Intelligent Systems for Monitoring the Integrity of Technical Objects Based on Distributed Fiber-optic Sensors

Ali Mekhtiev [1], Aliya Alkina [2], Alexandr Neftissov [3], Ilyas Kazambayev [3] and Lalita Kirichenko [3]

[1] *Saken Seifullin Kazakh Agrotechnical Universityy, 62 Zhenis Avenue, Astana, 010000, Kazakhstan*
[2] *Karaganda Technical University, 56 Nursultan Nazarbayev Avenue, Karaganda, 100000, Kazakhstan*
[3] *Astana IT University, Mangilik el street 55/11, Astana, 010000, Kazakhstan*

Abstract

This article provides an overview of existing intelligent systems for monitoring the integrity of extended objects based on distributed fiber-optic sensors. The results of the development of measuring systems using distributed fiber-optic sensors are presented. The analysis of existing solutions for constructing measuring systems is carried out. The main types of measuring schemes and principles of determining the integrity of extended objects are considered. The basic principles for the construction of fiber-optic sensors are defined. The analysis demonstrated achievements in improving measurement accuracy using various optical reflectometry methods. Shortcomings of measuring systems are revealed, and ways of elimination are established. Methods of filtration from overlays caused by mechanical overvoltages and temperature influences are considered. The difficulties of applying well-known works are determined. A review of the current state of development of artificial intelligence in the field of its application in measurement systems is carried out. It is revealed that the systems built based on an optical time domain reflectometer (OTDR) using a convolutional neural network (CNN) show higher quality indicators. The possibilities of using different types of neural networks to recognize various mechanical influences using machine learning are considered. The disadvantages and advantages of using neural network systems in measuring systems based on distributed fiber-optic sensors are identified, and the most optimal type is selected. The direction for further research and development of a technical condition monitoring system based on distributed fiber-optic sensors has been determined.

Keywords [1]

Fiber-optic sensor, optical fiber, monitoring system, neural network

1. Introduction

Currently, extended facilities are used to perform any technological tasks, a violation of the technical condition which can lead to small-scale or global accidents in the worst case. For this reason, intelligent continuous monitoring systems are needed to warn of integrity violations promptly. It is worth noting that the leading causes of damage can be both natural, and man-made phenomena, and sabotage, violations caused by the human factor. Special systems based on an optical time domain reflectometer (OTDR) are used to monitor the technical condition and ensure the safety of extended facilities. The systems consume a small amount of electricity, and electromagnetic interference is not induced in them. Sensors with phase-sensitive reflectometry are the most widely used, due to their sensitivity to mechanical vibrations. At the same time, increased sensitivity is the cause of false positives, which leads to an excess of information. Standard solutions do not allow for obtaining reliable results; therefore, it is necessary to improve the systems. Most often, such a solution is to amplify the optical signal [1]-[10]. Moreover, it is possible to determine the distance to the source of mechanical

Information Technology and Implementation (IT&I-2022), November 30 - December 02, 2022, Kyiv, Ukraine
EMAIL: barton.kz@mail.ru (A. 1); alika_1308@mail.ru (A. 2); shurik-neftisov@mail.ru (A. 3); ilyaskazambayev@gmail.com (A. 4), lalita17021996@gmail.com (A. 5)
ORCID: 0000-0002-2633-3976 (A. 1); 0000-0003-4879-0593 (A. 2); (A. 3); 0000-0003-0850-7490 (A. 4), 0000-0001-7069-5395 (A. 5);

deformations or vibrations by circulating the optical signal of the laser and the signal from the fiber under the test (FUT) [1], using Bragg gratings [2], by a phase shift of optical signals [3]. It is also possible to combine several of these methods [4], using a differential optical signal with a more straightforward design, but with a more complex software part [5]. In some cases, other approaches are used to implement the measuring part, in which a delay is created by installing a coil with an optical fiber [6]. At the same time, monitoring systems should consider the length of the distributed sensor and its impact on accuracy [6], [9]. Modernizing the hardware allows for solving problems with temperature influences and mechanical overvoltages. Despite this, before choosing or developing sensors, it is also necessary to pay attention to the complexity and cost of the design. The proof that non-traditional methods of constructing a measuring system are effective is presented in [14], [15].

Artificial intelligence systems are used to solve the problem of interference caused by humans and technology, namely, based on machine learning and neural networks. The result obtained is characterized by high accuracy in determining the source and nature of the alarming event [10]. Intelligent systems for determining the causes and location of accuracy are usually implemented using the method of error backpropagation [11], the method of filtering matches [12], and collapsing neural networks [13]. However, it should also be considered that the choice of the type of neural networks also depends on the number of samples, accuracy, and classification feature. The most widely distributed are collapsible neural networks due to their ability to process graphs and images [13].

Consequently, quite often, there are systems using distributed fiber-optic sensors built on phase-sensitive OTDR and CNN [13], which increases the device's cost, complexity, and size.

2. Methods and materials First level heading

Bibliometric analysis of the Elsevier group database (Scopus) was used as the main method when writing the article. 5,035 articles were found on this topic. The selection criteria for the study were: a) articles published from 2012 to 2022 were considered, b) systems for monitoring the state of extended objects used optical fiber as a sensor, c) systems for monitoring the state of extended objects had an intellectual component. The figure shows the statistics of the Scopus database on publications on this topic, broken down by year. Further, the research area was narrowed, and 20 sources were selected for analysis.

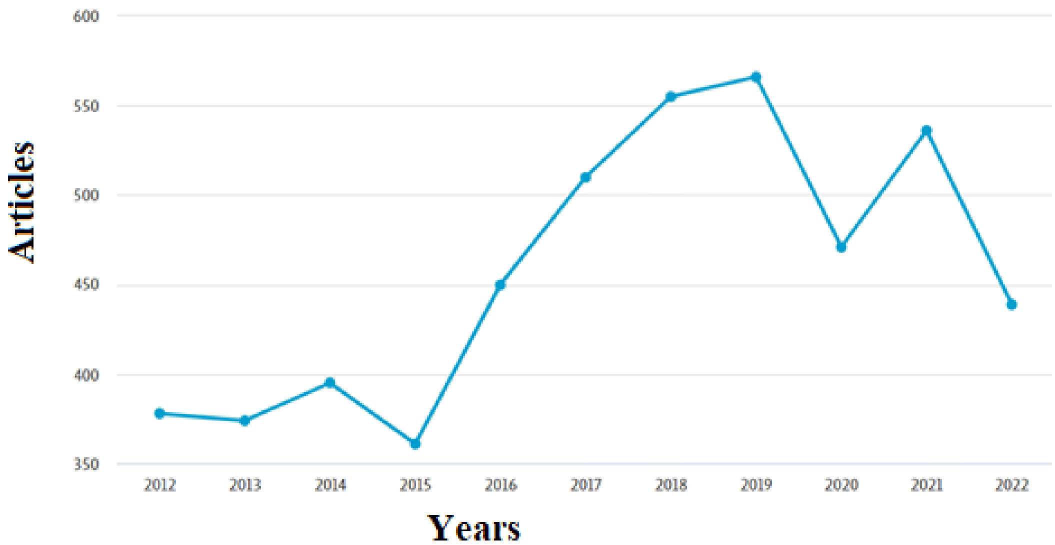

Figure 1: Statistics of published articles on the subject of the Scopus database by year

3. Measuring systems

When building the system, they are mainly used by the ϕ-OTDR, c-OTDR method. Moreover, each system performs certain functions, but the main direction developed is monitoring the state of extended objects. For ϕ-OTDR systems, interferometry systems are the most common [1]. The principle of interferometry: an optical information cable receives a signal in the form of a laser, which is then divided into two using special devices. In the first cable, the signal passes without delay, and in the second, the delay is generated using an optical fiber wound into a coil. The signals from the two cables are combined and sent to the photosensitive elements. The received signal can be processed as a dependence of light intensity on time. However, interference is easily induced in such a system. Therefore, the use of artificial intelligence is necessary. For example, in [1] the main instrument for measuring is an interferometer that determines the phase shift of the laser.

A pair of unbalanced Mach-Zender interferometers (MCI) with a time delay, created by a fiber, having a length 500m, was used as the measuring instrument of the HSL to measure the phase of the signal determined by time bands. The signal is represented as intensity and is measured by a photodetector (Figure 2). To eliminate interference, acoustic-optical modulation (AOM), which increases the optical signal amplitude, and an erbium-doped optical amplifier (EDFA), which restores the optical signal level, were installed in the standard circuit.

A laser with a small bandwidth frequency range acted as a source of information in the ϕ-OTDR system to achieve high efficiency of the adaptive pulse period (API) method, and low-frequency vibrations were measured.

