




Many-Objective Optimization of Mission and Hybrid Electric Power System of an Unmanned Aircraft

Teresa Donateo^(✉) , Claudia Lucia De Pascalis,
and Antonio Ficarella

Department of Engineering for Innovation, University of Salento, Lecce, Italy
teresa.donateo@unisalento.it

Abstract. This work aims at comparing different many-objective techniques for the optimization of mission and parallel hybrid electric power system for aircraft. In particular, this work considers, as input of the optimization, the specification of the flight mission, the size of the main components and the energy management strategy for a Medium Altitude Long Endurance Unmanned Aerial Vehicle (MALE-UAV). The goals of the optimization are maximization of electric endurance, minimization of overall fuel consumption, improvement of take-off performance and minimization of the additional volume of the hybrid electric solution with respect to the initial conventional power system. The optimization methods considered in this study are those included in the ModeFRONTIER optimization environment: NSGA-II, MOGA-II, MOSA (Multi Objective Simulated Annealing algorithm) and Evolutionary Strategy of type $(\mu/\rho + \lambda)$ -ES. Initially, appropriate metrics are used to compare the proposed methods in a simplified problem with only two objective functions. Then a complete optimization is performed, in order to underline the degradation of the proposed optimization methods as the size of the problem increases and to define the best method according to the number of objective functions.

Keywords: Many-objective optimization · Evolutionary algorithms
Hybrid electric aircraft · Performance metrics

1 Introduction

Thanks to the superior energy density of hydrocarbon fuels, internal combustion engines, in particular gas turbines, are the favorite technology in the aircraft propulsion field. However, engines have a lower efficiency and power-to-weight ratio when compared to electric motors. Hence, hybrid-electric propulsion systems have been proposed to take advantage of the synergy between engines and motors and to improve the overall fuel economy.

Since the late 1990s, a series of theoretical, experimental and commercial activities have focused on electric and hybrid electric power systems, initially only for secondary power (more-electric aircraft) but recently also for propulsion. A good review can be found in [1] however, the literature in this field is getting richer and richer in the recent years. Electric aircraft uses a battery-motor system to move the propellers instead of a

conventional thermal engine. Because of the limited energy density of batteries with respect to fossil fuel, the range of this kind of aircraft is quite low but so it is also its environmental impact. Hybrid electric aircraft exploits the advantages of both energy sources and converters. When the power request is very high, typically takeoff and first climb, the engine is helped by the battery through the electric machine that works as a motor. When the power request is low, i.e. in descent, the excess power of the engine can be used to charge the battery by using the electric machine as a generator. Some parts of the flight can also be performed in electric mode. The choice among the different operating mode is the so-called energy management strategy.

The design of a hybrid electric power system requires a complex optimization procedure because its performance will strongly depend on both the size of the components and the energy management strategy. The problem is particularly critical in the aircraft field because of the strong constraints in terms of weight and volume and of the necessity of adapting the flight specifications (altitude and speed) to the performance of the propulsion system. In the present investigation, the problem is addressed by linking an in-house code for the simulation of hybrid electric power systems with a commercial many-objective optimization software, namely Esteco ModeFRONTIER.

Real-world engineering design problems often involve the satisfaction of multiple performance indexes and, contemporarily, the respect of some constraints on the design variables. Automotive and aerospace, in particular, provide many examples of design challenges involving a large number of objectives (or goals) like that considered in this investigation.

When the functions to be optimized are more than one, a problem is named “multi-objective”, if they are more than three, it is called “many-objective optimization” [2–5]. In the study of Li et al. [3], a survey of many-objective evolution algorithms (MaOEA) is conducted. They are categorized into seven classes: relaxed dominance based, diversity-based, aggregation-based, indicator-based, reference set based, preference-based, and dimensionality reduction approaches.

In the industrial design, the role of multi- and many- objective optimization is more and more relevant, because the increasing computing power of modern computers provides designers with the ability of building complex parametric models that can be used to realize automatic optimization procedures. However, commercial optimization tools are often used without a deep knowledge of their behavior and in particular of their loss of performance when increasing the complexity of the problem [2].

Multi-objective optimization methods can be classified in aggregating methods (classical approach, with weighted or utility functions) and non-aggregating methods (classification of the population based on Pareto dominance). The concept of Pareto dominance or Pareto-optimal solution (2,3) is based on the identification of non-dominated solutions.

$$f_i(\bar{x}_j) \leq f_i(\bar{x}_i) \forall t = 1, \dots, k \forall j = 1, \dots, m \neq i \quad (1)$$

$$f_i(\bar{x}_j) \leq f_i(\bar{x}_i) \text{ for at least one } t \forall j \quad (2)$$

The set of all non-dominated solutions is called Pareto-front and is the final aim of any multi-objective optimization. Theoretically, a Pareto-front can contain a potentially

infinite number of optimal solutions. The task of a multi-objective optimizer is to provide to the decision-maker a trade-off surface as near as possible to the real one. The set of solutions generated by the optimizer is an approximation set and is characterized by different qualities: proximity or convergence, diversity and pertinence [4].

Convergence refers to finding a set of solutions that lie on or close to the true Pareto-optimal front. Diversity refers to finding a set of solutions that are diverse enough to represent the entire range of the Pareto-optimal front. Diversity is important because the approximation set should contain a good distribution of solutions, in terms of both extent and uniformity. Pertinence means that this set should only contain solutions in the decision maker's (DM) region of interest (ROI). In practice, and especially as the number of objectives increases, the DM is interested only in a sub-region of objective space. Thus, there is little benefit in defining trade-off regions that lie outside the ROI. Focusing on pertinent areas of the search space helps to improve optimizer efficiency and reduces unnecessary information that the DM would otherwise have to consider.

