The helicopter turboshaft engines parametric debugging using neural network technology

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Abstract

This research presents a mathematical model designed to optimize the helicopter turboshaft engines parametric tuning by accurately predicting engine performance characteristics through the integration of key operational parameters such as rotor speeds, fuel consumption rates, and temperature profiles. A neural network model is developed to capture the complex nonlinear relations between input parameters and engine performance outputs, employing a supervised training algorithm and an adaptive training rate to enhance convergence efficiency. The model demonstrates impressive performance metrics, achieving a prediction accuracy of 99.25 % and a mean squared error below 2.5 %. While the results are promising, the research identifies limitations related to the reliance on historical performance data and the potential for overfitting. Future studies are recommended to explore the various factors influence on engine performance, develop more adaptive neural network architectures, and conduct extensive field testing to ensure model robustness and effectiveness in real-world conditions. Ultimately, the integration of advanced predictive models into helicopter control systems will significantly enhance flight safety and operational efficiency.

Keywords

helicopter turboshaft engine, mathematical model, optimization, neural network, training algorithm, operation data and deviations

1. Introduction

Parametric debugging for helicopter turboshaft engines (TE) is a critical aspect in optimizing performance and ensuring reliability during flight operations [1]. Helicopter TE operate under varying conditions, which demand precise calibration and adjustment across multiple parameters to maintain efficiency and safety [2, 3]. The process involves fine-tuning various engine parameters, such as rotational speeds, temperatures, and fuel consumption rates, to align the engine's performance with expected operational standards [4]. This approach helps identify potential faults early, enhances the engine's operational longevity, and contributes to more effective engine control systems.

The helicopter TE parametric debugging importance stems from the increasing complexity of modern aviation engines and the demand for higher reliability in dynamic flight conditions [5]. As

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helicopters are often used in critical operations, ensuring optimal engine performance is paramount for both safety and operational efficiency. Advanced methods for parametric debugging allow for more accurate diagnostics, early detection of deviations in engine behavior, and timely corrective measures. This enhances overall flight safety, reduces maintenance costs, and supports the development of more robust systems for engine monitoring and control [6].

2. Related works

Research on helicopter TE has significantly advanced over the years, focusing on areas such as engine modeling, fault diagnosis, and control systems. Traditional parametric debugging approaches primarily rely on physical models based on thermodynamic principles, which describe the engine's behavior under various operating conditions [7, 8]. These models are often calibrated using real-world data and are effective for steady-state conditions. However, in transient modes, such as during takeoff or acceleration, physical models encounter limitations due to the complexity and nonlinearity of engine dynamics. Studies [9–11] emphasize the need for enhanced methods to capture these transient behaviors more accurately, which remain underrepresented in classical models.

Recent developments in helicopter TE fault diagnosis have shifted towards model-based and data-driven techniques [12]. Model-based approaches, such as Kalman filters [13, 14] or observer-based fault detection [15, 16], have been widely used for identifying deviations in engine performance. These methods, although effective in controlled environments, often struggle when faced with uncertainties in real-time operations or when sensors provide incomplete or noisy data. Data-driven approaches [17, 18] have gained traction, using historical performance data to detect anomalies through statistical or machine learning techniques. However, these methods are usually limited by the available data quality and quantity and often fail to account for rare or unexpected faults.

In the dynamic flight conditions context, where engine parameters change rapidly, traditional methods fall short in their predictive accuracy. Studies [19, 20] that these approaches do not fully exploit the complex relations between multiple engine variables, especially in nonlinear and nonstationary environments. Additionally, the increasing advanced control systems use, such as adaptive control and fault-tolerant systems [21, 22], requires faster and more reliable diagnostic techniques. This gap in real-time diagnostic capability highlights the need for more sophisticated methods capable of data large amounts processing and adapting to changing conditions during flight.

The neural networks application in the helicopter TE diagnostics and control is an emerging field that promises to the traditional methods limitations address many. Neural networks, particularly recurrent neural networks (RNN) [23] and long short-term memory (LSTM) networks [24], have the capacity to model complex temporal dependencies in engine behavior. Researches [25, 26] have demonstrated the potential of neural networks to improve fault detection and parameter estimation by training patterns directly from operational data. These models offer a more flexible and scalable solution, particularly in capturing transient and nonlinear behaviors that are difficult to model using conventional techniques.

Despite the promising results in the literature, there are still gaps in the application of neural networks for helicopter TE. Most existing studies focus on steady-state conditions or specific fault scenarios, while few address the full range of operating conditions, especially during transient modes. Additionally, the integration of neural networks with traditional diagnostic systems has been limited, with most implementations remaining experimental. These gaps highlight the need for further research into hybrid models that combine the strengths of physical and data-driven approaches.

The neural network approach offers significant advantages for the helicopter TE real-time diagnostics and control, particularly in handling the nonlinearity, noise, and uncertainties inherent in engine performance data. By continuously training from operational data, neural networks can improve predictive accuracy and provide earlier warnings for potential faults. Moreover, their ability to generalize from past data enables them to detect rare or complex fault patterns that might be missed by conventional methods. This justifies the need for a more comprehensive application of neural networks in the field, as they hold the potential to revolutionize engine diagnostics and enhance flight safety.