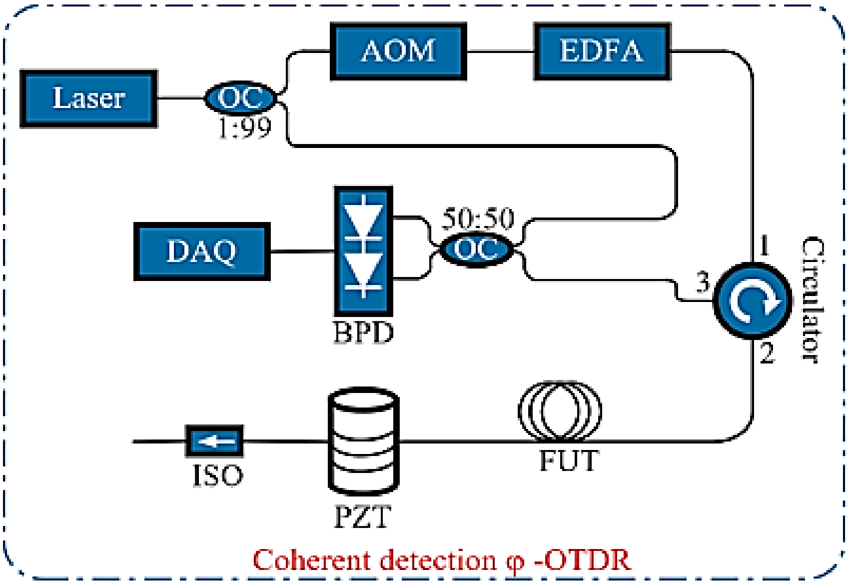

Figure 2: Adaptive pulse period system [1]

To exclude errors from thermal or other types of external influences, both MCI were performed isolated. Thus, the photodetector could record the purest signal in the form of a pseudo periodic sinusoid. Moreover, the HSV depends on the period of this graph and can be written in the form of the formula (1)

$$\alpha = \frac{c}{n \cdot \Delta L \cdot \tau_f}, \tag{1}$$

where α is the laser frequency shift, τ_f is the pseudo–period of the signal intensity, c and n are the amount depending on the speed of light in space, and the refractive index.

A laser with a bandwidth of 100 Hz and a wavelength of 1550 nm was chosen as the source of information. The laser light passes through an acoustic-optical modulator (AOM), and a fiber-optic amplifier (EDFA), and the already amplified signal passes through the fiber operating under the test (FUT). At the same time, through an optical connector (OC) with a ratio of 1 to 99, the optical signal from the laser enters the data acquisition board. The piezoelectric transducer generates mechanical vibrations using an electrical signal of a certain frequency. The reflected optical signal enters the optical connector (OC) with a 50-to-50 ratio and enters the photodetectors, the output signals recorded by the data acquisition board [1]. The standard phase-sensitive system is susceptible to mechanical and temperature overvoltages; the proposed system can work and consider these interferences. Moreover, polarization for this device is carried out by adding devices for frequency shift modulation and signal amplification. Therefore, interference imposed on the optical signal does not affect the operation of the device. However, it is worth noting that such a fiber-optic sensor has a complex design and does not consider the influence exerted by man and technology. At the same time, the study's results are presented for a rather short length of an extended object [1].

The design of the system proposed in [2] is shown in Figure 3. The technological process of determining the presence of vibration is similar to the above. However, in this case, two acousto-optic modulators (AOM1, AOM2) with different frequency shifts of 120 and 200 MHz were used. Moreover, the information received by the photodetector (PD) is then processed by special data collection and further processing systems (DAQ) and (Data Processing), respectively. Signals passing through special Bragg gratings (UWFBG1) – (UWFBGn) allow you to determine the distance to the source of vibrations. A light circulation device (Cir) makes it possible to achieve signal polarization. The pulse source (PG) creates a sinusoidal signal for modulation.

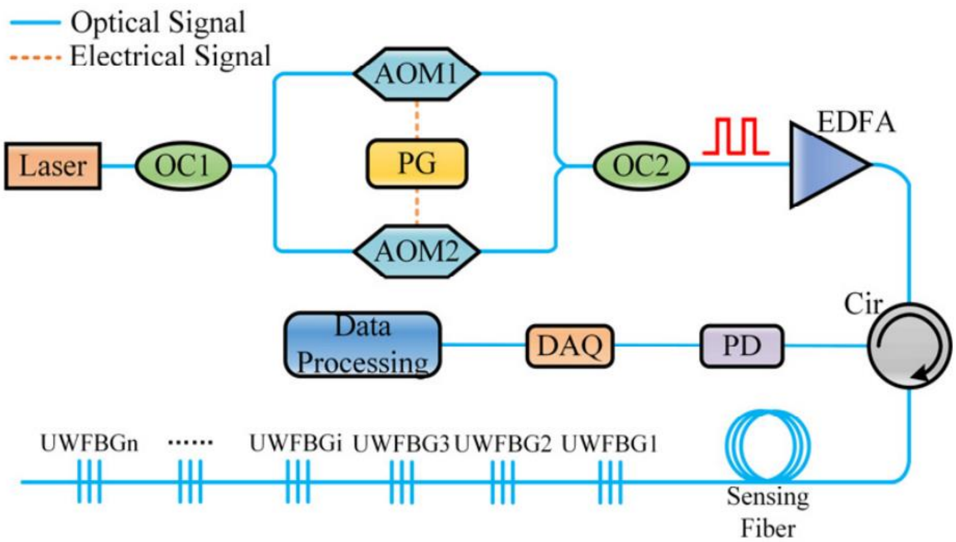

Figure 3: Block diagram of the system [1]

The experimental model was tested using a special vibration exciter, a feed stream with a frequency of 150 Hz. The phase value also changed with increasing current and amplification of the amplitude of mechanical vibrations (Figure 4). At the same time, the polarization-phase fusion unfolding algorithm differs from standard methods in its ability to accurately measure dynamic deformations based on restoring the actual phase signal from the raw with an amplitude signal. Such changes made it possible to achieve an extensive range of amplitude measurements, determined by the polarization signal, and good sensitivity, determined by the phase signal. However, the use of several Bragg gratings complicates the design and reduces the reliability of the whole system. Although it becomes quite easy to detect the damage's specific location, the system can also not recognize interference caused by humans or machinery.

In [3], a Sagnac interferometer in a fiber-optic vibration sensor was used for the perimeter security system to measure vibration. The task of this device is to polarize the signal, and the design is shown in Figure 5. Polarizers eliminate interference in the cable during measurement, and signal sources create the phase difference during mechanical deformation in the cables clockwise (CW) and the cable counterclockwise (CCW) in a closed system. In turn, the delay is created using special coils and polarizers. Thus, the intensity of the interference light becomes less sensitive to phase differences or minor vibrations close to zero. As an element that creates an electrical signal, a piezoelectric cylinder is used on which a polarizer is installed. In this case, the output signal $P(t)$ can be determined by the following mathematical expression

$$P(t) = K[1 + \cos(\Delta\varphi + \varphi_c cos 2\pi f_m t)], \quad (2)$$

where K – is the amplitude parameter, ν- is the interference efficiency, $\Delta\varphi$ – is the phase difference.

The phase modulation depth parameter φ_c is determined by the formula

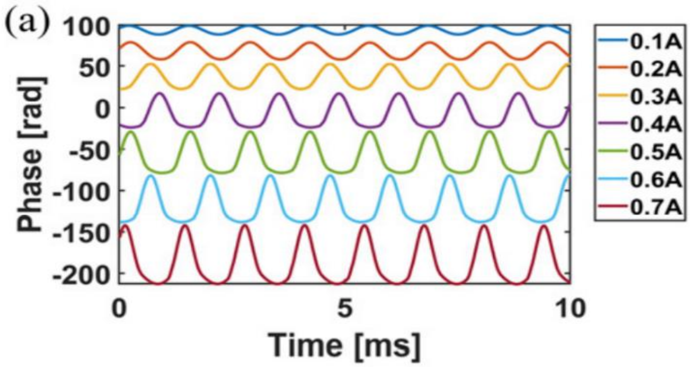

Figure 4: Graph of the phase value depending on the laser current strength [2]

In [3], a Sagnac interferometer in a fiber-optic vibration sensor was used for the perimeter security system to measure vibration. The task of this device is to polarize the signal, and the design is shown in Figure 5. Polarizers eliminate interference in the cable during measurement, and signal sources create the phase difference during mechanical deformation in the cables clockwise (CW) and the cable counterclockwise (CCW) in a closed system. In turn, the delay is created using special coils and polarizers. Thus, the intensity of the interference light becomes less sensitive to phase differences or minor vibrations close to zero. As an element that creates an electrical signal, a piezoelectric cylinder is used on which a polarizer is installed. In this case, the output signal $P(t)$ can be determined by the following mathematical expression

$$P(t) = K[1 + \cos(\Delta\varphi + \varphi_c cos2\pi f_m t)], \tag{2}$$

where K – is the amplitude parameter, v- is the interference efficiency, $\Delta\varphi$ – is the phase difference. The phase modulation depth parameter φ_c is determined by the formula

$$\varphi_c = 2\varphi_m \sin(\pi f_m t), \tag{3}$$

where φ_m– amplitude of the phase modulation depth.

