

Article

Helicopter Turboshift Engine Residual Life Determination by Neural Network Method

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Abstract: A neural network method has been developed for helicopter turboshaft engine residual life determination, the basis of which is a hierarchical system, which is represented in neural network model form, consisting of four layers, which determines the numerical value of the residual life. To implement a hierarchical system, a justified multilayer perceptron is used. A multilayer perceptron training algorithm has been developed, which, by introducing an initial parameter to the output layer, yields a prediction accuracy of up to 99.3%, and the adaptive Adam training rate ensures an accuracy of up to 99.4% in helicopter turboshaft engine residual life determination. A method for constructing a degradation curve has been developed that takes into account both the parameter predictions and similarities with past patterns, allowing you to determine the range of possible values of the residual life estimate, with a probability of up to 95%. The article considers an example of solving the task of determining the thermally stressed state of helicopter turboshaft engine compressor turbine blades and assessing their residual life. A computational experiment was carried out to determine the residual life of helicopter turboshaft engine compressor turbine blades, and the results, with 160 training epochs, recorded an accuracy of 99.3%, with a reduction in losses from 2.5% to 0.5% thanks to training process optimization by applying an adaptive training rate. The comparative analysis results showed that use of the multilayer perceptron as a hierarchical system gives better results than the classical RBF network and the least squares method. The first and second types of error were reduced by 2.23 times compared to the RBF network and by 4.74 times compared to the least squares method.

Keywords: helicopter turboshaft engines; residual life; compressor turbine blade; neural network; training; mean square error; accuracy; normalized exponential linear unit



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1. Introduction

1.1. Relevance of the Research

Helicopter turboshaft engines (TEs) are advanced components crucial for flight reliability and safety [1,2]. During operation, these engines experience wear, making it essential to evaluate their remaining lifespan to ensure timely maintenance and component replacement [3,4]. The longevity of helicopter TEs is influenced by numerous factors, such as operational intensity, environmental conditions, fuel and lubricant quality, as well as the effectiveness of regular maintenance [5]. Modern gas turbine engines (GTEs)

are equipped with diagnostic systems enabling real-time monitoring of key component conditions, significantly facilitating maintenance oversight [6].

The relevance of a helicopter TE residual life determination method lies in its critical role in ensuring flight reliability and safety. Helicopter TEs are high-tech components on which the operational readiness and safety of a helicopter directly depend. During operation, engines are subject to wear, and timely assessment of their residual life is necessary for planning maintenance and component replacement, which prevents possible emergencies. Determining residual life takes into account many factors, such as intensity and operation modes, environmental conditions, fuel quality and lubricants, as well as regularity and maintenance quality. Modern diagnostic systems built into helicopter TEs allow real-time monitoring of key component conditions, which significantly increases the prediction accuracy of their service life and reduces the risks associated with their failures.

1.2. State-of-the-Art

One of the primary objectives in assessing residual life involves accurately predicting the condition of various engine components [7]. To achieve this aim, mathematical modeling and data analytics techniques are employed, enabling predictions of future engine states using historical data and current measurements. It is crucial to acknowledge that component wear can exhibit nonlinear behavior, with distinct critical wear thresholds for different components, necessitating a holistic approach to data analysis [8].

Another crucial component is the implementation of regular diagnostic measures. These include vibration analysis [9,10], temperature and pressure measurements [11,12], and non-destructive testing methods [13,14]. These techniques can detect early signs of wear and damage, enabling preventive measures to avoid emergencies. For instance, vibration analysis can identify imbalance or bearing wear, while temperature measurements can highlight cooling or combustion issues [14].

However, despite their effectiveness, these methods also have critical drawbacks. They require highly qualified personnel to perform and interpret the diagnostic results, which increases the error risk [15]. At the same time, equipment for such diagnostic measures is expensive, increasing operating costs, especially for small airlines and private helicopter owners [16]. Diagnostic procedures often require the helicopter to be taken out of service, resulting in significant downtime and reduced operational efficiency [17]. There are also problems with the accuracy and sensitivity of these methods, as vibration analysis may not detect microcracks or initial stages of corrosion, and temperature measurements may not be accurate enough to detect extreme temperature fluctuations under certain conditions [18]. Non-destructive testing methods may not be effective in environments with high noise and vibration levels, reducing data accuracy and missing critical defects, thus increasing risk.

Based on the above, neural network methods [19–21] are becoming increasingly relevant and necessary in the determination of helicopter TE residual life. Neural network models trained on large amounts of engine operation data [22,23] can significantly improve accurate prediction of component wear and failure. These methods can account for complex nonlinear dependencies between various operating parameters. For example, this could be temperature, pressure, vibrations, and operating mode. Traditional analytical methods may not fully account for these parameters.

Neural networks enable real-time analysis of large amounts of data [24], uncovering hidden patterns and anomalies [25] that are challenging to detect with conventional diagnostic methods. This enhances diagnostic and prognostic accuracy while lowering the unexpected risk of engine failure. Neural networks also facilitate precise and detailed diagnostics of compressor turbine blades, crucial for preventing premature failures and optimizing routine maintenance [26]. Neural networks are flexible and reliable tools because they can adjust predictions in accordance with new data, which makes them an effective tool for helicopter TE operational status monitoring.

In addition, neural network methods can be integrated with existing diagnostic and management systems [27,28], providing a more comprehensive and pro-active approach to

maintenance. They can predict not only the time until the next maintenance but also the specific components that require attention, allowing you to optimize maintenance processes and reduce costs. The introduction of neural network technology into the helicopter TE monitoring system not only improves flight reliability and safety but also contributes to more efficient management of resources and costs [29,30].

Problems that remain unresolved include the nonlinear nature of wear, which makes it difficult to accurately predict the wear patterns of different engine components. Different components have their own critical wear points, requiring a comprehensive approach to data analysis. Diagnostic methods such as vibration analysis and temperature and pressure measurements may not be accurate or sensitive enough in environments with extreme temperature fluctuations and high noise and vibration levels.

To solve these problems, it is necessary to carry out a number of research and developments, including mathematical model development for helicopter TE residual life determination and a neural network model to improve the prediction and accuracy of wear diagnostics. It is also important to create effective algorithms for training neural networks to analyze large amounts of engine operation data and conduct a computational experiment to confirm the proposed model's effectiveness. Conducting a comparative analysis of the new method with classical methods, such as the least squares method, will reveal their advantages and disadvantages. This research will help to significantly improve helicopter TE residual life prediction accuracy and increase overall operation reliability and safety.

1.3. Main Attributes of the Research

The object of the research is the processes and characteristics of the helicopter TE residual life determination system.

The subject of the research includes the methods and means of the helicopter TE residual life determination system under flight operating conditions.

The research aims to develop and implement a neural network method for determining the helicopter TE's remaining life to increase the accuracy of predicting wear and component failures, engine operational status diagnostics, and monitoring improvements.

To achieve this aim, the following scientific and practical tasks were solved:

1. Development of a mathematical model for helicopter TE residual life determination.
2. Development of a neural network model for helicopter TE residual life determination.
3. Development of a neural network model training algorithm for helicopter TE residual life determination.
4. Conducting a computational experiment to determine helicopter TE residual life (using the example of determining TE compressor turbine blade residual life).
5. Conducting a comparative analysis of the results obtained for helicopter TE residual life determination with those obtained by classical methods, based on classical statistical methods for experimental data processing (for example, the least squares method).

