MULTIDISCIPLINARY OPTIMIZATION OF UNMANNED AIRCRAFT IN A SYSTEM OF SYSTEMS CONTEXT

Athanasios Papageorgiou*, Kristian Amadori, Christopher Jouannet**, Johan Ölvander***
***Linköping University, **SAAB Aeronautics**

Keywords: *MDO, UAV, SoS*

Abstract

This paper explores the use of Multidisciplinary Design Optimization (MDO) in the development of Unmanned Aerial Vehicles (UAVs) when the requirements include a collaboration in a System of Systems (SoS) environment. In this work, the framework considers models that can capture the mission, stealth, and surveillance performance of each aircraft, while at the same time, a dedicated simulation module assesses the total cooperation effect on a given operational scenario. The resulting mixed continuous and integer variable problem is decomposed with a multi-level architecture, and in particular, it is treated as a fleet allocation problem that includes a nested optimization routine for sizing a "yet-to-be-designed" aircraft. Overall, the models and the framework are evaluated through a series of optimization runs, and the obtained Pareto front is compared with the results from a traditional aircraft mission planning method in order to illustrate the benefits of this SoS approach in the design of UAVs.

1 Introduction

Over the past few years, the market of Unmanned Aerial Vehicles (UAVs) has experienced an accelerated growth which in turn has created a high level of competition among the involved companies [1]. In this environment of uncertainty and risk, it is important to constantly enhance the traditional product development process, and thus, state-of-the-art design tools as well as methodologies are a promising way to enable higher quality and faster completion times.

Multidisciplinary Design Optimization (MDO) is a method that has shown great potential in improving the knowledge of the product and in turn allowing better decisions to be made earlier in the process [2]. Over the years, the field of MDO has been constantly expanding, and at present, it is possible to solve even more intricate design problems by implementing novel integration architectures, taking advantage of state-of-the-art disciplinary models, and using efficient computing strategies [3].

To this end, one of the emerging improvement directions of MDO is to consider a higher and thus more abstract level of interactions where the active cooperation of various systems is taken into account in order to provide capabilities beyond those of each individual system [4]. This System of Systems (SoS) formulation has often been used in the way customers acquire new assets [5], and in this respect, it can be seen as an additional enhancement of the optimization framework where the traditional sizing task is combined with a resource allocation or network configuration problem [3]. As expected, this significantly more complex formulation raises new challenges in terms of problem decomposition, while at the same time, it creates additional requirements during the development of the disciplinary models which now have to be expanded in order to capture the physics of a collaboration scenario [6].

In this light, the main objective of this paper is to explore the use of MDO in the development of a new UAV design that is intended to contribute towards achieving better capabilities in an SoS environment. To illustrate the above, this case study makes the hypothesis that a potential customer is already in possession of two vastly different UAV platforms, and investigates if the development of an entirely new aircraft can improve the overall operational success. The

primary goal herein is to improve the search and rescue (SAR) capabilities through the use of an aircraft swarm that will be able to change the number and flight envelope of each asset in order to allow for better overall performance in terms of cost, surveillance, stealth, and payload delivery. On the whole, this work describes the development of the disciplinary models and the framework architecture for this hybrid MDO and SoS problem, whereas a set of optimization results is also presented in order to evaluate the proposed method and assess the benefits of the new additions for the design.
In total, this paper is comprised of six main chapters with the introduction being the first, and then followed by a short frame of reference on relevant topics. The disciplinary models, the framework architecture, and the optimization problem are presented in chapter three; while the obtained results, a discussion on the work, and a conclusive summary are given right after.

2 Frame of reference

2.1 Unmanned aircraft optimization

A multidisciplinary optimization framework for aircraft design should be first and foremost able to capture the mission performance [7], and thus, the most common development approach is to include a set of basic aeronautical disciplines in order to estimate the weight, the aerodynamic, the propulsion, and the stability characteristics [8], [9], [10], [11]. Moreover, a critical consideration is to align the fidelity of the models with the development stage that the MDO framework aims to enhance [12], and in this respect, an accepted methodology in conceptual design is to use simple tools that can enable a sufficient level of detail at a minimum computational expense [10], [11]. To this end, it can be seen that in UAV conceptual design weight estimation if computed by using empirical sizing formulas [11]; aerodynamics are calculated with analytical expressions or panel codes [10]; propulsion is evaluated by means of statistical or historical data [9]; and finally, stability and mission performance are assessed through systems of balance and energy equilibrium equations [8].

2.2 Electromagnetic and cost models

Although the above may be adequate for a basic aircraft performance MDO, the study of complex scenarios, like SAR operations, may often require further models in order to capture the extended design space [2]. An example of this are models from the field of electromagnetics for simulating the sensor coverage and radar signature of the aircraft [13], while at the same time, a cost model can also help to increase knowledge of the economic implications and bridge the gap between the engineering and marketing departments [14]. Here, the radar signature is usually studied in one direction (or “threat sector” or “view angle”) of interest [15], however, in more complex scenarios it is possible but also necessary to monitor two or even more critical directions [13], [16], [17]. Accordingly, the sensor performance can be captured with high-fidelity tools for establishing the communication performance [18] or with analytical electromagnetic formulas for predicting the area coverage [17] as well as the target detection probability [13]. Finally, as far as cost is concerned, there are in general limited alternatives due to the lack of available pricing information, and to this date, some of the possible solutions are to express it with simple weight-based empirical equations [8] or with regression models that use performance metrics as inputs in order to make predictions based on historical data [14].

