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Implementation of market price and raw material cost analysis in an MDO environment for unmanned aircraft

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Abstract
In recent years, a number of Multidisciplinary Design Optimization (MDO) frameworks and environments have been used to study and design unmanned aircraft. Most of them address the integration of aerodynamics and structural calculus to improve an already existing configuration. Others study non-conventional configurations and methods to marginally improve them. The field lacks, however, a comprehensive environment that includes both "hard" engineering disciplines such as aerodynamics and structural calculus, and "soft" disciplines such as market price estimation or logistics. In the past, we developed an MDO environment aimed at the design of remotely piloted aircraft systems (RPAS), which received the name RAMP (RPAS Advanced MDO Platform). This framework included aerodynamics and structural calculus, but also propulsion modelling, performance estimation, and estimation of the cost of the raw materials necessary to manufacture an RPAS, as well as the estimation of its market price.

To study the relationships between price and design parameters of professional-grade RPAS in the market, both civil and military, we used Factor Analysis (FA) and regressions. FA is a statistical method that has been used in many fields to describe interrelationships between variables referred to as factors. It is used to try and describe the behavior of a group of variables from a more reduced number of them. We used FA to understand what factors or parameters of the RPAS can be used to define the RPAS market. For these reasons, we present here the development of RAMP's module in charge of market price estimation, together with the first study of the factors driving the pricing of unmanned aircraft.

1. Introduction

During the last decade RPAS (Remotely Piloted Aircraft Systems) have experienced rapid growth and expansion across industries [1]. Their applications range from crop monitoring and mapping to package transportation. Depending on their intended role, however, their design receives two very different approaches: on one hand there are hobby-like designed RPAS and, on the other, unmanned aircraft that have been designed through aeronautical traditional techniques. The first group lacks the detail and expertise needed for them to be highly efficient, while the second requires large economic and time budgets. In order to address this situation, we designed an MDO environment with the GPPA architecture [2] for RPAS design, which uses traditional methods for aircraft design. This environment, which was named RAMP (RPAS Advanced MDO Platform) [3], can generate the preliminary design of an RPAS in approximately 7 hours while taking into account aerodynamics [4], structural calculus, engine performance and payload positioning. It can also estimate the price of the raw materials required to manufacture the RPAS, as well as its market price. The module for the last two estimations is the focus of the present work.

Setting the price of a product is a key decision in any market. Potential profitability depends on the price of a product, and it can mark whether an initial investment on new technology or assets is feasible. More so in a growing industry such as that of RPAS. For years, the price, operational, and manufacturing costs of commercial aircraft have been thoroughly studied [5,6]. While the Maximum Take Off Weight (MTOW) is commonly used as a main indicator of cost, number of parts and complexity are usual indicators as well [7]; also from a conceptual point of view [8]. More

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recently, genetic-causal models have been used to estimate life-cycle costs of aircraft [6,9,10]; and statistical models for commercial transportation aircraft have been developed [11,12]. On the other hand, very detailed bottom-up methodologies have been used to estimate accurate final costs of planes [8], but they generally require a frozen configuration in late stages of design, which makes them unsuitable for preliminary analysis. Costs of RPAS operation have also been studied before [13,14]. However, a study of the pricing of professional RPAS is yet to be published.

To study the price of professional-grade RPAS in the market, both civil and military, we used Factor Analysis (FA) and regressions. FA is a statistical method that has been used in many fields to describe interrelationships between variables referred to as factors [15]. It is used to try and describe the behavior of a group of variables from a more reduced number of them. In practical terms, it studies the covariance of a group of variables and selects a smaller group of variables that contribute the most to the covariance of the group. These variables, which are sorted in groups or “factors”, can help understand what variables define the outcome or characteristics of a subject. We intend to use FA to understand what factors or parameters of the RPAS can be used to define the RPAS market. FA’s aeronautical applications include the analysis of aircraft accidents [16], score predictors in the selection of pilots [17], and the market of UAV itself [18].

For these reasons, we present here the development of RAMP’s module in charge of market price estimation, together with the first study of the factors driving the pricing of unmanned aircraft.

2. Data gathering

We gathered data of 67 RPAS from Jane’s all the World’s Aircraft: Unmanned [19], which included the following variables: wing span (lb, m), overall length (lfus, m), maximum take-off/launching weight (MTOW, kg), payload (PL, kg), maximum level speed (MSpeed, m/s), ceiling (hmax, m), range (Rang, m), endurance (End, h). Additionally, when not available in the previous reference, we obtained the price (Price, $) of the RPAS from information on budget and number of RPAS sold in commercial transactions from a number of sources [20–51]; as well as the year that the RPAS were sold for that price (Year). This information is generally scarce, and more so when addressing military aircraft. As stated before, most times only the overall cost of a transaction involving RPAS, ground control systems and additional equipment is known. In such cases we divided the overall amount of the transaction by the estimated number of RPAS involved, given that all the additional elements included in the transaction are usually required to operate the RPAS. After the literature research, data on lb, MTOW, Year, and Price was found for all RPAS; while the variables lfus, PL, MSpeed, hmax, Rang, and End were missing a 7.4%, 10.4%, 5.9%, 10.4%, 11.9% and 2.9% of entries respectively. A 32.8% of the RPAS were missing, at least, one value.

