CHEMICAL ENGINEERING TRANSACTIONS
VOL. 33, 2013
Guest Editors: Enrico Zio, Piero Baraldi

ISBN 978-88-95608-24-2; ISSN 1974-9791
A publication of AIDIC
The Italian Association of Chemical Engineering
Online at: www.aidic.it/cet
DOI: 10.3303/CET1333110

Health Monitoring for Electro-mechanical Nose Landing Gear Door Actuator of a UAV, Based on Simulation Modelling and Data-driven Techniques

Susana Ferreiro*[,a], Andrés Jiménez[b], Jon Madariaga[a], Eva Novillo[b], Santiago Fernández[a], Andrés Alia[b], Esteban Morante[b]

[a]IK4-Tekniker, Iñaki Goenaga 5, 20600 Eibar, Gipuzkoa, Spain
[b]CESA, P.º John Lennon 4, 28906 Getafe, Madrid, Spain
susana.ferreiro@tekniker.es

Nowadays, the aerospace industry has to maintain and improve its global competitiveness and meet the demand of the new requirements which are constantly emerging. This need for improvement consists of two main issues that have to be considered: the reduction of economic costs and the technological advance. Both provide an additional value to the product. The aerospace industry, along with other industries, has found it necessary to develop more flexible and versatile systems, which are also economical, reliable and simple. The maintenance strategy is not stipulated in a clear and simple way and sometimes it requires Health Monitoring (HM) systems to allow monitors to determine the state of the systems for early detection of failures. Nevertheless, this technology is still in an early stage of development and more research is needed to demonstrate its feasibility.
This article presents the development of a HM system for an electro-mechanical nose-landing gear door actuator of an Unmanned Aerial Vehicle (UAV), based on a combination of simulation modelling and data-driven techniques. The aim of the work is to detect some failures at early stages so as to avoid a catastrophic fault that may cause serious damage to the UAV. The present work explains all the steps undertaken for a final HM system development: from the phase of data acquisition to that of the evaluation of the algorithms. This work is part of a Spanish national project in collaboration with the aeronautical systems company CESA, and it defines how to create a monitoring system from the actuator design stage. The main contribution of this system is to continuously measure the state and health of the actuator based on its internal frictions, the evolution along time of a ratio between the signal command and the measurement in every cycle of the effect produced by this command. The evolution of this ratio provides the opportunity to evaluate the loss of the performance on the actuator.

1. Introduction

Electromechanical actuators (EMA) aboard aircrafts have great potential to effectively contribute to the greening of air transportation. But the current EMA designs need to evolve in order to meet cost, reliability and weight requirements from the airframes.
The EMA developed by CESA with 15 KN load capability is based on single direct drive architecture with an **anti-jamming system** located inside the screw which is able to disconnect the Landing Gear Door from the screw avoiding in this way, any possible mechanical single failure (even screw jamming) assuring the extension of the Main Landing Gear Door in any condition (see Figure 1).
The innovation of this developed EMA is its capability to act just in the root cause of screw jamming by acting directly in the source of the problem, not previously implemented in any airborne actuator. Typical solutions used in the past by using clutches between Gear Boxes and screws did not solve the root cause of jamming problems because these kind of solutions avoid jamming events but only just before screws, not screw jamming itself. Other solutions used in the past were based on mechanical fuses used in case of jamming although most main disadvantage is the need to replace them. No training or actuation tests

could be performed with these kinds of systems. Innovation of the proposed solution would be unable until a failure or a degraded performance is detected internally by a clever Health Monitoring function implemented in ECU. It allows the auxiliary anti-jamming system to freely extend the Landing Gear Door by gravity or pushed by Landing Gear. If functional tests or training are required to assure the correct behaviour of this anti-jamming system, the proposed solution could be re-engaged easily after use by following an easy sequence.

