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Review

A Review of Diagnostic Methods for Hydraulically Powered Flight Control Actuation Systems

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Abstract: Aircraft systems are designed to perform functions that will aid the various missions of the aircraft. Their performance, when subjected to an unfamiliar condition of operation, imposes stress on them. The system components experience degradation due to fault which ultimately results in failure. Maintenance and monitoring mechanisms are put in place to ensure these systems are readily available when required. Thus, the sensing of parameters assists in providing conditions under which healthy and faulty scenarios can be indicated. To obtain parameter values, sensor data is processed, and the results are displayed so that the presence of faults may be known. Some faults are intermittent and incipient in nature. These are not discovered easily and can only be known through a display of unusual system performance by error code indication. Therefore, the assessed faults are transmitted to a maintenance crew by error codes. The results may be fault found (FF), no fault found (NFF), or cannot display (CND). However, the main classification of the faults and their origins may not be known in the system. This continues throughout the life cycle of the system or equipment. This paper reviews the diagnostic methods used for the hydraulically powered flight control actuation system (HPFCAS) of an aircraft and its interaction with other aircraft systems. The complexities of the subsystem's integration are discussed, and different subsystems are identified. Approaches used for the diagnostics of faults, such as model-based, statistical mapping and classification, the use of algorithms, as well as parity checks are reviewed. These are integrated vehicle health management (IVHM) tools for systems diagnostics. The review shows that when a system is made up of several subsystems on the aircraft with dissimilar functions, the probability of fault existing in the system increases, as the subsystems are interconnected for resource sharing, space, and weight savings. Additionally, this review demonstrates that data-driven approaches for the fault diagnostics of components are good. However, they require large amounts of data for feature extraction. For a system such as the HPFCAS, flight-management data or aircraft maintenance records hold information on performance, health monitoring, diagnostics, and time scales during operation. These are needed for analysis. Here, a knowledge of training algorithms is used to interpret different fault scenarios from the record. Thus, such specific data are not readily available for use in a data-driven approach, since manufacturers, producers, and the end users of the system components or equipment do not readily distribute these verifiable data. This makes it difficult to perform diagnostics using a data-driven approach. In conclusion, this paper exposes the areas of interest, which constitute opportunities and challenges in the diagnostics and health monitoring of flight-control actuation systems on aircraft.

Keywords: aircraft systems; fault detection; diagnostics; flight control system; IVHM; algorithm; classifier

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1. Introduction

The aircraft flight-control actuation system (FCAS) is a major system used on aircraft for overall piloting and control, whether the aircraft is used in a military or civil role. The system performs multi-functional duties to provide the aircraft with control, the capability for flight navigation, communication, surveillance, and manoeuvrability [1]. In both military and conventional aircraft designs, the FCAS also contributes significantly towards alleviating the extensive workload of pilots [2]. Thus, the efficient and safe operation of the system is of paramount importance to support safe, reliable, and proper use of aircraft.

An FCAS is composed of multiple, highly integrated subsystems. Each subsystem has specific duties intended for the same goal (control) under different conditions and times of flight. The subsystems are linked through the complex interconnections of components, in which the feedback or input of one subsystem is the output of another. Sometimes, feedback and control loops make fault detection and isolation in these systems extremely challenging [3]. Furthermore, the subsystems can be aligned in an integrated format for their dependency functions, in which faults can cascade from one subsystem to another, increasing the challenge of fault diagnostics [4]. In most cases, the degradation of components and subsystems begins as soon as they are used. If abnormalities can be traced at this time, faults will be easy to identify; however, this would not show the extent to which faults are traced unless the fault attributes are known. If the fault attributes are not known, deterioration continues progressively. Therefore, finding faults in the system becomes more difficult [5]. To mitigate, such that when failure occurs it is not a major event, diagnosis of the system components is required. This diagnosis is based on condition monitoring, which is the examination of symptoms, attributes, or characteristics. This can take time to achieve, so the resulting maintenance can be costly and disruptive. It leads to unscheduled maintenance activities that can be avoided through the continuous monitoring of the overall system health status.

With respect to health monitoring from the design perspective, if built-in test sensors are integrated within the overall system design for features extraction, the required continuous monitoring throughout the life cycle of the system or its components will be achieved [4]. However, while the sensors may provide information, they do not achieve the acquisition of a complete suite of technical information that would enable the implementation of a robust and proactive, condition-based maintenance (CBM) approach [6]. This is made worse if the reliability of the sensors themselves is distorted due to the presence of an unwanted noise in sensor signal. This is also true if there are not enough sensors to capture important data. However, the sensors themselves do appreciably add to the weight and cost of the aircraft [7]. Furthermore, the sensors are normally implemented at the component level or system level and are not sufficient to account for the subsystem level interdependencies as well as changes in the system's operational environments. Keeping these challenges in mind, how are the diagnostics of components or systems supported under a robust, CBM process?

To support a robust, CBM approach to the FCAS, it is vital to systematically explore the required technologies that allow for the real-time monitoring of the system and its health status at system, subsystem, and component levels [8]. To underpin the overall exploration, an in-depth literature review of the types of FCA subsystem diagnostics has been carried out as a first step. This review focuses on the different types of flight controls and their actuation system diagnostics, their failure modes and effects, existing CBM strategies, fault-diagnostic methodologies, and the effects of single or multiple faults for interacting components.

1.1. Motivation

The health monitoring of an entire system is achieved if the diagnostics and prognostics of the individual subsystems are approached as a system of systems (SOS) [9]. As a first step, a diagnostic of the components is performed using either a failure-modes analysis of the components or a time-to-failure prediction. This is to identify a faulty component that is affecting the system and track the propagation of that fault to other interacting components of the system.

Diagnostic analyses are therefore, performed to identify faults; in this way, different faults with similar fault signatures and characteristics will be known. This is not always easy in a HPFCAS with complex, nonlinear, and strong fault concealment. Additionally, individual components such as pumps, actuators, fluids, filters, and valves experience degradations, producing faults that add to the multiple faults affecting the system. These cause the delay of flights and increases in cost and maintenance downtime. Also, components are designed to account for the functions they perform. However, as soon as components are integrated into a system or subsystems, their roles are modified. These changes in role may also be due to the conditions under which they are intended to operate. Hence, a system with multiple faults makes it difficult to trace the origins of each fault. The faults associated with one subsystem may mistakenly link to another subsystem with attendance effect.

Fault diagnosis and isolation are required to ensure that the number of fleets in an organization is constantly monitored so that they may be available. To underscore this initiative, a thorough review of the diagnostics for FCASs is performed to identify the available methods used for the diagnosis of FCASs and observe their merits and demerits. Thereafter, this review will examine the possible areas of improvement and select or develop a suitable method that can be used to robustly, model the faults in an FCAS. This is intended to account for the devolution of FCASs as SOSs and to develop diagnostics to detect multiple faults in hydraulically powered FCASs.

1.2. Background to FCAS

FCASs are normally mechanical/electrical, mechanical/hydraulic and mechanical/hydraulic/electrical systems that transmit the control signals needed to drive the primary or secondary control surfaces [2,4]. They provide the required assistance that enables the response of the aircraft according to the pilot's command. FCASs include the components required to transmit flight-control commands from the pilot or other sources, such as the autopilot or trim systems, to the appropriate actuators, generating forces, and torques. These forces and torques are used to control the aircraft's flight path, altitude, airspeed, aerodynamic configuration, ride, and structural modes [3]. The performance of the FCAS directly influences aircraft performance and reliability; this makes it one of the most important systems in an aircraft.

1.3. Outline of the Paper

This review considered articles published in peer-reviewed journals and publications from various sources by experts in the industry, institutions, and stakeholders that addressed diagnostics or fault detection and propagation in aircraft FCASs, as is shown in Figure 1. These sources were searched, collated, and assessed. Thus, this study relied on a systematic review of the published scientific literature on fault detection and isolation.

Accordingly, the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines was adopted where published articles were included in the current study, if they were published in peer-reviewed journals with the main purpose of the article being directly related to diagnostics in aircraft FCASs [10]. Studies that were repetitive or did not meet all conditions were excluded. Electronic databases were searched for this purpose: namely, Science Direct, Scopus, IEEE, and ELSEVIER. Search keywords included aircraft system diagnostics, fault detection, and flight control system diagnostics. An initial screening was performed to collect all potential studies, relying on their titles and abstracts. These studies were then filtered after a full review of the article text to remove duplications.

In another parallel activity, researchers who have an interest in the fields of health monitoring, diagnostics, and prognostics were consulted to share their opinions. Relevant documentations on the subject area were simply contextualized to address the understanding of diagnostics in aircraft systems. This, together with the identified peer-reviewed articles, formed the collective source of information shown in Figure 1.

The resulting collection of one hundred documents included seventy peer-reviewed journal articles (70%), nineteen industrial reports and regulations (19%), nine conference and other symposia papers (9%), and two books (2%).

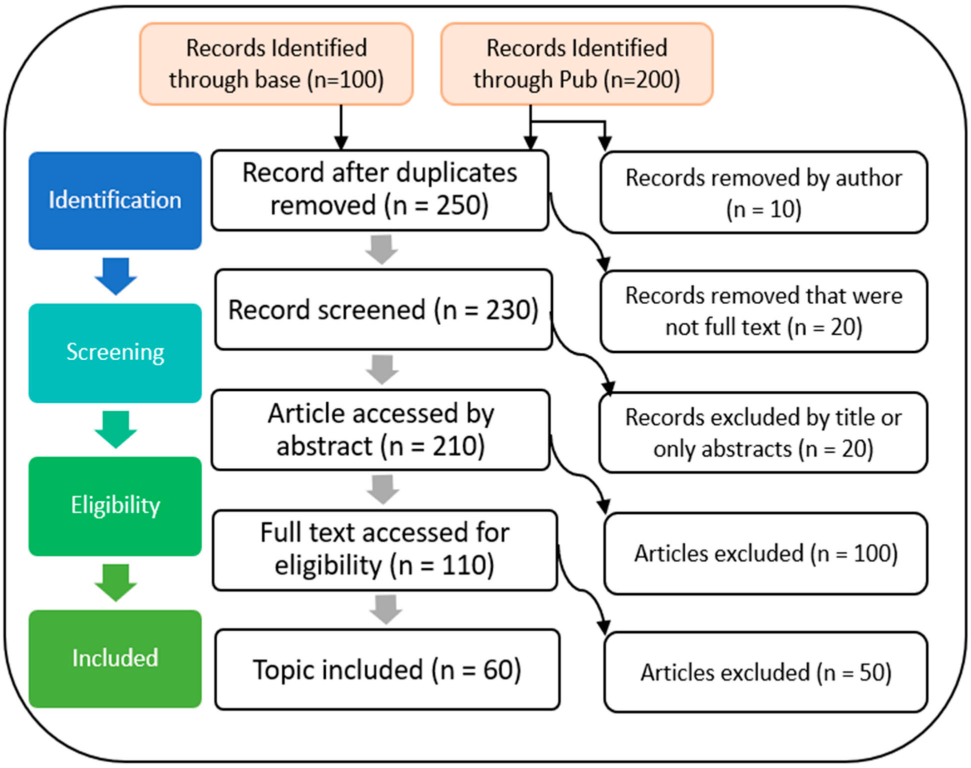

Figure 1. Guidelines for the review methodology.

