ATMOSPHERIC TURBULENCE ESTIMATION FOR HELICOPTER FLIGHT CONTROL SYSTEM DESIGN

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Abstract: Verification of Flight Control System (FCS) design against stabilization and performance requirements in turbulence[1] faces an awkward problem: the FCS is designed to reject disturbances and this makes it difficult to evaluate the actual turbulence level from flight test data. As a matter of fact, it is not possible to assess the FCS performance at different turbulence levels if it is not possible to have a reliable evaluation of the turbulence level itself. A good FCS design will counteract the effect of turbulence on aircraft attitude and rates by means of a very energetic control action. Hence, the turbulence level can be estimated by processing the residual aircraft upset and the FCS control action. This paper describes the design and validation of an atmospheric turbulence estimator used for the design of a helicopter FCS.

1. NOTATION

AFCS	Automatic Flight Control System
FCC	Flight Control Computer
FCS	Flight Control System
FRF	Frequency Response Function
LTI	Linear Time Invariant
PSD	Power Spectral Density

2. INTRODUCTION

In turbulent air environment the helicopter is subjected to fast and sudden variations of acceleration, angular rate, velocity, altitude and attitude. The occurrence of these events deteriorates the performance of the helicopter, jeopardizes the stability, damages the structure, decreases the passengers comfort and in the worst case it can compromise the mission. In this flight condition the pilot's perception of the turbulence is altered by the presence of the Automatic Flight Control System (AFCS). For a limited authority flight control system heavy turbulence could bring actuators near their full stroke. In this condition the AFCS might be unable to control the helicopter if a further increase of turbulence occurs and this could lead to loss of the helicopter's stability without the pilot being warned in time. The purpose of this work is to design an estimator able to give an indication about the turbulence level encountered while flying. This will allow to understand in which environmental conditions the control laws are tested during the design and development phase, and in the future to provide pilots with information about the dangerousness of the environment itself or to use the disturbance estimation in order to improve the turbulence rejection capabilities.

The dynamic model of the helicopter adopted to design the estimator is a MIMO state-space linear black-box model, obtained a continuous-time predictor-based subspace identification algorithm[2,3]. This identified black-box model was preferred over a first-principles physical model since it proved to be more accurate within the frequency range relevant to flight control.

In order to use the black box model a new method to couple the atmospheric turbulence (Von Kármán continuous gust model[1,4]) with the helicopter dynamics has been used. The implemented estimation algorithm takes as input the physical measurable flight data (residual angular rates and FCS control actions) and estimates the turbulence level in the frequency domain via power spectral density (PSD)and spectral power. The design of the estimator takes also into account the coherence of the identified model used to simulate the helicopter dynamics, limiting the estimation to the frequency range where it is more reliable.

A verification of the algorithm has been performed in simulation, reproducing the turbulence effects on the helicopter using the Von Kármán model and processing flight data into the estimator. The estimated disturbance has been compared to the injected disturbances, in terms of time history and spectral power.

Subsequently, an experimental validation has been carried out during a dedicated flight on the AW169 helicopter. The test has been executed in calm air condition, and a series of stimuli designed to reproduce the turbulence effects have been injected. The obtained flight data have been processed into the observer and the estimated disturbances have been compared to the artificial turbulence injected, in terms of time history, spectral power density and spectral power. The obtained results have been used to validate the estimation process in an operative context, where the real helicopter dynamics is present.

Finally the disturbance estimator has been used to identify the turbulence intensity level present in real flight, comparing the results obtained by the estimation with the intensity turbulence level indicated by the crew on the flight log.

3. ROTORCRAFT MODEL AND TURBULENCE SIMULATION

In this section the mathematical models used in this study are presented, both for the dynamics of the helicopter and for the turbulence affecting it.

3.1 Identified black-box model

The continuous-time Linear Time Invariant (LTI) black-box model used in this study has been obtained from data collected in a previous in-flight identification campaign; it is the most reliable representation of the helicopter dynamic response over the relevant frequency range. The LTI system is composed of the matrices A, B, C and D, in the form

$$\dot{x} = Ax + Bu \quad (1)$$

$$y = Cx + Du \quad (2)$$

where:

- u is the vector of the inputs variables of the model, namely the total commands of cyclic stick, collective and pedals, all expressed as a percentage (see Table 1).

nr	input
1	Longitudinal (100% fw)
2	Lateral (100% right)
3	Pedal (100% left)
4	Collective (100% up)

Table 1: Inputs of the black-box LTI model.