In summary, the main contribution of the research is the helicopter TE residual life estimation method using neural network technology, which makes it possible to predict helicopter TE residual life with high accuracy, using compressor turbine blades as an example.

Therefore, this research primarily assesses the efficacy of advanced neural network technologies in helicopter TE compressor turbine blade residual operational life prediction, emphasizing significant enhancements in predictive accuracy and error reduction over traditional methods.

2. Materials and Methods

Helicopter TEs operate under extreme conditions, subjecting materials to high temperatures, pressure, and mechanical stress. The primary materials used in these engines are heat-resistant alloys and ceramics, known for their strength, ductility, creep resistance, and thermal stability. These materials endure cyclic loads that cause fatigue, a process where repeated stress leads to microcrack formation and growth. Evaluating fatigue life requires considering load amplitudes, cyclic frequencies, and their effects on the material's

microstructure. Wear, caused by friction, abrasive particles, corrosion, and erosion, also critically impacts the engine's residual life, necessitating analysis of contact and surface properties. A comprehensive residual life assessment involves non-destructive testing, data analysis and predictive models using statistical methods, damage models, and machine training to predict defect development and determine the remaining service life. The complexity of residual life estimation demands a mathematical model that accounts for operating conditions, modes, maintenance, and component states, integrating time-based, condition-based, and predictive methodologies.

Helicopter TE residual life, R , is determined as the difference between the specified life, T_{max} , and the operating time, T_{exp} , which is adjusted by taking into account the engine components' status and operating conditions. The basic model of helicopter TE residual life estimation is determined by the expression:

$$R = T_{max} - T_{exp} - \Delta T, \quad (1)$$

where ΔT is a correction factor that takes into account the components' degradation and operating conditions, which is presented as the sum of individual factors:

$$\Delta T = \sum_{i=1}^n \Delta T_i, \quad (2)$$

where ΔT_i is the change in resource due to the i -th factor, for example, critical component wear, changes in operating conditions, maintenance quality, etc.

To assess the influence of the component's status, it is proposed to use nonlinear empirical dependencies or monitoring data that take into account exponential or polynomial trends in helicopter TE parameter behavior:

$$\Delta T_i = f_i(S_i), \quad (3)$$

where S_i is the operational status of the i -th component, expressed in degradation indicator terms (for example, blade wear, reduced compressor efficiency, etc.).

The residual resource assessment model (2) is evolutionary in the sense that it adapts flexibly to new research and monitoring data. An approach based on evolutionary nonlinear empirical relationships (3) makes it possible to include various indicators in the S_i degradation model, reflecting the specific engine components' operational status. Since the components' condition and wear can be subject to various defects and changes during operation, this model provides the opportunity to introduce new dependencies, $f_i(S_i)$, as new data and research are obtained. Thus, the model can constantly improve and adapt to changing conditions and requirements, providing more accurate predictions of helicopter TE residual life.

Using models (1)–(3), the diagnostic indicator's current value is predicted until it reaches a critical level, which is then used to determine the remaining resource of the component. A parameter change model is based on changes in long-term observations of diagnostic parameter R during operation and a suitable dataset is required, including the specific type of helicopter TE, for example, TV3-117 [31,32].

This model has a high degree of adaptability. This ensures its effectiveness in various operating scenarios. The model's adaptability is due to two main aspects:

1. The flexibility of including new factors (parameters) in the model allows you to integrate new factors that influence the operational status of the helicopter TE components using the function $f_i(S_i)$. This makes it possible to take into account component degradation from various aspects, such as blade wear, compressor efficiency loss, and others, as they are researched and their impact on engine life is identified.
2. The adaptability to changes in operating conditions indicates that the ΔT_i coefficients in the model are adjusted for changes in operating conditions. For example, if the

maintenance or operating conditions change, the factors may be revised to more accurately account for these factors.

In this case, a coefficient adjustment is provided under the influence of the change:

$$\Delta T_i = f_i(S_i, C), \quad (4)$$

where C is a parameter vector that takes into account the changes in operating or maintenance conditions.

The model (4) specifications depend on the helicopter TE parameters, which are diagnostic for residual life determination.

Based on the basic model, an appropriate algorithm is proposed for helicopter TE residual life estimation (Figure 1).

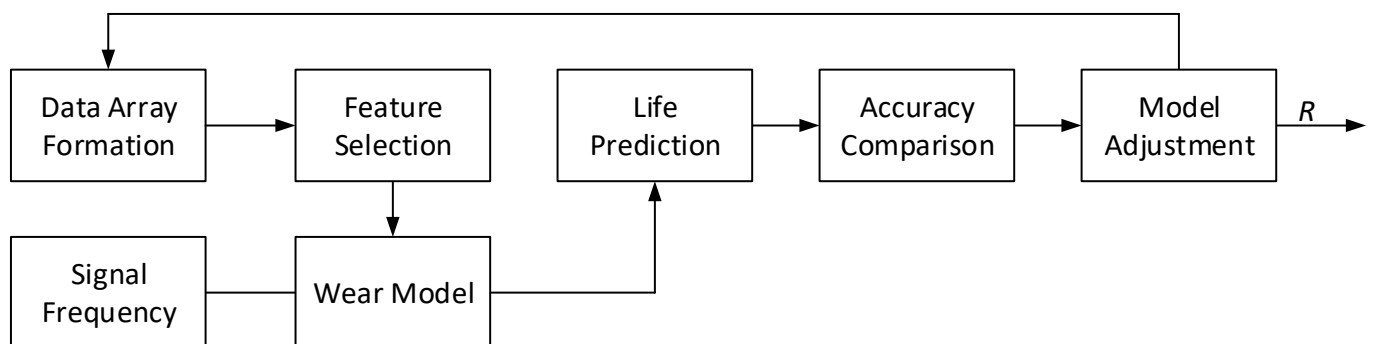


Figure 1. The helicopter turboshaft engine residual life adaptive assessment algorithm (author's research).

Figure 1 shows the following action sequence: 1—experimental data array formation obtained in helicopter TE operating mode; 2—informative feature selection, which consists of the fact that for subsequent processing, only those parameter values are selected that correspond to consumption of the particular element resource (for example, compressor turbine blades, etc.), 3—wear model, which describes the change process of helicopter TE element status depending on the time and operating conditions; 4—signal, upon receipt of which (with a given frequency) the wear model is retrained; 5—residual life prediction calculation based on the selected wear model, which allows you to determine the expected time before failure or the need for maintenance; 6—comparison of the results obtained by the prediction accuracy assessment with actual operating data; 7—model adjustment and algorithm based on identified discrepancies between predicted and actual values to improve the accuracy of the residual life prediction.

According to the proposed adaptive assessment algorithm (Figure 1), the work considers, as an example, solving the helicopter TE compressor turbine blade residual life determination task.

This research considers an example of solving the task of determining the thermally stressed state of helicopter TE compressor turbine blades and assessing their residual life according to the mathematical model presented in [33].

