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Wave analytical techniques-based fault initiation detection at middle voltage distribution feeders

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Abstract

This paper presents studies, findings and results of the fault initiation detection approach, which is based on wave analytical techniques at middle voltage distribution feeders of ADM Distribution Company (DisCo), Turkey. Predictive methods are implemented to determine root causes of fault initiations on the feeders, which cannot be detected with today's modern SCADA and relay protection systems that are not designed to prevent failure. In response, artificial intelligence-based machine-learning techniques, which accumulate experience in the current and voltage waveforms related to the failures, are addressed in the study. Thereby, distribution companies will be able to prevent failures that can result in a power outage on a large scale. The algorithms are tested on a feeder at ADM DisCo. The performance of the approach is discussed based on measurements. The root causes of fault initiations on the feeders, which cannot be detected with today's modern SCADA and relay protection systems, are identified successfully.

Keywords: Wave analytics, artificial intelligence, machine learning, distribution;

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1. Introduction

Every event that occurs in electrical power systems manifests itself in current and voltage waves as shapes that are known or not yet known fully but have certain characteristics [1]. While many of these events are related to routine operations (motor start-up, balanced capacitor manoeuvres etc.), some of them are events that occur in the network and turn into malfunctions that can cause damage to the equipment, especially power interruptions, if they occur. The root cause of some failures cannot be detected with today's modern SCADA systems and relay protection infrastructure, even with high-resolution devices, such as power quality measurement devices, or at least these devices are not designed to prevent failures.

1.1. Literature review

In Russell and Benner's [2] study, a new waveform analytics method is proposed. In this article, it is mentioned that the analysis of waveforms can also be carried out using human power, but since this will require highly experienced personnel for small changes and complex fault symptoms, such an analysis can be solved with specialised classification algorithms. The algorithms and analysers developed using such waveform analytics are previously explained through field applications and sample faults [3–5].

Wischkaemper *et al*. [3] stated that the occurrence stages of the faults are classified as one and zero in conventional distribution networks and the transition phase is not considered, and this classification cannot meet today's needs, and there are distinctive, detectable and noticeable changes on the current and voltage waves before many faults occur. Again, in the same article, the details of the analyser measurement infrastructure proposed for running such a classification algorithm are shared. It is detailed by Wischkaemper *et al.* [4] that an algorithm that detects such changes and can give warnings before malfunctions should have a strong and reliable library, and for this, libraries that have been created with the necessary measurement activities for many years.

The use of wave analytics algorithms in preventing fire or fatal accidents that may occur as a result of the contact of overhead lines with tree branches or falling to the ground may be one of the potential and common areas of use, as explained by Wischkaemper *et al.* [5]. It is explained that waveform algorithms can not only prevent emerging faults but also help the system operator in determining the root causes of occurring faults.

One of the methods used in waveform analytics is fuzzy logic applications. Waveform analytics methods include the classification of normal and abnormal events occurring in distribution networks. Current and voltage waves are used to classify the events that occur. However, the distortions and uncertainties in current and voltage waves require the classification algorithm to decide on a human-like structure. When the probability theory literature is examined by Zadeh [6], it is understood that the application that best represents the human-like decision-making algorithm is fuzzy logic. Fuzzy logic applications are widely used in electrical power systems. Chen *et al*. [7] used fuzzy logic to manage the uncertainty about the cause and approximate location of the faults occurring in the distribution networks, thus improving the fault detection time. Xu *et al*. [8] explained how the parameters of membership functions used in fuzzy logic-based classification algorithms should be created in cases where sufficient field data cannot be obtained. Since there is not enough literature about the shapes created by the faults in the project, the methods mentioned in this article have been used from time to time.

In conventional distribution networks, the cause of faults can be revealed manually by the authorities by examining the current and voltage RMS waveforms. Dynamic time warp (DZB)-based shape analysis algorithm can be used to have similar visual classification features to waveform analytics algorithms. DZB is used to detect RMS waveforms. DZB technique is generally used in voice recognition algorithms. Müller [9] used the DZB technique in music and motion.

