC}]. \]  

(7)

By achieving the weights vector, the harmonic component of the waveform studied in the \( m \)th sample is simply calculated from Equations (8) and (9) [31]:

\[ I_n(m) = \sqrt{\Re^2 2m-1(m) + \Re^2 2m(m)} \]  

(8)

\[ \varphi_n(m) = \cos^{-1} \left( \frac{\Re^2 2m(m)}{\Re 2m(m)} \right), \]  

(9)

The learning process of ADALINE is actually the process of modifying the weights of the grid. By modifying the grid weights, error between \( i_{ADA}(m) \) and \( \bar{i}(m) \) is minimised. To this aim, WHLR is used here. The output error of ADALINE \( (E) \) is defined as

\[ E = \frac{1}{2} \sum_{m} \{i(m) - i_{ADA}(m)\}^2 \]  

(10)

Because \( E \) depends on weights and the desired output, weights can be set so that \( E \) reaches its minimum value. If the partial derivative of squared error, related to the weights and bias, is available in the \( k \)th iteration, the following will be obtained [32]:

\[ \Delta \mathbf{R}_j(m) = -\mu \times \frac{\partial E}{\partial \Re_j(m)} \]  

(11)

\[ = \mu \times \{i(m) - \mathbf{R}(m)Y^T(m)\}Y_j(m) \]  

where \( \mu \in [0,1] \), in general. If \( \mu \) is large enough, learning can be achieved faster, but if \( \mu \) is too high, it may cause instability. Since it is necessary to ensure the sustainability of learning, \( \mu \) should be less than the inverse of the largest eigenvalue of the correlation matrix of the input vectors, \( (Y^T(m)Y(m)) \). Therefore, \( \Delta \mathbf{R}(m) \) is obtained from the following equation:

\[ \Delta \mathbf{R}(m) = \mu \times \frac{e(m)Y(m)}{Y^T(m)Y(m)}. \]  

(12)

Since the main signal may be contaminated by random noise in practice, and as the quick convergence of ADALINE is desirable, it is necessary to use a non-linear weight matching algorithm. Therefore, we can write:

\[ \Delta \mathbf{R}(m) = \mu \times \frac{e(m)Y(m)}{Y^T(m)\rho(m)}, \]  

(13)

where \( \rho(m) \) is defined as follows:

\[ \rho(m) = \begin{bmatrix} \text{Sgn}(Y_1(m)) \\ \text{Sgn}(Y_2(m)) \\ \vdots \\ \text{Sgn}(Y_{2N+2}(m)) \end{bmatrix} \]  

(14)
The WHLR states that the weight vector changes in ADALINE depend entirely on the changes between its input and output [13]. It is an excellent feature in terms of computational cost, as there is no need to calculate derivatives in this algorithm. Therefore, its computational speed is very good and will allow fast convergence of ADALINE.

Given Equation (12), the mathematical operations in each iteration are very few, so the hardware implementation is simple and it is well suited for online applications.

The process of ADALINE learning consists of three steps:

1. calculate the grid output \( i_{Adaline}(m) = \Re(m)Y^T(m) \) as well as the error \( e(m) = i(m) - i_{Adaline}(m) \);
2. compare \( E \) with \( E_o \) (the target error);
3. stop learning process if \( E \) is less than \( E_o \) or if the number of learning iterations has reached the maximum; and
4. calculate new weights \( (\Re(m) + 1) = \Re(m) + \Delta \Re(m) \) and then return to step (1).

It is emphasised that ADALINE is used here to track the waveforms of the study case rather than to extract waveform harmonics. So, when a symmetrical fault or a PS occurs in the power grid and the waveforms of the current change, ADALINE behaviour also changes. In fact, at these times, ADALINE cannot track the original waveform, and therefore, \( e(\theta) \) is no longer zero. Also, by examining the results of the simulations, it has been observed that compared to \( e(\theta) \), the behaviour of \( |e(\theta)| \) contains more important information. Also, after applying the MWAT to \( |e(\theta)| \) and then calculating the derivative of it, the resulted shape behaves quite differently in the above-mentioned situations, which can be used for presenting an appropriate PSB algorithm by creating a hierarchy.

