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Fault Detection And Isolation For Electro-Mechanical Actuators With Metaheuristic Algorithms: Sparrow Search, Honey Badger And Dandelion Optimizer

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Abstract

In the aerospace community, the More Electric Aircraft (MEA) concept represents one of the most popular research hotspots since its first introduction in the 1990s. MEAs, as the name implies, show an increased electrification in many subsystems. They typically entail the elimination of hydraulic power generation from the engine gearbox, the reduction of bleed air off-takes and the growing utilization of power electronics within the main engine's starter/generation system. The potential benefits range from an overall lower subsystem weight and a higher power management integration on board to Life Cycle Costs (LCCs) contractions, just to name a few. The Flight Control System (FCS) is not the first subsystem one may think about as far as electrification is concerned, but its implications on the hydraulic system sizing and design are definitely remarkable. In order to design a sized down hydraulic system, engineers and researchers are looking at electromechanical actuators (EMAs), which can seamlessly convert electrical energy into mechanical energy, without the need of hydraulic power. EMAs could be then employed to control primary and secondary flight controls surfaces. The main issue which is still preventing EMAs from taking over the flight control field in commercial aviation is linked to safety and reliability, and hence to certification. In fact, since EMA reliability cannot meet the required standards, practical EMA applications are severely limited. A way to boost the acceptance of these systems for safety critical applications could involve providing the aircraft FCS with additional checks and Fault Detection and Isolation (FDI) capabilities, integrated in a so-called Prognostic and Health Management (PHM) framework. This paper continues the already popular thread of FDI solutions for EMAs employing Metaheuristic Search Algorithms (MSAs) in a model-based FDI strategy by approaching new MSAs: Sparrow Search Algorithm (SSA), Honey Badger Algorithm (HBA), Dandelion optimizer algorithm (DOA). After a short introduction on EMA and MSA, the methodology is explained. Finally, a brief comparison between the methods and a conclusion section follows.

Keywords: FDI, EMA, electromechanical actuators, PHM, failure diagnosis, fault diagnosis, model-based, Sparrow Search Algorithm, Honey Badger Algorithm, Dandelion Optimizer Algorithm

1. Introduction

The aerospace sector has been going through a deep and significant technological evolution as every aircraft subsystem is constantly being improved. Being safety critical components, flight controls development plays a very important role in this transition.

In fact, over the years, flight controls have undergone drastic advancements and it is safe to say that flight controls rationale changes followed step-by-step technology evolution on the overall aircraft systems. In the earlier stages of aviation history, pioneers utilized wires connected to cockpit controls in order to maneuver biplanes (Moir and Seabridge, 2011). However, as aircraft speeds increased in the 1950s, especially in the transonic range, more advanced methods became necessary. To overcome these challenges, hydraulically powered actuators were introduced to enable powered surfaces on the aircraft. These actuators are employed to amplify the force applied by the pilot, thus reducing the physical effort needed to control the aircraft and minimizing the impact of increased loads on flight control surfaces.

The technological advancement which followed the introduction of hydraulically powered surfaces, along with the goal of reducing weight, resulted in the elimination of a direct mechanical link (i.e. cables and pulleys) between the pilot controls and the actuator. Instead, an electrical signal was implemented, giving rise to the Fly-By-Wire (FBW) technology. Currently, this technology is utilized in Electro Hydraulic Actuators (EHAs), which are widely used to control surfaces through electrical means while still being powered by hydraulics (Quattrocchi et al., 2022).

Nowadays, Electro-HydroStatic Actuators (EHSAs) represent the most advanced technology currently employable, although their implementation is still only partial and/or linked to the military aviation sphere. EHSAs aim to reduce energy consumption and weight by creating a local hydraulic circuit without the need for a general hydraulic system (Maré, 2017).

It is evident that there is a clear trend towards reducing reliance on hydraulic systems, and this trend extends beyond EHSAs. The next phase is closely linked to a broader change in aircraft design philosophy: the More Electric Aircraft (MEA) (Jones, 1999; Quigley, 1993). In fact, electrification of aircraft control systems is a rapidly evolving paradigm that has the potential to revolutionize the aviation industry.

