A98-31611

ICAS-98-4,9,3

OPTIMISATION OF THE STRUCTURAL DYNAMIC FINITE-ELEMENT MODEL FOR A COMPLETE AIRCRAFT.

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Abstract

A finite-element (FE) model for aeroelastic analyses, is a vast idealisation of the actual structure. In creating this idealised model, many approximations must be made and the model then tested against the results of a ground vibration test (GVT). Subsequent to the GVT, the FE model invariably requires modification; how to best carry out such modifications has been the subject of a large body of work presented in the literature over the past 30 years, without any generally satisfactory solution. More recently, the artificial intelligence tool of genetic algorithms have shown promise in the development of optimised FE models directly from experimental GVT data for simple structures and aircraft sub-structures. In this paper, it will be demonstrated how such processes can be used to optimise the FE model for a complete aircraft using simulated GVT data for an aircraft carrying underwing stores. Details of how such a process may be used to give unique, or minimum order, models will also be demonstrated and discussed.

1. Introduction

Mathematical modelling of complex systems inevitably requires many assumptions and idealisations (eg. compare the representation of the structural dynamic model of an F/A-18 as shown in Figure 1, with the real aircraft structure).

As the system becomes more complex, these assumptions typically lead to a model with poor predictive capabilities: this is the case with finite-element modelling of aircraft structures for dynamic analyses. Such an FE model is developed when the aircraft is in the design stage; when built, the aircraft is then subjected to a ground vibration test and the FE model is typically a poor predictor of the true structural behaviour.

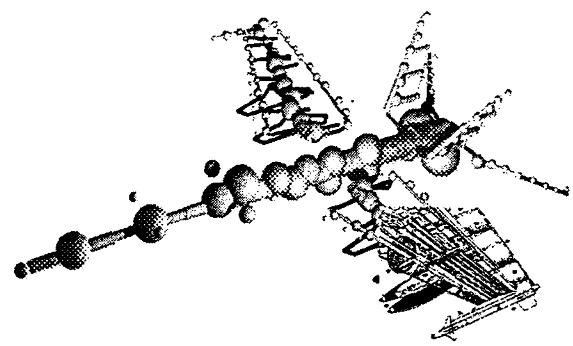

Figure 1. Finite-element model for structural dynamic analysis of an F/A-18; such a model is a considerable idealisation of the actual detailed structure shown here on the port wing.

The question that must then be addressed is: how should the model then be developed to better reflect the true behaviour of the structure? A process which has been proposed in Dunn[1&2], and is further developed in this paper, involves throwing away the initial model and developing a new model based on the GVT data. The basis of this procedure involves using the artificial intelligence optimisation tool of genetic algorithms to create an optimal FE model; where optimal is defined as the model which gives the best correlation with the experimentally determined transfer function. Previous work in Dunn[1] has demonstrated how such processes can be used on the relatively simple models of an aircraft tailplane and a truss structure. These models were similar in that they involved relatively few unknowns. The complexity of such optimisations, however, grows rapidly with the number of unknowns. For traditional optimisation techniques, this growth in complexity typically involves an exponential growth in processing time as the number of unknown parameters grows. In Dunn[3] it is demonstrated how genetic algorithms can result in far more efficient solutions than more traditional processes for structural dynamic model optimisation. In this paper, simulated GVT data for

21st ICAS Congress
13-18 September 1998
Melbourne, Australia

a General Dynamics F111C are used to demonstrate how these processes can be used for models with a large number of unknowns.

2. Genetic Algorithms.

The inspiration for GAs arose from the realisation that the result of the principles of Darwinian evolution in nature is the attempted solution of a vast optimisation problem. *Survival of the fittest* means that those individuals which are best suited to their environment are more likely to breed and therefore pass on some of their genetic material into subsequent generations. Genetic algorithms are a computer generated analogue of this process where the better individuals are chosen based on how they test against a specified cost function. For the case of using a GA to optimise mathematical models, the cost function is based on a measure of how well the model predicts actual measured data (or as in the case studied here, simulated data). The GA is started with a given population size of randomly generated individuals – where each individual is a potential complete solution to the problem. A value of *fitness* is then assigned to each individual. Breeding is done by selecting pairs from the original population in a weighted random process (where the weights are determined by the fitness such that the better solutions have a higher probability of breeding), and then swapping the properties of these pairs in a random manner to give rise to a new individual; this is done until a new population has been created. The processes of cost function evaluation and breeding etc. are repeated, over and over, until some stopping criterion is reached. There are many different ways of applying GAs; details of how they are applied for the case studied here can be found in Dunn[2&4].