### 2.2 MWAT

MWAT is a low-pass filter technique that has many applications in power systems protection [33]. This technique also has a very low sensitivity to noise. The average movement of the continuous time domain signal \( e(\theta) \) during the window of \( T_o \) is written as

\[
\tilde{e}(t) = \frac{1}{T_o} \int_{t-T_o}^{t} e(\theta) d\theta.
\]

By taking the Fourier transform from the impulse response, the MWAT frequency response can be obtained:

\[
E(j\omega) = e^{-j\omega T_o} \frac{\omega T_o}{2} \text{sinc} \left( \frac{\omega T_o}{2} \right),
\]

where \( \text{sinc}(\theta) = \sin(\theta)/\theta \). A graphical representation of Equation (17) is shown in Figure 1.

From Figure 1, it can be seen that MWAT completely eliminates nominal frequency components, passes DC component and weakens other components [20]. The MWAT output in \( f_o \) can be set to zero by selecting \( T_o = 1/f_o \). As shown in Figure 1(b), the filter phase response always results in delayed response due to the use of outdated data.

### 2.3 PSB operation

To give a more detailed explanation, we present the proposed strategy only for the single-phase current. When the fault detector unit in the DR recognises an abnormal situation and the fault classifier detects the symmetrical status, then the proposed algorithm starts to detect PS from symmetrical fault. During the PS, we can model the modulated current waveform for a 2 machine equivalent network as follows:

\[
i(t) = I_s \sin(2\pi f_s t + \phi_s) + I_r \sin(2\pi f_r t + \phi_r),
\]

where \( I_s \) and \( I_r \) are amplitudes of current signals with \( f_s \) and \( f_r \) frequencies, and \( \phi_s \) and \( \phi_r \) are the angles of the initial phase. During the PS, the frequencies of \( f_s \) and \( f_r \) vary substantially with the average of \( (f_s + f_r)/2 \). Also, in terms of symmetrical three-phase fault, the current signal resulted from the fault in \( f_r \) can be modelled as follows:

\[
i_r(t) = I_{mf} \sin(2\pi f_o (t - t_f)) + I_{mf} \sin(\phi - \alpha) e^{-\frac{R}{L} (t - t_f)},
\]

where \( I_{mf} \) and \( \phi \) are the maximum quantity of the steady-state component and the initial-phase angle of the fault current, \( \alpha = \tan^{-1}(2\pi f_o L/R) \), and \( R \) is the resistance and \( L \) is the reactance of the DR location to the fault location.
According to Equations (18) and (19), when a symmetrical fault or a PS occurs in the grid, the waveforms of the currents change, and so does the ADALINE behaviour. In fact, at these situations, ADALINE cannot accurately track the original waveform, and therefore, \( |\epsilon(t)| \) is no longer zero. ADALINE adapts well in the symmetrical faults, and \( |\epsilon(t)| \) quickly becomes zero in such a situation. But when a PS occurs, correct tracking is not achieved until the PS is cleared (because the waveform frequency changes while the adjusted frequency in ADALINE is always constant and equal to the nominal frequency of the network). Therefore, in PS situations, \( |\epsilon(t)| \) remains non-zero.

It is also observed by examining the results of the simulations that the behaviour of \( |\epsilon(t)| \) has better information than \( \epsilon(t) \), which after applying the MWAT to \( |\epsilon(t)| \), the resulting shapes behave completely different in the two situations. Finally, after a derivation, the index in (20) is presented for the PSB algorithm:

\[
Idx_{PSB}(m) = \frac{1}{\Delta t} \left\{ \frac{1}{N_C} \sum_{k=m-N_C+1}^{m} (|i(k) - i_{ADALINE}(k)|) - \frac{1}{N_C} \sum_{k=m-N_C}^{m-1} (|i(k) - i_{ADALINE}(k)|) \right\},
\]