2. Flight Control Actuation Systems

The FCAS of an aircraft consists of many different, complex subsystems to provide control to the aircraft according to how the FCAS is powered or energized. The following subsections present the background of elements or components and explain how they fit together in different FCAS topologies.

2.1. Mechanical Flight Control Actuation System

For a mechanical flight-control actuation system (MFCAS), shown in Figure 2, the system is a collection of mechanical parts such as pushrods, tension cables, pulleys, counterweights, and sometimes chains which directly transmit the forces applied at the cockpit controls to the control surfaces. References [1,2,4] show descriptions and different ways by which the MFCAS are installed in the aircraft. In this type of FCAS, the diagnosis focuses on the wear-out of components due to friction, clearance, and the elastic deformation of the transmission system to achieve good performance. With an increase in the size, weight, and flight speed of aircraft, it became increasingly difficult for mechanical control surfaces to overcome the aircraft aerodynamic forces. The main issues associated with the wear-out of components are vibrations, friction, and elastic deformation. These issues cause degradations, which result in mechanical system faults that propagate to failure.

Diagnostics of this type of FCAS focus on the attributes or characteristics of the individual components in terms of the fault attributes associated with ageing components and the impact they have on the entire system. The most suitable methods are diagnostics associated with mechanical systems that use verified safety-assessment tools, such as a failure modes, effects, and criticality analysis (FMECA), to compute failure rates and failure criticalities of the individual components and systems by considering all failure modes [11–13]. A fault tree analysis (FTA) of component failure rates and probabilities of various combinations of failure modes can then be employed. In a FMECA, a breakdown of the system into its subsystems and components is performed by working in a bottom-up approach. It begins with the failure modes each component can present and propagates these effects upwards to the higher system levels. A system's FMECA answers the questions as: "what are the problems that could arise?", "how are these problems likely going to occur?", "how serious are they if they happen?", and "how can these problems be addressed?" [13]. To add to this, techniques such as the Markov analysis, which computes the failure rates and criticality of various chains of events, can be utilized.

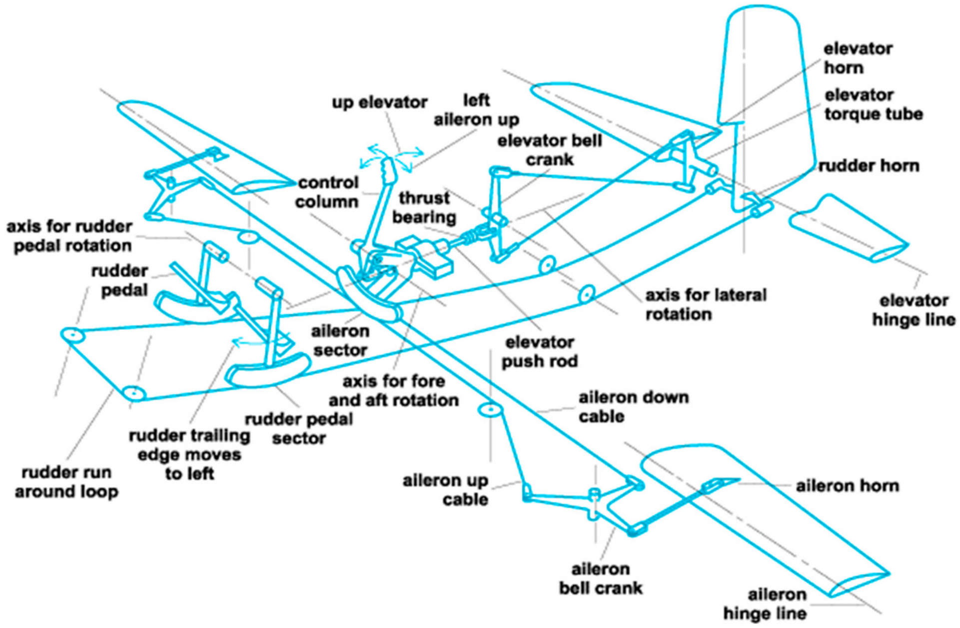

Figure 2. Mechanical flight-control actuation system showing structural parts [1].

Regarding an FTA, decisions are taken in accordance with the fault tree model of the system in the same way as a FMECA, in which higher-level, major subsystems are devolved into lower-level components in a descending order of complexity in the chain of failures. A diagnostic analysis is conducted by traversing the tree in a top-down approach. Thus, higher-level nodes relating to major subsystems and nodes corresponding to components or different failure modes are at a lower level. Usually, at every node of the tree, a system's parameter is compared to a baseline value and, depending on the result of the comparison, lower branches of the tree can be excluded. This algorithm terminates when it reaches the lowest nodes of the tree. Depending on the fault modes that the analysis aims to capture, different architectures of FCASs or their diagnostics can be developed.

In most cases, a common cause analysis, which evaluates failures that can affect multiple components and systems, is expected to be used for a robust diagnostic of the FCAS. Examining the component functions and a knowledge of the critical failure modes, based on data availability, is required for an easy diagnosis of the system.

2.2. Mechanical/Hydraulic Flight Control Actuation System

Aircraft designers recognized that the hydraulic system could divide the control-surface forces between the pilot and the hydraulic boosting mechanism [2]. This is because hydraulic power drives the aircraft surfaces according to the pilot's command using high pressure, exerting an increased force on the aircraft surface, as is shown in Figure 3. The diagnostics for the system, therefore, involve both mechanical and hydraulic components, with faults from both systems being considered. Here, cases of any single system or component failure (such as actuators, control spool housing, and valves), in a hydraulic system—or any combination of mechanical or hydraulic system failures, such as dual failure—are of diagnostic concern [9]. Dormant failures of components or subsystems that only operate intermittently, as well as common mode failures/single failures that can affect multiple systems, are considered part of the diagnostics process.

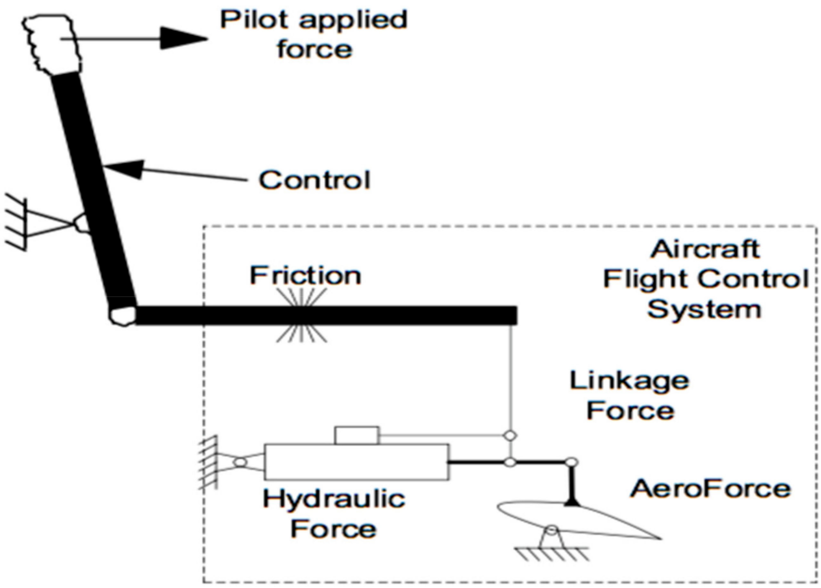

Figure 3. A mechanical/hydraulic FCAS [2].

2.3. Mechanical/Hydraulic/Electrical FCAS

A hydraulic power supply actuation system in combination with mechanical components and electrical systems forms the overall fault areas for diagnostics in this class of FCAS. The FCAS could be mechanical, electrical, hydraulic, or any combination of these systems. These provide the motive force necessary to move the flight control surfaces. Thus, actuation systems are intermediaries between all the flight control system needs and the force that drives the flight-control-surface motion [14]. To provide some force for moving the surfaces in hydraulic power systems, hydraulic actuators are used to convert hydraulic pressure into control-surface movements. The performance of the actuation system significantly influences the overall aircraft performance, and faults associated with the aircraft will dictate some requirements in the actuation system design and diagnostics.

Figure 4 shows a primary flight-control actuation system (PFCAS) unit, manufactured by Liebherr-aerospace, Germany, for aircraft use [15]. In this unit, the mechanical system, the electrical system, and the hydraulic system are all integrated and built into the actuation system. The integration shows that the core parts of these systems are mechanical parts, hydraulic parts, and electrical/electronic hardware with embedded software. A robust diagnostic of this system would be complex, as all the faults associated with the individual systems must be known. Hence, a diagnosis for the mechanical system, electrical system, and hydraulic system, respectively, as well as the actuator, will produce a result for the entire actuation system [16]. This implies that, for the best result, the diagnostic of the actuation system should be approached as a SOS [8,17].

