Intelligent method of measuring gas temperature of helicopter turboshaft engines with model error compensation

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Abstract
An innovative method for the helicopter turboshaft engines gas temperature measuring has been developed. It is based on a dynamic mathematical model with error compensation. The original nonlinear temperature dependence described by the function is linearly approximated by the Taylor expansion method, which allows taking into account the system's dynamic characteristics through a first-order differential equation. To eliminate the model's static and dynamic errors, a correction system with an adaptive PI controller has been implemented, whose parameters are selected using a neural network implementing online training. Simulation experiments conducted in the Matlab Simulink environment on real flight test data for the TV3-117 engine demonstrated high accuracy of parameter identification (up to 0.9975) and significant improvement in the transient process's dynamics in the model errors present in the ± 3% range. The experimental results confirm the proposed method's correctness and high efficiency, ensuring the system's stable operation in real time and demonstrating the prospects for further development of intelligent control methods.

Keywords
helicopter turboshaft engine, gas temperature measurement, model error compensation, adaptive PI controller, neural network

1. Introduction and related works

1.1. Motivation

In the rapid development context of helicopter aviation and increasing requirements for the helicopter turboshaft engines (TE) safety and efficiency, the gas temperature's accurate measurement is becoming critical to optimize the unit's operation [1–3]. Traditional measurement methods [4–6] are often subject to errors, which can negatively affect the engines' performance characteristics and service life. In this regard, the intelligent gas temperature measurement method with model error compensation developing relevance is due to the need to integrate modern artificial intelligence technologies and self-correction algorithms that can ensure the system's high accuracy and adaptability in real time, which will ultimately improve the helicopter TE reliability and safety.

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1.2. Related works

In modern research on the helicopter TE temperature conditions measuring, for example [7, 8], classical methods based on the pyrometers, thermocouples, and optical sensors used are widely used. These methods are often combined with mathematical models describing thermal processes in combustion chambers and gas flows. However, despite significant progress in sensor technology [9, 10] and modeling [11–13], the measurements accuracy remains limited due to the dynamic changes influence on engine operating conditions and the inevitable errors inherent in the models.

In recent years, there has been a trend towards integrating artificial intelligence and machine learning methods to improve the accuracy and adaptability of measurement systems. Research in this area is focused on the neural networks [14–17] and self-calibration algorithms [18, 19] used that allow real-time data correction and compensation for systematic errors. Such approaches demonstrate promising results, but they require significant computing resources and large training datasets, which complicates their practical application in limited response time conditions in aviation systems.

In addition to the above approaches, a number of researchers focus on the multi-sensor analysis and data fusion methods integration to improve the temperature measurements accuracy. In [20–22], big data processing algorithms are used that allow combining information from sensors' different types to minimize the noise and random errors impact. An integrated approach combining physical models, statistical analysis, and artificial intelligence algorithms opens up new possibilities for adaptive monitoring. However, their adaptation for real-time operation in helicopter TE remains an unsolved problem requiring further research.

The studies [23, 24] showed that fiber optic sensors provide high accuracy and protection against electromagnetic interference, and infrared thermography allows for contactless measurements. At the same time, [25, 26] states that CFD modeling and experimental data form accurate predictive models, and Kalman filters effectively correct dynamic indicators, reducing the noise impact. However, the these method's high cost and computational complexity make them difficult to use in real time.

Despite the successes achieved, issues related to dynamic compensation of model errors remain unresolved. Existing approaches [12, 16, 20] often cannot adequately respond to sudden changes in operating conditions, which leads to the errors accumulating in temperature measurements. In addition, the models' insufficient adaptability [7, 9, 21] and the sensor's universal self-correction algorithms [23, 25] lack of limits limit their application possibilities in helicopter TE real operating conditions.

Thus, there is a need to develop a new intelligent method for measuring gas temperature, compensating for model errors in real time. This requires the flexible adaptive systems integrating traditional measurement methods [3, 4] with innovative artificial intelligence algorithms creation [10, 14, 15, 27], which will significantly improve the helicopter TE operating parameters monitoring reliability and accuracy.

1.3. Goal and objectives

A goal of the paper is to provide measuring the helicopter TE gas temperature with compensating the model errors in real time. To reach this goal we formulated the following objectives: (i) to develop the intelligent method of measuring gas temperature; (ii) to create the neural network controller for implementation of the developed method.

2. Materials and methods

2.1. Development of the intelligent method of measuring gas temperature with corrected model error

It is known [1, 4, 28, 29] that in general the gas temperature in front of the compressor turbine model is represented as a function:

$$T_G = f\left(n_{TC}, n_{FT}, P_N, T_N\right), \tag{1}$$

where n_{TC} is the gas generator rotor speed (recorded on board the helicopter by the standard D-2M sensor); n_{FT} is the free turbine rotor speed (recorded on board the helicopter by the standard D-1M sensor); $P_N = P_N^0 \cdot \sigma_{rest} \cdot \left(1 + M^2 \cdot \frac{\gamma - 1}{2}\right)$ is the air pressure P_N inhibited value at flight altitude $h = h(t)$, P_N is the pressure at the ambient pressure sensor output (recorded on board the helicopter by the standard DP-11 sensor); $T_N = T_N^0 \cdot \left(1 + M^2 \cdot \frac{\gamma - 1}{2}\right)$ is the air temperature T_N^0 inhibited value at flight altitude $h = h(t)$, P_N^0 is the pressure at the ambient temperature sensor output (recorded on board the helicopter by the standard TT-11 sensor); σ_{rest} is the total pressure recovery coefficient in the helicopter TE inlet air section, $M = M(t)$ is the Mach number at flight altitude $h = h(t)$, γ is the adiabatic index [29, 30].