3. Materials and methods

This research proposes the helicopter TE parametric debugging mathematical model, which takes into account both static and dynamic engine characteristics. The model is based on the time series use of engine parameters recorded on board the helicopter: the gas-generator rotor r.p.m. $n_{TC}(t)$, the free turbine rotor speed $n_{FT}(t)$, gas temperature in front of the compressor turbine $T_G^*(t)$, the fuel consumption $Q_f(t)$ and other parameters [27, 28]. The model takes into account both standard engine operating parameters and deviations caused by external and internal influences. Additionally, the model allows for real-time analysis and adjustment to enhance engine performance and reliability.

The main engine dynamics are described by the nonlinear differential equations system in the form: this system models the complex interactions between various engine components and operational parameters.

Thus,

$$\begin{aligned}\frac{dn_{TC}(t)}{dt} &= f_1\left(n_{TC}(t), n_{FT}(t), T_G^*(t), Q_f(t), P_{ext}(t)\right),\\ \frac{dn_{FT}(t)}{dt} &= f_2\left(n_{TC}(t), n_{FT}(t), T_G^*(t), Q_f(t), P_{ext}(t)\right),\\ \frac{dT_G^*(t)}{dt} &= f_3\left(n_{TC}(t), n_{FT}(t), T_G^*(t), Q_f(t), P_{ext}(t)\right),\\ \frac{dQ_f(t)}{dt} &= f_3\left(n_{TC}(t), n_{FT}(t), T_G^*(t), Q_f(t), P_{ext}(t)\right).\end{aligned} \tag{1}$$

Functions f_1, f_2, f_3, f_4 describe interactions between engine parameters depending on its state, while $P_{ext}(t)$ represents external factors such as atmospheric pressure and turbulence.

To minimize deviations actual rotor speeds $n_{TC}(t)$, $n_{FT}(t)$, gas temperature $T_G^*(t)$, and fuel consumption $Q_f(t)$ from their nominal values n_{TC_nom}, n_{FT_nom}, $T_{G\_nom}^*$, Q_{f_nom} the following deviations are introduced [29]:

$$\begin{aligned}\Delta n_{TC}(t) &= n_{TC}(t) - n_{TC\_nom},\\ \Delta n_{FT}(t) &= n_{FT}(t) - n_{FT\_nom},\\ \Delta T_G^*(t) &= T_G^*(t) - T_{G\_nom}^*,\\ \Delta Q_f(t) &= Q_f(t) - Q_{f\_nom}.\end{aligned} \tag{2}$$

The objective function for minimizing deviations takes the form:

$$J = \int_0^T \left(\left(w_1 \cdot \Delta n_{TC}(t)\right)^2 + \left(w_2 \cdot \Delta n_{FT}(t)\right)^2 + \left(w_3 \cdot \Delta T_G^*(t)\right)^2 + \left(w_4 \cdot \Delta Q_f(t)\right)^2\right) dt, \tag{3}$$

where w_1, w_2, w_3, w_4 weighting coefficients defining the significance each parameter, and T is the final moment time. The parametric adjustment task reduces to minimizing the functional J, aiming to decrease deviations across key engine parameters.

To adaptively correct engine parameters in real-time, a neural network corrector [30] is introduced. Let the network NN receive deviations $\Delta n_{TC}(t)$, $\Delta n_{FT}(t)$, $\Delta T_G^*(t)$, $\Delta Q_f(t)$ as inputs, generating a corrective signal $u(t)$, which adjusts the engine control system:

$$u(t) = NN\left(\Delta n_{TC}(t), \Delta n_{FT}(t), \Delta T_G^*(t), \Delta Q_f(t)\right). \tag{4}$$

The neural network is trained on historical engine operation data and deviations, allowing for more precise parameter adjustments.

The corrective signal $u(t)$, generated by the neural network, is used to adapt control inputs for the engine. This can be described by the equation:

$$U(t+1) = U(t) + \alpha \cdot u(t), \tag{5}$$

where $U(t)$ is the control input vector for the system (such as fuel consumption rate, turbine blade angle), and α is the training coefficient that defines the speed adjustment.

To account for random disturbances (such as changes in external conditions or airflow instability), a stochastic component is introduced [31, 32]. External influences can be described as:

$$P_{ext}(t) = P_{ext\_nom}(t) + \xi(t), \tag{6}$$

where $\xi(t)$ is white noise with zero mean and variance σ^2. This accounts for random deviations and allows real-time adjustments to control parameters.

The overall control system for helicopter TE dynamics, considering the neural network corrector and stochastic perturbations, can be written as:

$$\frac{d\boldsymbol{X}(t)}{dt} = \boldsymbol{F}\big(\boldsymbol{X}(t), \boldsymbol{U}(t)\big) + NN\big(\Delta\boldsymbol{X}(t)\big), \tag{7}$$

where $\mathbf{X}(t) = \left(n_{TC}(t), n_{FT}(t), T_G^*(t), Q_f(t)\right)$ is the engine state vector, and $\mathbf{U}(t)$ is the control input vector. The neural network corrector NN adjusts the deviations $\Delta\mathbf{X}(t) = \left(\Delta n_{TC}(t), \Delta n_{FT}(t), \Delta T_G^*(t), \Delta Q_f(t)\right)$, ensuring precise engine control under uncertainty.

