REAL TIME ESTIMATION OF VTOL VEHICLE WEIGHT USING STANDARD ON-BOARD SENSORS

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Abstract
This paper presents an effective method for real time computation of the gross weight of vertical take-off and landing aircraft (specifically, a tiltrotor). Accurate in-flight estimation of gross weight allows computing fatigue life of vehicle's components and optimizing inspection or replacement of vehicle's life-limited parts, in order to reduce operating cost and enhance safety. Several techniques for determining gross weight are available in the literature, which mainly rely on hover performance charts, neural networks, and model based augmented state observers. The method presented in this paper estimates gross weight by solving forces balance equation when vehicle is trimmed in straight and level flight. In this condition, the balance equation depends on few variables, measured by standard on-board avionic sensors. The key innovation of proposed approach is the exploitation of system identification to tune the estimation algorithm parameters, by performing, just once, a calibration flight campaign in which vehicle's weight is known. After calibration campaign is completed, the proposed method applies very simple relations to estimate the weight every time the vehicle is trimmed in straight and level flight, whatever its configuration is (helicopter or aircraft). Since the weight varies slowly and most of the mission usually takes place in straight and level flight, this approach guarantees a reliable weight estimation during about the whole mission; moreover, it does not require any a priori knowledge of vehicle parameters neither huge dataset for algorithms training. Monte Carlo analysis, employing the FlightLab ERICA tiltrotor model for flight data generation, was used to assess the estimation method performance. Obtained results are very promising in terms of accuracy, precision and robustness to sensors errors.

1. INTRODUCTION

Accurate in-flight estimation of vehicle gross weight is an enabling technology for health monitoring systems, because gross weight knowledge allows computing aircraft structural loads, which significantly affect the fatigue life of vehicle components. Condition based maintenance systems can exploit this information to ascertain when life-limited parts need inspection or replacement[1], in order to increase reliability and availability of the vehicle, and consequently to enhance safety and reduce maintenance cost.

The knowledge of vehicle's weight is also valuable for other applications. Indeed, gross weight influences vehicle performance and its estimation is useful to improve pilots' situational awareness, allowing them to keep suitable flight safety margins[2]. In addition, such information is worthwhile for advanced flight control systems that perform gain scheduling in order to guarantee adequate handling qualities over the whole flight envelope, and that limit control inputs to avoid excessive loads on the structure[3]. Fault detection and identification systems[4] and algorithms for on-line estimation of critical flight parameters[5] can also take advantage of gross weight availability.
Several techniques for determining gross weight of helicopter and aircraft are available in the literature. Moffatt has proposed a simple estimation algorithm to determine the gross weight range (low, medium, high) of a helicopter only while it is hovering. This method relies on the hover performance chart included in the operators' manual and requires the measurement of few parameters (engine torque, hover height, pressure altitude and ambient temperature)[6]. In other works, estimation is easily computed by using weight on wheels force sensors information before take-off, combined with fuel consumption model[7], [8], [9]. This approach needs

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specific sensors and it is not applicable when weight suddenly changes during flight due to loads drop or acquisition, which is a common operation for helicopters. Approaches that are more complex exploit neural networks to get reliable weight estimation for helicopter[10], aircraft[4] and tiltrotor[11]. However, the results accuracy depends on the availability and accuracy of a sufficient amount of training data, and it rapidly decreases when estimation is carried out on the border or outside of the training dataset domain[12]. Moreover, the neural network needs rigorous training, which could be a time-consuming, expansive and laborious process. More recently, the Extended Kalman Filter (EKF) technique, which fuses sensor data and system analytical model, has been applied to weight estimation in the presence of measurement errors[3], [13]. Since the filter exploits an analytical model that represents an approximation of actual vehicle dynamics (in particular models of forces and moments experienced by the vehicle are usually affected by uncertainties), the influence on the weight estimation accuracy of modelling errors can be not negligible. Furthermore, stability issue can arise in the EKF due to linearization process for highly nonlinear system[14], such as rotorcraft. Apetre[15] combined a neural network with an EKF to create a hybrid algorithm that improves estimation while combating each method's individual issues. Zarovy and Costello also tried to overcome EKF limitations, by developing an extended state observer (ESO) algorithm[16]. It is a high-gain observer with an augmented state to estimate uncertainty in the system dynamics from any unknown source of error, such as model mismatch or external disturbances. A nice feature of the ESO is that it enables rigorous proof of observer stability for nonlinear systems. All the above listed techniques rely on dedicated sensors (weight on wheels force sensors) or huge amount of data for algorithm training (neural network) or detailed, although uncertain, model of vehicle dynamics (model-based observer).

The method proposed in this paper computes the weight by solving the vertical balance of external forces acting on the vehicle, that is, weight, aerodynamics and thrust, when the vehicle is trimmed in straight and level flight. Indeed, as well as other aircraft, vertical take-off and landing (VTOL) aircraft spend most of flight time in this condition. Considering that gross weight generally varies slowly with respect to vehicle dynamics, the estimation of gross weight only during trimmed straight and level flight phases guarantees the availability of an accurate estimation for almost the whole mission, while allowing a dramatic simplification of the estimation algorithm without significantly affecting its generality. In fact, in this flight condition the balance equation only includes very simple models of the external forces with few uncertain parameters that depend on the aerodynamic and thrust vehicle's characteristics. The key innovative idea of the proposed method is the exploitation of system identification to estimate the model unknown parameters by analyzing flight test data gathered during dedicated calibration flights, in which the vehicle's weight is known. The calibration shall be performed just once, before the weight estimation algorithm becomes operative. It allows tuning the parameters of the algorithm, which can be considered as a virtual sensor. The coupling of a simplified model, applicable in the selected flight condition, and of experimental calibration of estimation algorithm's parameters enables to reduce significantly the weight estimation error. Moreover, the proposed approach does not require any a priori knowledge about external forces modelling, except for model structure, neither huge dataset for algorithm training. The evaluation of balance equation for the selected model structure in trimmed straight and level flight condition only requires few variables (CAS, nacelle angle, vehicle attitude, collective and cyclic command), provided by standard on-board sensors, thus dedicated sensors (such as weight on wheels force sensors) are not needed. Finally, the algorithm estimates the weight by solving in closed form a static analytical equation; therefore, algorithm stability is not an issue, also in case the weight changes abruptly due to loads drop. Proposed methodology has been validated in simulation by employing the FlightLab ERICA tiltrotor detailed model[17], integrated with sensors error models, for flight data generation. Estimation results presented in the paper are very promising and highlight robustness to measurement errors.

The paper is structured as follows. First, the models exploited for weight estimation are introduced. Next, the estimation methodology is defined, including the description of the calibration algorithm and procedure. Then, the simulation environment, used for simulated flight data generation, and the scenario for the assessment of weight estimation method's performance are presented. Finally, the estimation results are shown and discussed. A section of conclusions ends the paper.