The performance of optimization methods with respect to the quality of the Pareto front for multi- and many-objective optimization is usually tested over mathematical problems [5]. In the present investigation, on the contrary, four different methods are compared with reference to a real-world engineering problem in the aircraft field. As already explained, the algorithms already implemented in the ModeFRONTIER environment were considered without changing their parameters. This commercial software was chosen because it is very user-friendly. Moreover, it allows a clear representation of the overall results of the optimization and an easy choice of the final configuration. On the other hand, as any other commercial software, it does not perform measurements of the performance of the optimization algorithm. In this work, the comparison of four optimization methods will be accomplished with the help of several performance metrics retrieved in literature and applied to the results of the ModeFRONTIER software after appropriate handlings.

1.1 Evolutionary Methods

The term evolutionary algorithm (EA) indicates a class of stochastic optimization methods that simulate the process of natural evolution. Based on the concepts of individuals, population, generation, selection and variation, natural evolution is simulated by an iterative computation process that is usually ended when a predefined maximum number of generations is reached. Other stop conditions, e.g., stagnation in the population or existence of an individual with sufficient quality, can be used to end the optimization.

Here follows a short description of the optimization methods implemented in modeFRONTIER and compared in the present investigation. NSGA-II is a fast and elitist multi-objective evolutionary algorithm. Its main features are: a fast non-dominated sorting procedure, the implementation of elitism, a parameter-less diversity preservation mechanism, a modified definition of dominance used to solve constrained multi-objective problems and the possibility to handle both continuous ("real-coded") and discrete ("binary-coded") design variables [7]. MOGA-II is a multi-objective genetic algorithm that uses a smart multi-search elitism. This elitism operator is able to preserve excellent solutions without bringing premature convergence

to local-optimal frontiers [7]. Evolution strategies are characterized by the following four properties: selection of individuals for recombination is unbiased, selection is a deterministic process, mutation operators are parameterized and therefore they can change their properties during optimization and individuals consist of decision parameters as well as strategy parameters. The standard notation of these methods is $(\mu/\rho +, \lambda)$ -ES; where λ is the number of off-springs generated by ρ parents at each step, μ parents are overall involved at each step [8]. MOSA is based on the well-known work of Kirkpatrick et al. (1983) [9] about Simulated Annealing (SA). In contrast with the original SA which is a single objective optimization method, MOSA is a genuine multi-objective optimization algorithm.

Despite their simplicity, EAs have proven themselves as a general, robust and powerful search mechanism for single and multi-objective optimizations also thanks to their ability to capture multiple Pareto-optimal solutions in a single simulation run. For this reason, they are extensively used in engineering applications.

However, EMOAs scalability to many-objective problems is critical. In particular, a deterioration of the search ability of Pareto dominance based EMO algorithms such as NSGA-II, an exponential increase in the number of solutions required for approximating the entire Pareto-front and a difficulty of the visualization of solutions are reported in literature. In the study of Ishibuchi et al. [6] the above mentioned difficulties are reviewed and demonstrated. In the present investigation, they will be addressed with reference to real world optimization problems.

2 The Optimization Problem

In this study, the optimization of both the hybrid electric power system for a Medium Altitude Long Endurance Unmanned Aerial Vehicle (MALE-UAV) similar to the General Atomics Predator RQ-1 and its mission specification is considered.

The UAV has an aspect ratio (b^2/S) equal to 19.1 and a wing load $W_0/S = 818.1 \text{ N/m}^2$ (where b is the wing span, S the wing area and W_0 the takeoff weight). The aircraft is modelled with an in-house simulation software named PLANE.S. [10]. The time histories of speed (V) and altitude (z) are used to perform, at any time step, the balance of the forces acting on the aircraft in the lift (L) and drag (D) directions. The thrust obtained from balance of forces is used to calculate the thrust power (THP) to be generated by the propeller that is connected to a planetary gear box. The gear box is used to perform the power-split between the engine and the electric machine.

As in all hybrid power systems, two energy sources are used. At any time step, a supervisory controller has to decide among the following operational modes:

1. Thermal, the engine produces all the power required by the propeller ($m = 1$);
2. Electric, the propeller shaft power is generated by the motor using the battery as only energy source ($m = 2$);
3. Charging, the engine generates the power to move the propeller and to charge the battery while the electric motor works as a generator ($m = 3$);
4. Power-split, both the engine and the motor generate mechanical power that is delivered to the propeller ($m = 4$).

Where m is a design parameter to be optimized during flight, (see Sect. 2.1).

In the present investigation, the following rule-based strategy is used. Mode 1 is used when the batteries' State of the Charge (SOC) is below a limit (SOCmin) and the engine is not able to charge the batteries. Mode 2 is used when the SOC is above the SOCmin and the electric drive is able to sustain the flight without the usage of the engine. In the case of modes 3 and 4, there is a further degree of freedom in the amount of power to be generated by the engine. The outputs of the supervisory control strategy are the current to/from the electrochemical storage system speed and torque of the engine. The electric power is assumed to be negative when the battery is in charge. The battery state of charge is allowed to vary between 20% and 90% to optimize the battery life [11]. The gearbox is modelled as a simple mechanical power split device with a mass of 20 kg and a efficiency of 0.9. In addition, the propeller is modeled as a black box with the following values of efficiency: 0.65, 0.7 and 0.8 at takeoff, climb/descent and cruise, respectively. The mass of the propeller is also assumed constant for all the designs.

