

AN ONLINE PARAMETER ESTIMATION TOOL

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Abstract

The first version of a new online parameter estimation tool is presented. Based on the maximum likelihood parameter estimation method, the tool is able to process measured data during a flight test and to deliver parameter estimates for a predefined model. Two decision methods are implemented for selecting flight data segments which are suitable for parameter estimation. First test results with simulated and measured flight data of DLR's research aircraft ATTAS are presented, showing the applicability of the tool and the implemented decision methods.

NOMENCLATURE

<i>active</i>	Segment activation indicator	$C_{M,t}$	Pitching moment coefficient of the tailplane
<i>ALT</i>	Altitude	ΔC_M	Additional pitching moment coefficient
a_x	Acceleration (x-direction)	e	Oswald factor
a_z	Acceleration (z-direction)	ε_t	Downwash angle at the tailplane
α	Angle of attack	$\Delta \varepsilon_t$	Additional downwash angle at the tailplane
α_t	Angle of attack at tailplane	$\frac{\partial \varepsilon_t}{\partial \alpha}$	Downwash angle change with angle of attack
α_{dyn}	Dynamic angle of attack of the tailplane	η	Elevator deflection
β	Angle of sideslip	f	Nonlinear state function
C_D	Drag coefficient	g	Nonlinear observer function
C_{D0}	Zero drag coefficient	i_t	Tailplane trim angle
ΔC_D	Additional drag coefficient	i, j, k	Indices
C_L	Lift coefficient	J	Cost function
C_{L0}	Zero lift coefficient	Λ	Aspect ratio
$C_{L\alpha}$	Lift curve slope	\mathbf{v}	Measurement noise vector
$C_{L\alpha_t}$	Lift curve slope of the tailplane	N	Number of measurements
$C_{L,\eta}$	Lift change due to elevator deflection	n_b	Number of first data segments
$C_{L,t}$	Lift coefficient of the tailplane	n_{out}	Number of weighted model outputs
$C_{L,wb}$	Lift coefficient of wing and body	Ma	Mach number
C_{M25}	Pitching moment coefficient at neutral point	p	Likelihood function
C_{M0}	Zero pitching moment coefficient	p	Roll rate
		Φ	Roll angle

q	Pitch rate
R	Measurement covariance matrix
S	Wing area
S_t	Tailplane area
σ	Standard deviation
θ	Pitch angle
Θ	Parameter vector
t	Time
Δt	Time step / delay
t_0	Start time
t_k	Discrete time
u	Control vector
V_{IAS}	Indicated airspeed
V_{TAS}	True airspeed
ξ	Aileron deflection
x	State vector
x_0	Initial state vector
y	Observation vector
z	Measurement vector

1. INTRODUCTION

Parameter estimation using flight test data is a common method in the development of aircraft simulation models. These models have various fields of application, for example investigations of flight dynamics and performance, design of flight control systems or loads assessment. Moreover, aircraft simulation models are implemented in simulators for pilot training.

The parameter estimation itself, which is part of the complete system identification process, can only be successful if the model structure is adequate to represent the physical behavior of the real system. So the model structure development of the dynamic system is usually strongly coupled with the estimation of the corresponding parameters by the evaluation of measured data. To obtain the necessary data for this system identification process extensive flight test campaigns with specified test maneuvers are performed. The maneuvers are designed to generate a particularly dynamic system response, which is required for effective parameter estimation. A common practice is to only check the measured data after the flight test campaign. If there was any failure in the measurement system or data recording, single flights or, in the worst case, the whole campaign has to be performed again.

An online parameter estimation tool, estimating the model parameters of a predefined simulation model, would be useful for various purposes:

- 1) Assessment of first estimation results in flight for a fixed model structure would give useful information about the maneuver performance. Having first satisfactory and confident estimation results in flight, cancellation of possibly redundant planned tests would be reasonable. Also misperformed maneuvers can be repeated immediately, or if there are some doubts concerning the maneuver success, a test could be preventively redone.
- 2) In the case of e.g. a missing measurement of an input signal due to a sensor malfunction the estimation of model parameters would fail. Using in-flight parameter estimation during a flight test such an estimation failure could be an indication for a broken sensor. The test could be aborted, the sensor replaced and the cost increase minimized.
- 3) It could be possible to detect aircraft performance degradations, resulting e.g. from aerodynamic icing or damaging of the lifting surfaces. The icing topic is addressed in various research projects, e.g. the DLR@UNI "Supercooled Large Droplet Icing" (SuLaDI) project including investigations of the effects of aerodynamic icing on the aircraft behavior, or a former three-year NASA research [1] resulting in the ICEPro concept.

Concerning these and other purposes it has to be distinguished between online (or in-flight) parameter estimation and real time parameter estimation. Online parameter estimation herein means that the first estimation results are obtained in flight but not in real time. In real time estimation the results are obtained during the maneuver conduction. For the first two named purposes it is acceptable to have a time delay between the end of a maneuver and the assessment of the estimation results. In case of performance degradation application the time delay has to be short enough to allow the pilot or autopilot to react to the new aircraft behavior.

There are various existing approaches for online and real time parameter estimation. For linear model formulations a real time equation error method in frequency domain is provided by Morelli [2,3]. Another approach for online estimation of the parameters of an aircraft model is the usage of Kalman filtering techniques. A comparison of two different filtering techniques is given by Campbell and Brunke [4]. A structure of an online implementation of parameter estimation is shown by Spaulding et al. [5]. In this online tool the parameter estimation is performed after a maneuver is finished using the equation error method for linear models [6]. The estimation results are checked concerning their Cramér-Rao bounds.

The online parameter estimation tool presented in this paper is similar to the tool presented in [5]. But the advantage of the online tool presented here is the possibility of also estimating parameters of nonlinear models because of using a time domain maximum likelihood method. For the development of the new online tool the DLR offline parameter estimation software was extended by several functionalities to receive and process the measured flight data. The tool is not finished yet, but the first version still allows an online implementation.

2. BACKGROUND ON PARAMETER ESTIMATION METHODS

For offline parameter estimation the methods are basically divided into time and frequency domain approaches. Moreover recursive and iterative methods must be distinguished. In TAB 1 an overview of important estimation methods is given. They are listed with the corresponding domain, the method characteristic (recursive or iterative) and the capability of estimating parameters of only linear or also nonlinear models.

Recursive methods provide a new parameter estimate with every time step by using the new information from the current measured data and the previously obtained results. Iterative methods are using predefined time segments of flight data, which means that the complete data segment has to be available by the time of the estimation. Within every iteration step the whole data are processed again which means the measured data are compared to the output of the simulation model with the current estimated parameters. With the obtained information the parameters are updated. Processing the whole data several times makes these methods per se more time consuming than the recursive methods. Another difference between recursive and iterative methods is that initial parameter values are needed for the latter estimation algorithms [7].

TAB 1 Different parameter estimation methods

Method	Domain		Model type
Fourier transform regression	freq.	recursive	linear
least squares method	time	iterative	linear
recursive (weighted) least squares	time	recursive	linear
extended Kalman filter	time	recursive	(non)linear
unscented Kalman filter	time	recursive	(non)linear
output error method (OEM)	time	iterative	(non)linear

Each estimation method has advantages and disadvantages. Considering an implementation to estimate the parameters of a linear model, all methods are applicable. For (almost) real time estimation applications the recursive methods are commonly used, because they deliver new parameter estimates whenever new data are available.

