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Serhii Vladov

ALGORITHMS FOR DIAGNOSTIC AND PARAMETER OF FAILURES OF CHANNELS OF MEASUREMENT OF TV3-117 AIRCRAFT ENGINE AUTOMATIC CONTROL SYSTEM IN FLIGHT MODES BASED ON NEURAL NETWORK TECHNOLOGIES

Kremenchuk Flight College of Kharkiv National University of Internal Affairs,
17/6, Peremohy str., Kremenchuk, 39605, Ukraine
E-mail: ser26101968@gmail.com

Abstract

The solution of the reliability increasing problem of the TV3-117 aircraft engine automatic control system (ACS) through the use of the algorithmic redundancy is offered. The purpose of research is development of algorithms of measuring channels' fault diagnostics and counteraction for input parameters of linear adaptive on-board engine model (LABEM) built into the ACS. The LABEM basic mathematics is shown. The static model is based on the throttle characteristics of the individual engine. The throttle characteristics was obtained in the acceptance tests or "race" in the operation after the service. The lower level dynamic linear mathematical model of a gas-turbine engine is obtained by state space method. The technical and theoretical difficulties of practical implementation of algorithmic reservation by the model are associated with the high dimensionality of the engine state space, that are significantly higher than the dimension of the vector of parameters measured on board. There is a problem of identification of sensor fault with subsequent replacement of the value by modeling information. The necessity of fault detection and isolation algorithms in is justified. To improve the reliability of the fuel circuit input information the Kalman-filtering algorithms with integrated fault detection and isolation logic for the measuring channels are used. The fault detection and isolation algorithms for sensors' channels measurement in dosing needle loop based on Kalman filters were described. The algorithms are based on the calculation of the fault signature as weighted sum of the squares of residuals (WSSR), which is compared with the selected threshold value. The practice results of engines' stand tests and MatLab simulation showed the high reliability and quality of TV3-117 aircraft engine ACS based on proposed algorithms.

Keywords: aircraft engine, automatic control systems, noisy environments, identification, built-in linear adaptive on-board engine mathematical model, measurement channel, algorithms of fault diagnostics and counteraction, fault detection and isolation, Kalman filter, fault signature

1. Introduction

In modern digital of aircraft engines automatic control systems (ACS), the increase in reliability in flight conditions is achieved through the creation of algorithmic information redundancy using the onboard mathematical model of the engine integrated in the ACS.

There is no exception and TV3-117 aircraft engine. Technical and theoretical difficulties in the practical implementation of redundancy using the model are associated with a high dimension of the state space of the engine, significantly exceeding the dimension of the vector of parameters measured on board. There is a problem of identifying a sensor failure, followed by replacing the information with a model value and recognizing a “failure” (configuration change) of the engine, which is general theoretical, regardless of the level of the used engine model. Therefore, increasing the level of the model does not automatically lead to an increase in the reliability of the self-propelled guns, and when performing the functions of identifying a faulty information channel and a failure of the engine assembly with its replacement in the self-propelled guns using the on-board mathematical model, adaptability to the mentioned changes in the state of the object is an important property. Thus, the urgent task of modern digital systems of aircraft engines ACS is to ensure the fault tolerance of algorithms [1]. In particular, the problem arises of identifying the failure of measuring sensors with the subsequent replacement of incorrect information.

To solve this problem, it is proposed to use the onboard mathematical model of TV3-117 aircraft engine, which should be adaptive to the mentioned changes in the state of the object [2, 3].

2. Linear adaptive on-board model of TV3-117 aircraft engine

LABEM (Linear Adaptive Onboard Engine Model) meets the requirements for compactness, speed and accuracy of displaying engine parameters in statics and dynamics in a wide range of operating modes, flight conditions and engine conditions. LABEM is built-in and is designed to work in conjunction with TV3-117 aircraft engine ACS in a real environment under engine operating conditions. In particular, in the event of a sensor failure, information from the faulty sensor should be replaced with a model value.

As the basis of the static model of the engine, the throttle characteristic of the individual engine is used, obtained on acceptance tests or on the "race" in operation after maintenance [4].

Let's consider the problem of identifying the characteristics of aviation engine on steady modes of its operation. In these modes, the engine is described by the equations of the form [5]:

$$f_1(A, U) = 0; \tag{1}$$

$$Y = f_2(A, X); \tag{2}$$

where f_1 and f_2 are nonlinear vector functions; A and U are vectors of engine parameters.

The identification problem reduces to the finding of a function f^*, which, with a given degree of accuracy, would correspond to the dependence:

$$Y^* = f^*(A, X). \tag{3}$$

Procedure identify characteristics of aircraft engine TV3–117 with the help of the neural network shown in fig. 1, where $\varepsilon_1 \ldots \varepsilon_n$ the deviation between the measured parameters of individual aircraft and engine parameters calculated using the neural network with the same control effects $U_1 \ldots U_m$; E – learning error for the neural network.

