Innovative Methods to Estimate Rotorcraft Gross Weight and Center of Gravity

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ABSTRACT

This paper presents the initial developments of a hybrid model for estimating a rotorcraft's Gross Weight (GW) and Center of Gravity (CG) which combines different models for different flight regimes in order to increase the accuracy of the estimates. The model will combine flight dynamics based models with data-driven models using a Kalman Filter (KF) – Neural Network (NN) framework.

A GW model based on the main rotor thrust during steady state motion is described. The operating condition of the rotor is determined by force and moment equilibrium of the entire helicopter, therefore the thrust values calculated from trim conditions can be used to estimate GW. A second model, described here and which will be incorporated in the hybrid approach, is based on NN. Data recorded by the Health and Usage Monitoring Systems (HUMS) onboard CH-53E rotorcraft is used in order to estimate GW at the first hover. Future developments are presented at the end of the paper.

INTRODUCTION

An accurate assessment of gross weight (GW) and center of gravity (CG) is critical for the determination of rotorcraft fatigue and life estimates since GW/CG affect static and dynamic characteristics of helicopters. Therefore GW and CG are valuable information in calculating reliable loads and remaining fatigue life. These in turn assist the condition based maintenance systems used to enhance safety and reduce the operating cost of helicopters. To capture GW/CG changes continuously throughout the flight, advanced methods are required as conventional methods are not sufficient and prone to errors.

This paper presents the initial developments of a hybrid model that will combine two knowledge sources: *expert* (physics-based, deterministic) and *learning from examples* (data-driven, stochastic). This hybrid model is needed to overcome the shortcomings and to take advantage of the strengths of two models presented in the literature: one is based on Neural Network (NN) [1-4] and the

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second one is based on Kalman Filter (KF) [5]. A KF approach provides accurate state estimation in the presence of noisy, biased or missing measurements due to fusion between the sensor data and physical system model [5]. At the same time KF is based on an analytical model which represents an idealization of rotorcraft dynamics, and total forces and moments need to be known in order to solve the differential system; consequently the influence of modeling error can be large. On the other hand, the NN-based approach is simple and straightforward and it has the freedom to identify and quantify the most significant parameters for prediction [1]. NN structure provides a multitude of efficient training algorithms for computing the parameters so as to best fit the training set. However, the accuracy the estimate depends on the availability and accuracy of the data and the network needs rigorous training, which is a time-consuming and laborious process. Furthermore, in order to include the rotorcrafts' degradation of performance over time, the NN needs to be retrained with large sets of data.

Therefore this paper investigates algorithms with the final goal of building a new model which will estimate GW/CG with a 1% - 2% accuracy. Since it is expected that different analytical models to be applied to different flight regimes, future work will combine all these modules in a compact application.

This paper is structured as follows: after this short introduction, two models used to calculate the helicopters' GW are presented: one is based on rotor thrust and one is based on NN. In the end an innovative, hybrid approach that combines NN and KF techniques is detailed and future work is given.

MODELS FOR GROSS WEIGHT ESTIMATION

Gross Weight Estimation Using Main Rotor Thrust

The operating condition of the rotor is determined by force and moment equilibrium of the entire helicopter. Consider force equilibrium for the helicopter in steady flight characterized by: rotor trust T and rotor drag H (which are defined relative to the referenced plane used), helicopter drag D (assumed in opposite direction to the free stream), velocity V and vertical weight W [6]. Referring to Figure 1, and resolving forces in the vertical direction:

$$W + D\sin(\tau_c) = T\cos(\theta - B_1) - H\sin(\theta - B_1) \qquad (1)$$

where θ is the angle between the vertical and shaft, positive nose up, B_1 is the amplitude of the longitudinal cyclic pitch and τ_c is the angle of climb. Since θ and B_1 are small angles, the above equation can be simplified to:

$$W + D\sin(\tau_c) = T \qquad (2)$$

which shows that the main thrust produced by the main rotor blades is used to balance the weight and to provide forward propulsive force which acts against aerodynamic drag. Given that $D\sin(\tau_c)$ is much smaller than W, it is finally obtained:

$$W = T \qquad (3)$$

Therefore, as a first approximation, determination of rotor thrust can provide a very good estimate of weight.

