

ON FLIGHT DYNAMICS MODEL IDENTIFICATION AND OPTIMAL FLIGHT TEST PROTOCOL DESIGN

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Abstract

The flight dynamics models have many important applications in aircraft development which imply that their reliability must be high. To fulfill this objective, AIRBUS has developed for years an identification process but new requirements like building more accurate models in a shorter time lead to revisit this process. In this context, an optimization methodology of the flight test protocols based on the **Genetic Algorithms (GA)** technique has been developed. After a presentation of the current identification process at AIRBUS, this paper describes this new methodology and shows with some examples that it constitutes a viable alternative to the current procedure.

1 Introduction

For each new civil aircraft program, a model of the flight dynamics is built and applied to:

- analyze the handling qualities of the new aircraft;
- design, validate and integrate systems (especially the flight control laws);
- assess the predicted load calculations;
- allow crew training on simulators in airline companies (see fig.1).

The growing development of numerical simulation in aviation industry has increased the constraint on the reliability of the flight dynamics model. For any application, the flight dynamics



Fig. 1 A380 flight simulator.

model must be the most representative of the real aircraft on its whole flight envelope.

This paper firstly describes the identification process applied today in AIRBUS to flight dynamics model identification. As the requirement for building an accurate aircraft model in a shorter time is permanent with a view to simulator certification, the issue of an optimization of the flight test protocols used to excite the aircraft is also tackled in a second part.

2 Aircraft identification process in AIRBUS

The aircraft identification process follows a schedule whose milestones are given by figure 2. Several phases can be distinguished in this timetable. The process starts by building a preflight model of the flight dynamics. Then, flight test protocols are performed on the real aircraft and the aerodynamic model is adjusted on the basis of the collected flight data. The type

certification deadline (tc) puts an end to this process. At that time, the aerodynamic parameter adjustments are frozen and the flight dynamics model is validated. Consequently, it can be used for pilot training simulation.

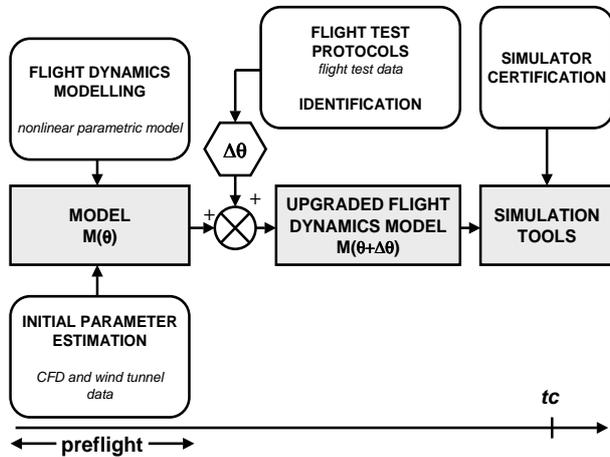


Fig. 2 Modelling, identification and certification timetable: from preflight model to certified simulator.

2.1 Flight dynamics modelling

Flight dynamics modelling is based on the non-linear equations of the flight mechanics. The external forces and moments for aerodynamics, propulsion and gravity are considered. The aerodynamic force and moment coefficients are parametrized as nonlinear functions of the attitude angles, angular velocities, control surfaces deflections and flight conditions ($Mach$ number (M) or $Angle\ of\ Attack$ (AoA), dynamic pressure, aircraft slats/flaps configuration...). They are calculated from look-up tables defined at several points of the flight domain. The parameters of the model correspond to the usual aerodynamic stability and control derivatives. Longitudinal and lateral dynamics as well as ground effects are modeled. Computational Fluid Dynamics (CFD) and wind-tunnel test data give a first estimation of the aerodynamic effects and allow to build a preflight model (see fig.3). However to reach an acceptable level of accuracy in simulation, the coefficients of the model must be adjusted on the

basis of flight test data obtained through a campaign of several flight tests.

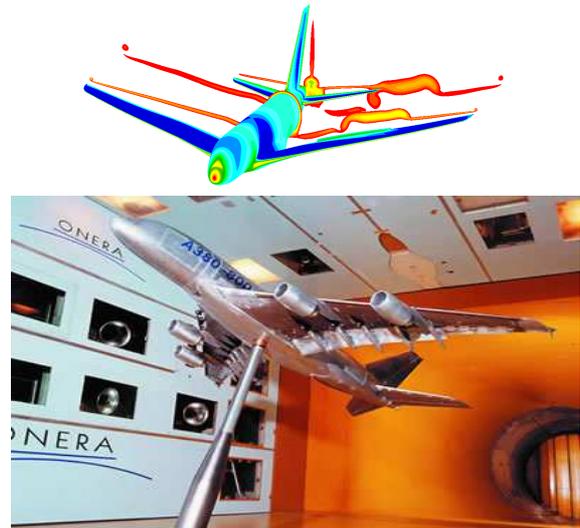


Fig. 3 CFD and wind-tunnel test data allow to build a correct preflight model and to gather *a priori* knowledge.

