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METHODS FOR AUTOMATING MODEL VALIDATION: STEADY-STATE IDENTIFICATION APPLIED ON GRIPEN FIGHTER ENVIRONMENTAL CONTROL SYSTEM MEASUREMENTS

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Abstract

Model Validation and Verification (V&V) has historically often been considered a final step in the model development process. However, to justify model-based design decisions throughout the entire system development process, a methodology for continuous model V&V is essential. That is, model V&V activities should be fast and easy to reiterate as new information becomes available.

Using a high fidelity simulation model of the Environmental Control System (ECS) in the Saab Gripen fighter aircraft as a guiding example, this paper further extends to an existing semi-automatic framework for model steady-state validation developed during ECS model validation efforts. Generic methods for identification of steady-state operation are a prerequisite for steady-state validation of industry grade physics based models against in-situ measurements. Four different established methods for steady-state identification are investigated and compared: steady-state conditions on the standard deviation estimated from in-situ measurements, conditions on the variation coefficient, t-test on the slope of a simple regression line, and comparison of differently estimated variances. The methods' applicability, on ECS measurements in particular, is evaluated utilizing steady-state identification needs defined during Gripen ECS model validation activities.

1. Introduction

Model-Based System Engineering *MBSE* [1] is playing an increasingly important role in the aeronautical industry as it is seen as a means to cope with ever-increasing demands for reduced lead times and costs [2]. Modeling and Simulation (M&S) is already used in early system development phases to increase the understanding of complex, highly integrated, and strongly coupled systems' behavior.

A growing number of early design decisions within the aeronautical industry rely on simulation results. Models of sub-systems are not only used to develop and evaluate the sub-system itself, but also for system level development, verification, training, etc. utilizing large-scale desktop simulation platforms or hardware in the loop (HIL) simulators. Such a strategy requires methodologies and tools for *efficient model integration*, which is in the scope of the EUREKA/ITEA3 research project *Open Cyber-Physical System Model-Driven Certified Development (OPENCPS)* [3]. To enable efficient model integration in large organizations, an ability to easily update, reintegrate, and reiterate models as new information becomes available is essential. In the model integration methodology used at Saab Aeronautics, assessment of model validity is seen as mandatory. Model validation is an iterative process that continues for at least as long as the system that the model represents is under development. However, as long as model validation requires a significant manual engineering effort, validation activities will be rare events during system development [4]. Transparent and highly automated methods for assessing a model's validity with respect to the current system configuration is therefore a key challenge in the development of methods for efficient model integration.

A semi-automatic framework for validation of aircraft vehicle system models was presented in [5]. The work presented here extends this framework, in particular regarding the topic of steady-state identification. Section 2 discusses some of the general challenges regarding automation of steady-state model validation.

In section 3, existing methods for steady-state identification are compared and evaluated using measurements from two different missions flown with the Gripen fighter aircraft. along with experience from V&V activities relating to the Gripen fighter's ECS model. The conclusions of the work are stated in section 4.

In addition, the industry grade application example, the Gripen fighter's Environmental Control System (ECS) simulation model, is presented below in sub-section 1.1.

1.1. Application example

A high fidelity physics-based model of the Gripen fighter's ECS along with measurements from the actual system are used when developing and evaluating the methods presented within the frame of this paper. Environmental Control Systems can be found in most manned civil and military aircraft and they typically supply f-unctions such as cockpit pressurization, cooling of avionics, pressurization of fuel system, etc. This particular model is developed in the Modelica-based commercial modeling tool *Dymola* [6]. The model is in short built to represent the true systems statics as well as selected dynamic behavior, enabling system steady-state performance investigations, analysis of pressure, temperature, and mass flow levels during hardware and software malfunctions, evaluation of conceptual design, and identification/prediction of system oscillations and transients. This high fidelity ECS model also serves as a platform for validating models of lower fidelity suitable for real time simulations with fixed step solvers that are exported to various large-scale simulators. This particular application makes the high fidelity ECS model essential in the model-simulator integration process.