2.3 System of systems applications

In general, a typical SoS problem is a time-dependent problem that is comprised of three levels and allows information to flow upwards to the top-level and downwards to the system and sub-system levels [6]. An SoS formulation with considerable interest for many organizations is the mixed continuous and integer variable problem where an optimization and analysis framework is used to investigate the benefits of adding a “yet-to-be-designed” aircraft to an existing fleet [5]. In its most common form, this problem aims to allocate new and old aircraft to specific routes in order to minimize the cost [19], [20], [21], [22], [23], [24], while a further variation is the minimization of aircraft noise by optimizing the landing approach procedures [6]. To tackle the advanced complexity of those problems, significant work is typically required in terms of decomposition, and it has been shown that this kind a mixed variable problem can be effectively solved by implementing an architecture which considers both an aircraft sizing but also an allocation domain [22], [24]. Overall, the aforementioned problems have been examined under several modifications, and some examples of this include a concurrent aircraft sizing, fleet allocation, and network route configuration [19], [23]; a simultaneous aircraft sizing and fleet allocation by considering uncertainty and risk sources like passenger demand [5], [20]; and lastly, a fleet allocation by taking into account both a traditional aircraft sizing and an aircraft family design task [21].

3 Problem formulation

3.1 Overview

The aim of the present work is to assess the capabilities of a fleet that is comprised of existing and yet-to-be-designed UAVs in a typical SAR operation. In this hypothetical scenario, all the activities are assumed to take place over a large area in the Mediterranean Sea that has been identified as a crossing point for refugees who are on their way to Europe's mainland. Here, the aim is to be able to provide good surveillance over the region of interest, whereas some additional considerations include the ability to quickly deliver medical supplies, to conceal the operations from other actors in the area, and to keep the monetary cost as low as possible.

In this application, the search zone is represented by a rectangular shape, and therefore, the deployed UAVs are expected to fly around it by following a racetrack pattern (See Figure 1). All the assets in this mission are scheduled to takeoff from a nearby military base, then cruise towards the search area, and finally, participate in the surveillance activities for as long as the endurance E_i of each aircraft type allows.

In the first variation of the problem, there are only two types of UAVs which will be denoted as type A and type B, whereas in the second variation, the fleet is expanded by using an entirely new aircraft which will be denoted as type C. For this case study, types A and B correspond to two vastly different aircraft that aim to satisfy a diverse set of requirements (See Table 1), while the specifications of type C are set in a way that can cover a range of the design space which lies between the two existing assets.

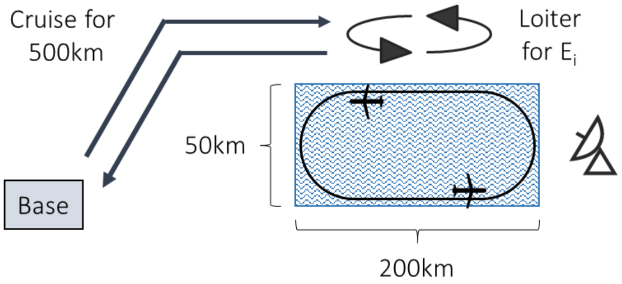

Fig. 1. Overview of the SAR scenario.

	Type A	Type B
Wing span [m]	38	18
Wing root chord [m]	2.6	1.4
MTOW [kg]	12000	1000
Fuel weight [kg]	6000	500
Payload [kg]	900	300
Max endurance [hrs]	26	20
Sensor range [m]	36000	22000
RCS [m^2]	1.6	0.8

Table 1. The specifications of type A and type B aircraft.

The decomposition of the problem is similar as shown in [5], [20], [21], [23], [24], and takes place in two levels which are the aircraft sizing and the SoS optimization (See Figure 2). The process starts with an optimizer which generates the design (fleet allocation) variables x_g that have a direct effect at a SoS-level (See Table 2), and then based on those values the aircraft sizing finds the design that has the best performance g based on a set of local variables x_l and subject to constraints c. Once the type C aircraft has been fully defined by the sizing process, its endurance E_C, weight W_C, and RCS σ_C values become available, and finally, all the UAVs are simulated together so that the problem objectives can be calculated and evaluated by the optimizer.

Since an SAR mission has many different aspects that need to be simultaneously considered, this leads in a multi-objective formulation where several metrics need to be monitored. Hence, each objective is normalized by using a reference maximum value which is denoted with the subscript *0*, and then the objectives are divided into two sets f_1 and f_2 which are combined in an aggregated function f by means of two user-defined weight factors ω_1 and ω_2 (See Equation 1). The first set of objectives f_1 is in respect to the desired positive elements of the mission, and it includes the average coverage time of each point within the search zone t_{cov} (a metric of surveillance efficiency measured in seconds) as well as the average amount of payload weight that can be delivered at each point within one minute w_{pay} (a metric of rescue abilities measured in kg). The second set of objectives is about the negative elements that this type of SAR mission may have, and those are namely the acquisition costs C_{acq} (the price of the entire SoS measured in M$), the operating costs C_{ope} (the price to fly each mission measured in K$), and lastly, the mean radar cross section (RCS) of the deployed aircraft σ_{ave} calculated at the exposed view angles (a metric of detectability measured in m^2).