According to [33], the algorithm for calculating the thermal stress of helicopter TE compressor turbine blades is based on the elementary balances method of prof. A. Vanichev [33], according to the implicit Crank–Nicholson scheme [34]. The method is applicable for stationary and non-stationary modes and objects of any shape without significant simplification of the geometry when divided into elements. The blade feather belt may include partitions, projections, bridges, etc. Based on the thermogas dynamic parameters of the helicopter TE in its specified mode, the compressor turbine blade temperature value in the sectional elements is determined. Based on the obtained temperature distribution in the

section, thermal stresses, σ_i , are calculated in all partition elements [35,36]. Having a given safety margin of:

$$K_\sigma = \frac{\sigma_{\tau,t}}{\sigma} = (1.5 \dots 2.5), \quad (5)$$

where σ is the maximum limit stress of long-term strength, which is determined as follows:

$$\sigma_{(\tau,t)} = \sigma \cdot K_\sigma, \quad (6)$$

which is used to find the Larson–Miller parameter of the helicopter TE compressor turbine blade material:

$$P = f(\sigma_{\tau,t}) \quad (7)$$

for each partition element, while parameter P depends on the operating temperature and duration of operation.

The compressor turbine blade service life (in hours) is determined as follows:

$$\tau = 10 \cdot \exp\left(\frac{P}{t + 273} - 20\right). \quad (8)$$

For the compressor turbine in takeoff operating mode, the operating life will be minimal, and this resource can be determined by the blade element, not with $t_{\max}$, but with $\sigma_{\max,real}$. In this case, the $\tau_{\min}$ calculation is carried out for all elements of the blade airfoil, and only then can the most dangerous place in the blade be found, the parameters of which are recorded by the onboard recorder [34].

When switching the compressor turbine operation to another mode, all parameter values in the path change, and from these new parameters, t_{blade} is determined. At the same K_σ , the long-term strength limit $\sigma_{\tau,t}$, the Larson–Miller parameter P , and the resource τ for this mode are determined according to (37)–(40), respectively.

The ratio of the current resource to the minimum acceptable resource determines the equivalent [34], given by:

$$\varepsilon = \frac{\tau}{\tau_{\min}} \quad (9)$$

between the arbitrary mode resource and takeoff mode as $\tau_{\min} = \frac{\tau}{\varepsilon}$.

In [34], the operating time in an arbitrary mode $(\Delta\tau)_i$ stated during a flight determines the takeoff mode resource consumption as:

$$\Delta\tau_{\min} = \frac{\Delta\tau_i}{\varepsilon_i}, \quad (10)$$

and for n modes, according to $\Delta\tau_i$, the resource consumption is determined as follows:

$$\Delta\tau_{\min} = \sum_{i=1}^n \frac{\Delta\tau_i}{\varepsilon_i}, \quad (11)$$

where $t_{\max}$ is the maximum element temperature.

Taking into account (1), the residual service life in takeoff operating mode is determined as follows:

$$\delta\tau_{\min} = \tau_{\min} - \Delta\tau_{\min}. \quad (12)$$

With the calculated temperature field over the entire compressor turbine blade for the helicopter TE in all operating modes and the actual temperature according to pyrometer readings (at measurement points), it is possible to determine the actual temperature distribution and service life τ for a dangerous element, reducing it to $\tau_{\min}$.

The use of neural network technologies in solving this task is highly expedient since it can significantly improve the prediction accuracy of the helicopter TE compressor turbine blades' thermal stress state and residual life. Neural networks are capable of taking into account complex nonlinear relationships between operational parameters and temperature

distributions, which significantly increases calculation reliability compared to traditional methods. In addition, neural network models can efficiently process large amounts of data and adapt to changing operating conditions, providing real-time analysis and engine components' condition prediction. This, in turn, helps to improve helicopter operation safety and optimize engine maintenance, since:

1. Neural networks allow you to customize a wear model for the specific characteristics of each engine.
2. With increasing operating time, neural networks adjust parameter changes in the model until the limit value is reached, which makes it possible to adapt to the changing wear rate of components.

In [37], a residual life model with a hierarchical system is proposed, which can be implemented by a neural network model for more accurate and efficient prediction of helicopter TE component residual life. Since helicopter TEs in operation work under changing atmospheric conditions, the residual life model hierarchical system is supplemented with an atmospheric parameters block: T_N^* and P_N^* are the temperature- and air pressure-inhibited values at flight altitude $h = h(t)$, and $\rho = \rho(t)$ is the air density at flight altitude $h = h(t)$. In this case, T_N^* and P_N^* are calculated as follows:

$$T_N^* = T_N \cdot \left(1 + M^2 \cdot \frac{k-1}{2}\right), P_N^* = P_N \cdot \sigma_{rest} \cdot \left(1 + M^2 \cdot \frac{k-1}{2}\right), \quad (13)$$

where $M = M(t)$ is the Mach number at flight altitude $h = h(t)$; σ_{rest} is the total pressure recovery coefficient in the helicopter TE air inlet section; T_N and P_N are the air temperature and air pressure at a given flight altitude, respectively; and k is the adiabatic exponent.

Taking into account the above, based on [37], a hierarchical neural network system is proposed for the helicopter TE residual resource model (Figure 2), in which “ $\times$ ” is a multiplier, Σ is an adder, R is a residual resource, f_i is a nonlinear function defined according to (4), w_{ij} are the neuron's weights, b_i are displacements, and x_{ij} is the helicopter TE input thermogas dynamic parameter, which can either be recorded on board the helicopter or calculated analytically. For example, the gas generator rotor r.p.m., n_{TC} , the gas temperature in front of the compressor turbine, T_G^* , and the free turbine rotor speed, n_{FT} , are recorded on board the helicopter. At the same time, for example, the air temperature behind the compressor, T_C^* , and the total gas pressure behind the compressor turbine, P_{TC}^* , are calculated analytically according to the helicopter TE universal mathematical model [38]. Also in Figure 2, the blocks highlighted with dotted lines mean mathematical models (3), in which the presence of a particular defect is determined (for example, broken compressor blades, combustion chamber burnout, etc.). In Figure 2, the blocks highlighted with red dotted lines mean a changing atmospheric conditions mathematical model.

The proposed hierarchical neural network system for determining helicopter TE residual life is evolutionary, incorporating mathematical models that account for various defects. As research progresses, new models can be added or existing ones can be modified to improve the accuracy of component degradation assessment. This system also includes a mathematical model for changing atmospheric conditions, allowing it to adapt dynamically to environmental factors. By integrating empirical data and analytical calculations, it ensures high accuracy and reliability in residual life predictions. Its ability to continuously update and incorporate new models makes it resilient to operational changes, providing an adaptive approach to controlling the helicopter TE's operational status.