- y is the vector of the measured outputs, *i.e.*, the physical response of the helicopter in terms of angular rates and linear accelerations (see Table 2). In the following the output equation will be also written by splitting the outut vector y into a component y_1 containing the angular rates and a component y_2 containing the linear accelerations, as follows:

nr	output
1	Roll rate p (deg/s)
2	Pitch rate q (deg/s)
3	Yaw rate r (deg/s)
4	Longitudinal acc N_x (g)
5	Lateral acc N_y (g)
6	Vertical acc N_z (g)

Table 2: Outputs of the black-box LTI model.

$$y_1 = C_1 x + D_1 u \quad (3)$$

$$y_2 = C_2 x + D_2 u. \quad (4)$$

- x is the state vector of the model. In the black-box model, states have no physical intepretation and the number of states is a trade-off between the model complexity and the accuracy of the input/output relationship.

3.2 Coupling with the turbulence model

The so-called body-fixed method[5,6,7] is commonly used to couple the atmospheric turbulence disturbances with the helicopter model. This method consists in adding the physical turbulence disturbances of the gust to the physical states of the helicopter model, adding in particular the gust linear velocities to the body linear velocities and the gust angular rates to the body angular rates, as follows

$$V = V_{wind} + V_{gust} \quad \omega = \omega_{body} + \omega_{gust}. \quad (5)$$

In the black-box model, however, the states have no physical interpretation, so it in not possible to add disturbances on the states themselves. An alternative solution to couple the turbulence to the dynamics of the helicopter has been found adding the turbulence disturbances to the physical output of the helicopter model as follows

$$\dot{x} = Ax + Bu \quad (6)$$

$$y = Cx + Du + D_d d, \quad (7)$$

where matrix D_d is given by

$$D_d = \begin{bmatrix} I_{3\times3} \\ 0_{3\times3} \end{bmatrix}$$

and the disturbances vector d is:

$$d = \begin{bmatrix} p_{gust} & q_{gust} & r_{gust} \end{bmatrix}^T.$$

In the Laplace domain, the input/output relation equivalent to equations (6) and (7) is given by:

$$y = \left(C(sI - A)^{-1}B + D\right)u + D_d d. \tag{8}$$

Finally, it is important to underline that this approach works only if the closed-loop helicopter dynamics is considered, because the flight control actuation rejecting the output disturbances excites the non-physical states.

3.3 Verification of the coupling method

The vailidity of the coupling approach described in the previous subsection has been verified by analysis, using a linearized physical helicopter model and evaluating the angular rate outputs, obtained with a simplified turbulence disturbance added on the angular rate of the helicopter model. Disturbances are added first on the states of the physical model and then on the output. Figure 1 shows the comparison between the angular rate outputs obtained in the two cases in terms of time history, PSD and spectral power. The validity of the proposed method is confirmed by the overlap of the time histories, the similarity of the PSD peaks (amplitudes and frequency) and the negligible difference in the power shapes.

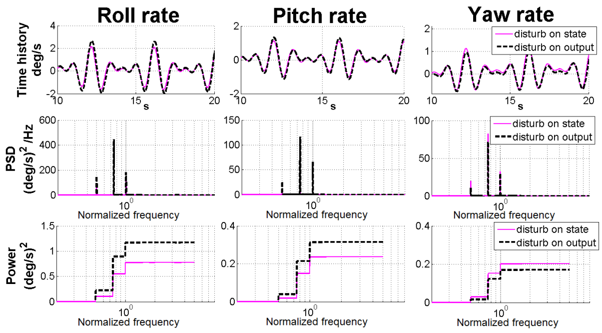

Figure 1: Output comparison

4. DISTURBANCE ESTIMATOR DESIGN

The disturbance estimator is designed to identify the turbulence level acting on the helicopter via PSD and spectral power.

4.1 Disturbance estimation algorithm

The disturbance estimator has been constructed by inverting the output equation (7) of the identified model, as follows

$$\hat{d} = (y_1 - C_1\hat{x} - D_1 u) \tag{9}$$

where:

- $\hat{d}$ is the estimate of the disturbance vector d;
- y_1 : is the vector of measured angular rates;
- $\hat{x}$: is the estimate of the state vector;
- u : is the vector of input variables;
- C_1, D_1 : are the matrices of the output equation of the LTI model corresponding to the angular rates.