2. MODELS FOR WEIGHT ESTIMATION

A VTOL aircraft combines the functionality of a conventional helicopter with the range and cruise speed performance of an aircraft. Consequently, the helicopter configuration usually is engaged for take-off, landing and when hover or low speed regime is required, whereas aircraft configuration works during cruise. The vehicle is trimmed in straight and level flight (whatever its configuration is) if all the following conditions hold:

c1. null acceleration (translational balance),

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c2. null roll angle (level wings),
c3. null vertical speed (constant altitude),
c4. constant wind.

Previous conditions also imply constant Calibrated Air Speed (V_C) and pitch angle. Moreover, the following hypothesis is assumed, which is verified by checking that the difference between pitch angle and angle of attack is equal to zero:

c5. null vertical wind.

The vertical forces balance equation is:

(1) $W = A_V + T_V$

where *W* is the vehicle's weight, A_V is the vertical component of aerodynamic force, and T_V is the vertical component of thrust force. The right-hand side of the above equation shall be made explicit in order to solve with respect to the weight. Therefore, the first step is the definition of the models of the external forces.

When all conditions c1 through c5 hold, the vertical component of the aerodynamic force coincides with the aerodynamic lift, denoted by *L*; furthermore, the angle of attack can be replaced by the pitch angle, whose measurement is deemed more reliable. A classical affine model is used for the aerodynamic lift[18], with null dynamic contributions (related to pitch rate and angle of attack derivative) due to the trim condition. The aerodynamic model is described by the following equations:

(2) $A_V = L = \frac{1}{2}\rho_0 V_C^2 S C_L(V_C^2)$

(3) $C_L(V_C) = C_{L0}(V_C) + C_{L\alpha}(V_C)\alpha + C_{L\delta}(V_C)\delta_e$

where ρ_0 is the air density at sea level, *S* is the aerodynamic reference surface, C_L is the aerodynamic lift coefficient, $C_{L0}, C_{L\alpha}, C_{L\delta}$ are the lift coefficient derivatives, α is the vehicle's angle of attack, and δ_e is the deflection of the aerodynamic longitudinal control surfaces.

To generalize the formulation, the values of aerodynamic derivatives are scheduled with respect to the CAS (V_C). It allows considering that each derivative has a different value when the vehicle is in aircraft (medium and high speed) or in helicopter (low speed) configuration. Moreover, when the VTOL is in helicopter configuration, the effective value of these coefficients could also vary with respect to the CAS, due to the effect of the rotor wake on the air flow around the wing.

In trim condition, the deflection of the aerodynamic longitudinal control surfaces is strongly correlated to angle of attack, that is:

(4) $C_{L\alpha}\alpha + C_{L\delta}\delta_e = C_{L\alpha}\alpha + C_{L\delta}k_\alpha\alpha = C'_{L\alpha}\alpha$

where $C'_{L\alpha}$ and k_α are an equivalent derivative and the correlation gain between δ_e and α, respectively. In the above relation, the dependency on the CAS of the derivatives is not shown, for simplicity. The model of the vertical aerodynamic force is obtained substituting Eq. (3) and Eq. (4) into Eq. (2), replacing the angle of attack with the pitch angle, and grouping the constant parameters:

(5) $\mathrm{A_V} = V_C^2[\mathrm{k_{L0}}(V_C) + \mathrm{k_{L\alpha}}(V_C)\vartheta]$

(6) $\mathrm{k_{L0}}(V_C) = \frac{1}{2}\rho_0 \mathrm{S C_{L0}}(V_C)$

(7) $\mathrm{k_{L\alpha}}(V_C) = \frac{1}{2}\rho_0 S C'_{L\alpha}(V_C)$

where ϑ is the vehicle's pitch angle, and $k_{L0}, k_{L\alpha}$ are the aerodynamic model parameters.

The applied thrust model is[19]

(8) $T = \frac{1}{2}\rho_0 \sigma\pi R^2(\omega_R R)^2 C_t$

where σ is the solidity ratio, R and ω_R are the rotor radius and angular speed, and C_t is the thrust coefficient. Assuming constant rotor angular speed (this hypothesis only affects the estimation in helicopter configuration, as shown in the following sections), the only variable in Eq. (8) is the thrust coefficient, the model of which is assumed affine with respect to rotor collective command. The parameters of the affine relation, denoted as k_{Ct0} and k_{Ct1}, are scheduled with respect to the vehicle's CAS[20]

(9) $C_t = k_{Ct0}(V_C) + k_{Ct1}(V_C)\delta_{coll}$

where δ_{coll} is the collective command. The thrust vector direction is assumed orthogonal to the rotor tip path plane, whose longitudinal attitude in trim condition is proportional to the cyclic command. The term T_V in Eq. (1) can be computed substituting Eq. (9) into Eq. (8), grouping the constant parameters, and projecting the thrust vector along the local vertical:

(10) $T_V = [k_{T0}(V_C) + k_{T1}(V_C)\delta_{coll}] sin(\vartheta + \vartheta_N + + k_{cic}\delta_{cic})$

(11) $k_{T0}(V_C) = \frac{1}{2}\rho_0\sigma\pi R^2(\omega_R R)^2 k_{Ct0}(V_C)$

(12) $k_{T1}(V_C) = \frac{1}{2}\rho_0\sigma\pi R^2(\omega_R R)^2 k_{Ct1}(V_C)$

where k_{T0}, k_{T1} are the thrust model parameters, ϑ_N is the nacelle angle, k_{cic} is the proportional gain between rotor cyclic command and rotor tip path plane longitudinal attitude, and δ_{cic} is the rotor cyclic command.

The explicit form of the vertical balance equation in trimmed straight and level flight is finally obtained by replacing Eq. (5) and Eq. (10) into Eq. (1):

(13) $W = V_C^2[k_{L0}(V_C) + k_{L\alpha}(V_C)\vartheta] + [k_{T0}(V_C) + + k_{T1}(V_C)\delta_{coll}] sin(\vartheta + \vartheta_N + k_{cic}\delta_{cic})$

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Equation (13) is rearranged in different forms, depending on the vehicle configuration (helicopter or aircraft), as described in the following subsections.

2.1. Helicopter Model

In helicopter configuration, the previous equation can be rewritten as follows

(14) $W = V_C^2[k_{L0}(V_C) + k_{L\alpha}(V_C)\vartheta] + sin(\vartheta + +\vartheta_N + k_{cic}\delta_{cic})[k_{T0}(V_C) + k_{T1}(V_C)\delta_{coll}]$

The nacelle angle is close to 90 degrees and the equation is applied at low CAS value. For the sake of simplicity, it is assumed that in trim condition at low speed, the variation of the argument of the sine in Eq. (14) due to the variation of vehicle weight is small; hence, the following equation holds:

(15) $sin(\vartheta + \vartheta_N + k_{cic}\delta_{cic}) = sin\overline{\Theta} \cong constant$

Consequently, for a given constant $V_C = \overline{V_C}$, the whole term in square brackets on the right-hand side of Eq. (14) is constant. This equation can be rearranged and evaluated at minimum vehicle's weight and at a generic weight. The measurements at minimum weight are denoted by the subscript *m*, whereas the measurements at a generic weight have the subscript *i*.

