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Artificial Intelligence Based Control Power Optimization on Tailless Aircraft
ARMD Seedling Fund Phase I Final Report

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Abstract

Traditional methods of control allocation optimization have shown difficulties in exploiting the full potential of controlling large arrays of control devices on innovative air vehicles. Artificial neutral networks are inspired by biological nervous systems and neurocomputing has successfully been applied to a variety of complex optimization problems. This project investigates the potential of applying neurocomputing to the control allocation optimization problem of Hybrid Wing Body (HWB) aircraft concepts to minimize control power, hinge moments, and actuator forces, while keeping system weights within acceptable limits.

The main objective of this project is to develop a proof-of-concept process suitable to demonstrate the potential of using neurocomputing for optimizing actuation power for aircraft featuring multiple independently actuated control surfaces. A Nastran® aeroservoelastic finite element model is used to generate a learning database of hinge moment and actuation power characteristics for an array of flight conditions and control surface deflections. An artificial neural network incorporating a genetic algorithm then uses this training data to perform control allocation optimization for the investigated aircraft configuration. The phase I project showed that optimization results for the sum of required hinge moments are improved by more than 12% over the best Nastran® solution by using the neural network optimization process.

Nomenclature

ANN	=	Artificial Neural Network
DEP	=	Distributed Electric Propulsion
FEM	=	Finite Element Model
HWB	=	Hybrid Wing Body
OREIO	=	Open Rotor Integration on a BWB Concept by Boeing
S&C	=	Stability and Control

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Purpose

This project investigates the potential of applying artificial intelligence methods like neurocomputing to the control allocation optimization problem of Hybrid Wing Body (HWB) aircraft concepts. Researchers from NASA Langley, Virginia Tech, and Boeing Research and Technology are exploring the use of artificial neural networks to develop innovative control algorithms minimizing control power, hinge moments, and actuator forces to keep system weights within acceptable limits.

HWB platforms feature multiple control surfaces, with large control surface geometries leading to large hinge moments and high control power demands. Due to the large number of control surfaces on an HWB, there is no unique relationship between control inputs and resulting aircraft response, i.e. different combinations of control surface deflections may potentially result in the same maneuver, but with large differences in control power.[1] While traditional methods of control allocation optimization may have limitations in exploiting the full potential of controlling large arrays of control devices, artificial neutral networks (ANN) are inspired by biological nervous systems and have successfully been applied to a variety of complex optimization problems (see e.g. Refs. 2-4).

This project employs a finite element based aeroelastic HWB model, as well as wind tunnel and flight test data from the Boeing X-48 flight demonstrator[5] to build a database that can be used to train an artificial neural network (ANN) to perform control allocation optimization for tailless aircraft at the conceptual design level (Fig. 1).

Figure 1: Boeing's X-48 Blended Wing Body demonstrator (NASA Photo).

Background

HWB aircraft concepts offer the potential to achieve significant fuel burn savings of over 25%, with resulting emissions reductions, as well as community noise benefits, therefore countering the impact of dramatic increases in future air traffic volume.[6,7] Recent wind tunnel testing indicates that control authority issues still exist (e.g. stall recovery and three-dimensional coupling effects[8]). Stability augmentation and control power optimization for these aircraft concepts can be enablers for their success.

The use of artificial intelligence to overcome the shortcomings of conventional methods for control allocation has not been explored to a significant extent in the open literature. A literature search yielded very few results, most of them not applicable to this critical need for HWB configurations. Artificial intelligence offers new ways to optimize control power while minimizing hinge moments and structural loads.

The proposed concept applies to the design and development stages of future air vehicles. If the research proves successful, artificial intelligence will be used to develop optimized control laws in a much more efficient manner than by using traditional methods; and these optimized

control laws are an enabler for an entire fleet of revolutionary aircraft. Although the control laws will be developed using artificial intelligence methods, there is no need to implement these tools on the aircraft itself; therefore, no certification issues are anticipated for such a solution.