The Fourier transform regression is a simple approach with fast computation capabilities, but it has some disadvantages. One is, that the model state variables have to be measurable and are assumed to be error free [7]. This method is commonly applied for real time inflight parameter estimation investigations [1,3].

For nonlinear models, recursive filtering methods like an extended Kalman filter which is also capable of real time implementation can be used. This method has the main disadvantage that the nonlinear model must be linearized for the estimation in any computational step, which can be time consuming [7,8]. Another filtering technique is the unscented Kalman filter, which can handle the estimation of nonlinear model parameters, but shows disadvantages in robustness and accuracy compared to iterative estimation methods like the time domain output error method. This method is also able to estimate parameters of nonlinear system models [9] and allows e.g. the estimation of parameters of complex aerodynamic models. Moreover it provides extra statistical information about the quality of the estimated parameters like standard deviations and correlation coefficients [7].

For the new tool the output error method was selected for parameter estimation. The method is most frequently applied at DLR's Institute of Flight Systems for any system identification and hence parameter estimation effort [9,10].

2.1. Output Error Method

The output error method allows the estimation of the unknown parameter vector Θ of a given system model. The formulation of a general nonlinear aircraft model corrupted only by measurement noise is given by

$$(1) \quad \dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), \Theta), \quad \mathbf{x}(t_0) = \mathbf{x}_0$$

$$(2) \quad \mathbf{y}(t) = \mathbf{g}(\mathbf{x}(t), \mathbf{u}(t), \Theta)$$

$$(3) \quad \mathbf{z}(t_k) = \mathbf{y}(t_k) + \mathbf{v}(t_k), \quad k = 1, \dots, N$$

where \mathbf{x} and \mathbf{y} denote the vectors of the aircraft states and observations, \mathbf{u} is the control input vector, and \mathbf{f} and \mathbf{g} are nonlinear functions describing the system's behavior [7]. The measurements \mathbf{z} are sampled at N time stamps and contain Gaussian white noise \mathbf{v} with zero mean and the covariance matrix \mathbf{R} . The measurement noise represents the error between the simulated and the measured model output. For an unknown measurement covariance matrix \mathbf{R} the maximum likelihood cost function, representing the probability of measurements for the parameter vector Θ , is given by

$$(4) \quad J(\Theta) = \det(\mathbf{R}).$$

With the assumption of uncorrelated measurement errors the determinant of the measurement covariance matrix considering the n_{out} weighted model outputs can be expressed as

$$(5) \quad \det(\mathbf{R}) = \prod_{i=1}^{n_{out}} \sigma_i^2,$$

For optimization of the cost function value the Gauss-Newton algorithm is usable. A detailed derivation of the output error method is given e.g. by Jategaonkar [7].

3. DEVELOPMENT OF THE ONLINE ESTIMATION TOOL

For system parameter estimation, DLR has developed the software tool ESTIMA since the 1980s. This tool provides optimized algorithms allowing a high-performance estimation of the parameters of an arbitrary complex system model. Different estimation methods are implemented, but the output error method is the one commonly used. Several pre- and post-processing options guarantee a quick and satisfactory handling of large data sets. The software package and the user models are written in the FORTRAN 77 language.

A scheme of the currently developed online estimation tool is shown in figure 1. The main functionality of the displayed structure is already usable and further developments will extend some capabilities. The tool is based on ESTIMA and includes some extensions to provide the online capability of the output error method.

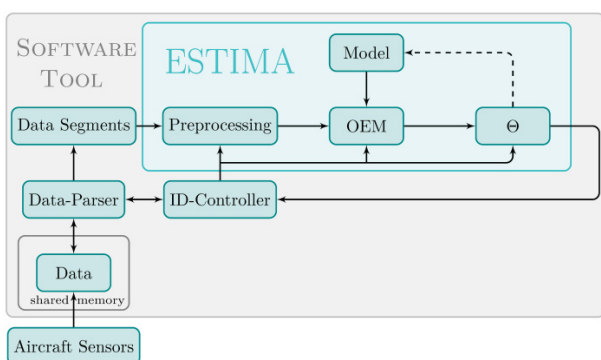


FIGURE 1 Scheme of the new online parameter estimation tool

3.1. Data Receiving Process

For using online parameter estimation as a feature in flight tests the aircraft has to be equipped with the necessary soft- and hardware. For flight tests it is desirable to install an external computer for running the estimation software during the test campaigns.

In this case there is the problem of passing the necessary data from the aircraft systems to the external estimation computer. The approach for sending the measured data from the flight data computer to the estimation computer is using standard networking technology. To pack and transfer data samples via Ethernet the "User Datagram Protocol" (UDP) seems suitable and is easy to implement. For transferring flight data via Ethernet a new UDP message is created and sent with every measurement time step containing an array of all required signals for the estimation. The message is received at a certain port on the estimation computer and stored for further processing.

3.2. Data Storage Management Process

To store the incoming data stream on the estimation computer a sufficiently sized shared memory object is used because it is fast accessible. In this case reading of larger data portions for the estimation would not be a time consuming matter, and the time delay between the start of

an ESTIMA run and the estimation result can be reduced. The process can be used to create, delete or reset the memory object.

Using shared memory for the data storage led to the following problem of passing the data to the estimation process: The new software routines of the online tool and the ESTIMA extensions are written in C/C++ language while standard ESTIMA is based on FORTRAN 77. Both languages provide common data types but have differences in the storage order. In C/C++ arrays are stored in column order while FORTRAN uses a row order. For the software interface between ESTIMA and the shared memory, this had to be considered during the development and all arrays are reshaped before they are passed to the estimation software.

3.3. Data Processing, Estimation and ID-Controlling Process

An important and also the most challenging point for the online parameter estimation tool proposed in this paper is searching for the relevant data segments (Data-Parser), starting the ESTIMA run and controlling the estimation results check (ID-Controller). This processing of the incoming data is the major part of the online estimation tool development and not finished yet.

As a part of this process a Data-Parser searches for data segments in the flight data stored in the shared memory object. Data segments which have been found by the Data-Parser are marked for further preprocessing (e.g. data filtering, calibration or unit conversion) and parameter estimation. The current implementation of the online parameter estimation tool does not provide a fully working Data-Parser. For this reason the data segments usable for the estimation must be marked while performing the test maneuver. An additional flag is used to indicate these data segments and is also sent in the UDP message to the estimation computer.

Controlling and checking functionalities of the new tool are sufficiently implemented, providing the ability to use the tool for testing purposes. If the Data-Parser has found a new data segment the estimation run can be automatically started. In the current implementation an estimation run is assumed to be successful if ESTIMA provides the final cost function value for the controlling process. It is not considered whether the parameter estimation was stopped because of the change in the cost function falling under the boundary value or the maximum number of iterations was reached. If ESTIMA is stopped due to an error during the estimation, the ID-Controller will recognize it by monitoring the ESTIMA process status. For such cases no estimation results are given back to the controller and the data segment is automatically discarded.

3.4. Graphical User Interfaces

For a comfortable usage of the online parameter estimation tool, currently three small "Graphical User Interfaces" (GUIs) with different tasks are provided:

- 1) Controlling the data storage
- 2) Controlling the data receiving process
- 3) Controlling the data processing and estimation

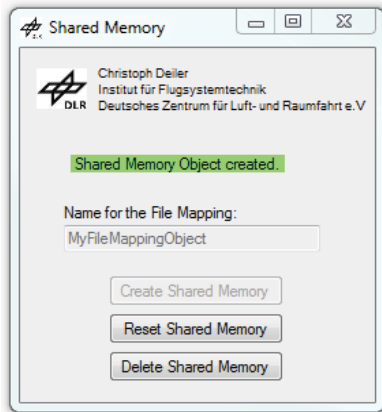


FIGURE 2 Graphical User Interface for managing the shared memory

The graphical user interfaces to manage the data storage (figure 2), to control the data receiver (figure 3) and to control the processing and the estimation tool (figure 4) are simple. For the data receiving process the specified port and the local computer IP are required. To interpret the incoming message a signal list is needed containing the number of signals, the signal names, dimensions and the sample time of the measurements.

