A Signal-Based, Single-Ended Method to Detect Broken Conductor Events with Series Arcing in Power Distribution Lines

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***Abstract*—This paper presents a signal-based, single-ended method to detect broken conductor events using Dynamic Mode Decomposition (DMD) with shapelet-based pattern recognition. The series arcing that occurs during the separation of the two ends of a broken conductor generates distinctive current signatures, which can be extracted and magnified using DMD, a sensitive spatio-temporal analysis tool. These current signatures are then characterized using shapelets, a pattern recognition tool. Once a critical shapelet is isolated for broken conductor event detection, incoming DMD signals are compared to the isolated shapelet segment using a sliding window. A broken conductor event is flagged if the Euclidean distance between the signal segment and the isolated shapelet falls below a pre-determined threshold. The method is validated on the IEEE 34-node system, where 83 broken conductor events are simulated throughout the feeder. The proposed algorithm achieves an 89.2% accuracy in broken conductor event detection with 100% non-fault security.**

***Index Terms*—Distribution system protection, dynamic mode decomposition, broken conductor event detection, shapelets**

I. Introduction

Broken conductor event detection remains a significant challenge in power system protection. This fault occurs when a power cable breaks or comes loose. Even though broken conductor faults are less common than others (such as shunt faults), their detection poses significant difficulties. Conductors are exposed to both natural and human-caused hazards that can lead to a break. These stresses include lightning strikes, tree impact, hardware abrasion, and material degradation [1].

A broken, energized cable touching the ground can result in a High-Impedance Fault (HIF) or a line-to-ground fault. Conventional protection devices are primarily designed to be sensitive to overcurrent conditions. If the fault current is substantial, a protective relay will likely detect it and isolate the line. However, in many cases, the resulting fault current is insufficient and may go undetected by conventional protection systems. Detecting a broken conductor fault while it is still mid-air is a strategy to mitigate the risk of wildfire ignition, thus avoiding potential loss of life, wildlife, and property. This mid-air detection, however, is not always technically feasible. It generally takes about one second for a broken conductor to reach the ground [1].

Analyzing the arc initiated by a conductor break can serve as an effective method for detecting the broken conductor condition. This phenomenon is characterized as "series arcing," which is the occurrence of an electrical arc due to a physical discontinuity in the circuit. It is important to note that both circuit breaker switching and conductor breaks can initiate series arcing during the interruption of current flow [2]. The underlying arc physics of these two events are similar, with the primary distinction being the speed at which the ends of the series arc separate (circuit breakers are designed to be much faster). Once the arc is initiated by a conductor break, its sustenance is a function of the arc voltage, electric field, arc temperature, and the varying levels of air ionization [3].

II. Background

Broken conductor event detection methods can be classified on single-ended or multi-ended. Single-ended methods rely on unbalanced current (e.g., checking if the current unbalance ratio, $|I_2/I_1|$, exceeds a threshold for an extended time), line charging current, or voltage distortion [2]. Multi-ended techniques require time-synchronized data from multiple locations (which is not always available) and fall into two main types: Voltage-based methods, which assert a broken conductor event detection if the voltage difference across the break is significant, or the rate-of-change of phase voltages on either side of the break has opposite polarity and exceeds a threshold; and impedance-based methods, in which a broken conductor event is declared if an impedance change exceeds a threshold, provided no shunt fault is simultaneously detected.

Detecting a broken conductor event typically requires stacking multiple logic conditions to reliably rule out other potential events. For a broken conductor fault to be confidently identified, several simultaneous conditions must be met, such as a gradually decreasing current magnitude and/or a gradually increasing resistance in a single phase for a significant duration (e.g., three AC cycles). In related research, such as [2], detection times often fall within the 0.2 to 0.3 second range. The greatest difficulty in this detection process lies in

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establishing appropriate lower and upper thresholds for the gradually decreasing current signal.

