

A COMPARATIVE STUDY OF DIFFERENT PROPULSION MODELS FOR HYBRID ELECTRIC AIRCRAFT

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ABSTRACT:

This paper addresses the topic of multi-disciplinary analysis (MDA) applied to hybrid electric aircraft (HEA) design focusing on the analysis of multi-fidelity models for hybrid electric powertrain design. The motivation behind this work is the retrofit of a turboprop aircraft with hybrid electric propulsion system. An adapted MDA for multi-fidelity conceptual aircraft design is set in place for the evaluation of the aircraft performance with a hybrid electric propulsion architecture. For the gas turbine system, high fidelity data have been used to develop multi-fidelity models with different levels of detail and complexity. These models have been integrated into the MDA to evaluate the performance of the vehicle for a given mission. Fuel consumption is the main metric used to assess the aircraft performance in the presence of uncertainty introduced on each propulsion model.

1. INTRODUCTION

Aviation currently accounts for around 13% of transport related emissions and around 2% of global greenhouse gases [3], however this number is expected to rise significantly considering the increasing air transportation demand [1,2]. The European Union Commission together with aviation industry players agreed on very ambitious goals to

reduce aircraft related emissions on the long term. In “Flightpath 2050” [4], the targets for CO₂, NO_x and perceived noise reduction have been set respectively to -75%, -90% and -65% relatively to a reference emission scenario in the year 2000. This challenge to reduce significantly the environmental impact of future aircraft requires innovative approaches in propulsion technologies and aircraft designs. In recent years, there has been increased attention towards hybrid electric vehicles; therefore, within the context of this study, hybrid electric propulsion technologies are investigated to assess the potential CO₂ emissions reduction.

However, the adoption of alternative power sources introduces new challenges at all stages of aircraft design from the conceptual to the detailed design phase. Conventionally, overall aircraft design (OAD) relies on well-established processes and equations that have been derived from the knowledge and the experience coming from existing aircraft and previous designs. Therefore, the introduction of a completely new technology raises challenges in the design of the aircraft inherent to the lack of data and information about existing aircraft. At the conceptual design stage, this lack of knowledge is addressed by developing and integrating into the design process new evaluation methods and models, which are able to predict the performance and the behavior of the technology we want to investigate.

The main activity of the conceptual phase is the design space exploration of different overall aircraft

concepts in order to select the most promising solutions and discard the configurations that are not feasible or not interesting. However, as for each configuration different levels of information or different models will be required, there is a true challenge in having a fair and reliable comparison of the results. In this paper, this challenge has been addressed by taking into account the modeling uncertainty associated to the outputs of each discipline due to model assumptions, numerical approximations as well as imprecise model parameters [23]. By propagating the uncertainties through the entire process up to the final outputs of the MDA (e.g. fuel burn, emissions, take-off weight), the comparison of different aircraft design configurations will not be based only on absolute values of the chosen performance metrics, but will also rely on information about the uncertainty associated to these results.

The baseline chosen for this work is the ATR42, a regional 48 seat turboprop aircraft (see Fig. 1). This type of aircraft was chosen because its typical flight distances, speeds and weights imply energy and power requirements that are limited compared to short-to-medium-haul jet aircraft, thus hybrid propulsion's viability may be proven even with short-term previsions for energy storage and motor power densities.

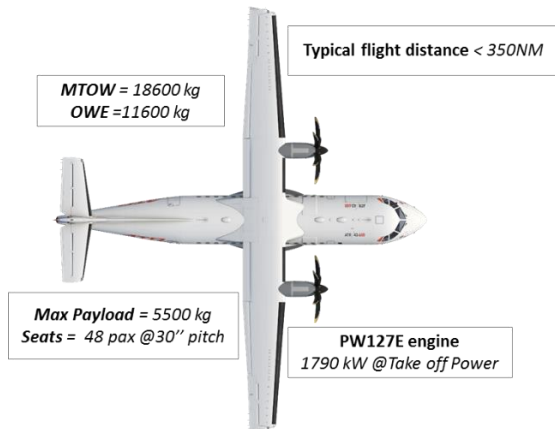


Figure 1: ATR 42 baseline aircraft

Therefore, the retrofit of the ATR42 with hybrid electric propulsion system will be analyzed and its impact on overall aircraft performance will be compared to the baseline aircraft. However, before that, a comparative study of different gas turbine models has been performed in order to determine

the most suitable model to reduce modeling uncertainties. Since the objective of this study is not the assessment of the potential emissions reduction of the hybrid electric version of the ATR42, only one configuration is presented among the potential architectures for hybrid electric propulsion (shown in Fig. 2). The main aim of the study is to show how the choice of the fidelity level of the models may affect the results, potentially leading to erroneous conclusions.