In order to construct the estimator the identified model has been used since it is highly reliable over the (limited) frequency range which is relevant with respect to the bandwidth of the turbulence disturbance. As will be illustrated in the following, this will allow to obtain accurate estimates of the disturbance, both with numerical and experimental flight data.

While the variables y and u can be measured thanks to dedicated sensors installed on-board the helicopter, the state vector x has to be estimated with a state observer. The state observer is discussed in the following subsection.

4.2 State observer

A state observer has been implemented to compute an estimate of the state vector x to be used in the disturbance estimator (9). The observer is built following the well-known theory of the Kalman filter[8]. The set of parameters needed for the Kalman filter are:

- Q_n : process noise covariance; obtained by the Von Kármán turbulence model literature and set as 0.148 for all the disturbances.
- R_n : measurement noise covariance, obtained by the sensor specification related to the measured output and set as 0.3 for all the outputs.
- P_n : initial value of the covariance of the state vector, for each state the initial value is set to 100, in order to speed up the transient of the Kalman filter.

Considering this covariance setting the Kalman filter requires $100\ s$ to reach the steady state: this is also the time needed for the estimation of an affordable turbulence level by the disturbance observer algorithm.

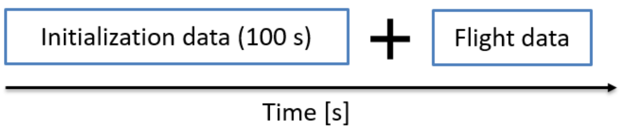

Figure 2: Kalman filter initialization

4.3 Data filtering

To avoid that the model error or the sensor measurement noise affects the disturbance estimation, input flight data must be pre-filtered. The filter has the following objectives:

- to ensure that the algorithm works mainly in the range of frequency where the identified model uncertainties are lower;
- to reduce the effect of unstable dynamics present in the model, associated with the dutch-roll mode;
- to remove the high frequency noise of the sensors.

The above requirements are depicted in Figure 3, in which a comparison of the magnitude of the FRFs of the black-box model, of the physical model and of a non-parametric estimate of the roll rate response to lateral input is shown. As can be seen from the figure, the two models match the non-parametric FRF very well over the frequency range of interest for turbulence estimation, hence the need for pass-band filtering to emphasize the estimation accuracy in that range.

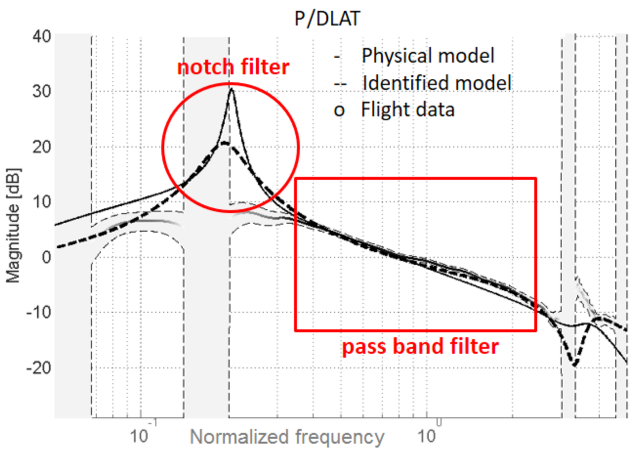

Figure 3: Magnitude of the FRFs of the black-box model, of the physical model and of a non-parametric estimate of the roll rate response to lateral input.

The matching of the above requirements produces a pass-band filter that has been used to pre-process all the flight data. The FRF of the filter is shown in Figure 4.

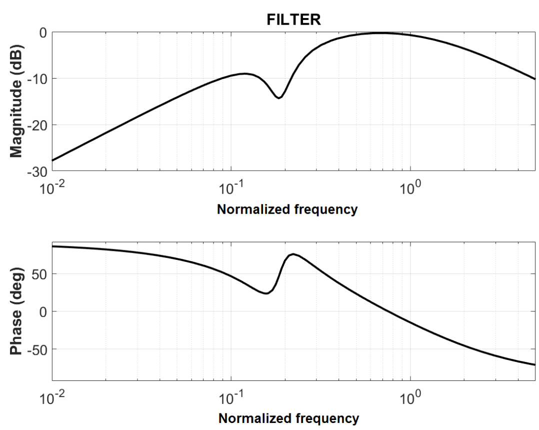

Figure 4: FRF of the data filter.