Scaling methods are considered for the most critical components of the hybrid power system, namely the engine, the motor and the battery. The scalable models used for the engine and the battery are described in [12].

2.1 Inputs of the Optimization

The UAV mission optimization is run starting from a typical mission profile of Predator RQ-1 shown in Fig. 1.

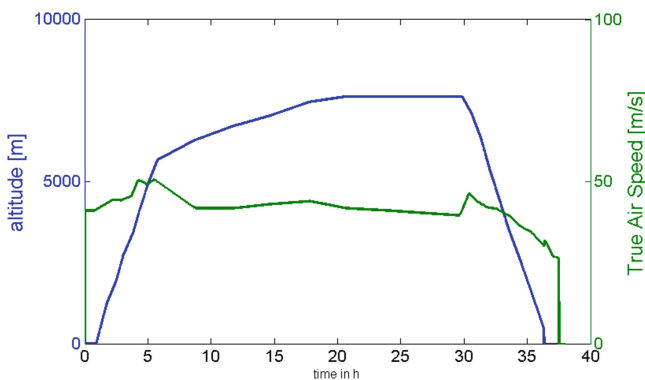


Fig. 1. A typical mission profile of Predator RQ-1

In particular, an in-house code was written to build a mission profile with the same phases of the real one, starting from inputs of Table 1. These inputs will be optimized together with some parameters concerning the design and the control of the hybrid electric power system, which are listed in Table 2.

The UAV flight mission is composed by these phases: take-off, two phases of climb characterized by different rates of climb, cruise, loiter, descent and landing. The starting

Table 1. Design parameters related to the UAV mission

Description	Unit	Min	Max	Step
Cruise speed	m/s	41.0	61.0	0.5
Cruise altitude	m	4900	6900	100
Loiter speed	m/s	37.0	57.0	0.5
Loiter altitude	m	6950	7450	25
Altitude of rate of climb switch	m	2300	3300	25
Rate of climb of the first part of the climb	m/s	0.224	0.424	0.05
Rate of climb of the second part of the climb	m/s	0.224	0.424	0.05
Rate of descent	m/s	0.144	0.344	0.01
Climb energy mode	–	1	4	1

Table 2. Design parameters concerning the sizing and the energy management

Parameters	Unit	Min	Max	Step
Nominal Engine power	kW	40	160	2
Battery elements in series		50	100	1
Battery nominal capacity (C)	Ah	20	150	2
Battery typology		3	5	1
Discharge current	C	0.5	20	0.1
Recharge current	C	0.1	1	0.01

values of the mission parameters for the optimization are obtained by the real mission of Fig. 1. The mission requirements are represented by the cruise range (926 km) and the loiter endurance (24 h).

2.2 Optimization Methods and Goals

The proposed optimization methods (NSGA-II, MOGA-II, MOSA and Evolutionary Strategy) are applied to two optimization problems, which differentiate for:

- the number of objective functions: two for simplified optimizations (multi-objective) and four for complete optimizations (many-objective), with the same aim of optimizing the hybrid electric power system of Predator RQ-1 UAV and its mission;
- the number of total design evaluated: 2500 for simplified optimizations, 10000 for complete optimizations.

In the complete optimization, the objective functions are electric endurance, overall fuel consumption, additional volume and take-off field length. In the simplified optimization, only electric endurance and overall fuel consumption are considered. Objective functions are scaled with respect to reference values of a baseline non-hybrid power system and modified so that all of them had to be maximize.

Evolution strategy method has: $\mu = 50$ $\rho = 2$ and $\lambda = 5$ in the simplified optimizations, $\mu = 100$ $\rho = 2$ and $\lambda = 10$ in the simplified optimizations.

3 Performance Analysis

Over the years, various performance indexes have been proposed in literature for multi- and many-objective optimizations. In this study, the first three metrics suggested by Riquelme et al. [13] are used to compare the different methods:

- *hypervolume* (or *S-metric*): based on the estimation of the hypervolume dominated by the approximated Pareto-front set and bounded by the reference point (percentage);
- *generational distance (GD)*: indicates how far approximated Pareto-front is from the real one;
- *inverted generational distance (IGD)*: similar to GD, it calculates the minimum distance by using real Pareto-front as reference instead of the approximation set.

In addition, the following parameters are also considered [14, 15]:

- *average distance (Davg)* between neighboring vectors of Pareto-front;
- *distance variance (Var)* between neighboring vectors of Pareto-front;
- number of *non-dominated solutions* or Pareto-optimal solutions (*NNS*);
- percentage of solutions of Pareto-front A dominated by Pareto-front B, $C(A,B)$;
- *maximum sum of the objective values (MaxSum)*: for each generation G , the maximum sum of the objective values is calculated as follows:

$$MaxSum(G) = \max \sum_{i=1}^K f_i(x) \quad \text{with } x \in G$$

where K is the number of objective functions, this measure evaluates convergence of solutions toward the Pareto-front around its center region;

- *sum of the maximum objective values (SumMax)*: the sum of the maximum objective value of each objective is calculated in each generation, G , as follows:

$$SumMax(G) = \sum_{i=1}^K \max f_i(x) \quad \text{with } x \in G$$

it evaluates convergence of solutions toward the Pareto-front around its K edges;

- *sum of the ranges of the objective values (Range)*: the sum of the range of objective values for each objective is calculated in each generation G as follows.

$$Range(G) = \sum_{i=1}^K [\max\{f_i(x)\} - \min\{f_i(x)\}] \quad \text{with } x \in G$$

this measure evaluates diversity of solutions in the objective space.