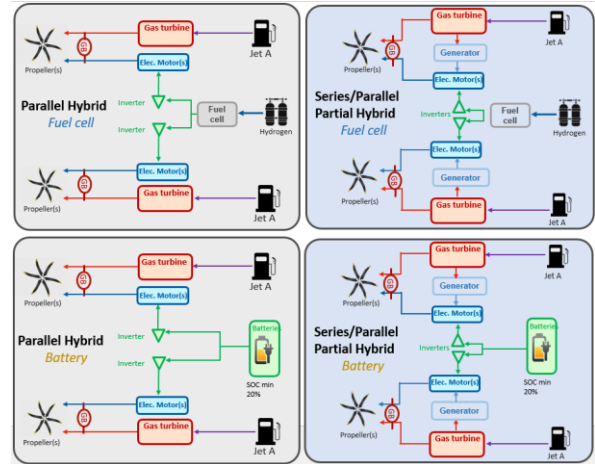


Figure 2: Overview of the potential hybrid electric architectures to be investigated

In section 2, the parallel hybrid electric aircraft (HEA) configuration chosen for this study is presented. The propulsive architecture comprising a conventional gas turbine and a fuel cell for the generation of the electric power is described together with the hybridization strategy employed during the flight mission. The main parameters describing the design mission as well as the reserve mission are also given.

Section 3 presents the MDA process set up for the study of both the conventional and the hybrid electric configurations. It shows the dependencies between the different disciplines and the main loops needed to converge to a solution.

In section 4, the methods used to model the behavior of all the components of the propulsive architecture are presented. The main focus is on the presentation of the four gas turbine models used to perform the comparative study.

In section 5, the MDA process is first used to compute the performance of the baseline aircraft in

order to validate the process and the methodology for the uncertainty propagation problem. Then, an adapted MDA is used to investigate the performance of the ATR42H and to perform a comparative study between different models for the gas turbine engine.

Finally, the conclusions are provided in section 6.

2. HYBRID ELECTRIC AIRCRAFT CONFIGURATION

Figure 3 shows the propulsive architecture of the ATR42 hybrid chosen for this study. It is a parallel hybrid electric configuration, where each propeller is supplied with power provided by both the fuel cells and the gas turbine. The fuel burnt by the engine produces mechanical power which is directly converted into kinetic energy by the propeller. At the same time, the electric power supplied by the fuel cells is transferred via the inverter to the electric motor, which converts the electric power into mechanical power. This power is finally transferred to the propeller by means of a gearbox.

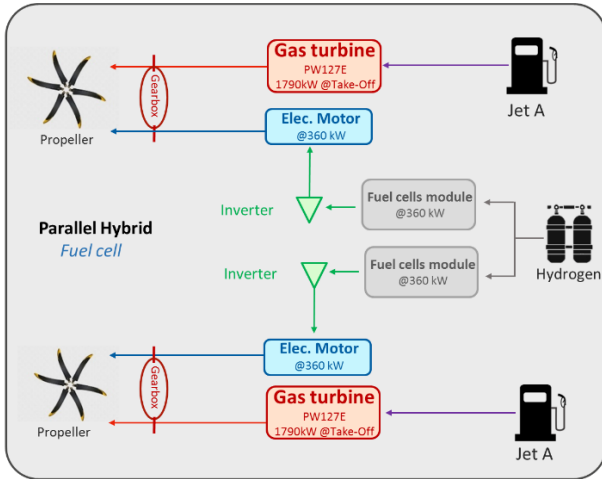


Figure 3: Hybrid electric architecture

The fuel cell module designed for this study generates 360 kW of electrical power and it consists of four independent fuel cell systems connected in parallel (as shown in Fig. 4). Each fuel cell system generating 90kW is composed of a fuel cell stack and of all the necessary components to ensure proper operation such as pumps, sensors,

compressors etc. The power output of the fuel cell stack depends on its size. As the power obtainable from a single cell is rather low in comparison to the power requirement for this application, multiple cells are stacked to achieve higher voltage and power.

Having more fuel cell stacks connected in parallel to provide the required power has a number of advantages compared to a single fuel cell stack capable to provide the 360 kW alone.

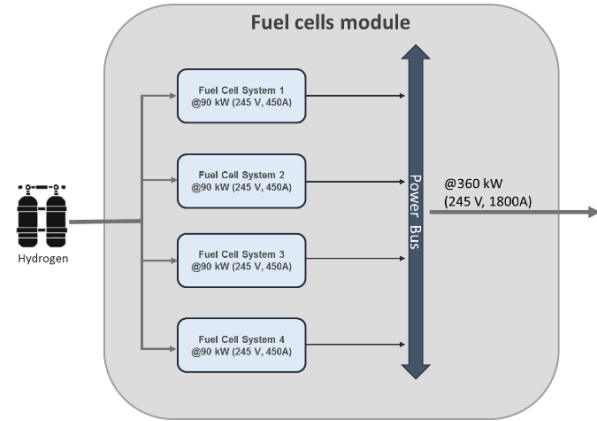


Figure 4: Schematic of a parallel connected fuel cell network

First, the reliability of a fuel cell stack may decrease as the number of cells in the fuel cell stack increases. Each cell may be subject to a number of failures due to many factors such as poisoning of the catalyst, water flooding etc. [5]. As a result, the fuel cell stack would be compromised, generating less power or, in the worst case scenario, no power at all. Second, the voltage of the electrical system is significantly reduced with the parallel architecture, therefore reducing the risks associated to too high voltage systems.

