MODELING OF SCALABILITY LAWS FOR UNMANNED AIR VEHICLES

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2016

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A thesis submitted to the

National University of Sciences & Technology

In partial fulfillment of the requirement for the degree of

Masters of Science

In

Systems Engineering

2016

STATEMENT OF ORIGINALITY

I hereby certify that the work embodied in this thesis is the result of original research and has not been submitted for a higher degree to any other University or Institution.

Date

M. Adnan Ashraf

Acknowledgements

I am grateful to Almighty Allah, who gave me the strength to complete my research work and thesis.

Special thanks to my supervisor Dr. Adnan Maqsood for his support, motivation and keen interest in this work. Without his support, I would not have been able to complete my thesis.

I would also like to express my gratitude to Dr. Zamir Hussain, who helped me with all the statistics involved and the overall layout of the results. I appreciate the involvement of my committee members Dr. Ammar Mushtaq, Dr. Zartasha Mustansar and Dr. Salma Sherbaz.

I am grateful to my parents and my brother, M. Imran Ashraf. They always keep me pushing to deliver the best that I could. It is through their love and support that I always have been able to achieve whatever I have aimed for.

Thanks to Research Center for Modeling and Simulation (RCMS) for providing me the platform and all the required facilities to carry out this work.

Sincerest thanks to my classmates, Kashif Ayub and Aliya Zafar. They helped me in brainstorming, organizing the ideas and in their implementation.

Summary

Scalability relationships are applied on systems to handle growing amount of data and generate governing laws of complex phenomena. Most complex and diverse fields including the nature itself follow simple scaling laws. Using these laws, raw data is converted into significant facts, relationships, patterns and trends to help in taking analytical decisions. It also helps in allocating resources optimally and to maximize the efficiency of systems.

Unmanned Air Vehicles (UAVs) are becoming the primary element of choice for versatile missions because of their number of advantages over manned aircrafts. Militaries around the world are raising separate divisions / units to handle UAV operations. Similarly, in civil, UAVs are being deployed for applications ranging from traffic control to food and books delivery. A huge amount of data about these UAVs is commercially available. Just like other areas of life where the scalability laws have played an important role in enhancing the scientific body of knowledge and suggested a way forward, UAVs should also take benefit from them.

This research work is a successful attempt in developing scalability laws on UAVs. Specifically, geometric parameters are used to identify the performance characteristics. The geometric parameters include wingspan, overall length, payload and maximum take-off weight. The performance characteristics, predicted from these geometric parameters include endurance, ceiling and maximum speed of the UAVs. These relationships are derived from linear regression technique and tested statistically. Results show that scaling is indeed a pervasive property in UAVs. Similarly, preliminary studies on scalability trends in birds are also modeled and studied.

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CHAPTER 1

Introduction

Life on earth follows scalability trends. Insects, birds and animals all have a scalable relationship among their ages, metabolic rates, speeds and so on. Likewise the life at cities follows scalability laws. Inspired by these relationships, scalability studies have been conducted in past for advancement in technology. Semiconductor devices and electronics have demonstrated scalable growth. In 1965, Gordon E. Moore predicted that the number of transistors in dense electronic circuits will double approximately every two years [1]. The prediction remained accurate for several decades. This scalable growth became industry standard for the coming generations of computers and electronics, and guided the designers and planners for long term planning and to set targets for research and development. Similarly most complex system of the universe i.e. life and its amazing diversity which spans over 21 orders of magnitude, obeys a host of empirical scaling laws [2].

The uncompromising need for Intelligence, Surveillance and Reconnaissance (ISR) systems is the main force driving the tremendous growth in Unmanned Air Vehicles (UAVs). ISR systems constitute a big portion of developed and developing countries defense budget that is approximately 5%. One estimate of global ISR market given by Defense Advanced Research Projects Agency (DARPA) in 2010 is $63.6 billion. UAVs are the need of modern era. From military commanders to commercial organizations, UAVs are the first element of choice for the ISR missions and also for hostile area operations. These UAVs are emerging in many different sizes and shapes. Ranging from High Altitude Long Endurance (HALE) to Nano Air Vehicles (NAVs) as shown in Figure 1.1, a huge number of UAVs are being manufactured and deployed for various purposes [3].

Figure 1.1: Types of UAVs

The performance characteristics of UAVs are shown in Table 1.1. Scalable trends should be found to handle this complex diversity among UAVs. Scalability laws need to be explored for technological advancements in this field for the designers, architects, strategic planners and manufacturers to know what they are going to achieve and would help them in setting the long term goals and targets.

Table 1.1: Performance Characteristics of UAVs

UAV Type	Abbreviation	Altitude (ft)	Endurance (hrs)	Ranges (km)
High Altitude Long Endurance	HALE	Over 30,000	170	Over 250
Medium Altitude Long Endurance	MALE	Up to 30,000	120	Up to 200
Tactical UAV	TUAV	Up to 18,000	15	160
Mini UAV	MUAV	Up to 12,000	5	25
Micro UAV	MAV	10,000	1-2	15
Nano UAV	NAV	3,000	Less than 1	10

For meeting the limitless hunger of warfighters for Intelligence, Surveillance and Reconnaissance (ISR) capabilities, the trend is shifting towards the unmanned systems as the primary vehicle of collecting information. Sensors packages on these unmanned systems collect information in the form of electrical signals, radar data, multispectral images in the air, over sea and ground [4]. These unmanned systems for ISR missions provide wide range of advantages:

- They reduce life-threatening risks carried by warfighters.
- They never wink and never tire.
- They represent a smaller target than their manned counterparts (for small-scale UAVs).
- They are relatively cheaper to replace & operate.
- They can equally perform lethal and non-lethal sorties.

Context diagram for a UAV is shown in Figure 1.2. It shows all the constituencies of the UAVs. Typically a UAV interacts with the operator inside ground control station, maintainer, environment and energy source.

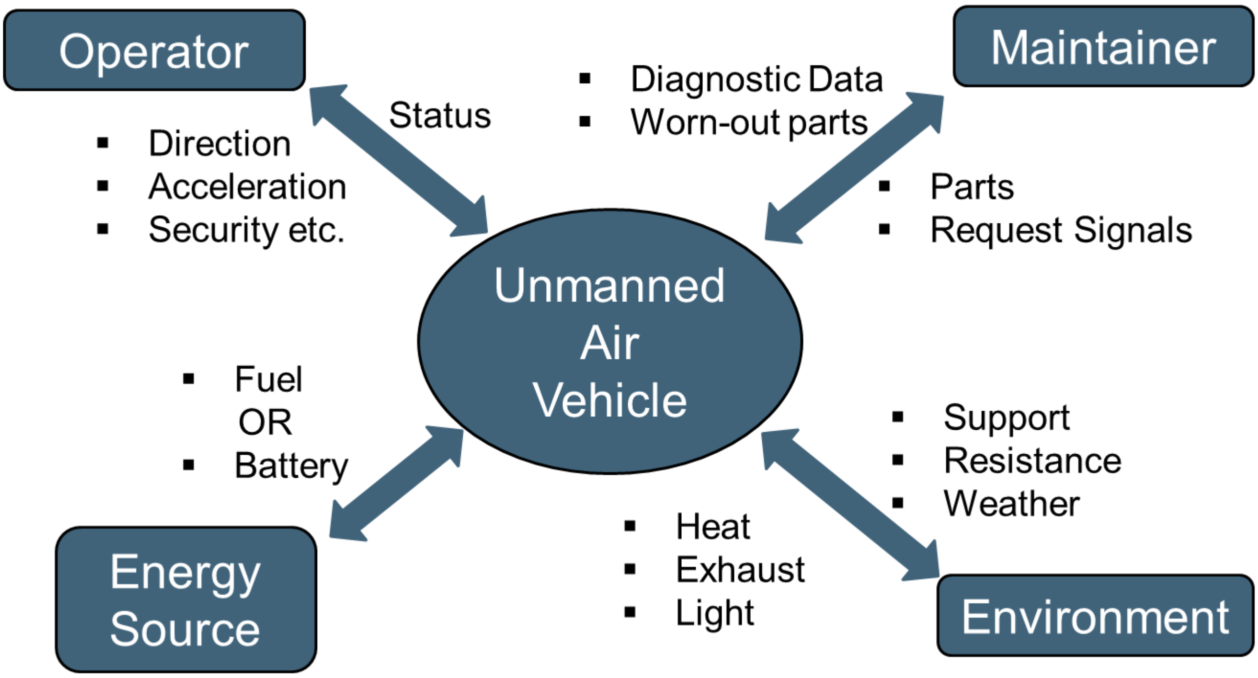

Figure 1.2: Context Diagram of an Unmanned Air Vehicle

In these ISR systems, the commanders need to see the big and unified picture of the battlefield. In this regard scalability laws will help commanders to get a better situational awareness by combining the best mix of the UAVs.

1.1. Area of Research

As UAVs have become a first element of choice for war fighters and civilians because of their relatively low cost, providing accurate ISR information for safe & remote operation, huge number of UAV development programs have been initiated worldwide [5]. ISR systems are all about agility, common operational picture and better situational awareness, so commanders quickly need to know what kind of UAVs or their combination are best for specific mission constraints. For certain specific mission constraints, a different kind of UAV needs to be developed with respect to its endurance, speeds, ceiling, operating heights and temperatures, fuel capacity and costs. Designers and architects start all over again for each kind of UAV and have no certain guidelines. Long term plans for the industry need estimated targets for the future designs.

Researchers in industry and academia, all over the world, are working on finding the best possible designs and solutions for complex UAV development problems. The industry needs specific targets and to be more precise it needs scalable relationships among multiple UAV parameters so that an achievable target could be quickly set. The purpose of the study is to explore scalability relationships among various available UAV parameters / characteristics, which would help the planners, designers, manufacturers and commanders to plan as per their desired targets.

1.2. Objectives of the Study

Technological problems demand technological changes as well as change in philosophy i.e. problem solving approach. The main objectives of the study are:

- Collection and presentation of various characteristics of fixed-wing UAVs
- Developing scalability relationships among UAV geometric and performance parameters using linear models
- Quantification of scalable relationships for conceptual layout of prospective systems with existing technological capabilities

1.3. Contributions

Certain valuable potential contributions made through this scholarly work are:

- Sizing of future UAVs with existing technological capabilities
- The findings will help to quantify the number and size of UAVs for ISR requirements
- Empirical relationships that would be helpful in conceptual designing of UAVs
- Documentation of one conference and one journal manuscript

1.4. Organization of the Thesis

This thesis comprises of five chapters. The brief outline of each chapter is given below:

Chapter 1 --- Introduction

This chapter provides an insight into the topic and areas covered in this research. The objectives and contributions are specified. A systematic outline of the report is given at the end of the chapter.

Chapter 2 --- Literature Review

A complete summary of the literature study is specified in this chapter. This chapter shows the importance of the scalability laws in complex systems.

Chapter 3 --- Problem Formulation and Description

In this chapter, our problem is elaborated. It also gives insight into the anticipated targets and the means to achieve them. All the analysis and tools being used are explained here.

Chapter 4 --- Results and Discussions

In this chapter, all the acquired results are presented and discussed. It explains how the results are acquired, how they are tested and what their significance is. The estimated results are also compared with the actual values.

Chapter 5 --- Scalability Studies for Birds

The results acquired for the bird's species are discussed in this chapter. Bird species are used in place of flapping wing UAVs. This chapter explains the procedure and importance of each result.

Chapter 6 --- Conclusions and Future Work

The conclusions, carefully drawn after results compilation, are presented in this chapter. Recommendations for the future work are also given.

CHAPTER 2

Literature Review

Nature is scalable. Inspired by this phenomenon, a number of scalability studies have been conducted by the researchers all over the world to find the relationships among different parameters. One of the most prominent among them is Moore's law. Moore's Law is a scalability study which established a relationship among the number of years and the growth in number of transistors per electronic chip. The law indicated that number of transistor in a dense electronic circuit will double approximately every two years [1] as shown in Figure 2.1.