The work in [4] proposes a fault detection logic with arcing alerts for systems with large penetration of inverter-based resources. This logic identifies series arcing by monitoring for a decrease in phase current and an impedance angle that falls within a capacitive window over a predefined time. The detection time is two AC cycles. In [5], the time variation of I_2/I_1 and I_0/I_1 is used to detect broken conductor events. The latter ratio is added to enable better differentiation between fault and non-fault scenarios. It is noted that this work is performed on a case-by-case basis, depending on the line.

The shortcomings of using $|I_2/I_1|$ as the detection method are exposed in [1]. These limitations include potential failure during low-load conditions and a lack of selectivity or directionality. Furthermore, relying on a time delay in the order of seconds presents a significant risk, as it might inadvertently cause a shunt fault. The paper proposes an alternative detection and location method that utilizes the line charging current, which involves checks for increases in current magnitude and angle. However, this method has its own constraints: it might not work for close-in broken-conductor faults and is challenged in multi-terminal systems, where the current may not become purely capacitive following the broken conductor event. Additionally, working with current unbalances and angles requires contextual information, such as the presence of shunt elements (reactors or capacitors), whose effects must be accurately accounted for. The paper in [6] proposes a broken conductor event detection method based on negative sequence voltage monitoring. The method's security was tested against non-fault events such as capacitor bank switching, load switching, and lateral branch switching. However, it encountered issues (or failed) with the last two event types.

Finally, signal-based protection has proven effective in handling detection and location of different fault types, such as low-impedance faults (using traveling waves) and high-impedance faults, with accuracies higher than 90% [7]–[9]. These algorithms are able to generalize from simulated fault data and use data-driven methods to set detection thresholds based on the system. Furthermore, they can easily be implemented on embedded devices for real-time implementation.

The contribution of this paper is to utilize Dynamic Mode Decomposition (DMD), a data-driven time-domain analysis technique valuable for power system waveform analysis, to detect anomalous transients and extract temporal features for data-driven models [10], [11]. We employ DMD alongside shapelet-based pattern recognition to detect broken conductor events with series arcing in a single-ended fashion (requiring no communications and no real-time operational data) within multi-terminal power distribution systems. The security of this method is assessed against non-fault cases, including normal operational data and non-fault events such as capacitor bank switching, load switching, and transformer (de-) energization.

III. BROKEN CONDUCTOR SERIES ARC MODELING

The series arc can be represented as a nonlinear resistance that increases proportionally to the growing distance between broken conductors [2], [12]. Of the several series arc models presented in the literature, the Schavemaker arc model is considered the most refined [13]. This model unifies the arc behavior across the high-current (Cassie-like) and low-current (Mayr-like) stages [14], [15], thereby ensuring a more robust and smoother arc simulation than its predecessors. The model is formally defined by the following equation:

$$\frac{1}{G}\frac{dG}{dt} = \frac{1}{\tau}\left(\frac{P_{arc}}{P_0 + P_1 P_{arc}} - 1\right), \tag{1}$$

where G is the arc conductance, P_{arc} is the arc power, τ is the arc time constant, and the total cooling power is defined by $P_0 + P_1 P_{arc}$, with P_0 and P_1 representing the constant and power-dependent cooling terms, respectively. In situations where the arc current and power P_{arc} are very high (such as in the early stages of a fault or far from current zero), P_0 becomes negligible compared to $P_1 P_{arc}$. Substituting this high-power approximation into the conductance equation yields:

$$\frac{1}{G}\frac{dG}{dt} \approx \frac{1}{\tau}\left(\frac{P_{arc}}{P_1 P_{arc}} - 1\right) = \frac{1}{\tau}\left(\frac{1}{P_1} - 1\right). \tag{2}$$

