MULTI-OBJECTIVE PARAMETER IDENTIFICATION FOR HELICOPTERS USING AUXILIARY TRIM INFORMATION

Anna Abà[1,2] **Marilena D. Pavel**[1] **Pierluigi Capone**[2] **Pieter-Jan Proesmans**[1]

[1]Delft University of Technology, Delft, The Netherlands
[2]ZHAW Zurich University of Applied Sciences, Winterthur, Switzerland

ABSTRACT

Classic rotorcraft parameter identification techniques estimate the unknown parameters by minimizing the mismatch between simulation model predictions and observed data. Various types of data can be used for this purpose, including local linear approximations of the system (e.g., in the form of frequency responses or state-space models), time series of input and output variables, and the states and inputs of the aircraft at trim. Current parameter identification methods essentially consider only one type of information at a time. This paper proposes a novel method that exploits all three types of information simultaneously, by embedding them in a multi-objective optimization framework. Although there are no examples of this approach in the aerospace literature, it is theoretically grounded in regularization theory and has been successfully applied to other fields of engineering. A detailed description of the method's implementation for rotorcraft parameter identification is provided. Preliminary results are presented for the identification of physical parameters in a nonlinear helicopter model, using a bi-objective approach that incorporates time-series and trim data.

INTRODUCTION

Simulation models are increasingly employed in a wide range of activities throughout the life cycle of an aircraft, from initial design and control laws development to certification and pilot training. In the case of helicopters and VTOL aircraft, achieving the required level of accuracy for these applications is especially challenging: on the one hand, nonlinear, high-order models are often necessary to correctly represent the nonlinear, high-order vehicle dynamics; on the other hand, prior knowledge of key model parameters is often limited or unavailable due to the complex physical phenomena involved (Refs. 1, 2). Parameter identification offers a powerful tool to support model development and update, as it provides estimates of the unknown parameters based on measured input-output data.

Classic aircraft parameter identification techniques use a *prediction error* approach (Fig. 1), i.e., estimate the unknown parameters by minimizing the mismatch between model prediction and observed data, when both the model and the actual system are excited by the same inputs (Refs. 3, 4). Different types of data can be used for this purpose, each with its own advantages and disadvantages; these include:

- Local linear approximations of the system - for example, in the form of frequency response curves or state-space models
- Time series of input and output variables
- States and inputs of the aircraft at trim

As will be explained in the next section, current methods essentially consider one type of information at a time.

This paper proposes a novel aircraft parameter identification method that exploits all three types of information simultaneously, by embedding them in a multi-objective optimization framework. Although there are no examples of this approach in the aerospace literature, it is theoretically grounded in regularization theory and has been successfully applied to other fields of engineering. The preliminary results presented at the end of this paper suggest that it can also be beneficial for the identification of nonlinear rotorcraft models.

The next two sections review state-of-the-art techniques for the parameter identification of nonlinear rotorcraft models, as well as the the theoretical foundations of the proposed method and its existing applications to other engineering domains. A detailed description of the method's implementation for rotorcraft parameter identification is then provided. Preliminary results are presented for the parameter identification of a physics-based helicopter model, using only time series and trim data (local linear models will be implemented at a later stage); the results are compared to those produced by a classical time-domain method. The paper concludes with a summary of findings and a discussion of future developments and potential applications.

PARAMETER IDENTIFICATION OF NONLINEAR ROTORCRAFT MODELS

Most techniques for aircraft parameter identification (Refs. 5–7) belong to the family of *prediction error methods*. The core idea behind these methods is to find the "best" set of parameter values by minimizing the error between the outputs predicted by the model and the actual (measured) system outputs. In practice, the size of the prediction error across the dataset is quantified using a scalar cost function, which is then minimized with respect to the parameters in what essentially becomes a numerical optimization problem (Ref. 3). The various techniques differ in how the cost function is defined and in the assumptions about system disturbances and properties of the prediction error; the most common are based on least-squares estimation (e.g., the Equation Error method (Ref. 8)) or on Maximum Likelihood estimation (e.g., the Output-Error (Ref. 9) and Filter-Error (Ref. 10) methods). The identification can be performed either in time or in frequency domain: in time domain, the methods are applied directly to the measured time-series of input and output variables; in frequency domain, the methods are applied to frequency response curves, power spectral densities, and the like, typically extracted from time-domain data using a Fourier transform.

A brief description of state-of-the-art procedures for the parameter identification of nonlinear rotorcraft models is provided below.

Frequency-domain methods

Frequency-domain techniques are particularly suitable for rotorcraft applications, thanks to their robustness to high noise and vibration levels and their straightforward applicability to unstable dynamic systems; their computational cost is also usually lower compared to time-domain, as the number of data points is limited and the solution to differential equations involves only algebraic operations. Due to these practical advantages, frequency-domain methods are by far the most commonly used by rotorcraft manufacturers and research institutions, as shown in a recent survey by the NATO STO AVT-296 Research Task Group (Ref. 1). The frequency response-based software suite CIFER® (Refs. 7, 11) is also widely used.

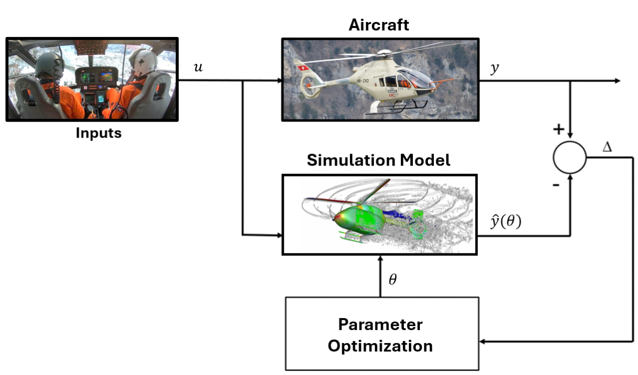

Figure 1. Basic working principle of prediction error methods

Many examples exist of frequency-domain identification applied to nonlinear models, including to the update of physics-based engineering simulations (Refs. 1, 11, 12). In all cases, the first step is the extraction of a local linear model from flight test data. In CIFER®, this is done by first deriving a linear non-parametric model in the form of a MIMO frequency-response matrix; if required, a state-space parametric model is then identified using a frequency-domain maximum likelihood estimator (Ref. 11). To identify the unknown parameters of a nonlinear model from this local linear approximation, two approaches are available:

- An "indirect" approach (Refs. 1, 11, 12) consists in replacing terms of the linear state-space model by analytical expressions in which the unknown parameters appear. For example, for physical parameters, possible formulations can be found in (Refs. 7, 13, 14). The parameters are then identified through a maximum likelihood method and used to update the nonlinear simulation model.
- A "direct" approach (Refs. 1, 15) consists in adjusting the parameters directly in the nonlinear model, based on observed discrepancies between the linearized simulation model and the data from flight tests; the discrepancies can relate either to the frequency response or to the values of stability and control derivatives. Typically, parameter sweeps are performed, and the values producing the minimum mismatch are selected.

The fact that the parameters are basically always estimated from linear models is an important limitation of frequency-domain techniques. For highly nonlinear systems such as rotorcraft, linear approximations are typically valid only within a limited range of the working point and may be dependent on the inputs applied (Ref. 16) - a fact that calls for careful experiment design and may cause issues when identifying full-envelope simulation models. In addition, any losses of information (e.g., on biases and linear trends) in the conversion from time to frequency domain result in missing or erroneous representations of the corresponding dynamic effects. Unless all these factors are properly accounted for, the parameters identified in the frequency domain may be far from optimal when applied to a nonlinear framework.

Renovations techniques

The so-called *renovations* techniques (Refs. 1, 17, 18) provide a systematic framework to enhance the fidelity of physics-based simulation models and use a similar approach to the one of frequency-domain methods.

