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An optimized fuzzy logic for the energy management of a hybrid electric air-taxi

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Abstract. The goal of this investigation is to model a hybrid electric air-taxi and minimize its fuel consumption by on-line energy management. Urban Air Mobility (UAM) is considered as a suitable way to reduce traffic congestion and pollution as well as increase mobility in metropolitan areas. Urban air-mobility is an interesting application for electric and hybrid-electric power systems because of limited speed (compared with longer distance commuters) altitudes up to 1000ft and short-range requirements that make possible electrification even with the limited performance of today batteries. However, in case of hybrid electric propulsion systems, the fuel consumption and the environmental impact depends on the energy management. After obtaining reference values of fuel economy over four different missions with the Dynamic programming method, this investigation proposes and optimize a fuzzy logic for the on-line energy management of the hybrid vehicle for UAM in order to minimize fuel consumption and, consequently, local environmental impact.

1 INTRODUCTION

Urban Air-Mobility (UAM), refers to safe, efficient, and clean urban transportation systems that move people and goods by air. UAM is enabled by new technologies and integrated into multimodal transportation systems and is expected to become a reality in Europe within 3-5 years according to the EASA (European Aviation Safety Agency). Urban air-mobility is based on vertical take-off and landing capability and characterized by the short-range requirements, limited speed (in comparison with longer distance commuters) and altitudes up to 1000ft [1]. This makes UAM a suitable application field for electrification even with the limited energy density of today batteries. Pure-electric and Hybrid Electric Propulsion Systems (HEPS) can be considered as alternatives for the air-taxi operation. Compared with Pure-electric power systems, HEPS have the advantages of longer endurance and range thanks to the presence of two energy storage systems: a fuel tank and an electric storage system (usually a battery). With respect to a conventional power system, the specific advantages of hybrid electric power systems for rotorcraft are higher reliability, increased operational lifetime thanks to reduction in the number of devices (e.g., gear, transmission,

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etc.), improved maintenance workability and lower operational costs together with lower noise and vibration levels [1]- [3]. As a further advantage, particularly relevant for single-engine rotorcraft for passenger transport, the battery pack allows for a few minutes of endurance in case of engine failure (electric back-up) [4]. These advantages need to be weighed against the increased weight and complexity of the resulting power system [5].

In this investigation, a rotorcraft for UAM with a parallel HEPS is considered [6]: the thermal engine and the electric motors are mechanically connected to the rotor shaft through a gear-box. Most studies in aerospace literature concentrates on the sizing of this kind of propulsion systems [7]-[9] but in HEPS, the power management of the multi-source operation is also critical. This issue can be addressed either with a heuristic approach (energy management strategies based on intuitive rules and correlations between the variables of the system) or with optimization-based approaches. Heuristic Control Techniques can be based on Fuzzy Logic controllers [10]-[11] and require a very low computational cost [12] but do not guarantee the optimal usage of the battery that is the goal of the optimization approaches. Optimization approaches can be performed either off-line at a global level or on-line with a local optimizer [6]. In the first case, the control strategy of the hybrid electric power system is designed for the typical mission of the vehicle. This procedure requires the drive cycle (or the mission profile in the aeronautic field) to be known a priori and do not assure the optimization of the energy flows in the real-world conditions. On the contrary, an on-line or local controller, performs a mathematical optimization of the energy flows on-board during the normal operation of the vehicle with or without a full knowledge of the actual driving/flight pattern.

This classification of the energy management strategies derives from the vast literature on the energy management of hybrid electric power system in the automotive field [6] but can be applied to the aerospace field too [13]. However, to be applied to the specific case of rotorcraft for air-taxi operation, these approaches need to be amended considering the specific goals and constrains of the application. To this scope, an off-line optimization of the energy management with the Dynamic Programming Method [6] was proposed by some of the authors in a previous investigation to provide insights on how to develop a suitable on-line energy management. The main result of the previous investigation was the possibility to define, for each mission, an optimal curve for the discharge of the battery along the mission that we will denote here as Reference State of Charge (RSOC). In this investigation, a heuristic strategy is developed by applying and optimizing a fuzzy logic where the input variables are the required power at the rotor shaft and the deviation from the actual battery state of charge from the RSOC, while the output is the sharing of required power between the thermal engine and the electric machines.

The novelty of this investigation with respect to the works in literature ([10]-[11]) is that the heuristic strategy is based on the concept of RSOC which requires only few information like the time duration of the different phases of flights that can be easily obtained in the UAM application.

2 THE AIR-TAXI POWER SYSTEM

A parallel hybrid electric coaxial rotor helicopter for Urban Air-Mobility is considered in this work (see Fig. 1.). Due to a confidentiality agreement, the technical specification of the vehicle and the size of the powertrain components will not be reported here and all data in the paper will be shown in a dimensionless way. In particular, the flight time will be scaled according to the average time of flight in normal air-taxi operation that will be referred to as t_{AT} and all data related to mechanical power will be scaled with the nominal power of the engine $P_{ice,nom}$. The electric machines nominal power ($P_{EM,nom}$) is such that the power hybridization degree of the system (defined as the ratio of electric power to total installed power) is equal to 0.45. The electric machines are fed by a Li-ion battery pack that is sized to allow, at any time, electric back-up operation in case of engine failure (see [14]).

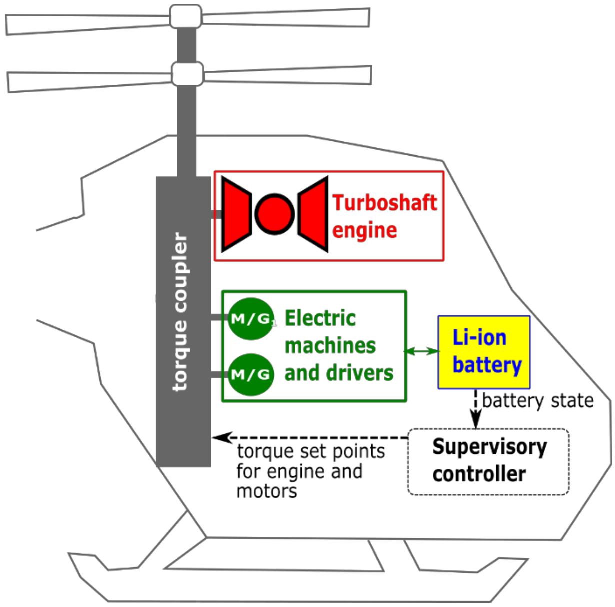


Fig. 1. Overview of the hybrid electric power systems.