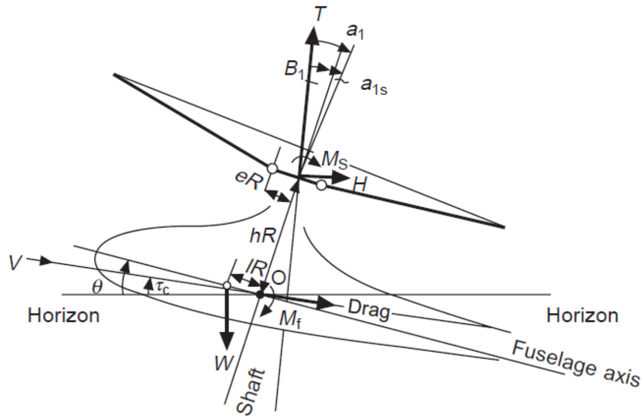
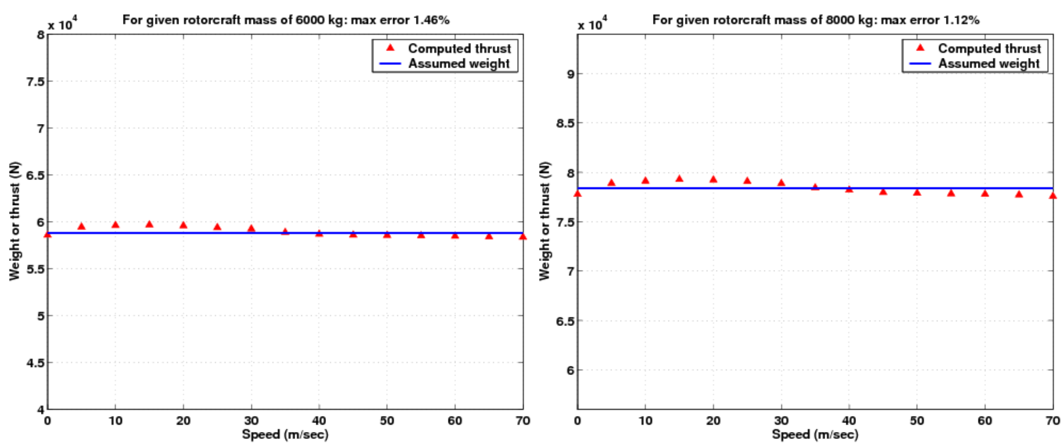


Figure 1. Longitudinal forces and moments of a generic helicopter [6].

In order to show how this approach can be used, two examples are shown here. The first one is using simulated data whereas the second one is using realistic data from a H-60 aircraft. For the first case, typical UH-60 helicopter data gathered from various sources [7, 8] is used as input in a flight dynamics software RotorLib FDM [9]. The trim conditions are determined at different airspeeds for a given rotorcraft mass of 6000 kg and the resulting thrust values are shown in Figure 2(a). It can be seen that the calculated thrust values are very close to the actual rotorcraft weight for all the chosen airspeeds (the maximum percentage error is 1.46). The calculations are repeated for a rotorcraft mass of 8000 kg and the results are shown in Figure 2(b). In this case the maximum percentage error is 1.12%.



(a) (b)

Figure 2. Comparison of computed thrust and given weight values for various speeds: (a) for a given rotorcraft mass of 6000 kg (the maximum percentage error is 1.46%); (b) for a given rotorcraft mass of 8000 kg (the maximum percentage error is 1.12%).