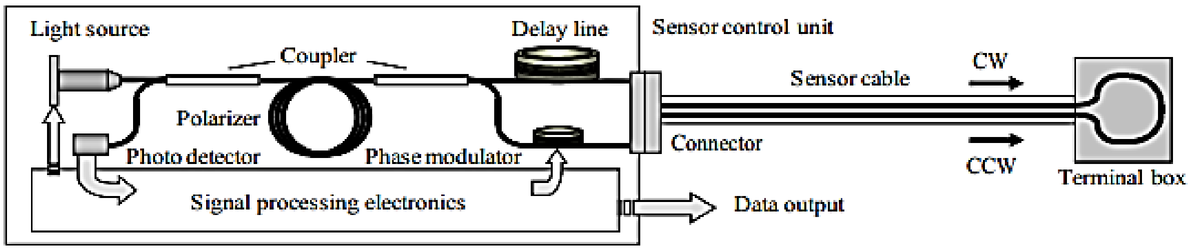

Figure 5: Optical vibration sensor design [3]

A fiber-optic sensor with single-point sensitivity is not enough to determine the location of the vibration source. The solution to this problem is to remove the delay line to reduce sensitivity. The sensor cable with flat sensitivity cannot detect the vibration position, so the delay line must be removed to reduce its sensitivity. At the same time, two sensors were used to determine the distance. The sensors were installed in such a way that the first sensor next to the terminal box had the least sensitivity to vibration, and the second sensor located next to the connector, on the contrary, had the maximum sensitivity to vibration. To determine the location is calculated by the ratio of the difference between the output signals to their sum.

The proposed system can process signals from interference, which is good for zone security systems and unauthorized access. However, the system cannot distinguish between other interferences. Vibrations from interference are the causes of a false alarm, due to which standard data processing systems will not be able to work correctly [3].

[4] shows the results of monitoring deformations of the artificial tunnel "Calabrese", performed using a distributed fiber-optic strain gauge based on stimulated Brillouin scattering. Field tests conducted using the BOTDA prototype are shown in Figure 6. The BOTDA sensor was used to determine the distribution of mechanical stresses along the two side walls of a 200 m long railway tunnel. It consists of eight adjacent sectors separated by joints with uneven spacing (the average length

of each sector is 25 m). Figure 7 shows the recorded data on the lengthening of the fiber in a time breakdown. The figure shows that in the second half of 2016, the fiber underwent elongation. After the measurement in June 2018, the fiber lengthened in all joints and even collapsed in several joints on the descent. The data obtained from fiber-optic sensors were then compared with data from Cosmo-SkyMed, which confirmed the presence of a landslide in 2018 in this area. Therefore, the experiment's results demonstrate the reliability of a fiber monitoring system for monitoring deformations of the tunnel structure.

The measurement of the system is not affected by the interference caused by mechanical overvoltages and temperature influences. At the same time, this solution allows you to determine the displacement of plates in the tunnel. The results obtained allow us to determine the technical condition of the object.

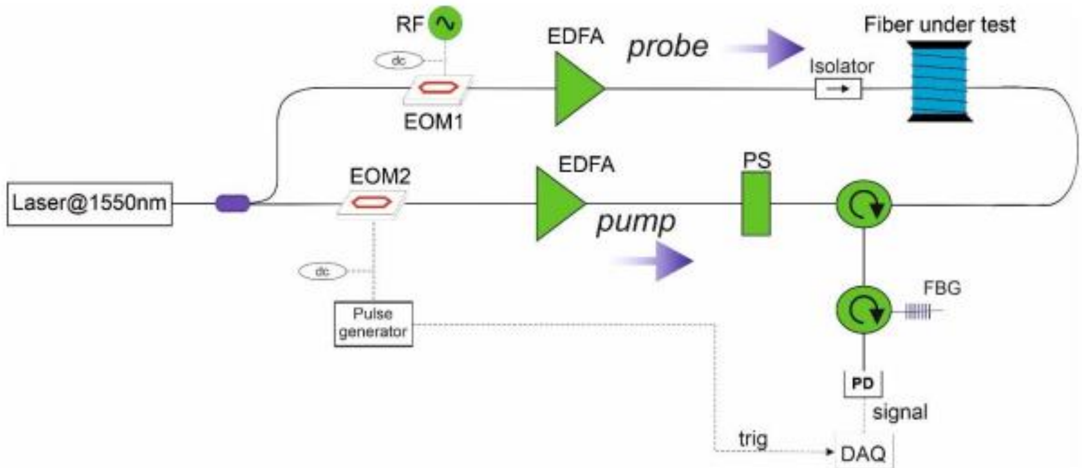

Figure 6: Experimental setup for optical analysis in the Brillouin time domain (BOTDA). (EAM1), (EOM2) - electro-optical modulators; (PS) - polarization switch; (EDFA) - erbium-doped fiber amplifier; (PD) - photodetector; (FBG) - Bragg fiber array; (DAQ) - data collection [4].

The solution described in [5] suggests using a difference signal of phase-sensitive reflectometry using deep learning systems to distinguish alarming events. The design of this system is shown in Figure 8. A laser is used as a source of information, sending a signal, amplified by a semiconductor optical amplifier (SOA) optical amplifier (EDFA). The signal is filtered from possible fluctuations, and then through the coils, the signal enters the sensing element. The use of an additional EDFA and filter allows you to collect data without interference.

By comparing the input and output signals, it is possible to determine the source of vibration and its location. The proposed system involves the use of deep learning, since in its absence the system cannot give an accurate result, namely, it cannot distinguish interference caused by a person or the movement of a machine from an alarm signal. The solution for the monitoring system requires a lot of space and complicates the structure of the system and its price. Having many devices to improve accuracy can also reduce the normal operation time of the device.

The system in [6] is designed to monitor the technical condition of power cables extended underwater (Figure 9). A 20 MW signal is generated as a light pulse with a duration of 8 ns by a distributed feedback laser (DFB) wavelength of 1550 using a DVS measurement unit based on ϕ-OTDR. Then, the optical signal is amplified by a fiber amplifier (EDFA 1) to increase the peak power to 1 watt to eliminate interference. EDFA 1) to increase the peak power to 1W to eliminate interference. The amplified signal is then filtered using a wavelet transform, the bandwidth of which is 100 GHz, and enters the sensor element through the circulator. Through the fibers from the cable under test.

As a result, the system can detect mechanical deformations of power cables under water. At the same time, the amplification of the optical signal makes it possible to eliminate interference caused by fluctuations in the information source. At the same time, such a system cannot be adapted to other extended objects since it does not consider temperature influences and mechanical overvoltages.

The possibility of using a Rayleigh reflectometer or C-OTDR is also considered [7]. When using these reflectometers, optical signals, usually generated in the form of pulses, are fed into the optical fiber at certain points in time with a period defining a "slow" time scale to determine transients in backscattering.

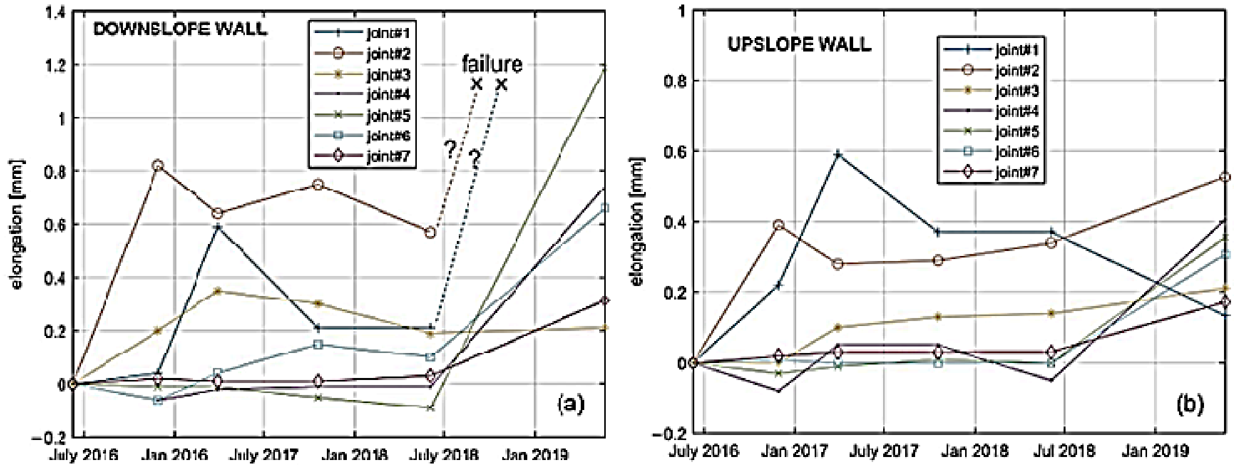

Figure 7: The relative elongation of the optical fiber over time, corresponding to the tunnel connections along (a) the up-sloping and (b) the down-sloping side walls [4].

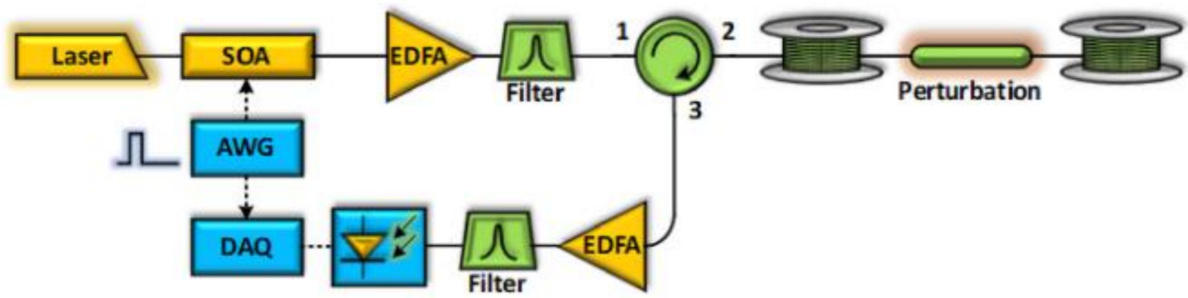

Figure 8: Diagram of the OTDR differential signal measurement system [5]

For each pulse, the value of the backscattering intensity is selected at a certain point in time with a constant interval during the passage of the laser pulse in the optical fiber. At the same time, to determine the intensity of the optical signal at a certain time, it is calculated as the sum of incoherent Iinc and coherent Icoh components. At the same time, the amount of information for processing is reduced, but the information at a certain point in time is sufficient to determine the location of the vibration source.

