

In-flight System Identification of the Ingenuity Mars Helicopter

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The 68th and 69th flights of NASA’s Ingenuity Mars Helicopter marked the first dedicated system identification flights of a powered-lift aircraft on another planet. Frequency-domain techniques, similar to those utilized in the Earth-based system identification campaign for Ingenuity, were employed for the first time under free-flight conditions on Mars. Chirp signals were injected into the swashplate cyclic controls for both legs of the two out-and-back flights. Frequency responses were computed from the flight data, using both the Direct Method (DM) and the Joint-Input-Output (JIO) approach, for the identification of stability and control derivatives in forward flight conditions. The resulting identified state-space models were compared against existing flight dynamics simulation models, showing excellent correlation in the higher frequency range. External disturbances were seen to introduce a bias in the identified lower frequency responses, which was partially mitigated using the JIO method. These findings will inform future modeling and flight testing efforts of Mars rotorcraft.

I. Nomenclature

A_0	=	automated sweep amplitude, deg
F, G	=	bare-airframe stability and control derivative matrices
G_{xy}	=	cross-spectra for input-to-output pair xy
$\mathcal{H}$	=	Hessian matrix of identification cost function
H_{xy}	=	frequency response from input-to-output pair xy
I	=	mass moment of inertia, kg · m ²
I	=	identified parameter insensitivity, %
J	=	cost function for parametric model and time-domain verification fit

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L	=	stability and control derivatives for roll axis
M	=	bare airframe mass matrix
M_{cyc}	=	cyclic pitch control mixing matrix
m	=	mass, kg
n_o	=	number of outputs
n_t	=	number of time history points for time-domain verification
n_ω	=	number of discretization points in frequency response
$\hat{T}_c$	=	composite frequency response estimate
TIC	=	Thiel Inequality Coefficient
$T_m(s)$	=	transfer function model
T_{fade}	=	time cue of linear fade-out in chirp signal, s
T_{rec}	=	length of chirp signal, s
u, v, w	=	longitudinal, lateral, and vertical velocity, m/s
V	=	wind velocity, m/s
W	=	$n_o \times n_o$ diagonal matrix of weighting factors for each output in time-domain verification
W_g, W_p, W_γ	=	cost weighting functions for response magnitude, phase, and coherence, respectively
Y, Z	=	lateral and vertical translational stability and control derivatives
y	=	perturbation model time-history response vector
y_{data}	=	perturbation time-history vector from verification flight data
δ	=	control input signal, deg
$\hat{\gamma}_{xy}^2$	=	coherence estimator for input-to-output response pair xy
ρ	=	atmospheric density, kg/m ³
σ	=	turbulence intensity, ft/s
ϕ, θ, ψ	=	euler body-axis roll, pitch and yaw attitude angles, deg
$\psi_{1,eff}$	=	azimuthal location of peak cyclic magnitude, deg
θ	=	blade pitch control input, deg
$\theta_{1,eff}$	=	mean/effective cyclic input, deg
θ_{mc}, θ_{ms}	=	maximum mean cosine and maximum mean sine cyclic angle, deg
θ_h	=	heading, deg
$\omega_1, \omega_{n_\omega}$	=	start and end frequency in computed frequency response, Hz
$\omega_{min}, \omega_{max}$	=	minimum and maximum frequency in chirp signal, Hz
ξ	=	kinematic coupling parameter between body-axis roll rate p and euler angle ϕ , 1/s

Subscripts

ext	=	auxiliary bare-airframe control inputs
G	=	ground frame
ls, lc	=	lower sine and lower cosine cyclic control
p, q	=	roll/pitch stability derivatives and control channels
us, uc	=	upper sine and upper cosine cyclic control
v, w	=	lateral and vertical speed stability derivatives
ϕ	=	roll angle stability derivatives

II. Introduction

THE Ingenuity Mars Helicopter became the first vehicle to demonstrate powered flight on another planet on April 19th, 2021. The helicopter was designed to perform five demonstration flights, executing fundamental flight sequences such as takeoff, climb, hover, descent, and low-speed translation. As such, no system identification elements were considered in the demonstration flight test plan. Given the initial assumptions about the vehicle’s performance, the complexity and risk of such maneuvers were too ambitious for the first test flights. Ingenuity, however, quickly surpassed original expectations as a technology demonstrator and evolved into an aerial reconnaissance and test platform. The flight envelope of Ingenuity was gradually expanded, informed by continuous analysis of the helicopter’s flight data, allowing the vehicle to enter an Operations demonstration phase as described in [1]. During this phase, Ingenuity showcased its aerial imaging capabilities, and the flight operations were adapted to support the science mission and operations of the Mars rover Perseverance [2]. In total, Ingenuity completed 72 flights.

The launch of Ingenuity was preceded by extensive modeling, simulation, and experimental testing efforts [3–6]. Earth-based testing of Mars rotorcraft, however, introduces limitations in model identification across an entire flight envelope due to the difficulties of reproducing the true Martian flight condition experimentally. Specifically, replicating representative atmospheric conditions simultaneously as a reduced gravity environment makes free-flight testing non-trivial, if not infeasible with current testing capabilities. Low-pressure testing facilities are space-constrained, and necessary gravity off-loading systems or tethering prohibits identification of a true free flight response of the vehicle. This holds especially true for forward flight testing in Mars atmospheric conditions, as the capability of low-pressure wind tunnel testing is both challenging and limited. Notwithstanding, the verification and validation (V&V) campaign of Ingenuity included an Earth-based system identification (sysID) test suite in NASA’s Jet Propulsion Laboratory (JPL) 25-foot Space Simulator. The scope was limited to hover and low-speed forward flight conditions, with the main objective of reducing modeling uncertainty and mission risk. The bare airframe dynamics were characterized taking a piecewise approach, where the vehicle was rigidly locked down or on a gimbal, in order to identify control derivatives

and rotational dynamics, respectively. Sensitivity to wind was assessed by mounting the vehicle to a mechanically swinging arm. A detailed account of this effort is given in [7]. A number of risk reduction tests in forward flight conditions were also performed [6], using a custom built fan array integrated in the 25ft Space Simulator [8]. However, while these test suites addressed key risks in the vehicle control system design, no system identification tests were conducted in true free-flight, and in particular, significant modeling uncertainty in the forward flight regime remained. This uncertainty has been of particular interest to reduce since, as will be discussed in Section III.B, the stability of rotorcraft in general, and Ingenuity in particular, has a strong adverse dependency on horizontal airspeed.

Given Ingenuity’s primary responsibility as an aerodynamic demonstrator and operational support, in-situ system identification was not prioritized until later in the flight campaign. While the flight software architecture theoretically supported commanding system identification sequences to the flight controller, the risks of performing such maneuvers early in the flight campaign were deemed too high. Moreover, the potential benefits were outweighed by the helicopter’s critical role in supporting science and operations objectives. As the mission progressed, however, Ingenuity demonstrated its robustness and performance, and the opportunity to perform in-situ system identification of rotorcraft dynamics in the Martian atmosphere was recognized as a valuable and realizable scientific and engineering feat. In late fall of 2023, Ingenuity made its way up to the Martian valley Neretva Valles. The topography was ideal for a forward flight test due to its flat terrain, and the first and second extraterrestrial system identification flights were successfully executed on December 15th and 20th, respectively.

In this paper, an overview of the vehicle properties and on-board flight control system of Ingenuity is given, including an account of the importance, and challenges, of characterizing forward flight dynamics of a Mars helicopter. Frequency-response system identification and its applicability to bare-airframe linear model identification for stability analysis and control design is discussed, highlighting the unique obstacles with closed-loop system identification testing. This is followed by an account of the design, planning, and execution of the sysID flight test campaign. Efforts in atmospheric disturbance modeling and wind estimation to support flight design and analysis are covered. Resulting frequency responses and identified linear models are presented and correlated with a-priori physics-based models. Lastly, the implications for future planetary powered-lift vehicle research and development are presented.

III. Flight Dynamics of Ingenuity

The flight dynamics of a Mars helicopter display significant differences compared to what would be observed on Earth. This is a direct consequence of not only the physical differences in the prevailing flight condition, but also the mechanical design requirements of a vehicle operating in the Martian environment. A detailed account of the flight dynamics of a Mars helicopter and its influence on Ingenuity’s design is given in [3, 7]. This section gives a brief overview of the vehicle characteristics, focusing on aspects relevant to forward flight dynamics and identification thereof.

A. Vehicle Characteristics

Ingenuity features a two-bladed, counter-rotating, coaxial, hingeless rotor system. The rotor diameter measures 1.2 m, and the total mass of the vehicle is approximately 1.8 kg. Because of the low atmospheric density on Mars, approximately 1-3% of Earth's, the tip speed is high, though limited by the low speed of sound on Mars. With the small radius, the resulting rotational speed is high, up to 2800 rpm, yielding a hover tip Mach number of $M_{\text{tip}} \lesssim 0.75$. Control of the vehicle is accomplished through collective and cyclic pitch control on both the upper and lower rotors, with actuator limits ranging from -4.5° to 17.5° and $\pm 10^\circ$ for the collective and cyclic pitch, respectively. Three servo motors actuate each swashplate, while two brushless, direct-drive propulsion motors spin the rotors. A more in-depth description of the vehicle's specifications is given in [4], and a picture of the final flight vehicle is shown in Fig. 1.



Fig. 1 The Ingenuity Mars Helicopter prior to launch. Credit: NASA JPL.

The development and design of the flight control system of Ingenuity is well covered in [6, 9, 10], including the avionics architecture and implementation. What follows is a highlight of the important properties and limitations of the flight control system, comprised of the guidance, navigation, and control subsystems, in the current context of in-flight system identification test design, execution, and analysis. System identification relies on measurements of system input-output pairs of interest. For Ingenuity, this equates to time series of collective and cyclic pitch angles, and the associated bare-airframe response, respectively. Estimates of the vehicle states, including the vehicle attitude, are provided to the control system by Ingenuity's vision-based navigation system by filtering readings from a set of sensors including a downward-facing grayscale camera, an Inertial Measurement Unit (IMU), and a laser-range finder (LRF). The IMU consists of an accelerometer and gyroscope. In addition, pre-flight calibration of roll and pitch attitude is aided by an inclinometer. The navigation software is a velocimetry-based algorithm (MaVEN) [10] which uses a terrain-feature mapping approach to derive state estimates. One implication of this is a strong favoring of feature-rich terrain; a lack thereof can result in degraded state estimates and even destabilization. Feature tracking also becomes increasingly difficult with increasing groundspeed. Moreover, the algorithm relies on the assumption of a planar surface model, the violation of which is also a potential source of position and heading drift. In [2], the sensitivity to terrain smoothness is

discussed and pointed out as one of the limitations of the navigation system. In addition to being a source of cross-track errors, rapid terrain discontinuities tend to be falsely attributed to abrupt inertial (vertical) velocity changes. This is due to an emergent conflict in the vertical channel from LRF and camera-based estimates and inertial measurements, which will engage the control system to inject (unwarranted) feedback. Throughout the flight operations planning for Ingenuity, including the dedicated system identification flights, anticipated terrain characteristics remained a key consideration in ensuring that the helicopter could be safely guided across the Martian landscape. This primarily involved avoiding steep slopes, large obstacles, and expanses of featureless terrain. The control system, described in [6, 9], was designed as a nested architecture with an outer translational control loop that feeds a reference to the inner attitude loop. The control design is fixed-gain across the flight envelope, with two sets of gains for two different RPM operating points depending on atmospheric density. To mitigate correlation in the control input signals, there is a static mixing of the direct swashplate to decouple the controlled input-output pairs. For instance, pitch and roll-aligned inputs, δ_q and δ_p respectively, are defined through a cyclic mixing matrix M_{cyc} and cyclic swashplate inputs $\theta = [\theta_{lc}, \theta_{ls}, \theta_{uc}, \theta_{us}]^T$ as

$$M_{cyc} \begin{bmatrix} \delta_p \\ \delta_q \end{bmatrix} = \begin{bmatrix} \theta_{lc} \\ \theta_{ls} \\ \theta_{uc} \\ \theta_{us} \end{bmatrix} \quad (1)$$

The frequency range of interest for control is from 0.15 to 8 Hz, and is a direct consequence of the fast dynamics of the small scale vehicle. The servo actuator bandwidth is 12 Hz, with an inner-loop crossover frequency around 2.5-3 Hz.