2. Automating model validation

Several definitions of the terms *verification* and *validation* exist, some of them are collected in the Generic Methodology for Verification and Validation (GM-VV) [7], the NASA Standard for Models and Simulations [8], and Department of Defense Directive Number 5000.59 [9]. Here, the term validation is interpreted as the process of determining the model's validity within its range of usage, i.e. to determine to what extent the model represents the physical system in the operational points, and during the dynamic events of interest. This interpretation is largely in line with the definitions given in [7], [8], and [9]. The extent to which the model represents the physical system is quantified via relevant validation measures put in relation to the model's *intended use* [10]. Hence, a concrete formulation of the intended use is a prerequisite for both model development and V&V activities.

Automating historical data validation, i.e. validation against existing measurements [11], comprises the automation of multiple required steps in the validation process, ranging from the specification of the model's domain of operation all the way to visualization and interpretation of V&V results. According to [12] and [5], the following steps are deemed mandatory for successful historical data model validation and all need to be automated to maximize automation in model V&V:

- <u>The model input dependencies need to be established.</u> The model's domain of operation is a space spanned by the feasible values of input variables. A clear definition of this space is essential for *coverage* [13] and system level validation metrics.
- <u>Identification of validation quantities.</u> The system variables that collectively describe the model's validity need to be identified before any validation simulation can be executed.
- <u>Identification of steady-state operation.</u> Steady-state operation needs to be identified

in the measurements for steady-state validation activities. The identification procedure can be executed before or after simulation if an entire flown mission is to be simulated. Furthermore, identifying steady-state operation prior to simulation provides the possibility of using coverage metrics to prioritize between which simulations are most suited for validation.

- Computation of steady-state validation metrics. The obvious purpose of V&V activities is to establish the model's validity within its specified domain of operation: the model's domain of validity. The selected validation metrics are the foundation of formulating this domain.
- Visualization of validation results. Once established, a model's validity needs to be communicated to the model's user in a comprehensible manner. This is a challenging task in the case of complex models with high dimensional domains of operation.

3. Steady-state identification

Model steady-state operation is here considered to be a time segment T, significantly longer than the system time constants, in which all observable system states remain "sufficiently constant" with respect to time. The wording "sufficiently constant" here means that all dynamics observed within a "sufficiently constant" interval can be classified as measurement noise. The minimum length of such an interval is here denoted as T_S. Steady-state is identified by means of a sliding window that monitors the steady-state constraints specified in sections 3.1, 3.2, 3.3, and 3.4. This sliding window has the length of the previously mentioned T_S.

The functionality of techniques dealing with practical problems, such as steady-state identification, is here viewed as the techniques' ability to produce the desired outcome. This functionality is not necessarily the sole requirement when choosing between available methods. It is rational to consider the measure "usefulness" when selecting method to tackle the problem at hand [14]. The "usefulness" of a method or technique is a subset of its functionality and the measure here includes the aspects of scalability, intuitiveness, and degree of required user expertise. As this paper considers historical data validation against measurements collected during flown missions, measurement noise is superimposed on model inputs. A pragmatic, but still clear, definition of steady-state is therefore of utmost importance in order to avoid misinterpretation of the validation results as well as to automate the validation procedure.

One key aspect of pragmatic model V&V, and steady-state identification in particular, is to minimize the degree of subjectivity in any applied technique. An important reason to minimize the required subjective expertise is that the degree of necessary present subjective system knowledge in many ways dictates the overhead required when performing V&V activities.

Regarding the topic of steady-state identification, operational points should not erroneously be identified as steady-state; i.e. *Type II errors* should be avoided. Such identified operational points will contaminate the results of model steady-state validity and lead to a model seen as a worse representation of reality than what it actuality is.

The latter identified need is of more importance than it is to ensure success in finding steady-state operation at conditions where such exists, i.e. to avoid *Type I errors*. However, measurements are often scarce and the erroneously "not at steady-state" condition should also be kept in mind when evaluating identification methods.

The identification method should be as intuitive as possible as such a method is more likely to be used during validation efforts other than in the presented application example. If the method is used on a wider scale, strengths and weaknesses will be highlighted and a wider range of user input regarding method improvements will be assessable.

