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FLIGHT LOADS ESTIMATION USING LOCAL MODEL NETWORKS

Martin Halle*, Frank Thielecke*
***Institute of Aircraft Systems Engineering**
Hamburg University of Technology
Hamburg, Germany

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Abstract

Nowadays flight load exceedance monitoring is an important task to the aircraft manufacturer as well as the operator. The estimation of flight loads is required during development and operation of an aircraft. The requirements are usually different for e.g. calculation of design loads for certification and operational loads monitoring of stress and fatigue. The ability to determine aircraft operational loads (more) precisely may reduce the time in maintenance and is an enabler for e.g. loads/fatigue monitoring at operator level.

In this paper the system identification method of local model networks is applied to the field of flight loads estimation targeting on-board aircraft systems. The design and development process of a flight loads estimation algorithm based on design and flight test data is presented.

1 Introduction

A committee of the Aerospace Industries Association (AIA) and the Air Transport Association (ATA) evaluated existing special inspection procedures for high load events like severe turbulence encounter or extreme manoeuvreing [1]. Instructions for such events are typically specified in aircraft maintenance manuals (to detect aircraft damage following an in-service event) and are typically referred to as "Unscheduled Maintenance" or "Special Inspections". The addressed safety recommendations by the National Transportation Safety Board (NTSB) raise concerns that structural damage due to high load events may not be found before returning the aircraft to service.

As a result, the committee has concluded that there are areas where improvements can be implemented. In particular, the recommendations include "the introduction of additional objective criteria using flight data to assist in the evaluation of events" and "the development of refined algorithms by the manufacturer that use multiple data parameters to arrive at improved evaluations of the severity of the loads actually experienced, and corresponding required actions".

An estimation of the loads acting on the aircraft during normal and abnormal operation is necessary. Targeting on-board systems several *indirect methods* with their own advantages and disadvantages exist. As the resources are generally restricted on-board an aircraft, efficient algorithms with a small resource footprint are desired.

Existing methods presented in the first section of this paper show a respectable performance. Methods like artificial neural networks (ANN's) provide a good compromise between estimation quality and resource consumption. Their memory consumption and computation time at run-time are very low, making a realtime-application in an aircraft during flight possible and feasible. Unfortunately such methods often lack aspects relevant for certification like transparency of the models.

Within [6] ANN's have been compared to a novel approach using local model networks

(LMN). Within the focus of this paper the approach based on local model networks is further investigated. Local model networks can be seen as a bridge between classical white-box methods and black-box methods like ANN's. The concept of local model networks will be explained in this publication and applied to estimating load quantities with the focus on events where high flight loads occur.

After a section dedicated to provide the problem description, special attention is paid to the data selection and the training process to obtain the models. While in [6] only flight test data has been used, within this paper a *2-step-approach* will be presented. At first, output data of design calculations is used to create a sophisticated database for training and validation. The data selection depends on the addressed load quantity, i.e. the load component at a structural aircraft part. Special care must be taken to address the whole flight envelope, for example depending on altitude and true air speed which is especially only available in the data of design calculations.

The modelling or training process to obtain the models to estimate flight loads is explained. This includes a description of problem-specific adaptations and parametrisation to the local model network approach. The character of the models is explained and it is shown, how a-priori knowledge can be applied to achieve better performance. An analysis of the structure and model parameters allows for an estimation of the robustness and quality of the model. In a second step the models are tuned using flight test data as it becomes available. This accounts for a typical aircraft development process, where load estimators are developed even before flight test data is available.

The results of applying the methodology to derive models for flight load estimation are presented. A comparison of the models created with data of design calculations and data from flight tests shows the quality of the estimation and provides an example, of how flight test data can be used for to update the existing models to improve the performance for an application in an real aircraft with real sensor input. The results are quantified with respect to the aircraft's limit loads (LL) and information is provided about what estimation quality can be achieved using the proposed method.

A summary concludes the results and provides an outlook for future research and application of the methodology in real-world scenarios and processes.

2 Existing methods

Flight loads can be measured directly by instrumenting an aircraft with strain gauges at dedicated points of the aircraft structure. While for test aircrafts this is the case, such measurements are not available on standard aircraft due to weight, high maintenance effort and costs. Therefore, indirect approaches are used instead. In this section a short overview about *existing indirect methods* to estimate flight loads with relevance to this paper is given.