This model does not take into account the static error influence in calculating the gas temperature on the on-board automated control system (ACS) time constant setting accuracy [31, 32], which leads to a deterioration in the transient processes quality in its operation. To analyze small deviations around the operating point (n_{TC0}, n_{FT0}, P_{N0}, T_{N0}) [33–35], function (1) is expanded into a Taylor series:

$$T_G \approx T_{G0} + \frac{\partial f}{\partial n_{TC}} \cdot \left(n_{TC} - n_{TC0}\right) + \frac{\partial f}{\partial n_{FT}} \cdot \left(n_{FT} - n_{FT0}\right) + \frac{\partial f}{\partial P_N} \cdot \left(P_N - P_{N0}\right) + \frac{\partial f}{\partial T_N} \cdot \left(T_N - T_{N0}\right). \tag{2}$$

The obtained approximation (2) of function (1) allows us to identify the model's sensitivity to changes in each parameter. To take into account dynamic effects, model (1) is presented as a first-order differential equation:

$$\tau \cdot \frac{dT_G}{dt} + T_G = f\left(n_{TC}, n_{FT}, P_N, T_N\right), \tag{3}$$

where τ is the time constant characterizing the system' inertia.

Since the quantities n_{TC}, n_{FT}, P_N and T_N are also subject to dynamic changes, we introduce their dynamics' equations:

$$\tau_{n_{TC}} \cdot \frac{dn_{TC}}{dt} + n_{TC} = n_{TC}^{meas}, \tag{4}$$

$$\tau_{n_{FT}} \cdot \frac{dn_{FT}}{dt} + n_{FT} = n_{FT}^{meas}, \tag{5}$$

$$\tau_{P_N} \cdot \frac{dP_N}{dt} + P_N = P_N^{meas}, \quad (6)$$

$$\tau_{T_N} \cdot \frac{dT_N}{dt} + T_N = T_N^{meas}, \quad (7)$$

where n_{TC}^{meas}, n_{FT}^{meas}, P_N^{meas}, T_N^{meas} are the measured values, and $\tau_{n_{TC}}$, $\tau_{n_{FT}}$, τ_{P_N}, and τ_{T_N} are the sensors' time constants corresponding.

To eliminate the static error influence in measuring gas temperature, compensation is introduced. Let $T_{G,ref}$ be the temperature measured by a thermocouple (standard); then the model error is defined as:

$$\Delta T_G = T_{G,ref} - T_G. \quad (8)$$

When switching to a new dynamic mode, the adjustment is carried out according to the rule:

$$T_{corr} = T_G + K \cdot \Delta T_G, \quad (9)$$

where K is the correction coefficient (at steady state, often $K = 1$). In this case, a condition is introduced on the model's change rate to ensure the transient processes stability:

$$\left| \frac{dT_G}{dt} \right| \leq \varepsilon_0 \quad (10)$$

with a threshold ε_0, which specifies the maximum permissible change in temperature per unit time.

In addition, the error compensation dynamics are specified through the integral action as:

$$I(t) = \int_{t_0}^{t} \Delta T_G(\xi) d\xi, \quad (11)$$

and, at the same time, a PI controller is introduced [36–38]:

$$T_{corr} = T_G + K_P \cdot \Delta T_G + K_I \cdot I(t), \quad (12)$$

where K_P and K_I are proportional and integral coefficients, respectively.

To improve accuracy, adaptive change of correction coefficient K is provided ac-cording to the following law:

$$\frac{dK}{dt} = \alpha \cdot \Delta T_G - \beta \cdot K, \quad (13)$$

where α and β are the adaptive scheme' parameters, allowing it to "adapt" to changes in dynamics. Taking into account all the effects considered, the final equation is presented as:

$$\tau \cdot \frac{d T_G}{dt} + T_G = A \cdot n_{TC} + B \cdot n_{FT} + C \cdot P_N \cdot \sigma_{rest} \cdot \left(1 + M^2 \cdot \frac{\gamma - 1}{2}\right) + D \cdot T_N \cdot \left(1 + M^2 \cdot \frac{\gamma - 1}{2}\right) + E, \qquad (14)$$

where A, B, C, D and E are empirical coefficients determined by system identification.