The first step is the identification of a linear state-space model of the aircraft from flight test data, using either a time- or a frequency-domain technique. Then, the stability and control derivatives of the identified model are compared to those of the linearized simulation model. The discrepancies observed in the derivatives are useful in two ways: on the one hand, if a sensitivity analysis or a physics-based study is conducted, they can point the user to the parts of the model most responsible for the mismatch with flight data; on the other hand, they provide corrective factors in the form of force/moment increments, that can be introduced in the simulation model to increase its fidelity.

Time-domain methods

Unlike frequency-domain methods, time-domain techniques have no theoretical limitations when it comes to identifying nonlinear systems. However, practical issues arise, mainly due to the following aspects:

- When applied to nonlinear systems, the optimization problem associated with parameter identification also becomes nonlinear and is often ill-posed (Refs. 5, 19): in addition to requiring greater computational effort, the optimization may reach a local minimum instead of a global one, or may not converge at all.
- To compute the time-domain outputs of the simulation model, classic methods such as output-error require the numerical integration of the model's dynamics equations; for inherently unstable and highly sensitive systems, this can lead to numerical divergence in both the simulation and the optimization (Ref. 6). More general methods such as filter-error, which compute states and outputs using state estimation techniques, are rarely usable in practice due to the excessive computational cost and to the frequent identifiability problems caused by low information content relative to the high number of unknowns (Ref. 5).

Despite their wide application to fixed-wing aircraft (see for example (Refs. 5, 6)), traditional time-domain parameter identification techniques remain uncommon for rotorcraft - with applications mostly limited to the identification of simple, lower-order models as in (Ref. 20). Two rare examples of classic time-domain identification applied to nonlinear, physics-based helicopter models can be found in (Ref. 21) and (Ref. 22).

A more recent approach to the time-domain identification of unstable systems derives from optimal control and is based on the concept of multiple shooting (Refs. 6, 23). Rather than integrating the system equations over an entire maneuver, the time domain is divided into smaller intervals, and the dynamics equations are only integrated within each interval; this makes the simulation less likely to diverge due to excessively amplified small perturbations. To preserve the continuity of the complete maneuver, the values of the states at the boundaries between shooting segments become additional unknowns in the optimization problem, and "gluing" constraints are introduced to force these values to be equal from one segment to the next. In (Ref. 24) and (Ref. 25), the multiple shooting approach is driven to the extreme of a full discretization, where as many shooting segments are taken as there are sample points; however, this method requires considerable computational effort due to the large size of the optimization problem, and can become impractical when dealing with high-order models or large amounts of flight data. In such cases, a better solution may come from hybrid approaches: for instance, (Ref. 26) proposes a single-multiple shooting method which applies multiple shooting only to the classic states of flight mechanics, while the rotor states are left unconstrained.

Parameter identification using trim data

In addition to matching an aircraft's dynamic response, a high-fidelity simulation model is also expected to accurately replicate its trim states - i.e., its steady-state operating points (Ref. 1). This means that, in the model as in the real aircraft, specific combinations of states and inputs must produce a condition of unaccelerated flight.

As many parameters have an influence on both the dynamic and the trim response, using trim data to update flight simulation models is a common practice. A key advantage of trim points is that they are not only required for parameter identification but also for other purposes, such as aircraft design and certification. Therefore, a typical flight test campaign will contain many more trim points than dynamic maneuvers usable for system identification. Additionally, since trim points are equilibrium conditions, they do not require elaborate input design and are not affected by unstable vehicle dynamics. They also tend to be less sensitive to noise, especially when the data are averaged over time (Ref. 27).

Methods that exploit trim data range from simple manual parameter tuning to more systematic approaches based on system identification, as described for example in (Ref. 28). In most cases, steady-state information alone is not sufficient to obtain accurate estimates of all the model parameters (Refs. 27, 29). Because of this, parameter tuning using trim data is performed prior to or in addition to the classical parameter identification, which instead focuses solely on matching the dynamic response.

It should be noted that, since most system identification maneuvers start from a trim condition, information on the aircraft steady-state response is also available in the time series used for time-domain identification. However, time-domain methods do not enforce an exact match of this trim condition: the initial states and inputs for the simulation are either extracted directly from the measurements (regardless of whether the model is actually trimmed in those conditions), or calculated separately using a trim routine and then corrected with bias terms to compensate for discrepancies with the data (Refs. 6, 30, 31). Either way, trim information will only have a marginal influence on parameter estimates.

Model stitching

Model stitching combines modeling and system identification techniques to produce continuous, quasi-nonlinear, full-envelope flight simulation models. In its classic architecture (Refs. 7, 32), a stitched model is composed of:

- a series of linear state-space perturbation models, each representing the aircraft dynamic response for a specific flight condition and configuration;
- a set of trim point data, recording the variation of trim states and controls over the full envelope;
- nonlinear equations describing the aircraft 6-DoF dynamics and the gravitational forces acting on the center of gravity.

The linear perturbation models and trim data are derived from flight test data and stored in lookup tables, to be interpolated as functions of airspeed and altitude; they are then combined with the nonlinear equations of motion and with the inertia model, which allow extrapolation to off-nominal loading configurations and flight conditions.

The stitching approach is often used in models for training and control design applications; it is also well suited to the simulation of unconventional rotorcraft and UAVs, as a means to obtain nonlinear full-envelope models even with limited knowledge of the underlying physics. Examples can be found, among others, in (Ref. 1), (Ref. 11), (Ref. 33), and (Ref. 34). In a recent work (Ref. 35), the linearization is applied only to rotor dynamics, while all the other components (equations of motion, inertia, airframe and control surfaces aerodynamics) are modeled by nonlinear equations.

Among the identification methods discussed so far, model stitching is the only one accounting for more than one type of information (Table 1). However, each type of data (the local linear models and the trim points) is interpolated separately from the other and affects different model parameters. In contrast, the novel method proposed in this paper uses all types of information at once to estimate the same parameters. The theoretical basis and existing examples of this approach are outlined in the following section.

MULTI-OBJECTIVE PARAMETER IDENTIFICATION: BACKGROUND AND EXAMPLES

The numerical optimization problem associated with prediction error methods consists in finding the minimum of a defined cost function J with respect to the unknown model parameters θ:

$$\underset{\theta}{\text{minimize}}\; J(\theta) \tag{1}$$

When applied to nonlinear systems, this problem is often ill-posed, whereby a unique solution may not exist, or may not depend continuously on the data (Refs. 19, 36) (Fig. 2). In such a case, finding an optimal set of parameters becomes challenging when not impossible.

Regularization techniques (Refs. 36, 37) improve the efficiency and effectiveness of the optimization by improving the

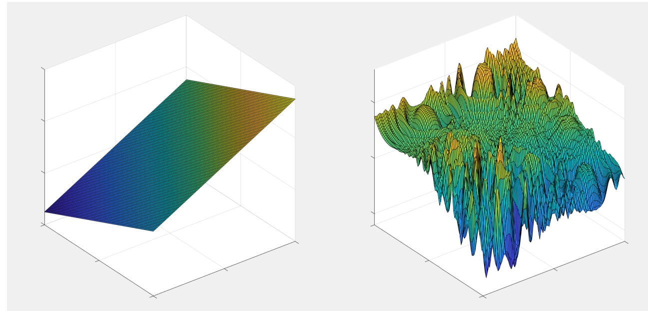

Figure 2. Representation of the hypersurfaces characterizing a linear (left) and a nonlinear (right) optimization problem with two parameters; the nonlinear problem may have multiple optima and discontinuities. (Ref. 16)

numerical properties of the problem (in other words, by making it more "regular"). They often do so by exploiting available prior knowledge about the system - for instance, *a priori* parameter values (Ref. 38), or of known/desirable properties such as the smoothness of the outputs (Ref. 4).

