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Predicting failures in fiber optic information transmission systems with support of machine learning

Predicción de fallos en sistemas de transmisión de información por fibra óptica con apoyo de aprendizaje automático

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ABSTRACT

The use of machine learning methods in fiber-optic information transmission systems (FOITS) is considered. The article discusses the basic operating principles of fiber optic systems and the problems they face, such as noise, nonlinear effects, and degradation of transmitted information. Describes various machine learning techniques used in FOITS to control and monitor performance, prevent intelligent decisions, and suppress nonlinear fiber optic noise. Approaches used in machine learning are presented, such as neural networks, classification and regression algorithms, their application in the analysis and optimization of FOITS, such as neural networks, support vector machines, classification and regression algorithms, their application in the analysis and optimization of fiber optic systems. This paper proposes a method for monitoring performance and predicting failures in optical networks based on machine learning. The results obtained allow us to draw conclusions about the most effective methods for predicting failures, which is of great practical importance for ensuring the reliability of communication networks and minimizing downtime.

Keywords: extra tree regressor; failure prediction; machine learning; random forest; regression algorithms; support vector regression

RESUMEN

Se considera el uso de métodos de aprendizaje automático en sistemas de transmisión de información por fibra óptica (FOITS). El artículo analiza los principios básicos de funcionamiento de los sistemas de fibra óptica y los problemas que enfrentan, como el ruido, los efectos no lineales y la degradación de la información transmitida. Describe diversas técnicas de aprendizaje automático utilizadas en FOITS para controlar y supervisar el rendimiento, prevenir decisiones inteligentes y suprimir el ruido no lineal en la fibra óptica. Se presentan enfoques utilizados en aprendizaje automático, como redes neuronales, algoritmos de clasificación y regresión, y su aplicación en el análisis y la optimización de FOITS. Este artículo propone un método para supervisar el rendimiento y predecir fallos en redes ópticas basado en aprendizaje automático. Los resultados obtenidos permiten extraer conclusiones sobre los métodos más eficaces para predecir fallos, lo cual es de gran importancia práctica para garantizar la fiabilidad de las redes de comunicación y minimizar el tiempo de inactividad.

Palabras clave: algoritmos de regresión; aprendizaje automático; bosque aleatorio; predicción de fallos; regresión de vectores de soporte; regresor de árbol extra

1. INTRODUCTION

The FOITS is a set of optical transmission lines and optical devices designed for the formation, processing and transmission of optical signals, the function of which is to transmit the signal with high reliability and accuracy.

Currently, FOITS operate at high speed and with large traffic. Analysis shows that backbone networks in fiber optic communication systems are growing exponentially at a rate of 30-60% per year and are expected to continue to grow (Gordienko et al., 2016).

Optical networks can cause serious consequences when they fail, such as data loss, computing problems, and blocking information transfer. Therefore, failure management in optical networks is necessary to ensure stable operation, maintain high levels of service and quickly recover from failures.

Reliability is described as the ability of a system or component to perform specified functions, maintaining its characteristics for a specified time within the established norms of the value of functional parameters while observing operating modes, rules for maintenance, storage and transportation (Senior, 2008; Berghmans et al., 2008; Nazarov et al., 2021). In FOITS, reliability is the ability of a system to transmit data with minimal losses, without failures and failures, to ensure stable operation of telecommunications services. Reliability forecasting allows you to determine the requirements for redundancy, assess the ability of the network to maintain reliability in extreme conditions and assess the impact of changes on the entire network.

With the expansion of the Internet, a growing number of services require extensive data transfer within optical networks. Failures in these networks can lead to significant data loss. To mitigate such losses, various optical network protection algorithms have been developed, such as shared-path protection, best-effort shared risk link group failure protection, among others. However, these algorithms primarily focus on reacting to failures, offering protection and reducing damage only after a failure has occurred. As a result, data loss still occurs due to the time delay involved in protection and recovery.