Given that the actuator performance directly influences the performance of the aircraft under all operating conditions, one method for diagnosis would be to focus on the actuator, which is the link between the flight control and the hydraulic system, assuming no fault is related to the mechanical system. For systems such as this, a data-driven methodology can be used to show how both novel and established diagnostic technologies can achieve an overall prognostic health monitoring (PHM) architecture [18]. Their approach does not require the physical modelling of the target system, so faster algorithms and lower development times can be achieved. However, the system health state is implicitly "modelled" through the monitoring of specific data characteristics (or "features") that are used within a classification environment. To assess the true health state of the monitored system, specific data must be known and used within a defined environment [11,19,20]. Hence, for a system that has not been used, or for a system whose classification environment is not known in terms of available data on its operation, diagnostics would be a challenge.

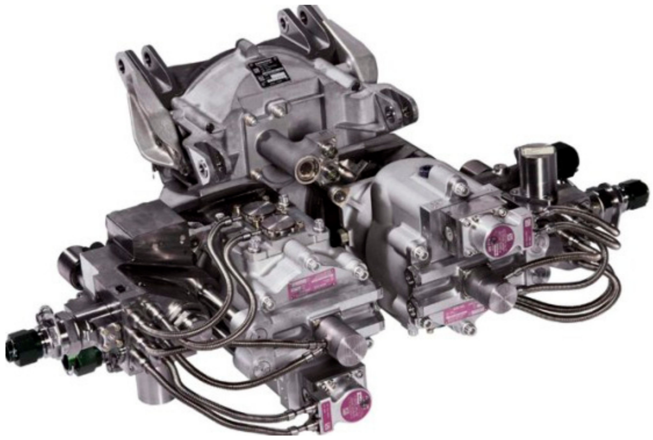

Figure 4. A power-control unit (PCU) as an integral part of the FCAS.

2.4. Summary

The various design structures of the three different types of FCASs have been described above. The different subcomponents of the FCASs were examined, with a view to bringing out the merits and demerits of the types of diagnostics that can be used. It was observed that the parameters defined for use in sensing data, that could be analysed for fault finding, varies depending on the type of FCAS.

In the case of an MFCAS, mechanical properties, such as the wear-out of components, vibrations, friction, and elastic deformation, are established as the sources of degradations that produce fault attributes. In a mechanical/hydraulic FCAS, the dormant failures of components or subsystems that only operate intermittently, as well as common mode failures/single failures that can affect multiple systems, are considered as part of the diagnostics process [4]. This is because the causes of faults can be described by sensing mechanical and hydraulic parameters, sometimes in combination, to evaluate fault attributes. Finally, in a mechanical/hydraulic/electrical FCAS, a triple combination of sensing parameters associated with the three subsystems—mechanical, hydraulic, and electrical—are used to measure fault characteristics. Hence, a good diagnostic for an FCAS is one that focuses on treating the entire FCAS as an SOS.

3. Experimental and Simulation Work Associated with FCAS

3.1. Existing Experimental Work

Experimental work on the health management systems for electro-mechanical actuators (EMA) has been conducted in which a model-based approach to the prognostics and health management of flight control actuators was used. This approach foretold the time-to-failure for each of the two critical, competitive failure modes: gear slipping and bearing seizures within the system [21]. These failures were at the component level. Only two features could be extracted from the fault parameters measured for the fault modes. However, a modern approach—one that can extract more than two fault parameter features under any situation—could improve the accuracy of the predictions for the entire system and not just the component.

In [22], the validation of a prognostic health management system for electro-mechanical actuators (EMAs) was performed to increase reliability. The work began with reviews of EMAs, using the FMECA in consultations with EMA manufacturers. Nominal outputs and less-nominal outputs of the physical models were selected. Prognostic health management algorithms were developed. These enabled diagnostic and prognostic experiments to be carried out, using the output values in tracking fault progression and predicting the remaining useful life of the actuator. Using the current drawn by the actuator, the angular velocity, the torque, and motor constants, to represent the physics-based nominal model of the EMA, the actuator was modelled as a DC motor, considering input voltage, winding inductance, resistance, and damping against the opposing torque. The nominal data required were collected by running the model under different load conditions to estimate the parameter changes in the motion profile of the actuator. A run-to-failure experiment was observed due to excessive heat, which caused damage to the winding insulation, a short circuit, and the failure of the motor due to an actuator jam, which had been injected as the fault.

Figure 5 shows a plot of motor temperature against time. The actuator jam was injected into the healthy actuator, and sensor measurements of the generated data were obtained. A region in which the healthy actuator can operate continuously for a specified period was selected from the manufacturer's design-performance specification, known as the 100% duty cycle. Motion and load profiles were designed to stay within this region. Thus, in [22] it was shown that as the motion profile was a sine wave of 8 cm peak-to-peak with a frequency of 0.5 Hz and the load was kept constant throughout at −50, +40, or +50 lb, increased friction from the jam resulted in additional current delivered into the test actuator motor. This was to perform the same load profile under different loading conditions from the nominal actuator.

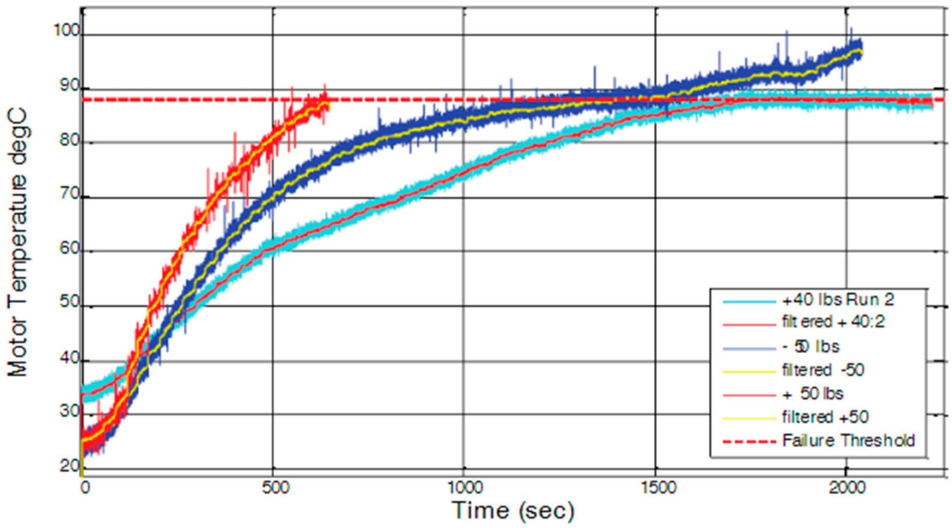

Figure 5. Plot of motor temperature against time showing run-to-failure data.

The entire experiment was performed on an EMA but did not take into account the faults associated with the individual systems that form an EMA. In addition to this, no new fault types were considered, and there was no execution of prognostic experiments in the flight environment. Therefore, the validation procedure required more experiments to be executed under the same conditions and faults of individual systems considered.

As an experiment, a comparison of data-driven fault-detection methods with applications in aerospace EMAs was reported in [23]. A model-free framework to equip electro-mechanical actuators was proposed and deployed in aerospace applications with health-monitoring capabilities. Many experiments were performed to acquire data, using both healthy and faulty components, with considerations for the standard regulations for the environmental testing of hardware. Various types of classification algorithms, such as logistic regression (LR), support vector machine (SVM), naive Bayesian (NB), and gradient tree boosting (GTB) algorithms were used. The choice of any of the algorithms was dictated by the classification result and is of the most interest with respect to understanding the type of data-generating process. The results showed that all chosen classifiers were discriminative: the algorithms developed for one classifier did not provide the same results when another classifier was used, despite using the same data values.

Based on these results, the application of the framework to other fault types was not investigated; nor were conditions that could not be deduced from the data, generated. Thus, it can be suggested that the combination of the proposed approach with a model-based methodology would provide a more robust and comprehensive fault-detection capability.

3.2. Existing Simulation Work for FCAS

Simulation work for an FCAS for diagnostics purposes should account for the total operation of the system, which involves the components of the entire system and the individual control processes. These include the way faulty scenarios can be injected into the system models. Simulation work for an FCAS associated with a MFCAS will be different from simulation work for a HPCAS because the components used in the processes are not the same. The different diagnostics employed will depend on the defined parameter estimation obtained during data acquisition [19,20,24]. This is substantiated by work in which a simulation model was developed and proposed for EMA-health-condition monitoring techniques [25]. This model was based on a simplified and complete Simulink approach. In this approach, an electro-mechanical actuator (EMA) using Simulink block sets for simulation, was implemented and tested. The simulation used a pilot input as a step signal to a PID controller. The controller sent signals to a brushless direct-current motor, coupled to a ball or roller screwed, through a reduction gearbox. This produced a linear motion output that drove the control surfaces to an angular displacement, depicted as the actuator response. Thus, as faults were injected into the system model, some measurement errors were observed in the actuator response, corresponding to the behaviour of a typical electro-mechanical FCAS.

The identified errors were related to faults due to the inertia of the mechanical parts, such as control surfaces, motors, gear, and leadscrews. Although these errors can be corrected using the PID controller parameters, the initial transient responses were included in the EMA performance responses. Hence, these showed the differences observed between the reference input signal and the control-surface responses as faults. Thus, considering the main input parameters of the system such as, the current to the motor and the speed, failure modes were built around the speed of the motor, sensor measurements, torque, and current.

In Figure 6, a controlled Simulink system model was used to illustrate an experimental information flow diagram of an electro-mechanical FCAS using a step pilot input function. The expected response is the outcome of the actuator response as measured. The output is obtained by the sensor measurements after suitable parameters for the PID position controller are selected. Errors are usually observed with different PID position controller values, but other faults due to components are also present in the system and can be diagnosed. Fault scenarios, such as a phase current that reduces the speed of the motor, sensor measurements, which depend on the sensor calibration, and torque values due to loadings on the control surfaces, are some of the possible fault attributes experienced due to the changing values of these parameters.

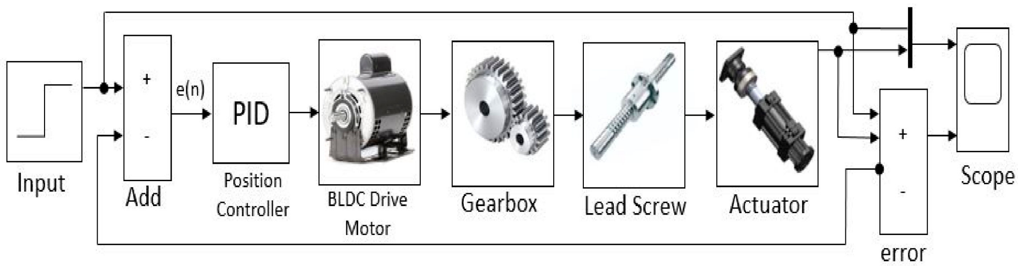

Figure 6. Control Simulink model of the electromechanical FCAS.