(16) $W_m = \left[\overline{V_C}^2 k_{L0}(\overline{V_C}) + k_{T0}(\overline{V_C})sin\overline{\Theta}\right] + +\overline{V_C}^2 k_{L\alpha}(\overline{V_C})\vartheta_m(\overline{V_C}) + k_{T1}(\overline{V_C})\delta_{coll_m}(\overline{V_C})\sin\overline{\Theta}$

(17) $W_i = \left[\overline{V_C}^2 k_{L0}(\overline{V_C}) + k_{T0}(\overline{V_C})sin\overline{\Theta}\right] + +\overline{V_C}^2 k_{L\alpha}(\overline{V_C})\vartheta_i + k_{T1}(\overline{V_C})\delta_{coll_i}\sin\overline{\Theta}$

In Eq. (16) ϑ_m and δ_{coll_m} depend on V_C, because, for a given minimum weight, the attitude and command in trim condition depend on the current speed. Subtracting Eq. (16) to Eq. (17) and rearranging, we get the following equation, which is applicable to weight estimation in helicopter configuration at fixed $CAS = \overline{CAS}$:

(18) $W_i = W_m + \overline{V_C}^2 k_{L\alpha}(\overline{V_C})(\vartheta_i - \vartheta_m(\overline{V_C})) + +k_{T\delta}(\overline{V_C})\left(\delta_{coll_i} - \delta_{coll_m}(\overline{V_C})\right)$

(19) $k_{T\delta} = k_{T1}(\overline{V_C})sin\bar{\Theta}$

In Eq. (18), ϑ_i and δ_{coll_i} are variable flight measurements whereas, for fixed CAS, all the other terms on the right-hand side are constant. It is worthy to note that Eq. (18) is a Taylor series truncated to first order of the weight function, which for constant CAS only depends on pitch angle and collective pitch. Since the introduced forces' models are affine, such first order approximation is exact. However, the affine models, as well as the introduced simplifying hypotheses on which they are based, are approximations, which affects the weight estimation accuracy.

2.2. Aircraft Model

When the vehicle is in trimmed straight and level flight condition and in aircraft configuration, the thrust is assumed horizontal or however with a negligible vertical component. Therefore, the thrust contribution in the Eq. (13) is cancelled. Moreover, based on the modelling assumption described in the previous section, the aerodynamic model parameters $k_{L0}, k_{L\alpha}$ are constant with respect to the CAS. Accordingly, Eq. (13) assumes the following simplified form:

(20) $W = V_C^2[k_{L0} + k_{L\alpha}\vartheta]$

For a given $V_C = \overline{V_C}$, Eq. (20) can be evaluated at generic, minimum and maximum weights. The measurements at generic weight have the subscript *i*, whereas the measurements at minimum and maximum weights are denoted by the subscript *m* and *M*, respectively:

(21) $W_i = \overline{V_C}^2[k_{L0} + k_{L\alpha}\vartheta_i]$
(22) $W_m = \overline{V_C}^2[k_{L0} + k_{L\alpha}\vartheta_m]$
(23) $W_M = \overline{V_C}^2[k_{L0} + k_{L\alpha}\vartheta_M]$

Next, Eq. (24) and Eq. (25) are obtained by subtracting Eq. (22) to Eq. (21) and Eq. (23) to Eq. (22), respectively:

(24) $W_i - W_m = \overline{V_C}^2 k_{L\alpha}(\vartheta_i - \vartheta_m)$
(25) $W_M - W_m = \overline{V_C}^2 k_{L\alpha}(\vartheta_M - \vartheta_m)$

Finally, computing $\overline{V_C}^2 \cdot k_{L\alpha}$ from Eq. (25), substituting into Eq. (24) and rearranging, the vehicle's weight is provided by the following equations:

(26) $W_i = W_m + k_W(W_M - W_m)$
(27) $k_W = (\vartheta_i - \vartheta_m)/\vartheta_M - \vartheta_m$

It is worthy to note that the pitch angle values at maximum and minimum weights ϑ_M and ϑ_m depend on the current value of the CAS. Indeed, Eq. (20) also highlights that for fixed weight, the trim pitch angle is an affine function of the reciprocal of square CAS.

(28) $\vartheta = \mathrm{s} \cdot \frac{1}{V_C{}^2} + \mathrm{i}$

The complete definition of this affine function only requires the knowledge of two parameters *s* and *i*, which depend on the considered fixed weight. The values of these parameters for maximum and minimum weights are estimated during the calibration.

3. WEIGHT ESTIMATION METHOD

The Eq. (18) and Eq. (26) provide two model formulations for helicopter and aircraft configurations, respectively; thus, two different weight estimation algorithms are used. The model's equations include some parameters, whose values shall be available in order to perform the weight estimation. As already said, these values are estimated by executing a calibration's flight campaign and applying to flight data the calibration algorithms that allow completely identifying the model. Indeed, the algorithms for weight estimation can be considered as a virtual sensor that, as well as any physical sensor, requires an experimental calibration to produce accurate measurements. Computed model equations are applicable in trimmed straight and level flight condition; therefore, the calibration of equations parameters shall be performed in the same flight condition. Since both weight estimation algorithm and parameters calibration work when the vehicle is trimmed in straight and level flight condition, an algorithm for the detection of such condition has been also defined. It is independent on vehicle configuration, runs continuously and enables the applicable algorithm when suitable conditions are satisfied.

Recapping, the proposed weight estimation method uses three different functionalities, implemented in dedicated algorithms:

- The first function, denoted as detection, continuously monitors the flight measurements and detects if the trim condition is satisfied; in such case, it enables the applicable (calibration or weight estimation) algorithm. This function also identifies the current vehicle configuration (helicopter or aircraft).
- The second function, denoted as calibration, computes the value of the model parameters by using flight measurements gathered in suitable flight tests. Since two different model formulations have been defined for helicopter and aircraft configurations, two different calibration algorithms are applied. The calibration is enabled by the detection function and is performed just once, before the weight estimation is operative.
- The third function, denoted as weight estimation, solves Eq. (13) to compute the vehicle's weight. Since Eq. (13) is rearranged in different forms for helicopter and aircraft configurations (due to different modelling of the relevant external forces), two different algorithms are applied to estimate the weight. This function is enabled by the detection function, which also selects the applicable estimation algorithm based on the identified configuration. The weight estimation can run only if calibration has already been completed.

Detection, calibration and weight estimation algorithms are described in details in the following subsections.