Approach

The project applies artificial intelligence to the HWB control allocation problem to optimize control surface schedules and minimize control power. An aeroelastic finite element model (FEM) provides the baseline for stability and control (S&C) analyses. Boeing Research and Technology provided control surface data, actuator characteristics, and aeroservoelastic modeling support to generate an accurate representation of the HWB baseline. The FEM model has been used to generate a database of hinge moment and actuation power characteristics for an array of control surface deflections.

A sufficient amount of training data is a prerequisite for successfully training an ANN for control allocation and to determine the proper size and architecture of the ANN, both of which are crucial for the success of applying neurocomputing to the problem of control power optimization. Phase I of the effort focused on the development of a proof-of-concept process demonstrating the feasibility of using neurocomputing for actuation power optimization (Fig. 2).
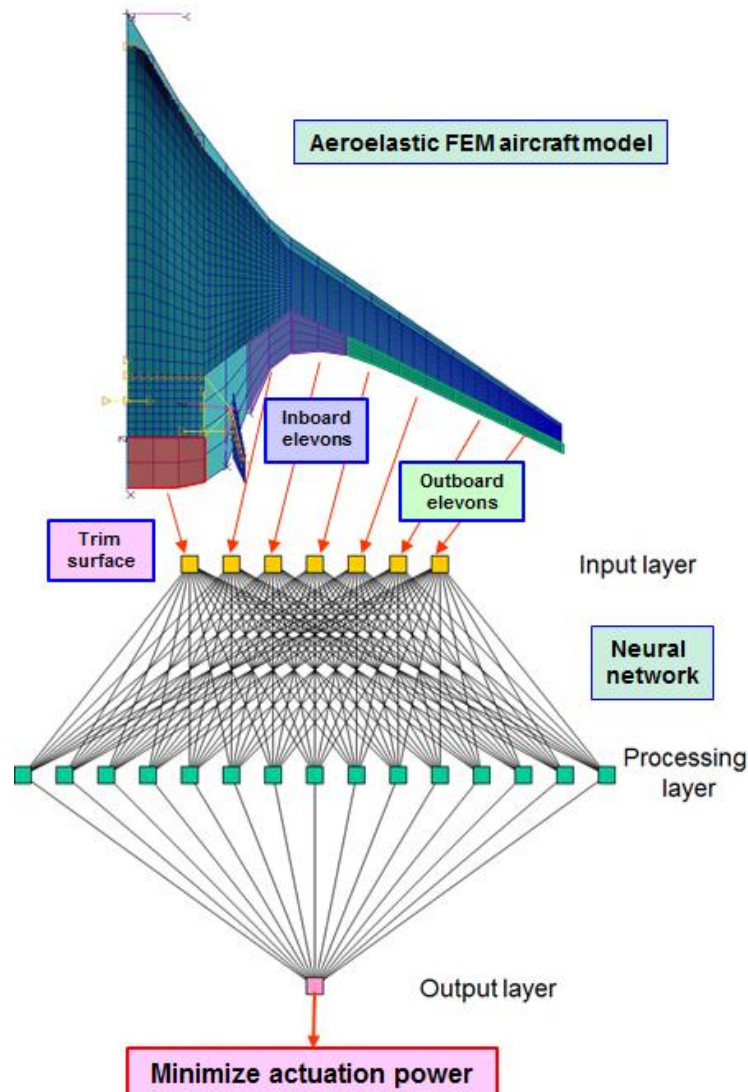

Figure 2: Using an artificial neural network for control allocation optimization.

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In the interest of maximizing the results and impact of the Phase I effort, some modeling simplifications were applied. While these limitations did not affect the validity of the Phase I results, they will be removed in the future to improve the value and practical usefulness of the approach. As will be described in the "Results" section, the total hinge moment sum from all active control surfaces was used as a proxy figure-of-merit to minimize actuation power. Future efforts will include the complete actuator dynamics developed by Boeing during the Phase I and therefore use actual actuation power as a figure of merit for the optimization. The Boeing actuator dynamics model was validated through X-48 wind tunnel and flight testing. The aeroelastic finite element analysis used a symmetric half model for an initial 2.5g pitch maneuver analysis.

