An Alternative View on Weight Estimation for the Aircraft Industry: Problems and MDO Solutions

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Weight estimation in aircraft design is very challenging due to the high number of variables involved in the creation of an accurate weight model, the numerous relationships between them and the high degree of uncertainty associated with the problem itself. This paper discusses a preliminary study on the use of fuzzy logic as an aid to the knowledge capture phase of the weight estimation process for aircraft structures. The results highlight the importance of multidisciplinary analysis in weight estimation from the preliminary stages of the aircraft design process.

Nomenclature

(a_i, b_i, c_i)	=	adaptable parameter set associated with layer 1 of adaptive network
A_i	=	defined fuzzy set associated input x
A/C	=	aircraft
$ANFIS$	=	Adaptive Network-based Fuzzy Inference System
B_i	=	defined fuzzy set associated with input y
CAD	=	computer aided design
F_{fuel}	=	total fuel load
F_{hyd}	=	total axial load due hydraulic system installation
FIS	=	Fuzzy Inference System
F_r	=	resultant hinge load
FZ	=	aerodynamic load applied on rib upper section
h	=	spar height at the rib location
I	=	second moment of area
$IFTE$	=	Inboard Fixed Trailing Edge
l	=	hinge line location with respect to spar datum
LSM	=	Least Squares Method
$MFTE$	=	Midboard Fixed Trailing Edge
n_{hyd}	=	number of hydraulic system attachment points on rib structure

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O_i^j = membership function associated with rule *i* and layer *j*
OFTE = Outboard Fixed Trailing Edge
(p_i, q_i, r_i) = parameter set associated with layer 3 of adaptive network
P_r = aerodynamic load applied on rib lower section
r_a = distance from a data point to the main cluster center
RMSE = Root Mean Square Error
TSK = Tagaki-Sugeno-Kang type of Fuzzy Inference System
w_i = rule firing strength
$\overline{w_i}$ = normalized firing strength
x, y = set of inputs
z = fuzzy output set
μ = shape of membership function
σ_{TH} = thermal stress

I. Introduction

The success of a new aircraft program is defined by the ability of the new design to satisfy the operational needs and requirements set by the customers. In addition to being reliable and technically robust, the aircraft needs to be able to justify its selling price and operating costs by providing adequate performance levels. The preliminary stage of the design of a new aircraft, in particular, is one of the most critical points for the attainment of the required commercial competitiveness. It is at this time that the design team determines whether the agreed operational capabilities are technically feasible and defines the best combination between performance and cost within the limits of available technology and other constraints.

Weight control, namely "the process by which the lightest possible airplane is derived within the constraints of the design criteria",[1] is an essential part of the design process of any aerospace vehicle. As a consequence, the fundamental task in a weight control program is weight estimation. Accurate estimations of aircraft weight are vital in the early stages of an aircraft design process. They drive all the major choices in configuration and layout as well as being the main foundation of performance predictions. An overestimate of Maximum Take-Off Weight (MTOW) will result in the aircraft not being competitive enough on the market. Conversely, an underestimation of the aircraft weight at the beginning of the design process could cause the manufacturers to incur financial penalties at production stage, due to both the time spent on the post-production weight reduction program and to the failure of the design to meet its targets. Overall, the key point in the design of a new vehicle is that an increase in MTOW will ultimately mean that the aircraft will not be able to carry its agreed payload according to the buyer's needs and requirements.

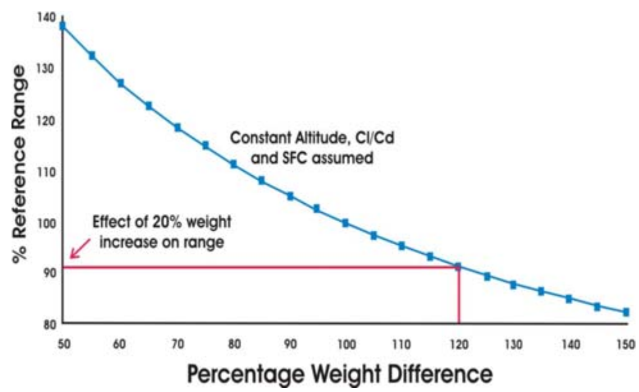


Figure 1: Influence of weight on range for propeller driven aircraft.[2]

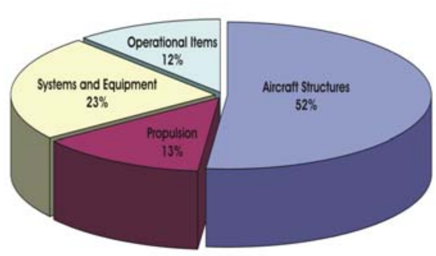


Figure 2: Aircraft empty weight breakdown. *Pie chart illustrating the empty weight breakdown for a commercial aircraft with the greatest contribution from structural and system weight.*

Figure 1 shows how weight can affect the range in the case of a propeller driven aircraft.[2] As an example, an aircraft, which is, at production stage, 20 percent heavier than expected will incur up to 10 percent reduction in available range. This value could double in the case of commercial jets.[2] Conversely, a 20 percent reduction in weight could result in up to 15 percent increased maximum range attainable by the design.

Structures and systems account for 75 percent of the total empty weight of a commercial aircraft, Fig. 2, a fraction which increases in the case of military designs. As a consequence, any inaccuracy in the prediction of their combined weight will have a snowball effect on a number of performance parameters, from maximum operative ceiling and endurance to maximum payload capacity. These, however, are also the two areas in which weight prediction is most challenging, due to the high number of variables involved in the analysis.

This paper presents an initial assessment of an approach to identify key weight estimation parameters at the preliminary stages of the aircraft design process. The methodology will focus on capturing driving parameters in the design of aircraft structures, as well as the effects of system installation on structural design from an MDO point of view.

II. Weight Estimation for Aircraft Design

Weight estimation has acquired considerably greater relevance in the aerospace industry from the moment it emerged as an individual analysis field in the 1930s. In recent years, the effort towards more effective and precise weight estimation methodologies has also been spurred on by an increasing demand for designs which are simultaneously cost effective as well as more environmentally friendly. The aerospace industry has, therefore, redirected its focus towards new configurations, weight saving materials and alternative production methods in order to satisfy the market demand.[3,4] As a result, traditional approaches to weight prediction are becoming limited in their reliability and accuracy.

The majority of current methodologies are of an empirical nature, since they are based on formulations which are statistically drawn from databases. As a consequence, their results tend to embody characteristics of conventional configurations and designs as well as established technologies rather than new trends.[5-8]

In order to improve weight estimation capabilities, empirical techniques have, therefore, been substituted by or combined with more accurate analytical and semi-analytical formulations, integrating load analysis with statistical techniques to encompass in greater detail the nature of aerospace designs and reduce the error in the prediction of their weight.[9-11] Initially these methods used to be stand-alone processes, aimed at generating final weight breakdowns for the purpose of performance estimation. This has changed considerably in the past few years when the analytical equations for weight derivation have started being linked to structural analysis,[12-16] and CAD modeling programs.[17]

Throughout the design cycle, however, these methods are never used separately. Empirical and semi-analytical formulations dominate the conceptual and preliminary stages, where the knowledge of the design is limited. At this stage the formulae tend to be simple and the weight being analyzed is related to a limited number of parameters.[18-20] This allows them to be well suited to provide rapid weight evaluation for different configurations and a quick definition of the design space. On the other hand, this constrains the level of accuracy that can be expected as a result of these types of analysis.