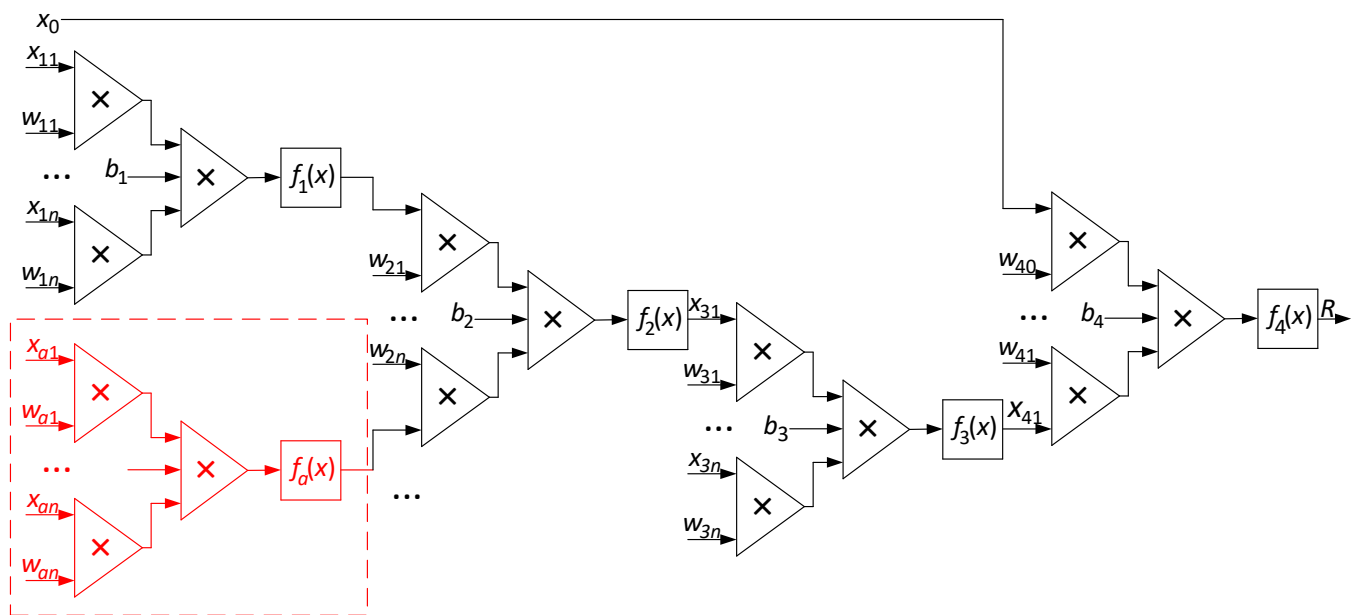


Figure 2. Scheme of the developed hierarchical neural network system for helicopter turboshaft engine residual life determination (author’s research, based on [33]).

3. Results and Discussion

To conduct a computer experiment, an initial training sample of 256 helicopter TE thermogas dynamic parameters obtained in flight operation mode was formed. The input data for determining the TE compressor turbine blade residual life were the temperature field over the entire compressor turbine blades for all helicopter TE operating modes, with numerical modeling of the temperature fields in helicopter TE elements given in [33]. The work used the results in [33] to determine the compressor turbine blade cross-section temperature field (Figure 3), of which the temperature T_i values consisted of a particular blade section.

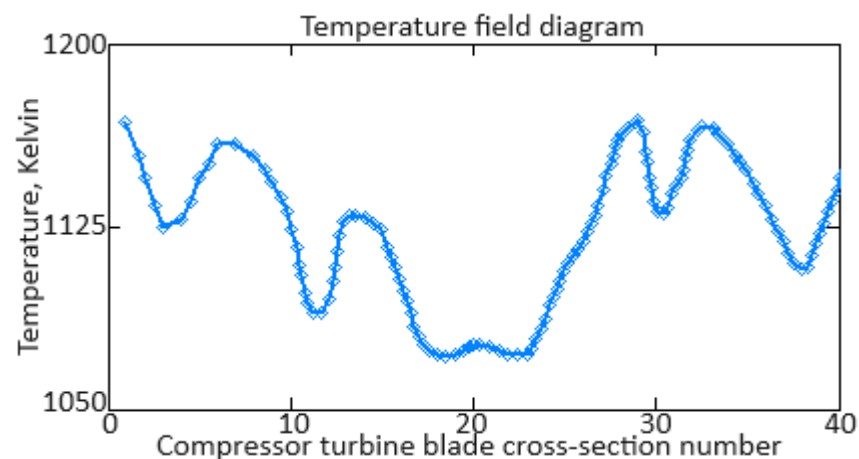


Figure 3. Diagram of the temperature field of a compressor turbine blade cross-section in a helicopter turboshaft engine (author’s research, based on [33]).

To compile a training sample according to Figure 3, 256 T_i values were uniformly determined. This process involved selecting 256 instances or data points from the dataset, such that each T_i value, representing a specific parameter or feature, was evenly sampled across the range of values observed in Figure 3. This approach ensured that the training sample was representative of the entire dataset, capturing the T_i value variability and distribution, as depicted in Figure 3. By uniformly selecting these values, researchers can

construct a robust training set that encompasses the diversity present in the data, thereby improving the neural network or model generalization and performance.

Before the computational experiment, the sample was preprocessed to assess its homogeneity using the Fisher–Pearson [39] and Fisher–Snedecor [40] criteria. This ensured the uniform distribution of temperature values and their suitability for further calculations, guaranteeing the correctness and reliability of the experimental results. At the input data preliminary analysis stage for calculating the Fisher–Pearson and Fisher–Snedecor criteria, the significance level adopted in the work was 0.01, which indicated the desired level of the probability of type I error when testing the hypothesis about the sample distribution and homogeneity normality. This stringent level of significance demonstrated confidence in the findings’ high standards, which was the accuracy and reliability of the temperature T_i values, ensuring particular importance in the compressor turbine blade cross-sections. The number of degrees of freedom was 1, which meant one type of parameter (temperature T_i values in the compressor turbine blade cross-sections) in the training sample. Thus, the Fisher–Pearson criterion and the Fisher–Snedecor criterion critical values, respectively, were $\chi^2_{critical} = 6.6$ and $F_{critical} = 2.62$. The obtained value of the Fisher–Pearson criterion, $\chi^2 = 5.415$, was less than $\chi^2_{critical} = 6.6$, which meant uniformity in the training sample of compressor turbine blade cross-section temperature T_i values (Table 1). The obtained value of the Fisher–Snedecor criterion, $F = 2.223$, was less than $F_{critical} = 2.62$, which confirmed homogeneity in the training sample of compressor turbine blade cross-section temperature T_i values (Table 1) when it was randomly divided into two equal samples of 128 elements each.

The training sample homogeneity determined according to the results obtained made it possible to normalize its elements. After normalizing the data, the temperature T_i values in the compressor turbine blade cross-sections would take on the values for which fragments are shown in Table 1. The results obtained made it possible to determine the optimal sample size of the compressor turbine blade cross-section T_i temperature field values: the training sample was 256 elements (100%), the control sample was 172 elements (67% of the training sample), and the test sample was 84 elements (33% of the training sample).

Table 1. Training sample fragments consisting of normalized T_i temperature field values in the compressor turbine blade cross-section (author’s research, based on [33]).

Number	1	2	...	72	...	133	...	205	...	256
T_i value	0.973	0.962	...	0.936	...	0.951	...	0.925	...	0.973

After the Fisher–Pearson and Fisher–Snedecor criteria were calculated, as well as normalizing the data, the training sample representativeness was assessed using cluster analysis with the k-means method [41,42]. This step was necessary to identify data groups or clusters with similar characteristics, which helped to identify possible internal patterns and structures in the data. Cluster analysis allows you to identify dataset parts that are similar in their characteristics, which contributes to a better understanding of its structure and properties. This makes the results more representative and allows for more efficient use of the sample for subsequent model training or decision making. To carry out cluster analysis using the k-means algorithm, from the training sample of the compressor turbine blade cross-section T_i temperature field normalized values (Table 1), training and test samples were randomly selected in a ratio of 2:1 (67 and 33%, respectively, which were the 172 and 84 elements) [43–45].

The data cluster analysis results from the training sample of compressor turbine blade cross-section T_i temperature field values (Table 1) revealed eight classes (classes I...VIII). That is, eight groups were present, which was indicated by similarities in both the training and test sample compositions (Figure 4).