The objective is to electrify all the utilities and sub-systems of the aircraft, which would lead to a multitude of benefits such as an increase in engine efficiency, a reduction in overall weight, better maintainability, lower operating costs, a more integrate power management system, and an alignment with stringent environmental requirements (e.g. Clean Sky Joint Undertaking projects). In this regard, the final challenge for a complete electrification of flight controls lies in the replacement of the current Electro-Hydraulic Actuators (EHAs) with Electro-Mechanical Actuators (EMAs).

In conclusion, the electrification of flight controls is a critical step towards achieving a sustainable and up-to-date aviation industry. The replacement of EHAs with EMAs is the final challenge in this regard, and the development of highly reliable safety-critical systems is a key focus area for many companies in the aerospace industry. Flight controls are good candidates for this transition given the advantages that their electrification can offer (e.g. weight, environmental policies and footprint, etc) (Baldo et al., 2023, 2022; Bertolino et al., 2023; Buticchi et al., 2023; Quattrocchi et al., 2022) and they attract attention from research centers and industries to overcome the remaining challenges.

2. Problem statement

Despite the numerous advantages of adopting EMAs for flight controls, their use is still currently restricted to non-safety-critical applications such as high-lift devices, air-brakes (Roussel et al., 2022) or experimental set ups.

The main reason is that implementing EMAs presents unique and very different challenges if compared to hydraulic systems: sensitivity to electromagnetic disturbances (EMC), mechanical jamming, and overheating issues are just some of the peculiar issues EMAs have to face. Among these challenges, jamming is particularly dangerous, as it could lead to loss of control of the aircraft. In fact, the jamming of the mechanical transmission would lead to the jamming of the entire mechanical chain leading to the lock of the aerodynamic surface itself with dramatic consequences.

On top of this critical failure point, another issue needs to be addressed. Unlike hydraulic systems, electrical failures do not typically provide warning signs before they occur. If hydraulic systems failures are somewhat gradually developing, this is not the case for EMA. Lastly, the lack of available data makes it even more difficult to study and analyze faults (Roussel et al., 2022) as well as the fault to failure process. The lack of available data is also preventing statistical analyses on the faults and their consequences.

One potential solution to achieve reliability comparable to hydraulic actuation systems is to introduce redundancies. However, this approach would complicate the system and negate the advantages discussed earlier. Redundancies lead to a loss of logistic reliability and are detrimental to the desired weight reduction; on top of that, redundancies are not always applicable due to the mechanical system in consideration.

An alternative path to ensure the required levels of safety and reliability could be to implement a Prognostic Health Management (PHM) framework (Bertolino et al., 2022). This framework aims to assess the system's health by detecting and identifying potential faults, a phase known as failure detection and identification (FDI). The technique should also be able to anticipate catastrophic failures and estimate the remaining useful life (RUL) of components.

PHM systems are being gradually adopted and looked after in every field of engineering, given the increasing amount of sensor and the introduction of the Industrial Internet of Things (IIoT) and Industry 4.0. Maintenance practitioners are looking for a reliable and seamless way to assess the equipment health status in an objective and replicable way.

If this failure management concept demonstrates its effectiveness in upholding safety standards, there could be potential for widespread adoption of EMAs as the primary flight control actuators. This would open doors for new maintenance strategies aimed at enhancing mission readiness, RAMS capabilities, and reducing overall life cycle costs (Dalla Vedova et al., 2020; Kordestani et al., 2023; Mazzoleni et al., 2017; Ranasinghe et al., 2022; Yin et al., 2022; Zio, 2022).

In this work we implemented the FDI by solving an optimization problem. Two models have been implemented in MATLAB-Simulink: the first, the Reference Model (RM), has the objective of simulating the response that would be presented by a real actuator subject to a fault. The second, the Monitor Model (MM), is iterated several times by a metaheuristic algorithm until its answer faithfully replicates that of the RM. Once the convergence between the two has been obtained, the parameters of the monitor model will be analyzed to evaluate the state of health of the actuator.