Accomplishments

The main objective of the Phase I effort was to develop a proof-of-concept process suitable to demonstrate the potential of using neurocomputing to optimize actuation power for aircraft featuring multiple independently actuated control surfaces (see Fig. 3). All the proposed work tasks and milestones were completed on time and within budget. All deliverables from the project partners were received by the Principal Investigator and directly contributed to the success of the project. The project team successfully laid all the necessary groundwork to continue the initial research in a follow-on project.
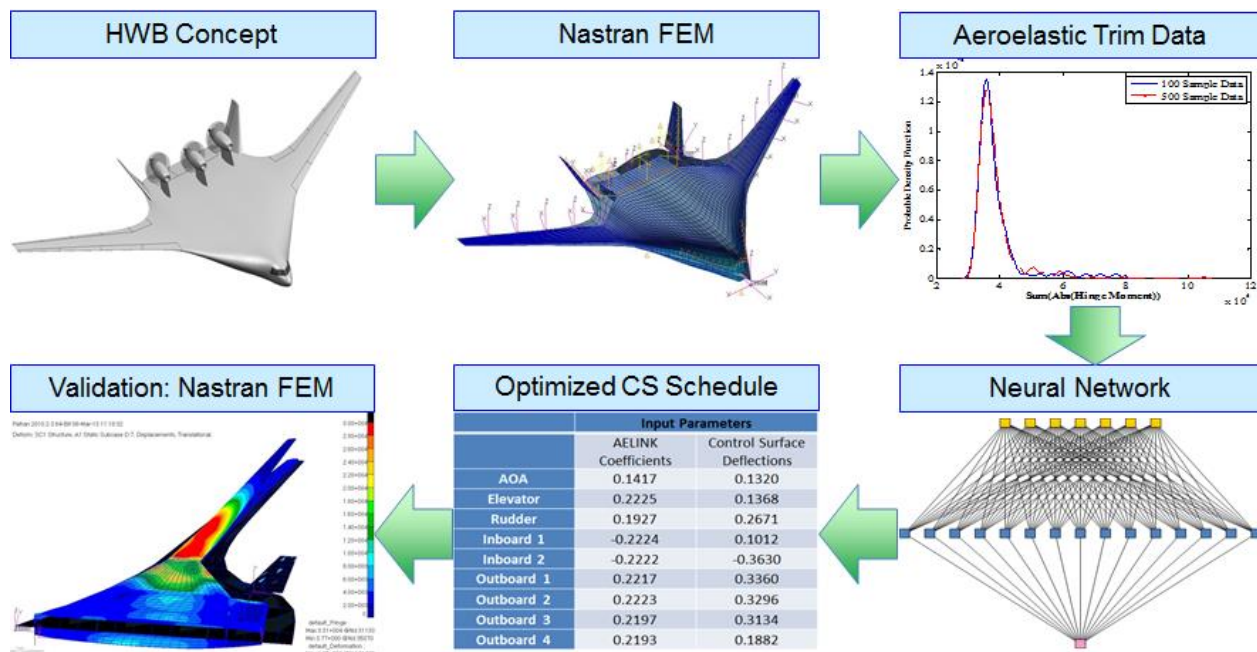

Figure 3: Proof-of-concept process to optimize actuation power through aeroservoelastic neurocomputing.

The key accomplishments from the Phase I project are outlined below:

- Established a complete proof-of-concept aeroservoelastic neurocomputing process to optimize actuation power for a representative 2.5g symmetric pitch maneuver.