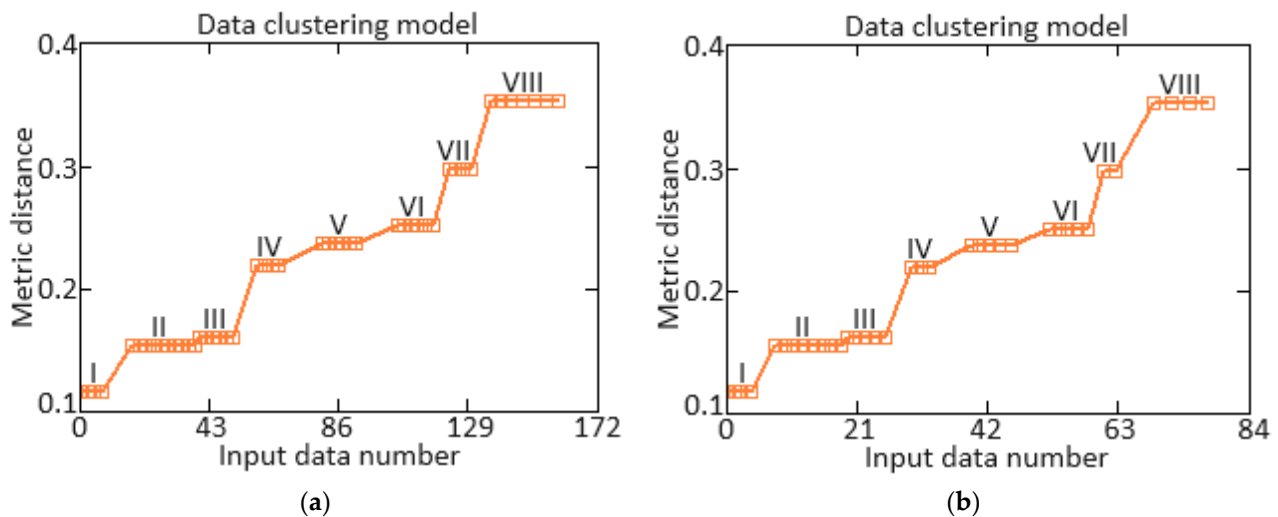


Figure 4. Cluster analysis results: (a) T_i values training set, (b) T_i values test set (author's research).

The training sample data used for the computational experiment to determine helicopter TE residual life (using compressor turbine blades as an example) were homogeneous and representative, ensuring accurate and reliable modeling results. This approach allowed effective analysis and prediction of helicopter TE residual life in operational reliability and durability terms. The helicopter TE compressor turbine blade residual service life was determined by predicting parameters until the control limit was reached, following models (1)–(4). The neural network used the engine components' state parameters, expressed as S_i degradation indicators (e.g., blade wear, compressor efficiency reduction), as input data (see models (5)–(12)). These inputs passed through hidden layers with NELU [46] activation functions, modeling complex dependencies. The output layer produced a prediction based on the correction factor ΔT , which was then used in (1) to calculate residual life. The model was trained using historical data of measured state parameters and known residual resource values. The first result from the experiment was a diagram estimating the residual resource, demonstrating the dynamics of the helicopter gas turbine engine service life under various operational factors. Figure 5 shows a diagram estimating the helicopter TE compressor turbine blade residual life based on temperature T_i values in the blade cross-sections.

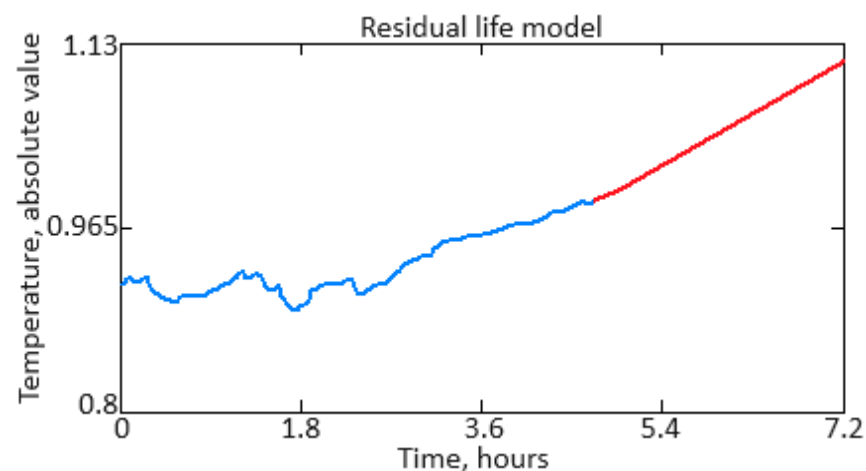


Figure 5. Diagram for helicopter turboshaft engine compressor turbine blade residual life assessment (author's research).

In Figure 5, the temperature values are given in absolute units (from zero to one) according to the gas dynamics similarity theory. The absolute temperature value exceeding

one (the segment highlighted in red) is a signal of the possible destruction of the helicopter TE compressor turbine blades. The curved part of Figure 5, shown in red, means the maximum probability of destruction of the helicopter TE compressor turbine blades. This curve indicates a portion of a component wear critical level where the component failure likelihood reaches its peak, requiring immediate maintenance or replacement. Analysis of this segment makes it possible to identify potential risks in a timely manner and take preventive measures, which significantly increases the safety and reliability of helicopter operations. According to Figure 5, the destruction period of the helicopter TE compressor turbine blades will begin in 5.0 h.

For determining the helicopter TE compressor turbine blade residual life based on similarities with patterns from the past, the analogies method was used. This method was based on comparing the current parameters of the blades' condition with historical data, where the residual resources are known. To do this, the components' current state was determined as $S_{current} = \{S_1, S_2, \dots, S_n\}$, where S_i is the i -th component state indicator (temperature T_i values in the compressor turbine blade cross-sections) [47–49]. H is a historical dataset containing state parameters and known values of the residual resource, given by:

$$H = \left\{ S_{hist,j}, R_{hist,j} \right\}_{j=1}^m, \quad (14)$$

where $S_{hist,j}$ is the state vector within the historical data j -th entry, and $R_{hist,j}$ is the corresponding residual resource.

For each dataset in H , a similarity metric to the current state $S_{current}$ was calculated. The work used the Euclidean distance, which was calculated as:

$$d_j = \sqrt{\sum_{i=1}^N (S_{current,i} - S_{hist,j,i})^2}, \quad (15)$$

where d_j is the distance between the current state and the historical data j -th record.

The k closest analogs (most similar records) were determined based on the similarity metric d_j . Let $\{S_{hist,j_k}, R_{hist,j_k}\}_{k=1}^k$ be the closest analog set, then the residual resource $R_{current}$ was defined as the weighted average of the closest analog residual resource values:

$$R_{current} = \frac{\sum_{k=1}^k \omega_k \cdot R_{hist,j_k}}{\sum_{k=1}^k \omega_k}, \quad (16)$$

where $\omega_k = \frac{1}{d_{j_k}}$ is a weight inversely proportional to the distance, which means that closer analogs have more weight.

Thus, the final residual life value, $R_{current}$, was the weighted average of the most similar historical data. This could take into account patterns from the past and adapt the prediction to current operating conditions.