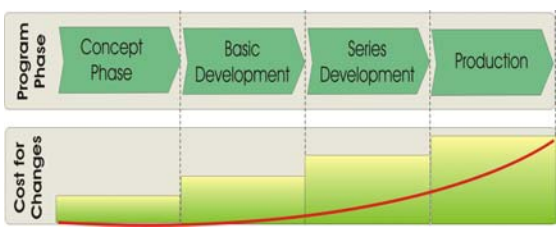


Figure 3: Design cost curve. *Graph showing the increase in cost penalties for design changes along the design process for a new aircraft.* [21]

Analytical formulations and computational techniques appear in the later phase of the preliminary design stage, where a final configuration has been selected and component level information is available. Although these methods allow for improved accuracy in the estimation of weight, they can only be applied late in the process where the cost for any redesign will have increased significantly compared to the concept phase, Fig. 3. As a consequence, it would be harder and less effective at this stage to apply any weight-saving modifications in the configuration.

The current trend is converging towards a more concurrent and multidisciplinary approach to the design process as a whole. Weight estimation has, therefore, acquired increased importance not only as the link between the various discipline areas but also a driver for the development of weight optimization techniques. An accurate and rigorous weight prediction is, as a consequence, the starting point for an optimal design. Clear identification and traceability of the sources of weight inefficiencies can focus the efforts on their elimination or substitution with a more efficient feature/component, for a reduction in the overall assembly weight and consequent performance enhancement.

III. Fuzzy Reasoning Approach to Weight Estimation

In order to successfully carry out the weight estimation task, it is important to be able to acquire adequate knowledge of the system being considered, as well as being able to "know what is not known" and account for it, Fig. 4.

The knowledge acquisition task needs to be comprehensive and allow the representation of different aspects of the system, ranging from materials and manufacturing processes to the understanding of the impact of different solutions on the final assembly/component weight. The increased knowledge of the design parameters and their effect on the overall solution not only results in greater accuracy in the weight prediction, but also in added confidence for the design team in the decision making process. Complete knowledge of the system, however, will never be possible. The number of variables and the nature of the design process itself permeate the weight estimation task with a certain degree of uncertainty which grows with the amount of innovation characterising the vehicle.

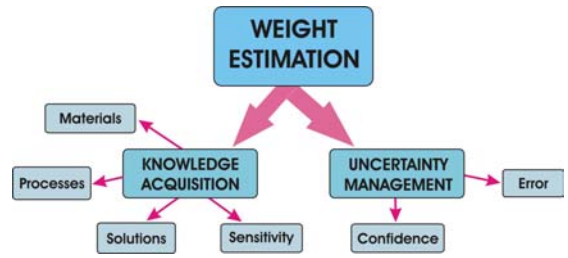


Figure 4: The weight estimation problem. *Diagram showing the decomposition of the weight estimation problem in its two main tasks.*

The main problem, therefore, is to be able to learn in an environment of uncertainty and imprecision. The field of soft computing appears to provide appropriate tools for this type of task. Techniques in this area have proved to be:[22,23]

1) tolerant of imprecision, uncertainty and approximations
2) robust to noisy environments
3) able to combine symbolic and linguistic attributes (i.e. definition of problem variables) with mathematical reasoning
4) able to provide explanation to reasoning strategies
5) flexible for modifications and extensions.

One of such tools that has been identified so far as a promising technique for solving this kind of problem is fuzzy logic, through the combined use of fuzzy reasoning and Fuzzy Inference Systems (FIS). The attractiveness of this technique lies in its ability to extract the rules driving the behavior of the system under consideration and translating them into a knowledge base that the design team can work with. The aim of this study is to explore the feasibility of its application as an aid to the weight estimation process.

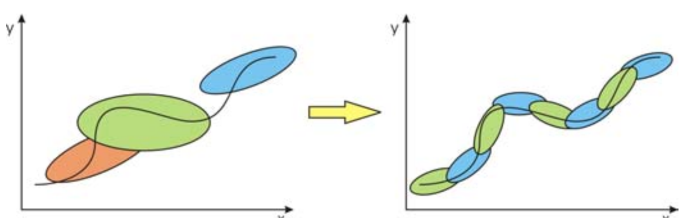


Figure 5: Fuzzy approximations. *Schematic representation of the evolution of fuzzy rules in the design process and its impact on the accuracy of system approximation.*

Fuzzy reasoning allows the description and approximation of a system by modeling it through a set of rules, defined via Boolean logic operators. Compared to conventional computing rules where "if" conditions trigger the applicability of the rule itself, fuzzy conditions provide definitions that can be partially true. This is well suited for trade studies on the design space at the preliminary stage where the boundaries of the sets of variables are imprecise. This representation of the system can aid visualization of the effects of several different combinations of design parameters on the final solution as well as allowing the accuracy of the solution to grow in parallel to the design process itself. [24] At the very early stages of the concept definition, in fact, the fuzzy sets will be large and able to approximate the system loosely. With increased definition of the design, the rule patches will get smaller, leading to improved approximations, Fig. 5.

For the successful application of fuzzy logic, the set of rules by which the system is modeled needs to be known from the onset. In preliminary aircraft design stages, however, such information may not necessarily be available. It is therefore vital to have a system that is capable of deriving its own sets of fuzzy rules, which in turn can be used in the description and approximation of the system. Adaptive Network-based Fuzzy Inference System (ANFIS) is a tool which is capable of constructing a set of if-then rules, with appropriate membership functions, to map the relationships existing between given input and output data pairs.[25, 26] For a given data set, this type of fuzzy inference system can be constructed and subsequently optimized by adaptive learning.

A. Adaptive Network-based Fuzzy Inference System (ANFIS) Modeling

Fuzzy Inference Systems are used in the formulation of fuzzy relationships between a given input and output by combining membership functions together with fuzzy operators and if-then rules.[27] The process is made up of four functional blocks, Fig. 6. The knowledge base block comprises the rule-base and database, with the rule-base containing the number of fuzzy if-then rules and the database defining the membership functions of the fuzzy sets used in the fuzzy rules. Membership functions define the degree to which an input is associated to a specific fuzzy set. The 'fuzzification' interface uses these membership functions to convert the set of numerical inputs into fuzzy inputs. The decision-making unit then selects the appropriate rules to apply based on the fuzzy inputs provided. The process ends with the conversion of the fuzzy result into a numerical output through the 'defuzzification' interface. [25]