In [7] a prototype of an indirect loads estimation at the wing butt line of a Grumman F-14B based on neural networks is presented. The model is based on measurement data obtained from an flight test program with standard structural manoeuvres and typical fleet operations. Several variables were monitored during flight, including the vertical load factor, Mach number, altitude, wingsweep angle, roll rate, angle of attack and the strain at butt line 10 of the aircraft. The results were evaluated by comparing the correlation coefficients between the predicted and measured strains. The conclusion is made that the neural network approach offers a viable alternative to standard regression analysis for predicting strains on airframes.

In [10] neural networks were used to predict strains resulting from manoeuvre loads in the empennage structure of a Cessna 172P. The purpose was to develop a methodology for the prediction of strains in the tail section of a general aviation aircraft that would not require installation of strain gauges. Linear accelerometer, angular accelerometer, rate gyro, and strain gauge signals were collected in flight, filtered and used to train the neural networks. This methodology has been improved in [11] based on manoeuvre recognition using neural networks with the focus on both cost saving and improving the horizontal tail predictions.

In [2] neural networks were used to model wing bending-moment loads, torsion loads, and control surface hinge-moments of the Active Aeroelastic Wing aircraft. Accurate loads models are required for the development of control laws designed to increase roll performance through wing twist while not exceeding load limits. Inputs to the model include aircraft rates, accelerations, and control surface positions. Neural networks were chosen because they can account for uncharacterised nonlinear effects while retaining the capability to generalise. Flight data for rolls, loaded reversals, wind-up-turns, and individual control surface doublets was used for load excitation. Results are presented for models of four wing loads and four control surface hinge moments. However, in [5] it is mentioned that the method based on neural networks was abandoned, because the high extrapolation required could not be easily analysed for uncertainty.

In [15] the development of a parametric-based indirect aircraft structural usage monitoring system using artificial neural networks is described. Flight data, obtained during strain-based operational loads measurement campaigns have been used to predict strains or stresses at key structural locations for several military aircraft types. It is concluded that this technology could provide the basis for accurate, cost-effective structural usage monitoring systems. Consequently in [16] and [17] a structural health and usage neural network (SHAUNN) monitoring system is proposed to predict stresses, strains, loads, or fatigue damage from flight parameters.

Another general overview of different publications in this field is also presented in [18].

Common to all the neural network based methods is while providing models with a good accuracy their lack of a robust extrapolation behaviour. In [6] it could be shown that local model networks are more robust due to their local linear models and a controllable extrapolation behaviour. It was summarised that local model networks clearly outperform neural networks. Therefore, within this paper local model networks are the preferred indirect approach and further developed.

3 Local model networks

The *local model network* (LMN) approach has been described by [12], [13], [14] and others. It makes use of a decomposition of the input-space to allow a specific modelling of different regions in the input-space, the *local models* or *subspaces*. While the models are obtained in an iterative, self-organising process to cluster the input space the model structure allows for physical interpretation and specific adaptation.

While different clustering algorithms exist [3], an axis-orthogonal decomposition of the input space is used in this paper. The local models are represented by rectangles, or, for problems of high dimensionality, by hyper-rectangles. The behaviour of the system is modelled locally by considering only the training-data samples which lie within a specific subspace.

For a specific subspace i out of m subspaces, a locally valid linear model is determined by a linear, multivariate least squares approximation. The vector of regression coefficients $\mathbf{w}$ is determined by a least squares approach from the matrix of input parameters $\mathbf{U}$ and the vector of output parameters $\mathbf{y}$.

$$\mathbf{w} = (\mathbf{U}\mathbf{U}^T)^{-1}\mathbf{U}^T\mathbf{y} \; . \tag{1}$$

For a system of k dimensions and an input vector $\mathbf{u}$, the linear model y_i is

$$y_i(\mathbf{u}) = w_0 + \sum_{j=1}^{k} w_j \cdot u_j \; . \tag{2}$$

Due to the linear approximation, the locally determined linear model y_i will extrapolate for input-samples beyond the subspace used to determine the model. The activity of the linear model is controlled by a *weighting-function* which is defined by normalised, specific Gaussians for each dimension. The center c of each Gaussian lies in the center of the local model. The standard deviation σ is chosen to cover the range of the subspace in the respective dimension, while asymptotically becoming zero outside of the subspace. For an input $\mathbf{u}$ of a system, the combined activity of all Gaussians for the current model i is determined by the local activation μ_i as

$$\mu_i(\mathbf{u}) = \exp\left(-\frac{1}{2}\sum_{j=1}^{k}\left(\frac{u_j - c_{i,j}}{\sigma_{i,j}}\right)^2\right) . \quad (3)$$