The presence of the filter limits the reliability of the estimates to the frequency range between 0.25 and 2.5. The complete estimation process is summarized in the block diagram depicted in Figure 5. As can be seen from the figure, the overall estimation process takes the flight data (u and y) as input and gives the estimated disturbances ($\hat{d}$) as output.

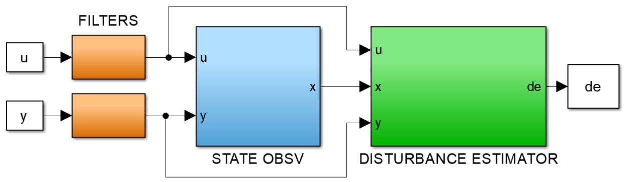

Figure 5: Complete estimation process

4.4 Turbulence intensity level definition

The intensity level of the turbulence is defined comparing the flight data with a predefined database of power spectral curves, obtained using the Von Kármán model to simulate several turbulence disturbances with different intensity levels. When the real flight data are processed by the algorithm, the obtained spectral power curve is compared with the Von Kármán database and the intensity level is deduced.

The simulated turbulence intensity is parametrized in function of the parameter W_{20}, related to the wind speed at $20\ ft$ above ground. Figure 6 shows the spectral power curves obtained simulating different intensities of turbulence. The values reached by the power curves indicate the turbulence level.

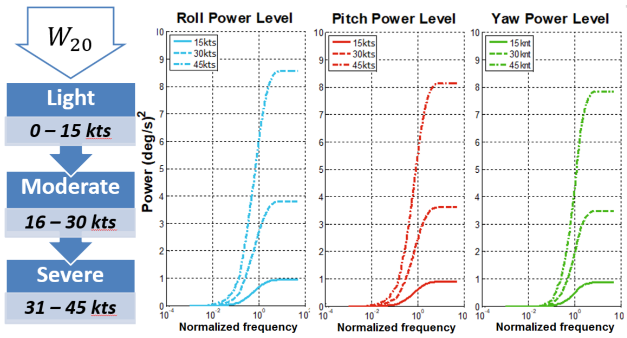

Figure 6: Simulated turbulence levels.

5. SIMULATION VERIFICATION

The validation of the disturbance estimator has been performed in simulation using the MATLAB/Simulink environment. In Figure 7 the simulation environment used for the verification is shown.

In particular, the subsystems involved in the simulation are:

- Helicopter model: to reproduce the dynamics of the helicopter a physical model, different from the black-box model used to design the estimator,

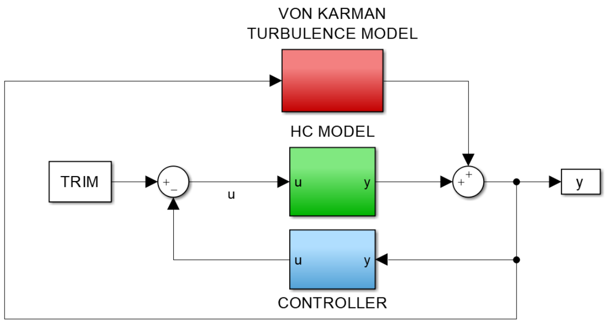

Figure 7: Simulation environment for the verification of the disturbance estimator.

is used. This choice permits to test the robustness of the disturbance estimator against modelling errors.

- Controller: the control laws used to stabilize the aircraft model are the same installed on-board the FCS (though limited to the angular rate stabilization on the pitch, roll and yaw axes).

- Von Kármán turbulence model: implemented to reproduce the effects of a turbulence disturbance.

The above-described simulation environmente has been used to generate the response of the helicopter in a gusty environment in closed-loop with the AFCS. The control input generated by the AFCS to reject the disturbances and the corresponding angular rates have been processed into the estimator. Finally the estimated disturbance has been compared with the injected one.