3.1 Results of the Simplified Problem

The simplified optimization is run by using the above-mentioned optimization methods with the same starting population (or Design of Experiment, DOE) for each of them. Optimizations are deliberately performed with standard set of parameters proposed by modeFRONTIER guide for each method, except for Evolutionary Strategy. In fact, the latter needs particular settings in order to obtain a number of total evaluated design equal to that of the other methods.

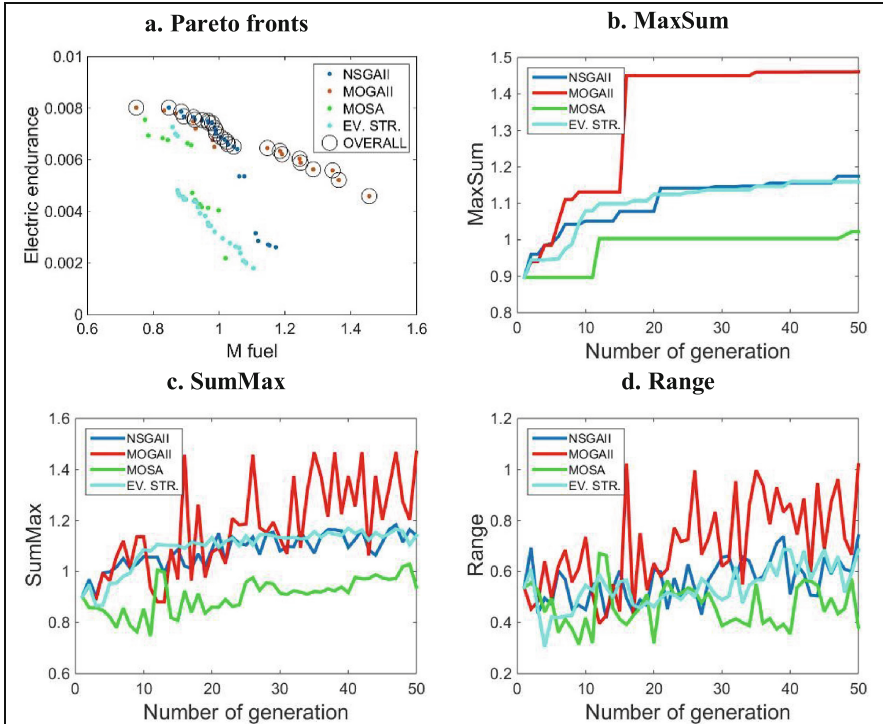


Fig. 2. Results of the simplified problem

Figure 2 compares the Pareto fronts found with the different methods, while Tables 3 and 4 shows the values of the proposed metrics. In particular, Fig. 2a shows the comparison of Pareto fronts from a qualitative point of view. The overall best Pareto-front shown this figure is obtained by merging the Pareto-optimal solutions found by all methods. In the simplified case, it corresponds in part to NSGA-II's Pareto-front and in part to MOGA-II's Pareto-front. Note that:

- NSGA-II is the best method in terms of number of Pareto-optimal solutions non-dominated by fronts of the other methods; it also is characterized by a good definition;

Table 3. Absolute metrics (simplified problem)

Parameter	MOGA-II	NSGA-II	MOSA	EV. STR.
n_NNS	16	25	14	29
Davg	0.0253	0.0082	0.0102	0.0062
Var	7.8287e-04	6.0694e-05	5.1337e-05	3.2478e-05
GD	0.0024	0.0060	0.0101	0.0122
IGD	0	0	0.0031	0.0032
hv	≈0.9190	≈0.7460	≈0.6410	≈0.5920

Table 4. Relative metrics (simplified problem)

C(A,B)	B				
A	MOGA-II	NSGA-II	MOSA	EV. STR.	OVERALL
MOGA-II	–	37.5%	0%	0%	37.5%
NSGA-II	32%	–	0%	0%	32%
MOSA	100%	100%	–	29%	100%
EV. STR.	100%	100%	55%	–	100%

- Although MOGA-II is dominated by NSGA-II in the first part of the graph and has a lower definition, it is able to explore regions where other methods fail;
- Results of MOSA and Evolutionary Strategy are dominated by the Pareto-fronts of both NSGA-II and MOGA-II;
- Evolutionary Strategy is the best method both in terms of number of non-dominated solutions and in terms of distance between them in the first part of the graph. In fact, the distance is lower and more regular than that of the other methods. This indicates a better Pareto-front definition and distribution compared to the other methods (see also the best values of indexes n_NNS, Davg and Var in Table 4).

In Table 3 the best method for each metric is highlighted in grey. Note that MOGA-II is characterized by the minimum values of GD and IGD. This means that its approximation set is the closest to the overall best Pareto-front. Moreover, it has the best value of hypervolume (hv), so Pareto-optimal solutions from MOGA-II cover the largest region in the space of solutions. As already pointed out, Evolutionary Strategy is characterized by the best values of n_NNS, Var and Davg, which indicate a better definition of Pareto-front.