In this case, the final temperature value, taking into account error compensation, is determined as:

$$T_{G,final} = T_G + K \cdot \Delta T_G, \qquad (15)$$

or, taking into account the PI controller, as

$$T_{G,final} = T_G + K_P \cdot \Delta T_G + K_I \cdot \int_{t_0}^{t} \Delta T_G(\xi) d\xi. \qquad (16)$$

2.2. Neural network controller development

The proposed controller' general structure (Figure 1) is based on the corrected error, which is represented as:

$$\Delta T_G(t) = T_{G,ref}(t) - T_G(t), \qquad (17)$$

where $T_{G,ref}(t)$ is the reference temperature measured by the thermocouple, and $T_G(t)$ is the model output (see (1) and (8)). In a classical PI controller, the output control action has the form:

$$u_{PI}(t) = K_P \cdot \Delta T_G + K_I \cdot \int_{0}^{t} \Delta T_G(\tau) d\tau. \qquad (18)$$

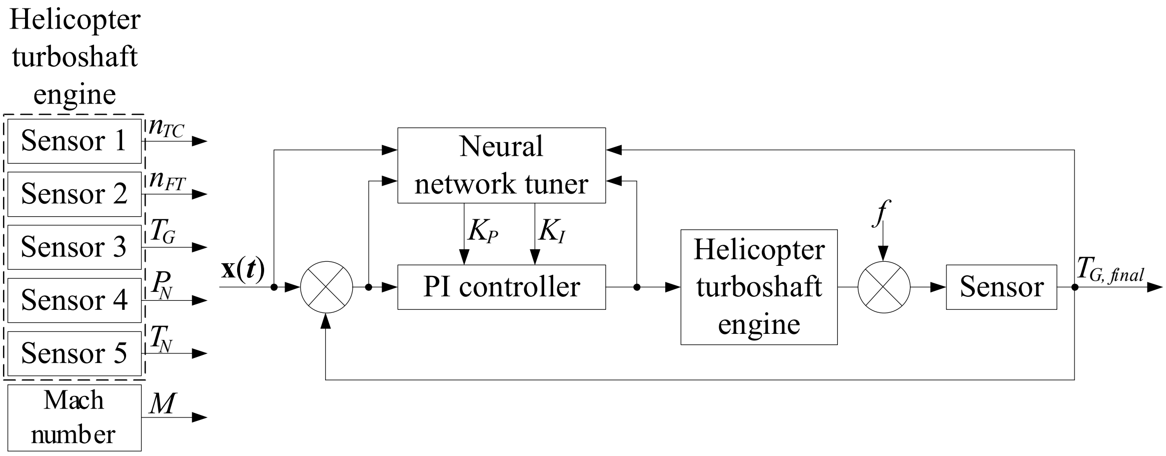

Figure 1: The proposed PI controller with neural network tuning. (author's development).

The proposed neural network PI controller extends this scheme by adaptively determining the coefficients K_P and K_I based on a feature vector reflecting the entire system's dynamics. To take into account the model' specific features, the input signals vector $\mathbf{x}(t)$ includes: the error' current value $\Delta T_G(t)$, the error' derivative $\Delta \dot{T}_G(t) = \frac{d\Delta T_G(t)}{dt}$, the gas generator and free turbine $n_{TC}(t)$ and $n_{FT}(t)$ operating parameters, the aerodynamic parameters: the Mach number $M(t)$, the pressure $P_N^0(t)$ and the temperature $T_N^0(t)$ (or their "slowed down" versions P_N and T_N. In this case, the model's change rate is additionally taken into account, for example, the value $\left|\frac{dT_G}{dt}\right|$, limited according to (10). Thus, the input vector $\mathbf{x}(t)$ is represented as:

$$x(t) = \left(\Delta T_G(t) \quad \Delta \dot{T}_G(t) \quad n_{TC}(t) \quad n_{FT}(t) \quad M(t) \quad P_N(t) \quad T_N(t) \quad \left|\frac{dT_G}{dt}\right| \right), \tag{19}$$

It is further assumed that a neural network with parameters $\mathbf{w}$ defines the input vector $\mathbf{x}(t)$ nonlinear mapping into a coefficients $[K_P(t), K_I(t)]$ pair:

$$K_P(t) = \varphi_P(x(t); w_P), K_I(t) = \varphi_I(x(t); w_I). \tag{20}$$

In the simplest case, one can use a single-layer neural network with nonlinear activation, for example, hyperbolic tangent (tanh). Then for each hidden neuron $h_j(t)$ (j = 1, ..., N_h) we obtain:

$$h_j(t) = \tanh\left(\sum_{i=1}^{n} \omega_{ij} \cdot x_i(t) + b_j \right), \tag{21}$$

and the outputs are calculated as:

$$K_P(t) = \sum_{j=1}^{N_h} v_{P,j} \cdot h_j(t) + b_P, K_I(t) = \sum_{j=1}^{N_h} v_{I,j} \cdot h_j(t) + b_I. \tag{22}$$

For the controller parameters' adaptive adjustment, the neural network is trained online using error backpropagation [39, 40]. The objective function can be defined as the mean square error between the reference and output temperatures:

$$J(t)=\frac{1}{2}\cdot\left(T_{G,ref}(t)-T_{G,final}(t)\right)^2. \tag{23}$$

The rules for updating the weights $\mathbf{w}_P$ and $\mathbf{w}_I$ are given by gradient descent:

$$\Delta w_P=-\eta\cdot\frac{\partial J(t)}{\partial w_P},\Delta w_P=-\eta\cdot\frac{\partial J(t)}{\partial w_P}, \tag{24}$$

where η is the training rate. This approach allows the neural network to "train" from model errors and adjust the controller coefficients in accordance with changes in the system dynamics.