Figure 8 shows a comparison between the estimated disturbance (solid line) and the injected one (dashed line). As can be seen from the figure, there

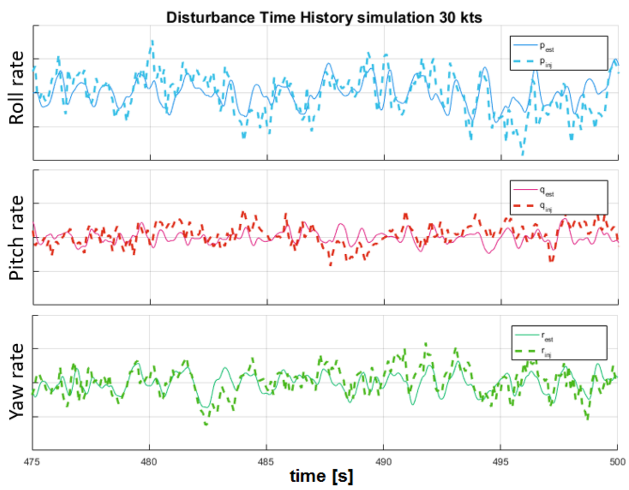

Figure 8: Comparison between the estimated disturbance (solid lines) and the injected one (dashed lines).

is a significant difference between the two signals, as the band-pass data filters described in Section 4.3 have not been included in the process, so that frequency content outside the frequency range of interest affects the performance of the estimator.

If now data pre-processing is taken into account, the estimation reliability is actually guaranteed in the frequency range defined by the filters, as can be seen from Figure 9, where a comparison between the estimated (solid line) and the filtered injected (dashed-dotted line) disturbances is shown.

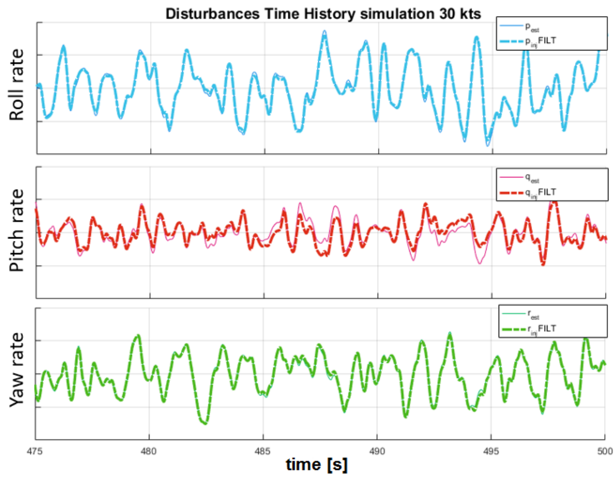

Figure 9: Comparison between the estimated disturbance (solid lines) and the filtered injected one (dashed-dotted lines).

The filtered injected disturbance is obtained by the Von Kármán turbulence model and filtered with the same filter used to pre-process the flight data, and it represents the optimal estimation that the observer can identify. Indeed the two signals match correctly ensuring the goodness of the disturbance estimation, limited to the frequency range defined by the filters.

In Figure 10 the spectral power curves obtained by the analysis of the estimated (solid line), injected (dashed line) and injected filtered (dashed-dotted line) disturbances are represented. The figure confirms clearly that data filtering can significantly reduce the estimation error, leading it to acceptable levels. Quantitative values for the relative estimation errors shown in Table 3. As can be seen, on all axes the relative error between the estimated and injected spectral power is around 30%, while while the relative error between the estimated and filtered injected spectral power is less than 10% on all axes, confirming the reliability of the estimation to the frequency range defined by the filters.

Relative error	**Roll rate**	**Pitch rate**	**Yaw rate**
Est - Inj	37 %	28 %	29 %
Est - Inj & Filt	5 %	10 %	3 %

Table 3: Relative errors of the spectral powers.

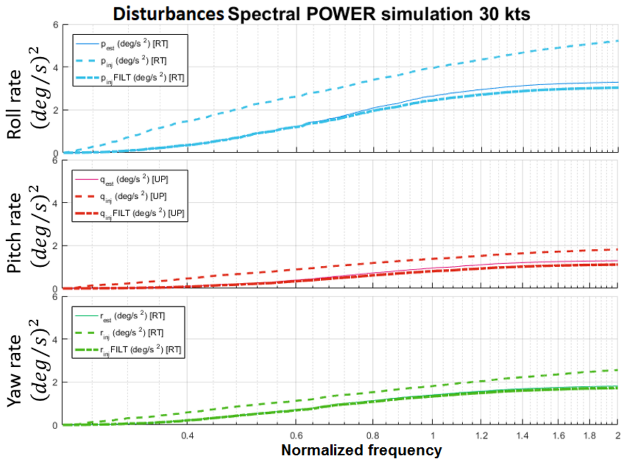

Figure 10: Spectral power of the estimated (solid lines), injected (dashed lines) and filtered injected (dashed-dotted lines) disturbances.