In classic regularization methods, each piece of additional information is included in the optimization as a penalty to the objective function. For example, when an *a priori* value θ^* of the parameter vector is available, this can be added as a quadratic norm of the type (Ref. 38):

$$\underset{\theta}{\text{minimize}} \left[J(\theta) + \lambda(\theta-\theta^*)^T\Lambda(\theta-\theta^*)\right] \tag{2}$$

where the amount of penalty is tuned by the scaling factor λ and the weighting matrix Λ.

Over the past three decades, works focusing specifically on nonlinear dynamic systems (Refs. 4, 19, 39) have introduced new methods for incorporating additional knowledge into the parameter identification process. In these approaches, the additional knowledge - usually referred to as *auxiliary information* - is introduced as either additional constraints or additional objectives, the latter case resulting in a multi-objective identification framework. The types of auxiliary information that can be used depend on the problem at hand and on the type of model being identified; examples include, but are not limited to:

- Known models to which the system's response is equivalent, either in a specific operating point (e.g., local linear models) or over a range of operating conditions (Refs. 4, 19).
- Steady-state information, such as static gains and equilibrium conditions (Refs. 4, 40, 41)
- Information on the stability of the system, for example, locations of poles and stable equilibrium points (Refs. 19, 42)
- Noise models with known or desired properties, e.g., linear noise models (Ref. 19).

Table 1. Types of information in state-of-the-art rotorcraft parameter identification techniques

	Method					
Information used	frequency domain	renovations	time domain	tuning with trim	stitching	THIS PAPER
linear models	✓	✓	✗	✗	✓	✓[b]
trim data	✗	✗	✗	✓	✓	✓
time series	✗	✗	✓	✗	(✓)[a]	✓
Used simultaneously	✗	✗	✗	✗	✗	✓

[a] (Ref. 35)

[b]To be implemented

Research from various fields of engineering (Refs. 27, 29, 41–51) shows that incorporating auxiliary information not only results in a better-posed numerical optimization problem, but can also reduce the variance of identified models due to uncertainty in the data. In particular, Aguirre et. al. (Refs. 29, 41, 42, 45, 48–51) propose a multi-objective approach combining dynamic and steady-state information, and have applied it to various parameter identification problems in electrical, electronic, and process engineering. Their results indicate that the multi-objective approach produces more accurate models than traditional parameter identification methods, especially when the information content in dynamic experiments is limited or affected by noise.

Most of the cited examples deal with the parameter identification of nonlinear "black-box" models, such as NARMAX models and neural networks. This paper shows that the benefits of a multi-objective parameter identification approach apply to other types of nonlinear models as well - for example, "white-box" models based on physical principles.

DESCRIPTION OF THE PROPOSED METHOD

Definition of objectives

The basic concept of the proposed parameter identification method is to combine different types of information about the aircraft - namely: time-series, trim data, and local linear models - by embedding them in a multi-objective optimization framework. The parameter identification problem from Eq. (1) becomes:

$$\underset{\theta}{\text{minimize}}\, \mathbf{J}(\theta) \tag{3}$$

where now $\mathbf{J}(\theta)$ is a vector of cost functions, each one corresponding to a different type of information:

$$\mathbf{J}(\theta) = [J_{\text{time}}(\theta), J_{\text{trim}}(\theta), J_{\text{linear}}(\theta)]^T \tag{4}$$

Time-series data The cost function for time-series data, J_{time}, can be defined using any method from traditional time-domain parameter identification (Refs. 5, 6). In this paper, the classic Maximum Likelihood cost function from Output-Error methods has been used (Ref. 6):

$$J_{\text{time}}(\theta) = \frac{1}{2}\sum_{k=1}^{N}[y(t_k) - \hat{y}(t_k|\theta)]^T R^{-1}[y(t_k) - \hat{y}(t_k|\theta)] + \\ + \frac{N}{2}\ln(\det(R)) \tag{5}$$

Where y and $\hat{y}$ indicate, respectively, the measured outputs and the outputs predicted by the model; N is the total number of samples; R is the covariance matrix of the prediction errors, which can be estimated in a maximum likelihood sense as:

$$R = \frac{1}{N}\sum_{k=1}^{N}[y(t_k) - \hat{y}(t_k|\theta)]\,[y(t_k) - \hat{y}(t_k|\theta)]^T \tag{6}$$

Trim data For trim data, the cost function J_{trim} has been defined as the mean square error between the actual and predicted trim condition. This approach is analogous to a classic least-squares method:

$$J_{\text{trim}} = \frac{1}{N_{\text{trim}}}\sum_{k=1}^{N_{\text{trim}}}[z_{\text{trim}}(k) - \hat{z}_{\text{trim}}(k|\theta)]^T[z_{\text{trim}}(k) - \hat{z}_{\text{trim}}(k|\theta)] \tag{7}$$

Where N_{trim} is the number of trim points and the vector z_{trim} indicates a generic set of inputs, states, and outputs of the aircraft in trim conditions:

$$z_{\text{trim}} = \begin{bmatrix} u_{\text{trim}} \\ x_{\text{trim}} \\ y_{\text{trim}} \end{bmatrix} \tag{8}$$

The vector $\hat{z}_{\text{trim}}$ - i.e., the trim response of the model - can be computed using any kind of analytical or numerical trim routine. Equation (7) is analogous to the cost function of a classic least-squares method (Ref. 3). Further refinements are also possible, such as applying individual weights to each trim point to compensate for noise in the data (Ref. 50).

Local linear models Information about local linear models can be incorporated in various ways. One option is to define a cost function based on the error between the frequency response of the model and that of the actual aircraft. Cost functions of this type are often used in classic frequency-domain identification methods; for example, a typical formulation uses Weighted Least Squares (Ref. 7):

$$J_{\text{linear}}(\theta) = \frac{20}{n_\omega} \sum_{k=1}^{n_\omega} W_\gamma \Big[W_g \big(|T(\omega_k)| - |\hat{T}(\omega_k, \theta)| \big)^2 + + W_p \big(\angle T(\omega_k) - \angle \hat{T}(\omega_k, \theta) \big)^2 \Big] \quad (9)$$

where $T(\omega)$ indicates a frequency response function, n_ω is the number of frequencies for which the response is evaluated, and different weighting factors are applied to gains and phases to make their errors comparable.

Another option is to define the cost function as some norm of the error on the stability and control derivatives of the local linear models (respectively, the one identified from the data and the one obtained by linearizing the simulation model). This approach already exists in rotorcraft parameter identification: in fact, it is used by frequency-domain methods and *renovations* techniques (Refs. 1,11,12,18). Yet another option is to compare the poles of the model with those of the actual aircraft, as suggested in (Ref. 19).

The incorporation of information from local linear models is currently under development and will be discussed in future publications. The preliminary results reported in this paper focus on a bi-objective parameter identification problem in which only time-series and trim data are considered.

Multi-objective optimization procedure

In most multi-objective optimization problems, no single solution can minimize all the objective functions at the same time, because the objectives tend to conflict with each other (Ref. 52). In this case, the optimization procedure does not return just one solution, but rather a set of solutions that represent the trade-offs between different objectives. These solutions are known as *efficient solutions* or *Pareto set*, and are characterized by the fact that it is impossible to further reduce any objective without increasing one or more of the others (Refs. 52, 53). Once a set of efficient solutions has been identified, the user selects the "best" solution according to some *decision-making* criterion (Ref. 52).

One may argue that the objectives in Eq. (4) should not be competing with each other: after all, they all relate to information about the same aircraft. This is true in theory but not in practice: in fact, the amount of noise in the data and the inputs applied affect each type of information in a different way; also, the data and the methods used to extract each type of information are typically different (Ref. 44). Therefore, it is reasonable to expect that each objective will be minimized by a somewhat different set of parameters.