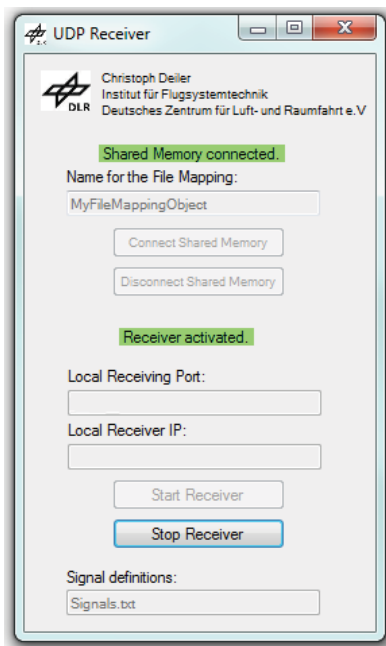


FIGURE 3 Graphical User Interface for controlling the data receiving process

The graphical user interface for controlling the processing and estimation provides different functions: Besides the connection/disconnection to the shared memory, the processing can be started and stopped. The user has also the possibility to restart the processing and to catch up to the last received data. Moreover, the user can choose between a continuous processing (“contin.”), waiting for new data being received, or a complete processing (“all”) without new data considered by selecting the corresponding button in the “Process” field on the lower right. For using the processing (Data-Parser) and in addition the estimation software the “Include ESTIMA

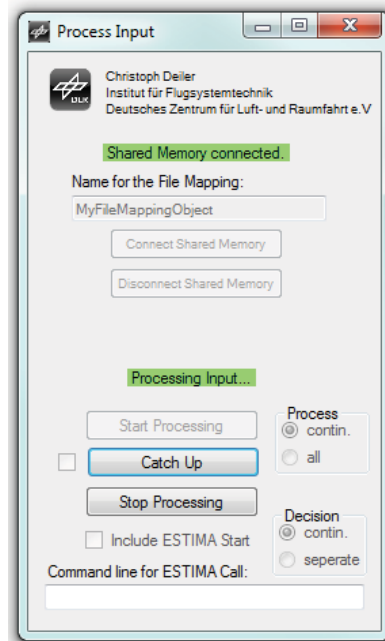


FIGURE 4 Graphical User Interface for processing input data

Start” checkbox must be marked. A command line is then needed for the definition of the ESTIMA executable and input file.

Furthermore it is possible to change the decision method (compare section 4) from continuous (“contin.”) to “separate” by selecting the corresponding radio button in the “Decision” field.

3.5. Software Integration Test

A software integration test was performed in order to find possible runtime errors in the new software. One of several ESTIMA parameter estimation examples was used: a standard second-order model to simulate the phugoid motion of the ATTAS aircraft. The provided measured flight data in ASCII format include the elevator input signal as well as the pitch angle for every time step. The example was performed twice, first using offline estimation and second using the new tool. To send the data to the receiving process a MATLAB/Simulink block was developed. The comparison of the results showed similar estimates for frequency and damping as well as for the cost function values, which indicates that so far the software is correctly implemented.

4. OUTPUT ERROR METHOD WITH ONLINE CAPABILITIES

As mentioned above, the iterative parameter estimation methods, like the output error method, have the disadvantage that in every iteration step the complete data are processed. The computational effort is proportional to the length of the data segments, which leads to long estimation durations of huge data segments as they are resulting from a flight test. In terms of time consumption small data segments would be preferable, but to enhance the accuracy of the model large data segments are needed. The main objective is to obtain the best possible parameter estimate during an acceptable timeframe.

To overcome these problems and reach the named goal the idea for the new online parameter estimation tool is to separate the data into small segments. Each of the segments contains only one single maneuver and the estimation delivers the best parameter vector. For a complete estimation only those segments, which deliver the best parameter estimation results, should be considered. Thereby the computational effort of the final, complete estimation can be reduced. Because the best estimation results are obtained from the data segments with the lowest cost function values (see Eq. (4)) only those segments should be selected.

By now, two decision methods based on the cost function value are provided with the first version of the online tool to select data segments. These decision methods are an approach to solve the problem of the identifiability of model parameters. Further developments may contain additional criteria like the standard deviations of parameter estimates. Like the Cramér-Rao bounds used in [5] they indicate the accuracy of an estimate. Hence low values of the standard deviation indicate best estimation results. This additional information about the standard deviation is anyway provided by maximum likelihood methods and could be evaluated with only minor computational effort. Assuming only white noise in the measurements the standard deviation gives a reliable indication of the estimation accuracy. But in case of colored measurement noise the resulting standard deviation values are too optimistic. To account for this effect an additional factor leads to a more reliable evaluation of the standard deviation [6]. In case of ESTIMA the product of five times the standard deviation σ is provided as default.

The estimation results depend on the formulation of the predefined simulation model. For the parameter estimates of a complete aerodynamic model steady flight data are needed as well as measurements of the dynamic behavior. But the decision methods are at risk to discard segments containing the measurements of a highly dynamic aircraft behavior instead of segments with steady flight data. The parameter estimation considering data of a steady flight condition should result in very low cost function values, because of the expected model accuracy for such a flight condition. In contrast in dynamic flight aircraft models are mostly less accurate and any deviation between model output and measurement leads to higher cost function values. So, a not considered physical effect in the dynamic model formulation or basically any model simplification can lead to bad estimation results respectively high cost function values although the data segment could be beneficial for the parameter estimates. This problem is currently not considered by the decision methods.

4.1. First Method: Continuous Improvement

In case of the continuous improvement every new data segment found by the Data-Parser is checked concerning its benefit for the final estimation. After finishing an ESTIMA run including a new data segment the cost function value will very likely differ from the previous one without the new data segment. If there is any improvement respectively a reduction of the cost function value, the new data are assumed to be beneficial for the estimation result and will be considered for future estimation runs. If it results in a worse cost function value, the data segment is

discarded for any further estimation and “deactivated” by the control algorithm.

There are two problems with this approach:

- 1) At the very beginning the first data segment is always the reference, so if that data segment delivers an excellent result corresponding to a very small cost function value, no other data segment is further considered. Even if the new estimation is good but not as good as the first one before, it is discarded.

To overcome that problem, one attempt could be to hold the first n_b data segments fixed and start with the decision after the $(n_b + 1)$ estimation run. Depending on the number of expected data segments the number n_b of fixed segments could be e.g. about 1 to 5. Moreover, this method may result in the problem that if the first n_b data segments contain erroneous maneuvers resulting in very poor or erroneous estimates, these segments would not be discarded. The complete estimation would be influenced and the results would not be as good as they could be without this erroneous and fixed segment. In the software tool the number of fixed segments n_b is set to 1 for this decision method. But if the first estimation results in an error and is not completed, the decision method fails.

- 2) The decision method is very restrictive, by only considering the data segments, which directly improve the cost function value.