Thus, the neural network adapts the PI controller coefficients depending on the system's current state. The original model features (sensor dynamics, aerodynamic parameters influence, total pressure recovery, limitation on the temperature change rate) are implemented due to:

1. The input vector $\mathbf{x}(t)$, which includes not only the control error, but also the parameters n_{TC}, n_{FT}, M, P_N, T_N and $\left|\frac{dT_G}{dt}\right|$.
2. The coefficients $K_P(t)$ and $K_I(t)$ adaptive selections, which change depending on the model's current state, which allows for the transient processes' correction under changing operating mode conditions.
3. Training on real data. When integrating with measuring signals from thermocouples and sensors, the neural network constantly adjusts its weights, which improves the ACS time constant adjustment quality.

Thus, the neural network PI controller's final control action is represented as:

$$T_{G,final}(t)=T_G(t)+\varphi_P(x(t);w_P)\cdot\Delta T_G(t)+\varphi_I(x(t);w_I)\cdot\int_0^t\Delta T_G(\tau)\,d\tau. \tag{25}$$

The developed neural network PI controller allows for the gas temperature's adaptive control, taking into account the model's both static and dynamic features, as well as limitations on the transient processes speed. Thus, the developed neural network PI controller is integrated into the original model, enhancing its features due to the coefficients' adaptive selection, which allows for achieving higher accuracy and stability of helicopter TE changing dynamics control under conditions.

3. Case study

To test the gas temperature measurement developed model with the model error compensation, implemented using a PI controller with neural network tuning (see Figure 1), a computational experiment was conducted, which research object was the TV3-117 engine [10, 14, 15, 27, 37, 41], which is the Mi-8MTV helicopter power plant part. According to the authors' team to the Ministry of Internal Affairs of Ukraine official request, within the research project "Theoretical and Applied Aspects of the Development of the Aviation Sphere" framework, registered in Ukraine under state number 0123U104884, the Mi-8MTV helicopter flight test data (n_{TC}, n_{FT}, T_G, P_N and T_N) were obtained, which were carried out at a flight altitude of 2500 meters above sea level for 320 seconds with a sampling interval of 0.25 seconds. The data (n_{TC}, n_{FT}, T_G, P_N and T_N at M = 0.7) obtained during the Mi-8MTV helicopter flight tests using the onboard monitoring system were preprocessed with the noise interference and anomalous values removal, after which they were transformed into time series is the parameters sequences ordered by time [42]. To ensure the time series comparability with the parameters' different scales, z-normalization $x_i = \frac{x_i - \frac{1}{N}\cdot\sum_{i=1}^{N} x_i}{\sqrt{\frac{1}{N}\cdot\sum_{i=1}^{N}\left(x_i - \frac{1}{N}\cdot\sum_{i=1}^{N} x_i\right)^2}}$ [43] was applied, which brings their values to a single range, setting the middle at zero and the standard deviation equal to one. This made it possible to form a parameters n_{TC}, n_{FT}, T_G, P_N and T_N training dataset, which fragment is presented in Table 1.

Table 1
The training dataset fragment during the TV3-117 engine operation

Number	n_{TC}	n_{FT}	T_G	P_N	T_N
1	0.982	0.979	0.983	0.999	0.998
...	...	...	...	...	...
373	0.987	0.982	0.982	0.998	0.997
...	...	...	...	...	...
562	0.989	0.981	0.982	0.998	0.999
...	...	...	...	...	...
797	0.983	0.982	0.983	0.997	0.997
...	...	...	...	...	...
965	0.992	0.982	0.987	0.999	0.998
...	...	...	...	...	...
1280	0.983	0.983	0.981	0.999	0.999

As the research' part, the training dataset's homogeneity was assessed using the Fisher-Pearson [44] and Fisher-Snedecor statistical tests [45], with a significance level of α = 0.01. This analysis revealed that the Fisher-Pearson test values were 13.225 for n_{TC}, 13.208 for n_{FT}, 13.215 for T_G, 13.295 for P_N, 13.297 for T_N, which is below the threshold value of 13.3. Similarly, the Fisher-Snedecor test values were 1.124 for n_{TC}, 1.123 for n_{FT}, 1.115 for T_G, 1.133 for P_N, 1.134 for T_N, which also does not exceed the critical value of 1.139. These results confirm both the training dataset homogeneity and the parameters' variances consistency under research. In addition, a cluster analysis was performed using the k-means method [46, 47], which made it possible to identify 8 separate groups, thereby confirming the both the training and test datasets represent the population. Note that these datasets were formed by randomly splitting in a ratio of 67 to 33 %, which ensures objectivity and balance in the data distribution. Based on the obtained results, the dataset-amounts optimizing process for sensor signals was carried out: the training dataset includes 1280 elements, the control dataset includes 858 elements, and the test dataset includes 422 elements. Such optimization creates a solid foundation for further research and timely prevention of engine failures during flight.