3.1. Detection Algorithm

The main aim of this algorithm is continuously monitoring the flight measurements, in order to

- Detect if the vehicle is in trimmed straight and level flight phase.
- Identify the current vehicle configuration (helicopter or aircraft).

The trimmed straight and level flight phase is detected if conditions c1 through c5 of previous section hold simultaneously and continuously for a sufficiently long time interval, denoted as ΔT. The value of ΔT shall be bigger than characteristic time of vehicle rigid body dynamics, in order to allow verifying if the current flight condition is stationary. On the other hand, it shall not be too long, in order to guarantee the pilot or the automatic control system is able to keep easily this stationary condition for the required time. In order to check if a flight measurement is constant (null or different from zero) during the timeframe ΔT, its linear approximation in ΔT is first computed:

(29) $\hat{Y} = bt + a$

where Y is a generic flight measurement, $\hat{Y}$ is the linear approximation of Y in ΔT, *t* denotes the time, *a* is the value of $\hat{Y}$ at *t* = 0, and *b* is the slope of the linear approximation of Y. The parameters *a* and *b* of Eq. (29) are estimated by using ordinary least square regression method, defined by the following relations[21]:

(30) $\mu_Y = \frac{1}{N}\sum_{i=1}^{N} Y_i$

(31) $\mu_t = \frac{1}{N}\sum_{i=1}^{N} t_i$

(32) $\sigma_Y^2 = \frac{1}{N}\sum_{i=1}^{N} Y_i^2 - \mu_Y^2$

(33) $\sigma_t^2 = \frac{1}{N}\sum_{i=1}^{N} t_i^2 - \mu_t^2$

(34) $b = \frac{1/_N \cdot \sum_{i=1}^{N}(t_i \cdot Y_i) - \mu_t \cdot \mu_Y}{\sigma_t^2}$

(35) $a = \mu_Y - b \cdot \mu_t$

where t_i is the measurement sampling time instant, Y_i is the measurement of Y at time t_i, N is the number of measurements of Y in ΔT, μ_Y and μ_t are the means of Y_i and t_i computed in the time frame ΔT, σ_Y and σ_t are the standard deviations of Y_i and t_i computed in

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the time frame ΔT. Y is constant in the time-frame ΔT if the variance of its measurements is small and the slope of its linear approximation is null, that is, the following relations are simultaneously satisfied:

(36) $\sigma_Y < thres1$
(37) $b < thres2$

where *thres1* and *thres2* are suitable thresholds, close to zero. Hence, the trimmed straight and level flight phase is detected if relations (36) and (37) hold for the measurements of acceleration, roll angle, vertical speed, CAS, pitch angle, and the difference between angle of attack and pitch angle.
The current vehicle configuration is identified by analysing the measurement of rotors nacelle angle. If the nacelle angle is below a positive threshold close to zero degrees continuously for ΔT, then the vehicle is in aircraft configuration; otherwise if the nacelle angle is above a threshold close but lower than 90 degrees continuously for ΔT then the vehicle is in helicopter configuration. In all other cases, the vehicle is transiting from helicopter to aircraft configuration or vice versa.
When both trimmed straight and level flight phase is detected and one configuration is identified, this algorithm selects and enables the applicable estimation algorithm.
Finally, the algorithm also filters the flight measurements to reduce the noise. Indeed, it computes the mean value of each variable on a sliding window, whose time duration is equal to ΔT. These mean values are then provided as input to the applicable estimation algorithm.

3.2. Calibration Algorithms

Two different calibration procedures and algorithms are applicable to helicopter and aircraft. However, it is worthy to note that calibration data can be acquired in the same flight test for both configurations, simply changing the configuration during the test.

3.2.1. Calibration in Helicopter Configuration

The calibration procedure in helicopter configuration requires the execution of at least three flight tests. In each test:

- the helicopter shall have a different and known calibration weight (minimum weight, maximum weight, and one or more intermediate weights);
- the vehicle shall fly in steady trimmed straight and level flight condition for a pre-defined time frame, at least at four different prefixed values of the CAS (set points);
- the measurements of CAS, pitch angle, and collective command shall be gathered.

Three set points are needed for calibration while one set point (verification point) is required for verification of the calibration result. The same set points shall be acquired for all the flight tests (that is, for all the calibration weights). Before executing the flight tests, the vehicle weights shall be measured. After the acquisition of all the set points in the different flight tests, the calibration algorithm analyses the data to compute all the parameters included in the weight estimation equation. The parameter W_m in Eq. (18) is set equal to the minimum weight used in calibration. In order to compute the other parameters, the algorithm repeats the same steps for each set point (different value of the CAS). First, the parameters ϑ_m and δ_{coll_m} are fixed equal to the mean values of pitch angle and collective command measured during trimmed straight and level flight condition at minimum weight. These mean values, provided by the detection algorithm, assume different values for different CAS. Next, Eq. (18) is evaluated for maximum weight and for all the available (at least one) intermediate weights, also using the already computed values of W_m, ϑ_m and δ_{coll_m}. Two or more equations are obtained, which include only two unknowns (because calibration weights are measured): the parameters $k_{L\alpha}$ and $k_{T\delta}$. Mean square technique is used to solve these equations and to estimate the model parameters, which assume different values for different CAS:

(38) $$\begin{bmatrix} k_{L\alpha}(\overline{V_C}) \\ k_{T\delta}(\overline{V_C}) \end{bmatrix} = (A(\overline{V_C})^T A(\overline{V_C}))^{-1} A(\overline{V_C})^T \Delta W$$

In Eq. (38), the apexes *T* and *-1* denote the matrix transpose and inverse, respectively. The matrices *A* and ΔW are defined by Eq. (39) and Eq. (40). They include the filtered flight measurements in trim straight and level flight condition, provided by the detection algorithm. The measurements gathered at maximum weight is denoted by the subscript *M*, whereas the ones acquired at intermediate weights are identified by the subscript *j=1…k (k=1* in case only one intermediate calibration weight is gathered).

(39) $$A(\overline{V_C}) = \begin{bmatrix} \overline{V_C}^2(\vartheta_1 - \vartheta_m(\overline{V_C})) & \left(\delta_{coll_1} - \delta_{coll_m}(\overline{V_C})\right) \\ \cdots & \cdots \\ \overline{V_C}^2(\vartheta_k - \vartheta_m(\overline{V_C})) & \left(\delta_{coll_k} - \delta_{coll_m}(\overline{V_C})\right) \\ \overline{V_C}^2(\vartheta_M - \vartheta_m(\overline{V_C})) & \left(\delta_{coll_M} - \delta_{coll_m}(\overline{V_C})\right) \end{bmatrix}$$

(40) $$\Delta W = \begin{bmatrix} W_1 - W_m \\ \cdots \\ W_k - W_m \\ W_M - W_m \end{bmatrix}$$

After the computation of all the parameters, a calibration look-up table is built for each of them. The table requires as input the value of the current CAS

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and provides as output the correspondent value of the estimated parameters ϑ_m, δ_{coll_m}, $k_{L\alpha}$ and $k_{T\delta}$. Concerning $k_{L\alpha}$, since the aerodynamic lift is null when air speed is null, and in order to avoid numerical error that can affect the calibration result, the value of the parameter is set to zero in hover condition, whatever the result of the calibration is.