To perform a statistical analysis and FA of the dataset, it was necessary to study the data and find the best method to impute the missing values. If the missing data followed particular patterns, the missing values should be inputted by taking that into account. Alternatively, entries of the dataset with missing values could be discarded. A first step to assess the imputation method is testing whether the data is missing completely at random or not. If that was the case, it could be imputed by using a random number generator with the variance and mean values of the data distribution as defining parameters. Little’s MCAR (Missing Completely at Random) test [52] checks whether this hypothesis is true. When used with our dataset, it failed to reject the null hypothesis (the samples are not MCAR). This means that the missing values in the dataset probably follow a trend or pattern. After removing the variable PL from the sample, Little’s MCAR test rejected the null hypothesis. This points to the PL as the culprit governing the missing values. Such a result seems reasonable, since PL is closely related to MTOW, and heavier RPAS are more likely to belong to the military segment of the market, for which the data is scarcer.

Figure 1 (left) shows the amount of entries (elements) in the database that are missing values and what variables those values belong to. The red squares mark the missing values, while white squares mark existing values. The right panel of Figure 1 shows the number of entries in the database that are missing values and how many. Analyzing the patterns of these missing values showed that they are not monotonic. In other words, the variables for which data is missing cannot be sorted in a way that the missing values for each variable are also missing for the previous variable. The existence of such patterns would ease the imputation of the missing values, since the patterns could be used to impute the data [53].

Markov Chain Monte Carlo (MCMC) Multiple Imputation (MI) is a method that is commonly used to impute missing data. On one hand MI is the standard method to replace missing data [54]. On the other hand, MCMC can reliably recreate a data distribution with the characteristics of the original distribution, even when the database is incomplete, better than non-MCMC methods [55]. Using MCMC-MI (which is indicated for no monotonic MCAR distributions [55]) with all variables resulted in PL values that were not physically reasonable. For instance, an RPAS cannot carry

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a PL heavier than its MTOW. Therefore, it was necessary to impute PL separately. Given that the PL missing values showed a clear trend, we deemed appropriate to impute them with a polynomial. A 3rd degree polynomial (y = x3109 – 3x210-5 + 0.2421x – 0.9612, where x is the MTOW of the RPAS; $R^2 = 0.9575$) was used for this task, given that polynomials of lower degree did not provide a value of R2>0.9, while those of greater degree did not provide a meaningful improvement (R<0.97). On the other hand, the imputation of the rest of the missing values with MCMC-MI was performed in SPSS [56], a statistics software package that provides this imputation method in an easy and convenient manner.

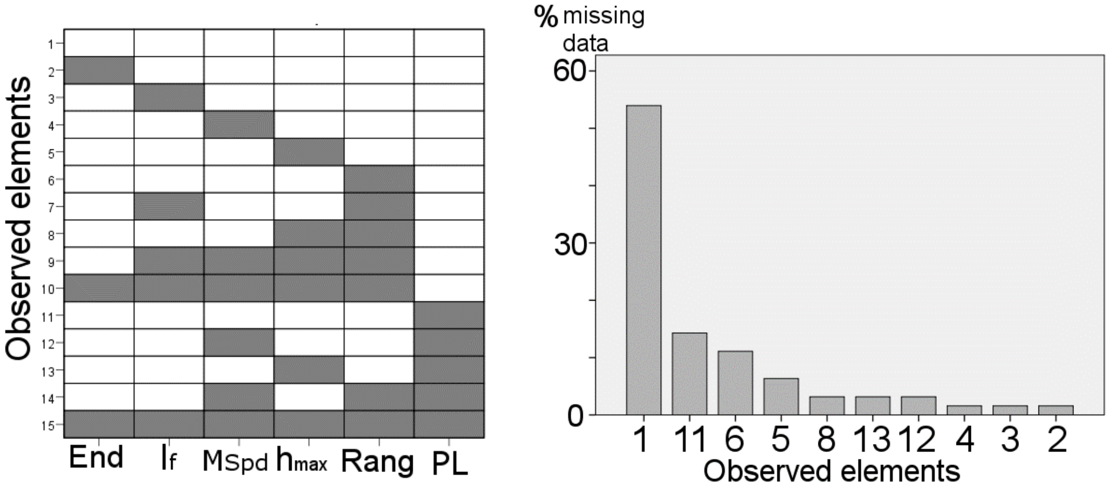

Figure 1: Number of elements that are missing values (left) for particular variables (dark), and number of elements missing particular percentages of values (right).

3. Factor Analysis

In order to know whether a FA can be carried out with a dataset, a Kaiser-Meyer-Olkin [56] test must be performed (eq. 1). It measures the proportion of variance that may be common for several variables. Values higher than 0.5 or (0.6, depending on the author) are considered suitable to perform FA. When this test was performed on the data, it resulted in a value of 0.791, which indicates that a FA is suitable. At the same time, Bartlett's test of sphericity [56] is used to test whether the variables in the data set are related or not. Values of significance lower than 0.05 suggest so. When applied to our data set, Bartlett's test of sphericity provided a significance lower than 0.001. This last value also suggests that FA can properly explain the relationships between the different variables.

$$KMO_j = \frac{\sum_{i\neq j} r_{ij}^2}{\sum_{i\neq j} r_{ij}^2 + \sum_{i\neq j} u_{ij}} \tag{1}$$

where r_{ij} are the elements of the correlation matrix, and u_{ij} are the elements of the partial correlation matrix of the dataset.

The next step is extracting the factors, or groups of variables, that explain the behavior of all the variables in the dataset. This is called "principal factors extraction". The aim is to explain the variations that exist within the dataset by using the least possible number of variables. These factors will be made of percentages of the variables in the dataset. Each consecutive variable that is extracted (added to the factor) explains a smaller fraction of the variables than the previous one. This way, the factors change until all variables have been extracted. Then, from all the progressively more complex factors that were created, one is chosen. The sedimentation graph from Figure 2 can be used to choose what number of factors to use. The eigenvalue of the factor represents the amount of information that it adds to the model. When using a sedimentation graph to study the factors that are going to be used, the ones before and after the main drop in the graph are selected. Table 1 shows communalities in each variable of the model. The extraction value of each variable represents the proportion of each variable's variance that can be explained by the model. In this method, the initial communalities are set at 1,0. Results show that more than 67% of the covariance of each variable can be explained by the model (each extraction value is greater than 0.67). In some cases (MTOW, lb, lfus, Year), the model explains more than a 90% of it (the extraction value is greater than 0.9).

