VALIDATION OF A HYBRID OBSERVER METHOD FOR FLIGHT LOADS ESTIMATION

Mike Montel*, Frank Thielecke*
***Hamburg University of Technology**
Institute of Aircraft Systems Engineering
Nesspriel 5, 21129 Hamburg, Germany

mailto: mike.montel@tuhh.de, frank.thielecke@tuhh.de

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Abstract

In this paper, a novel model-based loads monitoring method is introduced, that allows for a high precision in the estimation of flight loads. The new method is based on the hybridization of two state-of-the-art loads estimators (a Luenberger observer and a local model network approach) and combines the individual advantages of the underlying methods. The hybrid method features an accurate estimation of structural loads due to manoeuvres and gusts even for high load events and can be set up for a given and suitable flight test database with low effort. Therefore, the hybrid method provides a cost-efficient set up of an accurate aircraft loads monitoring system. The paper focuses on the introduction of the hybrid method for loads estimation and its validation by means of an extensive flight test database containing high manoeuvre and gust load events, which has been acquired using the ultra-light test aircraft UW-9 Sprint.

1 General Introduction

Loads monitoring is of increasing importance in the context of aircraft efficiency enhancement. It provides a detailed knowledge of structural loading due to flight manoeuvres and gusts. A loads monitoring system provides information about the value and position of loads, which can be used for component specific overload detection as well as a prediction of fatigue damages. This allows targeted inspections on the ground and enables a reduction of aircraft on-ground time during maintenance and overhaul. If highly accurate loads information were available, inspections after high load events will only be performed when necessary and no relevant load events will be missed. Therefore, a loads monitoring system contributes to the enhancement of aircraft cost-efficiency and safety.

Loads monitoring can be achieved either by measurement of load proportional quantities or by model-based loads estimation.

Measuring the loads involves a considerable amount of measurement effort, since a large number of load sensors is required. Each sensor has to be calibrated and must be maintained regularly.

Using a model-based loads estimator, no additional measurement equipment is required. The structural loads are derived from alternatively measuring signals and an additional model approach. For implementation in commercial aircraft, existing design models and available measuring signals, such as global accelerations, air data and control surface deflections can be used.

In civil aviation, a profitable use of a structural loads monitoring system is only feasible if highly accurate information about component loads are available. An underestimation of the load amount could lead to a miss of a relevant load event. An overestimation could lead to an incorrect warning and thus to the initiation of unnecessary and costly inspection measures.

Loads models developed in the aircraft design and certification process are usually conservative, according to the aviation regulations (e.g. CS 25.301 [1]). For this reason, the use of design models in the loads estimation algorithm would lead to an overestimation of the structural loads and thus to unnecessary inspections. In order to obtain the required accuracy with a model-based loads estimator based on design models, time-consuming corrections of the physical models are necessary.

As a result of a discrepancy between the required accuracy in the determination of the loads and the effort involved in the implementation, structural loads monitoring systems are rarely used in civil aviation.

The hybrid method introduced in this paper provides a higher accuracy in the loads estimation and a lower development effort, compared to the state-of-the-art methods. The hybrid observer therefore reduces the discrepancy between accuracy and implementation effort and offers an efficient use of a loads monitoring system in civil aviation.

2 State-of-the-Art Loads Observers

Today various model-based loads estimation methods are available. In [2] an overview of known methods is given. A common method for loads estimation is a loads observer, which in general is a model-based approach for the reconstruction of structural loads, as shown in Fig. 1. The observer estimates the structural loads based on measured pilot commands and state variables for any desired location of the aircraft structure. The observer can either be data-based modelled or physically modelled.

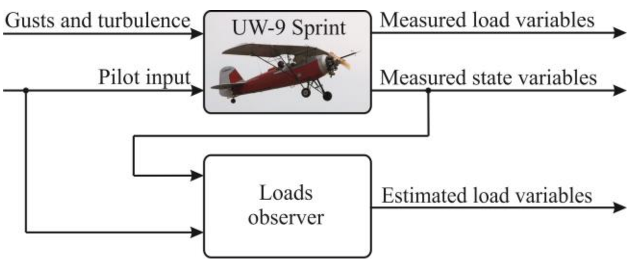


Fig. 1. General loads observer concept [3]

The development of a data-based loads observer is mainly based on flight test data. Both the model structure and the model parameters are identified by means of measurement data. The accuracy of a data-based loads observer strongly depends on the quality and quantity of the underlying data. Therefore, a consistent, valid test database is a prerequisite for a data-based loads observer.

In [4, 5] a data-based loads estimation method is introduced. The loads model is developed by training of a local model network (LMN) by means of flight test data. The relationship between the input variables and the load variables is modelled using local-linear transfer functions. The method is characterized by a high accuracy in the determination of manoeuvre loads, but has not yet been validated for gust loads [4]. The model structure of a local model network can easily be interpreted. This is a key advantage of the LMN in terms of the evaluation and adaptation of the physical model behaviour, in particular for the definition of the extrapolation behaviour. However, the accuracy of data-driven methods is higher in the range of the training database.

A physically modelled loads observer is based on a model structure, which is derived from basic physical equations. Model parameters are identified from flight test data. The model is subject to physical laws, even in the extrapolation range, which is important for overload detection.

