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Original Research Article

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INTELLIGENT DEVICE FOR DIAGNOSTICS AND FAILURE PREDICTION OF FIBER-OPTIC COMMUNICATION LINES BASED ON DIGITAL MONITORING

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Abstract. *In the context of intensive growth in the volume of transmitted information and the complexity of telecommunication network architecture, improving reliability of fiber-optic communication lines at the operational stage is becoming particularly relevant. This paper proposes an approach to intelligent diagnostics of fiber-optic information transmission system elements based on the parameters of digital monitoring of optical modules. The feasibility of using diagnostic data on the power of the optical signal, temperature, power voltage, and laser current to assess the current state of the line and identify signs of degradation is analyzed. A structural diagram of a hardware-software device is proposed, providing continuous data collection, their adaptive processing, and the formation of real-time prognostic estimates. For processing diagnostic parameters, a machine learning model adapted for the built-in microcontroller platform and focused on failure risk classification and intelligent diagnostics of line elements. The results of experimental studies based on real operational data confirm the possibility of early detection of potential failures and increasing the reliability of fiber-optic communication lines.*

Keywords: fiber-optic communication lines; digital monitoring; failure forecasting; degradation of optical components; intelligent data processing; technical condition diagnostics; reliability of telecommunication networks.

1. Introduction

The development of digital technologies, the constant growth of the volume of transmitted information, and the increasing demands on communication quality require higher reliability of telecommunication systems. Under these conditions, fiber-optic information transmission systems (FOITS) occupy a special place in modern communication infrastructure, providing high-speed data exchange over long distances [1]. The number of internet users has doubled between 2014 and 2024, which is equivalent to an average annual growth of approximately 7.23% [2]. The constant increase in data transmission speed, the complication of network architecture, and the increased load on communication channels lead to increased failure probability, parameter degradation, and increased requirements for the stable operation of these systems. Fiber optic information transmission systems are placing increasingly high demands on reliability and fault tolerance. To ensure the timely detection of malfunctions and prediction of failures, intelligent diagnostic tools are necessary that can not only record current changes but also make predictions based on accumulated data. Predicting malfunctions is crucial during operation, as it allows for early detection of failures and minimizes downtime. Failure forecasting methods based on the analysis of historical data and intelligent monitoring systems, particularly machine learning, can analyze failure data volumes, predict possible failures, adapt to changing operating conditions, and eliminate them before they occur [3,4]. This, in turn, allows for early maintenance, automatic parameter correction, and fault-tolerant control of fiber-optic communication systems.

Although the failure forecasting method allows for the detection of possible failures, it is necessary to develop a diagnostic tool that allows for continuous monitoring with adaptive data processing to continuously monitor the state of elements. Of particular interest is the use of DDM (Digital Diagnostic Monitoring) functionality integrated into SFP (Small Form-factor Pluggable) modules, as well as the prospects for their integration with microcontrollers and intelligent algorithms.

A number of works consider various approaches to the diagnosis and monitoring of fiber-optic communication lines and optical modules. The system presented in the work [5] provides power monitoring, channel switching in case of failure, and reflected signal detection, however, the architecture does not support intelligent analysis. An analysis of the reliability of SFP modules was conducted based on long-term monitoring of digital diagnostic monitoring parameters, within which the possibility of using DDM data to assess degradation processes was shown; however, hardware platform diagnostics and failure forecasting have not been implemented and are limited to assessing correlational relationships [6]. A model of a fiber-optic communication line diagnostics device based on the analysis of attenuations and disruptions in the line has been proposed, however, the device does not support digital monitoring functions and does not provide for the application of intelligent data processing algorithms [7]. Modern approaches to free-spatial optical communication and mirror-based optical structures are considered, where the potential of digital monitoring as a tool for monitoring the state of optical systems is noted and the need to supplement it with intelligent analysis tools is emphasized [8]. The architecture and basic capabilities of implementing digital diagnostic monitoring functions in SFP modules are described, while issues of degradation analysis and failure forecasting are not addressed [9]. An optical module for digital diagnostics with real-time measurement of temperature, voltage, current, and optical power is presented, however, parameter processing the module analyzes the data according to a fixed algorithm without implementing prognostic functions [10]. A mechanism for automatic correction of optical power during signal level decrease based on digital diagnostic monitoring data, oriented towards control actions and not providing for the assessment of residual resource and failure probability of communication line elements [11], has been implemented.