- Developed a full aeroelastic model suitable for analyzing a representative HWB platform developed by Boeing. The non-proprietary Boeing OREIO (Open Rotor Engine Integration
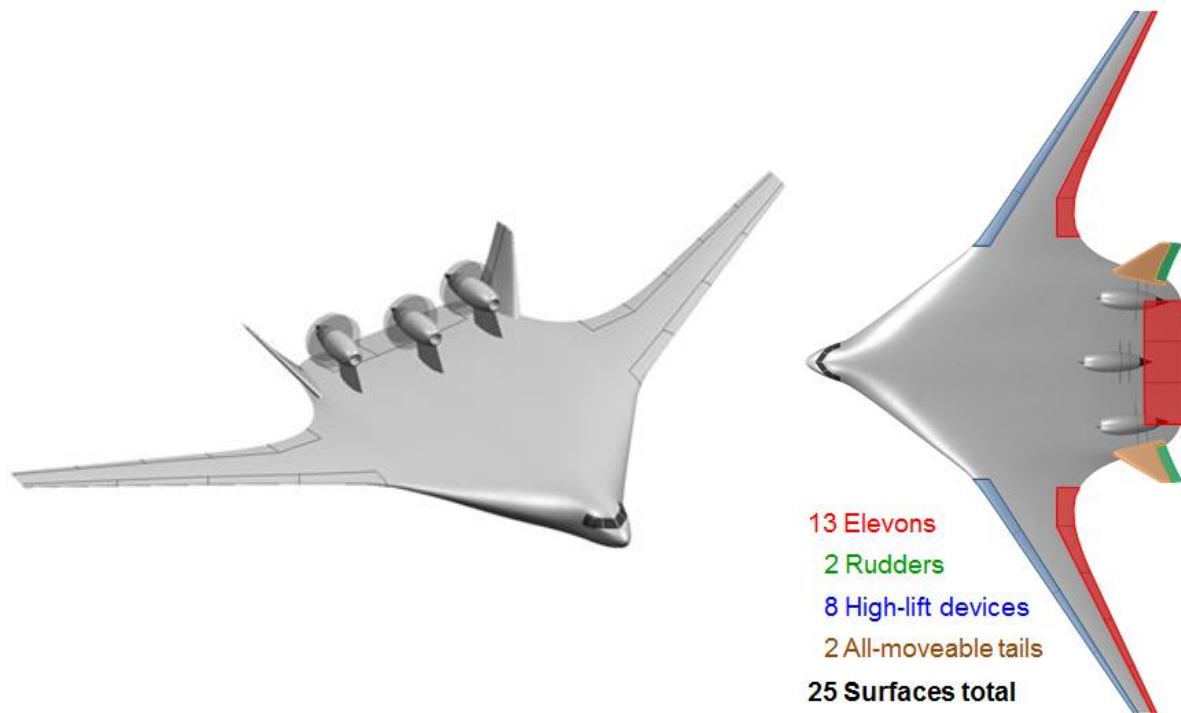
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Figure 4: The Boeing OREIO features up to 25 control surfaces and high lift devices. (OREIO = Open Rotor Engine Integration and Optimization on an HWB[9])
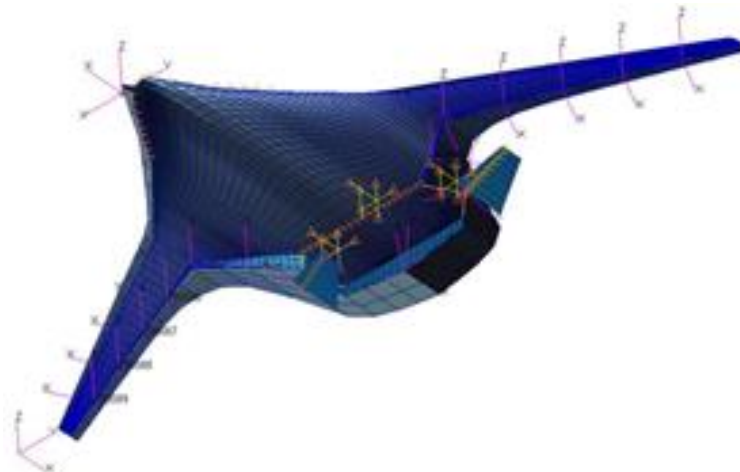