Since $\frac{1}{\tau}\left(\frac{1}{P_1} - 1\right)$ is approximately constant, the rate of change of $\ln(G)$ is also constant. This implies that G changes exponentially, which causes a near-linear resistance effect. As the current approaches zero, P_{arc} becomes small, and consequently, the $P_1 P_{arc}$ term becomes negligible compared to P_0. The equation then simplifies to the Mayr model with an exponential conductance decay:

$$\frac{1}{G}\frac{dG}{dt} \approx \frac{1}{\tau}\left(\frac{P_{arc}}{P_0} - 1\right). \tag{3}$$

Therefore, a simplified way of simulating a series arc fault can be divided into two stages: first, a small, gradual increase in the fault resistance; and second, a rapid increase as the arc becomes unstable due to the conductors separating. Experimental data validates this assumption. The series arc resistance observed in multiple experiments, such as those described in [16], shows an initial, gradually rising part (building up to 10 or 20 Ω over almost the entire arc event duration). This is then followed by an exponential increase, which leads to arc instability and collapse. This behavior aligns well with field data provided in various papers [1], [2], where broken conductor event recordings show a gradual, almost linear decrease in the current magnitude of the affected phase for approximately 100 to 400 milliseconds. This decrease is then followed by a sudden current collapse in less than one or two AC cycles (about 20 to 30 milliseconds). Based on this 2-stage behavior, broken conductor events were simulated using a variable resistor governed by the following heuristically obtained logic:

1) Linear Stage: The series resistor increases linearly from 0 Ω to 40 Ω over a 100-millisecond period.

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2) Exponential Stage: Defined by $P_0 = 1000$ W, $P_1 = 0.99$, and $\tau = 0.1$ milliseconds.

IV. Methodology

A. Dynamic Mode Decomposition

Dynamic Mode Decomposition (DMD) is a data-driven method that identifies a set of spatio-temporal modes associated with specific frequencies and growth/decay rates [17]. For linear systems, the DMD modes and frequencies correspond directly to the system's normal modes. For nonlinear systems, DMD provides a reduced-order approximation of the modes and eigenvalues of the Koopman operator, simplifying the analysis of complex dynamics [10]. The core idea is to approximate the underlying dynamics of a sequential set of vectors $\{x_1, x_2, \ldots, x_m\}$ as a best-fit linear operator A:

$$x_{k+1} \approx A x_k. \tag{4}$$

The operator A is formulated as $A = X_m X_{m-1}^{\dagger}$, where $\dagger$ is the Moore-Penrose pseudo-inverse, and X_{m-1} and X_m are data matrices:

$$X_{m-1} = [x1 \quad x2 \quad \ldots \quad x_{m-1}], \tag{5}$$

$$X_m = [x2 \quad x3 \quad \ldots \quad x_m]. \tag{6}$$

The process to find the eigenvectors Φ and eigenvalues Λ has the following steps:

1) Singular Value Decomposition (SVD) of X_{m-1}:

$$X_{m-1} \approx U \Sigma V^H. \tag{7}$$

2) Compute the low-rank approximation of A:

$$\tilde{A} = U^H A U = U^H X_m V \Sigma^{-1}. \tag{8}$$

3) Factorize $\tilde{A}$. The non-zero eigenvalues Λ of $\tilde{A}$ are the same as those of A:

$$\tilde{A} W = W \Lambda. \tag{9}$$

4) Reconstruct the DMD eigenvectors Φ of A:

$$\Phi = X_m V \Sigma^{-1} W. \tag{10}$$

Applying DMD to three-phase power system signals yields a set of two complex eigenvalues, $\lambda_1 = \alpha_1 \pm j\beta_1$ and $\lambda_2 = \alpha_2 \pm j\beta_2$. Under normal operating conditions, the real parts of these eigenvalues, α_1 and α_2, are constant and near zero in sets of signals without DC offset; whereas the imaginary parts, β_1 and β_2, correspond to the nominal frequency, 377 rad/s (60 Hz). During an abnormal event, the real parts α_1 and α_2 increase significantly in magnitude, and the imaginary parts β_1 and β_2 deviate considerably from its normal value. It is important to note that α_2 is preferred as a sensitive indicator of power quality events and is used in this work for broken conductor event detection [10], [11].