In [5], conditions were applied on the ECS model inputs in order to deduce steady-state operation (i.e. all observable system states are steady according to the specified conditions). ECS model experience, supported by model input sensitivity analysis, verified the simplification of only utilizing model inputs as sufficient during ECS model validation. However, individual and somewhat subjective conditions were placed on each investigated signal. If instead a generic steady-state identification method is implemented on every relevant variable, the experience and pre-processing workload can be reduced significantly.

Here, four different established methods of measurement for steady-state identification are investigated and evaluated for the presented industrial application. The goal is to find an objective, scalable, and intuitive method that requires as little system expertise as possible according to the needs stated in the paragraphs above. The investigated methods are applied and evaluated on existing flight measurements of altitude and Mach number, which are inputs common to aircraft vehicle systems and their corresponding physics-based models. All the investigated methods are applicable on any individual model variable that needs to be restricted to certain bounds during steady-state operation. All individual conditions can then be combined into a system level steady-state condition.

Steady-state operations identified in sections 3.1, 3.2, 3.3, and 3.4 are presented as operational points and not as steady-state intervals. Measurements of Mach number and altitude during two different missions flown with the Gripen fighter aircraft are used when evaluating the described methods. The steady-state operational points are computed as the mean value of all samples within the identified interval and plotted in the middle of the time segment.

3.1. Conditions on the standard deviation

As mentioned in section 3, one approach for steady-state identification is to compute the signal standard deviation for successive intervals of measurements via a sliding window. If the standard deviation remains below specified threshold values, the interval is considered to be in steady-state [15]. This particular method was implemented when validating the Gripen fighter's ECS model with satisfactory results implementing the conditions

$$\sigma(Alt) \leq 10$$

and

$$\sigma(Mach) \leq 0.009$$

on the standard deviation of model input variables. These threshold values were determined via input sensitivity analysis aided by (subjective) system expertise. In Figure 1, identified signal level steady-state operation is shown as circles plotted on top of measurements of altitude and Mach number. The standard deviation is estimated as the square root of the mean square deviation from the expected value assuming independent and identically distributed observations. The method was deemed as satisfactory as it did not identify (according to subject matter experts) non-steady state as steady and it captured the desired steady-state operational points.

A drawback with the presented approach is that it relies on subjective expertise regarding the standard deviation threshold values. Even though it was possible to tune these threshold values such that a desired result was achieved, the method requires each threshold value to be tuned individually. The method is therefore not generic to any signal as it is and it requires significant overhead if scaled to combine conditions on many signals.

3.2. Conditions on the variation coefficient

The method described in section 3.2 is modified in order to cope with the drawback of poor scalability. If the standard deviation is instead expressed as

$$C_V(Y) = 100 \cdot \frac{\sigma(Y)}{\mu}, \tag{1}$$

a coefficient normalized by the sampling interval expected value $\mu = E[Y]$, the measure becomes independent of the unit of the variable in question [16]. The standard deviation is in Equation (1) expressed as $\sigma(Y)$, where Y denotes the set of observations made within each interval of measurements extracted via a sliding window.