Analysis of existing devices and diagnostic methods has shown the need to develop a device designed to diagnose failures in the elements of the SFP module based on diagnostic data obtained from SFP modules with DDM technology for analysis and processing, including predicting the level of fiber degradation, residual service life, and failure probability of elements using machine learning algorithms, and with the possibility of subsequent transmission of forecasting results through the communication module to the user's external devices.

2. Materials and methods of research

The device is designed to collect, analyze, and predict parametric and functional failures of fiber-optic communication line elements based on diagnostic data (Fig. 1). Unlike known solutions, the device allows forecasting the state of network components in real time using a pre-trained machine learning model integrated into the microcontroller system [12].

The operating principle of the device consists of several stages. In the first stage after power supply, the device is activated. The SFP module (1) with the DDM digital monitoring system, is connected to the fiber-optic communication line, transmits and receives the optical signal. The microcontroller (2) acquires diagnostic parameters from the DDM interface of the SFP module system for the $P_{Tx}(t)$ transmitter and $P_{Rx}(t)$ receiver power values, module temperature $T(t)$, power voltage $U(t)$, and bias current $I(t)$ through a standard digital interface (Fig.1). As a microcontroller (2), ESP32 is used, which has an embedded wireless communication module and necessary interfaces for questioning the DDM system, interaction with external modules and data transmission.

The obtained data is structured and transmitted to the adaptive information processing unit (3), where their analysis is carried out using a pre-loaded trained machine learning model obtained from the external learning system (12). The ESP32-S3 microcontroller, which is manufactured by Espressif Systems [13,14], serves as an adaptive information processing module. This product was chosen for its combination of high computing power, energy efficiency, built-in external interfaces, and neural network support (including TensorFlow Lite Micro).

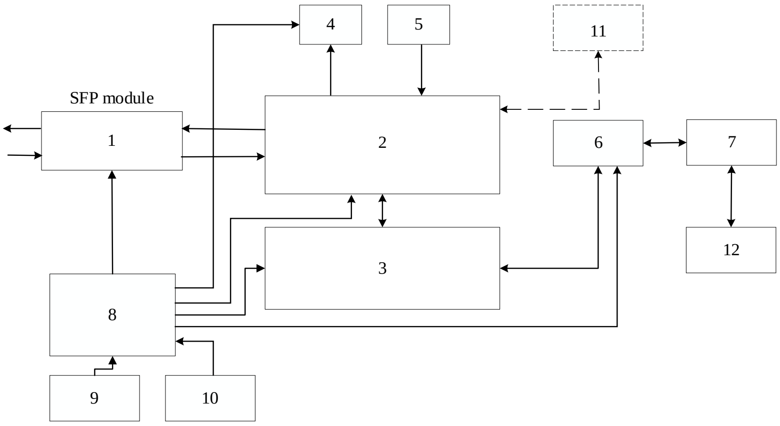


Fig. 1. Structural diagram of the fiber-optic communication line element diagnostics device. 1-SFP Module, 2-microcontroller, 3- adaptive information processing unit, 4- display, 5- control unit, 6- communication module, 7-database, 8- power supply control system, 9- power supply from source, 10- battery, 11- EEPROM (Electrically Erasable Programmable Read-Only Memory), 12-external learning system

The adaptive information processing module, built on the basis of ESP32-S3, represents an intelligent platform for predictive diagnostics of FOITS, capable of analyzing the parameters of optical elements and predicting failures. The forecasting results are displayed on the display (4), and also transmitted through the communication module (6) via a wireless interface to the user's external devices. Simultaneously, the microcontroller stores current diagnostic parameters and forecasting results in EEPROM (Electrically Erasable Programmable Read-Only Memory) (11) and database (7). The user can access the database remotely through a computer or server, view saved data, generate reports, and monitor the line's status. During operation, the control unit (5) coordinates the device's operation, and the power supply control system (8) controls the power supply from source (9) and battery (10), ensuring the device's autonomous operation.