Therefore, early warning and proactive protection are necessary. Some studies have proposed risk models that reroute high-risk services to lower-risk paths to prevent damage from potential failures in optical backbone networks (Dikbiyik et al., 2014). Other research has introduced risk-aware models aimed at preventing data loss in data center networks (Weigang et al., 2016). Additionally, k-edge and k-node models have been developed to protect optical mesh networks and data center networks from multiple failures, such as those caused by disasters, major power outages, or large-scale attacks (Huang et al., 2016). While these approaches offer ways to switch services or back up data when a risk is identified for a particular link or node (primarily in disaster or attack scenarios), they often do not focus on forecasting risks. There is still a need for effective methods to predict equipment failures in optical networks and take protective measures before a failure occurs. By anticipating equipment failures in everyday operations, the protection strategies based on risk-aware models could be adapted to address routine equipment faults, resulting in a more resilient optical network and significantly enhancing the user quality of experience (QoE).

Recent publications have demonstrated various approaches to reducing nonlinear phase noise, addressing system impairments in fiber communications, monitoring optical performance, and performing data detection in visible light communications. Given that failure prediction is an estimation problem and operating data contain inherent relationships, machine learning is well-suited for addressing this challenge. Researchers believe that this advanced technology holds significant potential for effective optical network failure prediction. However, as far as we know, machine learning algorithms have not yet been applied to predicting failures in optical network equipment.

2. MATERIALS AND METHODS

Classification of failures in FOITS in accordance with their causes are shown in Table 1 (Rausand et al., 2020).

Table 1. Classification of failures in FOITS

Types of failures	Causes	Manifestation
Constructive Failures	Imperfect design due to the use of outdated technologies; failure to consider specific operating conditions; violation of design and construction standards	Incorrect selection of fiber diameter, insufficient shielding from interference, errors in cable route design, uneven signal distribution, insufficient protection of amplifiers from external influences
Manufacturing failures	Process irregularities such as poor-quality control in production, material defects, component assembly errors	Formation of microcracks in optical fiber, core curvature, deviations in cladding geometry, presence of impurities or contamination in fiber material, defects in welded joints
Operational failures	Violation of established rules and operating conditions for fiber-optic information transmission systems	Cable damage due to excessive bending, poor quality connections, mechanical damage during installation, contamination of connectors, signal degradation due to insufficient optical power
Degradational failures	Aging of materials under the influence of temperature, humidity, radiation; natural wear and tear.	Gradual decrease in fiber transparency, deterioration of coating characteristics, decomposition of adhesive joints, loss of shell strength, appearance of microcracks, deterioration of the transmission characteristics of the system over time

The analysis showed that the main causes of failures in FOITS are mechanical damage, thermal effects, moisture and water damage, electromagnetic interference, connector and connection problems, equipment problems, natural disasters and power supply failures. Also, failures in fiber optic communication systems can vary depending on many factors such as network type, geographic location, operating conditions, etc.

Destabilizing factors on telecommunication networks during the year is shown in Figure 1 (Xujamatov, 2024).

