Data-Driven Stochastic Identification of a UAV Under Varying Flight and Structural Health States

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ABSTRACT

This paper presents the assessment of a stochastic data-driven global modelling framework for data-driven state awareness under varying flight (airspeed) and structural (damage) states. The proposed framework utilizes stochastic Vector-dependent Functionally Pooled (VFP) models that compound data pertaining to different flight states to develop a single "global" model representing the system dynamics. In this case, the system identification procedure is implemented for an Unmanned Aerial Vehicle (UAV) modeled in ASWING, which is a low-fidelity aeroelastic software for aerodynamic, structural, and control-response analysis of aircraft with flexible wings and fuselages. A series of dynamic simulations is performed for flight states corresponding to varying airspeed and damage size. Simulated signals are used for the stochastic system identification process involving both parametric and non-parametric analyses. The identified VFP model accurately represents the system dynamics and outperforms its non-parametric counterparts. The modelling method is shown to be effective and accurate in identifying the aeroelastic response for an expanded range of flight and structural states using sample data obtained within that range.

INTRODUCTION

The future of aircraft design lies in incorporating biological concepts and altering the current structural framework to accommodate these changes. In order to develop self-aware systems, similar to biological organisms, these vehicles should be able to detect changes in their operation, environment and their own structural health state to make appropriate changes in their behavior or action [1,2]. Current systems rely on user input or pre-programmed commands that cannot consider the situation or health state of the vehicle when making decisions. Traditional control is afforded by data generated during

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the design phase of the vehicle that determines its flight envelope. As a result, there are safety margins included in the design of these control systems that ensure the vehicle is only operational in a particular portion of the envelope for the majority of its life. Autonomous "fly-by-feel" aerial vehicles have the potential to overcome this limitation by allowing the system to analyze its own health and environmental conditions, and make decisions that optimize reduction in cost, risk and benefit overall safety and performance [1]. Such autonomous decisions will be made without direct communication, enabling increased survivability in adverse conditions. Allowing for maximum utilization of the flight envelope by adjusting the service region of the aircraft will extend its life span compared to traditional vehicle maintenance and operational procedures [1, 2].

When it comes to the aeroelastic behavior, dynamic aeroelastic effects resulting from the interaction of the aerodynamic, elastic, and inertial forces require careful consideration throughout the design phase of the aircraft and pose a major safety-critical factor in the qualification of aircraft into service [3–6]. Efforts towards developing system and model identification techniques for data-driven aeroelastic modeling, damage assessment and online parameter estimation have been previously made [1, 7–10], however the treatment of constantly varying operating and structural states remains a significant challenge that needs to be addressed. Previous work has introduced a stochastic global identification framework utilizing Vector-dependent functionally pooled (VFP) models based on experimental data from a self-sensing composite wing [11], while various forms of VFP models have been also used in previous studies on the topic of probabilistic damage detection, localization and quantification [12–14].

The main objective of this study is the data-driven stochastic identification of the aeroelastic response of a UAV under collectively-varying flight (airspeed) and structural (healthy and damaged) states. The second objective is the critical assessment of stochastic non-parametric and parametric approaches under the considered operating states. This paper utilizes the ASWING software platform [15, 16] for the low-fidelity approximation of the aeroelastic response of the UAV and collection of dynamic simulation data during free flight. The obtained signals are subsequently used for the stochastic identification of the aeroelastic response of the UAV via non-parametric and parametric time-series representations, including autoregressive (AR) and "global" VFP model-based approaches.

THE UAV MODEL AND RECORDED SIGNALS

The aircraft model investigated is a modified Hawk Ultralight sailplane. The UAV is simulated in ASWING, a low fidelity aeroelastic platform for efficient analysis of aerodynamic, structural and control response of mid to high aspect ratio flexible aircraft. Aircraft structures are represented as a series of interconnected Euler-Bernoulli beams, representing the fuselage, wing, horizontal and vertical stabilizers with aerodynamic and structural properties defined at various points along the beam. The control surfaces are also represented as lift and moment derivatives along the length of the wing. The aerodynamic effects are modelled with a lifting line model using the Prandtl-Gluaert compressibility transformation and wing aligned trailing vorticity [15].

