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Neural networks for the identification of degraded components of aircraft fuel quantity system

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Abstract. The physical and software architecture design of the fuel system of high-performance aircrafts is very complex and represents a challenging topic for aeronautic engineers. Among the main functionalities, there is the calculation of the on board fuel quantity, consisting in data computed by the fuel gauging sub-system, shown to the pilot on the cockpit display and used by the flight control system for aircraft controllability. Due to the large number of sensors and to a strongly ramified calculation code, faults and performance degradation of components, are difficult to be detected/isolated, since the operation would require an invasive investigation on the aircraft. To reduce the impact of the fault detection and isolation process in terms of time and costs, a digital twin of the fuel system has been developed and coupled with a condition-monitoring algorithm based on machine-learning methods. It is thus possible to quickly replicate the mission profiles during which the faults can occur, to calculate the residual fuel mass in parallel with the fuel computer and to precisely identify which component caused the system failure. A neural network, trained on experimental flight data, has been developed to provide reliable data. Once validated , the neural network is coupled with a 0D model that simulates the movement of the fuel inside the tank. In this way, it is possible to obtain the mass of fuel, simulating any flight mission profile. This approach optimizes the analysis of system malfunctions in terms of time and costs, highlighting unexpected mass values, otherwise undetectable. The reliability of the neural network can clearly be increased by training the algorithm with additional flight data, which can be derived from experimental or virtual flights simulated using the 0D model. The versatility of this process makes it applicable for different aircrafts as well as for further developments.

Introduction

During last years, more and more studies and applications are focusing on Artificial Intelligence (AI). AI allows to solve complex problems by processing large amounts of data. In industrial context, investing in the development of new products that use artificial intelligence recommends optimizing time/costs thanks to its versatility and taking advantage of predictive analysis with autonomous machine learning [1,2].

In particular, in the aeronautical industry, AI, supported by digital models, can be a valid support in predicting behavior problems from complex aircraft systems which are constituted of different subsystems with dedicated functionality. With data acquired during the operational life of the aircraft, it is possible to train a machine learning algorithm for debugging failures that have occurred on one or more functionalities, or for predicting new ones. In this context, the digital twin of the aircraft can be a valid support for testing the system recursively, avoiding experimental tests. The knowledge enhanced with this type of activity would allow the deploy of more accurate future system already in the design phase.

This paper presents the application of machine learning, supported by a digital twin, for the identification of the degradation of the fuel gauging system components. For this purpose, two models have been developed that can run alone or interact with each other:

1. Behavioral System Model: tank volume discretization in AMESsim starting from 3D CAD data. The model describes the whole tank geometry and connect each tank compartment domain with the respective rib and spar holes. Imposing the motion due to the aircraft manoeuvre, it is possible to simulate the fuel dynamics inside the tank. Furthermore, the engine feeding, refueling, defueling and venting subsystem has been modelled.

2. Neural Network (NN) for Fuel Gauging: Machine-learning based model developed in Matlab/Simulink environment, which, starting from probes and load factors data, determines the total quantity of fuel. This model exploits the Neural Networks capability to interpolate and extrapolate complex multi-dimension data with very high accuracy without the use of fuel gauging design algorithm.

Fuel Gauging System

The main function of fuel management and gauging subsystem is to provide an accurate measure of on-board fuel quantity [3]. The probes and compensators of gauging system relate to fuel computer, that elaborate the signals derived by gauging component and calculate total fuel mass and aircraft lateral and longitudinal CG position. The fuel tanks quantity data are displayed on cockpit to be available for pilot during flight and are used by the flight control system for aircraft controllability.

Fuel System Behavioral Model

This kind of model is necessary to be used to train a neural network by replacing data retrieved from experimental flights, allowing save time/cost to run tests on the system that would otherwise not be possible in terms of number and variety.

The model has been developed in two phases: the first is the extraction of geometry from CAD data of fuel tank in Catia V5 and then 1D sketching in Simcenter AMESim 2021.1. The CAD contains details (presence of flanges or grooves) and elements (presence of rivets, gaskets) which are not of interest for this application. For this reason, each compartment within the tank has been approximated as a closed cuboid following ribs, spars, top surface and bottom surface of the tank. The tank compartments geometry has been discretized through Amesim Aircraft Fuel System library, and then the whole tank reconstructed with holes, pumps and probes using Amesim 1D sketching (Fig. 1). The model has been validated by matching flight tests: probe signals and fuel mass outputs by Amesim model has been correlated with the same data available from flight recorder, refining the simplifications made on tank geometry. This model can be considered the digital twin of fuel system: it makes possible to simulate the behavior of the fuel inside the tank and thus the center of gravity displacement used by the flight control system for aircraft controllability. In particular, it is possible to have as output the wetted height of fuel probes starting from aircraft load factors and initial fuel quantity. These data can be used to monitor life cycle of the probes and their eventual degradation comparing simulation and real flights data.