For the reader interested in looking further into the philosophy of GAs, some good starting points are Holland[5] and Forrest[6]. Introductory reading on the application of GAs can be found in Goldberg[7], Whitley[8], Beasley *et al*[9] and Mitchell[10].

3. General Dynamics F111C Model

General Dynamics created a very detailed finite–element model of the F111C based on modelling the detailed structure including spars, ribs, skins etc. Based on the symmetry of the aircraft, only one half of the aircraft was modelled. For dynamic analyses, the mass and stiffness matrices created by this FE model were analytically reduced to 80 degrees–of–freedom for the model with symmetric boundary conditions. These 80 by 80 matrices were acquired by the Australian Department of Defence for aeroelastic analyses for Australia's F111C fleet. For the purposes of the analyses carried out here, these reduced matrices have been used to create simulated GVT frequency response functions. The mass distribution for the original model is shown in Figure 2.

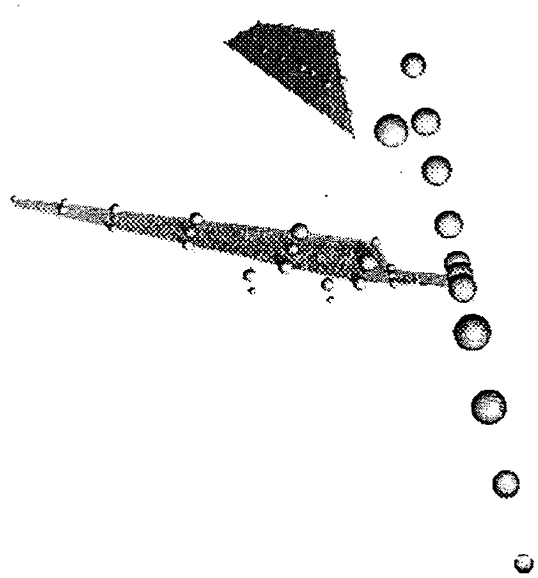

Figure 2. Mass distribution for General Dynamics F111C reduced model.

The aim here is to take the simulated undamped frequency response functions (FRFs) and attempt to develop a beam/mass FE model which will give a good approximation to these data.

3.1 Simulated data

The model from General Dynamics is fully constrained at a point on the fuselage just aft of the wing attachment. This has the effect of breaking the model into two: a forward fuselage/ wing model and an aft fuselage/empennage model. The simulated data are generated by applying sinusoidal loads at the locations shown by the arrows in Figs. 3 & 4 and collecting the FRFs at a range of freedoms, a few of which are shown in these figures (26 measurement freedoms were used in the analysis of the forward fuselage/wing model, and 16 for the aft fuselage/empennage model).

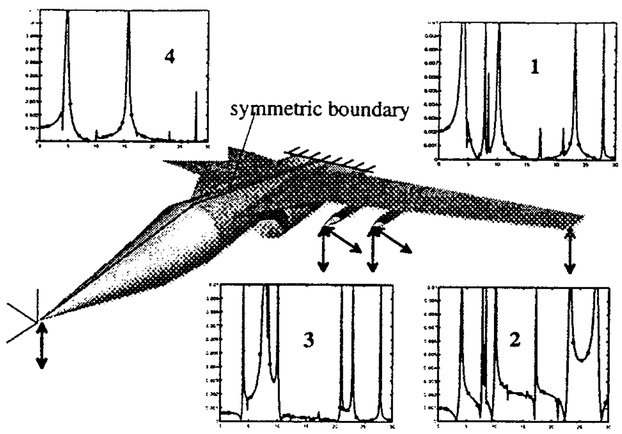

Figure 3. Diagram showing forward fuselage/wing of an F111C as represented in that part of the General Dynamics model. Simulated GVT measurements were taken at 26 degrees of freedom, four of which are shown here: 1, wing tip heave; 2, wing tip pitch; 3, in-board store yaw, and; 4, fuselage nose heave.