In this application, a flight mission is a time sequence of the basic flight regimes of a helicopter: take-off, climb, forward flight, hover, descent and landing. To account for the variability of flight conditions typical of UAM application, four profiles of power request, altitude and speed vs time were considered as shown in Fig. 2. Mission #A is a schematic power request proposed by the industrial partner of the project, the other three missions were obtained, after appropriate scaling, from a previous work [4]. Note that the flight of the four missions (that we will denote as t_M) ranges between $0.55t_{AT}$ and $1.25t_{AT}$.

The proposed power system can work in four different modes in each flight regime. In thermal mode, the power request at the shaft is satisfied using only the engine. In electric mode, the electric drive moves the shaft while the engine is off or idling. In power assist mode, the electric machines and the engine together move the shaft. This operational mode is very useful during the take-off and climb phases where the power request is higher than in the other flight regimes. Finally, the turboshaft engine could be used to charge the battery during the flight. The electric mode is the only available in case of engine failure (electric back-up operation) while in the normal operation the selection of the operational mode is performed by the energy management strategy.

In this investigation, the energy management strategy will be optimized with the constraint of keeping the battery sufficiently charged during the whole mission (so to allow electric back-up at any time in case of engine failure even in the case of aged battery) while the goal will be to the minimization of fuel consumption, not only to save money but above all to reduce the environmental impact of the helicopter during the normal operation including the four missions #A (j=1),#B (j=2),#C (j=3),#D (j=4).

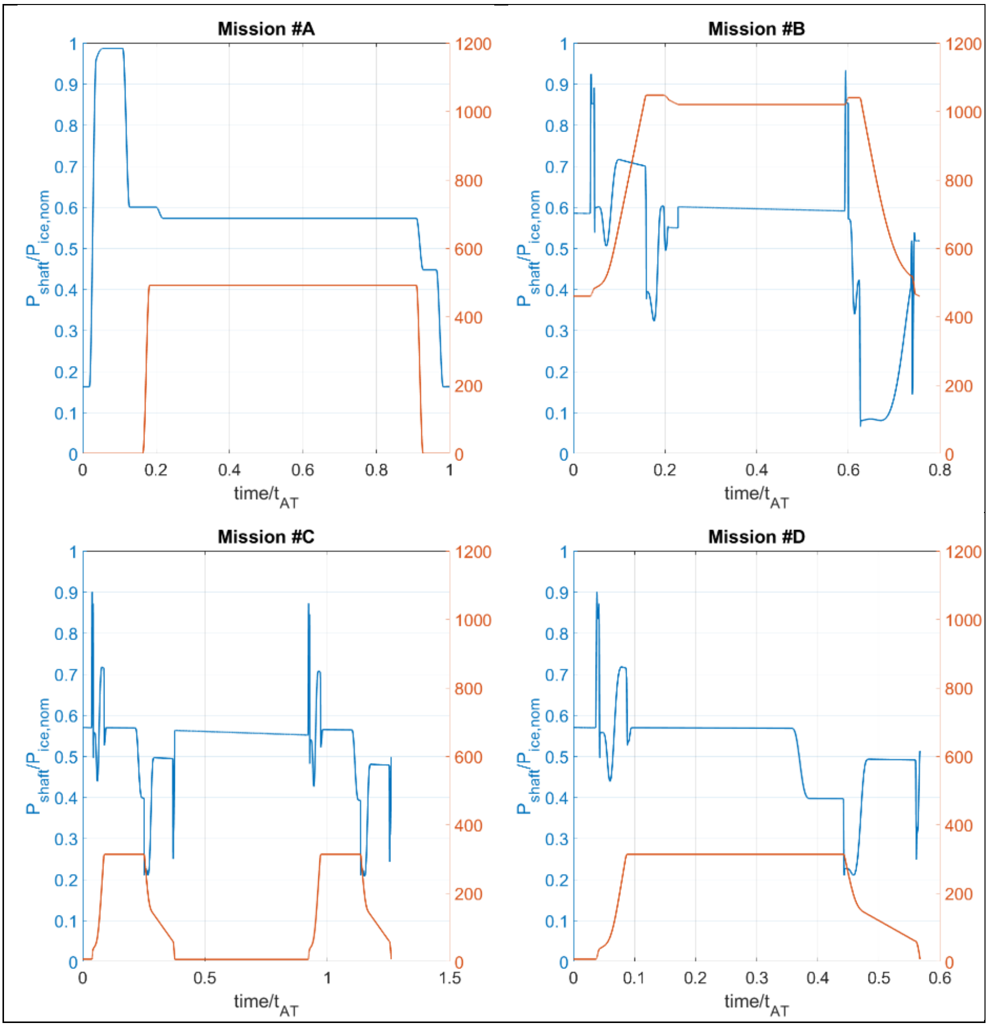


Fig. 2. Proposed missions for the air-taxi operation, t_{AT} is average time of flight in normal air-taxi operation.

2.1 The model of the powertrain

An in-house simulation code with the flow chart of **Fig. 3** was developed for this application. The model takes as inputs the altitude, speed and power shaft profile of the mission. At this state of the investigation, the shaft speed is assumed constant but as a further development, a dynamic model of the rotor will be included.

The supervisory controller implements the energy management strategy and decides the set points of the engine and the electric machine in terms of required torque, according to power request, desired rotational speed of the shaft, reference SOC curve, battery actual state of charge (SOC) and state of health (SOH).

The electric machines are modelled through the curve of motor maximum continuous torque and an efficiency map. The dynamic behaviour is taken into account with a mechanical time constant [15]. The inputs are the torque set point, the required shaft speed, and the battery voltage.