One method for the realisation of a physical loads estimator is a Luenberger observer. It reconstructs non-measurable state variables of dynamic systems from observations of the system inputs and outputs [6]. The determination of the non-measurable state variables is based on a simulation with a system model. By injection of the residuals of the simulated and measured output variables to the derivatives of the states of the observer, the reconstruction can also be achieved even if the initial condition is unknown. Furthermore, it gives the opportunity to estimate disturbances, such as gusts and turbulences. The observation theory of Luenberger was developed for linear systems, but can also be applied to non-linear systems [2].

In [7] a non-linear aircraft model [8] is integrated into a Luenberger observer for estimating manoeuvre and gust loads in flight. The estimation of gust loads is challenging since dynamic wind disturbances are not measured in common aircraft. In [7] an estimation of the wind disturbances becomes feasible by injection of selected output variables, which are proportional to the disturbances. The method has been validated in [3, 9] for the estimation of wing and empennage loads and has shown promising results. A disadvantage of the physically modelled loads observer methods is the time-consuming development process, which is required in order to achieve a high accuracy in the loads estimation.

3 Hybrid Loads Observer

The hybrid loads observer combines two state-of-the-art loads observer methods to one observer. A non-linear Luenberger observer is used to incorporate physical a priori knowledge (e.g. from existing design models). As a result of the physically based model structure, the calculation of structural loads is possible for unknown manoeuvres and high load events. The Luenberger observer is able to estimate loads due to physical effects that are considered in the model structure. Not modelled physical effects and uncertainties in the model parameters lead to inaccuracies in the loads estimation [3]. In order to compensate remaining uncertainties, the loads estimation is improved by means of additional correction models. These models are derived from flight test data using the local model network approach.

The combination of the two observer methods is carried out in accordance to Fig. 2. The component loads estimated by the Luenberger observer $\underline{\hat{y}}_{L,Lue}$ are improved with the correction term $\underline{\hat{y}}_{L,LMN}$ calculated by the LMN. The state equation of the hybrid observer corresponds to the equation of a Luenberger observer

$$\dot{\underline{\hat{x}}}_{Hyb} = \dot{\underline{\hat{x}}}_{Lue} = \dot{\underline{\hat{x}}}_S = f(\underline{\hat{x}}_S, \underline{u}) + \underline{\underline{L}} \cdot \Delta \underline{y}_S \quad (1)$$

where $\underline{\hat{x}}_S$ are the state variables of the observer, $\underline{u}$ are the pilot commands, $\underline{\underline{L}}$ is the observer gain matrix and $\Delta \underline{y}_S$ are the residuals of measured and estimated output variables. The output equation for the estimated loads is

$$\underline{\hat{y}}_{L,Hyb} = \underline{\hat{y}}_{L,Lue}(\underline{\hat{x}}_S, \underline{u}) + \underline{\hat{y}}_{L,LMN}\left(\underline{\hat{x}}_S, \underline{u}, \underline{\hat{y}}_{L,Lue}\right) \quad (2)$$

wherein $\underline{\hat{y}}_{L,Lue}$ are the basic loads estimated by the Luenberger observer and $\underline{\hat{y}}_{L,LMN}$ is the loads update calculated by the local model network. Finally, $\underline{\hat{y}}_{L,Hyb}$ is the highly accurate loads estimation of the hybrid observer.

3.1 Basic Loads Estimation

The basis of the hybrid observer is a Luenberger observer that performs a physically based calculation of the component loads and provides an estimation of the disturbance input. The model structure of the Luenberger observer is illustrated in Fig. 2. An essential component of the Luenberger observer is an aircraft model for determining the state and output variables. The aircraft model was developed by means of physical equations according to [8]. Its parameters were identified in [10, 11, 12] from flight test

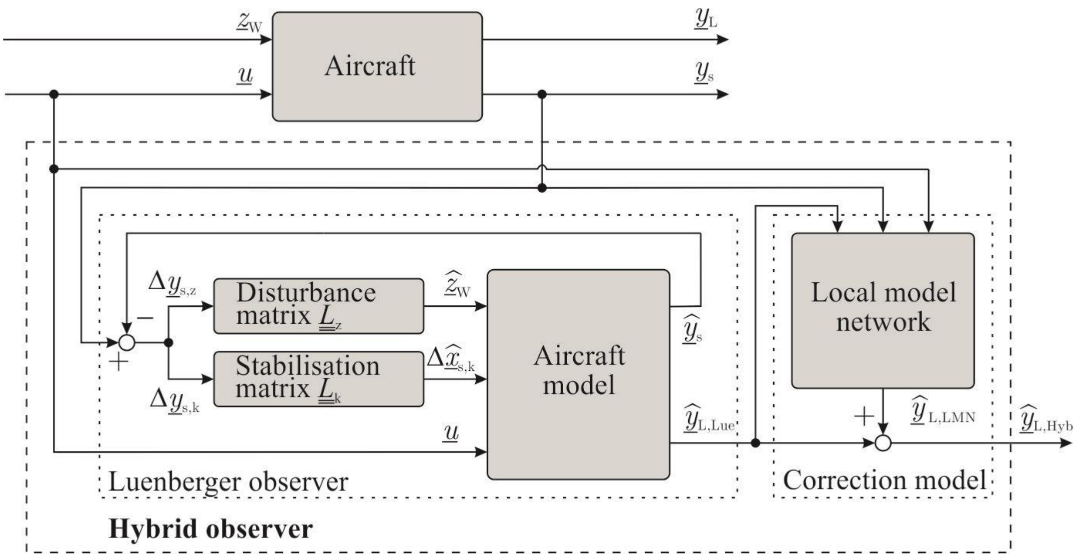


Fig. 2: Model structure of the hybrid loads observer

data using the output error method. The simulated state vector $\underline{\hat{x}}_S$ consists of the flight path velocities $\underline{\hat{V}}_K$, the angular rates $\underline{\hat{\Omega}}_K$, the Euler angles $\underline{\hat{\Phi}}$, the relative position of the aircraft $\Delta\underline{\hat{s}}_g$ and the wind velocities $\underline{\hat{V}}_W$, that is