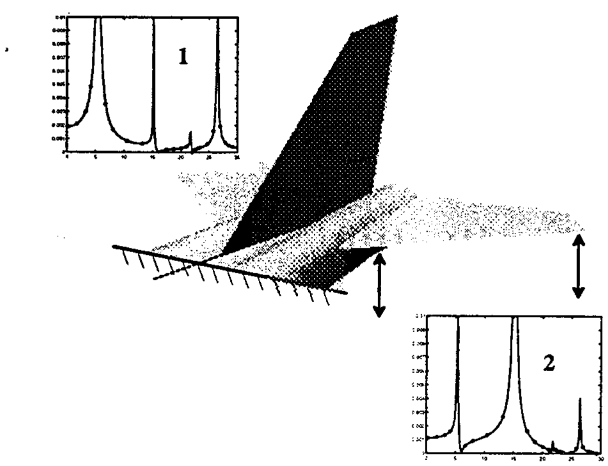

Figure 4. Diagram showing aft fuselage/empennage of an F111C as represented in that part of the General Dynamics model. Simulated GVT measurements were taken at 16 degrees of freedom, two of which are shown here: 1, aft fuse tip heave, and ; 2, stabilator tip heave

4. Creating an Optimal Beam/Mass Model.

The aim of the exercise here, is to take the simulated GVT data from the General Dynamics mass and stiffness matrices, and create an optimal simple beam/mass model which gives a satisfactory representation of the data. Optimality, is defined by attempting to achieve the following cost function:

$$\min(\varepsilon(\mu,\kappa)) = \sum_{j=1}^{N}\sum_{i=1}^{n}\left\| \chi_{i,j}(\mu,\kappa) \right| - \left| \chi'_{i,j} \right\| \qquad (1)$$

where ε, the error between model prediction and measurement, is defined as a function of the mass and stiffness properties, μ and κ respectively. ε is defined as the sums of the absolute difference between the modulii of the model FRF predictions, $\chi(\mu,\kappa)$, and measurements, χ', for the n freedoms measured at the N selected frequencies

A general beam/mass model is created for which the geometry of the aircraft and the positions of model nodes are defined. Beam elements of unknown stiffness are then used to join these nodes and unknown masses are added to the nodes. The GA optimisation will then attempt to determine the values of these unknown stiffness and mass properties by attempting to satisfy eqn. 1. Each beam can require up to four properties to define its stiffness: extensional stiffness; bending stiffness – out-of-plane; bending stiffness – in-plane, and; torsional stiffness. Each mass can require up to seven properties to fully define it: offsets from the node in each of the three principal co-ordinates; the magnitude of the lumped mass, and; the rotational inertias about each of the three orthogonal axes. In practice, however, all of these possible unknowns are not required. In the case of the wing, for example: for aeroelastic analyses, the extensional stiffness and the in-plane bending are of little value, so these are assumed rigid and the remaining stiffness properties of out-of-plane bending and torsional stiffness for each wing element are all that is required. Similarly for the wing mass properties: out-of-plane offset from the node is considered zero as is the yaw inertia of each mass element.

The constraints to the optimisation process here are: the geometry is fixed – as has already been described – and the properties must be physically sensible; ie. masses and stiffnesses must be ≥ 0. Within these constraints, the mass and stiffness properties will typically be allowed to search over a very large range covering a number of orders of magnitude; for example the wing stiffness properties were initially allowed to vary between 10^7 to 10^{11} lb in^2.

4.1 Optimised forward fuselage/wing model

The initial modelling for the forward fuselage and wing involved searching for 96 unknown properties. A fundamental feature of such modelling is that, *a-priori*, there is very little information as to how complex the model is required to be to give satisfactory agreement to the experimental data (a measure of model complexity can be taken as the number of unknown properties required to define the model). A method of determining models of minimal complexity is described in detail in Dunn[11] and will be briefly described here:

- Run the optimisation procedure – in this case a GA – a number of times such that there are a number of results where the better cost functions (eqn. 1) are very similar and the model predictions give a satisfactory representation of the experimental data;
- compare the properties found for these results;
- where this comparison shows little variation, assume the property is being determined uniquely;
- where the comparison shows a great deal of variation for similar cost function, assume that either the property is not required, or that property and one or more of its neighbours can be combined into one.
- repeat this process until all parameters appear to be defined uniquely and the model still gives a satisfactory representation of the data.