The hybridization strategy consists in the full exploitation of the electrical power available during the flight phases of climb and cruise of the design mission. The gas turbine power varies in order to deliver only the necessary amount of power to fly at the same speeds and time to climb (TTC) as the baseline aircraft. Table 1 summarizes the main mission parameters used and Figure 5 illustrates the power profiles along the mission. The green and red dashed lines represent respectively the power generated by each gas turbine and electric motor. The solid blue line represents the flight altitude and

it shows clearly all the different flight phases. It can be seen how the electric power is required only during the climb and cruise phases of the design mission and the gas turbine supplies all the power needed for the reserve mission.

Design Mission	200 NM
Mission Altitude	FL170
TAS cruise speed	298 kts
TTC	12.7 min
CAS climb speed	160 kts
CAS descent speed	250 kts
Reserve mission	100 NM Diversion 30 min Holding
Diversion Altitude	16000 ft
Holding Altitude	1500 ft

Table 1: Mission parameters

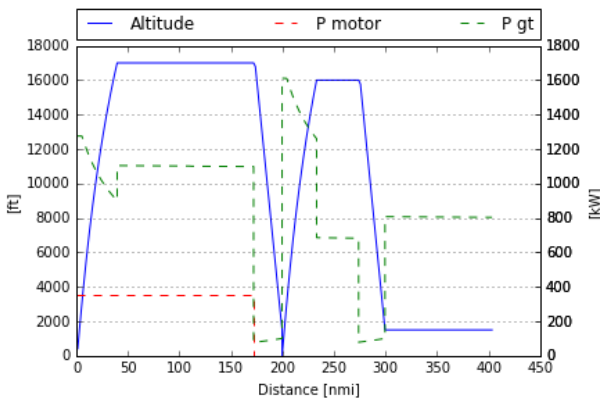


Figure 5: Mission profile with electric and gas turbine power levels (one engine)

The geometry and the structural weight of the hybrid electric configuration (ATR42H) analyzed in this paper are identical to the one of the conventional reference aircraft. Therefore, the hybrid aircraft must respect the same max take-off weight (MTOW) limitation of the baseline.

The gas turbine is also unchanged, thus there are no gains to be expected in terms of engine weight or drag reduction. This choice, whilst conservative on the potential benefits introduced by the hybrid electric propulsion, allows the design of the electric powertrain and electric system taking into account only the nominal condition. With the same MTOW and the same gas turbine power, the hybrid aircraft will be able to take-off and fly the full mission even with a complete failure of the electric propulsion system. Therefore, the electric power system doesn't need to be oversized to take in to account

failure cases and redundancies which would introduce additional mass penalties.

The performance of this hybrid electric configuration with respect to fuel burn and emissions has been evaluated using a MDA process which is described more in detail in the next section.

3. SET UP OF A MDA PROCESS FOR THE EVALUATION OF AIRCRAFT PERFORMANCE

Multi-disciplinary design analysis is a powerful method, which is able to handle the large amount of dependencies between all the disciplines involved in a classical design problem. Some platforms have been developed for the preliminary and conceptual designs of innovative aircraft architectures. In [6], the authors present the theory and architecture of OpenMDAO and some applications such as trajectory optimization, wing design, and structural topology optimization. In [7], the Multi-disciplinary design analysis and optimisation platform developed by ONERA and ISAE-SUPAERO named FAST is used for the preliminary sizing of a medium range blended wing body.

For this study, a conceptual aircraft design platform named RHEA (Regional Hybrid Electric Aircraft) design tool based on FAST, is used to set up a MDA process in order to evaluate the performance of the given aircraft configuration for a given mission. For the conventional aircraft architecture, the simulation starts with an initial guess of take-off weight (TOW) equal to the MTOW, which is given as input. The aerodynamic module computes the drag polar and the aerodynamic forces with respect to the flight conditions and to the aircraft geometry provided as an input ".xml" file. Using the aircraft geometry and the MTOW provided as input, the weight module computes the masses of the different aircraft components. Based on a segment-by-segment simulation using time step integration, the performance module solves the equations of motion to evaluate the performance of the vehicle throughout the mission in terms of fuel consumption and CO2 emissions. At the last step, TOW is updated with the value calculated as a sum of the Operating Empty Weight (OWE) evaluated by the weight module, the total fuel needed to perform the mission (FW) and the given payload weight (PW) (see Eq. 1). The iterations continue until the

difference between the value of TOW used to perform the mission and the one calculated at the last step is lower than a given tolerance.

$$TOW = OWE + FW + PW \quad (1)$$

In the case of hybrid electric aircraft's simulations, the weight module computes also the masses of the electric propulsion system (e.g. electric motors, inverters, fuel cells, hydrogen storage etc.). The TOW is fixed and equal to the MTOW of the aircraft. The performance module calls the fuel cell model to evaluate hydrogen consumption throughout the mission. At the last step, the payload weight is updated with the value calculated as the difference between the MTOW and the aforementioned weights of the conventional case, plus the hydrogen fuel weight (HFW) and with the OWE taking into account the masses of the electric propulsion system.

$$PW = MTOW - OWE - FW - HFW \quad (2)$$

This approach ensures that the TOW of the aircraft will not be greater than the MTOW, therefore no structural sizing is needed. The mass penalties deriving from the introduction of the electric propulsion system are counterbalanced by the reduction of the payload weight.