The normalised weighting-function Φ_i is determined as

$$\Phi_i(\mathbf{u}) = \frac{\mu_i(\mathbf{u})}{\sum_{j=1}^{m}\mu_j(\mathbf{u})} . \quad (4)$$

The equation for the local model network follows to

$$\hat{y}(\mathbf{u}) = \sum_{i=1}^{m}\left(\Phi_i(\mathbf{u})[w_{i,0} + \sum_{j=1}^{k} w_{i,j}\cdot u_{i,j}]\right) . \quad (5)$$

The structure of the resulting model is depicted in figure 1. Due to the overlapping character of the Gaussians, the predictions made by the different locally accurate models are superimposed in boundary regions leading to a steady transition between adjacent local models. As stated in [9]

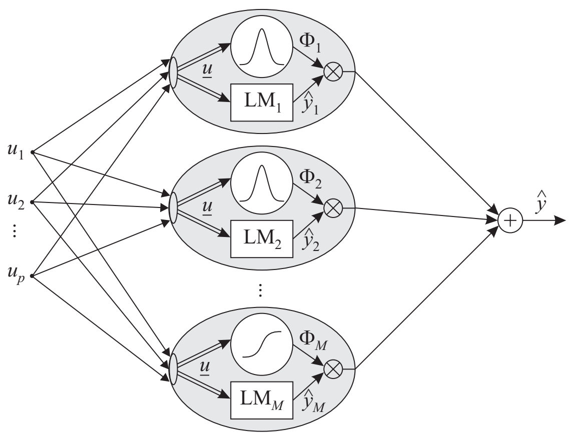

Fig. 1 Structure of a local model network

the physical interpretability of local model networks is a clear advantage over classical ANN's. In each local model the effect of each input parameter is interpretable.

The input-space decomposition is an iterative process leading to a steadily increased accuracy of the local model network. The decomposition is based on an initial global model by bisecting the input-space orthogonally to each input dimension, resulting in two new local models per input dimension. The bisection, or "cut" which leads to the largest reduction in the global prediction error is chosen. The decomposition stops at either a certain prediction error or a certain maximum number of local models.

4 Problem definition

The structural loads occurring during flight at the root of the vertical tail plane (VTP) of a transport aircraft are modelled using the LMN approach. The flight loads generally considered are the bending moment M_x, the torsional moment M_z and the lateral force F_y (see figure 2). These loads, with special attention drawn to high load occurrences, shall be modelled using aircraft system parameters available during flight, not requiring any additional sensors. As the lateral force

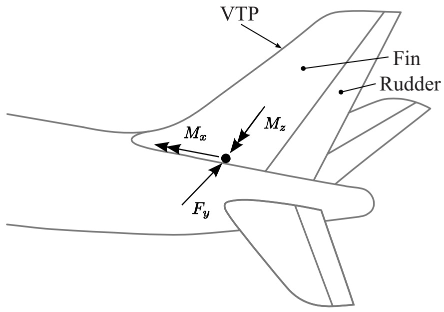

Fig. 2 Load components at the root of a VTP

features a high correlation with the bending moment, it has been excluded for this paper as it does not give a significant gain in understanding the aspects of the considered modelling approaches.

The structural loads arise as a result of external loads caused by the interaction of the aircraft with the environment. They are classed by their dynamic character into *steady loads* as in steady flight conditions and *incremental loads*, induced by manoeuvres or inhomogeneous flow conditions caused by gusts. At any position of the structure the local structural load F_{loc} in flight is the result of the superimposed external loads, namely aerodynamic loads F_{Aero}, propulsional loads F_{Prop}, inertial loads F_{Inert} and gravitational loads F_{Grav}:

$$F_{loc} = f(F_{Aero} + F_{Prop} + F_{Inert} + F_{Grav}) . \quad (6)$$

In this paper the loads to be determined are internal structural loads, assuming the knowledge of the external loads as well as a mathematical representation of the mapping function represented by the aircraft so that aircraft system parameters represent the occurring external loads. The task is to identify the character of the mapping function as a mathematical formulation. The mathematical formulation is derived by applying the LMN approach and has been introduced in [6].