2.2 Experimental protocol and flight tests description

Flight test protocols are designed and flown for some relevant and operational points in the flight envelope of the aircraft. Then, interpolations between these points allow to build an accurate model over the whole flight domain of the aircraft. The nonlinearities and the complexity of the aerodynamic model lead to estimate up to 100 parameters for each flight test point of the aircraft flight envelope. As a result, between 1000 to 1500 ground and flight tests are performed to identify all the parameters.

Each flight test can be described as follows: after an aircraft trim phase at the selected flight condition, a computer generated pulse signal for a given deflection level is directly sent to one control surface (*aileron*s, *spoiler*s or *rudder* for the lateral flight - *elevator* for the longitudinal flight) and the free response of the aircraft is recorded for about thirty seconds. Then, the pilot who has no direct action during these initial steps, recovers the aircraft to stabilize it again

at the flight test point. Several deflection amplitudes are done to identify the nonlinear effective-nesses. After that, the pilot stabilizes the aircraft at the next flight domain condition and the whole procedure is performed again.

In the case of the lateral flight, these tests are typically:

- roll and yaw rate responses through input signals sent to ailerons, spoilers and rudder;
- steady state sideslip. This kind of test allows to estimate accurately ratios between stability and control derivatives (see fig.5 and 6);
- more piloted flight tests such as: dynamic engine failure, engine out trim and minimum aircraft control speed (maximum rudder deflection) which allow to estimate particular nonlinearities.



Fig. 4 Dutch Roll flight test through a spoilers pulse input.

They bring relevant information for the identification of the aerodynamic parameters and are based on the experience of our specialists. The simplicity of the input signals in the current flight tests allows to keep the aircraft responses readable by our experts. Natural modes of the aircraft such as dutch roll (see fig.4), spiral stability and roll response for the lateral flight and phugoid and short period for the longitudinal flight are observed on the data and provide,

through the analysis of the specialists, a first qualitative idea of the adjustments required in the model. However, combined with the complexity of the model, it can lead to design exhaustive experimental protocols. Consequently, the total flight test time allocated to the identification process can be huge.

2.3 Identification methodology

Aircraft flight dynamics identification is carried out according two methodologies based on different principles:

- the first one determines the aerodynamic forces and moments applied to the aircraft and uses an equation error approach to analyze the steady state sideslip flight tests. This allows to estimate some nonlinearities;
- the second one deals with the application of the output error approach (**OEA**) and allows to estimate more precisely the aerodynamic parameters from all the maneuvers sent to the aircraft.

The identification process is based on the information available in the specific steady state sideslip experiments (see fig.5 and 6). Some states of the aircraft are piloted to be kept near zero during this type of flight test while the aircraft is stabilized at a given sideslip amplitude. Several sideslip levels are swept. This allows to determine the dependence of some coefficients towards the sideslip effect. By a comparison with the real aircraft, some relations can be established and ratios are estimated between particular state and control derivatives. The sideslip nonlinearities can be identified as well as nonlinear effectivenesses (see fig.6).

Parameter estimation is then completed by the application of the **Output Error Approach (OEA)** (see fig.7) to the data collected during the flight test campaign. It allows to estimate more precisely the corrections of the aerodynamic parameters to be applied. State derivatives and

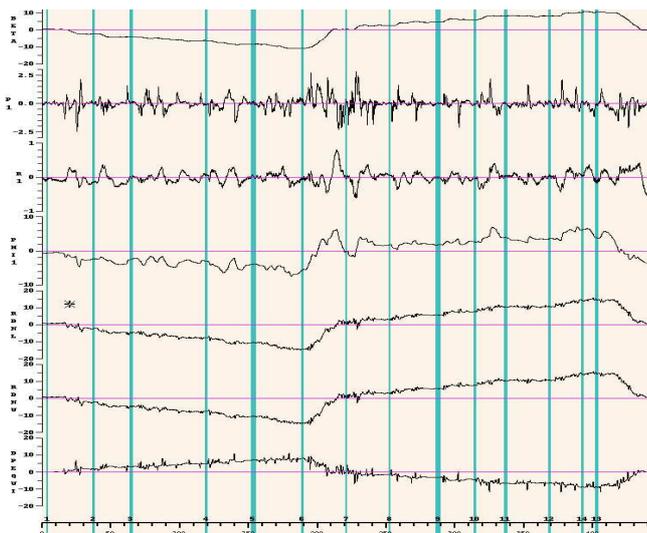


Fig. 5 Steady state sideslip data processing. Selection of the stabilized sideslip phases.