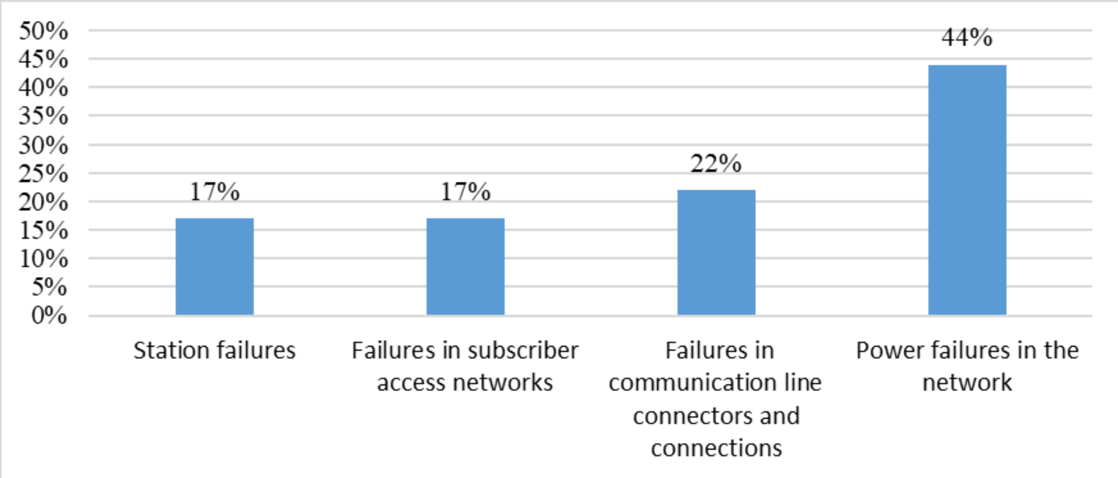

Figure 1. Destabilizing factors affecting the performance of telecommunication networks

To improve the performance and efficiency of FOITS, it is necessary to ensure the reliability of all its components, including methods for diagnosing elements and assemblies (Wang et al., 2021b; Davronbekov et al., 2014). The use of optical amplifiers helps to linearize the spectral characteristics of the system, which increases the length of the regeneration section and, thus, increases the reliability of data transmission over optical fiber (Davronbekov, 2016; Hakimov & Davronbekov, 2007).

The use of optical amplifiers and fiber lasers doped with rare earth ions increases the gap between regeneration points, reduces the need for additional amplifiers and regeneration equipment, which leads to an increase in the likelihood of failure-free operation of FOITS (Davronbekov & Juraeva, 2022; Davronbekov & Juraeva, 2023).

Conventional fault management techniques are based on threshold methods or statistical probability models, but they are limited in addressing complex and dynamic scenarios. The application of artificial intelligence for traffic forecasting, topology design, route calculation, distribution and fault management in optical networks is of paramount importance to ensure their reliability and stability. These methods are based on machine learning algorithms that are selected and modified for different failure modes according to the data and model objectives (Wang et al., 2021a).

Machine learning (ML) is a key area of artificial intelligence where systems can extract patterns from data, learn from them, and make decisions with minimal human intervention (Gu et al., 2020). To predict failures, it is important to monitor the status of the light path and optical components and then switch to the backup channel in advance to prevent failure.

An estimate of transmission quality and an estimate of the bit error rate can be used to predict light path failures (Lu et al., 2021). Assessing light path quality before deployment helps optimize optical network design and planning. Machine learning models are widely used to evaluate service quality. They are usually more robust to parameter uncertainties and require less computational resources than analytical models.

ML algorithms aim to extract information from data based on its characteristics, often called attributes or features. ML methods can be classified into the following categories (Musumeci et al., 2019):

- Supervised machine learning, which uses labeled data, where there is a historical set of input data (features) and corresponding output data. Problems can be either regression (for continuous values) or classification (for discrete values).

- Unsupervised machine learning, in which data is not labeled. Tasks include clustering (identifying similarities between data) and anomaly detection (identifying deviations in data).

- Semi-supervised machine learning, a combination of supervised and unsupervised approaches, is used in problems with partial data labeling.

- Reinforcement learning, the agent interacts with the environment to maximize the reward received for actions over time, learning from feedback.

Based on data on the number of failures, failure times and failure recovery times, the problem of predicting failures in FOITS is mainly reduced to a regression problem, since it is necessary to predict a continuous value, in particular the time until the next failure or the recovery time after a failure. For this reason, this work analyzes the algorithms that were used to predict failures in fiber-optic lines.

SVM (Support Vector Machine) is basically a binary classification algorithm that identifies support vectors from training data and uses them to construct a decision function. The data received from the optical network operator is divided into two groups: equipment failure data and normal data.