4.1 Data selection

For methods using training data like artificial neural networks and local model networks the selection of the data for training and validation is vital to achieve a good model accuracy. Ideally the input range is evenly sampled as within regions where less or no data is available the models will interpolate or extrapolate which can cause problems [6]. With flight test data this is not the case so special attention has to be paid to prepare good training data.

A data base containing the aircraft system parameters from a specific transport aircraft is used. It was gathered through structural design calculations and in different flight test campaigns. For the flight test campaigns, the aircraft was equipped with additional sensors to determine the structural loads at specific stations of the vertical tail plane for the reference.

The synchronised data base covers about 4400 of so-called load cases of design calculations [19] and 6 hours of flight test data for different flight conditions, the latter only within a safe flight envelope [4] and not distributed homogeneously. Only the data of normal aircraft flight operations will be considered for modelling. Manoeuvres used to stimulate failure cases like one engine out events are not considered. The explicit knowledge about the covered manoeuvres allows to select data with similar manoeuvres for training and validation. Figure 3 shows such classification. The manoeuvres of the design calculations are grouped and represent a good coverage of the speed/altitude range.

The advantage of design calculations over flight test data is that they account for extreme

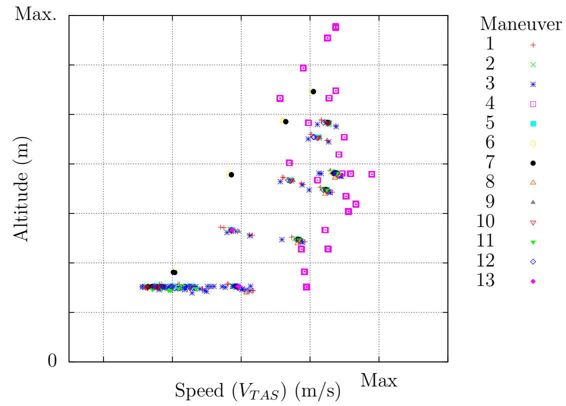

Fig. 3 Altitude/speed of design calculations

load cases. In real flight tests, flight loads are usually below 80% limit load. Models based only on flight test data would extrapolate at high loads which usually leads to less accuracy. In [6] only flight test data was used to create flight load models which caused an uncertainty for high loads as such were not sufficiently present within the data. To cope with such, a *2-step approach* is proposed hereby. First, data from design calculations is used to create and train the models focussing on high loads. Second, flight test data is used to refine the models. [1]

All samples within both data bases are copied and mirrored in lateral direction as the aircraft can be assumed as being symmetrical. Therefore the lateral symmetry of the aircraft can be taken into account to extend the coverage of the data bases. Only parameters with lateral character such as the bending moment, lateral acceleration, sideslip angle, rudder-angle, roll rate/acceleration and yaw rate/acceleration are copied with reverted signs, the other parameters (like the angle of attack, dynamic pressure and mass) are copied without manipulation similar to [2] and [6].

The data selection out of the data of the design calculations makes use of a-priory knowledge as following: For each characteristic flight condition the data of the related manoeuvre is removed completely and added to the validation

[1] The first step can also be seen as a model reduction. The data from the design calculations it based on several complex non-realtime models using large parameter data bases [19].

data to ensure an independency between training- and validation data. With the remaining data, to focus on high loads, data below a certain limit load threshold is greatly reduced. In [6] a method was used that completely removed data below a certain threshold with respect to the 1D limit load for each load component (the maximum allowable load).

This approach has been improved by taking correlated 2D load envelopes for combined loads into account. The occurrence of load combinations can stress structural components significantly more. An example for this is the structural load on an aircraft wing spar generated by shear and torsion. The 2D load envelopes are available throughout the aircraft structural design and describe the relation between two load components such as bending (M_X) and torsional moment (M_Z) by means of the maximum allowable loads as depicted in figure 4. In the image it can be seen that

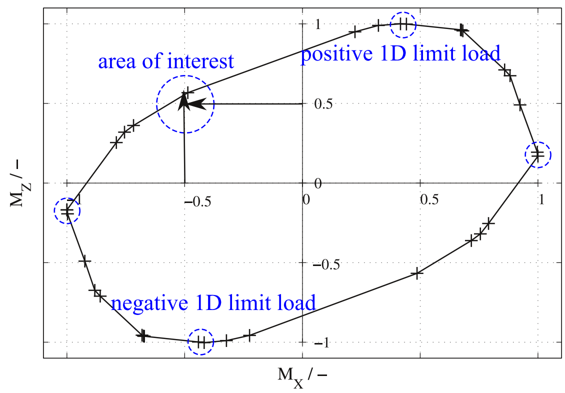

Fig. 4 2D load envelope torsional/bending moment

an amount of -50% in M_X and +50% 1D limit load in M_Z can already stress the aircraft structure to the limit at that point. For the data driven modelling approach enough training data in regions at the border of the load envelope should be made available (as depicted with the “area of interest” in figure 4). Additionally all data points that form the convex hull with respect to the 2D load envelopes for each of the 4400 design calculations are kept in the training data for both load components. Thus it is ensured that the training data covers the areas with highest loads with respect to the load envelope for each manoeuvre.