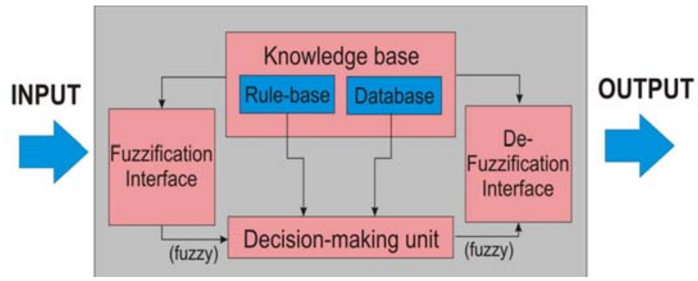


Figure 6: Fuzzy Inference System. *Block diagram illustrating the FIS modeling process.*[25]

FIS can be categorized into three main types depending on the type of rules adopted and how they are applied, Fig 7. For both type 1 and type 2, the partial output is a product or minimum of the degrees of match of the fuzzy inputs. However, type 1 systems tend to have the overall output represented as a weighted average of each rule's partial fuzzy output, whereas type 2 FIS derive their overall output by applying a "max" operation to the qualified partial fuzzy output. In Type 3 systems, also known as Tagaki-Sugeno-Kang (TSK) FIS, the overall output is still computed as weighted average of each rule's output as in Type 1 FIS, however each rule's partial output is a linear combination of the input variables plus a constant term. Of all the fuzzy inference types, the TSK FIS is the only system that is capable of working efficiently with adaptive techniques due to the nature of its partial outputs.

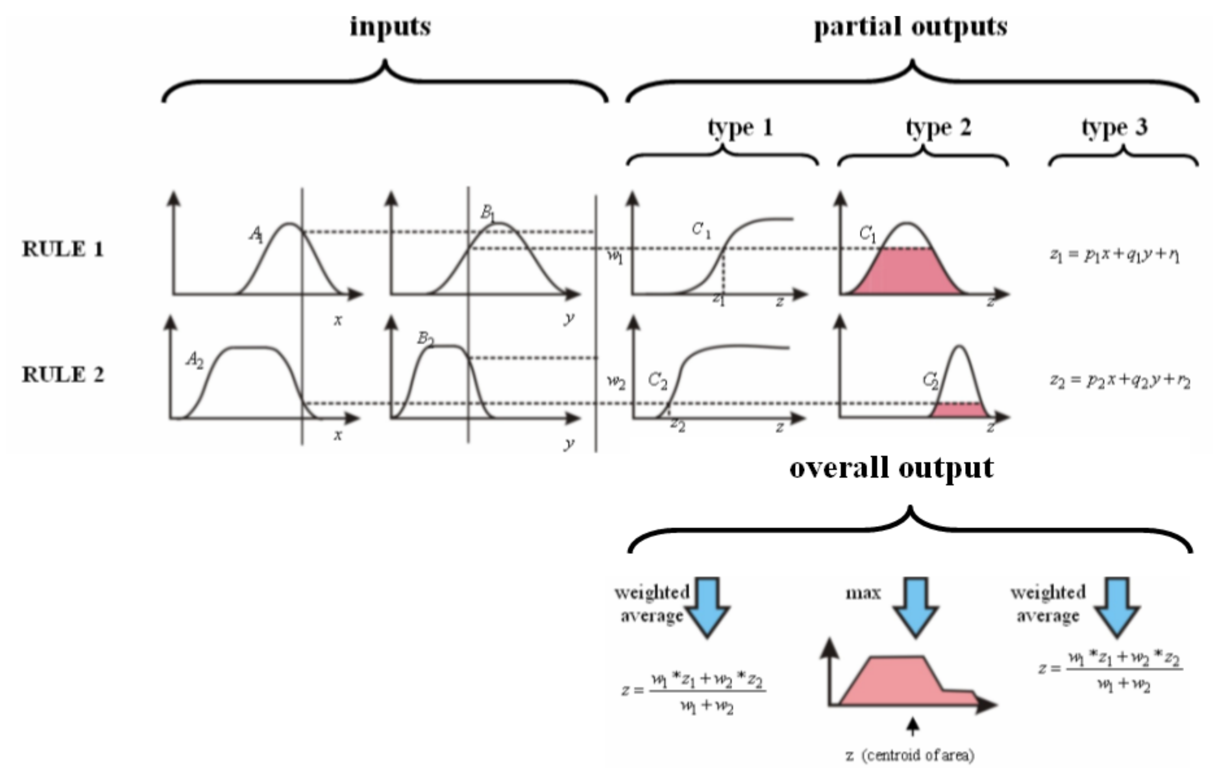


Figure 7: Types of Fuzzy Inference Systems. *Schematic drawing showing the three types of FIS and their calculated fuzzy output.* [25]

Adaptive techniques are aimed at changing some parameters of FIS in order to better reflect the relationships existing in a given set of data through supervised learning. This is achieved by linking the FIS to a multilayered feed forward network made up of nodes and directional links, Fig 8.[25,28] Each node performs a particular function based on incoming signals as well as a set of parameters pertaining to that node. The nodes can either be adaptive (i.e. square in shape with associated parameters) or fixed (i.e. circular in shape). The parameters associated with the adaptive nodes can be updated using back propagation and hybrid learning techniques in order to match a given training data set.

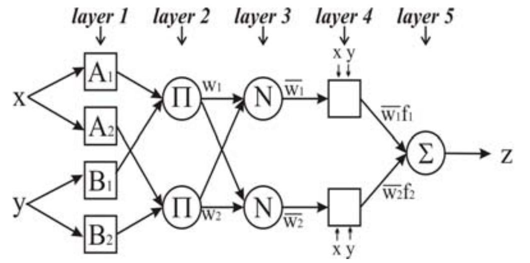


Figure 8: Adaptive network. *Example layout of a TSK FIS adaptive network with two sets of inputs.* [25, 28]

The method by which the adaptive process is conducted can be illustrated with the example below. A network with two sets of inputs x and y, and an output z, which contains two TSK type fuzzy rules of the form:

Rule 1: if x is A_1, and y is B_1, then $z_1 = p_1x + q_1y + r_1$

Rule 2: if x is A_2, and y is B_2, then $z_2 = p_2x + q_2y + r_2$

can be represented by the structure in Figure 8. The adaptive (square) nodes occur in layers 1 and 4, and the fixed (circular) nodes in layers 2, 3 and 5.

In layer 1, the adaptive node yields a nodal output given by:

$$O_i^1 = \mu_{A_i}(x) \tag{1}$$

where O_i^1 is the membership function which determines the degree to which a given input (x) belongs to a defined fuzzy set μ_{A_i} is associated with the shape of the membership being used.[25, 27, 28] The shape of the membership function can include triangular, trapezoidal, Gaussian and bell shaped functions. For example, a bell shaped membership function with a maximum and minimum input of 1 and 0 can be represented by:

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}} \tag{2}$$

where $\{a_i, b_i, c_i\}$ is the adaptable parameter set associated with this layer.