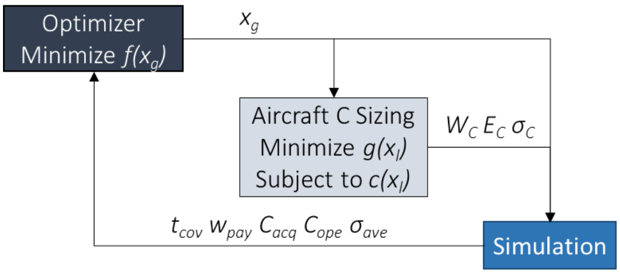

Fig. 2. The decomposition of the SoS problem.

<table>
<tr><td>Number of A, B, C [-]</td><td>0</td><td colspan="2">1</td><td>2</td><td>3</td><td>4</td></tr>
<tr><td>Type A altitude [m]</td><td colspan="2">14500</td><td colspan="2">16000</td><td colspan="2">17500</td></tr>
<tr><td>Type B altitude [m]</td><td colspan="2">4500</td><td colspan="2">6000</td><td colspan="2">7500</td></tr>
<tr><td>Type C altitude [m]</td><td colspan="2">9500</td><td colspan="2">11000</td><td colspan="2">12500</td></tr>
<tr><td>Type A speed [m/s]</td><td colspan="2">185</td><td colspan="2">190</td><td colspan="2">195</td></tr>
<tr><td>Type B speed [m/s]</td><td colspan="2">65</td><td colspan="2">70</td><td colspan="2">75</td></tr>
<tr><td>Type C speed [m/s]</td><td colspan="2">125</td><td colspan="2">130</td><td colspan="2">135</td></tr>
<tr><td>Type C payload [kg]</td><td colspan="2">450</td><td colspan="2">600</td><td colspan="2">750</td></tr>
<tr><td>Type C sensor range [m]</td><td colspan="2">27000</td><td colspan="2">29000</td><td colspan="2">31000</td></tr>
</table>

Table 2. The SoS-level (fleet allocation) design variables.

$$
\begin{aligned}
max\, f(x_g) &= \omega_1 \times f_1 - \omega_2 \times f_2 = \\
&= \omega_1 \times \left(\frac{t_{cov}}{t_{cov,0}} + \frac{w_{pay}}{w_{pay,0}}\right) - \\
&-\omega_2 \times \left(\frac{C_{acq}}{C_{acq,0}} + \frac{C_{ope}}{C_{ope,0}} + \frac{\sigma_{ave}}{\sigma_{ave,0}}\right)
\end{aligned} \tag{1}
$$

3.2 Sizing

The objective of the sizing module is to identify the best aircraft design that will fit the needs of each evaluated SoS combination. Since the SoS-level optimization poses requirements on both mission efficiency and cost, it is important that those are cascaded to the local sizing problem as well. To this end, the costs, the coverage, and the payload abilities can be represented by the endurance as it includes weight, aerodynamic, and propulsion terms, while in addition to this, the local fitness function g needs to also have an RCS term so that the stealth features are equally expressed in the design (See Equation 2).

Apart from that, and in order to increase the realism and ensure a flyable concept, a set of constraints was also added to the problem formulation. First, the balance and stability constraints make sure that each configuration is trimmed (ΣF, ΣM) but also that aircraft with a similar static margin (SM) are being compared, and secondly, the space constraints guarantee that there is enough room to accommodate the sensor system (l_S) and the selected engine unit (l_E).

$$
\begin{aligned}
&min\, g(x_l) = \left(-\frac{E_C}{E_{C,0}} + \frac{\sigma_C}{\sigma_{C,0}}\right) \\
&s.t. \quad c(x_l): \quad \Sigma F = \Sigma M = 0 \quad l_S < l_{S,av} \\
&\qquad\qquad\qquad\quad 0 < SM < 15 \quad l_E < l_{E,av}
\end{aligned} \tag{2}
$$

As far as the general configuration of the yet-to-be-designed UAV is concerned, this is comprised of features that will enable good mission but also surveillance performance. More specifically, the selected baseline airframe was set to have a slender fuselage and wings of high aspect ratio in order to increase endurance, whereas, a V-tail stabilizer as well as a fuselage-integrated turbofan engine were considered in order to reduce the radar signature (See Figure 3). For reasons of simplicity but also weight balance, all the sensor electronic units were assumed to be placed in a dedicated space in the front of the fuselage, while the surveillance was achieved by using patch-type apertures which were fixed on the skin of the fuselage.

Here, the aircraft sizing (local) design variables x_l, are a representative sample of parameters that is expected to have a significant effect on the mission performance and the cost of the aircraft. For this case study, only a small number of wing and fuselage parameters were taken into consideration, while the upper and lower bounds were set to be in-between the values which were defined for types A and B (See Table 3).

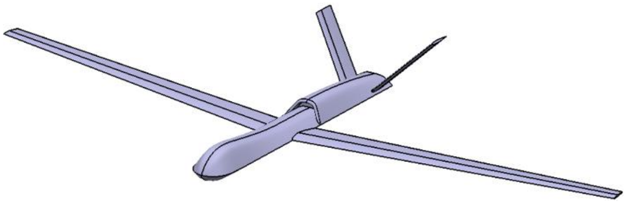

Fig. 3. The baseline CAD model of the type C aircraft.

