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MODERN APPROACHES TO PROGNOSTICS AND HEALTH MANAGEMENT OF AN AIRCRAFT ELECTROMECHANICAL ACTUATOR

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Abstract. In connection with implementing the concept of electric airplanes, it is necessary to ensure the high reliability of electromechanical actuators (EMAs) as important components of aviation systems. The structural composition of an EMA and the types of its faults are considered. Fault diagnosis methods based either on EMA modeling or the analysis of signals received during EMA operation, as well as hybrid methods combining both these approaches, are reviewed. The advantages, disadvantages, and difficulties in applying these approaches are investigated. Special attention is paid to EMA diagnosis methods based on deep learning, which process signals in automatic mode and implement complex fault diagnosis. The concept of aircraft equipment health management (in particular, EMA health management) is presented based on assessing the technical condition and prognosticating the remaining useful life in order to prevent faults before their occurrence. Several hybrid approaches with prognostics are highlighted to solve the aircraft health management problem. Finally, Russian R&D results in the field of machine learning-based aviation health management are reviewed.

Keywords: aircraft, electromechanical actuator (EMA), fault diagnosis, health management, prognostics.

INTRODUCTION

The concept of electric airplanes, among other improvements, calls for gradually replacing hydraulic actuators with aircraft electromechanical actuators (EMAs), which will provide significant advantages over hydraulic actuators in flight control [1, 2]. As is believed, this replacement will significantly reduce weight and life cycle cost, decrease environmental impact, and increase reliability for aircraft. The use of EMAs is becoming more common, but their widespread application has been slowed by limited experience from the safety and reliability point of view and is currently largely restricted to non-safety-critical systems. It is crucial to assess the implications of replacing a hydraulic subsystem with its electrical alternative in terms of equipment use, implementation, monitoring, reliability, and safety. Problems arise that are less important for hydraulic actuators, such as electromagnetic compatibility, mechanical jamming, and overheating due to high currents [3]. To support the use of EMAs, reliable prognostic tools are needed to provide an accurate assessment of their factual technical condition and remaining useful life. EMAs and the related opportunities and challenges were reviewed in [4, 5].

Actuators are safety-critical components of aircraft systems, and an undetected actuator fault may have serious consequences; therefore, condition-based maintenance is necessary to improve EMA performance and ensure reliability, safety, and cost reduction.

Innovative prognostic and diagnostic methodologies based on numerical modeling are becoming a fundamental tool for the early detection of EMA faults. *Prognostics and Health Management* (PHM) systems are a relatively new field of research for diagnosing the current technical condition and predicting the failure time and remaining useful life of a system or component based on its signals [6]. Such systems are intended for maintenance scheduling in order to ensure failure-free system operation based on a set of numerical models. These models must be properly tuned to reproduce the behavior of EMAs in terms of static and dynamic response (e.g., currents, voltages, velocity, position, etc.) [7, 8]. For this purpose, it is necessary to simulate EMA operation under normal conditions as well as in the presence of incipient faults. The results, trends, and predicted values of the model must be thoroughly validated on detailed and extensive experimental datasets. The experimental validation of models on test rigs is a widespread method in engineering applications involving the development of new models for monitoring and control [9].

Signal processing methods and statistical tools with different types of sensors, the fast Fourier transform, vibration frequency analysis, and time-frequency analysis are applied in EMA fault diagnosis [10–13]. However, these methods can be time-consuming, labor-intensive, and unreliable. In recent years, a new approach has been developed to automate fault diagnosis and prognosticate faults based on deep learning methods. These methods classify different EMA states using different types of neural networks, such as denoising autoencoders, deep trust networks, and convolutional neural networks. Unlike traditional methods, deep learning ones can extract effective fault features directly from monitoring signals and classify faults simultaneously [14, 15].

The goal of this paper is to study and analyze modern approaches to diagnose and prognosticate the technical condition of an aircraft electromechanical actuator, as well as their prospects and the difficulties that currently hinder their practical application.

1. AN ELECTROMECHANICAL ACTUATOR: STRUCTURAL COMPOSITION AND FAULT TYPES

Most EMAs consist of a servomotor, an electric power actuator circuit, mechanical components, an actuator control unit, and some sensors [16, 17]. The electric power actuator receives a signal from the actuator control unit and outputs an appropriate power current to the actuator's servomotor. The servomotor converts electrical energy into mechanical energy and brings executing units into operation. Depending on motion kinematics, these units are divided into translational, turn, and rotary motion mechanisms. When implementing feedback control, feedback sensors are installed in EMAs; monitoring sensors are installed to control the actuator's technical condition.

The following types of faults are distinguished in EMAs: a motor fault, an electrical power actuator fault, and a mechanical component fault [18].

Motor faults mainly include a bearing fault, a stator winding fault, and a rotor fault. Bearing faults are the degradation, spot corrosion, and destruction of the bearing cage. Bearing faults may cause friction imbalance and abnormal vibration, reducing motor efficiency and performance. Stator winding faults include a winding breakage, an electrical short, etc. A winding breakage is usually due to high motor starting currents; it sharply decreases EMA output torque and increases winding currents. An electrical short is mainly caused by prolonged thermal aging; it increases winding currents and heat generation by the motor. Motor rotor faults are rotor shaft eccentricity and rotor demagnetization. Shaft eccentricity disturbs the electromagnetic balance and causes abnormal vibration during operation. Rotor demagnetization is usually due to motor overheating; it reduces motor efficiency and increases stator current and motor temperature.

The main faults in the electric power actuator are as follows: an electrical short and disconnection of the electric bridge, and electric shocks of the power supply capacitor.

Common mechanical faults include excessive degradation, pitting (indentation of metal surfaces at high voltage contact points), back channel jamming, and poor lubrication. Excessive degradation occurs mainly on the ball screw and fixed-end bearings. Severe degradation of the ball screw may cause failure of the entire EMA system. Pitting is mainly due to surface fatigue; it increases EMA vibration. Back channel jamming occurs when deforming the return tube or accumulating debris on the return tube; it may deteriorate the friction condition of the EMA, generate large amounts of heat, and drastically reduce the thermodynamic performance characteristics. Insufficient and contaminated lubrication increases friction and EMA degradation.

2. EMA FAULT DIAGNOSIS METHODS

2.1. The Types of Diagnostic Methods

EMA fault diagnosis methods are mainly divided into model-based methods, *data-driven methods* (in which the system is treated as a black box), and hybrid methods [18–20].

The principle of model-based fault diagnosis methods is to synchronously run EMA models and the real EMA system and estimate the difference between their state signals, which are measured by various sensors and collected by a data acquisition system. The output residuals of the signals of the simulation models and real systems are used to diagnose the technical condition of EMAs.

Model-based fault diagnosis has the following advantages [18]:

• Creating an accurate model of an existing system facilitates comprehending the physical mechanism of its internal interactions. Fault modeling allows generating signals to train automated fault recognition algorithms as well as to test and compare algorithms, diagnostic and prognostic procedures, and functions [21].

• The results obtained by model-based fault diagnosis methods can be clearly explained by a dynamic model, and the degeneration degree of the system can be determined by comparing the parameter deviations or the residuals.

• Model-based methods do not require much real data to train fault diagnosis algorithms. Good training and diagnostic results can be achieved using a small amount of training data [22].

However, model-based fault diagnosis methods for EMAs suffer from several drawbacks.

• For each particular model of the systems being diagnosed, appropriate mathematical models have to be developed, which is a challenge. Accurate dynamic models are often computationally intensive, which places high demands on computing performance.

• During EMA operation, electromagnetic force, thermal stress, and mechanical stress have a complex interaction mechanism, and an accurate mathematical model is difficult to create. As a result, one uses simplified models approximately reflecting the characteristics of physical systems. In this case, model-based fault diagnosis methods can determine whether a fault has occurred in EMA but cannot accurately identify the faulty component. Detailed dynamic models are needed for each component to perform a more accurate diagnosis.

Data-driven fault diagnosis methods do not require complex mathematical models of EMAs; they extract features for diagnosing the technical condition of EMAs from sensor signals [23]. Signal processing techniques play an important role in EMA fault diagnosis. The quality of initial data and the correlation between signals and faults strongly influence the effectiveness of diagnostic algorithms. The operating conditions of EMAs often change even during normal operation, which makes the state signals highly nonstationary and non-periodic. The influence of different operating conditions is eliminated by oversampling, i.e., the signals are synchronized with selected key signals. For example, several signal processing methods can be used during feature extraction to identify fault frequencies synchronized with the motor position in signal data [24]. In this case, feature extraction and fusion methods are employed to select the features relevant to the failure mode and exclude the irrelevant ones. The wavelet transform is widely used in feature extraction for EMA fault diagnosis [25, 26].