This work is the natural development of the research activities presented in (Baldo et al., 2023, 2022; Dalla Vedova et al., 2019, 2020). The structure is modified to include more updated algorithms but the main rationale and structure behind the FDI routine remains unchanged.

After the introduction a quick overview of the PHM methods commonly employed is provided. The methodology is then explained along with metaheuristic algorithms and the employed models. A results section as well as a discussion and conclusion section follows.

3. PHM for EMAs

As previously discussed, the implementation of a robust failure management and prevention system appears to be the most viable approach in enabling a comprehensive and secure electrification of the flight controls, eliminating the need for additional redundancies.

On top of that, the need for more efficient maintenance methodologies has led to the idea of proactive approaches such as condition-based maintenance (CBM), predictive maintenance or prescriptive maintenance based on PHM output actionable data. These approaches offer several benefits including improved decision making, increased operational efficiency, and cost savings through reduced maintenance and repair work, as well as fewer unexpected faults. However, they rely entirely on PHM results and data.

PHM focuses on using analytical methods based on historical data and/or real-time measurements to detect and isolate faults, and to predict the system's health state and Remaining Useful Life (RUL) accurately to enhance the operational readiness. The ultimate objective, beyond the scope of this paper, is to achieve a PHM system that can establish safety conditions, enabling EMAs adoption as a primary flight control system.

3.1. Different approaches

The development of PHM frameworks can be derived from various philosophies and approaches, typically classified into three distinct groups: data-driven, model-based, and hybrid approaches (Errandonea et al., 2020; Kordestani et al., 2023; Ranasinghe et al., 2022). PHM practitioners are able to select the most suitable approach based on considerations such as system type, client expectations for outcomes, and the characteristics of available data, including type, quality, and quantity.

Every approach possesses its own set of strengths and weaknesses, making it impossible to definitively assert that one methodology is universally superior to another. In order to gain a deeper understanding of this matter, the key attributes associated with the first two approaches are analysed. The hybrid approach combines the model based and data driven ones. By doing so, some insights will be gained into why the authors have opted to adopt a model-based philosophy in our research.

The data-driven approach is applicable to systems where there is limited understanding of their underlying physics, but there is a wealth of failure data available. These data can include historical observations, real-time condition monitoring data, and records of previous failures. By analysing and categorizing the features extracted from this data, it is possible to obtain insights into the health conditions of the systems. The main strengths of the data-driven technique are its cost-effectiveness and the speed at which algorithms can be developed. However, there are certain challenges associated with this approach, such as the difficulties in processing large datasets, acquiring the necessary data (especially in fields like aerospace), and the potential inaccuracies and not explicable behaviours that can arise during the analysis process (Sutthithatip et al., 2022).

The alternative approach to data-driven is model-based. In this approach, a mathematical model is used to approximate the physics and dynamic response of a system. The simulation of this model is then compared to the expected behaviour of the real actuator during normal operating conditions, which are usually defined through previous tests. By comparing the simulation to the real actuator's behaviour, we can determine the state of health of the system. This approach allows us to move away from relying on a large amount of historical data on failures.

Compared to the data-driven approach, this technique requires a deep understanding of the system (from a physical, mathematical, behavioural point of view) in order to develop a suitable model that does not oversimplify or overfit the real-life process. This task becomes increasingly time-consuming as the system complexity increases. As referenced before, due to the challenges in obtaining adequate data on the failure modes and the prompt availability of already developed and validated high fidelity models, we have decided to adopt a model-based approach.

4. Methodology and MSAs

As stated before, given the scarcity of real-life data, the authors decided to design a model-based FDI strategy instead of a more "data intensive" data-driven model.

The main rationale behind the methodology has been deeply explained in (Baldo et al., 2022) and (Baldo et al., 2023) where all the details have been clearly explained. The interested reader should consider these references for more details on the developed approach as in the following section just a simple explanation is provided.