Figure 5: Finite element model of the Boeing OREIO used for the study.

and Optimization on an HWB[9]) concept was chosen for this task (see Figs. 4 and 5). Boeing provided control surface geometries and developed actuator dynamics models based on a Simulink analysis model that was validated through X-48 wind tunnel and flight testing. Details regarding the structural and aeroelastic modeling of the OREIO configuration can be found in Refs. 10 and 11.

- Generated an aeroelastic trim database containing up to 2,500 Nastran® aeroelastic TRIM[12] solutions. For this purpose, the baseline Nastran® model is used to perform a large number of maneuver-trim analyses with randomly generated linkage coefficients between the different control surfaces. Latin Hypercube Sampling is used to generate random Nastran® AELINK[12] card coefficients for each individual Nastran SOL144 static aeroelastic TRIM analysis.[13] A Matlab® script then reads trim variables, control surface deflections, and stores all this information for post-processing and optimization using artificial neural networks.

- Investigated neural network topologies (number of layers/neurons) and learning algorithms to train the neural network using the aeroelastic trim database. A neural network with one hidden layer of up to 300 neurons was chosen as the network to perform the actuation power optimization. The hidden layer neurons were trained using a hyperbolic tangent sigmoid transfer function, while a single output neuron featuring a linear transfer function represents the required actuation power.

- Optimized the neural network using a genetic algorithm to develop sets of control surface linkage coefficients minimizing the sum of all control surface hinge moments, which was the figure-of-merit used as a representation of total required actuation power.

- Quantified the optimization results by demonstrating a more than 12% improvement over the best Nastran® solution by using the neural network optimization process.

Results From the Seedling Phase I Effort:

Figure 6 shows the probability density function of the training data generated by the FEM analysis for different numbers of test cases. During the network training process, the least squares error between the pre-computed results and ANN predictions is minimized through back-propagation by adjusting the weights and biases of the individual neurons. With each generation, the fitness value is reduced until it is flattening out after about 60 generations, indicating that the neural network is fully trained at this point. A genetic algorithm is used to minimize the absolute sum of the hinge moments.
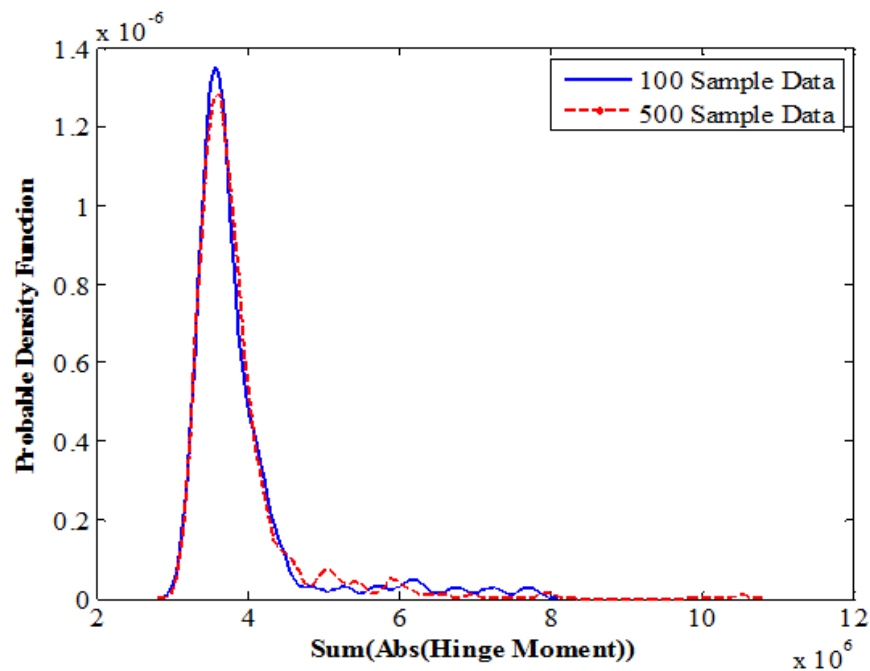

Figure 6: Training data probability density function.