The verification of the correct execution of the calibration is carried out by using flight data of a further set point, the verification point, which is not exploited for the parameters' estimation. Indeed, for all the available calibration weights (which are known), the weight estimation algorithm (described in the next section) is performed in the verification set point. The estimated weights are compared to the known weights: if the estimation error is below a pre-fixed threshold for all the calibration weights, then the calibration is confirmed; otherwise, it shall be executed again.

The minimum number of acquisition points (set points number multiplied for flight tests number) is twelve. Since each acquisition lasts few tens of seconds, and considering manoeuvring time to reach each set point and to stabilize the vehicle, the total minimum flight test time for helicopter calibration campaign is less than half an hour. The number of tests (different calibration weights) and set points (different CAS) can increase to improve the weight estimation accuracy. Indeed, the tuning of the weight estimation algorithm is performed only in the set points, whereas between the set points a linear interpolation of the algorithm parameters is applied. The linear interpolation introduces an approximation error, which decreases by making denser the set points matrix. In the same way, increasing the number of flight tests, that is the number of calibration weights, allows collecting a bigger number of equations for the computation of the model parameters and consequently, the error on the estimation of the calibration parameters is minimized in more points of the weight range variation. Concerning the selection of CAS value for the set points, it is worthy to recall that the CAS shall vary from hover condition (null speed) to a maximum value that still guarantees the validity of hypothesis defined by Eq. (15), that is, few tens of knots. When in operation, the weight estimation in helicopter configuration shall be performed within the same CAS envelope. As already discussed, this envelope limitation does not affect significantly the applicability of the weight estimation algorithm, due to typical VTOL operations.

3.2.2. Calibration in Aircraft Configuration

The calibration procedure in aircraft configuration requires the execution of two flight tests. In each test:

- the aircraft shall have a different and known calibration weight (minimum weight W_m and maximum weight W_M);
- the vehicle shall fly in steady trimmed straight and level flight condition for a pre-defined time frame, at three different prefixed values of the CAS (set points);
- the measurements of CAS and pitch angle shall be gathered.

It is worthy to remark again that the calibration weights for aircraft calibration coincide with two of the weights used for helicopter calibration; therefore, for each weight the same flight test could include both calibrations. The same set points shall be acquired for both the flight tests. Calibration needs two set points, whereas one set point (verification point) is required for verification. The calibration set points shall be close to the flight envelope limits in aircraft configuration, that is, maximum CAS (denoted by V_{CM}) and minimum CAS (denoted by V_{Cm}). The verification point can be selected anywhere between the other two calibration set points.

Figure 1 shows the pitch angle as function of CAS, defined by Eq. (28), for minimum and maximum weights.

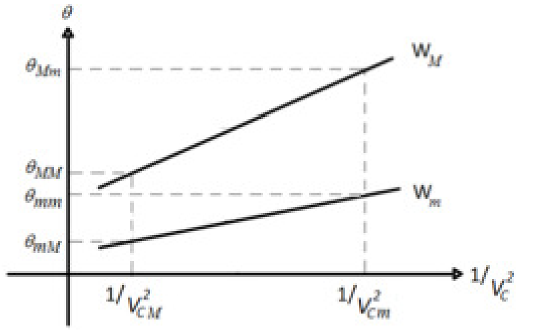

Figure 1. Pitch angle as function of reciprocal of square CAS for minimum and maximum weight

The calibration algorithm computes the slope and the intercept of these curves through the following relations, which only require the knowledge of two set points $(1/V_C^2, \vartheta)$ for each value of the weight.

(41) $s_{\mathrm{m}} = (\vartheta_{\mathrm{mM}} - \vartheta_{\mathrm{mm}})/(1/V_{\mathrm{Cm}}^2 - 1/V_{\mathrm{CM}}^2)$

(42) $i_{\mathrm{m}} = -(\vartheta_{\mathrm{mM}} - \vartheta_{\mathrm{mm}})/(V_{\mathrm{CM}}^2/V_{\mathrm{Cm}}^2 - 1) + \vartheta_{\mathrm{mm}}$

(43) $s_{\mathrm{M}} = (\vartheta_{\mathrm{MM}} - \vartheta_{\mathrm{Mm}})/(1/V_{\mathrm{Cm}}^2 - 1/V_{\mathrm{CM}}^2)$

(44) $i_{\mathrm{M}} = -(\vartheta_{\mathrm{MM}} - \vartheta_{\mathrm{Mm}})/(V_{\mathrm{CM}}^2/V_{\mathrm{Cm}}^2 - 1) + \vartheta_{\mathrm{Mm}}$

where ϑ_{mm}, ϑ_{mM}, ϑ_{Mm}, ϑ_{MM} are the pitch angles at minimum CAS and minimum weight, maximum CAS and minimum weight, minimum CAS and maximum weight, maximum CAS and maximum weight, respectively; s_m and s_M are the slopes of the curve at minimum and maximum weight, respectively; i_m and i_M are the intercepts of the curve at minimum and maximum weight, respectively. All the above pitch

Presented at 46th European Rotorcraft Forum, Moscow, Russia, 8-11 September, 2020

angles are mean values of the measurements gathered in the trim points, and provided by the detection algorithm. The parameters W_m, W_M, s_m, i_m, s_M, i_M, represent the output of the aircraft calibration. The verification of the correct execution of the calibration requires the application of weight estimation algorithm (described in the next section) to the data gathered in the verification set point and the comparison of estimated weights with known calibration weights. If the estimation error is below a pre-fixed threshold for both maximum and minimum weight, then the calibration is confirmed; otherwise, it shall be executed again.
The minimum number of acquisition points (set points number multiplied for flight tests number) is six, which is one half with respect to helicopter calibration. Consequently, the flight time for the aircraft calibration is about half the flight time for helicopter calibration.

4. WEIGHT ESTIMATION ALGORITHMS

During operations, after completion of the calibration, the weight estimation uses very simple relations, described in the following subsections for the helicopter (HC) and aircraft (AC) configurations.

4.1. Weight Estimation in HC Configuration

When the detection algorithm detects the trimmed straight and level flight condition and the helicopter configuration, it enables the helicopter weight estimation algorithm. The algorithm requires as input the mean values of CAS, pitch angle and collective command, computed by the detection algorithm by processing the flight measurement gathered in the last ΔT seconds. It also needs the calibration parameters. The algorithm executes the following steps:

- Check if the current measurement of mean value of the CAS is within the CAS range analysed during the helicopter calibration, in affirmative case, execute the estimation.
- Use the current mean value of the CAS to query the calibration look up tables in order to get the applicable values of the calibration parameters ϑ_m, δ_{coll_m}, $k_{L\alpha}$ and $k_{T\delta}$.
- Use the current mean value of CAS, pitch angle and collective command, and the calibration parameters to evaluate Eq. (18) and to compute the weight estimation.