In the following section, some of the methods used to evaluate the outputs of each discipline involved in the MDA process are briefly described.

4. MDA MODELS

The key disciplines involved in the MDA are aerodynamics, weights and propulsion. For each discipline, multiple computational models are available with different levels of detail using physics-based methods as well as empirical or semi-empirical correlations. Each model accounts for a certain level of modeling errors, which induces a modeling uncertainty on the output of the model. These uncertainties may be caused by model assumptions and numerical approximations as well as imprecise model parameters [23]. Generally, the models with high level of detail and many parameters are able to better describe the physical phenomena or system of interest with respect to a simpler model. However, low level of detail of the

model does not always involve low accuracy of the results. In fact, when the physical phenomenon or the system is well known and there are enough related available information, a simple model can be calibrated to perfectly predict its behavior. In fact, in the MDA process set up for this study, aerodynamics and weights models, whilst using simple well-known semi-empirical correlations, result in an accurate evaluation of the aerodynamic coefficients and the weight breakdown respectively. For example, for the aerodynamic module, the availability of the manufacturer's data for the geometry of the aircraft allowed us to avoid introducing any sources of data uncertainty into the model. Moreover, its results in terms of drag coefficients at different lift coefficients and Mach numbers were calibrated according to manufacturer's flight data, resulting in a maximum mean squared error (MSE) of 10^{-6} . Concerning the propulsion module and in particular the gas turbine model, due to the complex physical behavior of a gas turbine, when compared to reference manufacturer's data, it was not possible to reach a satisfactory accuracy of the results with a simple and computationally cheap model as for the aerodynamics and weights modules. Therefore, it was decided to undertake a comparative study of four different gas turbine models with different levels of detail and complexity. Among the ones available from literature, two models have been chosen and are presented in section 4.2. Moreover, two multi-fidelity models have been developed combining the aforementioned models with available high fidelity data as described in section 4.2.3.

4.1. Electric propulsion models

The electric propulsion system is composed of: electric motor, inverter, fuel cell system and hydrogen storage system. These components have been modeled using published or assumed values for specific energy (E_{sp}), specific power (P_{sp}) and efficiency to determine their performance (see Table 2). As presented in section 2, based on the hybridization strategy chosen for this study, the electric power system is always working at one single operating point, therefore no performance maps were needed to determine the efficiency of the electric motors, inverters and fuel cells as a function of the power load. Instead, one constant

value of efficiency was given as input, based on published values representing state of the art technology levels.

Fuel cell system efficiency	40%	[20]
Fuel cell system P_{sp}	650 W/kg	[20]
Electric motor efficiency	97%	[17]
Electric motor P_{sp}	7 kW/kg	[17]
Inverter efficiency	98%	[18]
Inverter P_{sp}	11 kW/kg	[18]
Liquid H2 storage E_{sp}	5 kWh/kg	[19]

Table 2: Components' performance parameters

4.2 Gas turbine models

Gas turbine models suitable for preliminary aircraft design generally go from simple semi-empirical relations capable of determining the main engine performance parameters as a function of atmospheric conditions, to 0D models where a physics-based method is used to compute average flow conditions at the inlet and the exit of each engine component. For example, Vratny [9] and Pornet [10] used commercial software for gas turbine performance calculations based on 0D thermodynamic equations named Gasturb to evaluate fuel flow and shaft power tables. Engine performance properties are extrapolated from these tables and used in the MDA process to evaluate overall performance of hybrid electric aircraft. In [8], a simplified analytical gas turbine model using experimentally derived factors has been used for the development of a conceptual design method for hybrid electric aircraft. In the proposed model, the available power at a given flight condition is calculate as a function of the sea-level-static power and a so called power lapse coefficient. The fuel flow required by the gas turbine is computed as a function of the throttle and flight state (altitude, Mach number) using a fuel flow map.

The two models employed for this study are briefly introduced in the following sections. Within the MDA process, these models take as inputs altitude, Mach and engine throttle and calculate the available power and the specific fuel consumption as illustrated in Figure 6.

The available power at the propeller shaft (P_{shaft}) given by the sum of the gas turbine and electric motor power is then converted into forward thrust (T_{prop}) using Eq. (3).