B. Forward Flight Dynamics

A consequence of forward flight is that as the helicopter transitions from hover, the aerodynamic and inertial forces it experiences increase the coupling between lateral-longitudinal and vertical dynamics due to the azimuthal asymmetry of the rotor loads. This coupling tends to have an adverse impact on vehicle stability and flying qualities. In particular, helicopters commonly experience an angle-of-attack instability, or sometimes referred to as a pitch-heave instability. This instability is mainly attributable to the rotor dynamics, that results in an increased sensitivity to pitch moments due to vertical airspeed perturbations [11]. Considering the low-frequency response associated with the bare-airframe dynamics, this instability expresses itself as a positive stability derivative M_w , with body-frame vertical velocity w . This unstable mode was anticipated and observed for the Ingenuity Mars helicopter as well [7]. Furthermore, the lack of aerodynamic damping of the flapping dynamics in the thin Martian atmosphere led to the implementation of a considerable stiffening of the hingeless rotor system of Ingenuity, including both the blades and the hub. While this adaptation pushed the poorly damped flapping modes well beyond the control system's bandwidth, thus reducing the risk

of detrimental resonant coupling which could compromise stability, the stiffening also resulted in a large increase in hub moments from the rotor. As a result, Ingenuity exhibited a faster transient response to gust and a pitch-heave instability that grew more rapidly with increasing advance ratio [3] than what would have been observed with a less stiff rotor. The root loci in Fig. 2 show how the characteristic longitudinal phugoid mode, marked in red, moves further into the right-half plane as the horizontal airspeed increases, as a consequence of an increasing M_w and the kinematic coupling between pitch rate and vertical acceleration. This has important implications for the control design, as it greatly affects the controllability of the system; inaccurate modeling of these dynamics may erode stability margins.

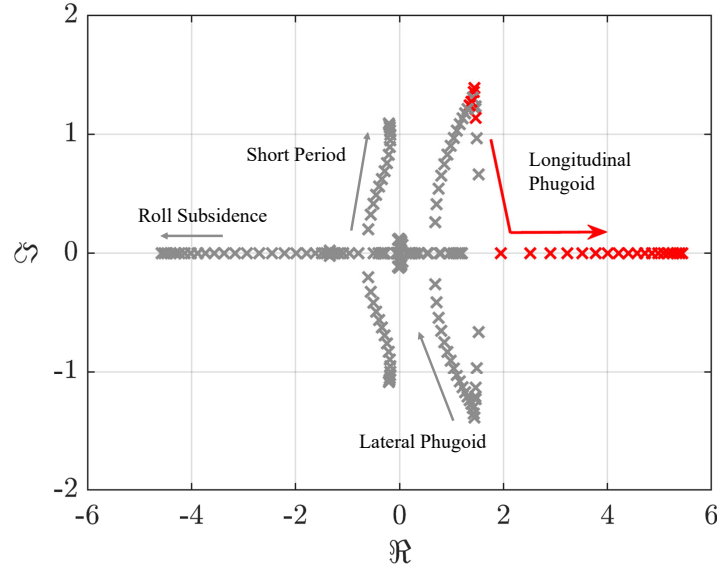


Fig. 2 Root loci of the bare-airframe dynamics with increasing horizontal airspeed (simulation).

C. Modeling and Simulation

The primary analysis tool for flight dynamics and control design in the development and analysis of Ingenuity was the Helicopter Control Analysis Tool (HeliCAT) [7], built on the DARTS/DSHELL multibody simulation framework developed at JPL [12]. The framework allows for end-to-end time domain simulations of the vehicle dynamics, featuring modeling capabilities of actuators and sensors, terrain, wind, contact dynamics, and flight software integration. Rigid body representations of the rotor, mast, landing gear, and fuselage are connected by hinges to build up the full multi-body model. Aerodynamic forces on the rotors are computed based on blade-element theory, and a Peters-Pitt type finite state dynamic inflow model is utilized to capture global effects of the induced rotor wake on the flight dynamics. HeliCAT allows for the extraction of full and reduced order linear models around vehicle trim points used for control system design and stability analysis. The resulting linear time periodic (LTP) systems inherent to rotorcraft are reduced to linear time invariant systems through a state expansion approach using harmonic decomposition as detailed in [7].

IV. Frequency-Response System Identification

Frequency-domain methods for rotorcraft flight dynamics naturally lend themselves to stability analysis and control system design, in particular because of their applicability to unstable systems. The frequency-response method for system identification of aircraft as embodied in Comprehensive Identification from Frequency Response (CIFER) is used throughout this work, the implementation of which is covered at length in [13].

A. Methodology

At a high level, the system subject to identification is excited by input signals designed to generate a dynamic response rich in spectral content across the frequency region of interest. The collected time series are used to estimate the single-input/single output (SISO) frequency responses $\hat{H}_{xy}(f)$, defined in Eq. (2), where $\hat{G}_{xx}$, $\hat{G}_{yy}$, $\hat{G}_{xy}$, are the input-, output-, and cross-spectra, respectively.

$$\hat{H}_{xy}(f) = \frac{\hat{G}_{xy}(f)}{\hat{G}_{xx}(f)} \quad (2)$$

A parametric aircraft dynamic response model can then be fit to the set of frequency responses.

To determine the extent of sufficiently correlated spectral content, the coherence, $\hat{\gamma}_{xy}^2(f)$, of the frequency response of an output signal y to input x is calculated as defined in Eq. (3). Ranging from 0 to 1, the coherence measures the fraction of the output spectrum that is linearly attributable to the input spectrum at a given frequency. Generally, a coherence greater than 0.6 indicates the response has sufficient quality over the frequency range of interest [13].

$$\hat{\gamma}_{xy}^2(f) = \frac{|\hat{G}_{xy}(f)|^2}{|\hat{G}_{xx}(f)||\hat{G}_{yy}(f)|} \quad (3)$$

A parametric model can then be fit to the associated frequency response, optimized to a coherence-weighted cost function defined by Eq. (4), with number of discrete frequency points, n_ω , over the frequency range ω_1 and ω_{n_ω} . In Eq. (4), $|T_c| - |T_m|$ and $\angle T_c - \angle T_m$ define the difference between the magnitude and phase of the data and model transfer functions. $W_g = 1.0$ and $W_p = 0.01745$ are the weights for the magnitude and phase of the frequency response, respectively, and are the recommended values and have shown to be perfectly adequate for a wide range of rotorcraft applications [13]. $W_\gamma(\omega) = [1.58(1 - e^{-\gamma_{xy}^2})]^2$ is a weighting function dependent on the value of the coherence function at each frequency. The desired upper bound for a model fit is a cost of $J \leq 100$, and a cost $J \leq 50$ indicates a near identical fit response.

$$J = \frac{20}{n_\omega} \sum_{\omega_1}^{\omega_{n_\omega}} W_\gamma [W_g (|T_c| - |T_m|)^2 + W_p (\angle T_c - \angle T_m)^2] \quad (4)$$

The insensitivities of the identified model parameters, I , indicate which parameters are not important in the selected model structure. The Cramer-Rao (CR) bounds reflect both parameter insensitivity and correlation, and define the

minimum expected standard deviation of the model parameters. Both are expressed as percentages of the i -th identified parameter θ_i and are defined in Eq. (5) and Eq. (6), respectively, where $\mathcal{H}_{ii}$ represents an element in the Hessian matrix, $\mathcal{H}$, of the identification cost function. According to [13], $I \leq 10\%$ and $CR \leq 20\%$ reflects a sufficiently accurate identified model.

$$I_i = \left| \frac{\frac{1}{\sqrt{\mathcal{H}_{ii}}}}{\theta_i} \right| \times 100\% \quad (5)$$

$$CR_i = \left| \frac{\sqrt{(\mathcal{H}^{-1})_{ii}}}{\theta_i} \right| \times 100\% \quad (6)$$

B. Challenges of Closed-Loop System Identification

Rotorcraft are typically open-loop unstable [11]. As such, the intrinsic premise of in-flight system identification is that the control system must be engaged throughout the flight to stabilize the vehicle. Although minimal interaction from control feedback is preferable for system identification purposes, identifying bare-airframe dynamics from closed-loop test conditions is theoretically possible [14]. This section highlights the limitations and concerns in real-life applications. In practice, active feedback control can potentially suppress bare-airframe excitation inputs, especially in low-frequency regions below the crossover frequency of the control system. Ultimately, this will reduce the signal-to-noise ratio (SNR) and, consequently, may deteriorate the accuracy of the extracted frequency response. Of particular concern is the presence of noise and/or external disturbances, which can pose serious challenges when combined with feedback regulation [13]. While noise to the input signal is a lesser concern in general, potential pollution of output data includes atmospheric disturbances, response to unmodeled secondary inputs or non-linearities, as well as measurement noise in sensors or errors in the navigation system outputs. In these instances, closing the loop introduces correlation between the control inputs and the noise, which in turn biases the estimated frequency response relative to the true response. Fig. 3 shows a block diagram schematic of a single-input-single-output (SISO) closed-loop pitch rate response in the presence of disturbance, with mixer **C**, feedback controller **K**, bare-airframe plant **P**, tracking command inputs u , bare-airframe control inputs δ_q , external bare-airframe input directly summed to the swashplate δ_{ext} , external noise n , and (measured) pitch rate q .

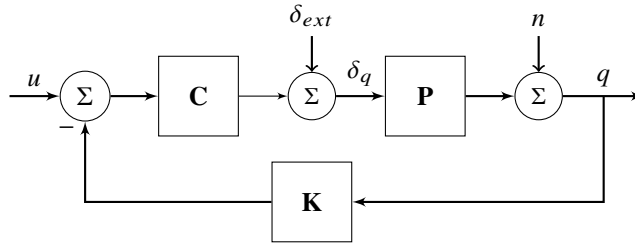


Fig. 3 Schematics of closed-loop pitch rate q response model in the presence of noise.

The bare-airframe pitch rate frequency response, q/δ_q , can be estimated using the Direct Method (DM) through the auto and cross-spectras as defined in Ref. 13,

$$H_{\delta_q q} = \frac{G_{\delta_q q}}{G_{\delta_q \delta_q}}. \quad (7)$$

Under the assumption of no measurement or process noise, Eq. (7) is an unbiased estimator in the case of active feedback. Similarly, Eq. (7) is also unbiased regardless of noise level if no feedback control is engaged. However, the emergence of a non-zero auto-spectra $G_{\delta_q n} \neq 0$, due to noise being fed back through active feedback regulation, yields a biased frequency response $\hat{H}$. In the simplified case of unity feedback from Fig. 3, the biased frequency response $\hat{H}_{\delta_q q}$ as derived in [13] becomes

$$\hat{H}_{\delta_q q} = H_{\delta_q q} + \frac{G_{\delta_q n}}{G_{\delta_q \delta_q}}. \quad (8)$$

The second term in the right hand side of Eq. (8) is the bias error, the magnitude of which has a strong dependency on the signal-to-noise ratio. Notably, in scenarios where noise excitation predominates, the computed frequency response using the Direct Method approach may still show satisfactory coherence, potentially providing a misleading indication of the quality of the response and jeopardizing the accurate identification of the bare-airframe dynamics. In general, it is important to ensure sufficient input signal magnitude prior to the flight test to minimize the bias error. In [13], a rule-of-thumb is recommended to retain a SNR (in a Power Spectral Density (PSD) sense) above three to limit the bias error to less than 10%. This is not always possible, due to uncertainty in the test condition and/or the actuator limits. Approaches to system identification in the presence of unknown disturbances through modeling of disturbance effects on vehicle dynamics explicitly and implicitly to attain disturbance-free dynamics are presented in [15, 16]. However, when no dynamic features of the disturbance are known, such as the periodicity and magnitude, the separation of system dynamics and disturbances effects is a highly non-trivial problem; notably, the case of unknown and non-periodic disturbances is particularly ill-posed. The subsequent section presents an alternative approach to the Direct Method to resolve the issue of correlated noise bias.

C. The Joint-Input-Output method

Akaike [17] introduced the Joint-Input-Output (JIO) method as a means to address the issue of measurement noise correlation in the analysis of systems with feedback. In recent work, it has also shown great success in sysID applications with highly correlated inputs [18, 19]. The JIO method is a post-processing step to the DM. Instead of directly computing the bare-airframe response, JIO is a two-step process that includes two intermediate responses with the introduction of a reference signal. In the context of the pitch rate response and choosing the reference signal as the

external swashplate input δ_{ext} as illustrated in Fig. 3, this becomes

$$H_{\delta_q q} = H_{\delta_{ext} \delta_q}^{-1} H_{\delta_{ext} q}, \text{ where} \quad (9)$$

$$H_{\delta_{ext} \delta_q} = \frac{G_{\delta_{ext} \delta_q}}{G_{\delta_{ext} \delta_{ext}}}, \quad H_{\delta_{ext} q} = \frac{G_{\delta_{ext} q}}{G_{\delta_{ext} \delta_{ext}}} \quad (10)$$

With this approach, Eq. (9) is unbiased even in the cases where $G_{\delta_{qn}} \neq 0$. From Eq. (10), it follows that the overall accuracy of the JIO method is predicated upon the quality of the intermediate responses. Additionally, the coherence estimator with the JIO method does not have a closed form expression as is the case for DM. Instead, it has to be reconstructed from the coherence of the two intermediate responses. The strategy chosen for this work is to take a (weighted) minimum out of the two, which may lead to an under-prediction of the actual signal coherence [18]. Guidelines and considerations when using the JIO for closed-loop system identification in rotorcraft applications are detailed in [20].

V. Flight Test Planning and Design

Extensive simulation-based testing preceded the in-flight sysID campaign to support the design and planning of the flights. The ultimate objective of the simulation process was to design a flight that balanced obtaining the best data quality with sufficient risk tolerance while complying with the operational constraints of the vehicle.