In this research, the developed mathematical model is implemented in a neural network basis [33–37]. The proposed neural network (Figure 1) model consists of several layers, each serving a specific function to achieve optimal performance in helicopter TE parametric adjustment. The architecture includes an input layer, multiple hidden layers, and an output layer. Each layer consists of neurons that process information, passing it to the next layer through activation functions.

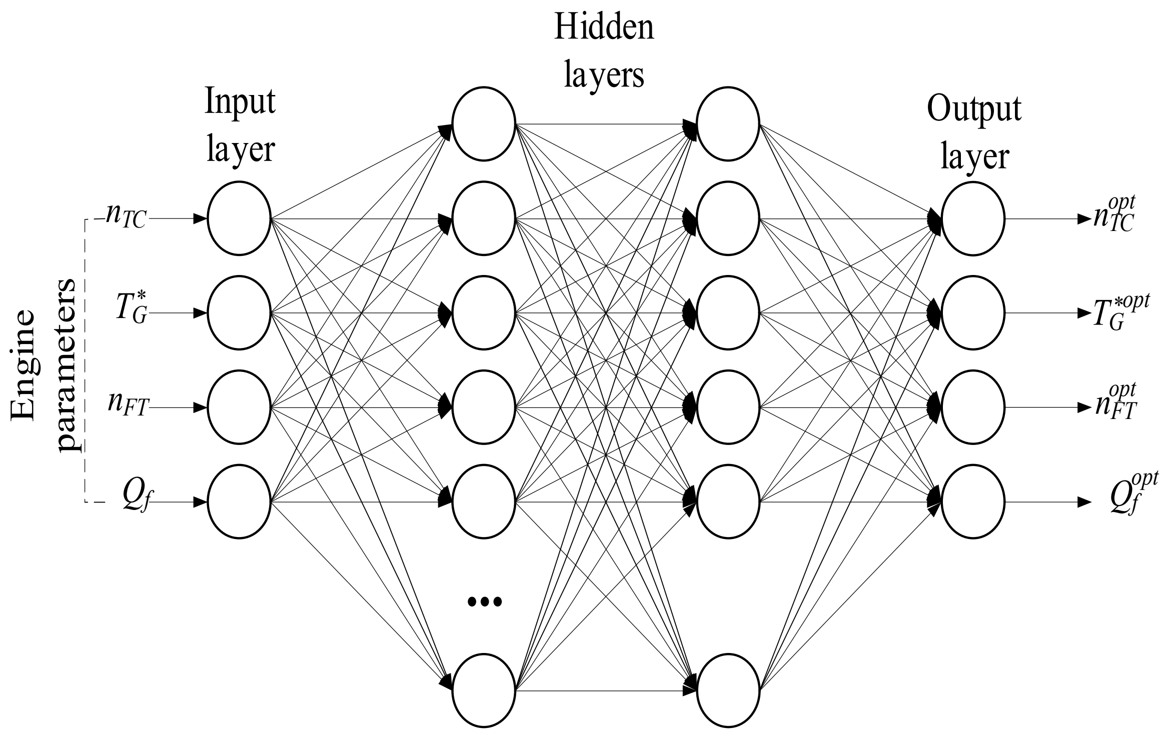

Figure 1: The proposed neural network architecture (author's research).

The architecture consists of an input layer that receives deviations in parameters and external influences, followed by multiple fully connected hidden layers equipped with activation functions to effectively capture complex relations among the input data. Finally, the output layer generates corrective signals aimed at adjusting engine parameters, ensuring optimal performance and responsiveness to identified deviations.

The input layer is composed of four neurons, each corresponding to a specific input signal representing deviations from nominal values: $\Delta n_{TC}(t)$ for the deviation in gas generator rotor speed, $\Delta n_{FT}(t)$ for the deviation in free turbine rotor speed, $\Delta T_G^*(t)$ for the deviation in gas temperature, and

$\Delta Q_f(t)$ for the deviation in fuel consumption. This layer processes these deviation signals, serving as the initial stage for capturing critical information necessary for subsequent computations and adjustments within the system.

The neural network architecture includes three hidden layers, each designed to progressively refine and abstract the input features. The first hidden layer comprises 64 neurons with a SmoothReLU (Rectified Linear Unit) activation function, developed by this authors group in [27], capturing non-linear relationships and providing an initial level of abstraction from the input signals. The second hidden layer, consisting of 32 neurons and utilizing SmoothReLU activation, further refines these representations, enhancing the model's ability to generalize across varying input scenarios. The third hidden layer, with 16 neurons and SmoothReLU activation, reduces dimensionality while preserving essential information in preparation for output generation. The output layer features a single neuron with a linear activation function, producing a corrective signal $u(t)$ that is applied to the control inputs for engine adjustments, ensuring optimal performance and response to deviations.