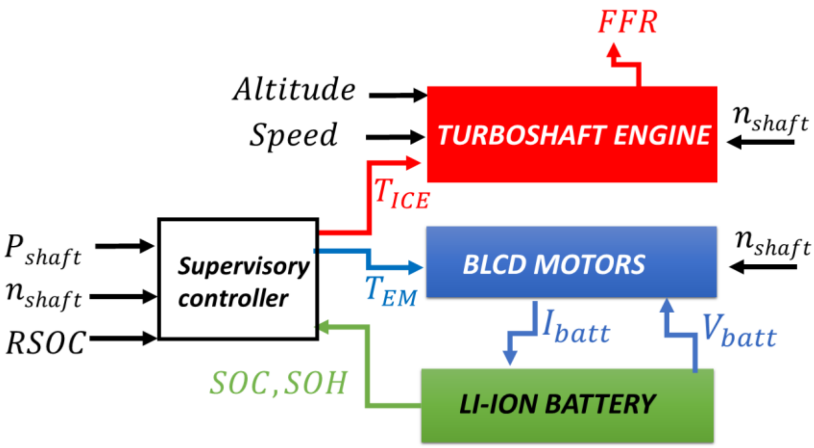


Fig. 3. Flow chart of the in-house model

In this investigation, the battery is simulated with an electric equivalent circuit [6] where the Open Circuit Voltage OCV is a mapped as a function of the battery state of charge, while the internal resistance R depends on the specification of the battery and varies along the battery life. However, to take into account the Peukert effect (i.e. the reduction of the battery actual capacity when increasing the discharge power), the effective current I_{eff} is calculated as:

$$I_{eff} = I \cdot \left(\frac{I}{I_{nom}}\right)^{n-1} \tag{1}$$

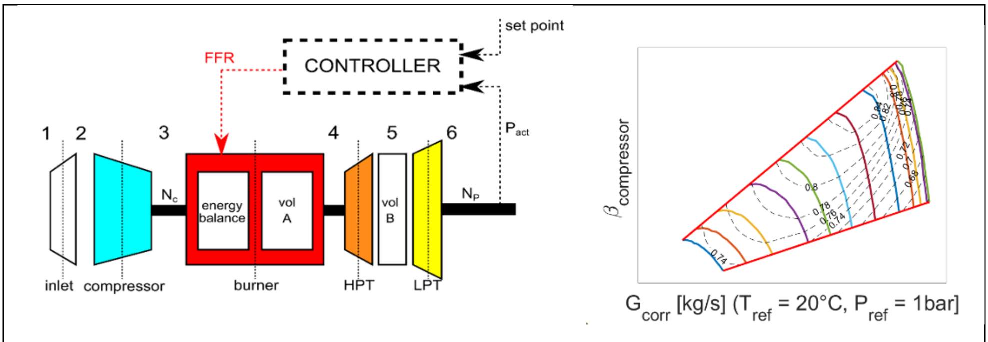
Where n is the Peukert coefficient of the battery, I_{nom} is the current at which the nominal capacity C is referred to.

Using the effective current, the state of charge of the battery SOC is upgraded, at any time during the mission, as:

$$SOC(t) = SOC(t_0) - 100 \cdot \int_{t_0}^{t} \frac{I_{eff}(t)}{C} dt \tag{2}$$

Another important characteristic of the proposed battery model is that the values of capacity, internal resistance and Peukert coefficient are updated with the battery cycle life (defined by the number of discharge/charging *cycles*) that is one of the inputs of the energy management strategy. For more details about the aging model, please refer to [16].

The engine considered in this investigation is a two-spool turboshaft engine with the High Pressure Turbine (HPT) connected to the compressor and rotating at speed N_c. The Low Pressure Turbine (LPT) is connected to the rotor shaft and rotates at the nominal speed of the shaft (N_p). The inlet (1-2) is modelled as a ram-air element with a constant efficiency (0.9). However, due to the low airspeeds of the air-taxi helicopter, this effect is quite negligible. The compressor (2-3) and the two turbines (4-5 and 5-6) are represented as gas-path components where the values of the output streams (total pressure, temperature, density and mass flow) are calculated from their current state and values of the input streams according to their performance maps. In particular, the compressor map is used to obtain the corrected mass flow rate and isentropic efficiency as a function of the corrected rotational speed and pressure ratio. It is shown qualitatively at the right side of Fig. 4.



a) Dynamic model of the turboshaft b) Compressor efficiency map

Fig. 4. Main blocks of the turboshaft dynamic sub-model

The burner dynamics (3-4) is represented by its temperature that is calculated with an energy balance using as input the fuel flow rate (FFR). The pressure drop across the combustion chamber is assumed equal to 2% of the input stream pressure.

The simulation of the mass balance is performed with the inter-component volume (ICV) method as applied in [17]. The dynamics of the fluid pressure in the ICV volumes A and B of Fig. 4 can be written as:

$$\frac{dP}{dt} = \frac{RT}{V}\frac{dm}{dt} = \frac{RT}{V}(\dot{m}_{in} - \dot{m}_{out}) \tag{3}$$

Where the variation of mass is due to the difference between the mass flows going into ($\dot{m}_{in}$) and out ($\dot{m}_{out}$)of the volume during transients while it is zero in stationary conditions. In equation (3), P and T are the pressure and temperature in the ICV at each time step, V is the volume and R the specific constant of the gas (universal gas constant divided by the molecular mass of the gas).

The balances of the work between the components on the same shaft can be written, for the conventional power system, as:

$$\dot{N}_c = \left(\frac{30}{\pi}\right)^2 \cdot \frac{1}{IN_2} \cdot \frac{P_{HPT} - P_C}{N_c} \tag{4}$$

$$\dot{N}_p = \left(\frac{30}{\pi}\right)^2 \cdot \frac{1}{IN_1} \cdot \frac{P_{LPT} - P_{load} + \mathrm{P}_{EM}}{N_p} \tag{5}$$

Where IN_1 and IN_2 are the inertial of the two systems, P_{HPT}, P_{LPT} and P_C are the instantaneous power of the two turbines and the compressor while P_{load} is the power of the load (i.e. the rotor in this specific application) and P_{EM} is the power delivered by the electric machines.

However, the dynamic of the power shaft has not yet been implemented and N_p is assumed constant. For more details on the engine model, please refer to [18].

3 The energy management

In a previous investigation [14], an enumerative optimization technique (Dynamic programming) was applied to a quasi-static model of the same powertrain in order to obtain the target values of fuel consumption for a given mission and to provide insights into how to develop a suitable on-line energy management strategy.