Figure 1 shows the model in the ASWING environment. The sensors are defined

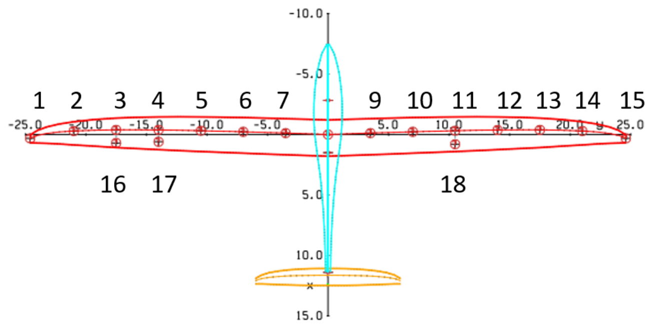

Figure 1. UAV in ASWING environment with prescribed sensors along wing.

at specific locations along the wing and their function is determined by the specified output variable. Various collocated sensors have been used to obtain acceleration, strain, displacement, and angle of attack data. The model has 18 sensors distributed along its wing, 15 along the main axis and 3 along the trailing edge. The indicative results presented in this work use the acceleration data from sensor 18 along the trailing edge. The dynamic simulation from ASWING outputs a time series signal of the data to which identification techniques are applied. The software, in addition, has the capability to complete modal analysis of the input model and identify the modal frequencies and flutter speed [16]. This capability allows identification of the relevant modes to wing vibration that may be captured by the sensors. The flutter speed is determined from this aeroelastic analysis to be at 160 ft/s. For each flight state probed, the airspeed, attitude and sensor data are collected. The flight states captured here maintain a range of airspeeds and damage sizes. The damage is introduced as a reduction in the local stiffness of up to 24% in a beam element located near the wing root. Table I lists the modal frequencies for the considered damage cases, indicating the limited effect of the damage on the system dynamics.

The sampling frequency was set at 100 Hz. The signal length used for analysis is a 30 s section during steady state free-flight of the UAV in simulation. The acceleration signals are filtered through a low pass Chebyshev Type II filter to cut off the higher frequency data and downsampled, reducing the bandwidth to 25Hz. The signal properties and simulation parameters are summarized in Table II. A set of flight states are considered with airspeeds ranging from 40 to 150 ft/s with an increment of 10 ft/s and damage size variation of 0% to 24% with an increment of 4%. The combination of both parameters results in a grid of 84 unique flight states. White-noise excitation signals to the wing are stimulated through minor flap deflection.

TABLE I. SYSTEM MODAL FREQUENCIES (V = 150 FT/S)

Mode	0%	4%	8%	12%	16%	20%	24%
1	3.9155	3.9130	3.9104	3.9077	3.9051	3.9023	3.8981
2	5.0384	5.0310	5.0235	5.0157	5.0077	4.9995	4.9868
3	6.4785	6.4746	6.4706	6.4666	6.4625	6.4584	6.4520
4	7.3482	7.3367	7.3252	7.3136	7.3019	7.2902	7.2724
5	7.4281	7.4288	7.4294	7.4299	7.4303	7.4307	7.4309