To get beyond the first step in this process, the initial model complexity must be sufficient to enable a solution which will model the experimental data; an example where this was not the case will be seen in the next section on the aft fuselage/empennage modelling. For the forward fuselage/wing modelling, however, the initial model complexity was sufficient. After going through the above procedure a number of times, the model complexity was reduced such that only 64 properties were required. Examples of where the model complexity were reduced are:

- the wing was initially described by nine beams requiring nine bending stiffnesses and torsional stiffnesses; this was reduced to seven bending and torsional stiffnesses.
- roll inertias at each of the mass elements on the wing were found to be not required, and
- pitch inertias at each of the mass elements on the fuselage were found to be not required.

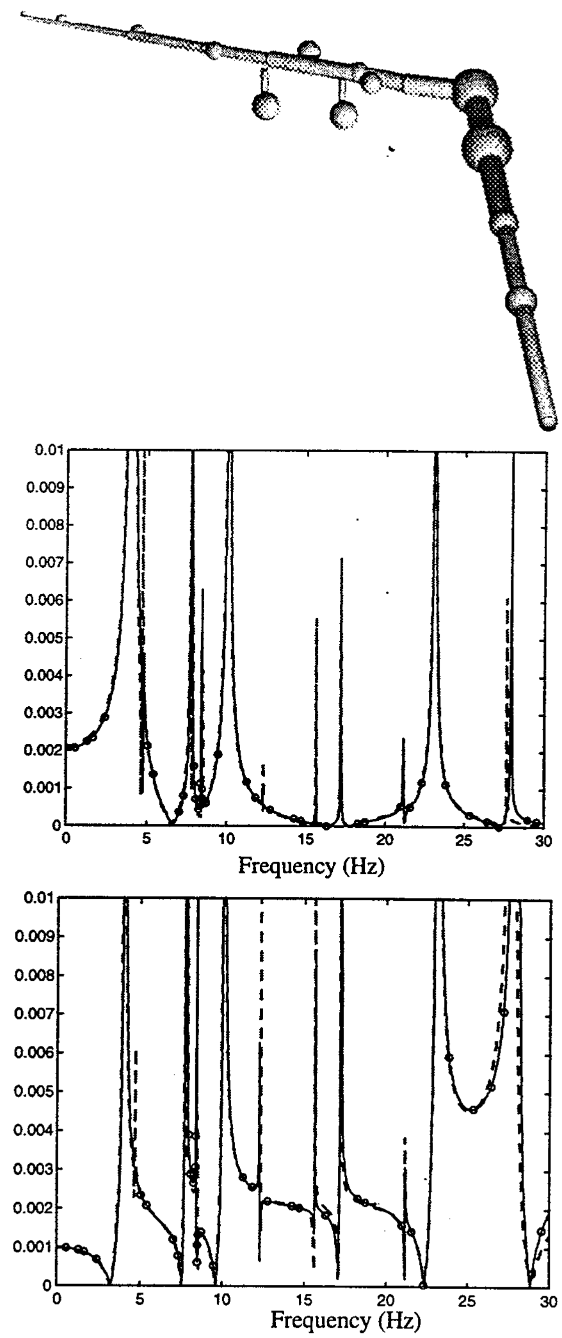

Figure 5. Depiction of the optimised forward fuselage/wing model and the model predictions (dashed lines) compared with the original data (solid lines) for wing tip heave (first graph) and wing tip pitch. The circles on the FRFs show the data points used in the cost function evaluation.

A diagram of the optimised model and its predictions compared with the simulated measurements are shown in figure 5. Given that techniques used to improve models based on GVT data more commonly used modal frequencies, a comparison of these is typically presented and is shown here in Table 1.

Mode	GD model (Hz)	optimised beam/mass(Hz).
1. wing bend.	4.07	4.04
2. fuse. bend	4.81	4.70
3. i/b store yaw	7.76	7.74
4. o/b store yaw	7.81	7.85
5. i/b store pitch	8.41	8.48
6. wing bend	10.1	10.0
7. wing torsion	12.2	12.3
8. fuse bend	15.7	15.7
9. o/b store pitch	17.2	17.2
10. i/b store sway	21.2	21.2
11. wing bend	23.1	23.1
12. wing torsion	27.9	27.7

Table 1. Comparison of modal frequencies for the original GD and optimised beam/mass model.

4.2 Predictions based on optimised model

The optimised model can now be tested as to its predictive capabilities. This will be done by re-running the original GD model in two new configurations: i. no underwing stores, and ii. underwing stores and full wing fuel. These results, along with the beam/mass model predictions, for the bending freedom at the wing tip for configurations i & ii are shown in Figs 6&7 respectively.