To obtain the target values for fuel saving, the problem was addressed as a typical optimum control problem where the control variable is discretized and defined as:

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$$u_{DPM}(h) = \frac{P_{EM}(h)}{P_{EM,nom}}, \; with \; 0 \leq u_{DPM} \leq 1 \tag{6}$$

where $P_{EM,nom}$ is the nominal power of the electric machine and $P_{EM}(h)$ is the shaft power produced by the electric drive at time step h during the selected mission j.

By selecting an appropriate value for u, all possible operating mode can be obtained: electric ($u_{DPM} = 1$), ICE ($u_{DPM} = 0$), power assist ($0 < u_{DPM} < 1$). Battery recharge ($u_{DPM} < 0$) was initially considered but then excluded because it was found not useful in terms of fuel saving (see [14]).

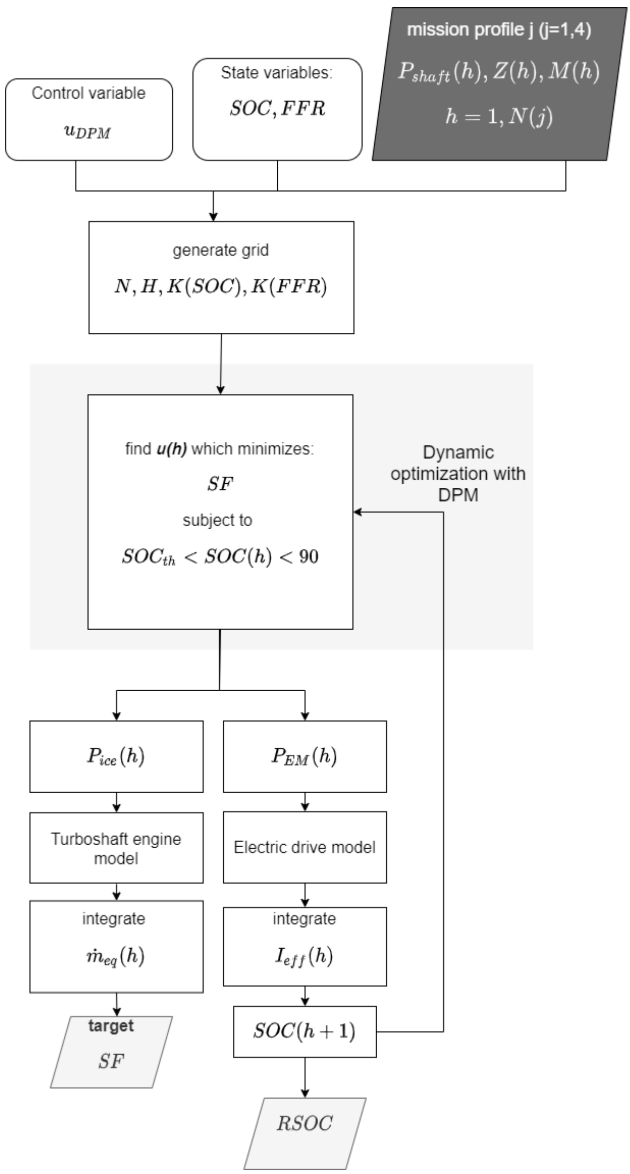

Fig. 5. Flowchart of the global optimization with DPM

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The objective function was the Saved Fuel as expressed by eq. (7) while the state variables considered were the battery SOC and the Fuel Flow Rate (FFR) of the engine.

$$SF(j) = \frac{fuel_B(j) - fuel(j)}{fuel_B(j)} \; with \; j = \#A, \#D \tag{7}$$

Where $fuel(j)$ is the fuel burn on mission j with the proposed energy management strategy while $fuel_B(j)$ is the benchmark value for the same mission obtained by using only the engine (thermal mode) all over the mission. The higher this metric, the better the energy management strategy.

The constraints introduced in the optimization are:

$$SOC_{th}(SOH) < SOC(t) < 90\% \tag{8}$$

$$P_{ice}(h,j) + P_{EM}(h,j) = P_{shaft}(h,j) \; \forall h = 1, N(j) \; with \; j = 1,4 \tag{9}$$

Where P_{shaft} is the power request of the mission (i.e. the value shown in **Fig. 2** discretized with the selected time step). Moreover, it proved necessary to introduce some constraints to avoid too fast transition of the engine operating point. In particular, a penalization was added to SF when the difference in the amount of FFR of two sequential instants is higher than 3.6 kg/h. The problem was solved with the well-known Dynamic Programming Method (DPM) [6] using the flowchart of Fig. 5.

The most interesting result of the DPM is that for all missions (see Fig. 6 for mission #D), the optimal line of SOC decreases during the manoeuvres of climbing and descent while it shows a plateau during the phases of hovering and cruise (i.e. when the rotorcraft works at constant speed and altitude). A similar behaviour was found for all missions but the SOC needs to be kept always higher in the case of aged battery (*cycles* =400) than in the case of new battery (*cycles*=1) as can be seen in Fig. 6.

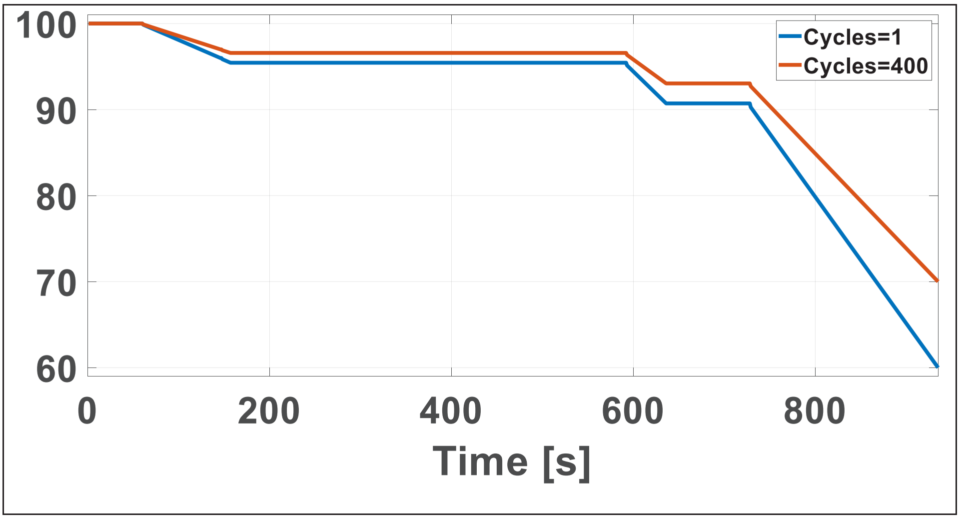

Fig. 6. RSOC curves for mission #D with new and aged battery

3.1 The fuzzy logic and its optimization

In this investigation, a fuzzy logic based on the RSOC concept was developed and optimized. The inputs considered for the fuzzy logic are the instantaneous deviation from the RSOC curve ($dSOC = SOC(t) - RSOC(t)$) and the required power shaft.