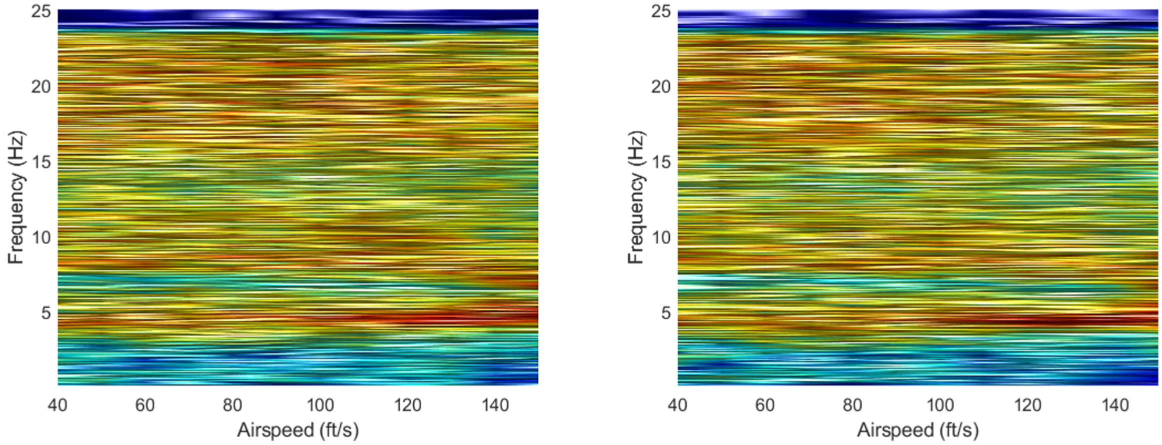

Figure 2. Non-parametric power spectral density magnitude estimates versus airspeed for the healthy (left) and maximum-damage size (24% reduced stiffness) states (right).

NON-PARAMETRIC IDENTIFICATION

Non-parametric analysis is conducted on 30-second-long acceleration signals using Welch-based power spectral density (PSD) estimation (MATLAB function *pwelch.m*). The method applies a Hamming window, with a segment length of 1000, to the data with 98% overlap. This identification process allows for extraction of useful information on the system dynamics from the sensor signals, also serving to set a precedent for the parametric analysis.

In Figure 2, the PSD estimates are presented for increasing airspeed in the range $[40-150]$ ft/s and a specified value for damage size. The left subplot indicates the PSD for the healthy state (0% reduced stiffness) and the right subplot the corresponding PSD for maximum damage size (24% reduced stiffness). The onset of flutter due to the coupling of modes is expected for the UAV model as the airspeed increases. Both subplots indicate the convergence of modes in the lower frequency range [0 - 10] Hz. Strong frequency responses observed at approximately 5 and 8 Hz coalesce at 6Hz, providing an indication of flutter. In addition, the PSD of the damaged state reveal the effect of damage on the structure through increased amplitude of vibration approaching the flutter speed.

Figure 3 presents the PSD estimates for two indicative airspeeds, 60 ft/s and 150 ft/s, versus increasing damage size in the range [0 - 24] %. Comparing both subplots,

TABLE II. SIGNAL PARAMETERS

Sampling frequency: $f_s = 100$ Hz
Filter: Low pass Chebyshev Type II
Signal bandwidth: 25 Hz
Airspeed: $40 - 150$ ft/s with 10 ft/s increment
Damage Size: $0 - 24$ % with 4% increment
Total number of states: 84
Signal length in samples (s): $N = 3000$ (30 s)

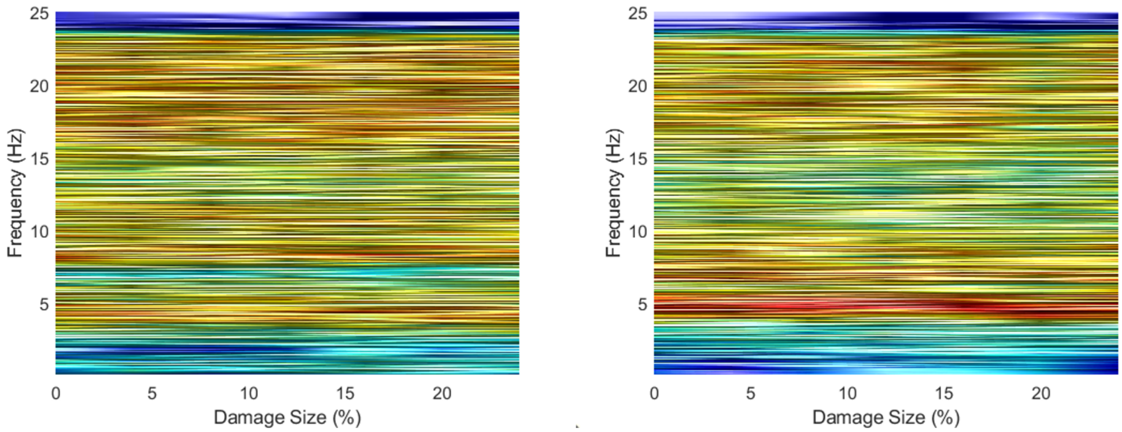

Figure 3. Non-parametric spectral density magnitude estimates versus damage size for set airspeeds 60 ft/s (left) and 150 ft/s (right).

the PSD amplitude is greater, as expected, for the higher airspeed (V = 150 ft/s, right subplot). The wing aeroelastic frequencies remain more or less constant across different damage sizes which is in agreement with Table I. The small size of the damage would explain the negligible effect it has on the dynamics of the UAV.