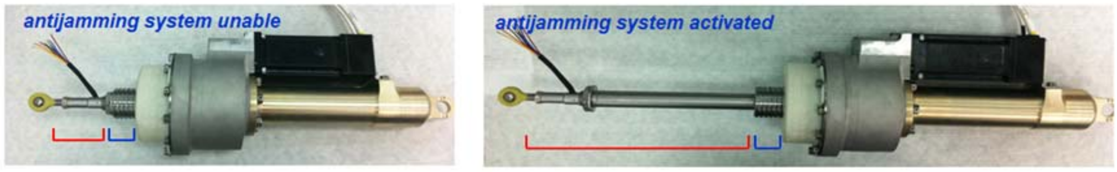

Figure 1: Antijamming system

The objective of this work is to implement a Health Monitoring System for the EMNOLDGDA actuator. The monitoring system would be able to identify some faults of the system, which would be notified to the control unit which is responsible to execute the actions that it considers appropriate to prevent them in real time (i.e. the activation of the anti-jamming system). Monitoring information would be available to be used by the control unit to monitor the estate of the UAV in real time and it could be saved to its evaluation on the ground as shown in Wang (2012). It would allow to schedule for the maintenance of the UAV and make predictions about the future behaviour of the system. This work is focuses on the use of machine learning algorithms for the development of algorithms for early detection of some faults of the system. We have opted for the evaluation and the use of these algorithms due to their capacity to face nonlinear functions, which makes them suitable. They are already being implemented and integrated into Prognostics and Health Management (PHM) systems developed for some aeronautical applications, as shown in Ferreiro (2012) and are working to overcome unscheduled maintenance problems by integrating all the condition monitoring, health assessment and prognostics into an open and modular architecture and then further supporting the operator by adding intelligent decision support tools.

2. HM approach based on Simulation modelling and Data-Driven techniques

This work introduces the development of a HM system based on the monitoring and diagnostics of EMNOLGDA electro-mechanical actuator at full system level. Usually, the main barrier to achieve good algorithms that comprise the HM system is to obtain the data from which to establish patterns of the system behaviour and test theories. Early in the project in which this work was carried out, neither the actuator nor its test bench were completed or available, this is because they were still a design phase, thus making the real experimentation unfeasible. As a consequence, a model based on simulation modelling was developed, taking into account initial requirements and design specifications. This model has been updated as new specifications have been obtained, until the development of the final simulation model. This final model is able to fix the behaviour of the actuator by means of simulation techniques (Simulink model), which makes it possible to analyze, identify and select those signals to be utilized for the development of the state detection and prediction algorithms of the HM system of the actuator, and also to be monitored later in the real EMA system as input to these algorithms.

2.1 ‘EMNOLGDA’ Simulation Modelling

In order to model an electromechanical (EM) actuator, the physics to be considered have to be defined first. In this paper the dynamics mechanical behaviour of the actuator as well as the control and power signals governing the actuator have been considered. The model development platform is Simulink®. Figure 2 shows a block diagram of the actuator: the system block includes the mechanical behaviour of the actuator, the motor block is a simple representation of the actuator motor and converts current into actual torque/force applied to move the actuator, the control block computes current commands based on the set-point and the measured actuator position and velocities. Additional blocks have also been included to consider external forces (perturbations) and friction phenomena.

A state-space representation has been used to define the machine mechanics. Prior to that, the mass and stiffness matrixes of the actuator are computed based on the characteristics of the different components (inertias, stiffnesses, screw pitch, gearboxes, etc.). Such matrixes can be analytically obtained for the considered degrees of freedom. Once the dynamic characteristics of the system are defined, a modal reduction is applied and the dominant vibration modes are concentrated in state-space form for the simulation. The system is controlled through a conventional PI controller used in actuators, where nested position and velocity loops are used. The velocity loop includes a PI controller while the position loop comprises just a proportional gain. It is assumed the bandwidth of the current loop is much higher than the mechanical bandwidth or other control loops (position, velocity), so an ideal current loop is considered (transfer function equal to 1).