Thus, a diagram was obtained for helicopter TE compressor turbine blade residual life estimation based on similarities with patterns from the past (Figure 6), where the "blue curve" means current data, "gray curves" mean historical data, and "•" means failure moments.

Historically, temperature versus time curves for helicopter TE compressor turbine blades have shown a nonlinear increase with a gradual slowdown near a limiting value due to a combination of factors, such as thermomechanical fatigue, oxidation, and erosion.

The helicopter TE compressor turbine blade residual life estimation diagram based on similarities with patterns from the past was developed based on the Dynamic Time Warping (DTW) algorithm [50,51]. This method allows you to compare current data with historical time series, taking into account possible time distortions, and find the degradation

patterns that are closest in shape. The use of DTW provides time sequences with more accurate alignment, making it possible to take into account not only linear changes but also nonlinear shifts in time, which significantly improves the prediction accuracy and identification of critical moments of blade failure.

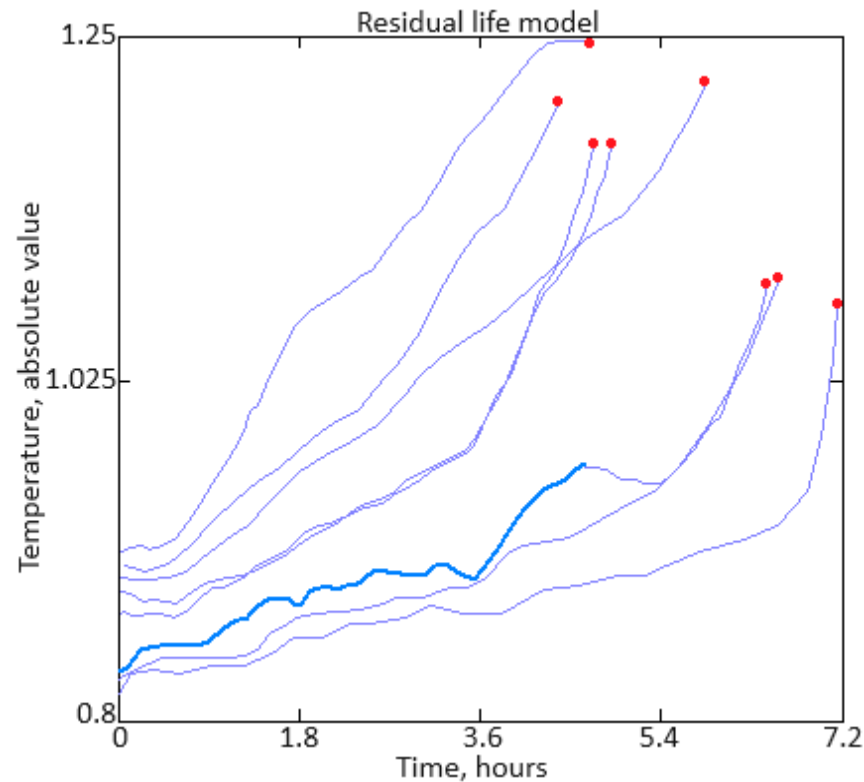


Figure 6. Diagram for assessing the helicopter turboshaft engine compressor turbine blade residual life based on similarities with patterns from the past (author's research).

In this diagram (Figure 6), the turbine blades' operational status and current parameters are compared with historical data. Failure points indicate those points in the past where components reached their life limit and failure occurred. Comparing current data with historical patterns allows you to identify similar conditions and use information about past failures to predict residual life. This technique allows inferences to be made about the time to potential failure based on analogies to previously observed cases, which contributes to more accurate and reliable planning of maintenance and component replacement. According to Figure 6, at times $t = 4.35, 4.63, 4.71, 4.90, 5.84, 6.45, 6.58$, and 7.15 h, there is the probability of helicopter TE compressor turbine blade destruction. These times correspond to significant parameter deviations, indicating critical states of compressor turbine components. During these periods, significant changes in temperature and vibration are observed, indicating increasing degradation and increased likelihood of failure.

It is noted that the drop in temperature on one of the curves for assessing helicopter TE compressor turbine blade residual life, while an increase is observed in the other curves, may be associated with a local defect in the material affecting thermal conductivity, a change in the air flow nature due to geometric deviations, or an error in the measurement process.

Based on the diagrams assessing the helicopter TE compressor turbine blade residual life through parameter prediction and similarities with historical patterns, a degradation curve was formulated integrating both approaches to enhance prediction accuracy. Parameter prediction determined current wear trends and expected component behavior using established degradation models, while historical pattern similarity validated and adjusted these predictions based on past data. This integrated approach constructed a degradation curve that combined current data with historical analogs, presenting current blade con-

dition parameters and identifying potential failure points based on past patterns. This unified curve offers a more reliable understanding of wear rates and probable remaining service life, facilitating efficient planning for component maintenance and replacement to enhance helicopter TE operation safety and reliability.

To construct a degradation curve, it was proposed to combine the current parameter predicting results and analogy data, that is:

$$S_{degradation}(t) = \alpha \cdot S_{current}(t) + (1 - \alpha) \cdot S_{pred}(t), \quad (17)$$

where $S_{degradation}(t)$ is the integrated degradation curve, and α is the coefficient that determines each method contribution.

The degradation curve, which takes into account both parameter prediction and analogy with historical data, was defined as:

$$D(t) = S_{degradation}(t). \quad (18)$$

where $D(t)$ is the final degradation curve showing the combined prediction of the helicopter TE compressor turbine blades' condition.

To check the adequacy of the constructed degradation curve, it was assumed that $P(t)$ is the residual life prediction (time to failure) for compressor turbine blades at time t , and $D(t)$ is the actual residual life at the same time. Then, the adequacy criterion, Q , was defined as the mean square error between the predicted and actual residual life throughout the operation's entire period:

$$Q = \frac{1}{M} \cdot \sum_{i=1}^M (P(t_i) - D(t_i))^2, \quad (19)$$

where Q is the adequacy criterion, and M is the number of time points for which degradation data are available.

The results obtained made it possible to construct a helicopter TE compressor turbine blade residual life degradation curve, presented in Figure 7.

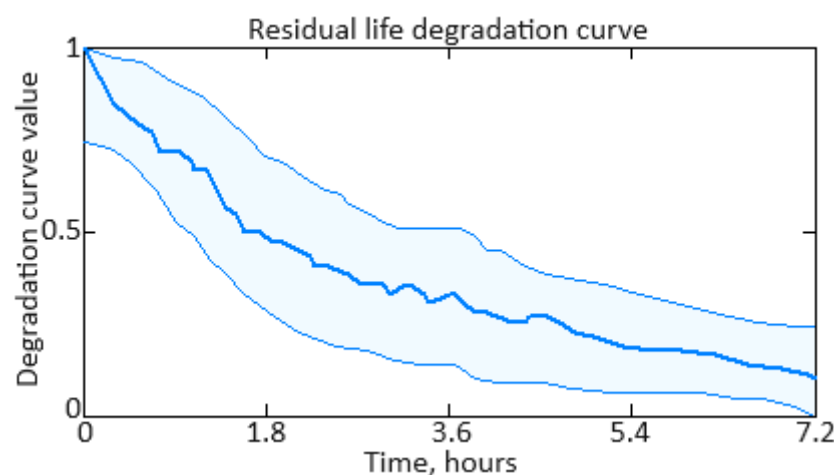


Figure 7. The helicopter turboshaft engine compressor turbine blade residual life degradation curve (author's research).