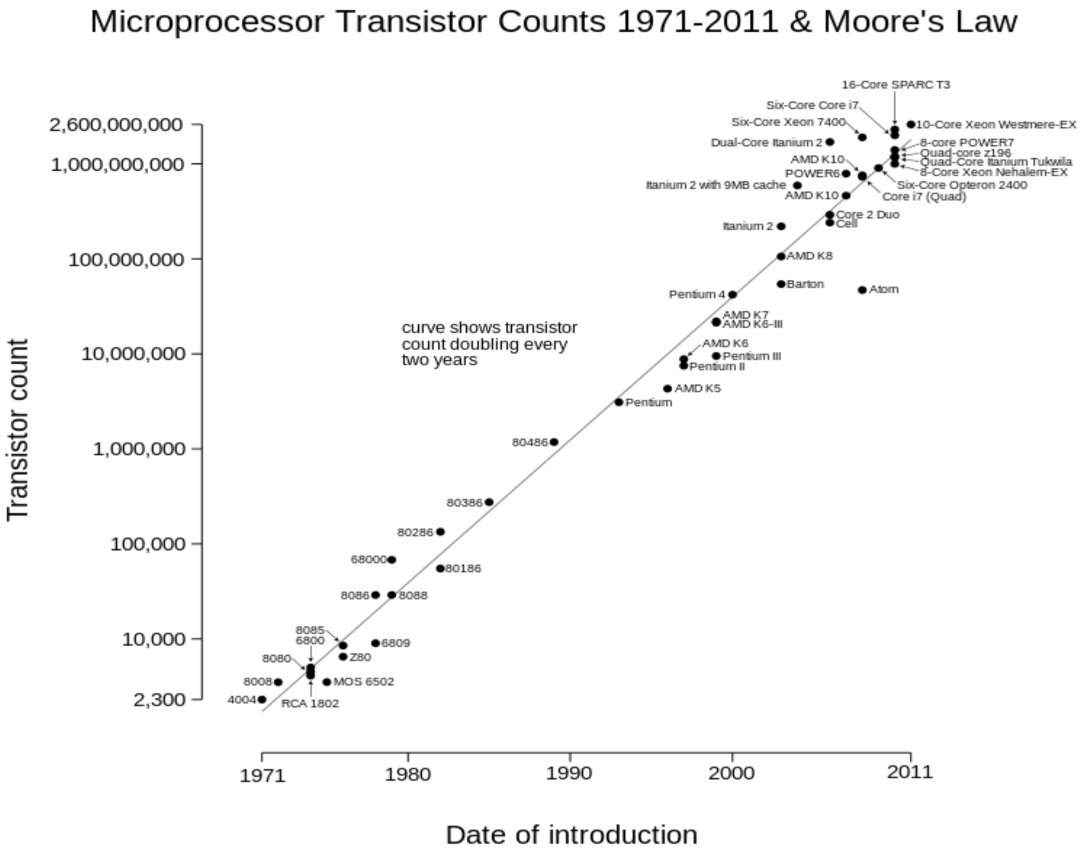

Figure 2.1: Microprocessor Transistor Count and Moore's Law

Similarly this study also established a relationship among manufacturing cost per component and number of components per chip. For simple components, cost per component is inversely proportional to number of components. Figure 2.2 shows that as number of components increases, the cost increases resulting in a parabolic curve [1].

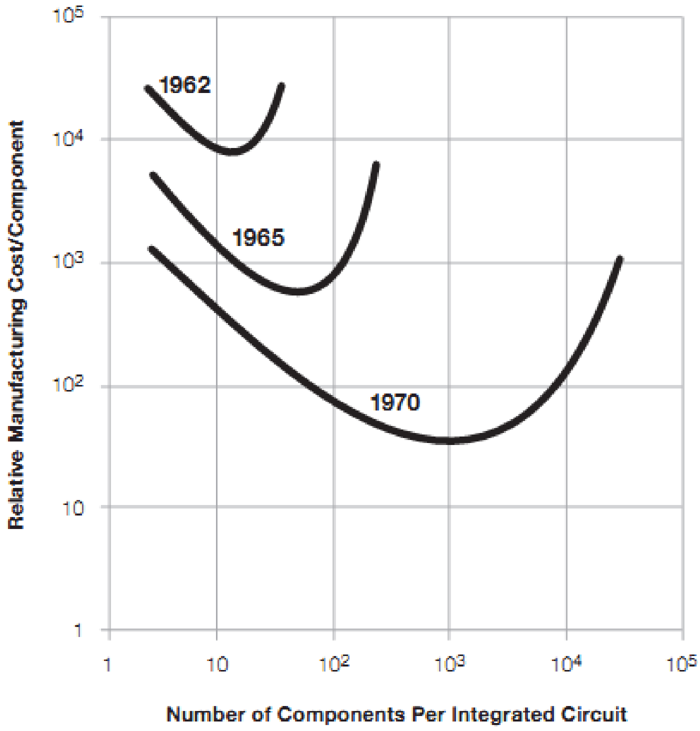

Figure 2.2: Relationship among Transistors/chip and relative Cost

This study and its results with its predictions proved to be accurate since its introduction in 1965 and became an industry standard for the planners, designers and manufacturers.

Most recent and noticeable scalability studies are conducted by Geoffrey West. These studies contain relationships in almost every field of life ranging from animals metabolic rates to the life in big cities of the world. These studies span around the simple power law relationships i.e. $Y = \alpha (X)^{\beta}$ with the exponents that are simple multiples of ¼ (e.g. ¼ , ¾ etc.) [2]. The graph plotted among the masses and metabolic rates follows a linear relationship as shown in Figure 2.3.

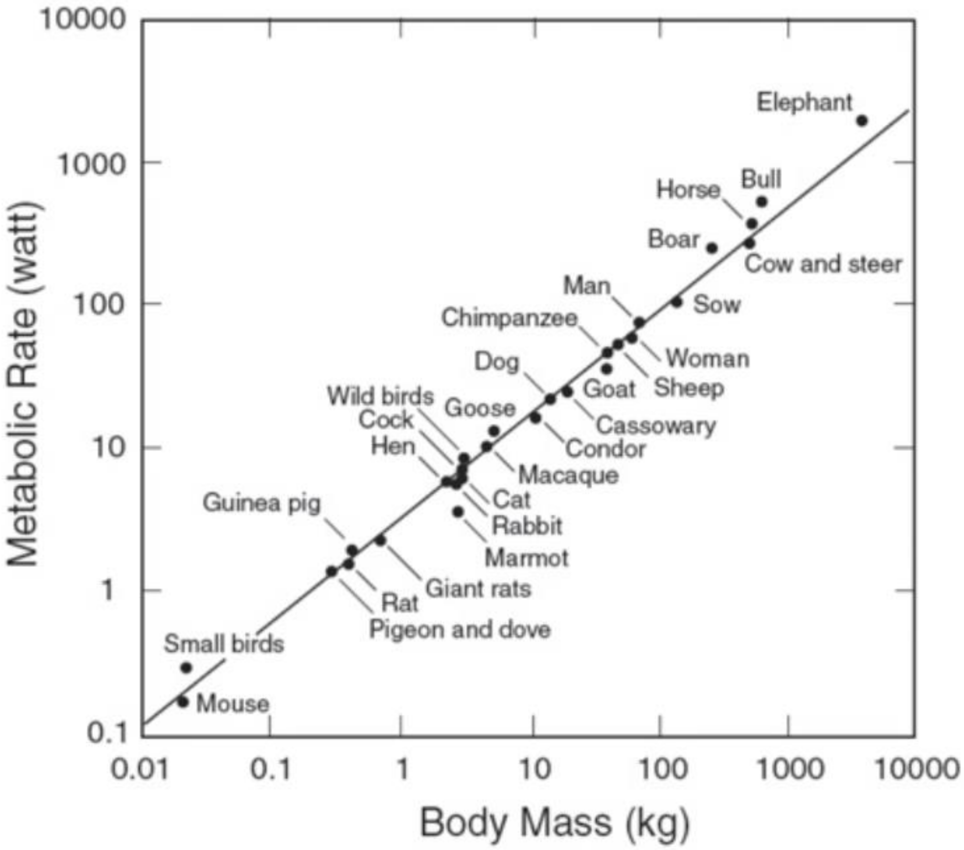

Figure 2.3: Relationship among Mass and observed Metabolic Rates

Some of the results from the recent scalability studies in biology are as under:

- Bigger the specie is, less energy per body is needed for its total energy requirements
- Pace of life systematically slows with increasing size [6]
- Human population with all its parameters also follows these simple scaling laws [7]
- Similarly scaling holds true for all physiological processes and life history over the entire spectrum of life [8]

The exponents of the power law relationship $Y = \alpha \, (X)^{\beta}$ fall into three categories:

- β = *1* (Linear)
- β < *1* (Sublinear)
- β > *1* (Super linear)

Similarly the scalability is also found in the linguistics. One of the vital events involved in human evolution is advent of composite languages. Surprisingly, there exists scalable trends that are common to all languages. G.K Zipf studied this scalability in 1949 and is known as Zipf’s law [9]. It states that the frequency of a word decays as a universal power law of its rank. Many studies indicates that Zipf’s law is pledge of figurative reference and gives insight into the evolution of human race as well as human behavior [10].

Unmanned Air vehicles (UAVs) are capable of locating, recognizing and attacking moving vehicles, enemy forces, weapon systems and other major targets. These are also capable of locating friendly forces and non-combatant civilians. Intelligence, Surveillance and Reconnaissance (ISR) components are sensor systems that collect raw data for the Command, Control, Communication and Computation (C4) components which analyze the collected information, decide the best possible solution and distribute the processed information to relevant nodes for further action. The fact that C4 and ISR are almost always united into a single acronym not only highlights their interdependency, but also the distinctions in which these issues have been discussed in the past. Driven by a host of civilian, homeland security, and military objectives, UAVs have emerged as the platform of choice for warfighters conducting surveillance and reconnaissance operations in hostile environments [11]. As a new class of air vehicle, these systems face many unique challenges that make their design and development difficult. Fortunately, the development of larger-scale UAVs over the past 30 years provides some insight and guidance into the anticipated performance of fixed-wing UAV future designs. Using data from previously developed UAVs, it is possible to extrapolate geometric and performance parameters of the future UAVs. Figure 2.4 and Figure 2.5 illustrate such scaling trends for UAV payload, wingspan and Gross Take-off Weight (GTOW). Surprisingly, over a broad range of UAV Wingspan, the payload and GTOW scales linearly on logarithmic scale [12].

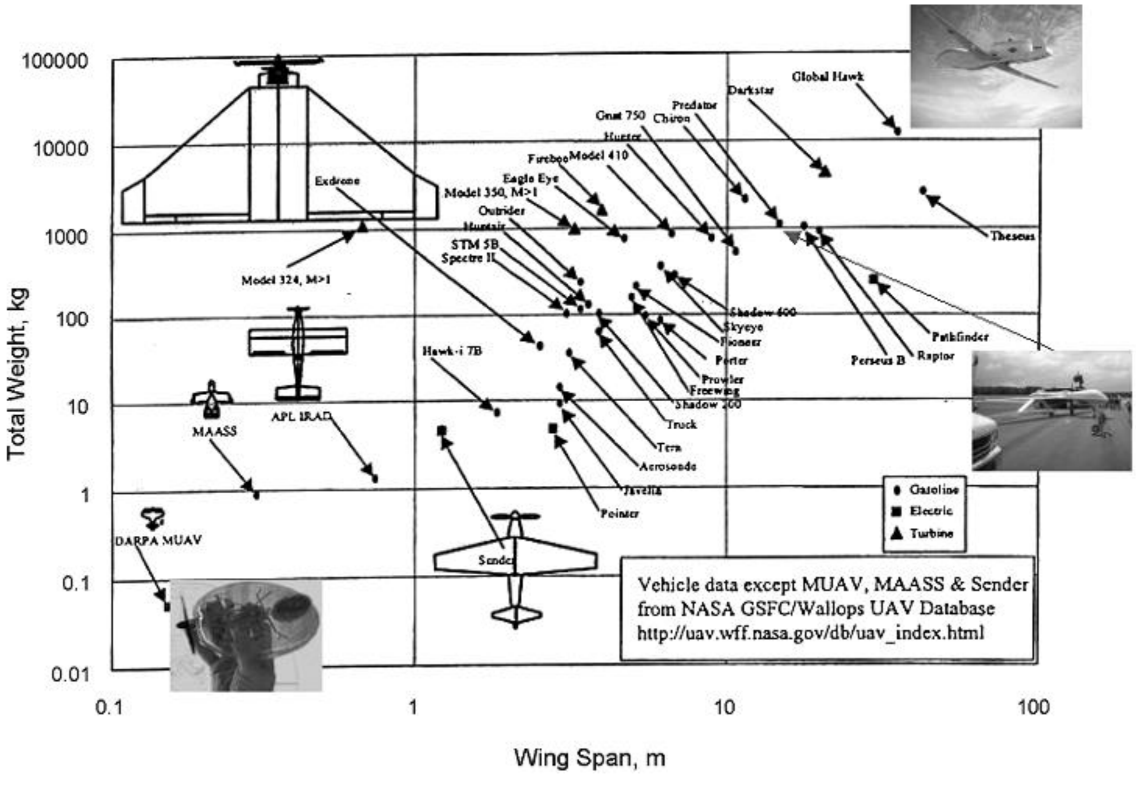

Figure 2.4: Scaling of UAVs

This figure illustrates that as the UAV's size increases from MAV to HALE, the relationship among the wingspan and total weight follows almost a linear relationship.

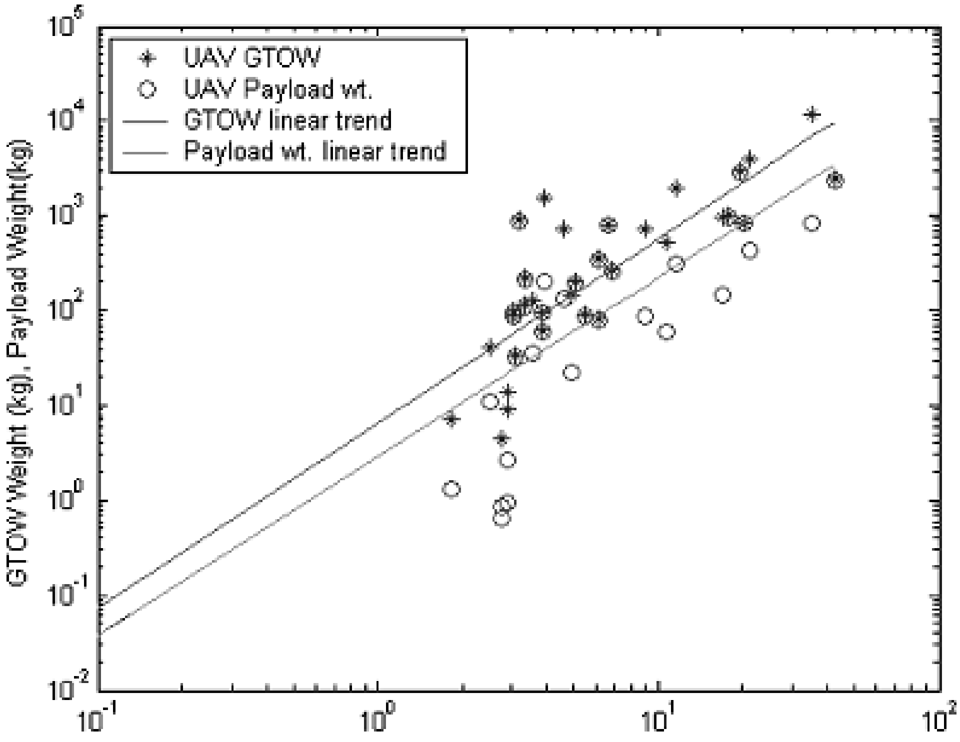

Figure 2.5: UAV GTOW and Payload Vs Wingspan

Extending this linear scaling trend, gives the first guess for the Wingspan, Payload and GTOW of the UAV. Similarly, extending the linear curve fit for endurance provides some insight into expectations for the endurance of UAVs. Figure 2.6 displays the GTOW of various MAV designs vs endurance. It represents substantial progress in the field, as the industry have a set target *(>60 min*) with *(<200g*) GTOW.