GLOBAL MODEL IDENTIFICATION UNDER VARYING STATES

Global model identification using the available signals involves baseline model identification for a single state and global model identification for the entire range of states. The model identification involves model order selection through autoregressive (AR) models and model parameter estimation through the VFP framework. The resulting models are VFP-AR models, which combine both AR and VFP model structures to assist in determining the model parameters as explicit functions of the flight states that in this case are defined by the airspeed and the structural health state.

An AR model of order n is fit to the output sensor data for one single flight state to determine a suitable model order to capture the system dynamics. The AR model is defined as [17]:

$$y[t] + \sum_{i=1}^{n} a_i \cdot y[t-i] = e[t] \qquad e[t] \sim \text{ iid}\,\mathcal{N}\big(0, \sigma_e^2\big) \tag{1}$$

with normalized discrete time t, output vibration signal $y[t]$, AR polynomial order n, AR model parameters a_i, stochastic model residual $e[t]$, which is white, Gaussian, identically independently distributed with zero mean and variance σ_e^2. The identification process estimates successive AR models of increasing order to identify the best fit for the signal data (MATLAB function *arx.m*). The model order is selected using several validation methods including the Bayesian Information Criterion (BIC), residual sum of squares normalized by signal sum of squares (RSS/SSS), frequency stabilization plots and residual autocorrelation functions [17, 18].

The model order determined from examining individual flight state cases enables development of the global VFP-AR model. This model uses functional data pooling techniques to combine data from all the flight states for model estimation. The VFP-AR model has the form [11, 12, 18]:

$$y_{\boldsymbol{k}}[t] + \sum_{i=1}^{n} a_i(\boldsymbol{k}) \cdot y_{\boldsymbol{k}}[t-i] = e_{\boldsymbol{k}}[t] \tag{2}$$

$$e_{\boldsymbol{k}}[t] \sim \text{iid}\,\mathcal{N}\big(0, \sigma_e^2(\boldsymbol{k})\big) \quad \boldsymbol{k} \in \mathbb{R}^2, \quad E\{e_{k_{i,j}}[t] \cdot e_{k_{m,n}}[t-\tau]\} = \gamma_e[k_{i,j}, k_{m,n}] \cdot \delta[\tau] \tag{3}$$

with normalized discrete time t, output vibration signal $y_k[t]$, designated AR polynomial order n, AR model parameters $a_i(k)$, stochastic model residual $e_k[t]$, which is white, Gaussian, identically independently distributed with zero mean and variance $\sigma_e^2(k)$. k indicates the flight state vector which specifies k^1 and k^2, the specific airspeed and damage states respectively, for each simulated experiment. E represents the statistical expectation, $\delta[\tau]$ the Kronecker delta, and $\gamma_e[k_{i,j}, k_{m,n}]$, the covariance of the residual series.

The VFP model parameters $a_i(\boldsymbol{k})$ are modeled as explicit functions of the flight vector $\boldsymbol{k}$ (which contains the airspeed and damage size components):

$$a_i(\boldsymbol{k}) = \sum_{j=1}^{p} a_{i,j} \cdot G_j(\boldsymbol{k}) \tag{4}$$

with $G_i(\boldsymbol{k})$ representing the mutually independent basis functions (polynomials of two variables) that span the p-dimensional functional subspace determining the AR parameters [18].

The VFP-AR model of equations (2)–(4) is parameterized in terms of the estimated parameter vector $\boldsymbol{\theta} = [\ a_{1,1}\ a_{1,2}\ \ldots\ a_{i,j}\ ]^T\ \forall\ \boldsymbol{k}$ to be estimated from the available signals. Using the formulated linear regression framework the unknown parameter vector $\boldsymbol{\theta}$ can be estimated based on minimization of the Ordinary and Weighted Least Squares (OLS/WLS) criteria [18].

