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Neural network-based prediction of technical failures in communication networks

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Abstract: This article discusses the problem of automated forecasting of the technical condition of train radio communication networks within the railway sector of Uzbekistan. The technical characteristics of existing systems, the theoretical model of signal propagation, and the main causes of failures are examined in detail. Traditional forecasting approaches are shown to be limited, as they often fail to adequately reflect nonlinear processes, the influence of electromagnetic interference, and the impact of maintenance activities. To address these shortcomings, an automated forecasting approach based on artificial neural networks is proposed. This method makes it possible to identify both sudden and gradually developing faults in advance, thereby increasing overall system reliability, supporting effective planning of technical maintenance, and reducing operational costs. Practical experiments carried out on railway sections confirmed the effectiveness of the proposed methodology. Overall, the use of neural networks for forecasting is considered a scientific and practical solution for enhancing the reliability of train radio communication systems, improving safety, and accelerating the gradual transition toward digital communication technologies.
Keywords: Train radio communication, telecommunication networks, neural networks, predictive maintenance, fault forecasting, technical condition monitoring, reliability, readiness coefficient, railway communication systems, digital technologies

1. Introduction

Railway transport represents one of the key sectors of a country's economic and social infrastructure, and its operation must consistently meet high standards of safety and efficiency. Ensuring traffic safety and managing transportation processes critically depend on operational-technological communication systems (OTCS). These systems provide continuous information exchange among train drivers, dispatchers, station attendants, and technical personnel. Therefore, train radio communication (TRC), which constitutes an integral part of OTCS, is required to guarantee a high level of reliability and continuity, serving as one of the fundamental conditions for safe and stable railway operations [1].

At present, TRC systems in Uzbekistan primarily operate within the hectometer (HF/VHF low-band) and meter (VHF high-band) frequency ranges. These ranges have been in practical use for many years and were once considered effective solutions. The advantage of the hectometer range lies in its ability to provide long-distance signal transmission. However, due to its high sensitivity to atmospheric noise and industrial electromagnetic interference, reliable communication is frequently disrupted. The meter range, in contrast, ensures higher-quality voice transmission, yet its dependence on line-of-sight propagation leads to significant signal attenuation in mountainous areas and especially within long tunnels.

Currently, TRC equipment and line infrastructure in Uzbekistan are physically outdated. Corrosion in antennas and cables, contamination of insulation, and loosening of contacts gradually deteriorate signal quality. As a result, "uncertain radio coverage zones" emerge within the network, where train drivers cannot maintain stable communication with dispatchers, thereby reducing the overall level of operational safety [1].

Traditional monitoring methods do not allow timely identification of such problems. In the existing system, signal levels are recorded only once every quarter using laboratory railcars. However, new faults that occur in the interval between inspections may remain undetected for several months. Increasing the frequency of inspections would sharply raise operational costs. Consequently, the automated forecasting of parametric faults has become an urgent and essential task.

Reliability indicators of train radio communication networks. One of the most important concepts in assessing the efficiency and safety of technical systems is reliability. In TRC networks [2], reliability is evaluated using the readiness coefficient (K_g):

$$K_g = \frac{T_p}{T_p + T_b}$$

where:

- T_p – the total operating time of the TRC channel,
- T_b – the recovery time after a failure.

If failures occur infrequently or recovery is carried out very quickly, the value of K_g approaches one. This indicates that the system is highly reliable. Conversely, if failures occur frequently or the recovery process takes a long time, the value of K_g decreases significantly, reflecting reduced system reliability.

For TRC systems, maintaining the readiness coefficient within the range of 0.95–0.98 is considered one of the essential safety requirements. In practice, however, especially when using outdated equipment, this indicator often does not exceed 0.90–0.92. Therefore, enhancing the reliability of existing systems requires not only the rapid detection of failures but, more importantly, their prediction in advance [3].

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Empirical observations on the railways of Uzbekistan show that TRC systems operating in the hectometer band are frequently affected by atmospheric noise, resulting in repeated signal losses. In the meter band, sudden attenuation or complete loss of the signal is observed in mountainous areas or inside tunnels. Under such conditions, the recovery time (T_b) increases, leading to a reduction in the readiness coefficient. Consequently, minimizing T_b is a fundamental requirement for improving the reliability of TRC systems.