The objective is to conduct the FDI routine throughout the different stages of the aircraft's operational life; the standard procedure involves comparing the dynamic response of an actual actuator with that suggested by the monitoring model. The parameters obtained at the end of the FDI routine will indicate any deviation from the normal operating conditions, highlighting the detected fault, as better explained in the next paragraphs.

As mentioned before, in order to develop the system without real life data, the authors used two mathematical models, which have been developed in MATLAB-Simulink environment with the addition of SimScape blocks.

The first model is used to address the lack of data by replacing the actual actuator with a high-fidelity model known as the Reference Model (RM). This RM will serve as a numerical test bench where failures can be simulated. The second model is a low-fidelity model called the Monitor Model (MM), which is driven by a set of top level parameters (TLP). Each TLP is linked to a physical failure and has been used to monitor a specific failure.

To perform the health check, the MM is run multiple times, adjusting the TLPs with each iteration. The goal of these iterations is to minimize the discrepancy between the RM and the MM model trend and behavior. The difference between the two models is quantified using a suitable fitness function. Once the minimum discrepancy is achieved thanks to two stopping criteria, the generated TLPs (denoted as "K_{opt}" in Figure 1) are analysed to determine the system's health and identify potential failures. More details are provided in the following sections as well as in (Baldo et al., 2023; Battaglia, 2023).

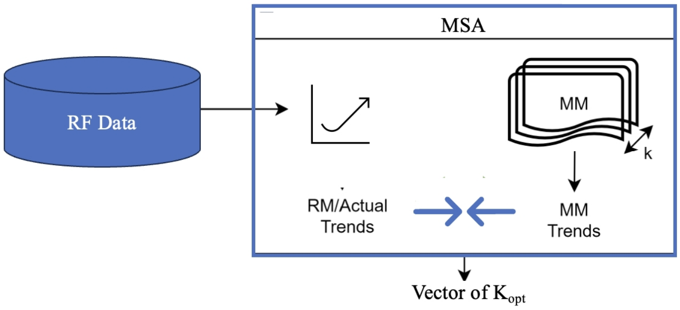

Fig. 1. FDI methodology overview. Data coming from the RF model (which is used instead of actual trends) is compared with MM trends via the fitness function by the MSA. At the end of the optimization process the output vector is used to identify the fault and its magnitude.

Finding the TLPs that minimize the discrepancy is essentially an optimization problem. To solve this problem, we have decided to employ state-of-the-art bio-inspired metaheuristic algorithms.

5. MSAs

Bio-inspired optimization algorithms are becoming increasingly used in solving optimization problems on a large scale. There is a wide variety of these algorithms in the literature, each with its own distinct characteristics and limitations (Molina et al., 2020). The objective of optimization problems is to find the best possible solution through multiple iterations (Agushaka and Ezugwu, 2022; Beheshti and Shamsuddin, 2013; Dalla Vedova et al., 2020; Devika and Gowda Karegowda, 2023; Yadav et al., 2022). These optimization algorithms are typically categorized as deterministic or stochastic. If deterministic algorithms propose exact solutions but are subject to certain limitations (such as strong initial assumptions, scalability issues, large amounts of data, high nonlinearity in the problem to be optimized, etc.), stochastic (heuristic) ones offer greater flexibility and ease of testing for handling large optimization problems (Devika and Gowda Karegowda, 2023). Metaheuristic algorithms leverage the search characteristics of heuristic algorithms, providing efficient computational cost but without guaranteeing an optimal solution.

Metaheuristics can draw inspiration from various sources, including biological species' behavior (e.g., animals or groups of insects), physical phenomena, geographical phenomena, and even human phenomena. Therefore, bio-inspired metaheuristic algorithms (Bio-MSAs) form just one subset of the broader family of metaheuristic algorithms.