B. Shapelets

Shapelets are short, discriminative time-series segments used in classification tasks [18] and valued for their interpretability, pattern localization, and robustness—characteristics that enable rapid pattern matching without complex training. In this work, DMD is used to generate a collection of signals which are then aggregated to create an initial prototype shapelet S. This prototype shapelet is computed as the index-wise average of aligned, cropped DMD segments ($\alpha_2^{(\mathrm{i})}$, the real component of the second DMD eigenvalue λ_2), which captures the most representative temporal shape of the fault event behavior [10]. The equation for the prototype shapelet S with a shapelet length L is:

$$S_j = \frac{1}{N} \sum_{i=1}^{N} \alpha_{2,j}^{(i)} \quad \text{for } j = 1, 2, \ldots, L. \tag{11}$$

C. Broken Conductor Event Detection

To perform broken conductor event detection using the DMD-processed signals, a sliding window algorithm is employed. This method works by moving a window of length L across the real part of the second DMD eigenvalue $\alpha_{2,\text{window}}$ and calculating the Euclidean distance D between the windowed segment and the predefined shapelet S, which is representative of the broken conductor event behavior. This distance, $D = \|\alpha_{2,\text{window}} - S\|_2$, quantifies the similarity between the current signal segment and the known fault profile. The minimum distance observed across the entire signal is used as the matching metric. A fault is identified if this minimum distance falls below a pre-determined threshold, which is previously obtained via batch simulations to optimize the balance between detection sensitivity and security. The distance D and the threshold are dimensionless, as the DMD eigenvalues do not have units. Furthermore, to enhance computational efficiency and potentially improve accuracy, a smaller, isolated segment of the prototype shapelet may be used in the windowing process.

D. The Test System

This study employs the IEEE 34-node test feeder, shown in Fig. 1, as an unbalanced distribution network model. It operates primarily at 24.9 kV, with a transformer between nodes 832 and 888 stepping it down to 4.16 kV. The topology includes long lines and high-load sections, plus capacitor banks at nodes 844 and 848. The system was modeled in PSCAD/EMTDC. The study simulated a broken conductor event on each phase at 33 non-substation locations, generating a dataset of 83 events. All fault data was captured at the substation (node 800) with a 40 kHz sampling rate. This rate was chosen to achieve an optimal balance between the uniqueness of the resulting shapelet patterns and the computational cost. While lower sampling rates compromised shapelet reliability, higher rates offered minimal performance benefit for broken conductor event detection despite a significant increase in computational effort. The raw signals and resulting DMD

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analysis for a set of signals containing a broken conductor event on node 806 are shown in Fig. 2 and Fig. 3, respectively.

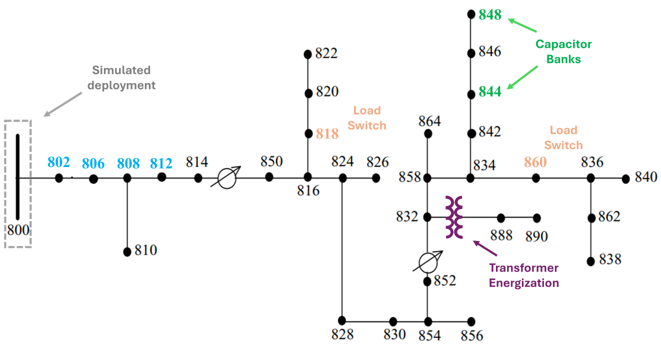

Fig. 1. IEEE 34-node system diagram.