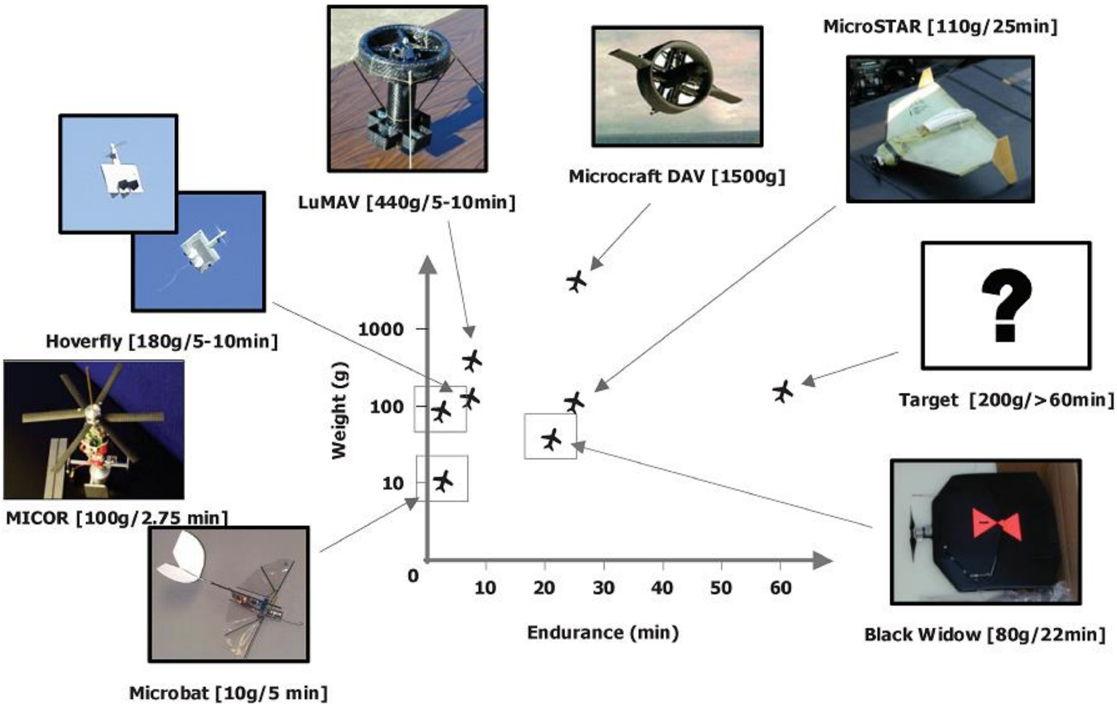

Figure 2.6: UAV Endurance Vs Weight

Taking guidance from the nature reveals that the wingspans, wing loadings and the speeds of the birds and insects follow a scalable relationship. This relationship is shown in the Figure 2.7, the great flying diagram [12].

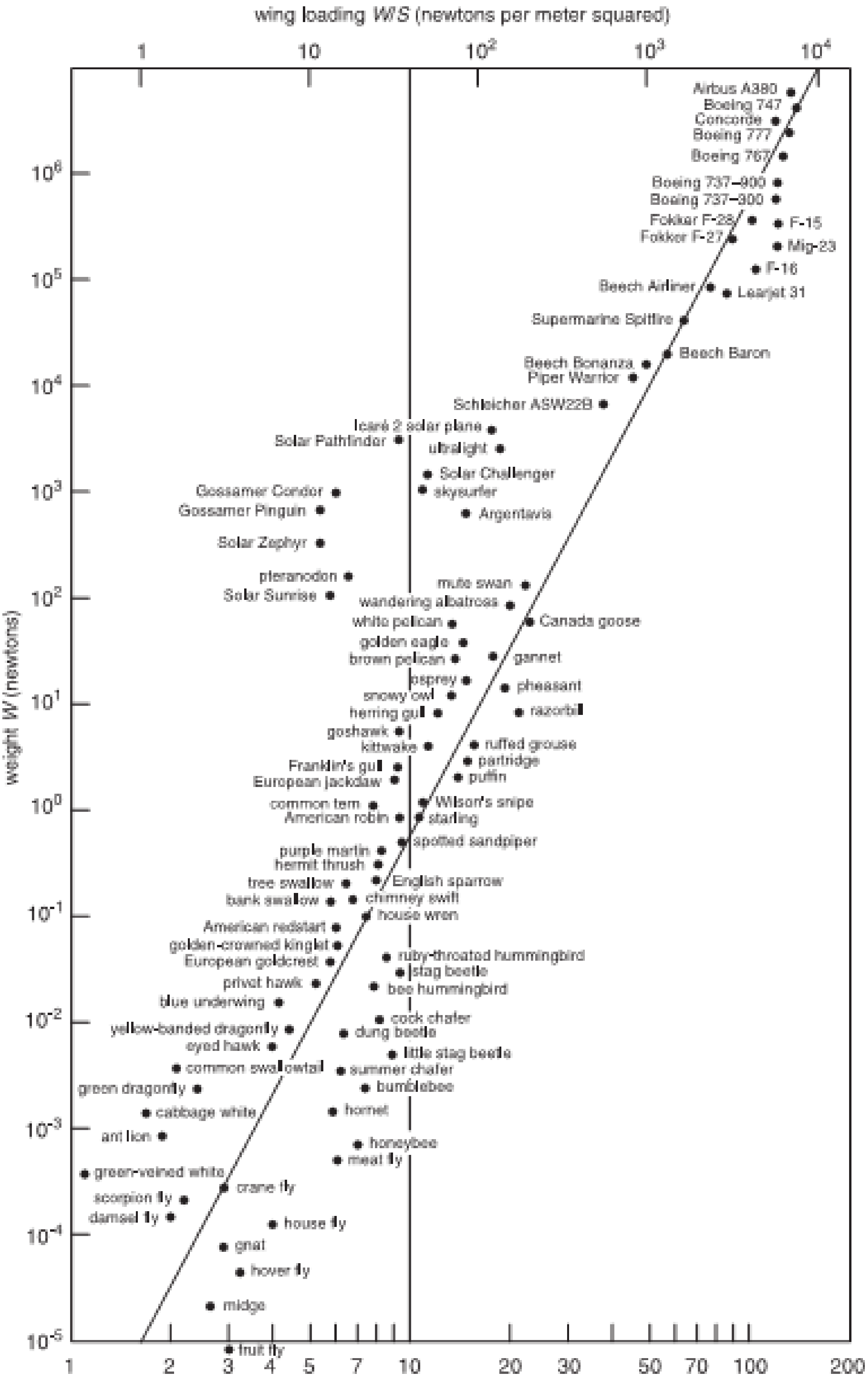

Figure 2.7: Great Flying Diagram

Missing Links in the Literature

Scalability studies have been conducted in almost every complex field of life and technology and it yielded significant results. But to-date no scalability study have been conducted for UAVs to know the patterns and trends. The primary tool that can been used for this purpose is regression analysis.

It is proposed that if statistics based simple power laws are developed based on primitive geometric parameters, several performance parameters can be approximated with high confidence. This approach will help to circumnavigate the tedious processes of detailed geometric modeling and extensive involvement of aerodynamic and propulsion information, as shown in Figure 2.8.

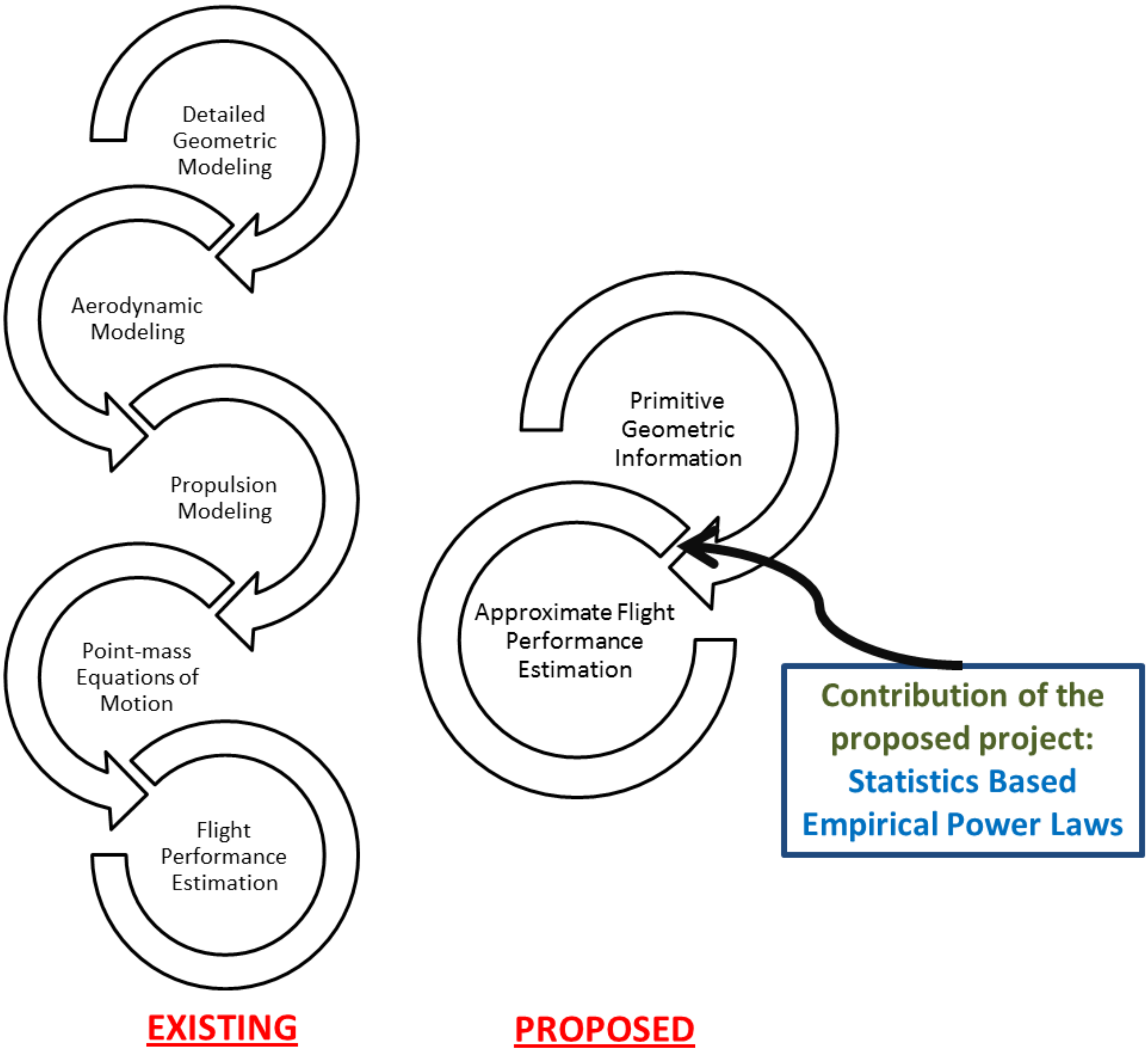

Figure 2.8: **Comparison between existing and proposed approaches for flight performance estimation**

CHAPTER 3

Problem Formulation and Description

Finding Scalability relationships for the state of the art Unmanned Air Vehicles is a tedious job and hence it should be modularized. The adopted methodology for the research, as shown in Figure 3.1, started with the collection of data and selection of the available parameters for the study. The collected data has been analyzed to develop regression relationships in MATLAB® and Mini-Tab®. The estimates are rigorously tested statistically and a strong mathematical base is established, leading to a useful final product of the research work.