	Fuselage width [m]	Fuselage height [m]	Fuselage length [m]	Wing span [m]	Wing root chord [m]	Wing taper ratio [m]	Wing sweep [°]
Upper	1.1	0.9	10	24	1.8	0.3	0
Baseline	1.3	1.1	11	28	2.0	0.4	10
Lower	1.5	1.3	12	32	2.2	0.5	20

Table 3. The bounds of the sizing design variables.

Overall, the aircraft sizing module consists of 7 disciplinary models which were developed by using low- to medium-fidelity computational tools and software solutions. The proposed framework is herein oriented towards fast evaluation times which are necessary for conceptual design, however, it has also been developed as a flexible platform that also allows for higher-fidelity codes to be considered if this is deemed necessary.

- The CAD model was developed in CATIA (See Figure 3), and it includes a number of morphological parametrization features as well as a surface mesh function that allows it to be used in the RCS calculations.
- The aerodynamic performance is calculated with TORNADO which is a vortex lattice method implemented in MATLAB [25]. TORNADO gives good predictions for the lift and induced drag, while the parasite, interference, and friction drag components are calculated with analytical formulas that can be found in [26].
- The weight and the mission parameters are estimated with empirical sizing equations [27] which have been implemented in the MATLAB-based tool DIBA that was developed by SAAB Aeronautics.
- The propulsion specifications are defined by means of available statistical data that can be found in DIBA, and then they are represented as "rubber" engines that can be scaled up or down to fit each application.
- The stability and trim are assessed through basic balance equations within an iterative loop that changes the wing and tail incidence angles as well as their apex positions until the desired conditions have been achieved.
- The sensor efficiency uses an electro-optical sensor model that has been based on linear electromagnetic formulas [28] in order to calculate properties such as the gain, the range, and the power.
- The RCS is calculated by analyzing the CAD representation of the UAV (See Figure 3) with the Physical Optics tool POFACETS which was developed by the US Naval Postgraduate School [29]. Compared to the other framework models, this process is much more computationally expensive, and thus, metamodels of the RCS for each one of the studied view angles were herein created as shown in [13], [17].

The integration of the aforementioned models was done in modeFRONTIER and it was based on the Multi-discipline Feasible (MDF) architecture [30]. Here, instead of using additional constraints, the couplings are resolved through the use of an iterative loop which guarantees feasibility of the obtained solution at every iteration of the optimizer (See Figure 4).

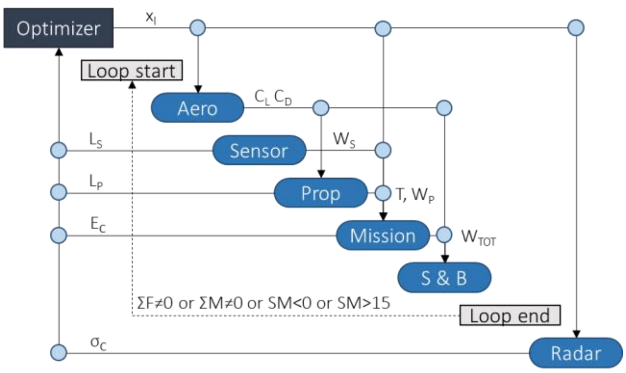

Fig. 4. The aircraft sizing decomposition architecture.

On the whole, the process starts with an optimizer that generates the local design variables x_l; then it moves on to the iterative loop where the coupled models are evaluated repeatedly until the stability and balance constraints (*SM*, *ΣF*, *ΣM*) have been met; and finally, it concludes with an analysis of the uncoupled models followed by an evaluation of the objective function g and the constraints c.

3.3 Simulation

The simulation module is a MATLAB code that was developed for assessing the performance of UAV swarms in a SAR scenario. In the current version, the module receives the characteristics of each UAV type as well as the mission specifications, and then it calculates important SoS metrics through the use of discrete time step simulations. For each time step, the simulation tool uses the position of each aircraft and the sensor properties to compute the coverage of the area (See Figure 5), while in addition to this, it takes into account the speed, altitude, and available payload in order to determine the amount of rescue supplies that can be delivered at each point within a certain amount of time.

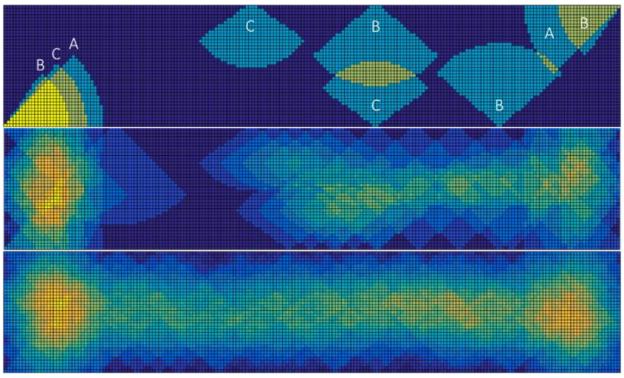

Fig. 5. The accumulated coverage time at 1sec (up), 600sec (center), and 1200sec (down) for N_A=2, N_B=4, N_C=3.