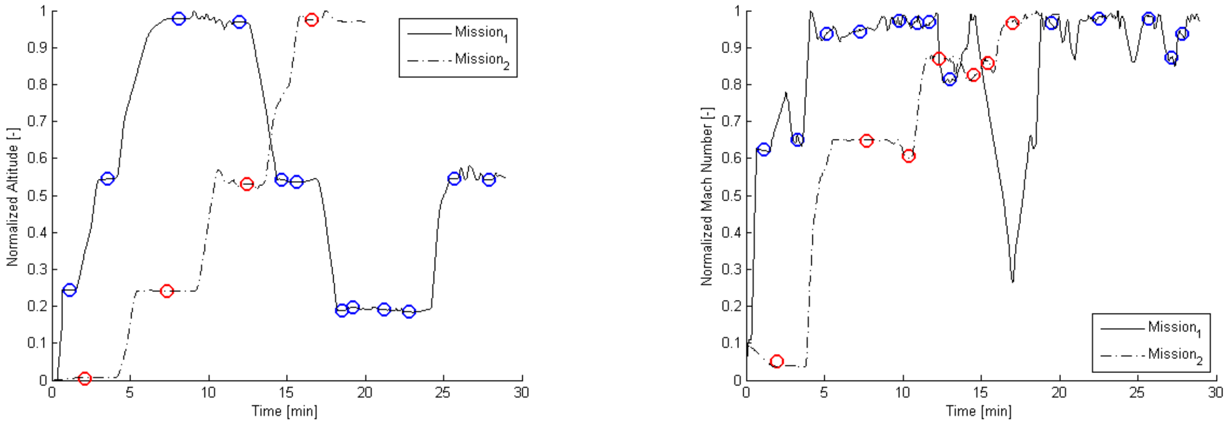

Figure 1. Steady-state operation identified via conditions on the standard deviation. Steady-state operation is identified in measurements of altitude (left) and Mach number (right) from two different flown missions.

Unlike the previously described method, placing individual conditions on the standard deviation of each investigated signal, this method is generic to any signal as one single condition on the variation coefficient C_V, expressed as a percentage, is needed. The steady-state operational points, shown as red and blue diamonds in Figure 2, are identified via a set condition of $C_V < 0.4\%$ applied on the measurements. A condition set such that as many as possible of the points identified in Figure 1 are found without identifying non-steady state operation as steady. Furthermore, one significant drawback that is not visualized in Figure 2 becomes apparent if the expected value of an investigated interval is zero. The method will not be applicable in such a situation as is.

3.3. T-test on regression slope

A well-known and fairly straightforward method to detect the presence or absence of trends in measurement data is to fit a simple regression slope to a data set using a least squares method. A two-tailed t-test is then applied on the slope ($\hat{\beta}$) of the regression line to determine whether the null hypothesis ($H_0 : \beta_0 = 0$), that the true slope is equal to zero, can be accepted at some relevant significance level α [15], [17].

A detailed description of such hypothesis tests is provided in [16] . The test statistic

$$t_{score} = \frac{(\hat{\beta} - \beta_0)}{SE_{\hat{\beta}_0}}, \tag{2}$$

which follows the t-distribution is computed under the assumption that independent observations of the dependent variable y are drawn and that observed values of the dependent variable are normally distributed for each value of the independent variable x. Large values of t_{score} favor the rejection of the null hypothesis. If the probability of observing an extreme a value as t_{score} is higher than $\alpha/2$, then the two tailed t-test dictates that the null hypothesis is to be rejected, at significance level α, and the operational point is determined to be unsteady. In Equation (2),

$$SE_{\hat{\beta}_0} = \frac{\sqrt{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2/(n-2)}}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}} \tag{3}$$

is referred to as the standard error of the slope. The measured dependent values are expressed as y_i in Equation (3) and the least squares estimated values as $\hat{y}_i$. The independent variable x_i is the time of sample i and $\bar{x}$ is the mean time of the sampling interval.