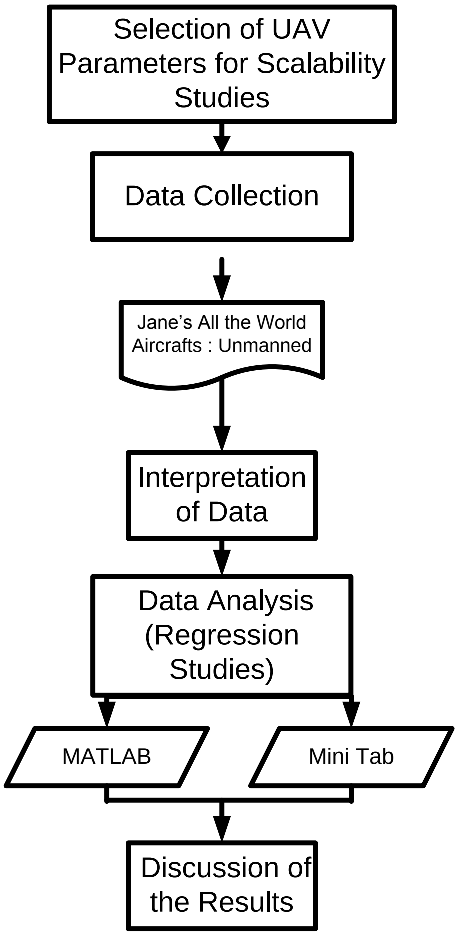

Figure 3.1: Adopted Methodology

3.1. Data Sources

For the authenticity of the results, the data needs to be coming from the most credible and proven sources. *Jane's All the World Aircrafts* [13] publishes the aircrafts features from the beginning of aircraft development times. This publication along with the *Jane's All the World Aircrafts: Unmanned* [14] and *Jane's Unmanned Aerial Vehicles and Targets* [15] is used as the primary source of the data. Data of the Mini and Micro UAVs is collected from a report prepared by the *Federal Research Division, Library of Congress* under an interagency agreement with the office of Defense Research and Engineering [16]. Bird's data [17], [18], [19] is collected from the Biology Journals i.e. *PLOS Biology, IBIS and The Journal of Experimental Biology.* The published data is reported using the radar estimation techniques and applying Allometric and Phylogenetic effects. The data contains 135 Fixed Wing UAVs from 28 different countries of the world. The overall data is given in Appendix A.

3.2. Data Description

The data is collected from 27 different countries from all over the world. The complete description of the data is given in Table 2.

Table 3.1: Data Classification

TUAV : 60	MUAV : 32	MAV : 40	MALE : 10	HALE : 5	NAV : 3

France : 19	USA : 20	Pakistan : 10	Italy : 05
Germany : 16	UK : 06	Israel : 28	Russia : 11
Greece : 01	Malaysia : 01	South Africa : 03	Ukraine : 05
Iran : 03	Netherlands : 03	Spain : 02	China : 01
Iraq : 02	Serbia : 01	Sweden : 02	Norway : 01
Jordan : 03	Singapore : 03	Switzerland : 01	Japan : 05
Korea : 03	Slovenia : 01	Taiwan : 01	

For the current study, the available data regarding various parameters of the UAVs have been divided into two categories, Geometric Parameters and Performance Parameters. Four geometric parameters are considered as independent variables including Wingspan (W), Fuselage Length (L), Payload (P) and Maximum Take-off Weight (MTOW) while three performance parameters considered as the dependent variables include Endurance (E), Ceiling (C) and Maximum Speed (MS) of the UAVs. The collected data is subsequently used to develop simple power laws and linear regression models using MATLAB ® / MINITAB ®.

Regression Analysis is a statistical process for estimating the relationship among variables. It includes many techniques for modeling and analyzing several variables, when focus is on the relationship between a dependent variable and one or more independent variables. Regression Analysis helps in understanding how dependent variable changes when one of the independent variable is varied.

The simplest regression model is the simple linear regression model, which is written as:

$$y = \beta_0 + \beta_1 x + \varepsilon \text{ -------- } \textbf{(3.1)}$$

Where "y" is dependent (response) variable

β_0 is intercept (mean of dependent variable when x is zero)

β_1 is slope (change in y w.r.t x)

These β_0 & β_1 are called regression coefficients.

ε (Random part) explains variability of response about the mean.

This regression analysis is a set of procedures based on a sample of "n" order pairs (x_i, y_i), i= 1,2,3,….,n, for estimating and making inferences on the regression coefficients. These estimates can then be used to estimate mean values of dependent variables for specified value of x. Various validation methods have been used to assess the quality of the developed model(s) and its resultant estimates such as Anderson Darling test, R-squared, Adjusted R-Squared, t-test and f-test.

1) **R-Squared**

   R^2 designates the proportion of variance in the dependent variable which is predictable from independent variable. It is a statistical test, used in the perspective of statistical models with the purpose of either the prediction of future consequences or the testing of hypotheses based on the related information. It provides the measure of accuracy of observed outcomes as replicated by the model. The R^2 value ranges from 0 to 1. If the data set have *n* values identified as $\{Y_1 <\ldots < Y_n\}$ each associated with a predicted value $\{f_1 <\ldots < f_n\}$. The R^2 value is calculated by

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad \text{--------} \ (3.2)$$

where

Sum of Square of residuals (SS_{res}) is given by

$$SS_{res} = \sum_i (y_i - f_i)^2 \ \text{--------} \ (3.3)$$

And the *total Sum of Squares (SS_{tot})* by

$$SS_{tot} = \sum_i (y_i - \bar{y})^2 \ \text{--------} \ (3.4)$$

2) **Adjusted R-Squared**

To measure how successful the fit is in terms of explaining variation of data. Adjusted R^2 is just a change of R^2 that adjusts the amount of terms in a statistical model. Adjusted R^2 calculates the proportion of the variation in the dependent variable caused by the predicting variables. The adjusted R^2 is calculated by

$${R^2}_{adjusted} = 1 - \frac{(1-R^2)(N-1)}{N-p-1} \ \text{--------} \ (3.5)$$

Where *"R^2"* is the sample R squared value, *"p"* is number of predictors and *"N"* is total sample size.

3) **t-test**

t-test is a statistical hypothesis test, in which test statistics follow a t-distribution under the null hypothesis. It is used to conclude if two sets of given data are considerably different from each other. It is most frequently applied when the test statistics follow normal distribution and the value of scaling term is known. If the scaling term is not known and hence substituted by an estimate based on the given data. So it is used to assess significance of the individual regression coefficients. The t value is calculated by

$$t = \frac{M_x - M_y}{\sqrt{\frac{S_x{}^2}{n_x} + \frac{S_y{}^2}{n_y}}} \text{ -------- (3.6)}$$

$$S^2 = \frac{\sum(x-M)^2}{n-1} \text{ -------- (3.7)}$$

where "M" is mean, "n" is number of score per group and "x" is individual score.

4) **F-test**

It is a statistical test where the test statistics have an F-distribution under the null hypothesis. It is most frequently used is the comparison of statistical models, fitted to given data set, for identifying the model that best fits the population from which the data is sampled. Precise f-tests results when the models have been fitted to the data using least squares. It is used to assess the overall adequacy of the model. F value is stated as the ratio of variances of two observations. The association between the variance of two data sets can lead to many estimates. The formula for F test is

$$F\ value = \frac{\sigma_1{}^2}{\sigma_2{}^2} \text{ -------- (3.8)}$$

where σ^2 is the variance and given by

$$\sigma^2 = \frac{\sum(x-\overline{x})^2}{n-1} \text{ -------- (3.9)}$$

where "x" is the given value, "x^{-}" is the mean value and "n" is total number of terms.

CHAPTER 4

Results and Discussions

The collected data has been used to develop a linear regression model between each of the dependent variable and the independent variables. The correlation matrix of the parameters in log transformed form is

$$M_{Corr} = \left(\begin{array}{llllllll} & W & L & P & MTOW & E & C & MS \\ W & 1.0000 & 0.7614 & 0.6146 & 0.6986 & 0.5172 & 0.8627 & -0.041 \\ L & 0.7614 & 1.0000 & 0.7979 & 0.9011 & 0.5526 & 0.5391 & 0.3438 \\ P & 0.6146 & 0.7979 & 1.0000 & 0.9412 & 0.7051 & 0.5546 & 0.5394 \\ MTOW & 0.6986 & 0.9011 & 0.9412 & 1.0000 & 0.7775 & 0.5502 & 0.5644 \\ E & 0.5172 & 0.5526 & 0.7051 & 0.7775 & 1.0000 & 0.4978 & 0.5087 \\ C & 0.8627 & 0.5391 & 0.5546 & 0.5502 & 0.4978 & 1.0000 & -0.133 \\ MS & -0.041 & 0.3438 & 0.5394 & 0.5644 & 0.5087 & -0.133 & 1.0000 \end{array}\right)$$

Where *“W”* is Wingspan, *“L”* is Fuselage Length, *“P”* is Payload and *“MTOW”* is Maximum Take-off Weight (MTOW) while *“E”* is Endurance, *“C”* is Ceiling and *“MS”* is Maximum Speed of the UAVs.

Correlation matrix contains the values of correlation coefficient between all the variables. There is a highly positive correlation between the independent variables while the dependent variables have either very low positive or negative correlation between them. The correlation between dependent and independent variables is strong positive depicting that the movement of the variables is accompanied with each other. To develop an appropriate regression model for the estimation of the magnitude of dependency, backward elimination procedure is used. The development was started with including all the independent variables for each dependent variable. The correlation between the variables was carefully assessed and the variables having very low positive or negative correlation were dropped. Variables having p-value greater than 5% level of significance for t-test were also dropped. Overall adequacy of the model has been tested using F-test at 5% level of significance. The detail of developed model(s) for each of the dependent variable are given below.

4.1. Linear Regression Model

4.1.1. Endurance

Endurance have positive correlation with each of the independent variables showing strong relationship among them. After dropping the MTOW, the model with best subset of predictors is

$$\log(Endurance) = -0.342 + 2.08\log(Wingspan) - 1.24\log(Length) + 0.268\log(Payload) \text{ --------------------------------- } (4.1)$$

Table 4.1 summarizes the statistical results for this model. R^2 and $R^2_{adjusted}$ are 89% and 88.3% respectively. P-values for all the variables are less than 5% and the p-value of less than 5% for the F-test demonstrates the overall adequacy of the model. Table 4.1 also illustrates the standard errors (S.E) of the estimated regression coefficients indicating that regression coefficients are not zero for the Type-1 error rates.

Table 4.1. Statistical Results for Endurance with best subset of variables

Predictor	**Coef**	**SE Coef**	**T**	**P**	
Constant	-0.3419	0.06454	-5.3	0.000	
log (Wingspan)	2.0776	0.1363	15.24	0.000	
log (Length)	-1.2408	0.2216	-5.6	0.000	
log (Payloads)	0.2682	0.06282	4.27	0.000	
S = 0.203270		**R^2 = 89%**		**$R^2_{adjusted}$ = 88.3%**	
Analysis of Variance					
Source	**DF**	**SS**	**MS**	**F Ratio**	**P**
Regression	3	16.0253	5.3418	129.28	0.000
Residual Error	48	1.9833	0.0413		
Total	51	18.0086			

4.1.2. Maximum Speed

Correlation between maximum speed and wingspan is negative whereas it is averagely positive for the other independent variables. Length and payload are dropped because of high p-value. The resulting model with best subset of predictors is

$$\log(Max\ Speed) = 1.93 - 0.851 \log(Wingspan) + 0.445 \log(MTOW) \text{ --------------- } (4.2)$$

R^2 and $R^2_{adjusted}$ are now 71.9% and 70.9% respectively. Results are summarized in Table 4.2. All the variables have p-values of less than 5% and the overall adequacy of the model is depicted by the f-test. It also have a p-value of less than 5%. Standard errors are also not zero.

Table 4.2. Statistical Results for Maximum Speed with best subset of variables

Predictor	**Coef**	**SE Coef**	**T**	**P**	
Constant	1.9256	0.05806	33.17	0.000	
log (Wingspan)	-0.8514	0.09887	-8.61	0.000	
log (MTOW)	0.4453	0.03865	11.52	0.000	
S = 0.159179		**R^2 = 71.9%**		**$R^2_{adjusted}$ = 70.9%**	
Analysis of Variance					
Source	**DF**	**SS**	**MS**	**F**	**P**
Regression	2	3.3791	1.6895	66.68	0.000
Residual Error	52	1.3176	0.0253		
Total	54	4.6967			

4.1.3. Ceiling

Ceiling has high correlation with the wingspan and other independent variables. However, p-value filter left us with only one predictor, Maximum Take-off Weight. The relationship can be expressed as:

$$\log(Ceiling) = 2.69 + 0.432 \log(MTOW) \text{ ------------------ } (4.3)$$

R^2 and $R^2_{adjusted}$ are about 60%. T-test confirms the adequacy of the individual relationship while f-test is depicting the overall adequacy of the model with p-value of less than 5% level of significance. Results are summarized in Table 4.3.

Table 4.3. Statistical Results for Ceiling with MTOW

Predictor	**Coef**	**SE Coef**	**T**	**P**	
Constant	2.6851	0.09843	27.28	0.000	
log (MTOW)	0.4321	0.04756	9.09	0.000	
S = 0.272076		**R^2 = 60.5%**		**$R^2_{adjusted}$ = 59.7%**	
Analysis of Variance					
Source	**DF**	**SS**	**MS**	**F**	**P**
Regression	1	6.1102	6.1102	82.54	0.000
Residual Error	54	3.9974	0.0740		
Total	55	10.1076			

4.2. Cross Validation of the Estimated Results

Regression models obtained for Endurance, Maximum Speed and Ceiling are rigorously tested and appears to be statistically reliable but they should still be validated practically. For this purpose the data set for 54 UAVs is used and the obtained estimated results are compared with the actual values of these parameters. Based on the final equation of each of the performance parameter, the estimated values are quite close to the actual values and represent a low degree of error. Most of the estimated values are quite close to the actual values, some of them are underestimated and very few of the values are overestimated. For example, for EMT LUNA, the estimated endurance is 4.2 hours while the actual endurance is 4 hours. Similarly for EADS 3 Sigma Nearchos, the estimated value of Maximum Speed is 219.7 Km/h while the reported value is 220 Km/h. CSIST Kestrel II have a ceiling of 3660 m while its estimated value of ceiling is 3800m. On an average the estimated values for these 54 UAVs are showing just a lag of 0.26 hours for endurance, 225.84 m for ceiling and 21.77 km/h for maximum speed. The difference in the values is almost negligible or lies in the tolerable range. These comparative results are given in Appendix B.