3.3. Simulation Modelling Coupled with Experimental Work

One study developed an accurate model and simulation of the mechanical power transmission within a roller-screw for EMAs, with special attention paid to friction compliance and inertia effects [26]. It proposed non-intrusive experiments for the identification of model parameters with an integrator- or system-oriented view. The actuation models in the work were the type that would reproduce the energy losses and the main dynamic effects, meaning they could withstand noise and disturbances.

The control handle was supplanted by an electric motor, while the models were subjected to sudden loads and disturbances and a precise actuation was obtained within the specified settling time. The study was built on control theories in which the model experienced the effects of parameter variations on the system's stability and performance. These were analysed and showed prospects for diagnostics if performance and stability are used as the matrix. However, the researchers could not trace the sources from which these parameters were changed such as the power supply, torque, motor current, screw displacement per revolution, or the PID values. The values of these parameters were to be evaluated in quantifiably for fault measurements and prediction.

In Figure 7a, the EMA system model was built in Simulink and simulated. Thereafter, the numerous blocks were reduced to a subsystem for clarity and simplification, as it is shown in Figure 7b.

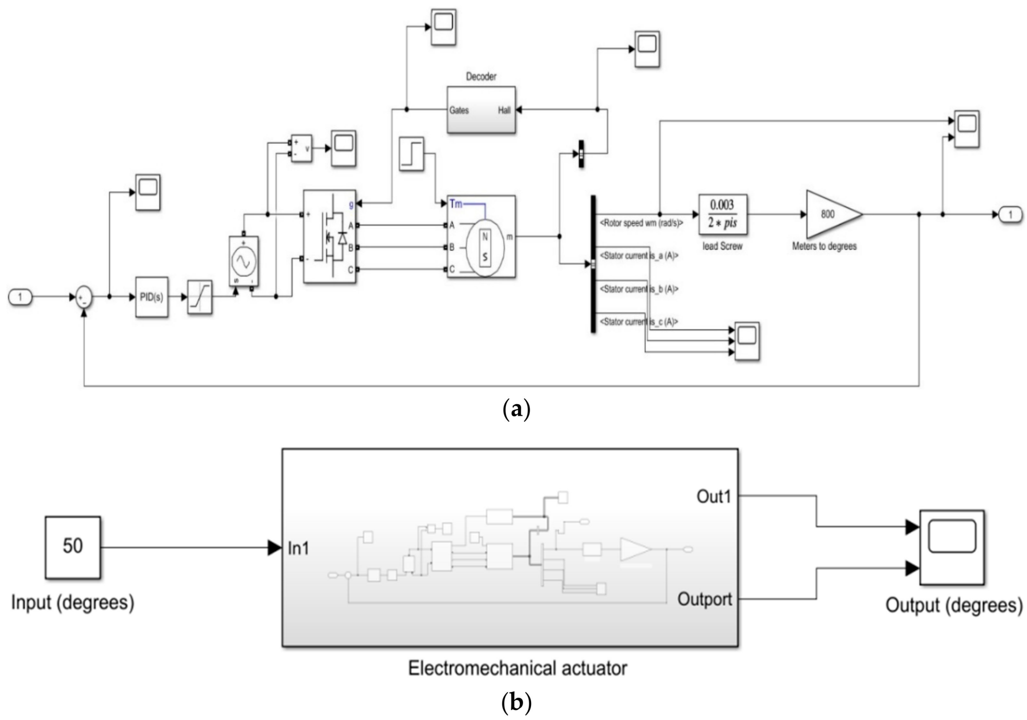

Figure 7. (**a**) EMA system model blocks built for individual components. (**b**) EMA system model blocks were reduced to a subsystem showing input and output responses from built-in blocks.

The model was able to handle disturbances and non-linearities but could not account for the causes of the disturbances. It also annulled the effect of a sudden load on the motor. While the model could achieve the desired actuation within a very short settling time, this was at the limit of the PID controller. These effects are shown as the EMA response in Figures 8–10 [26].

The EMA model was simulated with changes in the motor speed due to different loads on the actuator. The results were collected by plotting the motor speed vs. time due to loadings at 0.5 s, shown in Figure 8. Also shown in Figure 8 (lower line) is a plot of the actuator position vs. time. The effects of other parameters, such as the changing values of the controller, are shown in Figure 9.

If parameters do not change rapidly and do not produce disturbing effects, such as causing fault or instability to be introduced to the model, they do not affect the EMA system response. This is as shown in Figure 10.

In a related study, the actuator model was first structured with respect to the bond-graph theory [12]. A formalism that enables a clear identification of the considered effects or model requirements and associated causalities for model implementation was enacted. This required a clear physical understanding of the entire actuator model. This research work provided a system-level model of the mechanical power transmission in an inverted, roller-screw EMA. They proposed a generic modelling and testing procedure to identify and validate the EMA model without need for intrusive measurements or detailed design data.

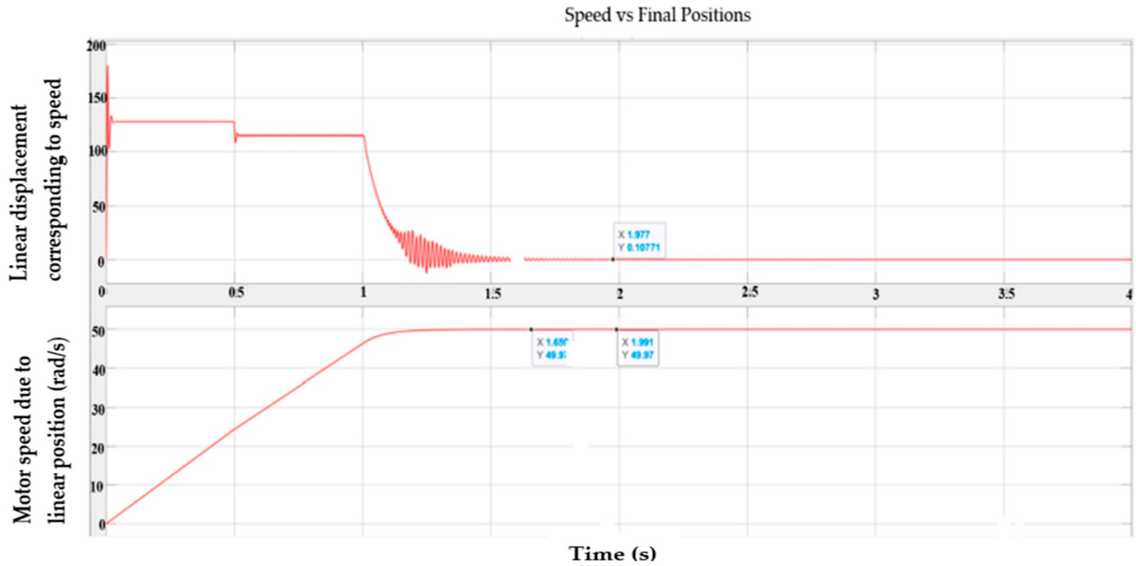

Figure 8. Motor and actuator response for a sudden load at 0.5 s, depicting speed and final position plots against time.

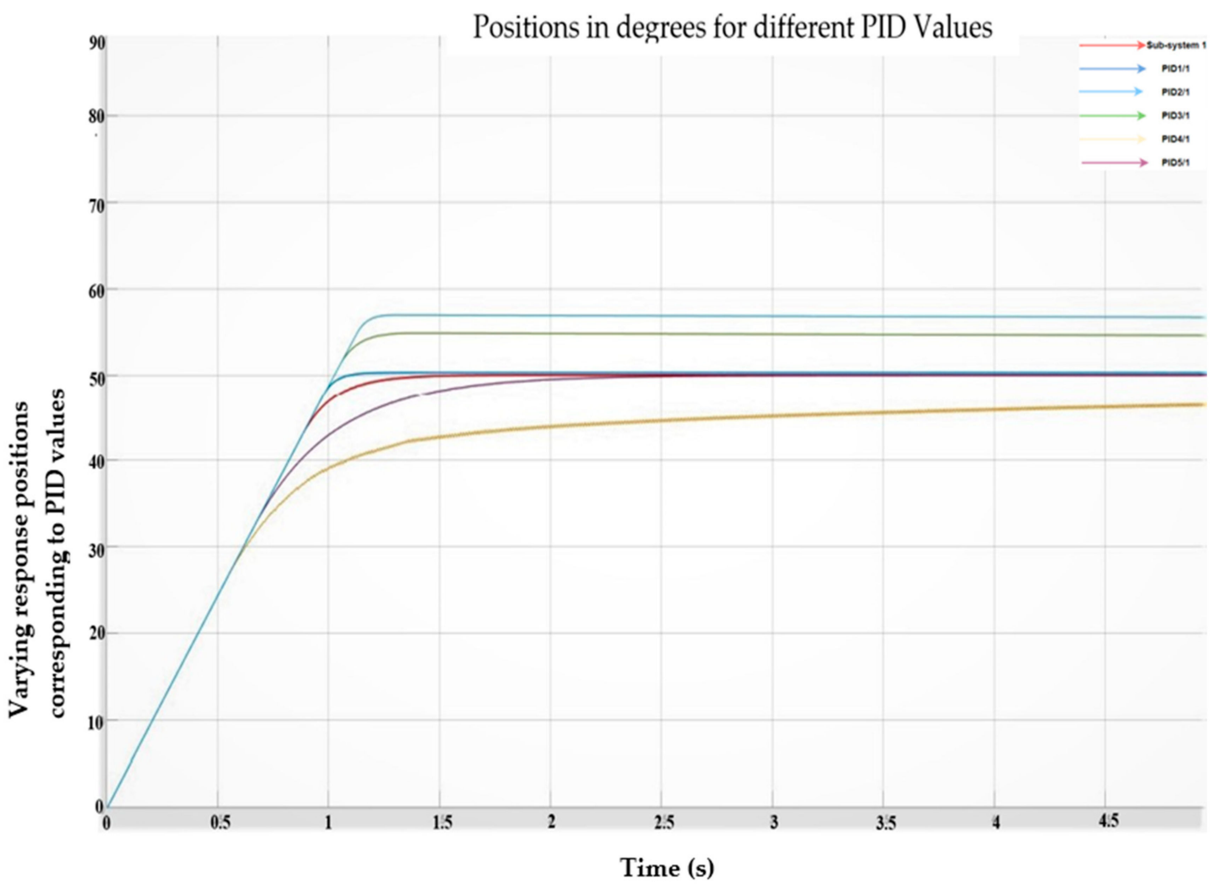

Figure 9. Responses of the actuator for different PID values.