2. Research methodology

Theoretical model of signal propagation. The primary function of TRC systems is to ensure continuous and reliable communication between the train driver and the dispatcher. The stability of communication primarily depends on the propagation characteristics of radio waves and the effective transmission distance of the signal. Therefore, accurate modeling of signal propagation and the establishment of theoretical foundations are of crucial importance in TRC networks [4].

One of the fundamental requirements for communication quality in train radio systems is that, at any point within a given section, the train driver must maintain reliable contact with at least two stationary base stations located on opposite sides. Based on this principle, the normative condition can be expressed as follows:

$$r_1 + r_2 - 3 \geq l$$

where:

- r_1 and r_2 – the reliable communication ranges (in km) between the locomotive and the stationary base stations on the left and right sides, respectively,
- l – the total length of the section (in km).

If this condition is met, the train driver will be able to maintain simultaneous communication with two base stations at any point along the section. This serves as a fundamental guarantee of operational safety requirements [5].

In radio communication systems, the communication range can be calculated using the following formula:

$$r = \frac{A_{tx} - u_{min} - A_{ant.loss} - \sum a_{st} - \sum a_{lin} - \sum a_{loc}}{a_H}$$

where:

- A_{tx} – output signal level of the transmitting station, dB;
- u_{min} – minimum useful signal level at the receiving station, dB;
- $A_{ant.loss}$ – antenna transition losses, dB;
- $\sum a_{st}$ – attenuation in stationary equipment, dB;
- $\sum a_{lin}$ – attenuation in feeder lines, dB;
- $\sum a_{loc}$ – attenuation in locomotive equipment, dB;
- a_H – attenuation coefficient per kilometer of transmission line, dB/km.

This formula provides an accurate evaluation of the signal quality and coverage range of train radio communication systems. Any variation in these parameters can have a significant impact on the overall result [6].

The output signal level (A_{tx}) is the key indicator of the transmitter's power. The higher the power, the greater the achievable communication distance. However, excessive power consumption increases energy costs and may violate electromagnetic compatibility requirements.

The minimum useful signal (u_{min}) represents the lowest value necessary for the receiving station to distinguish the signal from background noise. This parameter depends on the sensitivity of the receiving equipment and the prevailing noise level.

Losses ($A_{ant.loss}$, $\sum a_{st}$, $\sum a_{lin}$, $\sum a_{loc}$) denote the attenuation occurring during antenna transition, propagation along the transmission line, and within locomotive equipment. In practice, these losses often represent the primary reason for signal quality degradation.

The per-kilometer attenuation coefficient (a_H) characterizes the natural decrease in signal strength along the guiding line [7]. It depends on the material of the line, cable quality, and surrounding environmental conditions.

By applying the theoretical model of signal propagation, it is possible to preliminarily assess signal quality and coverage distance in TRC systems. This enables:

- optimal selection of inter-station distances,
- accurate design of antenna placement,
- timely maintenance of transmission lines,
- reduction of operational costs.

However, the model is based solely on static calculations and does not fully account for factors such as equipment aging, gradual degradation, and the influence of external electromagnetic environments over time. Therefore, for forecasting parametric failures, more effective approaches are required – in particular, *automated prediction methods based on neural networks* [8].

The criticality of failures depends on both their rate of impact and the possibility of detection. Sudden failures are usually recognized immediately and can typically be eliminated within a short period of time. Gradual failures, on the other hand, are more hazardous since they may remain unnoticed for an extended period while posing a significant threat to operational safety.

On the railways of Uzbekistan, gradual failures represent the most frequent and problematic category. Such faults cannot be reliably detected through traditional quarterly inspections, as they tend to develop and intensify in the intervals between scheduled checks. Therefore, the ability to forecast these failures in advance and to predict their potential occurrence has become a crucial necessity [8].

The time-dependent nature of failures provides an important opportunity for forecasting. For example, if the resistance of a cable is observed to increase on average by 0.2–0.5 Ohm per kilometer annually, this trend can be used to determine the rate of degradation and to estimate the subsequent decline in signal quality. Similarly, antenna misalignment occurring after each severe wind event can be tracked and predicted based on statistical data.