With features, the technical condition of EMAs can be determined using a classifier for fault diagnosis. If fault-irrelevant features are supplied to the classifier, learning will have a small rate and a poor effect. Principal Component Analysis (PCA) can be applied to extract fault-relevant classification features and reduce the dimension of the feature vector. PCA characterizes the process state by projecting the acquired data into a lower-dimension space. This dimension reduction method preserves the correlation between measurements by optimally capturing data variability [27].

However, data-driven fault diagnosis methods for EMAs face some application difficulties as follows.

• Under different degrees and types of faults, a large amount of data is required to train diagnostic algorithms. The effectiveness of diagnosis strongly depends on the quality of the available data. However, in most cases, aircraft cannot fly with faulty EMAs, so fault data are difficult to obtain. The absence of available experimental data considerably complicates studies. Many algorithms have been validated only theoretically or been tested only on mathematical modeling data.

• In the case of severe noises or complex systems, advanced signal processing methods and feature extraction algorithms are usually required. As a result, data-driven diagnostic methods often place high demands on the computing power of the system.

• Data-driven methods typically require high sampling rates of the state signals. Thus, the actuator control unit must have powerful computational and memory capabilities.

Also, hybrid diagnostic methods are used for EMA fault diagnosis; they combine the advantages of both data-driven and model-based diagnostic methods. For example, model-based methods are adopted to generate necessary data, and then data-driven methods are applied to process these data and implement fault diagnosis [28].

2.2. EMA Fault Diagnosis Based on Deep Learning

Traditional machine learning methods are widely used for diagnosing EMA faults. A detailed review of such methods can be found in [18]. However, within these traditional data-driven approaches, features are extracted manually. The corresponding processes heavily rely on prior knowledge, diagnostic experience, and sophisticated signal transformation methods, which are computationally intensive and time-consuming; the effectiveness of diagnosis largely depends on the fault characteristics selected. With sufficient training data, deep learning models automatically process the original signals and implement comprehensive intelligent fault diagnosis. However, since EMAs are often used in high-reliability and safety-critical equipment, it is difficult to obtain balanced data on failure modes [29].

A modified *Long Short-Term Memory* (LSTM) model was applied to detect and isolate EMA faults in [30]; the effectiveness of this method was confirmed by NASA open data. An LSTM neural network is a deep learning network intended to study long-term dependencies because it can store information for a considerable time. Several denoising autoencoders were combined to diagnose EMA faults accurately; see [31]. However, these methods perform well only under sufficient data and balanced samples, which is difficult to implement in most EMA fault diagnosis scenarios.

Convolutional neural networks are used for feature extraction under unbalanced data. A 2D convolutional neural network and an optimized model based on the Softmax activation function were proposed for diagnosing EMA ball screws using motor current signals [32]; as a result, feature extraction and classification were improved under different loads and unbalanced samples. Unsupervised parallel data were used, and EMA fault diagnosis was implemented using different sensors based on a convolutional neural network [33]. However, these methods do not settle the diagnosis problem under small samples.

A generative adversarial network was proposed for fault diagnosis under a small-sized sample based on vibration signals [34]. Adversarial autoencoders are used to convert autoencoders into generative adversarial networks. A generative adversarial network based on a conditionally variational autoencoder was presented to solve the unbalanced sampling problem under different operating conditions [35]. A complex data-driven approach was proposed to implement reliable fault diagnosis for EMAs using only vibration signals [29]; this approach combines the capabilities of a convolutional neural network for feature extraction with semi-supervised learning and data generation of an adversarial autoencoder under different operating conditions and unbalanced sampling. A ball screw transmission fault detection method based on a deep trust network was proposed in [36]. Frequency spectra of a combined dataset collected from multiple sensors were used.

The presence of redundant data increases the load on software and hardware. A semi-supervised sparse autoencoder was used to process the data observed and extract sparse features in order to improve the accuracy of fault detection while reducing the data [37]. The temporal and spatial relationships were investigated by a multi-channel LSTM network to build a time series model for fault detection and isolation based on the difference between the parameter values measured by the sensors and their values calculated by the autoencoder. According to the validation results, this method can effectively diagnose EMA faults.

A hybrid spatial unit was combined with a temporal synchronized attention-based recurrent unit with seasonal-trend data decomposition procedures [38]; this approach demonstrated good results in both fault diagnosis and prognostics of EMAs.

A simulation model of EMAs was described, and typical EMA faults were analyzed in [39].

In particular, EMA *simulation* was divided into three separate parts according to its composition: a permanent magnet synchronous motor, a gearbox, and a ball screw.

The permanent magnet synchronous motor was modeled by the equations

$$\begin{cases} u_d = R_a i_d + L\dfrac{di_d}{dt} - P_m \omega_m L i_q \\ u_q = R_a i_q + L\dfrac{di_q}{dt} + P_m \omega_m L i_d + P_m \omega_m \psi_{f_m} \\ T_L = T_e - J\dfrac{d\omega_m}{dt} - B\omega_m \\ = 1.5 P_m \psi_{f_m} i_q - J\dfrac{d\omega_m}{dt} - B\omega_m \end{cases}$$

with the following notations: u_d, u_q and i_d, i_q are the equivalent voltage and equivalent current, respectively, in the rotor principal component system with the coordinates *d* and *q*; R_a is the equivalent resistance of coil winding; *L* is the equivalent inductance; P_m is the number of motor pole pairs; ω_m is the rotor mechanical angular velocity; ψ_{f_m} is the equivalent magnetic chain; T_e is the motor output electromagnetic torque; *J* is the equivalent rotational inertia of the motor rotor; *B* is the rotor damping factor; finally, T_L is the combined load resistive torque.

When ignoring the transmission gap, friction torque, and other influencing factors, the mathematical model of the reduction gear set has the form

$$\theta_g = \theta_m / N_i,$$

where θ_g is the output angular displacement of the reduction gear set; θ_m is the output shaft angular displacement of the motor; N_i is the reduction ratio of the reduction gear set.

The screw gap, deformation, friction, and other influencing factors being neglected, the mathematical model of the ball screw is as follows:

$$x_g = \frac{\theta_g}{2\pi} P_h,$$

where x_g denotes the output displacement of the ball screw and P_h is the lead of the ball screw drive.

Based on this model, a method with the SAE-BiLSTM neural network was applied for fault diagnosis; see Fig. 1. In this method, the networks are trained offline with known normal and faulty data. The trained networks are uploaded into the onboard system for online diagnosis and fault detection.

The method for diagnosing EMA faults includes the following steps [39].

• The data are collected and pre-normalized to the range [0, 1].

• Training is carried out: a sparse autoencoder (SAE)-based feature extraction network is trained to perform adaptive sensor data extraction on an already collected dataset containing normal operating states and fault states. This approach ensures dimension reduction and compression while preserving significant features. Next, a BiLSTM network-based regressor is trained using the normal state feature data, which are applied to build a time series model and find the residuals between the estimated and measured values of normal and faulty data. (A BiLSTM network consists of LSTM neurons and the bidirectional recurrent neural network model.) Then a Softmax-based classifier is trained to classify the faults using the resulting differences and the corresponding fault types.

• The three networks obtained from the training process are applied for fault diagnosis. The processed monitoring data are first passed through the SAE network for data downscaling and feature extraction. Then the residuals between the single-step forward estimated and measured data are calculated; if these residuals exceed a fault threshold, a fault is reported and the fault data are sent to the Softmax network for fault classification (isolation).