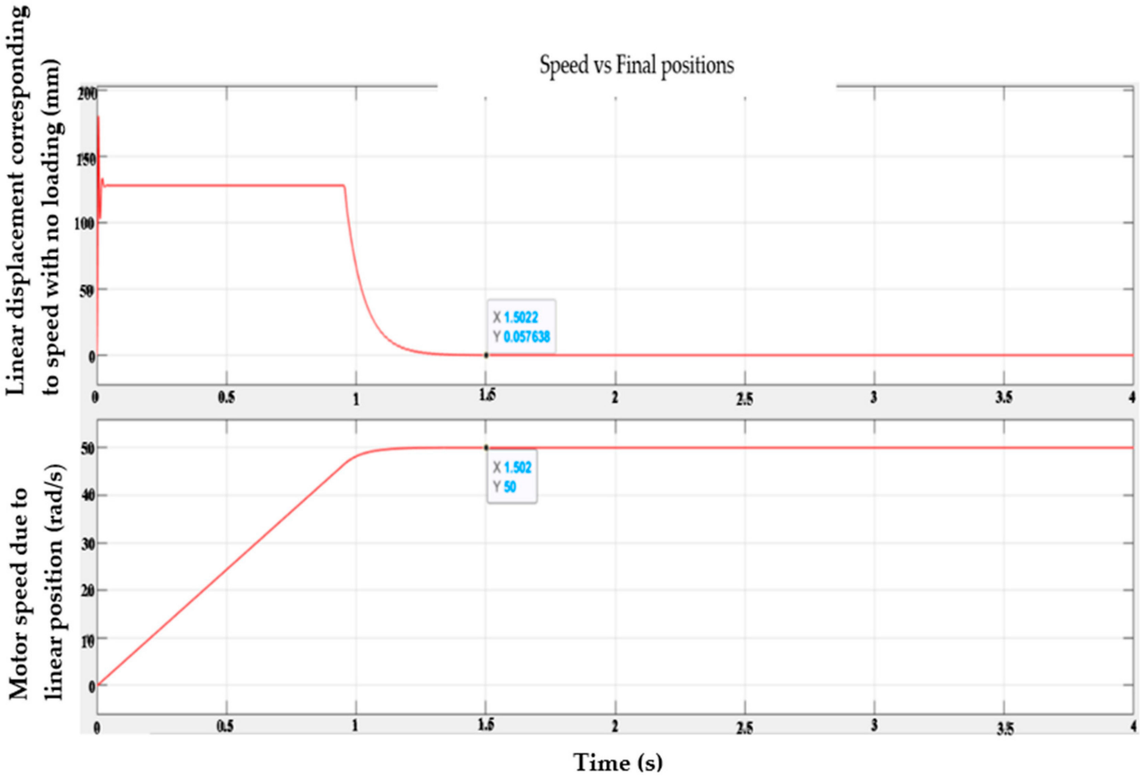

Figure 10. No effect of parameter changes on the demanded speed by the motor.

The EMA model development focused on important effects which are often neglected such as transmission compliance, which is aided by gear/shaft couplings and roller-screw friction. The results showed that the EMA efficiency can reduce significantly with operating conditions. In fact, as the rotating body movement provided the input, the resulting translational output was measured. The limit of rolling movement in the circular manner was divided into four quadrants of operation, with the period in each quadrant noted. With a strong effect from transmitted loads at different periods during operation, the quadrants of operation were considered, which agrees with [26] with respect to transmission compliance due to friction. In this modelling and simulation approach, position control was applied to a low-dynamic state variable (position being the second time integral of acceleration). The simulated and experimental positions could be quite similar, even if the upper state variables were badly predicted by the model due to the filtering effect of a double integration of the position distance to provide acceleration.

However, the required force control was applied to the high-dynamic state variables (acceleration) and, for this reason, the performance prediction accuracy was much more sensitive to modelling errors. Therefore, the identification of inertias and compliances to develop transmission models that are capable of reproducing effort losses and poor reversibility with confidence are needed. For the study in [12], the model was particularly important for sizing the electrical motor and its inverter, as their thermal load would be highly impacted by the actuator output force and velocity, reflected through the mechanical transmissions at motor and power electronics levels. This model approach may not be suitable for a HPFCAS.

An EMA-system-level model was proposed to reproduce these effects with confidence; it was validated with mixing time and frequency domain experiments under torque or velocity disturbances. According to the study, the proposed generic friction model proved valuable as no significant parameter variations were detected in more than one year of use.

For the HPFCAS, the sizing of the electrical motor and its accessories needs to be monitored with a laser sensor, as their thermal load would be highly impacted by the actuator output force and velocity. This is intended to limit the operation of the motor within tolerance. However, the limiting factors would affect the capacity of the motor speed. This is reflected through the hydraulic transmission power at various components' levels, with effects on pressure gain/losses versus the mass flow in the hydraulic system. Adopting this model would not work, but a model that accounts for the peculiarities of the hydraulic system properties would help in achieving better diagnostics results.

3.4. Summary

In reviewing the experimental and simulation research work regarding the diagnostics of FCASs, it can be observed that most of the works were performed on MFCASs. The most relevant works studied FCASs that utilized EMA systems for their actuation. Diagnostic work on HPFCASs is not well covered; this provides opportunities for ongoing studies. The few experimental and simulation works considered in this review analyse the modelling and simulation of FCASs using defined parameters according to the design and requirements of the FCAS model created. Attempts are made to propose diagnostic capabilities based on their results; however, clear cut diagnostic procedures are still ambiguous. For MFCAS models that involve an EMA, mechanical and electrical parameters such as inertia motor speed, current, torque, friction, and loading were chosen as some of the parameters whose changes in value could trigger measurable quantities for faults diagnostics. In a HPFCAS, for which the measured properties consist of hydraulic components, a change in hydraulic parameters such as pressure, temperature, quantity of flow, are relevant. These are in addition to those parameters relevant for an MFCAS, which are also included in parameter estimations for diagnostics. This was not fully captured in most of the simulated works and, even where it is considered, only a classical control approach is used.

4. Integrated Vehicle Health Management (IVHM) and Diagnostics for FCAS

4.1. Overview of IVHM

An integrated vehicle health management (IVHM) system normally uses sensor data to detect faults in components and subsystems (i.e., diagnostics), to predict the remaining useful life (i.e., prognostics) and assist maintenance engineers and operators. Many discoveries on diagnosis, prognosis, and the mitigation of faults in different aircraft systems are achieved through the model-based [27] and signal-based fault detection and isolation techniques. For example, as a signal-based method for diagnosis, ref. [17,28,29] used signal processing to provide promising tools in the form of decomposition algorithms, benefiting from their low computation cost, empirical mode decomposition, and variational mode decomposition. These qualities allowed the researchers to undertake a real-time diagnosis with an on-line, electrical signal time-series data analysis. Thus, the input variables were the current and voltage collected, and weather data simulated by a regional climate model. Decomposition algorithms, such as the fast Fourier transform and wavelet transform algorithms, were used to extract additional features from time series. The information collected comprised the gain and the phase of the signal for each frequency value. These characteristics carried information that was not available for the data in the time domain. However, the scope of the research was limited to stationary or periodic signals. Although the wavelet transform (WT) tool, which is applicable to non-stationary and transient signals was used, its usage is highly dependent on the time series characteristics and cannot be easily deployed for a HFCAS.

The use of a signal-based fault diagnosis for system models evolves from the need to condition sensor measurements and real-time domain analyses to identify measured variables that are sensitive to faults and features extraction [30]. Here, time series signal processing, such as a fast Fourier transform, that changes data into a frequency domain, —which carries characteristics that are not found in the time domain for fault diagnosis—is analysed [31]. This enables the selection of the most suitable tool for highlighting the symptoms (data processing) and interpreting the symptoms to make a diagnosis. Therefore, ref. [31] uses signal-based methods for extracting features and further inputs these features into a classifier for fault recognition.

In a research study, ref. [32] the diagnosis of a faulty ignition system due to degradation was discussed. The researchers evaluated the possible fault effects caused by the starter motor or fuel-igniter system in a feasibility study. The methodology used involved the signal processing of acoustic data, for which microphones were used as the sensing elements. It was suggested that the derived parameters could be compared to find healthy limits in detecting fault and degradation in systems. This technique was used on an auxiliary power unit of an aircraft; however, as the sensor data used was acoustic, the technique's possible application in evaluating a HPFCAS diagnosis remains to be investigated.

One disadvantage is that, in the case of signal processing, the features are manually designed and thus may have a lack of objectivity. Secondly, feature extraction and pattern recognition are conducted using independent models, which cannot be jointly optimized globally for all systems. Machine-learning algorithms could therefore be adopted by these methods, which would enhance their capacity to deeply mine the essential features of a fault. A breakthrough in artificial intelligent (AI), shows that deep learning, a component of the AI, holds the potentials to overcome such deficiencies.

Based on deep learning, deep neural networks can automatically learn the complex, nonlinear relations implied in a signal, which can then be globally optimized. This will achieve the high-level features of multi-dimensional data in a complex system such as a HPFCAS, whose characteristics of strong fault concealment, powerful, nonlinear time-varying signals, and a complex vibration transmission mechanism for fault diagnosis exist. These qualities have spurred a substantial research interest and efforts in the IVHM approach to systems. Thus, IVHM has become diverse across many investigations, so that it can be applied to different systems such as the FCAS. Consequently, different model-based methods have been identified, amongst which are mathematical or physics models, data-driven models, and combinations of the two methods, known as hybrid models [22].