The research involved a computational experiment, whose main objective was to obtain the transient process results of the developed PI controller with neural network tuning with the gas temperature model error of ± 3 % and with the gas temperature model error correction of ± 3 %. These deviations (± 3 %) of the gas temperature value were selected based on the modern helicopter TE performance characteristics analysis, where this value is taken as the limit value during the unit's normal operation. The permissible limit of ± 3% is due to the fact that it is with such deviations that the aerodynamic and thermodynamic processes stability is maintained, which ensures optimal engine operation and minimizes the excessive wear or emergency situations risk [48–50].

To conduct a computational experiment in the Matlab Simulink software environment, an integrated computational model was developed, including a helicopter TE dynamic model, a PI controller algorithm with neural network tuning, and a module for compensating for the gas temperature model error (Figure 2).

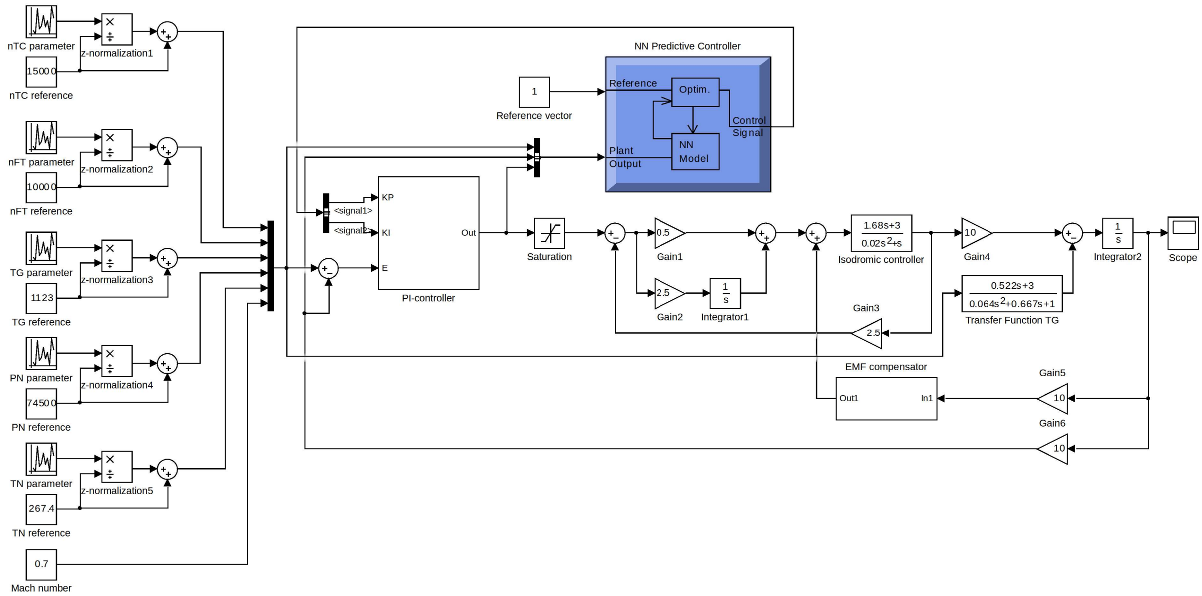

Figure 2: Developed integrated computational model in the Matlab Simulink software environment. (author's development).

Figure 3 shows the gas temperature model transient processes with a gas temperature model error of ± 3% (Figure 3 a, b) and with a gas temperature model error correction of ± 3% (Figure 3 c, d), from which it is evident that the gas temperature model error has a negative effect on the transient processes' quality (curves 1 and 2 differ in Figure 3 a, b).

This difference is due to the fact that the gas temperature model (1), which may have an error, is used to correct the thermocouple time constant. As soon as the gas temperature takes its constant value in the steady-state operating mode (in Figure 3 a, the exit time is approximately 4.5 seconds), the thermocouple time constant adjustment is switched off until the next transient process. The model error ceases to affect the steady-state operating mode, since the thermocouple readings are used without correction (in Figure 3, it is evident that curve 1 gradually transforms into curve 2 over a period of 1…2 seconds).

Curve 1 shows the transient response at the controller output implemented according to the classical self-adjusting gas temperature controller diagram. Curve 2 illustrates the transient response at the developed PI controller with neural network adaptation output (see Figure 1). Curve 3 represents the signal received from the thermocouple output. Thus, it can be concluded that the additive error affects only the measuring device's dynamic operating mode. One of the ways to eliminate this inaccuracy is to correct the gas temperature model error. It is evident from Figure 3, c, d that the gas temperature model error is compensated, and when applying a disturbance (the transient process noted at the 8th second), the model-corrected value is used. It is obvious that the transient process's quality is not determined by the gas temperature model error.

Figure 4 shows the gas temperature model transient processes with an admitted error of ± 3% when the temperature changes according to a sinusoidal law. It is clear that initially the 2% error had a negative impact on the transient processes’ quality (curves 1 and 2 differ). Then, at the 3.5 second mark, the model error is eliminated, and then the model signal without the error is applied (curves 1 and 2 coincide).