(20)

where \( Idx_{PSB}, N_C \) and \( \Delta t \) are the PS detection index, the number of samples per power cycle, and the sampling interval, respectively. Also, with a little simplification of Equation (20), we get

\[
Idx_{PSB}(m) = f_o \times \left| \frac{i(m) - i_{ADALINE}(m)}{|i(m-N_C) - i_{ADALINE}(m-N_C)|} \right|,
\]

(21)

Therefore, as the symmetrical situation is initially detected by the DR, \( Idx_{PSB} \) abruptly takes a significant value. In the case of PS (stable or unstable), this index has some oscillations but will still have a significant non-zero value. Therefore, if \( Idx_{PSB} \) index remains greater than zero for a quarter of the power-cycle time, it means that PS has occurred, and thus the proposed algorithm activates the PSB. \( Idx_{PSB} \) becomes greater than zero in the case of symmetrical faults, as well. However, it quickly becomes zero within a time period very smaller than a quarter of the power cycle. Therefore, \( Idx_{PSB} \) index along with a time index equal to a quarter of the power cycle can be used to discriminate PS from symmetrical faults.

It is also worth mentioning that in the case of an unstable PS event, the \( Idx_{PSB} \) index becomes zero after a period of time greater than a quarter of the power cycle. Therefore, the proposed algorithm resets the PSB.

Another challenge is when a symmetrical fault occurs during a PS. According to Equations (18) and (19), in the event of a symmetrical fault and in order to accurately match ADALINE with the current waveform, \( A_{DC} \) in Equations (1) and (7) should take a non-zero value. Therefore, it can be seen that the change of \( A_{DC} \) absolute value versus the time can be a good parameter for detection of symmetrical faults. Also, the derivative of this parameter has quick significant changes which can be used in fault detection. Therefore, the following index is introduced to detect symmetrical faults:

\[
Idx_{FLT}(m) = \frac{1}{\Delta t} \left( \frac{Re_{2N+1}(m)}{Re_{2N+1}(m-1)} \right),
\]

(22)

where \( Idx_{FLT}, Re_{2N+1}(m) \) and \( Re_{2N+1}(m-1) \) are the symmetrical fault detection index, and \((2N+1)\)th component of ADALINE weight vector in the \( m \)th and \( (m - 1) \)th samples, respectively. If the value of this index exceeds zero, it means that symmetrical fault has occurred and the PSB should be reset immediately. A very important characteristic of this index is that it can quickly detect difficult situations in which symmetrical fault occurs during a PS.

Flowchart of the proposed PSB algorithm for detecting symmetrical three-phase faults from PS is shown in Figure 2.

### 3 | SIMULATION RESULTS

#### 3.1 | Results of under-study network

In order to investigate the accuracy of the proposed strategy, a two-area four-machine western systems coordinating council (WSCC) power system, with 230 kV and 60 Hz is used. This power system is simulated in the PSCAD/EMTDC software environment. Sampling of the current is performed at the frequency of 1.2 kHz. In the under-study network shown
in Figure 3, DR R1 is embedded in L1 and in Bus-7 for transmission line protection. The outputs of a 600:5 current transformer and a 230 kV:110 V voltage transformer feed the relay. The proposed strategy is implemented for the relay R1, while various PS, and symmetrical fault conditions are tested.

In the next three sections, the proposed method will be compared with the conventional concentric circle method (CCCM). In the CCCM, the time setting is set to 1.5 cycle for distinguishing a PS from a symmetrical fault.

3.1.1 Stable PS

A three-phase fault is generated to simulate a stable PS on L2 near Bus 7 in 0.5 s. After seven cycles, the transmission line is tripped by the high-voltage circuit breakers. Consequently, the impedance path of relay R1 is within the zone-3 characteristic (Figure 4(a)). In this case, the relay may intersect L1 unless it is blocked. The cross-time of the impedance path for this sample is 175.8 ms, which is higher than the set value. The CCCM correctly detects the PS and activates the PSB at 1.021 s (Figure 4(b)). The current passing through L1 is gradually increasing over the time due to the PS, as shown in Figure 5(a). According to Figure 5(b), the \( I_{ds_{PSB}} \) index for each phase is greater than zero. Therefore, the proposed method activates the PSB quickly. Since the \( I_{ds_{PSB}} \) index is not set to zero, the relay will not be allowed to issue a trip commands. Therefore, in this situation, the CCCM and proposed strategy are able to correctly detect the PS.