In the second example, the pilot inputs such as longitudinal and lateral cyclic position, collective position and pedal position are obtained from the Health and Usage Monitoring Systems (HUMS) installed on a UH-60R aircraft and they are used as inputs in the RotorLib flight dynamics software [9] where subsequently the main rotor thrust is calculated. The relevant input values are: collective 21.73%, cyclic lateral 24.18%, cyclic longitudinal 10.048%, pedal 48% and ground speed 59.42 m/sec. The rotor blade properties used are characteristics of the UH-60R aircraft: radius 8.17 m, chord 0.5334 m, lift curve slope 0.11, zero lift drag coefficient 0.007, twist -18 and number of blades 4. In the calculation of rotor thrust, the rotor RPM is a crucial parameter which is not precisely known, hence the thrust is calculated at different RPMs as shown in Table 1.

The HUMS box also has information about the rotorcraft weight which is derived from initial configuration and fuel burn rate. For these cases the weight at the flight configuration is shown in fourth column of the table. The rotor thrust as shown in Table 1 is comparable to the weight calculated from fuel burn rate with an error smaller than 1 %.

Table 1. Rotor thrust determined at different RPM.

RPM	Computed thrust (N)	Computed thrust (kg force)	Given mass (kg)	% Error
240	80331.1	8191.5	8197	0.0671
270	93774.6	9562.4	9568.8	0.0669
300	107727.1	10985.2	10992.5	0.0665

Future work will incorporate this model in a hybrid model as explained in the last Section of the paper.

Gross Weight Estimation Using a Neural Network Model

This section presents a model to compute rotorcraft GW using Neural Network (NN) and data recorded by the Health and Usage Monitoring Systems (HUMS) onboard CH-53E rotorcraft. A NN-based model which uses as input several HUMS parameters is used to estimate initial/take-off GW. In order to train and validate the model, the take-off weight as recorded in the pilot's log is used. It is believed that the pilot's log is more accurate that the GW provided by the HUMS.

Neural Network (NN) is among the relatively straightforward methods proposed for GW and CG estimation [1-4]. The same steps are applied in all cases, the differences being the aircraft considered (SH-60B in [1], V-22 for in [2, 3]), the source of input parameters (real flight data in [1, 2], simulated flight data in [3]), the NN architecture and type (radial basis or back-propagation) and the selection of the input parameters (4 parameters in [1] and 13 parameters in [2, 3]). One of the advantages of this method is the freedom to identify and quantify the most significant parameters for prediction. Reference [1] considers only 4 HUMS recorded data: engine torque, longitudinal stick position, altitude and collective stick position whereas [2, 3] consider 13 HUMS recorded data: left rotor torque, right rotor torque, left rotor longitudinal cyclic control, right rotor longitudinal cyclic control, left rotor lateral cyclic control, right rotor lateral cyclic control, nacelle angle, pedal position, pitch attitude, roll attitude, radar altitude, density altitude and normal load factor. In all the cases, the results of the NN approach are validated by comparison with the measurements and the error is relatively small.

As explaind in the last Section of the paper, the distinct aspect of our development is the fact this model will be just a part of the global hybrid model. The data obtained from NN will represent pseudo-measurements for the Kalman Filter model.

CH-53E HUMS data

Data collected from 108 flights obtained from 9 CH-53E aircraft conducting regular operations was utilized for model development in hover. Two sets of data were available: (a) initial pilots' logs and (b) HUMS box data. Using a regime recognition algorithm developed previously by our team and detailed in reference [10], the HUMS data was separated into distinct flight regimes. From HUMS data, values at four instants were extracted and used: rotor start (RS), first take-off (TO), first hover and (4) landing. A further investigation was conducted in order to better understand the data and a few details are described here.

Figure 3 presents aircraft GW measured in lb provided by the HUMS and estimated by the pilot at the beginning of the flight. The figure shows four sets of data for each flight: (1) data recorded by the HUMS at rotor start, (2) data recorded by the HUMS at first hover, (3) initial data as given in the pilot's log and (4) GW computed as the sum of empty weight, crew (from pilot's log) and fuel estimated by the HUMS. Figure 3(b) shows the absolute error between the pilot's log and the HUMS data at rotor start: the average error is 8.5%.

