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Original Scientific Article

SIMULATION-BASED STUDY OF STRUCTURAL CHANGES IN ELECTRICAL TIME-SERIES SIGNALS

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Abstract This paper uses statistical indicators to address the detection of changes in electrical signals typical of industrial and power systems. A dedicated MATLAB algorithm was developed to identify change points by tracking shifts in signal behaviour and statistical properties. To evaluate the method, synthetic signals were generated through simulation to reproduce the common patterns observed in these systems, allowing testing under different operating conditions and varying noise levels. The results demonstrate that the algorithm detects change points reliably across multiple scenarios, showing flexibility and robustness. This study highlights the value of simulation-based signal generation as a controlled environment for testing detection methods. It provides a foundation for future applications to more complex real-world electrical signal analysis tasks.

Keywords
break points, energy system, noise, segmentation, signals, simulation, time series

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1 Introducton

Analysing signals from electrical and energy systems has represented a significant challenge in recent years due to their inherent complexity, variability and noise. Simulation-based approaches have become increasingly important, as they allow reliable monitoring and testing of methods for the timely detection of changes in such signals, essential for maintaining the stability, efficiency and safety of modern energy and industrial infrastructures [1]. Structural changes, often called breakpoints, may reflect events such as faults, switching operations, or load variations, and detecting them accurately is important for system diagnostics and control.

Detecting structural changes in these signals is challenging, and statistical methods are used widely to support this process [2]. These methods quantify how much each data point differs from typical behaviour and can account for multiple variables simultaneously [3]. In addition to classical statistical approaches, recent research has explored machine learning techniques [4], including clustering [5], classification [6] and deep learning methods [7], to detect changes in more complex or high-dimensional signals. Various approaches have been presented in the literature, differing in their assumptions, the types of signals they analyse, and how changes are detected [8]. This classification helps in selecting the most suitable method for a given application. Figure 1 shows a diagram summarising this taxonomy of techniques, providing an overview of the main strategies for identifying breakpoints in time-series signals. As shown in Figure 1, methods can be classified into three main categories: supervision, data type, and detection mode. Supervised methods use labelled training data and typically apply classification or regression techniques, while unsupervised methods rely on statistical tests or clustering without prior labels. Methods can handle univariate signals with a single variable or multivariate signals involving multiple sensors or features [9]. Finally, they operate in either offline/batch mode, analysing data after collection, or in online/real-time mode, detecting changes as new data arrives.

This study uses a MATLAB-based simulation framework to investigate the detection of structural changes in synthetic electrical time-series signals. The signals were generated to resemble patterns found commonly in energy and industrial systems, providing a controlled environment to test different detection approaches. Various scenarios are explored, including step changes, ramp variations and shifts in noise levels, allowing an assessment of how the methods respond under different conditions. This framework is a practical basis for developing and evaluating change detection techniques before applying them to real-world electrical signals.

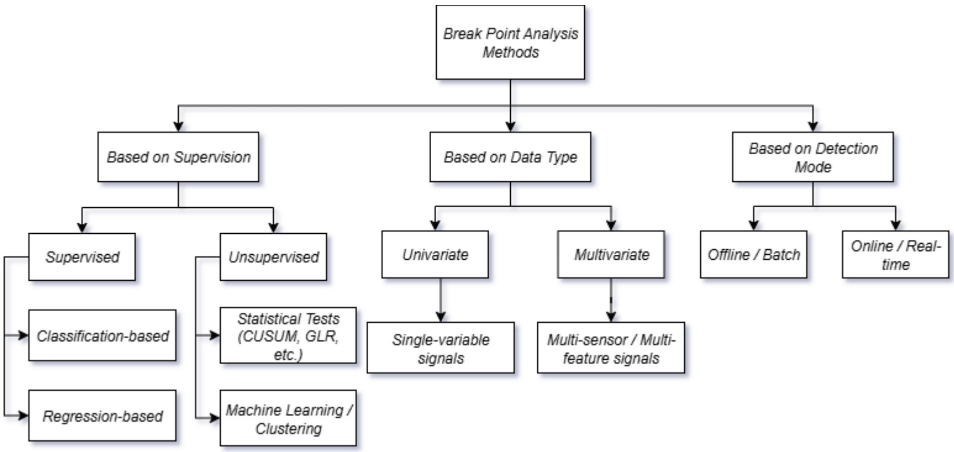

Figure 1: Overview of Structural Break Analysis Techniques

2 Detecting structural changes in data

Understanding the local behaviour of signals is crucial for identifying changes in their structure. Structural signal changes are detected by analyzing key statistical descriptors, such as the mean, variance, and covariances between signal components.