The proposed method can work accurately to determine fluctuations in extended blocks. Unlike conventional ϕ-OTDR systems, the information coming from the photodetector is less, allowing for a short period to obtain accurate data. The main disadvantage is the complexity of the system and the calculation of fluctuations. Thus, in the presence of many accidental external influences, the system's operation may be incorrect. The study presented in [8] should also be noted to select a monitoring system. Choosing a measuring system with high accuracy and sufficient sensitivity is usually challenging to detect a violation of integrity or changes in technical conditions. An experiment was conducted to compare the ϕ-OTDR and OTDR interferometry systems (Figure 10).

In both cases, a narrow-band laser with distributed feedback (DFB-FL) with a power of 10 MW and a bandwidth of 5 kHz was used. The laser creates an optical signal, amplified using an acoustic-optical modulator (AOM), an optical amplifier doped with erbium (A). The amplified signal is filtered by a fiber-optic lattice filter (F) and enters the circulator (C), which is again converted by devices F and A. The installation for the ϕ-OTDR system uses a standard optical connector, where the signal is divided and fed to three photodetectors (PD1-PD3). In the case of OTDR interferometry, an additional connector is used, from which signals are sent to two rotating Faraday mirrors.

The obtained results showed that in the case of standard ϕ-OTDR systems, the polarization was insignificant, and for the OTDR interferometric system, the polarization was performed independently of the input and output optical signal and was reduced. The use of both methods has demonstrated that phase-sensitive reflectometry is less sensitive than interferometric. However, the use of rotating

Faraday mirrors in the system increases the design and complicates the system, and may affect the reliable operation of the system

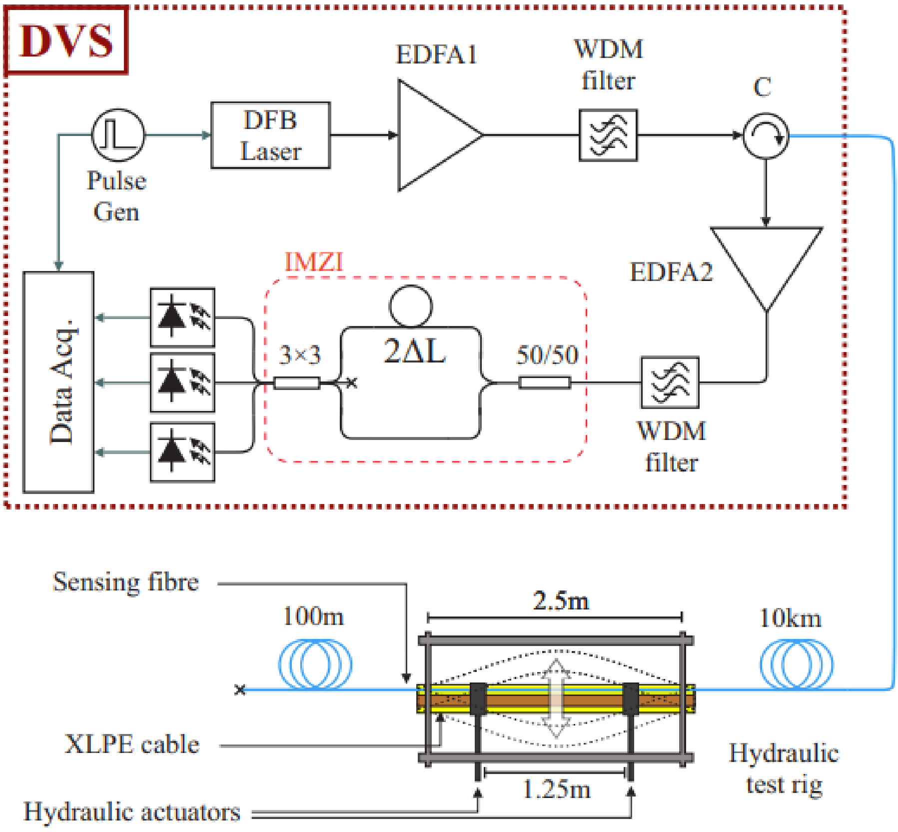

Figure 9: Monitoring scheme of underwater power cables [6]

Systems for monitoring the technical condition of facilities with a length of up to 75 km were presented in [9]. The measurement principle is based on the use of a laser diode with a wavelength of light of 1480 nm. The WDM device then converts the optical signal into a signal with a wavelength of 1550 nm. The signal is then distributed through a circulator (CIR), amplified using an erbium-doped optical amplifier (EDFA), a narrow-band laser (NLL) with a wavelength of 1550 nm, an acoustic-optical modulator and an EDFA optical amplifier, and through the next circulator (CIR) enters the Bragg array and a photodetector from which information is received to the data collection card (DAC). Piezoelectric transducers were used to determine vibration, to which a signal from the function generator (FG) was applied.

The results obtained during the study [9] demonstrate the device's accuracy for objects with a length of up to 75 km. Amplification schemes allow you to eliminate interference in a helpful signal; however, the system for such objects may be inaccurate since the number of spatial points for random effects increases.

At the same time, well-known methods using interferometers are widely used since they are able to work accurately, but traditional methods do not imply a solution to eliminate interference. The proposed articles above offer solutions to eliminate interference caused by undesirable mechanical, and temperature influences. At the same time, these systems are difficult to apply in a more complex environment, where undesirable mechanical influences are not just natural, but also man-made. The main disadvantages of the use of interferometers are their complexity, size, and cost, as well as the small resolution of the receivers. In further studies, more optimal options are proposed for the implementation of a cable protection system relative to the measuring device.

The device designed by the authors does not use known solutions for the construction of fiber-optic sensors: optical interferometry, reflectometry, fiber Bragg gratings, or long-period fiber gratings. A quartz single-mode sensor of the G standard was used as a sensitive sensor.652. A light spot profile is used to identify the impact on the sensor. The advantages of the developed system are the cost and the possibility of practical implementation in mines, where the requirements for the safe operation of systems and devices are increased.