System Modeling for a Single State

The AR model identification process shown here is for a single airspeed (60 ft/s) and the largest damage size case (24% stiffness reduction). Initial AR model order selection for a single flight state utilizes the Bayesian Information Criterion (BIC) and Residual Sum of Squares (RSS) over Signal Sum of Squares (SS) criteria, leading to an AR(30) model. The frequency response function (FRF) of the selected parametric model is provided in Figure 4. Similar to the non-parametric PSD, this figure exhibits the FRF for four different damage cases comparing a lower (60 ft/s) and near-flutter (150 ft/s) airspeed. From Figure 4 it can be readily observed that the effect of damage is quite small in terms of the FRF magnitude for both airspeeds.

System Modeling under Multiple Flight and Structural States

Global model identification uses the VFP-based parametric stochastic identification method. The modelling is based on 84 (12 airspeeds $\times$ 7 structural states) operating

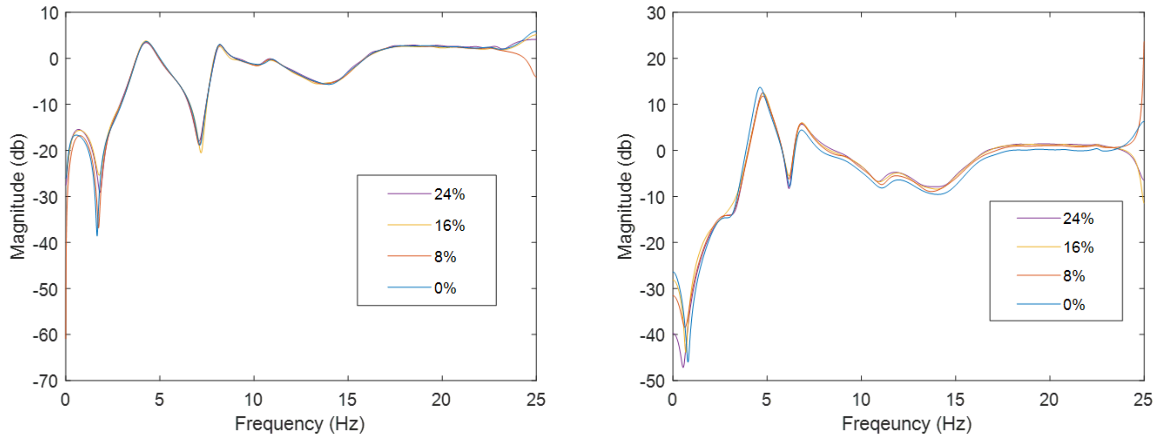

Figure 4. Parametric AR-based frequency response comparison for different damage cases and airspeeds of 60 ft/s (left) and 150 ft/s (right).