Figure 3 shows the values of the objectives (the so-called *Pareto front*) corresponding to the efficient solutions of the bi-objective problem in "Case 1" of the "Results" section. A classic time-domain identification method, focused only on matching the time-series data, would converge to point **A**. On the other hand, if only trim data were used as objective, the optimization would converge to point **B**. The other points along the solid line represent all possible trade-offs between the two objectives.

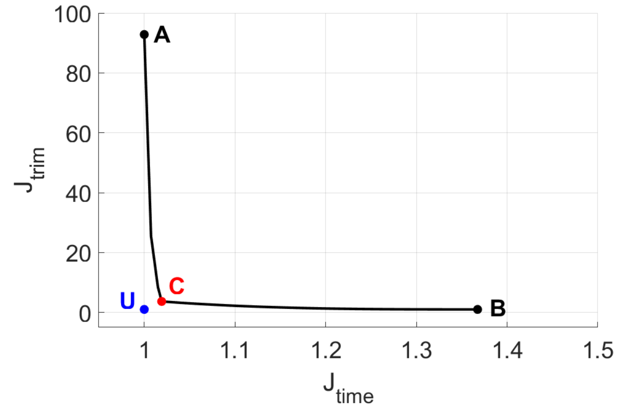

Figure 3. Pareto front for the parameter identification problem in "Case 1"

Determining the Pareto set The efficient solutions were calculated using the so-called ε*-constraint* method (Refs. 52,53). This consists in minimizing only one of the objectives, while forcing the other objectives to remain below a certain threshold. In the case of the optimization problem from Eq. (3)-(4):

$$\underset{\theta}{\text{minimize}}\; J_{\text{time}}(\theta) \quad \text{subject to:} \quad \begin{array}{c} J_{\text{trim}}(\theta) \leq \varepsilon_{\text{trim}} \\ J_{\text{linear}}(\theta) \leq \varepsilon_{\text{linear}} \end{array} \quad (10)$$

Eq. (10) is a classic constrained optimization problem that can be solved with any of the established techniques for single-objective optimization (Refs. 54,55). To scan the entire Pareto set, the procedure must be repeated several times with different values of $\varepsilon_{\text{trim}}$ and $\varepsilon_{\text{linear}}$.

Another widely used approach to compute the Pareto set, applied for instance in (Refs. 29, 41, 42, 45, 48–51), is to combine all the objectives into a single function using a weighted sum; this function is then minimized multiple times, each time changing the values of the weights. Though very simple, this approach is typically less efficient than the ε-constraint method, and can only identify convex portions of the Pareto set (Ref. 53).

Choosing the best solution Decision-making criteria for multi-objective parameter identification can be based on engineering judgment or on quantitative metrics.

Criteria of the first type typically imply that the user has some kind of underlying preference regarding the best solution (Ref. 41). For example, the user may define acceptable bounds for each objective (Ref. 4), or may attribute different weights to the various objectives based on the degree of confidence in the data (Ref. 46).

On the other hand, criteria based on quantitative metrics do not require any *a priori* preferences. A straightforward metric is the distance between the Pareto front and the *utopia* point, i.e., the condition that would be achieved if all objectives could be minimized simultaneously (point **U** in Fig. 3). Although the utopia condition is not typically achievable in practice, it is possible to choose the Pareto solution that comes closest to it, by minimizing (Ref. 52):

$$\text{minimize} \sqrt{\sum_{i=1}^{n_J} \left(\frac{J_i - \min(J_i)}{\max(J_i) - \min(J_i)} \right)^2} \tag{11}$$

where the distances are normalized to account for different scaling of the objectives. This is the criterion used in this paper; as will be shown in the following sections, it appears to produce satisfactory results.

Using Eq. (11), point **C** can be found even without determining the rest of the Pareto set (Ref. 52). With this approach, the computational load of parameter identification reduces significantly, as only $n_J + 1$ single-objective optimization problems have to be solved (the first n_J are needed to compute the utopia point). However, computing the entire Pareto set is usually advisable, as it provides a more comprehensive view of the problem at hand and enables the user to make more informed decisions (Ref. 41).

Other quantitative metrics are defined in terms of the simulation error computed over a set of maneuvers that were not used for the parameter identification. This approach selects the best solution as the one minimizing either the root mean square of the simulation error (Ref. 41) or the correlation between simulation error and model output (Ref. 29).

Some practical considerations

Computational load Multi-objective parameter identification requires the solution of multiple numerical optimization problems. Each individual problem is solved iteratively, and typically each iteration computes not only the values of all objectives, but also their gradients with respect to the parameters (Ref. 53). As a result, the computational effort is much higher than in classic parameter identification, where only one numerical optimization is performed.

One way to reduce the computational load consists in determining only one efficient solution, rather than the whole Pareto set, using Eq. (11) as an optimization objective. On the other hand, if the entire Pareto set is estimated, each iteration of Eq. (10) can be initialized with the solution from the previous iteration; this way, the constrained optimization algorithm will typically converge after only a few steps.

Scaling Since many numerical optimization methods are highly sensitive to problem scaling, it is a good practice to normalize both the parameters and the objective functions so that their values, and possibly also the gradients $\partial J/\partial\theta$, have similar orders of magnitude. In the examples presented in this paper, scaling is applied as follows:

- Scaling factors for the parameters are defined based on either *a priori* values or the expected range of variation.

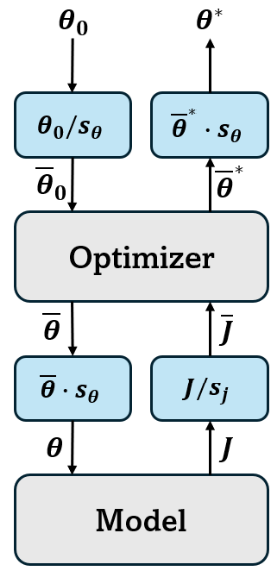

Figure 4. Scheme of the procedure for parameter and objective scaling. (Ref. 53, adapted)

- When performing a single-objective optimization, the objective is scaled by $J(\theta_0)$, i.e., the value calculated using the initial parameter guesses.
- When performing a multi-objective optimization, each objective is scaled by its value at the utopia point.

To avoid making modifications to the simulation model, these scale factors are applied only at optimizer level, while the model continues to work with unscaled variables (Fig. 4).

Simulation instability In relation to the limitations of time-domain methods discussed earlier, the method proposed in this paper promises to improve on the first aspect - related to ill-posed problems - but does not address the issue of simulation instability. For particularly unstable rotorcraft models, it may be necessary to combine both the multi-objective and a multiple-shooting technique; this is easily done thanks to the flexibility of the multi-objective optimization framework (Ref. 4), but the computational load may increase significantly.

PRELIMINARY RESULTS

The following examples demonstrate the application of the multi-objective parameter identification method to a simple problem - namely, the estimation of physics-based parameters in a nonlinear, 3DoF model of the Bo-105 helicopter. The model has been developed in MATLAB® at TU Delft and includes the three longitudinal degrees of freedom as well as the uniform main rotor inflow dynamics (Ref. 56).

As anticipated, the current parameter identification framework uses only two objectives - time-series and trim data -

while local linear models have not yet been incorporated. The optimization problem from Eq. (3) is then reduced to:

$$\underset{\theta}{\text{minimize}}\; \mathbf{J}(\theta) = [J_{\text{time}}(\theta), J_{\text{trim}}(\theta)]^T \tag{12}$$

The bi-objective identification problem (12) is solved as described in the previous section: first, the Pareto set is computed using the ε-constraint method; then, the best efficient solution is selected based on the decision-making criterion (11). The single-objective optimization sub-problems are solved using the function *fmincon* from the MATLAB® Optimization Toolbox,[1] with user-specified gradients for objectives and constraints.

The time-series cost function $J_{\text{time}}(\theta)$ is defined as in Eq. (5) and calculated using the following outputs:

$$y = [q, \vartheta, n_x, n_z, \text{TAS}]^T \tag{13}$$

where q and ϑ are the pitch rate and pitch angle of the fuselage, n_x and n_z are the horizontal and vertical load factors, and *TAS* is the true airspeed of the helicopter.