To ease the restrictions, in the current implementation of this decision method for activation of new data segments, the following criterion is used:

$$(6) \quad active_i = \begin{cases} 1 & \text{if } J(\theta)_i < 5 \cdot J(\theta)_{i-1} \\ 0 & \text{if } J(\theta)_i > 5 \cdot J(\theta)_{i-1} \end{cases}$$

To account for some variation within the cost function value after a new data segment is added the factor 5 for the decision was chosen. It is assumed that this value is sufficient to account for the above described problem with higher cost function values in dynamic flight.

4.2. Second Method: Separate Computation

The second implemented decision algorithm is based on a separate computation of each data segment, resulting in different parameter estimates and cost function values. After successfully completing the individual parameter estimations, the algorithm decides which data segments are activated for a final estimation. For activation of the data segments the median value of all so far obtained cost function values $(J(\theta)_1 \dots J(\theta)_j)$ is considered as decision criterion:

$$(7) \quad active_i = \begin{cases} 1 & \text{if } J(\theta)_i < \text{median}(J(\theta)_1 \dots J(\theta)_j) \\ 0 & \text{if } J(\theta)_i > \text{median}(J(\theta)_1 \dots J(\theta)_j) \end{cases}$$

The median value has a significant advantage compared to the arithmetic mean: For a vector containing a certain number of values the mean value of all entries is influenced by each entry itself. Having only one entry with a large value and all others with small values, the arithmetic mean of all entries is shifted to the large value.

The median value, which is represented by the middle of all values, is not influenced by single large entries. In maximum likelihood parameter estimation the cost function can vary with several powers of ten for poor estimations. So, to minimize the influence of an outlier the median is used as decision criterion and always half of the data segments are considered. After all estimations are performed a final parameter estimation using all active data segments is started.

5. FIRST RESULTS

Various tests of the online estimation tool were conducted, showing the applicability of the two different decision algorithms. Two different test cases are shown within this paper: First, using the formerly identified simulation model of DLR's research aircraft ATTAS [11] flight test maneuvers at different trim points were simulated and aerodynamic parameters were estimated. The simulation contained no additional noise and the signals were generated bias free.

Second, measured flight data of the ATTAS aircraft recorded during a former identification campaign are used for the test of the estimation tool.

All tests had been performed with a mobile workstation including a quad core CPU with 2.4 GHz and 8 GB RAM and running with a 64 bit Windows 7.

5.1. Aerodynamic Model of the Longitudinal Motion for the Estimation Tool Test

The aerodynamic model of the longitudinal motion of the ATTAS used for the tool tests is formulated as a 2-point model, containing a separated formulation for the wing/body combination and the horizontal tail [12]. In general this leads to the following formulation of the lift coefficient equation

$$(8) \quad C_L = C_{L,wb}(C_{L0}, C_{L\alpha}, \alpha, Ma, q, \dots) + \frac{S_t}{S} C_{L,t}(C_{L\alpha_t}, C_{L\eta}, \alpha, \eta, \dots) \cos(\alpha_{dyn} - \varepsilon_t),$$

For the first test of the online parameter estimation tool, only the parameters of the basic aerodynamics are estimated. For the wing/body combination as well as for the horizontal tail only a linear lift curve is considered. The angle of attack at the horizontal tail

$$(9) \quad \alpha_t = \alpha + i_t - \varepsilon_t + \alpha_{dyn}.$$

is derived from the angle of attack at the wing α , the tail trim angle i_t , the downwash angle ε_t at the tail and the dynamic angle of attack α_{dyn} resulting from a pitch

movement. The downwash angle describes the wing influence on the tail, including the time delay Δt considering the transport lag of a change in the flow from the wing to the tail. A good approximation for the downwash angle at the horizontal tail is given by

$$(10) \quad \varepsilon_t = \frac{\partial \varepsilon_t}{\partial \alpha} \alpha(t - \Delta t) + \Delta \varepsilon_t.$$

The total drag coefficient of the whole aircraft has various influencing parts. Beside the zero drag coefficient C_{D0} , the lift-induced drag and some additional drag components ΔC_D can be considered. For the lift-induced drag a quadratic drag polar is assumed, which is calculated from the total lift coefficient C_L . The total drag coefficient is modeled as

$$(11) \quad C_D = C_{D0} + \frac{1}{e\pi\Lambda} C_L^2 + \Delta C_D$$

The pitching moment coefficient related to the wing/body geometric neutral point is formulated as:

$$(12) \quad C_{M25} = C_{M0} + C_{M,t} + \Delta C_M.$$

5.2. Maneuver for Parameter Estimation

For parameter estimation special maneuvers are commonly used to excite the aircraft's dynamic modes and to obtain the necessary responses. Step inputs have proven their effectiveness for such a task. At the DLR the so called 3-2-1-1 sequence is mostly preferred for generating input command signals [7,9]. As an input command for the aircraft primary flight controls, this signal can easily be flown manually.

The "3-2-1-1" input signal contains four alternating positive and negative steps. The first step has a duration of $3 \cdot \Delta t$, followed by a step with a duration of $2 \cdot \Delta t$. Two more step inputs with a duration of Δt complete the maneuver, like it is shown in figure 5 for a modified 3-2-1-1 elevator input η . For the signal modification the amplitudes of the step inputs are altered in order to reduce the eventual offset from the initial trim point. With the amplitude of only 80 % of a predefined value for the first step input the aircraft does not move as far from its trim point as for 100 % amplitude. The subsequent steps have higher amplitudes to cause sufficient excitation and a similar amount of energy as the unmodified signal [7]. The second step has 120 % amplitude of the predefined value and the last two have 110 %. To further reduce the problem of running away from the trim point to one side during the long first step input command, the 3-2-1-1 input sequence is performed twice. The second time the deflection signs are reversed, meaning the step inputs are performed in the opposite direction [7].

For the longitudinal motion phugoid and short period are excited by a 3-2-1-1 elevator input command and the responses are suitable for reliable estimation of aerodynamic parameters of an aircraft model of the longitudinal motion as described in section 5.1.

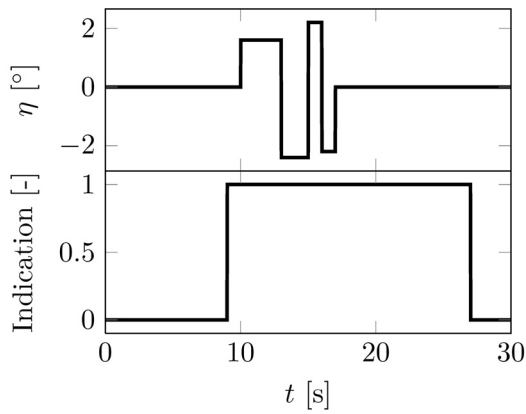


FIGURE 5 Elevator input command and maneuver indication flag during simulation run

5.3. Aerodynamic Parameters

For the first tests of the online parameter estimation tool several parameters of the above described aerodynamic model (see section 5.1) are estimated. Nominal parameter values resulting from former ATTAS system identification campaigns are listed in TAB 2 for flap setting SP (1°) and TAB 3 for flap setting 14° . Only the shown six parameters were estimated.

The nominal parameter values were used to evaluate the test results and the applicability of both decision methods. The comparison of these values with the results of the tool tests (see sections 5.5 and 5.6) will show the applicability of a decision method. Small deviations are assumed to indicate satisfactory test results.

The usage of the initial values given in TAB 2 and TAB 3 led to comparable results for all the conducted estimations. The initial values are selected arbitrarily but far enough away from the nominal values, to provide a bad initial point for the parameter estimations.