The neural network training follows a supervised training approach, using historical data of engine operations and their corresponding corrective actions. For training, historical engine performance data $\Delta n_{TC}(t)$, $\Delta n_{FT}(t)$, $\Delta T_G^*(t)$, $\Delta Q_f(t)$ is collected and target outputs $u(t)$ (corrective signals) are taken. Data preprocessing involves normalizing the input data to scale it between 0 and 1, followed by splitting the dataset into training, validation, and test sets to facilitate effective model training and evaluation. The output signal $u(t)$ is calculated using the current weights and biases:

$$u = W_3 \cdot SmoothReLU(W_2 \cdot SmoothReLU(W_1 \cdot \boldsymbol{X} + b_1) + b_2) + b_3, \tag{8}$$

where W_i are weight matrices, b_i are bias vectors, and $\mathbf{X}$ is the input vector.

The loss function is represented as the mean square error [38, 39] and is defined as:

$$L = \frac{1}{n} \cdot \sum_{i=1}^{n} \left(u_{true}(i) - u_{pred}(i)\right)^2, \tag{9}$$

where u_{true} is the actual corrective signal and u_{pred} is the predicted signal.

The gradients are calculated using backpropagation as:

$$\frac{\partial L}{\partial W_i} = \frac{\partial L}{\partial u} \cdot \frac{\partial u}{\partial W_i}. \tag{10}$$

Parameter updating with adaptive training rate using the Adam optimizer [40] is performed as:

$$\begin{gathered} m_t = (\beta_1 \cdot m_{t-1}) + (1 - \beta_1) \cdot \frac{\partial L}{\partial W_i}, v_t = (\beta_2 \cdot v_{t-1}) + (1 - \beta_2) \cdot \left(\frac{\partial L}{\partial W_i}\right)^2, \\ \widehat{m}_t = \frac{m_t}{1 - \beta_1^t}, \hat{v}_t = \frac{v_t}{1 - \beta_2^t}, W_i = W_i - \frac{\eta_t}{\sqrt{\hat{v}_t} + \epsilon} \cdot \widehat{m}_t, \end{gathered} \tag{11}$$

where m_t is the first moment estimate, v_t is the second moment estimate, $\widehat{m}_t$ and $\hat{v}_t$ are the bias-corrected first and second moment estimates, η_t is the initial learning rate adjusted based on the parameter update.

It is noted that at the neural network (see Figure 1) training initial stage, adaptive parameters for adaptive training algorithms are initialized. For Adam, for example, the parameters are initialized as: $m = 0$ (first moment vector), $v = 0$ (second moment vector), $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-8}$ (to prevent division by zero) [38–40].

The training process involves repeating the parameters initialize, forward pass and loss calculation for a specified number of epochs until the loss converges, ensuring that the model effectively learns from the data. Following training, model performance is evaluated on validation and test datasets, with hyperparameters adjusted as necessary to mitigate the risk of overfitting. Upon successful training and validation, the model can be deployed within the onboard control system, facilitating real-time corrective adjustments to engine parameters, thereby enhancing overall performance and operational efficiency.

The proposed innovative model for the parametric adjustment of helicopter gas turbine engines combines a robust mathematical framework with an advanced neural network architecture, enabling real-time optimization and adaptive control of engine parameters. The mathematical model effectively captures the dynamic relationships between critical operational variables, such as rotor speeds, gas temperature, and fuel flow, using precise equations that characterize engine behavior under varying conditions. Complementing this, the neural network leverages a multi-layered architecture with adaptive learning rates, allowing for efficient learning from historical data and improving the model's capability to generalize and respond to unforeseen operational scenarios. This hybrid approach not only enhances the accuracy of performance predictions and corrective actions but also contributes to improved engine reliability and efficiency, positioning the model as a cutting-edge solution in aviation technology.

4. Results

The subject of this study is the TV3-117 TE [41, 42], which powers the Mi-8MTV helicopter and its various modifications. This engine is widely used in both civil and military aviation. The recorded parameters onboard the helicopter include: $n_{TC}(t)$, representing the gas-generator rotor speed (measured by the D-2M sensor); $n_{FT}(t)$, indicating the free turbine rotor speed (measured by the D-1M sensor); and $T_G^*(t)$, representing the gas temperature before the compressor turbine (measured by a set of 14 T-101 thermocouples) (Table 1) [43–45]. Additionally, atmospheric conditions such as flight altitude (h), temperature (T_N), pressure (P_N), and air density (ρ) are considered as input variables. For this study purposes, these atmospheric parameters are assumed to remain constant. Furthermore, the engine's dynamic behavior under various flight conditions is thoroughly analyzed to optimize its performance and reliability. The collected data allows for accurate modeling of the engine's operational behavior, serving as a foundation for further improvements in control and diagnostics systems.