The fuzzy rules are then applied in layer 2 and fired based on their individual firing strength, which is calculated by multiplying the single incoming signals given by:

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i = 1,2 \tag{3}$$

The normalized firing strength ($\overline{w_i}$), which is the weight of the rule based on the structure of the entire network, is then calculated in layer 3, based on the individual firing strengths,

$$\overline{w_i} = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \tag{4}$$

The outputs of layer 3 are then fed into layer 4 and the corresponding partial nodal output calculated,

$$O_i^4 = \overline{w_i} z_i = \overline{w_i}(p_i x + q_i y + r_i) \tag{5}$$

where (p_i, q_i, r_i) is the adaptable parameter set associated with each square node in this layer. The overall output (layer 5) is then computed as a summation of all the incoming signals,

$$O_i^5 = overall \quad output = \sum_i \overline{w_i} z_i = \frac{\sum_i w_i z_i}{\sum_i w_i} \tag{6}$$

This final output however, may not necessarily provide an accurate representation of the training data set in the first instance. In such cases, the adaptable parameters sets associated with layers 1 and 4 can be changed to improve the quality of the approximation. ANFIS is a type of fuzzy TSK model with the ability to learn from a given set of training data and adapt its set of parameters to match the system through a hybrid learning technique, which combines gradient based and least squares methods.[25, 27, 28] Each step (epoch) of the hybrid learning cycle comprises two phases: a forward pass and a backward pass. In the forward pass, the input data and functional signals are sent forward and used in the calculation of the node output. The parameter set associated with the calculated output node is then evaluated using least squares method. The functional signal is then carried forward throughout the network until the error measure is calculated. The derivative of the error measure with respect to the parameters in each output node (error rates) is then calculated and propagated from the output end towards the input end (back propagation) and the parameters set updated accordingly using gradient based optimization methods.[25,28] The parameters can be updated either after the complete training data set has been submitted known as the batch or offline learning, or they can be updated after each input-output pair has been presented.

B. Variable Selection

One of the major issues regarding the acquisition of knowledge of a system in the weight estimation environment is the large number of associated variables. Fuzzy models have the capability of dealing with multiple combinations of input variables. However, with such capabilities come associated problems, including overcomplicated models, which are computationally expensive. It is crucial, therefore, from the modeling perspective, to be able to reduce the number of parameters to an optimum, by eliminating variables that have little or no impact on the performance of the model itself. This not only makes the model much simpler, but also improves its usability and reliability.

One way of selecting the appropriate input variables for the problem in hand has been illustrated by Chiu.[29] The process is initiated with the development of an initial fuzzy model containing all possible input variables through subtractive clustering. This method generates rules in the locations where there is a cluster of data. Each data point is considered as a potential cluster center, with the value of its potential dependent on the number and Euclidean distance, r_a, of neighboring data points. The data point with the highest potential is then selected as the main cluster center and the value of the remaining ones is subtracted as a function of the potential main center cluster. This method determines the number of rules and the associated rule parameters, which can in turn be tuned or optimized using ANFIS to minimize the root mean square error (RMSE) of the output with respect to the checking data. The importance of each input variable is then determined by the systematic elimination of variables and their associated rules. This allows the effect on the performance of the whole model to be analyzed. This process is deployed in five main steps, Fig. 9:[29]

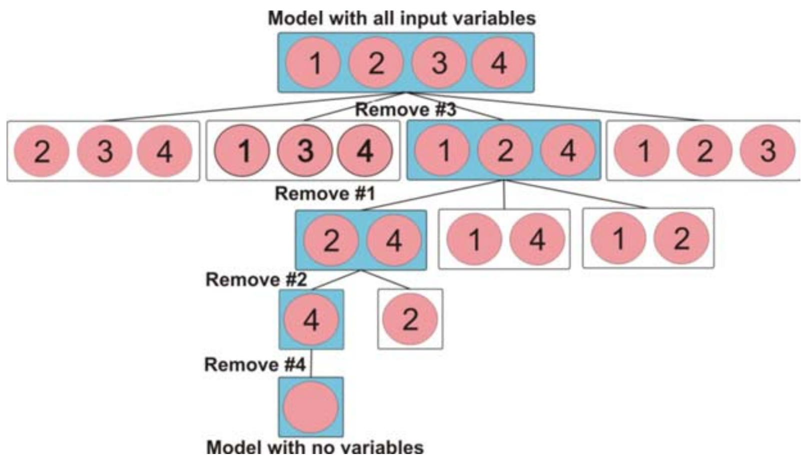


Figure 9: Variable selection process. *Method of systematic variable selection proposed by Chiu.* [29]

1) Performance evaluation on checking data RMSE of initial model with all candidate input variables
2) Performance evaluation with systematic variable removal
3) Identification of most efficient partial set
4) Subsequent variable elimination and re-iteration of step 3
5) Choice of best performing variable set based on the minimum RMSE calculated across the various models.

A final fuzzy model can then be generated using subtractive clustering in conjunction with ANFIS based only on the best performing set of variables as inputs to the system.

IV. Application of Fuzzy Modeling for Aircraft Structural Weight Estimation Problems

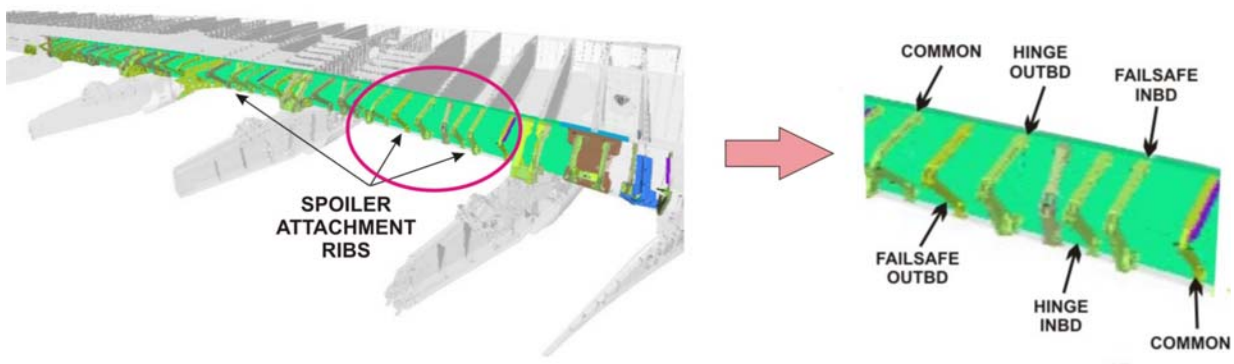
The wing is one of the most complex and critical components of an aircraft. It is the main source of lift and houses numerous vital systems and structural subassemblies. Approximately 55 percent of its weight comprises primary structures making up the wingbox, 15 percent can be traced back to the various types of moveable surfaces housed in both its leading and trailing edge and 5 percent of miscellaneous items (i.e. paint, sealant, etc.). The remaining 25 percent comprises fixed secondary structures.

The size and function of the wingbox primary structures justify the use of computationally expensive tools, such as FEA and complex modeling techniques, from the onset of the design process. As a result, greater knowledge of the behavior of these components is being acquired in early design stages, allowing higher confidence in the weight estimation process. The methods applied for the derivation of weight of the secondary structures, and in particular of the fixed trailing edge, however, are still highly empirical even in the later stages of design, resulting in a higher degree of uncertainty in the results. The development of analytical methods, which are able to represent both the numerous functions covered by the secondary structures and the complex integration with the systems housed in it, is very challenging. At the same time, it is currently infeasible to apply FEA to these subassemblies from the onset of the design process, from both a cost-to-weight point of view and its limited capability to fully include system installation issues. The application of ANFIS is one of the possible answers to the solution of this complex problem.