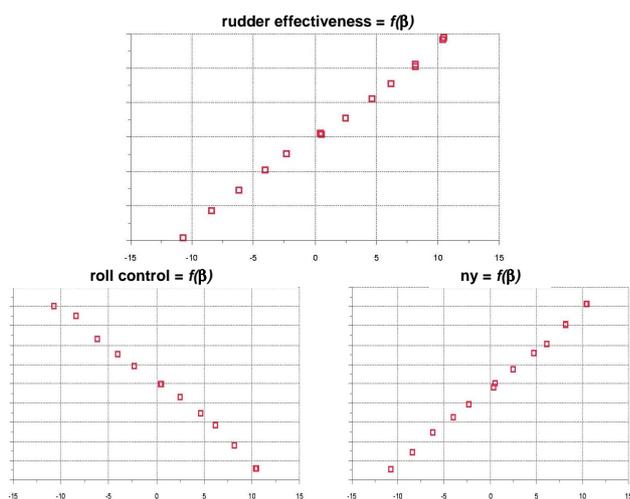


Fig. 6 Analysis of the stabilized points. Sideslip dependency of some variables.

deflection effects as well as particular nonlinearities are estimated. They allow to refine the global and stationary effects in the flight dynamics model.

As the experts have a preflight model of high quality at their disposal, this identification methodology which is based on the minimization of an output error criterion computed from the measurements and the simulated outputs, appears well adapted for the nonlinear estimation of

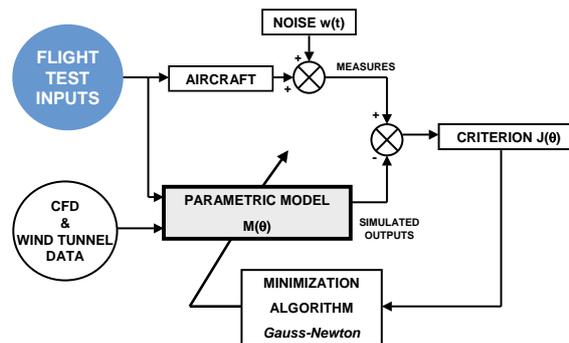


Fig. 7 The OEA methodology

the aerodynamic parameters. It reproduces with a good quality the global aircraft behaviour in simulation while it is more difficult and it requires more time of analysis to distribute precisely the adjustments between all the aerodynamic effects. Thus, some difficulties subsist: for example, the processing of the information through test data does not allow to separate some aerodynamic effects accurately. Single input excitations generally provide a good estimation of the control surface effectivenesses while it is more difficult to sort the aerodynamic effects corresponding to the state variables (*sideslip, roll and yaw rates for the lateral flight*). A higher level of accuracy is possible by modifying the identification process and especially the flight test protocol.

3 New requirements

Even if flight dynamics modelling and identification methodology have reached a high level of maturity at AIRBUS, the accuracy improvement of the estimated parameters and the reduction of the total flight test time are permanent concerns. The schedule for aircraft simulator certification becomes shorter and shorter (see fig.2) and the constraint on the reliability of the flight dynamics model for simulation increases. Combined with a reduction of the flight test campaign costs, these factors raise a need for optimizing the flight test protocols. Moreover, the application of new control law strategies (new designs, management of structural loads and passenger comfort, handling

qualities performance...) involves the design of more accurate flight dynamics models. Consequently, a thought about an optimization of the current experimental protocols dedicated to flight dynamics model identification has started. It aims at improving the accuracy of the model in simulation while reducing the flight test campaign costs.

As the aerodynamic parameter estimation process is dependent on the quality of the inputs sent to the aircraft, a new optimization methodology has been developed in order to design more informative flight test protocols. It uses the principles of the **Genetic Algorithms (GA)** optimization technique. It is capable of generating through an evolutive process an optimal set of several input signals constituting a flight test protocol.