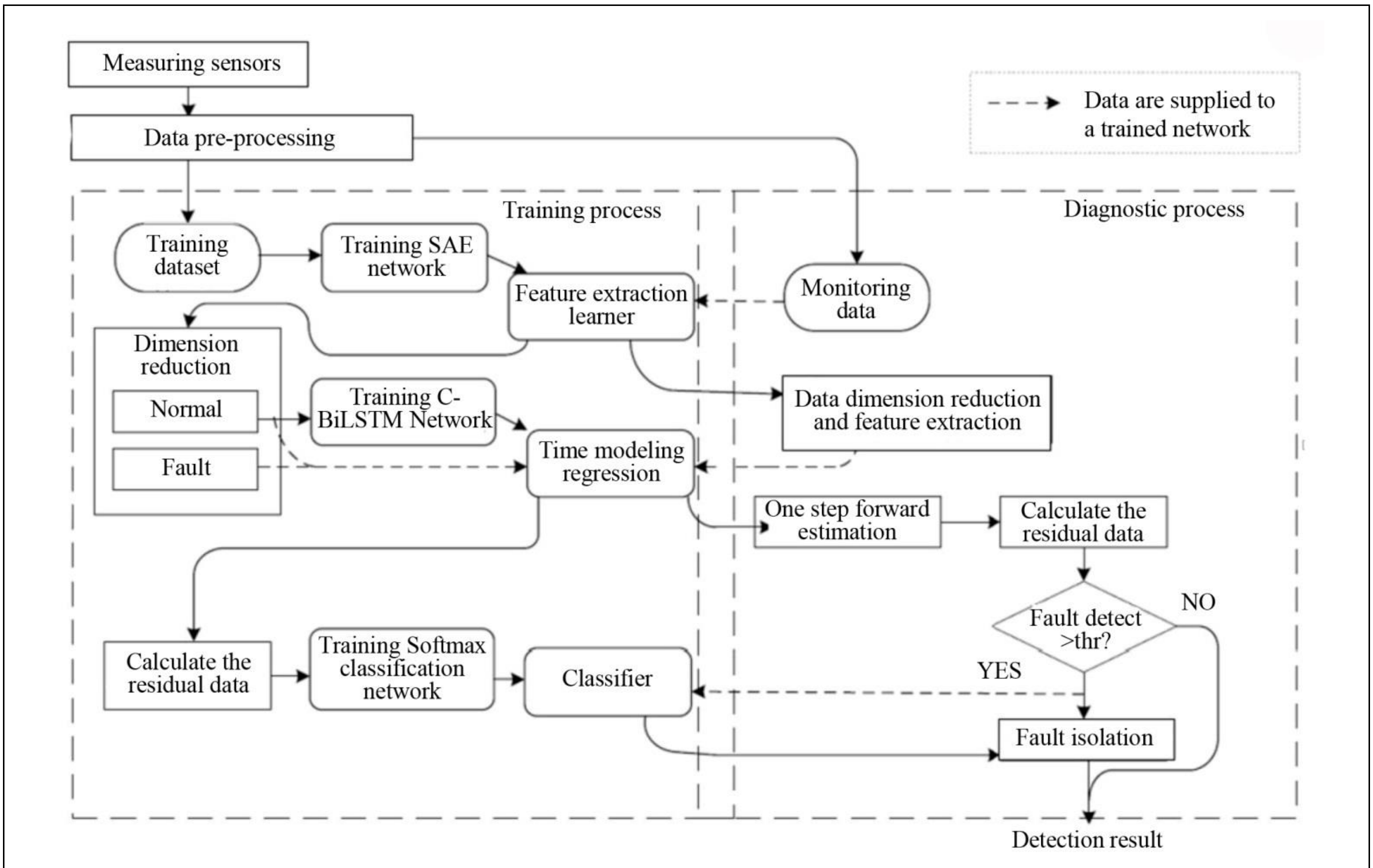

Fig. 1. The EMA fault diagnosis scheme based on deep learning [39].

2.3. EMA Fault Diagnosis Based on a Multiscale Convolutional Neural Network

A feature fusion method for diagnosing EMA faults involving a multiscale convolutional neural network was proposed in [14]. This method consists of four consecutive steps: multiscale transformation, feature learning, feature fusion, and fault classification. EMAs operate in complex conditions with speed and load variations and under high environment noise. Multiscale transformation implementation in a convolutional neural network improves the diversity and complementarity of fault-related features.

The multiscale transformation is the sampling of a signal with different degrees of detail. For a given 1D signal $\{x\}$ of length N, several consecutive signals $\{y^{(k)}\}$ with different degrees of detail are created using a simple downsampling process. Figure 2 shows a signal at three different scales (Scale 1, Scale 2, and Scale 3).

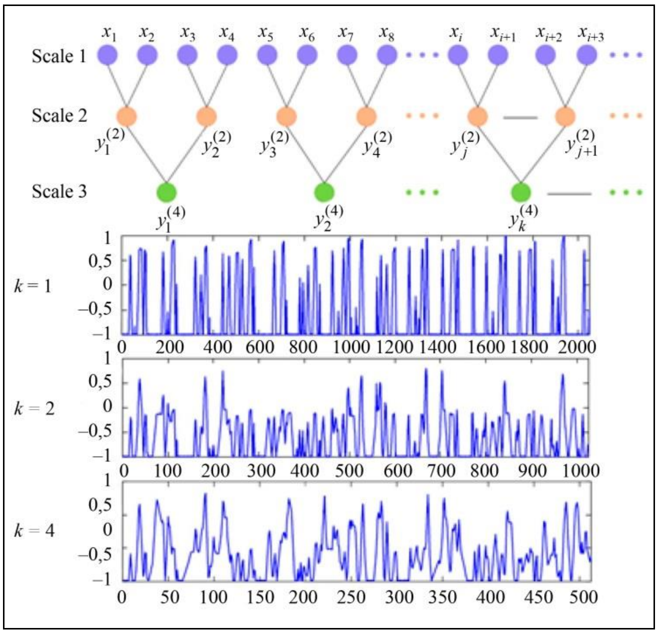

Fig. 2. The multiscale downsampling of a signal.

Several filtered signals with different scales can be obtained. The number of such signals is related to the details and trends of the feature learning.

Multiscale downsampling is mathematically described as follows:

$$y_j^{(k)} = \frac{1}{k} \sum_{i=(j-1)k+1}^{jk} x_i, 1 \le j \le \frac{N}{k},$$

where k denotes the scaling factor.

To learn the features after obtaining the signals $\{y^{(k)}\}(k=1, 2, 4)$ with different sampling scales, these signals are passed in parallel through the pairs of convolutional layers $\left(C1^{(k)}, C2^{(k)}, C3^{(k)}\right)$ and fusion layers $\left(P1^{(k)}, P2^{(k)}, P3^{(k)}\right)$ for learning at different time scales. In particular, filters (convolutional kernels) of different sizes are used for signals with different sampling scales; as a result, each parallel convolutional layer at the same level can obtain the characteristics of different high- and low-frequency features, thus improving the diagnostic performance of the model.

The first convolution layers $\left(C1^{(1)}, C1^{(2)}, C1^{(4)}\right)$ have a signal length of N, $N/2$, $N/4$, respectively. For each first convolution, the size of the corresponding convolutional kernel decreases with increasing k, which facilitates better extraction of useful features.

For each signal $\{y^{(k)}\}(k=1, 2, 4)$, a certain number of new feature maps are generated after the layers $C1^{(k)}$ and $P1^{(k)}$. These feature maps are input data for the layer $C2^{(k)}$; the operations are repeated, and new feature maps are generated. Similarly, with K convolutional kernels used in the layer $C3^{(k)}$, the merge layer $P1^{(k)}$ outputs K new feature maps:

$$q^{(k)} = [p_1, p_2, \ldots, p_K].$$

The final representation of a feature q has three different scales:

$$q = \left[q^{(1)}, q^{(2)}, q^{(4)}\right].$$

Consequently, compared to the traditional single-scale representation, multiscale feature learning has a wider feature coverage range, which facilitates the extraction of additional features and provides a better effect for the next fault classification step.

The attention mechanism is used as an effective feature fusion mechanism. The network can selectively enhance useful functions to detect faults and suppress invalid ones.

A combination of a fully connected hidden layer and a Softmax layer is used to perform classification. The feature vector q obtained in the previous step is supplied to the input of the fully connected layer. The hidden layer uses ReLU as the activation function, whereas the output layer uses the Softmax function.

Let Y be the EMA state category label. Assume that there are n categories in total. In other words, given an input sample x, the probability that this label belongs to category c is defined as follows:

$$p(Y=c|x;\,\theta)=\operatorname{softmax}\left(\theta_c^{\mathrm{T}}x\right)=\frac{\exp\left(\theta_c^{\mathrm{T}}x\right)}{\sum_{j=1}^{n}\exp\left(\theta_j^{\mathrm{T}}x\right)},$$

where $\theta=\left[\theta_1,\,\theta_2,\ldots,\,\theta_n\right]$ is the parameter to be learned in the model; $1/\sum_{j=1}^{n}\exp(\theta_j^{\mathrm{T}}x)$ is the normalized function, and $\sum_{j=1}^{n}P_j=1$.