Table 4 shows a comparison of the Pareto-fronts in terms of percentage of Pareto-front A dominated by Pareto-front B. It is possible to observe that NSGA-II has the lowest percentage of dominated solutions. This is probably because its Pareto-front dominates the other methods in a part of the graph of Fig. 2a (in fact, MOGA-II has this characteristic too), but also because NSGA-II has a higher number of non-dominated solutions compared to MOGA-II thanks to its better definition.

Figure 2b, c and d respectively show comparison of MaxSum, SumMax and Range of the different methods. Figure 2b shows that MOSA converges faster than the other methods and Evolutionary Strategy is characterized by the slowest convergence. But MOGAII first and then NSGA-II move to and reach higher values.

Figure 2c shows a gradual improvement of SumMax parameter during the execution of all methods, this suggests a difficulty in finding a set of non-dominated solutions that covers the entire real Pareto-front within a small number of generations; however, the steepest positive trend (so the best) is that of MOGA-II. Figure 2d shows that MOGA-II is characterized by the best capability of exploring the space of solutions, this is also confirmed by Fig. 2a, as above stated. Finally, MOGA-II finds the highest percentage of real and feasible design. From this point of view, NSGA-II is second, Evolutionary Strategy third and MOSA the worst.

According to these considerations, MOGA-II can be said to be the best method for the optimization problem with only two objective functions.

3.2 Results of the Complete Problem (Many-Objective Optimization)

A complete optimization is run by using the same optimization methods used for the simplified problem, with same initial population. Like in the simplified case, optimizations with NSGA-II, MOGA-II, MOSA and Evolutionary Strategy are deliberately performed with the values of parameters proposed by ModeFRONTIER manual, except for Evolutionary Strategy. By using these settings, Evolutionary Strategy evaluates 12753 designs, but only the first 10000 are considered in order to compare methods over the same number of evaluations.

Figures 3 and 4 show the qualitative comparison of the methods. Again, the overall best Pareto-front is approximated by individuating the Pareto-optimal solutions of the set consisting of the designs evaluated by all the methods.

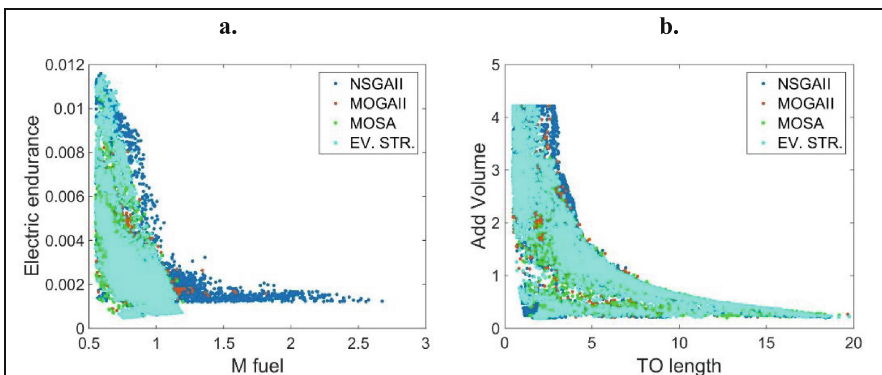


Fig. 3. Pareto fronts (complete problem)

In Fig. 3a and b compares the Pareto fronts by representing the objective functions in pairs. It is possible to observe that NSGA-II is able to explore regions that other

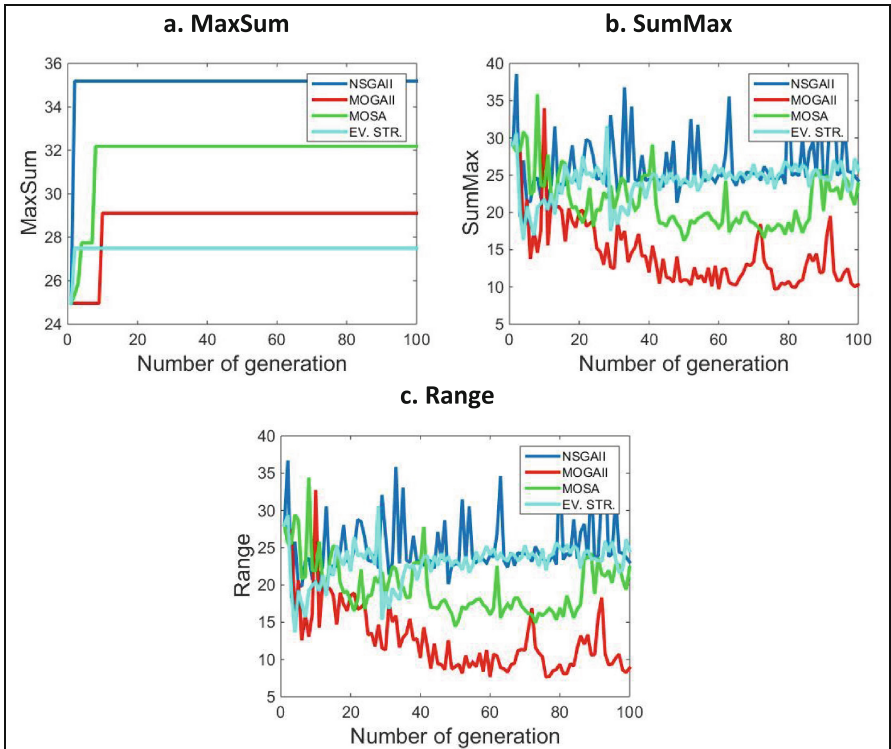


Fig. 4. Results of the complete problem

methods do not reach. Evolutionary Strategy is the best in terms of non-dominated solutions and distance, but also MOGA-II and NSGA-II are characterized by a good definition of the Pareto front. MOSA is again the worst. These considerations are confirmed by the values of parameters n_NNS and D_{avg} in Table 5.