4 Experimental protocol optimization

4.1 Problem formulation

The state of the art in the field of **Optimal Input Design (OID)** points out as a reference the methodology developed by E. A. Morelli and V. Klein ([2] and [5]) which applies the principles of *Dynamic Programming (DP)*. This method builds dynamically an optimal input towards a mathematical criterion. Due to some limitations of the **DP** optimization technique (discretization, CPU time...), we have developed a new algorithm which applies the principles of the *Genetic Algorithms (GA)* optimization technique for solving **OID** problems. It is able to solve a large panel of optimization problems:

- **Single Flight Test with Single Input (SFTSI)**;
- **Multiple Flight Tests with Single Input (MFTSI)**;
- **Single Flight Test with Multiple Inputs (SFTMI)**;
- **Multiple Flight Tests with Multiple Inputs (MFTMI)**.

The **MFTSI** framework corresponds to the closest formulation for optimizing the current flight test protocols. This optimization methodology builds an optimal set of n ($n \geq 1$) input signal(s) towards an optimization criterion which is significant of the global accuracy of the estimation. The most common criteria used for optimization are based on the *fisher's information matrix F*:

- $\text{tr}\mathbf{F}$: represents the amount of information available through the set of flight tests but does not take into account the possible correlations between the effects;
- $\log(\det\mathbf{F})$: is indicative of the global sensitivities collected for a given set of flight tests. Inputs which maximize this scalar norm are called *D-optimal*;
- $\text{tr}\mathbf{F}^{-1}$: is equal to the sum of the variances of the parameter estimation errors. \mathbf{F}^{-1} is known as the *dispersion matrix*. The inputs which minimize this criterion are called *A-optimal*;
- λ_{\max} of \mathbf{F}^{-1} : is equal to the maximum radius of the uncertainty ellipsoid.

We have chosen to minimize the trace of the dispersion matrix. The optimization is subject to some constraints: the designed input signals must be feasible and their use in flight test condition must respect safety constraints. Moreover, as the identification is made for one flight condition of the aircraft envelope¹, input and output limitations must be introduced to avoid any departure of the aircraft from this point. The candidate input signals chosen for each flight test are multistep signals whose amplitudes can be chosen among the break points of the look-up tables. Another input forms are possible (ramp, sinus...). By combining several deflection amplitudes in an

¹so that the experimental conditions can be considered stationary over the whole flight tests composing the experimental protocol

only single flight test a significant gain in the total flight test time can be made thanks to this optimization algorithm.

For improving the overall level of accuracy, research works have shown that it was valuable to add closed-loop flight tests in order to separate strongly correlated aerodynamic effects [7]. In this case, only a reference input signal sent to a control law has to be optimized. An alternative solution will consist in sending a set of correlated inputs to the dynamic system so that system outputs will be decorrelated. These two approaches have their own advantages:

- the synthesis of correlated inputs in open-loop in a **OID** framework can be highly parametrized and offers numerous degrees of freedom;
- the closed-loop framework is potentially more robust towards model uncertainties;
- the flight test constraints of the optimization problem can be managed more easily in the closed-loop framework because some states of the aircraft are commanded by a control law;
- existing control laws can be used at first to realize the closed-loop solution, especially the decoupling control laws.

and their own drawbacks:

- constraints may be difficult to manage in the open-loop case;
- fewer degrees of freedom are available for the closed-loop optimization;
- the closed-loop framework is a new optimization problem in which little experience has been accumulated.

Using closed-loop experiments together with more classical open-loop tests appears as a new idea in the identification domain which brings new perspectives for the field of **Optimal Experiment Design (OED)**. The optimization

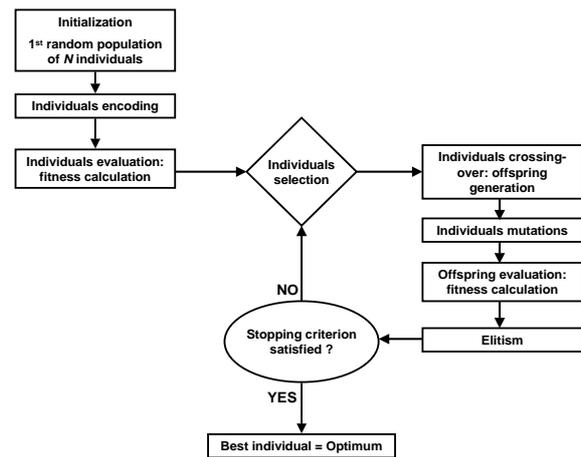


Fig. 8 Principle of the GA optimization technique.

tool developed to tackle **OID** problems is able to optimize flight test protocols composed of open-loop and closed-loop experiments. The latter feature is essential to optimize a global information in a **MFTSI** framework which mixes open-loop input signals and closed-loop reference inputs. Thus, optimization results and conclusions can be made in order to analyze the relevance of the closed-loop information contains in experimental protocols.