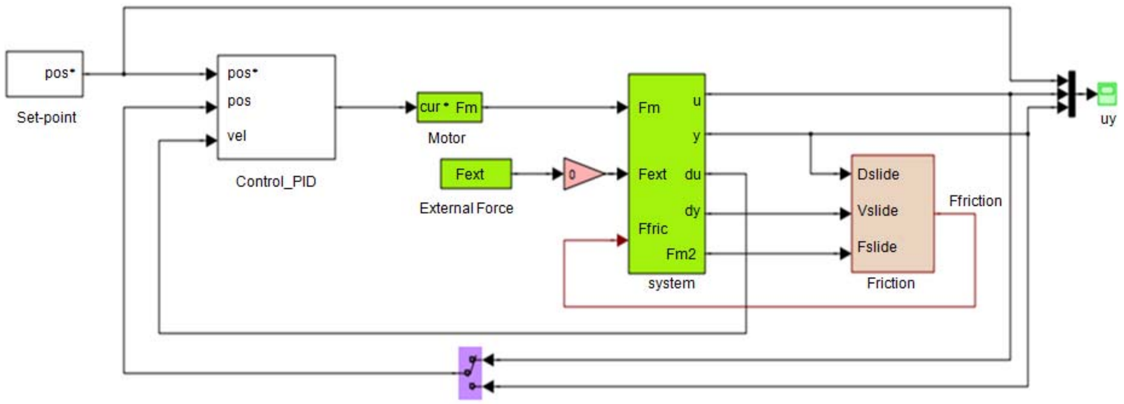

Figure 2: Simulink model of EMA

All signals within the model can be monitored for HM algorithm analysis and development purposes.

2.2 Description of the Failure Modes

The following failure modes have been considered so far in this work: friction induced failures, motor degradation, backlash and external perturbation effects.

Friction is an external perturbation opposed to the actuator movement. A friction model has been implemented in the model in order to consider the implications of excessive friction. The friction model includes both static and dynamic regimes. In the static regime friction is proportional to the applied force up to a tuneable limit. When such a limit is surpassed, sliding movements between the contacting surfaces occur and the dynamic friction regime applies (Coulomb's law based). Two friction set-ups corresponding to low and high speeds have been used. At low speeds, friction force reduces as speed increases so that a smooth transition occurs from stop to movement. This is the so-called Stribeck effect and it is related to the formation of a thin lubricant layer that separates the contacting surfaces. At high speeds, under lubricated conditions, an additional viscous friction term has been included, which implies a friction force increase with velocity.

Lubrication and friction increase failures are related to various mechanical problems. By varying the friction coefficients within the model, the effect of such failures can be analyzed.

Although the rest of non-linearities mentioned above (backlash, motor degradation and external perturbations) are not further explained in this section, they have also been implemented for the HM system.

2.3 Experimental Setup

The simulation model, explained in the previous two sections, reproduces the completed extension-wait-retraction movement of the EMA in 6 seconds. The time is enough to capture the entire process because the speeds and lengths have been set in the simulation model, is this, necessary taking into account the specifications of the EMNOLGDA. According to the behaviour defined for the system and set into the Simulink model there are more phases in the movement: from tini to tini+1 (phase 1) the system accelerates to the maximum speed; from tini+1 to tini+2 (phase 2) the system moves to constant speed; from tini+2 to tini+3 (phase 3) the system decelerates reaching the stop approximation speed 'vdamp'; from tini+3 to tini+4 (phase 4) the system moves to constant speed 'vdamp'; and finally from tini+4 to tini+5 (phase 5) the system decelerates until the system brakes completely. The extension process is then completed. Next, it remains stopped (waiting) 'twait' time and the process is repeated in the opposite direction (retraction process).