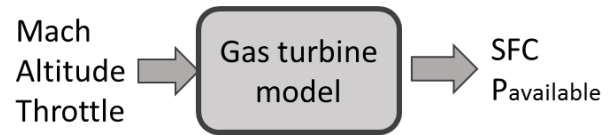


Figure 6: Inputs and outputs of the gasturbine model

$$T_{prop} = \frac{\eta_{prop} P_{shaft}}{speed} \quad (3)$$

The propeller efficiency (η_{prop}) is determined at each condition during the flight mission using the H568F propeller response surface provided by the company.

4.2.1 L0 gas turbine model

The first model was proposed by Stuckl in [11] and, as of now, it will be referred to as L0 model. It uses Eqs. (4) and (5) to estimate the available power and the specific fuel consumption SFC (lb/hr/shp).

$$P_{available} = P_{TakeOff} * (M^2 + 1) * \left(\frac{\rho}{\rho_0}\right)^{0.7} \quad (4)$$

$$SFC = SFC_{takeOff} * \frac{1}{(0.258 \log(p_{corrected}) + 1)} \quad (5)$$

Equation (4) calculates the available power taking into account altitude effects and the velocity. The maximal power that a gas turbine engine is able to generate is affected by the altitude due to the change in air density. Moreover, due to pressure recovery in the engine air intake, the power increases with flight velocity. The specific fuel consumption of the engine is influenced by engine size, engine throttle and atmospheric conditions. The SFC is modeled as relative increase of the specific fuel consumption at take-off, taken from the PW127 engine datasheet. Throttle setting and atmospheric conditions are taken into account with the corrected part-load factor $p_{corrected}$ as given in Eqs. (6) and (7):

$$p_{corrected} = \frac{p\sqrt{\theta}}{\delta} \quad (6)$$

$$p = \frac{P}{P_{maxRated}} \quad (7)$$

where θ and δ are respectively the ambient pressure ratio and the temperature ratio.

4.2.2 L1 gas turbine model

The second model, referred to as L1 model, consists in the characterization of a twin-shaft free turbine engine architecture to reproduce the performances of the PW127 engine which equips the ATR42. The gas turbine architecture is shown in Fig. 7.

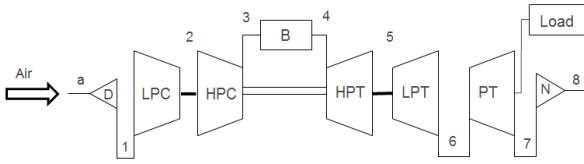


Figure 7: Gas turbine architecture

The L1 gas turbine model evaluates the available power and the specific fuel consumption by computing the thermodynamic properties of the air flow at the inlet and the outlet of each engine component and by solving the power balance equations of the low pressure and high pressure spools. At the design point, available data from the engine's manufacturer were used to characterize engine's components, such as compressor pressure ratios, max turbine inlet temperature and compressors' bleed airflow. The component efficiencies were estimated using representative values relative to the state-of-art engine technology according to [13]. The off-design analysis is performed following the method described by Mattingly [13] and Oates [14]. The components' efficiencies are assumed to be constant, therefore no scaled performance characteristics are calculated from the original performance maps. The off-design performance is calculated only by considering relations related to the gas-generator's turbine and compressor matching and the power turbine and exhaust nozzle matching.

4.2.3. Multi-fidelity gas turbine models

High fidelity data of the engine performance provided by ATR, were used to build an error model based on the difference between the reference values and the calculated ones of the L0 and L1 models. We note x the vector of the inputs of the gasturbine module (Eq. (8)), $\delta P(x)$ the difference between the values of available power (Eq. (9)) and $\delta SFC(x)$ the difference between the values of specific fuel consumption (Eq. (10)).

$$x = [\text{Altitude, Mach, throttle}] \quad (8)$$

$$\delta P(x) = P_{ref}(x) - P_{model}(x) \quad (9)$$

$$\delta SFC(x) = SFC_{ref}(x) - SFC_{model}(x) \quad (10)$$

where the subscript "ref" refers to the reference value and the subscript "model" refers to the calculated value of the model (L0 or L1). The vector x consists of 166 points called training points for which the reference and the model values are both known. The training points are not uniformly distributed over the domain, but they have higher density in the regions representing the operating conditions of the gas turbine for the conventional aircraft (high throttle settings). $\delta P(x)$ and $\delta SFC(x)$ have been evaluated at these specific points and approximated by a surrogate model for each value of x . This was done using the Surrogate Modeling Toolbox (SMT), an open-source Python package consisting of libraries of surrogate modeling methods [22].

The choice has been made to use a kriging model (also called Gaussian Process interpolation) as surrogate model. This kind of surrogate model has two main advantages:

- Once constructed, the cost of evaluating the surrogate model is negligible.
- An estimate of the modeling uncertainty is intrinsically provided by the kriging model.