4.2 Basic principles of the GA optimization methodology

As the optimization problem formulation is global and complex (with a high combinatoriality), the use of a global and evolutionary optimization technique such as **GA** appears well adapted. The resulting algorithm follows the usual steps of the **GA** technique described in the theory [1]. The basic principle of such an iterative optimization methodology is summarized by the figure 8.

An important point in our optimization algorithm concerns the choice of a relevant parametrization for handling in an easy way the elementary input signals through the iterations. Each elementary input signal can be completely described by: the shape of a basic signal (in our study, the steps); and by the coordinates of each switching instant in the two-dimension subspace $\mathcal{E} = (time, amplitude)$ (see fig.9). The time and

amplitude parameters will be optimized in the procedure.

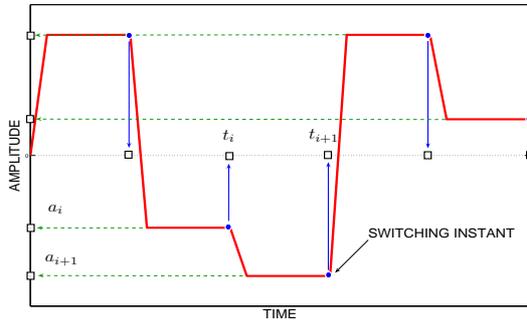


Fig. 9 Elementary input signal parametrization

As **GA** corresponds to a global optimization technique, an initialization is needed. A first random population of N ($N \in \mathbb{N}^*$) experimental protocol(s) is built. Each individual of the population must be admissible towards the constraints.

Then, in the main loop of the algorithm, a search for an optimal solution is accomplished thanks to the stochastic operators of the **GA** optimization technique. These stochastic operators operate as a function of the *fitness* associated to each individual of the current population. This *fitness* notion is based on the criterion value of one individual and can be interpreted as a mean to characterize the quality of this individual. Through the iterations, the mathematical parameters evolve and reach the optimum values. The quality of the optimum value (local/global) is dependent on the size of the population N , on the homogeneity of the initial random population and on some parameters proper to the stochastic operators of the **GA** technique.

4.3 Comparison with Dynamic Programming

This new optimization approach has been compared with the reference methodology using **DP**. Table 1 shows a qualitative comparison of the advantages and drawbacks of the two methods. The main advantage of the **DP** solver is its ability to manage easily the constraints of the problem

Table 1 Comparison between the **DP** and **GA** solvers.

| DP | GA |
|--|---|
| PRINCIPLE | |
| Builds dynamically an optimal input signal - Bellman principle | Builds globally a set of input signals - GA optimization technique |
| CPU TIME | |
| polynomial | linear |
| ADVANTAGE(S) | |
| <ul style="list-style-type: none"> - easy computation; - easy constraint management. | <ul style="list-style-type: none"> - easy computation; - global optimization; - search for a global optimum; - linear CPU time; - flexible optimization. |
| DRAWBACK(S) | |
| <ul style="list-style-type: none"> - space discretization; - CPU time prohibitive for high combinatory; - not very suitable for high complex OID problems. | <ul style="list-style-type: none"> - dependent on initialization; - dependent on population size; - highly parametrized; - stochastic method. |

while the use of the **GA** algorithm implies that the constraints are checked *a posteriori* for every individual created. Nevertheless, **GA** offers the possibility to optimize complex flight test protocols composed of several experiments. Combined with a linear CPU time when optimization complexity increases, the solver using **GA** is a viable alternative to the **DP** algorithm.

4.4 Discussion

The experimental protocol optimization raises some important questions that must be addressed in order to enhance the performances of any optimization methodology in this field (see also [3]). In comparison with the usual flight tests, the design of optimal inputs for flight experiments can lead to a loss of readability in the data collected during the flight test campaigns. This is an important point since the application of parameter estimation is strongly based on the experience and the know-how of the specialists at