Most famous Bio-MSAs can be categorized into two main types: Evolutionary Algorithm (EA), Swarm based algorithm (SBA) (Devika and Gowda Karegowda, 2023). A third type, Plant based methods, also exist but they are not much suitable for our case study, so our research will focus on the two approaches mentioned above.

EAs are inspired by nature and are based on the Darwinian theory of evolution. In each iteration, the initial population evolves towards a better condition through recombination, mutation, and selection processes. The individuals with the best fitness function are allowed to reproduce more and move towards better research points based on the information provided by the research space (Bäck, 1996).

Swarm based methods, on the other hand, are based on the behavior of swarms and groups of biological beings. The exchange of information and resources among them, even if not volontary, leads to optimization towards a better overall condition of the swarm. These interactions can be mathematically formulated in order to be coded. Each algorithm offers a different approach to problem resolution, making some more suitable for certain problems than others. This is why it is important to consider characteristics such as convergence speed, ability to avoid local minima (or maxima), and exploration and exploitation capability when adopting a certain method.

The exploration phase evaluates the entire search space to identify a set of solutions close to the optimum, while the exploitation phase focuses on finding optimal solutions among the best candidates chosen in the previous phase. Striking the right balance between exploration and exploitation is crucial for an effective search process.

To partially overcome the limitations of certain algorithms and improve performance in finding the optimal solution, it is even possible to combine multiple algorithms to create hybrids (e.g. the hybridization of two popular algorithms: the Particle Swarm Optimization (PSO) and the Grey Wolf Optimizer (GWO)) (Chtita et al., 2022). This combination leverages the GWO's strong exploration capabilities and the PSO's effective exploitation capabilities.

Out of the various algorithms available in the literature, the choice for this work was made by considering several aspects. The aim is to explore the potential of the most recent methodologies compared to more traditional techniques that have already been well-tested, while also considering the performance achieved in previous applications.

The three chosen algorithms are the Sparrow Search Algorithm (SSA) (Xue and Shen, 2020), Honey Badger Algorithm (HBA) (Hashim et al., 2022), and Dandelion Optimizer Algorithm (DOA) (Zhao et al., 2022).

The details of rationale behind the specific MSA is well beyond the scope of this conference paper, the interested reader should take into consideration reading the reported references for each MSA as well as (Battaglia, 2023), where the underlying algorithm principles and the implementing details are explained in depth. For reasons of clarity in the next sub sections the idea behind each algorithm as well as some implementation principles are reported.

5.1. Sparrow Search Algorithm (SSA)

Presented by Jiankai Xue and Bo Shen in 2020 (Xue and Shen, 2020), SSA is a reliable algorithm that falls within the swarm intelligence thread. It has shown good performance compared to traditional algorithms such as PSO and GWO, as demonstrated in (Gharehchopogh et al., 2023; Xue and Shen, 2020). In this paper, the original version of the algorithm proposed in (Xue and Shen, 2020) has been used, although it is worth noting that there have been subsequent modifications to address occurrences of premature convergence (Awadallah et al., 2023). The algorithm draws inspiration from the foraging behaviour of sparrow flocks, given the superior intelligence compared to other species and the capability maintain consistent patterns and a well-defined hierarchy over time. The population is divided into hunters or producers and scroungers, each assigned specific roles. Hunters are responsible for searching for food, while scroungers obtain food directly from the hunters. The flow chart which has been followed to create the algorithm can be found in (Awadallah et al., 2023), while the pseudocode and implementation details can be found in (Battaglia, 2023) along with other initialization details.

The fitness function is linked to the energy level of each sparrow, since scroungers try to enhance their energy level to become producers. Scroungers work is to send out alarms when a predator is seen, so that producers can guide the flow towards a different research space.