For the trim objective function $J_{\text{trim}}(\theta)$, the definition of Eq. (7) is used; the vector of generalized outputs z_{trim} comprises the trim values of the collective and longitudinal input, and of the pitch angle ϑ:

$$z_{\text{trim}} = [\text{col}, \text{lon}, \vartheta]^T \tag{14}$$

In the simulation model, $\hat{z}_{\text{trim}}$ is calculated using a numerical trim routine based on the Newton-Raphson method (Ref. 57). The same routine is also used to initialize the simulation of dynamic maneuvers.

The dataset used for parameter identification is part of the Bo-105 flight test data collected by the GARTEUR Action Group AG06 (Ref. 58). The following maneuvers have been used:

- **Time-series (10 test points):**
  Collective and longitudinal 3-2-1-1 at 80kt +
  Collective and longitudinal doublets at 20kt and hover
- **Trim (24 test points):**
  Forward flight trim at various speeds (14 points) +
  The trim conditions at the beginning of each time-series

The following subsections analyze two different examples of parameter identification problems:

- **Case 1:** All the identified parameters affect both the dynamic and the trim response of the helicopter.
- **Case 2:** All the identified parameters affect the dynamic response, but only some have an effect on trim.

In both cases, the results produced by the multi-objective approach are compared to those of a traditional output-error identification in time domain.

[1] https://www.mathworks.com/help/optim/ug/fmincon.html

Case 1

In this first example, the parameter to be identified consist of:

- the linear twist (θ_{twist}) of the main rotor blades
- the lift curve slope ($C_{L\alpha\,HT}$) of the horizontal stabilizer

Both parameters influence both the steady-state and the dynamic response of the model.

A comparison between the model identified with the multi-objective approach, the one identified using the classic time-domain method, and the data of the actual helicopter, is reported in the following figures and in Table 2.

As expected, the model obtained via multi-objective identification provides more accurate predictions of the trim conditions (Fig. 5), particularly with regard to collective inputs. The remaining discrepancies in pitch attitude and longitudinal command are likely due to the unmodeled interference of the rotor wake on the horizontal stabilizer, which prevents a correct matching of low speed trim points during the identification.

Figure 6 compares the predicted dynamic response for a series of validation maneuvers (i.e., maneuvers not used for identification) consisting of collective and longitudinal doublets at 80kt. It should be noted that a certain mismatch with flight tests is inevitable, as the response of the real helicopter includes non-negligible roll rate and lateral acceleration, which cannot be captured by a simple longitudinal model. Nonetheless, it is evident that the multi-objective approach, while identifying a solution that is not strictly optimal in terms of dynamic response error, does not significantly degrade the results compared to the traditional approach. In fact, the novel method even produces an improvement in the prediction of the rotor coning angle β_0, probably as a result of the better matching of trim conditions.

Finally, a comparison of the values of the identified parameters (Table 2) shows that, while the classic time-domain approach tends to significantly overestimate θ_{twist} and underestimate $C_{L\alpha\,HT}$, multi-objective identification yields estimates that are much closer to the actual helicopter parameters. The larger discrepancy in the value of $C_{L\alpha\,HT}$ may again be due to the unmodeled wake-tail interference.

Case 2

This second example uses the same setup as Case 1, but adds a third parameter - the moment of inertia I_{yy} - that only affects the helicopter's dynamic response.

The comparison of trim predictions (Fig. 7) and of validation maneuvers (Fig. 8) confirms the observations from the previous case: the multi-objective identification approach results in a more accurate matching of the steady-state response, without producing any evident deterioration in the dynamic response.

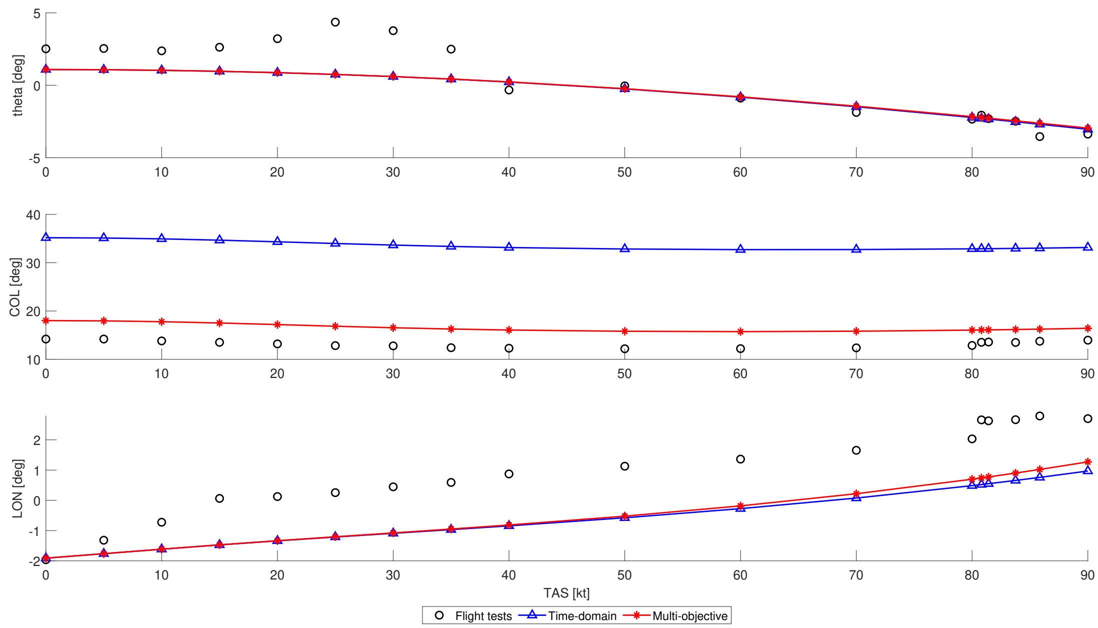

Figure 5. Comparison of predicted trim conditions - Case 1

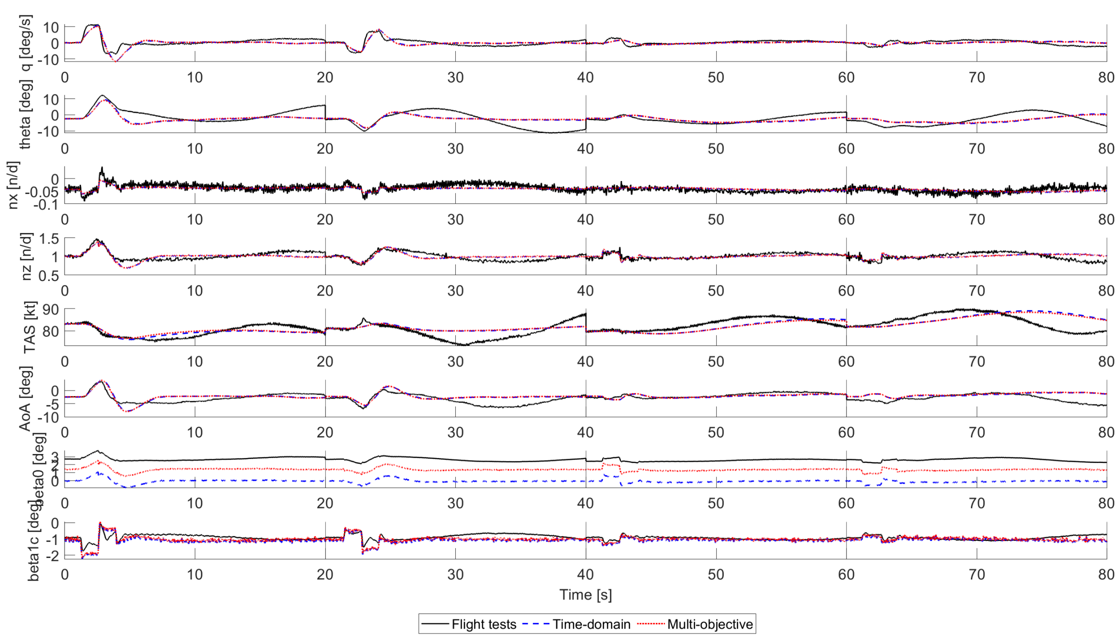

Figure 6. Comparison of validation maneuvers - Case 1

Table 2. Comparison of parameter values - Case 1

		time-domain	multi-objective	actual Bo-105
θ_{twist}	[deg/m]	-7.6719	-3.0138	-1.6329
$C_{L\alpha HT}$	[rad^{-1}]	0.9451	1.1209	6.2166