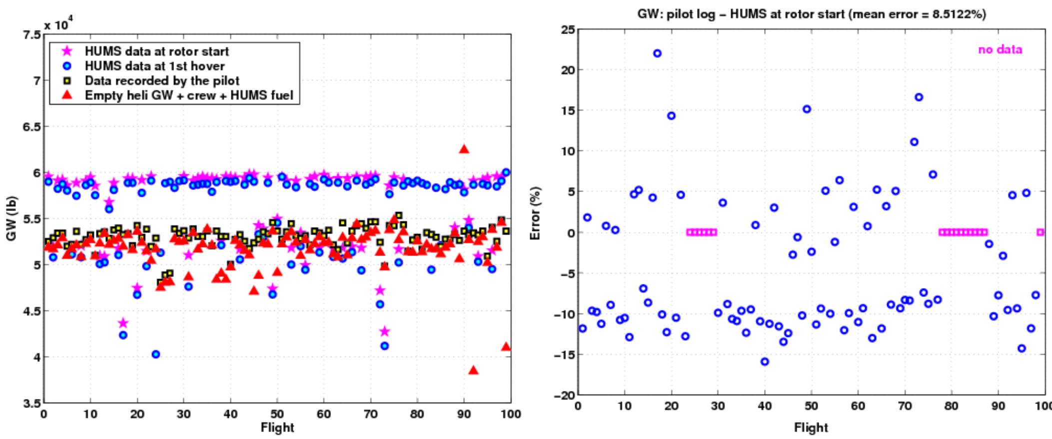
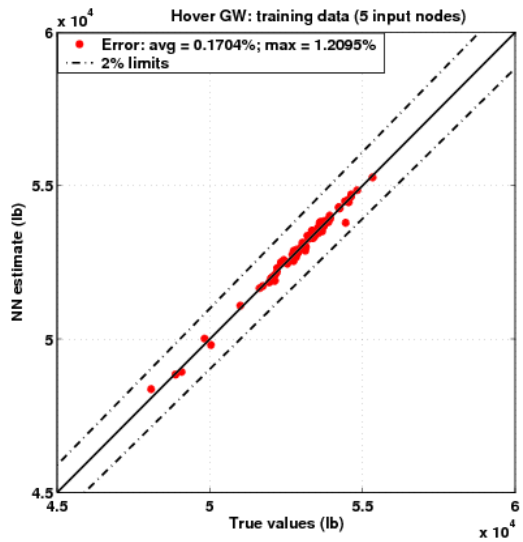


Figure 3. (a) Aircraft Gross Weight (lb) provided by: (1) HUMS at rotor start, (2) HUMS at first hover, (3) pilot at the beginning of the flight, (4) sum of empty weight, crew (from pilot's log) and fuel from HUMS; (b) Absolute error the average error is 8.5%.