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The sedimentation graph from Figure 2 can be used to choose what number of factors to use. The eigenvalue of the factor represents the amount of information that it adds to the model. When using a sedimentation graph to study the factors that are going to be used, the ones before and after the main drop in the graph are selected.

Table 1: Variable communalities and extraction values.

	Initial	Extraction
lb	1,000	0,918
lfus	1,000	0,901
MTOW	1,000	0,956
PL	1,000	0,831
hmax	1,000	0,863
MSpeed	1,000	0,699
Rang	1,000	0,864
End	1,000	0,676
Year	1,000	0,973
Price	1,000	0,791

This is because their eigenvalues are of a similar order of magnitude, which is higher than that of the factors after the drop. Adding the factors after the drop to the model would not noticeably improve its information and would complicate it [57]. In Figure 2, the drop is present after factors 1 and 2. However, a second drop can be observed after the third factor. In addition, only components with eigenvalues greater than 1 are usually extracted. In this case the third factor's eigenvalue is very close to the unit (Table 2) and it would add almost a 10% of explained variance to the model, so we decided to include it as well. The three selected factors are the non-rotated factors that are shown in Table 3.

Once the factors were chosen, they were rotated to increase their correlation with the variables of the model. We will use an example to explain the meaning of this rotation: If the factors were a reference axis and the variables were points in a 2D plot, rotating the factors would be the same as rotating the axis of the plot so that the points show a stronger correlation with the factors. Rotating the factors helps in understanding the association of variables and factors. Table 4 shows the amount of variance that can be explained by the three chosen factors once they have been rotated. When the factors are rotated, the amount of each variable that is associated with each factor changes.

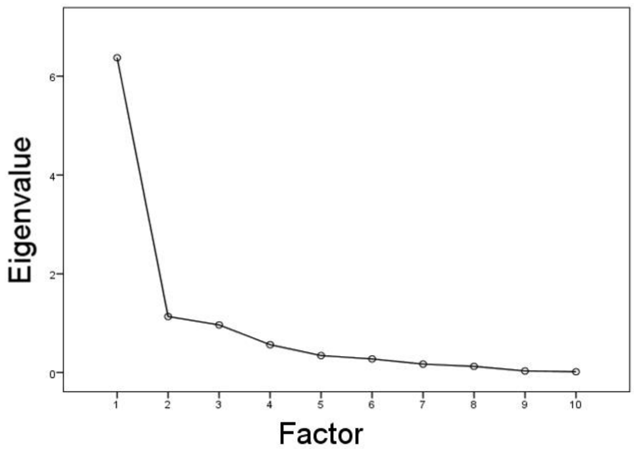

Figure 2: Sedimentation graph.

The total amount of covariance that the rotated factors explain does not change, but it is redistributed among them. This is the same as saying that the RPAS database can be equally characterized both by the non-rotated factors and by the rotated factors. Using the analogy of the 2D plot from before, because the rotation of the factors is the same as a rotation of the reference axis, the points in the rotated reference will have different coordinates. Because the factors are artificial variables that are built from other variables, the amount of each original variable contained in each factor changes after the rotation. The total amount of the original variables that the factors explain remains the same.

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The exact composition of each factor before and after the rotation can be found in Table 3. The non-rotated Factor 1 is highly correlated with all the physical variables, which would suggest that this factor is related to the technical facet of the RPAS. However, once rotated, the correlation with the Range and Year drops, which made this factor end up as a representative of the size of the RPAS. At first, Factor 2 was mostly correlated with the Price of the RPAS, but the rotation made it correlate principally with the Range and have a number of bridge variables as well. Finally, Factor 3 was clearly correlated with the Price before the rotation, and more so afterwards. Some variables also act as bridge variables between factors. Clear cases of this behavior are PL, hmax, MSpeed and End, which act as bridges between Factors 1 and 2. The reason behind these changes is that rotation tends to maximize the differences between factors. Therefore, variables that are highly correlated will tend to stay together, while more independent variables will isolate at a particular factor. This seems to be the case with the Range and Price, which clearly shifted to Factors 2 and 3 after the rotation. Variables that were clearly related to the overall size of the RPAS remained together.

These correlations suggest that the dataset of RPAS can be characterized by just three mostly independent variables. One of them (Factor 1) represents the size of the RPAS, another one (Factor 2) represents their range, while the third one (Factor 3) represents their market price.

Table 2: Amount of variance explained by each factor and their eigenvalues.

Factor	Eigenvalue	% of variance	Cumulative %
1	6,373	63,733	63,733
2	1,133	11,335	75,068
3	0,965	9,652	84,720
4	0,564	5,643	90,363
5	0,343	3,428	93,791
6	0,276	2,764	96,555
7	0,173	1,725	98,280
8	0,125	1,251	99,532
9	0,031	0,307	99,839
10	0,016	0,161	100,000

Table 3: Association of each factor to the variables.

Variable	Non-rotated Factor			Rotated Factor		
	1	2	3	1	2	3
lb	0,955	-0,064	0,034	0,947	0,238	0,045
lfus	0,926	0,070	0,028	0,919	0,103	-0,094
MTOW	0,920	-0,170	0,161	0,791	0,430	0,146
PL	0,880	0,344	-0,252	0,733	0,569	0,041
hmax	0,878	0,244	-0,003	0,692	0,661	-0,053
MSpeed	0,830	-0,071	-0,072	0,639	0,524	-0,127
Rang	0,776	0,302	-0,412	0,095	0,882	0,063
End	0,719	-0,365	0,163	0,559	0,766	-0,039
Year	0,633	-0,371	0,503	0,314	0,740	-0,172
Price	-0,058	0,742	0,648	0,011	-0,056	0,985

Table 4: Amount of variance explained by each rotated factor and eigenvalues.