Table 5. Absolute metrics (complete problem)

Parameter	MOGA-II	NSGA-II	MOSA	EV. STR.
n_NNS	3946	4204	1668	4871
D_{avg}	0.0411	0.0413	0.0586	0.0405
Var	0.0051	0.0013	0.0022	7.6688e-04
GD	0.0270	0.0444	0.0288	0.0243
IGD	0	1.5701e-16	0	8.6736e-19
hv	≈0.4230	≈0.4640	≈0.4190	≈0.4050

Evolutionary Strategy is characterized by the minimum value of GD, a value of IGD very close to the best ($8.6736e-19 \approx 0$), the best values of n_NNS , a value of Dav_g close to the best and the best value of Var. It is the approximation set closest to the overall best Pareto-front. Moreover, it has a good definition and the best distribution. NSGA-II is characterized by the maximum value of hypervolume (hv), i.e. its Pareto-optimal solutions cover a larger region of the space of solutions (see Table 5, where the best method for each metric is again highlighted in grey).

Table 6 shows a comparison of the methods in terms of percentage of solutions of Pareto-front A dominated by Pareto-front B. It is possible to observe that NSGA-II has the lowest percentage of dominated solutions when compared to the others.

Table 6. Relative metrics (complete problem)

C(A,B)	B				
	MOGA-II	NSGA-II	MOSA	EV. STR.	OVERALL
A	–	38%	7%	6%	28%
MOGA-II	–	38%	7%	6%	28%
NSGA-II	4%	–	5%	15%	18%
MOSA	27%	32%	–	35.6%	50.1%
EV. STR.	24.8%	35.4%	8.1%	–	35.6%

Figure 4a, b and c report the trends of MaxSum, SumMax and Range for the different methods. NSGA-II and Evolutionary Strategy converge faster than the other methods and NSGA-II reaches the highest values of all indexes. Figure 4b shows an almost flat trend for NSGA-II and Evolutionary Strategy and a decreasing tendency for MOGA-II and MOSA. This suggests a difficulty in finding a set of non-dominated solutions that covers the entire real Pareto-front within a small number of generations. However, in terms of SumMax, NSGA-II and Evolutionary Strategy perform better thanks to their non-negative trends. Figure 4c shows that NSGA-II is characterized by the best capability of exploring the space of solutions as confirmed also by the analysis of Fig. 3a.

Finally, NSGA-II finds the smallest percentage of errors and an acceptable percentage of unfeasible designs. On the contrary, MOSA shows a high number of errors, but less unfeasible solutions. MOGA-II seems to be the best in terms of real and feasible designs found in the optimization.

Thus, the best methods for the optimization problem with four objective functions seem to be NSGA-II and Evolutionary Strategy. The first shows also a better relative coverage (see Table 6); therefore, it should be preferred in this kind of applications.

4 Discussion of the Results

A comparison between simplified and complete optimizations is done in order to study how the behavior of the different methods changes as the number of objective functions increases.

Since the simplified optimizations evaluated 2500 total design, while the complete optimizations evaluated 10000 total designs, only the first 2500 evaluated designs of the latter are considered in this analysis. Moreover, the Pareto-fronts are first analyzed with reference to the two objective functions of the simplified problem (Fig. 5). The other two objectives are shown in Fig. 6.

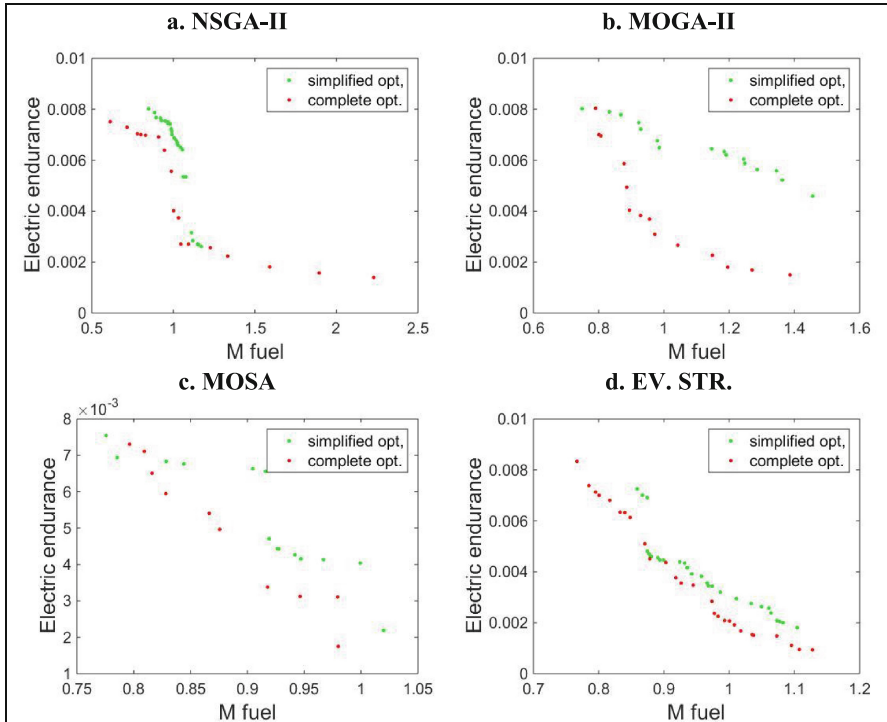


Fig. 5. Simplified versus complete optimization problems about electric endurance and fuel consumption