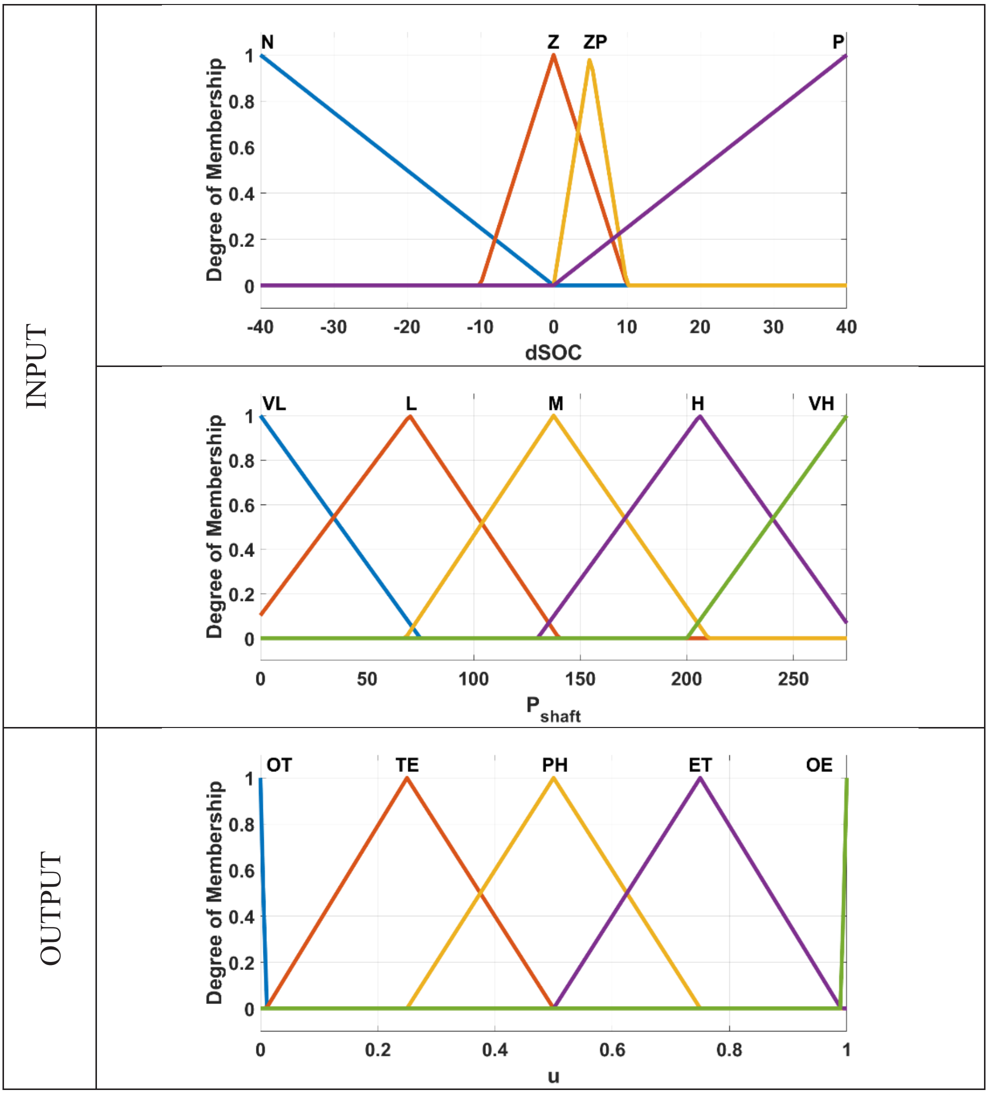

Fig. 7. Example of membership functions for inputs and output ($dSOC = SOC(t) - RSOC(t)$)

The following classes are considered for $dSOC$: N (negative), Z (near zero but negative), ZP (near zero but positive), P (positive). For the shaft power, the levels are VL (very low), L (Low), Medium (M), H (High) and VH (Very High).

The output variable of the fuzzy logic is the torque split ratio [6] between the electric machine and the thermal engine defined as:

$$u = \frac{T_{EM}}{T_{EM} + T_{ICE}} \tag{10}$$

The output variable u is classified as OT (only thermal engine), TE (thermal-electric power assist with 25% from the electric machines), PH (thermal-electric: power assist with 50% from the electric machines) ET (electric-thermal: power assist with 75% from the electric machines), OE (electric only). Note that the battery charging is not considered because of the results of the DPM as discusses also in [14].

The membership functions were built with the MATLAB Fuzzy logic designer tool and are shown in Fig. 7.

Each membership function is defined by the x coordinate of the vertexes i.e. the minimum, maximum and medium values of the variable in each class.

The inference scheme used in the investigation is shown in **Table 1** and consists of a set of i*f …then* rules with connectors AND. The first line at the left side of **Table 1** is to be read as follows: *if dSOC is N* (negative) *AND Pshaft is VL*, *THEN u=OT* and so on for the other lines.