Table 1
The training dataset fragment

Number	The gas-generator rotor r.p.m. n_{TC}	The gas temperature in front of the compressor turbine T_G^*,	The engine inlet pressure P_{in}^*	The fuel consumption G_T
1	0.973	0.961	0.983	0.973
…	…	…	…	…
42	0.983	0.966	0.988	0.977
…	…	…	…	…
139	0.988	0.950	0.992	0.970
…	…	…	…	…
256	0.985	0.952	0.984	0.971

During the training dataset pre-processing phase, homogeneity is assessed, followed by the division into control and test subsets, along with an evaluation of their representativeness through cluster analysis. To evaluate the homogeneity of the training dataset, the Fisher-Pearson criterion [46] is employed, utilizing observed frequencies and comparing them against critical values of χ^2, where the degrees of freedom $r - k - 1 = 13$ and the significance level $\alpha = 0.01$. This methodology enables the statistical significance determination, which is accepted only when the likelihood of obtaining these or more extreme outcomes under the null hypothesis is less than 1 %. The computed value of $\chi^2 = 5.721$ remains below the critical threshold of 6.6, thereby the samples consistency validating and the normal distribution hypothesis supporting.

To further affirm homogeneity, the Fisher-Snedecor criterion [47] is applied, which calculates the ratio of the larger variance to the smaller variance, with degrees of freedom $r - k - 1 = 13$ and significance level α $\alpha = 0.01$. The calculated value of $F = 2.224$ does not surpass the critical value of 2.58, reinforcing the samples' consistency and the normal distribution hypothesis. The training and test subsets representativeness is examined using cluster analysis, which aims to partition the input data set X (refer to Table 1) into k distinct clusters, where k is a clusters pre-defined number. Each cluster comprises objects deemed more similar to one another than to those from other clusters. The k-means clustering method is utilized, focusing on minimizing the total squared distances between the objects in a cluster and their centroids. Each object x_i in the set X is allocated to the nearest centroid according to the equation $C_i = \arg\min_j \|x_i - \mu_j\|^2$, where μ_j represents the initial centroids and $\|x_i - \mu_j\|^2$ signifies the Euclidean distance between object x_i and centroid μ_j. Subsequently, centroids are recalibrated as the objects average within each cluster using $\mu_j = \frac{1}{|C_j|} \cdot \sum_{x_i \in C_j} x_i$, where $|C_j|$ denotes the objects quantity in the j-th cluster. The calculations for C_i and μ_j are reiterated until variations in cluster distribution become minimal. The algorithm concludes when none of the centroids undergo significant alterations or upon reaching the predetermined iteration count [48, 49].

The results from the cluster analysis conducted on the training sample data (see Table 1) revealed eight distinct classes (I…VIII). Following a random selection process, training and test samples were formed in a 2:1 ratio (67 % training and 33 % testing). The cluster analysis performed on both subsets unveiled the presence of eight groups, indicating a similarity in composition between the training and test samples. The inter-group distances are nearly identical in both subsets, confirming the comparability of their compositions (refer to Figure 2). Thus, an optimal sample size was established, consisting of 256 elements for training (100 %), 172 elements for control (67 % of the training sample), and 84 elements for testing (33 % of the training sample).

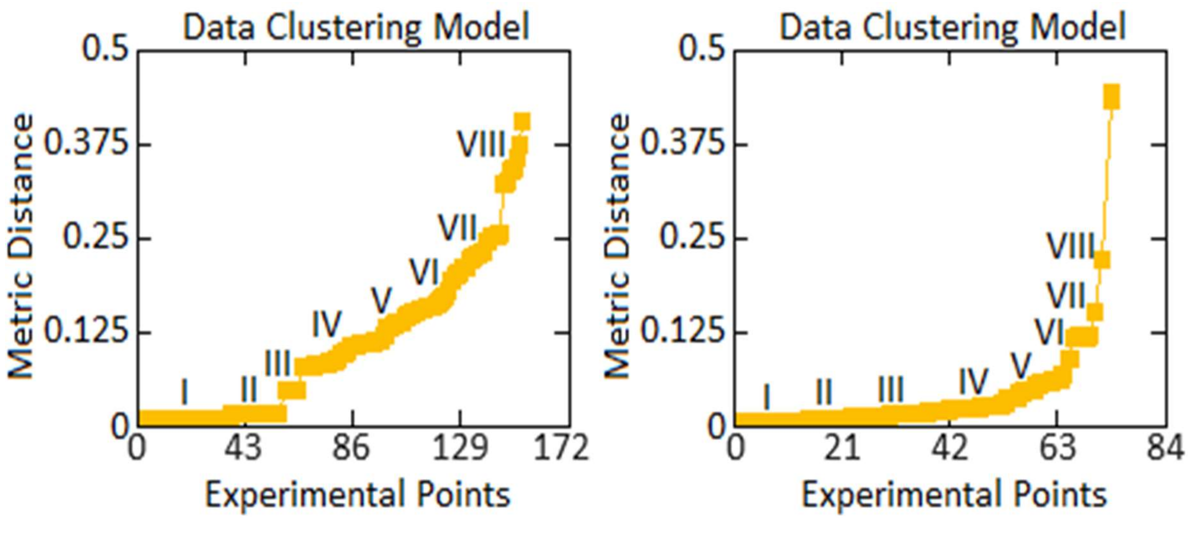

Figure 2: The cluster analysis results, where "left figure" denotes the training dataset, "right figure" denotes the test (author's research).