5.2. Honey Badger Algorithm (HBA)

The HBA is similar to the SSA, it belongs to the swarm intelligence category and it was initially proposed by Fatma A. Hashim, Essam H. Houssein, Kashif Hussain, Mai S. Mabrouk, Walid Al-Atabany in 2021 (Hashim et al., 2022). The HBA has been developed to handle a very peculiar problem which is often linked to MSA: premature convergence to local minima or maxima (Hashim et al., 2022; Lin et al., 2022). HBA aims to address this problem by balancing the exploration and exploitation phases: as a result, it shows superior performance compared to traditional algorithms like the PSO and GWO in several areas (Hashim et al., 2022; Khan et al., 2022; Lin et al., 2022).

The HBA draws inspiration from the feeding behavior of the honey badger, a mammal which locates its prey underground or by searching for honey. The feeding process can be divided into two phases: digging mode and honey mode. In digging mode, the honey badger relies on its acute sense of smell to approximately determine the prey's location (exploration) and subsequently selects the optimal spot to dig and reach it (exploitation). A random parameter between 0 and 1 is used to switch between the exploration and exploitation phases. The flow chart and the pseudocode which has been used to create the algorithm can be found in (Battaglia, 2023) along with other initialization and implementation details.

5.3. Dandelion Optimizer Algorithm (DOA)

The third selected algorithm is the Dandelion optimizer (DOA), which was first presented in 2022 by Shijie Zhao (Zhao et al., 2022). It is one of the most recent methods mentioned in the literature, and its basic version is available in the Matlab central repository. The positive results achieved in (Elhammoudy et al., 2023), where this methodology was applied to CEC2017 benchmark functions and compared to 9 well-known algorithms, have encouraged us to consider using this algorithm for our case study. Moreover the implementation is quite straightforward and the initialization phase requires a small number of parameters.

The DOA is based on the reproductive cycle of the dandelion plant. This plant consists of a stem and a spherical head made up entirely of seeds. These seeds are dispersed by the wind to ensure the continuation of the species (Elhammoudy et al., 2023). The reproductive cycle of the dandelion can be divided into three phases: the rising stage, the descending stage, and the landing stage. The flow chart and the pseudocode which has been used to create the algorithm can be found in (Battaglia, 2023) along with other initialization details.

5.4. Fitness function

Optimization algorithms aim to find the most efficient solution by using specific evaluation criteria for each algorithm during each iteration. This set of criteria is referred to as the Fitness Function (FF) which is often a mathamatical equation. In other words, the algorithm behaviour is driven by the trend of the FF. In our case, during each iteration, a dynamic response will be generated by running the Monitor model and the equivalent current iLF is taken into account. This value will then be compared with the counterpart of the Reference model (iHF), which represents how the real system would respond in the event of a failure.

To accurately replicate the behavior of the reference model, the response of the monitor model will be adjusted by modifying the TLP based on the result of the MSA as explained before. Specifically, there are 8 coefficients, k_i, which can have values ranging from 0 to 1 depending on the severity of the failure. The objective is to find the combination of parameters that minimizes the difference between the two currents iLF and iHF.

After some analyses on several formulations, the Root Mean Square Error (RMSE) has been used as a fitness function, by taking into account the eight fault parameters with (1), where the n stands for the numer of data points.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(i_{LF} - i_{HF})^2} \tag{1}$$

After the optimization process the error has been calculated with Eq 2 while, a performance coefficient (PC) has been used to take into account both the accuracy and the computational time.

The PC has been employed in accordance with (Dalla Vedova et al., 2020) and is reported in (3).

$$Err = \sqrt{\sum_{i=1}^{6}\left(k_i - k_{i,RM}\right)^2 + k_{6,RM}\left(k_7 - k_{7,RM}\right)^2 + \left(k_8 - k_{8,RM}\right)^2} \tag{2}$$

$$PC = 100 \cdot \left(1 - \frac{Err_i * t_i}{\sum_{i=1}^{3} Err_i * t_i}\right) \tag{3}$$

Equation (3) uses Err_i to represent the percentage error of the failure being analyzed, and t_i to represent the time taken in seconds. The denominator of the equation serves to normalize the numerator with respect to the results of all three algorithms. It is hence straightforward that high values of Err_i and/or t_i have a negative impact on the performance of the PC.