After the feature transformation, special attention is paid to finding the hyperplane that is optimally distant from the class boundary points in the data, which is the key focus of the algorithm. In the process of generating points from two probability density functions, the search for a hyperplane is associated with the determination of a decision boundary tending to maximum similarity (Khan et al., 2022).

SVM searches for an optimal separating hyperplane that maximizes the distance between the closest points of different classes, called support vectors.

The SVM algorithm is an efficient and accurate classification tool, especially when data is limited, making it attractive for WDM optical network applications.

Unlike classification, which uses SVM algorithms, Support Vector Regression (SVR) is a machine learning method used for regression analysis. The main goal of SVR is to find a function that approximates the relationship between input variables and a continuous target variable while minimizing the prediction error.

SVR seeks to find the hyperplane that best fits data points in continuous space. To do this, the input variables are mapped into a multidimensional feature space, where a hyperplane is searched in such a way as to maximize the distance between the hyperplane and the nearest data points, as well as minimize the prediction error.

SVR is capable of handling non-linear relationships between variables by using a kernel function to transform data into multidimensional space. This makes it a powerful tool for solving regression problems, especially in cases where there are complex relationships between the input variables and the target variable.

Linear regression is one of the most popular regression analysis methods, often used in predictive modeling projects. This is the simplest type of regression and can be used both to work with a single predictor (variable), called simple linear regression, and to work with multiple predictors, called multiple linear regression.

The essence of linear regression is to use linear functions to predict values based on the data available in the model (Saleh & Layous, 2022). Linear models are simple parametric methods that can be effectively applied to many problems, even when the data has significant nonlinearities.

The Random Forest algorithm is a widely used machine learning technique used for both classification and regression. It is based on the concept of ensembles of decision trees, where the diversity of models is increased by randomly sampling features at each node.

The process of constructing decision trees in a random forest involves selecting the best feature to split at each node. However, it is randomized by selecting a random subset of features and then selecting the best one. This allows you to increase the diversity of trees and improve the generalization ability of the model.

The advantages of Random Forest include good generalization ability, the ability to handle large volumes of features and data, and automatic detection and removal of noise and anomalies. This algorithm can be used, for example, to identify the causes of failures in optical networks or to predict future values of network parameters for the purpose of early detection of possible failures (Araújo et al., 2023).

The ExtRa-Trees algorithm is an ensemble learning method that combines the concept of random forests with additional randomness in the selection of split points. Unlike conventional random forests, ExtRa-Trees uses all the training data and randomly selects features and split points for each tree. This helps reduce overfitting and increase model diversity. As a result, ExtRa-Trees provides a reliable and accurate regression model with a small amount of computation (Geurts et al., 2006).