The adaptive information processing module, in which the machine learning model is implemented, is given special attention. The main goal of model training is to form a training model of a machine learning algorithm capable of using diagnostic parameters obtained from the SFP module through the DDM interface (Fig.2). At the initial stage of task formation, the model type is based on the set task. The goal is to determine the failure risk level: low/medium/high and the degradation value, as well as the residual service life. The proposed device architecture supports classification and regression tasks. In this study, only a classification model was implemented and experimentally tested to determine the level of failure risk.

The data should be prepared in a convenient and standardized format for model training. For this, the characteristics are normalized (reduced to a single scale):

$$x_i^{norm} = \frac{x_i - \mu_i}{\sigma_i} \tag{1}$$

where x_i^{norm} - normalized value; x_i - parameter value for the i-th measurement; μ_i - the average value of this characteristic for all data; σ_i - standard deviation of a trait for all data.

Class or predicted value tags are created, for classification:

$$y = \begin{cases} 0; Q(t) < 0,3 \\ 1; 0,3 \le Q(t) < 0,7 \\ 2; Q(t) \ge 0,7 \end{cases} \tag{2}$$

for regression:

$$y = t_{failure} - t \tag{3}$$

Threshold values are selected based on equipment technical passports and preliminary degradation analysis results. The values can be adapted to specific operating conditions.

When choosing a model for implementing predictive diagnostics, it is necessary to consider several important factors, especially those related to the limitations of embedded systems:

- low dimensional size and permissible computational load for the ESP32-S3 microcontroller;
- support for real-time forecasting;

Interpretation of results, necessary for assessing, forecasting, and explaining the causes of identified risks.