A. Operational Conditions and Constraints

The selected target site for the sysID flight tests was in the lower section of Neretva Vallis, a region believed to be an ancient river valley. This area offered exceptionally flat terrain, which was critical for minimizing disturbances and ensuring clean data collection during the excitation maneuvers, as pointed out in Section III.A. The timing also coincided with a pause in Ingenuity’s primary reconnaissance role, as the rover was engaged in a scientific task at Gnaraloo Bay.

On-planet sysID is limited in terms of both observing and controlling the testing environment, particularly regarding atmospheric density and wind conditions, while also respecting constraints on power, thermal, and actuator limits. The prevailing atmospheric density at the time window considered for the sysID flights could be estimated to approximately $\rho = 0.014 \text{ kg/m}^3$ based on available data collected by the Perseverance rover, and did not directly impact the operational planning of the flights. Bounding the airspeed, however, was a key factor in planning the test campaign, leading to the choice of “out-and-back” flights. This trajectory offers additional insight into prevailing wind conditions, as the helicopter experiences both potential headwinds and tailwinds (assuming relatively constant wind throughout the flight), thus bounding the differential airspeed between the two legs. It also offers a telecommunications advantage, since take-off and landing occur in close proximity, ensuring reliable communication with the Perseverance rover. The main

drawback of the two-legged profile is that sweep time in steady flight is reduced due to the additional accelerations and decelerations. Given the power constraints limiting total flight time to about 150 seconds, the usable window for a frequency sweep at 10 m/s is just under 30 seconds.

B. Atmospheric Disturbance Modeling

Including the effect of noise and external disturbances on the vehicle response is integral for assessing flight risk and the extent of potential degradation in the quality of the system identification results as discussed in Section IV.B. Unsteady wind is a dominant source of disturbance, and a simple model was developed to include the effect of atmospheric turbulence on Mars in the simulation campaign. It is noted that the scope of the effort is not intended to be a highly accurate characterization of the planetary boundary layer of Mars. Rather, the primary motivation is to assess the potential implications of unsteady wind conditions on the test flight.

Conventionally, modeling atmospheric turbulence effects on aircraft flight dynamics leverages a continuous (PSD) approach. Turbulence is assumed to be frozen in time and space, isotropic and homogeneous [21]. A common choice is the Dryden model, which has spectral densities in a rational closed form. Linear forming filters, parameterized with turbulence intensity, σ , and length scale, L , are driven with Gaussian noise to generate time series of the wind velocity components, derived to replicate the theoretical PSDs [22]. The original parametrization of the Dryden model is specified for Earth applications in the Military Specification MIL-F-8785 [23] and served as a starting point for an augmented model for a Mars helicopter. The Mars 2020 rover Perseverance [24] is equipped with a suite of sensors comprised in the Mars Environmental Dynamics Analyzer (MEDA), including both a pressure and a wind sensor [25]. While previous efforts characterized Martian vortices and dust devils using MEDA data [26, 27], this study leverages wind sensor data to fit a Dryden type model in order to generate representative wind gust time histories to inject as perturbations to the horizontal and vertical velocity channels in the full simulation environment. An upper-end estimate for turbulence intensity $\sigma = 10$ ft/s was found based on correlation with power content at low frequencies of the MEDA data. The MEDA data has a sampling frequency of up to 2 Hz, prohibiting fitting a meaningful length scale L , which was left as the default from the MIL-F-8785.

C. Automated Sweep Design

The automated chirp signals (frequency sweeps) injected into the rotor cyclic inputs were designed with reference to [13]. The chirp signal has the form

$$\delta = A_0 f(\omega) \sin(\theta(t)), \quad (11)$$

with amplitude A_0 , amplitude shaping $f(\omega)$, and frequency progression $\theta(t)$ governed by

$$\theta(t) = \int^t \omega_{min} + C_2(e^{\frac{C_1\tau}{T_{rec}}} - 1)(\omega_{max} - \omega_{min})d\tau, \quad (12)$$

where ω_{min} and ω_{max} represent the sweep minimum and maximum frequency, respectively. The parameters governing the frequency progression were chosen according to conventionally recommended values $C_1 = 4.0$ and $C_2 = 0.0187$ [13]. Remaining parameter values were chosen to comply with operational constraints, including power and actuator limits as accounted for in Section V.A, while retaining acceptable coherence in the frequency region of interest. To this end, the frequency sweeps were evaluated in simulation, based on the resulting coherence in the identified frequency responses from the nonlinear HeliCAT simulation model and the ability to re-construct the response from the associated linearized model.

The sweep record length, T_{rec} , is typically set by the-rule-of-thumb $T_{rec} \geq 4T_{max}$, where $T_{max} = 1/\omega_{min}$. Commonly, two full cycles at ω_{min} is included in the sweep to ensure sufficient low frequency content in the data. Theoretically, one time period of a frequency mode of interest is enough for identification purposes, but a shorter sweep length will increase the risk of response degradation caused by e.g. noise and disturbance [13]. The time window allocated for the sweep in the proposed flight sequence, limited by power constraints and acceleration/deceleration time, results in an upper bound of $T_{rec} = 22$ sec when including a padding of trimmed flight in the beginning of the sysID sequence.

Determining ω_{min} becomes a trade-off between capturing lower-frequency dynamics of interest as accounted for in Section III.B, while adhering to the allotted sweep record length T_{rec} . Given the requirements, a nominal value of $\omega_{min} = 0.1$ Hz was chosen such that $T_{rec} \approx 2T_{max}$. No full cycle inputs were included in the sweep design due to the limited sweep time and available capabilities in the flight software. The maximum frequency, ω_{max} , was set to 10 Hz in order to be beyond the inner-loop crossover frequency but below the actuator bandwidth frequency.

The frequency sweep is injected during forward flight when the trimmed cyclic control effort aligned with the direction of travel is non-zero. A large steady-state control effort increases the risk of transient control saturation, degrading the control system's ability to maintain stability. The sweep amplitude was evaluated and chosen to achieve acceptable coherence while ensuring that no sustained control saturation would occur when also considering additional cyclic efforts associated with navigation errors (e.g. due to terrain) and atmospheric disturbances. Amplitude shaping in the form of a one-period fade-in and a cued linear fade-out with respect to time around the crossover frequency was also implemented to mitigate excessive control feedback amplification and avoid sharp drops at the edges of the input signal. Figure 4 shows an example automated sweep that was injected directly into the swashplate, corresponding to $\delta_{q,ext}$ in Fig. 3, with amplitude $A_0 = 0.7$ degrees. In the presence of turbulence with intensity $\sigma_n = 10$ ft/s, Figure 4 also illustrates the actual resulting servo input when the automated sweep has been superimposed with the fed-back control signal resulting in $\delta_{q,cmd}$.

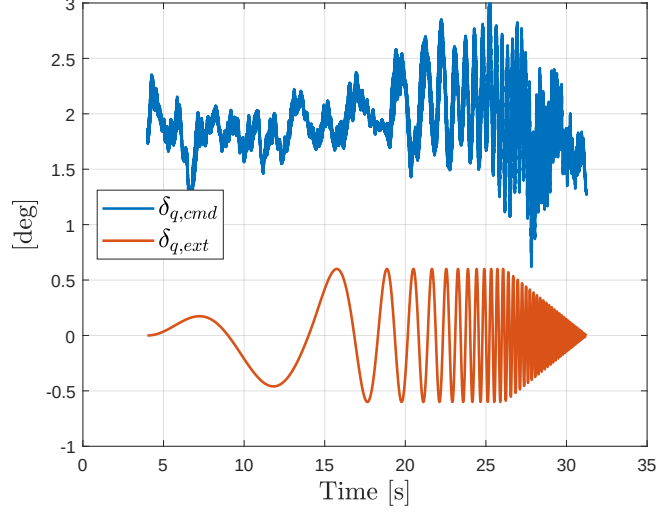


Fig. 4 Simulated designed automated sweep $\delta_{q,ext}$ and total fed-back control signal $\delta_{q,cmd}$ as commanded to the swashplate.

Without the inclusion of atmospheric disturbance in the simulation, even a small sweep amplitude of $\delta_{q,ext} = 0.4$ degrees was shown to yield coherence close to unity in the computed frequency response as illustrated in the on-axis pitch rate response in Fig. 5.

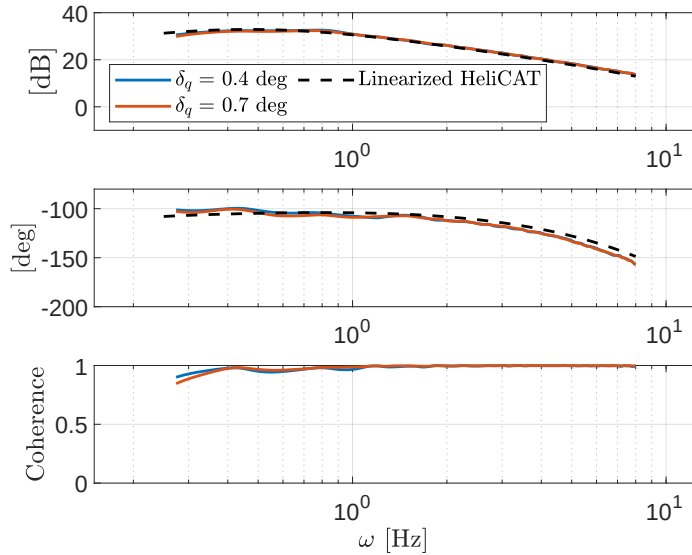


Fig. 5 Simulated pitch rate response to pitch aligned input q/δ_q with varying sweep amplitude A_0 .

Moreover, the correlation with the linearized HeliCAT model is excellent as shown in Fig. 5, indicating that the perturbation method used to extract the linearized simulation model introduced no significant numerical errors. However, as accounted for in Section IV.B, identification of the bare-airframe dynamics in closed-loop conditions must consider potential degradation due to noise and disturbances. To this end, simulations were also run with unsteady wind disturbances with the nonlinear simulation model in HeliCAT. Note that wind time histories were not generated

with the atmospheric disturbance model described in Section V.B as this model was not implemented in the HeliCAT simulation environment where the final tests were conducted. The wind disturbance model in HeliCAT does not feature any higher frequency content, as compared to the tuned Dryden-type model. As illustrated in Fig. 6, the impact of this low-frequency random wind perturbations on the computed vehicle bare-airframe response is dominantly expressed as a bias and a coherence drop in the low frequency region. As the auxiliary sweep excitation $\delta_{q,ext}$ is directly superimposed with the control-gained reference trajectory, the control system interprets the sweep as a disturbance and tries to suppress it. Below the crossover frequency, the controller is successful in suppressing the "disturbance," resulting in little aircraft motion and a large noise-to-signal ratio. Above the crossover frequency, the control system is not able to suppress the aircraft motion to the sweep to the same extent, and consequently the signal-to-noise ratio increases and the frequency response bias decreases.

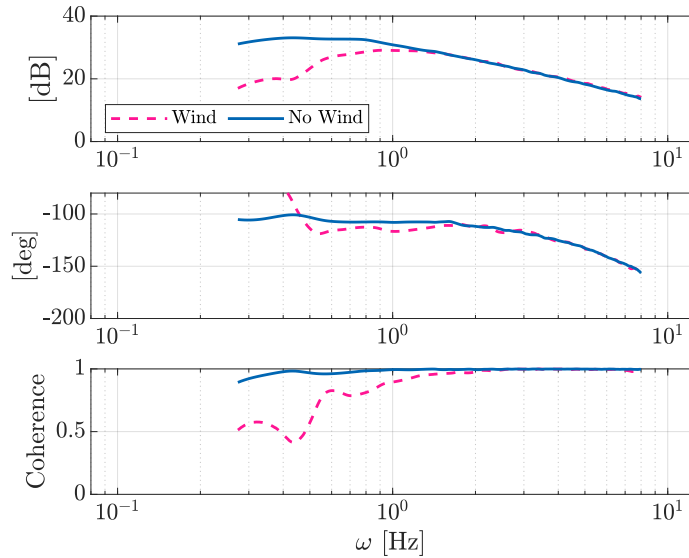


Fig. 6 Simulated pitch rate response to pitch aligned input q/δ_q with sweep amplitude $A_0 = 0.6$ degrees in the presence of random wind.

To better characterize the impact on the identified responses as a function of signal-to-noise ratio (SNR), simulated sweeps were run with the turbulence model described in Section V.B for a range of turbulence intensities. The power spectral density of the pitch rate in trim forward flight, denoted by $[\hat{G}_{qq}(f)]_{\text{trim}}$, was computed from a closed-loop history of the angular response q when subject to turbulence. This was then compared to the the forced pitch rate PSD during a commanded sweep under the same level of turbulence intensity, $[\hat{G}_{qq}(f)]_{\text{sweep}}$. The power drop, $[\hat{G}_{qq}(f)]_{\text{sweep}} - [\hat{G}_{qq}(f)]_{\text{trim}}$, for varying turbulence intensities is illustrated in Fig. 7.