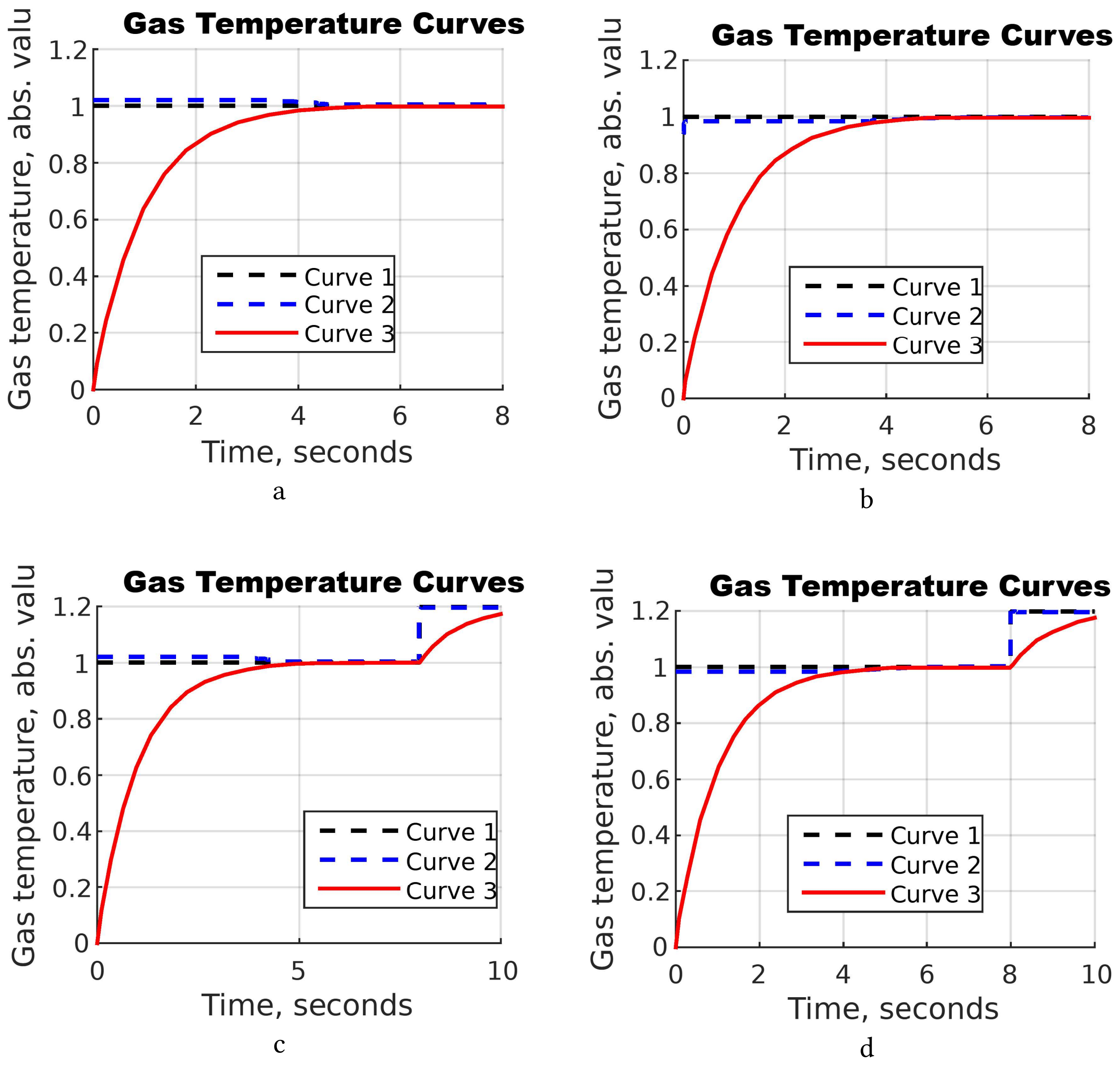

Figure 3: The gas temperature model modeling results: (a) with an error of + 3% without correction of the gas temperature model; (b) with an error of −3% without correction of the gas tempera-ture model; (c) with an error of +3% with correction of the gas temperature model; (d) with an error of −3% with correction of the gas temperature model. (author's development).

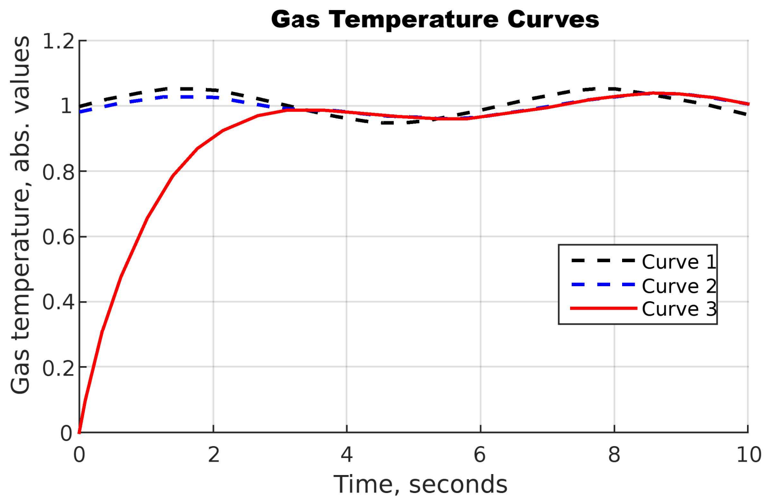

Figure 4: Results of the gas temperature modeling transient processes with a model error of +3% when the gas temperature changes according to a sinusoidal law. (author's development).