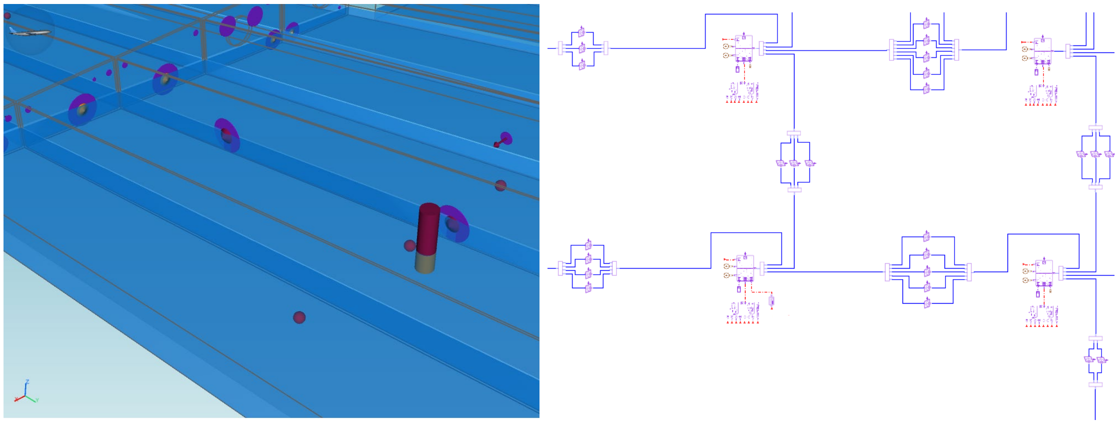

Fig. 1 – AMESim model

NN for Fuel Gauging

For the development of the NN it is necessary to have a training dataset correlating NN inputs with NN outputs that must be as large as possible. This approach is useful when one or more output variables depend on several input variables: in this case it is not always easy or possible to find an analytical correlation using more traditional methods. The resulting model will be a black box with the possibility of being stimulated in different ways.

In this application the main goal of the model is to correlate the signals of the fuel probes and aircraft load factors with the quantity of fuel inside the tank. This correlation can derive either from experimental flights or from virtual flights simulated using the digital twin model, either way the reliability of the neural network increases automatically by increasing the number of flight data provided to the algorithm. Different NN configurations have been studied: the most performant NN as trade-off between accuracy and training time required, resulted in a two-layer feedforward network with sigmoid hidden neurons and linear output neuron exploited with Bayesian regularization training algorithm.

The main application of this NN is the investigation of degraded component of fuel system: a test has been reported in Fig. 2 and Fig. 3. The signal supplied by a specific probe during the test flight is taken, and in one case it is fictitiously amplified (Test #1) and in the other fictitiously reduced (Test #2) for a limited amount of time, as shown in Fig. 2. This determines an altered trend of the computed mass of fuel contained in the tank, clearly departing from the actual trend. In particular, in Fig. 3 it is possible to observe that an amplification on the signal of this specific probe determines a reduction (almost a rigid translation) of fuel; opposite effect on the total mass for a reduction of the signal. This is an expected trend: indeed, the relationship between probe output signal and fuel mass is not univocal, each probe concurs with different weight to fuel quantity computation. Using the described NN algorithm, it is possible to identify which probe is degraded comparing NN fuel mass data with flight fuel quantity.

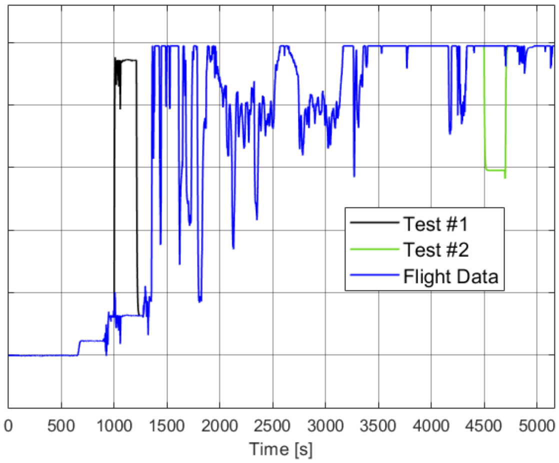

Fig. 2 - Probe Signal Output

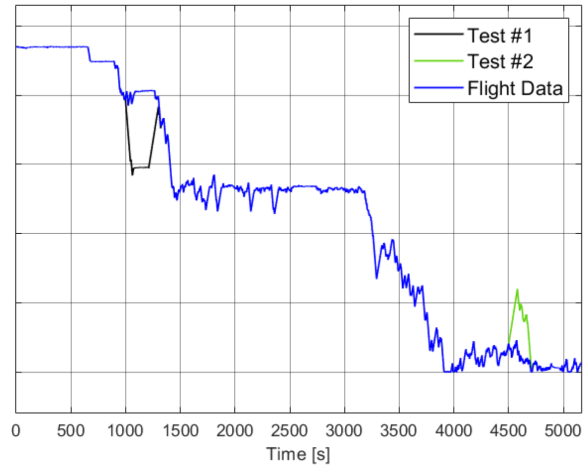

Fig. 3 - Total Fuel Mass

Conclusion

The paper presents the modelling activity carried out for on-service aircraft fuel system: a digital twin has been developed coupled with a machine learning algorithm. The results provide high accuracy with respect to flight test data, by permitting to predict faults and performance degradations of fuel system components with a robust approach as well as by avoiding invasive investigation of the aircraft. Therefore, this approach, highlighting unexpected mass values, optimizes in terms of time and costs the analysis of system component malfunction cases which would otherwise be more time demanding and invasive. The generality of this process makes it applicable for different on-service aircraft as well as for further developments.

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