Factor	Eigenvalue	% of variance	Cumulative %
1	4,211	42,110	42,110
2	3,204	32,036	74,146
3	1,057	10,574	84,720

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4. Estimation of the market price

The second objective of this research is being able to accurately estimate the market price of an RPAS. In order to do so, we studied the price as a function of the rest of the variables of the dataset. The results of the steps taken to obtain a regression to estimate the price of the RPAS are shown in the residual plots of Figure 3. A residual is the difference between the predicted value of the variable (Price in this case) and its real value, and they are calculated by comparing the real price of the RPAS in the dataset with the estimations from the regression.

The first step was calculating a preliminary linear regression including every variable of the model with Price as the predicted variable. This regression showed heteroscedasticity, which can be seen in the cone-like shape of Figure 3 (panel A). This means that, when the linear regression was used to predict the price of the RPAS in the sample, the variability of the result was not homogeneous throughout the sample. The predictions of the linear regression also showed X-axis unbalance, which is shown as points concentrated on one side of the axis. This suggests non-linear relationships between the variables, as well as outliers that do not follow the same trends as the rest of RPAS. A log-transformation of the predicted variable removed most of the heteroscedasticity and some of the X-axis unbalance (Figure 3, panel B). Further log-transformation of several predicting variables (MTOW, MPL and Rang) was necessary to completely remove the heteroscedasticity and X-axis unbalance. Additionally, four outliers were removed. Two of them showed outlier behavior in two partial residual plots (MSpeed and hmax), and the other two in one partial plot (MSpeed). The removal of these four outliers notably reduced the standard deviation of all but three variables (Price, Year and End) (Figure 3, panel C).

The linear regression initially performed had a R2= 0,562; while a step by step linear regression including all variables and their log-transformed versions resulted in an R2= 0,643 that used MTOW, Year, Radius, Log(hmax), Log(End), hmax, MSpeed, lb, PL and Log(MTOW) as predictors.

Univariate plots of each variable with Log(Price) showed that there was, at least, one solution with better estimates. lb's best correlation was achieved by using a logarithmic function; hmax's with a linear function; PL's with a second-degree polynomial; lfus' with a logarithmic function; MSpeed's with a linear function; End's with a second-degree polynomial; MTOW's and Range's with a logarithm. The greatest value of R2 for Year was 0.0716 for an exponential function, which is negligible. We tested, therefore, the following combination of the previous functions:

$$\begin{gathered} Ln(Price) = \beta_0 + \beta_1 * Ln(lb) + \beta_2 * Ceiling + \beta_3 * MPL + \beta_4 * MPL^2 + \\ \beta_5 * Ln(lfus) + \beta_6 * MaxSpeed + \beta_7 * Endurance + \beta_8 * Endurance^2 + \\ \beta_9 * Ln(MTOW) + \beta_{10} * Ln(Range) \end{gathered} \tag{2}$$

An SPSS analysis of this non-linear regression resulted in the following values:

$\beta_0 = 10{,}631$; $\beta_1 = -0{,}232$; $\beta_2 = 0$; $\beta_3 = 0{,}005$; $\beta_4 = -6{,}105 * 10^{-6}$; $\beta_5 = 0{,}702$; $\beta_6 = -0{,}007$; $\beta_7 = 0{,}045$; $\beta_8 = -0{,}001$; $\beta_9 = 0{,}582$; $\beta_{10} = 0{,}001$.

This combination of values (which removed hmax from the regression) has a value of R2=0,655, which is greater than that obtained with the original linear regression. A comparison of the predicted Price and residual for each of the RPAS in the dataset can be seen in Figure 3 (panel C).

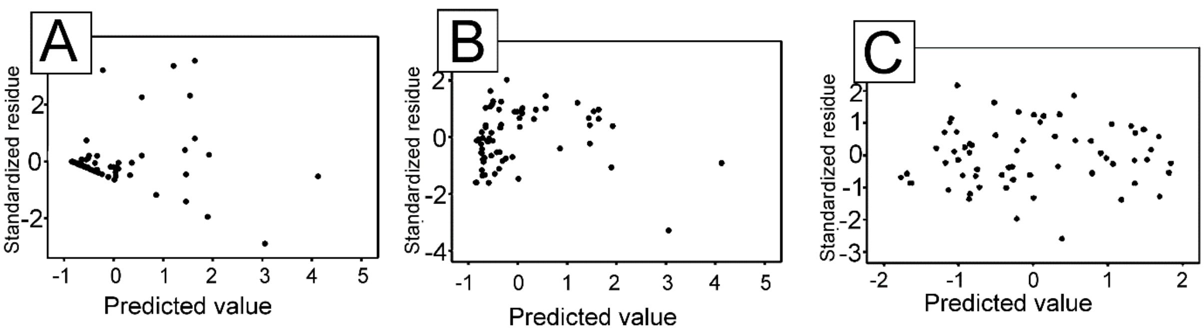

Figure 3: Residual plots of the initial regression (Panel A), log-transformed regression (Panel B), and final non-linear regression (Panel C).