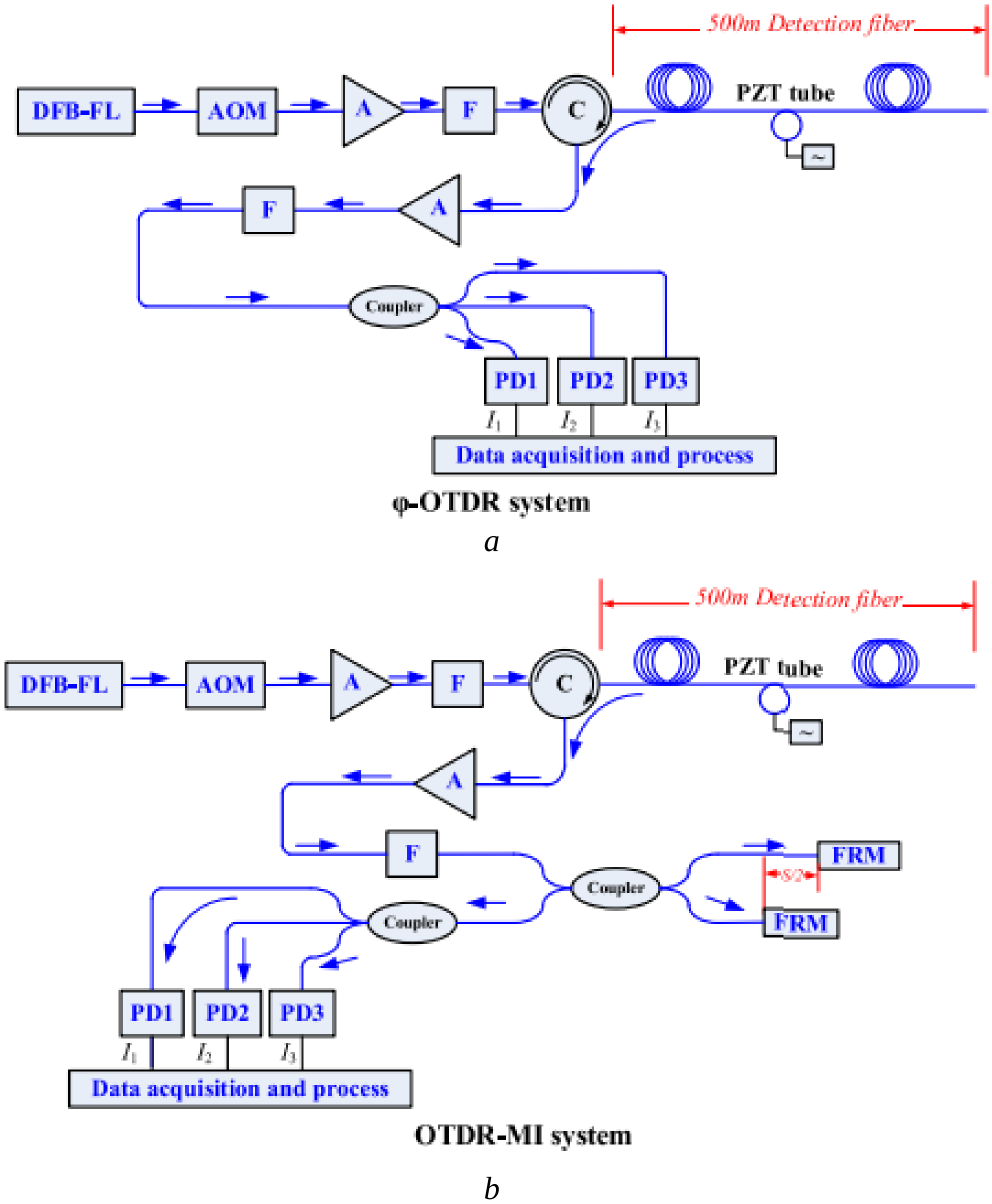

Figure 10: Experimental scheme for φ-OTDR (a) and OTDR interferometry (b) [8]

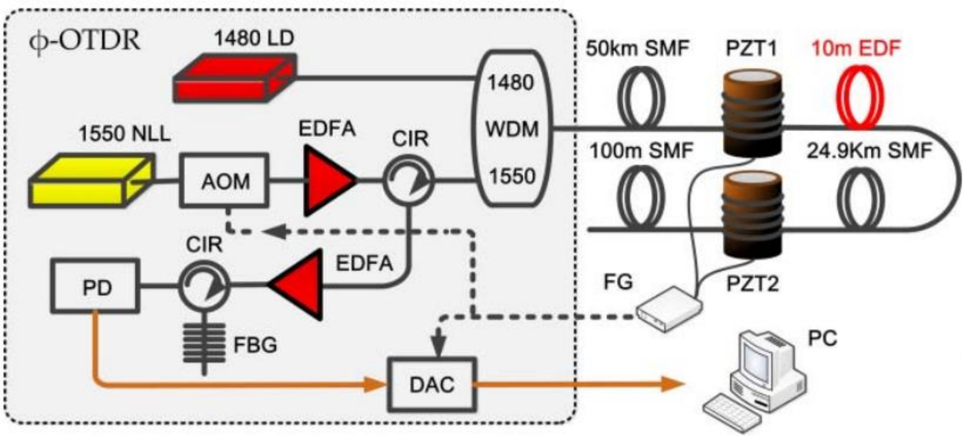

Figure 11: Data collection scheme for extended objects [9]

In [10], fiber-optic sensors were developed to control the pressure measurement on the elements of the shaft supports, and their design is shown in Figure 12.

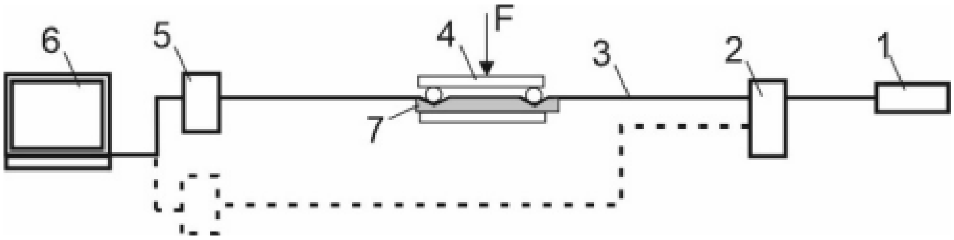

Figure 12: Block diagram of the sensor device for monitoring the pressure measurement on the elements of the shaft supports: (1) radiation source, (2) optical splitter, (3) optical fiber, (4) clip, and micro-connector, (5) CMOS photo matrix, (6) personal computer, (7) software. [10]

4. Application of artificial intelligence

Machine learning in extended object monitoring systems with the fiber-optic sensor system is used to eliminate interference and noise and improve operation parameters.

In [11], a neural network is proposed to eliminate unwanted disturbances and interference in monitoring systems (interference caused by man, wind, mechanical overvoltage, and temperature) Φ-OTDR. The distributed security system detects human intrusion on oil or gas pipes, high-voltage cables, and large structures. It is based on the method of fiber-optic sensing to detect and localize multiple weak vibrations along the sensitive fiber. In the article, the interference is identified by distinguishing the neighboring measuring trends of the optical signal for the Φ-OTDR system. Dynamic signals when pulses are applied or their temporal sequence can also be obtained by accumulating periodic data collection at different points [T1, T2, ..., TM] for each spatial point, and then the analysis of temporal and spatial signals is performed, the results of the analysis demonstrate the development of alarming events at certain points in time (Figure 13).

Further, energy distribution coefficients are used to determine the event that occurred in the system. These coefficients are obtained by decomposing the signals. When the disturbance increases, certain coefficients increase, and an event can be identified by determining the growth. To separate the cause of an alarming event, namely human intrusion, from environmental interference, a 3-layer neural BP ANN is constructed. The BP ANN architecture is shown in Figure 14.

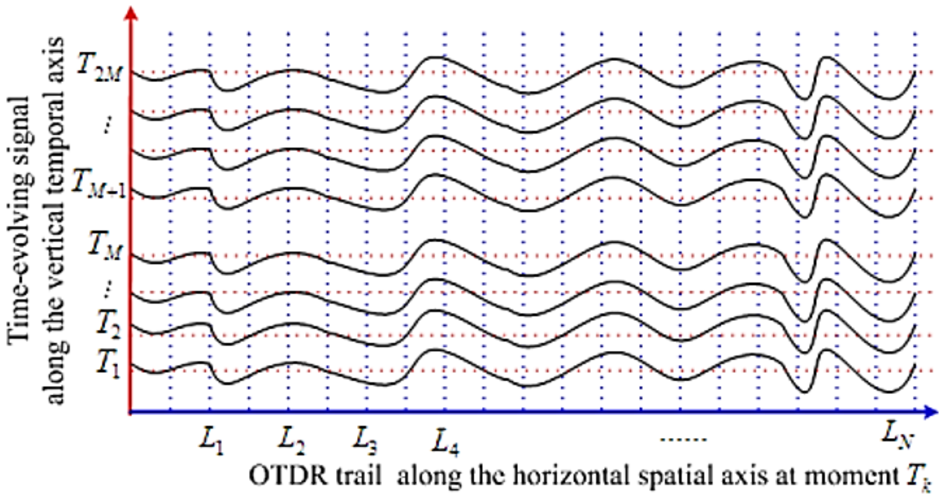

Figure 13: Alarm events traces [11]

The experiments showed the following results: Identification Rate (IR) - 89.19%, Probability of Detection (PD) - 86.15%, and Nuisance Alarm Rate (NAR) - 1.75%. BP ANN accuracy rates are inferior to solutions using other neural networks. The φ-OTDR zoonding systems use machine learning based on a feature extractor that uses coincidence filtering (MF)to eliminate interference and determine the nature of the impact in [12]. This method reduces noise effects only in disturbances.

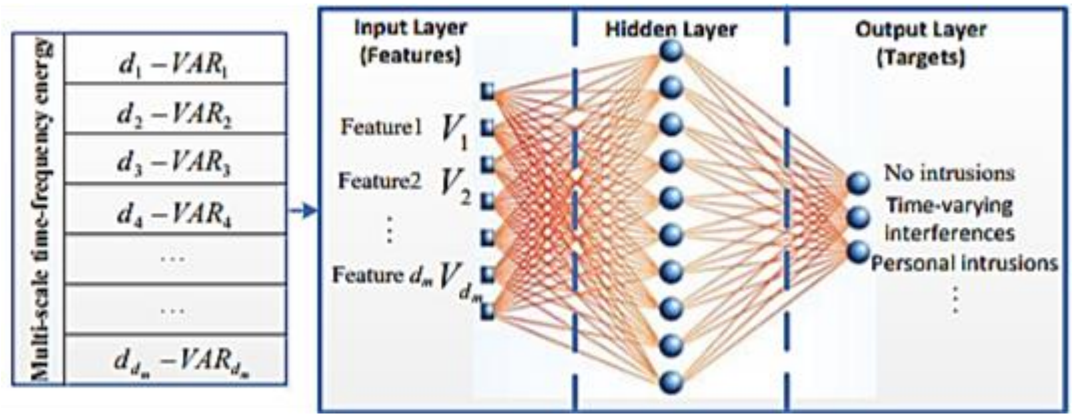

Figure 14: BP ANN Architecture [11]

The process of obtaining information about an alarming event is done by decomposing the optical signal. To extract the features, the Level Crossing (LC), Short-Time Fast Fourier Transform (ST-FFT), and Discrete Wavelet Transform (DWT) tools were used. The random forest (RF) algorithm was used to classify perturbation regions. According to the results, the measurement error decreases with the number of trends (Figure 15). The disadvantage of this method is that noise is reduced only point-by-point at the site of disturbances to reduce processing costs. In contrast, there are methods to reduce interference and noise for the entire sensing system.