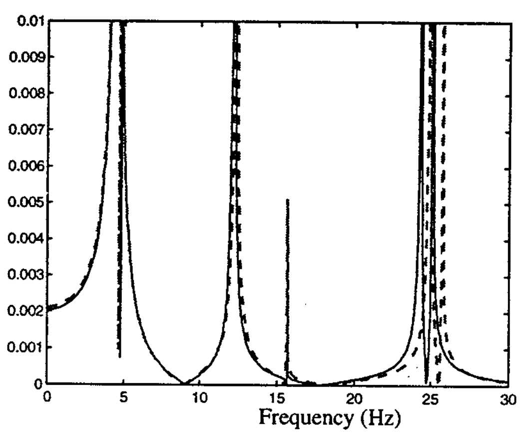

Figure 6. Optimised model predictions (dashed line) compared with GD model for the forward fuselage/wing with no underwing stores.

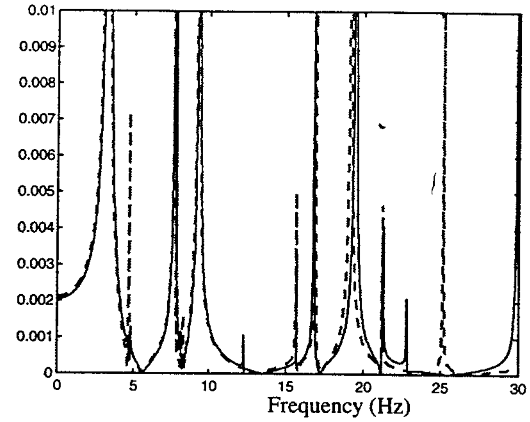

Figure 7. Optimised model predictions (dashed line) compared with GD model for the forward fuselage/wing with underwing stores and full fuel.

As can be seen in Figs 6&7, and comparing with the wing bending behaviour in Fig 5, the behaviour of the wing bending is quite different from that in the original configuration at which the optimisation was carried out. The predictive results, as shown by the dashed lines, are generally very good. Discrepancies do become apparent at higher frequencies as is most evident in the case for the full wing fuel with underwing stores case. Here, the higher-order wing torsion mode – at 27.9 Hz in the original configuration – has dropped to around 22.5Hz, but the model has predicted that it would fall to 25Hz. Nevertheless, every other mode is very well predicted.

4.3 Optimised aft fuselage/empennage model

A similar procedure to that used for the forward part of the model was carried out for the aft model. The layout of the model is as depicted in Fig. 8. The initial representation required the optimisation of 46 unknown parameters. As can be seen for the model predictions shown in Fig 8, the stabilator tip behaviour seems to be well modelled, but examination of a freedom on the fuselage makes it clear that a mode is not being represented.

Having a feature of the experimental data not being represented by the model resulting from the optimisation procedure in this manner, suggests that the initial model representation was not sufficiently complex. To investigate how the model configuration should be changed to better predict the measured behaviour, the nature of the four modes of vibration in this frequency range were examined, as shown in Fig. 9.

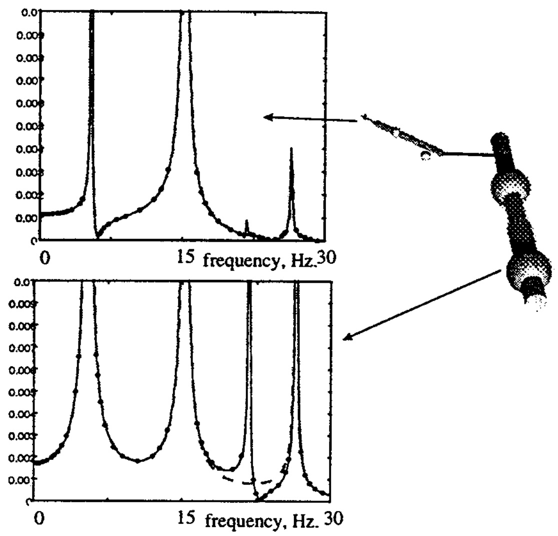

Figure 8. Initial aft model configuration showing stabilator tip heave (top graph) and fuselage heave.