The AELINK control surface linkage coefficients in Nastran® define relationships between individual control surface deflections and an "independent" control surface, which in the present case is the center "elevator" surface in Fig. 7. For this study, the range of allowable control surface deflections has been limited to the [-1,1] interval, and the overall analysis data base for the 2.5g maneuver case included 2,500 samples. Future studies will further increase this interval to avoid extrapolation on the critical AELINK coefficients.
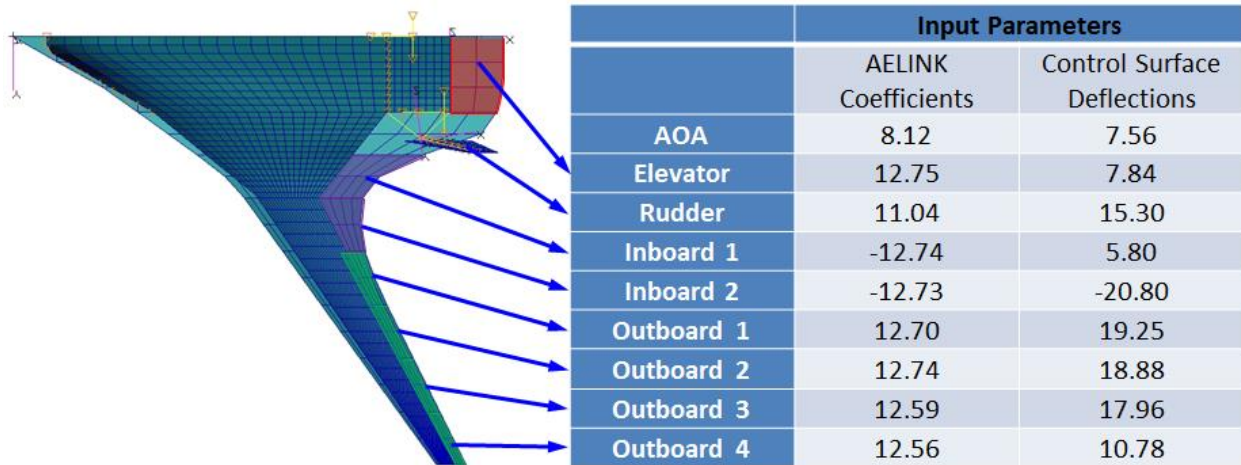
		Input Parameters	
		AELINK Coefficients	Control Surface Deflections
AOA		8.12	7.56
Elevator		12.75	7.84
Rudder		11.04	15.30
Inboard 1		-12.74	5.80
Inboard 2		-12.73	-20.80
Outboard 1		12.70	19.25
Outboard 2		12.74	18.88
Outboard 3		12.59	17.96
Outboard 4		12.56	10.78

Figure 7: Optimized control surface deflections (in degrees) for a Boeing OREIO 2.5g symmetric pitch maneuver.

The neurocomputing process was applied to a symmetric half model of the Boeing OREIO, featuring eight actuated control surfaces, i.e. seven trailing edge flaps and the rudder (Fig. 7). To improve engine noise shielding, the OREIO vertical tails are highly canted,[14] resulting in a significant amount of pitch authority for the rudder. To test the potential of the neurocomputing process, optimization of the neural network was performed using both, the AELINK control surface deflection coefficients and the direct values of the individual control surface deflection angles. The obtained control surface deflections minimizing the total hinge moment sum for both cases are highlighted in Fig. 7 and although quite similar, the deflections for both approaches are not identical, thus further highlighting the fact that different control surface deflection schedules may result in similar actuation power requirements.