Thus, while sudden failures can generally be eliminated through prompt technical maintenance, gradual failures can only be identified using forecasting systems, particularly automated approaches based on neural networks [9–11].

Although traditional forecasting methods are theoretically simple and relatively easy to apply in practice, they do not fully correspond to the actual conditions of TRC systems. These methods describe degradation processes only in a generalized manner and fail to account for complex electromagnetic environments, maintenance activities, and abrupt changes in operating conditions. As a result, their application on the railways of Uzbekistan often leads to inaccurate forecasts.

To overcome these limitations, more flexible methods capable of modeling complex processes are required, such as *artificial neural networks* [12]. The following section provides a detailed discussion of the theoretical foundations and practical implementation of such approaches.

3. Results and Discussion

Automated approaches based on neural networks. As a rule, the occurrence of unstable radio communication zones is associated with unexpected or gradually developing faults along the signal propagation path, as well as the influence of electromagnetic noise.

Unexpected faults may arise within the operational limits of equipment performance. Such failures typically occur either spontaneously or as a result of external impacts. Examples include interruptions, short circuits, contact disconnections, insulation breakdowns, or mechanical damage. However, this category of faults is relatively easy to detect, since the location of the damage can usually be identified and eliminated quickly by conducting an external inspection of feeder lines and antenna equipment [13].

Gradual failures are characterized by the progressive degradation of parameters such as $\sum a_{st}$, $\sum a_{lin}$, $\sum a_{loc}$, and a_H. As a result, the overall communication range decreases, and unstable coverage zones appear in certain sections of the network.

The causes of such failures may include corrosion of transmission lines, deterioration of contact quality, contamination of insulators, disruption of cable connections, reduction of the quality factor in resonant and locking circuits, changes in antenna radiation patterns, as well as degradation of feeder components due to aging or water ingress.

Detecting gradual failures is complex, yet they manifest intermittently, which allows their occurrence to be diagnosed. For automated diagnostics, the primary input data are the signal levels recorded from stationary base stations. The results of these measurements are represented in the form of a two-dimensional vector [14].

$$\bar{u}_t = \begin{vmatrix} u_{a1} & u_{a2} & \cdots & u_{am} \\ u_{b1} & u_{b2} & \cdots & u_{bm} \\ \cdots & \cdots & \cdots & \cdots \\ u_{g1} & u_{g2} & \cdots & u_{gm} \end{vmatrix},$$

where u_{gm} denotes the average voltage at the locomotive receiver, m represents the kilometer mark, and g corresponds to the active base station.

The data presented in this form must first undergo preprocessing, where all missing elements are restored through interpolation, and the measured signal levels are aligned with the corresponding points (linked to each kilometer of the section).

Neural network architecture. For forecasting tasks, a multilayer perceptron (MLP) architecture is most commonly applied. Its main components are as follows:

- *Input layer* – vectors representing signal levels and contextual predictive factors.
- *Two hidden layers* – performing nonlinear transformations.
- *Output layer* – predicted signal levels and vectors of technical condition.

The activation function selected is the sigmoid:

$$f(x) = \frac{1}{1 + e^{-x}}$$

Since the sigmoid function is differentiable, it enables the efficient application of gradient-based training algorithms, such as backpropagation [15].

Mathematical model. The mathematical model of the neural network can be expressed through the following system of equations:

$$c_j = f\left(\sum_{i=1}^{r} a_i \alpha_{ij} + \chi_j\right), \qquad j = 1, \dots, r_1,$$

$$k_s = f\left(\sum_{j=1}^{r_1} c_j \beta_{js} + \eta_s\right), \qquad s = 1, \dots, r_2,$$

$$q_h = f\left(\sum_{j=1}^{r_2} k_s \gamma_{sh} + \upsilon_h\right), \qquad h = 1, \dots, n,$$

where:

- a_i – elements of the input vector (signal levels and factors),
- α, β, γ – synaptic weights,
- χ, η, υ – bias coefficients of the neurons,
- c_j, k_s, q_h – outputs of the first hidden layer, second hidden layer, and output layer, respectively.

The output vector q_h represents the predicted signal levels and the technical condition of the system.