The mean of a signal segment is calculated using equation 2.1:

$$\mu = \frac{1}{m}\sum_{i=1}^{m} x_i \tag{2.1}$$

where x_i are the individual data points in the signal segment and m is the total number of points in the segment.

The variance of the signal segment is calculated using equation 2.2:

$$\sigma^2 = \frac{1}{m-1}\sum_{i=1}^{m} (x_i - \mu)^2 \tag{2.2}$$

The covariance between two signal components is calculated using equation 2.3:

$$\mathrm{Cov}(X, Y) = \frac{1}{m-1}\sum_{i=1}^{m}(x_i - \mu_X)(y_i - \mu_Y) \qquad (2.3)$$

where x_i and y_i represent the individual data points in the signal segment, and μ_X and μ_Y are the mean values of the respective signal components. Covariance measures how two signal components vary together, indicating whether they tend to increase or decrease simultaneously. A positive covariance means that both components generally increase together, while a negative covariance indicates that they tend to move in opposite directions.

Significant deviations in these statistical descriptors are used to decide whether a structural change has occurred. The approach monitors how these descriptors evolve and flags potential breakpoints when meaningful shifts are observed.

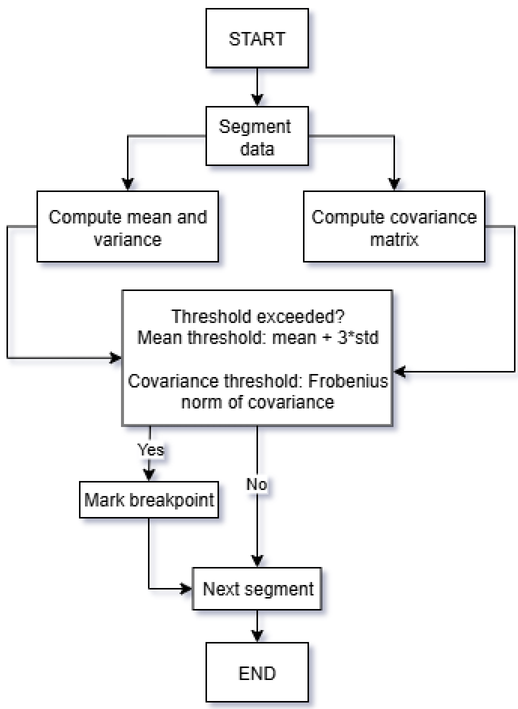

Figure 2: Flowchart of the proposed method

To provide a clearer overview of the method, Figure 2 illustrates a flowchart of the proposed method. The algorithm processes the signal in consecutive segments and monitors structural changes continuously. For each new segment, statistical descriptors including the mean, variance and covariance matrix are computed not only for the current segment but also in combination with the preceding n segments, establishing a local baseline that captures recent signal behaviour. The descriptors of the current segment are then compared against this baseline. A breakpoint is flagged if the mean deviates beyond the predefined threshold, or if the covariance matrix exceeds its threshold (measured via the Frobenius norm). This simultaneous evaluation ensures that both magnitude changes and shifts in component relationships are detected promptly.

3 Testing and analysis of the simulated signals

The validation of the proposed approach is conducted on signals generated in MATLAB and designed to capture the characteristics typical of electric drive systems and energy applications. These simulated signals provide a controlled environment for observing structural changes and evaluating the method's responsiveness under varying conditions. For this purpose, three representative data series are considered, each forming the basis for a separate case. The following list presents these cases, which are analysed individually in the subsequent sections:

- **Case 1**: Step change analysis
- **Case 2**: Noise variation analysis
- **Case 3**: Complex signal dynamics

3.1 Analysis of Step Changes in Signal

Step changes are sudden shifts in a signal that appear commonly in electrical and energy systems, such as when a load suddenly changes or a switch is activated. One common example of step changes occurs in PWM signals of voltage and current pulses in inverters. Analysing these shifts provides insight into the system response, identifies potential issues, and supports the design of effective control strategies. In power systems, step changes are associated frequently with switching events, grid disturbances, or fault occurrences, where detecting variations in the mean value of signals plays a key role in system monitoring and protection. Figure 3 shows the simulated step signals with added Gaussian noise with a Standard Deviation of 15. The proposed algorithm identified seven breakpoints, corresponding to the moments of sudden change in the signal.