6. ARTIFICIAL TURBULENCE STIMULUS DESIGN

The in-flight validation of the disturbance observer requires the definition of a controlled and repetitive stimulus capable of reproducing the turbulence effects on the helicopter in a deterministic way. The stimulus is designed as a fictitious additional input added on the angular rate and attitude measurements downstream the sensors, as shown in Figure 11

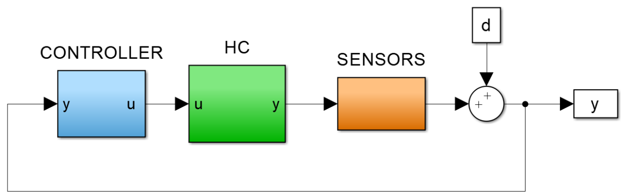

Figure 11: Stimuli addition scheme.

The AFCS receives the sensors output measurements with the addition of the stimulus and performs a control action on the longitudinal, lateral and pedal commands in order to reject the disturbance. These command inputs will provoke on the helicopter dynamics an effect similar to the turbulence disturbance (as proved in Section 3.3). The disturbance stimulus has been implemented directly in the AFCS software, so it must be as simple as possible in order to reduce the used throughput. The assumptions underlying the design of the stimulus can be summarised as follows:

- The power of the stimulus injected must be equal to the one of the Von Kármán turbulence model.
- The disturbance shall not change the trim point of the helicopter.
- The amplitude of the artificial turbulence shall not require the saturation of the series actuators.

Considering these key points, eight doublets on the angular rates and eight correspondent variations of attitude have been assembled. The stimulus has been designed in order to have a succession of positive and negative attitude variations. Furthermore, each square wave has a different period in order to cover the frequency range of interest, and different amplitude: this allows to modify the shape of the spectral power curve, fitting better the Von Kármán power spectral curve. The complete stimulus has a duration of 25 seconds, which is a good trade-off between the power spectral resolution obtained and the crew shaking. The designed stimulus is represented in Figure 12, while in Figure 13 the time history, PSD and spectral power of the turbulence simulated with the Von Kármán model and the artificial turbulence stimulus are compared.

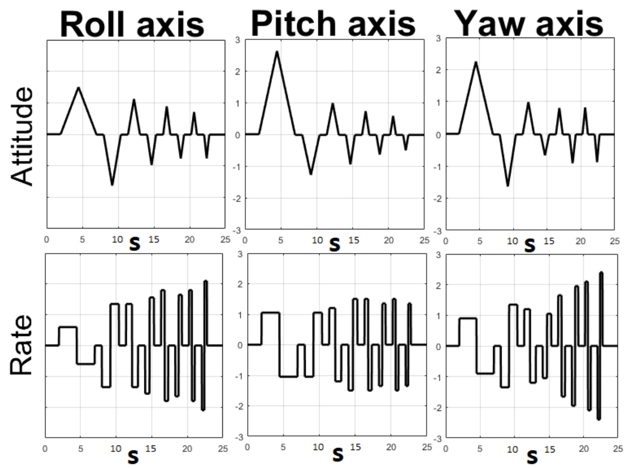

Figure 12: Time histories of the designed stimulus: attitude (top) and rates (bottom).

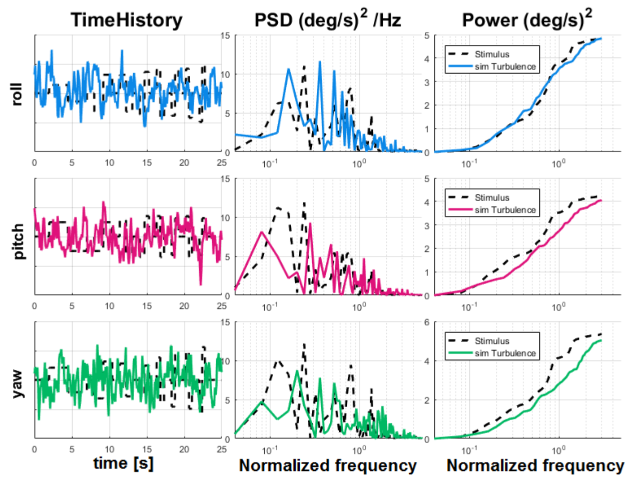

Figure 13: Von Kármán turbulence simulation (solid lines)) & stimulus (dashed lines).