Error function and training. During training, the neural network outputs are compared with real measurements. The error function is defined as:

$$\Phi_i = \frac{1}{2}\left(u_{gi} - u_{gi}^{(t+1)}\right)^2,$$

where u_{gi} is the real signal level and $u_{gi}^{(t+1)}$ is the predicted signal level.

The training objective is formulated as:

$$\max(\Phi_i) \le \Delta,$$

where Δ is the maximum permissible prediction error.

Using a gradient optimization algorithm, the synaptic weights and biases of the neurons are iteratively adjusted.

In the simplest case, a single parameter, time, serves as the main argument for forecasting. In such cases, the problem can be solved by applying mathematical methods of extrapolating previous measurement results over time. However, in the present context, these methods exhibit several limitations:

- it is impossible to construct an accurate predictive model without studying the operational history of the system over a long period or by incorporating additional types of data;
- changes in parameters cannot be adequately described without proper mathematical characterization;
- all mathematical forecasting methods are treated as open systems, where errors at the input are fully transmitted to the output, thus negatively affecting

prediction accuracy;
- obtaining accurate forecasts requires consideration of all measures undertaken to improve the technical condition of TRC equipment, which is not feasible within the framework of purely mathematical methods;
- at the initial stage of operating a fully modernized TRC network (e.g., during electrification), the necessary conditions for forecasting using mathematical methods are not present.

This problem can be partially addressed through prediction based on the theory of statistical classification (pattern recognition), where extrapolative relationships are established from the available initial data. However, the inability to resolve poorly formalized aspects of the forecasting process and the relatively low accuracy of the results prevent these methods from being applied effectively.

These shortcomings can be overcome by employing neural network (NN) algorithms, which extrapolate within the feature space of the technical system's states. In general, the procedure for automated prediction of failures in train radio communication networks using NNs is illustrated in Figure 1.

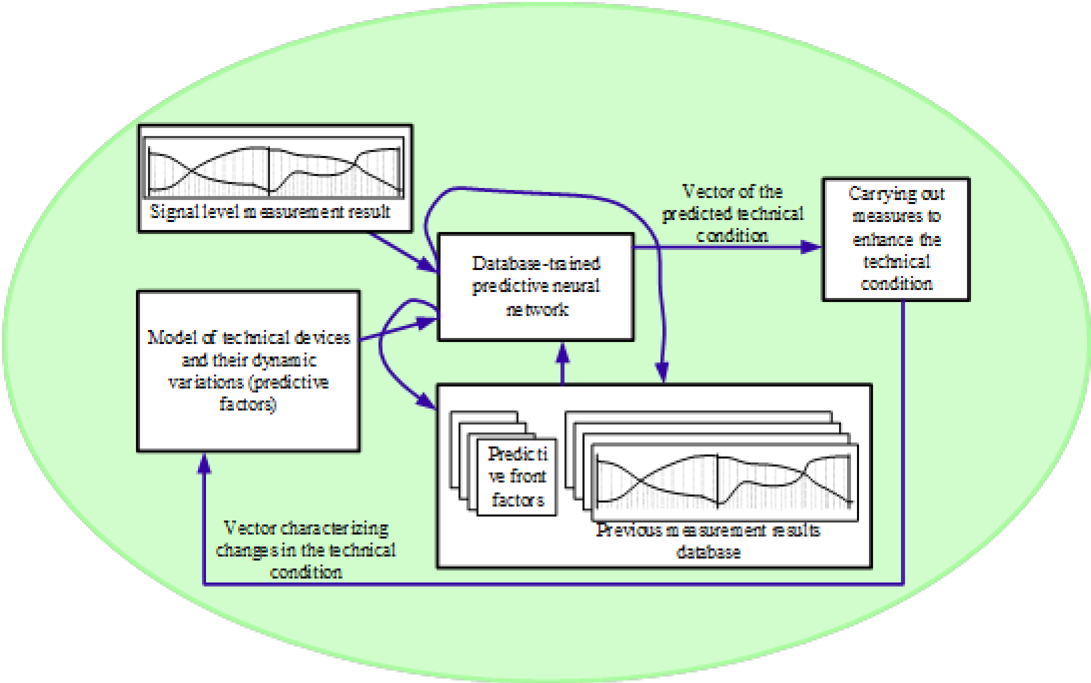

Figure 1. Automated procedure for forecasting failures in train radio communication networks

The central component of this structure is the neural network trained on a database formed from previous measurement results. Once the signal levels from stationary base stations are recorded, they are combined with data reflecting quality changes in equipment, line devices, and guiding channels, and then fed into the neural network as input. At the output, a vector is generated that represents the predicted future technical state of the TRC system. Based on these results, preventive maintenance measures are developed and implemented in practice.