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5. Estimation of the cost of raw materials

Within RAMP, each element of the RPAS (body, wing, vertical and horizontal stabilizers) has a defined material and dimensions. The material can be homogenous (aluminum, steel alloys and different plastics) or non-homogenous (CFRP). The amount of homogenous raw material that is used for the aircraft is estimated as a volume, which is calculated from the dimensions of the RPAS' parts and their thickness. On the other hand, the estimations of CFRP needs are based on surface area. Each part of the aircraft has defined dimensions and a number of layers that may vary during the optimization. From these variables, a total surface area of CFRP is calculated. The total price of raw materials is estimated as the amount of each material multiplied by their market prices, as shown in equation 2.

$$Price_{raw} = \sum V_{hom} Price_{hom} + \sum S_{CFRP} Price_{CFRP} \tag{3}$$

6. Aircraft optimization

The full model, once implemented in RAMP, was used to design a RPAS with an objective mission. This objective mission consisted in gathering particles from the air with a total flight duration of one hour, at a maximum altitude of 1000 m. The RPAS must be man-portable. From this mission, the following requirements were drawn:

- Endurance of, at least, 60 min.
- Flight speed of, at least, 45 kn.
- Payload of, at least, 0.1 kg.
- Weight lower than 15 kg.
- Wingspan and length lower than 1 m.

Figure 4 shows the three most typical behaviors that were found during the tests. Panel A shows the evolution of the optimization from a model with classic configuration, while panels B and C show two alternative evolutions of the optimization: canard to classic configuration (panel B), and canard to dragonfly (this name comes from having both wing and horizontal stabilizer at the same position) configuration (panel C).

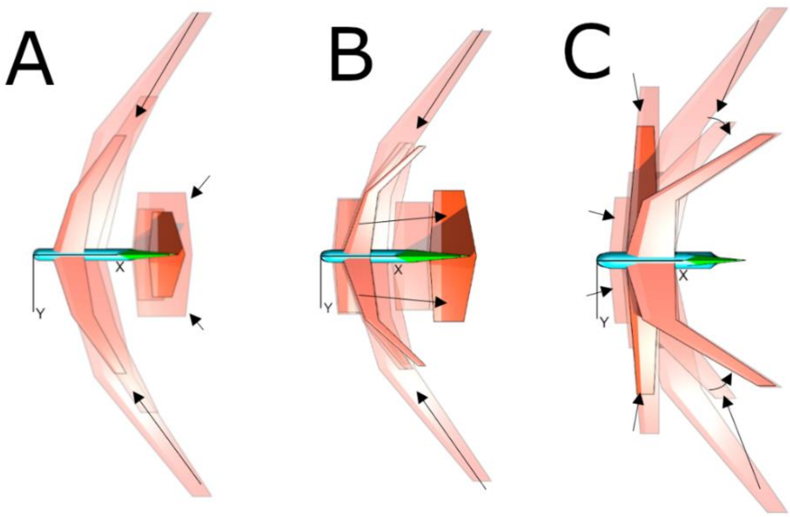

Figure 4: Three types of evolution of the optimization. Plane A remained in a classical configuration during the optimization (panel A); plane B evolved from a canard configuration to a classic configuration (panel B); plane C evolved from a canard configuration to a dragonfly configuration (panel C).

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Figure 5 shows the evolution of the estimation for the cost of the raw materials during the optimization. A notable point of the final RPAS models is that all three ended up with a similar cost around $200, regardless of their configuration. Figure 6 shows the evolution of the estimation of the market price of the three RPAS. Unlike the cost of the raw materials, the estimated market prices of the RPAS vary widely. The highest price corresponds to plane A (panel A in Figure 4), the intermediate price corresponds to plane B (panel B in Figure 4), and the lowest price corresponds to plane C (panel C in Figure 4). The difference in price cannot come from the differences in configuration since the configuration itself does not play a role in the estimation of the market price of the RPAS. In fact, Figure 7 shows that the evolution of the MTOW during the optimization presents similar results as the market price. The MTOW is strongly aligned with the factor associated to the size of the RPAS and is the main difference between the three models. A comparison of maximum speeds (Figure 8) also shows great differences. The influence of this factor is opposite to that of the MTOW since its coefficient is negative, which helps explain plane B's lower price.

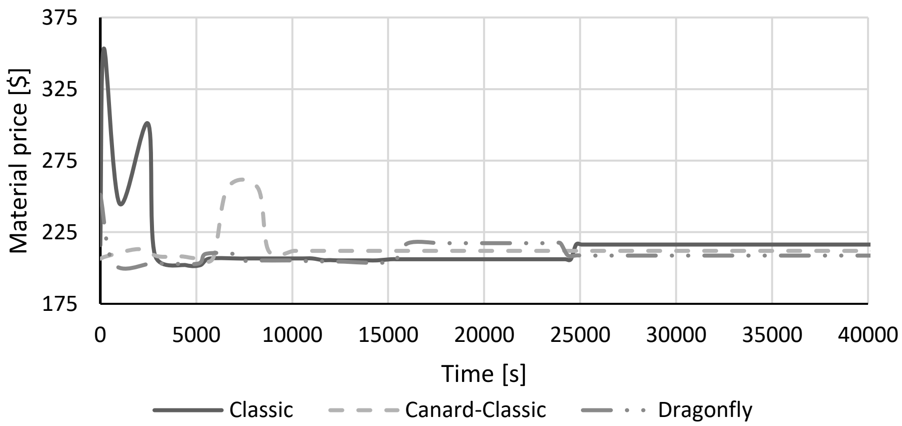

Figure 5: Evolution of the price of the building materials during the optimization.