The prediction is formed by the differential signal δ for each t^{th} time data-vector:

$$\delta_t(s) = \gamma_t(s) - \gamma_{t+1}(s), \tag{4}$$

For every t^{th} trace the equation is

$$\delta_t(s) = 2\sum_{y=1}^{Y-1}\sum_{z=Y}^{Z} r_y r_z\left[\sin(\varphi_y - \varphi_z) - (\varphi_y - \varphi_z - \varphi_\rho)\right], \tag{5}$$

Where φ_y and φ_z are the phasor angles of Rayleigh backscattering signal (RBS) time data vectors from the two regions of both location sides along with perturbation, r_y, r_z are the amplitudes of the according phases. The differential signal was acquired for the different numbers Y and Z of the samples for each region. The phase φ_ρ is the direct measurement of the particle displacement in the optic fiber and consists of both primary and unwanted phases:

$$\varphi_\rho = \mathrm{F}(\varphi_n + \theta_\rho). \tag{6}$$

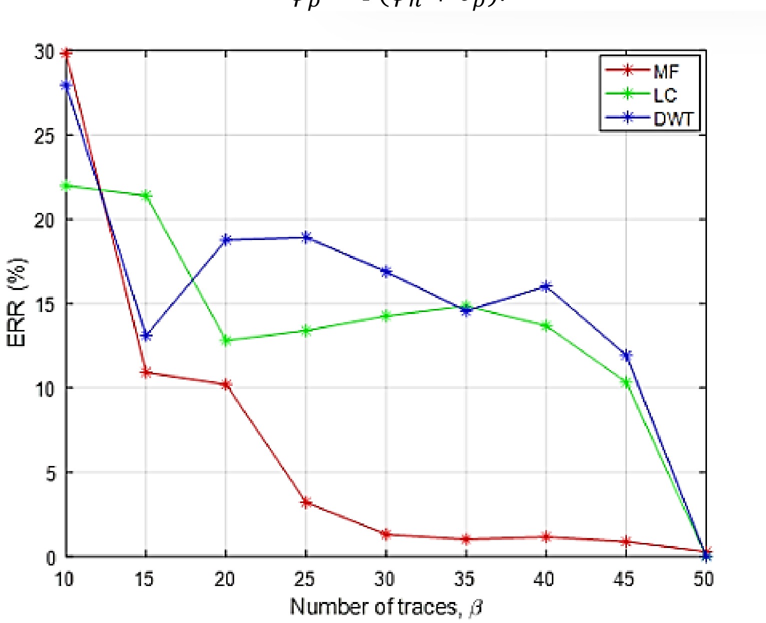

Figure 15: BP ANN Architecture [12]

Here F is the mapping function of the $\delta_t(s)$ representing the angle φ_ρ through combination of the φ_n and θ_ρ signals. Therefore, the correlation vector with consideration of the Spearman correlation coefficient is

$$R[n] = 1 - \frac{6\sum_{j=1}^{\beta}\left(\delta_j(n)-\delta_j(n+1)\right)^2}{N_r\left(N_r{}^2-1\right)}, \tag{7}$$

where n varies from 1 to $N_r - 1$.

In [13], a system using a neural network and a sensor based on fiber-optic distributed acoustic sensing (FDA) was proposed. The system is based on phase-sensitive optical reflectometry in the time domain (8-OTDR) with a low-fiber Bragg lattice (wFBG) for detecting partial discharges (PD) in power cables. Partial discharge (PDC) precedes damage and destruction of insulation in power cables, so it is important to recognize it early. The study proposes a PDC recognition method based on a convolutional neural network (CNN) model to identify several types of PDC: internal PDC, coronal PDC, surface PD.

PD signals were extracted by decomposition and reconstruction. Next, one-dimensional data on PDC signals, which were collected by the sensing system, were transformed into two-dimensional maps of time-frequency characteristics. Next, images of MFCC objects are sent to the CNN classification model for recognition. The training time of the CNN model is reduced when using the characteristics of PDC signals in the time frequency domain. Experimental results showed accuracy of 96.3%, sensitivity - 96.4% and specificity - 98.7% achieved.

The CNN model used a dataset with 10x cross-validation. The training set is divided into 10 parts, 832 test samples were used. Figure 16 shows the architecture of the CNN model. The architecture of the CNN model consists of two convolutional layers. Both are followed by the top union layer. Convolutional layers apply various filters to the input image to extract characteristic features, and combining layers reduce the size of the output data of the convolutional layer. The efficiency of the CNN model was evaluated by the average value of the obtained accuracy, sensitivity, and specificity, the results obtained with the other six existing traditional methods. The CNN model has the best accuracy indicators.

In [17], a convolutional neural network in the φ-OTDR system is proposed to increase adaptability and noise immunity. Using the digital image processing method, a training set for training a neural network was obtained. Thus, correspondence was established between the initial data and the vibration distribution. Three different types of vibration on a sensitive fiber were used to test the feasibility of the deep learning temporal-spatial detection (DL-TSD) method.

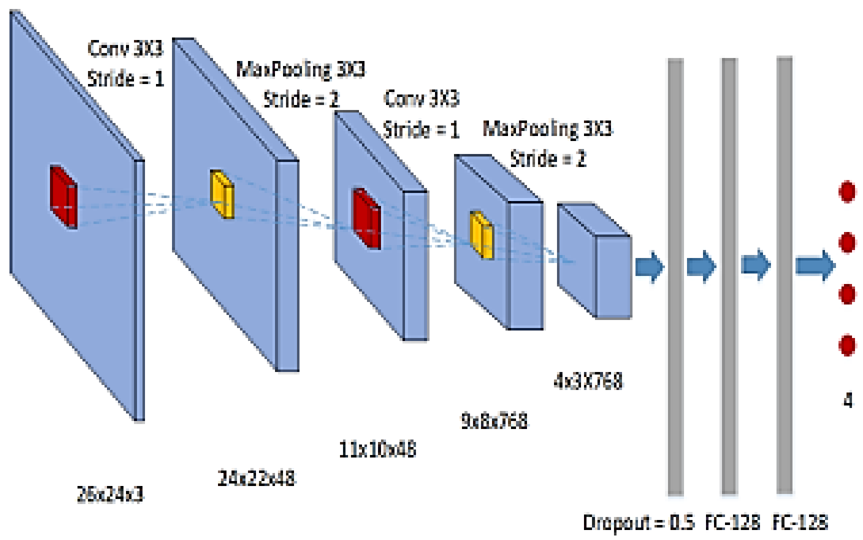

Figure 16: CNN model architecture [13]

Due to continuous learning with the help of a training set, the neural network can match the input image with the vibration distribution. The process of practical application also coincides with the testing process. Pixel accuracy reaches 99.95%. DL-TSD also has adaptability and noise protection Figure 17 shows the process of testing and training DL-TSD

The neural network was built on the proportion of the light intensity I_t collected at time t over the intensity of probe pulse E_0, scattering coefficient ψ_ι, the phase of the i-th scattering center β_i and $\Delta\varphi$ phase variation generated by the vibration

$$I_t \propto E_0^2 \sum_{i=m}^{M} \beta_i + 2E_0^2 \sum_{j>i}^{M} \sum_{i=m}^{M} \beta_i \beta_j \cos(\psi_j - \psi_\iota + \Delta\varphi). \quad (8)$$

The information the values collected through time for neural network was represented in the two-dimensional temporal-spatial matrix $I = [I_1,\ I_2, \dots, I_n]^n$.

The encoding of the I through time and mapping to the high dimensional feature space the convolutional operation was applied:

$$Z^l(x,y,ch) = ReLU(\textstyle\sum_{ch}(\boldsymbol{Z^{l-1}} * w_{ch}^l)(x,y)) = Cov^l(\boldsymbol{Z^{l-1}}(x,y)) \quad (9)$$

Here Z^l is the output of the l-th convolution operation, w^l is the l-th convolution kernel, $ReLU$ is the activation function, x, y, ch is the row, column, and channel of Z. The prediction $Z_{predict}$ was made on the two-dimensional temporal-spatial matrix I converted into gray-scale I_{gray}. The mathematical equation for the $Z_{predict}$ was acquired from L convolution operations:

$$Z_{predict}(x,y) = \sigma\left(Cov^L \circ Cov^{L-1} \circ \dots \circ Cov^1\left(I_{gray}(x,y)\right)\right) = (1 + e^{\left(-Cov^{(L)}\left(\boldsymbol{I_{gray}}(x,y)\right)\right)}) \quad (10)$$

To negate the error from the noise the idealized results I_{ideal} was used as labels. The loss function was obtained from the mean square error:

$$\arg_\theta min \frac{1}{xy} \sum_{k=1}^{xy} (Z_{predict}(x,y) - I_{ideal}\ (x,y))^2 \quad (11)$$

$$I_{ideal}(x,y) = \begin{cases} 1 & (x,y) \in vibration\ region \\ 0 & else \end{cases} \quad (12)$$

In [18], a method of time sequence recognition and knowledge mining based on hidden Markov models (HMM) was proposed for the pipeline technical condition monitoring system by the OTDR method. The results with experimental data from real tests showed 98.2% recognition accuracy. HMM is a classic machine learning model, which has now lost relevance due to the predominance of deep learning (RNN, LSTM) models.