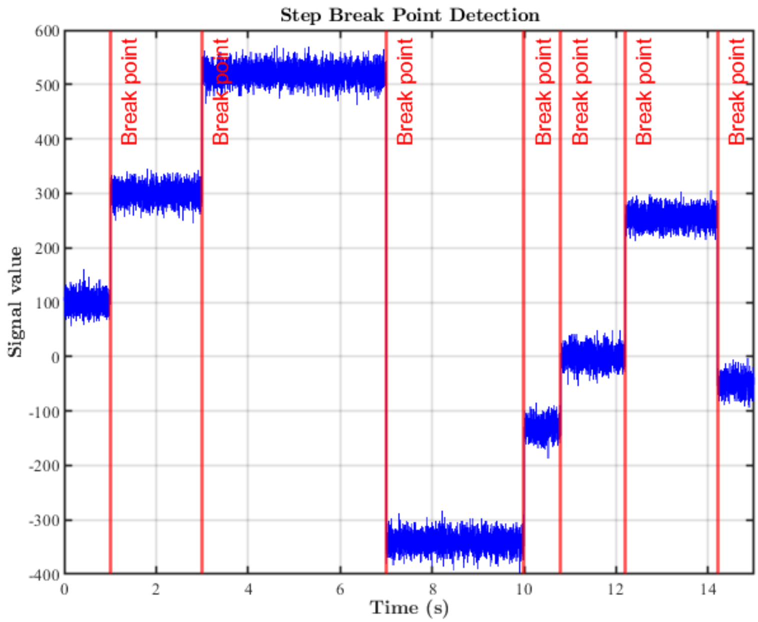

Figure 3: Identification of step changes in the signal mean

3.2 Analysis of Noise Variations in a Signal

Every measurement in power systems is inevitably affected by noise, originating from imperfections in the equipment and the surrounding environment. It is typically represented as Gaussian white noise, and its presence is evident in almost all voltage and current recordings across transmission and distribution networks. Variations in noise intensity can point to changes in operating conditions, disturbances in the grid, or transient events that affect the measurement quality. Figure 4 shows a simulated signal with Gaussian noise of varying intensity, where the algorithm identified two breakpoints corresponding to transitions in variance. In contrast, the mean value of the signal remained unchanged.

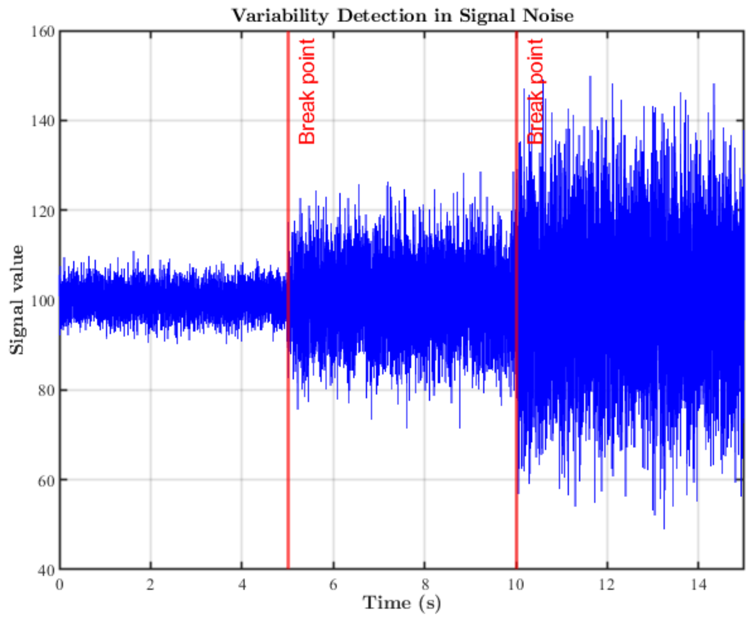

Figure 4: Identification of step changes in signal variance

3.3 Analysis of Complex Signal Dynamics

A more complex signal was simulated, to evaluate the algorithm further, consisting of multiple segments with different mean values. At the same time, the variance remained constant, reflecting variations observed commonly in power system measurements. The signal can represent the rotor speed of a generator or electric motor, where operating conditions or load changes shift the average value over time, while the measurement noise remains relatively constant. It includes an upward ramp, two step segments at constant levels, and a downward ramp, as illustrated in Figure 5.