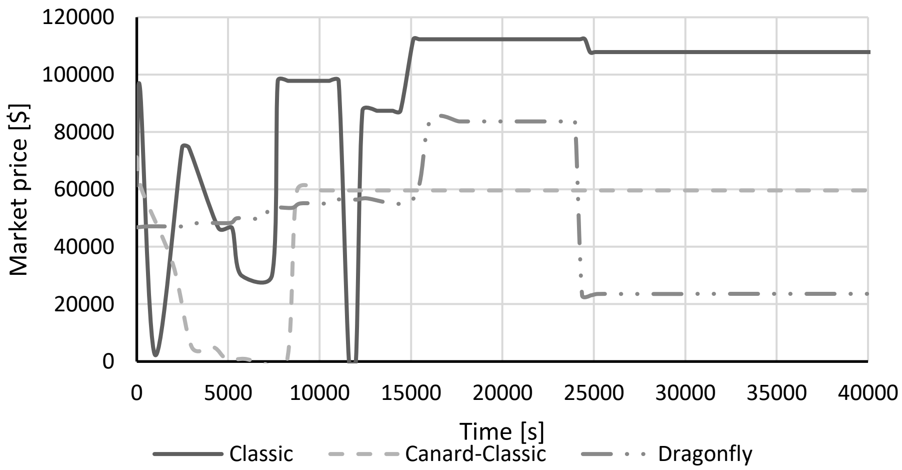

Figure 6: Evolution of the estimated market price during the optimization.

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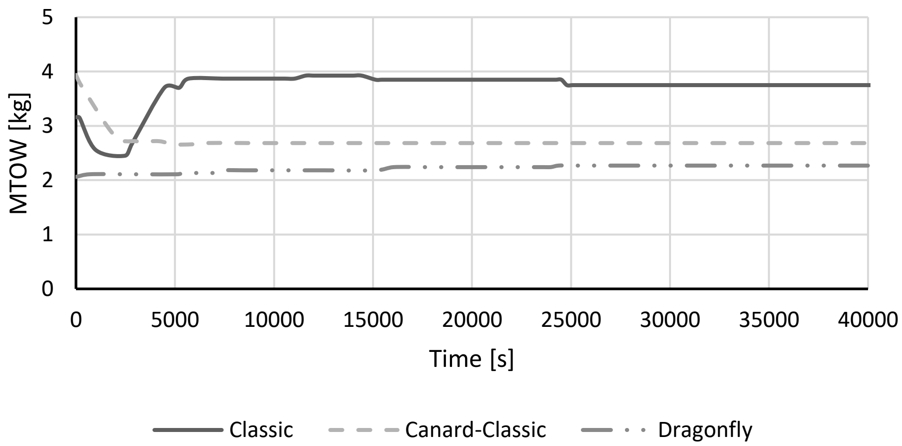

Figure 7: Evolution of the MTOW during the optimization.

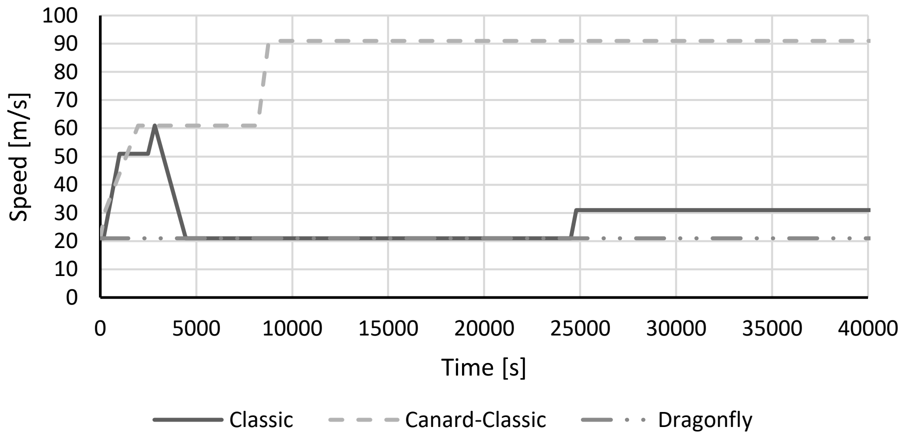

Figure 8: Evolution of the flight speed during the optimization.

7. Conclusions

Even though the field of RPAS is very opaque and the information is scarce, we could find clear trends and relationships to characterize their market and the factors driving their price. In particular, the characteristics of RPAS currently available in the market can be explained by three defining factors: size, performance, and price.

These results are not surprising, since the size of a RPAS greatly limits the kind of missions that it can undertake, and the conditions under which it can be deployed. In a similar manner, performance (range and endurance) define the type of RPAS.

A surprising result, however, is the fact that these two factors are relatively independent. This points out to the versatility of RPAS and the availability of several sizes of RPAS with similar performances, as well as RPAS of similar size but with different performances. Another conclusion that can be drawn from this result is that the RPAS industry is still not mature. If it was, each kind of mission would be performed by a very particular kind of RPAS given that they would be greatly optimized. This could also be related to the third factor: price. The fact that the price is so independent from the other two factors suggests that the RPAS market behaves like a monopoly, or an oligopoly at most, where the price of the product is not completely related to its quality/performance. It is well known that military RPAS tend to be developed in joint efforts with governments. This is an important entry barrier of the market that prevents new agents from competing with already stablished RPAS contractors.

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As for the possibility of explaining the RPAS' price by the other variables, results show that it can be done to some extent. However, there is still a considerable amount of unexplained variance that could be due to socio-political factors and/or the contour conditions of the market itself. As mentioned before, the RPAS industry works at large like an oligopoly (mostly the military segment), which increases the arbitrariness of RPAS pricing. Still, managing to achieve a predicting regression with a R2=0.655 is remarkable. In the future, gathering additional data and considering more variables can prove very valuable towards the improvement of the pricing model, but also testing new models, such as a machine learning regression model. On the other hand, the estimations of the price of the building materials of the RPAS should be extended to a full costs model of the company or, at least, the manufacturing and commercialization costs of the RPAS. With regards to the optimization results, it is interesting to note that the estimated prizes of the raw materials that are necessary to build each aircraft are very similar. This is reasonable since their sizes are similar. However, it is noteworthy that their estimated market prices are so different. It could be due to the different performance delivered by each RPAS. Further data points, or alternative models could point out to whether this is really due to the market or the suitability of the model.