Using laboratory railcars, signal levels are periodically recorded, and the results are entered into the database, enabling the neural network to be retrained. In this way, the model is continuously refined and improved over time.

In general, forecasting using a neural network consists of the following main stages:

- collection of initial data and their normalization into a unified format;
- synthesis of the predictive architecture of the neural network;
- training of the neural network with empirical data samples to form the predictive model;
- obtaining the forecast result for the specified prediction horizon;
- verification of the predictive model against established criteria and its preparation for practical application.

The application of neural networks for forecasting parametric failures in TRC networks has demonstrated high effectiveness in practice. Results indicate that this approach provides significantly greater accuracy compared to traditional methods and allows for efficient planning of maintenance activities even under complex operational conditions. However, like any technological solution, neural networks possess both advantages and limitations. At the same time, numerous prospects exist for further improving this approach in the future [16].

By employing neural networks, "uncertain communication zones" in TRC systems can be identified well in advance. For example, in the Kamchik tunnel, hazardous areas caused by signal attenuation can be predicted by the neural network several weeks beforehand. This provides dispatchers and technical staff with the opportunity to take preventive measures in advance. As a result, the overall safety of train operations is significantly enhanced.

The architecture of the predictive neural network is illustrated in Figure 2.

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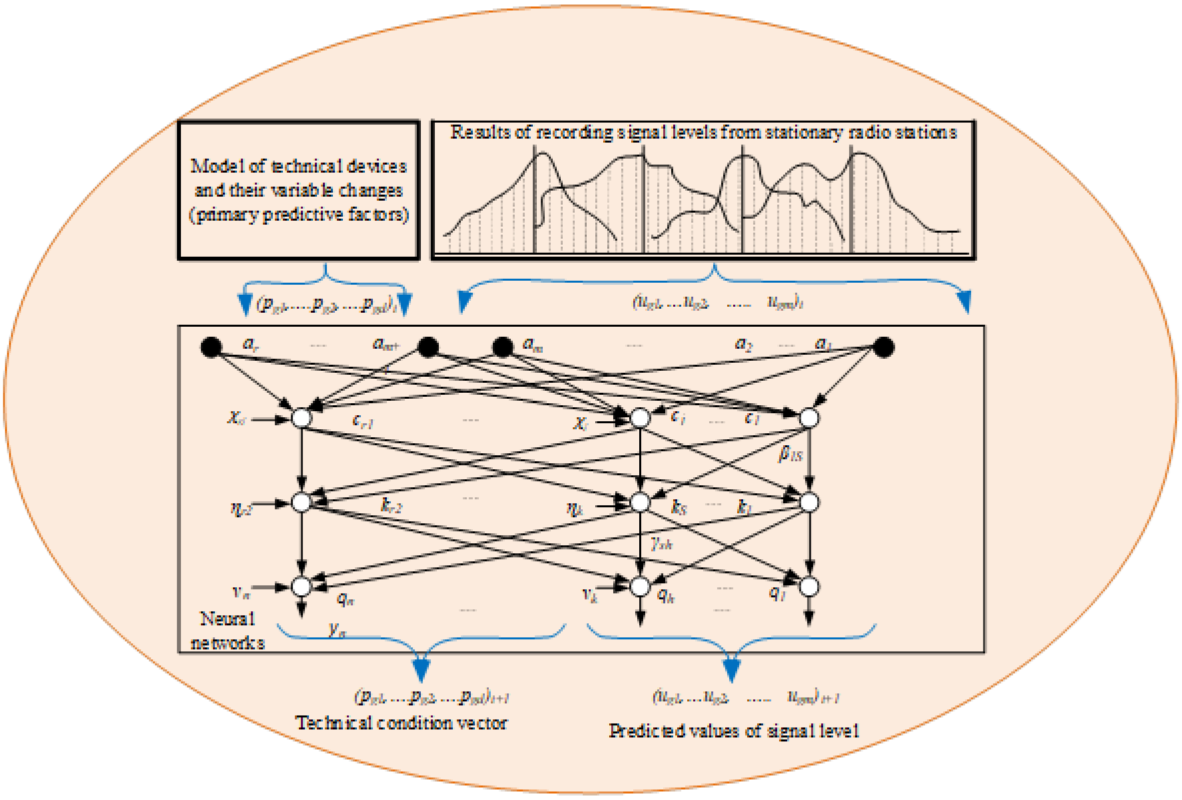