Within the scope of the project literature review, the reports published by the institutions where similar projects were carried out before were also examined. A similar project to the DAK R&D Project is the 'Distribution Fault Anticipator (DFA)' project initiated by the 'Electric Power Research Institute' (abbreviated as EPRI). The related project was started in 2000 and research continued for about 10 years. Processes in the project named DFA are shared in EPRI [10]. According to the information obtained from these reports, a special analyser was designed within the scope of the project; the related analyser was put into use by hundreds of feeders of many distribution companies; and different failure scenarios were tested with a data collection process that lasted for approximately 5 years over real failures. As a result, algorithms have been enriched and made reliable. In our project, the experiences gained in the DFA project were used.

As an output of the DFA project, three products were developed, and their patents were published. Manivannan [11] explains the details of a fuzzy logic-based classification algorithm in electric power systems. The use of fuzzy logic in the classification technique is explained through sample membership functions. Detection of events that occur in electrical power systems using the relevant signals and the determination of their root causes are explained in [12]. The phase difference removal method developed to more accurately determine the distinguishing features of the events occurring in electrical power systems from normal mains voltage and current is explained in [13].

Another publication examined during the literature review phase is the doctoral dissertations on electrical power systems classification algorithms. The algorithms developed for the classification of normal or abnormal events occurring in distribution feeders with live measurements carried out at the feeder's heads are explained in [14]. The properties of the measured signals are determined using signal processing and shape analysis methods, and then they are classified using fuzzy logic techniques. Arc formation, which is one of the event definitions of the classification algorithm, and the effects of arc formation on current and voltage waves are examined [15].

In data analysis, the method of artificially producing many copies of the original data set and using it in the analysis is called the bootstrap method [16]. According to this technique, a new artificial data set can be created by taking completely random sampling from the existing data set. In the artificial data set, some of the elements in the original data set may appear once, some may appear more than once or some may not be included at all.

1.2. Purpose of the study

Being aware of this reality, ADM and GDZ Distribution System Operators (DSO) have carried out an R&D project to prevent the emerging faults by developing algorithms that examine the fault symptoms, current and voltage waveforms in the distribution feeders. In this way, by increasing the awareness of failures in distribution feeders, distribution companies will be able to prevent failures and prevent heavy failures that will damage equipment. The technology developed in the project provides information flow to the fault maintenance and repair teams in the feeders they are responsible for, and they perform the activities they have realised by evaluating the information they have previously obtained only from the fault to the fault.

2. Materials and Methods

A self-learning, artificial intelligence (AI)-assisted decision-making product that accumulates experience in the resolution of current and voltage waves related to the events that occur in the network following the network is not yet used in the networks. The proposed approach in this study is based on monitoring whether the network is functioning properly, expanding its knowledge and experience library with every new event, detecting changing conditions and renewing its parameters on its own, making decisions and suggestions and transferring and using its knowledge to different regions of the same distribution company when appropriate.

The proposed approach, which is based on wave analytical techniques (WAT), enables the DSOs to perform their studies more efficiently and with increased awareness. Another benefit of the approach is to ensure that corrective maintenance on equipment can be carried out long before a malfunction occurs, under favourable weather and operating conditions when signs of malfunction occur. Figure 1 shows a schematic description of the fault detection and response in grid operation using the conventional grid operation and WAT technology, respectively.

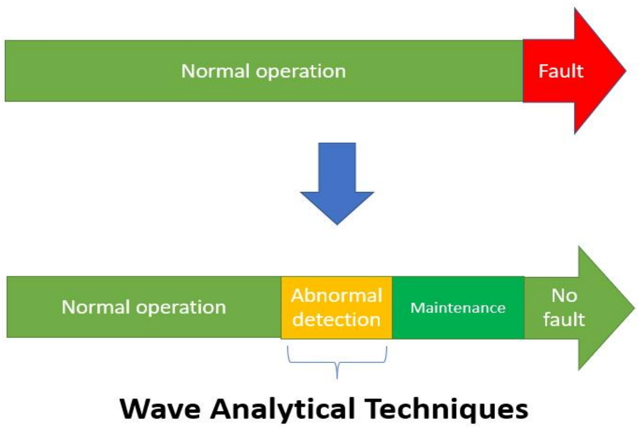

Figure 1. Schematic description of the fault detection and response in the grid operation under WAT technology

The principle of the WAT approach is shown in Figure 2. The concept is based on the detection of the pre-fault condition through current and voltage waveform records.