AIRBUS. However, the use of softwares which apply some theoretical estimation methodologies justifies such an optimization. Consequently, the experimental protocols tends to become in a short-range forecast a mix of usual and optimized tests. The use of a global optimization technique such as **GA** for solving **OID** problems raises the issue of the interest to have a global optimum at our disposal for parameter estimation. Since we know that the search for a global optimum can be time consuming, attention must be paid to the fact that suboptimal solutions exist and could be used without losing the overall performances of the parameter estimation in terms of accuracy, flight test time and practical implementation of the inputs. Actually, the choice of a global optimization technique is mainly justified by the ability that global methodologies have to tackle high dimension optimization problems. Because of the global characteristic of the experimental protocol optimization formulation, this latter feature is a key factor for the choice of a mathematical optimization method. Besides, as any experimental protocol optimization is made over a preflight model, the optimal set of inputs designed must be robust with respect to potential uncertainties and undermodellings. Indeed, if the flight test time performance can be guaranteed through the mathematical formulation of the optimization problem, the performances in terms of accuracy can only be obtained in flight under the hypothesis that the preflight model corresponds exactly to the real aircraft that is practically never the case. This last point constitutes the main limitation and the paradox of the optimal experiment and input design fields. Some interesting research works by E. Walter and L. Pronzato [4] dealing with robust optimization can potentially help us in our application of optimal experiment and input design for aircraft parameter estimation and can provide a theoretical support to enhance the performances of our optimization algorithm.

5 Results

The case of the lateral flight is considered. The standard protocol is composed of eleven flight

tests with a pulse input. 34 parameters are to be estimated:

- *sideslip*, *roll* and *yaw rates* effects over the three aircraft axis for the lateral flight (9 parameters);
- 5 deflection level effects for *ailerons* and *spoilers* (22 parameters);
- global *rudder* effect (3 parameters).

In this example, the objective of the optimized protocol is to reach an equivalent level of estimation accuracy with a reduced number of flight tests and a reduced flight test time. Three optimized flight tests were selected:

- optimized *ailerons* input signal;
- optimized *spoilers* input signal;
- optimized *rudder* input signal.

The numerical results of this optimization are given in table 2. They show that a significant gain in the flight test time can be made by optimizing the input signals of a current protocol design and by concatenating pulses with different amplitudes for a given control surface into an only single optimized input sequence. The number of experiments is divided by 4 while the level of accuracy is only 22 percent over its initial value.

Table 2 Comparison of standard and optimized flight test protocols.

| PROTOCOL | CURRENT | OPTIMIZED |
|------------------------|---------------|-----------------------|
| NUMBER OF EXP. | 11 | 3 |
| CRITERION | 0.0718 | 0.0876 (+22%) |
| FLIGHT TEST TIME (FTT) | 352 secs | 96 secs (−73%) |
| FTT PER EXPERIMENT | 32 secs | 32 secs |

As the input signals are optimized over the total flight test time of each flight test, we can arbitrarily add for these optimized experiments a free response of the aircraft since the gain in the global flight test time is significant (−73%)

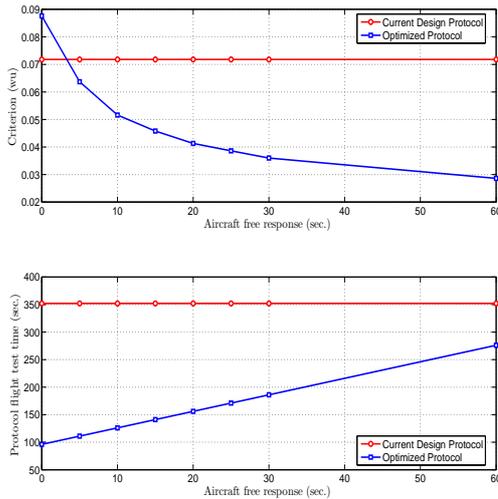


Fig. 10 Potential gain in flight test time through optimized input signals. Effect of the record of an aircraft free response in the optimized data.

and allows us to proceed this way. Thus, as a quantity of information is added through free aircraft responses, we can look for a gain in the level of accuracy provided by the optimized protocol design. Figure 10 shows the effects both on the accuracy of parameter estimation and the total flight test time of an additive free aircraft response. A significant gain in estimation accuracy can be made without penalizing the total flight test time since optimized input signals are designed. The reference values for the current protocol design are given by the red lines.

OED and **OID** results are now entered in a phase of validation in flight. A flight test campaign has been flown in order to validate the theoretical results obtained in simulation. The aim is to demonstrate that this kind of new input signals is able to provide at least the same level of accuracy for parameter estimation as in the usual flight test protocols while it is able to reduce significantly the total flight test time. Figures 11 and 12 show two examples of optimized input signal sent to one control surface of a large transport civil aircraft.