4.3. Scaling Trends

Using “Y” as dependent variable (performance parameters) and “X” as independent variable (geometric parameters), the power law scaling is

$$Y = \alpha\,(X)^{\beta} \text{ --------- (4.4)}$$

where “α” is the normalization constant and “β” is the exponent. The obtained results reveal that scaling trends exist in the development of the UAVs. Robust and proportionate scaling exponents have been found for different performance parameters of the UAVs, indicating an exponential growth. Obtained exponents lie in two different categories, $\beta>1$ (super linear) and $\beta<1$ (sub linear), where β is always clustering around similar values. Scaling trends for each of the performance parameters are discussed next.

4.3.1. Endurance

Table 4.4 summarizes the scaling results for endurance. R^2 for wingspan, length, MTOW and Payload is 0.78, 0.69, 0.68 and 0.72 respectively. Correlation between these variables and endurance is also very high. Other goodness of fit test statistics show that the scaling curves are adequate fit for the acquired data and hence depicting a high confidence. The linear regression model for each of the geometric parameter is given below.

Table 4.4. Scaling Results for Endurance Vs Geometric Parameters

Geometric Parameter	**α**	**β**	**95% CI**	**Goodness of Fit**				
X				**R^2**	**$R^2_{adjusted}$**	**SSE**	**DFE**	**RMSE**
Wingspan	0.87	1.20	(1.08,1.32)	0.78	0.77	622	103	2.45
Length	0.56	1.86	(1.58,2.15)	0.69	0.68	1386	83	4.08
MTOW	0.03	0.94	(0.80,1.08)	0.68	0.68	2164	103	4.58
Payload	0.27	0.88	(0.76,1.00)	0.72	0.72	2054	79	5.09

Wingspan and Length scale super linearly with Endurance depicting that a small increase in these parameters will significantly increase the Endurance. MTOW and Payload scale sub linearly and hence increase in these parameters will decrease the Endurance of the vehicle. The scaling curves are shown in Figure 4.1.

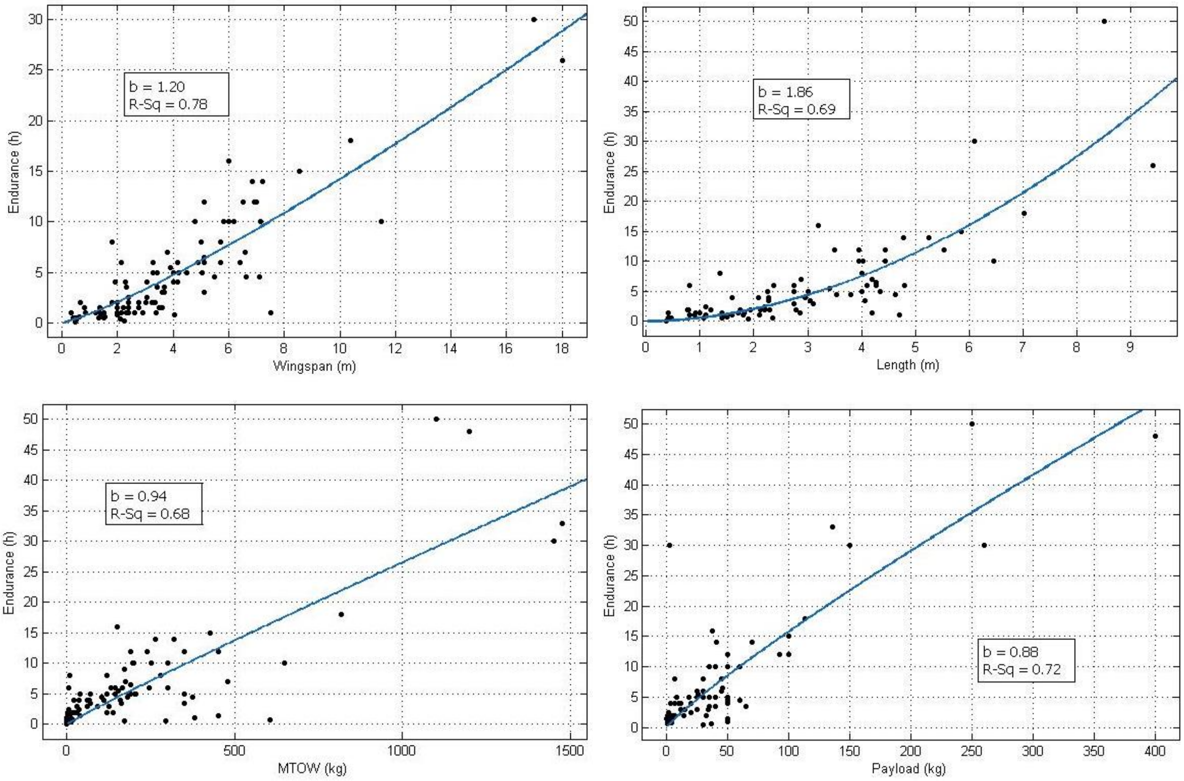

Figure 4.1: Scaling Curves for Endurance

4.3.2. Maximum Speed

Correlation matrix shows that the maximum speed have poor correlation values for all the geometric parameters. Scaling results for maximum speed are shown in Table 4.5. R^2 values are quite low for the maximum speed for all the individual relationships and therefore the results are not adequate. The linear regression model for each of the geometric parameter is given below.

Table 4.5. Scaling Results for Maximum Speed Vs Geometric Parameters

Geometric Parameter	α	β	95% CI	Goodness of Fit				
X				R^2	$R^2_{adjusted}$	SSE	DFE	RMSE
Wingspan	243	0.131	(-0.123,0.384)	0.01	0.002	8.07E+06	95	291.4
Length	131	0.686	(0.40,0.97)	0.21	0.203	5.84E+06	84	263.7
MTOW	90.7	0.242	(0.14,0.34)	0.23	0.223	5.78E+06	95	246.7
Payload	131	0.239	(0.074,0.404)	0.16	0.14	4.25E+06	70	246.6

The results show very weak relationship of Maximum Speed with the independent variables. R-square values are very low and the entire parameters show sub linear trend. These trends show that maximum speed of the vehicle does not depend on a single independent variable. The scaling curves are shown below:

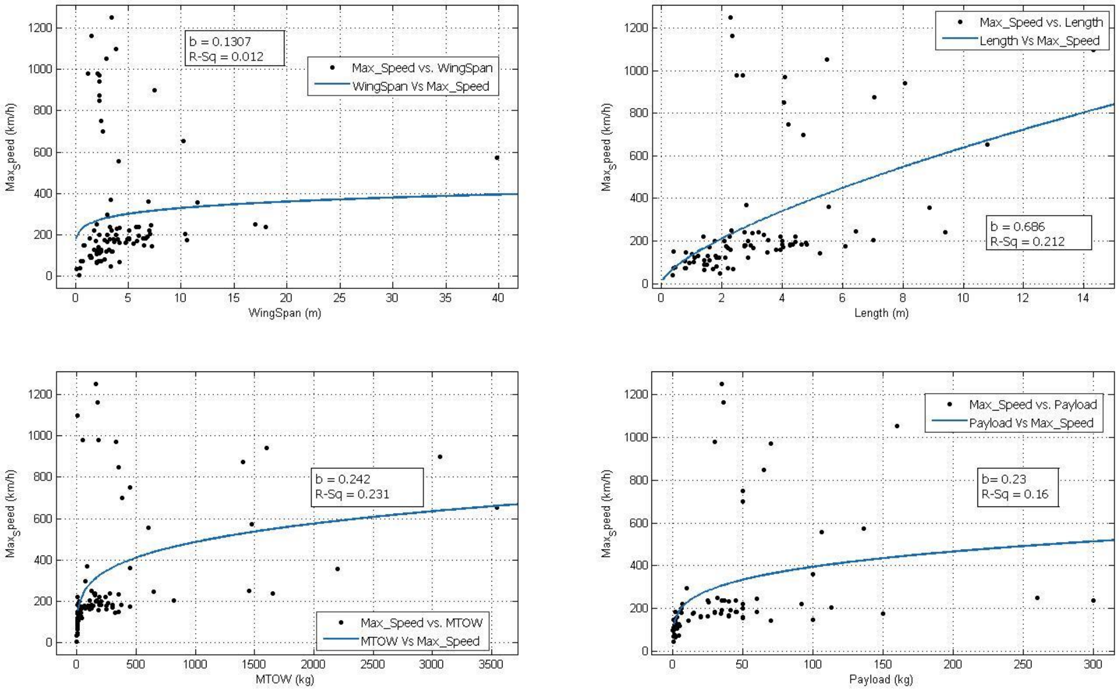

Figure 4.2: Scaling Curves for Maximum Speed

4.3.3. Ceiling

Correlation matrix shows that the ceiling has high correlation values for all the geometric parameters. Scaling results for ceiling are shown in Table 4.6. R^2 values are quite low for the maximum speed for all the individual relationships. The exponential co-efficient is also sub-linear. The linear regression model for each of the geometric parameter is given below.

Table 4.6. Scaling Results for Ceiling Vs Geometric Parameters

Geometric Parameter	**α**	**β**	**95% CI**	**Goodness of Fit**				
X				**R^2**	**$R^2_{adjusted}$**	**SSE**	**DFE**	**RMSE**
Wingspan	462	1.325	(1.215,1.236)	0.8	0.79	1.00E+09	93	3281
Length	2357	0.525	(0.325,0.724)	0.287	0.278	5.69E+08	83	2618
MTOW	995	0.314	(0.226,0.402)	0.411	0.405	9.12E+08	92	3150
Payload	1033	0.437	(0.295,0.578)	0.382	0.371	7.05E+08	73	3109

Wingspan have a very strong relationship with the ceiling. The relationship is also showing that it scales super linearly with the ceiling. A small increase in Wingspan can significantly increase the ceiling of the vehicle. Rest of the parameters scale sub linearly with the ceiling and have low R-square value. This shows a weak relationship of ceiling with these parameters. The scaling curves are shown below;

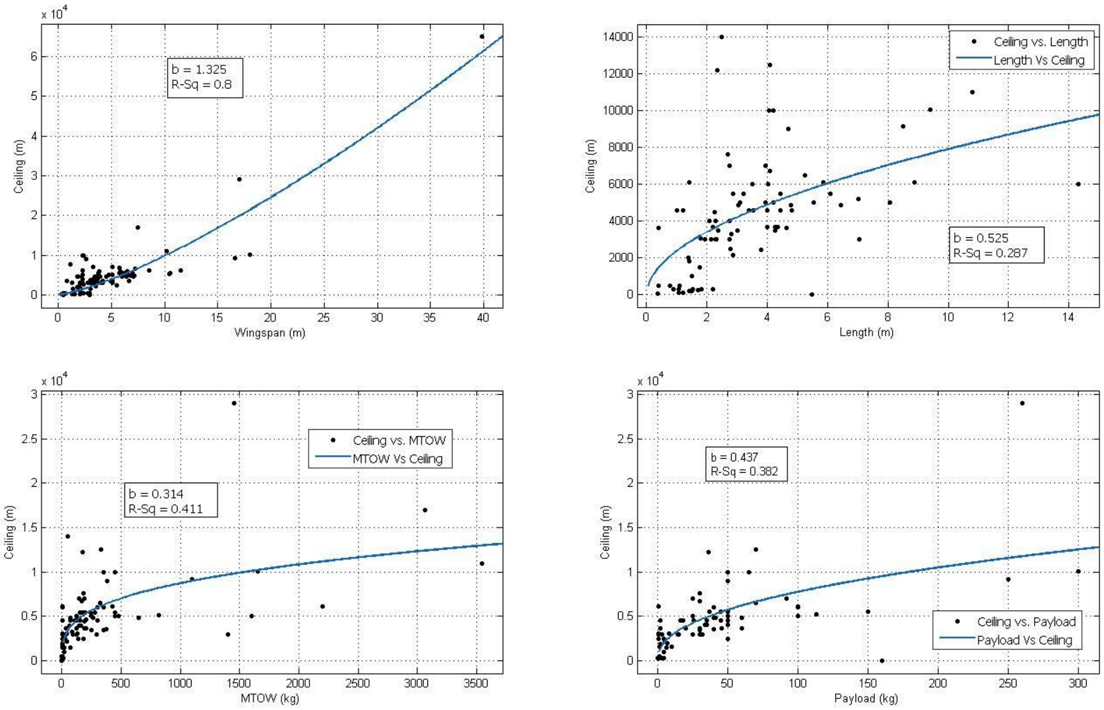

Figure 4.3: Scaling Curves for Ceiling

4.4. Summary

Endurance depends upon wingspan, length and payload while the maximum speed of the vehicle depends upon maximum take-off weight. Ceiling also shows strong dependency with wing span. These relationships take the power law form showing the exponential growth for ceiling as the weight of the vehicle increases. The results acquired from these relationships / models are quite encouraging and useful as well as it opens many avenues for future research related to the estimation of various characteristics of UAVs. These can further be improved by clustering the data and finding the relationships for each class of the UAVs.