The multiscale convolutional neural network will predict the result for any given input sample. The predicted value of the model will maximally correspond to the true value when minimizing the distance between them, i.e., the model's loss function

$$L(\theta)=-\frac{1}{m}\left[\sum_{i=1}^{m}\sum_{k=1}^{K}I\{y_i=k\}\log\frac{\exp\left(\theta_k^{\mathrm{T}}x\right)}{\sum_{j}^{K}\exp\left(\theta_j^{\mathrm{T}}x\right)}\right],$$

where m is the number of samples or the input lot size; $I\{\cdot\}$ is the index function:

$$I\{y_i=k\}=\begin{cases}1 \text{ if } y_i=k\\ 0 \text{ if } y_i\neq k.\end{cases}$$

To minimize the loss function, the neural network weights need to be optimized and tuned. For this purpose, the optimizer applies the backpropagation algorithm:

$$\theta^{*}=\arg\min_{\theta}L\left(f\left(x;\,\theta\right),\,y\right),$$

where θ^{*} is the optimal parameter of the model; $L(\cdot)$ is the loss function; $f(\cdot)$ and y are the output and target value of the model, respectively.

The 2D visualization of the classification process was also provided in [14]; see Fig. 3. First, the samples of different categories of the original signal are mixed and inseparable (Fig. 3a); as the layers are passed, the samples are separated (Figs. 3b–3g); after the Softmax layer, they are far apart (Fig. 3h).

According to the experimental results [14], in scenarios with high noise and variable loads, the proposed method has better performance than modern fault diagnosis methods, such as convolutional neural networks with wide first-level kernels [40] and multiscale convolutional neural networks [41].

3. PROGNOSTICS AND HEALTH MANAGEMENT OF EMAS

3.1. Predictive Maintenance

Aircraft maintenance activities account for 10–20% of the total operating costs. Optimizing aircraft maintenance costs by introducing prognostics and health management was mentioned in numerous studies; for example, see [42–47].

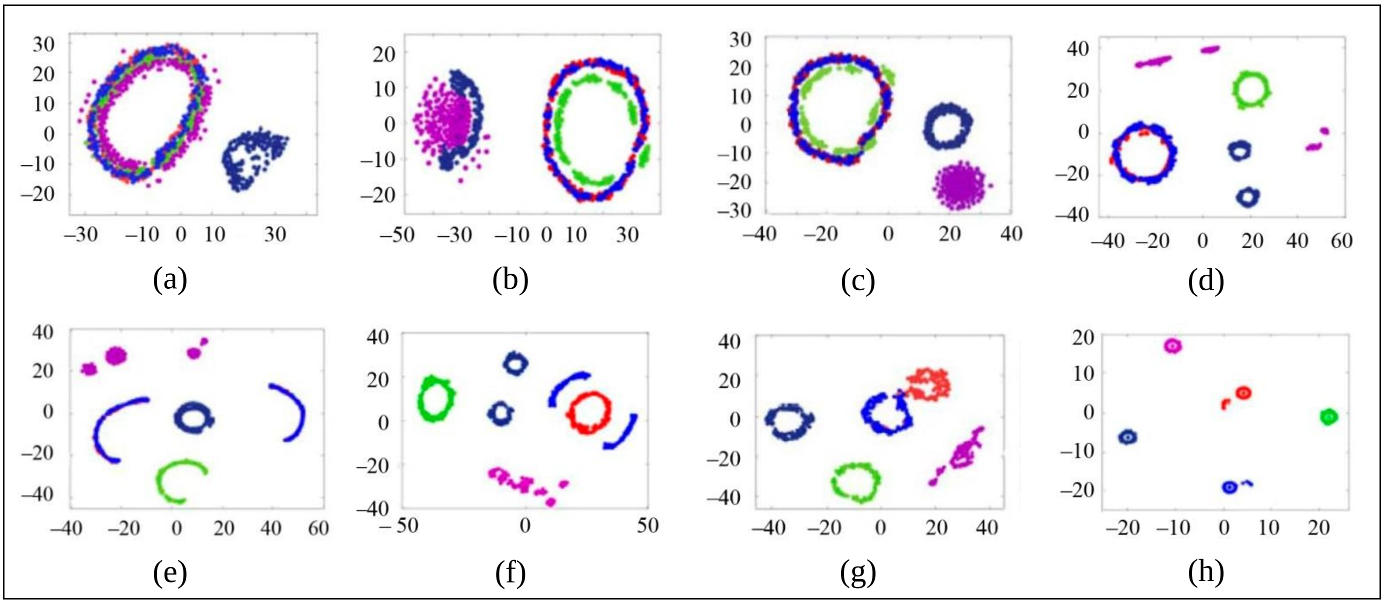

Fig. 3. The 2D visualization of the classification process of the multiscale convolutional neural network.

Maintenance with prognostics and health management is performed if necessary based on the technical condition of a component to prevent faults before their occurrence rather than at certain intervals independently of the current condition. Such maintenance requires proactive assessment of the technical condition and prediction of the remaining useful life of components and subsystems in real time, based on models, based on data, or using hybrid methods [48]. The main advantages and drawbacks of different methods have been discussed in subsection 2.1. A model-based method for early detection and isolation of EMA faults was proposed in [49]. This method identifies the abnormal behavior of EMA under two progressive faults: partial stator phase turn-to-turn fault and static rotor eccentricity. The models to assess the technical condition and prognosticate the remaining useful life onboard have to be carefully validated before use. A test rig for the experimental validation of EMA models under nominal conditions and in the presence of incipient mechanical faults (friction changes and increased backlash in the reduction gear set) was described in [9].

The application of machine learning methods for health prognostics in aviation is associated with several problems [50]. The operational data generated by an aircraft maintenance system are very unbalanced because aircraft components fail extremely rarely during flights and the data are biased towards normal operation. In this case, special analysis techniques are needed to counteract the data imbalance. Another problem is the lack of open datasets, which limits research in this area [46].

A method for detecting rare failures in aircraft predictive maintenance using deep hybrid learning based on an unbalanced dataset was presented in [51]. The corresponding model involves two stages, namely, an autoencoder to detect rare failures and a convolutional neural network with *Bidirectional Gated Recurrent Units* (BGRUs) to predict the next failure occurrence. The method was assessed using real aircraft maintenance system data. According to the assessment results, this method is effective in predicting component failures on a predetermined significant period.

Currently, the literature mainly deals with predicting the technical condition and remaining useful life of aircraft engines [52–55]. Several hybrid approaches based on physical models and data analysis have been proposed to estimate the remaining useful life. Different hybrid architectures have been proposed depending on the type of information processed and the combination of information fragments. At the moment, there is no universal prognostic model, and its choice depends on the particular characteristics of the individual subsystems under consideration [56].

Nowadays, the challenges in EMA prognostics and health management cannot be properly addressed due to insufficient real in-service failure data: EMAs are mostly used in aircraft non-safety-critical systems, and failures are very rare. Therefore, model-based methods are mainly applied.

3.2. EMA Fault Diagnosis Based on Metaheuristic Algorithms

A model-based EMA fault detection and isolation tool with a genetic algorithm was investigated in [57]. The approach was tested to detect several common faults. As was observed, the proposed strategy can accurately assess system performance in the presence of multiple failure modes affecting the same signals simultaneously. However, the required computation time makes the strategy suitable for detecting and isolating EMA faults during routine maintenance only, not in real-time operation.

The use of bio-inspired metaheuristic algorithms for detecting hidden faults, incipient failures, and their progress during operation in order to prevent the potentially dangerous failures of a typical airborne EMA was investigated in [3, 58, 59].

EMA failures are rare, and real data are difficult to obtain. Therefore, modeling data were used in [3]: the high-accuracy *reference model* (RM) [60] and the low-accuracy *monitoring model* (MM) [61] for almost real-time modeling. The models were experimentally verified on the experimental test rig [9].

In particular, the most critical failures for EMA were modeled: dry friction, a backlash, an electrical short, rotor eccentricity, and the drift of the proportional gain of the PID controller. The failures were modeled using failure parameters ranging from 0 to 1 to characterize different failure scales, each associated with a specific failure. By varying the failure parameters, the cited authors simulated the behavior of the executing unit under different conditions. During the prognostic procedure, the MM was executed with some set of failure parameters. The vector of failure parameters for which the difference between the predicted and actual trends is small enough was determined to detect a failure, including its type and scale. The optimization algorithm finds the vector of failure parameters that minimizes the objective function

$$e_{tls} = \sum_i \frac{\left(I_{MM,i} - I_{RM,i}\right)^2}{\left(\frac{\Delta I_{RM,i}}{\Delta T}\right)^2 + 1} \cdot \Delta T,$$

where $I_{MM,i}$ and $I_{RM,i}$ are the current outputs of the MM and RM, respectively, at time instant i. The quadratic error characterizing the difference between the values of the model outputs was estimated, where ΔT is the integration step.