Figure 5 shows the signal at the developed PI controller output (see Figure 1) with single jumps in gas temperature and the stabilization mode zone allocation in relation to the process shown in Figure 3, c.

According to Figure 5, when single jumps in the input signal (changes in gas temperature) occur, a quick response is observed at the controller output. After each jump, the signal gradually moves into the stabilization zone, where a new stable level is established. This zone reflects the correction mechanism's operation, which, thanks to the coefficients (K_P and K_I) adaptive adjustment through the neural network, minimizes the model error consequences and allows the system to return to a stable state. Comparison with the process without compensation (as can be seen, for example, in Figure 3, from which the initial data are taken) shows that the neural network adaptive PI controller implementation can significantly reduce the model error impact. The signal at the controller output becomes smoother, which indicates the gas temperature measurement dynamics and increased accuracy adjustment. Rapid adaptation to abrupt changes and the stable mode's subsequent establishment are important for maintaining optimal operating conditions for helicopter TE.

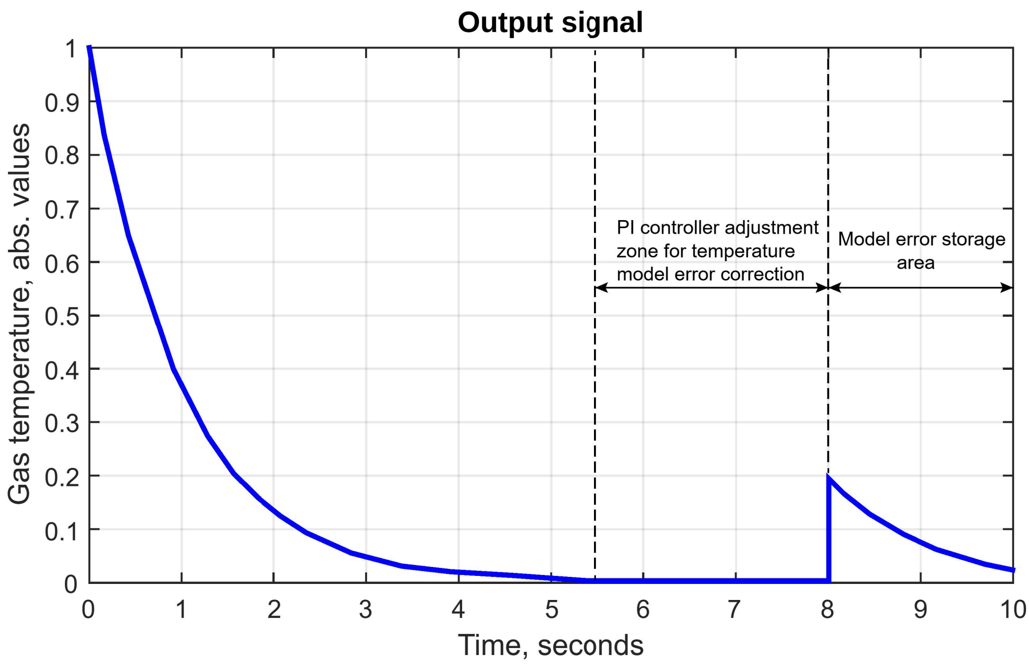

Figure 5: Diagram of the signal at the developed PI controller output for single jumps in gas temperature and allocation of the stabilization mode zone. (author's development).

The model error value (ε_0) choice is determined using the free turbine rotor speed sensor. Depending on the free turbine rotor speed n_{FT}, the gas temperature model error in the current operating mode is calculated from the model error dependence on the frequency diagram (Figure 6). The curve in Figure 6 is the model errors real values approximation based on [51–53].