In model-based fault diagnosis methods, models are developed and deployed based on some fundamental understanding of the physics of the plant or process [33]. These methods can further be classified as qualitative or quantitative. The role of a specialist with expert knowledge is extremely valuable. Thus, the model hypotheses and goals must be clearly stated. The characteristics of the target engineering application will determine the type of modelling and its degree of sophistication [22,26,34]. In the quest for model-based diagnosis methods, questions, such as: how complex is the system? Is the physics well understood? What kind of data are available, and what is the acquisition rate? Is it a real time application? What is the level of uncertainty (of inputs, parameters, models, and outputs)? Come to mind [12]. Thus, ref. [30] used these approaches, which required many technical aspects, such as data, mathematical expressions, equations, and algorithms to combine with signal processing in the diagnosis of a hydraulic system. Hydraulic state parameters, such as the state of the hydraulic actuator and hydraulic system leakage, were measured and used to extract corresponding features using a mathematical model. Other parameters included: the change in flow of a hydraulic system, the vibrations and noises occurring in hydraulic system components (such as the hydraulic pump), and the pressure signal of the hydraulic cylinder, valves, and the hydraulic actuator.

Thus, the corresponding relationship between the measured signals and faults to achieve a diagnosis is described. This type of fault diagnosis compensates for the inefficiency of using manual data statistics for applying an objective parameter measurement and the advantage of signal processing. However, these are not sufficient for a model-based approach to be totally useful. Hydraulic FCASs are non-linear, time-varying systems with shortcomings, such as their difficulties with feature extraction. Therefore, unless the knowledge of the model creation establishes a complex mathematical model, other factors are known for subsequent application.

It is important that a model-based fault-diagnosis approach deals with the correct issue and help to solve the correct problem. Hence, a high-quality model will not be helpful if it relates to an issue that is not the main concern of the approach [22]. Conversely, asking a model to answer increasingly detailed questions can be counterproductive, because this would require even more features of the real system to be included in the model.

Thus, since the model-based approach adopts mathematical or physics modelling, models need to be "requisite"; that is, they must have an identified context and purpose, with a well-understood knowledge base. They must also be supervised by users and audiences, and possibly developed within a particular time constraint. Today, this is solved by the application of some machine-learning techniques if historic data is available; the models are otherwise tested on required physics assets [35]. In modern-day research activities, the application of AI in the field of machine learning under unsupervised learning can be used for such model-based approaches to diagnostics.

In the data-driven diagnosis and prognostics method, which usually uses a large amount of data to learn the degradation pattern (nominal model), a learning model that can utilize historic data and predict future health [33,36–38] is required. Usually, this run-to-failure data is typically accelerated data produced in a laboratory environment, from which healthy and degraded data are collected under emulated operational conditions. In [13], it was shown that understanding a system's fault modes can provide feedback for the design of new products. This can easily be achieved by working with required data, which can then be made more robust to faults. These data will enable intelligent fault-detection features to be embedded in the system. This is corroborated by [22], in which a data-driven model was chosen based on machine learning and statistical algorithms to identify and evaluate system faults. Data was collected, extracted, and analysed from a real system—the auxiliary power unit of an aircraft. Recognized patterns were detected in the data, and these were correlated with known fault modes, after which statistical methods were used to assigned probabilities to components being either healthy or faulty.

Data-driven diagnosis models are purely statistical and AI-based; however, the expert system methods, which involve rule- or case-based reasoning, can also infiltrate the data-driven approach, since their application is only on available data [13,35,39,40]. In [41–44], this was proven by using machine-learning intelligent classification algorithms to classify a dataset used in data driven models. Specifically, ref. [45] evaluated the performance of three kinds of damage samples. Namely, the inner ring damage, outer ring damage, and the healthy condition of the mechanical equipment (bearing). These artificial damages were injected manually by three different methods: electric discharge machining, drilling, and manual electric engraving. These samples were obtained from data collected for real bearing damage samples caused by accelerated lifetime tests using scientific test rigs [46]. The experiments conducted using the dataset demonstrated an intelligent fault-diagnosis method based on training that utilized one feature extractor and one classifier for classification accuracy.

However, one gain associated with the data-driven model approach for diagnosis is the important use of machine learning techniques. These are of two types: supervised learning, which trains a model on known input and output data so that it can predict future outputs; and unsupervised learning, which finds hidden patterns or intrinsic structures in input data [22,34]. These correlate with system-observed measurements for a health state and solve regression and classification problems [35,44].

Considering healthy or faulty scenarios, values are assigned for the probability of a system or component being healthy or faulty (statistical analysis). These techniques have been proven to be successful in isolating both component and sensor faults. Apart from this, other AI with variations in algorithms used in data-driven model approaches for diagnosis exist [46,47]. Examples of these include, neural networks, artificial neural networks (probabilistic and dynamic), principal component analysis (or different dimensionality reduction algorithms), non-linear principal component analysis, and the partial least squares. These and many others are not explicitly discussed in this paper. However, their fundamental characteristics and their main objectives fall into the methods described under data-driven models.

For an improved diagnosis using data-driven methods, specifically, more feature extractors concerning features and the training of more classifiers for fault pattern recognition will enhance fault diagnosis capability, since separate classifiers are trained for feature extractor algorithms than for fault pattern recognition. Real-life conditions can sometimes be hard to mimic; therefore, a combination of both mathematical and data-driven models to form a hybrid model for analysis has been shown to be more useful [20,35,48].

It is worthy to note that the mathematical models of model-based fault diagnostic approaches comprise statistical models or physical models to account for system conditions, diagnostics, and the tracking of degradation. Usually in a physical-model-based diagnostic approach, the simulation is based on the identification of potential failure mechanisms and failure modes for the physical system; that is, the effect by which a failure is observed to occur in the system. One research study conducted [11] used a model to monitor physically meaningful parameters that offer excellent early fault-detection capabilities even when the system operation meets or exceeds the minimum requirements. This was because small parameter shifts exist which potentially indicate the early stages of fault progression [38]. These can still be detected or traced. Therefore, if health classifications are performed using these physical parameters, multiple competitive failure modes can be monitored [11,41].

The challenge here is that some attributes of the physics-based models are constructed using first principles or mathematical laws. They are also combined with phenomenological closure models (e.g., constitutive models such as friction models, damping models, boundary conditions, and joints), whose parameters have a clear physical interpretation. This makes it difficult to build high-fidelity, time-consuming computational models of complex engineering systems for diagnostic analysis. Therefore, combinations of models can be made to achieve better results. If models are homogeneously combined, they remain the same as the parent models. For instance, combining either two physics models or two data-driven models will still produce physics or data-driven models respectively; however, in combination, they can produce more accurate results or achieve a faster response [13,35,49–51]. Hybrid models are produced for heterogeneous combinations. They are a combination of physics-based and data-driven models for diagnosis approaches. In one research study, ref. [46] authors tested a methodology on two engineering datasets—one for crack growth and the other for filter-clogging—to prove the efficacy of a hybrid model. The performance of the methodology showed that hybrid models improve accuracy, robustness, and applicability, especially in the case of where minimal data are available. Hence, because data-driven models employ historical data to construct a statistical or AI-based model aimed at capturing the degradation process, they involve a large amount of failure degradation data, which may be difficult to obtain. On the other hand, physics or mathematical models require expertise in the application field and tend to be computationally excessive to apply. The hybrid model tends to be better in analysing the forecast of failure degradation in a system.

In summary, IVHM activities have, for many years now, focused on a wide range of diagnostic methods. These have been proposed for either the system or component level. Currently, the most rapidly emerging concept within the diagnostic community is that of system-level diagnostics. This is targeted at accurately detecting faults and establishing the timely replacement of the faulty components to effectively restore the system to a healthy state. System-level diagnostics is of great value for faults that are complex in nature. These faults have a prominent impact at system-level functionality. A prominent outcome of systems-level diagnostics is that it enables a comprehensive understanding of the overall system's fault modes, causes, and effects. These are used as feedback to improve the design life cycle of new products, offering robust diagnostics capability. This underscores the relevance of IVHM diagnostic tools for different model-based approaches. However, machine learning and AI should comprise the key tools to be employed for robust fault-diagnosis approaches.

4.2. Diagnostics

Diagnosis is defined in this paper as the practice of identifying the nature of a problem (fault) through the examination of its symptoms, conditions, and signs. It is an act that recognizes attributes or characteristics which signify a malfunction or failure in a system or components due to the presence of faults. Hence, diagnostic methodologies are the techniques or methods of identifying or creating conditions for distinctive symptoms and characteristics. These would distinguish healthy and degraded scenarios in a component or system. Ongoing research shows many ways by which diagnostics are carried out [16]. Some techniques depend on imaging or image tests, others rely on pulse signals, while many depend on parametric conditions, such as temperature, pressure, volume, power, speed, voltage, and current [19]. Hence, diagnostics would depend on the data or sensor set that is employed to generate the data. These come with procedures associated with the different diagnostics tools used. Model-based methods use a physics model of the system or component under examination to conduct the analysis. Physical parameters calculated by the model are compared with system observations and, by using various techniques, faults can be detected, and their root cause can be isolated. Model-based methods can be further separated into two major categories. One category is found in an approach developed by the Control Engineering community: fault detection and isolation (FDI) [52]. Another category, which is also relevant, is an approach developed by the diagnostic AI community. Both approaches depend on the knowledge of how the physics models of the systems are created or formed.

Diagnostics in aircraft systems transform raw sensor data into useful information regarding the present condition of aircraft systems and their components for the purpose of addressing likely causes of failure. It is reasoned that diagnostics, prognostics, and the mitigation of systems are applications of different knowledge-based reasoning in the IVHM approach to solving system problems.

Diagnostics for Mechanical and Hydraulic FCAS

Diagnostic work on an electromechanical actuation system has been carried out, using robust modelling for actuator fault detection and failure prediction, following a model-based approach [11,42,43,53]. The physical modelling of the system and identified parameters, such as command signals, friction, damping coefficient, and step change in actuator position, were used to develop a model with responses that were focused on the bearing friction. These advanced parameters were used to create the simulation model, the techniques, and a suitable algorithm to predict the time-to-failure for each failure mode in the system [18,20–22]. The simulation of bearing failure was created using a single model parameter, such as the friction coefficient, and the results were compared with the normal system response, as shown in Figure 11.