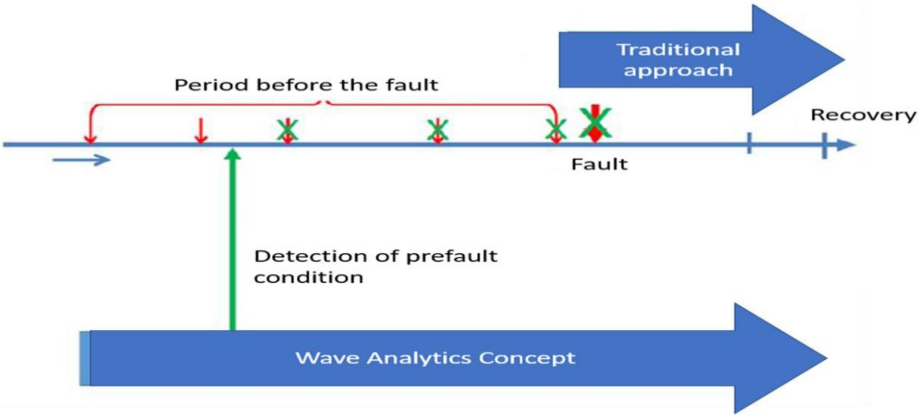

Figure 2. Principle of the WAT approach

3. Results

3.1. WAT algorithms developed in the study

Within the scope of the project, different methods used in electronic engineering and data processing were brought together and new and unique algorithms were developed and coded to be applied to the measurements taken from current and voltage waveforms. The main software developed within the scope of the project was written using Python 3.4 programming language. During the project, field tests were carried out and the effects of these tests on waveforms were examined and algorithms were written to detect them. These algorithms are:

- Algorithm for detecting load connection to voltage transformer (GYB algorithm)
- Algorithm for detecting similarities of different RMS waveforms (DZB algorithm)

3.1.1. GYB algorithm

The GYB algorithm is used at MV distribution centres in rural areas where there is no transformer for internal loads. It has been developed to detect the deteriorations that occur as a result of connecting the loads to rectifiers used to charge the battery groups feeding the DC equipment to the secondary of the measurement voltage transformers. The measuring equipment in the electrical distribution centres receives signals from the measuring voltage transformers. Meanwhile, if devices other than the measuring device are connected to the secondary of the measuring voltage transformer and these devices are drawing loads through the voltage transformer, this causes the measuring device to read voltage signals that are subject to periodic distortions. However, in reality, there is no deterioration in the voltage of the 34.5 KV busbar. Therefore, this situation causes power quality measurement devices to take measurements as if there is high distortion in voltage waves, especially the total harmonic distortion (THD) value by making wrong readings.

Distinguishing steps of the algorithm that can detect the load connected to the voltage transformer has been determined through measurements and tests carried out in the field. The most important distinguishing feature of this problem is the periodicity in the THD value in voltage measurements. The rectifiers connected to the secondary voltage transformer is activated when the charge rate of the batteries drops below a certain level, and they are switched off when the batteries reach a certain level of charge. This causes the THD in voltage measurements during the day to increase during the load time, and then, after the batteries are charged, the distortion level returns to normal. For example, measurement results taken from the ALCI substation of ADM DSO on 09.09.2018 are shown in Figure 3. In the upper panel, flickering occurs at the peaks of the red sine wave (one of them is circled in blue). In the lower panel, the THD value is seen as 3.4%. The THDS value of the ALCI Root MV bus voltage value measured under normal conditions is around 1%; this increase in the THD value is due to the flicker.