Secondly, the scaling trends show that scaling is indeed a pervasive property for the UAVs. Different UAVs are in fact scaled versions of each other. As in the form of power law $Y = \alpha X^{\beta}$, important relationships are shown in the following Table.

Table 4.7: Power Law Relationships

Geometric Parameter	Performance Parameter	β	Relationship
X	**Y**		$Y = \alpha X^{\beta}$
Wingspan	Endurance	1.20	$\boldsymbol{0.87\ (X)^{1.20}}$
Length	Endurance	1.86	$\boldsymbol{0.56\ (X)^{1.86}}$
MTOW	Endurance	0.94	$\boldsymbol{0.03\ (X)^{0.94}}$
Payload	Endurance	0.88	$\boldsymbol{0.27\ (X)^{0.27}}$
Wingspan	Ceiling	1.32	$\boldsymbol{462\ (X)^{1.32}}$

$\beta>1$ represents the super linear growth as in the case of wingspan for both endurance and ceiling, and length for endurance. This super linear growth emphasis on a fact that, as wingspan and length increases marginally from a threshold value, the endurance increases rapidly. Similar is the case for ceiling. $\beta<1$ represents a sublinear growth. Payload and MTOW for endurance have sublinear growth whereby depicting a decreasing effect. $\beta=1$ shows a linear trend. The value of exponent for MTOW and endurance is approximately close to 1 and shows a linear growth.

CHAPTER 5

Scalability Studies for Birds

Bird's data consists of 140 species. The parameters taken for the study are Wingspan, Wing Area, Flapping Frequency and total Body Mass. The data is given in Appendix C. Flapping Frequency is the dependent variable while the others are independent variables. Primary purpose of this study was to find the relationship of Flapping Frequency as this could not be achieved in the fixed wing UAVs. Relationships among other parameters are also estimated using the available data. The results acquired for the universal power law i.e. $Y = \alpha\ (X)^{\beta}$ are shown in Table 5.1.

Table 5.1: Scaling Trend Results for Birds

Parameter	Parameter	a	b	95% CI	Goodness of Fit				
X	Y				R^2	R^2_{adj}	SSE	DFE	RMSE
Wingspan	Mass	0.528	2.63	(2.47,2.79)	0.92	0.92	25.75	137	0.433
Wingspan	Area	0.13	1.81	(1.69,1.92)	0.92	0.91	0.436	136	0.056
Mass	Area	0.213	0.68	(0.64,0.72)	0.91	0.91	0.438	136	0.056
Wingspan	Frequency	5.11	-0.67	(-0.79,-0.55)	0.82	0.81	41.11	29	1.19
Mass	Frequency	4.79	-0.22	(-0.30,-0.14)	0.53	0.52	106.9	29	1.89

Flapping Frequency have strong relationship with Wingspan and Body Mass. Negative sub linear co-efficient shows that for longer wingspans and higher body masses, flapping frequency will be low. The scaling curve also suggests that for the bigger birds, flapping frequency is low. Some of the results are obvious like wingspan and area are supposed to increase with each other. Similarly body mass and area should increase directly. But it have been proved that up to a high extent, these relations are following universal power law. The results with scaling curves are discussed individually.

5.1. Mass Vs Wingspan

The scaling curve is shown in Figure 15. R^2 value is very high i.e. 0.92 and shows how well the curve fits the data. The trend lies in the super linear range. It can be seen from the Figure 5.1 that as wingspan increases, the mass of the bird’s body increases exponentially. This can also be said for the vice versa.

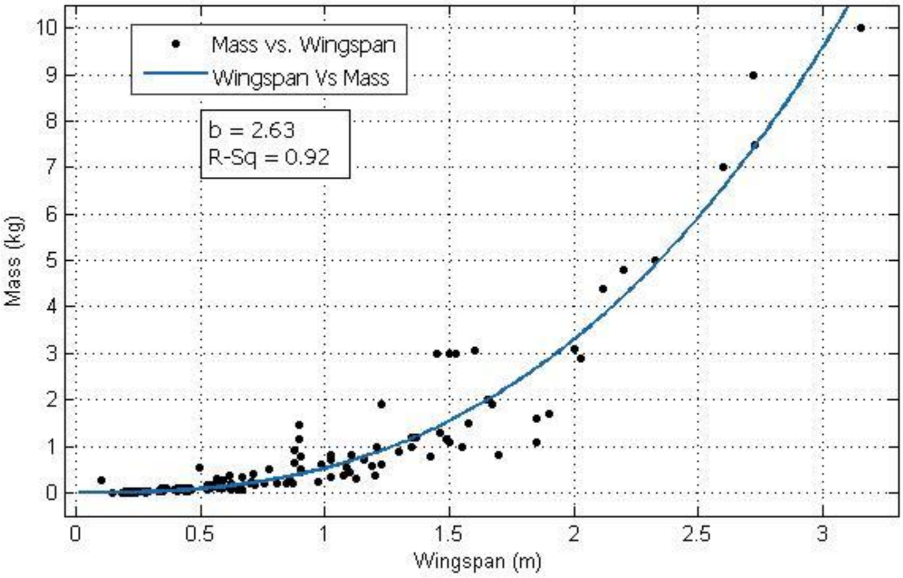

Figure 5.1: Body Mass Vs Wingspan

5.2. Body Area Vs Wingspan

Similarly the relationship between wingspan and total body area is following the universal power scaling law. The scaling curve is shown in Figure 5.2. R^2 value is very high i.e. 0.92 and the scaling exponent lies in the super linear range. The curve shows an exponential increase for Area as the Wingspan increases.

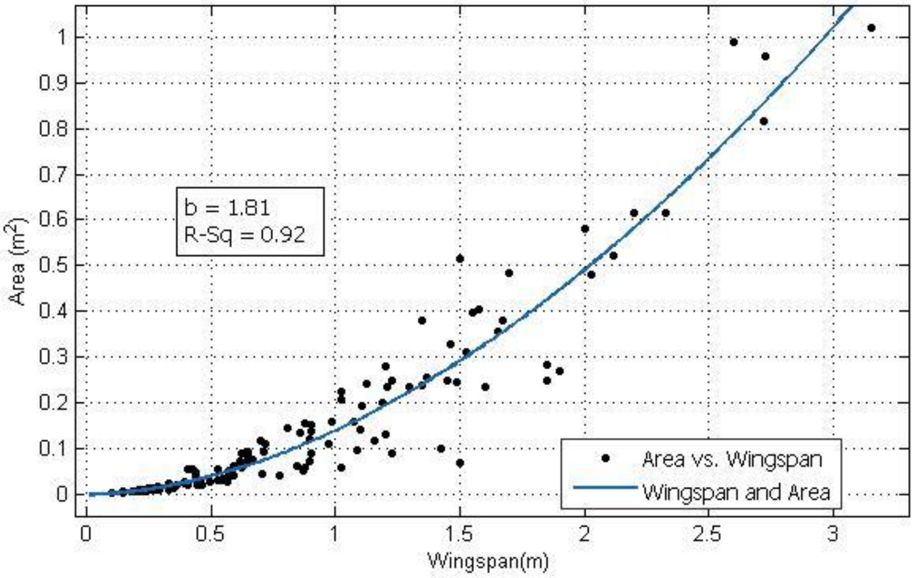

Figure 5.2: Body Area Vs Wingspan

5.3. Total Body Area Vs Body Mass

Body mass vs body area is also an obvious relationship i.e. as mass increase the body area will also increase. It have been found out that this increase is also following the universal power scaling law. This scaling curve is shown in Figure 5.3. R^2 value is 0.91 and the scaling exponent lies in sub linear range. The body area converges to a value depending upon the value of body mass.

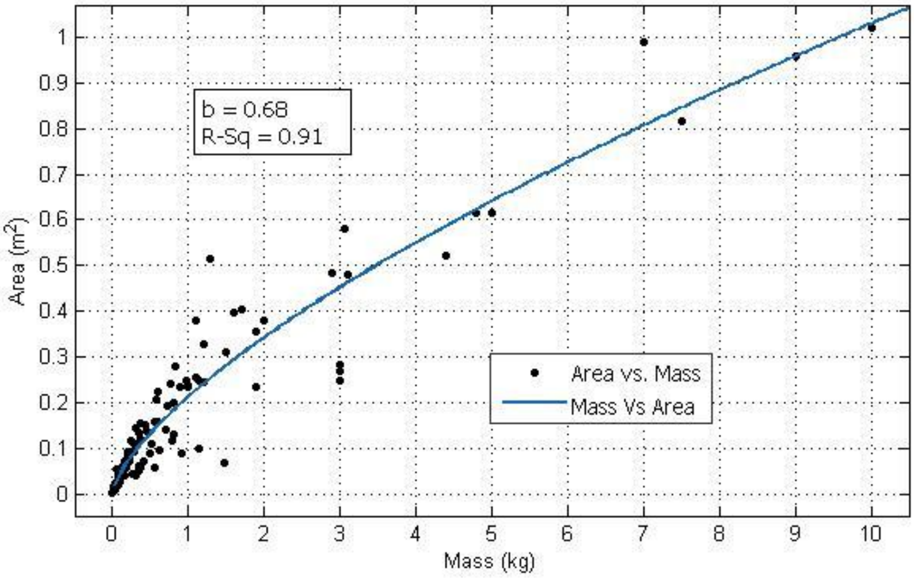

Figure 5.3: Body Area Vs Body Mass

5.4. Flapping Frequency Vs Wingspan

The most important of all the results is the relationship of flapping frequency with wingspan. The scaling curve shown in Figure 5.4 shows that as the wingspan increases, the flapping frequency decreases exponentially, following the power law. This relationship shows that bigger a bird is, smaller will be the flapping frequency of its wings. The R^2 value for this relationship is 0.82 and the exponent is negatively sub linear.

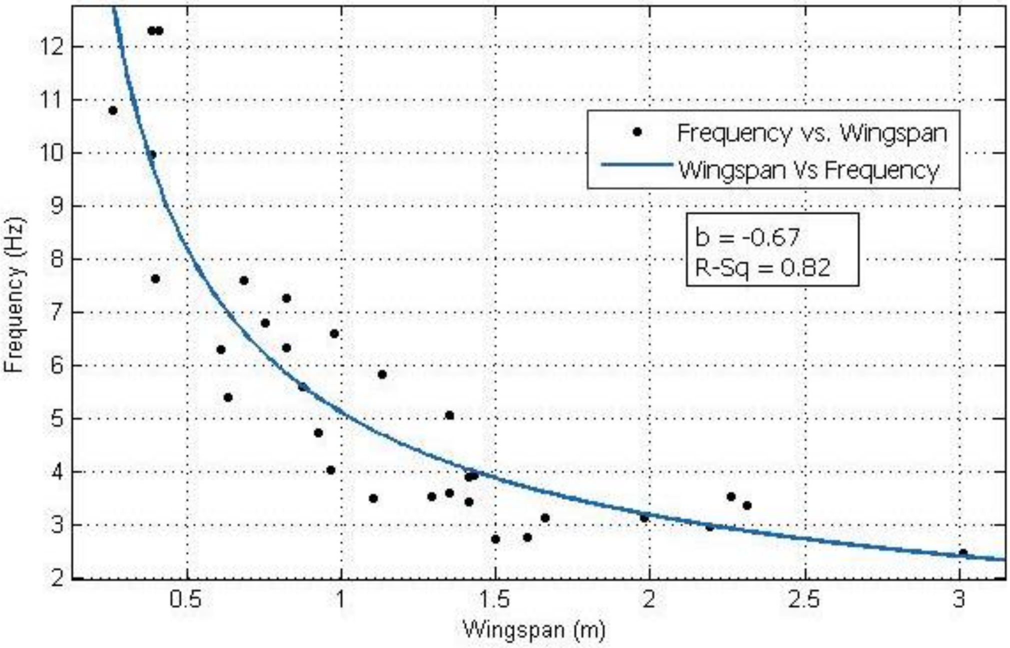

Figure 5.4: Flapping Frequency Vs Wingspan

5.5. Flapping Frequency Vs Body Mass

Flapping frequency have a strong relationship with the body mass. The scaling curve is shown in Figure 5.5. The curve reveals that as the body mass increases, flapping frequency decreases. This relationship have a moderate R^2 value i.e. 0.53 and scaling exponent is negatively sublinear.