Table 1 shows that for both cases, the total sum of the hinge moments is less than the best Nastran solution, with more than 12% improvement when using the control surface deflection angles as the input parameter. As a validity check, both control surface deflection data sets

	Input Parameters	
	AELINK Coefficients	Control Surface Deflections
Minimum from Aeroelastic Trim Data Set	1.7309e+06	1.7309e+06
Neural Network	**1.6579e+06**	**1.5418e+06**
Nastran Validation (SOL 144 Using NN AELINK Coefficients)	1.6600e+06	1.5418e+06
% Error	0.1242%	5.7791e-14%
Improvement over best Nastran case	4.4%	12.3%

Table 1: 2.5g Maneuver optimization results for the total sum of hinge moments (in lb-in) as a proxy for actuation power.

were used as fixed values for a Nastran® SOL 144 aeroelastic trim solution to check whether Nastran would reproduce the results when using the predictions from the optimizer. Table 1 shows that the Nastran FEM analysis for the actuation power proxy matched the neural network prediction within numerical accuracy.

Potential Impact on NASA or National Aeronautics Challenges

Reducing actuation power is an enabler for ultra-efficient commercial transport aircraft and therefore directly impacts the National Aeronautics Challenges of simultaneously reducing fuel consumption, emissions, and noise of future air traffic. HWB aircraft and other innovative concepts suitable for this research offer the potential to achieve significant fuel burn savings of over 25%, with resulting emissions reductions, as well as community noise benefits, therefore countering the impact of dramatic increases in future air traffic volume. As a result, the proposed research directly applies to three of the six ARMD Strategic Thrust areas:

- Innovation in Commercial Supersonic Aircraft
- Ultra-Efficient Commercial Transports
- Transition to Low-Carbon Propulsion

The process can easily be adapted to other innovative and unconventional configurations. Potential candidates currently under development by other NASA projects are shown below:

Low Boom Supersonic Vehicles: These vehicles have proven to be extremely difficult to trim for cruise conditions, making this an even greater challenge for maneuvers (Fig. 8). In addition, their very thin airfoils require detailed structural and aeroservoelastic models for realistic analyses, which is generally beyond the scope of traditional flight controls models.

Figure 8: NASA Low Boom Supersonic Transport Concept.

Distributed Electric Propulsion (DEP) Vehicles: The control laws required to ensure a robust transition control in pitch, roll, and yaw, while achieving high cruise aerodynamic efficiency are depending on a new approach for control allocation. Actuation power optimization is crucial on these vehicles to satisfy their stringent power management requirements and weight savings goals. In addition, multiple distributed concentrated masses and control surfaces, combined with high structural flexibility and significant configuration changes make these concepts ideal candidates for the proposed neurocomputing process. An example of a DEP vehicle is shown in Fig. 9.

Figure 9: Greased Lightning (GL-10) Distributed Propulsion (DEP) Vehicle flight demonstrator.

Changes to Current Concept of Operation for the Proposed Concept to Achieve Practical Application

The proposed concept applies to the design and development stages of future air vehicles. If the research proves successful, artificial intelligence will be used to develop optimized control laws in a much more efficient manner than by using traditional methods; and these optimized control laws are an enabler for an entire fleet of revolutionary aircraft. The proposed approach reduces power requirements, hinge moments, structural loads, and therefore overall vehicle weight, therefore allowing us to exploit the full potential of innovative aircraft with multiple distributed control surfaces.

The process is easily applicable to other innovative and unconventional configurations. Without the necessity to implement artificial intelligence on the aircraft itself, no certification issues are associated with such a solution.

Conclusions

During the course of this project the researchers developed a proof-of-concept process to demonstrate the potential of using neurocomputing for optimizing actuation power for aircraft featuring multiple independently actuated control surfaces. A Nastran® aeroservoelastic finite element model was used to generate a learning database of hinge moments and actuation power characteristics for a symmetric 2.5G pull-up maneuver using various sets of control surface deflections. An artificial neural network incorporating a genetic algorithm then used this training data to perform control allocation optimization for the investigated aircraft configuration. The phase I project showed that optimization results for the sum of required hinge moments are improved by more than 12% over the best Nastran® solution by using the neural network optimization process.