Finally, computed weight is saturated between vehicle's empty weight and maximum take-off weight values, reported on the flight manual.

4.2. Weight Estimation in AC Configuration

When the detection algorithm detects the trimmed straight and level flight condition and the aircraft configuration, it enables the aircraft weight estimation algorithm. The algorithm requires as input the mean values of CAS and pitch angle, computed by the detection algorithm by processing the flight measurement gathered in the last ΔT seconds. It also needs the calibration parameters. The algorithm exploits the affine dependence of vehicle's weight with respect to the pitch angle and executes the following steps:

- Use Eq. (28) and calibration parameters s_m, i_m, s_M, i_M to compute the pitch angles for trimmed straight and level flight condition at minimum weight W_m and maximum weight W_M corresponding to the current mean value of the CAS, denoted by ϑ_m and ϑ_M, respectively.
- Use Eq. (27) and the values of ϑ_m and ϑ_M to compute the weight gain k_W corresponding to the current mean value of the pitch angle.
- Use Eq. (26) and calibration parameters W_m and W_M, to compute the weight estimation.

Finally, the weight estimation is saturated between vehicle's empty weight and maximum take-off weight values available on the vehicle's flight manual.

5. SIMULATED FLIGHT DATA GENERATION

To assess the performance of the proposed method, weight estimation was applied to simulated flight data of the ERICA (Enhanced Rotorcraft Innovative Achievement) tiltrotor concept, shown in Figure 2, and developed in the framework of the European NICETRIP project (Novel Innovative Competitive Effective Tilt Rotor Integrated Project)[17]. It is a 10-tonnes tiltrotor (medium large size), for transportation purposes, which covers a wide flight envelope, from hovering over low-speed helicopter condition to high-speed airplane mode. The aircraft has a total length, including the empennage, of 18.845 m and a wing span of 14 m. The distance between the rotor axes of revolution is equal to 15 m. The two rotors are four-bladed and have a diameter of 3.7 m each. Unconventional features are tiltable outer wings and a small rotor diameter. Within NICETRIP, a detailed high-fidelity simulation model of ERICA was developed in FlightLab environment[22], which is the leading commercial software tool for rotorcraft modelling and analysis. The choice of such a comprehensive tool allows providing accurate aeromechanic results for a large number of experiments in a reasonable CPU time.

Presented at 46th European Rotorcraft Forum, Moscow, Russia, 8-11 September, 2020

Figure 2. ERICA concept[23]

The ERICA model version used in this paper requires as control inputs the reference signals to the autopilot. Indeed, the model includes a complete flight control software, to emulate autopilot (with speed and altitude control), automatic nacelle control system, rotor actuation command control, and power management control. The rotors blades are supposed to be rigid with gimbal articulation. The detailed aerodynamic model has been derived through CFD analysis and comprehends the rotor-induced flow dynamics, evaluated by using a finite state wake model[24] with 33 state variables and 4 inflow harmonics. The inertial and air data sensors model is also included, which adds noise to the true flight measurements:

(45) $y_m = y_t + b + \eta$

where y_m is the measured variable, y_t is the true variable, b is the stochastic bias, and η is the zero mean white Gaussian noise. The bias is constant along a whole simulation but its value differs from one simulation to the other. In each simulation, the bias realization is computed through a stochastic draw from a zero mean Gaussian distribution. The standard deviations of white noise and bias distribution are derived from typical COTS sensors, and are listed in Table 1. The proposed method also needs the knowledge of the vehicle weight when calibration is performed. Its measurement is assumed to be affected by zero mean white Gaussian noise, whose standard deviation is set equal to 50 Kg.

Table 1. Measurements noise characterization

Signal	White Gaussian Noise Standard	Stochastic Bias Standard Deviation
CAS [Kn]	2	0.4
Pitch angle [deg]	0.5	0.1
Angle of attack [deg]	0.5	0.1
Roll attack [deg]	0.5	0.1
Vertical speed [ft/min]	50	10
Acceleration [m/s^2]	0.05	0.01
Nacelle attack [deg]	0.5	0.1
Cyclic command [deg]	0.25	0.06
Collective command [deg]	0.125	0.03

6. WEIGHT ESTIMATION RESULTS

The ERICA model is used to generate simulated flight data for the performance assessment of the proposed weight estimation method. To this aim, 55 simulations are produced, which differ for vehicle's configuration, weight and airspeed. Five different weight values are considered for both configurations, regularly spaced between allowable maximum and minimum vehicle weights. Each simulation lasts about 60 seconds and includes at least 10 seconds of steady trimmed straight and level flight condition. Flight measurements are sampled at 25 Hz. Table 2 and Table 3 list the flight tests executed in helicopter configuration and aircraft configuration, respectively.

Table 2. Flight tests in helicopter configuration

Test N°	CAS [Kn]	Weight [Kg]	Test N°	CAS [Kn]	Weight [Kg]
1	0	8506.9	16	10	10008
2	3	8506.9	17	12	10008
3	5	8506.9	18	15	10008
4	10	8506.9	19	0	10758.8
5	12	8506.9	20	3	10758.8
6	15	8506.9	21	5	10758.8
7	0	9257.4	22	10	10758.8
8	3	9257.4	23	12	10758.8
9	5	9257.4	24	15	10758.8
10	10	9257.4	25	0	11509
11	12	9257.4	26	3	11509
12	15	9257.4	27	5	11509
13	0	10008	28	10	11509
14	3	10008	29	12	11509
15	5	10008	30	15	11509

Table 3. Flight tests in aircraft configuration

Test N°	CAS [Kn]	Weight [Kg]	Test N°	CAS [Kn]	Weight [Kg]
31	140	8506.9	44	200	10008
32	160	8506.9	45	220	10008
33	180	8506.9	46	140	10758.8
34	200	8506.9	47	160	10758.8
35	220	8506.9	48	180	10758.8
36	140	9257.4	49	200	10758.8
37	160	9257.4	50	220	10758.8
38	180	9257.4	51	140	11509.0
39	200	9257.4	52	160	11509.0
40	220	9257.4	53	180	11509.0
41	140	10008	54	200	11509.0
42	160	10008	55	220	11509.0
43	180	10008			

Presented at 46th European Rotorcraft Forum, Moscow, Russia, 8-11 September, 2020

Tests number 1, 4, 6, 13, 16, 18, 25, 28, 30 provide set points data for calibration in helicopter configuration. Calibration verification is performed analysing flight data of tests number 3, 15, 27. All the other tests are employed for performing helicopter weight estimation. It is worthy to note that the considered CAS envelope, limited at 15 knots, could be enlarged if more calibration set points are used. In aircraft configuration, tests number 31, 35, 51, 55 are selected for calibration, because they are placed in the vertices of the considered flight envelope in the CAS-weight plane. Calibration also exploits the data of flight tests number 33, 53, used as verification points. Aircraft weight estimation is carried out analysing the remaining tests.
The time frame ΔT applied within the detection algorithm for calibration and estimation in both configurations is set equal to 5 seconds. The calibration verification is performed allowing a maximum estimation error equal to 5% of the current calibration weight. Three different analyses are executed to assess the estimation method performance.