In [19] was used a machine learning method, when first the OTDR signal was processed with an n-th order difference suppressing the differential signal to solve the problem of low OTDR event detection rate. The peaks of the differential signal are extracted to reduce the complexity of calculations. Next, the objects are marked and sent to a machine learning-based classifier for offline learning. The trained model is used for online forecasting to output detected events. The algorithm has been tested using 500 OTDR traces; the results show that the detection speed of connection events reaches 95% after 200 iterations.

CNN models are a popular tool in constructing intelligent systems for monitoring the technical condition of extended objects with and using fiber. So, in [20], when creating CNN, support vector machines (SVMs) are used as a classifier, and also to visualize the CNN workflow, the methods are used: T-distributed stochastic embedding of neighbors (T-SNE) and displaying the activity of classes with a weighted gradient (Grad-CAM). The model of this CNN is shown in Figure 18.

To work with the CNN +SVM model, 11,997 images were used for eight categories of events. Experimental results showed a neural network accuracy of 94.17%. The work contains the largest number of images used for training a neural network among all other works considered.

The article [21] uses machine learning to differentiate data in a fiber-optic system with distributed acoustic sensors (DAS) to recognize vibration events caused by human movement. DAS consists of φ-OTDR and uses artificial Rayleigh scattering centers for amplification. This work also uses convolutional deep neural networks to identify people’s actions and other events that produce acoustic signals. Machine learning was used for training: controlled and non-controlled. Experimental results demonstrate a 76.25% accuracy in recognizing human personalities by supervised machine learning and more than 77.65% by using unsupervised machine learning. Currently, vibration event recognition systems use machine learning and show higher recognition accuracy rates.

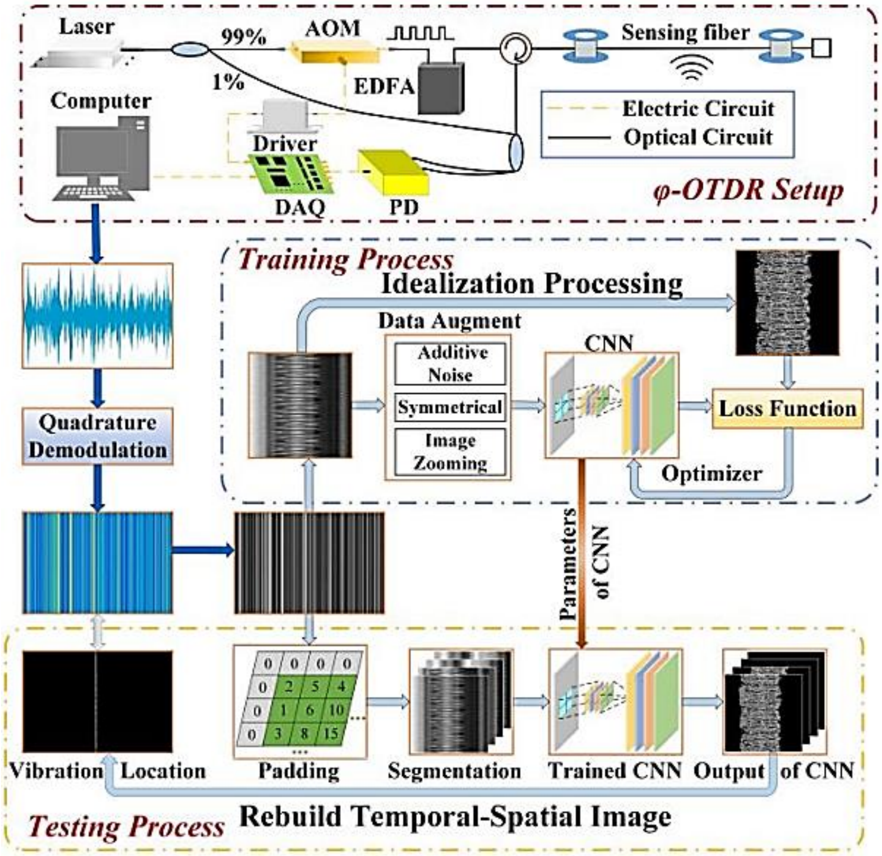

Figure 18: DL-TSD method, which contains the learning process and the testing process. [17]

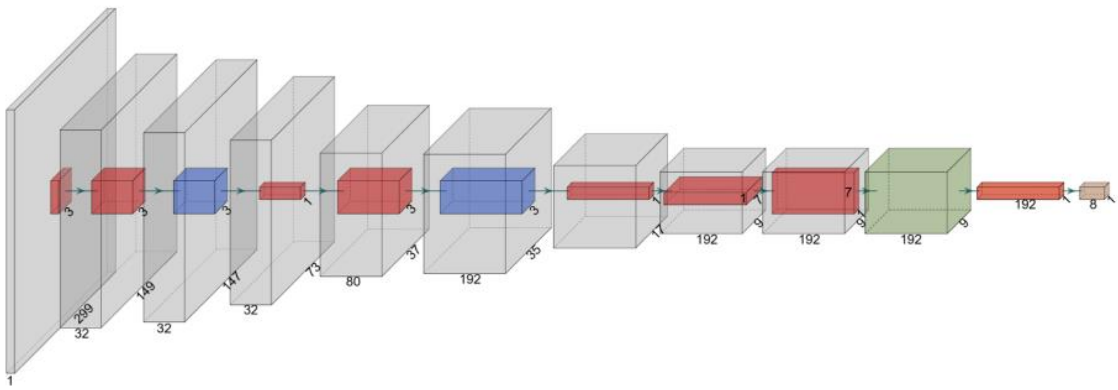

Figure 18: CNN model (red cube is the convolution operation, the blue cube is the maximum union operation, and the green cube is the average union operation) [20]

To improve classification accuracy in systems using fiber optic based on C -OTDR technology under challenging environmental conditions and interference, [22] proposed a multi-shot learning classification method. This method is based on time series transmission and cyclic data processing. With the lack of some minor types of samples required for target samples, the article's authors developed the following procedure: all available data samples are converted into RGB images, using the Mel-spectrum feature extractor; these images are suitable for entering into a deep learning network. Then the amount of data using Time series transmission (TST) and CycleGAN increases. Further, the extended data set is used as a training set for the trained AlexNet network (this network is trained in advance). The experimental result of the proposed method showed an average accuracy of the classification of secondary classes of the set of 79.28%. In [23], the average accuracy results were improved; in this work, an event recognition method based on the low-frequency kepstrum coefficient (MFCC), a superposition algorithm, was used. Experimental results based on 8185 samples from 8 event classifications show classification accuracy of 99.55% and 97.95% in two networks with different depths. In [24], for a distributed fiber-optic perimeter security system based on Φ-OTDR for fiber vibration recognition, the use of the time-frequency response (TFC) method is proposed. Several types of probabilistic neural networks (PNNs) are used for this. As a result of experiments, with a detection range of the system of 10 km, with a range of interference of 1 km, the accuracy of event recognition is more than 95%. The probe response time is about 1.366 s. For distributed fiber-optic security systems, such vibration detection accuracy is a good result.

5. Discussions

According to the analyzed literature, the main problem in technical condition monitoring systems is interference caused by mechanical overvoltages and temperature influences. So, in [1], the solution to eliminate interference is to add EDFA and AOM to the system, as a result, the signal is amplified, and the interference is attenuated. In [2], interference was eliminated by parallel AOM with different bandwidth frequencies. It is worth noting that in other cases, the same methods were used, except [7] and [8], where other methods were used to eliminate interference, namely C-OTDR, separating the signal into coherent and incoherent components and OTDR interferometry, respectively. Thus, the accuracy was higher than when using standard reflectometry systems. The disadvantages of these systems are the complexity of the system and the large size relative to the standard ones. Further studies will consider systems with smaller sizes and simpler circuits. However, it is worth noting that despite the principle of implementing measuring systems, intelligent systems capable of processing complex graphics and images are needed for information processing.

For very extended objects, as in [9], the signal intensity will depend on many random parameters, especially since such a system may be too sensitive to external influences from the movement of machinery or people while considering that the intensity of the optical signal also depends on the purity of the laser. Neural networks were used to process information and improve the recognition of noise and external influences. Although the described variant with BF ANN [11] can increase the accuracy in determining the nature and location of vibrations, the systems using CNN showed the most excellent accuracy [13], [14], [17]. The analysis of the results of different neural networks, shown in [12], where BP ANN (87%), SVM (85% and 92.9%), PNN (90.8%), CNN (96.3%), SRC (94.9%) were compared, demonstrates well. It was also found that it is better to use a convolutional neural network to increase adaptability and noise immunity [13] and probabilistic neural networks to recognize fiber vibration [24]. In further studies, based on this review, special systems will be developed to measure mechanical deformations and vibrations with a smaller design and the cost of creating equipment. At the same time, based on the analysis of the literature on measuring systems, it can be concluded that the optical fiber is susceptible to small vibrations. For this reason, despite all possible ways to eliminate interference by hardware, it is necessary to create a neural network capable of processing information from the received graphs or images for accurate operation.