Furthermore, the simulation tool provides an estimation of the total cost and total RCS of each fleet. The cost is calculated with statistical data regressions which are expressed in the form of weight- and endurance-based equations that are given in [27] as well as [31], and it is divided into two components which are namely the acquisition (airframe, sensor system, ground equipment) and the operating (personnel, maintenance, fuel) costs. The stealth features of each asset are defined by using the signal to noise ratio (SNR) that the ground radar receives based on the radar-range equation which illustrates the relation between the transmitted power P_t, the aircraft RCS σ, and the distance R (See Equation 3). Once the SNRs of the deployed aircraft have been computed, the radar-range equation is used again in order to compute the normalized RCS σ_i of each asset that the ground radar system can "see" at its maximum range R_{max}, and then the average RCS of the entire fleet σ_{ave} is calculated.

$$SNR = \frac{P_t D_g^2 \sigma \lambda^2}{(4\pi)^3 R^4 k B_n T_s} \qquad (3)$$

4 Results

The SoS-level optimization problem of Equation 1 was solved through a metaheuristic approach as also shown in [6], [19], [20], [21], [22], [23], and in particular, with the non-dominated sorting genetic algorithm (NSGA-II). The NSGA-II algorithm can handle both continuous ("real coded") and discreet ("binary coded") variables, while at the same time, it also enables the concurrent evaluation of independent individuals which can significantly reduce the computational burden if parallel processing is implemented. For this application, the settings included an initial population of 100 individuals, which was allowed to evolve for 100 generations, whereas the cross-over and mutation probabilities where set to be 50% and 90% respectively.

Moreover, the aircraft sizing optimization that is presented in Equation 2 was performed with a gradient-based method, since it is a much smaller problem than the one in the SoS-level. Here, the adaptive filter sequential quadratic programming (AFilterSQP) algorithm was used as it can reduce the total number of evaluations but also guarantee fast convergence when the gradients can be computed with high-precision.

In total, the results that are presented herein include 7 optimization runs of the SoS-level problem for both the A+B as well as the A+B+C formulation (See Table 4 and 5). For each run, a different combination of objective weights ω_1 and ω_2 is used, and by means of this "weighted-sum" method it is possible to generate a Pareto front of non-dominated solutions between the desired f_1 and the non-desired f_2 characteristics of the design (See Figure 6). Note here, that the A+B formulation can only use a maximum of 8 aircraft (12 in A+B+C), and therefore, it can only cover a much smaller area of the design space.

(ω_1,ω_2)	(2,8)	(3,7)	(4,6)	(5,5)	(6,4)	(7,3)	(8,2)
f [-]	-4.96	-4.47	-3.46	-1.04	4.71	13.46	24.68
t_{cov} [sec]	1670	3483	5155	6694	7828	9255	10106
w_{pay} [kg]	2.2	4.9	8.7	9.6	12.3	15.1	17.9
C_{acq} [M$]	29.3	58.7	88.6	117.4	151.2	185.1	219.0
C_{ope} [K$]	25.3	50.3	85.2	101.8	129.9	156.9	185.3
σ_{ave} [m^2]	0.95	0.99	1.12	1.07	1.11	1.17	1.09
N_A [-]	0	0	1	1	2	2	3
N_B [-]	2	3	1	3	4	1	4
N_C [-]	1	2	2	3	2	4	3
H_A [km]	-	-	17.5	17.5	16	14.5	16
H_B [km]	7.5	4.5	4.5	6	7.5	7.5	6
H_C [km]	9.5	12.5	11	12.5	9.5	11	11
V_A [m/s]	-	-	185	190	185	195	190
V_B [m/s]	70	70	65	75	65	75	70
V_C [m/s]	130	135	135	125	125	130	135
P_C [kg]	450	750	750	600	450	750	600
R_C [km]	31	30	31	31	31	29	31

Table 4. The SoS-level results in the A+B+C formulation.

(ω_1,ω_2)	(2,8)	(3,7)	(4,6)	(5,5)	(6,4)	(7,3)	(8,2)
f [-]	-5.31	-4.62	-4.45	-1.75	2.43	8.38	16.26
t_{cov} [sec]	1128	1471	1899	3033	3575	4362	4974
w_{pay} [kg]	1.5	4.9	8.1	8.3	12.2	13.6	16.5
C_{acq} [M$]	21.6	47.6	67.2	82.1	108.4	129.6	149.4
C_{ope} [K$]	11.8	28.6	49.7	63.9	83.3	90.4	113.3
σ_{ave} [m^2]	0.89	1.04	1.51	1.24	1.46	1.22	1.43
N_A [-]	0	1	2	2	3	3	4
N_B [-]	3	2	0	2	1	4	2
H_A [km]	-	14.5	17.5	14.5	16	17.5	17.5
H_B [km]	6	7.5	-	4.5	6	4.5	6
V_A [m/s]	-	185	195	185	190	195	190
V_B [m/s]	70	75	-	70	65	70	75

Table 5. The SoS-level results in the A+B formulation.