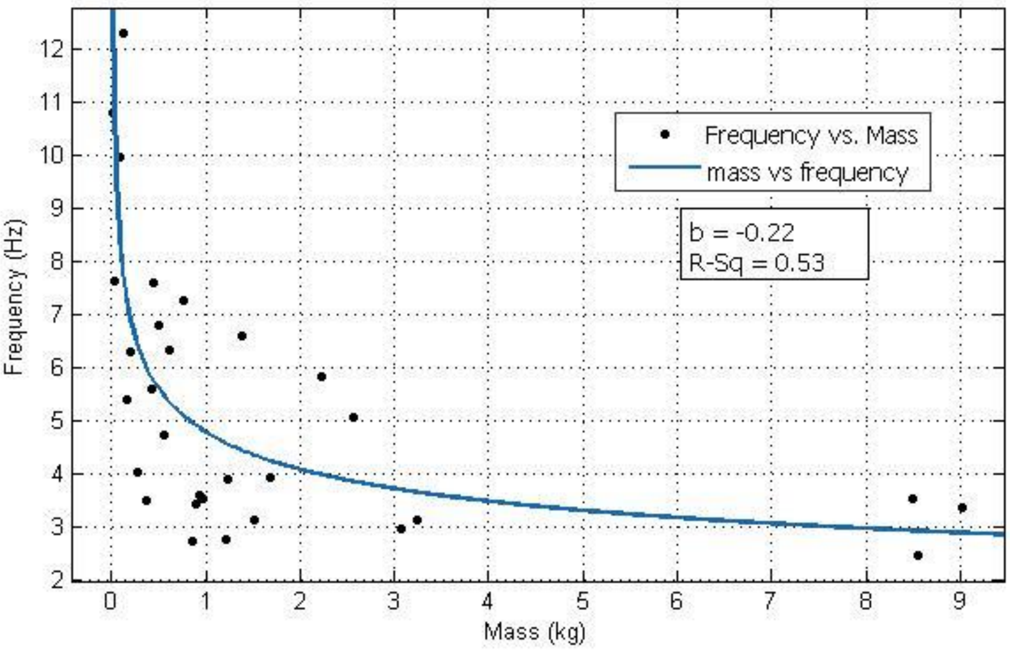

Figure 5.5: Flapping Frequency Vs Body Mass

CHAPTER 6

Conclusions & Future Work

6.1. Conclusions

Unmanned Air Vehicles data is gathered from all around the world including 28 countries and 140 vehicles. This data is mostly from the recognized Jane's All the World Aircrafts. This data is analyzed for scaling trends being followed and then for the possible relationships using regression analysis. It have been found out that universal scaling laws exist in the UAVs and the relationships with the best subset of predictors have been derived for the estimation of critical characteristics of the UAVs including wingspan, fuselage length, payload, maximum take-off weight, endurance, ceiling and maximum speed. The performance parameters including endurance, ceiling and maximum speed depends upon geometric parameters that include wingspan, length, maximum take-off weight and payload. The scaling trends are analyzed for power law i.e.$Y = \alpha X^{\beta}$, where Y is performance parameter and X is geometric parameter. The trends are tested based on the R^2 criteria for measuring the best fit. The regression analysis is used for converting this data into significant relationships. These relationships are tested using t-test, f-test, R^2 and R^2_{adjusted} test. The scaling trends exist in the UAVs for almost all the parameters and the linear models have been developed for all the parameters. The cross validation of results show very low error upon comparison with the actual values. These linear models can be used to estimate the flight performance even if very little information about the geometric parameters is available.

6.2. Future Work

The recommendations about the future work are as under,

1. The primary and major challenge in this work was to collect the data. As the data have been collected for the 140 vehicles, this data set should be improved to enhance the quality of the fitted curves and the adequacy of the linear models.
2. The data set as a whole is used to find the linear models. This data should be clustered for each UAV type. This will enhance the quality of the results and reduce the error in the estimated values and the actual values.
3. The scaling trends should be compared with the scaling trends of the birds. This will help in the design of the future UAVs.

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Appendix A

UAVs Data

Platform	Type	Wing Span (m)	Length (m)	Payload (Kg)	MTOW (Kg)	Ceiling (m)	Endurance (h)	Max Speed (Km/h)
EADS DeS Fox AT	TUAV	3.60	2.75	15	90	3000	3	180
EADS Des Surveyor-600	TUAV	2.30	4.06	65	350	10000	3.5	850
EADS Des Surveyor-2500	TUAV	6.92	5.53	100	450	5000	12	360
EADS Des Tracker	MUAV	3.60	1.40		7.5		1.5	
SAGEM Crecerelle	TUAV	3.28	2.74	35	145	4000	5	240
SAGEM Sperwer	TUAV	4.20	3.00	40	350	3500	5	235
SAGEM Sperwer HV	TUAV	2.40	4.20	50	450	10000	1.5	750
SAGEM Sperwer LE	TUAV	6.50	3.50	100	350	6000	12	148
SAGEM TMD3	MUAV	3.40	2.10		9.0		1	120

Dornier DO	MAV	0.42			0.5		0.5	
EMT Aladin	MAV	1.46	1.50		3.0	200 m	0.75	90
EMT LUNA	MAV	4.17	2.28	3	37	3000	4	160
EMT Mikado	MAV	0.50			0.5		0.33	
EMT X-13	TUAV	5.10			130	3050	6	180
Rheinmetall KZO	TUAV	3.42	2.28	35	161	4000	3.5	1250
Rheinmetall Fledermaus	TUAV	3.42	2.25	50	190	4500	5	220
Rheinmetall Taifun	TUAV	2.26	2.08	50	160	4000	4	200
EADS 3 Sigma Nearchos	TUAV	5.10	3.95	92	190	7000	12	220
ADE Nishant	TUAV	6.64	4.63	60	375	3600	4.5	185
AAI/IAI RQ-2 Pioneer	TUAV	5.11	4.26	45.4	190	3660	6.5	185
ADS Dornier CL-289	MUAV	1.32	5 .0	30	295	3000	0.5	
Northrop Grumman/IAI RQ-5A Hunter	TUAV	10.4	7.01	113	816	5180	18	204
HESA Ababil	TUAV	3.33	2.80		83	3300		370
Qods Mohadjer	MAV	3.80	2.87		175	5485	7	200

Qods Talash	MAV	2.10	1.90		11		0.41	120
MIC L-29	MALE	10.2	10.8		3540	11000		655
MIC RPV-20		7.45		20				
Aeronautics Aerolight	TUAV	4.00		8	40	3050	5	
Aeronautics Aerosky	TUAV	4.50		18	70	4575	5	
Aeronautics Aerostar	TUAV	6.20		50	200	5485	10	
EMIT Blue Horizon	MALE	6.00	3.20	37	150	5485	16	240
EMIT Sting	MALE			400	1200		48	
IAI Harpy	TUAV	2.00	2.30	32	120	3000	2	250
IAI Cutlass	TUAV	1.83		16	125	4575		
IAI Heron	MALE	16.6	8.50	250	1100	9145	50	
IAI I-See	MUAV	2.90	1.80	0.8	7.5	3050	1	
IAI I-View	TUAV	5.70	4.10	30	165	6705	6	
IAI Searcher	TUAV	8.55	5.85	100	426	6100	15	
IMI ADM-141 ITALD	TUAV	1.55	2.34	36.3	172.5	12200	0.58	1163
IMI Delilah	TUAV	1.15	2.70	30.0	185	7620		979
Rafael Skylite	MUAV	1.50	1.10		6.0		1	
Silver Arrow Hermes 180	TUAV	6.00	4.43	35	195	4570	10	194

Silver Arrow Hermes 450	TUAV	10.5	6.10	150	450	5480	30	176
Silver Arrow Hermes 1 500	MALE	18.0	9.40	300	1650	10060	26	240
Silver Arrow Seagull	MUAV	2.14	0.80		5.5		6	74
Silver Arrow Skylark	MUAV	2.40	2.20	4.0	5.5	300	2	74
Galileo Falco	TUAV	7.20	5.25	70	320	6500	14	144
Galileo Mirach 150	TUAV	2.60	4.70	50	380	9000	1	700
Galileo Nibbio	MALE	2.30	4.10	70	330	12500		972
JAI I-Wing	MUAV	1.25	1.05			91		
JAI Jordan Falcon	TUAV	4.00	2.95	6	60		4	180
JAI Silent Eye	MUAV	1.8O	1.20			91		
KAI Night Intruder 300	TUAV	6.40	4.80	45	300	4570	6	185
KARI Durumi	MALE	3.20	1.80	2.5	15.		30	130
CTRM Aviation Eagle ARV	TUAV	7.16	6.45	60	648	4880	10	246
Dutch Space MATE	MUAV	2.40	0.90		6.0	300	1	
AWC Bravo	TUAV			20	110		4	160

AWC Mk I	TUAV	2.74	2.13	14	30	3000	2	175
AWC Mk II	TUAV	3.66	2.74	34	60	4000	3	175
AWC Vision	TUAV			25	120	3000	5	166
DGMP Hud Hud I	TUAV	3.05	2.19	20	35	3660	2.5	165
DGMP Hud Hud II	TUAV	3.66	3.05	40	70	4875	3.5	165
NDC Vector	TUAV	7.09	3.54		105	4570	4.5	205
Tupolev Tu-141 Strizh	TUAV	3.87	14.3		6.2	6000		1100
Tupolev Tu-143	TUAV	2.24	7.06		1400	3000	0.21	875
Tupolev Tu-243	TUAV	2.24	8.06		1600	5000	0.21	940
Yakovlev Pchela	TUAV	3.25	2.78		138	2500	2	180
Utva Gavran	MUAV	2.00	1.50	4	16	1000	0.75	
Cradance Golden Eagle	MUAV	0.65	0.77	0.0	0.85	500	2	72
ST Aero MAV-1	MAV	3.00	2.50	20	80			
Aviotech RVM04	MUAV			11	36		4	145
ATE Vulture	TUAV	5.10	3.10	25	125	5000	3	
Kentron	TUAV	7.00	4.43	50	240	5480	12	222

Seeker								
Kentron Seraph	MALE	2.90	5.49	160		12.20		1052
INTA ALO	MUAV	3.03	1.75	6	20	1500	2	200
INTA/Ceselsa SIVA	TUAV	5.81	4.02	40	300	6000	10	170
Saab SHARC	MALE	2.10	2.50		50	14000		979
RUAG Ranger	TUAV	5.70	4 .6	45	280	5480	8	240
CSIST Kestrel II	TUAV	5.00	4.00	30	120	3660	8	185
KhGAPP Inspektor	TUAV	4.77	3.94	50	250	5000	10	160
NPS Remez-3	MUAV	2.00	0.78	3.0	10.		2	105
BAE Systems Phoenix	TUAV	5.50	3.80	50	180	2440	4.5	157
Cranfield A3 Observer	MUAV	2.40		4.0	30	2500	2	126
Meggitt ASR-4 Spectre	TUAV	3.28	2.74	25	144.7	7000	6	240
UTS Mercury	MUAV			11	30		3	
AAI RQ-7 Shadow 200	TUAV	3.89	3.40	25.3	154	4575	5.5	228
AAI Shadow 400	TUAV	5.05	4.34	30.0	201	3660	5	185

AAI Shadow 600	TUAV	6.83	4.77	41.0	265	4875	14	193
ACR Silver Fox	MUAV	2.13	1.52	2.3	10.	305	1	129
AeroVironment Helios	HALE	75.2	3.66	100	825	21340	4320	51.5
AeroVironment FQM-1 51 A	MUAV	2.74	1.83	0.9	4.3	300	1.5	80
AeroVironment Raven	MUAV	1.37	0.91	0.1	2.2		1.5	97
Aurora Flight Sciences Chiron	TUAV	11.5	8.89		2200	6100	10	355
Aurora Flight Sciences GoldenEye 50	MUAV	1.37		1.4	7.3	1525	1	185
Northrop Grumman Global Hawk (RQ-4B)	HALE	39.8		136	1474.1	65000	33	574
General AtomicsMQ-1C	MALE	17.0		260	1451.4	29000	30	250
Aurora Flight Sciences GoldenEye 100	MUAV	3.05		10.	68.0	1525	4	296
ASN–15	MAV				6.5		1	

AZIMUTH 2	MAV	2.9	1.82	2	9	300		120
EPSILON 1	MAV	0.48	0.38		0.45	30	0.1	40
ODIN	MAV	0.61			0.41		0.6	
ALADIN	MAV	1.5	1.4		3	200	0.5	90
CAROLO P50	MAV	0.5	0.4		0.5	457	0.5	74
CAROLO P330	MAV	2.3	1.4	0.3	5	6096	1	111
CAROLO T200	MAV	2	1.4	2	5	1829	1	65
DO–MAV	MAV	0.41					0.5	
MIKADO	MAV	0.49	0.46		0.5		0.5	75
BIRD EYE 100	MAV	0.85	0.80	0.3	1.3		1	148
BIRD EYE 500	MAV	2	1.6		5		1	111
BOOMERANG V2	MAV	2.4	1.1	1.2	5	500	2.5	120
CASPER	MAV	2	1.7	0.2	4.7	250	1.5	70
MOSQUITO 1.5	NAV	0.34			0.5	90	1	
ORBITER	MAV	2.2	1	1.5	6.5	4572	1.5	139
CORVO	MAV	1.8	1.37	6.8	7.7	2000	8	222
GABBIANO	MAV	3.34	1.93	0.5	4.5	3000	2	46
DELFLY (Flapping Wing)	NAV	0.35			0.017			6
RECCE D6	MAV	1.42	1.06	0.5	2.8	305	0.55	100
IRKUT–2F	MAV	2		0.3	2.8	2500	1	
SKYBLADE	MAV	1.8	1.2			4572	2	129

SPOT	NAV	0.15			0.068			36
AIST–1	MAV	1.2	0.8	0.3	2		1	
ALBATROSS–4	MAV	2		3			2	
BEKAS	MAV	1.9	1.6		20		4	170
REMEZ–3	MAV	2		3	10		2	105
Luna X-2000		4.17	2.36	40		3500	6	70
Shahpar		6.6	4.2		480	5000	7	
Jasoos		4.9	4.27	30	245	3480	6	180
Mukhbar	TUAV	3.5	2.86	5	40	2133.6	1.5	120
ZALA 421-08	MAV	0.8	0.41	1.7	9	3600	1.5	150
Lavochkin La-17		7.5	8.4		3065	17000	1	900
AAI RQ-2 Pioneer		5.2	4		205	4600	5	200
AAI RQ-7 Shadow		4.3	3.4		170	4572	9	204
Aerojet SD-2		4.06	4.9	106	605	6100	0.75	556
RQ-20 Puma		2.8	1.4		5.9		2	83