6.1. Clean Flight Data

This analysis aims at evaluating the error due to modelling assumptions on which the proposed estimation method is based. The flight data used for both calibration and estimation are clean, that is, they are not affected by measurement noise neither by constant bias. Moreover, the calibration weights are assumed exactly known. The calibration results are listed in Table 4 and Table 5. Table 4 highlights that helicopter parameters depend on CAS in nonlinear form, confirming the need for scheduling with respect to the air speed. It is worthy to note that, being the structure of the model used for data generation completely different from the simplified one applied for weight estimation, it is impossible to define true values for the calibration parameters to be compared with the calibration results for validation purpose. Figure 3 and Figure 4 show the estimation errors for helicopter and aircraft configurations, respectively.

Table 4. Calibration results for helicopter configuration (clean flight data)

Calibration parameters	***Estimated value***		
	CAS = 0 Kn	CAS = 10 Kn	CAS = 15 Kn
W_m [Kg]	8506.9	8506.9	8506.9
ϑ_m [deg]	1.4	-2.0	-3.0
δ_{coll_m}[deg]	13.5	13.2	12.8
$k_{L\alpha}$[Kg/deg]	0	-13.0	-2.9
$k_{T\delta}$ [Kg/deg]	936.6	1293.5	1118.8

Table 5. Calibration results for aircraft configuration (clean flight data)

Calibration parameters	***Estimated value***
W_m [Kg]	8506.9
W_M [Kg]	11509
s_m [deg/kn^2]	1.39 x 10^5
i_m [deg]	-5.3
s_M [deg/kn^2]	1.94 x 10^5
i_M [deg]	-5.5

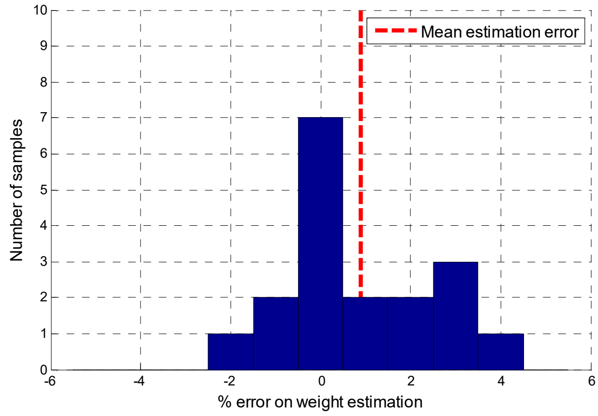

Figure 3. Weight estimation error in percentage of true weight (helicopter configuration, clean flight data)

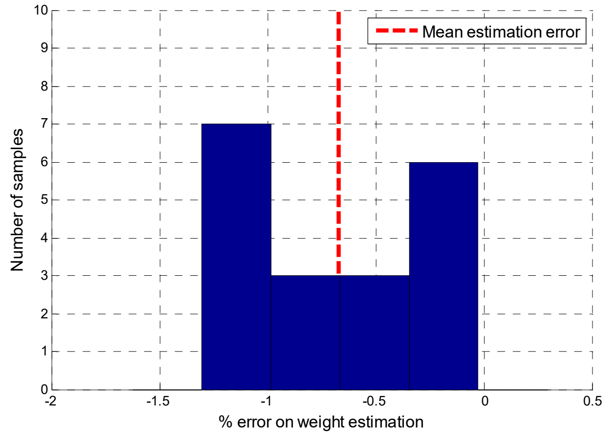

Figure 4. Weight estimation error in percentage of true weight (aircraft configuration, clean flight data)

The modelling assumptions introduce a small but not negligible weight estimation error, which is more evident for the helicopter case due to the higher complexity of the related actual model. For helicopter, mean and maximum errors are equal to 0.88% and 4.4% of the true weight, respectively. The maximum error corresponds to test number 21 that, among the processed tests, is one of the farther from the calibration set points in the CAS-weight plane. A denser set points matrix could improve these results. Mean and maximum estimation errors for aircraft configuration are -0.67% and -1.29% of the true weight, respectively (negative error means

Presented at 46th European Rotorcraft Forum, Moscow, Russia, 8-11 September, 2020

underestimated weight). It is worthy to remark that, due to the limited number of tests performed, the results in both the figures are not fully representative of the actual statistical distribution of the weight estimation errors.

6.2. Flight Data Affected by Zero Mean Noise

This analysis considers the effect of zero mean white Gaussian noise, in order to evaluate robustness to measurement errors of the proposed estimation method. Measurement biases are set to zero. For each configuration, two Monte Carlo analyses are carried out: one is applied to the calibration and the other to estimation of the weight. In each Monte Carlo the flight conditions listed in Table 3 and Table 4 are simulated several times applying different realizations of the flight data measurement noise. Concerning calibration, the known value of calibration weight is supposed affected by a zero mean stochastic error, which has a different realization each time the calibration is repeated. In total, 1000 runs are considered. Regarding weight estimation, 750 runs are executed. In each run, in addition to the different realizations of the flight data measurement noise, a different set of calibration parameters is randomly selected among the ones obtained performing the calibration Monte Carlo.
In helicopter configuration, 258 calibrations on 1000 trials passes the verification check, whereas the other are rejected (25.8% success rate). This result is influenced by the implemented control system performance, which is not able to hold the target set points for the required time frame. It is worthy to remark that when it happens, the detection algorithm instantly reports the warning requiring to acquire again only the missed set point without repeating the whole calibration procedure. Instead, the procedure shall be completely repeated if the set points are correctly gathered and calibration parameters computed, but the verification of the calibration fails. Besides optimizing the vehicle's control system, the calibration success rate could also be improved by relaxing the thresholds of the detection algorithm (see Eq. (34) and Eq. (35)) and/or the threshold of the calibration algorithm on allowable weight estimation error during calibration verification. But these solutions imply a degradation of weight estimation accuracy.
Weight estimation results are shown in Figure 5. Mean and standard deviation of the estimation error are 0.44% and 1.67% of true weight, respectively.