The resulting data base is divided into training data where round-about 80% of the data base is used, and the remaining 20% added to the validation data.

For local model networks, the data selection is done iteratively in the presented approach. One of the strengths of local model networks is their transparent character that can help to visualise model deficits. The following example shows how such insight has been incorporated to improve the training data and therefore the estimation. As explained in a previous section local model networks are a compound of local linear models with a gaussian function defining the activity of the linear model. Figure 5 shows for one of the independent validation data sets (manoeuvres) the simulation results with respect to the reference values in the upper part and the influence of the two most dominant local models (no. 2 and 10 out of 15) based on their weighting functions in the lower part. Large outliers can be

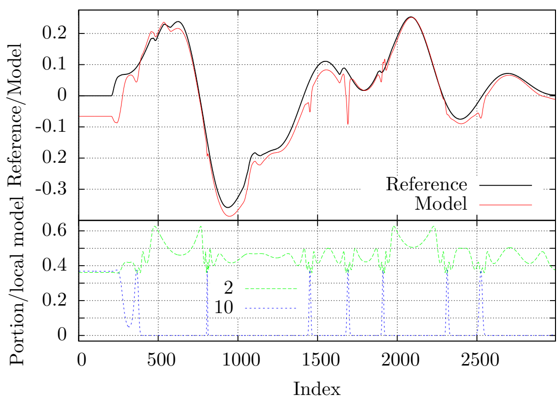

Fig. 5 Model weights with respect to outliers

observed in the simulation results (for example at appr. index 1700) that obviously correspond to the local model no. 10. Investigating this particular local model reveals that its local linear approximation function for this particular subspace is based on only a few samples leading to a high gradient in one dimension (the load factor N_y in that case). Providing more samples into this subspace or even manually tune the parameters of the local linear approximation function reduces such outliers significantly.

4.2 Parameter selection

To model the loads by means of a mapping function it is necessary to identify parameters, which describe the state of the aircraft sufficiently with respect to the considered target loads and is based on the approach as presented in [6], similar to [10], [15] and [16].

Most significantly for loads on the vertical tail plane are the rudder angle δ_r (depending on the aircrafts angle of attack α), the sideslip angle β, the rate of roll p, true airspeed V_{TAS}, the aircraft mass W and the lateral load factor N_y.

Table 1 summarises the selected parameters used within this study for each of the considered load components.

Table 1 Selected parameters to model VTP loads

Description	Symbol
Angle of attack	α
Sideslip angle	β
Elevator trim angle	δ_i
Elevator angle	δ_q
Rudder angle	δ_r
Longitudinal load factor	N_x
Lateral load factor	N_y
Vertical load factor	N_z
Roll rate	p
Roll acceleration	$\dot{p}$
Yaw rate	r
Yaw acceleration	$\dot{r}$
Dyn. pressure	q_{dyn}
Aircraft mass	W
True airspeed	V_{TAS}

To simplify obtaining a mapping function describing the relation between the input and the output parameters combinations of selected input parameters are used such as the lateral acceleration N_y is weighted with the aircrafts mass W, giving a lateral force

$$F_y = W \cdot N_y \,, \tag{7}$$

or angle of attack is weighted with the dynamic pressure q_{dyn} as the lift L generated by a reference wing area S is proportional to the dynamic pressure q_{dyn} and the airfoils angle of attack α [8].

As presented in [6] parameters like the aircrafts mass and the dynamic pressure show a static behaviour in comparison with the bending moment. Some parameters like the lateral load factor, the angle of attack and the yaw acceleration show a dependency with a highly linear character. Others like the rudder input, yaw or roll rate show no clear dependency in the first place. Nevertheless such parameters play a significantly role to separate the input space with respect to the flight condition for the local model network approach.

The output parameters (loads) are normalised to 100% limit load, a load of 1 denotes 100% limit load.