$$\underline{\hat{x}}_S = \left[\underline{\hat{V}}_K^T \;\; \underline{\hat{\Omega}}_K^T \;\; \underline{\hat{\Phi}}^T \;\; \Delta\underline{\hat{s}}_g^T \;\; \underline{\hat{V}}_W^T\right]. \tag{3}$$

The simulated output vector $\underline{\hat{y}}$ consists of the output variables of the aircraft motion $\underline{\hat{y}}_S$ and the component loads $\underline{\hat{y}}_{L,Lue}$

$$\underline{\hat{y}} = \begin{bmatrix} \underline{\hat{y}}_S \\ \underline{\hat{y}}_{L,Lue} \end{bmatrix} = \underline{g}(\underline{\hat{x}}_S, \underline{u}) . \tag{4}$$

The Luenberger observer contains two observer gain matrices, see Fig. 2. The observer gain matrix $\underline{\underline{L}}_z$ allows for an estimation of the unknown disturbance input $\underline{\hat{x}}_{S,z} = \underline{\hat{z}}_W$ (gusts and turbulences). The observer gain matrix $\underline{\underline{L}}_k$ enables an improvement of the simulated state variables $\underline{\hat{x}}_{S,k}$. Eq. (1) becomes to

$$\dot{\underline{\hat{x}}}_S = f(\underline{\hat{x}}_S, \underline{u}) + \begin{bmatrix} \underline{\underline{L}}_z & 0 \\ 0 & \underline{\underline{L}}_k \end{bmatrix} \cdot \begin{bmatrix} \Delta\underline{y}_{S,z} \\ \Delta\underline{y}_{S,k} \end{bmatrix}. \tag{5}$$

In the combined state and disturbance observer, the injection vector $\underline{\hat{y}}_S$ is subdivided into the parts $\underline{y}_{S,z}$ and $\underline{y}_{S,k}$. The vector $\underline{y}_{S,z}$ is used for the estimation of the disturbances and is

$$\underline{y}_{S,z} = \left[\ddot{x}_{Kf}, \ddot{y}_{Kf}, \ddot{z}_{Kf}, \dot{p}_{Kf}, \dot{q}_{Kf}, \dot{r}_{Kf}\right]^T. \tag{6}$$

It consists of translational and rotational accelerations which are directly proportional to the disturbance input (wind disturbances directly lead to accelerations of the aircraft). The residuals are calculated from the measured ($\underline{y}_{S,z}$) and estimated output variables ($\underline{\hat{y}}_{S,z}$) as

$$\Delta\underline{y}_{S,z} = \underline{y}_{S,z} - \underline{\hat{y}}_{S,z} . \tag{7}$$

The vector $\underline{y}_{S,k}$ in Eq. (5) is used for the improvement of the state variables and is

$$\underline{y}_{S,k} = \left[\Phi, \Theta, \Psi, p_{Kf}, q_{Kf}, r_{Kf}, u_{Af}, v_{Af}, w_{Af}, z_{Kg}\right]^T. \tag{8}$$

It consists of the Euler angles, angular rates, velocities and altitude. By feedback of the residuals of these variables via the observer gain matrix $\underline{\underline{L}}_k$ an improvement of the aircraft states $\Delta\underline{\hat{x}}_{S,k}$ becomes feasible [7]. The residuals are finally calculated from the measured ($\underline{y}_{S,k}$) and the estimated output variables ($\underline{\hat{y}}_{S,k}$), they are

$$\Delta\underline{y}_{S,k} = \underline{y}_{S,k} - \underline{\hat{y}}_{S,k} . \tag{9}$$

The estimated disturbance input $\underline{\hat{z}}_W$ and the calculated state update $\Delta\underline{\hat{x}}_{S,k}$ are fed into the aircraft model (see Fig. 2), where the component loads are finally calculated.

For the calculation of the component loads, distributed aerodynamic forces are taken into account. The distributed aerodynamic forces are computed using an aerodynamic model based on the Vortex Lattice Method [8] and are scaled by aerodynamic forces calculated in the previously identified aerodynamic model. The scaling process is described in [9]. The distributed aerodynamic forces are condensed at the mass points (*MP*) by the nearest neighbour method. This procedure provides the distributed forces and Moments $\underline{F}^{MP,i} = \left[F_x, F_y, F_z, l, m, n\right]$. The loads $\underline{y}_{L,Lue}^{LS,j} = \left[Q_x, Q_y, Q_z, M_x, M_y, M_z\right]$ are calculated at the so called loads output stations (*LS*) by summation of the forces and moments $\underline{F}^{MP,i}$. For a single pair of mass point and loads output station, Eq. (10) can be derived. Fig. 3 shows the mass points and loads output stations of the right wing of the aircraft.