Note that a better definition of the Pareto front for the first two functions is obtained in the simplified problem. This is an obvious result because in the complete problem it is necessary to find a compromise between more conflicting objectives. In fact, the results related to the other two functions are very poor in the simplified problem because they are not included in the optimization process (Fig. 6).

The percentages of Pareto-optimal solutions of the complete optimization dominated by those from the simplified problem are: 93.3% for MOGA-II, 72.2% for NSGA-II, 80.0% for MOSA and 85.71% for Evolutionary Strategy. However, Fig. 5a confirms the good performance of NSGA-II in a many-objective optimization. In fact, the complete optimization with NSGA-II explores a region of the solutions space that is not found in the simplified optimization. This also implies that not all Pareto-optimal solutions of the complete problem are dominated by those of the simplified case. On the other hand, Fig. 5d shows a similar behavior of Evolutionary Strategy in the two cases.

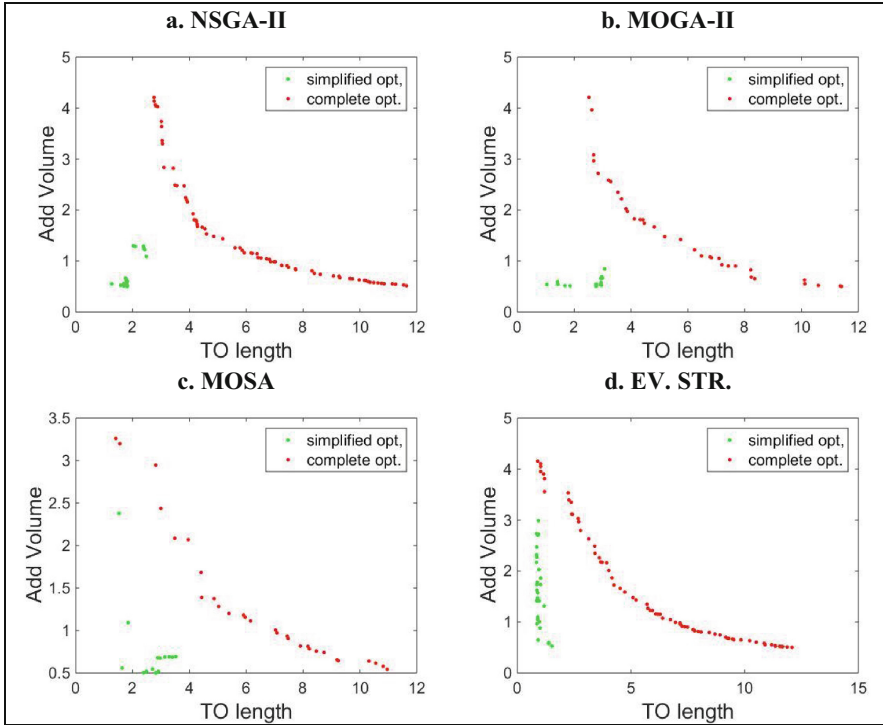


Fig. 6. Simplified versus complete optimization problems about additional volume and take-off length

Comparison in terms of MaxSum, SumMax and Range, still referred to electric endurance and fuel consumption, shows that in the complete optimization NSGA-II converge slower, but moves to higher values. Moreover, NSGA-II is able to cover a wider region of the overall best Pareto-front in the complete optimization, in fact the trend of SumMax is still gradual but is steeper than that of the simplified optimization, and has better capabilities of exploration in the complete optimization. It is possible to observe the same for Evolution Strategy, while this is not true for MOGA-II. MOSA converges faster in the complete optimization, but it shows worse search capability, so it probably converges to local optimal solutions.

In modeFrontier, both NSGA-II and Evolution Strategy use non-dominated/crowding distance sorting techniques [7], MOGA-II uses a multi-search elitism that combines random selection and directional crossover [16], while search method of MOSA is based on random perturbations of the points [17]. So, probably, as the number of objective functions increases, the crowding distance sorting technique allows a better search than the other methods.

A general worsening of the other parameters is found in the complete optimization, except for the parameter of hypervolume. Since hypervolume is critical in this kind of applications, the SMS-EMOA algorithm [18] will be considered as further investigation. Unlike modeFRONTIER codes, SMS-EMOA is written as an open source code.

Therefore, it will be possible to better understand its mechanisms (for example, the handling of unfeasible designs) and to introduce opportune changes.

Note that this work refers to a state-of-the-art real-world engineering problem. A similar problem is addressed in [19] where the authors use the same optimization environment in an optimization problem with four goals.