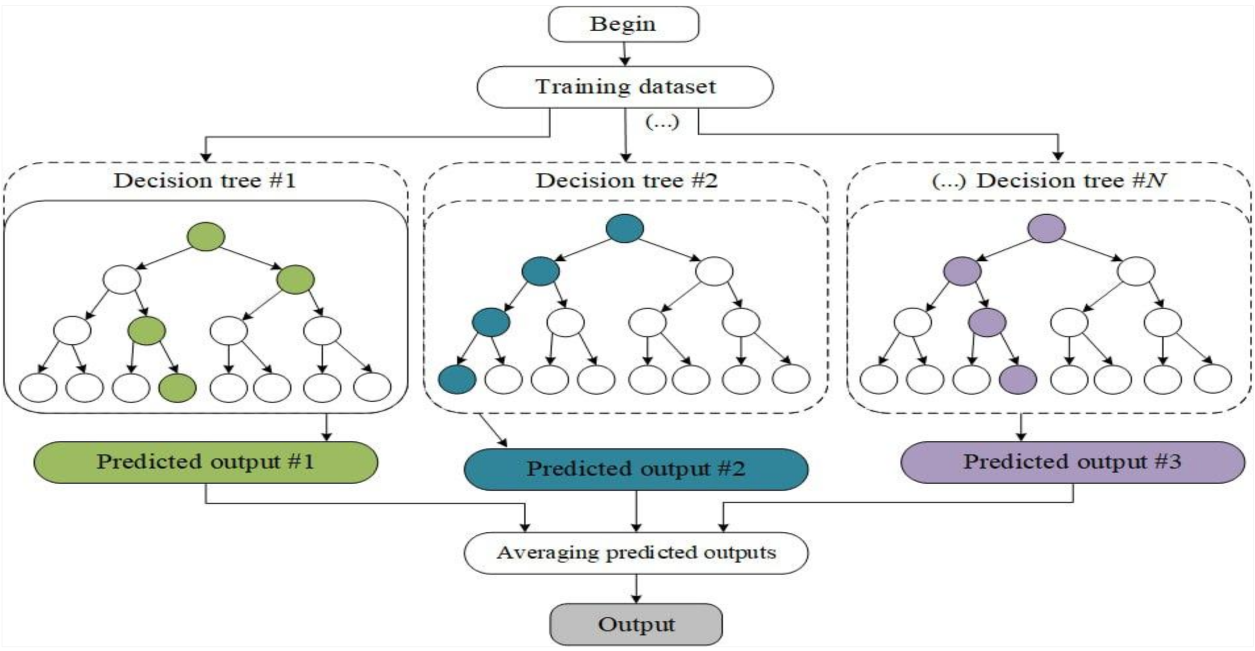

Figure 2. ExtRa-Trees algorithm structure for regression problems

Extra-Trees, unlike random forest, uses random subsets to train base models and combines data to predict outcomes. However, its special feature is that it selects the best feature through random node splitting and has a structure that includes several decision trees. Each tree consists of a root node, split nodes, and leaf nodes. When analyzing data, the algorithm splits it into random subsets of objects at the root node, treating each subset as a split/child node (Figure. 2). The splitting process continues until the end node is reached. For each tree, outcome predictions are calculated and then combined across different trees. The predictions of each tree are combined to produce a final prediction based on the majority vote in classification problems and the arithmetic mean in regression problems (Tran et al., 2023).

The data was predicted by comparing performance estimates using metrics such as RMSE (Root Mean Squared Error) and R^2 - coefficient of determination, the formulas for which can be presented as follows (Davronbekov et al., 2024):

$$\boldsymbol{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (1)$$

where n - number of observations, $\hat{y}_i$ - model-predicted value of the dependent variable, y_i - actual value of the dependent variable.

$$\boldsymbol{R^2} = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(\bar{y}_i - y_i)^2} \quad (2)$$

where $\bar{y} = \frac{1}{l}\sum_{i=1}^{l} y_i$ - mean value of the target variable.

3. RESULTS AND DISCUSSION

Based on statistical data on the number of failures and recovery times in fiber-optic transmission networks, the possibility of predicting, preventing possible failures and, as a result, increasing the reliability of the network based on machine learning algorithms is considered. After the extensive collection of the data for a span of 4 years, data collection quality is examined and the linearity is found in the continuity as well as in the failure time. Through an extensive choice of machine learning algorithms, Linear regression algorithm was selected to develop a model or predicting failures (Weigang et al., 2016). For extra comparisons, other traditional machine learning models like SVR, Random Forest, ExtRa-Trees regressor, MLP regressor, Gradient Descent were developed and checked for predictability performance.