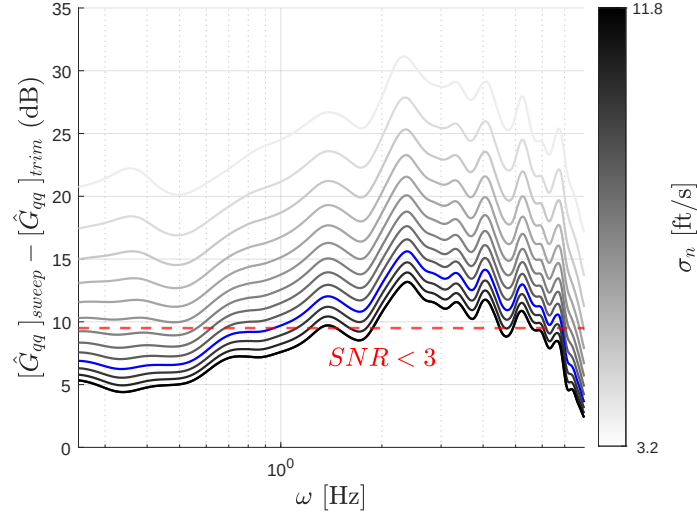


Fig. 7 Comparing forced pitch rate to trim pitch rate power spectral densities as function of modeled turbulence intensity σ_n .

In Fig. 7, the blue line corresponds to the level of turbulence that was found representative from the MEDA data during the model fitting in Section V.B. As described in detail in [13], achieving an average SNR of at least three means that the forced pitch rate response PSD exceeds the trim pitch rate PSD by at least 9.5 dB across the frequency range relevant for identification. This limit is outlined in red in Fig. 7, and it is observed that for levels of turbulence intensity of the reference level $\sigma_n = 10$ ft/s and larger, this limit is violated for frequencies below 1 Hz. Consequently, using the Direct Method to estimate the frequency responses at these levels of disturbance may risk introducing a non-negligible bias. The resulting pitch rate frequency responses computed with the SISO Direct Method are shown in Fig. 8 and shows how the response attenuates and the coherence drops in the low frequency region when the signal to noise ratio decreases as turbulence intensity increases.

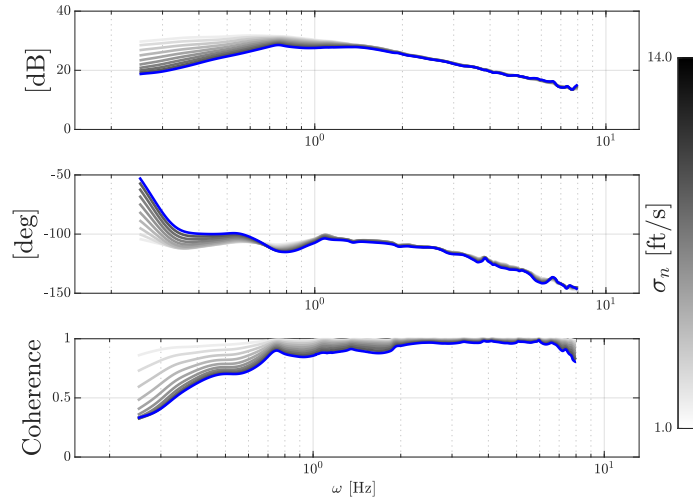


Fig. 8 Simulated pitch rate q response to pitch aligned input δ_q as function of modeled turbulence intensity σ_n .

While the observed bias is predominantly a function of SNR, the shortening of the frequency sweep record length, T_{rec} , due to operational constraints of the vehicle, may also have an adverse effect on the quality of the low-frequency response, exacerbating this effect. To counter the degradation in the quality of the data from turbulence, the JIO method, as covered in Section IV.C, was employed to improve the identified response from the simulated frequency sweeps with turbulence. Fig. 9 compares the linearized HeliCAT model with the identified models calculated from the frequency sweep simulation data using both the Direct Method and the JIO method. The magnitude of the response computed with the JIO method exhibits less attenuation in the lower frequencies compared to the Direct Method, and more closely aligns with the underlying model. It is noted that the Direct Method has a higher coherence below crossover, however, this may partially be due to artificial inflation from the fed back control in response to the disturbances.

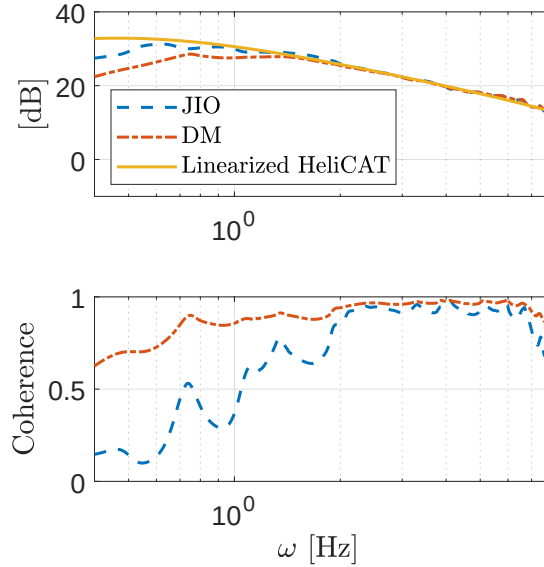


Fig. 9 Comparison of identified pitch rate responses from the nonlinear simulation model, using the Direct and JIO methods, with the linearized HeliCAT model in the presence of atmospheric turbulence, $\sigma_n = 10$ ft/s.

Having verified that the sweep would not saturate control limitations and gained confidence in the model extraction methodology, the final set of sweep parameters was determined to be $T_{rec} = 22$ s, frequency range from $\omega_{min} = 0.1$ to $\omega_{max} = 10$ Hz, $T_{fade} = 15$, and sweep amplitude $A_0 = 0.6$ deg. Figure 10 shows the required lower rotor sine cyclic control effort throughout the simulated out-and-back flight with the final sweep parameter values and integrated flight software, including terrain considerations and random wind disturbance. No transients exceed the actuator limit and the results do not exhibit any control saturation. The spikes observed in Fig. 10 are due to sharp changes in the commanded reference pitch angle, which are induced by a commanded acceleration/deceleration.

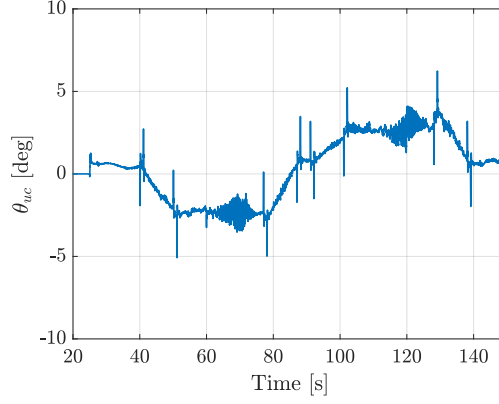


Fig. 10 Upper cosine cyclic, θ_{uc} , control effort for simulated out-and-back flight, with final sweep parameters.

D. Parametric Model Identification

The final frequency sweeps were run with the full integrated flight software in HeliCAT with the final sweep parameter values and commanded groundspeed of 10 m/s. A successful simulated test flight should facilitate reconstruction of the linear response and stability and control derivatives of the "true" linear model. A reduced-order, longitudinal-only linear state space model formulated in groundspeed coordinates was considered for derivative identification, assuming no significant cross-axis coupling (recall that the direction of forward flight is defined in the lateral direction given Ingenuity's starting orientation). Defining state vector $x = [u_G, w_G, q, \theta]^T$, with u_G and w_G denoting longitudinal and vertical groundspeed respectively, and control $u = \delta_q$, the linear dynamics are modeled by

$$M\dot{x} = Fx + Gu \quad (13)$$

where the mass matrix M , stability and control derivative matrices, F and G , respectively, are defined in Eq. (14), with derivatives subject to identification highlighted in green. Note that when expressed in groundspeed coordinates, a non-zero attitude stability derivative M_θ emerges as a linear combination of speed derivatives, M_u and M_w , and airspeed components.

$$M = \begin{bmatrix} m & 0 & 0 & 0 \\ 0 & m & 0 & 0 \\ 0 & 0 & I_{yy} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad F = \begin{bmatrix} X_u & X_w & X_q & X_\theta \\ Z_u & Z_w & Z_q & Z_\theta \\ M_u & M_w & M_q & M_\theta \\ 0 & 0 & \xi & 0 \end{bmatrix}, \quad G = \begin{bmatrix} X_{\delta_q} \\ Z_{\delta_q} \\ M_{\delta_q} \\ 0 \end{bmatrix} \quad (14)$$

Without any disturbances, the identified model response from the nonlinear sweep simulation data shows almost perfect correlation with the linearized model, as illustrated in Fig. 11. Notably, despite the relatively short sweep length,

the lower frequency response of the identified model is in excellent agreement with the reference linearized simulation model.

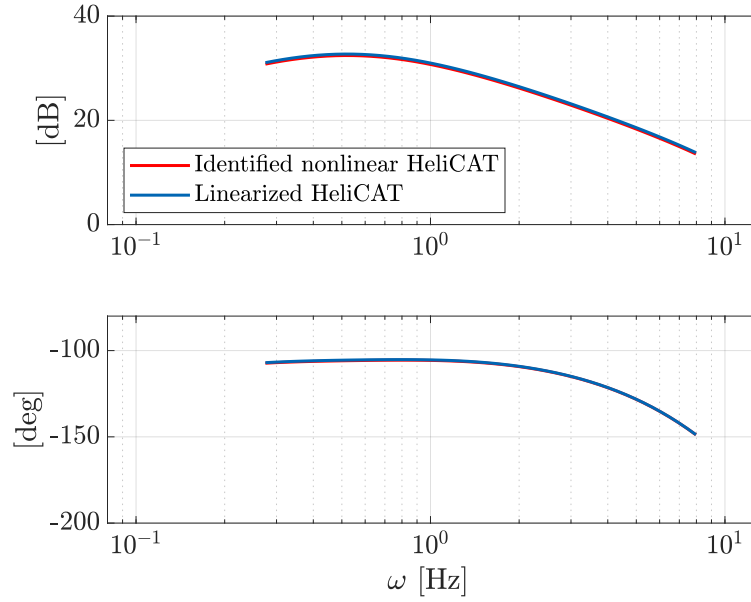


Fig. 11 Comparison of on-axis pitch rate q response of identified simulation model from nonlinear sweep data without disturbance to linearized HeliCAT model.

The fit derivatives associated with the response model in Fig. 11 are presented in Table 1. While originally taken as free variables in the parametric model, the speed derivatives M_u and M_w exhibit very high insensitivities due to the lack of low-frequency content and dominance of M_θ in the response. Including them as derivatives to fit severely degrades the quality of the overall fit, and as a result, both were taken as model-based for the presented fits. The fit pitch damping derivative M_q also exhibits Cramer Rao bound and insensitivity exceeding the guidelines, as shown in Table 1. The cost $J = 13.3$ of the final fit was well below the recommended guideline $J \leq 100$.

Table 1 Identified derivatives from simulated frequency sweeps without disturbance. Density $\rho = 0.014 \text{ kg/m}^3$, cost $J = 13.3$.

	M_q	M_θ	M_{δ_q}
Linearized Model	0.033	0.33	8.91
Identified	0.035	0.34	8.72
CR bound, %	38.6	15.3	5.0
Insensitivity, %	19.0	5.7	1.8

Including the turbulence disturbance in the non-linear simulation results in a biased frequency response computed with DM, as illustrated in Fig. 8. A comparison of the frequency responses associated with linear models identified

using the DM and JIO method, respectively, in the presence of turbulence of intensity $\sigma_n = 10$ ft/s is presented in Fig. 12. Note that the atmospheric density was changed to $\rho = 0.0137$ kg/m³ for this simulation due to updated density predictions for the time of flight test. While the JIO method tends to mitigate the magnitude attenuation below crossover, the bias, when compared to the true linearized model, remains.

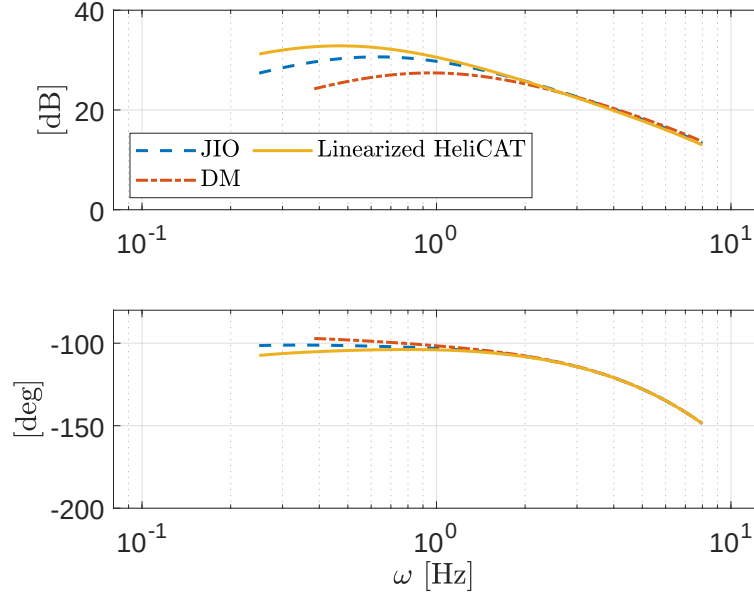


Fig. 12 Comparison of pitch rate response q/δ_q of identified models from simulated sweep in presence of turbulence disturbance, using the JIO and DM method.