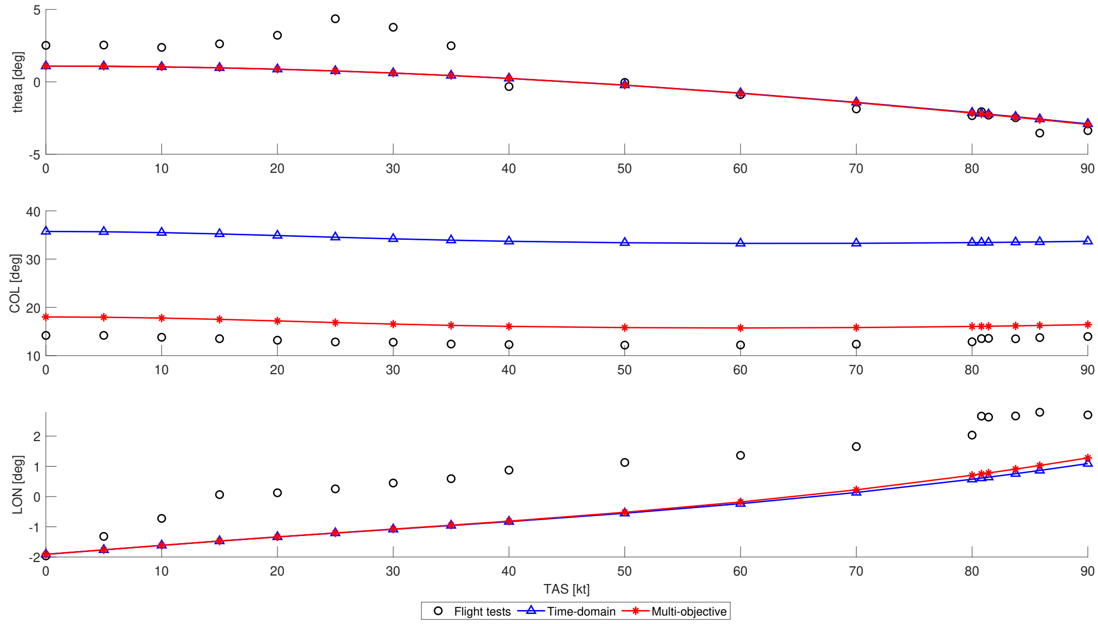

Figure 7. Comparison of predicted trim conditions - Case 2

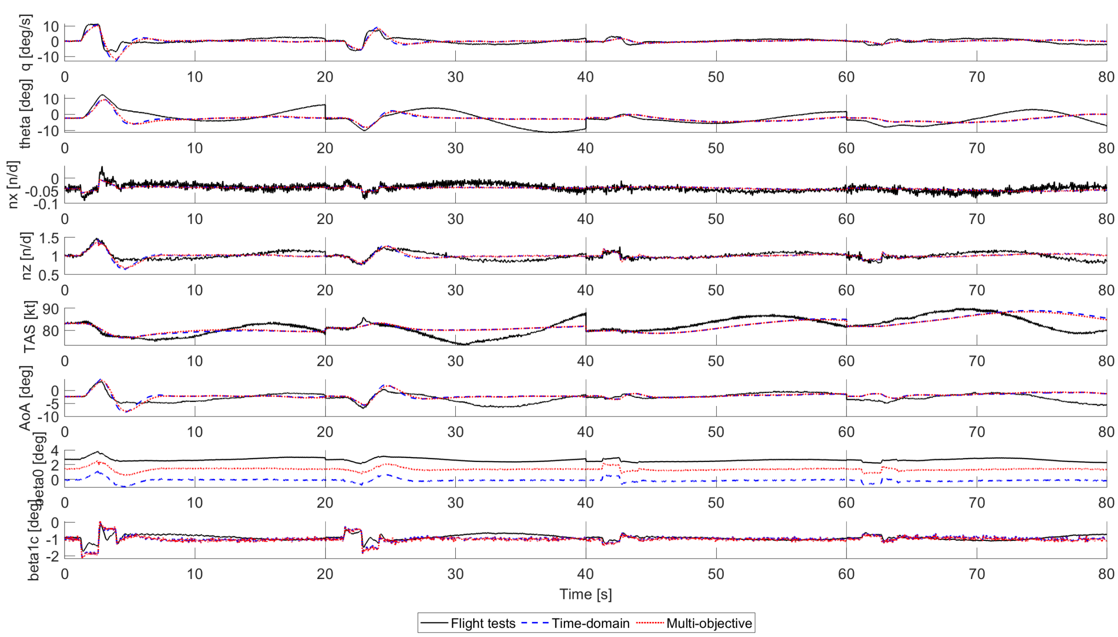

Figure 8. Comparison of validation maneuvers - Case 2

Table 3. **Comparison of parameter values - Case 2**

		time-domain	multi-objective	actual Bo-105
θ_{twist}	[deg/m]	-7.8220	-3.0132	-1.6329
$C_{L\alpha HT}$	[rad^{-1}]	1.2323	1.1403	6.2166
I_{yy}	[kg m^2]	4106	4910	4973

An interesting result emerges from the comparison of parameter estimates (Table 3): in addition to providing better estimates of the parameters that are affected by both objectives, the multi-objective approach also appears to remarkably improve the accuracy of the moment of inertia. A possible explanation is that the auxiliary information introduced by this approach helps separate the effects of the various parameters, resulting in a global improvement of the parameter estimates.

CONCLUSIONS

A novel approach for the multi-objective parameter identification of nonlinear rotorcraft models has been introduced. This approach had never been applied to aircraft and allows to simultaneously exploit different types of information (time series, trim points, and local linear models), which are typically considered separately in traditional parameter identification techniques.

Guidelines for implementing and solving the multi-objective optimization problem have been provided. A quantitative metric has been proposed that can be used either as a *decision-making* criterion to select the best solution from the Pareto set, or as a parameter identification objective to identify a single efficient solution.

Preliminary results for the special case of a bi-objective identification problem using time-series and trim data indicate that the proposed approach can considerably improve the prediction of trim conditions, without significantly degrading the predicted dynamic response. Also, by introducing additional information in the parameter identification process, it can facilitate the separation of effects and increase the overall accuracy of parameter estimates.

The computational effort involved in multi-objective identification is much higher than that of traditional, single-objective identification techniques. Therefore, the proposed method is especially suitable for applications requiring high levels of model fidelity, such as the development or update of high-fidelity engineering simulation models. It can also be helpful when dynamic data are limited or corrupted by noise, and all available types of information have to be taken into account.

Future work will incorporate local linear models into the multi-objective identification framework, and will further explore the capabilities of this approach by testing it on different types of models and parameter identification problems.