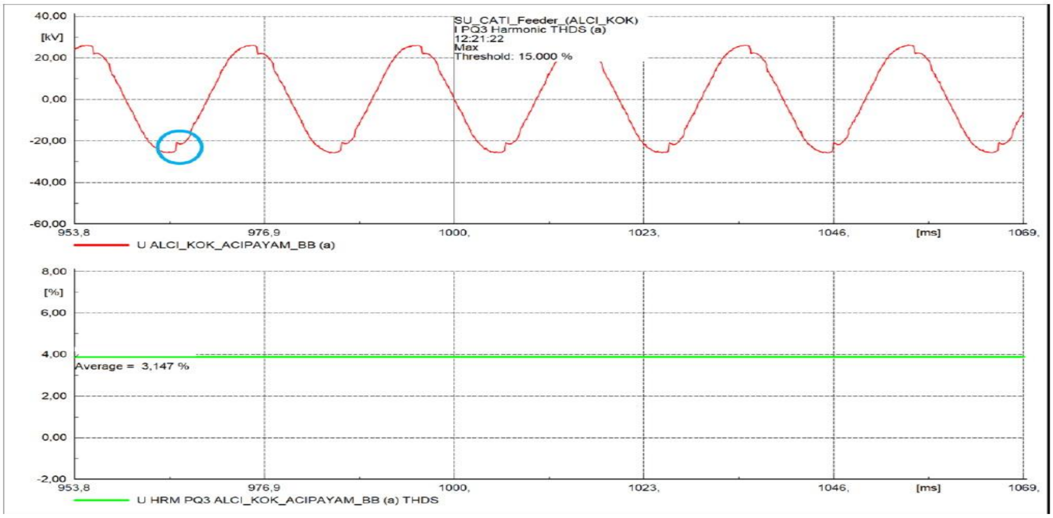

Figure 3. Voltage distortion example due to load connection to measurement voltage transformer

When the aforementioned flickers are examined for longer periods, it has been determined that flickering occurs for about 60 seconds; then the flickering stops for about 2 seconds and then reappears, and this situation repeats itself periodically during the charging time of the battery packs. In Figure 4, RMS measurement results of approximately 5 minutes in the same centre are shown. The upper panel shows the voltage THD value; the second panel shows the RMS value of the measured voltage; and the third panel shows the active and reactive power values drawn from the feeders that supply the substation. When the graphs are examined, it is seen that the THD value decreases from 4% to 1% every 60 seconds (i.e., the flickering explained above disappears), stays here for about 2 seconds and then rises to 4% again. In the same period, it is seen that there are periodic increases in the voltage graph, but there is no change in the total drawn current (power values). If there was a periodic deterioration in the voltage of the 34.5 kV busbar as mentioned, it can be evaluated that this would only be possible with very high-power draws that disrupt the voltage in the network. However, when the graphs are examined, such a power draw is not seen from the feeders in the centre. This is a distinctive feature that indicates the load connected to the voltage transformer.

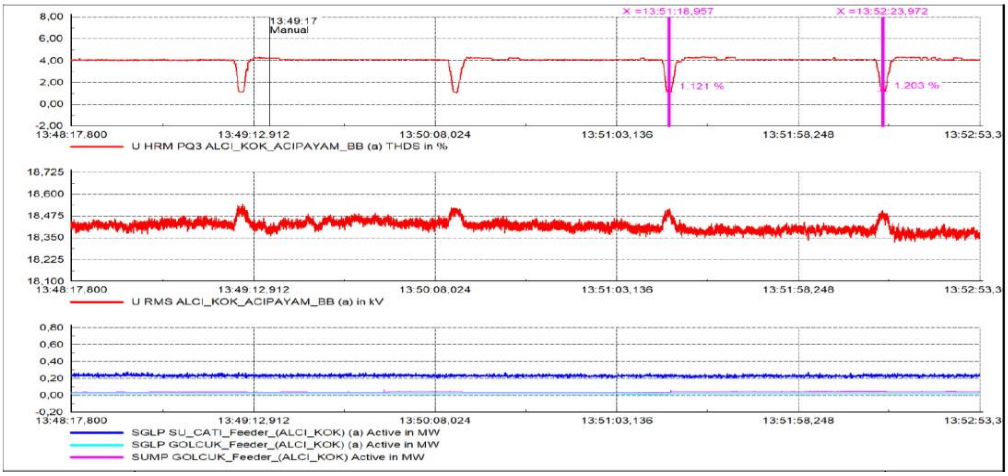

Figure 4. Periodicity in the THD value, voltage values and total load drawn from the feeders

3.1.2. DZB algorithm

The most important feature of the project is the development of smart algorithms that can detect rapid changes or differences in current and voltage waves that cannot be distinguished by the human eye. The DZB algorithm has been developed exactly in this context and is an algorithm that uses the latest examples of data processing techniques. This algorithm allows the shapes of the RMS measurements to be compared with each other and to reveal the similarities in these shapes. The DZB algorithm uses the 'dynamic time warping' technique, which is used to detect similarities in sound waves.