The associated identified derivatives are presented in Table 2. Whereas the control derivative M_{δ_q} is fit within reasonable accuracy compared to the true model, the primary effect of the introduced noise-correlation bias is a significant overprediction of the angle-of-attack derivative M_θ . Consistent with Fig. 12, the JIO method results in less of an overestimation and yields a more favorable fit cost. Note that pitch rate damping M_q was excluded from the fit and taken as modeled due to its large insensitivity.

Table 2 Comparison of identified derivatives in the presence of disturbance using the JIO and Direct Method, $\rho = 0.0137$ kg/m³.

	M_θ	M_{δ_q}	Cost, J
Modeled	0.26	8.1	-
JIO Method	0.49	8.47	7.38
Direct Method	1.13	8.89	21.59

The accuracy of the identified models were also verified in the time domain using a closed-loop pitch-aligned doublet in the nonlinear simulation without wind or other exogenous disturbances and is presented in Fig. 13. Given the highly

unstable nature of the open-loop system, the responses from the JIO, DM, and linearized HeliCAT models diverge rapidly, and only a short segment of the start of the doublet is shown. The observed improvement in the frequency domain using the JIO method over the Direct Method is reflected in the ability to match the nonlinear truth model more closely in the time domain. The linearized HeliCAT model exhibits excellent agreement with the simulated nonlinear response, further confirming the validity of the linearization procedure. Model predictive accuracy in the time-domain is quantified by evaluating the root mean square fit error, J_{rms} , defined in Eq. (15), where n_t is the number of time-history points in the verification data record, n_o is the number of outputs, y_{data} is the perturbation flight data time-history vector, y is the perturbation model time-history response vector, and W is the $n_o \times n_o$ diagonal matrix of weighting factors for each output. The Theil Inequality Coefficient (TIC), a normalized criterion of model predictive accuracy, is also calculated where a TIC = 0 and a TIC = 1 corresponds to a perfect predictive capability and no predictive capability, respectively [13]. Table 3 reveals that the J_{rms} for all models satisfy the cost guidelines $J_{rms} \leq 0.5$ to 1 indicating a sufficient level of time-domain accuracy. The J_{rms} values are exceptionally small due to the small magnitude of the output. All models are also near the Theil Inequality Coefficients (TIC) guidelines of $TIC \leq 0.3$, indicating sufficient model predictive accuracy [13].

$$J_{rms} = \sqrt{\left(\frac{1}{n_t n_o}\right) \sum_{i=1}^{n_t} [(y_{data} - y)^T \mathbf{W} (y_{data} - y)]} \quad (15)$$

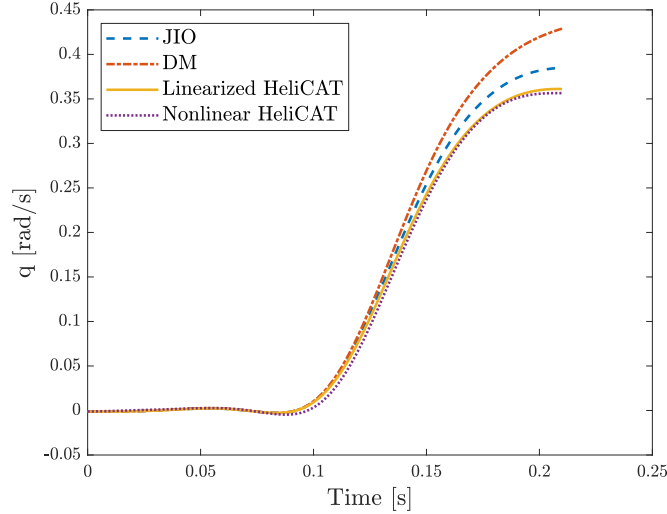


Fig. 13 Time-domain verification results comparing the pitch rate response from a pitch-aligned doublet input at 10 m/s in simulation to the extracted JIO, DM, and linearized HeliCAT models.

Table 3 Time-Domain Costs from a HeliCAT Nonlinear Simulation at 10 m/s Groundspeed.

	Cost, J_{rms}	TIC
Linearized HeliCAT	0.066	0.31
JIO Method	0.066	0.31
Direct Method	0.067	0.30

In summary, the presented simulation studies that preceded the system identification flight tests informed the design of the flight path and frequency-sweep inputs. This design ensured that the vehicle would not be destabilized in flight while still providing sufficient data quality to reconstruct the underlying simulation model, provided that the signal-to-noise ratio was adequate. The analysis also highlighted potential limitations of the chosen approach and offered guidance on the appropriate processing and interpretation of the test results. The impact of elevated disturbance levels, specifically atmospheric turbulence, was manifested as a bias in the low-frequency response when computed using the Direct Method, resulting in an overprediction of the angle-of-attack derivative M_θ . The use of the JIO method mitigated this effect, although it was accompanied by a significant reduction in the observed signal coherence.

VI. Flight-Test Results

Flights 68 and 69 occurred in Neretva Vallis on the Martian mornings of December 15th and 20th, 2023, respectively. Both flights followed an out-and-back trajectory, where the first leg of both flights was in the Northeast direction, and subsequently, the return leg was in the Southwest direction as indicated in red on the map in Fig. 14. A snapshot from the Return To Earth (RTE) camera taken during Flight 68 is displayed to the right in Fig. 14.

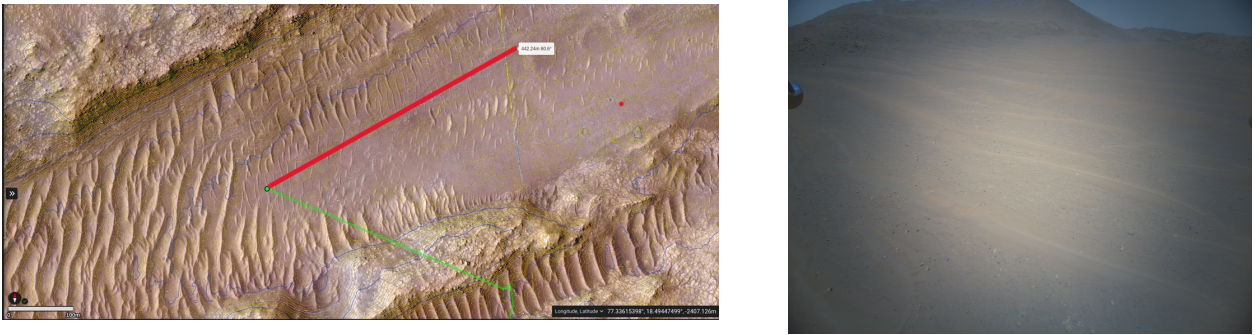


Fig. 14 Left: Top-view map of Neretva Vallis with the sysID flight trajectory marked in red. Right: An RTE camera image taken during Flight 68. Credit: NASA JPL.

Each leg included an acceleration to a constant 10 m/s longitudinal groundspeed before executing the designed frequency sweep excitation. Fig. 15 shows the estimated groundspeed velocity in all axes, as provided from the navigation subsystem, during the system identification sections. In addition to the 10 m/s commanded longitudinal groundspeed, the groundspeed heave velocity, w_G , exhibits a slight negative, constant off-set from zero, as well as an observable variation. Whether this unsteadiness is attributable to actual inertial velocity changes or noisy predictions due to variations in the terrain remains inconclusive.

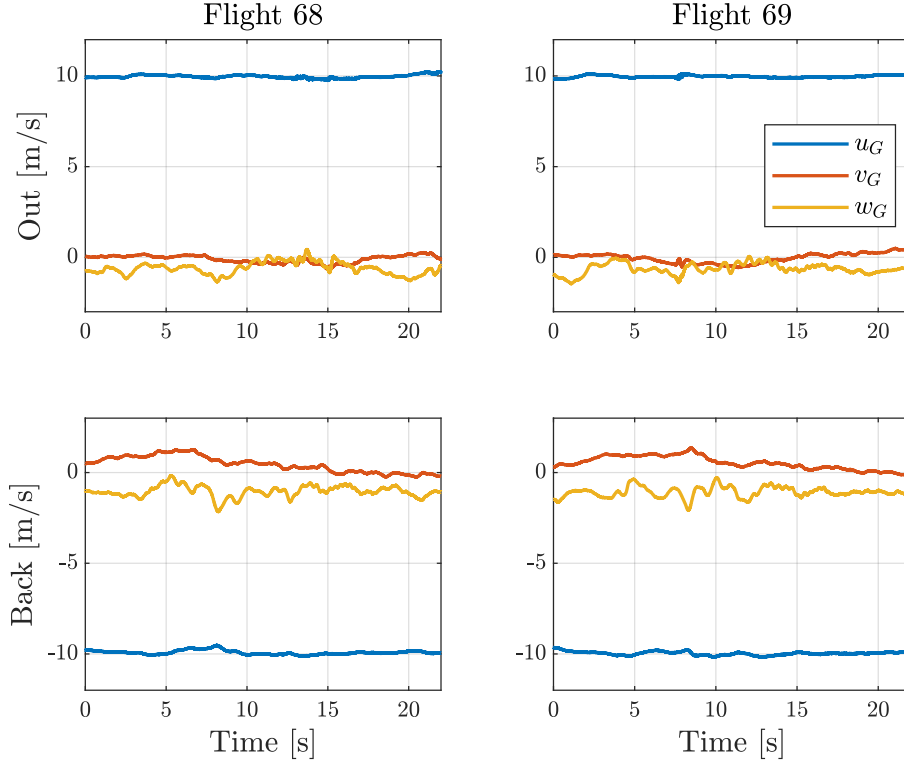


Fig. 15 Groundspeed velocities estimates from the navigation system during the system identification portions of Flight 68 and 69.

As rehearsed in the simulation campaign, the sweep signal was injected into the pitch-aligned inputs δ_q (predominantly the cosine cyclics θ_{lc} and θ_{uc}) so as to have the input excitation signal aligned with the direction of flight. The flights were nearly identical, with the exception of the sweep amplitude, where Flight 69 featured a larger amplitude of 0.7 degrees compared to 0.6 degrees in Flight 68. Time series of the unfiltered pitch and pitch-aligned inputs throughout the sweep portions of the flights are shown in Fig. 16. Note that while the pitch-aligned input dominated, the cross-axis pitch-aligned input was also engaged, especially in Flight 68, suggesting the presence of a notable crosswind. Fast, transient control responses in both pitch and roll channels are observed in the beginning/middle of the out portions of both flights. It is hypothesized that these spikes relate to violations of the planar assumption of the terrain.

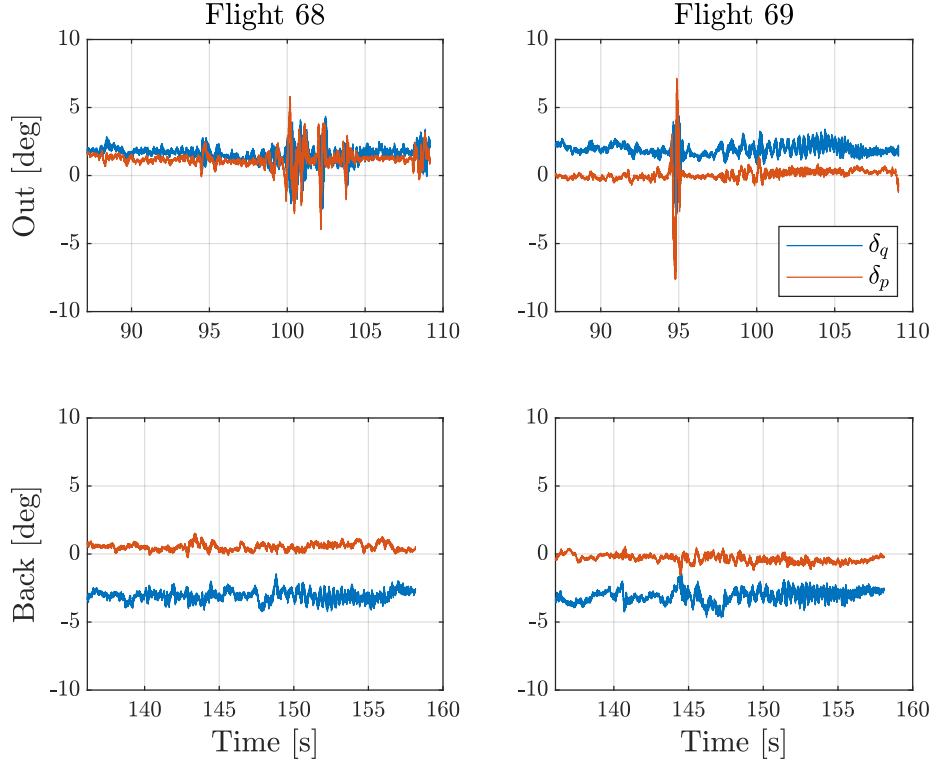


Fig. 16 Roll and pitch-aligned control inputs during system identification portion of Flight 68 and 69.