Author contacts:

Anna Abà,	A.Aba@tudelft.nl
Marilena D. Pavel,	M.D.Pavel@tudelft.nl
Pierluigi Capone,	pierluigi.capone@zhaw.ch
Pieter-Jan Proesmans,	P.Proesmans@tudelft.nl

REFERENCES

1. Tischler, M. B., White, M. D., Cameron, N., D'Agosto, S., Greiser, S., Gubbels, A., Guner, F., He, C., Horn, J., Hui, K., Jones, M., Juhasz, O., Lehman, R., Miller, D., Myrand-Lapierre, V., Nadeau-Beaulieu, M., Nadell, S., Padfield, G. D., Pavel, M., Prasad, J. V. R., Ragazzi, A., Richard, S., Scepanovic, P., Seher-Weiß, S., Stroosma, O., Soong, J., Taghizad, A., Tobias, E., Xin, H., Yavrucuk, I., and Lee, O., *Rotorcraft Flight Simulation Model Fidelity Improvement and Assessment*, Paper STO-TR-AVT-296 in Technical Report RDP, NATO Science and Technology Organization, May 2021.

2. Abà, A., Pavel, M. D., and Capone, P., "A "User's Guide" to System Identification Methods for Helicopter and VTOL Applications," 50th European Rotorcraft Forum, 2024.

3. Ljung, L., *System Identification: Theory for the User*, Prentice Hall Information and System Sciences Series, Prentice Hall PTR, Upper Saddle River, NJ, second edition, 1999.

4. Johansen, T. A., "Multi-Objective Identification of FIR Models," *IFAC Proceedings Volumes*, Vol. 33, (15), June 2000, pp. 917–922. DOI: 10.1016/S1474-6670(17)39870-1.

5. Klein, V., and Morelli, E. A., *Aircraft System Identification: Theory and Practice*, AIAA Education Series, AIAA, American Institute of Aeronautics and Astronautics, 2006.

6. Jategaonkar, R. V., *Flight Vehicle System Identification: A Time-Domain Methodology*, Paper 245 in Progress in Astronautics and Aeronautics, AIAA, American Institute of Aeronautics and Astronautics, second edition edition, 2015.

7. Tischler, M. B., and Remple, R. K., *Aircraft and Rotorcraft System Identification: Engineering Methods with Flight-Test Examples*, AIAA Education Series, AIAA, American Institute of Aeronautics and Astronautics, 2006.

8. Klein, V., "Identification Evaluation Methods," AGARD Lecture Series, AGARD Lecture Series 104: Parameter Identification, 1979.

9. Iliff, K. W., and Taylor, L. W., "A Modified Newton-Raphson Method for Determining Stability Derivatives from Flight Data," Computing Methods in Optimization Problems - 2, 1969.

10. Mehra, R., "Identification of Stochastic Linear Dynamic Systems Using Kalman Filter Representation," *AIAA Journal*, Vol. 9, (1), 1971, pp. 28–31. DOI: 10.2514/3.6120.

11. Berger, T., Tobias, E. L., Tischler, M. B., and Juhasz, O., "Advances and Modern Applications of Frequency-Domain Aircraft and Rotorcraft System Identification," *Journal of Aircraft*, Vol. 60, (5), September 2023, pp. 1331–1353. DOI: 10.2514/1.C037275.

12. Fegely, C. E., Xin, H., Tischler, M., and Juhasz, O., "Flight Dynamics and Control Modeling with System Identification Validation of the Sikorsky X2 Technology Demonstrator," AHS 72nd Annual Forum, May 2016.

13. Chen, R., "Effects of Primary Rotor Parameters on Flapping Dynamics," NASA Technical Paper NASA Technical Paper 1431, NASA National Aeronautics and Space Administration, Ames Research Center, Moffett Field, California, 1980.

14. Padfield, G. D., *Helicopter Flight Dynamics: Including a Treatment of Tiltrotor Aircraft*, John Wiley & Sons, Inc, Hoboken, NJ, third edition edition, 2018.

15. Basset, P., and Brocard, M., "A Fenestron Model for Improving the Helicopter Yaw Dynamics Flight Simulation," 30th European Rotorcraft Forum, 2004.

16. Schoukens, J., and Ljung, L., "Nonlinear System Identification: A User-Oriented Road Map," *IEEE Control Systems*, Vol. 39, (6), December 2019, pp. 28–99. DOI: 10.1109/MCS.2019.2938121.

17. Lu, L., Padfield, G. D., White, M., and Perfect, P., "Rotorcraft Simulation Renovation through System Identification," 36th European Rotorcraft Forum, 2010.

18. Lu, L., Padfield, G. D., White, M., and Perfect, P., "Fidelity Enhancement of a Rotorcraft Simulation Model through System Identification," *The Aeronautical Journal*, Vol. 115, (1170), August 2011, pp. 453–470. DOI: 10.1017/S0001924000006102.

19. Johansen, T. A., "Identification of Non-Linear Systems Using Empirical Data and Prior Knowledge—an Optimization Approach," *Automatica*, Vol. 32, (3), March 1996, pp. 337–356. DOI: 10.1016/0005-1098(95)00146-8.

20. Kaletka, J., Tischler, M. B., von Grünhagen, W., and Fletcher, J. W., "Time and Frequency-Domain Identification and Verification of BO-105 Dynamic Models," *Journal of the American Helicopter Society*, Vol. 36, (4), October 1991, pp. 25–38. DOI: 10.4050/JAHS.36.25.

21. Jategaonkar, R. V., Fischenberg, D., and von Gruenhagen, W., "Aerodynamic Modeling and System Identification from Flight Data-Recent Applications at DLR," *Journal of Aircraft*, Vol. 41, (4), July 2004, pp. 681–691. DOI: 10.2514/1.3165.

22. Hosseini, B., Barth, A., Hajek, M., and Holzapfel, F., "Helicopter Parameter Estimation Based on A Nonlinear Physics-Based Model," AIAA Scitech 2021 Forum, January 2021. DOI: 10.2514/6.2021-1530.

23. Bock, H. G., and Plitt, K. J., "A Multiple Shooting Algorithm for Direct Solution of Optimal Control Problems," *IFAC Proceedings Volumes*, Vol. 17, (2), July 1984, pp. 1603–1608. DOI: 10.1016/S1474-6670(17)61205-9.

24. Göttlicher, C., *System Identification for Aerial Applications Using Optimal Control Methods*, Ph.D. thesis, Technische Universität München, Munich, Germany, 2019.

25. Hosseini, B., Steinert, A., Hofmann, R., Fang, X., Steffensen, R., Holzapfel, F., and Göttlicher, C., "Advancements in the Theory and Practice of Flight Vehicle System Identification," *Journal of Aircraft*, Vol. 60, (5), September 2023, pp. 1419–1436. DOI: 10.2514/1.C037269.

26. Bottasso, C. L., Luraghi, F., and Maisano, G., "On Time-Domain Parameter Estimation Techniques Applicable to First-Principle Rotorcraft Models," 35th European Rotorcraft Forum, September 2009.

27. Aguirre, L., Donoso-Garcia, P., and Santos-Filho, R., "Use of a Priori Information in the Identification of Global Nonlinear Models-a Case Study Using a Buck Converter," *IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications*, Vol. 47, (7), July 2000, pp. 1081–1085. DOI: 10.1109/81.855463.

28. Krämer, P., Gimonet, B., and v Grünhagen, W., "A Systematic Approach to Nonlinear Rotorcraft Model Identification," *Aerospace Science and Technology*, Vol. 6, (8), December 2002, pp. 579–590. DOI: 10.1016/S1270-9638(02)01200-2.

29. Barroso, M. F. S., Takahashi, R. H. C., and Aguirre, L. A., "Multi-Objective Parameter Estimation via Minimal Correlation Criterion," *Journal of Process Control*, Vol. 17, (4), April 2007, pp. 321–332. DOI: 10.1016/j.jprocont.2006.10.005.

30. Maine, R. E., and Iliff, K. W., "AGARD Flight Test Techniques Series. Volume 2. Identification of Dynamic Systems," Technical Report AGARD-AG-300-VOL-2, AGARD, Advisory Group for Aerospace Research & Development, 1985.