TAB 2 Nominal aerodynamic model parameters and initial values for the estimation, flaps SP (1°)

Parameter	Nominal Value	Initial Value for estimation
C_{L0}	0.2315	1.0e-02
C_{D0}	3.8278e-02	1.2e-03
C_{M0}	0.1252	0.2
$C_{L\alpha,wb}$	4.6517	2.20
$C_{L\alpha,ht}$	2.8482	1.8482
$C_{L\eta}$	1.8673	0.8673

TAB 3 Nominal aerodynamic model parameters and initial values for the estimation, flaps 14°

Parameter	Nominal Value	Initial Value for estimation
C_{L0}	0.3264	1.0e-02
C_{D0}	3.6250e-02	1.2e-03
C_{M0}	0.1111	0.2
$C_{L\alpha,wb}$	4.5616	2.20
$C_{L\alpha,ht}$	3.1788	1.8482
$C_{L\eta}$	1.8089	0.8673

5.4. Measurement Signals for the Estimation

Various signals are sent to the estimation computer in every time step via the Ethernet connection. The following measurements are required for the estimation:

- elevator deflection, tailplane trim angle and flap setting,
- engine speed and used fuel,
- true airspeed and calibrated airspeed,
- angle of attack,
- pitch angle and pitch rate,
- accelerations in longitudinal and vertical direction,
- longitudinal and vertical speed,
- aircraft horizontal position and altitude,
- Mach number, static pressure and temperature.

In addition the model state variables are pitch rate, pitch angle, vertical speed, horizontal speed and altitude. The measured values of the states are used as initial values in the estimation process. Arbitrarily chosen for the tool tests, the initial values for the altitude and the pitch rate are fixed and the other initial values were estimated. Again, no lateral state is considered.

5.5. Simulated Flight Data

Various identification maneuvers simulated with the DLR ATTAS simulation model are used to partly recreate a typical flight test program for parameter estimation purposes. Starting from steady horizontal flight at different trim points the test maneuvers were used to excite the aircraft's eigenmodes.

The simulation model is written in FORTRAN and compiled in form of a Simulink S-Function. Using a Simulink model containing this S-Function the simulations are performed in real time. A Simulink block for sending the flight data via Ethernet (UDP messages) to the estimation computer represents the interface to the online parameter estimation tool.

For the testing with simulated flight data the following six trim points had been used:

- $ALT = 3000$ m, with indicated airspeeds of $V_{IAS} = 130$ kts, 150 kts, 200 kts, and

- $ALT = 4000$ m, with indicated airspeeds of $V_{IAS} = 130$ kts, 150 kts, 200 kts.

At each trim point a modified 3-2-1-1 sequence, as described in section 5.2, is used for generating the elevator input command (see figure 5). After 9 s in horizontal flight, the maneuver indication flag is set to one, as mentioned in section 3.3, and 1 s later the elevator input is commanded. The maneuver indication lasts 18 s, and after 30 s of simulation time, the aircraft is brought to the next trim point. Every elevator input is performed twice, for the purposes explained in section 5.2. Consequently with the six trim points 12 maneuver respectively data segments are provided for the parameter estimation.

In order to recreate partly an actual flight test with these 12 data segments for testing the estimation tool, one simulated maneuver is assumed to be performed erroneously and not as intended. This corresponds to a manually flown flight test, in which the pilot commands a wrong input or the aircraft is influenced by strong atmospheric disturbances. To consider such a wrong input command, the third maneuver at a trim point in 3000 m altitude with 150 kts indicated airspeed contained additionally to the elevator input command a commanded aileron deflection, as shown in figure 6. A doublet was chosen for the aileron input, because it was assumed that the pilot would recognize the wrong command and would try to compensate the roll movement.

The aileron command resulted in about 40° bank angle left wing down, which led to significant deviations from horizontal flight condition. The third maneuver was assumed to lead to poor estimation results because of the additional lateral movement, which was not covered by the predefined model of the longitudinal motion used for the parameter estimation. With no state variable accounting for the lateral motion the model is not able to match the coupled motion.

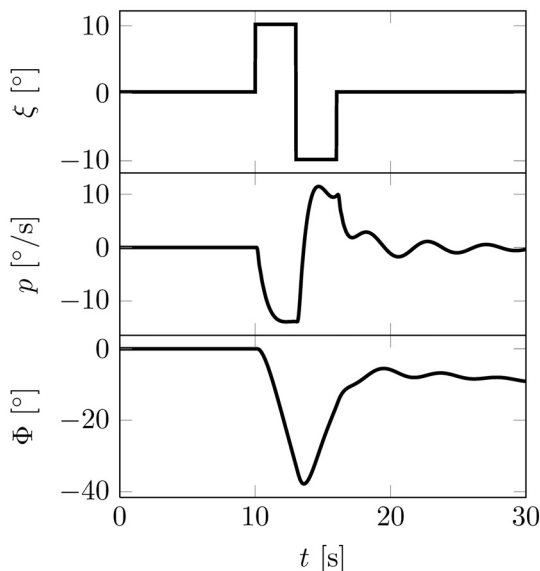


FIGURE 6 Aileron input command during erroneous flight test maneuver

In TAB 4 the results of two online estimation tool runs are given, one run for each decision method. Beside the duration of the calculation the activation indication (see sections 4.1 and 4.2) is listed for each of the 12 data segments.

TAB 4 Results of online parameter estimation tool runs with simulated data, using the different decision methods

Segment	Continuous Improvement		Separate Computation	
	Duration	active	Duration	active
1	1.47 s	yes	1.47 s	no
2	2.27 s	yes	1.50 s	no
3	3.54 s	no	1.08 s	no
4	2.81 s	yes	1.29 s	yes
5	5.38 s	no	1.15 s	yes
6	5.36 s	no	1.51 s	yes
7	4.00 s	yes	1.50 s	no
8	4.52 s	yes	1.51 s	no
9	5.39 s	yes	1.06 s	no
10	6.24 s	yes	1.15 s	yes
11	10.63 s	no	1.15 s	yes
12	9.90 s	no	1.45 s	yes

Comparison of the results using the two methods shows that finally different segments are activated. Using the first decision method leads to an activation of 7 data segments in contrast to separate computation which only takes 6 data segments into account. For this example the computational effort for the separate computation method is with only 15.82 s of accumulated calculation time shorter than that of the continuous improvement method with 61.55 s.

In case of the separate computation decision method, after all maneuvers are finished the final estimation was performed and lasted for 5.94 s. The overall time duration for the estimation increases to 21.76 s. This is only about a third of the computation time needed for the continuous improvement decision method.

The best parameter estimation gained by the first decision method is available after the last maneuver is taken into account and no new estimation has finally to be performed (see section 4.1). In this example the estimation including the 10th segment is favorable according to the decision algorithm. With duration of 6.24 s it lasted a bit longer than

the final estimation using the second decision method needing 5.94 s. But the cost function value is three powers of ten smaller, which indicates a better fitting model for the given data used in the estimation. Considering the third maneuver with the additional input both algorithms discard this data segment, because of too large cost function values.