It is worth noting that in Figure 7, the “gray zone” means a 5% confidence interval indicating the range of possible values for the residual life estimate with a 95% probability. This interval allows you to visually assess the uncertainty degree in the model's predictions and takes into account possible variations in the data associated with the operating conditions, component wear, and other factors. Having a gray area around the main curve helps

maintenance and operations professionals to better understand the predicted reliability and make more informed decisions when planning repairs and component replacements.

It is noted that, at the initial moment in time, the upper limit of the confidence interval coincides with the beginning of the degradation curve (both values of the degradation curve and the confidence interval upper limit are equal to one) since at the initial operation stage there are no data on degradation, and the theoretical model predicts the maximum resource. In this case, the beginning of the degradation curve corresponds to the moment when the first signs of degradation become detectable.

The mean square error between the predicted and actual helicopter TE compressor turbine blade residual life was chosen as an adequacy criterion due to several factors:

1. The mean square error, as a model adequacy criterion, is a standard metric for assessing the predicted quality and models.
2. Expression (19) takes into account degradation data at all available time points, which provides an overall model adequacy overview throughout its operation.
3. Averaging the error over the entire sample allowed us to assess the overall adequacy of the model throughout the operation's entire period.
4. The model predicts the mean square error in real data and identifies deviations, which allows you to quickly detect and correct inaccuracies and inconsistencies.
5. Expression (19) is a simple and understandable way to assess the model's adequacy, which makes it convenient for use by engineers and equipment maintenance specialists.

To calculate the adequacy criterion for the helicopter TE compressor turbine blade residual life degradation curve in Figure 7, 256 experimental points were selected in steps of 0.028 s. As a calculation result, $Q = 0.0058$ (or 0.58%) was obtained, which meant that the model demonstrated a degradation curve with very high adequacy, since $Q \rightarrow 0$.

A comparative analysis was performed on the accuracy of the neural network (developed multilayer perceptron), classical RBF network of the 7–2–1 structure, and the classical least squares method (LSM) for solving the helicopter TE compressor turbine blade residual service life determination task using one parameter, the temperature T_i values in the compressor turbine blade cross-sections (Figure 8).

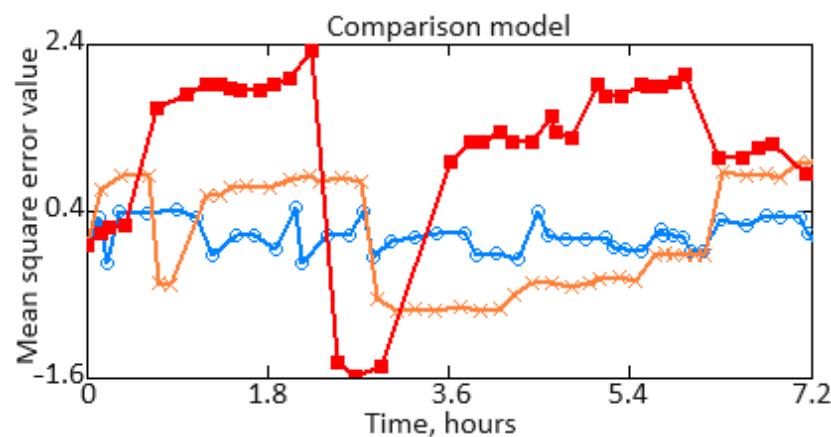


Figure 8. Diagram of changes in MSE in the model of helicopter turboshaft engine compressor turbine blade residual life determination for the developed multilayer perceptron (blue curve), classical RBF network (orange curve), LSM (red curve) (author's research).

It was found that the MSE when using the developed multilayer perceptron (blue curve in Figure 8) was 4.81 times less than when using an 8th order polynomial regression model built using LSM (red curve in Figure 8) and was 2.55 times less when using the classical RBF network (orange curve in Figure 8). At the same time, the developed multilayer perceptron provided an MSE value for solving the helicopter TE compressor turbine blade residual life determination task that did not exceed 0.424%; classical RBF network—1.079%; MNC—2.038%.

To analyze the neural networks' stability to changes in input data (Table 2), additive noise was added in the form of white noise with zero mathematical expectation and standard deviation $\sigma_i = 0.025$ [52–54]. In this research context, white noise has the following conditions:

1. Zero expected value means that the average of all noise values is zero.
2. Standard deviation $\sigma_i = 0.025$ means that it characterizes the spread of noise values relative to the average value. In this case, the standard deviation was 0.025, which indicated a small spread of values.
3. A uniform distribution of the power spectral density means that the noise energy is equally distributed across all frequencies.

The computational experiment results showed that the value of the error in solving the helicopter TE compressor turbine blade residual life determination task under noise exposure did not exceed 0.424% using the developed multilayer perceptron; classical RBF network—1.079%; MNC—2.038%.

Based on a comparative analysis of the helicopter TE compressor turbine blade residual life determination model using a neural network and classical methods, the following conclusions were made:

1. Neural networks solve the helicopter TE compressor turbine blade residual service life determination task more accurately than traditional methods: the identification error at the output of the developed multilayer perceptron was 4.81 times lower than that of the regression model obtained using LSM.
2. The error of solving the helicopter TE compressor turbine blade residual life determination task using the developed multilayer perceptron did not exceed 0.424%; for the classical RBF network, it was 1.079%, while for the LSM, it was 2.038%.
3. Neural network methods are more robust to external disturbances: for a noise level $\sigma_i = 0.025$, the error in solving the helicopter TE compressor turbine blade residual life determination task when using the developed multilayer perceptron increased from 0.424 to 0.611%; for the classical RBF network—from 1.079 to 1.877%, and for the LSM—from 2.038 to 3.933%.

Table 2 shows the comparative analysis results of the helicopter TE compressor turbine blade residual life determination task solution using the developed multilayer perceptron, the classical RBF network, and the LSM, according to metrics [43,44,55,56]. The analysis highlights the accuracy and efficiency of each method in predicting the residual life.

Table 2. Comparative analysis results (author's research).

Metrics	Developed Multilayer Perceptron	Classical RBF Network	Least Squares Method
MSE	0.611	1.877	3.933
MAE	0.781	1.369	1.983
RMSE	0.781	1.369	1.983
MAPE	1.03%	2.05%	4.84%
R ²	0.993	0.971	0.837
ME	0.053	0.116	0.634
MedAE	0.068	0.132	0.311
sMAPE	1.03%	2.05%	4.80%
GMSE	0.134	0.258	0.612
r	0.997	0.986	0.928
RMSLE	0.057	0.113	0.264
Hit Rate	70.3%	36.7%	17.2%
Max Error	0.0385	0.0616	0.132
Huber Loss	4.17×10^{-5}	0.000118	0.000334

The results obtained (Table 2) confirmed that the developed multilayer perceptron was the best in all of the above metrics, demonstrating minimal errors and maximum compliance with the true value of the residual resource. At that time, the LSM application was the worst, showing maximum errors and minimum consistency.

Table 3 shows the improved quality metric results for solving the helicopter TE compressor turbine blade residual life determination task using the developed multilayer perceptron, a classical RBF network, and LSM. These improvements indicated the effectiveness of the proposed neural network architecture in enhancing the residual life assessment's reliability and precision for helicopter turbine blades.

Table 3. The calculated improvement degree of the helicopter TE compressor turbine blade residual life determination task solution using the developed multilayer perceptron with a classical RBF network and the least squares method (author's research).