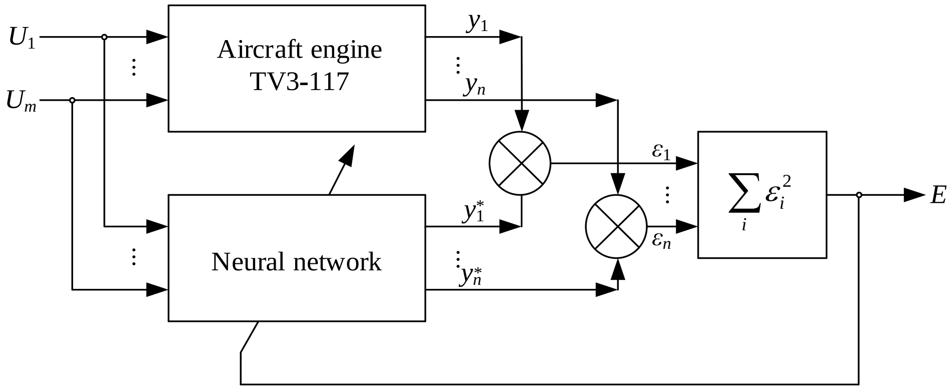

Fig. 1. Scheme of building a neural network identifier

Thus, the task of identifying the engine TV3–117 is based on the training of the neural network, which is to adjust its weight based on the condition:

$$E = \sum_{i=1}^{n} \left(y_i - y_i^* \right)^2 \to \min. \tag{4}$$

In this paper, the method of the identification problem solution in the neural network basis is used to identify the multi-mode model of the aircraft engine TV3-117.

It is assumed that the set of stable operating modes of aviation engine TV3-117 is described by a set of functional dependencies with respect to the values of the following engine parameters:

$$n_{sp} = f_1\left(G_{T_{sp}}\right);\ G_{air_{sp}} = f_2\left(G_{T_{sp}}\right);\ P^*_{2_{sp}} = f_3\left(G_{T_{sp}}\right);$$
$$T^*_{2_{sp}} = f_4\left(G_{T_{sp}}\right);\ T^*_{3_{sp}} = f_5\left(G_{T_{sp}}\right);\ R_{sp} = f_6\left(G_{T_{sp}}\right); \tag{5}$$

where $G_{T_{sp}}$ – specific value of fuel consumption (kg/s);

n_{sp} – specific value of the rotor frequency of the turbine compressor (%);

$G_{air_{sp}}$ – specific value of the air consumption (kg/s);

$P^*_{2_{sp}}$ and $T^*_{2_{sp}}$ – respectively, the pressure (kPa) and temperature (K) are calculated for the turbine compressor;

$T^*_{3_{sp}}$ – specific value of the gases temperature behind the compressor turbine (K);

R_{sp} – specific value of the engine thrust is shown.

The process of transition from the physical parameters of the engine to the given values (and back), carried out using the neural network model of the aircraft engine TV3–117, shown in fig. 2, where the conversion of the measured (physical) parameters of the engine to the reduced, which correspond to the standard atmospheric conditions $T_N^* = 288{,}15$ K, $P_N^* = 760$ mm Hg is carried out with the help of the operator $F(\bullet)$, which is described by the expressions (1) and (2), and the inverse transition – using the operator $F^1(\bullet)$ by the formulas of the gas-dynamic similarity:

$$n_{sp} = n\sqrt{\frac{288}{T_N^*}};G_{air_{sp}} = \frac{G_{air}\cdot 760}{P_N^*}\sqrt{\frac{288}{T_N^*}};P_{2_{sp}}^* = P_2^*\cdot\frac{760}{P_N^*};$$

$$T_{2_{sp}}^* = T_2^*\cdot\frac{288}{T_N^*};T_{3_{sp}}^* = T_3^*\cdot\frac{288}{T_N^*};R_{sp} = R\cdot\frac{760}{P_N^*};\quad (6)$$

and the influence of flight conditions on the parameters of the air entering the engine is thus considered as:

$$T_N^* = T_N\left(1+\frac{k-1}{2}M^2\right);\quad (7)$$

$$P_N^* = P_N\sigma_{rec}\left(1+\frac{k-1}{2}M^2\right)^{\frac{k}{k-1}};\quad (8)$$

where T_N and P_N – respectively, the temperature (K) and pressure (mm Hg) air at a given flight altitude; T_N^* and P_N^* are inhibited values of these parameters at a given altitude; k – adiabatic index; M – the number of flaps the flight; σ_{rec} – full recovery rate of full pressure in the air intake.

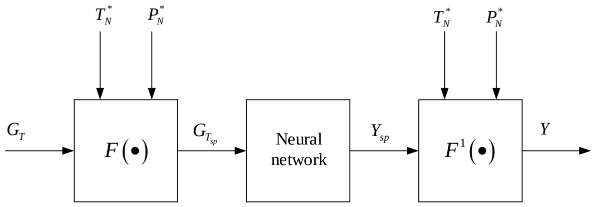

Fig. 2. The scheme of transition from the neural network model of the aircraft engine TV3-117 in the given parameters to the model in physical quantities

Let's consider the example of the identification characteristics problem solution of the aircraft engine TV3-117 based on its operation, recorded regarding the standard atmospheric conditions.