Figure 2. Predictive neural network architecture

In traditional approaches, emergency maintenance operations require substantial costs, since eliminating failures after they occur demands more resources and time. A forecasting system, on the other hand, enables precise planning of preventive maintenance. For instance, if antenna adjustments or cable replacements are carried out before an emergency situation arises, overall expenses can be reduced by up to thirty percent.

Neural networks can be retrained on the basis of newly collected data. Consequently, the system is continuously updated and adapts even when technical conditions change. For example, if the TRC system transitions from analog to digital equipment, the neural network can be retrained in a short period using the new parameters while continuing to function effectively [17].

Signal attenuation and electromagnetic interference often exhibit nonlinear characteristics. Conventional extrapolation methods cannot fully capture such dynamics. Neural networks, however, are capable of efficiently modeling and learning these complex nonlinear dependencies.

A comparative analysis of traditional forecasting and neural network-based forecasting is presented in Table 2.

Furthermore, the neural network-based forecasting system can be integrated with other systems currently being deployed in Uzbekistan Railways. For example, it can be combined with DMR base stations, GPS/GLONASS monitoring systems, and SCADA platforms to create a unified control center. This integration ensures not only reliable management of radio communication but also comprehensive monitoring of other technical subsystems.

Table 2

Comparison of traditional forecasting and neural network-based forecasting

Indicators	Traditional methods (extrapolation, ARIMA)	Neural network-based forecasting
Forecast accuracy	±3–4 dB	±1.5 dB
Historical data requirement	Long-term (years)	Can be trained even with short-term data
Consideration of maintenance	No	Yes
Adaptation to EM environment	Not fully reflected	Adaptive
Practical efficiency	Moderate	High (accuracy improvement of 20–25%)

The results of the discussion demonstrate that a neural network-based forecasting system can significantly enhance the reliability of TRC within Uzbekistan Railways. The advantages of this approach outweigh its limitations, as it ensures safety, reduces operational costs, and brings the system closer to meeting modern technological requirements. In the future, this approach may be further improved through integration with emerging technologies such as the Internet of Things (IoT), fifth-generation (5G) communication, and the Future Railway Mobile Communication System (FRMCS), thereby evolving into a more advanced and comprehensive solution [17].

4. Conclusion

This study examined the problem of forecasting parametric failures in TRC networks. First, the technical characteristics of existing systems, the theoretical model of signal propagation, and the causes of failures were analyzed. It was concluded that traditional forecasting methods are insufficient under real operating conditions, as they fail to account for maintenance activities and the complexity of the electromagnetic environment.

A neural network-based forecasting approach was proposed. This method enables the processing of signal levels and the modeling of complex nonlinear processes. The results showed that uncertain communication zones can be identified one to two months in advance, with a prediction error of approximately ±1.5 dB, compared to ±3–4 dB for traditional methods. The readiness coefficient of the TRC system can thus be increased to 0.98.

In Uzbekistan Railways, challenges such as attenuation of VHF signals, atmospheric noise in the HF band, and antenna misalignment across certain sections were effectively addressed through neural network-based forecasting. This approach not only improves safety but also reduces operational costs by up to thirty percent [18].

Overall, neural network-based forecasting represents a practical and scientifically grounded solution for significantly enhancing the reliability of TRC systems in Uzbekistan Railways. Moreover, it provides a robust foundation for the gradual transition of these systems to advanced digital technologies, including DMR, TETRA, and FRMCS.

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