During the ramp segments, the mean changes continuously, leading the algorithm to detect multiple breakpoints. While these may appear as false positives, they reflect actual changes in the signal metrics over time. In contrast, the step segments produce distinct, isolated breakpoints that indicate abrupt shifts in the mean. This behaviour shows that the algorithm can distinguish between gradual and abrupt changes. At the same time, the constant variance ensures that the detected breakpoints correspond to actual shifts in the signal level rather than to random fluctuations.

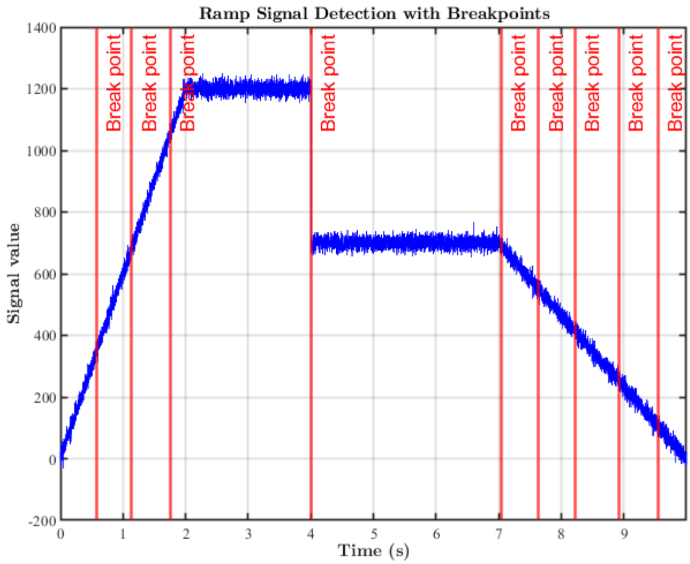

Figure 5: Identification of ramp changes in the signal structure

4 Conclusion

This paper presented a statistical approach for detecting changes in electrical signals encountered commonly in industrial and power systems. The proposed MATLAB algorithm was evaluated using simulated signals that included step changes, ramps and variations in variance, representing scenarios such as sudden load changes, switching events and rotor speed fluctuations. The results indicate that the algorithm can distinguish between abrupt and gradual changes and identify breakpoints corresponding to actual shifts in the signal mean or variance, while minimising the influence of measurement noise, although continuous transitions such as ramps may lead to multiple detected breakpoints. Several limitations were observed, as the evaluation relied on simulated signals that do not capture the complexity of real-world environments fully. The algorithm depends on basic statistical measures which may reduce robustness in the presence of fast or irregular changes, and outliers can affect detection accuracy further. These limitations motivate the proposed directions for future research directly. Future research should therefore extend the validation to real-world power system data, investigate methods to improve robustness to outliers, and explore adaptive strategies for handling varying signal characteristics. Comparative studies with alternative breakpoint detection and machine learningbased techniques would help clarify the relative advantages of the proposed approach, while also providing benchmarks for assessing performance under different operating conditions. Despite these limitations, the method offers notable advantages: its reliance on simple statistical descriptors ensures low computational effort and straightforward implementation, making it suitable for lightweight or embedded monitoring applications where real-time performance is essential. Overall, the study demonstrates that simulation-based signal generation provides a controlled environment to evaluate detection methods and supports the potential application of the algorithm to practical power system monitoring and analysis.

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Povzetek v slovenskem jeziku

Simulacijska študija strukturnih sprememb v časovnih vrstah električnih signalov. V tem članku so za zaznavanje sprememb v električnih signalih, značilnih za industrijske in energetske sisteme, uporabljeni statistični kazalniki. Razvit je bil namenski MATLAB-ov algoritem za prepoznavanje točk sprememb z beleženjem premikov v obnašanju signala in njegovih statističnih lastnostih. Za oceno metode so bili s simulacijo ustvarjeni sintetični signali, ki ponazarjajo pogoste vzorce v teh sistemih, kar je omogočilo testiranje pri različnih obratovalnih pogojih in različnih ravneh šuma. Rezultati kažejo, da algoritem zanesljivo zazna točke sprememb v številnih scenarijih ter s tem izkazuje prilagodljivost in robustnost. Študija poudarja vrednost simulacijskega ustvarjanja signalov kot nadzorovanega okolja za preizkušanje metod zaznavanja. S tem postavlja temelje za prihodnje uporabe pri zahtevnejši analizi realnih električnih signalov.