$$\begin{bmatrix} Q_x \\ Q_y \\ Q_z \\ M_x \\ M_y \\ M_z \end{bmatrix}^{LS,j} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & -\Delta z & \Delta y & 1 & 0 & 0 \\ \Delta z & 0 & -\Delta x & 0 & 1 & 0 \\ -\Delta y & \Delta x & 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} F_x \\ F_y \\ F_z \\ l \\ m \\ n \end{bmatrix}^{MP,i} , \tag{10}$$

$$\underline{y}_{L,Lue}^{LS,j} \quad = \quad \underline{\underline{T}}_{LS,MP} \quad \cdot \underline{F}^{MP,i} . \tag{11}$$

For the calculation of the component loads at all output stations of the right wing, a total transformation can be derived based on the single pair transformation Eq. (10), that is

$$\begin{bmatrix} \underline{y}^{LS10} \\ \underline{y}^{LS9} \\ \underline{y}^{LS8} \\ \underline{y}^{LS7} \\ \underline{y}^{LS6} \end{bmatrix} = \begin{bmatrix} \underline{\underline{T}}_{LS10,MP12} & 0 & \cdots & 0 \\ \underline{\underline{T}}_{LS09,MP12} & \underline{\underline{T}}_{LS09,MP11} & \cdots & 0 \\ \underline{\underline{T}}_{LS08,MP12} & \underline{\underline{T}}_{LS09,MP11} & \cdots & 0 \\ \underline{\underline{T}}_{LS07,MP12} & \underline{\underline{T}}_{LS09,MP11} & \cdots & 0 \\ \underline{\underline{T}}_{LS06,MP12} & \underline{\underline{T}}_{LS09,MP11} & \cdots & 0 \end{bmatrix} \cdot \begin{bmatrix} \underline{F}^{MP12} \\ \underline{F}^{MP11} \\ \vdots \\ \underline{F}^{MP07} \end{bmatrix} . \tag{12}$$

Equation (12) is part of the aircraft model within the Luenberger observer and allows the

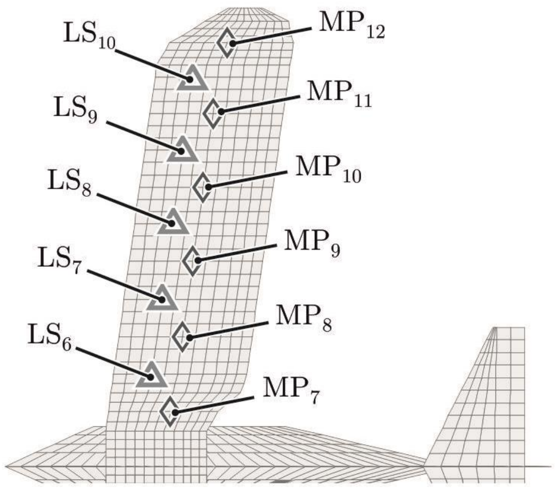


Fig. 3: Mass points and output stations (right wing)

computation of the component loads due to manoeuvres and gusts.

Additional information about the method can be found in [3, 9], where the development of the Luenberger observer is described in detail, including the determination of the observer gains and a description of the loads model.

3.2 Loads Estimation Update

Due to defects in the model structure or uncertainties in the model parameters of the Luenberger observer, inaccuracies in the loads estimation may result [3]. These inaccuracies could be compensated by costly physical modelling and parameter identification. A more efficient way of compensation is presented in this paper. To compensate for the remaining inaccuracies, LMN-based correction models are developed.

The local model network approach is a data-based modelling technique that identifies both, the model parameters and the model structure from test data. For this purpose, the method divides a complex modelling problem into simple solvable subspaces approximated by local-linear models (LLM).

Local model networks are multiple input single output systems. Therefore, each load quantity (e.g. shear force, bending or torsion at one specific position of the aircraft structure) has to be modelled by a separate local model network. Depending on the load quantity to be modelled, the required input variables $\underline{u}_{LMN}$, such as pilot commands and measured state variables, are made available to the LMN. Fig. 4 shows the structure of a local model network.

Each local model network consists of $i = 1..M$ local-linear models and corresponding weighting functions ϕ_i which define the range of validity of the particular local-linear model and are defined by normalised, specific Gaussian functions. The center of each Gaussian lies in the center of the local model and the standard deviation is chosen to cover the range of the subspace in the respective dimension [4]. According to [13], the output variable (here: the load update $\hat{y}_{L,LMN}$) is calculated by

$$\hat{y}_{L,LMN} = \sum_{i=1}^{M} \hat{y}_{L,i} \cdot \phi_i \, . \qquad (13)$$

The linear models $\hat{y}_{L,i}$ are determined by linear combination of the p input variables $\underline{u}_{LMN}$ [13]

$$\hat{y}_{L,i} = w_{i0} + w_{i1} \cdot u_{LMN,1} + \cdots + w_{iP} \cdot u_{LMN,P} \qquad (14)$$

wherein the coefficients w are determined by a least squares approach from the input and output variables [4]. The weighting functions ϕ_i depend on the input variables $\underline{u}_{LMN}$ and have the property [13]

$$\sum_{i=1}^{M} \phi_i(\underline{u}_{LMN}) = 1 \, . \qquad (15)$$

The proportion of each LLM of the model output is controlled by a weighting function. The weighting and superposition of the models according to Eq. (13) offers the possibility to model a non-linear system behaviour and limit the influence of individual models locally. In