The linear structure of this model gives high performance and reliability of the account, and the introduction of non-linear coefficients of the coupling matrices helps to achieve the necessary identification accuracy in a wide range of engine operating modes and control actions.

Of particular importance for the reliable operation of ASC is the validity (conditionality) of the input information LABEM. The hardware redundancy implemented in practice provides for duplication of measurements of all input parameters using a two-channel system.

To ensure the fault tolerance of the LABEM algorithms, it is proposed to implement additional logic blocks designed to determine the possible uncontrolled failure of one of the measurement channels.

3. Choice of neural network topology

The choice of neural network topology is described in detail in [5]. For the solution of the problem of identification the multi-model aircraft engine TV3-117 in neural basis as basic architectures were selected and perceptron neural networks radial basis function (RBF). The expediency of using these architectures of neural networks is based on the analysis of the neural network and the classical methods of identification error. At this stage, the optimal structure of the neural network of the perceptron type should be chosen to solve the identification problem of the multi-mode aviation engine model TV3-117 based on the neural network.

In fig. 3 the experimental dependence $E = f(N)$ is constructed, where E – error of training of the neural network; N – the number of neurons in the hidden layer (it is assumed that the number of neurons in the input layer is equal to 1, in the output layer – 6). In the same figure, a similar dependence for a neural network of the RBF type is given.

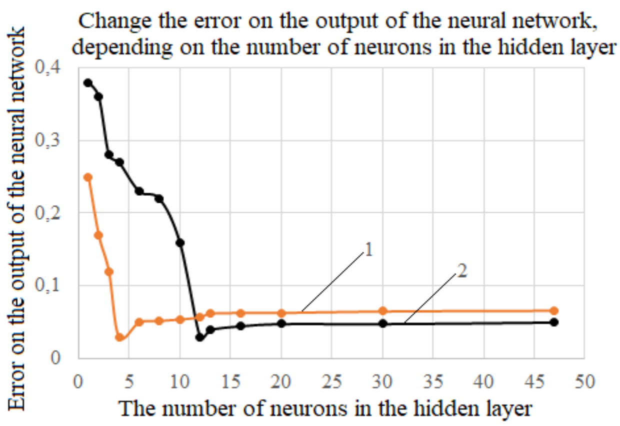

Fig. 3. The choice of optimal complexity of neural networks structures for solving the direct identification problem: 1 – perceptron; 2 – RBF

As can be seen from fig. 4, the optimal structures of neural networks are:

– for the perceptron – the structure (1–4–6), that is, 1 neuron – in the input layer; 4 neurons – in a hidden layer and 6 neurons – in the original layer of the neural network;

– for RBF – the structure (1–12–6), that is, 1 neuron in the input layer; 12 neurons in the radial (hidden) layer and 6 neurons in the original layer. These neural network models allow you to calculate the six listed above engine parameters as a function of the indicated fuel consumption $G_{T_{sp}}$. As an activation function of the neural network, the perceptron uses a sigmoid function.

he neural network RBF is a two-layer network (fig. 4), in which the first layer carries a nonlinear transform of the input parameter $G_{T_{sp}}$ without the use of adjustment weights, and the initial layer combines the received outputs of the 1st layer by calculating their linear weighted combination.

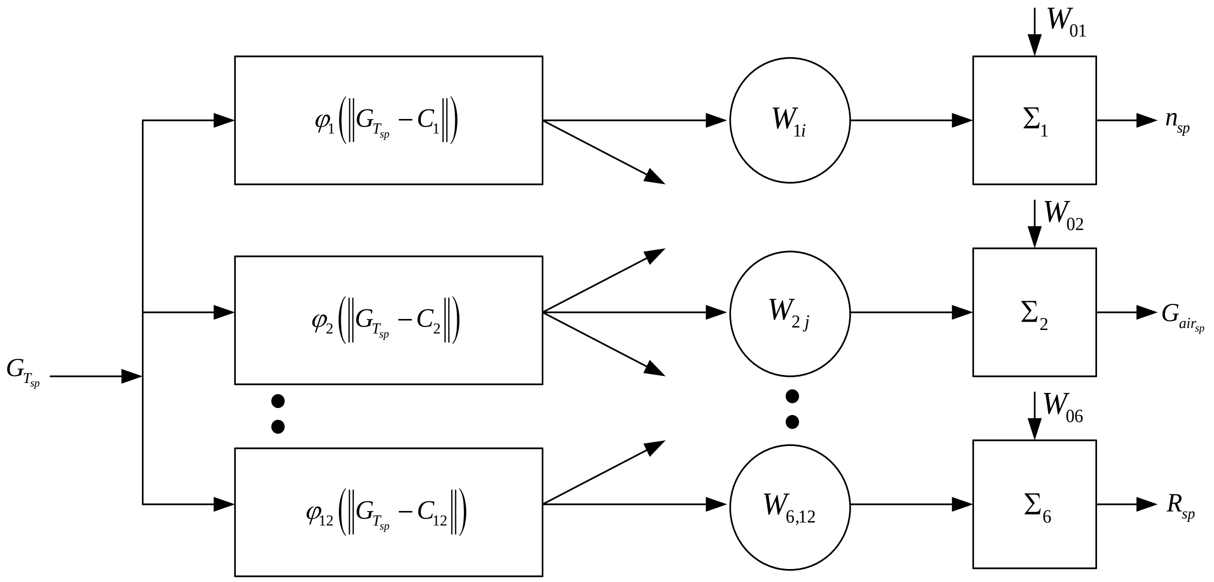

Fig. 4. Structure of RBF neural network

Outputs of the neural network RBF described by the equation:

$$Y_i = W_{oi} + \sum_{j=1}^{n} W_{ij} f_j(U); \tag{9}$$

where $i = 1, 2,\ldots, n$; $U = G_{T_{sp}}$ – input signal; W_{ij} – weights of connection (i = 1, 2, …, 6; j = 1, 2, …, 12); W_{oi} – offset value at the i-th output of the neural network; $f_j(U)$ – activation functions of the neural network, which are defined in the class of Gaussian functions:

$$f_j(U) = e^{-\frac{(U-C_j)^2}{2\sigma_j^2}}; \tag{10}$$

where C_j – value that determines the position of the center (standard) j-th class; σ_j – the width of the Gaussian function $f_j(U)$.

Adjusted parameters of the neural network RBF in fig. 4 is the weights W_{ij}, W_{oi} (i = 1, 2, …, 6; j = 1, 2, …, 12), since they are linearly related to the outputs of the neural network and, therefore, with a learning error, then their values can be found directly using the method of least squares, while minimizing the total square error of the neural network:

$$E = \frac{1}{2}\sum_{r=1}^{R}\sum_{i=1}^{n}\left(Y_i^{(r)} - Y_{io}^{(r)}\right)^2; \tag{11}$$

where $Y_i^{(r)}$ – the output of the neural network in the r-th experiment, that is, upon presentation of the network r-th input image $U^{(r)}$; $Y_{io}^{(r)}$ – i-th desired output of the neural network for the input $U^{(r)}$; R – the number of different experiments (the size of the training sample); n = 6.

Calculating the value of partial derivatives

$$\frac{\partial E}{\partial W_{io}} = \sum_{r=1}^{R}\left(Y_i^{(r)} - Y_{io}^{(r)}\right); \tag{12}$$

$$\frac{\partial E}{\partial W_{ij}} = \sum_{r=1}^{R}\left(Y_i^{(r)} - Y_{io}^{(r)}\right) f_j\left(U^{(r)}\right); \tag{13}$$

i = 1, 2, …, n; j = 1, 2, …, m;

and equating them to zero based on the expression:

$$Y_i^{(r)} = W_{io} + \sum_{j=1}^{m} W_{ij} f_j\left(U^{(r)}\right); \tag{14}$$

i = 1, 2, …, n;

we arrive at a system with $n(m + 1)$ linear equations for $n(m + 1)$ unknown coefficients W_{ij}, W_{oi} (i = 1, 2, …, n; j = 1, 2, …, m).

Unlike the frequent situation, when the use of gradient methods for adjusting the parameters of the perceptron leads only to the achievement of local minima, here the finding of the weight of connections is faster and more accurate.

4. Diagnostics and parry failures of fuel flow sensors

Diagnostics and parry failures of fuel flow sensors (G_T) are based on the application of Kalman filtering algorithms with built-in logic for detecting and localizing a measuring channel failure. The possibility of using Kalman filters in LABEM of the class under consideration has been proved on the basis of statistical processing of field engine test data [6].

At the input of the mathematical model of the engine, a fail-safe Kalman-filtration unit is connected, including a mathematical model of the channel of the metering needle (MN), which allows to obtain the calculated value of fuel consumption from the control signal of the position of the piston of the metering needle (x_{set}) received from the ACS. The output signal of the MN model is the predicted (model) value of the position of the piston x, which is fed to the input of the differential valve model (differential pressure controller), where it is converted into a G_T signal.

A Kalman recursive filter is connected at the output of the metering needle model. Its necessity is due to the presence of external and internal interference in the channel of the metering needle. The Kalman filter is a proportional link with a variable gain, which is determined in real time as a result of solving the problem of minimizing the mathematical expectation of the squared error of the identifiable parameter x, taking into account the obtained optimal estimate x_{opt} at the previous moment. The Kalman coefficient sets the probabilistic ratio of the model (calculated predicted) and measured components by the sensor in the optimal assessment of the piston displacement [7].

Since the measured value is used to obtain the optimal estimate, the urgent task is to ensure reliable detection and localization of faulty measuring channels for fault detection and localization, for which it is proposed to include additional logic in Kalman filtering algorithms. It is also proposed to use Kalman filter banks (fig. 5) [8] to estimate the accuracy of the measurement of a group of sensors, which allow generating a vector (matrix-column) of deviations:

$$\boldsymbol{\varepsilon}^i = \overset{i}{\mathbf{x}}_{opt} - \mathbf{z}^i_{mv}; \tag{15}$$

where for i-sensor: $\boldsymbol{\varepsilon}^i$ – estimate error, $\overset{i}{\mathbf{x}}_{opt}$ – optimal estimate (at the output of the corresponding Kalman filter), $\mathbf{z}^i_{mv}$ – measured piston displacement.