Table 1. Rules of the fuzzy logic

dSOC=N	P_{shaft}	**u**
	VL	OT
	L	OT
	M	OT
	H	OT
	VH	OT

dSOC=Z	P_{shaft}	**u**
	VL	OT
	L	OT
	M	OT
	H	OT
	VH	OT

dSOC=ZP	P_{shaft}	**u**
	VL	OE
	L	ET
	M	ET
	H	TE
	VH	TE

dSOC=P	P_{shaft}	**u**
	VL	OE
	L	OE
	M	OE
	H	ET
	VH	ET

Table 2. Physical meaning of the numerical optimization inputs

Class	**Min**	**Medium**	**Max**
N	-40	-40	*max_n_SOC*
Z	*min_z_SOC*	0	*max_z_SOC*
ZP	0	*med_zp_SOC*	*max_zp_SOC*
P	*min_p_SOC*	40	40

For each input of the optimization, the range and step of variation were set as reported in Table 3.

Table 3. Range and step of variation of the numerical optimization inputs

Variable	**Min**	**Max**	**Step**
max_n_SOC	-35	0	0.5
min_z_SOC	-20	-0.5	0.5
max_z_SOC	0	20	0.5
med_zp_SOC	0.1	20	0.5
max_zp_SOC	3	20	0.5
min_p_SOC	0	35	0.5

Since the results of the fuzzy logic are very sensitive to the membership functions of the variable *dSOC*, a numerical optimization with Genetic Algorithms (GAs) was performed in the *Esteco Modefrontier* © optimization environment using as inputs the variables reported in italics in **Table 2** that defines the membership functions of the variable *dSOC*.

The flow chart of the optimization is shown in **Fig. 8**. Note that the input block also includes the variable *cycles* because the optimization was performed twice, the first time with the battery at the beginning of its life (*cycles*=1) and the second with the aged battery (*cycles*=400).

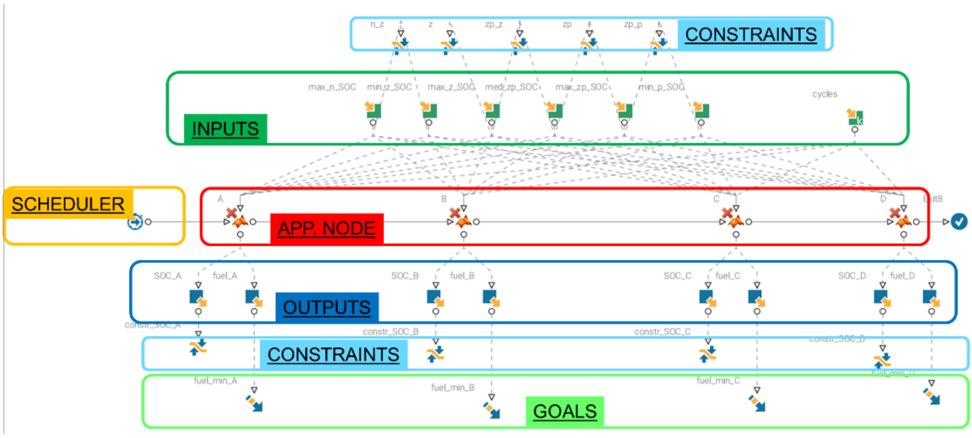

Fig. 8. Flowchart of the optimization

GAs are one of the most widely used optimization tool in engineering design problems because they are robust, general, easy to use and implicitly parallel (they can handle multi-objective optimization problems). The authors chose for this investigation the NSGA-II Genetic Algorithm because it was found to behave better than the other algorithms available in Modefrontier in a previous investigation [19].

The in-house Matlab script implementing the Fuzzy logic is used as application node to calculate the outputs of the optimization: the overall consumption in each mission and the final SOC. The four values of fuel consumptions are used as goals to be minimize.

The final SOC is used as constraint because it was desired not to discharge the battery over 60% and 70% with the new and aged battery, respectively. Other constraints shown in the upper part of **Fig. 8** are used to ensure the physical meaning of the membership functions:

$$\begin{cases} max_{n_{SOC}} > min_{z_{SOC}} \\ max_{z_{SOC}} < med_{zp_{SOC}} \\ max_{zp_{SOC}} > min_{p_{SOC}} \end{cases} \tag{11}$$

The optimization was run with 50 individuals for 100 generations for each value of *cycles* (1 and 400) with the standard setting proposed by the Modefrontier software for the NSGA-II scheduler. The results of the multi-objective optimization for the non-aged battery are shown in **Fig. 9** in the objectives space, two goals at a time. The plots show either the totality of the cases analysed in the search and the Pareto solutions. It can be noticed that the Pareto region is concentrated in a very narrow region so that it is quite indifferent to choose one or another of these solutions. Nevertheless, the optimisation problem cannot be treated as a single objective because we can notice that there is no linear correlation between the fuel saving data, above all between mission #A and #B.