TAB 5 Results of the parameter estimation with simulated data, both decision methods, flaps SP (1°)

Parameter	Continuous Improvement		Separate Computation	
	$5 \cdot \sigma$	Δ Nominal	$5 \cdot \sigma$	Δ Nominal
C_{L0}	0.52 %	5.69 %	0.76 %	7.98 %
C_{D0}	0.16 %	21.36 %	0.22 %	12.58 %
C_{M0}	0.20 %	1.19 %	0.31 %	9.48 %
$C_{L\alpha,wb}$	0.15 %	6.83 %	0.34 %	3.94 %
$C_{L\alpha,ht}$	0.21 %	1.91 %	0.29 %	2.87 %
$C_{L\eta}$	0.21 %	1.70 %	0.30 %	3.28 %

A proof of match for the aerodynamic model with the finally estimated parameters is given in figure 7 for the first decision method. The simulation of the model defined in section 5.1 using the estimated parameters matched the simulated flight test data quite well for the given elevator input commands. The results of the best parameter estimation are listed in TAB 5. The error magnitudes (Δ Nominal) between the estimated parameter values and the nominal values given in TAB 2 are small, except for the zero drag coefficient C_{D0} . The value of five times the standard deviations σ of the estimated parameters is far below 1%, which indicates a good accuracy of the estimates.

In figure 8 a proof of match for the results of using the second decision method is given. Compared to the simulated flight data using the complete 6-degrees-of-freedom model the simulation of the model of the longitudinal motion with the parameter estimates shows some minor discrepancies. But the entire match is also satisfying, although the estimation results show larger parameter deviations from the nominal values. As given in TAB 5 the error magnitudes between the nominal and the estimated parameters are partly larger than using the first decision method, confirming the assumption of a poorer model match. But the standard deviation values of the estimated parameters are also very small.

5.6. ATTAS Flight Data

One of the latest system identification flights with the DLR research aircraft ATTAS had been conducted in 2003. The existing flight data contain various maneuvers with 3-2-1-1 sequences as elevator input commands. To test the online parameter estimation tool data of four maneuvers are sent to the estimation computer. All maneuvers were manually marked by setting the additional flag. The third maneuver was performed with an angle of sideslip β of 4° , which leads to a coupling of the longitudinal and the lateral aircraft motion. This data segment is assumed to result in bad parameter estimates for the given model and should be discarded by the decision methods. All maneuvers had been performed at an altitude between 5200 m and 5500 m at true airspeeds of 180 kts respectively 200 kts and with a flap deflection of 14° . The nominal parameter values of the aerodynamic model for that flap deflection are given in TAB 3. For this first test no bias correction was implemented respectively no bias was estimated.

To get an overview of the estimation results TAB 6 contains the estimation durations and activation indication for each decision method and data segment. The separate computation method results in two active elements for the complete estimation, in contrast to the continuous improvement considering three segments. Both methods discard the third segment with the additional lateral movement resulting from the angle of sideslip. With an overall computational effort of 11.72 s the continuous improvement method needs about twice as much time as the other decision method (5.61 s). Including the final estimation needed for the separate computation method the complete duration increased to 7.42 s, still being faster than the first method.

TAB 6 Results of online parameter estimation tool runs with flight data, using the different decision methods

Segment	Continuous Improvement		Separate Computation	
	Duration	active	Duration	active
1	1.17 s	yes	1.17 s	yes
2	1.90 s	yes	1.26 s	yes
3	6.19 s	no	2.28 s	no
4	2.46 s	yes	0.90 s	no

The deviations of the estimates from the nominal parameter values of the aerodynamic model are given in TAB 7. For the aerodynamic zero coefficients C_{L0} , C_{D0} and C_{M0} the deviation is between about 40 % and 60 %, which should be a result of the missing bias correction. In contrast the other three parameters were satisfactorily estimated, varying not more than six percent from the nominal values.

TAB 7 Results of the parameter estimation with flight data, both decision methods, flaps 14°

Parameter	Continuous Improvement		Separate Computation	
	$5 \cdot \sigma$	Δ Nominal	$5 \cdot \sigma$	Δ Nominal
C_{L0}	1.02 %	57.28 %	1.08 %	57.01 %
C_{D0}	1.16 %	44.04 %	1.18 %	43.02 %
C_{M0}	0.97 %	38.78 %	1.07 %	38.53 %
$C_{L\alpha,wb}$	1.33 %	0.41 %	1.70 %	2.22 %
$C_{L\alpha,ht}$	0.73 %	5.26 %	0.86 %	5.05 %
$C_{L\eta}$	0.77 %	5.48 %	0.91 %	5.11 %

Like in section 5.4 a proof of match comparing the measured flight data and the simulation results, using the estimated aerodynamic parameters, is given in figure 9 and figure 10 for each decision method. Showing only the active data segments used for the estimation each figure indicates a satisfactory match of measurement and simulation.

With more flight data, further tests could be performed, which would lead to a more precise investigation on the decision method applicability.

6. CONCLUSION

In this paper the first version of a new online parameter estimation tool and the results of first tests are presented. Using the DLR estimation software ESTIMA, which is based on a time domain output error method, the tool provides different modules to receive, store and process the measured flight data. Two decision methods are implemented to evaluate the estimation results and to include or discard data segments containing test maneuvers in terms of computational effort and parameter identifiability.

Both decision methods have shown satisfactory results for the final parameter estimation of a predefined aerodynamic model. Using simulated flight data with several 3-2-1-1 input command sequences at different trim points, each estimated set of parameters delivered mostly only small deviations from the nominal values, which had been obtained during former ATTAS system identification campaigns. As expected, the computational effort of the separate computation method was much smaller than for the method with continuous improvement. With only four segments of the flight data the tool could not completely show its capabilities. But the test results are promising and the tool was working well despite the partly poor parameter estimates.

Moreover, the parameter estimates were well comparable for both decision methods, and with shorter overall estimation time, the separate computation method was more promising in the tests. Because of the mentioned

disadvantages and limitations of the continuous improvement decision algorithm and the test results, the separate computation method seems preferable for the given test data.

7. FUTURE WORK

Several points for the further development of the online parameter estimation tool will be addressed:

- In addition to the cost function value as basis for the decision, further criteria may be considered to improve the decision methods.
- For measurement signal correction a preceding online flight path reconstruction could be used for the calculation of the biases before the parameter estimation is started. Another possibility is to estimate the biases together with the parameters.
- Another task for future development of the online estimation tool is to implement an automatic search algorithm (Data-Parser), generating the data segments for the estimation due to different criteria without any further interaction. Possible characteristics to search for could be e.g. a significant change of the aircraft state vector, namely the angular rate and linear velocities, or the energy spectrum of the dynamic aircraft response to any excitation – input command or maybe atmospheric disturbances – which should cover the frequencies of the aircraft's eigenmodes.
- Moreover some flight tests have to be conducted to prove the functionality of the data transfer and the parameter estimation in flight. Also more tests to evaluate both presented decision methods are necessary.

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LITERATURE

- [1] Gingras, David R.; Barnhart, Billy P.; Ranuado, Richard J.; Ratvasky, Thomas P. and Morelli, Eugene A.: *Envelope Protection for In-Flight Ice Contamination*. 47th Aerospace Science Meeting, Orlando, Florida, USA, January 5-8 2010. AIAA 2010-8141.
- [2] Morelli, Eugene A.: *Real-time parameter estimation in the frequency domain*. Journal of Guidance, Control, and Dynamics Vol. 23, No. 5, p. 812-818, September-October 2000.
- [3] Morelli, Eugene A.: *In-Flight System Identification*. AIAA Atmospheric Flight Mechanics Conference and Exhibit, Boston, Massachusetts, USA, August 10-12 1998. AIAA 98-4261.
- [4] Campbell, Mark E. and Brunke, Shelby: *Nonlinear Estimation of Aircraft Models for On-line Control Customization*, IEEE Aerospace Conference, Big Sky, Montana, USA, March 10-17 2000.