A. Wing Fixed Trailing Edge Structure

The fixed trailing edge is the section of the wing extending aft of the rear spar and acts as support for ailerons, spoilers, shroud box and shroud panels. It is mainly made up of ribs which are designed to transmit the aerodynamic loads acting on the moveable surfaces and panels to the rear spar. It can be split into three sections:

1) Inboard Fixed Trailing Edge (IFTE), which houses landing gear attachments and false rear spar assembly
2) Midboard Fixed Trailing Edge (MFTE), which comprises spoiler and flap track attachments
3) Outboard Fixed Trailing Edge (OFTE), which includes aileron supports and outer falsework.



(a) **(b)**

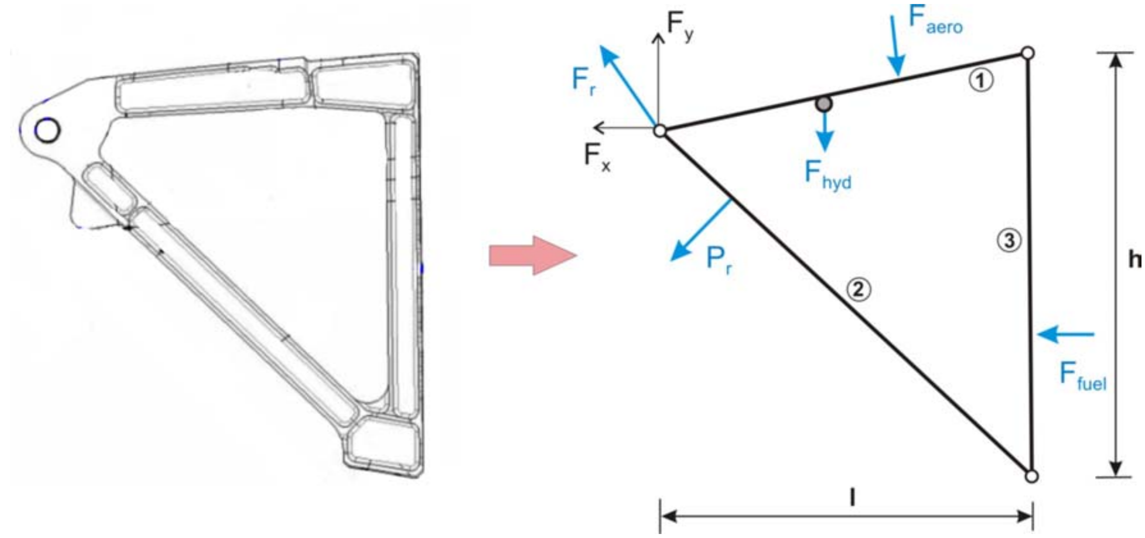
Figure 10: MFTE assembly. *Figure showing a general MFTE assembly (a), highlighting spoiler attachment ribs and their nomenclature (b).*

For the purpose of this study only spoiler hinge attachment ribs in the MFTE have been considered, Fig. 10. The main function of spoiler hinge ribs is to provide fixed attachment points for the spoilers. The individual ribs create a restraint for the moveable surface in the hinge line direction as well as in the two axes perpendicular to it. Each spoiler is moved by a single actuator, fixed to the rear spar by an actuator bracket and supported on each side by an actuator hinge rib. Hinge ribs between spoilers are used as a common attachment point to the adjacent moveable surfaces. Critical spoilers have failsafe ribs to prevent the detachment of the spoiler in case of failure of any of the actuator hinge ribs. Typical spoiler attachment ribs are "A" shaped, allowing the aerodynamic contour of the upper surface to be preserved as well as providing space allocation for systems and system support.

In order to make the weight model representative of the real structure, it is important to be able to embody the actual design of the component/assembly being evaluated. In the case of spoiler hinge ribs, the design is driven by both loading consideration as well as the need to maintain the aerodynamic integrity of the wing. Figure 11 shows a schematic representation of the positive loads acting on a spoiler hinge rib. Aerodynamic load (F_{aero}) is applied on the upper section of the rib via direct attachment to the upper skin panel and on the lower section via a strut connecting it to the lower skin panel (P_r). The resultant load from the axial hinge force components (F_r) is applied directly on the spoiler hinge line. In the case of a composite wing spar, vertical stiffeners appear on its aft side. The design of spoiler hinge ribs located where a stiffener would be present, include a vertical section, which replaces the external integral spar stiffener. In order to ensure that the weight model is able to represent this design feature, fuel loads (F_{fuel}) acting on the spar at the location of rib attachment have been included where applicable.

System installation considerations has been included in the analysis by considering the total axial load resulting from system attachment (F_{hyd}) on individual ribs as well as the number of attachment points on the rib structure (n_{hyd}). For the purpose of this study, only hydraulic installation has been taken into account due to the greater proportion of its loading on the rib structure compared to other systems.

To account for the effects of differences in thermal expansion at composite to metal interfaces, an applied thermal stress (σ_{TH}) of 20MPa was added as an input to the structure.



(a) **(b)**

Figure 11: Idealization of a spoiler attachment rib. *The figure shows a spoiler attachment rib (a) and its schematic representation, showing the three sections, the positive forces applied on it and it global geometrical parameters.*

B. Model Development

In order to achieve the overall aim of identifying the effect design parameters have on the component structural weight, the initial parameterization of the problem for ANFIS modeling was developed by considering three main parameter classifications:

1) Global variables
2) Local variables
3) Loads.

Spar height (h) at the individual rib location and hinge line datum (l), Fig 11, were chosen as global geometric definition of the fixed trailing edge. These variables would be readily available from the onset of the design as soon as the team has agreed on a wing geometrical definition. Moreover, they would be able to link the rib to a specific spanwise location and an unambiguous rib type by considering geometry and location of the individual spoilers. Second moments of areas have been selected as variables to locally define the different rib sections: I_1, I_2 and I_3 represent sectional properties for top, bottom and vertical section respectively. This has been preferred to the geometrical definition of individual flanges in order to both reduce the number of variables to a minimum and allow the design to be more generic.

The different loads acting simultaneously on the ribs have all been included as variables. Their values are the maximum that the structure would be designed for, including retracted and extended spoiler setting as well as intact and failed conditions where applicable.

Two weight models were created. Model A evaluates the rib weight without considering the impact of system loads, whilst model B includes variables linked to loads due to hydraulic system installation. As a consequence, model A was initialized with 10 input variables while model B with 12, Table 1. The ANFIS toolbox in Matlab[27] was used for the development of both FIS structures.