In Figure 11, the normal operation of the actuator is shown in blue for a known value of friction coefficient and depicts the actual response when provided with the step input command in black. The green, pink, and red curves show the responses due to changing values of the friction coefficient due to degradation in terms of moderate, high, and severe quantities, respectively. It is an approach to condition-based maintenance which provides an early detection of developing faults. However, the algorithm operated only on flight-control command or response data. The approach employs a mathematical, dynamic model of the actuation system that was directly tied to the physical processes associated with the health of the components—in this case, the actuator and its bearing. According to [47,50,51], this resulted in an intelligent monitoring system that often works well under any load profile, including steady-state and transient performance. It also works with unanticipated conditions of loading and operational regimes, as the only selected parametric factor is friction. However, what if the selected parametric factors were more than one? This would mean that the model configuration would change along with its mathematical derivations. Consequently, more analyses would be involved to address the contributions of the sensor sets from the additional parameters.

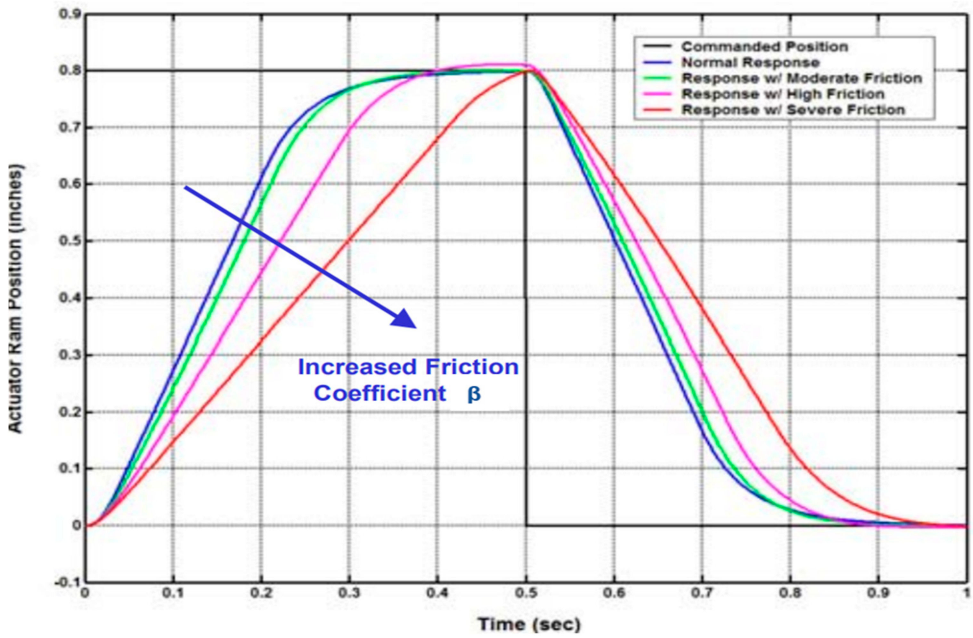

Figure 11. Actuator position against time for changing values of actuator bearing friction coefficient.

The approach was corroborated in [23,35,54], which agreed on using a model, whose physical meaningful parameters are monitored, to offer excellent early fault-detection capabilities. Such that, a set of values for these parameters are taken as dataset values, under which normal operating conditions are defined. A temporal variation of extreme values from these datasets is obtained by measuring the sensor outputs of two sensors, with the actuator responses due to command inputs. If these two sets of values are represented by plotted points whose x-coordinates represent their minimum values and y-coordinates represents their maximum values within a time response, the plot forms a cell.

For different conditions of operation and changing values of parameters chosen for measurement, the different measurement values from the sensors can be observed and plotted. Cells produced in this way have multiple values with corresponding points—especially in a time-varying field such as actuator response—creating a span in a space so that a point represents the extreme values at one time-step. For analysis, a cell's scalar variation over time is characterized as residues so that the area over which corresponding points spread in the span space provides a good measure. This means that the wider these points spread, the higher the cell's temporal variation is. This is called the parity space for the actuator system response.

The residuals that are created come from pairing all the functional relationships between components at a specific time step or over a specific time range that is observed between the inputs and outputs of a system. It represents the divergence between the expected behaviour and the observed sensor outputs when degradation affects components. A quantitative measure of the achievable level of the residuals implies the presence of fault attributes.

However, parity space must be optimized to narrow the divergence for actuator fault detection and isolation. It is observed that there are small parameter shifts when the system performance falls short of the requirements. These indicate the stages of fault progression. Thus, if these are detected and tracked, health classification and prognostics can be performed using the values of the physical parameters measured and a suitably designed algorithm.

The approach may be applicable to the isolation of the most advanced failure mode, but it can also be used to identify the fastest progressing ones. These could be failure modes that ultimately have the shortest time-to-failure. For this reason, if multiple, competitive failure modes are monitored, it could be difficult to separate and identify them distinctively.

In [20], a model-based fault-detection and diagnostic method was applied using input and output signals to dynamic-process models. These methods agreed with [21,30,45,55], not only on parameter estimation and parity space equations, but also on state observers. In this case, signal-modelling approaches were developed that generated several symptoms indicating the difference between the nominal and faulty status for a mechanical system. Model-based methods of fault-detection were developed by using input and output signals and the application of dynamic-process models. The signal approaches were processed to generate several symptoms indicating the difference between nominal and faulty statuses. Based on different symptoms, fault diagnostic procedures were followed, in which the different symptoms observed determine the fault by applying classification or inference methods.

These approaches, involving model-based techniques, are complex and time-consuming because the knowledge of the basic attributes, such as the model parameters (both old and current) if such a system is already in used, is not necessarily available. The control model itself, the diagnostic classifiers for fault identifications, and scalars all must be known for all the components of the model.

The diagnostic methods currently available are mainly for different components and systems in the aircraft. In each of the methods, the knowledge and techniques applied depend on engineering and computer skills, especially in manipulating data attributes to determine healthy and faulty systems. One of these components' diagnostics analysis [31] used a layered clustering algorithm to propose the diagnosis of multiple faults in a hydraulic system, but with emphasis on an aircraft hydraulic pump. These faults occur simultaneously; thus, the failure analyses of these types of faults are carried out based on diagnostic sensors designed according to the faults' risk priority numbers and the characteristics of different fault-feature-extraction methods. If most serious failures are distinguished with the individual signal processing, the clustering diagnosis algorithm will be based on the statistical average presence of the fault features calculated from vibration signals.

However, if the different faults follow different probability distributions, when compared to the fast Fourier transform-based signal processing diagnosis method, the faults will require pattern recognition. A combination of the signal-processing method and a classification algorithm can diagnose the multiple faults, occurring synchronously, with a higher precision and reliability. According to [45,56], two of the most typical classifiers for pattern recognition are an artificial neural network (ANN), an intelligent algorithm with an input layer, hidden layer and output layer. Another is a support vector machine (SVM), a computational learning method for the classification of small samples. These are machine learning (ML) algorithms, but the construction and training of both the SVM and ANN, respectively, are dependent on the experience of the user. For the SVM, a supervised ML algorithm that can be used for both classification or regression challenges, ref. [30] stated that the usage of the SVM for fault diagnosis of a hydraulic system is complex and deficient because training an SVM for large-scale samples is hard to achieve. Secondly, SVM is not ideal for a multi-classification problem.

However, in data-driven models of HPFCASs, there are large numbers of samples required and with an increase in system components, fault propagation together with degree of damage; the number of fault modes will significantly increase.

If the systems are made up of other subsystems, the faults generated by these subsystems, also add up to the diagnostic analysis. More knowledge, skills, and techniques in algorithm development are required.

Thus, in the current diagnosis method, emphasis is placed on consolidating on the knowledge of past efforts by involving the typical model approaches of physics/mathematical, data-driven, and hybrid. Also, to leverage on the intelligent techniques employed through signal processing, vibration analysis, and the use of algorithms such as fuzzy logic, neural networks, ANN, and SVM [57]. These are now building blocks for the use of AI and ML in modern diagnosis. Although, several machine-learning- and deep-learning-based modules are used to explore good results in fault detection and diagnosis, nevertheless, users and human experts must be knowledgeable in understanding the insights of the modules.

Another reason is related to the lack of availability of labelled historical data; this deficiency, makes the use of supervised models unfeasible. For example, ref. [46] used explainable AI to investigate faults in rotating machinery (mechanical) using feature extraction, fault detection, and fault diagnosis. This still involved signal processing for vibration features in the time and frequency domains for extraction. Additionally, the verification of a fault presence in an unsupervised manner is based on algorithms used to detect anomalies. The explanation to interpret models through unsupervised classification and root cause analysis was intensive. These effectively showed different mechanical faults in the three datasets generated and used for the research work.

However, in most cases, AI algorithms for fault diagnosis, such as the= k-nearest neighbour approach (k-NN), which is defined as an instance-based learning algorithm is on the principle that the instances within a dataset will, generally, exist near other instances; that is, with similar properties for a given training set of classified instances [58]. For Naive Bayes classifier, classification method based on Bayes' Theorem, and the conditional independence assumption for a given training set, SVM and ANN, all these four have become popular due to their robustness and adaptation capabilities. Also, they do not require full prior physical knowledge (which may be difficult to obtain in practice) and are among the various algorithms applied most in fault diagnoses. Although they are used to classify faults, they are usually intended to be trained with labelled data (supervised training) and examples of conditions under which faults may occur. These are not always available or known in the industry. In addition, most AI technologies still require large volumes of data labelled for both normal and fault conditions, dramatically limiting their industry application. This is motivated by recent advances in deep learning.

In the evaluation of hydraulic system diagnosis as a class of typical, complex, nonlinear systems, ref. [59] proposed a deep learning model with multirate data samples to extract features from multirate sampling data automatically without expertise. It was demonstrated that high diagnostic and fault-pattern recognition accuracy could be achieved even when the imbalance degree of the sample data was large.