7. FLIGHT TEST RESULTS

7.1 In-flight validation

The verification procedure executed in simulation and described in Section 5 has been repeated during a dedicated flight. The injected disturbances are the artificial turbulence stimuli described in Section 6; during the flight several injections with different intensity have been performed. The feedback of the crew is positive: the effects on the helicopter due to the stimuli are representative of real turbulence and consistent with the injected intensity level. The collected flight data are pre-filtered and processed into the observer, and the estimated disturbances are compared with the injected ones. In Figure 14 the time histories of the estimated (solid line), injected (dashed line) and filtered injected (dashed-dotted line) disturbances are shown. As reported in Section 5 also for the flight data the best estimation obtainable from the algorithm is the filtered injected disturbance.

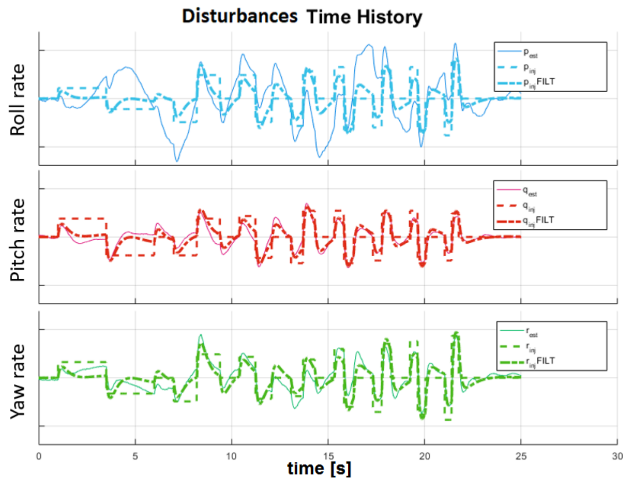

Figure 14: Time histories of the estimated (solid lines), injected (dashed lines) and filtered injected (dashed-dotted lines) disturbances.

In Figure 15 a comparison of the obtained PSDs is represented. It can be noticed from the estimated PSDs that the algorithm recognizes effectively the frequency spectra where the disturbances are injected. The errors are mainly present at low frequency, where the identified model is less reliable and the attenuation of the filter is less effective.

In Figure 16 a similar comparison of the obtained spectral powers is represented. The relative errors (in terms of spectral power), listed in Table 4, are below 10% on the pitch and yaw axes, confirming the validity of the estimation. On the roll axis, on the other hand, the relative error increases to 19%. This because the dutch-roll mode of the helicopter used for the flight test is not well represented by the black box identified model (see the difference between the physical and the black-box models on the lateral dynamics in Figure 3).

7.2 Intensity level identification

The validated algorithm has been used to identify the turbulence intensity level from data collected during a flight in real turbulence. The intensity level

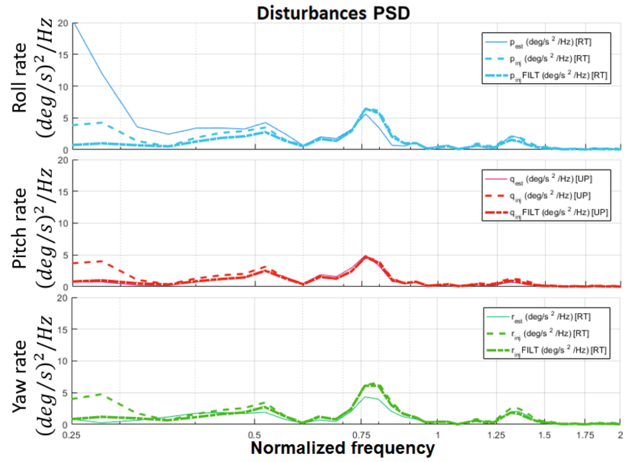

Figure 15: PSDs of the estimated (solid lines), injected (dashed lines) and filtered injected (dashed-dotted lines) disturbances.

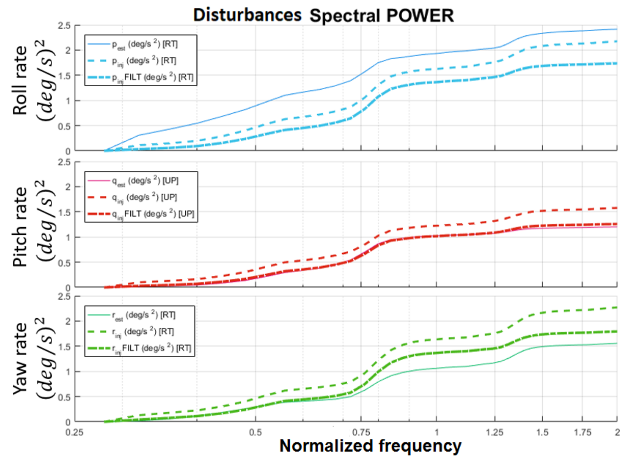

Figure 16: Spectral power of the estimated (solid lines), injected (dashed lines) and filtered injected (dashed-dotted lines) disturbances.