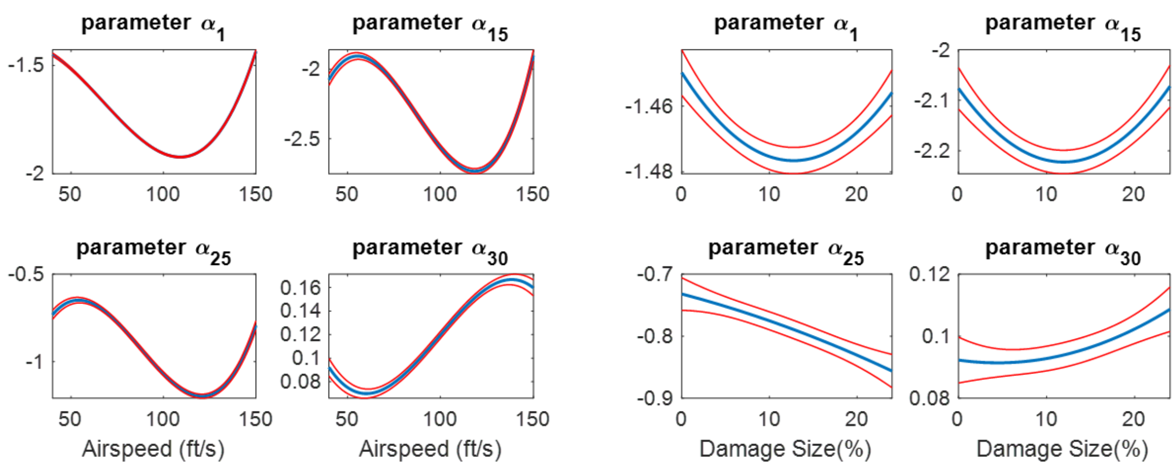

Figure 5. Indicative VFP-AR$(30)_{10}$ model parameter evolution versus airspeed (left subplots) and damage size (right subplots). The mean value of the parameters is depicted in blue, while the 99% confidence intervals are shown in red.

states simulated for sensor number 18. Airspeed and damage size increments used are $\delta k_1 = 10$ ft/s and $\delta k_2 = 4\%$, respectively. The VFP modelling process uses the conventional AR model order selected from the single flight state modelling. The functional subspace is selected based on the BIC and RSS/SSS criteria for increasing functional basis dimensionality. The minimum value of the basis dimensionality is chosen based on the frequency response that agrees with the non-parametric analysis. With these considerations, the selected functional subspace dimensionality is 10, with RSS/SSS value of less than 0.1%. The VFP model identification results in a VFP-AR$(30)_{10}$. The final VFP model selected represents the system response over the entire range of flight states.

The general variation of the estimated parameters is provided in Figure 5, which includes indicative 2-dimensional VFP-AR model parameters versus with airspeed and

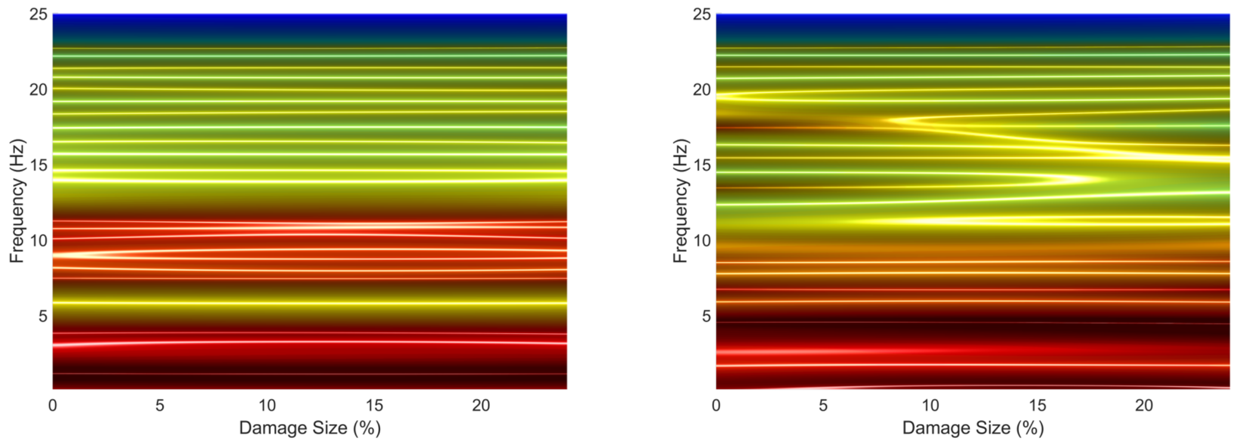

Figure 6. Indicative parametric FRF magnitude results based on the VFP-AR$(30)_{10}$ global model versus increasing damage size for set airspeed of 60 ft/s (left) and 150 ft/s (right).