5 Results

In this section, the 2-step modelling process for the bending moment M_X using the LMN approach is presented. The LMN approach provides only a few parameters to adjust, explained in the following:

1. The *splitting ratio* defines how often a subspace is split in each iteration step. A ratio of 1:1 means it is split exactly in the middle resulting in two equally sized new local models. A ratio of 1:2 results in actually 2 splits being computed with 1/3 to 2/3 and 2/3 to 1/3 respectively. This can lead to a faster convergence as the algorithm is able to adapt to non-linear and non-centered regions more quickly. In this study a ratio of 1:5 has been chosen.

2. The *smoothness factor* controls the overlapping effect of local models by means of the width of the Gaussian weighting function. A smoothness factor smaller than 1 narrows the respective Gaussian leading to more sharp contours while a smoothness factor larger than 1 increases the smoothness by widening the Gaussians leading to a more continuous contour between local models. As a potential drawback, the latter may degrade a good local linear adaption in

the subspace due to the increased influence of the local models in the direct neighbourhood. In this study a smoothness factor of 0.8 has been selected.

3. The *maximum number of models* is the termination criteria to stop the training. In this study it has been set to 15.

To visualise the results with respect to the 2D envelopes, a new *2D criteria* has been developed that considers the models for torsional and bending moment together and is explained hereby.

It is based on a *radial coefficient* where each correlated load condition is determined by two load components $C1$ and $C2$ provided by the the respective load envelopes. Such load condition can be defined by the angle φ and the absolute value of its distance to the origin as visualised in figure 6.

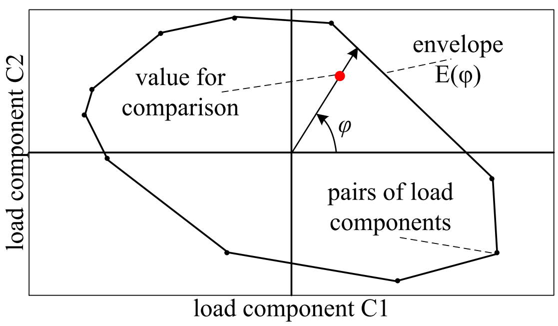

Fig. 6 Definition of radial coefficient

For a comparison to the limit load, this line is lengthened until it intersects the envelope. The distance of the intersection point to the origin is the limit load for this load condition. The *radial coefficient* is the ratio of the load condition and the limit load at this angle and is given by

$$\mathrm{RC} = \frac{\sqrt{C1^2 + C2^2}}{E(\varphi)} \quad . \tag{8}$$

The value of $RC \leq 1$ represents loads lower than limit load and $RC > 1$ when limit load is exceeded. By plotting these values for the model and reference a correlation graph is created that visualises the quality of the estimation with respect to both load components. A good estimation results in a distribution within a small band near the diagonal. Offsets or a twisting of the distribution against the diagonal give information about the behaviour depending on loads levels.

For the pair of torsional and bending moment the achieved local model networks for these load components successfully generalise on the data. Figure 7 shows the result for the training session with regard to the training and validation data set based on the data of the design calculations using the beforehand mentioned correlation graph.

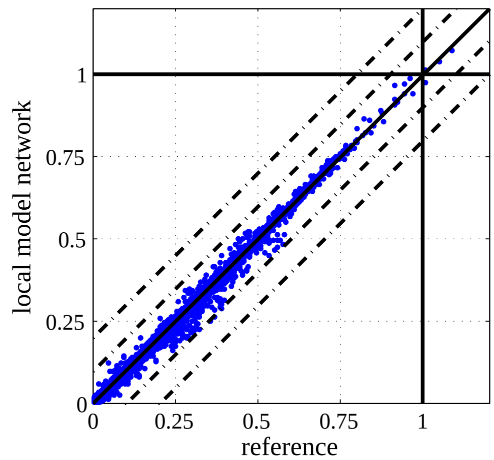

Fig. 7 RC correlation plot torsional/bending moment

The dotted lines mark a tolerance range of 10 and 20% estimation error. It can be seen that using the models for bending and torsional moment the *2D criteria* can be satisfied using the local model networks. No major outliers are observed, all values are within the tolerance range of 10%. This is superior to the approach presented in [6] where correlated loads were not considered.