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References

1. Cameron, D. and Princen, N., "Control Allocation Challenges and Requirements for the Blended Wing Body," AIAA Paper 2000-4539, AIAA Guidance, Navigation, and Control Conference and Exhibit, August 14-17, 2000, Denver, CO.
2. Haykin, S., Neural Networks - A Comprehensive Foundation, 2nd Edition, Prentice Hall, July 1998.
3. Ansari, N., Hou, E., Computational Intelligence for Optimization, Kluwer Academic Publishing Group, Norwell, MA, 1997.
4. Tagliarini, G.A., Christ, J.F., and Page, E.W., "Optimization Using Neural Networks," IEEE Transactions on Computers, Vol. 40, No. 12, Dec. 1991, pp. 1347-1358.
5. Risch, T., Cosentino, G., Regan, C.D., Kisska, M., and Princen, N., "X-48B Flight-Test Progress Overview," AIAA-2009-0934, 47th AIAA Aerospace Sciences Meeting and Exhibit, January 5-8, 2009, Orlando, Florida.
6. Collier, F. S., Thomas, R, Nickol, C. A., Lee, Chi-Ming, Tong, M. "Environmentally Responsible Aviation - Real Solutions for Environmental Challenges Facing Aviation, 27th International Congress of the Aeronautical Sciences, Paper No. 802, Nice, France, 19-24 September, 2010.
7. Liebeck, R.H., "Design of the BWB Subsonic Transport", AIAA-2002-0002, 40th AIAA Aerospace Sciences Meeting and Exhibit, January 14-17, 2002, Reno, NV.
8. Gatlin, G.M., Vicroy, D.D., and Carter, M.B., "Experimental Investigation of the Low-Speed Aerodynamic Characteristics of a 5.8-Percent Scale Hybrid Wing Body Configuration," AIAA Paper 2012-2669, 30th AIAA Applied Aerodynamics Conference, June 25-28, 2012, New Orleans, LA.
9. Pitera, D.M., DeHaan, M., Brown, D., Kawai, R.T., Hollowell, S., Camacho, P., Bruns, D., and Rawden, B.K., Blended Wing Body Concept Development with Open Rotor Engine Integration, NASA/CR–2011-217303, The Boeing Company, Huntington Beach, California, November 2011.
10. Gern, F.H., "Finite Element Based HWB Centerbody Structural Optimization and Weight Prediction," AIAA-2012-1606, 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference, April 23-26, 2012, Honolulu, Hawaii.
11. Gern, F.H., "Conceptual Design and Structural Analysis of an Open Rotor Hybrid Wing Body Aircraft," AIAA Paper 2013-1688, 54th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference, April 8-11, 2013, Boston, Massachusetts.
12. MSC Nastran 2008, Quick Reference Guide, MSC Software Corporation, 2 MacArthur Place, Santa Ana, CA 92707, USA, 2008.
13. Rodden, W.P. and Johnson, E.H. (Editors), MSC.Nastran Version 68, Aeroelastic Analysis User's Guide, MSC Software.
14. Thomas, R.H., Burley, C.L., Lopes, L.V., Bahr, C.J., Gern, F.H., and Van Zante, D.E., "System Noise Assessment and the Potential for a Low Noise Hybrid Wing Body Aircraft with Open Rotor Propulsion," AIAA Paper 2014-0258, 52nd Aerospace Sciences Meeting, SciTech 2014, January 13-17, 2014, National Harbor, Maryland.

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14. ABSTRACT

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15. SUBJECT TERMS

Actuation power; Aeroelasticity; Artificial intelligence; Fight controls; Finite element; Neurocomputing; Structures

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