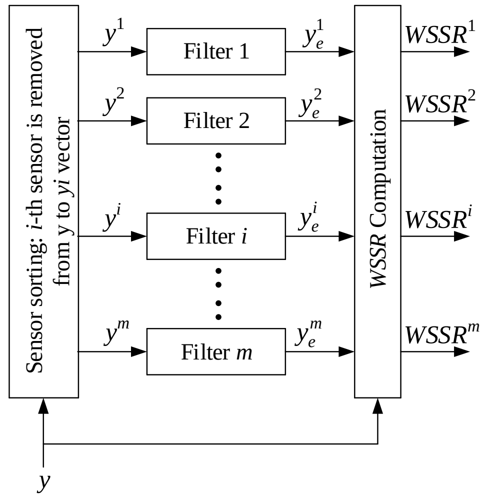

Fig. 5. Structure of bank of Kalman filters

To identify the sensor failure, the matrix of weighted sums of squares of deviations **WSSR** (Weighted Sum of the Squares of Residuals) is calculated, which is also called the sign or signature of the failure [9, 10], using the matrix equation:

$$\mathbf{WSSR}^i = \frac{\mathbf{W}^i_r \left(\boldsymbol{\varepsilon}^i\right)^T \boldsymbol{\varepsilon}^i}{\Sigma^i}; \tag{16}$$

where matrix $\Sigma^i = diag\left[\boldsymbol{\sigma}^i\right]^2$.

The vector $\boldsymbol{\sigma}^i$ represents the standard (passport) deviations of the i-sensor and normalizes the deviation vector. The matrix of scalar weights $\mathbf{W}_r$ includes engineering settings that are selected so that the level of the elements of the **WSSR** matrix does not exceed a predetermined threshold value in a state when all the sensors are operational.

If $\mathbf{W}_r$ – identity matrix and the equality $\varepsilon^i = \sigma^i$ is observed, the corresponding element of the **WSSR** matrix is equal to the number of measuring channels in the group under consideration. For the case $\varepsilon^i \neq \sigma^i$, the simplified formula is applicable:

$$WSSR = \sum \frac{\varepsilon^2}{\sigma^2}. \tag{17}$$

It should be noted that expression (17) is also valid for one channel of a two-channel sensor.

To detect channel failure of one sensor, the corresponding WSSR is compared with a threshold value, the value of which is selected by expert judgment based on statistical processing of experimental data for an individual engine. It should be borne in mind that a small threshold value can lead to false alarms, a large one can reduce the sensitivity of the system to failures. In [10, 11], it is recommended to choose a failure signature in the range of 1.5 ... 2. In the present work, a threshold equal to 2 was chosen. The algorithm for detecting and localizing the channel failure of the piston stroke sensor channel is illustrated in table.

Table

Algorithm for detecting and localizing the channel failure of a two-channel sensor

$WSSR_1$	$WSSR_2$	Situation	The output is
≤ 2	≤ 2	Both channels working	Filtered (Kalman) channel measurement with the smallest *WSSR*
≤ 2	≥ 2	Second channel failure	Filtered (Kalman) measurement of the first channel
≥ 2	≤ 2	First channel failure	Filtered (Kalman) measurement of the second channel
≥ 2	≥ 2	Both channels failed	Piston displacement model value *x*

5. Integration of bank of Kalman filters with neural network technologies

The general architecture of the developed system is shown in fig. 6. The functionality of the Kalman filter bank with the advanced state vector is summarized as follows [8]:

1. When there is no sensor or actuator fault, with or without component faults, all Kalman filters should retain low fault indicator signals, indicating there is no sensor/actuator fault, and should generate accurate health parameter estimates.

2. When one of the sensors or actuators failed, with or without component faults, only the one filter with the correct hypothesis should generate a low fault indicator signal and accurate health parameter estimates.