The authors compared different bio-inspired metaheuristic algorithms:

– *Differential Evolution* (DE), which conceptually follows natural evolutionary principles [62, 63];

– *Particle Swarm Optimization* (PSO), which is the most common swarm intelligence algorithm based on bird flocks or schools of fish [64, 65]. In this algorithm, a swarm can determine optimal solutions by exchanging information between particles;

– *Grey Wolf Optimization* (GWO), which is an optimization algorithm based on a rigid hierarchy among population members. Individuals with higher fitness estimates have a greater influence on the optimization process [66, 67].

The comparison results (the average error in percent) of these algorithms for each failure mode are shown in Fig. 4. For each failure mode, two different levels between 0 and 1 were modeled: high (0.75) and low (0.25).

DE showed a slightly smaller error than other algorithms for low-intensity signals. GWO turned out to be more accurate for high-level failures (e.g., an electrical short and the drift of the proportional gain). PSO was most accurate for the backlash errors in general, high static eccentricity, and low proportional gain. Such results indicate that metaheuristic algorithms are very sensitive to the problem formulation; none of the investigated algorithms outperforms the others in every situation. PSO is the leading algorithm with the best results under multiple failures and the most computationally efficient algorithm.

4. RUSSIAN R&D RESULTS

Russian researchers apply neural network and machine learning-based approaches to the diagnosis and prognostics of aircraft engines [68–70] and EMAs [71–78].

Experts of Perm National Research Polytechnic University presented comprehensive analysis results on using machine learning methods for diagnosing asynchronous electric actuator motors on a laboratory test rig [71]. The problem of determining the motor serviceability is reduced to binary classification for each fault type and the search for high-accuracy classification algorithms.

According to the analysis results, the most effective approach is to construct a classifier ensemble with the following methods:

– random forest, which reduces the overtraining problem;

– a multilayer perceptron, which is a class of artificial neural networks with the ability to find approximate solutions of extremely complex problems;

– gradient boosting, which handles categorical features and nonlinearities;

– an improved form of the gradient boosting algorithm to increase classification accuracy.

The developed classification system demonstrated good prospects for industrial implementation due to its low cost and high reliability.

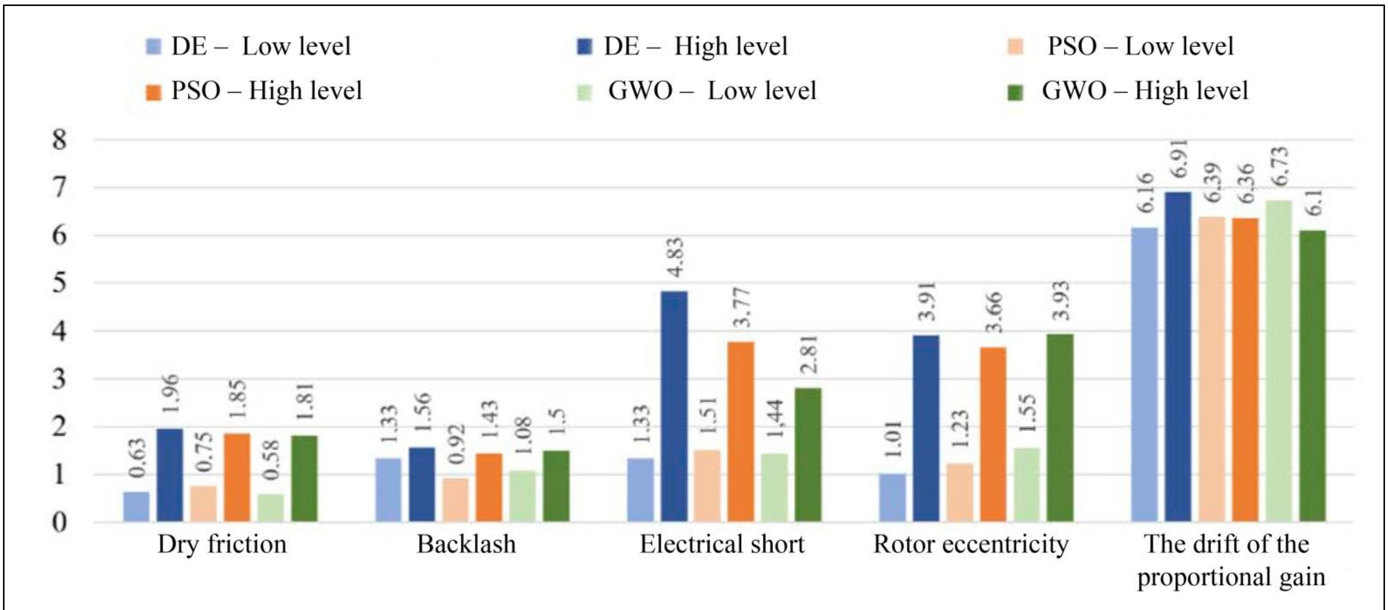

Fig. 4. The average error (in percent) of different algorithms for each failure mode.

Abnormal situations due to control actuator failures and an algorithm for detecting such failures were considered at Moscow Aviation Institute [72]. This algorithm is based on solving two problems: identifying the aircraft motion model and classifying the features of a failure situation using neural network methods. Three types of control actuator failures were analyzed: the loss of actuator efficiency, actuator "freezing" when an abnormal situation occurs, and the combination of the two types of failures. When modeling the control surface actuator failure, the aerodynamic coefficients containing the deflection value of this surface were modified. Two transformation schemes were implemented: when the variable containing the control surface deviation is present in the aerodynamic coefficient in explicit and implicit form. An F-16 fighter aircraft was the object of the diagnostic model. In flight modeling, the autopilots of the angles of attack, pitch, and roll were considered in the control system, which are responsible for maintaining the specified angular position of the aircraft. The motion model was described by a system of ordinary differential equations. For this system, the numerical solution of the Cauchy problem was obtained by the Runge–Kutta method of the fourth order. The observation data were the values of angular velocities and command signals from the control system channels. The features of a failure situation were recognized based on observations of the cross-correlation functions of angular velocities. The relationship between the pairs of angular velocities can be quantified and represented as a function. When a control actuator failure occurs, this relationship is violated. The neural network models of the cross- and autocorrelation functions of angular velocities were used to classify actuator failures.

Experts of the Central Aerohydrodynamic Institute (TsAGI) proposed an approach to testing aircraft executing units in order to verify the performance of the tested actuator under dynamic external loads corresponding to different flight modes [73]. After proper development, this approach is currently being used to debug fault diagnosis algorithms for both conventional servo-valve hydraulic actuators and EMAs with neural networks. The experimental testing of electric actuators is to identify drawbacks in the actuator design or in the tuning of its control system. The executing unit tests conducted at TsAGI can be qualified as follows:

– the isolated tests of executing units and their elements, as well as the signal paths of flight control systems;

– verification of aircraft surface actuating systems for flight control;

– testing of the "plant–control system–executing unit" control loop.

The results of these tests can be used as a formal basis for issuing the first airworthiness certificate.

The Trapeznikov Institute of Control Problems, the Russian Academy of Sciences (ICS RAS), cooperates with TsAGI to develop and master technologies, methods, and algorithms for building an early diagnosis system for electromechanical systems using machine learning. The purpose of these R&D works is to create and verify machine learning algorithms for searching and formalizing relationship patterns between the controlled parameters (on the one hand) and the assessment and prognostics of electromechanical systems (on the other hand).

A full-scale sample of the mathematical model of the steering servo actuator for a medium-range UAV with a takeoff weight of 400 kg was described in [74], including its development and verification based on static and dynamic characteristics. The model is intended to create an early diagnosis system for servo actuator faults. Servo actuator state assessment was formulated as a classification problem based on data mining algorithms. A generalized scheme was proposed for data generation and analysis to assess the technical condition of the servo actuator.

This scheme was used to build an early detection algorithm for EMA failures due to changes in dissipative losses in the mechanical gearbox; see [75, 76]. The EMA operation data during takeoff—12 parameters—were generated using a mathematical model. Based on the proposed informative feature selection algorithm, four parameters were taken as neural network inputs, and 50 neural networks were trained. According to the computational experiments, reducing the number of input parameters decreased the number of neurons, accelerated the training process of neural networks, and improved the accuracy of calculations.