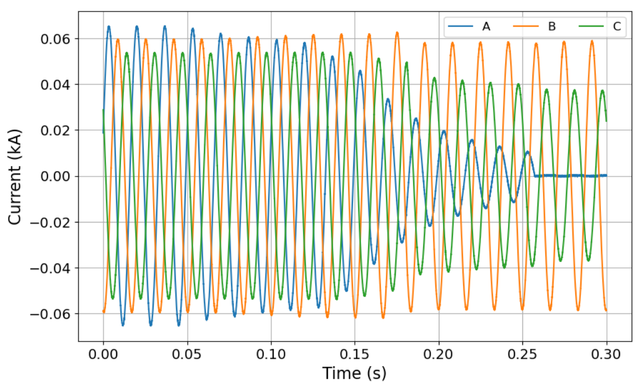

Fig. 2. Three-phase current signal showing a broken conductor event initiation at 0.05 s and arc extinction near 0.15 s.

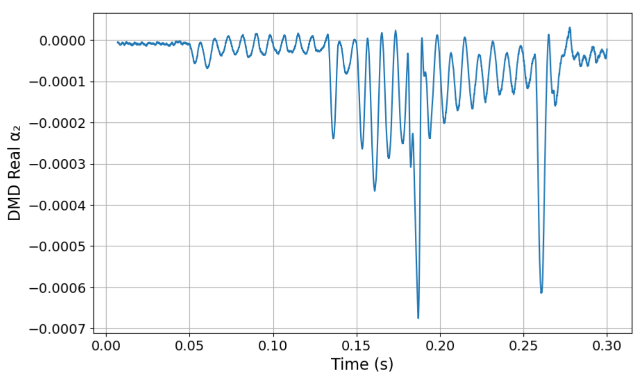

Fig. 3. DMD analysis on three-phase broken conductor event signal.

V. Results

The proposed broken conductor event detection method relies on current measurements and is deployed at node 800, the substation. Validation is conducted by evaluating signals containing broken conductor fault instances as well as introducing an additional array of non-fault signals that are produced using the three-phase, pre-fault currents associated with each corresponding fault. That is, for each of the 83 faults simulated on the test network, there are 83 corresponding signals that represents normal operating conditions before any fault has occurred. These new signals serve as fault-free counterparts to the original broken conductor event signals and thus, should not reflect a positive detection. Furthermore, an additional 10 non-fault cases are introduced that include transients demonstrative of select specialized instances. This includes four capacitor bank switching events, four load switching events, and two transformer (de-) energization events that are meant to assess the robustness of the method in differentiating genuine fault events from common operational transients. This results in a total testing archive of 176 events containing a variety of both broken conductor and non-fault signal profiles used to validate the accuracy of the proposed detection method.

Producing the initial prototype shapelet is done by selecting 12 fault signals occurring immediately downstream of the deployment node 800, as illustrated by the blue text in Fig.1. Faults occurring at nodes 802, 806, 808 and 812 are each sampled at 40 kHz and include a Signal-to-Noise Ratio (SNR) of 50 dB to accurately reflect the noise conditions expected in field measurements. These signals undergo DMD analysis, from which the normalized real α_2 component is averaged to an 800-sample window that defines the initial prototype shapelet, whose unique pattern captures distinguishing characteristics of the broken conductor event. To improve both computational efficiency and robustness, a smaller, 400-sample, isolated shapelet is further extracted by identifying the most discriminative portion of the fault signature as depicted in Fig.4. This secondary shapelet is used as the primary detection feature in a sliding-window batch simulation against the 176 aforementioned events to yield highest matching Euclidean distance scores across all instances. Analysis of these scores yielded a maximum threshold of approximately 0.0014286 before flagging as a broken conductor fault.

The detection results, summarized in Fig. 5, show that, out of 83 fault events, 74 are detected correctly when the Euclidean distance between the real part of the second DMD eigenvalue, α_2, at some point along the transient and the isolated shapelet falls below the pre-defined threshold. The undetected broken conductor events, all occurring on laterals (nodes 810, 826, 856, 864, 848, 862, and 838), indicate that pre-fault current is the primary influencing factor, not distance