6 Conclusion

The optimization methodology applying **GA** presented in this paper has provided promising theoretical results. A better quality of the estimation and a reduction of the total flight test time can be obtained. Similarly, the idea to mix closed-loop information with usual open-loop information seems interesting to separate some aerodynamic effects. A first flight campaign including both optimized and closed-loop flight tests has been performed on a large transport civil aircraft to evaluate this method. In the future, we can expect that optimized tests realized in open or closed-loop will constitute an informative complement of the standard flight tests used today to identify the flight dynamics models.

References

- [1] Holland, J. H. *Adaptation in natural and artificial systems*. University of Michigan press, 1975.
- [2] Morelli, E. A. *Practical input optimization for aircraft parameter estimation experiments*. PhD.Report, George Washington University JI-AFS, DC, 1993.
- [3] Breeman, J. H., Mulder, J. A. and Sridhar, J. K. *Identification of dynamic systems - applications to aircraft - part 2: nonlinear analysis and manoeuvre design*. AGARD-AG-300, Vol.3 Part 2, 1994.
- [4] Walter, E. and Pronzato, L. *Identification de modèles paramétriques à partir de données expérimentales*. Masson, 1994.
- [5] Morelli, E. A. and Klein, V. *Application of system identification to aircraft at NASA Langley research center*. Journal of Aircraft, 42, pp.12-25, 2005.
- [6] Seren, C., Bommier, F., Bucharles, A., Verdier, L. and Alazard, D. *Flight test protocol optimization using genetic algorithms*. 14th IFAC Symposium on System Identification Proceedings, 29-31 March 2006, Newcastle, Australia.
- [7] Seren, C., Bommier, F., Bucharles, A., Verdier, L. and Alazard, D. *Optimal experiment and input design for flight test protocol optimization*. AIAA Atmospheric Flight Mechanics Conference and Exhibit Proceedings, 21-24 August 2006.