Informative feature search algorithms for EMA prognostics were presented in [77]. For this purpose, time series analysis methods and genetic algorithms were applied. The algorithms were investigated and verified on the data obtained using a mathematical model of the EMA and resource bench tests of the UAV collectorless electric motor.

The effectiveness of a fault diagnosis algorithm for EMAs based on neural networks that formalize data patterns was studied in [78]. An informative feature selection scheme with convolutional methods for neural network training was also presented. The experimental studies on determining the technical condition of EMAs (serviceable, pre-emergency, and emergency) due to changes in backlash and dry friction were described.

CONCLUSIONS

The foreign and Russian studies devoted to model-based, data-driven, and hybrid methods of EMA fault diagnosis have been reviewed. The main efforts of researchers are focused on deep learning methods in order to analyze large amounts of data obtained during EMA operation. Deep learning methods allow extracting effective fault features directly from monitoring signals and simultaneously performing fault classification.

Fault diagnosis and classification are only the first steps on the way to prognostics and health management of EMAs. An important role in ensuring the safety and reliability of aircraft systems is played by technical condition assessment and remaining useful life prediction during operation in order to anticipate possible equipment failures and prevent them.

The approaches considered above are innovative, they are initiated by the rapid development and significant achievements in the application of neural network technologies and deep learning in some practical areas. This survey indicates a great interest of researchers, especially foreign ones, in such approaches to diagnose and predict EMA faults. However, they are at the stage of development and studies so far. The results of simulation modeling and test rig experiments show good prospects and the need to develop these methods further. Also, the existing challenges on the way to their practical application have been described.

One of the main problems in developing EMA health management systems is the difficulty in obtaining necessary data: EMAs are not yet widespread in aircraft, and their failures are quite rare. Currently, data provided by modeling and test rigs are used for studies. In practice, the proposed approaches may turn out less effective due to real EMA operating conditions and the environment's impact.

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REFERENCES

1. Garcia Garriga, A., Ponnusamy, S.S., and Mainini, L., A Multi-fidelity Framework to Support the Design of More-Electric Actuation, *Proceedings of the AIAA Aviation Forum. Multidisciplinary Analysis and Optimization Conference*, Atlanta, 2018. DOI: 10.2514/6.2018-3741.
2. Adu-Gyamfi, B.A. and Good, C., Electric Aviation: A Review of Concepts and Enabling Technologies, *Transportation Engineering*, 2022, vol. 9, no. 4. DOI: 10.1016/j.treng.2022.100134.
3. Baldo, L., Querques, I., Dalla Vedova, M.D.L., et al., A Model-Based Prognostic Framework for Electromechanical Actuators Based on Metaheuristic Algorithms, *Aerospace*, 2023, vol. 10, no. 3. DOI: 10.3390/aerospace10030293.
4. Li, J., Yu, Z., Huang, Y., and Li, Z., A Review of Electromechanical Actuation System for More Electric Aircraft, *Proceedings of the IEEE International Conference on Aircraft Utility Systems (AUS)*, Beijing, China, October 10–12, 2016, IEEE: New York, 2016, pp. 490–497.
5. Annaz, F.Y., and Kaluarachchi, M.M., Progress in Redundant Electromechanical Actuators for Aerospace Applications, *Aerospace*, 2023, vol. 10(9). DOI: 10.3390/aerospace 10090787.
6. Fu, S. and Avdelidis, N.P., Prognostic and Health Management of Critical Aircraft Systems and Components: An Overview, *Sensors*, 2023, vol. 23, no. 19. DOI: 10.3390/s23198124.
7. Bertolino, A.C., De Martin, A., Jacazio, G., and Sorli, M., Towards a PHM System for Electromechanical Flight Control Actuators, *Proceedings of I-RIM 2020*, Torino, 2020. DOI: 10.5281/zenodo.4781001.
8. Bertolino, A.C., De Martin, A., Jacazio, G., and Sorli, M., Design and Preliminary Performance Assessment of a PHM System for Electromechanical Flight Control Actuators, *Aerospace*, 2023, vol. 10. DOI: 10.3390/ aerospace10040335.
9. Baldo L., Berri P.C., Matteo D. L., et al., Experimental Validation of Multi-fidelity Models for Prognostics of Electromechanical Actuators, *Proceedings of the 7th European Conference of the Prognostics and Health Management Society*, Torino, 2022, vol. 7, no.1, pp. 32–42. DOI: 10.36001.phme.2022.v7i1.3347.
10. Cai, B., Zhao Y., Liu, H., and Xie, M., A Data-Driven Fault Diagnosis Methodology in Three-Phase Inverters for PMSM Drive Systems, *IEEE Transaction on Power Electronics*, 2017, vol. 32, no. 7, pp. 5590–5600.
11. Sudhawiyangkul, T. and Isarakorn, D., Design and Realization of an Energy Autonomous Wireless Sensor System for Ball Screw Fault Diagnosis, *Sensors and Actuators A Physical*, 2017, vol. 258, pp. 49–58.
12. Chirico, A. and Kolodziej, J.R., Fault Detection and Isolation for Electro-Mechanical Actuators Using a Data-Driven Bayesian Classification, *SAE International Journal of Aerospace*, 2012, vol. 5, no. 2, pp. 494–502.
13. Chirico, A.J. and Kolodziej, J.R., A Data-driven Methodology for Fault Detection in Electromechanical Actuators, *Journal of Dynamic Systems, Measurement and Control, Transactions of the ASME*, 2014, vol. 136, no. 4. DOI: 10.1115/1.4026835.
14. Song, Y., Du, J., and Li, S., Multi-Scale Feature Fusion Convolutional Neural Networks for Fault Diagnosis of Electromechanical Actuator, *Applied Sciences*, 2023, vol. 13, no. 15, art. no. 8689. DOI: 10.3390/app13158689.
15. Wang, J., Zhang, Y., Luo, C., and Miao, Q., Deep Learning Domain Adaptation for Electro-Mechanical Actuator Fault Diagnosis Under Variable Driving Waveforms, *IEEE Sensors Journal*, 2022, vol. 22, no. 11, pp. 10783–10793.
16. Derrien, J.-C. and Securite, S.D., Electromechanical Actuator (EMA) Advanced Technologies for Flight Controls, *Proceedings of the 28th International Congress of the Aeronautical*

Sciences (ICAS 2012), Brisbane, 2012. URL: https://icas.org/ICAS_ARCHIVE/ICAS2012/PAPERS/291.PDF.