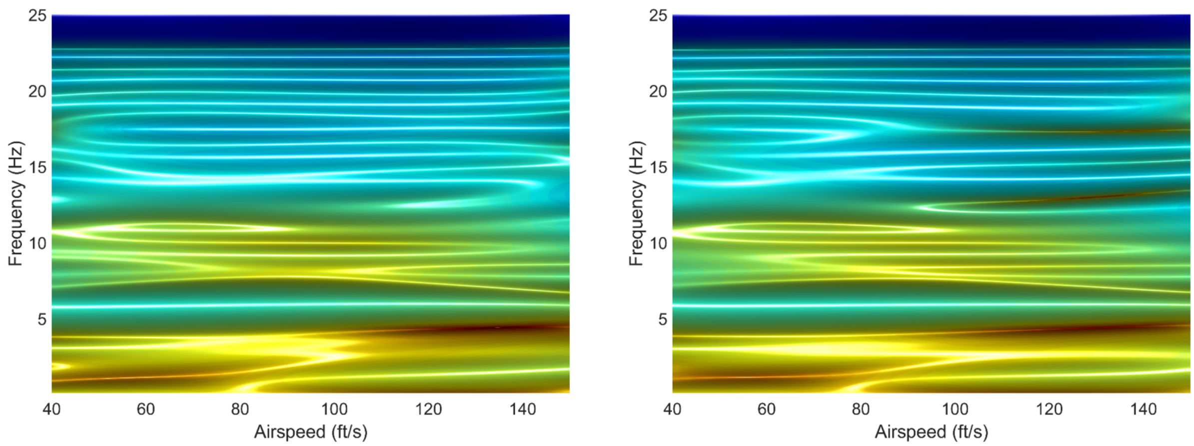

Figure 7. Indicative parametric FRF magnitude results based on the VFP-AR$(30)_{10}$ global model versus airspeed for the healthy (left) and maximum damage (right) structural states.

damage size. The 99% confidence intervals for the model parameters are also indicated as they reflect the modeling uncertainty. Figure 6 presents the frequency response magnitude varying with damage size for two indicative airspeeds. The left subplot corresponds to a set airspeed of 60 ft/s and the right to 150 ft/s. The lower airspeed shows strong aeroelastic modes around 4 Hz, 8 Hz, and in the $10-12$ Hz range. For 60 ft/s the effect of damage seems limited to the mode separation at 9 Hz for 4% damage size. In the case of the higher airspeed (150 ft/s) we observe significant changes in the aeroelastic frequencies compared to 60 ft/s. The effect of damage is evident in the mode separation at 17.5 Hz for 8% damage size. In addition, for the case of the 4% damage size the mode separation around 20 Hz can be observed. The increased damage sensitivity in the higher frequencies is expected near the flutter speed.

Utilizing the identified VFP-AR model, FRF magnitudes as a function of airspeed are provided in Figure 7 for the healthy (left subplot) and maximum damage (right subplot) structural states. The frequency resolution is 0.01 Hz and the airspeed resolution is 0.1 ft/s. This parametric response also clearly indicates the approach of flutter. As the airspeed increases, the convergence of modes in the lower frequency range < 10 Hz is observed. The modes around 4 Hz and 8 Hz begin to converge with increasing airspeed towards 6 Hz, which is the expected flutter frequency based on the ASWING model. The magnitude of the response also increases in intensity towards the flutter speed as seen in both subplots. Comparing these figures to the corresponding from the non-parametric analysis, it is evident that the accuracy of the VFP parametric model outperforms the non-parametric counterparts.

CONCLUDING REMARKS

This work aims to explore a recently-introduced stochastic identification framework for data-driven awareness under varying operating states defined by multiple airspeeds and structural health states. Using a low-fidelity aeroelastic software, ASWING, a simplified model of a UAV was established and dynamic simulation data were collected under 84 flight states. Parametric and non-parametric system identification techniques were applied to the collected data resulting in development of a final global VFP model that can accurately represent the aeroelastic response and system dynamics under the admissible states. The identified VFP model is characterized by functional dependencies between the flight state and model parameters, i.e. the model parameters are functions of the airspeed and the damage size. By using the entire data set, the process captures cross-correlations between different flight states, estimating parameters as a function of the flight state and reducing the number of overall estimated parameters. The single model developed accurately captures the system state for the entire range of airspeed and damage size explored, eliminating the need for data representing each individual state. Comparisons of the parametric and non-parametric analysis prove the accuracy of the identified stochastic global VFP model. In addition, we have determined that ASWING is a useful tool for fast and efficient analysis of a system model using the global modelling technique.

This work only uses data from one sensor location and type to identify a model. Future development could incorporate different sensor types and locations in this process. ASWING, being a low-fidelity platform only provides an approximation of the UAV behavior, thus higher fidelity models may be also employed for further investigation.

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