Table 1. Input variables for fuzzy models. *The table shows the variables used for the initialization of model A and model B.*

	MODEL A	MODEL B
GLOBAL	l h	l h
LOCAL	I_1 I_2 I_3	I_1 I_2 I_3
LOADING	F_{aero} F_r F_{fuel} P_r σ_{TH}	F_{aero} F_r F_{fuel} P_r σ_{TH} F_{hyd} n_{hyd}

The reference database was built on 36 examples of spoiler attachment ribs, related to two aircraft models. The first design considered (Aircraft 1) is representative of a long-range civil transport. Its wing is of a traditional layout, with composite wing panels and metallic spars. In the case of Aircraft 2, both wing covers and spars are of composite design. The reference database was split into 25 examples for model training and 11 for validation of the optimized model structure.

C. Variable Selection Process

The method of variable selection proposed by Chiu was applied for the optimization of the two fuzzy models, with checking error on the testing database as the selection criterion. Subtractive clustering was preferred for the derivation of the model structure due to the large number of inputs required for the analysis. A cluster radius of $r_a = 0.4$ with accept and reject ratio of 0.5 and 0.15 was used for both model A and B since it allowed for a good compromise between accuracy of solution and overall model complexity.

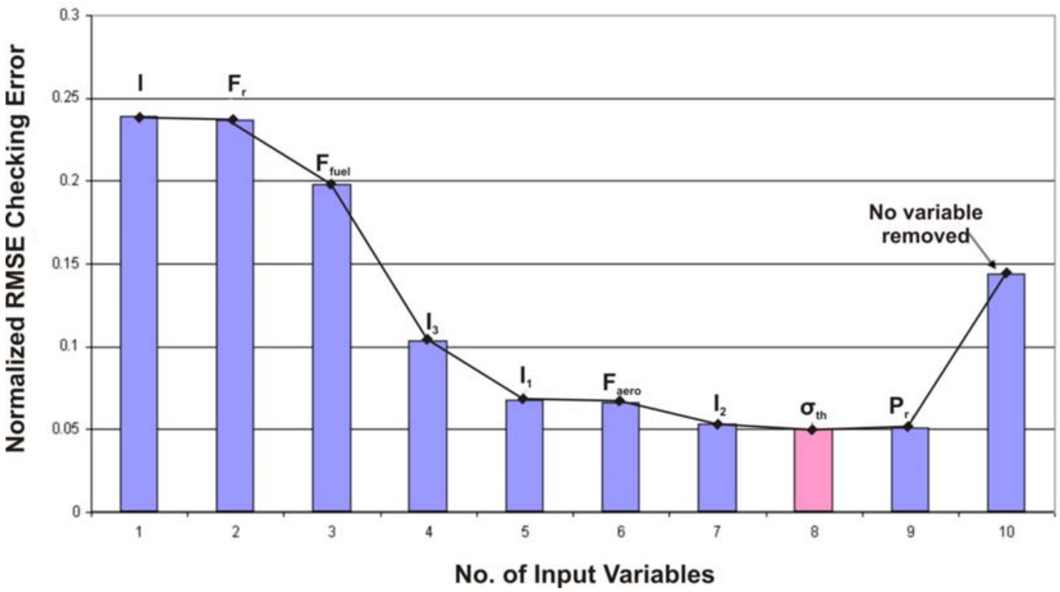


Figure 12: Process of variable removal for model A. *The chart shows the variable removal process for model A. Each bar indicates the normalized checking error associated with the removal of a specific variable at each stage of the analysis, as annotated. The first bar represents the model at the last stage of the process after the elimination of variable l, leaving h as the only input.*

An initial checking RMSE of 0.144 on the initialized model A was achieved, which was reduced to 0.050 at 8 variables, Fig. 12. The optimum model was attained by removing both thermal effects and strut loads from the initial input variable set, thus defining them as the least influential parameters. This is reasonable if related to the design process of the component, which is primarily driven by spoiler loads. This is also confirmed by the results of the model optimization process, where hinge load is the last loading variable eliminated. From the point of view of the geometrical definition of the ribs, the most significant parameter for the evaluation of the weight is the spar height, being the last parameter left after the removal of the hinge line location.

Model B, on the other hand, showed a better initial performance, with a checking RMSE of 0.077 on the full set of 12 inputs, Fig. 13. This was reduced to an optimum value of 0.056 with 9 inputs. In this case, the optimum model was obtained by subsequent removal of three variables, namely thermal effect, and second moment of area for bottom and vertical section. The small relative importance of these parameters is understandable. In a similar way to model A, thermal loading is not a design driver for the component. In addition to this, the vertical section only appears in a limited number of examples and its properties are relatively minor compared to the other two sections. The results of the optimization process also suggest the smaller influence of the bottom section of the rib on the final design weight, mainly due to the fact that the load sustained by this part of the structure is comparatively less to that on the top section. The most significant parameter was found to be the hinge load, as it had the greatest impact on model accuracy.

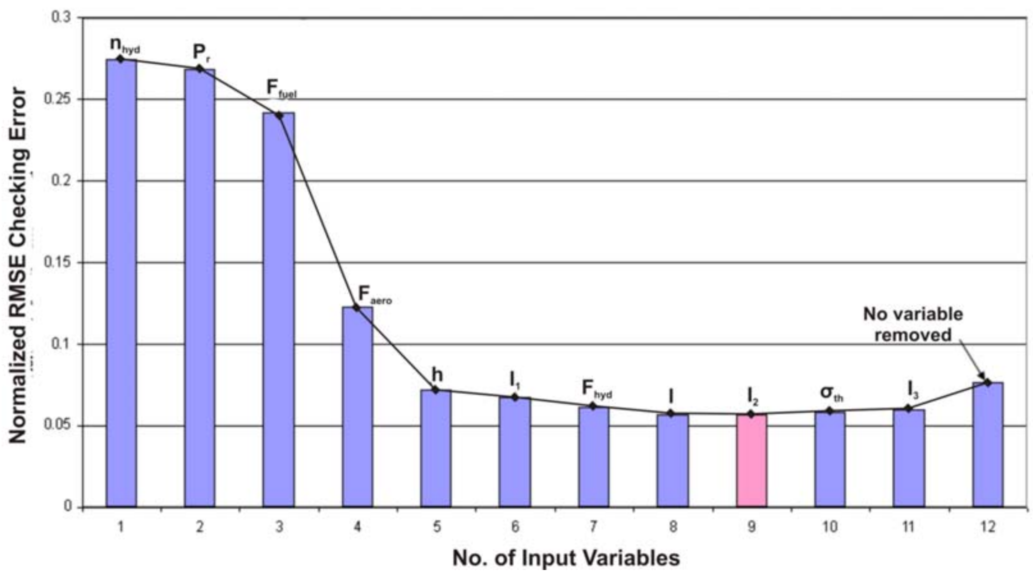


Figure 13: Process of variable removal for model B. *The chart shows the variable removal process for model B. Each bar indicates the normalized checking error associated with the removal of a specific variable at each stage of the analysis, as annotated. The first bar represents the model at the last stage of the process after the elimination of variable n_{hyd}, leaving F_r as the only input.*

Although the best performance occurs with 8 input variables for model A and 9 for model B , it can be seen from the results that 7 and 8 variables for A and B respectively are still capable of achieving a relatively accurate approximation. A compromise can therefore be made between accuracy of results and model simplicity based on the information at hand at the time of the analysis. In the case of the selection of a simpler model, this process allows the quantification of the error resulting from the choice of a smaller variable set, therefore enabling the designer to compensate for this in weight estimation process.