References

[1] Teal Group. Teal Group Predicts Worldwide Civil Drone Production Will Soar Over the Next Decade 2018.
[2] Aliaga-Aguilar H, Cuerno-Rejado C. Generic parameter penalty architecture. Struct Multidiscip Optim 2018;58:1559–69. doi:10.1007/s00158-018-1979-2.
[3] Aliaga-Aguilar H. RPAS Design : an MDO Approach. Universidad Politécnica de Madrid, 2018. doi:10.20868/UPM.thesis.51374.
[4] Aliaga-Aguilar H, Cuerno-Rejado C. Development and validation of software for rapid performance estimation of small RPAS. Adv Eng Softw 2017;110:1–13. doi:10.1016/j.advengsoft.2017.03.010.
[5] Marx WJ, Mavris DN, Schrage DP. A hierarchical aircraft life cycle cost analysis model. AIAA Aircr Eng Technol Oper Congr 1st Los Angeles CA UNITED STATES 1921 Sept 1995. doi:10.2514/6.1995-3861.
[6] Curran R, Castagne S, Early J, Price M, Raghunathan S, Butterfield J, et al. Aircraft cost modelling using the genetic causal technique within a systems engineering approach. Aeronaut J 2007;111:409–20. doi:10.1017/S000192400000467X.
[7] Curran R, Kundu AK, Wright JM, Crosby S, Price M, Raghunathan S, et al. Modelling of aircraft manufacturing cost at the concept stage. Int J Adv Manuf Technol 2006;31:407–20. doi:10.1007/s00170-005-0205-8.
[8] Scanlan J, Hill T, Marsh R, Bru C, Dunkley M, Cleevely P. Cost modelling for aircraft design optimization. J Eng Des 2002;13:261–9. doi:10.1080/09544820110108962.
[9] Castagne S, Curran R, Rothwell A, Price M, Benard E, Raghunathan S. A generic tool for cost estimating in aircraft design. Res Eng Des 2008;18:149–62. doi:10.1007/s00163-007-0042-x.
[10] Curran R. Integrating Aircraft Cost Modeling into Conceptual Design. Concurr Eng 2005;13:321–30. doi:10.1177/1063293X05060698.
[11] Wei W, Hansen M. Cost economics of aircraft size. J Transp Econ Policy 2003;37:279–96.
[12] Jun M. Uncertainty Analysis of an Aviation Climate Model and an Aircraft Price Model for Assessment of Environmental Effects. Massachusetts Institute of Technology, 2007.
[13] Valerdi R. Cost Metrics for Unmanned Aerial Vehicles. Infotech@Aerospace, Reston, Virigina: American Institute of Aeronautics and Astronautics; 2005, p. 1–6. doi:10.2514/6.2005-7102.
[14] Zych T, Selig M. Preliminary design and cost analysis of a family of unmanned aerial vehicles. 13th Appl. Aerodyn. Conf., Reston, Virigina: American Institute of Aeronautics and Astronautics; 1995, p. 977–85. doi:10.2514/6.1995-1883.
[15] Stewart DW. The Application and Misapplication of Factor Analysis in Marketing Research. J Mark Res 2014;18:51–62.
[16] O'HARE D, Wiggins M, Batt R, Morrison D. Cognitive failure analysis for aircraft accident investigation. Ergonomics 1994;37:1855–69. doi:10.1080/00140139408964954.
[17] Biggerstaff S, Blower DJ, Portman CA, Chapman AD. The Development and Initial Validation of the Unmanned Aerial Vehicle (UAV) External Pilot Selection System. Pensacola, FL: 1998.
[18] Polo A. Análisis del mercado militar de UAV mediante Análisis factorial. 2015.
[19] Streetly M. Jane's All the World's Aircraft:Unmanned 2015-16. IHS; 2016.
[20] Deagel. Polish Army Selects Aeronautics as Supplier of Orbiter Mini UAV Systems n.d. http://www.deagel.com/news/Polish-Army-Selects-Aeronautics-as-Supplier-of-Orbiter-Mini-UAV-Systems_n000005158.aspx%0A.
[21] The Register. Watchkeeper Numbers Revealed n.d. http://www.theregister.co.uk/2007/06/15/watchkeeper_numbers_revealed/%0A.
[22] Defense Industry Daily. The Larks, Still Bravely Singing, Fly… Elbit's Skylark UAVs. Def Ind Dly n.d. http://www.defenseindustrydaily.com/the-larks-still-bravely-singing-fly-elbits-skylark-uav-04444/%0A.