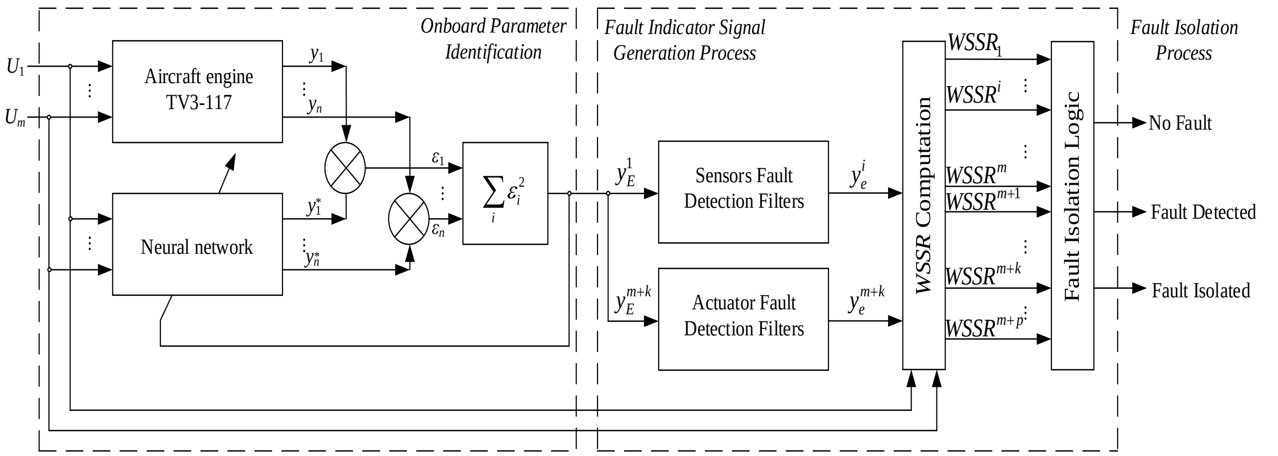

Fig. 6. FDI system architecture

The fault indicator signals generated by the above approach must be further processed in order to identify a fault. The FDI process can be completed by integrating the bank of Kalman filters with fault isolation logic as shown in fig. 6. In general, fault isolation logic is constructed from detection thresholds and decision rules. The decision rules check for fault indicator signal violation of the pre-established detection thresholds. If the necessary rules for the existence of a fault are satisfied, then the fault isolation logic declares a fault. Fault isolation is achieved if a fault is declared for all the fault indicator signals except for the one corresponding to a correct fault hypothesis. The development of fault isolation logic is application-dependent. An example will be given in the following section where the FDI design methodology is applied to an aircraft engine model [8].

6. Neural network training using the extended Kalman filter method

The Kalman filter is an effective recursive filter that, based on a number of noisy and incomplete measurements, allows you to evaluate the internal state of a dynamic system and is used in a wide range of technical devices, from car speedometers to radios and radios. A typical task for the Kalman filter is to evaluate past, current, or future values of the position, velocity, or acceleration of a dynamic system for which its linear or instantaneous linearized model is known.

Neural network training is a rather unexpected application for Kalman filtering theory and, at the same time, very effective: on the one hand, the quality of such training is at the level of the best second-order packet algorithms, such as the Levenberg-Marquardt method or quasi-Newton methods [12] and, on the other hand, training is carried out online, which is relevant in the case of large-volume samples and management tasks. There are various modifications of this training method, which in one way or another increase its effectiveness: multistream learning [13], which minimizes the risk of falling into a local minimum, batch form training [15], which allows processing several recent measurements in one times, the decoupled extended Kalman Filter [13], which is used to save computing resources. Recently, new implementations of the Kalman filter have been proposed, which have greater computational accuracy and, therefore, provide improved convergence: the Kalman filter based on the square root [14, p. 960] and Kalman cubic filter [15, p. 787]. In this paper, we describe the simplest and most technologically advanced implementation of training using the extended Kalman filter, the "Global Extended Kalman Filter" (GEKF).

In all these cases, training a neural network is considered as the task of assessing the true state of some unknown "ideal" neural network that provides zero mismatch, under the conditions in this case we take the values of the weights of the neural network $w(k)$, and under the mismatch – the current learning error $e(k)$.

This dynamic learning process can be described by a pair of equations in the state space. The equation of state is a model of a process representing the evolution of the vector of weights under the influence of a random process $\xi(k)$, which is considered white noise with zero mathematical expectation and the well-known diagonal covariance matrix Q:

$$w(k+1) = w(k) + \xi(k); \tag{18}$$

The output equation is a linearized model of the neural network $y = g\left(\sum_j w_j^{(2)} f\left(\sum_i w_{ji}^{(1)} x_i\right)\right)$,

where $w^{(1)}$ – hidden layer neuron weights, $f(\cdot)$ – activation functions of hidden layer neurons, $w^{(2)}$ – output layer neuron weights, $g(\cdot)$ – activation functions of output layer neurons per cycle k, noisy random process $\zeta(k)$, which is considered to be white noise with zero expectation and the known diagonal covariance matrix R:

$$h(k) = \frac{\partial y\left(w(k), v(k), x(k)\right)}{\partial w} + \varsigma(k); \tag{19}$$

where $w(k)$ – neural network weights, $v(k)$ – postsynaptic potentials of neurons, $x(k)$ – network input values. Calculation of instantaneous differential values $\frac{\partial y}{\partial w}$ produced by back propagation. Mismatch $e(k)$ calculated by the formula:

$$e(k) = t(k) - y(k); \tag{20}$$

where $t(k)$ – target value for neural network, $y(k)$ – real output of the neural network.

Before training the neural network, the initialization stage passes. The covariance matrices of measurement noise $R = \eta I$ and dynamic learning noise $Q = \mu I$, matrix size $L \times L$ and $N \times N$, respectively, are specified, where L – number of output neurons, N – number of weighting coefficients of the neural network. The coefficient η has the meaning of learning speed, we have η = 0.001, the coefficient μ determines the measurement noise, in this article it is accepted $\mu = 10^{-4}$. The covariance matrix P of size $N \times N$ and the zero-measurement matrix H of size $L \times N$ are also specified at the initialization stage.