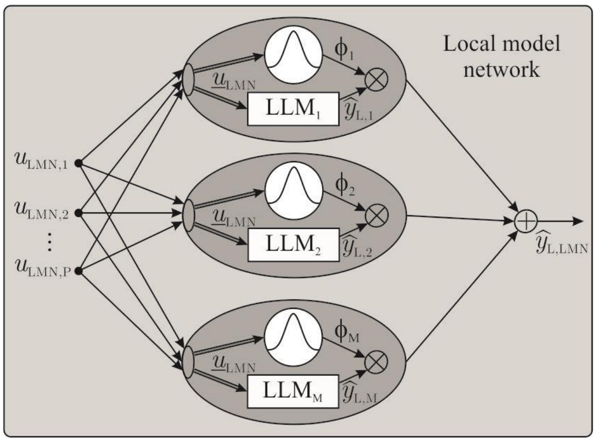


Fig. 4: Local model network structure [13]

this manner, the extrapolation behaviour of the LMN can specifically be influenced, as well.

Since no physical derivation of the model equations is required using the LMN method, the model update can be developed in shortest time for a given flight test database. The accuracy of the basic loads estimation can significantly be improved due to the simultaneous training of the model structure and parameters. The significant increase in accuracy coupled with ease of implementation distinguishes the hybrid observer method from the current state of the art.

4 Implementation and Validation

The hybrid loads observer method is validated using the ultra-light aircraft UW-9 Sprint [14]. It is ideally suited for the validation of loads observer methods, since it has a high gust sensitivity due to a low wing loading. Even on days with light turbulence, relevant gust load factors appear, which makes an efficient flight test program possible. In addition, the UW-9 Sprint is equipped with a suitable flight test instrumentation and tolerates high maximum load factors of $n_{z,max} = 4.0\ g$ and $n_{z,min} = -1.5\ g$.

4.1 Flight Test

For the purpose of the loads observer development and validation, the test aircraft is equipped with a flight test instrumentation for the measurement of the pilot inputs, state variables and component loads. Fig. 5 gives an overview of the measuring system.

The loads measurement is used for the training of the LMN and for the validation of the hybrid observer. The component loads are measured via strain gauges, that are mounted at the front and rear wing spars. For reasons of simplification, only a loads distribution in span wise direction is taken into account. In the direction of the chord length, the sum of loads of the front and rear spar is measured. All loads are determined for the loads output stations (LS) located at the 50 % chord length line of the wing. The calibration of the loads sensors is described in [9]. Fig. 6 shows the positions of the strain gauges and loads output stations at the right wing. At each wing load station, shear forces Q_z and bending moments M_x can be measured.

For the development and validation of loads observer methods, a comprehensive flight test database was acquired using the test aircraft UW-9 Sprint. Manoeuvres suitable for aircraft system identification [15] are used for the development and validation of the observers, as well. In addition, further flight manoeuvres are defined which represent an appropriate complement for the identification and validation of loads observer methods, such as high-G-roll manoeuvres and steady flights in turbulent atmosphere.

Tab. 1 gives an overview of the recorded test data. Each manoeuvre was repeated at different points of the flight envelope, with various excitation amplitudes and in different conditions of atmospheric turbulence.

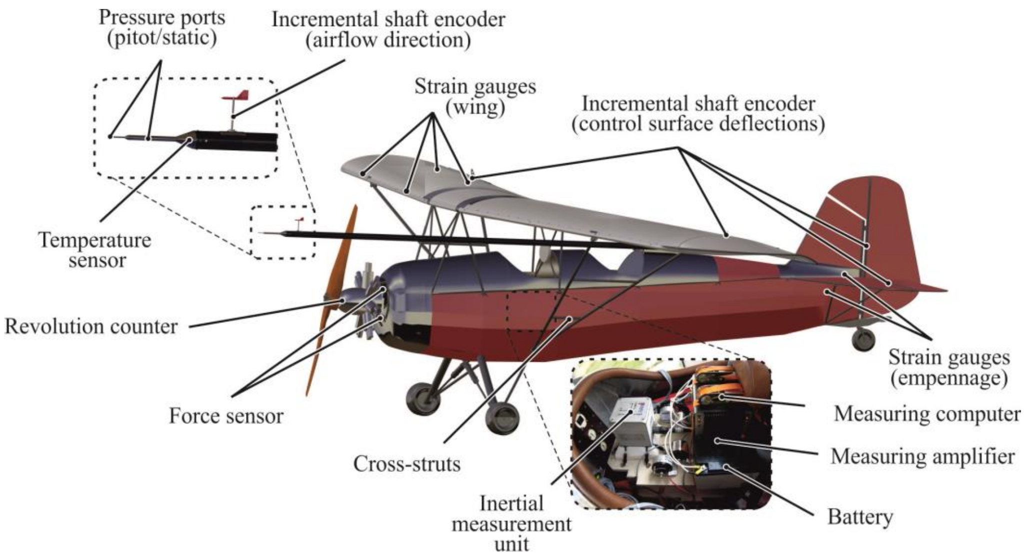


Fig. 5: Flight test aircraft UW-9 Sprint with flight test instrumentation [9]

Tab. 1: Entire flight test database

Manoeuvre type	quantity
Short period maneuvre	116
Phugoid manoeuvre	26
Push-over-pull-up	114
Level turn	30
Thrust variation	38
Bank-to-bank roll	94
Dutch roll manoeuvre	136
Steady heading steady sideslip	52
Wings leveled sideslip	26
Acceleration and deceleration	29
High-G-roll manoeuvre	38
Steady flights	147
Total	847

For the development of the hybrid observer, 111 manoeuvres are selected from the entire database and are combined to an identification set. Tab. 2 shows the contained manoeuvres.