The DZB algorithm can detect whether an event that has occurred before in a feeder is repeated later and if it does, on what dates. In this way, faults that started to appear beforehand and started to show themselves in certain ways in RMS measurements can be detected quickly with this algorithm. Different variations of this software have been developed in the study. The user can compare the shape of any two RMS measurements he wants through the software. In this way, indistinguishable similarities can be revealed by the algorithm.

Dynamic time warping is used to compare two time series. The DZB technique creates a so-called penalty matrix to compare two time series. If two waveforms compared to each other are called X and Y waves, then the inputs of the penalty matrix are the difference between each point of the X wave and each point of the Y wave. In Figure 5, the penalty matrix created in MATLAB for an example X and Y waves is shared. As the difference between the relevant point of the X wave and the relevant point of the Y wave increases, the penalty matrix becomes white, and as the difference decreases, the colour evolves towards black. When comparing the two waveforms, DZB calculates the total penalty using the penalty matrix. If the total penalty exceeds a certain threshold value, then it is deduced that the two waveforms are far from being like each other. The total penalty value consists of the sum of the penalty matrix entries on the path from the bottom left corner of the penalty matrix to the top right corner, following the rules below. This path is called the 'bending path'. For the NxM penalty matrix, the path that satisfies the following three rules simultaneously is called the inflection path:

- Rule 1: p1 = (1.1) and pL = (N, M)
- Rule 2: Monotonic increase
- Rule 3: Step increment condition: pl+1-pl ϵ {(1.0), (0.1), (1.1)}

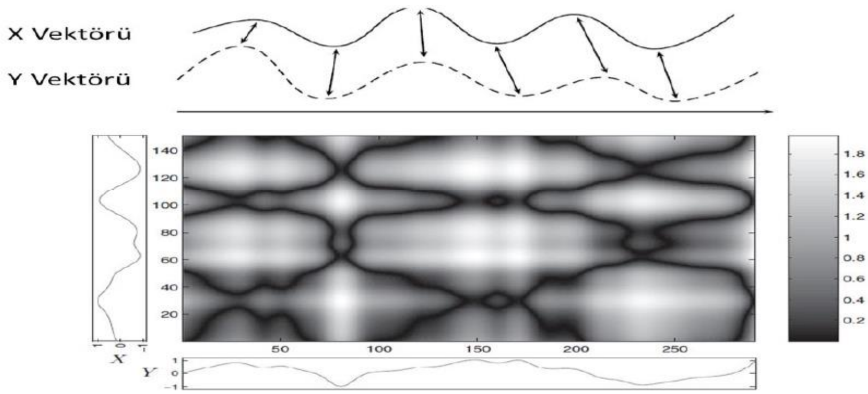

Figure 5. Creating the penalty matrix for X and Y waves

Rule 1 states that the bending path should start at the bottom left corner entry of the matrix and end at the top right entry. Rule 2 requires that there be no reduction in the number of columns or rows while moving on the bending path. Rule 3 requires increments to be made in columns and/or rows as a maximum of one cell while advancing on the bending path. An example bending path is plotted on the penalty matrix in Figure 6. The path drawn in yellow is not a bending path as it does not comply with the monotonic increase rule (Rule 2). The path drawn in white shows the bending path. The way of bending is also a punishment as it is the only path with the smallest penalty and the only way to go to the lower left upper right corner of the matrix. In the penalty matrix, the bending path design is considered.