- [5] Spaulding, Timothy J.; Naddy, Cory J.; Hines, Jennifer P.; Knowlan, Garrett W.; Riley, Danny G.; Schaffer, Zachary T. und Jorris, Timothy: *Near Real-time Parameter Estimation in the C-12C*. AIAA Atmospheric Flight Mechanics Conference, Portland, Oregon, USA, August 8-11 2011. AIAA 2011-6275.
- [6] Klein, Vladislav and Morelli, Eugene A.: *Aircraft System Identification - Theory and Practice*. AIAA Education Series. AIAA, Reston, Virginia, USA, 2006.
- [7] Jategaonkar, Ravindra V.: *Flight Vehicle System Identification – A Time Domain Methodology*, Volume 216, Progress in Astronautics and Aeronautics. AIAA, Reston, Virginia, USA, 2006.
- [8] Bauer, Jeffrey E. and Andrisani, Dominick: *Estimating Short-Period Dynamics Using an Extended Kalman Filter*, AIAA/SFTE/DGLR/SETP 5th Biannual Flight Test Conference, Ontario, Canada, May 22-24 1990. AIAA 1990-1277.
- [9] Hamel, Peter G. and Jategaonkar, Ravindra V.: *Evolution of Flight Vehicle System Identification*. Journal of Aircraft, Vol. 33, No. 1, p. 9-28, January-February 1996.
- [10] Jategaonkar, Ravindra; Fischenberg, Dietrich and Gruenhagen, Wolfgang von: *Aerodynamic Modeling and System Identification from Flight Data - Recent Applications at DLR*. Journal of Aircraft, Vol. 41, No. 4, p. 681–691, July-August 2004.
- [11] Fischenberg, Dietrich: *ATTAS In-Air Aerodynamikmodell*. DLR Institutsbericht (IB 111-97/31), Braunschweig. 1997.
- [12] Mönnich, Wulf: *A 2-Point Aerodynamic Model for Identification*. (in German: *Ein 2-Punkt-Aerodynamikmodell für die Identifizierung*) Symposium 'Systemidentifizierung in der Fahrzeugdynamik'. DFVLR-Mitteilung 87-22, Paper No 3.1, 1987.

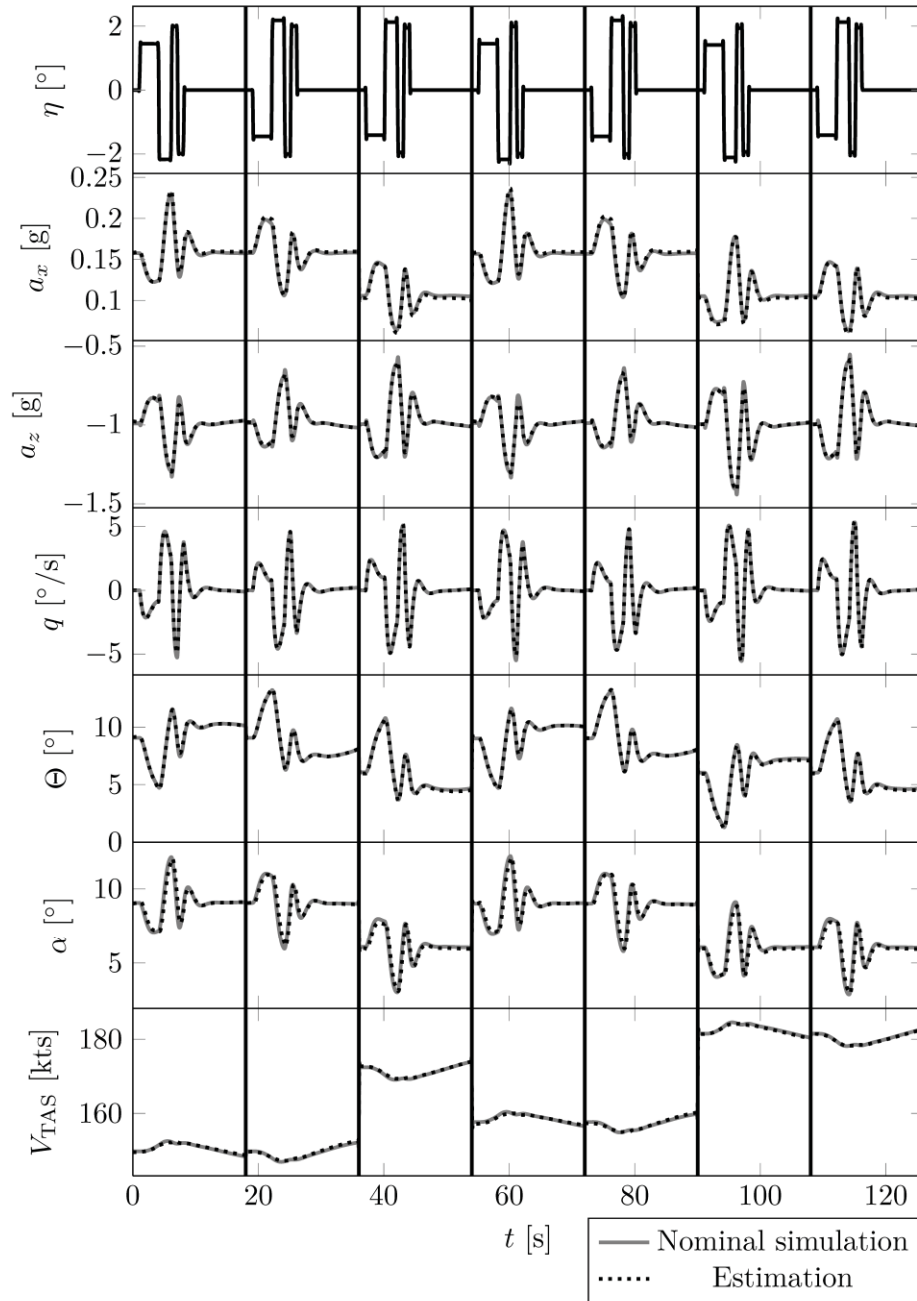


FIGURE 7 Continuous improvement method, proof of match: nominal simulated flight data and simulation results with estimated model parameters (longitudinal motion), active data segments