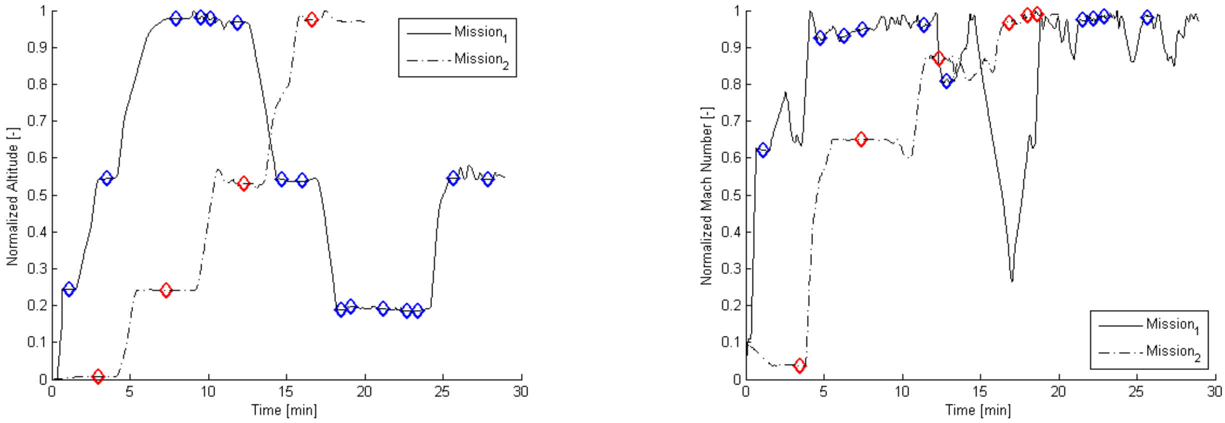

Figure 2. Steady-state operation identified via conditions on the variation coefficient. Steady-state operation is identified in measurements of altitude (left) and Mach number (right) from two different flown missions.

The total number of samples in the interval are denoted n in Equation (3), $n-2$ are the degrees of freedom of simple linear regression where the 2 is the sum of the total number of dependent and independent variables.

The described method is applied on measurements of Mach number and altitude implementing a significance level of $\alpha = 0.05$. The resulting steady-state operational points are plotted as crosses on top of the measurements in Figure 3.

An obvious weakness of the method, identified by [15], is that non-periodic oscillations will render regression slopes that are momentarily zero, resulting in Type II errors. This effect is clearly illustrated on the right hand side of Figure 3 as the Mach number at $Time{\sim}17min$ of the flown mission depicted as the solid curve, is known to be unsteady from previous system investigations, see Figure 1. However, the method in itself introduces very little subjectivity as the significance level is the only necessary method design parameter. The method is therefore considered to be generic regarding all measurements of mass flow, pressure, temperature, etc. available for the implementation example.

3.4. Ratio of differently estimated variances

Steady-state identification via a condition set on a ratio of differently estimated variances is another feasible approach [15].

The implemented measurement population variance estimation methods are given by Equation (4) and Equation (5). Equation (4)

$$Var_1(Y) = \frac{1}{n-1}\sum_{i=1}^{n}(y_i-\mu)^2 \tag{4}$$

describes the variance as the mean square deviation from the expected value $\mu = E[Y]$.

The division by $n-1$ ensures an unbiased sample variance estimation [16]. In Equation (5),

$$Var_2(Y) = \frac{1}{(n-1)}\sum_{i=1}^{n-1}(y_{i+1}-y_i)^2\,, \tag{5}$$

the variance is described as the sum of the square of the differences between two consecutive observations y_{i+1} and y_i. A total of $n-1$ such differences can be formulated if n observations are made. The population Y denotes the set of n samples of the quantity y contained within one time interval extracted from the measurements via the sliding window.