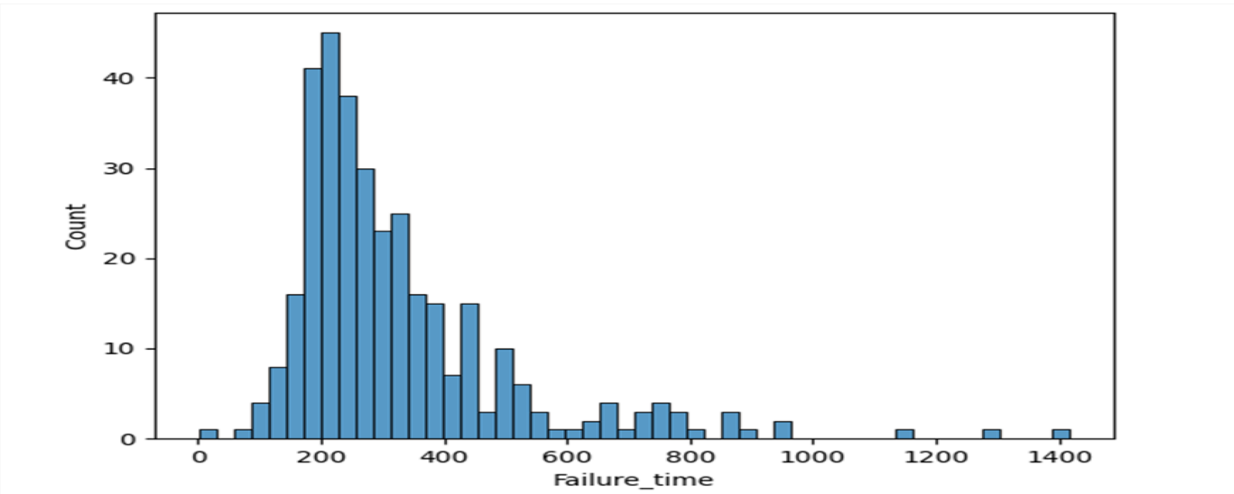

Figure 3. Histogram indicates the failure time occurrences with the recorded failure time in minute

According to the collected data (Figure.3), the highest failure accoracnce were collected through 189 to 350 minute range. As can be clearly seen from the histogram Figure 3, the most frequent failure times were between 180 and 500 minutes.

The collected data included the collection time, failure time, the continuity of the failure, the number of failures as well as the month of the failure. Depending on the distribution of the data, some of the outliers above 600 interruptions were cleaned and the rest of the data were fed into the Linear Regression model to make predictions. After building the machine learning models.

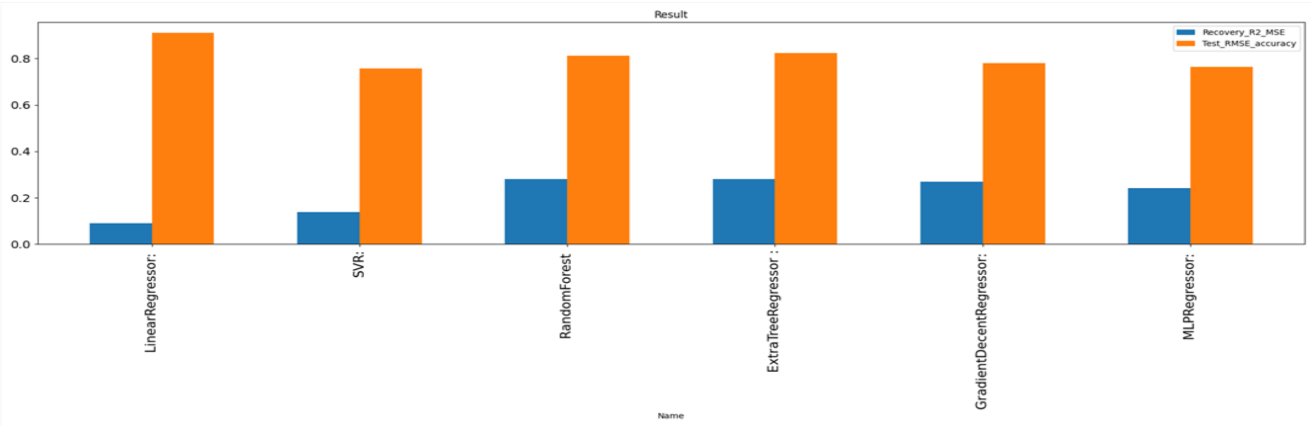

Figure 4. The predicted values of RMSE accuracy and R squared recovery

Linear Regression model showed the best RMSE accuracy with 91% and the least recovery R squared value. Extra Tree Regressor machine learning model indicated the highest recovery R squared value with 28% and 82% RMSE accuracy. The other ML models performed almost similarly with Extra Tree Regressor model with being around 80% of RMSE accuracy and 20% of Recovery R squared value (Figure.4) and in table 2 the overall RMSE accuracy as well as the R-squared values are presented.