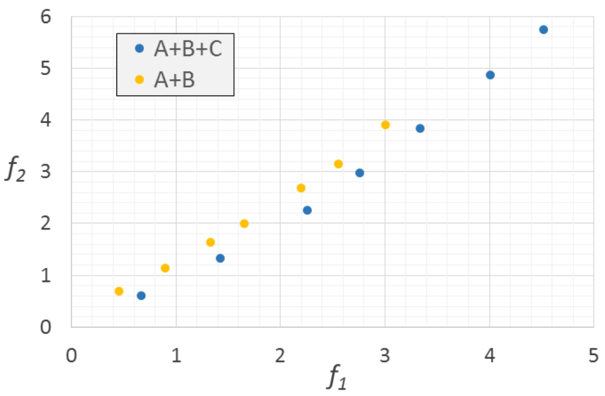

Fig. 6. The Pareto front for A+B+C as well as A+B.

Finally, for each one of the identified non-dominated designs, there is a unique type C configuration that was specifically developed for that particular SoS combination. The airframe configuration of the recommended yet-to-be-designed type C aircraft is presented visually in Figure 7 by using an overlapping outer mold line sketch of the top- and front-view, while the performance specifications (Endurance E, RCS σ, maximum takeoff weight W_{TO}, and fuel weight W_{FL}) are given in Table 6.

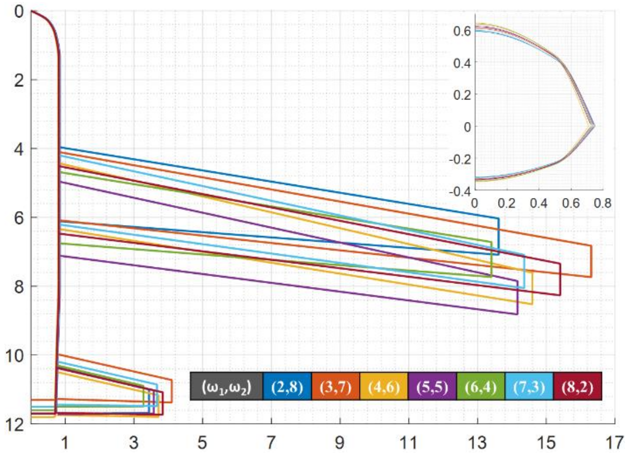

Fig. 7. Design visualization of the various type C aircraft.

(ω_1,ω_2)	(2,8)	(3,7)	(4,6)	(5,5)	(6,4)	(7,3)	(8,2)
E [hrs]	24	23	22	24	22	23	22
σ [m^2]	1.2	1.4	1.2	1.3	1.1	1.0	1.4
W_{TO} [kg]	6324	6724	6512	5992	7342	6612	6604
W_{FL} [kg]	3470	3534	3182	3156	3629	3350	3300

Table 6. Performance specs of the various type C aircraft.

5 Discussion

To begin with, the obtained results from the proposed hybrid SoS and MDO formulation show a significant improvement in the SAR capabilities if a yet-to-be-designed UAV is taken into account in the traditional fleet allocation problem. This is first supported by comparing the numerical results regarding the value of the objective f, where it can be seen that for all combinations of ω_1 and ω_2 the A+B+C formulation illustrated a better fitness function than the A+B (See Tables 4 and 5). Although there can be no direct visual comparison between the aforementioned optimization runs, it can also be clearly seen in the Pareto front of Figure 6 that the desired mission characteristics are generally better when a type C aircraft is considered. More specifically, the A+B+C formulation illustrates a better f_1 value for the same f_2 value, which means that it is possible to spend more time on each point and deliver more payload for the same cost and radar signature as in the A+B approach.

As far as the SoS-level variables in the A+B+C formulation are concerned, there is no distinct pattern that can be observed, apart from the fact that in every combination there is at least one type C aircraft (See Table 4). To no surprise, the above can be attributed to the predefined design specifications of type C, which in this case study were set to be in-between those of type A and B (See Table 6). As a result, this makes it possible to cover a much broader area of the design space, and in turn, it allows the optimizer to locate a much better set of f_1 and f_2 points through the use of more suitable fleet combinations.

What is more, it can be seen that the fleet combinations which result in better area coverage and payload delivery capabilities tend to depend more on type A as the weight ω_1 increases (See Table 4 and 5). As stated before, type A is associated with high endurance but also higher costs (See Table 1), and therefore, it is preferred by the optimizer in the upper segments of the Pareto front where the aforementioned mission characteristics are more important than costs and radar signature. Accordingly, in the lower part of the Pareto front there is the opposite tendency, and thus, it can be inferred that in order to minimize the undesirable effects of an SAR mission it is recommended to use multiple smaller assets than just a few big ones.

Furthermore, concerning the rest of the SoS-level variables there is no concrete conclusion to be made regarding the altitude and speed, which according to Tables 4 and 5 do not appear to follow any particular trend. In general, in both the A+B and the A+B+C formulation, the aforementioned variables take several values within the given bounds, which is a good indication that the algorithm was able to capture the underlying cooperation effects between the involved assets. On the same note, it can be observed that various combinations of payload and sensor range are used to define the yet-to-be-designed UAV (See Table 4), which can be viewed as a further indication that each time there is a need for a different "optimal" aircraft in order to compliment the operations of the swarm.