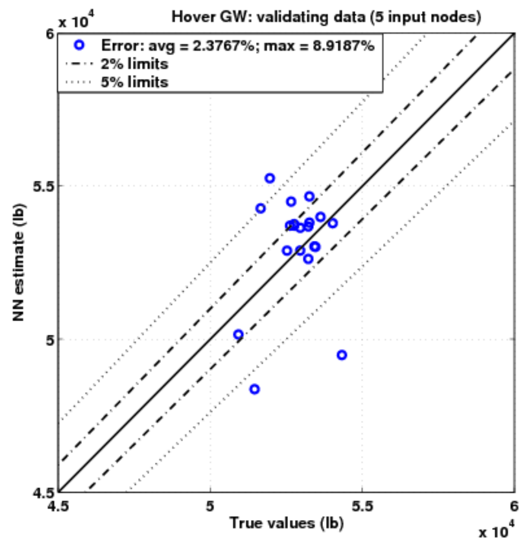
Results

In order to illustrate the NN approach, this section presents two examples. The CH-53E HUMS data at first hover is used and a feed-forward, back-propagation NN is built to train and test the data. The true and predicted values of the GW are compared in order to evaluate the model capabilities. A feed-forward, back-propagation NN which has five parameters in the input layer (altitude rate, average torque, engine 1 torque, X and Y components of air velocity) is used. Three hidden layers, with ten, six and three neurons are used while the output layer consists of only one neuron which defines the GW. Among 98 total data points, 78 were used for training and 20 for validating. The NN weights associated with each link between two nodes are also shown; the thicknesses of the links are proportional to their magnitudes with negative weights shown in red and positive ones shown in green. A software called Easy NN-plus © [11] is used to train and test the data.

The true and predicted values of GW are compared in Figure 4 in order to evaluate the model capabilities: Figure 4(a) presents a comparison for the training set and shows that the average training error is below 0.2% whereas the maximum training error is approximately 1.2%. Figure 4(b) displays a comparison for the validation set and shows an average error of 2.4% and a maximum error of 9%.



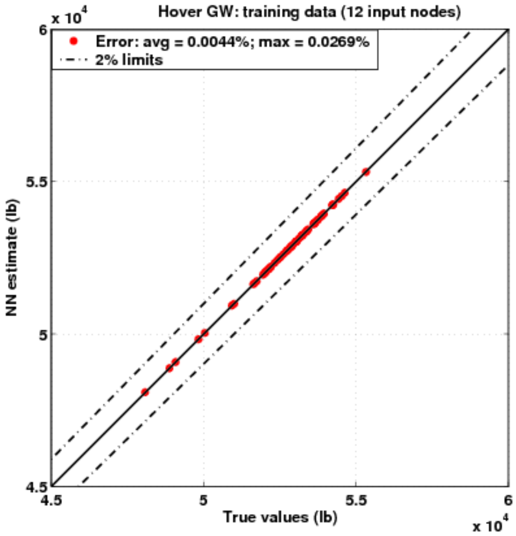
(a)

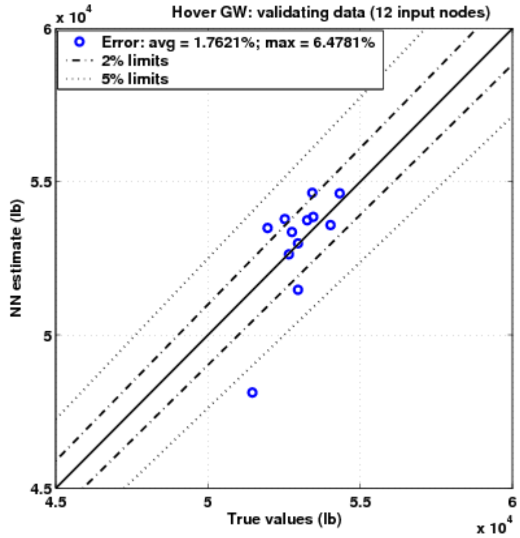


(b)

Figure 4. True values vs. predicted values: (a) training set (the average error is below 0.2%); (b) validating set (the average error is below 2.5%). Among 98 total data points, 78 were used for training and 20 for validating.

The second example shows that these errors decrease if the number of inputs in the NN increases. In this case among the 12 input nodes considered, five are from the previous case while the rest are the four components of the input vector (collective stick position, lateral cyclic position, longitudinal cyclic position, pedal position) and the three components of the Euler's angle vector (heading, pitch, roll attitude). In this case only 83 data points were available because of missing or erronous flight parameters. Among the 83 total data points, 71 were used for training and 12 for validating. The true and predicted values of GW for both the training and validating sets are presented in Figure 5: Figure 5(a) presents a comparison for the training set and shows that the average training error is around 0.004% whereas the maximum training error is approximately 0.027%. Figure 5(b) displays a comparison for the validation set and shows an average error of 1.8% whereas the maximum error is approximately 6.5%.