17. Qiao, G., Liu, G., Shi, Z., et al., A Review of Electromechanical Actuators for More/All Electric Aircraft Systems, Proceedings of Institution of Mechanical Engineers. Part C: Journal of Mechanical Engineering Science, 2018, vol. 232, no. 22, P. 4128–4151. DOI: 10.1177/0954406217749869.
18. Yin, Z, Hu, N., Chen, J., et al., A Review of Fault Diagnosis, Prognosis and Health Management for Aircraft Electromechanical Actuators, *IET Electronic Power Applications*, 2022, vol. 16, no. 11, pp. 1249–1272. DOI: 10.1049/elp2.12225.
19. Jian, F., Mare, J.-C., and Yongling, F., Modelling and Simulation of Flight Control Electromechanical Actuators with Special Focus on Model Architecting, Multidisciplinary Effects and Power Flows, *Chinese Journal of Aeronautics*, 2017, no. 30 (1), pp. 47–65.
20. Cui, Z., Jing, B., Jiao, X., et al., The Integrated-Servo-Actuator Degradation Prognosis Based on the Physical Model Combined With Data-Driven Approach, *IEEE Sensors Journal*, 2023, vol. 23, no. 9, pp. 9370–9381. DOI: 10.1109/JSEN.2023.3248323.
21. Randall, R.B., The Use of Simulation Models to Generate Data Corresponding to Faults in Machines, *Proceedings of the 8th International Conference on Reliability, Maintainability and Safety (ICRMS-2009)*, Chengdu, 2009. DOI: 10.1109/ICRMS.2009.5269971.
22. Mazzoleni, M., Di Rito, G., and Previdi, F., *Electromechanical Actuators for the More Electric Aircraft*, Cham: Springer, 2021. DOI: 10.1007/978-3-030-61799-8.
23. Hopf, K. and Reifenrath, S., Filter Methods for Feature Selection in Supervised Machine Learning Applications, Review and Benchmark, Cornell University, *arXiv: 2111.12140v1[cs.LG]*, 2021. DOI: 10.48550/arXiv2111.12140.
24. Chirico, A.J., Kolodziej, J.R., and Hall, L., A Data Driven Frequency Based Feature Extraction and Classification Method for EMA Fault Detection and Isolation, *Proceedings of the 5th Annual Dynamic Systems and Control Conference joint with the JSME 2012 11th Motion and Vibration Conference*, Houston, 2012. DOI: 10.1115/DSCC2012-MOVIC2012-8749.
25. Jing, J., Liu, H., and Lu, C., Fault Diagnosis of the Aircraft Electromechanical Actuation System Based on WPD-STFT Time Frequency Entropy and PNN, *Vibroengineering Procedia*, Oct. 2017, vol. 14. DOI: 10.21595/vp.2017.19247.
26. Li, J., Meng, G., Xie, G., and Jia, Y., Sensor Fault Diagnosis Based on Wavelet Packet and SOM Neural Network, *Chinese Journal of Sensors and Actuators*, 2017, vol. 30, no. 7, pp. 1035–1039. DOI: 103969/j.issn.1004-1699.2017.07.011.
27. Ruiz-Cárcel, C. and Starr, A., Data-Based Detection and Diagnosis of Faults in Linear Actuators, *IEEE Transactions on Instrumentation and Measurement*, 2018, vol. 67, no. 9, pp. 2035–2047. DOI: 10.1109/TIM.2018.2814067.
28. Narasimhan, S., Roychoudhury, I., Balaban, E., and Saxena, A., Combining Model-Based and Feature-Driven Diagnosis Approaches – A Case Study on Electromechanical Actuators, *Proceeding of the 21st International Workshop on Principles of Diagnosis Held Jointly with Annual Conference of the PHM Society*, Portland, 2010, vol. 2, no. 2. DOI: 10.36001/phmconf.2010.v2i2.1936.
29. Wang, C., Ding, Y., and Ma, J., An Adversarial Model for Electromechanical Actuator Fault Diagnosis under Nonideal Data Conditions, *Neural Computing and Applications*, 2022, vol. 34, no. 1115, pp. 5883–5904. DOI: 10.1007/s00521-021-06732-x.
30. Yang, J., Guo, Y., and Zhao, W., Long Short-Term Memory Neural Network Based Fault Detection and Isolation for Electromechanical Actuators, *Neurocomputing*, 2019, vol. 360, pp. 85–96. DOI: 10.1016/j.neucom.2019.06.029.
31. Yang, N., Shen, J., Jia, Y., and Zhang, J., Fault Diagnosis of Electromechanical Actuator Based on Deep Learning Network, *Proceedings of the 39th Chinese Control Conference (CCC)*, Shenyang, 2020, pp. 4002–4006. DOI: 10.23919/CCC50068.2020.9189666.
32. Riaz, N., Shah, S.I.A., Rehman, F., et al., A Novel 2-D Current Signal-based Residual Learning with Optimized Softmax to Identify Faults in Ball Screw Actuators, *IEEE Access*, 2020, vol. 8, pp. 115299–115313. DOI: 10.1109/access.2020.3004489.
33. Siahpour, S., Li, X., and Lee, J., Deep Learning-based Cross-sensor Domain Adaptation for Fault Diagnosis of Electromechanical Actuators, *International Journal of Dynamics and Control*, 2020, vol. 8, pp. 1054–1062. DOI: 10.1007/s40435-020-00669-0.
34. Ding, Y., Ma, L., Ma, J., et al., A Generative Adversarial Network-based Intelligent Fault Diagnosis Method for Rotating Machinery under Small Sample Size Conditions, *IEEE Access*, vol. 7, pp. 149736–149749. DOI: 10.1109/ACCESS.2019.2947194.
35. Wang, Y., Sun, G., and Jin, Q., Imbalanced Sample Fault Diagnosis of Rotating Machinery Using Conditional Variational Auto-encoder Generative Adversarial Network, *Applied Soft Computing Journal*, 2020, vol. 92, no. 7, art. no. 106333. DOI: 10.1016/j.asoc.2020.106333.
36. Zhang, L., Gao, H., Wen, J., et al., A Deep Learning-Based Recognition Method for Degradation Monitoring of Ball Screw with Multi-sensor Data Fusion, *Microelectronics Reliability*, 2017, vol. 75, pp. 215–222. DOI: 10.1016/j.microrel.2017.03.038.
37. Yang, J., Guo, Y., and Wanti, Z., An Intelligent Fault Diagnosis Method for an Electromechanical Actuator Based on Sparse Feature and Long Short-Term Network, *Measurement Science Technology*, 2021, vol. 32, no. 9. DOI: 10.1088/1361-6501/abfbab.
38. Zhang, X., Tang, L., and Chen, J., Fault Diagnosis for Electro-Mechanical Actuators Based on STL-HSTA-GRU and SM, *IEEE Transaction on Instrumentation and Measurement*, 2021, vol. 70. DOI: 10.1109/tim.2021.3127641.
39. Tao, X., Guo, Y., Zhao, W., et al., Fault Detection and Isolation of Electromechanical Actuator Based on SAE-BiLSTM, *Journal of Physics: Conference Series*, 2023, vol. 2472, art. no. 012031. DOI: 10.1088/1742-6596/2472/1/012031. (Proceedings of the 13th Asia Conference on Mechanical and Aerospace Engineering (ACMAE 2022).)
40. Zhang, W., Peng, G., and Li, C., A New Deep Learning Model for Fault Diagnosis with Good Anti-Noise and Domain Adaptation Ability on Raw Vibration Signals, *Sensors*, 2017, vol. 17, no. 3. DOI: 10.3390/s17020425.
41. Jiang, G., He, H., Yan, J., and Xie, P., Multiscale Convolutional Neural Networks for Fault Diagnosis of Wind Turbine Gearbox, *IEEE Transaction on Industrial Electronics*, 2018, vol. 66, no 4, pp. 3196–3207. DOI: 10.1109/TIE.2018.2844805.
42. Kordestani, M., Orchard, M.E., Khorasani, K., and Saif, M., An Overview of the State of the Art in Aircraft Prognostic and Health Management Strategies, *IEEE Transactions on Instru-*