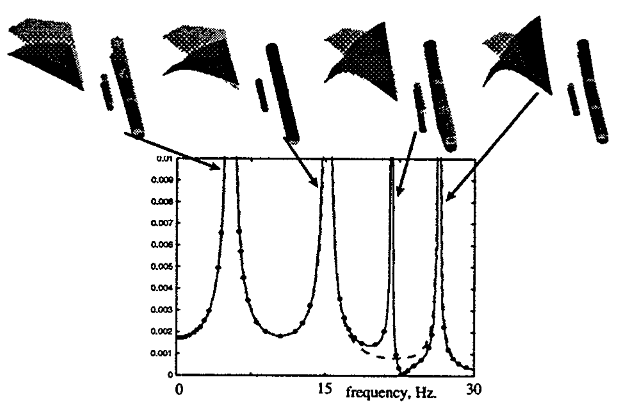

Figure 9. Diagram showing the four modes of vibration of the aft fuselage/empennage GD model.

As can be seen in Fig. 9, the main feature of the mode not being modelled is that it contains significantly more engine motion than the other modes. For the first model configuration, it was intended that the engine could simply be represented as an added mass on the fuselage centre line; the results shown in Fig. 9 clearly suggest this was wrong. The configuration was therefore changed to explicitly model the engine, as shown in Fig. 10, and the whole procedure repeated. The resulting optimised model predictions for the heave freedom on a fuselage node are also shown in Fig. 10. The final model required the optimisation of 31 properties.

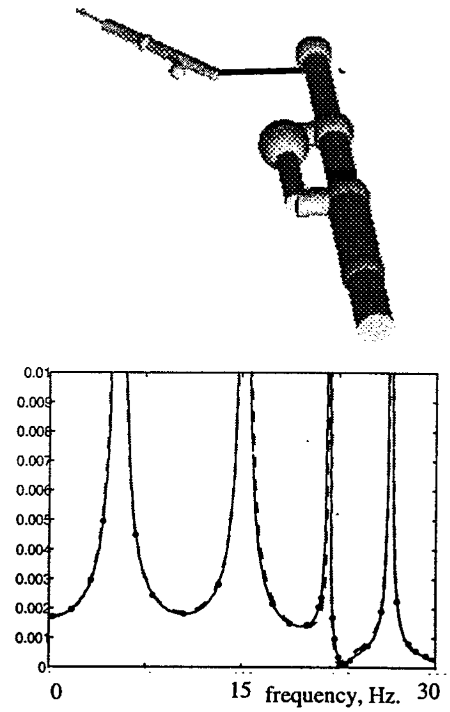

Figure 10. Aft model configuration showing the optimised model predictions (dashed line) and the original model data for a heave freedom on the fuselage.

5. Complete F111C model

Given the completed two parts of the model, these may now be put together as shown in Fig 11. This model, as for the original data, is for the aircraft with symmetric boundary conditions along the fuselage centre line.

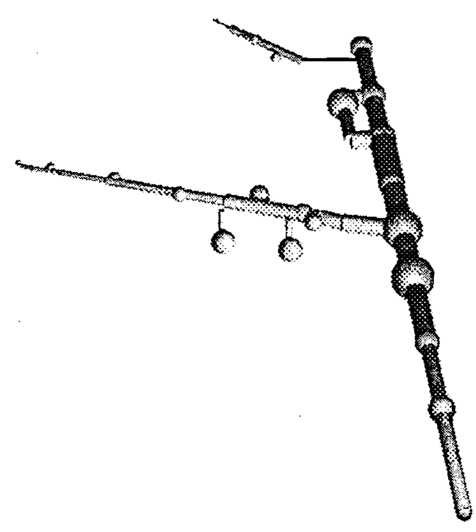

Figure 11. Complete optimised F111C model with symmetric boundary conditions.

5 Conclusion

The greatest difficulty in tackling the problem of optimising complex mathematical models – those involving a high degree on interaction between properties – arises from the solution time required when more than a few unknown properties are required. Previous work by this author has suggested that the artificial intelligence optimisation tool of genetic algorithms may be an efficient tool for tackling such problems with a large number of unknown properties. The results presented here have demonstrated that such methods can successfully overcome the problem of the number of unknowns by solving for a symmetric model of an F111C aircraft. The simulated data used were taken from a model supplied to the Australian Department of Defence by General Dynamics and the nature of this model meant that the problem was broken into two parts: the forward part of the model involved the optimisation of 64 properties and the aft model required the optimisation of 31 properties. For traditional optimisation processes, optimising this many parameters would be an almost impossible task.

It has also been demonstrated how such model optimisation processes can be used to gain a valuable insight into the complexity of the mathematical model required to represent the desired behaviour.

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