The first task to be performed is to test the effect of the induction of each fault in the behaviour of the system and to determine the ranges of the observed differences in the signals with respect to their behaviour without fault. This allows us to check whether the required resolution for detecting such variations in the signals may be problematic or not for the final implementation. A straightforward initial

analysis has concluded that the accelerations (vibrations) and the current signals are those that are the most useful. Nevertheless, the acceleration signal was not available in the EMNOLGDA system and this would have to be calculated from the position signal, making it a noisy and not very useful signal for analysis. Moreover, to add accelerometers in the system is not a viable option and finally it was decided to study the current signal as an alternative signal to try to obtain the algorithms based on its information together with the use of data-driven techniques.
Figure 3 shows the current signal, along the finished extension-wait-retraction movement, for the normal behaviour of the actuation system and when friction fault is injected, as well as the range of difference between them trough the signal.

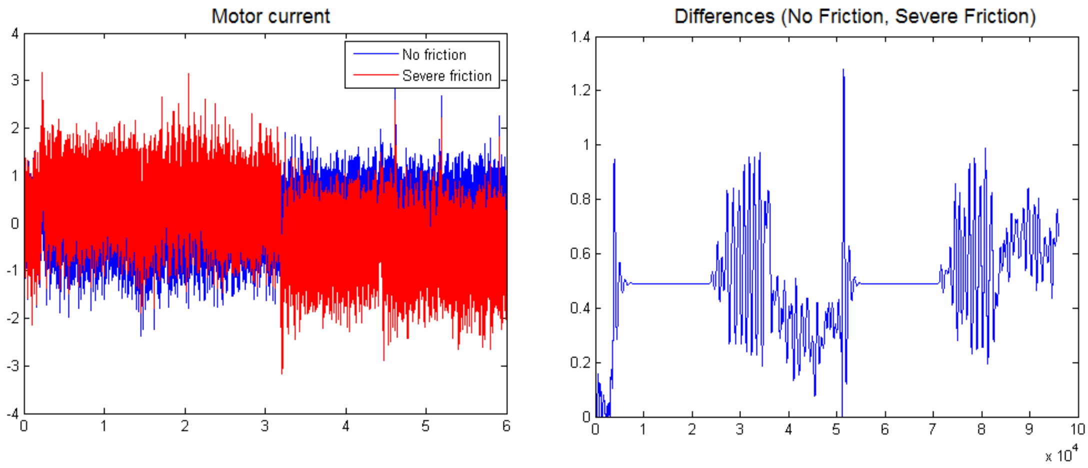

Figure 3: current signal and differences between normal behaviour and when there is friction

In order to develop the Health Monitoring system for the electro-mechanical nose landing gear door actuator of the UAV, based on a combination of simulation modelling and data-driven techniques, datasets related to the actuator in the extension-retraction control system are required. These datasets include the data of actuator normally working during extension-retraction process.
The simulation modelling has been performed in this work and different levels of fault according to the fault modes were added. In this way, the simulation data under different levels of fault can be accessed and collected, as well as normal behaviour data. Furthermore, the simulation model incorporates an additional noise which makes the model non-deterministic. According to the description of the faults for the system, ten patterns have been assigned respectively: the system working normally, friction (mild/moderate/severe), motor degradation (mild/moderate/severe) and backlash (mild/moderate/severe). The simulation tests have been performed for both normal and abnormal operating conditions, and several tests for each case have been collected in datasets. However, the simulation has been carried out independently and there is no more than one fault injected at the same time.
Next, the signal has been split into the 11 aforementioned phases (5 for the extension movement + 1 wait + 5 for retraction movement) and a pre-signal processing has been performed, transforming them into a series of statistical variables (predictors) corresponding to the time domain signal, in order to subtract computation and processing time.
In order to develop the final models for the early detection of these faults by supervised techniques it is necessary to classify or label the data (tests) collected during the simulation tests. The final datasets, one for each phase of the extension-retraction process, from which the learning process is performed by applying machine learning algorithms, consist of tests that include both the signal predictors and the type of fault that has been introduced (class or label).