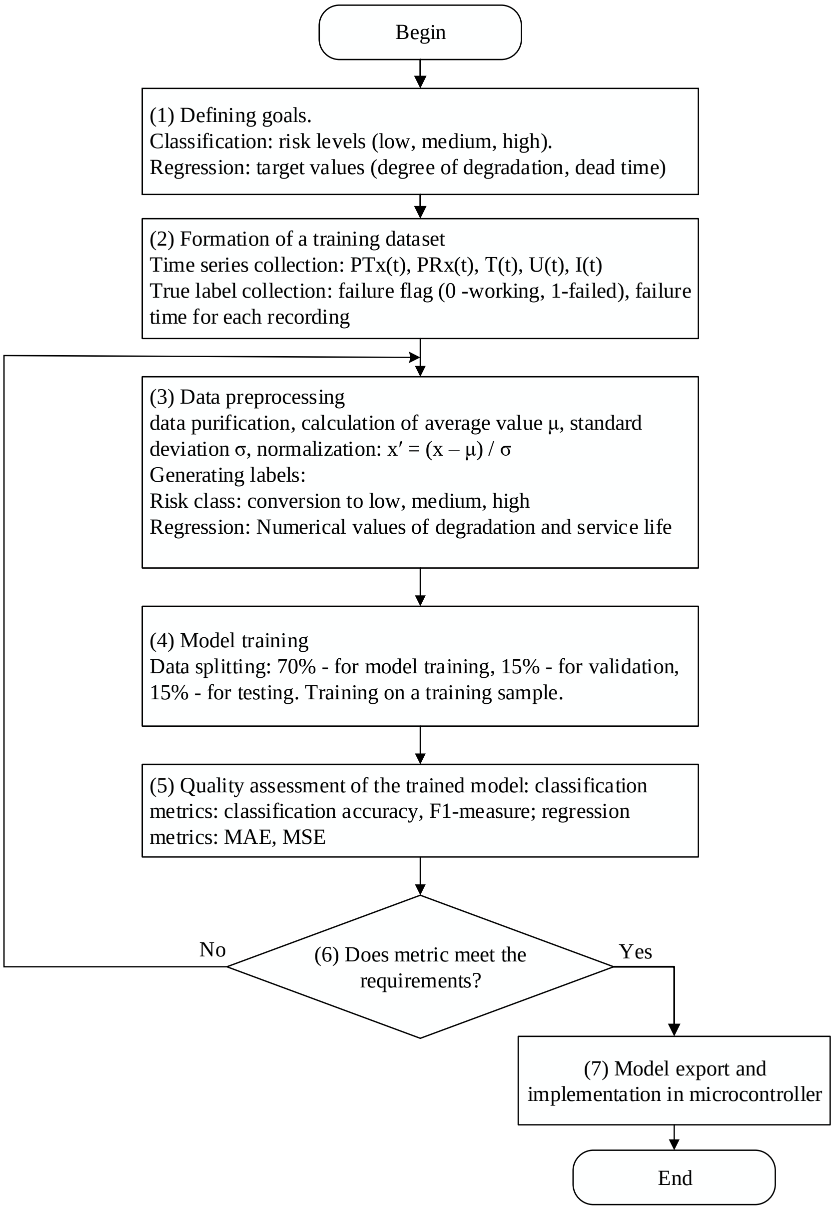


Fig.2. Algorithm for training an ML model for export to a microcontroller

The principle of operation of the device in normal operating mode: after power supply, the microcontroller automatically initiates a sequence of questioning of the DDM SFP module system with an interval of 1 s. With each sample, the laser temperature, power voltage, laser displacement current, as well as the emitted and received optical power are recorded. Data is transmitted to the adaptive information processing module. Based on a pre-trained neural network model, the module forms a forecast of the failure probability of key elements and residual fiber resource; the complete processing cycle —from the moment of sampling to the issuance of the forecast result — does not exceed 5 s. The obtained forecasts are accompanied by a time mark, visualized on a touchscreen in the form of trends and text messages, and simultaneously published through a wireless channel to external user services. In parallel, diagnostic samples and corresponding forecasts are archived in the EEPROM ring buffer and replicated into the internal database. Such an algorithm ensures continuous (“on-line”) observation of the line’s state without data loss even with high-frequency parameter fluctuations. In the warning signal mode: when one of the predicted degradation threshold metrics reaches 70% of the critical level by default, the microcontroller generates an alarm event. On the display, a “red” dialog box automatically opens, indicating the reason and the recommended action (for example, “The probability of fiber breaking after ≈72 hours - check the area between points A-B”). Simultaneously, a notification is sent through the communication module via the Web-Push or MQTT-push protocol to the operator's registered devices, indicating the date, time, module identifier, and current statistics. Therefore, the operator receives a warning long before the actual failure and can plan prevention without stopping traffic.

In emergency mode and battery power: in case of sudden loss of external network power or critical hardware error, the power control unit instantly switches the load to the built-in battery. At this point, the device switches to standalone mode: the display lighting and data transmission are switched off, but the collection of diagnostic parameters, forecasting, and logging continue as before. All events recorded during battery operation are marked with a special “backup power” flag. After restoring the main power supply and network connection, the microcontroller automatically discharges the latest archive data, including the time of failure, to the external database, which gives the operator a complete picture of the emergency situation. If necessary, the log file can be manually exported through the user interface.

Such a sequence of modes guarantees the continuity of monitoring, allows for timely warning of impending failures, and ensures data preservation even in emergency situations, thereby increasing the overall reliability of fiber-optic communication lines.

To implement the device failure forecasting function, a trained machine learning model is used, formed based on real diagnostic logs obtained during nine months of operation of twelve fiber-optic communication line main nodes. The dataset consisted of 1,000 labeled samples, each represented by five DDM-based diagnostic features. The data were randomly divided into 70% training and 30% testing subsets. For the MLP classifier, 20% of the training data were internally allocated for validation during the learning process. After training, the network is quantized to 8-bit TensorFlow Lite format, the final file, approximately 180 Kbytes, is signed with the SHA-256 control sum and placed in the protected HTTPS repository of the external training system. The ESP32-S3 microcontroller, when initialized, executes a request to this repository, automatically compares the control sum of the local and available models, and upon the appearance of a new version, uploads the file to the second section of the internal Flash memory; switching to the updated model occurs after re-launching without user intervention. During operation, the input vector for the network is a sliding window from the last fifty samples of diagnostic data (about 50 seconds of observations), supplemented by a sine-cosine representation of the time of day; the hardware neural processing unit of the ESP32-S3 nucleus performs an interference in 4-5 seconds at a clock frequency of 240 MHz, after which the microcontroller compares the obtained probability value with a threshold of 0.8, duplicates the result in the EEPROM and the database, displays it on a touch screen, and publishes it through the wireless channel. Such a software and hardware solution guarantees the reproducibility of the method, provides local forecast calculation without involving external computing resources, and allows for regular improvement of model accuracy through automatic updating from the training system.