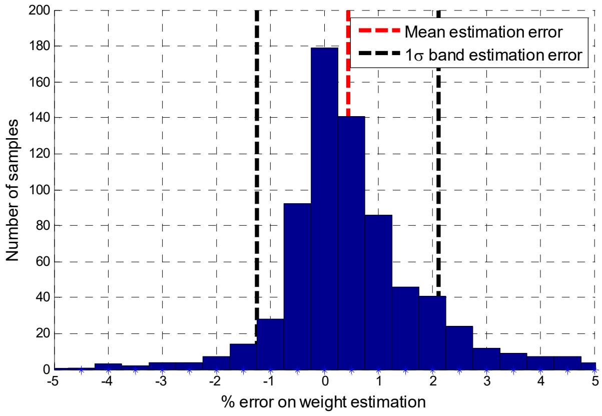

Figure 5. Weight estimation error in percentage of true weight (helicopter configuration, flight data affected by zero mean noise)

Success rate for aircraft configuration calibration is 80.7% (807 calibration accepted on 1000 trials). This better result with respect to helicopter configuration depends on the higher stability of the vehicle at higher speed and the minor number of set points to be acquired in aircraft configuration. Figure 6 presents weight estimation output. Mean and standard deviation of the estimation error are -0.73% and 1.08% of true weight, respectively. Obtained results are excellent, with error almost always below 3% of true weight.

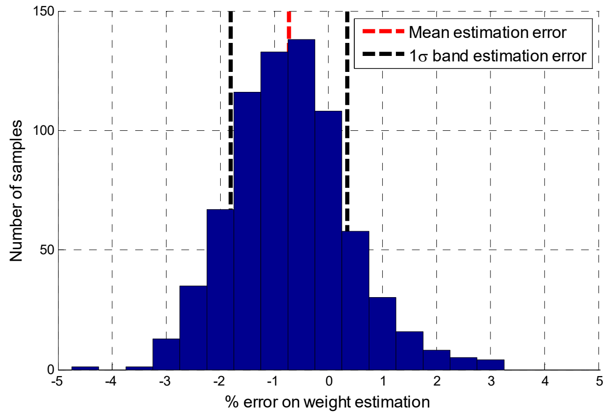

Figure 6. Weight estimation error in percentage of true weight (aircraft configuration, flight data affected by zero mean noise)

Globally, these results are very close to the one obtained from clean flight data, confirming the robustness of the algorithm with respect to zero mean measurement noise. The modelling assumptions are still the main source of the small estimation error.

6.3. Flight Data Affected by Bias and Zero Mean

Presented at 46th European Rotorcraft Forum, Moscow, Russia, 8-11 September, 2020

Noise

This analysis considers the effect of zero mean white Gaussian noise and stochastic constant bias on all the flight data. The Monte Carlo analyses described in the previous section are applied to this case, too. The only difference is constituted by the different sensors model adopted. Calibration success rates for helicopter and aircraft configurations are 25.1% and 74.4%, respectively. They are in line with the results of previous Monte Carlo analyses, and same considerations as above hold.
Figure 7 presents helicopter weight estimation results. Mean and standard deviation of the estimation error are 0.37% and 1.89% of true weight, respectively. Aircraft estimation results are shown in Figure 8. In this case, mean and standard deviation of the estimation error are -0.56% and 2.96% of true weight, respectively. The introduction of the biases produces a slightly increase of standard deviation (more relevant for aircraft configuration). The mean errors are in practice unchanged with respect to the analysis with null bias. They also keep the same sign, in all the presented analysis, probably due to the effect of some modelling assumptions adopted by the method. Overall, the obtained results are still very good, demonstrating robustness to measurement errors.

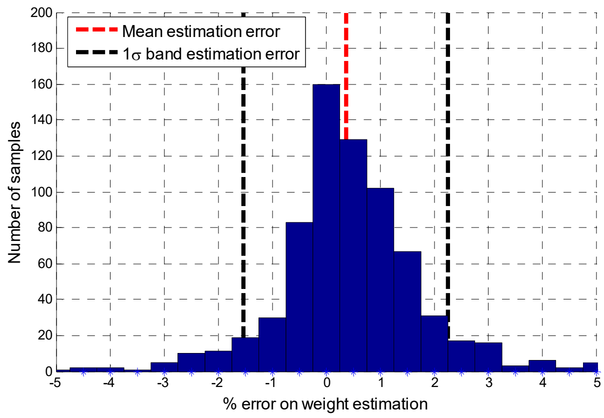

Figure 7. Weight estimation error in percentage of true weight (helicopter configuration, flight data affected by bias and zero mean noise)

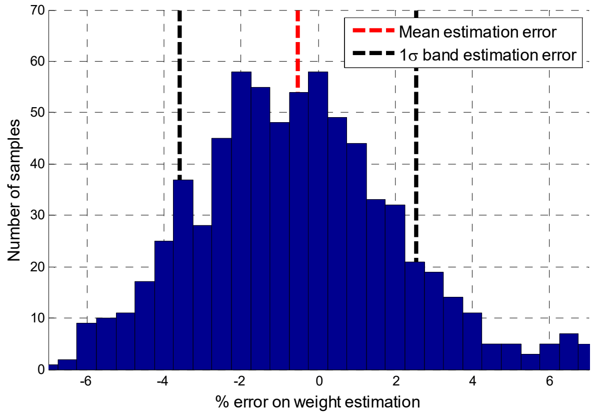

Figure 8. Weight estimation error in percentage of true weight (aircraft configuration, flight data affected by bias and zero mean noise)

7. CONCLUSIONS

A simple and effective method for real time estimation of the weight of VTOL aircraft has been presented. The proposed approach exploits calibration flights, in which the vehicle's weight measurement is known, to tune the estimation algorithm parameters. Indeed, the algorithms for weight estimation could be considered as a virtual sensor that, as well as any physical sensor, requires an experimental calibration to produce accurate measurements. During operations, the method estimates the weight by solving simple static relations, suitable for real time implementation. The application of the method to simulated flight data of a tiltrotor aircraft, generated by using a high-fidelity simulator developed in FlightLab environment, allowed to assess its performance.
Presented Monte Carlo analyses highlighted that mean estimation error is always below 1% of the true vehicle's weight and is robust to measurement errors, for both aircraft and helicopter configurations. The standard deviation of estimation error slightly degrades when measurement noise is introduced. However, it remains below 3% of true weight, also in the worst case, demonstrating robustness to sensors errors. The main source of the obtained small errors is related to the approximation derived by modelling assumptions on which the method is based. These errors could be probably significantly reduced by increasing the number of set points and calibration weights used during the calibration flight tests. All these topics will be subject of future investigations.
Overall, proposed method demonstrated very interesting results in terms of accuracy, precision and robustness to sensors errors. Its application during normal operations could produce significant benefits, such as improved maintenance systems, reduced operating costs, enhanced safety and reliability.

Presented at 46th European Rotorcraft Forum, Moscow, Russia, 8-11 September, 2020

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