Relative error	**Roll rate**	**Pitch rate**	**Yaw rate**
Est - Inj	$2\ \%$	$20\ \%$	$28\ \%$
Est - Inj & Filt	$19\ \%$	$3\ \%$	$10\ \%$

Table 4: Relative errors of the spectral powers.

obtained from the estimator has been compared to the intensity level indicated by the crew during the flight. When the disturbance estimator works with flight data, it identifies the effects of equivalent turbulence acting on the outputs. The initial indication of the turbulence level has been obtained by the flight log analysis, where the pilot indicates his perception of the turbulence level present during the flight.

Two main flight phases have been used: the first in calm air condition and the second in moderate turbulence condition. In Figure 17 the two phases have been individuated from the analysis of the angular rate amplitude registers on-board; the moderate turbulence effect is more visible on the roll axis after $500\ s$, suggesting a lateral gusty environment.

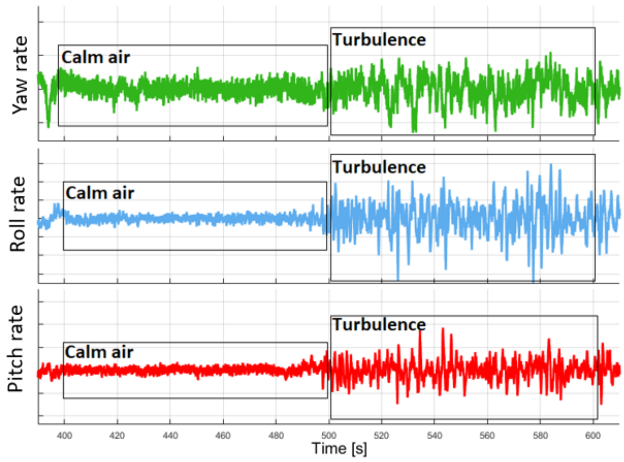

Figure 17: Angular rates flight data.

The data relative to the two phases has been processed with the estimator and the results compared. In Figure 18 are shown the spectral power curves obtained by the analysis of the estimated disturbance. The calm air phase (dashed line) and turbulence phase (solid line) deduced by the results obtained with the Von Kármán turbulence model (see Figure 6). Despite the maximum error of 19% identified on the roll axis during in-flight validation (see Table 4), the spectral power of the estimated turbulence remains in the moderate region on the lateral axis and it is consistent with the turbulence level perceived by the crew.

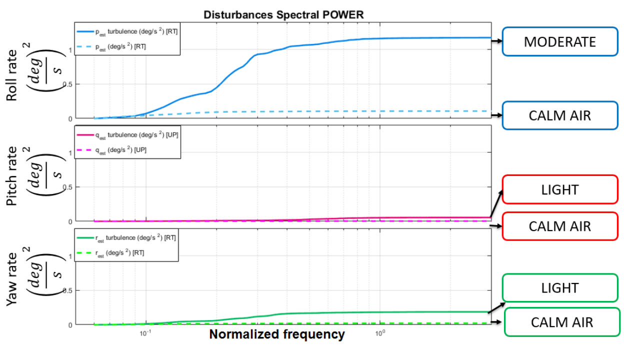

Figure 18: Spectral power curve.

8. CONCLUSIONS

The problem of estimating the turbulence level from measured input/output data has been considered and an estimation scheme has been presented and discussed. The disturbance estimation algorithm, based on the inversion of the output equation of the helicopter dynamics coupled with the Von Kármán turbulence models, has been verified in simulation, where the obtained results are consistent with the disturbance injected, limited to a frequency range of the helicopter model reliability. To validate the turbulence observer in flight, an alternative method to simulate the turbulence effects on the helicopter dynamics has been defined. The addition of the turbulence disturbances on the sensor output permits to excite correctly the same helicopter states affected by the real turbulence at the same frequency and with the same amplitudes (Figure 1). Finally the algorithm has been tested with data from a real turbulent flight, from which it produced results consistent with the crew perception.

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