31. Hohenemser, K. H., and Yin, S. K., "Computer Experiments in Preparation of System Identification from Transient Rotor Model Tests, Part 2," Technical Report NASA-CR-137571, June 1974.

32. Tobias, E. L., and Tischler, M. B., "A Model Stitching Architecture for Continuous Full Flight-Envelope Simulation of Fixed-Wing Aircraft and Rotorcraft from Discrete Point Linear Models," Technical Report SPECIAL REPORT RDMR-AF-16-01, Aviation and Missile Research, Development and Engineering Center, Redstone Arsenal, United States, April 2016.

33. Deiler, C., Mönnich, W., Seher-Weiß, S., and Wartmann, J., "Retrospective and Recent Examples of Aircraft and Rotorcraft System Identification at DLR," *Journal of Aircraft*, Vol. 60, (5), September 2023, pp. 1371–1397. DOI: 10.2514/1.C037262.

34. Greiser, S., "Uncertainties in Modeling Helicopter Dynamics: A Framework Applied to System Identification Results," 41st European Rotorcraft Forum, September 2015.

35. Simonelli, A., *Development of a Novel System Identification Modelling Technique - Nonlinear Dynamic Inversion Stitching Applied to Rotorcraft*, MSc, Delft University of Technology, Delft, The Netherlands, 2024.

36. Tikhonov, A. N., Goncharsky, A. V., Stepanov, V. V., and Yagola, A. G., *Numerical Methods for the Solution of Ill-Posed Problems*, Springer Netherlands, Dordrecht, 1995. DOI: 10.1007/978-94-015-8480-7.

37. Nelles, O., *Nonlinear System Identification: From Classical Approaches to Neural Networks, Fuzzy Models, and Gaussian Processes*, Springer, Cham, Switzerland, second edition edition, 2021.

38. Ljung, L., “System Identification: An Overview,” *Encyclopedia of Systems and Control*, edited by J. Baillieul and T. Samad, Springer, London, 2019, pp. 1–15. DOI: 10.1007/978-1-4471-5102-9_100-2.

39. Tulleken, H. J. A. F., “Grey-Box Modelling and Identification Using Physical Knowledge and Bayesian Techniques,” *Automatica*, Vol. 29, (2), March 1993, pp. 285–308. DOI: 10.1016/0005-1098(93)90124-C.

40. Thompson, M. L., and Kramer, M. A., “Modeling Chemical Processes Using Prior Knowledge and Neural Networks,” *AIChE Journal*, Vol. 40, (8), 1994, pp. 1328–1340. DOI: 10.1002/aic.690400806.

41. Nepomuceno, E. G., Takahashi, R. H. C., and Aguirre, L. A., “Multiobjective Parameter Estimation for Non-Linear Systems: Affine Information and Least-Squares Formulation,” *International Journal of Control*, Vol. 80, (6), June 2007, pp. 863–871. DOI: 10.1080/00207170601185053.

42. Nepomuceno, E. G., Takahashi, R. H. C., Aguirre, L. A., Neto, O. M., and Mendes, E. M. A. M., “Multiobjective Nonlinear System Identification: A Case Study with Thyristor Controlled Series Capacitor (TCSC),” *International Journal of Systems Science*, Vol. 35, (9), July 2004, pp. 537–546. DOI: 10.1080/00207720412331285977.

43. Aguirre, L., Barroso, M., Saldanha, R., and Mendes, E., “Imposing Steady-State Performance on Identified Nonlinear Polynomial Models by Means of Constrained Parameter Estimation,” *IEE Proceedings - Control Theory and Applications*, Vol. 151, (2), March 2004, pp. 174–179. DOI: 10.1049/ip-cta:20040102.

44. Aguirre, L. A., Barbosa Alves, G., and Vieira Corrêa, M., “Steady-State Performance Constraints for Dynamical Models Based on RBF Networks,” *Engineering Applications of Artificial Intelligence*, Vol. 20, (7), October 2007, pp. 924–935. DOI: 10.1016/j.engappai.2006.11.021.

45. Barbosa, B. H. G., Aguirre, L. A., Martinez, C. B., and Braga, A. P., “Black and Gray-Box Identification of a Hydraulic Pumping System,” *IEEE Transactions on Control Systems Technology*, Vol. 19, (2), March 2011, pp. 398–406. DOI: 10.1109/TCST.2010.2042600.

46. Barbosa, A. M., Caldeira Takahashi, R. H., and Aguirre, L. A., “Equivalence of Non-linear Model Structures Based on Pareto Uncertainty,” *IET Control Theory & Applications*, Vol. 9, (16), October 2015, pp. 2423–2429. DOI: 10.1049/iet-cta.2015.0408.

47. Correa, M., Aguirre, L., and Saldanha, R., “Using Steady-State Prior Knowledge to Constrain Parameter Estimates in Nonlinear System Identification,” *IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications*, Vol. 49, (9), September 2002, pp. 1376–1381. DOI: 10.1109/TCSI.2002.802345.

48. Freitas, L., Barbosa, B. H. G., and Aguirre, L. A., “Including Steady-State Information in Nonlinear Models: An Application to the Development of Soft-Sensors,” *Engineering Applications of Artificial Intelligence*, Vol. 102, June 2021, pp. 104253. DOI: 10.1016/j.engappai.2021.104253.

49. NEPOMUCENO, E. G., TAKAHASHI, R. H. C., AMARAL, G. F. V., and AGUIRRE, L. A., “NONLINEAR IDENTIFICATION USING PRIOR KNOWLEDGE OF FIXED POINTS: A MULTIOBJECTIVE APPROACH,” *International Journal of Bifurcation and Chaos*, Vol. 10, (5), 2003, pp. 1229–1246. DOI: 10.1142/S0218127403007187.

50. Teixeira, B. O. S., and Aguirre, L. A., “Using Uncertain Prior Knowledge to Improve Identified Nonlinear Dynamic Models,” *Journal of Process Control*, Vol. 21, (1), January 2011, pp. 82–91. DOI: 10.1016/j.jprocont.2010.10.008.

51. Hafiz, F., Swain, A., Mendes, E. M. A. M., and Aguirre, L. A., “MultiObjective Evolutionary Approach to Grey-Box Identification of Buck Converter,” *IEEE Transactions on Circuits and Systems I: Regular Papers*, Vol. 67, (6), June 2020, pp. 2016–2028. DOI: 10.1109/TCSI.2020.2970759.

52. Miettinen, K., *Nonlinear Multiobjective Optimization*, Springer, New York, NY, UNITED STATES, 1998.

53. Martins, J. R. R. A., and Ning, S. A., *Engineering Design Optimization*, Cambridge University Press, Cambridge, 2022. DOI: 10.1017/9781108980647.

54. Nocedal, J., and Wright, S. J., *Numerical Optimization*, Springer Series in Operations Research, Springer, New York, second edition, 2006.

55. Nayak, S., *Fundamentals of Optimization Techniques with Algorithms*, Elsevier, London, United Kingdom San Diego, CA, United States, 2020.

56. van Holten, T., “Helicopter Performance, Stability and Control,” Lecture notes, Delft University of Technology, Faculty of Aerospace Engineering, Delft, The Netherlands, 2002.

57. Capone, P., and Abà, A., “The Use of Discrete Rotating Virtual Blades to Suppress the N/Rev Oscillations in Flight Mechanics Analyses,” 51st European Rotorcraft Forum, 2025.

58. Padfield, G., Dequin, A.-M., Haddon, D., Kampa, K., Basset, P., Grünhagen, W., Haverdings, H., and McCallum, A., “Predicting Rotorcraft Flying Qualities through Simulation Modelling. A Review of Key Results from GARTEUR AG06.” 22nd European Rotorcraft Forum, 1996.