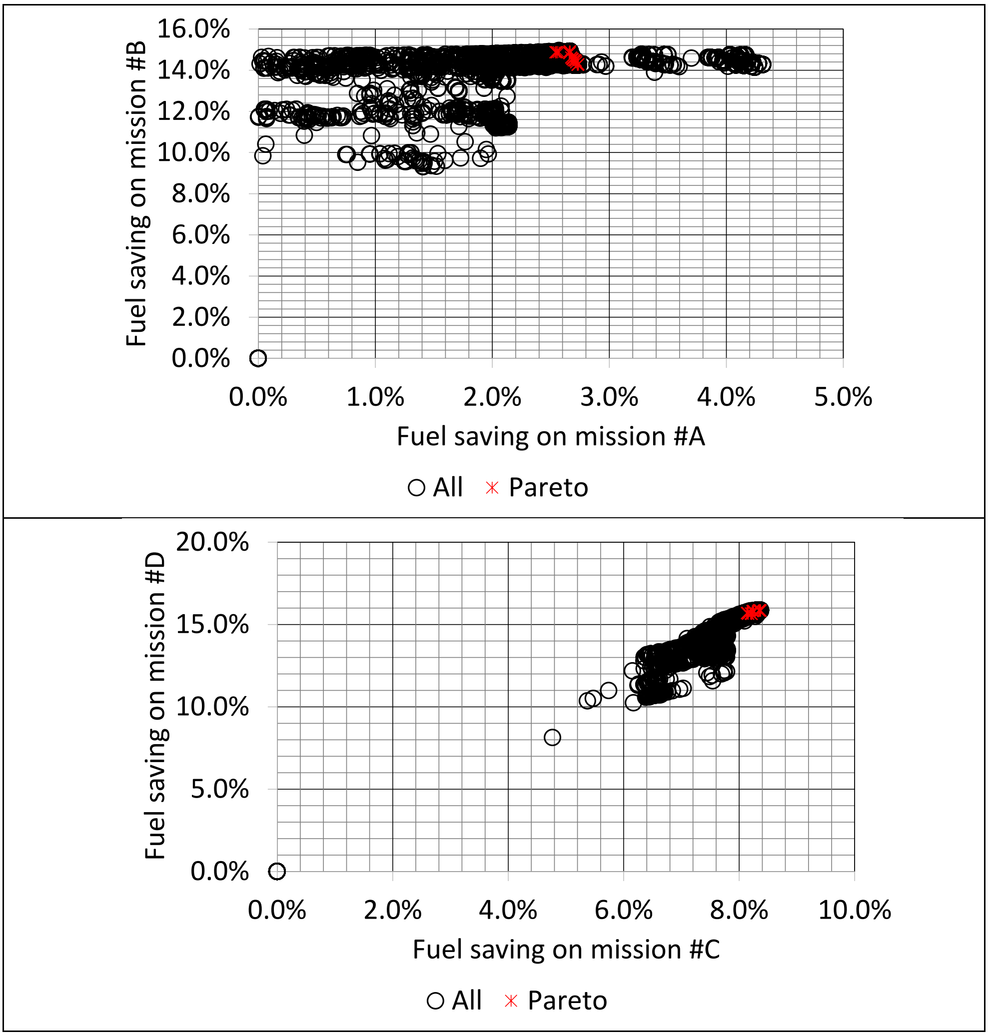

Fig. 9. Results of the multi-objective optimization for the non-aged battery

4 Analysis of the results

Due to the confidentiality issues, the results of the investigation are reported in terms of "Saved Fuel" (SF) as defined in eq. (7).

The fuzzy logic strategy before and after optimization is compared with the Dynamic Programming Method in **Fig. 10**. From this comparison we can discuss two aspects: the effectiveness of the optimization and the effect of mission. For the first issue, we can notice that the numerical optimization of the membership functions determined a larger improvement of the performance of the Fuzzy logic strategy on all missions but in particular on #A and #C where the non-optimized fuzzy logic gave poor results. In fact, the fuel consumption was almost the same of the only thermal case meaning that the hybridization is useless, if not harmful, in these missions. The optimized strategy reached very high percentage of fuel saving on mission #B and #D almost reaching the results of the DPM, in particular for mission #D. Mission #A appears to be the hardest to optimize probably because

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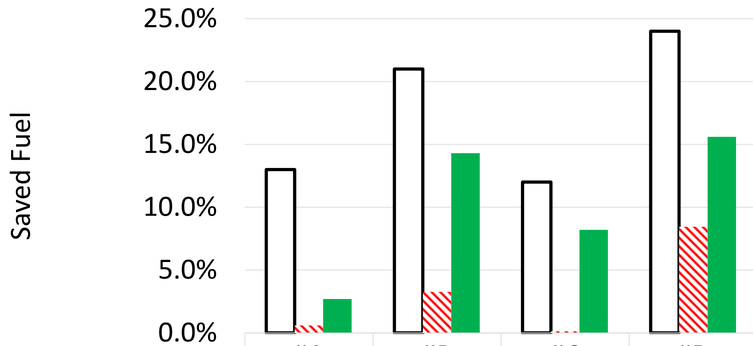
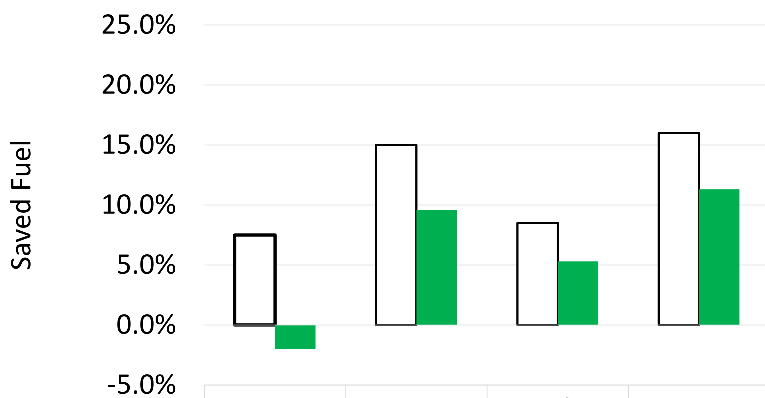
the very regular power profile with respect to the other missions (see **Fig. 2**) that makes less effective the hybridization.



	#A	#B	#C	#D
DPM	13.0%	21.0%	12.0%	24.0%
Fuzzy (original)	0.6%	3.3%	0.1%	8.4%
Fuzzy_optimized	2.7%	14.3%	8.2%	15.6%

Fig. 10. Results of the fuzzy logic before and after the optimization compared with the Dynamic Programming Method (new battery)



	#A	#B	#C	#D
DPM (aged)	7.5%	15.0%	8.5%	16.0%
FUZZY (aged)	-2.0%	9.6%	5.3%	11.3%

Fig. 11. Optimized fuzzy logic vs Dynamic Programming Method (aged battery)

In both cases, DPM and Fuzzy logic, the results of the energy management are strongly affected by the state of heath of the battery as underlined in **Fig. 11** that shows the results with the aged battery (*cycles*=400). Once again, the worst results are obtained for mission #A where it was obtained a worse fuel consumption than in the thermal case. For the other missions, the fuzzy logic reached good levels of fuel saving, compared with the DPM.

The effect of aging on the fuel economy of the hybrid electric powertrain is due to two factors. The first one is that the RSOC curve is different for the two cases (**Fig. 6**) and requires the battery to be "more charged" than in the case of the new battery to allow the backup electric landing. Moreover, being the electric power drawn by the motors the same in both cases, the aged battery needs to give a higher current because of the increased internal resistance and is discharged faster because its capacity is reduced and the Peukert effect is worsened by aging.

5. Online implementation of the proposed strategy

The DPM method is very time consuming and cannot be applied on-board because it requires a fully knowledge of the mission profile while the results of the fuzzy logic can be easily implemented on board as a 3D map as shown in **Fig. 12**. As shown in this investigation, however, it is important to add a further dimension in the map to include the effect of the battery aging.