mentation and Measurement, 2023, vol. 72, art. no. 3505215. DOI: 10.1109/TIM.2023.3236342.
43. Rezaeianjouybari, B. and Shang, Y., Deep Learning for Prognostics and Health Management: State of the Art, Challenges, and Opportunities, *Measurement*, 2020, vol. 163, no. 4. DOI: 10.1016/j.measurement.2020.107929.
44. Lei, Y., Li, N., Guo, L., et al., Machinery Health Prognostics: a Systematic Review from Data Acquisition to RUL Prediction, *Mechanical Systems and Signal Process.*, 2018, vol. 104, pp. 799–834. DOI: 10.1016.j.ymssp.2017.11.016.
45. Berri, P.C., Dalla Vedova, M.D.L., and Mainini, L., Computational Framework for Real-time Diagnostics and Prognostics of Aircraft Actuation Systems, *Computers in Industry*, 2021, vol. 132. DOI: 10.1016/compind.2021.103523.
46. Stanton, I., Munir, K., and Ikram, A., Predictive Maintenance Analytics and Implementation for Aircraft: Challenges and Opportunities, *System Engineering*, 2022, vol. 26, no. 137. DOI: 10.1002/sys.21651.
47. Scott, M.J., Verhagen, W.J.C., Bier, M.T., and Marzocca, P., A Systematic Literature Review of Predictive Maintenance for Defence Fixed-Wing Aircraft Sustainment and Operations, *Sensors*, 2022, vol. 22, no. 18. DOI: 10.3390/s22187070.
48. Ismail, M.A.A., Balaban, E., and Windelberg, J., Spall Fault Quantification Method for Flight Control Electromechanical Actuator, *Actuators*, 2022, vol. 11, no. 29. DOI: 10.3390/act 11020029.
49. Belmonte, D., Dalla Vedova, M.D.L., and Maggiore, P., Prognostics of Onboard Electromechanical Actuators: a New Approach Based on Spectral Analysis Techniques, *International Review of Aerospace Engineering*, 2018, vol. 11, no. 3. DOI: 10.15866/irease.v11i3.13796.
50. Zhang, J., Tian, J., Li, M., et al., A Parallel Hybrid Neural Network with Integration of Spatial and Temporal Features for Remaining Useful Life Prediction in Prognostics, *IEEE Transaction on Instrumentation and Measurement*, 2023, vol. 72. DOI: 10.1109/TIM.2022.3227956.
51. Dangut, M.D., Jennions, I.K., King, S., and Skaf, Z., A Rare Failure Detection Model for Aircraft Predictive Maintenance Using a Deep Hybrid Learning Approach, *Neural Computing and Applications*, 2023, vol. 35, no. 4, pp. 2991–3009. DOI: 10.1007/s00521-022-07167-8.
52. Hasib, A.A., Rahman, A., Khabir, M., and Shawon, M.T., An Interpretable Systematic Review of Machine Learning Models for Predictive Maintenance of Aircraft Engine, Cornell University, *arXiv:2309.13310v1[cs.LG]*, 2023. DOI: 10.48550/ arXiv.2309.13310.
53. Khan, K., Sohaib, M., and Rashid, A., Recent Trends and Challenges in Predictive Maintenance of Aircraft's Engine and Hydraulic System, *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, 2021, vol. 43, no. 8. DOI: 10.1007/s40430-021-03121-2.
54. Boujamza, A. and Lissane Elhaq, S., Attention-Based LSTM for Remaining Useful Life Estimation of Aircraft Engines, *IFACPapersOnLine*, 2022, vol. 55, no. 12, pp. 450–455. DOI: 10.1016/j.ifacol.2022.07.353.
55. Wang, C., Zhu, Z., and Lu, N., A Data-Driven Degradation Prognostic Strategy for Aero-Engine under Various Operational Conditions, *Neurocomputing*, 2021, vol. 462, no. 3, pp. 195–207. DOI: 10.1016/j.neucom.2021.07.080.
56. Chao, M.A., Kulkarni, C., Goebel, K., and Fink, O., Fusing Physics-based and Deep Learning Models for Prognostics, *Reliability Engineering and System Safety*, 2022, vol. 217, no. 3. DOI: 10.1016/j.ress.2021.107961.
57. Aimasso, A., Berri, P.C., and Dalla Vedova, M.D., A Genetic-based Prognostic Method for Aerospace Electromechanical Actuators, *International Journal of Mechanics and Control*, 2021, vol. 22, no. 2, pp. 195–206.
58. Baldo, I., Vedova, M.D.L., Querques, I., and Magglore, P., Prognostics of Aerospace Electromechanical Actuators: Comparison between Model-based Metaheuristic Methods, *Journal of Physics: Conference Series*, 2023, vol. 2526, no. 1, art. no. 012073. DOI: 10.1088/1743-6596/1/012073.
59. Dalla Vedova, M.D.L., Berri, P.C., and Re, S., A Comparison of Bio-inspired Meta-heuristic Algorithms for Aircraft Actuator Prognostics, *Proceedings of the 29th European Safety and Reliability Conference*, Hannover, 2019. DOI: 10.3850/978-981-11-2724-3_0476-cd.
60. Berri, P.C., Dalla Vedova, M.D., and Maggiore, P., A Lumped Parameter High Fidelity EMA Model for Model-Based Prognostics, *Proceedings of the 29th European Safety and Reliability Conference*, Hannover, 2019, pp. 1086–1093. DOI: 10.3850/978-981-11-2724-3_0480-cd.
61. Berri, P.C., Dalla Vedova, M.D.L., Maggiore, P., and Viglione, F., A Simplified Monitoring Model for PMSM Servoactuator Prognostics, *Proceedings of the MATEC Web of Conferences*, Osaka, 2018. DOI: 10.1051/matecconf/ 201930404013.
62. Randall, R.B., The Use of Simulation Models to Generate Data Corresponding to Faults in Machines, *Proceedings of the 8th International Conference on Reliability, Maintainability and Safety (ICRMS-2009)*, Chengdu, 2009. DOI: 10.1109/ICRMS.2009.5269971.
63. Ahmad, M.F., Isa, N.A.M., Lim, W.H., and Ang, K.M., Differential Evolution: A Recent Review Based on State-of-the-Art Works, *Alexandria Engineering Journal*, 2022, vol. 61, no. 5, pp. 3831–3872. DOI: 10.1016/j.aej.2021.09.013.
64. Kennedy, J. and Eberhart, R., Particle Swarm Optimization, *Proceedings of the IEEE International Conference on Neural Networks*, Perth, 1995, pp. 1942–1948. DOI: 10.1109/ICNN. 1995.488968.
65. Darwish, A., Bio-inspired Computing: Algorithms Review, Deep Analysis, and the Scope of Applications, *Future Computing and Informatics Journal*, 2018, vol. 3, no. 2, pp. 231–246. DOI: 10.1016/j.fcij.2018.06.001.
66. Mirjalili, S., Mirjalili, S.M., and Lewis, A., Grey Wolf Optimizer, *Advances in Engineering*, 2014, vol. 69, pp. 46–61. DOI: 10.1016/j.advengsoft.2013.12.007.
67. Kumar, V. and Kumar, D., An Astrophysics-inspired Grey Wolf Algorithm for Numerical Optimization and its Application to Engineering Design Problems, *Advances in Engineering Software*, 2017, vol. 112, P. 231–254. DOI: 10.1016/advengsoft.2017.05.008.
68. Egorov, I.V. and Sokolov, M.P., Comparison of the Efficiency of Neural Network Algorithms with Factor Analysis Methods When Diagnosing the Technical Condition of a Gas Turbine Engine, *Nauchnyi Vest. Mosk. Gos. Univ. Grazhd. Aviats. Ser. Ekspluatats. Vozdushn. Transp. Remont Aviats. Tekh.*, 2007, no. 123, pp. 89–95. (In Russian.)
69. Sokolov, M.P., Zemskov, A.A., and Kuts, M.S., Trends in Maintenance Diagnostics of Aircrafts Power Equipment and Transmission, *Transport, Mining and Construction Engineering: Science and Production*, 2022, no. 15, pp. 37–46. (In Russian.)
70. Mikhailov, A., Karavay, M., and Farhadov, M., Inverse Sets in Big Data Processing, *Proceedings of the 11th IEEE International Conference on Application of Information and Commu-*

nication Technologies (AICT2017), Moscow, 2017, vol. 1, pp. 40–43.
71. Sal'nikov, S.V., Solodkii, E.M., Vishnyakov, D.D., et al., Machine Learning-Based Diagnosis of an Induction Motor, *Proceedings of XXVI International Conference on Soft Computing and Measurement (SCM'2023)*, St. Petersburg, 2023, vol. 1, pp. 295–300. (In Russian.)
72. Tiumentsev, Y.V., and Kozlov, D.S., Neural Network Techniques for Fault Identification of Aircraft Sensors and Actuators, *Trudy MAI*, 2012, vol. 52. (In Russian.)
73. Erofeev, E., Khaletskiy, L., Skryabin, A., and Steblinkin, A., Methodologies and Test-Rig Configurations for the Experimental Improvement of Flight Control Actuation Systems, *Proceedings of the Conference "Recent Advances in Aerospace Actuation Systems and Component,"* Toulouse, 2018, pp. 109–116.
74. Veresnikov, G.S., Goutsevyich, D.E., and Skryabin, A.V., The Development of Mathematical Model for Investigating the Algorithms of Estimation and Prediction of UAV Electromechanical Actuator Technical State, *Izvestiya SFedU. Engineering Sciences*, 2019, no. 7, pp. 170–181. (In Russian.)
75. Veresnikov, G.S., Skryabin, A.V., and Bazhenov, S.G., The Development of Algorithms for EMA Fault Early Detection System, *Proceedings of the 32nd Congress of the International Council of the Aeronautical Sciences*, Shanghai, 2020. URL: https://www.icas.org/ICAS_ARCHIVE/ICAS2020/data/preview/ICAS2020_0239.htm.
76. Veresnikov, G.S., Lebedev, V.G., Ogorodnikov, O.V., and Golev, A.V., Fault Detection Technique for Electromechanical Actuator of the Aircraft Using Neural Networks, in *Lecture Notes in Mechanical Engineering*, Cham: Springer, 2021, pp. 519–528.
77. Veresnikov, G.S. and Skryabin, A.V., Feature Selection Algorithms for Forecasting Technical Condition of Electromechanical Actuator, *Proceedings of the 14th International Conference on Management of Large-Scale System Development (MLSD)*, Moscow, 2021. URL: https://ieeexplore.ieee.org/document/9600182/.
78. Veresnikov, G.S. and Skryabin, A.V., Diagnostics of Mixed Type Failures in the Aircraft Electromechanical Actuator Gear by Using Neural Networks, *Proceedings of the 15th International Conference on Management of Large-Scale System Development (MLSD)*, Moscow, 2022, URL: https://ieeexplore.ieee.org/document/9600182.

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