In view of this, the results from aircraft sizing reveal that the included MDO process was able to tackle this part of the problem by locating a fitting design for each set of requirements which were cascaded from the SoS-level (See Figure 7 and Table 6). Here, it can be seen that a larger wing span and root chord are necessary when a higher payload needs to be carried, whereas the wing surface area is relatively smaller for low payload and sensor range requirements in order to make further weight savings. Additionally, since flying at a low altitude is expected to increase the chances of being detected, is can be observed that in those instances this ended up driving the final design by generating configurations which had compact wing dimensions. On the whole, the general trend in all optimization runs is a preference towards high aspect ratio wings as well as a long and slender fuselage since those characteristics can result in an increased endurance, while at the same time, the radar signature is herein expressed by means of swept back wings and a flattened hexagonal fuselage shape that combines minimum height with maximum width values.

Finally, regarding the decomposition of the problem, it can be argued that the proposed two-level architecture was able to tackle the fleet allocation and aircraft sizing in an efficient but also robust way. The analysis of the performance showed that on an average each evaluation of the SoS-level required 180 seconds (120 for sizing and 60 for simulation), which indicates that a nested optimization loop combined with low-fidelity tools can be a suitable solution for the early stages of the development process. For this application, a multi-objective formulation was avoided since the goal was to compare specific design points, however, this is clearly an additional possibility that can be used at a relatively small time penalty when the aim is to generate a complete Pareto front.

Future investigations on the existing framework include the change in the execution order (first sizing and then allocation) as seen in [19], [20], [21], [23], while a point of further interest would be to evaluate the performance of different algorithms and the use of response surfaces. Overall, the present work aims to give the end-user the freedom to navigate through the design space whilst having full control over the models and the architecture, and in this respect, this framework should be seen as a first but also modular approach towards capturing the effects of multidisciplinary UAV design within a SoS context.

6 Conclusions

The work that is presented in this paper addresses the issue of UAV design when a higher and thus more complex level of fleet interactions needs to be taken into account. To illustrate the above, a hypothetical search and rescue scenario is herein introduced, and it is investigated whether or not a yet-to-be-designed aircraft can improve the mission performance.

First, this paper presents the development details of the disciplinary models that are needed in order to be able to capture the physics of this scenario. For this conceptual design stage simple aeronautical analysis tools are employed to calculate the field performance, while at the same time, this works extends to the development of electromagnetic codes and a mission simulation module which aim to explore the design space when search activities are considered.

At a secondary level, this paper elaborates on a two-level decomposition architecture, and in particular, it shows that the problem can be efficiently tackled by dividing it into two parts which are namely the fleet allocation and the aircraft sizing. The proposed strategy enables designers to consider SoS formulations that include mixed continuous and integer variables, whereas in addition to this, it is also possible to perform a quick optimization by means of a metaheuristic search like genetic algorithms.

Finally, this paper concludes by presenting a set of optimization results which aim to verify the functionality of the framework and evaluate this hybrid SoS and MDO formulation against other design approaches. Overall, several optimization runs are herein performed to generate a Pareto front between cost and mission efficiency, and it is found that better capabilities can be achieved when the traditional fleet allocation includes a “yet-to-be-designed” UAV.

References

[1] "Unmanned Aircraft System (UAS) Service Demand 2015-2035: Literature Review and Projections of Future Usage," John A. Volpe National Transportation Systems Center, Cambridge MA, February 2014.

[2] T. W. Simpson and J. R. Martins, "Multidisciplinary Design Optimization for Complex Engineered Systems: Report From a National Science Foundation Workshop," *Journal of Mechanical Design,* vol. 133, no. 10, p. 101002, 2011.

[3] J. Agte, O. de Weck, J. Sobieszczanski-Sobieski, P. Arendsen, A. Morris and M. Spieck, "MDO: assessment and direction for advancement—an opinion of one international group," *Structural and Multidisciplinary Optimization,* vol. 40, no. 1-6, pp. 17-33, 2009.

[4] H. Liu, Y. Tian, Y. Gao, J. Bai and J. Zheng, "System of systems oriented flight vehicle conceptual design: Perspectives and progresses," *Chinese Journal of Aeronautics,* vol. 28, no. 3, pp. 617-635, 2015.

[5] N. Davendralingam and W. Crossley, "Robust Approach for Concurrent Aircraft Design and Airline Network Design," *Journal of Aircraft,* vol. 51, no. 6, pp. 1773-1783, 2014.

[6] S. V. Subramanian and D. A. DeLaurentis, "Application of Multidisciplinary Systems-of-Systems Optimization to an Aircraft Design Problem," *Systems Engineering,* vol. 19, no. 3, pp. 235-251, 2016.

[7] A. Gazaix, P. Gendre, E. Chaput, C. Blondeau, G. Carrier, P. Schmollgruber, ... and T. Kier, "Investigation of Multi-Disciplinary Optimisation for Aircraft Preliminary Design," in *SAE Technical Paper Series*, 2011.

[8] B. Morrisey and R. McDonald, "Multidisciplinary Design Optimization of an Extreme Aspect Ratio HALE UAV," in *9th AIAA Aviation Technology, Integration, and Operations Conference (ATIO),* 2009.

[9] N. V. Nguyen, J.-W. Lee, M. Tyan and D. Lee, "Possibility-Based Multidisciplinary Optimisation For Electric-Powered Unmanned Aerial Vehicle Design," *The Aeronautical Journal,* vol. 119, no. 1221, p. 1397–1414, 2015.