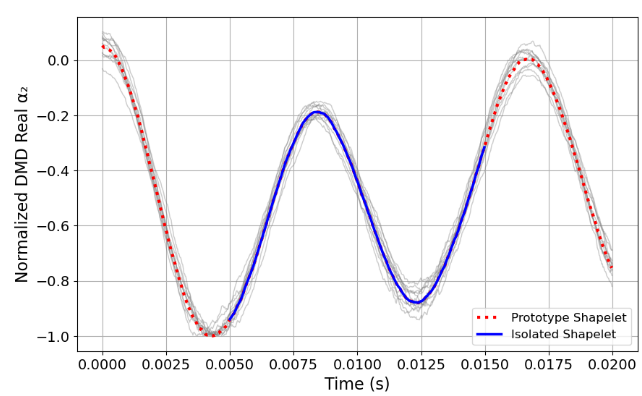

Fig. 4. Prototype and isolated shapelets derived from cropped section of aggregated sample faults.

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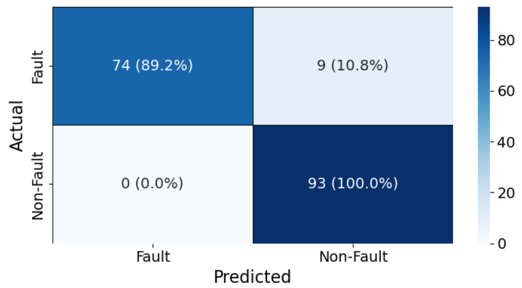

Fig. 5. Confusion matrix.

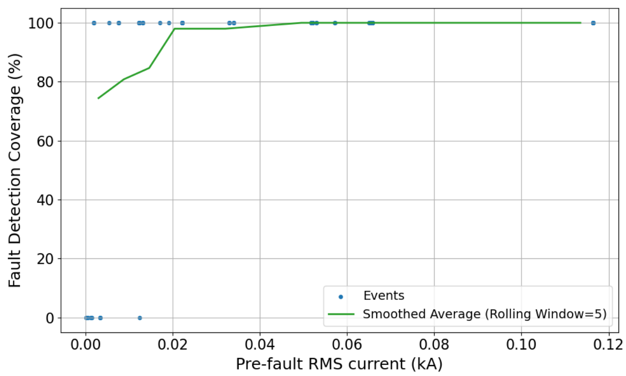

Fig. 6. Detection rate compared to pre-fault current.

(as seen by similar behaviors at near-substation node 810 and far-end node 862). The proposed method may miss events on nodes with low current flow. While one missed event at node 848 had a pre-fault current of 12 A, most undetected cases had a pre-fault current of 3 A or less, as shown in Fig. 6.

Regarding non-fault cases, the proposed method did not trigger a fault on normal operation noise or other events such capacitor, bank switching, load switching, or transformer (de-) energization. Therefore, the proposed algorithm achieves a 100% non-fault security. However, it is important to note that setting the right threshold was crucial to avoid false tripping.

VI. Conclusion

The proposed signal-based, single-ended DMD-shapelet methodology enables the fast and accurate identification of distinct modal patterns characteristic of broken conductor events involving series arcing, requiring less than 0.25 seconds of post-fault data for reliable detection in power distribution systems. The method is based on isolating a short, highly discriminative shapelet segment and then using a sliding-window matching algorithm based on Euclidean distance measurements. This process delivered strong performance, demonstrating 100% security against non-fault events and achieving an 89.2% overall detection accuracy across the entire set of simulated broken conductor events, thereby preventing false tripping caused by normal system operations, including measurement noise, capacitor bank switching, load switching, or transformer (de-) energization. While the approach is effective for both close-in and far-away faults, the detection rate diminishes for broken conductor events located in system laterals with low pre-fault current flow. Relative to state-of-the-art methods, this technique offers several advantages: it does not require real-time system configuration data (such as the status of shunt reactors or capacitors), it has been tested on a highly-branched distribution system, and it does not use a time-delay to differentiate a broken conductor event, which enables a potentially faster detection time. Future work will focus on a sensitivity analysis involving series arc parameters.

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