2.4 Experimental Results and Evaluation

Afterwards, some algorithms based on machine learning techniques have been used. Machine learning as defined in Mitchell (1997) is a subfield of artificial intelligence and its aim is to develop algorithms that allow the machines to learn from data in order to develop programs which are able to induce models that improve their performance over the time from data. It is a knowledge induction process. The aim within this work is to acquire knowledge about the phases of the current signal that may contain information, from which the type of fault can be determined different degrees of severity in order to avoid a catastrophic failure in the EMA. Machine learning mixes mathematical elements with statistics and computational

sciences. The development of the present work has been performed using Weka software, which is a collection of machine learning algorithms written in Java and developed by the University of Waikato (Australia). Some of these algorithms have been utilized and tested with the datasets of the defined phases of position set-point of the EMA: based on probabilities (BayesNet, NaiveBayes), classification trees (J48, ID3), induction rules (JRip, Ridor), k-nearest neighbors (IB1, IB5), logistic regression (Logistic) and neural networks (MultilayerPerceptron).
In the case of friction, mild friction is not detectable by the algorithms. They do not discern the variance among datasets in order to identify the differences between the normal behaviour and the injected fault. However, some of these algorithms obtain good results to predict moderate and severe friction. The best two approaches to predict moderate friction seems to be J48 and JRip. They provide an estimated success rate of 71.90 % and 71.10 % respectively when tested for the phase 2 dataset, although ID3 and BayesNet reach similar results too. Moreover, ID3 and BayesNet obtain the best performance to detect severe friction (see Table 1), their result being very close to 90 % of estimated success rate for the phase 8 dataset. But there are other algorithms with similar estimated success rate, J48 and JRip. It must be highlighted that for both moderate and severe friction prediction, these algorithms (J48, JRip, ID3 and BayesNet) obtain valid results for the phase 2 and 8 datasets.

Table 1: Severe friction (μ_e)

	Algorithm									
Phase	BayesNet	NaiveBayes	Logistic	Multilayer Perceptron	IB1	IB5	JRip	Ridor	J48	ID3
phase 1	50.00	39.60	28.30	25.90	05.40	05.30	50.00	48.70	50.00	50.00
phase 2	87.10	78.00	86.80	87.10	54.00	70.70	84.40	83.80	85.90	86.60
phase 3	50.00	41.20	22.90	28.20	06.20	05.10	50.00	48.90	50.00	50.00
phase 4	64.30	60.10	72.50	61.60	08.40	38.40	72.30	68.40	62.40	64.30
phase 5	50.00	29.80	21.60	28.80	05.20	05.30	49.40	48.30	50.00	50.00
phase 6	75.50	65.80	72.60	65.20	18.10	46.50	78.30	74.10	73.60	75.50
phase 7	50.56	25.97	22.76	26.43	07.53	07.02	49.36	48.72	50.56	50.56
phase 8	87.60	79.90	82.10	81.00	29.10	71.80	86.60	84.20	86.60	87.60
phase 9	50.00	37.50	20.70	28.70	06.00	06.00	49.30	47.10	50.00	50.00
phase 10	70.90	59.10	64.60	63.70	07.40	33.90	73.30	66.20	68.80	70.90
phase 11	50.00	45.10	20.30	27.90	05.90	06.00	50.00	48.60	50.00	50.00

The main conclusion is that the algorithms provide better results when they are tested in the datasets of the phases in which the movement takes place at constant speed: phases 2 and 8. That is because in these phases the operating conditions remain constant. Moreover, it can be observed that Bayesian methods, induction rules and classification trees are the algorithms which provide the best results. And as a final remark, they are very intuitive and easy to implement into the system. That is the reason why they have been proposed to be implemented in EMNOLGDA in order to detect friction and other failures from the current signal extracted from the extension movement.