DOI: 10.13009/EUCASS2019-303

[23] UAV Skylark n.d. http://defense-update.com/newscast/1208/news/151208_uav_skylark.html#more%0A.
[24] Raghuvanshi V. India Finalizes $3B Blueprint for UAV Fleets. DefensenewsCom 2016. http://www.defensenews.com/story/defense/air-space/2016/03/20/india-finalizes-3b-blueprint-uav-fleets/81637026/%0A.
[25] Bryson AM, Williams S. Review of Unmanned Aerial Systems (UAS) for Marine Surveys. Sydney: 2015.
[26] Adams E. Surveillance Superdrone. Pop Sci 2006:15. https://www.popsci.com/draganfly-innovations/article/2006-03/surveillance-superdrone.
[27] Egozi A. BlueBird seals SpyLite deal with Chilean army. FlightglobalCom 2013. https://www.flightglobal.com/news/articles/bluebird-seals-spylite-deal-with-chilean-army-384395/%0A.
[28] Sperwer n.d. http://defense-update.com/products/s/sperwer.htm%0A.
[29] Aerostar Tactical Unmanned Aerial Vehicle n.d. http://www.airforce-technology.com/projects/aerostaruav/.
[30] Noviny L. Czech Troops to Use U.S. ScanEagle Drones; Reconnaissance drones will be used to increase the safety of patrols. Prague Post 2015. http://www.defense-aerospace.com/articles-view/release/3/160859/us-donates-scaneagle-uavs-to-czech-army.html%0A.
[31] Parkes M, Johnson C. Applications for Unmanned Aerial Vehicles in Electric Utility Construction. 2016.
[32] Sánchez G, Valenzuela MM, Cadavid ES. Vehiculos no tripulados en Latinoamerica. InfodefensaCom 2013:85.
[33] Hodgson AJ, Noad M, Marsh H, Lanyon J, Kniest E. Using Unmanned Aerial Vehicles for surveys of marine mammals in Australia: test of concept. 2010.
[34] ADAMOWSKI J. Russian Defense Ministry Unveils $9B UAV Program. RpdefenseCom 2014. http://rpdefense.over-blog.com/tag/adcom systems/%0A.
[35] Turkish Aerospace Industries. Glob Mil Rev n.d. http://globalmilitaryreview.blogspot.com.es/2011/04/turkish-aerospace-industries-anka.html%0A.
[36] CropCam Agricultural UAV. Micropilot Store n.d.
[37] Hambling D. U.S. Navy Plans to Fly First Drone Swarm This Summer. MilitaryCom 2016. https://www.military.com/defensetech/2016/01/04/u-s-navy-plans-to-fly-first-drone-swarm-this-summer.
[38] Cardinal II Unmanned Aircraft System. Airforce-TechnologyCom n.d. http://www.airforce-technology.com/projects/cardinal-ii-unmanned-aircraft-system/ http://taiwantoday.tw/news.php?unit=6,23,6,6&post=12212%0A.
[39] Analysis. Airforce-TechnologyCom n.d. http://www.airforce-technology.com/features/feature65494/%0A.
[40] La voz n.d. http://archivo.lavoz.com.ar/suplementos/economia/07/12/09/nota.asp?nota_id=142319%0A.
[41] Mele P. L'export armato italiano ai regimi dell'ex URSS. Intervista a Giorgio Beretta. Rai News n.d. http://www.rainews.it/dl/rainews/articoli/L-export-armato-italiano-ai-regimi-dell-ex-URSS-Intervista-a-Giorgio-Beretta-b0a850b2-32fd-457e-b715-9f43da2b047e.html?refresh_ce%0A.
[42] Russian UAVs in Combat. StrategypageCom 2015. https://www.strategypage.com/dls/articles/Russian-UAVs-In-Combat-9-9-2015.asp%0A.
[43] Egozi A. Swiss parliament approves Hermes 900 deal n.d. https://www.flightglobal.com/news/articles/swiss-parliament-approves-hermes-900-deal-416483/%0A.
[44] La Franchi P. UAV directory 2006 ACRONYMS. Flight Int 2006:32–59.
[45] Kim S. Feasibility analysis of UAV technology to improve tactical surveillance in South Korea's rear area operations. Naval Postgraduate School, 2017.
[46] Siminski J. The Polish soldiers have recovered the lost drone. TheaviationistCom 2014. https://theaviationist.com/tag/flyeye/%0A.
[47] Wilhelm S. This new Washington-made drone can remain airborne for days, could help spot fishery poachers. BizjournalsCom 2015. http://www.bizjournals.com/seattle/news/2015/08/05/this-new-washington-made-drone-can-hover-for-days.html?ana=twt%0A.
[48] STEVENSON B. Paris picks Patroller for UAV requirement. FlightglobalCom 2016. https://www.flightglobal.com/news/articles/paris-picks-patroller-for-uav-requirement-421137/%0A.
[49] ADAMOWSKI J. Russian Defense Ministry Unveils $9B UAV Program. Rpdefense.over-BlogCom 2014. http://www.rpdefense.over-blog.com/tag/adcom systems/%0A.
[50] Maveric UAS n.d. https://www.guavas.info/drones/Prioria Robotics, Inc.-Maveric UAS-328%0A.
[51] Sánchez G, Valenzuela MM, Cadavid ES. Vehículos aéreos no tripulados en Latinoamérica. InfodefensaCom 2013:85.
[52] Little RJA. A Test of Missing Completely at Random for Multivariate Data with Missing Values. J Am Stat Assoc 1988;83:1198–202. doi:10.1080/01621459.1988.10478722.
[53] Horton NJ, Kleinman KP. Much Ado About Nothing. Am Stat 2007;61:79–90. doi:10.1198/000313007X172556.
[54] Schafer JL. Multiple imputation: a primer. Stat Methods Med Res 1999;8:3–15. doi:10.1191/096228099671525676.

DOI: 10.13009/EUCASS2019-303

[55] Takahashi M. Statistical Inference in Missing Data by MCMC and Non-MCMC Multiple Imputation Algorithms: Assessing the Effects of Between-Imputation Iterations. Data Sci J 2017;16:37. doi:10.5334/dsj-2017-037.
[56] IBM Knowledge Center n.d. https://www.ibm.com/support/knowledgecenter/en/SSLVMB_sub/statistics_kc_ddita_cloud/spss/product_landing_cloud.html (accessed March 9, 2018).
[57] Thompson B. Exploratory and confirmatory factor analysis: Understanding concepts and applications. 2004. doi:10.1037/10694-000.