Metrics	Improvements When Using the Developed Multilayer Perceptron	
	Classical RBF Network	Least Squares Method
MSE	3.07	6.44
MAE	1.75	2.54
RMSE	1.75	2.54
MAPE	2.00	4.70
ME	2.19	12.0
MedAE	1.94	4.60
sMAPE	2.00	4.70
GMSE	1.92	4.60
RMSLE	2.00	4.60
Hit Rate	1.92	4.10
Max Error	1.60	3.40
Huber Loss	2.80	8.00

Thus, the work carried out a computer experiment consisting of determining the helicopter TE compressor turbine blade residual resource using a neural network model. The specific conditions of the experiment included the use of data collected during helicopter flight, such as air temperature and pressure at various altitudes, air density, air speed, engine load, and other operational parameters. This real-world data were used to train and test a neural network model to accurately predict the turbine blade residual life based on changing flight conditions and operational loads.

Table 4 shows the first and second types of calculating errors when solving the helicopter TE compressor turbine blade residual life determination task using the developed multilayer perceptron, the classical RBF network, and the least squares method.

Table 4. The first and second types of calculating errors when solving the helicopter TE compressor turbine blade residual life determination task (author's research).

Error Type	Developed Multilayer Perceptron	Classical RBF Network	Least Squares Method
Type I error, %	0.754	1.681	3.574
Type II error, %	0.447	1.063	2.119

These errors were used to evaluate the method for determining the residual life of the helicopter TE compressor turbine blades, allowing for conclusions about its practical applicability and the necessity for further research. The results (Table 4) showed that use of the developed multilayer perceptron made it possible to reduce the first and second types of errors by 2.23 times compared with use of the classical RBF network, and by 4.74 times compared with use of the least squares method when solving the helicopter TE compressor turbine blade residual life determination task.

For four classification classes (True Positives, True Negatives, False Positives, and False Negatives), a confusion matrix was developed (Table 5). Each cell of the confusion matrix shows the actual class (rows) times the number classified as the predicted class (columns) for each method [57,58].

Table 5. Developed confusion matrix (author’s research).

Actual\ Predicted	Developed Multilayer Perceptron	Classical RBF Network	Least Squares Method
True Positives	97	3	0
True Negatives	3	88	2
False Positives	1	6	8
False Negatives	0	3	92

The confusion matrix indicated that the developed multilayer perceptron was the most accurate method, correctly classifying the majority of instances across all classes with minimal misclassifications. The classical RBF network, although performing well, displayed slightly more errors, particularly in differentiating between “True Negatives” and “False Positives” classes. The least squares method showed the lowest accuracy, with significant misclassifications, especially confusing instances of “True Positives”, “True Negatives”, and “False Positives” classes, while performing better for the “False Negatives” class. Overall, the developed multilayer perceptron clearly surpassed the other methods, followed by the classical RBF network, with the least squares method ranking lowest in classification quality.

Table 6 shows the ROC analysis results. Thus, use of the proposed multilayer perceptron gave high accuracy with a low level of false positive results; use of the classical RBF network also gave high accuracy, but was 1.23 times lower than the proposed multilayer perceptron. Use of the least squares method gave the lowest accuracy with the highest number of false positives.

Table 6. ROC analysis results (author’s research).

Actual\ Predicted	Developed Multilayer Perceptron	Classical RBF Network	Least Squares Method
True Positives	96	89	0
True Negatives	2	8	10
False Positives	275	260	290
False Negatives	25	41	100
TPR	0.79	0.64	0
FPR	0.010	0.029	0.31
AUC	0.862	0.717	0.295

Thus, the research results allowed us to establish the following:

1. The relevance of the helicopter turboshaft engine residual life determination method is substantiated, which lies in its critical role in ensuring flight reliability and safety, since timely assessment of engine conditions, taking into account many operating factors and environmental conditions, makes it possible to plan maintenance and component replacement, preventing emergencies, and increasing the resource prediction accuracy thanks to modern diagnostic systems.
2. A method for determining the residual life of helicopter turboshaft engines has been developed based on a hierarchical system utilizing neural network technologies. The experimental results showed that using a multilayer perceptron within this hierarchical system yielded a maximum root-mean-square error of no more than 0.424 when applied to solving the task of estimating the residual life of the compressor turbine blades of helicopter turboshaft engines.
3. Based on the backpropagation algorithm, a multilayer perceptron training algorithm has been developed, which, by introducing the initial parameter x_0 to the output layer, improved the helicopter turboshaft engine residual life prediction accuracy and use of the adaptive Adam training rate provided high accuracy (up to 99.3%) in solving the helicopter turboshaft engine compressor turbine blade residual life

determination task. It has been experimentally proven that use of the developed multilayer perceptron training algorithm made it possible, with 160 training epochs, to ensure an accuracy of 99.3% and reduce losses to 0.5% in solving the helicopter turboshaft engine compressor turbine blade residual life determination task.

4. Based on the helicopter turboshaft engine compressor turbine blade residual life assessment through parameter prediction and similarities with patterns from the past, a method for constructing a degradation curve has been developed. This method integrates parameter prediction and historical data analogies to enhance the accuracy of service life prediction and maintenance planning, thereby mitigating failures. Experimental validation showed that the mean square error between predicted and observed residual resource over the entire operational period did not exceed 0.0058 (0.58%), approaching zero, indicating the high adequacy of the constructed degradation curve.
5. The results of solving the helicopter turboshaft engine compressor turbine blade residual life determination task using the developed multilayer perceptron as a hierarchical system were compared with the classical RBF network and the least squares method, which made it possible to reduce the first and second types of errors by 2.23 times compared with the use of the classical RBF networks, and by 4.74 times compared to using the least squares method.

4. Conclusions

It is substantiated that helicopter turboshaft engine residual life determination, which is critical for flight reliability and safety, is carried out with high accuracy using modern diagnostic systems and predicting methods. However, their key disadvantage is their inability to detect hidden patterns and anomalies, which makes the use of neural networks appropriate for analyzing large amount of data in real time and improving the diagnosis and prediction accuracy.

A method is proposed for helicopter turboshaft engine residual life determination based on a hierarchical system using neural network technologies. It has been experimentally proven that this method makes it possible to determine with high accuracy (the maximum root mean square error did not exceed 0.424) the helicopter turboshaft engine compressor turbine blade residual life.

The developed algorithm for training a multilayer perceptron using the backpropagation algorithm, with the initial parameter on the output layer and the adaptive Adam training rate, provided an accuracy of 99.3% and reduced losses to 0.5% when determining the compressor turbine blade residual life.

The developed method for degradation curve construction, based on predicting parameters and similarities with past patterns, makes it possible to accurately predict service life and plan maintenance, and the root-mean-square error between the predicted and actual remaining life was only 0.0058 (0.58%), which confirmed the model's high adequacy.

A comparison with the classical RBF network and the least squares method showed that the proposed method reduced the first and second types of errors by 2.23 times and 4.74 times, respectively.

Thus, this article primarily evaluates the effectiveness of advanced neural network technologies in predicting the residual life of helicopter turboshaft engine compressor turbine blades, highlighting substantial improvements in predictive accuracy and error reduction compared to classical methods. A clear direction for future research involves adapting the neural network system for integrated monitoring of helicopter turboshaft engine operations [44,59,60].

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