6. Faults

One essential step towards the development prognostics and health management (PHM) strategies stands in the classification and prioritization of potential failures in order to design the PHM strategy correctly. This is typically achieved through two famous failure analysis methodologies: Failure Mode, Effects, and Criticality Analysis (FMECA) and Fault Tree Analysis (FTA).

As stated before, unlike hydraulic systems, electromechanical actuators present distinct challenges in terms of failure management. The lack of premonitory signals for certain failures limits the use of EMAs to secondary flight controls. The FMECA conducted by (Mazzoleni et al., 2017) reveals 1950 failure modes, which can initially be categorized into four groups according to (Yin et al., 2022) and (Balaban et al., 2009): motor faults, power electronics faults, mechanical faults, and sensor faults. Additionally, the FMECA conducted by (Balaban et al., 2009): provides a comprehensive list of potential EMA failures, allowing for in-depth analysis through the FTA conducted by (Mazzoleni et al., 2017).

From the various failures discussed in the references, we have injected five faults. Each one is linked to one (or more) TPL called k_i:

- friction fault
- backlash fault
- short circuit fault
- eccentricity fault
- proportional gain drift (to simulate a fault in the controller)

This has been accomplished by applying coefficients to the parameters of the nominal conditions in the monitoring model and reference model.

Each failure has been implemented in the RM as well as in the MM according to the fidelity of the model with two magnitude: high magnitude and low magnitude. Further details can be found in (Battaglia, 2023).

7. Models

As stated before, a total of two models have been employed in this study: the RM and the MM.

The detailed description of the models and their underlying principles and blocks are beyond the scope of this paper, hereafter a short explanation of the simulation models and blocks is provided for the reader's clarity.

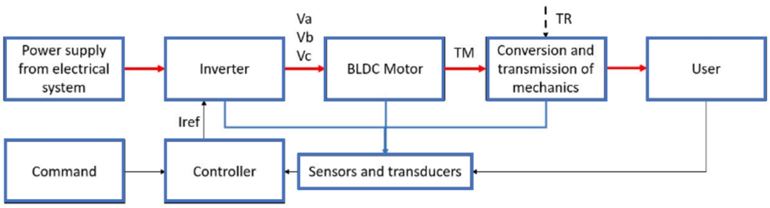

Fig. 2. HF model block diagram. High power connections in red.

Figure 2 shows the block diagram of the RM. The controller, built in a Proportional Integral Derivative (PID) fashion, is the core of the system and compares the command received as input with the signals coming from the position and speed sensors. The controller sends the commands to the inverter using the reference current (I_{ref}) to transform the electrical power supplied by the system into a three-phase current (V_a, V_b, V_c) of the Pulse Width Modulation (PWM) type. The electric motor will then generate a specific speed and torque (TM) based on the PWM signals it receives. Lastly, the motion conversion and transmission block, considering the resistance torque (TR) applied to the aerodynamic surface, provides the user with their desired position command.

The MM is a simplified version of the RM. The simplifications made were required to reduce computational costs associated with multiple iterations this model is subjected to. Despite these simplifications, we can confidently state that the reduction in accuracy is minimal, as reported in (Battaglia, 2023). The most significant variation lies in the absence of the three-phase inverter and the shift towards a one-phase equivalent system. By operating with just one phase, we can effectively decrease the integration step by a significant amount. Details of the RM and MM can be found in (Baldo et al., 2023; Berri, 2021; Berri et al., 2019, 2021; Quattrocchi, 2023).

8. Results

Results have been obtained following the flowchart reported in Figure 3. MATLAB version 2022b has been used to design and run the simulation and algorithms. The monitor model is set to run in accelerator mode and the fast restart feature has been activated in order to keep the model compiled when performing multiple simulations in an iterative cycle. As expected, the stopping criteria in Figure 3 have a significant impact on computational performance. Based on the expected calculation times and required level of precision, a mixed solution has been selected: both a maximum of 150 iterations and a tolerance of 10^{-3} in the root mean square error (RMSE) have been imposed. The optimization will hence conclude once either of these limits is reached.