A. Density and Wind Estimation

Linearized flight dynamics models are only valid around their trim point, including environmental operating conditions such as atmospheric density and windspeed. Since Ingenuity lacks the sensing capability to directly measure density and airspeed, both need to be indirectly inferred or measured independently. Density measurements are derived from the MEDA sensors on the Perseverance rover, and the average atmospheric density at the flight altitude was taken and extrapolated and found to be $\rho = 0.0137 \text{ kg/m}^3$ for both flights. A previous malfunction of the wind sensors on Perseverance prohibited obtaining direct wind measurements [27]. Instead, an alternative methodology to inversely estimate vehicle airspeed from the control actuator data was used.

An estimate of the airspeed magnitude and direction can be derived from the low frequency cyclic control effort of the vehicle [2]. By comparing the filtered in-flight cyclic and collective inputs to simulated trim cyclic and collective solutions for a variety of forward flight speeds, the approximate airspeed magnitude can be backed out through an interpolated look-up table. To correlate the cyclic inputs specifically, the root mean square of the maximum sine cyclic, θ_{ms} , and maximum cosine cyclic, θ_{mc} , inputs are calculated and referred to as the mean cyclic or effective cyclic, defined in Eq. (16).

$$\theta_{1,eff} = \sqrt{\theta_{ms}^2 + \theta_{mc}^2} \quad (16)$$

The mean cyclic input in trimmed flight at airspeeds ranging from hover to 30 m/s at an atmospheric density of

$\rho = 0.014 \text{ kg/m}^3$ and rotor RPM 2700 is shown to the left in Fig. 17. The HeliCAT Ingenuity model was trimmed in increments of one m/s and the data was interpolated in between. As evident from Fig. 17, the mapping from airspeed to trim solution is non-monotonic, indicating that a single cyclic input could provide two possible airspeeds. To resolve this, evaluating the concurrent collective rotor input anchors which side of the curve the current flight condition is most likely to be in, as shown to the right in Fig. 17.

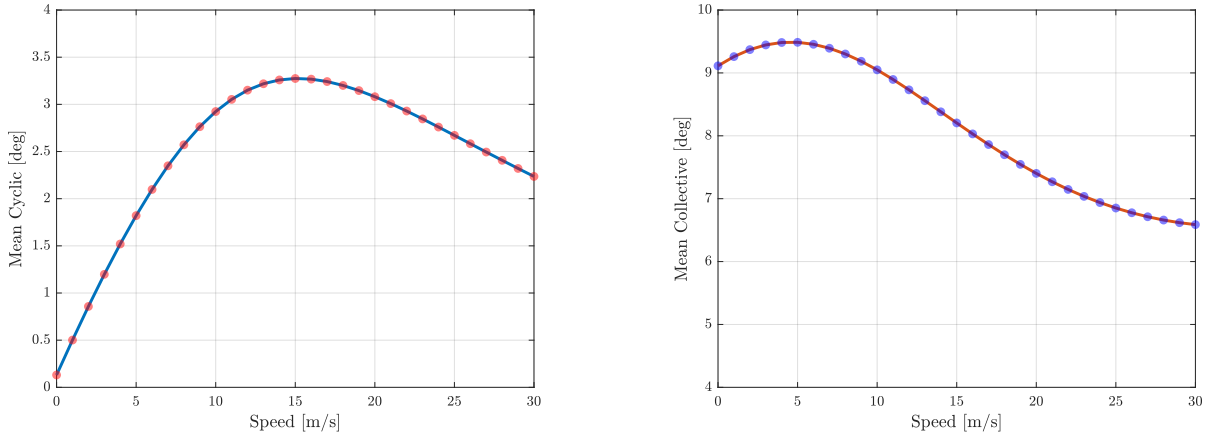


Fig. 17 Left: Mean cyclic trim solutions as a function of airspeed. Right: Mean collective trim solutions as a function of airspeed.

The wind direction can be approximated following a similar approach, making predictions based off of the rotor cyclic inputs as derived in Eqs. (17) and (18),

$$\psi_{1,eff} = \tan^{-1} \left(\frac{\theta_{ms}}{\theta_{mc}} \right) \quad (17)$$

$$\theta_h = \psi - \psi_{1,eff} \quad (18)$$

where θ_h is the heading, ψ is the orientation of Ingenuity in the inertial frame and $\psi_{1,eff}$ is the azimuthal location of peak cyclic magnitude. Note that Ingenuity does not typically change azimuthal orientation when changing heading. Given the estimated airspeed and heading, along with the groundspeed and direction from the navigation system, the windspeed vector is determined as the groundspeed vector minus the airspeed vector.

Using this approach, the wind magnitudes and directions were extracted and are shown in Fig. 18. Notably, the out legs exhibit significant variability, with large magnitude and direction spikes. A drawback of the control effort based estimation approach is that it is difficult to conclusively attribute these spikes to physical wind, since there is no way to isolate the gust response from any other noise or disturbance that has engaged the feedback control.

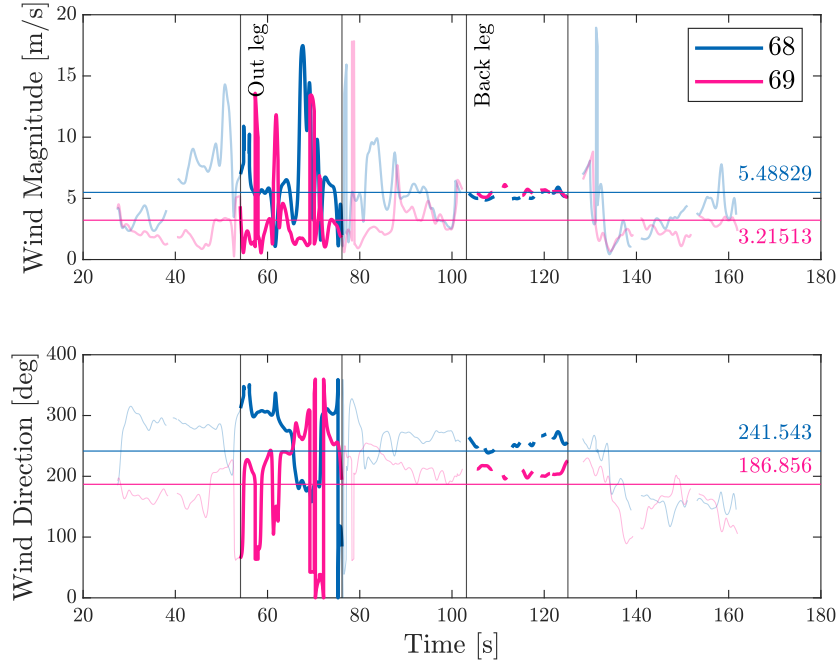


Fig. 18 Wind magnitude and direction for Flights 68 and 69.

To obtain a linearized model around a set trim point, a trim condition with a constant airspeed must be determined. Combining the windspeeds in Fig. 18 with the groundspeed, the airspeed in the heading direction was calculated. More specifically, the wind vector was split into components in the direction of the forward flight and in the cross-axis. It is important to note that the average value of airspeed varies depending on the approach used to compute the mean.

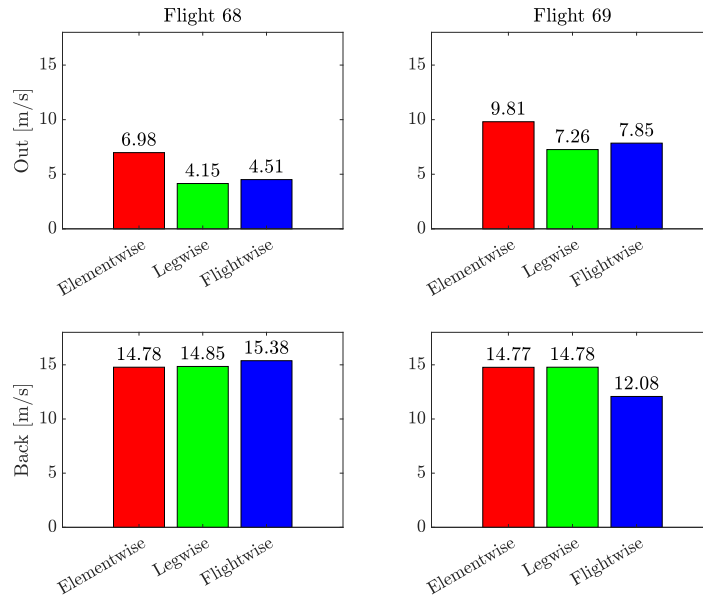


Fig. 19 Comparing methods for calculating mean airspeeds.

Three different methods utilizing the windspeed estimates to obtain mean wind conditions during the sysID sequence

from the swashplate inputs are outlined below, and the results presented in Fig. 19 for each leg of the two flights:

- 1) Element-wise: Calculate the airspeed at every time step, and then average the airspeed across the leg at the end.
- 2) Leg-wise: Average the wind magnitude and direction for each leg (1 value for each leg), then calculate the airspeed at each timestep, and then average the airspeed across the leg at the end.
- 3) Flight-wise: Average the wind magnitude and direction for each flight (1 value for each flight), then calculate the airspeed at each timestep, and then average the airspeed across the leg at the end.

The approaches differ in how much the wind is assumed to change throughout the flight. The element-wise method has the smallest time resolution, and thus, heavily relies on the ability to identify wind magnitude and direction from the control inputs at shorter time scales. As a result, it has a tendency to highly weight outliers, attributing any spikes in control inputs to sharp variations in wind, which may not always be physical. Conversely, the flight-wise approach assumes that the wind magnitude and direction remains constant for the duration of the entire flight, at the cost of not capturing potentially significant time variation in the wind condition. The leg-wise approach is a trade-off between the two, assuming the wind condition can vary from leg to leg, but not within each leg, and is the condition assumed for all further analysis. From Figs. 18 and 19, it is concluded that, on average, both out legs experienced a tailwind, while both back legs experienced a headwind, providing four separate airspeeds anchor points for model identification. As a final note, the lack of direct wind measurements, and the resulting reliance on indirect model-based estimates, introduces uncertainty and potential prediction errors in determining the trim point around which the linear models are identified. Estimating this uncertainty, as well as the sensitivity to prediction errors, is considered an important area for future research.

B. Frequency Responses

Unless stated otherwise, all responses shown in this section refers to a comparison of pitch rate response to a pitch aligned input, q/δ_q . The frequency responses from each leg for Flight 68 and 69 computed using the SISO Direct Method is presented in Fig. 20. Frequency responses were generated using CIFER with a frequency range of 0.15 Hz to 10 Hz and averaging over five separate window sizes. All four legs demonstrate a similar trend: good coherence in the higher frequency region ($\omega \geq 1$ Hz), and a loss of coherence at the lower frequencies. Out of all four, the back leg of Flight 69 demonstrates the best coherence across the entire frequency region of interest. This may be partly due to the slightly larger sweep amplitude improving the signal-to-noise ratio, and possibly less prevailing disturbances during this particular leg, although the latter remains inconclusive based on the available data.

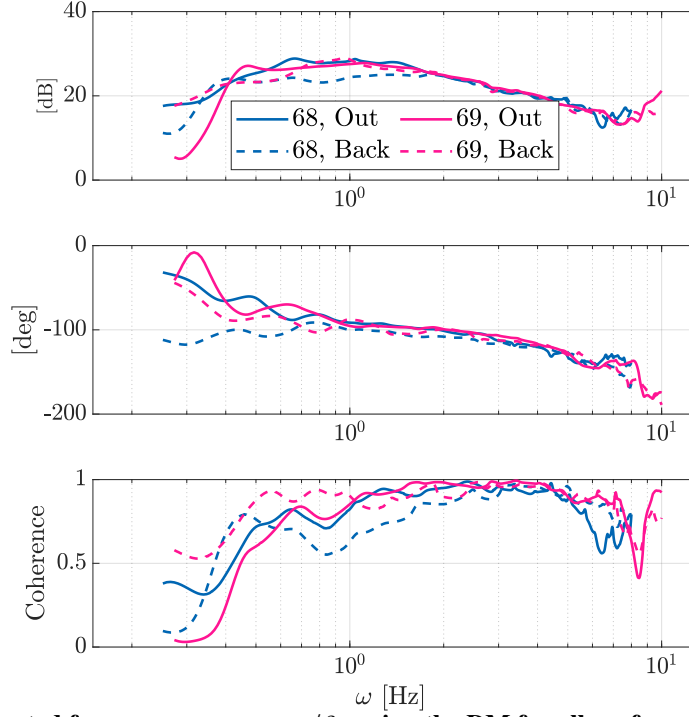


Fig. 20 Computed frequency response p/δ_p using the DM for all performed frequency sweeps.