6. Conclusion

Distributed fiber-optic sensors based on the φ-OTDR principle have become widely used in monitoring systems for the technical condition of extended objects with a length of up to 1 km. A different approach is used for objects with a distance of up to 75 km [9]. They can perceive information about mechanical deformations and vibrations; however, although these solutions have been improved by adding devices for signal polarization, which helps to exclude possible overlaps due to mechanical overvoltages and temperature effects, they are not able to distinguish the type of vibration source, thereby reacting to interference caused by the movement of people, animals, machinery. There are many solutions, but most are performed using interferometry on the principle of φ-OTDR, a laser generating optical signals with a wavelength of 1550 nm.

However, such devices have the following disadvantages: instability to interference, large size, and high cost. At the same time, it is worth noting that distributed sensors will be sensitive to minor vibrations as the length of the sensing element increases [10]. Thus, the sensors can perceive false alarm signals in the presence of human-created interference. To achieve the accuracy of the work, it is necessary to use an intelligent system for recognizing the nature of the influence and determining its location. Having analyzed the existing systems for monitoring the technical condition of extended objects that contain fiber-optic sensors and use neural networks as an intellectual part, we can conclude that the highest accuracy rates are shown by collapsing neural networks [12].

7. References

[1] R. Zinsou, Y. Wang, X. Liu, Q. Bai, Y. Wang and B. Jin, "Adaptive Pulse Period Method for Low-Frequency Vibration Sensing With Intensity-Based Phase-Sensitive OTDR Systems," in IEEE Access, vol. 8, pp. 41838-41846, 2020, doi: 10.1109/ACCESS.2020.2977000

[2] R. Hong et al., "Enlarging Dynamic Strain Range in UWFBG Array-Based Φ-OTDR Assisted With Polarization Signal," in IEEE Photonics Technology Letters, vol. 33, no. 18, pp. 994-997, 15 Sept.15, 2021, doi: 10.1109/LPT.2021.3079186

[3] T. Kumagai, S. Sato and T. Nakamura, "Fiber-optic vibration sensor for physical security system," 2012 IEEE International Conference on Condition Monitoring and Diagnosis, 2012, pp. 1171-1174, doi: 10.1109/CMD.2012.6416369

[4] Minardo, A.; Catalano, E.; Coscetta, A.; Zeni, G.; Di Maio, C.; Vassallo, R.; Picarelli, L.; Coviello, R.; Macchia, G.; Zeni, L. Long-Term Monitoring of a Tunnel in a Landslide Prone Area by Brillouin-Based Distributed Optical Fiber Sensors. Sensors 2021, 21, 7032. https://doi. org/10.3390/s21217032

[5] M. Adeel et al., "Impact-Based Feature Extraction Utilizing Differential Signals of Phase-Sensitive OTDR," in Journal of Lightwave Technology, vol. 38, no. 8, pp. 2539-2546, 15 April15, 2020, doi: 10.1109/JLT.2020.2966413

[6] A. Masoudi, J. A. Pilgrim, T. P. Newson and G. Brambilla, "Subsea Cable Condition Monitoring With Distributed Optical Fiber Vibration Sensor," in Journal of Lightwave Technology, vol. 37, no. 4, pp. 1352-1358, 15 Feb.15, 2019, doi: 10.1109/JLT.2019.2893038

[7] P. Rohwetter, R. Eisermann and K. Krebber, "Random Quadrature Demodulation for Direct Detection Single-Pulse Rayleigh C-OTDR," in Journal of Lightwave Technology, vol. 34, no. 19, pp. 4437-4444, 1 Oct.1, 2016, doi: 10.1109/JLT.2016.2557586

[8] C. Wang, Y. Shang, W. -A. Zhao, X. -H. Liu, C. Wang and G. -D. Peng, "Investigation and Comparison of Φ -OTDR and OTDR-Interferometry via Phase Demodulation," in IEEE Sensors Journal, vol. 18, no. 4, pp. 1501-1505, 15 Feb.15, 2018, doi: 10.1109/JSEN.2017.2785358.

[9] Z. Sha, H. Feng, Y. Shi, W. Zhang and Z. Zeng, "Phase-Sensitive OTDR With 75-km Single-End Sensing Distance Based on RP-EDF Amplification," in IEEE Photonics Technology Letters, vol. 29, no. 16, pp. 1308-1311, 15 Aug.15, 2017, doi: 10.1109/LPT.2017.2721963

[10] Yugay, V., Mekhtiyev, A., Madi, P., Neshina, Y., Alkina, A., Gazizov, F., Afanaseva, O., Ilyashenko, S. Fiber-Optic System for Monitoring Pressure Changes on Mine Support Elements. Sensors 2022, 22, 1735. https://doi.org/10.3390/s22051735

[11] H. Wu, S. Xiao, X. Li, Z. Wang, J. Xu and Y. Rao, "Separation and Determination of the Disturbing Signals in Phase-Sensitive Optical Time Domain Reflectometry (Φ-OTDR)," in Journal of Lightwave Technology, vol. 33, no. 15, pp. 3156-3162, 1 Aug.1, 2015, doi: 10.1109/JLT.2015.2421953

[12] Adeel, M., Tejedor, J., Macias-Guarasa, J., & Lu, C. (2019). Improved Perturbation Detection in Direct Detected ϕ-OTDR Systems using a Novel Match Filtering Approach. IEEE Photonics Technology Letters, 1–1. doi:10.1109/lpt.2019.2940297

[13] Che, Q., Wen, H., Li, X., Peng, Z., & Chen, K. P. (2019). Partial Discharge Recognition Based on Optical Fiber Distributed Acoustic Sensing and a Convolutional Neural Network. IEEE Access, 7, 101758–101764. doi:10.1109/access.2019.2931040

[14] Neftissov, A.V., Andreyeva, O.A., Sarinova, A.Z. Investigation of the properties of reed switches in devices for resource-saving relay protection of the electrical part of power plants (2021) AIP Conference Proceedings, 2337, 030010 DOI: 10.1063/5.0046558

[15] Neftisov, A.V., Talipov, O.M., Andreeva, O.A., Kirichenko, L.N. Determination of changes in the parameters of reed switches in resource-saving relay protection devices of the electrical part of power plants (2022) Journal of Physics: Conference Series, 2211 (1), № 012017. DOI: 10.1088/1742-6596/2211/1/012017

[16] Zh Sarinova, A., Drobinsky, A.V., Kirichenko, L.N. Investigation of the Operating Parameters of Rectifier Devices Using Modern Software Tools (2022) Journal of Physics: Conference Series, 2211 (1), 012023 DOI: 10.1088/1742-6596/2211/1/012023

[17] Wang, P., Lv, Y., Wang, Y., Liu, X., Bai, Q., Zhang, H., & Jin, B. (2020). Adaptability and Anti-noise Capacity Enhancement for OTDR with Deep Learning. Journal of Lightwave Technology, 1–1. doi:10.1109/jlt.2020.3016712

[18] Wu, X. Liu, Y. Xiao and Y. Rao, "A Dynamic Time Sequence Recognition and Knowledge Mining Method Based on the Hidden Markov Models (HMMs) for Pipeline Safety Monitoring With Φ-OTDR," in Journal of Lightwave Technology, vol. 37, no. 19, pp. 4991-5000, 1 Oct.1, 2019, doi: 10.1109/JLT.2019.2926745

[19] . Z. Yang, D. Hong, X. Feng and J. Xie, "A Novel Event Detection Method for OTDR Trace with High Sensitivity Based on Machine Learning," 2021 2nd Information Communication Technologies Conference (ICTC), 2021, pp. 265-269, doi: 10.1109/ICTC51749.2021.9441614

[20] 16 Shi, Y., Wang, Y., Wang, L., Zhao, L., & Fan, Z. (2020). Multi-event classification for Φ-OTDR distributed optical fiber sensing system using deep learning and support vector machine. Optik, 221, 165373. doi:10.1016/j.ijleo.2020.165373

[21] Peng, Z., Wen, H., Jian, J., Gribok, A., Wang, M., Huang, S., Liu, H., Mao, Z.-H., Chen, K.P. Identifications and classifications of human locomotion using Rayleigh-enhanced distributed fiber acoustic sensors with deep neural networks (2020) Scientific Reports, 10 (1), № 21014, DOI: 10.1038/s41598-020-77147-2

[22] Shi, Yia;Dai, Shangweia;Liu, Xinyua;Zhang, Yingchaoa;Wu, Xinjiea;Jiang, Taoa. Event recognition method based on dual-augmentation for an Φ-OTDR system with a few training samples. Journal of Optical Communications and Networking. May 2022. vol 14, no 5, pp 365 DOI10.1364/OE.468779

[23] Shi, Y., Liu, X., Wei, C. An event recognition method based on MFCC, superposition algorithm and deep learning for buried distributed optical fiber sensors (2022) Optics Communications, 522,№ 128647 DOI: 10.1016/j.optcom.2022.128647

[24] Tabi Fouda, B. M., Han, D., An, B., & Chen, X. (2020). Research and Software Design of an Φ-OTDR-Based Optical Fiber Vibration Recognition Algorithm. Journal of Electrical and Computer Engineering, 2020, 1–13. doi:10.1155/2020/5720695