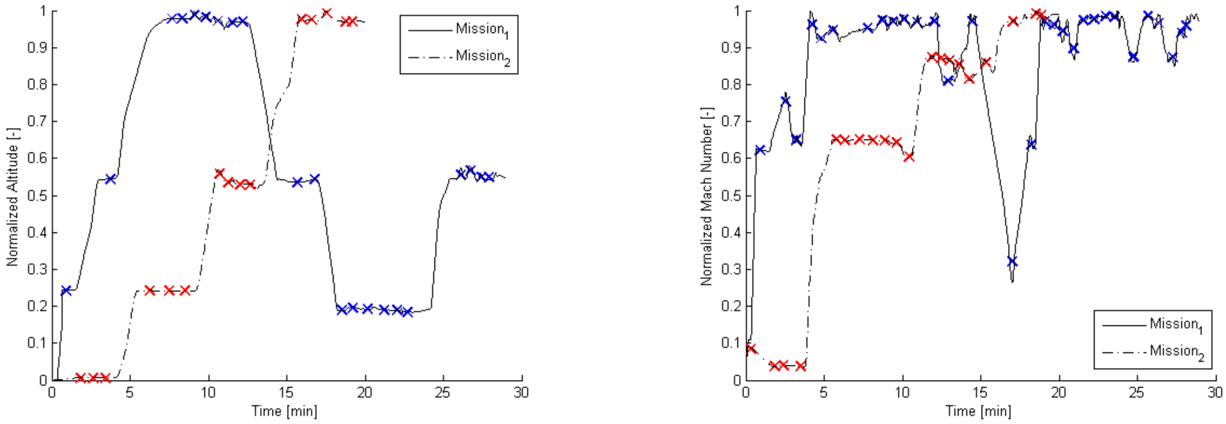

Figure 3. Steady-state operation identified via two tailed t-tests on regression line slope coefficients. Steady-state operation is identified in measurements of altitude (left) and Mach number (right) from two different flown missions.

The first measure of the variance, presented in Equation (2), is independent of the order of observations and is therefore affected by present variations in the expected value. The mean square successive difference of estimating the variance is not independent of the order of observations and does not account for trends in the expected value [18]. Comparisons of the two different methods enable steady-state identification. If in steady-state, the ratio R between the variances estimated using Equation (4) and Equation (5) is ideally equal to one. However, in practice, the two estimated values of variance forming the ratio will never be identically equal as a result of present random noise [15].

This introduces an obvious drawback of the method as steady-state acceptance criteria need to be formulated if the method is to be used and steady-state has to be defined by an interval on the ratio R.

Steady-state operation identified in measurements of Mach number and altitude is presented as squares in Figure 4. The steady-state conditions on the ratio of variances is tuned to $R < 4.5$ such that as many as possible of the points identified in Figure 1 are found without identifying non-steady state operation as steady. The investigated method fails to identify several steady-state intervals that were deemed to be steady in Figure 1.

3.5. Comparison of methods

The steady-state operational points identified with the different investigated methods are combined, for each method, via a logical *and* rendering four different two-dimensional domains, as shown in Figure 5.

The conditions are here combined such that steady-state, on a system level, is only triggered if all conditions are true for at least the minimum length of one steady-state interval T_s, see section 3. This means that all individual conditions may be fulfilled at the same instant in time without a resulting global steady-state as the globally identified steady-state time T may be shorter than T_s.

As mentioned earlier, the method of applying steady-state conditions on the standard deviation was implemented successfully during ECS model validation efforts, successful in terms of identifying steady-state operation in Mach number and altitude measurements for model validation purposes. Steady-state operation identified implementing steady-state conditions on the standard deviation, shown as circles in Figure 1 and Figure 5, is considered “correct” when comparing the different methods investigated.

None of the methods can be said to be fully objective as they all need one or more design parameters to be specified.

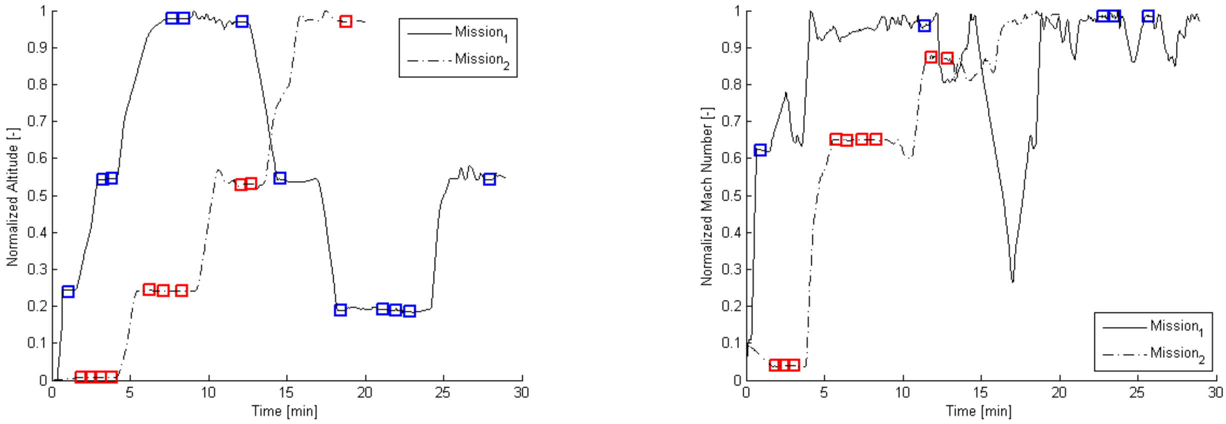

Figure 4. Steady-state operation identified via conditions on a ratio of two differently estimated variances. Steady-state operation is identified in measurements of altitude (left) and Mach number (right) from two different flown missions.