To assess the neural network's efficacy in the subsequent training stage, both accuracy (Figure 3) and loss (Figure 4) are quantified. The accuracy metric reflects the percentage of correct predictions, whereas the loss metric represents the average squared error of the predictions, illustrating the extent to which they differ from the actual values. To determine the precise calculations ratio for $\Delta n_{TC}(t)$, $\Delta n_{FT}(t)$, $\Delta T_G^*(t)$, $\Delta Q_f(t)$, the accuracy metric is employed (Figure 3) and is calculated at training epoch t using the following expression [50, 51]:

$$Accuracy_t = \frac{1}{N} \cdot \sum_{i=1}^{N} I\left(\hat{n}_{TCi}^{t} = n_{TC}\right). \tag{12}$$

As illustrated in Figures 3 and 4, these metrics demonstrate that the neural network model achieves a remarkable prediction accuracy of 99.25 % and operates effectively, with the mean squared error remaining below 2.5 %. Moreover, the substantial decrease in the loss function from 2.5 to 0.5 % signifies an improvement in the model's performance throughout the training process.

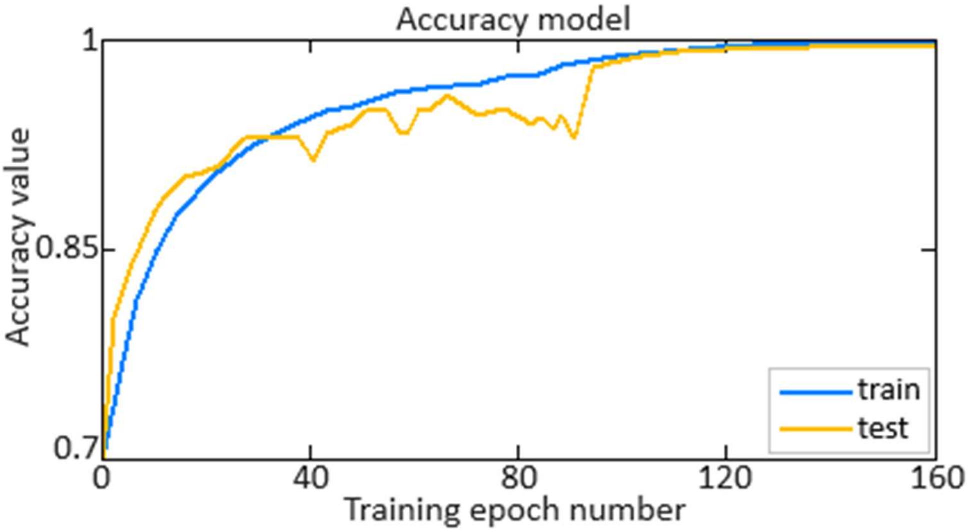

Figure 3: The accuracy metric diagram (author’s research).

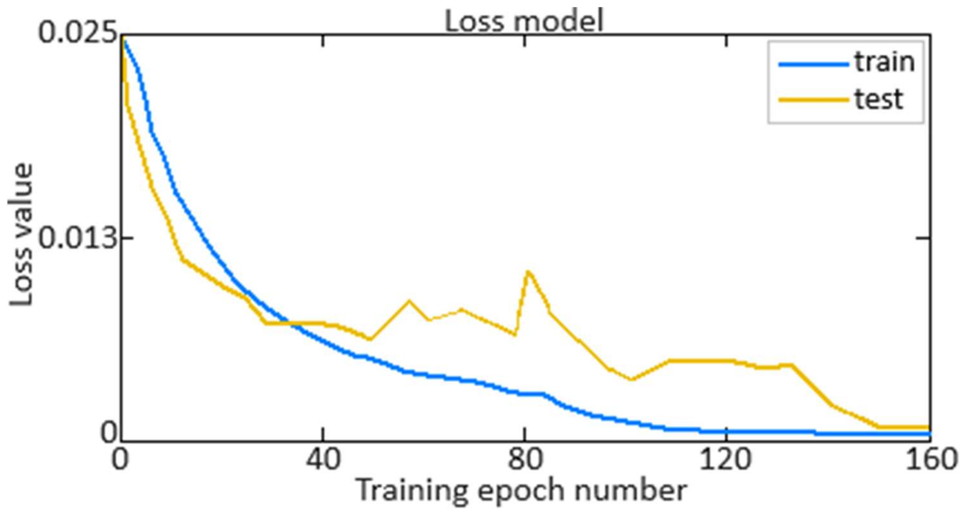

Figure 4: The loss metric diagram (author’s research).