The training phase is carried out online, the correction of the weights of the neural network is sequentially performed for each example of the training sample. On the cycle k following actions are performed.

1) The new value of the output of the neural network is calculated $y(k)$, "direct pass" of the neural network is performed.

2) The "reverse pass" of the neural network is performed: the differential values are calculated by the back propagation method $\frac{\partial y}{\partial w_i}$, $i = \overline{1, N}$. This is done using the same technique as in the error back propagation method, but the local gradients for the

output neurons are set not equal to the current error $e(k)$, but to constant 1, which, with all the same calculations, provides the values of the Jacobians of the outputs of the neural network $\frac{\partial y}{\partial w_i}$ instead of gradients $\frac{\partial (e(k))^2}{\partial w_i}$, because $\frac{\partial (e(k))^2}{\partial w_i} = 2e(k)\frac{\partial y}{\partial w}$. Observation matrix is formed $H(k)$:

$$H(k) = \left[\frac{\partial y}{\partial w_1}, \frac{\partial y}{\partial w_2}, \ldots, \frac{\partial y}{\partial w_N}\right]^T. \qquad (21)$$

3) The current network error is determined $e(k)$ according to the formula (21), deviation matrix is formed $E(k)$ size $1\times L$:

$$E(k) = [e(k)]. \qquad (22)$$

4) The new values of the weights of the neural network are calculated $w(k+1)$ and correlation matrices $P(k+1)$ according to the formulas:

$$K(k) = P(k)H(k)^T\left[H(k)P(k)H(k)^T + R\right]^{-1}; \qquad (23)$$

$$P(k+1) = P(k) - K(k)H(k)P(k) + Q; \qquad (24)$$

$$w(k+1) = w(k) + K(k)e(k); \qquad (25)$$

where $K(k)$ – Kalman gain matrix, its dimension $N\times L$. Actions 1 – 4 are performed for all elements of the training set.

The correlation matrix P updated at each step contains second-order information about the error surface, which provides an advantage to the Kalman advanced filter method compared to first-order learning methods, such as gradient descent and its modifications.

7. Simulation results in the Matlab package

Simulation results of cases when both measuring channels of a two-channel piston displacement transducer are serviceable (a signal from a sensor with a lower *WSSR* is taken as the output signal for detecting and localizing failure) and in the event of a second channel malfunction that occurs at time $t = 2.1$ s (as an output signal of failure detection and localization of a signal is taken from a serviceable sensor), in the Matlab package with further processing in the MathCAD package, are shown in fig. 7.

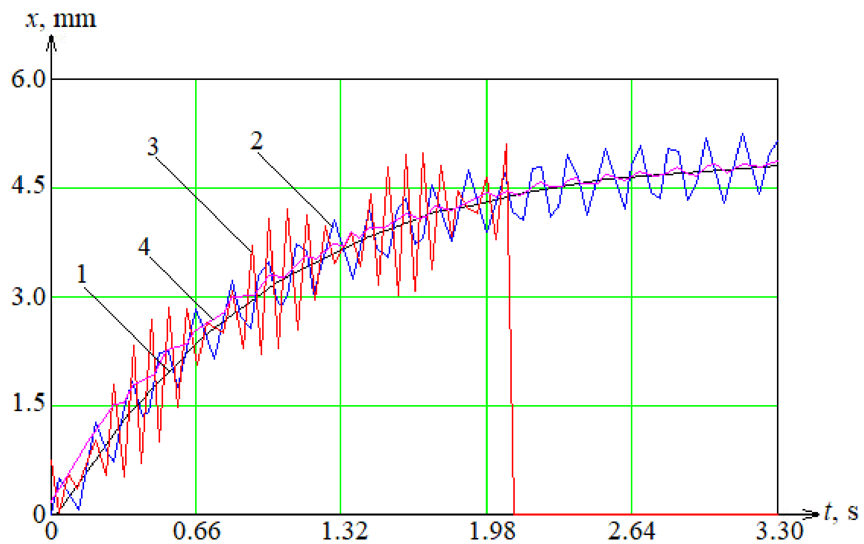

Fig. 7. The simulation results in the Matlab environment of situations when both measuring channels of a two-channel sensor are operational and if the second channel fails (1 – model value; 2, 3 – measurement of the first and second channel; 4 – output signal)

8. Conclusions

Testing the developed fail-safe algorithms as part of LABEM showed that the average relative dynamics error is 0.168 %. In statics, with a maximum G_T flow rate, the error is reduced to 0.01%, which corresponds to modern accuracy requirements for TV3-117 aircraft engine ASC.

All this confirms the efficiency and practical value of the developed algorithms.