D. The Final Models

Figure 14 shows the individual results from model A and B on hinge ribs from the two representative transport aircraft. The addition of system integration considerations in the model, although slightly increasing its complexity, has improved its generalization capabilities. As shown, both models have been able to approximate the ribs closely, with the exception of Aircraft 2 hinge rib spoiler 1 inboard, hinge ribs spoiler 3 inboard and outboard. This can be attributed to the simplistic way thermal effects have been accounted for. A constant thermal stress of 20MPa was applied to all the ribs without considering the proportion of their areas interfacing with a composite component.

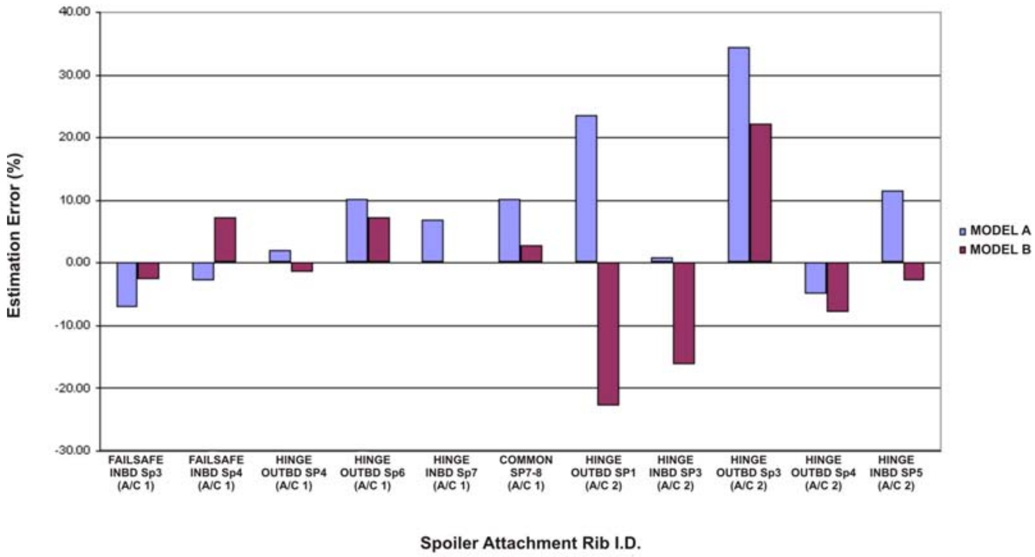
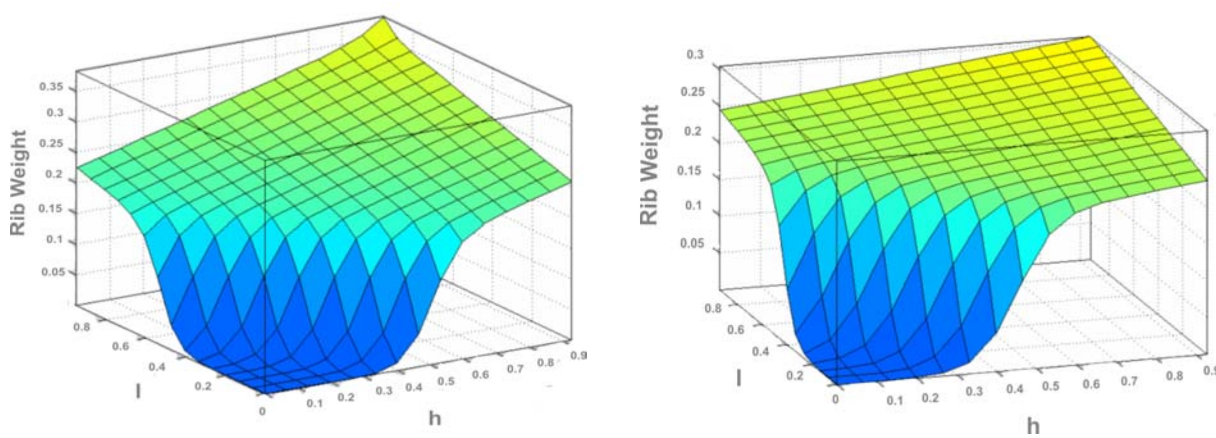


Figure 14: Error on elements of testing database. *The chart shows the percentage error on the individual ribs in the testing database for both model A and B.*

For example, in the case of Aircraft 1 only the skin panels are composite while the rear spar is of metallic design. This results in the top surface of the rib top section being in full contact with a composite skin panel and the bottom section being attached to it only via a small fraction of its lower area. In the case of the Aircraft 2 on the other hand, both skins as well as the rear spar are composite which results in the addition of a vertical component where spar stiffening is required. As a consequence, a higher fraction of the rib is subjected to thermal effects. This, however, has not been fully accounted for in the fuzzy model, which may be the cause of the higher discrepancies in the estimated results. Had this been represented more accurately rather than with a constant value, the system would have recognized its impact on the final design weight, yielding improved performance in both models.

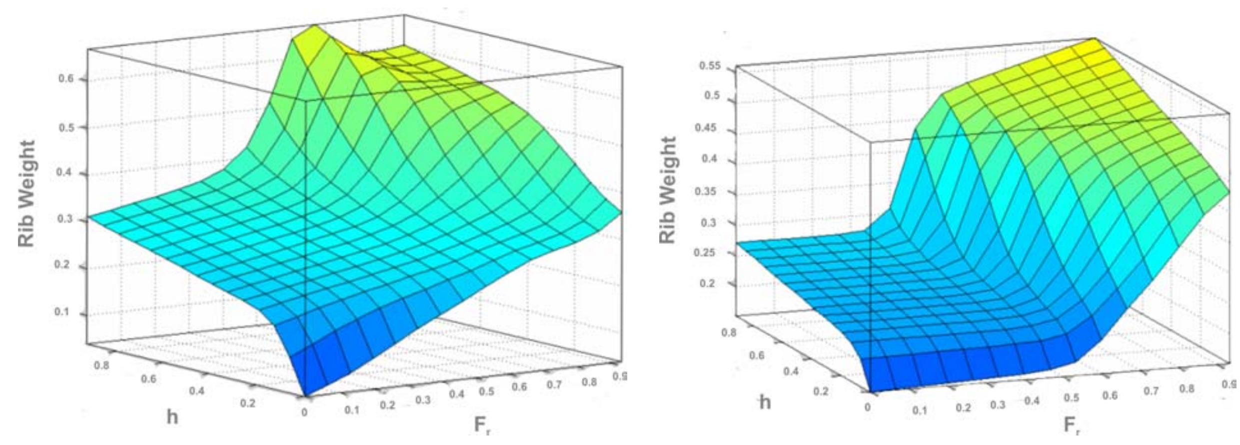


(a) **(b)**

Figure 15: Rib weight vs. rib height and length. *The figure shows the variation in spoiler attachment rib weight with respect to rib height and length for model A (a) and model B (b).*

Both models have managed to accurately capture existing relationships between the different variables and the final output. The addition of the hydraulic system installation parameters, however, has impacted the degree with which the chosen variables affect the rib weight. Figure 15 shows the combined effect of rib height and length on the component weight. In both cases, the direct proportionality between the input variables and the output has been identified, however the proportion to which they impact the output has diminished in model B. In terms of weight prediction, the results show that, for the same applied loading, model A attributes a maximum of 20 percent additional weight to the structure, a proportion which relates to the impact of hydraulic system loads on the final component weight.