Table 2. Comparative accuracy of ML models by RMSE and R-squared values

Models / Value	LineaR Regression	SVR	Random Forest	Extra Tree Regressor	Gradient Descent Regressor	MLP Regressor
RMSE	92%	78%	80%	82%	79%	78%
R-squared value	18%	18%	28%	28%	28%	26%

After some predictions, the developed ML models showed relatively good results with the failure time as well (Figure 5).

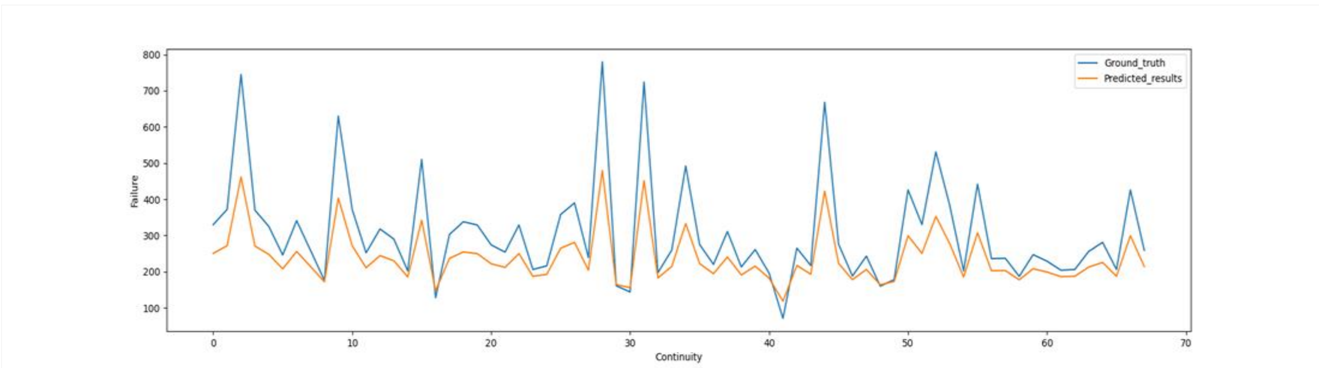

Figure 5. Results of developed ML model compared to the ground truth failure time

The Figure. 5 shows the results of predicted values of the data and the ground truth for the failures and continuity of the failures at a given time period. Developed machine learning algorithm accurately confirms the predictability of the failures in the process with the correct backing fa ilure continuity time.

CONCLUSIONS

Extensive data on the times and dates of failures has been successfully used to create machine learning models that can predict when failures will occur with high accuracy. After building the machine learning models, it was found that the linear regression model showed the best accuracy, expressed in the value of RMSE (root mean square error) - 91%, with the lowest value of R-squared recovery. The Extra Tree Regressor machine learning model showed the highest recovery R-squared value of 28% and RMSE of 82%. Other machine learning models also performed well, with an accuracy of about 80% for RMSE and 20% for R-squared recovery.

The developed machine learning models showed relatively good results in predicting the timing of failures. Thus, the results of the study indicate the potential of using machine learning models to predict failure timing, which can be useful for optimizing maintenance processes and preventing failures.

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CONFLICT OF INTEREST

There is no conflict of interest related to the subject matter of the work.

AUTHORSHIP CONTRIBUTION

Conceptualization, data curation, formal analysis, research, visualization, writing -original draft, writing -correction and editing: Juraeva, N., Davronbekov, D. and Turdiev, U.

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