Tab. 2: Identification database

Manoeuvre type	quantity
Short period maneuvre	15
Phugoid manoeuvre	7
Push-over-pull-up	10
Level turn	1
Bank-to-bank roll	26
Dutch roll manoeuvre	32
Steady heading steady sideslip	10
Wings leveled sideslip	6
Steady flights	4
Total	111

The range of the identification data set is reduced compared to the range of the entire database. While for the identification only manoeuvres are taken into account, in which the structural loads reach a maximum of 60 % of the limit load, the entire database contains manoeuvres with loads of up to 80 % of the limit load. In this way an investigation of the extrapolation behaviour becomes feasible.

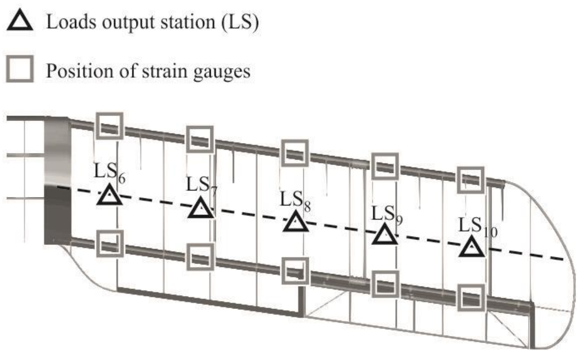


Fig. 6: Positions of loads output stations (right wing)

4.2 Parameter and structure identification

For the development of the Luenberger observer, initially the parameters of the contained aircraft model were identified using the output error method [3, 10, 11, 12]. The aircraft model was subsequently integrated into the Luenberger observer.

The observer gain matrices $\underline{\underline{L}}_Z$ and $\underline{\underline{L}}_k$ are tuned in a modelling environment under minimisation of a cost function in reference to the design of a linear Kalman filter, but not by solving the filter algebraic Ricatti equation, but by minimization of the sum of the autocovariances of the observer estimation error for N simulation steps, that is

$$J(\underline{\Theta}) = \frac{1}{N}\sum_{k=1}^{N}\left[\underline{y}_{Lue} - \underline{\hat{y}}_{Lue}\right]^T \left[\underline{y}_{Lue} - \underline{\hat{y}}_{Lue}\right]. \qquad (16)$$

Due to computing expenditure and with regard to the convergence of the optimization problem, only a few selected items of the observer amplification matrices are tuned, all other elements are set to zero [7]. The parameter tuning procedure is explained in detail in [3, 9].

For the training of the local model networks, both the input and the output variables of the LMNs are required. The output variables $\underline{\hat{y}}_{L,LMN}$ are calculated based on Eq. (2). The LMNs shall improve the loads estimation of the Luenberger observer, so that the loads estimation of the hybrid observer corresponds to the loads measurement. In other words, the LMNs shall provide the remaining difference between the loads estimation of the Luenberger observer and the loads measurement. For this reason, the LMNs are trained with the residual of the loads estimation of the Luenberger observer and the loads measurement

$$\underline{\hat{y}}_{L,LMN} = \underline{y}_L - \underline{\hat{y}}_{L,Lue}\,. \qquad (17)$$

For the input variables of the LMNs, the following signals are used

$$\left[\underline{u}^T\ \underline{y}_S^T\ \ \underline{\hat{y}}_{L,Lue}^T\right] = \left[\xi\ n_P\ n_z\ \underline{V}_{Af}^T\ \underline{\Omega}_{Kf}^T \ldots \right. \\ \left. \ldots\ \underline{\dot{\Omega}}_{Kf}^T\ \ \hat{M}_{x,Lue}^{LS5}\ \ \hat{M}_{x,Lue}^{LS6}\right]. \qquad (18)$$

Besides the measured aileron deflection ξ, propeller speed n_P, vertical acceleration n_z, velocities $\underline{V}_{Af}^{T}$, rotation rates $\underline{\Omega}_{Kf}^{T}$ and rotation accelerations $\underline{\dot{\Omega}}_{Kf}^{T}$, additionally the estimated wing root bending moments $\widehat{M}_{x,Lue}^{LS5}$ and $\widehat{M}_{x,Lue}^{LS6}$ of the left and right wing are used as input signals. The bending moments at the wing root, estimated by the Luenberger observer, support the calculation of the correction signals at the wing. This procedure is comparable to an addition of further sensor signals to the input data space, with the difference, that the additional signals are not measured, but estimated.

The LMNs are identified using the SIGMA tool (subspace identification for generic modelling and analysis) introduced by Halle [4]. A separate local model network is identified for each load variable, based on the identification database given in Tab. 2.

An important property of the structure of the LMNs is its simplicity compared to loads observers solely based on local model networks [4, 5]. This can be explained by the preceding estimation of loads by the Luenberger observer. The Luenberger observer physically estimates the basic loads and their main dynamic. This makes the correction problem less complex. As a result, a reliable extrapolation of the correction signal over the boundary of the identification database becomes possible, which is a feature of the hybrid observer.