Database (7) is an embedded SQLite table placed in the flash memory of microcontroller 3: it does not require a separate hardware unit, but is logically highlighted because it stores a long-term archive of diagnostic samples and forecasts. The MCU (Microprogrammed Control Unit) writes new lines there, and the communication module 6 unloads them to external systems upon request.

The technical result of the developed device is an increase in the reliability of fiber-optic communication lines due to the implementation of diagnostics and forecasting of parametric and functional failures of fiber-optic communication line elements based on the analysis of diagnostic data obtained from SFP modules with the support of DDM technology. The possibility of measuring the transmitter power, receiver power, power voltage, module temperature, laser displacement current is provided, thereby predicting the level of fiber degradation, residual service life, and the probability of element failures. The combination of these effects necessitates a significant increase in the reliability and fault tolerance of fiber-optic communication lines, reduces maintenance costs, and improves the quality of telecommunications services provided.

The diagnostic device for fiber-optic communication line elements with adaptive information processing differs from existing solutions [7-12] in that it additionally contains an adaptive information processing module (3), a display, a communication module, a network power source, a power control unit (Table 1). Microcontroller (2) is capable of transmitting diagnostic parameters from the DDM system to an adaptive information processing module, which is designed to predict parametric and functional failures of fiber-optic communication line elements using a pre-trained machine learning model. There is also an opportunity to transmit results via a communication module via a wireless channel to the user's external devices in real-time, and diagnostic parameters and forecasting results are stored in energy-independent memory and a database.

Table 1. Devices and methods for diagnosing failures elements in fiber-optic communication lines

Method / System	**Method Description**	**Main Limitations / Advantages**	**Reference**
Integrated semi-active CWDM system with a circulator	Provides optical power monitoring, channel switching in case of failure, and reflected signal detection.	The architecture is limited to CWDM systems, does not include intelligent data analysis.	[7]
Reliability assessment of optical transceivers based on SFP parameter monitoring	Long-term reliability analysis of SFP modules using Digital Diagnostic Monitoring (DDM) parameters.	DDM is used only for correlation analysis without performing predictive diagnostics.	[8]
Optical cable diagnostic device	Analysis of attenuation and disturbances in fiber-optic communication lines.	Does not support DDM and lacks intelligent diagnostic or predictive capabilities.	[9]
Monitoring system for optical SFP transceiver modules	System architecture based on DDM integrated into SFP modules.	DDM functionality is implemented only for parameter monitoring.	[10]
Optical module with digital diagnostic method	DDM-enabled optical module providing monitoring of temperature, supply voltage, laser bias current, and optical power.	Does not include intelligent data processing, employs a fixed diagnostic model, and does not support failure prediction.	[11]
Optical power adjustment method based on the optical module and terminal	Automatic adjustment of optical power using the DDM database.	DDM is used only for operational control; historical data storage, intelligent analysis, and predictive capabilities are not provided.	[12]

3. Results and discussion

Modeling and model training were conducted in the MATLAB environment using neural network modeling tools. The application of the MATLAB software environment made it possible to implement a complete cycle of model construction and verification, i.e., data preparation and architecture selection, visualization of learning convergence, and analysis of quality metrics. comparative experiments were conducted with machine learning models - MLP (Multilayered perceptron), Decision Tree and Random Forest (Table 1). The performance of the evaluated models was assessed using Accuracy, Precision, Recall, F1-score, and ROC-AUC (Table 2), since the dataset was highly imbalanced, with approximately 98.3% of the samples corresponding to the normal operating state and only 1.7% representing fault conditions. Decision Tree and Random Forest models achieved the best overall performance, whereas the MLP classifier demonstrated lower Recall despite its high Accuracy and Precision. Among the evaluated models, the Random Forest classifier achieved the highest ROC-AUC value (0.9986) while maintaining an Accuracy of 99.67%, a Recall of 100%, and an F1-score of 0.9091. Therefore, the Random Forest model was selected for implementation in the proposed intelligent diagnostic device due to its superior predictive performance and robustness.