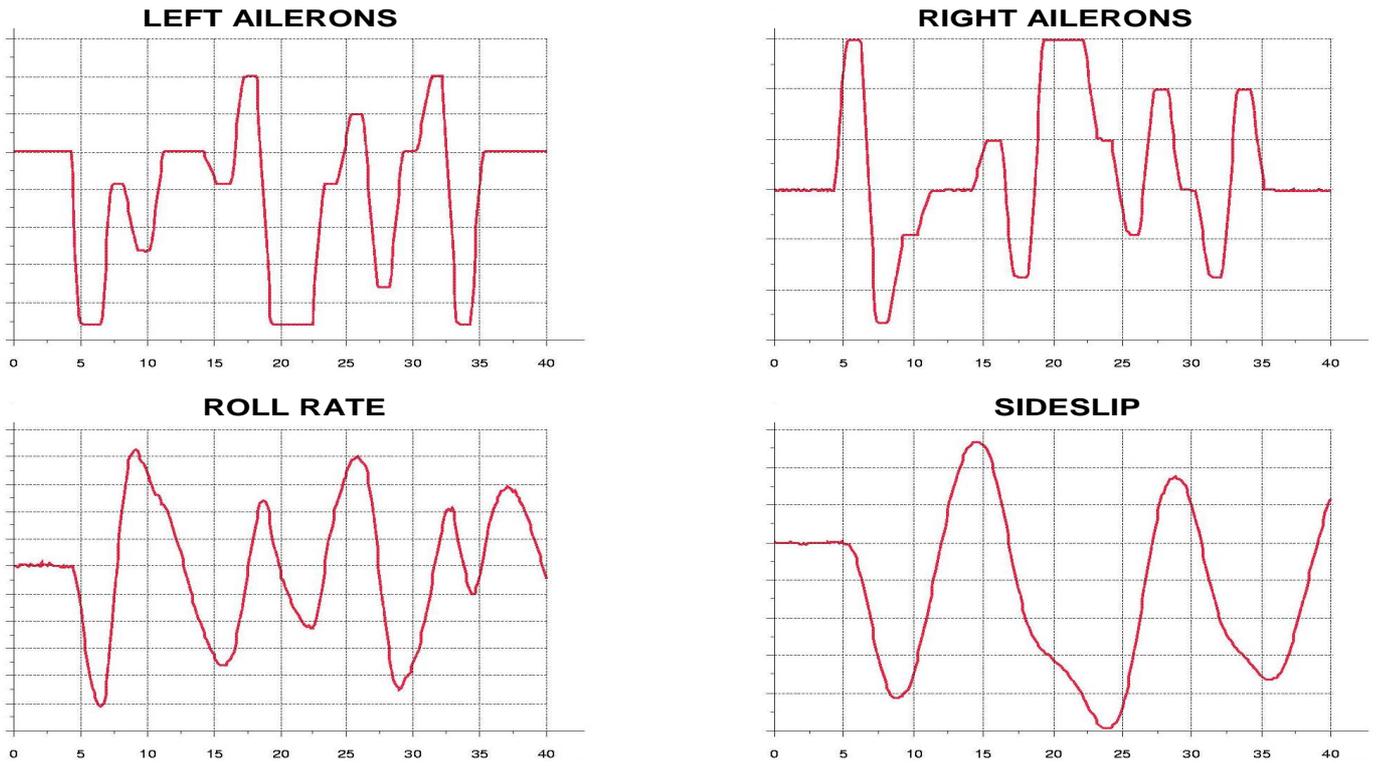


Fig. 11 Example of optimized ailerons flight test.

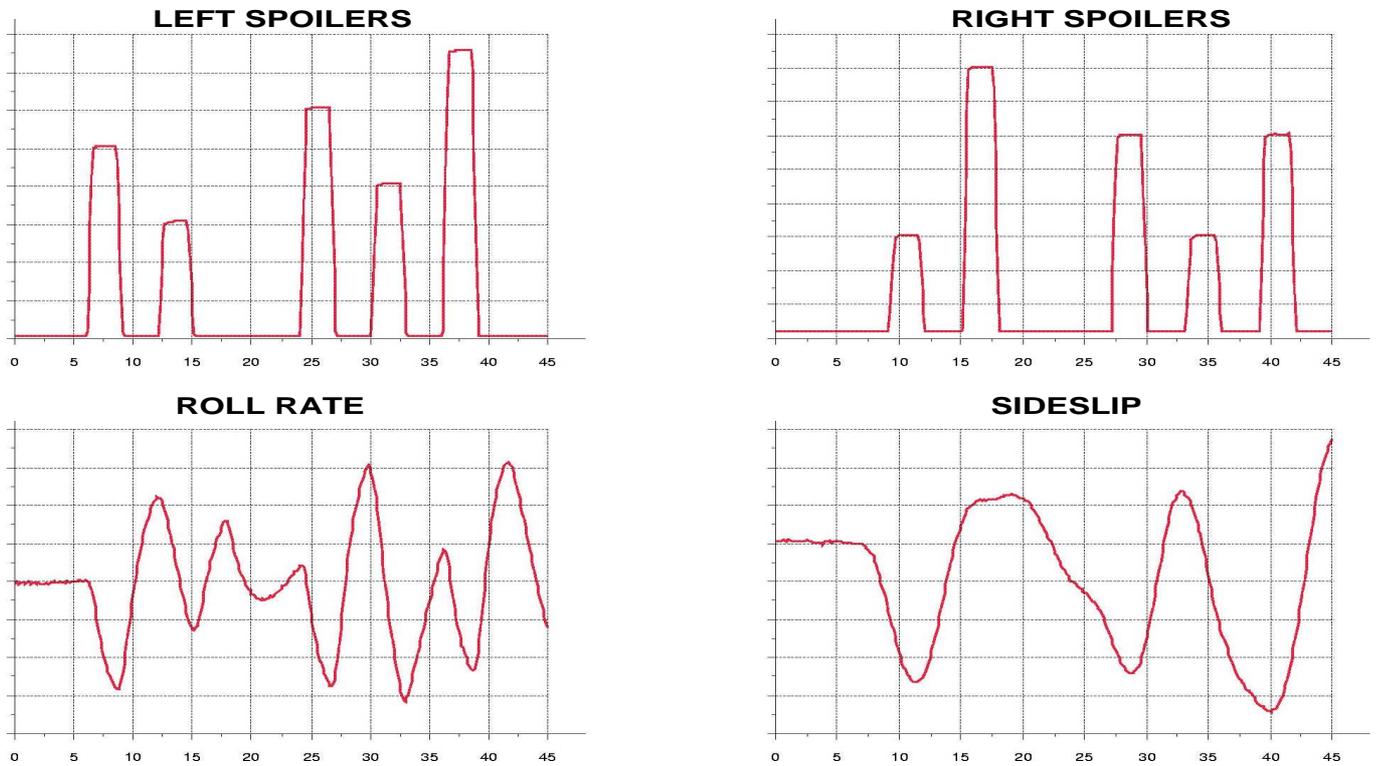


Fig. 12 Example of optimized spoilers flight test.