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С.І. Владов

Алгоритми діагностики та парирування відмов каналів вимірювання системи автоматичного управління авіаційного двигуна ТВ3-117 у польотних режимах на основі нейромережевих технологій

Кременчуцький льотний коледж Харківського національного університету внутрішніх справ,
вул. Перемоги, 17/6, Кременчук, Україна, 39605
E-mail: ser26101968@gmail.com

Пропонується розв'язання задачі підвищення надійності системи автоматичного управління (САУ) авіаційного двигуна ТВ3-117 на основі введення алгоритмічної надмірності. Метою дослідження є розробка алгоритмів діагностики та парирування відмов вимірювальних каналів для вхідних параметрів вбудованої в САУ лінійної адаптивної бортової математичної моделі авіаційного двигуна ТВ3-117 (LABEM). Наведено основні співвідношення LABEM. В якості основи статичної моделі двигуна використовується дросельна характеристика індивідуального двигуна, отримана на здавальних випробуваннях або на «гонці» в експлуатації після проведення обслуговування.

Динамічна лінійна модель авіаційного двигуна ТВ3-117 нижнього рівня будується за методом простору станів. Технічні і теоретичних проблем практичної реалізації резервування за допомогою моделі пов'язані з високою розмірністю простору станів двигуна, що істотно перевищує розмірність вектору вимірюваних на борту параметрів. Виникає проблема ідентифікації відмови датчика з подальшим заміщенням інформації модельним значенням. Обґрунтовано необхідність побудови алгоритмів виявлення і локалізації відмов вимірювальних каналів двоканальних датчиків, що діють в умовах перешкод. Для підвищення надійності вхідної інформації по контуру витрати палива застосовуються алгоритми Калман-фільтрації з вбудованою логікою виявлення та локалізації відмови вимірювального каналу. Описано алгоритми виявлення та локалізації відмов датчиків в контурі дозуючої голки на основі фільтрів Калмана. Алгоритми будуються на обчисленні сигнатури відмови як зваженої суми квадратів відхилень (WSSR), яку порівнюють з обраним пороговим значенням. Результати випробувань на моторному стенді і моделювання в середовищі MatLab показали, що застосування запропонованих алгоритмів в складі LABEM дозволяє досягти високих показників надійності і якості автоматичного управління.

Ключові слова: надійність, система автоматичного управління авіаційного двигуна ТВ3-117, перешкоди, ідентифікація, вбудована лінійна адаптивна бортова математична модель двигуна, вимірювальний канал, алгоритми діагностики та парирування відмов, виявлення і локалізація відмови, фільтр Калмана, сигнатура відмови

С.И. Владов

Алгоритмы диагностики и парирования отказов каналов измерения системы автоматического управления авиационного двигателя ТВ3-117 в полетных режимах на основе нейросетевых технологий

Кременчугский лётный колледж Харьковского национального университета внутренних дел,
ул. Победы, 17/6, Кременчуг, Украина, 39605
E-mail:ser26101968@gmail.com

Предлагается решение задачи повышения надежности системы автоматического управления (САУ) авиационного двигателя ТВ3-117 на основе введения алгоритмической избыточности. Целью исследования является разработка алгоритмов диагностики и парирования отказов измерительных каналов для входных параметров встроенной в САУ линейной адаптивной бортовой математической модели авиационного двигателя ТВ3-117 (LABEM). Приведены основные соотношения LABEM. В качестве основы статической модели двигателя используется дроссельная характеристика индивидуального двигателя, полученная на сдаточных испытаниях или на «гонке» в эксплуатации после проведения обслуживания. Динамическая линейная модель авиационного двигателя ТВ3-117 нижнего уровня строится по методу пространства состояний. Технические и теоретические трудности практической реализации резервирования с помощью модели связаны с высокой размерностью пространства состояний двигателя, существенно превышающей размерность вектора измеряемых на борту параметров. Возникает проблема идентификации отказа датчика с последующим замещением информации модельным значением. Обоснована необходимость построения алгоритмов обнаружения и локализации отказов измерительных каналов двухканальных датчиков, действующих в условиях помех. Для повышения надежности входной информации по контуру расхода топлива применяются алгоритмы Калман-фильтрации со встроенной логикой обнаружения и локализации отказа измерительного канала. Описаны алгоритмы обнаружения и локализации отказов датчиков в контуре дозирующей иглы на основе фильтров Калмана. Алгоритмы строятся на вычислении сигнатуры отказа как взвешенной суммы квадратов отклонений (WSSR), которую сравнивают с выбранным пороговым значением. Результаты полунатурных испытаний на моторном стенде и моделирования в среде MatLab показали, что применение предложенных алгоритмов в составе LABEM позволяет достичь высоких показателей надежности и качества автоматического управления.

Ключевые слова: надежность, система автоматического управления авиационного двигателя ТВ3-117, помехи, идентификация, встроенная линейная адаптивная бортовая математическая модель двигателя, измерительный канал, алгоритмы диагностики и парирования отказов, обнаружение и локализация отказа, фильтр Калмана, сигнатура отказа

Serhii Vladov (1989). Candidate of Technical Science.
Department of Physical and Mathematical Disciplines and Informatics, Kremenchuk Flight College of Kharkiv National University of Internal Affairs, Ukraine.
Education: Kremenchuk Mykhailo Ostrohradskyi National University, Ukraine (2012).
Research area: system analysis, aviation engine, neural networks.
Publications: 80.
E-mail: ser26101968@gmail.com
ORCID: 0000-0001-8009-5254