So far, the models are based on data from design calculations. When applying these models to flight test data one would expect a good performance. To show the characteristics a special VTP manoeuvre of type rudder multi-step is chosen. During this manoeuvre the pilot commands steps of different amplitudes to the rudder which results in a large lateral load factor N_y and causes large bending moments on the VTP. As shown in figure 8 the simulation results are very noisy.

The reason is, that within the data from design calculations there is no (sensor) noise on the input data. For flight test data that is not the case. Sensitive input parameters to the model like the

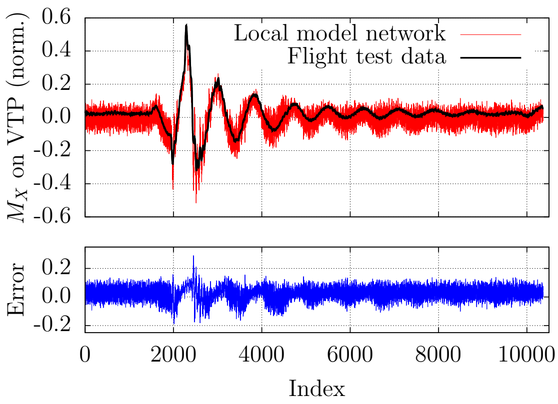

Fig. 8 Manoeuvre simulation with flight test data

load factors N_x, N_y and N_z are quite noisy, as shown in figure 9.

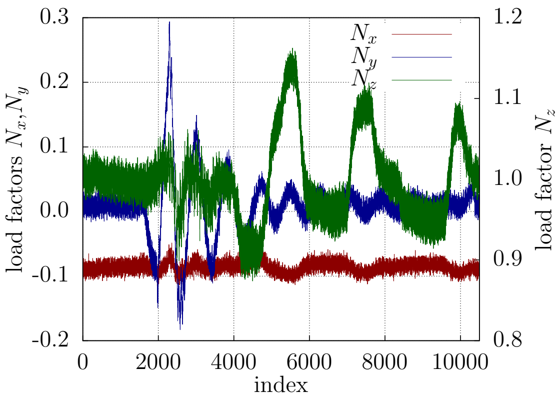

Fig. 9 Characteristic of sensitive input parameters

To deal with this, the second step of the proposed 2-step approach is needed and explained hereby. For data-driven methods there are generally several possibilities. For example, the flight test data could be directly included in the training data in the first place or based on the knowledge about sensor noise the training data could be modified by applying a similar noise ratio.

Within this study, the best results have been achieved by re-training the existing models based on a modified training data base. Assuming that the mapping function of the local LMN is generally correct the structure is kept fixed and all parameters of the local models are re-estimated using the original training data expanded with new training data from flight tests. The flight test data is pre-processed as explained for the data of the design calculations to cover the available input range best. The result for the updated models with respect to the manoeuvre from above is shown in figure 10.

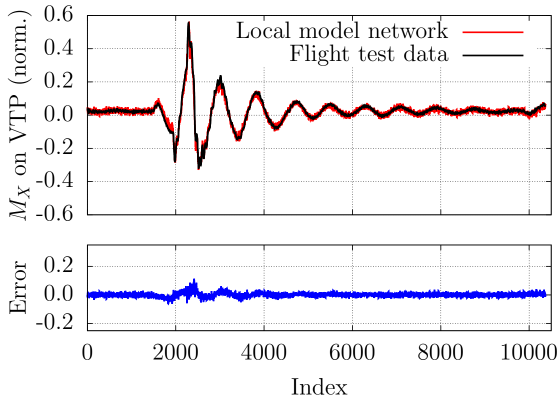

Fig. 10 Man. sim. with F/T data & improved models

The noise level and therefore the error for this manoeuvre has been greatly reduced. To compare the overall performance the correlation between the local model network and the flight test data with respect to the bending moment M_X is analysed.

Figure 11 shows the results for the complete flight test based validation data before the parameter update in contrast to 12 which shows the results after.