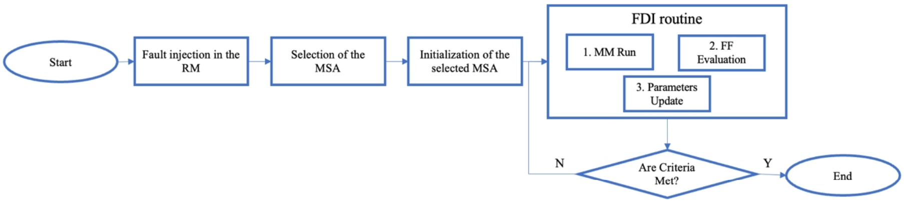

Fig. 3. FDI routine flowchart.

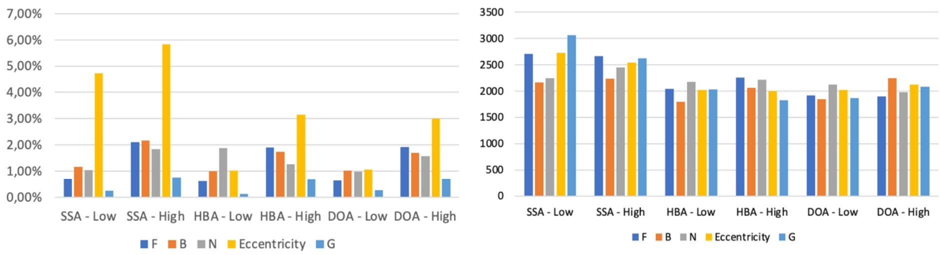

Fig. 4. Simulation results. (a) Accuracy for SSA, HBA and DOA for high and low magnitude faults (Failure – F, Backlash – B, Short Circuit – N, Eccentricity and Proportional Gain Drift – G);
(b) Computational time in seconds for the same data.

The results in terms of PC are reported in the table below:

Table 1. Results with error and PC; the best performing values are reported in bold.

Algorithm	Computational time [s]	Err [%]	PC [%]
SSA	2541.1	2.05	54.74
HBA	2039.9	1.33	72.22
DOA	**2009.4**	**1.28**	**73.04**

The computer used for the simulations has the following characteristics: Intel i7-7700HQ CPU @ 2.81GHz and 16 Gb of RAM.

9. Discussion and conclusions

To address the optimization problem of predicting failures in EMAs for primary flight controls, the authors have selected and employed three of the most recent algorithms available: SSA, HBA and DOA.

Based on the simulated results, the DOA algorithm is the most suitable candidate for our application in terms of both error and computational cost. The HBA algorithm exhibits very similar values and also proves to be an excellent optimization strategy. On the other hand, the SSA algorithm performs less satisfactorily with higher error values and calculation times compared to the first two.

The SSA algorithm has lower exploration capabilities compared to the other two, making it more susceptible to local minima. Furthermore, the SSA algorithm requires a greater number of parameter definitions during the initialization phase, such as the percentage of producers, scroungers, and other random values. Since these algorithms are stochastic, even slight variations in boundary conditions can affect the obtained solution.

It is worth noting that the calculation time is heavily influenced by the number of times the fitness function is calculated, which corresponds to the number of times the monitor model is simulated. Specifically, the SSA algorithm requires 30% more calculations than the HBA and DOA algorithms during the iterative cycle.

For future work, various paths can be pursued: searching for more recent algorithms or reevaluating the implementation of the algorithms incorporating improved versions proposed in the literature.

Trade-off analyses to determine the number of iterations that lead to convergence of the result can be carried out as well as assessing the algorithm's approximation capabilities directly with root mean square error (RMSE).

To conclude, it is important to note that the steps outlined in this paper are essential but must be integrated in a larger framework where the resulting FDI conclusion can be ingested and processed to become actionable data through RUL estimation and prognosis.

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