Table 2. Performance comparison of the evaluated machine learning models

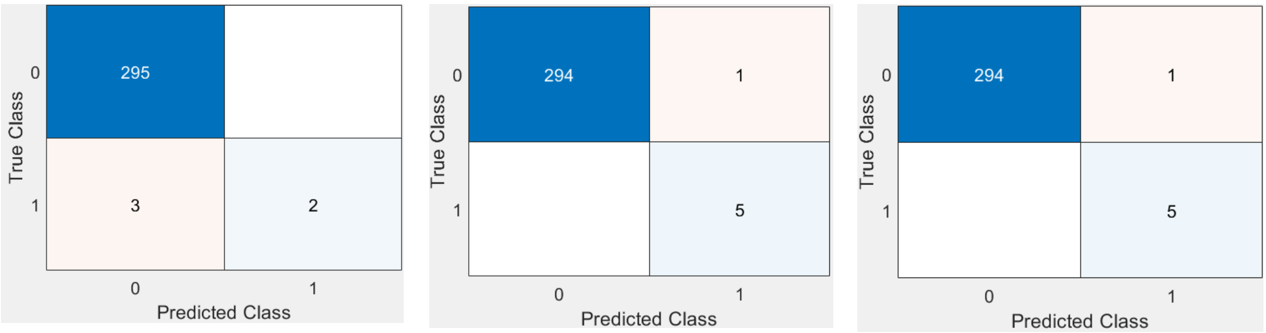
Model	Accuracy	F1-score	Precision	Recall	ROC-AUC
MLP	0.9900	0.5714	1.0000	0.4000	0.9925
Decision Tree	0.9967	0.9091	0.8333	1.0000	0.9983
Random Forest	0.9967	0.9091	0.8333	1.0000	0.9986

The dynamics of training the MLP neural network for loss function is presented in Table 3. As shown in the figure, the training was completed at the 18th epoch as a result of fulfilling the early stop criterion when achieving minimal error in the validation set. The value of the loss function decreased from 0.161 to 0.0115. The gradient decreased from 0.383 to 0.0044, indicating the convergence of the model. The Scaled Conjugate Gradient optimization method was used. This graph confirms the stability of learning and the absence of signs of overtraining.

Table 3. MLP neural network learning dynamics

Parameter	**Initial Value**	**Final Value**	**Target Value**
Epoch	0	18	1000
Elapsed Time	–	00:00:08	–
Performance	0.1610	0.0115	0
Gradient	0.3830	0.0044	1×10^{-6}
Validation Checks	0	6	6

The confusion matrices for the MLP, decision tree, and random forest classifiers shown in Figure 3 provide an analysis of the classification results. The MLP classifier correctly identified most normal samples but failed to detect three fault samples. In contrast, the Decision Tree and Random Forest classifiers correctly identified all fault samples while producing only one false positive.



a) b) c)

Fig.3. Confusion matrices: (a) MLP, (b) Decision Tree, and (c) Random Forest

The architecture of a trained MLP neural network used for binary classification of the module's state is shown in Fig.4. A vector consisting of five diagnostic characteristics is fed into the input: transmission power (P_{Tx}), reception power (P_{Rx}), temperature (T), voltage (U), and current (I). The hidden layer contains 10 neurons and utilizes a fully connected structure using the activation function. The result of the hidden layer is transmitted to the output layer, where another linear transformation is performed with the addition of displacements. The output layer consists of two neurons and forms a probability vector of the input data belonging to one of the two classes (correct/failure) using the Softmax activation function.