3.1.2 Three-phase symmetrical fault

A three-phase fault is generated in 75% of L1 with resistance of 10 \( \Omega \). The start time of the fault is 1.7 s; Figure 6(a) shows the impedance path of DR R1.

The CCCM determined the motion time to be at 0.83 ms. According to Figure 6(b), the CCCM does not operate because the permanence time of the impedance path calculated by the CCCM is less than the threshold.

As shown in Figure 7(a), the amplitude of the current signal increases after the fault starts. As a result, the \( I_{ds_{PSB}} \) index (Figure 7(b)) becomes a significant amount at the time of the fault. But (according to Figure 7(b)), the time period in which \( I_{ds_{PSB}} \) is greater than zero is less than a quarter of the power cycle. Hence, the algorithm does not recognise it as a PS. However, according Figure 7(c), the \( I_{ds_{FLT}} \) index becomes greater than zero, as well. This means that symmetrical fault has occurred. Figure 7(d) shows that the proposed algorithm has not activated the PSB. Therefore, in this situation, CCCM and proposed methods are able to accurately detect the PS.
3.1.3 | Unstable PS

In order to create an unstable PS, a three-phase fault is created in the transmission line L2 for a 20-power-cycle interval. This will cause an unstable PS with a frequency of 2.7 Hz. As shown in Figure 8(a), the apparent impedance will enter zone 2 from DR R1. In this situation, CCCM will not allow DR R1 to trip the transmission line. The time taken to cross the outer circles and zone 3 by the impedance path is 14.2 ms, which is less than the threshold. Hence, according to Figure 8(b), the CCCM wrongly recognises the PS status as a fault and does not start the PSB operation.

As shown in Figure 9(a), the amplitude of the current signal increases after the start of the PS, then it decreases. As a result, the index $\text{Idx}_{\text{PSB}}$ becomes a significant amount at the moment of PS. Hence, the PSB is activated in 1.158 seconds. The $\text{Idx}_{\text{PSB}}$
index fluctuates after the PSB activation, but the amplitude of fluctuations is very large. At $t = 1.388$ s, when the value of the $Idx_{PSB}$ index is zero (i.e. the PS is unstable), the proposed algorithm disables PSB properly according to Figure 9(c). Therefore, in this situation, unlike the CCCM, the proposed method is able to correctly detect the PS.

### 3.1.4 Three-phase fault during PS

As the most important part of the proposed method, the PSB algorithm in the DR should correctly identify the symmetrical fault during the PS. Therefore, to check the accuracy of the proposed method under the mentioned conditions, at the moment of 0.56 s on 75% of L1 of Bus 7, during a fast PS, a three-phase fault is also generated. Figure 10(a) shows three-phase currents for this situation, with a PS occurring at the moment of 0.251. According to Section 2.3, the $Idx_{PSB}$ index starts to increase when the PS begins at 0.251 s as shown in Figure 10(b), and the PSB is activated at 0.256 s according to Figure 10(d). However, according to Figure 10(c), with the occurrence of a symmetrical fault at 0.56 s, the $Idx_{FLT}$ index suddenly exceeds zero and therefore the symmetrical fault status is identified. In this case, the proposed algorithm resets the PSB according to Figure 10(d).

### 3.1.5 Effect of high-resistance faults on the proposed strategy

In this section, the performance of the proposed strategy facing symmetrical high impedance faults (although happening infrequently) such as 100, 200, and 500 Ω faults is examined. The proposed approach works appropriately in the situations under consideration. Two examined situations are presented in this section. It is assumed that faults occur during a PS in both the cases.