Figure 12 shows a representation of a multirate data sample structure in which grey squares represent uncollected data. The multirate data samples have the characteristics of inadequacy, consistency, and information asymmetry. Inadequacy reflects in the missing values of the variables with a low sampling rate, which are represented by the grey squares in Figure 12. Consistency refers to the variables at each sampling rate which are uniform and complete, as can be seen in the green squares. Information asymmetry indicates that variables with different sampling rates contain disproportionate information. In a functional process, high-sampling-rate variables are usually mostly process variables which do contain limited process information, whereas low-sampling-rate variables are more quality-related variables; hence, they contain more valuable information. Therefore, in an analysis, downsampling methods subsample variables with higher sampling rates so that all variables obey the same sampling rate. On the other hand, up-sampling methods use high-sampling-rate variables to predict the missing values of the low-sampling-rate variables.

Generally, the fault diagnosis of hydraulic systems is still challenging because data samples collected from the hydraulic system are always in different sampling rates, and the coupling relationship between the components, brings difficulties to accurate data acquisition. In addition to hydraulic systems having features of multiple sampling rates, different components of hydraulic systems may fail individually or simultaneously, and it will be more difficult to diagnose multiple components. The effect, components have on the health status of systems can be described in two ways. Therefore, the diagnosis of a system is better achieved, as suggested by researchers, if the two ways are considered. In one of the ways, ref. [60] in his work on the diagnosis of ECS, stated that focusing on the degradation of components would mask component-level analysis. Hence, the necessary and best way to identify the health status of a system is for a system-level diagnosis to be performed. In this way, the effects of more than one fault affecting the system at the same time can be investigated. This is regarded as the second way.

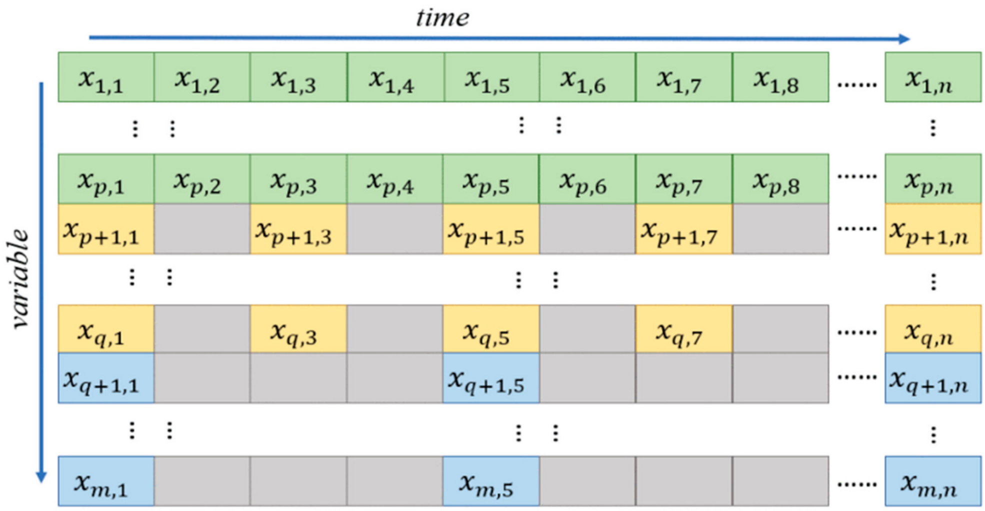

Figure 12. An example of multirate sample data [59].

Of course, earlier diagnostic tools such as the Bayesian network, expert knowledge, or other techniques were used on maintenance data to demonstrate this approach. For many diagnostics capabilities, this brand of AI, in its simplest form as first principles, was adopted, and a set of multiple neural networks were trained to recognize different faults in systems. The conclusion reached was that if each set of neural networks is trained to recognize the fault occurring in each component, or the health status, a degraded component will be known. This helps the system-level diagnosis, which is at multiple levels. Again, these approaches would depend on how good classifiers are generated and trained for the different faults observed from the components. The authors demonstrated this by proposing a diagnostic methodology which was used and applied to two systems: the environmental control system and the auxiliary power unit of an aircraft [60]. A dedicated classifier was assigned for each examined component and the training strategy for multiple scenarios (considering multiple component faults simultaneously) that could occur in a system. The authors concluded that the classifiers identified non-linearities in the training data very accurately, and therefore defined correct decision boundaries to be taken. A limitation of this approach was in the sparse data availability for classification; severity needs to be established for different components with same fault signature or contributions to the fault scenario [61]. Therefore, the classification of large number of components is difficult to manage. Additionally, for a system such as the HPFCAS, which has some of its system faults as dynamic faults, ways in which the proposed methodology could be used are still not yet implemented, as the examples of fault modes that were considered were not dynamic.

Therefore, by separating a HPFCAS into subsystems and applying the hybrid model approach with AI and ML techniques, a robust diagnosis to address the degradation in the system will be achieved.

4.3. Challenges

For a multisystem such as the FCAS on an aircraft, a principal understanding of the physics of the system for a model-based diagnostic method is crucial. The system must be separated into different systems, and the physics-based knowledge of the separated systems must be well understood.

Another potential issue is the availability of historic data sets: obtaining data from sensors or from historical usage of the system is challenging. An appropriate sensor technology must be used to obtain the right data. Second, the right algorithm must be selected for the diagnostics tool. In this review, it was found that accessibility to historic data was problematic, since sufficient data and algorithm development to match the different diagnostic models was lacking. Further observations are included as follows:

- In the hydraulic system, any single system or component failure, e.g., actuator or valve leakage, is a principal failure mode.
- Any combination of failures, e.g., dual electrical or hydraulic system failures, or any single failure in combination with any probable hydraulic or electrical failure, are principal failure modes.
- Common mode failures/single failures (e.g., leakage) that can affect multiple systems are principal failure modes.
- The increased pressure delivered to the actuation system is a function of the increase in rpm of the pump and percentage openings of the valves; thus, faults in these components affect the pressure response of the entire system.
- The actuator should be able to hold the control surface at a required position with a load applied in either direction up to a defined maximum load magnitude.
- The effect of the actuator frequency-response characteristics (gain and phase lag) on low- or high-frequency vibration modes that should be minimized constitutes fault on the system that requires diagnosis.

4.4. Opportunities

The diagnosis and health monitoring of complex systems is an ongoing study. Efforts made by the diagnostic community to achieve success have been considerable, but more efforts are still required.

In hydraulic systems, most diagnosis methods proposed or used are based on the individual components. There is a huge gap in examining the entire system because, apart from the component faults, multiple faults occur in the system and their origins cannot be traced to any single component easily.

Diagnostic methods used for individual components may vary from one component fault to the other, which necessitates the use of different algorithms for multiple faults. How can these known faults in the system be organized to fall under a comprehensive diagnosis?

With the different techniques and the advancement of learning, it is hoped that the diagnosis of complex systems, such as hydraulic systems, with their nonlinear nature and concealment of fault characteristics, will be addressed using different modern techniques of fault detection and isolation.

The diagnostic methods available for aircraft FCASs were reviewed, and it was found that there are multiple faults that affect the system. If the system can be broken down into smaller subsystem units, more robust diagnostic capabilities will be achieved.

Hence, a strong knowledge of AI and its applications will provide good opportunities for research in these areas. By separating a system into subsystems and applying hybrid model approaches, AI technology promises to provide a robust diagnosis for the system. Lastly, having known the diagnosis of the individual subsystems, it will be possible to create a digital twin of the FCAS which can be utilized for the real-time diagnosis of the entire system.

5. Conclusion

In this review paper, diagnostic methods available for aircraft FCASs were reviewed. Their pros and cons were identified for the different types of FCAS.

Diagnostic methods for systems that consist of many subsystems are complicated, as an analysis must include the contributions of faults to a system either directly or by propagation from another system.

The past efforts towards the diagnosis of systems and components using the three different types of diagnostics model approaches (physics or mathematical model, data-driven model, and hybrid model) were discussed.

It was established that the possible diagnostic methods available for fault detection and isolation in FCASs depended greatly on the type of the FCAS and the data required for diagnostic tools.

A single diagnostic model with its algorithm is not sufficient due to multiple faults in the system; hence, a hybrid method involving model-based (physics-based knowledge of the system), and data-driven methods combined is proposed for diagnostics of the hydraulically powered FCASs.

It is proposed that breaking down a system into individual subsystems which contribute to faults in the entire system will be easier. Additionally, the type of algorithm to be used for diagnosis should include the modern AI and ML techniques.

The performance indicators or condition indicators (indices or variables) for identifying the healthy and faulty scenarios applicable to systems can be harmonized if the system is broken down into SOS.

Based on their functions and the complexities of their subsystems used on the aircraft, the HPFCAS was chosen for detailed consideration in modelling faults and proposing a diagnostic method.

6. Future Work

The data-driven methods appear to provide rich data sets for diagnosis, but their combination with other methods provide better results. Therefore, obtaining large experimental or historic datasets for diagnosis is required.

Efforts should be intensified through the creation and simulation of models for these systems that could serve as sources of data for analysis and robust diagnostics for aircraft systems.

Additionally, the use of modern techniques, such as artificial intelligence and machine learning, for the development of diagnostics algorithms promises to be a revolution in diagnosis.

Future work is required in which system models will be created, possible faults are introduced and injected into these models to create better opportunities for system diagnosis.

Therefore, HPFCAS models should be created, and fault injection mechanisms on the models be developed so that datasets will be obtained, and diagnostic algorithms will be used to propose diagnostic methods.

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Nomenclature

AP	Autopilot
AI	Artificial Intelligence
BLDC	Brushless Direct Current
CBM	Condition Based Maintenance
CND	Cannot Display
EMA	Electromechanical Actuation
FC	Flight Controls
FCAS	Flight-Control Actuation System
FCS	Flight Control System
FDI	Fault Detection and Isolation
FF	Fault Found
FMECA	Failure Modes Effects and Criticality Analysis
FTA	Fault Tree Analysis
HPFCAS	Hydraulic Primary Flight-Control Actuation System
IVHM	Integrated Vehicle Health Monitoring
KF	Kalman Filter
MFCAS	Mechanical Flight-control actuation System
ML	Machine Learning
NFF	No Fault Found
PFCAS	Primary Flight-control actuation System
PHM	Prognostics Health Monitoring
SOS	System of systems
RPM	Revolution Per Minute
RUF	Remaining Useful Life

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