4.3 Validation of the hybrid observer

The hybrid observer is validated using the complete flight test database according to Tab. 1. Fig. 7 shows the comparison of measured and by the hybrid observer estimated bending moments at the output stations $LS6$ and $LS10$. In these correlation plots, the observer accuracy can be assessed visually for the extensive database. They show the ideal line and the error tolerance lines with a deviation of 10 and 20 percent of the estimated loads, normalized by the limit loads (LL). In addition, the local average errors μ_r and standard deviations σ_r are shown in the diagrams at three locations (lower (l): 0 % LL, mean load (m), upper (u): 70 % LL).

The validation demonstrates the high accuracy of the hybrid observer method for the entire flight test database. The average errors and the standard deviations are small over the total load range. The slightly increased values at $LS10$ can be explained by the generally smaller loads in the outer wing area.

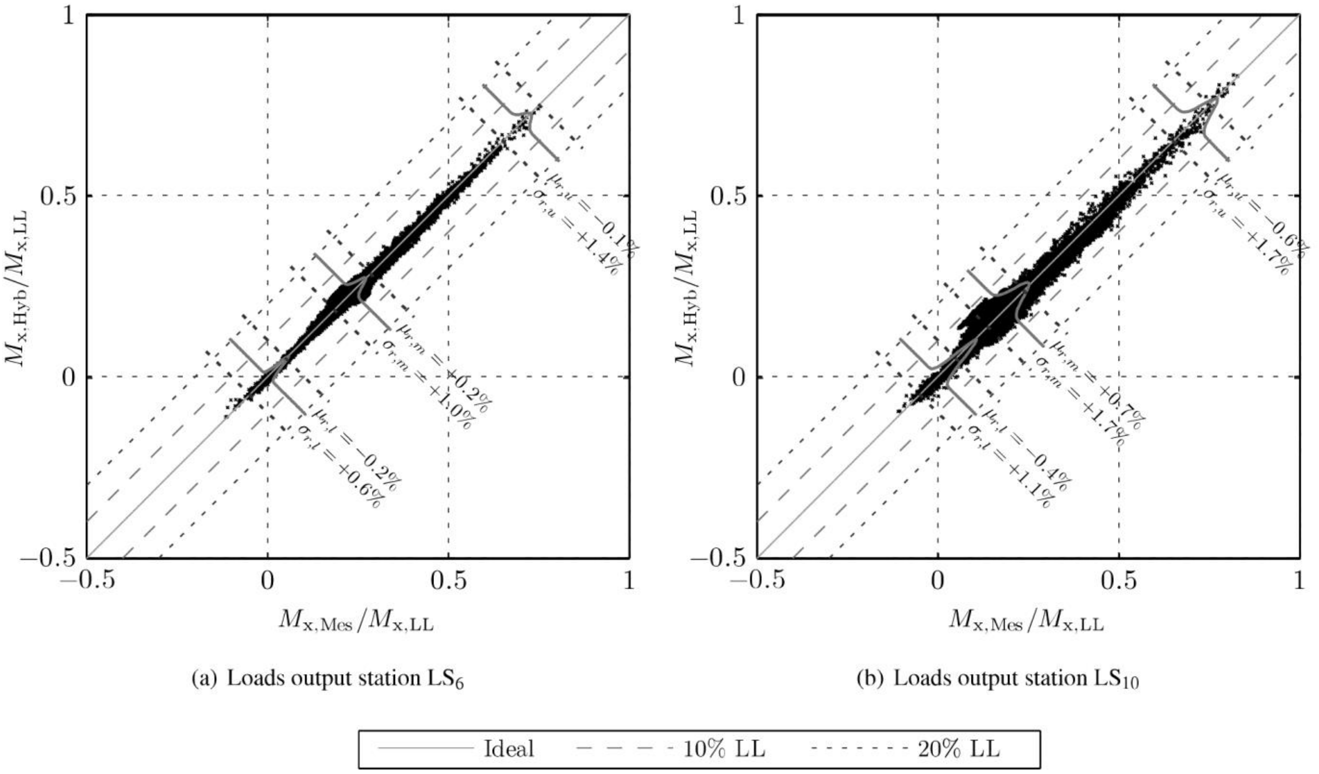
In comparison to the result of the hybrid observer, Fig. 8 shows the validation result for a loads estimator solely based on the Luenberger observer method according to [9, 3] applied to the same flight test database. Particularly at loads output station $LS10$ major deviations occur in the loads estimation using only the Luenberger observer. The inaccuracies can be attributed to not modelled elastic effects of the wing structure. The accuracy of the Luenberger observer could be significantly improved by the application of the hybrid observer.

The hybrid observer was identified using the 111 manoeuvres of the identification database (see Tab. 2) including maximum loads of 60 %LL. The hybrid observer is also able to estimate loads in the extrapolation range up to 80 %LL with high accuracy. The same good estimation result can even be achieved for manoeuvres that were not part of the identification database, such as the high-G-roll manoeuvre.