2.5 Functional failures

Table 2 summarizes the failure modes described above, as well as indicates potential consequences and functional failures for each case.
No fault modelling allows to identify the potential fault in the specific component, but the failure could be due to several components. And if a functional level diagnostic of the system is required, each component of the actuator must be modelled by multi-physics modelling. Nevertheless, from this modelling it is possible to derive the effects of some malfunctions of the system as explained in Table 2. Taking this information into consideration it is possible to make further decisions and take actions to prevent a catastrophic failure. For example, in the case of EMNOLDGA actuator, if serious friction in the opening of the landing gear was detected, then the anti-jamming system would be launched in order to prevent serious damage. Or if moderate friction was predicted, scheduled maintenance actions would be carried out when the UAV landed.

3. Conclusions and Future work

The reliability of the actuator in the flight control system is an important issue that usually depends on some testing performance under extreme operating conditions. The implementation of the HM system improves the reliability of the actuator, monitoring and providing the state detection by taking into account some faults that may generate and cause damage to the actuator as well as its malfunction (i.e. excessive wear or jamming).

The work introduces some steps to be performed in order to develop a HM system from the design stage of the actuator, when there is no test bench to experiment. It demonstrates the effectiveness of machine learning algorithms to realize the system state detection, as well as to decide which parts of the signal contain more information (variance) to distinguish between the normal behaviour and some faults. These algorithms are not commonly used in some fields of application but they have great potential to be applied and obtain valid results and they should be evaluated. Besides, as fault degrees can be detected, it would make it possible to predict the remaining useful life by adopting some regression methods, taking into account the working life of the system and using the result of the state detection for every operating cycle.

The most important result of this research is that the HM system, based on the current signal and some of the machine learning algorithms, is able to detect the friction fault at different levels in order to provide the report to the actuator control unit that should take the required actions (i.e. use the anti-jamming mechanism). Nevertheless, the algorithms need to being readjusted and further work includes real experimentation, being planned but still pending, and final validation.

Table 2: Summary of contemplated failure modes

Simulated failure	Potential consequence	Potential functional failure
Degraded motor	- Slower actuator response - Irregular behaviour risk if current saturates - Risk of surpassing equivalent thermal torque	- Motor heats up: stop and/or burn - Motor not capable of moving load (according to requirements)
Friction increase	- Slower and more damped system - Increase of required torque - Irregular behaviour risk if current saturates - Risk of surpassing equivalent thermal torque	- Wear of contacting elements - Actuator blocking due to excessive friction - Motor heats up: stop and/or burn - Motor not capable of moving load (according to requirements)
Backlash	- Actuator does not move for a while during inversions - Non-linear behaviour: strong discontinuities in the force applied on the conducted element during inversions	- Enhanced fatigue/wear of elements involved in backlash - Positioning precision loss
External force	- Increase of required torque (worse if the force is applied in the opposite direction to the movement) - Irregular behaviour risk if current saturates - Risk or surpassing equivalent thermal torque	- Fatigue of mechanical elements of perturbation is periodic and sustained - Motor heats up: stop and/or burn - Motor not capable of moving load (according to requirements)

Acknowledgements

The authors gratefully acknowledge the support of the CENIT-E 2009 programme for Research and Technological Development, which aims to acquire new knowledge and developing technologies to reduce environmental impact and increase the efficiency of UAVs taking into account five technological areas: materials, processes, platforms, operation and life cycle. This article summarizes work performed as part of CENIT-E project SINTONIA 'Unmanned Systems Oriented to the Null Environmental Impact'.

References

Ferreiro, S., Arnaiz, A., Sierra, B., and Irigoien, I., 2012, Application of Bayesian networks in prognostics for a new Integrated Vehicle Health Management concept, Expert Systems with Applications, 39(7), 6402-6418.

Mitchell, T. M., 1997, Machine Learning, McGraw-Hill, Inc., New York, NY.

Wang, J., Ding, W., Lu, A., 2012, Design of UAV Ground Auxiliary Warning System Based on Data Mining, in Prognostics and System Health Management (PHM), 2012 IEEE, 1-4, DOI: 10.1109/PHM.2012.6228828.