5 Conclusions

The present work compares the behaviors of different optimization methods in the multi- and many- objective optimization of a parallel hybrid electric power systems for aircraft. In particular, NSGA-II, MOGA-II, MOSA and Evolutionary Strategy ($\mu/\rho + \lambda$)-ES methods have been applied to two optimization problems differentiating for the number of total individuals analyzed and for the number of objective functions: two for the simplified optimization (multi-objective) and four for the complete one (many-objective). Both qualitative analyses of the Pareto fronts and quantitative performance indexes are used for the comparison.

In this preliminary work, the authors deliberately considered only evolutionary methods (EAs) available in the ModeFrontier platform and the default values of each of their parameters, in order to test quality of solutions that can be obtained from a commercial software by non-specialized users.

The results of this investigation show that MOGA-II is the best in the multi-objective optimizations with only two objective functions, while NSGA-II performs very well in the many-objective optimization. However, Evolution Strategy shows interesting results in terms of definition and distribution of the Pareto-front in both cases. On the other hand, the only non-evolutionary algorithm considered in the investigation (i.e. MOSA) gives always the worst Pareto front. In addition, a general worsening of the behavior of the optimization methods was found when shifting from the multi- to the many-objective optimization. Optimization methods specifically developed for many-objective problems will be considered as further investigation.

This work refers to a specific state-of-the-art real-world engineering problem. Future works will include other EAs that will be tested both on benchmark problems and on other real-world engineering problems in the aeronautical and space fields.

References

1. Pomet, C., Isikveren, A.T.: Conceptual design of hybrid-electric transport aircraft. *Prog. Aerosp. Sci.* **79**, 114–135 (2015)
2. Gimelli, A., Muccillo, M., Sannino, R.: Multivariable and multiobjective optimization for cogeneration plants. Part A: methodology. In: *La Termotecnica*, pp. 55–58 (2015)
3. Li, B., Li, J., Tang, K., Yao, X.: Many-objective evolutionary algorithms: a survey. *ACM Comput. Surv.* **48**(1), Article No. 13 (2015)
4. Fleming, P.J., Purshouse, R.C., Lygoe, R.J.: Many-objective optimization: an engineering design perspective. In: Coello Coello, C.A., Hernández Aguirre, A., Zitzler, E. (eds.) *EMO 2005*. LNCS, vol. 3410, pp. 14–32. Springer, Heidelberg (2005). https://doi.org/10.1007/978-3-540-31880-4_2

5. Zitzler, E., Knowles, J., Thiele, L.: Quality assessment of pareto set approximations. In: Branke, J., Deb, K., Miettinen, K., Słowiński, R. (eds.) *Multiobjective Optimization*. LNCS, vol. 5252, pp. 373–404. Springer, Heidelberg (2008). https://doi.org/10.1007/978-3-540-88908-3_14
6. Ishibuchi, H., Tsukamoto, N., Nojima, Y.: Evolutionary many objective optimization: a short review. In: *Proceedings of 2008 IEEE Congress on Evolutionary Computation*, Hong Kong, 1–6 June 2008, pp. 2424–2431 (2008)
7. ModeFRONTIER 2014, Update 1, Version Number 4.6.1 b20150227, User Manual (2014)
8. Beyer, H.-G., Schwefel, H.-P.: Evolution strategies a comprehensive introduction. *Nat. Comput.* **1**, 3–52 (2002)
9. Kirkpatrick, S., Gelatt Jr., D., Vecchi, M.P.: Optimization by simulated annealing. *Science* **220**(4598), 671–680 (1983)
10. Donateo, T., Ficarella, A., Spedicato, L.: Development and validation of a software tool for complex aircraft powertrains. *Adv. Eng. Softw.* **96**, 1–13 (2016). <https://doi.org/10.1016/j.advengsoft.2016.01.001>
11. Lam, L.L., Darling, R.B.: Determining the optimal discharge strategy for a lithium-ion battery using a physics-based model. *J. Power Sources* **276**, 195–202 (2015)
12. Donateo, T., Ficarella, A.: Designing a hybrid electric powertrain for an unmanned aircraft with a commercial optimization software. *SAE Int. J. Aerosp.* **10**, 1–12 (2017)
13. Riquelme, N., Lücken, C.V., Baran, B.: Performance metrics in multi-objective optimization. In: *Computing Conference (CLEI), Latin American* (2015)
14. Donateo, T., De Risi, A., Laforgia, D.: Choosing an evolutionary algorithm to optimize diesel engines. In: *TCN CAE 2005*, University of Lecce, Department of Engineering for Innovation, Lecce, Italy (2011)
15. Lee, S., von Allmen, P., Fink, W., Petropoulos, A.E., Terrile, R.J.: Comparison of multi-objective genetic algorithms in optimizing Q-law low-thrust orbit transfers. In: *GECCO 2005*, 25–29 June 2005, Washington, DC, USA (2005)
16. Rigoni, E., Poles, S.: NBI and MOGA-II, two complementary algorithms for multi-objective optimizations. In: *04461 - Practical Approaches to Multi-Objective Optimization* (2005)
17. Rigoni, E.: MOSA Multi Objective Simulated Annealing. Technical report 2003-003, ESTECO (2003)
18. Beume, N., Naujoks, B., Emmerich, M.: SMS-EMOA: Multiobjective selection based on dominated hypervolume. *Eur. J. Oper. Res.* **181**, 1653–1669 (2007)
19. Aksugur, M., Inalhan, G.: Design, build and flight testing of a VTOL tailsitter unmanned aerial vehicle with hybrid propulsion system. In: *Ankara International Aerospace Conference*, Ankara, Turkey (2011)