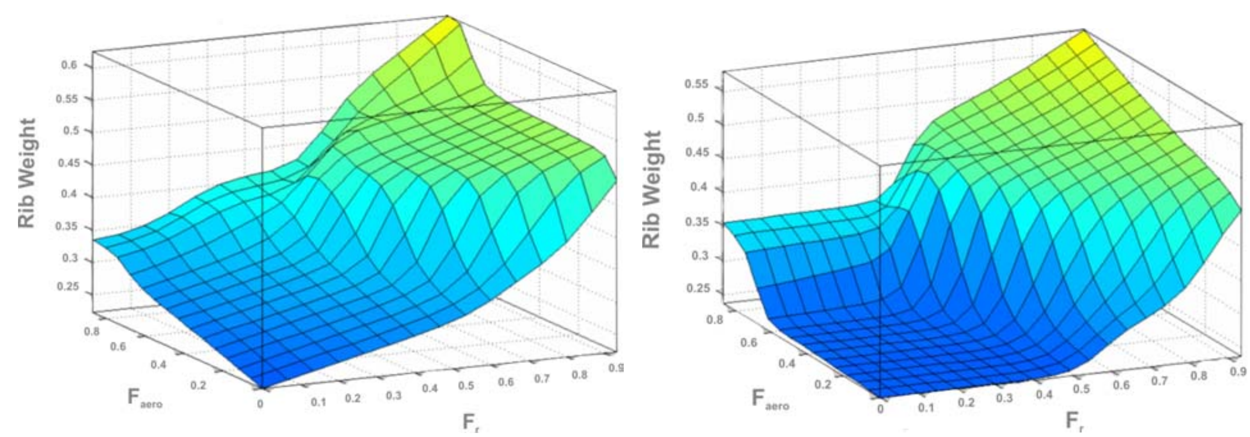
Hinge load is the loading parameter which affects the rib weight the most. Model B is able to represent this more closely as shown in Figure 16: both rib height and hinge loading, in fact, contribute to the increase in the final output however the representation of the true impact of the loading is more closely embodied in model B than model A, where the proportion of the rib weight associated to its height is much higher.



(a) (b)

Figure 16: Rib weight vs. aerodynamic load and rib height. *The figure shows the variation in spoiler attachment rib weight with respect to hinge aerodynamic loading and rib height for model A (a) and model B (b).*

Model B has also been able to capture a more representative picture of the role that the different types of loading play on the structure. Aerodynamic and hinge load influence the majority of the structure. For a rib with spar height equal to hinge line datum, an increase of both loading will result in the increase of the structural weight of the component with a greater weight impact attributed to hinge loading, Figure 17. Model A, however, erroneously applies an additional 8 percent of structural weight on the rib from this types of loading, which in model B is related to systems being attached to the structure itself.



(a) (b)

Figure 17: Rib weight vs. aerodynamic and hinge loads. *The figure shows the variation in spoiler attachment rib weight with respect to hinge and aerodynamic loading for model A (a) and model B (b).*

Overall, model B provides a better representation of the multidisciplinary nature of the problem. The addition of system installation parameters allows a more complete understanding of the sources of weight inefficiencies. During the design process, the design of the structures tends to be conducted separately from that of the system architecture and it assumes an overall greater importance. From Fig. 18, however, it is possible to note how hinge load and the load resulting from hydraulic installation impact rib weight. The impact of system loading on the rib structural weight, although not as considerable as that resulting from hinge loading conditions, is still noticeable and neglecting it would result in an incomplete and unrepresentative estimation of the component weight.

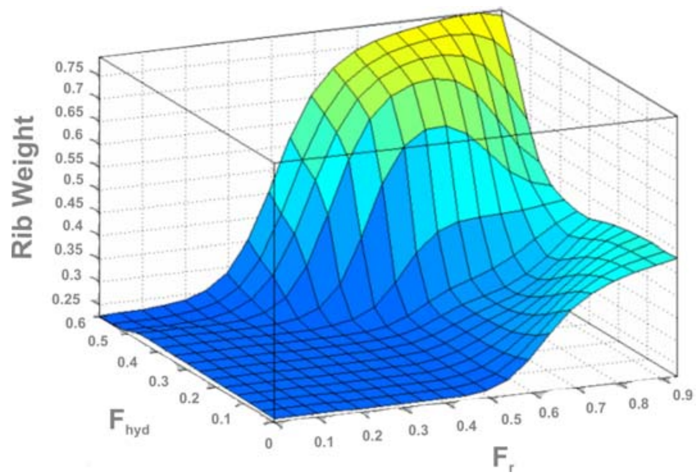


Figure 18: Rib weight vs. hinge load and hydraulic system load. *The figure shows the variation in spoiler attachment rib weight with respect to hinge loading and hydraulic system loading for model B.*

V. Conclusion

Weight estimation in aircraft design is very challenging due to the high number of variables involved in the creation of an accurate weight model, the numerous relationships between them and the high degree of uncertainty associated with the problem itself. This paper discusses the results of a preliminary study on the use of fuzzy logic as aid to the knowledge capture phase of the weight estimation process for aircraft structures.

Adaptive Network-based Fuzzy Inference System combined with subtractive clustering techniques was applied to the development of a weight model due to its capability of dealing with a high number of variables in a highly uncertain environment. In addition to this, the adaptive nature of this tool made it highly suited for the analysis of a system where knowledge of its driving rules is unavailable.

Spoiler attachment ribs in the fixed trailing edge were chosen as initial test cases for this study. The weight estimation of these types of structure is highly representative of the complex interactions existing between structural and system architectures. For this reasons, two distinctive fuzzy models were created, one analyzing the structure in isolation and the other including the effects of system installation on the component weight.

The results from this preliminary study show the importance of a multidisciplinary approach to weight estimation and its applicability at early design stages. The addition of system installation parameters in the analysis not only improved the generalization capabilities of the fuzzy model, but also allowed a more realistic visualization of the causalities between the variables.

Future work will focus on expanding the applicability of this approach to a global scale. In terms of individual components, the model could be restructured to provide both weight and sizing information. This could be achieved by splitting the task into two separate modules: a sizing module and a weights module. Using the loads information as input parameters, the minimum sectional properties of the rib beams capable of withstanding the given loads will be determined. These properties can then be combined with other geometric and material properties as input variables in a weight estimation module to determine the structural weight of the rib. This method could be further expanded to include the analysis of the whole fixed trailing edge, including the effects of the different types of systems. Ultimately, the approach could be used in reverse to investigate the effects of structural arrangements on systems weight.

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