The performance evaluation of the developed neural network (Figure 1) is carried out using essential quality metrics, including accuracy, precision, recall, F1 score, and AUC-ROC. These metrics provide a comprehensive assessment of the model's ability to make accurate predictions, reduce errors, accurately identify relevant instances, and maintain a balance between precision and recall. The F1 score provides insight into the harmonic mean of precision and recall, while AUC-ROC evaluates the model's ability to differentiate between classes at various thresholds, ensuring resilience in diverse operational contexts. These metrics are computed using the following expressions [52–54]:

$$Precision = \frac{TP}{TP + FP}, \tag{13}$$

$$Recall = \frac{TP}{TP + FN},$$

$$F1 - score = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall},$$

$$AUC - ROC = \int_{0}^{1} TPR \cdot \left(FPR^{-1}(t)\right) dt.$$

In this context, several key terms are utilized to assess the model's performance: True Positives (*TP*) refer to instances correctly identified as positive, representing relevant cases accurately detected by the model. False Positives (*FP*) indicate instances incorrectly classified as positive, highlighting irrelevant cases mistakenly identified as relevant. Conversely, True Negatives (*TN*) signify instances accurately classified as negative, while False Negatives (*FN*) represent relevant instances the model failed to identify. The True Positive Rate (*TPR*) measures the proportion of actual positives correctly identified, calculated as $TPR = \frac{TP}{TP+FN}$. Meanwhile, the False Positive Rate (*FPR*) assesses the proportion of actual negatives incorrectly identified as positives, computed as $FPR = \frac{FP}{FP+TN}$. Collectively, these metrics offer valuable insights into the classification performance of the model, aiding in the evaluation of its effectiveness in detecting relevant instances while minimizing erroneous classifications.

The evaluation metrics reveal significant insights into the model's performance: a precision score of 0.989 indicates that 98.9% of the instances classified as positive are indeed relevant, reflecting a high level of accuracy in the model's positive predictions. A recall score of 1.0 signifies perfect sensitivity, meaning the model successfully identifies all relevant instances without missing any, showcasing its comprehensive detection capability. Finally, the F1-score of 0.994, which is the harmonic mean of precision and recall, highlights the model's balanced performance, indicating that it maintains both high precision and recall rates effectively. Collectively, these scores suggest that the model operates with exceptional reliability and accuracy in identifying relevant instances within the dataset.

The evaluation metrics provide important insights into the model's classification performance: the *TPR* = 0.833 indicates that the model correctly identifies 83.3 % of actual positive instances, demonstrating a strong sensitivity in detecting relevant cases. The *FPR* = 0.0136 signifies that only 1.36 % of actual negative instances are incorrectly classified as positive, reflecting a low level of erroneous positive predictions and enhancing the model's reliability. The *FNR* = 0.0095 shows that the model fails to identify only 0.95 % of actual positives, which is a minimal proportion, indicating high effectiveness in recognizing relevant instances. Lastly, an AUC-ROC score of 0.844 suggests that the model has a good capability to distinguish between positive and negative classes across various thresholds, with a value closer to 1 indicating better performance. Collectively, these metrics reveal that the model is effective in achieving a balance between sensitivity and specificity while maintaining robust discrimination power in classifying instances.

The results obtained in this study enabled the optimal helicopter TE parameter values prediction (Table 2), ensuring acceptable performance for safe flight operations. Through the analysis of recorded onboard data, including gas-generator rotor speed, free turbine rotor speed, and gas temperature, combined with constant atmospheric parameters, the developed models provide a reliable framework for predicting engine behavior under various flight conditions. These predicted parameters are crucial for maintaining engine stability, minimizing risk, and enhancing the helicopter operations overall safety and reliability in both civil and military aviation.

Table 2
The optimal helicopter TE parameter values predicted values

Set number	The gas-generator rotor r.p.m. n_{TC}	The gas temperature in front of the compressor turbine T_G^*,	The engine inlet pressure P_{in}^*	The fuel consumption G_T
1	0.985	0.972	0.984	0.972
2	0.986	0.973	0.987	0.974
3	0.984	0.971	0.983	0.973
4	0.985	0.972	0.986	0.971
5	0.983	0.978	0.983	0.971
6	0.987	0.977	0.987	0.977
7	0.990	0.979	0.991	0.972
8	0.985	0.973	0.983	0.975
9	0.986	0.973	0.987	0.973
10	0.985	0.978	0.984	0.974

5. Discussions

In this research, a mathematical model (1)–(7) has been developed to optimize the helicopter TE parametric tuning. This model focuses on accurately predicting engine performance characteristics by integrating various operational parameters, including rotor speeds, fuel consumption rates, and temperature profiles. By employing a systematic approach to data analysis and parameter estimation, the model enhances the helicopter TE understanding behavior under different operating conditions.

A neural network model (see Figure 1) has been developed to implement the mathematical framework for the helicopter TE parametric tuning optimizing. This model is designed to capture complex nonlinear relations between various input parameters and engine performance outputs, leveraging an architecture that typically includes multiple layers, such as input, hidden, and output layers. The training process (8)–(11) involves a supervised learning algorithm, where the model is exposed to a dataset comprising historical engine performance data and corresponding operational conditions. Utilizing backpropagation, the model adjusts its weights and biases through iterative optimization, minimizing the loss function that quantifies the difference between predicted and actual outputs. An adaptive training rate is incorporated to enhance convergence efficiency, allowing for dynamic adjustments based on the model's performance during training. By employing this approach, the neural network not only trains to predict engine behavior accurately but also improves its capability to generalize across various operational scenarios, thus facilitating effective parametric tuning in real-time applications.

A homogeneous and representative training dataset (see Table 1 and Figure 2) has been formulated, consisting of input parameters crucial for the helicopter TE optimal tuning. This dataset includes key operational variables such as rotor speeds, fuel consumption rates, temperature readings, and other relevant metrics that influence engine performance.