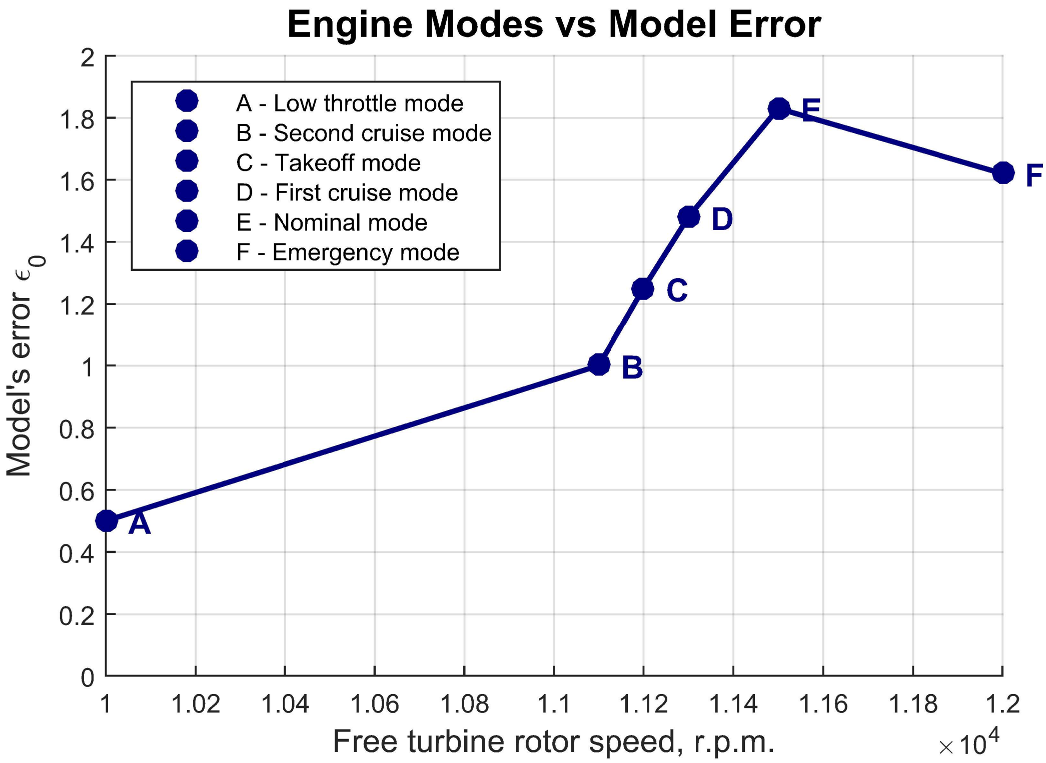

Figure 6: Diagram of the model error on free turbine rotor speed dependence. (author's development).

An example of the helicopter TE gas temperature model error determining the free turbine rotor speed's certain value is presented based on the following data: 11300 rpm is the first cruising mode (model error value +1.48 %); 11500 rpm is the nominal mode (model error value +1.79 %). To calculate the error value between the first cruising and nominal operating modes, for example, at a free turbine rotor speed of 11400 rpm, the following analytical expression is used:

$$\varepsilon_0(11400)=\left(\frac{1.79-1.48}{11500-11300}\right)\cdot(11400-11300)+1.48=1.635\,\%. \tag{26}$$

According to the obtained results, at 11300 rpm (the first cruising mode), the model error is +1.48 %, and at 11500 rpm (nominal mode), it is +1.79 %. Linear interpolation for 11400 rpm yielded an error value of 1.635 %, which indicates a uniform change in the error between the modes. These results demonstrate the accurate model correction possibility depending on the free turbine rotor speed.

4. Discussions

In this research, the helicopter TE gas temperature measuring method has been developed, which is based on a dynamic model, where the initial temperature dependence is specified by function (1) and linearized through the Taylor expansion (2) with subsequent representation in the first-order differential equation form (3), which allows taking into account the system's dynamics. To compensate for the static error, a correction term with the coefficient K (9) is used, and the integral and proportional control (12) are supplemented by an adaptive change in the coefficient according to the law (13). In addition, the neural net-work used for the PI controller coefficients dynamic adjustment (20)–(22) ensures the method's adaptation to changing operating conditions and high measurement accuracy.

The obtained results demonstrate that the adaptive method for compensating for model errors using a neural network implementation to adjust the PI controller coefficients allows for a significant increase in the helicopter TE gas temperature measuring accuracy (parameter identification up to 0.9975), which is confirmed by simulation experiments: in the model error of ± 3 % presence, the out-put signal dynamics is significantly improved–a rapid recovery after temperature jumps and the signal transition to the stability zone are observed (Figures 3–5), which specifies the method's effectiveness in minimizing the model errors impact and the automated control system ensures reliable operation in real conditions.

The obtained results demonstrate the developed method's high accuracy and adaptability; however, a limited number of limitations require additional analysis. The developed measurement model is based on a nonlinear dependence linear approximation (Taylor expansion), which can lead to a decrease in the assessment correctness with abrupt changes in operating conditions or in the strong disturbances event. The experimental validation was carried out under conditions close to the normal operating mode (model error ± 3 %), which limits the extrapolating possibility of the results to more extreme or unpredictable scenarios. The computational costs associated with the neural network online training for the PI controller coefficients adaptive adjustment require optimization for real implementation in systems with limited resources.

Future research prospects include expanding the model to include more complex nonlinear effects and dynamic modes and adapting it to different engine types and operating conditions [54]. Field testing to verify the system's performance in real-world conditions is recommended, as is research into the more advanced machine learning algorithms use [55] to improve adaptability and reduce computational load. An important area for future work is the multisensor analysis integration [56], which will improve error compensation algorithms and ensure the ACS more stable operation.

5. Conclusions

The helicopter turboshaft engine's gas temperature measuring innovative method has been developed, which is based on a dynamic model using a nonlinear dependencies linear approximation and compensation for static and dynamic model errors using an adaptive PI controller with a neural network. The applied approach, implemented through (1)–(3) for the system's dynamic description, (9)–(13) for error correction, and (20)–(22) for the coefficient's adaptive adjustment, allows achieving high accuracy of parameter identification (up to 0.9975) and ensures stable system behavior even in the model error's presence in the range of ± 3 %.

Simulation experiments conducted in the Matlab Simulink environment demonstrated that the proposed method significantly improves the transient processes dynamics: after sharp temperature jumps, a quick response and subsequent establishment of a stable mode are observed. Thus, the developed method allows for the model errors to influence effective compensation and adaptation to changing operating conditions, which is an important factor for increasing the helicopter turboshaft engine's reliability and safety.

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Declaration on Generative AI

The authors have not employed any Generative AI tools.

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