[10] K. Amadori, C. Jouannet and P. Krus, "Use of panel code modeling in a framework for aircraft concept optimization," in *Collection of Technical Papers - 11th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference,* 2006.

[11] S.-M. Choi, N.-V. Nguyen, W.-S. Kim, J.-W. Lee, S. Kim and Y.-H. Byun, "Multidisciplinary unmanned combat air vehicle system design using multi-fidelity analysis," in *48th AIAA Aerospace Sciences Meeting Including the New Horizons Forum and Aerospace Exposition*, 2010.

[12] P. Piperni, A. DeBlois and R. Henderson, "Development of a Multilevel Multidisciplinary-Optimization Capability for an Industrial Environment," *AIAA Journal,* vol. 51, no. 10, p. 2335–2352, 2013.

[13] A. Papageorgiou, M. Tarkian, K. Amadori and J. Ölvander, "Multidisciplinary Optimization of an Unmanned Aircraft Considering Radar Signature,

Sensors Performance, and Trajectory Constraints," *Journal of Aircraft*, 2016.

[14] R. E. Peoples and K. E. Willcox, "Value-Based Multidisciplinary Optimization for Commercial Aircraft Design and Business Risk Assessment," *Journal of Aircraft*, vol. 43, no. 4, p. 913–921, 2006.

[15] R. Mäkinen, J. Periaux and J. Toivanen, "Multidisciplinary shape optimization in aerodynamics and electromagnetics using genetic algorithms," *International Journal for Numerical Methods in Fluids*, vol. 30, no. 2, pp. 149-159, 1999.

[16] H. Tianyuan and Y. Xiongqing, "Aerodynamic/Stealthy/Structural Multidisciplinary Design Optimization of Unmanned Combat Air Vehicle," *Chinese Journal of Aeronautics*, vol. 22, no. 4, pp. 380-386, 2009.

[17] A. Papageorgiou, J. Ölvander and K. Amadori, "Development of a Multidisciplinary Design Optimization Framework Applied on UAV Design by Considering Models for Mission, Surveillance, and Stealth Performance," in *18th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*, 2017.

[18] J. Neidhoefer, J. Ryan, B. Leahy and V. Tripp, "Cooperative multi-disciplinary design of integral load bearing antennas in small UAVs," in *47th AIAA Aerospace Sciences Meeting including the New Horizons Forum and Aerospace Exposition*, 2009.

[19] I. M. Chamseddine and M. Kokkolaras, "Bio-Inspired Heuristic Network Configuration in Air Transportation System-of-Systems Design Optimization," *Journal of Mechanical Design*, vol. 139, no. 8, 2017.

[20] P. W. Jansen and R. E. Perez, "Coupled Optimization of Aircraft Design and Fleet Allocation with Uncertain Passenger Demand," in *2013 Aviation Technology, Integration, and Operations Conference*, 2013.

[21] P. Jansen and R. Perez, "Coupled Optimization of Aircraft Family Design and Fleet Assignment for Minimum Cost and Fuel Burn," in *12th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference and 14th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*, 2012.

[22] C. Taylor and O. D. Weck, "Coupled Vehicle Design and Network Flow Optimization for Air Transportation Systems," *Journal of Aircraft*, vol. 44, no. 5, pp. 1479-1486, 2007.

[23] G. Marwaha and M. Kokkolaras, "System-of-systems approach to air transportation design using nested optimization and direct search," *Structural and Multidisciplinary Optimization*, vol. 51, no. 4, pp. 885-901, 2014.

[24] M. Mane, W. A. Crossley and A. Nusawardhana, "System-of-Systems Inspired Aircraft Sizing and Airline Resource Allocation via Decomposition," *Journal of Aircraft*, vol. 44, no. 4, pp. 1222-1235, 2007.

[25] T. Melin, "A vortex lattice MATLAB implementation for linear aerodynamic wing applications," MA Thesis, Royal Institute of Technology (KTH), Stockholm, 2000.

[26] E. Torenbeek, Advanced Aircraft Design: Conceptual Design, Technology and Optimization of Subsonic Civil Airplanes, John Wiley & Sons, 2013.

[27] D. P. Raymer, Aircraft design: A conceptual approach, Reston, VA: American Institute of Aeronautics and Astronautics, 2012.

[28] C. A. Balanis, Antenna Theory: Analysis and Design, 3 ed., Wiley-Interscience, 2005.

[29] F. Chatzigeorgiadis, "Development of a Code for a Physical Optics Radar Cross Section Prediction and Analysis Application," MA Thesis, US Naval Postgraduate School, Monterey, California, 2004.

[30] J. Martins and A. Lambe, "Multidisciplinary design optimization: A survey of architectures," *AIAA Journal*, vol. 51, no. 9, pp. 2049-2075, 2013.

[31] J. Cherwonik and A. Wehrley, "Unmanned Aerial Vehicle System Acquisition Cost Research: Estimating Methodology and Database," USA: The Office of the Deputy Assistant of the Army for Cost and Economics, Washington D.C., 2003.

Acknowledgements

The authors would like to acknowledge the financial and technical support which they received from the HISyM-NFFP7 project that was funded jointly by Linköping University and SAAB AB.

Contact Author

athanasios.papageorgiou@liu.se