The conducted experiments showed that this configuration has sufficient generalizability while maintaining low computational load, making it suitable for embedding in the ESP32-S3 microcontroller. Subsequently, the model was trained on labeled diagnostic data and exported to the TensorFlow Lite Micro format, which ensured correct integration into the adaptive information processing module implemented on the target hardware platform. The graph of the change in the loss function during the learning process of the MLP model is shown in Fig. 5. The curves on the graph show a decrease in error in training, validation, and test samples. The minimum error value in the validation sample was achieved in the 12th period (0.029975), marked by the intersection of the green line with the horizontal line "Best." After this point, an increase in validation error is observed, indicating the beginning of retraining. The early stop mechanism automatically completed the training in the 18th era to prevent the degradation of the model's generalizability.

The discrepancy between the validation and testing curves after the 12th era further demonstrates how sensitive the model is to retraining, given the limited training data set. This suggests adding regulation methods and possibly increasing the training set. However, the generalizability obtained from the model may be sufficient for the purposes of developing diagnostic tasks using built-in tools, which is confirmed by the stable behavior of the loss function in the test set until the end of training.

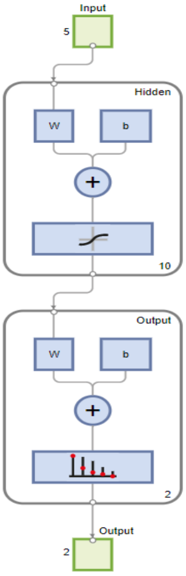


Fig. 4. MLP trained neural network architecture diagram

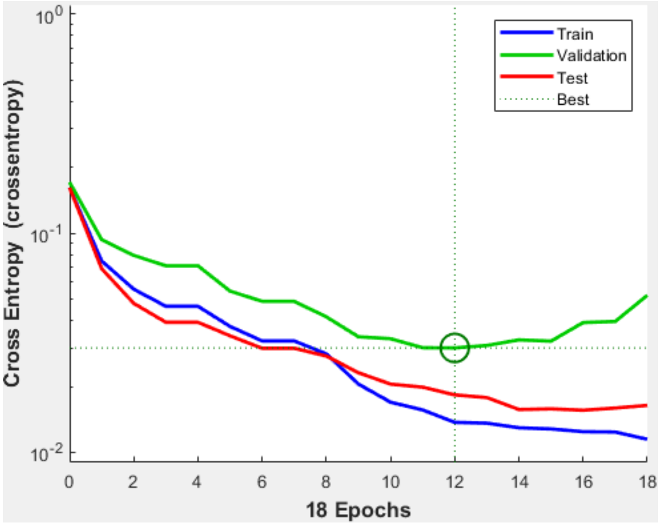


Fig. 5. Reducing errors in training, validation and test samples

4. Conclusion

Analysis of existing devices and methods for diagnosing fiber-optic information transmission systems showed that most of the applied solutions are focused on monitoring current parameters and local adjustment of operating modes, and do not provide failure forecasting and estimation of the residual resource of communication line elements. In this regard, a model of a diagnostic device based on the collection and processing of digital monitoring parameters of optical modules with the support of DDM technology and the integration of intelligent analysis algorithms has been proposed. The developed device architecture includes an adaptive information processing module that implements the assessment of the current technical condition of fiber-optic communication line elements, forecasting the probability of failures through machine-learning-based classification of the technical condition. The proposed device architecture is extensible and can be complemented in future work with regression models for quantitative degradation assessment and remaining useful life prediction. The device operates in real time and provides automatic transmission of diagnostic results to the user, which expands the possibilities of managing the reliability of fiber-optic information transmission systems.

Conflict of interest statement

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

CRediT author statement

Juraeva N.I.: Conceptualization, Methodology, Writing-original draft, Writing - review and editing. **Davronbekov D.A.:** Investigation, Visualization. **Boboev A.A.:** Software, Validation. The final manuscript was read and approved by all authors

Statement on the use of Artificial Intelligence.

During the preparation of this manuscript, artificial intelligence tools were used solely for language editing and grammatical improvement. No AI tools were used to generate scientific content, analysis, results, or conclusions.

Data Availability Statement

For the practical implementation of the developed device, real failure data provided by the telecommunications organization “Uzbektelecom” JSC were employed. In connection with privacy and data protection requirements, original datasets cannot be made publicly available.

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