After modeling the error between the models' and the reference's values, two multi-fidelity models (LOMF, L1MF) were obtained by correcting the output of each model with the modelled error. As the error is approximated by an analytical model provided by kriging technique, the resulting multi-fidelity model, called LOMF (resp. L1MF), is

obtained as the sum between the L0 model (resp. L1 model) and the kriging model. For example, for the L0MF model, the outputs relative to the SFC and the power are calculated as in Eqs. (12-13).

$$SFC_{L0MF}(x) = SFC_{L0}(x) + \varepsilon_{0_SFC}(x) \quad (12)$$

$$P_{L0MF}(x) = P_{L0}(x) + \varepsilon_{0_P}(x) \quad (13)$$

For the L1MF, we have some similar expressions (see Eqs. (12bis-13bis)).

$$SFC_{L1MF}(x) = SFC_{L1}(x) + \varepsilon_{1_SFC}(x) \quad (12bis)$$

$$P_{L1MF}(x) = P_{L1}(x) + \varepsilon_{1_P}(x) \quad (13bis)$$

where ε denotes the kriging model associated to the error for the SFC or the power.

For sake of simplicity, perfectly dependent kriging models will be considered in the resolution of the MDA. Numerical validations of this simplification have been assessed in [15]. Thus, in the following the kriging models ε_{0_SFC} , ε_{0_P} , ε_{1_SFC} and ε_{1_P} are defined as in Eqs. (14-15-14bis-15bis).

$$\varepsilon_{0_SFC}(x) = \mu_{0_SFC}(x) + \sigma_{0_SFC}(x)\xi_{0_SFC} \quad (14)$$

$$\varepsilon_{0_P}(x) = \mu_{0_P}(x) + \sigma_{0_P}(x)\xi_{0_P} \quad (15)$$

$$\varepsilon_{1_SFC}(x) = \mu_{1_SFC}(x) + \sigma_{1_SFC}(x)\xi_{1_SFC} \quad (14bis)$$

$$\varepsilon_{1_P}(x) = \mu_{1_P}(x) + \sigma_{1_P}(x)\xi_{1_P} \quad (15bis)$$

where ξ are independent and identically distributed standard normal random variables. The terms μ and σ are respectively the mean value and the standard deviation and their expressions are given analytically by the kriging interpolation. For more details about the kriging model, the reader can refer to [21].

By performing a set of simulations, each with a randomly chosen value of ξ , many results will be obtained from the MDA. Therefore, constructing the multi-fidelity models as shown in this section allows analyzing the results in terms of mean value and variance. Main results for the conventional and hybrid configuration are shown in the next section.

5. RESULTS

First, the performance of the conventional configuration of the ATR42 is evaluated with the four different gas turbine models in order to validate the MDA process and the methodology for the uncertainty propagation problem. Then, the hybrid electric configuration is analyzed to investigate the discrepancy between the results of the different gas turbine models.

5.1. Conventional architecture

The performance of the conventional ATR42 in terms of fuel consumption have been evaluated on the given mission of 200 NM (see Table 1) and on a longer mission of 500 NM. The calculated values have been compared to reference performance data obtained by replacing the gas turbine model with the reference data of engine performance provided by ATR. The results of the models will be presented in terms of relative error of the calculated block fuel with respect to the reference results.

The block fuel values obtained with the L0 and L1 models show respectively a relative error of +1.7% and +5.8% for the 200 NM mission (+3% and +5.9% for the 500 NM) with respect to the reference values as given in Table 3. The results of the multi-fidelity models are shown in Figs. 8 to 11. Mean value and variance (calculated with Bessel's correction) of the results of each model, estimated based on 500 sampling points are summarized in Table 4.

	L0	L1
200 NM	+1.7%	+5.8%
500 NM	+3%	+5.9%

Table 3: Relative error of the calculated block fuel with respect to the reference results for the conventional architecture.

For both missions, the mean values of the multi-fidelity models' results are closer to the reference value than the corresponding mono-fidelity model (L0 or L1). For example, for the 200 NM mission, the absolute value of the relative error between the calculated and the reference block fuel reduces from 1.7% with the L0 model to 0.13% with the L0MF model (5.8% with the L1 model to 2.19% with the L1MF model). However, the variance of the results of the L1MF model is always lower than the one of the L0MF model. This is related to the capability of the surrogate model to predict the error between the mono-fidelity model and the reference.

The more accurate the mono-fidelity model is to predict the performance of the gas turbine, the easier it is for the kriging model to predict the model errors. This results in a lower variance associated to the results of the multi-fidelity model.

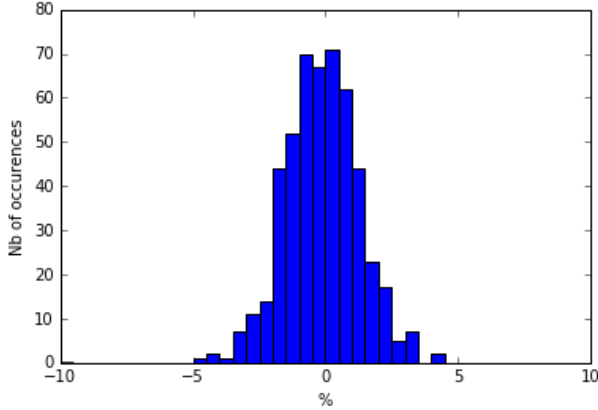


Figure 8: LOMF model's results distribution on the 200 NM mission for the baseline configuration. Histogram based on 500 sampling points.