A computational experiment established that the evaluation metrics reveal the neural network model's prediction accuracy of 99.25 % (see Figure 3) and effective operation, with a mean squared error below 2.5 %. A notable reduction in the loss function from 2.5 to 0.5 % (see Figure 4) signifies significant performance enhancement during training. Key metrics indicate that a precision score of 0.989 reflects high accuracy in positive predictions, while a recall score of 1.0 confirms the model's ability to identify all relevant instances, showcasing comprehensive detection capability. The F1-score of 0.994 highlights the model's balanced performance in maintaining both precision and recall.

Further analysis shows a True Positive Rate (*TPR*) of 0.833, indicating strong sensitivity, and a False Positive Rate (*FPR*) of 0.0136, which enhances reliability by showing that only 1.36 % of actual negatives are misclassified. A False Negative Rate (*FNR*) of 0.0095 signifies high effectiveness in recognizing relevant instances. Lastly, an AUC-ROC score of 0.844 illustrates robust discrimination between positive and negative classes across thresholds. Collectively, these metrics confirm the model's effectiveness in balancing sensitivity and specificity while maintaining strong classification power.

The neural network model quality assessing obtained results made it possible to obtain the helicopter TE optimal thermogas-dynamic parameters set (see Table 2), at which the flight will be as safe as possible. The results obtained in this research, while promising, are subject to several limitations that warrant consideration. The developed mathematical model (1)–(7) for optimizing helicopter TE parametric tuning primarily relies on historical performance data, which may not encompass all potential operating conditions, leading to reduced generalizability in real-world scenarios. Furthermore, the neural network model's architecture, despite its capability to capture complex nonlinear relationships, may be sensitive to overfitting, particularly if the training dataset does not adequately represent the operational variables full spectrum, such as variations in environmental conditions or anomalies during engine operation.

Additionally, the use of an adaptive training rate, while beneficial for convergence, may introduce instability if not carefully managed, potentially affecting the model's reliability. The metrics indicating high prediction accuracy (99.25 %) and low mean squared error (< 2.5 %) suggest effective performance; however, these figures must be interpreted with caution, as they do not account for potential biases in the training dataset or limitations in the model's assumptions regarding engine behavior. Lastly, while the quality assessment of the neural network enabled the optimal thermogas-dynamic parameters identification for safe flight (see Table 2), the practical implementation of these parameters in diverse operational environments necessitates further validation through extensive field testing to ensure their robustness and effectiveness under varying conditions.

The prospects for further research in helicopter TE parameter optimization involve a deeper exploration into the influence that various factors have on engine performance under dynamic operating conditions. Future studies may focus on developing more complex and adaptive neural network architectures capable of efficiently processing and analyzing data in real time, which would improve prediction quality and enhance model resilience to external disturbances. Additionally, comparing different machine learning algorithms and their combinations would be beneficial in identifying the most effective optimization approaches. It is essential to consider the impact resulting from changing climatic and operational conditions on engine behavior, which will require expanding the database and incorporating additional variables. Finally, integrating developed models into helicopter control systems and testing them in real flight conditions will be crucial for verifying the reliability and effectiveness of proposed solutions, thereby contributing to enhanced aviation engine safety and efficiency.

6. Conclusions

The research developed a mathematical model to optimize the helicopter turboshaft engines parametric tuning, demonstrating a high level of accuracy in predicting engine performance characteristics. By integrating key operational parameters such as rotor speeds, fuel consumption rates, and temperature profiles, this model significantly enhances the helicopter TE understanding behavior across varying operating conditions. The neural network inclusion further strengthens this framework by effectively capturing complex nonlinear relationships between input variables and engine performance outputs, allowing for more precise parametric tuning in real-time applications.

The model's training process, leveraging a representative dataset of historical engine performance data, has resulted in impressive performance metrics. With a prediction accuracy of 99.25 % and a low mean squared error below 2.5 %, the neural network demonstrates its capability to generalize well across different operational scenarios. Moreover, metrics such as precision, recall, and F1-score indicate a robust ability to identify relevant instances while maintaining a balance between sensitivity and specificity. These findings highlight the potential for applying this model to enhance safety and efficiency in helicopter operations.

Despite the promising results, the research identifies several limitations that must be addressed. The reliance on historical performance data may limit the model's generalizability to all potential operating conditions, and the neural network’s architecture could be prone to overfitting if the training dataset is not sufficiently diverse. Additionally, the adaptive training rate, while beneficial, requires careful management to avoid introducing instability. Therefore, the high prediction accuracy should be interpreted with caution, considering potential biases and limitations inherent in the training data.

Future research avenues include exploring the influence of various factors on engine performance and developing more complex neural network architectures for real-time data analysis. A comparative study of different machine learning algorithms may also yield insights into the most effective optimization approaches. Expanding the database to encompass a wider range of climatic and operational conditions is essential for improving model robustness. Ultimately, integrating these developed models into helicopter control systems and conducting extensive field tests will be critical for verifying their reliability and enhancing aviation engine safety and efficiency.

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