Figure 11(a) shows a high impedance fault with a 100 Ω resistance which occurs at $t = 0.94$ s during a PS. Based on Figure 11(b) and (d), at the moment of 0.814 s that PS is detected, PSB is activated. But at 0.94 s, despite the intangible change in the current amplitude, the $Idx_{FLT}$ index immediately detects the symmetrical fault status and then resets the PSB. Therefore, the proposed method correctly identifies the moment of fault occurrence.

In another study, a 300 Ω fault is created at 1.3 s during a PS. According to Figure 12, it is clear that the proposed strategy identifies the PS status at 1.255 s and activates the PSB. But, as the symmetrical fault occurs, it resets the PSB at 1.3 s and allows the DR to function.

### 3.1.6 Effect of noise on the proposed strategy

As mentioned before, the proposed strategy here is based on ADALINE and MWAT. Since both tools are very noise resistant, the proposed method has a high resistance against the noise. In this section, several simulations are performed in the presence of White Gaussian noise with signal-to-noise ratio (SNR) 20, 40, and 50 dB, in which the proposed strategy performs correctly in all the tests.

Let us consider a situation in which Figure 10(a) is contaminated with White Gaussian noise with SNR = 20 dB. In order to
have a better evaluation of the proposed method, a short time window is considered. The blue colour in Figure 13(a) shows the noise-free waveform and the red colour indicates the noisy waveform. Figure 13(b) shows that as soon as a fault occurs, the value of $Idx_{FLT}$ becomes greater than zero, and the proposed strategy issues the reset command for the PSB in 0.56 s. Figure 13 illustrates that the presence of noise with SNR = 20 dB does not impose any delay or negative effect on the PSB function.

3.1.7 Proposed strategy compared with related works

In this section, the proposed strategy is compared with CCCM and the method presented in [20]. For this purpose, 300 different situations are created, including stable and unstable PS, symmetrical faults, symmetrical faults during PS occurrence with different impedances, and noisy symmetrical fault during the PS in the under-study network (Figure 3). The results of the simulations and comparison are given in Table 1. Each entry in Table 1 indicates the rate of the correct detections carried out by each method in the specified occurrence.

As seen, the CCCM functions always correctly (i.e. it activates the PSB) when 50 PS phenomena with different slip frequencies lower than 1.6 Hz happen. It functions always correctly when regular symmetrical fault occurs, as well. However, it cannot function correctly in all other situations.

The scheme presented in [20] always reacts correctly in the first four phenomena, as well. However, in the noisy conditions, and when high impedance SFs occurs during the PS, the proposed method outstands the method in [20]. The last row in Table 1 shows the functioning speed of the methods. As seen, the speed of the proposed method is considerably higher than the others.

| Occurrence                        | CCCM (time setting = 25 ms) | Method in [20] | Proposed strategy |
|----------------------------------|-----------------------------|----------------|-------------------|
| PS with slip frequency < 1.6 Hz  | 50/50                       | 50/50          | 50/50             |
| SF                               | 50/50                       | 50/50          | 50/50             |
| PS with slip frequency > 1.6 Hz  | ×                           | 50/50          | 50/50             |
| SF during the PS                 | ×                           | 50/50          | 50/50             |
| High Impedance SF during the PS  | ×                           | 45/50          | 49/50             |
| Noisy SF (SNR = 20 dB) during the PS | ×                           | 48/50          | 50/50             |
| Speed                            | 1.5 cycle                   | 1/2 cycle      | 1/4 cycle         |

CCCM, conventional concentric circle method; PS, power swings; SF, symmetrical fault; SNR, signal-to-noise ratio.

4 CONCLUSION

This paper presents a novel fast strategy for PSB, based on the use of ADALINE and the MWAT. The current waveforms are first detected by the ADALINE. Then the measure of the ADALINE learning error function is calculated, and after applying the MWAT, two new indices are presented. These indices are well able to distinguish symmetrical faults from PS. The simulation results show that the proposed strategy correctly identifies the PS as well as the symmetrical three-phase
faults during the PS even in high impedance fault occurrence or noisy condition. The high speed of ADALINE and the MWAT, along with their simplicity of calculation and resistance to noise, guarantees online implementation of the proposed method and its correct performance in the presence of noise.

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