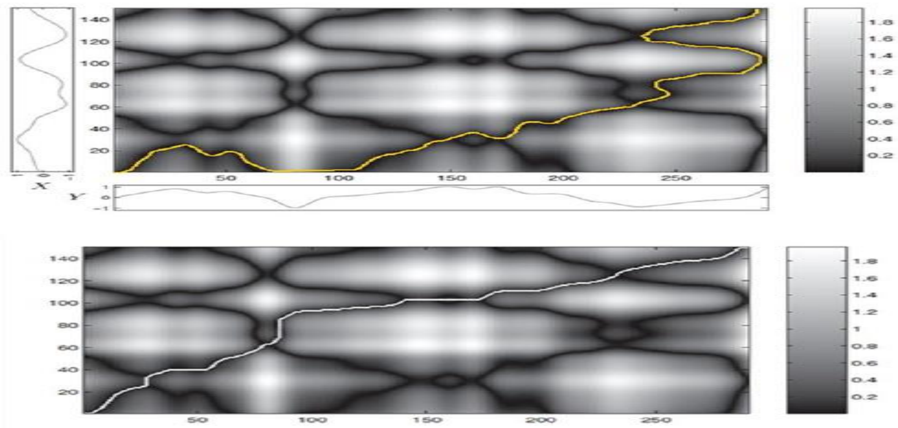

Figure 6. Indication of the bending path on the penalty matrix

An example penalty matrix is shared in Figure 7. In this matrix, it is possible to go from the upper left corner to the lower right corner by using only zero-input matrices in accordance with the definition of the bending path. In this case, the penalty value will be zero and it will be understood that the two waveforms being compared are very similar to each other.

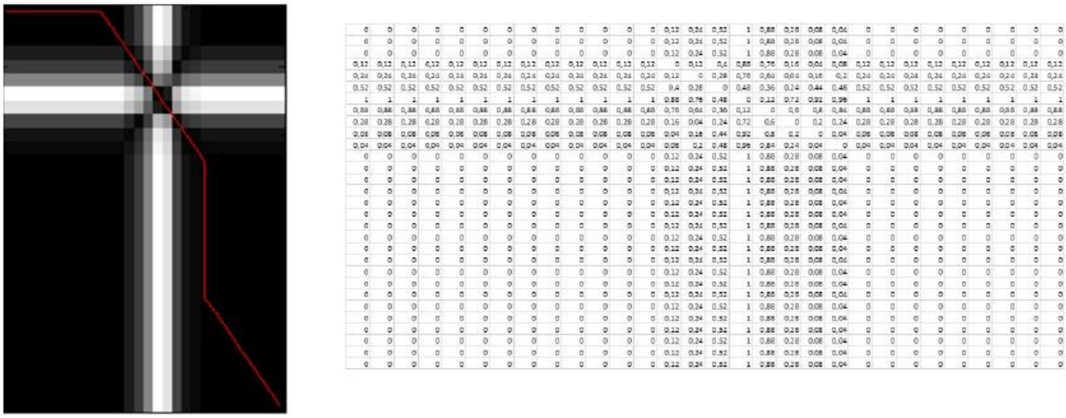

Figure 7. An example bending path (red in the left image) and the associated penalty matrix

In distribution networks, it is possible for waveforms created by the same event to appear in different structures as a result of measuring using different time, location, magnitude, duration and measuring devices. The waveforms created by the same event can be categorised into the following four ways:

- Time axis displacement or shift;
- Scaling;
- Bending or extending its time;
- Noise.

The different appearance of waveforms on sample figures is shown in Figure 8. If the wave, which is caused by the same root cause, occurs in different ways due to the reasons explained above, then the penalty values calculated with the DZB technique can produce suggestive results. Waveforms with the same root cause appearing in different shapes due to the reasons explained above were examined with the DZB technique and the penalty values were calculated as shown in Figure 8. As a result of comparing two different waves with each other, a very high penalty value was calculated compared to the penalty values calculated in the previous figures.