The loss of low frequency coherence suggested potential contamination from noise and/or wind disturbances where the SNR is believed to be below the rule-of-thumb for adequate excitation. In Section V.C, the JIO method was shown to partially recover the true response in the presence of disturbance, and the same approach was applied to the flight test data and compared to the DM. Both methods were compared to the linearized HeliCAT models for the leg's respective airspeed and density. The resulting responses for Flight 68 and Flight 69 are shown in Fig. 21 and Fig. 22, respectively. For brevity, the linearized HeliCAT models are denoted by "HeliCAT." Given the JIO method's sensitivity to the quality of intermediate responses, computing these responses proved particularly challenging for the out leg of Flight 68, shown to the left in Fig. 21. To obtain numerically meaningful results, the nominal minimum frequency was increased from 0.15 Hz to 0.8 Hz, ensuring that the coherence of the intermediate responses did not drop to zero. Understanding the root cause to the differences between the four legs with regards to achieved coherence, and resulting quality of the response estimates, remains speculative with the data at hand. The time series in Fig. 16 from the out leg of Flight 68 exhibits more erratic behaviour and excursions from the commanded sweep input, which could be a clue to the observed degradation in the results. The improved coherence for Flight 69 could again be partly attributed to the increased sweep amplitude. Consistent for all legs, however, is that above approximately 1 Hz, the computed responses show excellent correlation with the physics-based model, indicating that the higher-frequency dynamics were successfully identified during the V&V campaign of Ingenuity. Below 1 Hz, the magnitude of the identified responses is seen to diverge from

the model, exhibiting a more pronounced attenuation as well as phase increase. This closely resembles the observations made in Section V.C, specifically in Figs. 8 and 12, where increasing wind disturbances introduced a similar bias in the low-frequency region.

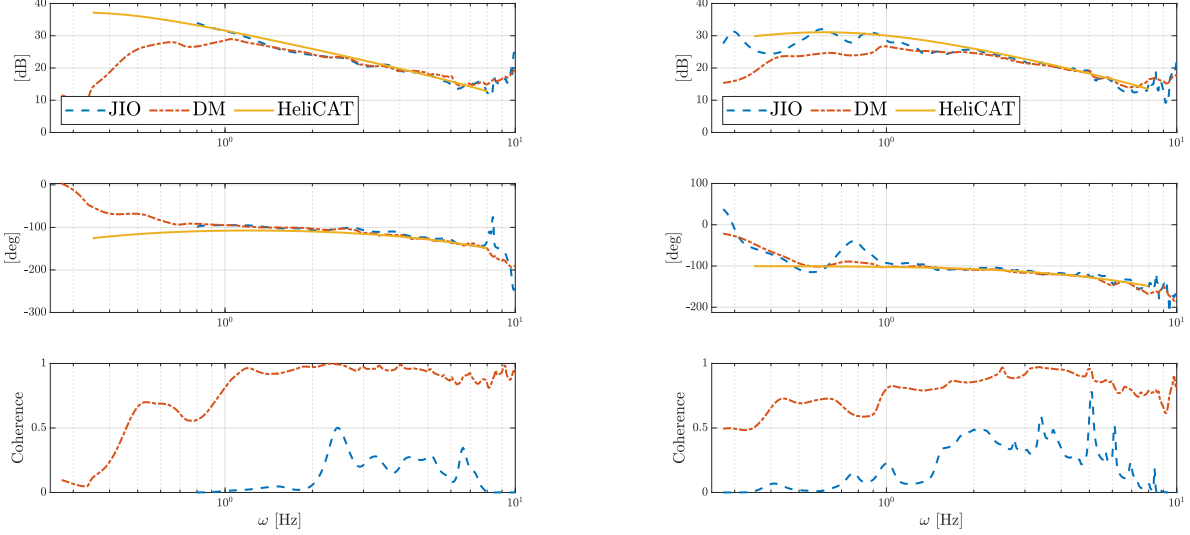


Fig. 21 Comparison of frequency response p/δ_p using the DM and JIO methods for Flight 68. Left: Out leg. Right: Back leg.

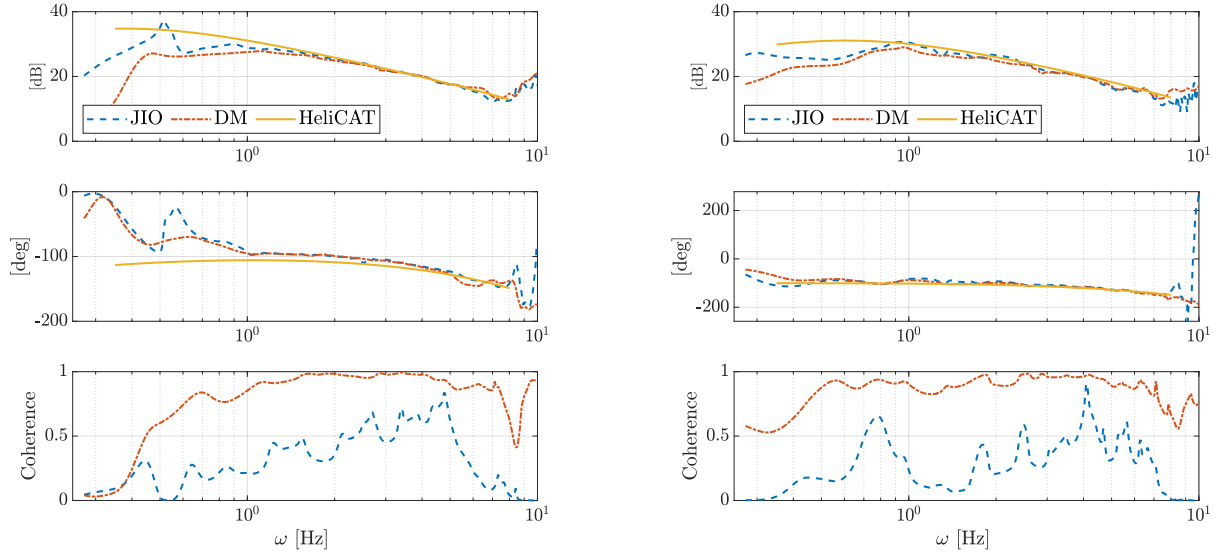


Fig. 22 Comparison of frequency response p/δ_p using the DM and JIO methods for Flight 69. Left: Out leg. Right: Back leg.

While the JIO response in Figs. 21 and 22 matches both the magnitude and phase of the linearized HeliCAT model marginally better, the coherence is far lower than that of the Direct Method's. At lower frequencies in particular, the coherence with the JIO method falls short of the recommended guideline to ensure accurate model identification. As pointed out in [20], the attainable accuracy of the final JIO response is reliant on high SNR as well as coherence with the

chosen reference signal and the bare-airframe input and output. A closer examination of these intermediate responses consistently showed a coherence drop below crossover, which propagates to the poor results shown in Figs. 21 and 22. This observation needs to be taken into consideration when assessing the reliability of the identified derivatives from these responses. In [28], an approach to use the Direct and JIO method in concert for a winged compound helicopter with highly-correlated control inputs was presented, where the method with resulting highest quality response in a specific frequency region was used to identify the derivatives of interest in a sequential manner. This approach is appealing, yet the potential artificial coherence inflation in the DM responses due to fed-back noise is a complicating factor for the current study. While the coherence from the DM looks mostly satisfactory, albeit still exhibiting a reduction at lower frequencies, part of the frequency content is hypothesized to be polluted with the presence of exogenous inputs, which was the primary motivation to utilize the JIO method initially. The indicated response bias at the lower frequencies as shown in Figs. 7 and 8 is a nuance that constrains the quality evaluation of the two different methods.

C. Model Comparison

Reduced-order lateral linear models as formulated in Eq. (14) were extracted, using CIFER. Due to their high insensitivities, M_q , M_u and M_w were fixed, while M_θ and M_{δ_q} were freed. Linear models using the DM for all legs are compared to a 10 m/s longitudinal airspeed linearized HeliCAT model in Fig. 23.

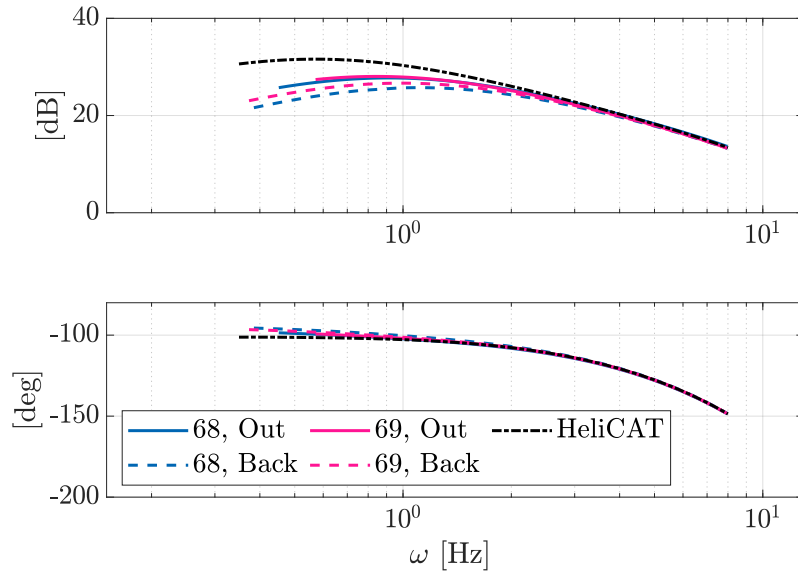


Fig. 23 Comparison of fit models with DM for all frequency sweeps.

As expected, given the frequency responses the linear models are fit to, there is a consistent discrepancy between the identified models versus the linearized HeliCAT model in the lower frequency region. Yet, the trend of a larger attenuation with airspeed (below crossover) is successfully captured in the identified models, which is expressed as a

magnitude delta between the out and back flights (recalling that the back flights featured a higher horizontal airspeed due to the headwind). Theoretically, the observed bias could be an indication of a larger angle-of-attack instability than initially modeled. However, the relatively small delta, despite a substantial change in airspeed between the two flights, speaks to the fact that rather than a larger gradient in M_θ to airspeed than expected, the bias is more likely to be originating from disturbances and/or noise. Fig. 24 and Fig. 25 show the comparison for Flight 68 and Flight 69 respectively, with the out leg to the left and back leg to the right, contrasting the DM with the JIO method. The two back leg JIO models show less attenuation in the lower frequencies, aligning closer with the physics-based model. As seen in Fig. 12, these response characteristics could be well replicated by including atmospheric disturbance in the simulation environment. This provides additional evidence that the discrepancy in observed and modeled bare-airframe pitch-rate response may not conclusively be attributed to a modeling flaw, but rather that noise is being fed-back during the sweeps and is contributing to a response bias that can be partially mitigated using JIO techniques.

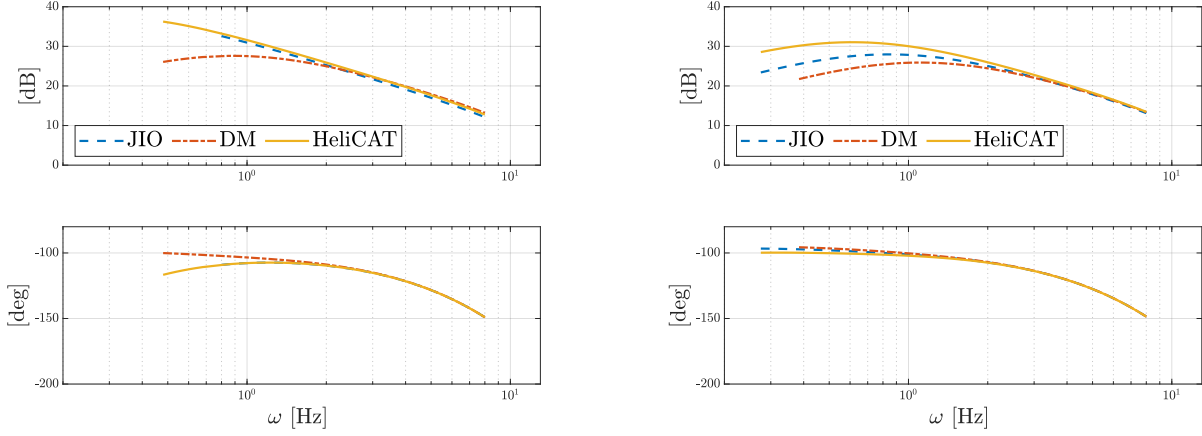


Fig. 24 Comparison of fit models using DM and JIO method for Flight 68. Left: Out leg. Right: Back leg.

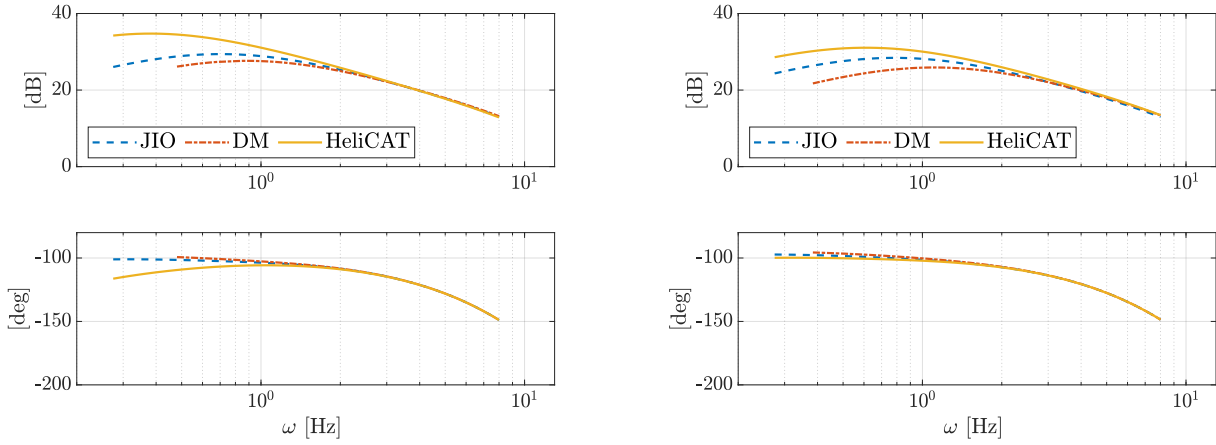


Fig. 25 Comparison of fit models using DM and JIO method for Flight 69. Left: Out leg. Right: Back leg.