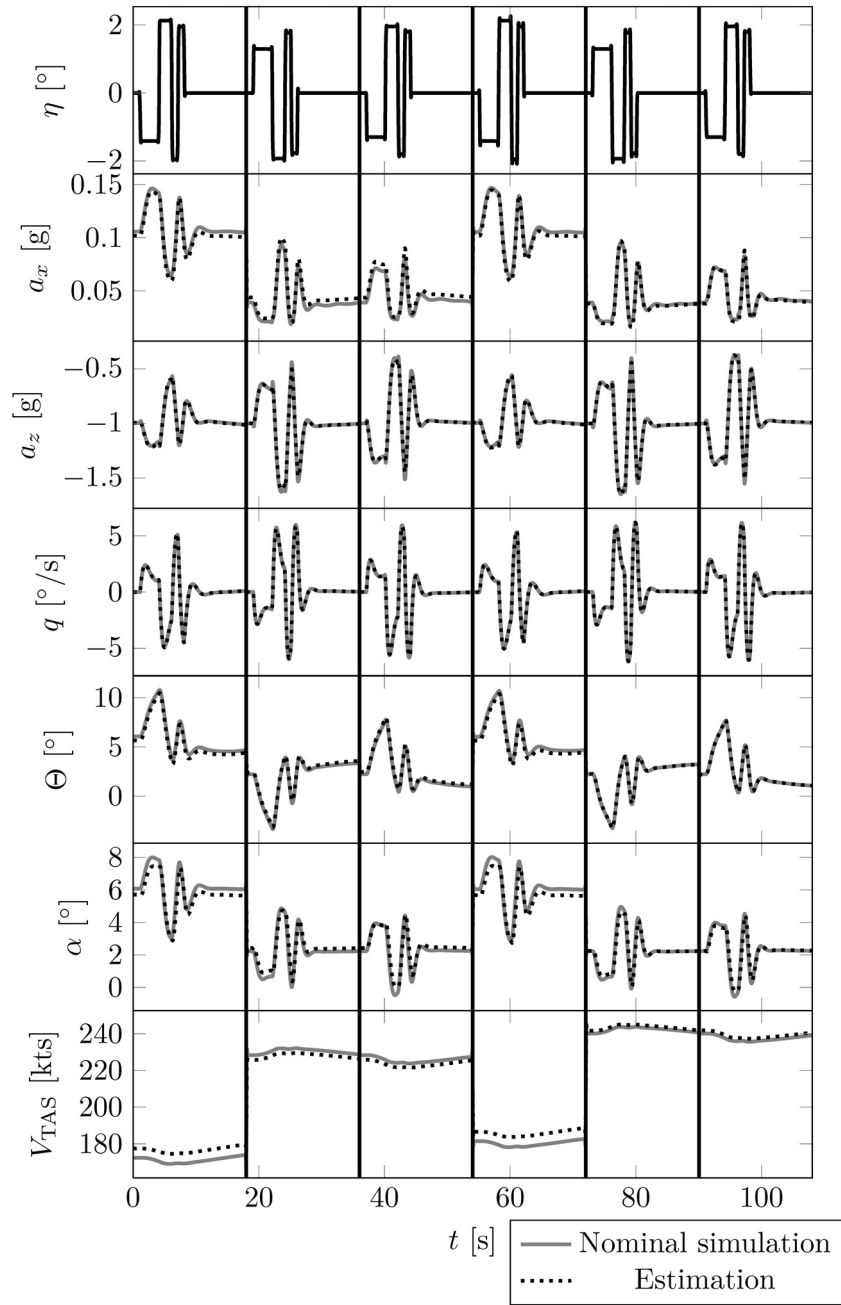


FIGURE 8 Separate computation method, proof of match: nominal simulated flight data and simulation results with estimated model parameters (longitudinal motion), active data segments

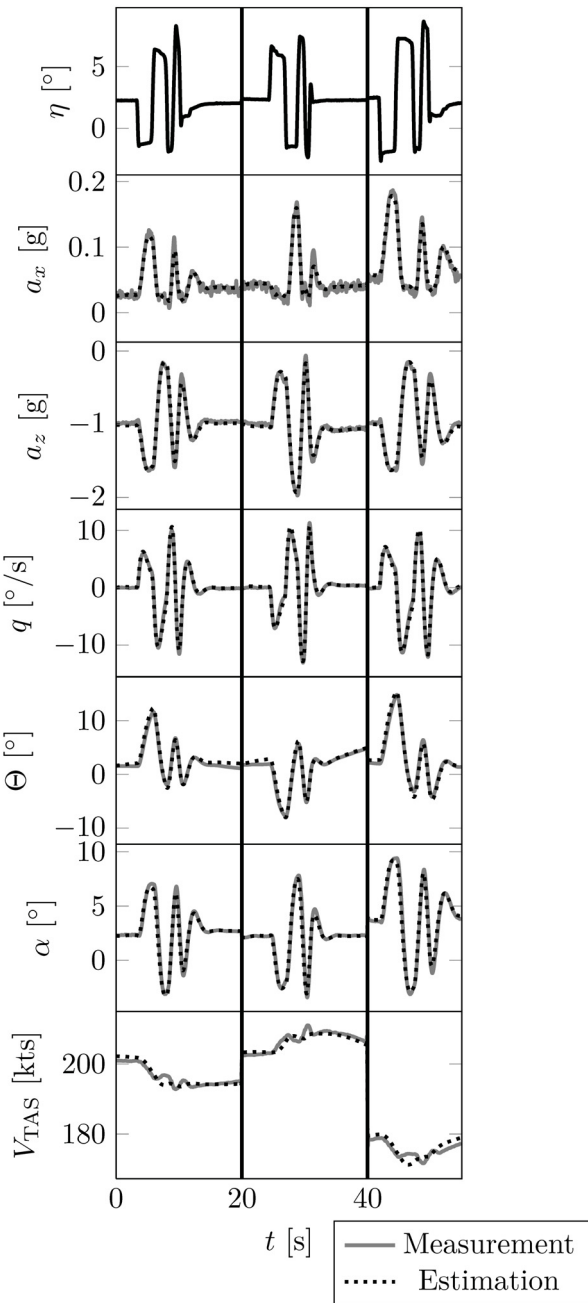


FIGURE 9 Continuous improvement method, proof of match: ATTAS flight data and simulation results with estimated model parameters (longitudinal motion)

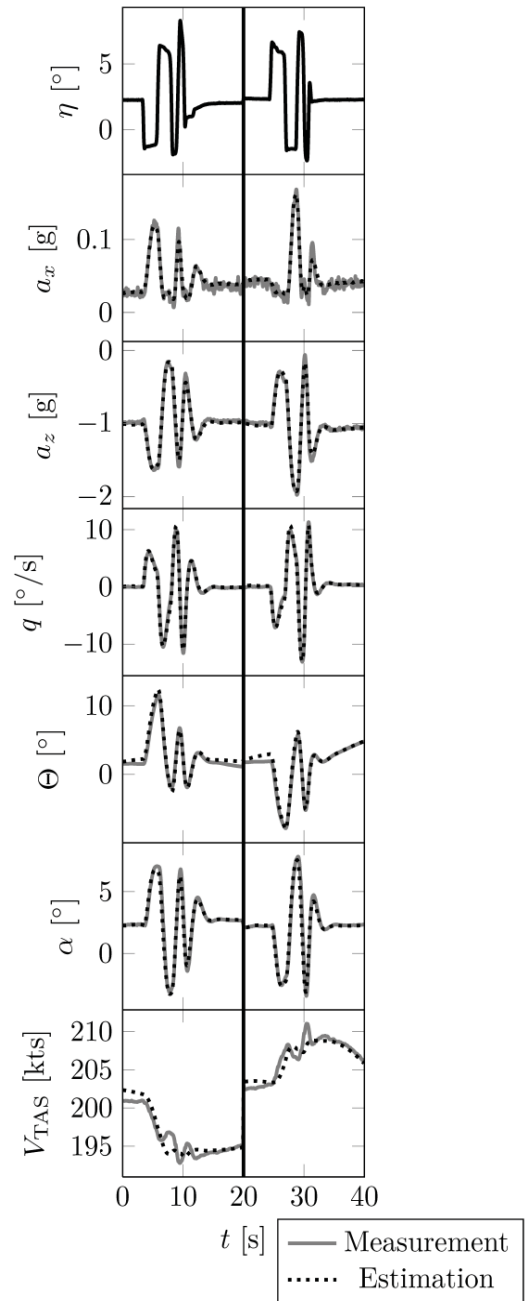


FIGURE 10 Separate computation method, proof of match: ATTAS flight data and simulation results with estimated model parameters (longitudinal motion)