(a) (b)

Figure 5. True values vs. predicted values: (a) training set (the average error is around 0.004%); (b) validating set (the average error is around 1.8%).

Several improvements will be considered in future work: (a) a sensitivity analysis will be conducted to investigate the most influential HUMS variables, (b) different network architectures will be tested to check any error reductions and (c) algorithms for data cleaning and smoothing will be investigated.

Gross Weight Estimation Using a Hybrid Approach

As the GW/CG estimation problem is based on both the accuracy of data and the fidelity of flight dynamics theory, a hybrid model that combines data and analytical models such that to reduce both sources of errors will be developed. This framework represents the main engine of the future model and will provide innovative ways to solve rotorcraft problems in the real flight dynamic domain. Therefore, the final objective of this work is the development of an advanced, hybrid model that will have the following advantages:

- Fuses the powerful estimation capabilities of the KF scheme with the strong learning capabilities of the NN in order to improve accuracy within the required 2%, give prediction for different regimes and be self-corrective;
- Provides innovative ways to solve rotorcraft problems in the real flight dynamic domain; Among these complex problems, parameter identification and regime recognition can be easily implemented.

Figure 6 shows an approach where KF is the main process whereas NN provides pseudo measurements for KF. In the pure Kalman filter based GW estimation technique, weight which is an unknown parameter in the dynamical equations, is treated as an additional state parameter, which has to be estimated. Flight data (e.g. engine torque, altitude, airspeed, yaw rate, sideslip, pitch and roll attitude, etc.) will be used in a NN in order to compute the GW for a helicopter which will be treated as measurement data in KF. KF is a model which cannot stand by itself but it needs an analytical model which describes a dynamical system. As shown in Figure 6, several combinations of these models will be tested.

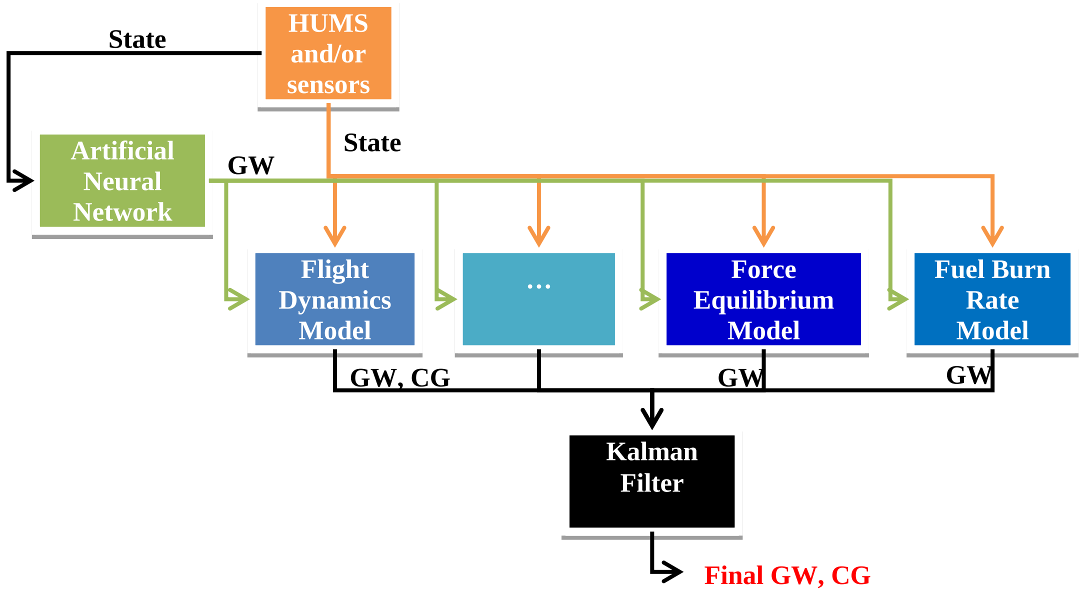


Figure 6. Multiple sources of GW and CG data combined with a KF and NN.

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