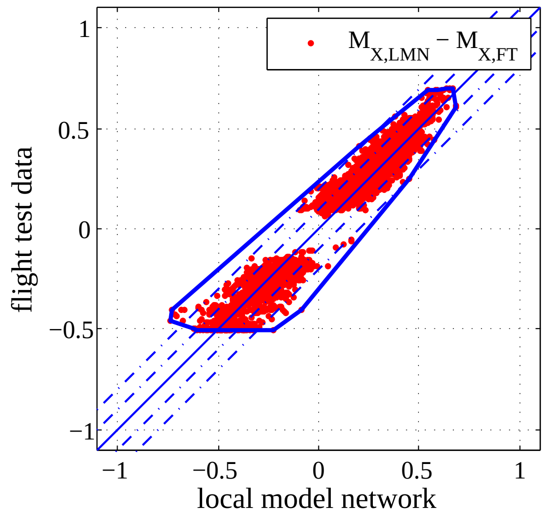

Fig. 11 Correlation original LMN and F/T data

The plots show for each sample of the flight test data (the red dots) the values for the bending moment normalised to the limit load by means of a correlation plot. Additionally the blue line

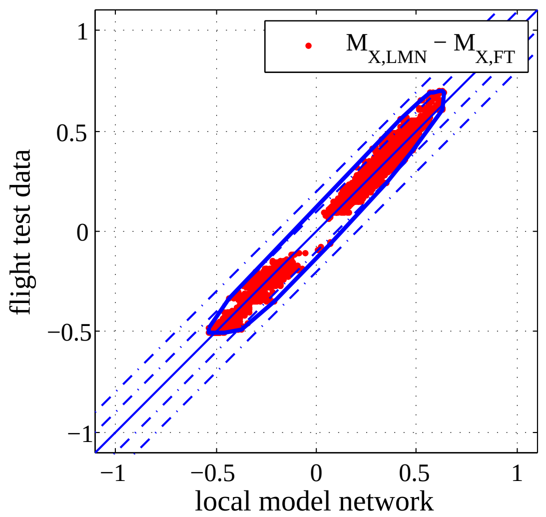

Fig. 12 Correlation improved LMN and F/T data

marks the convex hull of the data points to better visualise maximum outliers. Again, two dotted lines mark an estimation error of 10 and 20% respectively. While with the original model the error margin is exceeded, the optimised model shows a better performance although the error margin of 10% is slightly exceeded. As mentioned initially and also depicted in the figures, the flight test data rarely exceeds 80% limit load. Similar observations can be made with the torsional moment M_Z.

6 Summary

The development of loads monitoring systems in aircrafts is driven by the intention to allow specific component loads monitoring without requiring complex and costly installations for direct loads measurement. For the purpose of indirect modelling approaches, neural networks are well known from the literature. By using available flight parameters, the considered loads can be formulated by different modelling approaches, while typically so-called multi layer perceptrons are used.

In [6] a new approach based on local model networks has been presented to estimate flight loads targeting on-board aircraft systems. It is based on a data driven system identification method similar to neural networks. The training data used to develop the models is vital to achieve good results as interpolation and extrapolation is the weak spot of such methods. Inspired from the literature in [6] only flight test data has been used to create the training data the model is based on. The drawback is that flight test data rarely exceeds flight loads by more that 80% of the limit load. Focussing on high loads this is a disadvantage.

Within this paper the concept is improved by introducing a *2-step approach*. It makes use of data from structural design calculations to create initial flight load estimators that cover the flight envelope of the targeted aircraft as good as possible including high loads. Such data is usually available even before the aircraft exists [19]. In the second step the models are refined and optimised based on data from flight tests to account for the characteristics of measurements from onboard aircraft sensors. While data from design calculations is free of noise, flight test data is not which affects the estimation quality. Therefore using the existing models a parameter update is carried out based on an extended training data base that includes flight test data.

Previous work addressed models for single load components successfully. However, there are cases where a combination of load components stresses the aircraft structure even more. Combined loads are expressed by tables representing load envelopes that evolve during the design process of the aircraft structure. In this study, to account for combined loads a *2D criteria* based on such load envelopes has been introduced and the models for each load component are no longer developed and assessed independently.

During modelling, the transparent character of local model networks helps to address model deficits. Each local model of a local model compound has influence to its neighbours in the related subspace of the input data. It has been shown that local models can be identified that cause outliers when applying the overall model to validation data. Providing additional training data or adjusting model parameters manually helps to resolve such issues.

The results for developing flight load estimators for a load station at the vertical tail plane of an aircraft have been presented. The models generalise well on both: data from design calculations and flight test data. For the models developed within this study an error margin of 10% limit load is rarely exceeded but is always below 20% limit load.

To help with modelling aspects based on local model networks an in-house software framework has been developed and utilised. By means of a modelling assistant it helps to setup the training and validation data, modelling parameters and provides methods to assess the results accordingly.

Further studies will investigate the application of this concept to different structural parts of an aircraft, namely horizontal tail plane, fuselage and wing.

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