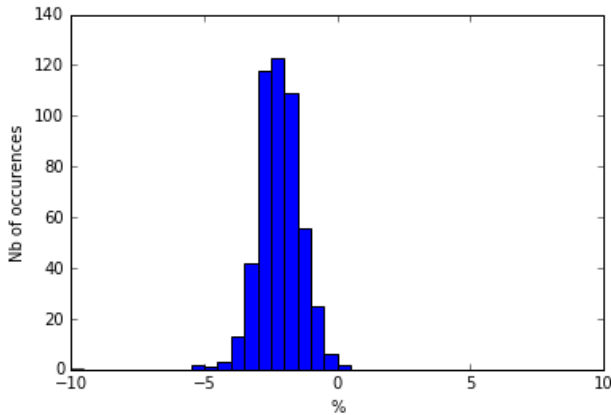


Figure 9: L1MF model's results distribution on the 200 NM mission for the baseline configuration. Histogram based on 500 sampling points.

		LOMF	L1MF
200 NM	Mean value	-0.13 %	-2.19 %
	Variance	1.918	0.598
500 NM	Mean value	-0.740 %	-2.248 %
	Variance	2.727	0.937

Table 4: Mean value and variance of the results of each multi-fidelity model for the baseline configuration. Estimation is done based on 500 sampling points.

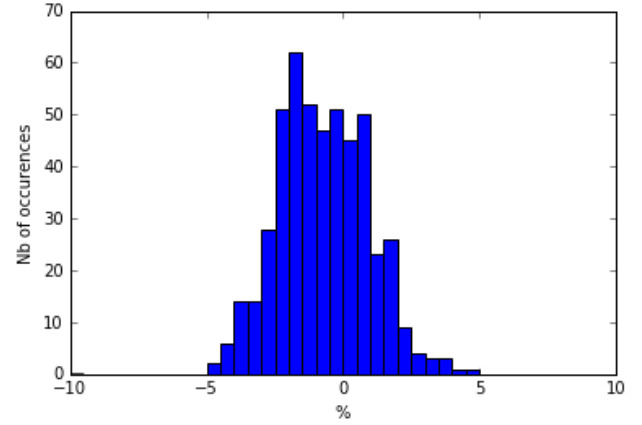


Figure 10: LOMF model's results distribution on the 500 NM mission for the baseline configuration. Histogram based on 500 sampling points.

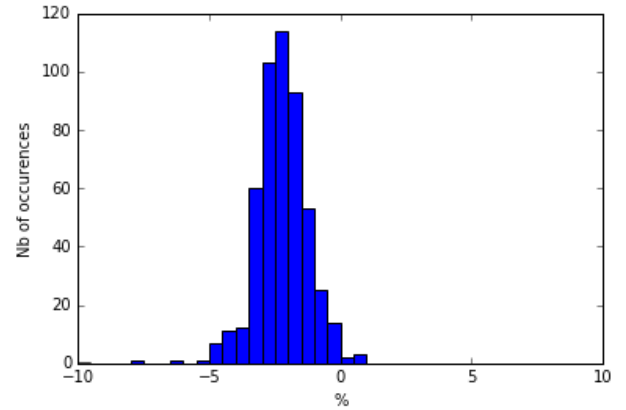


Figure 11: L1MF model's results distribution on the 500 NM mission for the baseline configuration. Histogram based on 500 sampling points.

5.2. Hybrid electric architecture

For the hybrid electric configurations, the results for the given mission of 200 NM will be presented in terms of percentage reduction of the block fuel per passenger with respect to the reference value of the conventional configuration. As mentioned in section 3, the maximum number of passengers that the hybrid electric aircraft configuration designed for this study is allowed to accommodate is expected to be lower than the conventional capacity of the ATR42. Since the OWE of the aircraft increases due to the installation of the hybrid electric systems, in order to respect the same MTOW limitation of the conventional ATR42, the max payload weight of the aircraft decreases.

Nevertheless, the results obtained with L0 and L1 models show that for the 200 NM mission the hybrid electric configuration gives a potential reduction of block fuel per passenger respectively of -8.9% and -2.4% (as shown also in Table 5). There is a considerable difference between the results of these two models, therefore without additional information it would be impossible to conclude about the performance of the hybrid electric aircraft configuration. The multi-fidelity models are therefore used in order to analyze the aircraft performance taking into account the modeling uncertainty associated to the results.

The results of each multi-fidelity model are shown in Figs. 12 and 13. Table 6 summarizes the mean value and variance of the results.