5 Conclusion

The hybrid loads observer method represents a combination of a Luenberger observer and a local model network. For the development of the hybrid observer, a Luenberger observer is initially developed to incorporate physical a-priory knowledge into the hybrid approach. The additional use of the local model network method compensates for remaining uncertainties in the loads estimation, e.g. due to not modelled physical effects. The local model networks are identified by means of flight test data and are used to improve the basic loads estimation of the Luenberger observer. The previous calculation of the basic loads with the Luenberger observer leads to a low complexity of the local model networks.

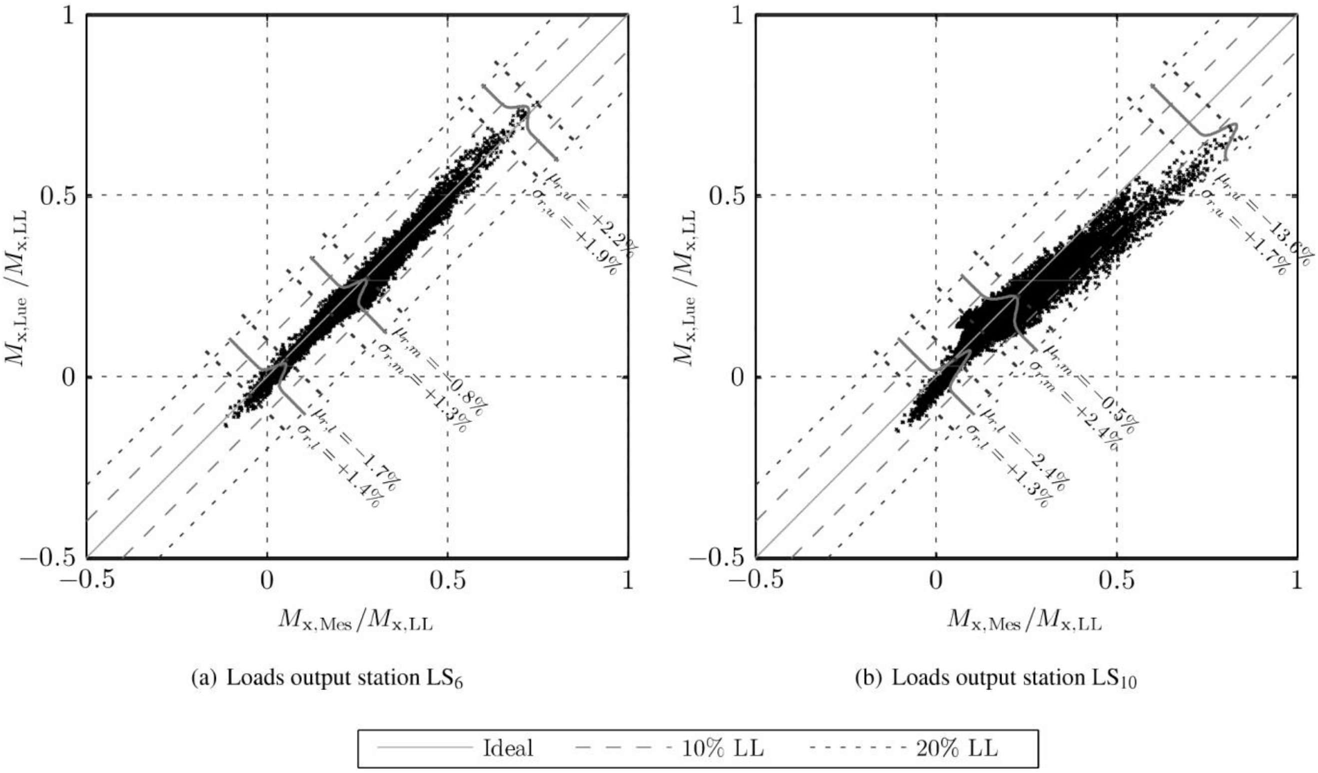
A high accuracy in the loads estimation over the entire flight envelope becomes feasible using the hybrid loads observer approach. Even outside the training data space, for example in the case of high load events in the extrapolation range or in the case of unknown manoeuvre types, only small errors occur in the loads



(a) Loads output station LS_6

(b) Loads output station LS_{10}

Fig. 7: Validation of the hybrid observer with the entire flight test database (847 manoeuvres)



(a) Loads output station LS_6

(b) Loads output station LS_{10}

Fig. 8: Validation of the Luenberger observer with the entire test database (847 manoeuvres)

estimation. The average error of the estimated bending moment in the upper, extrapolated load range at both considered loads output stations is less than 1 % with a standard deviation of less than 2 %.

By application of the hybrid loads observer method, a structural loads monitoring system with high accuracy and low development effort can be set up. Initially, a Luenberger observer is set up. Modelling deficiencies in the plant model or conservative load assumptions in the design model could lead to inaccuracies in the loads estimation. This would lead to missed load events or false notifications of the loads monitoring system. For an efficient usable structural loads monitoring system, an additional correction step is necessary, which can be complex and time-consuming in the case of physical modelling.

In the development of a hybrid loads observer, the correction is not physically based but data-based and is realised by the local model network method. The correction models can be quickly identified from flight test data. In this way, a rapid implementation of the hybrid loads observer is made possible. The hybrid loads observer thus fulfils the requirements of an economically usable structural loads monitoring.

For the further development of the hybrid observer method, the model structure should be examined in order to determine to which extend the physical model structure can be reduced and be compensated by local model networks. An increased proportion of the local model networks leads to a reduced model complexity and computation time, which is a prerequisite for a real-time application, e.g. within a load alleviation system.

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