For the out leg of Flight 68 specifically, due to the reduced attainable low-frequency content, only the control

derivative M_{δ_q} was subject to identification with the JIO method. Similar to the frequency response, use of the JIO method improves the correlation of the fit parametric models with the linearized HeliCAT model in the lower frequency range, with the exception of the Flight 68 out leg where direct comparison in this region is prohibited.

Four short segments, denoted by A, B, C, and D respectively, of the in-flight frequency sweep were used for time-domain verification and are presented in Fig. 26 and in Table 4, comparing the linearized HeliCAT, identified DM, and JIO models. Given the highly unstable nature of the models, each segment is short and the subsequent amplitude of the output response is small. The results are highly sensitive to what state the vehicle is in when the segment starts, specifically if the vehicle is at a true trimmed condition and, to a lesser extent, the cutoff frequency of the filter applied to the time histories. As a result, both the J_{rms} cost and TIC for each of the four fits shown in Fig. 26 vary, where only the A segment satisfies both the $J_{rms} \leq 0.5$ to 1 criteria, and $TIC \leq 0.3$ criteria. Qualitatively, the linearized HeliCAT models most closely match the flight model, followed by the JIO model and the DM model for both the A and B segments, similar to the time-domain verification during the simulation campaign and despite having marginally higher TIC values. However, this trend is inverted in segment C, where the DM model shows the closest correlation. For segment D, all linear models (DM, JIO, and linearized HeliCAT) exhibit almost identical predicted responses.

Table 4 Time-domain costs from Flight 69.

Segment	Linearized HeliCAT		DM		JIO	
	Cost, J_{rms}	TIC	Cost, J_{rms}	TIC	Cost, J_{rms}	TIC
A	0.026	0.30	0.028	0.29	0.027	0.29
B	0.024	0.50	0.024	0.47	0.024	0.48
C	0.026	0.53	0.025	0.47	0.025	0.50
D	0.020	0.67	0.020	0.67	0.020	0.67

D. Identification of Derivatives

The fit M_θ and M_{δ_q} derivatives, including cost J , insensitivity I and Cramer-Rao (CR) bounds are presented in Tables 5 and 6 for Flight 68 and in Tables 7 and 8 for Flight 69. Identified parameters with CR bounds and/or insensitivities that exceed the rule of thumb are marked in red, which is true for all identified M_θ derivative values using the JIO responses. It is also noted that the fitting cost J is consistently lower using the JIO responses.

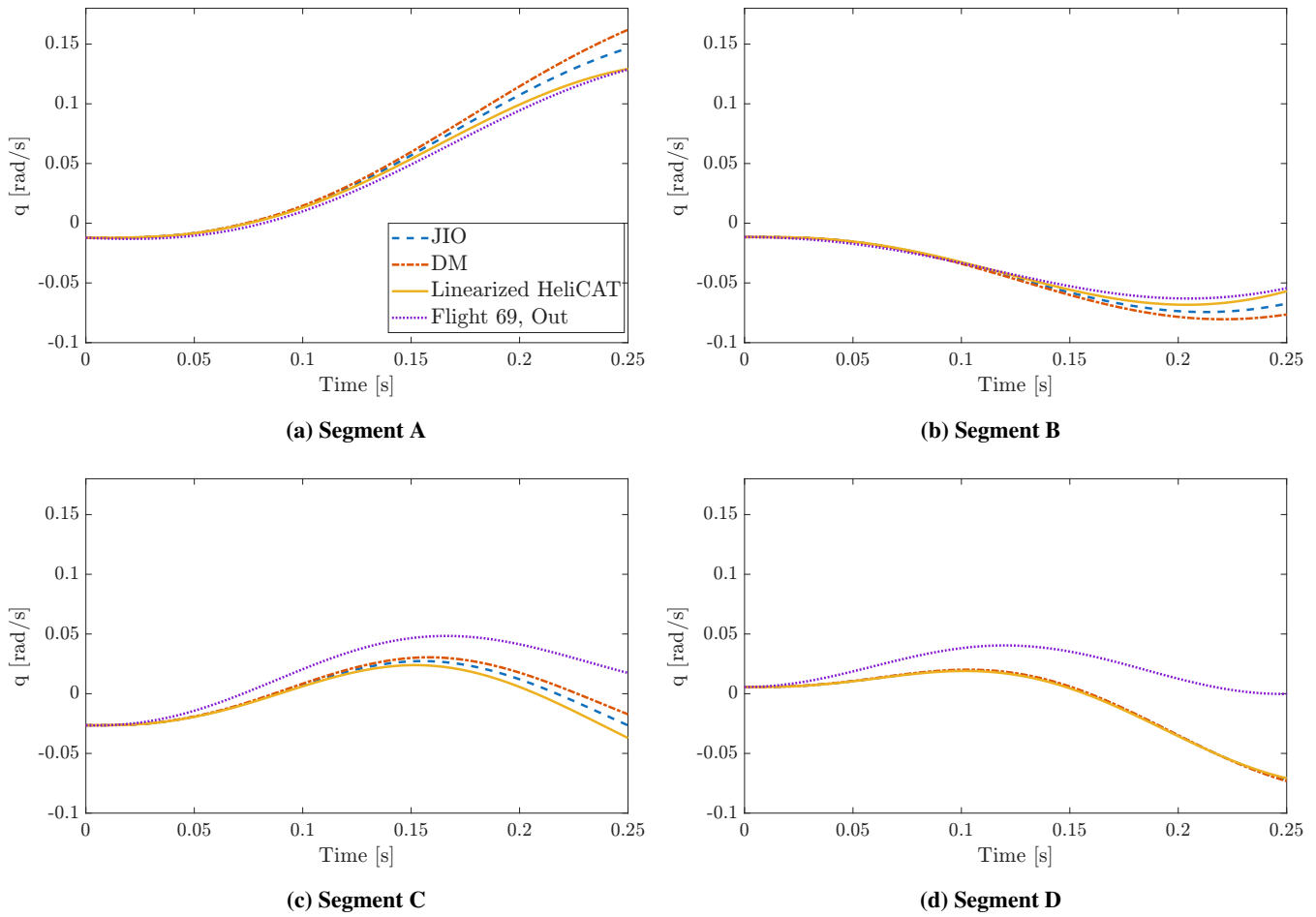


Fig. 26 Time-domain verification results comparing the pitch rate response from a short segment of Flight 69 to the extracted JIO, DM, and linearized HeliCAT models.

Table 5 Fit derivatives from Flight 68, out leg.

	Linearized HeliCAT	DM				JIO			
	Value	J	Value	I , %	CR Bound, %	J	Value	I , %	CR Bound, %
M_θ	0.054	31	0.97	6.7	18	1.4	-	-	-
M_{δ_q}	7.9		8.4	2	18.6		7.4	6.9	13

Table 6 Fit derivatives from Flight 68, back leg.

	Linearized HeliCAT	DM				JIO			
	Value	J	Value	I , %	CR Bound, %	J	Value	I , %	CR Bound, %
M_θ	0.46	28	1.5	4.9	14	4.7	0.88	32	93
M_{δ_q}	8.6		8.7	2.1	6.1		8.3	5.3	15.1

Table 7 Fit derivatives from Flight 69, out leg.

	Linearized HeliCAT	DM				JIO			
	Value	J	Value	I , %	CR Bound, %	J	Value	I , %	CR Bound, %
M_θ	0.15	29.5	0.96	6.7	18.7	14.6	0.60	18	45.2
M_{δ_q}	8.0		8.4	2.0	5.5		8.2	3.9	9.8

Table 8 Fit derivatives from Flight 69, back leg.

	Linearized HeliCAT	DM				JIO			
	Value	J	Value	I , %	CR Bound, %	J	Value	I , %	CR Bound, %
M_θ	0.45	28.6	1.52	4.9	14.5	5.2	0.76	14.2	38.0
M_{δ_q}	8.6		8.6	2.0	6.2		8.2	4.3	11.4

Both approaches arrive at control derivatives close to the modeled value; the derivatives from the linearized simulation model all fall within the Cramer-Rao bounds of the identified derivatives from the flight tests as shown in Fig. 27, which mirrors the excellent correlation seen in the frequency responses above cross-over in Figs. 24 and 25. Larger uncertainties are observed in the derivatives resulting from the JIO models, in particular for M_θ , likely due to the noticeable reduction in coherence. The apparent response attenuation in the lower frequencies are expressed as a significant over-estimation of M_θ , in particular with the DM, which is consistent with previous observation. Whereas the values of the derivatives are off-set, both methods capture the modeled trend with airspeed, meaning that the larger velocities give a larger value for M_θ . This gradient is overestimated in the DM results, while underestimated with JIO, when comparing to the physics-based model.

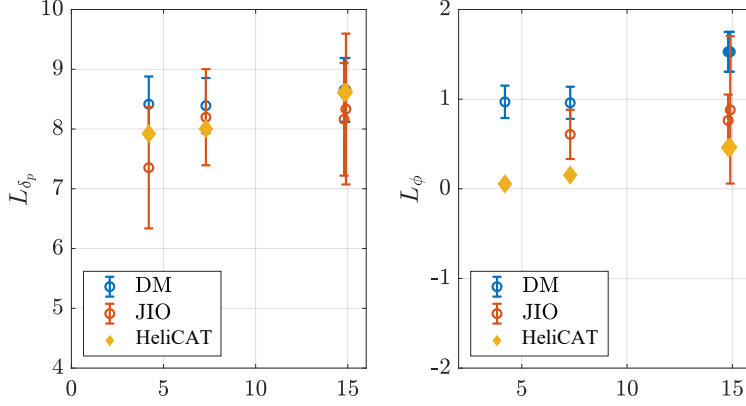


Fig. 27 Resulting fit derivatives from all frequency sweeps using both DM and the JIO method.

VII. Conclusions

This paper detailed the motivation, design, and results from two system identification flights of the Ingenuity Mars Helicopter executed in late December of 2023. The flight tests aimed to identify key vehicle stability and control characteristics in forward flight, motivated by the lack of experimental data in this flight regime; the ultimate goal was to validate existing physics based simulation models. In addition, the effort was a first-time demonstration of a methodology for in-situ system identification of planetary aerial vehicles, setting a precedent to inform future Mars rotorcraft research efforts. The following conclusions were supported by the results:

- 1) The identified linear models from the flight data showed excellent correlation with a-priori physics based models in the higher frequency range, $\omega > 1.5$ Hz. In particular, the pitch-aligned control derivative M_{δ_q} was fit within the Cramer-Rao bounds when compared to the linearized HeliCAT model.
- 2) Estimates of the prevailing wind conditions during the two flights were derived from cyclic control efforts. The estimates showed that the vehicle experienced a significant head (and tail) wind, reaching up to 15 m/s horizontal airspeed. No sign of instability or sustained control saturation was observed.
- 3) While trends in stability and control derivative values with increasing airspeed were captured in the identification results, the presence of external disturbances and/or noise was seen to introduce a bias in the computed bare-airframe roll-rate frequency responses in the lower frequency region, in particular when using the Direct Method. This was primarily expressed as an overpredicted angle-of-attack derivative, M_{θ} .
- 4) The response bias could be reduced for two of the collected time series that had sufficient coherence between the commanded reference signal and swashplate excitation when utilizing the Joint-Input-Output method, albeit with a significant reduction in input-to-output coherence in the computed bare-airframe response. The identified model using the JIO method yielded a favorable fitting cost J and a fit angle-of-attack derivative M_{θ} in better agreement with the simulation model when compared to the Direct Method. This was partially validated in the

time-domain given proper selection of the analyzed flight segment, where the JIO model showed a small visual matching improvement over the DM model.

- 5) Notwithstanding the successful demonstration of the developed procedures for in-flight sysID, lessons for future flight testing were learned, and are listed as follows. A larger excitation signal would act to improve the SNR and improved coherence. A longer sweep duration may also aid in improving the quality of the estimated response, specifically at lower frequencies. In addition, exciting the system directly at the bare-airframe inputs, as was done in this test, likely aggravated the impact of noise; excitation through reference-tracking commands is expected to give a better SNR and a reduction in correlated noise biasing the bare-airframe response. Adding vehicle instrumentation for airspeed measurements would allow for a more accurate characterization of the vehicle trim condition and improve the accuracy of the anchoring point used for linear model extraction. This feature would also help identify more suitable flight times to minimize wind disturbances.

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