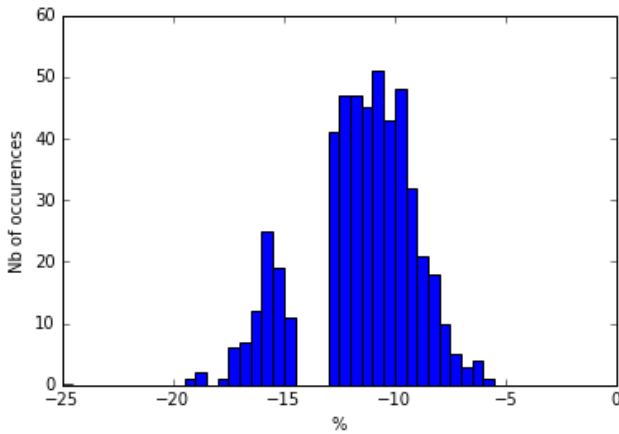


Figure 12: LOMF model's results distribution on the 200NM mission for the HEA configuration. Histogram based on 500 sampling points.

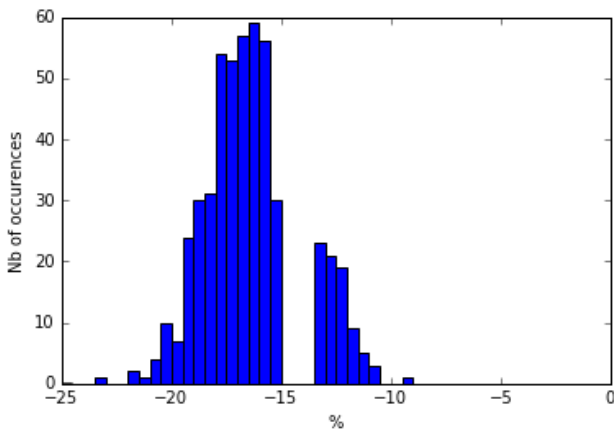


Figure 13: L1MF model's results distribution on the 200 NM mission for the HEA configuration. Histogram based on 500 sampling points.

	L0	L1
200 NM	-8.9%	-2.4%

Table 5: Percentage reductions of the block fuel per passenger for the HEA configuration with respect to the reference value of the conventional configuration

		LOMF	L1MF
200 NM	Mean value	-11.5 %	-16.5 %
	Variance	6.01	4.82

Table 6: Mean value and variance of the results of each multi-fidelity model for the HEA configuration. Estimation is done based on 500 sampling points.

Analyzing the results of the LOMF model, the potential reduction of block fuel per passenger of the HEA configuration seems to be included in a rough interval ranging from -20% and -5%. With the L1MF model it was possible to reduce the uncertainty of the results which gives a potential reduction approximatively between -20% and -10%. However, both the multi-fidelity models show a considerable increase of the variance of the results with respect to the results of the conventional configuration. This can be justified by the different operational points at which the gas turbine engine of the hybrid configuration is working. In fact, due to the contribution of the electric motors to supply the required power, the throttle setting of the gas turbine is lower than the baseline configuration. As mentioned in section 4.2.3, the training points used to build the error model have higher density in the region at high throttle, which results in a lower variance of the error estimated within this region.

The characteristic bimodal distribution of the results observed in Figs. 12 and 13 can be attributed to the fact that the represented variable in the histogram is the ratio between a real number (block fuel) and an integer (number of passengers). The number of passengers is calculated dividing the payload weight (obtained with Eq. 2) by the passenger weight and approximating the result at the lower integer number. Therefore, each mode represents a change in the number of passengers the aircraft can transport.

Moreover, assuming that the hydrogen used by the fuel cells to generate electrical power is completely derived from green power sources, the only source

of CO₂ emissions is the combustion of fuel in the gas turbine engines. Since CO₂ emissions from the aforementioned combustion are directly proportional to the fuel consumption, the reduction of CO₂ emissions per passenger is equivalent to the one of block fuel.

6. CONCLUSIONS

In this paper, the performance of an ATR42 retrofitted with a parallel hybrid propulsion architecture comprising a conventional gas turbine and a fuel cell powertrain have been investigated with a MDA platform called RHEA design tool. In order to deal with the modeling uncertainties introduced by the methods used to describe the disciplines involved in a classical aircraft design problem, high-fidelity aircraft's manufacturer data have been used to verify and validate the results computed by each model. For some disciplines (e.g. aerodynamics and weights) the models were accurate enough to give results with a negligible error when compared to reference data. However, for some others it was not possible to achieve an acceptable accuracy of the results. Specifically, it was the case for the gas turbine model, therefore in order to assess the potential advantages of the selected hybrid electric configuration, multi-fidelity models were constructed and used into the MDA to provide more reliable results.

By comparing the results of the four gas turbine models employed to perform this study, it can be concluded that relying only on the results of the models L0 and L1 would led to erroneous and contradictory results. However, the availability of high-fidelity data allowed creating two multi-fidelity models which converged towards similar results.

These results shall not be interpreted as an assessment of the performance of the hybrid electric version of the ATR42. In fact, the hybrid architecture, the hybridization strategy and the assumptions used for the sizing of the electric power system and hydrogen storage represent only a potential scenario which was chosen as a test case for this study to set up the methodology for the modeling uncertainty propagation and to perform the comparative study of the different gas turbine models.

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