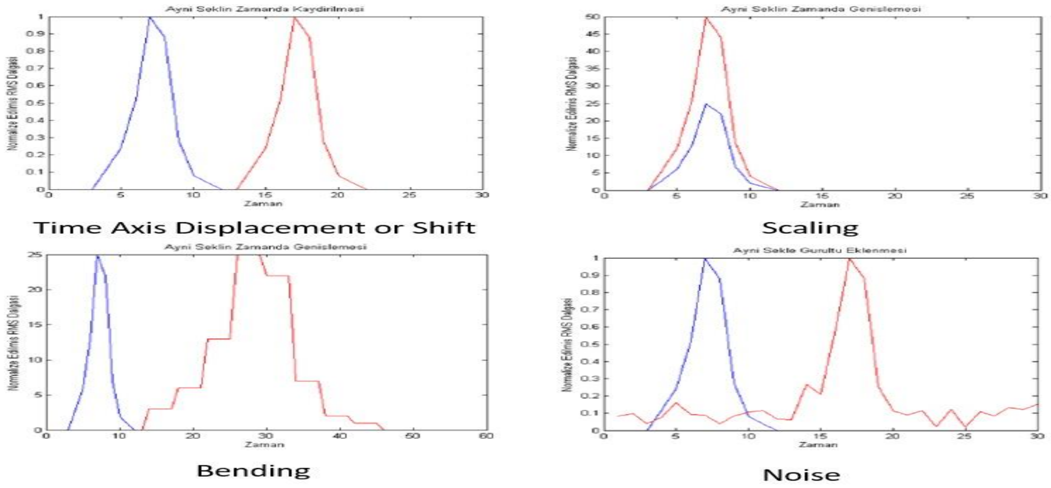

Figure 8. Waveforms created by the events look different

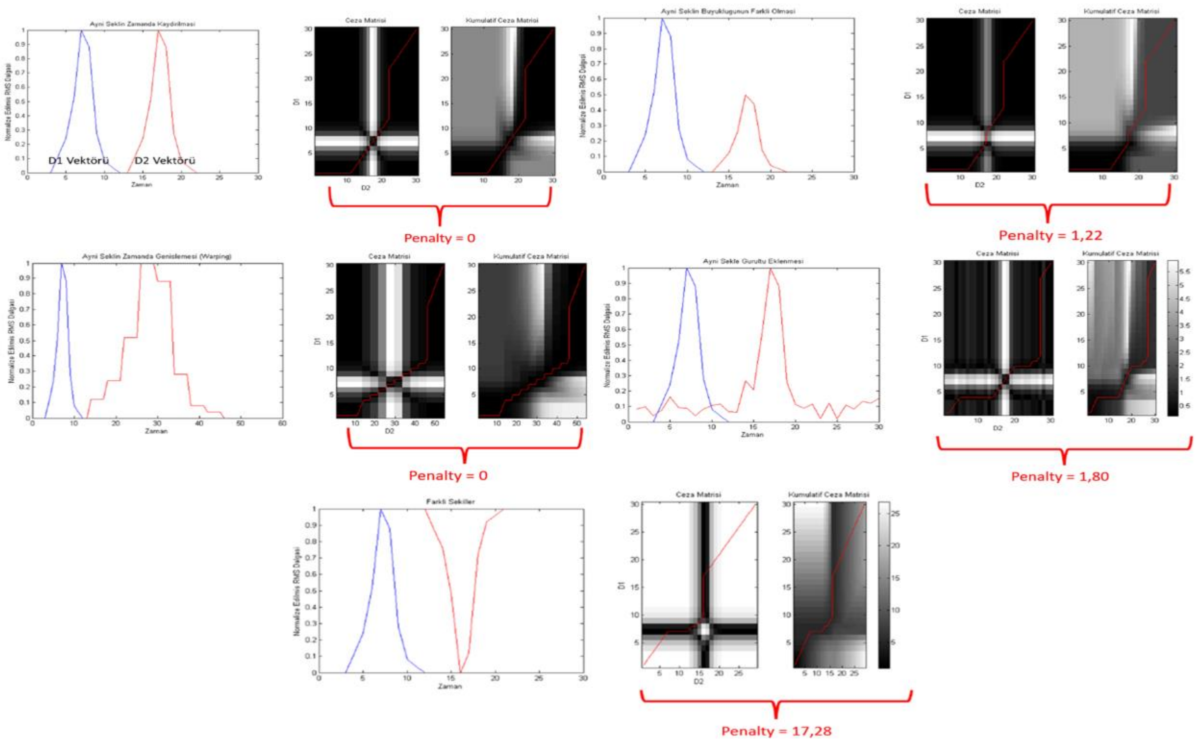

Figure 9. Penalty values

4. Conclusion

As mentioned earlier, the sum of the matrix inputs on the bending path gives the penalty value, which is an indication of how similar the two waveforms being compared are. The higher the penalty value, the more different the two waves are. The fault initiation detection approach, which is based on WAT, is described. The approach is based on AI-based machine-learning techniques, which accumulate experience in the current and voltage waveforms related to the failures.

Predictive methods are implemented at middle voltage distribution feeders of ADM Distribution Company, Turkey, successfully to determine the root causes of fault initiations on the feeders, which cannot be detected with today's modern SCADA and relay protection systems that are not designed to prevent failure.

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