The first evaluated technique applies conditions on the standard deviation. These conditions need to be specified for each signal in which steady-state is to be determined; however, setting conditions on the standard deviation is fairly intuitive as the thresholds have an intuitive meaning in relation to the investigated quantity. Furthermore, if this technique is modified such that a condition is instead placed on the variation coefficient, then a single generic condition is required for steady-state identification.

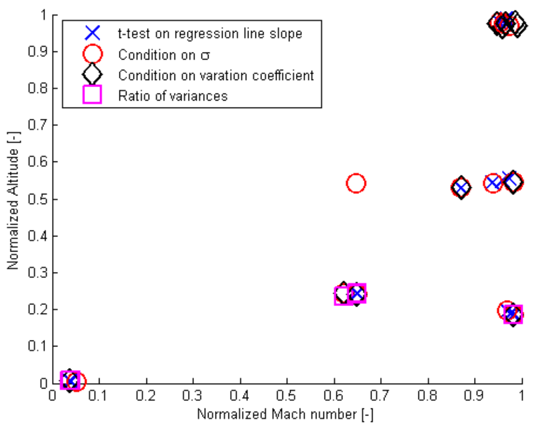

Figure 5. Identified steady-state operational points implementing combined conditions on altitude and Mach number

The t-test needs specification of the parameter describing the level of significance, α, and a bound needs to be set on the ratio of differently estimated variances if the fourth method is to be used.

In terms of scalability, the three latter methods are here considered to be generic to any flight measurements as they are directly applicable on any signal. Setting conditions on the standard deviation is not convenient in terms of scalability.

The method applying conditions on the variation coefficient C_v was sufficient to determine steady-state in relation to the identification performed during ECS model's validation, cf. Figure 1 and Figure 2. The t-test approach has one significant drawback: it identifies non-steady state as steady if non-periodic oscillations are present, cf. Figure 1 and Figure 3. The last investigated technique is conservative in finding points compared to the other two; however, it does not identify non-steady-state operation as steady which is the most important aspect (as long as measurements are abundant), cf. Figure 1 and Figure 4

4. Discussion and conclusions

Pragmatic methods for automatic steady-state identification is an essential aspect when automating steady-state model validation.

Four different methods for steady-state identification have been investigated with respect to flight measurement data from the Gripen fighter's ECS. A set of needs regarding method subjectivity, scalability, and ability to identify steady-state are formulated. The method of comparing differently estimated variances and the method of steady-state identification via a condition on the variation coefficient C_V are deemed to be the most suitable techniques for identifying ECS steady-state in flight measurements. These two methods both introduce one single subjective and generic design parameter in addition to the sliding window design, which is deemed to result in good scalability and little introduced subjectivity. Differentiating between these two methods is difficult and the only objective difference between the two is that the ratio of variances is slightly more conservative at identifying steady-state. This property has in the present study not been shown to be pronounced enough for the technique to be less valuable as available measurements are fairly plentiful, and the conclusion is that both techniques are feasible for the considered application. However, computing C_V includes normalizing by the signal expected value of the investigated interval, see Equation (1). The method is not applicable for signals where zero is a feasible expected value. This drawback was not relevant during validation of the ECS application example but it should be kept in mind when selecting method for other applications.

All investigated methods operate on a sliding window of measurement data. The size of this window needs to be designed to provide a desired weight between measurement noise and actual transients affecting the signal behavior. Specifying the window size requires system expertise regarding the system time constants, which introduces subjectivity into all of the investigated methods. Methods to modify the techniques to cope with this problem have not yet been investigated.

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