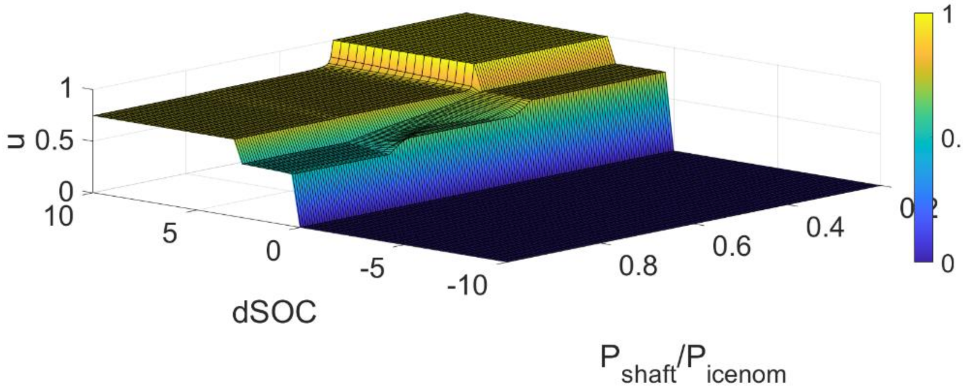


Fig. 12. 3D maps for on-line implementation (new battery)

Another requirement of the proposed heuristic strategy is the knowledge of the RSOC curve. In this application, it was obtained by the DPM optimization while in on-line application must be obtained by some flight information like the expected sequence of flight regimes and the expected total flight time. However, this information can be easily obtained in this application and could be updated during the flight because the calculation of the RSOC curve is not computationally onerous.

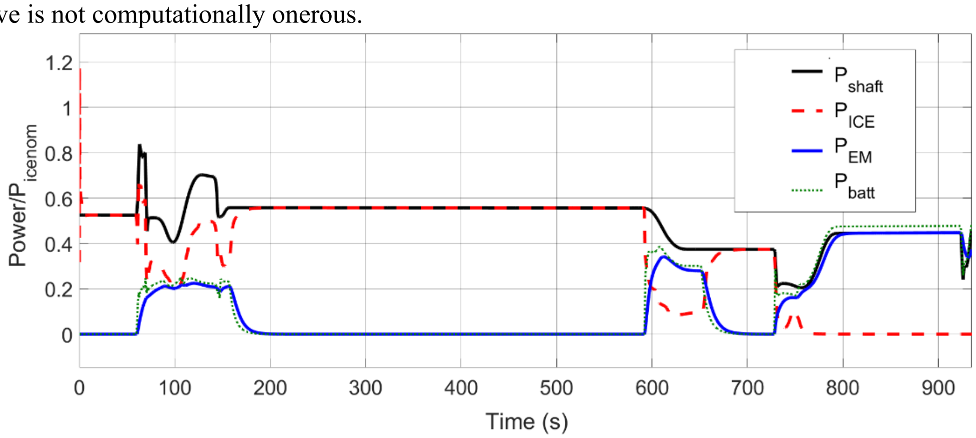


Fig. 13. Results of the dynamic model with the 3D optimized map (mission #D, non-aged battery)

The plots of **Fig. 13** shows the power distribution among the different components of the powertrain as obtained with the 3D map and the dynamic model presented in the previous section. **Fig. 14** compares the actual SOC curve with the RSOC trend implemented in the strategy, showing that the proposed strategy is able to follow reasonably well the desired discharge trend for the battery and to obtain almost the same values of overall fuel consumption either with the full logic and with the 3D map for the mission #D. Similar results are found for the other missions except #A that needs to be further investigated.

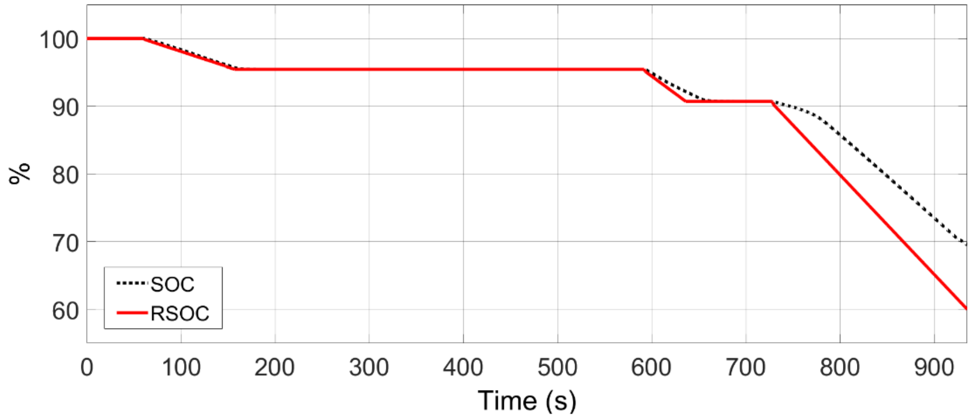


Fig. 14. Desired vs actual State of Charge of the battery (mission #D, non-aged battery)

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CONCLUSIONS

A fuzzy logic rule-based energy management strategy was proposed in this investigation for a parallel hybrid electric power system for air-taxi service. The power system was modelled with an in-house dynamic model that is also presented here and analysed over four different mission profiles.

The membership functions of the fuzzy logic were optimized with a multi-objective genetic algorithm in order to minimize fuel consumption in the four missions using as reference the optimal battery discharge curve obtained with the application of the Dynamic Programming Method. The optimization was repeated with the battery at the beginning and at the end of its life to take into account the battery degradation due to aging effects.

With respect to using only the engine during the whole mission, the proposed optimized fuzzy logic allows fuel saving from 3% to 16%, depending on the specification of the mission, The results of the investigation also showed that the aging of the battery strongly affects the fuel economy of the hybrid system, so that the best improvement of fuel consumption was of 11% with respect to the thermal case when the battery was considered at the end of its life.

Further investigations will deal with the development of a comprehensive model of the rotorcraft by including the rotor dynamics so to analyse the transient behaviour of the hybrid electric power systems as a consequence of the pilot commands. In this way, it will be possible to test the proposed energy management strategy under generic flight simulated conditions.

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