Appendix B

Comparative Analysis

Platform	Estimated Endurance (h)	Actual Endurance (h)	Estimated Max Speed (km/h)	Actual Max Speed (km/h)	Estimated Ceiling (m)	Actual Ceiling (m)
EADS DeS Fox AT	3.85	3	211	180	3421	3000
EADS Des Surveyor-600	1.38	3.5	567	850	6152	10000
EADS Des Surveyor-2500	10.4	12	248	360	6857	5000
SAGEM Crecerelle	3.99	5	283	240	4204	4000
SAGEM Sperwer	6.19	5	340	235	6152	3500
SAGEM Sperwer HV	1.35	1.5	612	750	6857	10000
SAGEM Sperwer LE	16.2	12	234	148	6152	6000
EMT LUNA	4.28	4	125	160	2330	3000
Rheinmetall KZO	5.47	3.5	286	1250	4398	4000
Rheinmetall	6.12	5	308	220	4725	4500

Fledermaus						
Rheinmetall Taifun	2.85	4	406	200	4387	4000
EADS 3 Sigma Nearchos	8.24	12	219	220	4725	7000
ADE Nishant	10.4	4.5	237	185	6338	3600
AAI/IAI RQ-2 Pioneer	6.23	6.5	219	185	4725	3660
Northrop Grumman/IAI RQ-5A Hunter	18.8	18	229	204	8868	5180
EMIT Blue Horizon	11.7	16	172	240	4266	5485
IAI Harpy	1.73	2	397	250	3874	3000
IMI ADM-141 ITALD	1.03	0.58	579	1163	4532	12200
Silver Arrow Hermes 180	7.74	10	193	194	4778	4570
Silver Arrow Hermes 450	24.6	30	174	176	6857	5480
Silver Arrow Skylark	1.53	2	86.	74	1022	300
Galileo Falco	11.0	14	206	144	5918	6500
Galileo Mirach 150	1.39	1	530	700	6374	9000

KAI Night Intruder 300	8.57	6	221	185	5755	4570
CTRM Aviation Eagle ARV	8.10	10	284	246	8027	4880
AWC Mk I	2.94	2	163	175	2128	3000
AWC Mk II	4.98	3	174	175	2871	4000
DGMP Hud Hud I	3.90	2.5	160	165	2275	3660
DGMP Hud Hud II	4.55	3.5	186	165	3069	4875
Kentron Seeker	11.7	12	186	222	5226	5480
INTA ALO	3.68	2	125	200	1786	1500
INTA/Ceselsa SIVA	8.46	10	240	170	5755	6000
RUAG Ranger	7.10	8	237	240	5586	5480
CSIST Kestrel II	5.76	8	182	185	3874	3660
KhGAPP Inspektor	6.11	10	262	160	5319	5000
BAE Systems Phoenix	8.59	4.5	201	157	4616	2440
Meggitt ASR-4 Spectre	3.65	6	283	240	4200	7000
AAI RQ-7	4.00	5.5	251	228	4315	4575

Shadow 200						
AAI Shadow 400	5.32	5	227	185	4841	3660
AAI Shadow 600	9.64	14	198	193	5455	4875
ACR Silver Fox	1.63	1	124	129	1324	305
AeroVironment FQM-1 51 A	1.70	1.5	69.	80	919.	300
CAROLO P330	1.22	1	85.	111	981.	6096
CAROLO T200	1.52	1	96.	65	981.	1829
BOOMERANG V2	2.62	2.5	82.	120	981.	500
CASPER	0.64	1.5	93.	70	955.	250
ORBITER	2.61	1.5	100	139	1099	4572
CORVO	1.74	8	128	222	1182	2000
GABBIANO	2.05	2	59.	46	937.	3000
RECCE D6	0.72	0.55	99.	100	764.	305
Jasoos	5.10	6	254	180	5273	3480
Mukhbar	2.57	1.5	151	120	2410	2133.6
ZALA 421-08	0.99	1.5	273	150	1265	3600
Aerojet SD-2	4.08	0.75	446	556	7793	6100

Appendix C

Bird's Data

Platform	**Mass (kg)**	**Wing Span (m)**	**Area (m^2)**
Regulus regulus	0.006	0.145	0.0046
Regulus ignicapillus	0.006	0.145	0.005
Phylloscopus trochilus	0.009	0.193	0.007
Hippolais polyglotta	0.011	0.188	0.0061
Sernus serinus	0.011	0.215	0.0076
Carduelis flammea	0.011	0.225	0.0083
Acrocephalus palustris	0.012	0.195	0.0066
Acrocephalus scirpaceus	0.012	0.19	0.0062
Sylvia curruca	0.012	0.185	0.0073
Ficedula hypoleuca	0.013	0.238	0.0091
Carduelis spinus	0.013	0.215	0.0072
Riparia riparia	0.014	0.278	0.0096
Hippolais icterina	0.014	0.223	0.0081
Muscicapa striata	0.015	0.243	0.011
Phoenicurus ochruros	0.016	0.245	0.0106
Phoenicurus phoenicurus	0.016	0.223	0.0099
Sylvia communis	0.016	0.208	0.0073
Carduelis carduelis	0.016	0.233	0.0088
Anthus pratensis	0.017	0.235	0.0108

Motacilla flava	0.017	0.25	0.0103
Erithacus rubecula	0.017	0.21	0.0095
Saxicola ruberta	0.017	0.225	0.0095
Delichon urbica	0.018	0.275	0.0107
Carduelis cannabina	0.018	0.233	0.0093
Parus major	0.019	0.24	0.0106
Prunalla modularis	0.02	0.2	0.0092
Sylvia borin	0.02	0.223	0.0093
Sylvia atricapilla	0.02	0.215	0.0089
Hirundo rustica	0.021	0.333	0.0133
Motacilla alba	0.021	0.275	0.0127
Sylvia hortensis	0.021	0.225	0.0105
Fringilla coelebs	0.021	0.265	0.0124
Hirundo daurica	0.022	0.33	0.0154
Anthus trivialis	0.022	0.26	0.0126
Fringilla montifringilla	0.022	0.255	0.0125
Emberiza hortulana	0.023	0.26	0.0138
Ptyonoprogne rupestris	0.024	0.333	0.0113
Oenanthe oenanthe	0.024	0.29	0.0137
Lullula arborea	0.027	0.285	0.0164
Carduelis chloris	0.027	0.26	0.0112
Lanius collurio	0.03	0.225	0.0145
Acrocephalus arundinaceus	0.031	0.265	0.0117
Alauda arvensis	0.036	0.33	0.0194

Apus pallidus	0.042	0.44	0.0263
Apus apus	0.044	0.45	0.017
Calidris alpina	0.047	0.405	0.0156
Monticola saxatilis	0.05	0.35	0.0204
Merops apiaster	0.058	0.465	0.0273
Actitis hypoleucos	0.058	0.395	0.0244
Charadrius hiaticula	0.065	0.525	0.0207
Chlidonias leucopterus	0.068	0.65	0.0545
Caprimulgus ruficollis	0.069	0.665	0.0567
Upupa epops	0.07	0.44	0.0422
Glareola pratincola	0.08	0.625	0.0503
Sturnus vulgaris	0.08	0.395	0.0224
Tringa ochropus	0.085	0.59	0.0289
Streptopelia senegalensis	0.088	0.425	0.0304
Turdus philomelos	0.089	0.345	0.0214
Turdus merdula	0.094	0.363	0.028
Turdus pillaris	0.1	0.405	0.0318
Glareola nordmanni	0.1	0.64	0.054
Apus melba	0.105	0.57	0.0304
Turdus viscivorus	0.109	0.448	0.0358
Gallinago gallinago	0.11	0.455	0.0271
Curious cursor	0.115	0.54	0.0407
Cuculus canorus	0.12	0.575	0.0508
Falco naumanni	0.15	0.65	0.0611

Philomachus pugnax	0.16	0.53	0.0429
Falco vespertinus	0.165	0.72	0.0728
Garrulus glandarius	0.18	0.55	0.0595
Elanus caeruleus	0.2	0.81	0.0899
Accipiter nisus	0.2	0.625	0.07
Falco tinnunuculus	0.21	0.755	0.684
Vanellus vanellus	0.21	0.845	0.082
Falco subbuteo	0.215	0.87	0.095
Accipiter brevipes	0.22	0.7	0.0739
Corvus monedula	0.23	0.705	0.0768
Falco concolor	0.25	0.975	0.1196
Pterocles senegallus	0.26	0.59	0.044
Larus ridibundus	0.28	0.105	0.0946
Ardeola ralloides	0.29	0.86	0.111
Pterocles coronatus	0.3	0.565	0.043
Circus pygarus	0.3	1.125	0.1463
Columba Livia	0.35	0.665	0.064
Asio flammeus	0.35	1.025	0.1343
Falco eleonorae	0.36	1.2	0.0509
Anas querquedula	0.38	0.615	0.0588
Circus macrourus	0.38	1.075	0.1553
Larus canus	0.38	1.2	0.1209
Pelecanus orientalis	0.41	0.715	0.072
Circus cyaneus	0.43	1.1	0.1539

Corvus frugilegus	0.45	0.9	0.1373
columba palumbus	0.5	0.775	0.0904
Falco pelegrinoides	0.51	0.9	0.1102
Nycticorax nycticorax	0.56	1.085	0.16
Alectoris chukar	0.56	0.495	0.0582
Buteo buteo vulpinus	0.579	1.188	0.207
Circus aeruginosus	0.6	1.225	0.2248
Corvus corone	0.61	0.985	0.1577
Plegadis falcinellus	0.63	0.875	0.0986
Falco biarmicus	0.7	1.025	0.1418
Corvus ruficollis	0.72	1.16	0.1944
Larus fuscus	0.77	1.425	0.243
Numenius arquata	0.78	0.9	0.1189
Hieraaetus pennatus	0.8	1.105	0.2004
Falco peregrinus	0.8	1.025	0.1328
Milvus migrans	0.83	1.7	0.2805
Pernis apivorus	0.9	1.3	0.2364
Anas acuta	0.91	0.875	0.0918
Ardea Purpurea	0.97	1.35	0.2488
Egretta alba	1	1.55	0.235
Buteo buteo buteo	1	1.205	0.2404
Milvus milvus	1.1	1.85	0.3803
Accipiter gentilis	1.1	1.5	0.2564
Anas platyrhynchos	1.14	0.895	0.1015

Larus cachinnans	1.15	1.49	0.2496
Buteo rufinus	1.2	1.37	0.3281
Corvus corax	1.2	1.35	0.2472
Aquila pomarina	1.3	1.465	0.5153
Mergus merganser	1.48	0.895	0.068
Pandion haliaetus	1.5	1.575	0.3125
Ardea cinerea	1.6	1.85	0.3979
Ciraetus gallicus	1.7	1.9	0.4058
Platalea leucorodia	1.9	1.225	0.2341
Neophron percnopterus	1.9	1.675	0.3555
Hieraaetus fasciatus	2	1.65	0.3792
Aquila nipalensis	2.9	2.025	0.4853
Phalacrocorax carbo	3	1.45	0.249
Ciconia nigra	3	1.5	0.2842
Phoenicopterus ruber	3	1.525	0.2715
Ciconia ciconia	3.07	1.6	0.58
Aquila heliaca	3.1	2	0.4815
Aquila chrysaetos	4.4	2.12	0.5237
Haliaeetus albicilla	4.8	2.2	0.6151
Grus grus	5	2.325	0.6157
Gyps fulvus	7	2.6	0.9889
Torgos tracheliotus	7.5	2.725	0.8162
Aegypius monachus	9	2.72	0.9588
Pelecanus onocrotalus	10	3.15	1.019

Platform	**Wing Span (m)**	**Frequency (Hz)**	**Mass (kg)**
Chaffinch	0.262	10.8	0.0228
Starling	0.384	9.97	0.0884
South Georgia diving petrel	0.388	12.3	0.122
Wilson’s storm-petrel 0	0.396	7.65	0.035
Common diving petrel 0	0.408	12.3	0.133
Sparrowhawk	0.611	6.3	0.196
Dove prion 0	0.635	5.42	0.155
South Georgia pintail 0	0.682	7.62	0.437
Wood pigeon	0.751	6.81	0.495
Sheathbill	0.822	6.35	0.61
Wigeon	0.822	7.27	0.77
Cape pigeon 0	0.875	5.61	0.418
Hooded crow	0.925	4.74	0.553
Black-headed gull	0.963	4.04	0.28
Eider	0.978	6.6	1.39
Common gull	1.1	3.5	0.364
Blue-eyed shag 2	1.13	5.85	2.23
Common buzzard	1.29	3.54	0.964
Cormorant	1.35	5.09	2.56
Herring gull	1.35	3.61	0.925
White-chinned petrel 1	1.41	3.93	1.23
Kelp gull 0	1.41	3.46	0.89
Southern skua 1	1.43	3.95	1.69

Red kite	1.5	2.75	0.851
Grey heron	1.6	2.79	1.21
Great black-backed gull	1.66	3.14	1.51
Giant petrel 3	1.98	3.14	3.24
Black-browed albatross 3	2.19	2.97	3.08
Whooper swan 8	2.26	3.56	8.5
Mute swan	2.31	3.37	9.01
Wandering albatross 8	3.01	2.49	8.55