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Artificial Intelligence Based Control Power Optimization on Tailless Aircraft

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NASA Aeronautics Research Mission Directorate (ARMD)

2014 Seedling Technical Seminar

February 19–27, 2014

Outline

- Innovation
- Project Team
- Technical Approach
- Results from The Phase I Seedling Effort
- Potential Impact of the Innovation
- Distribution/Dissemination
- Next Steps
- Conclusions

Innovation

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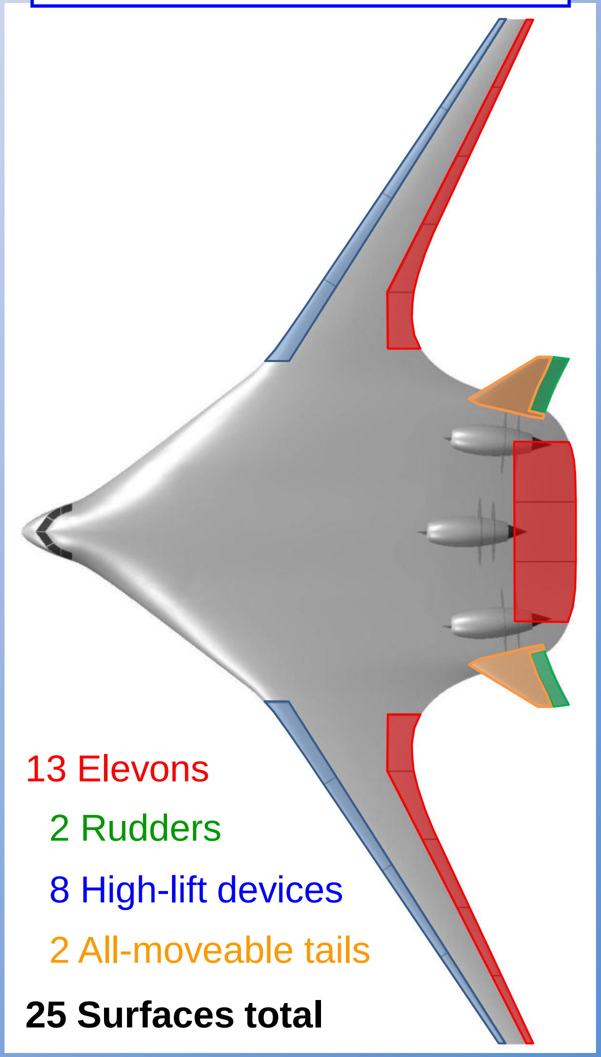
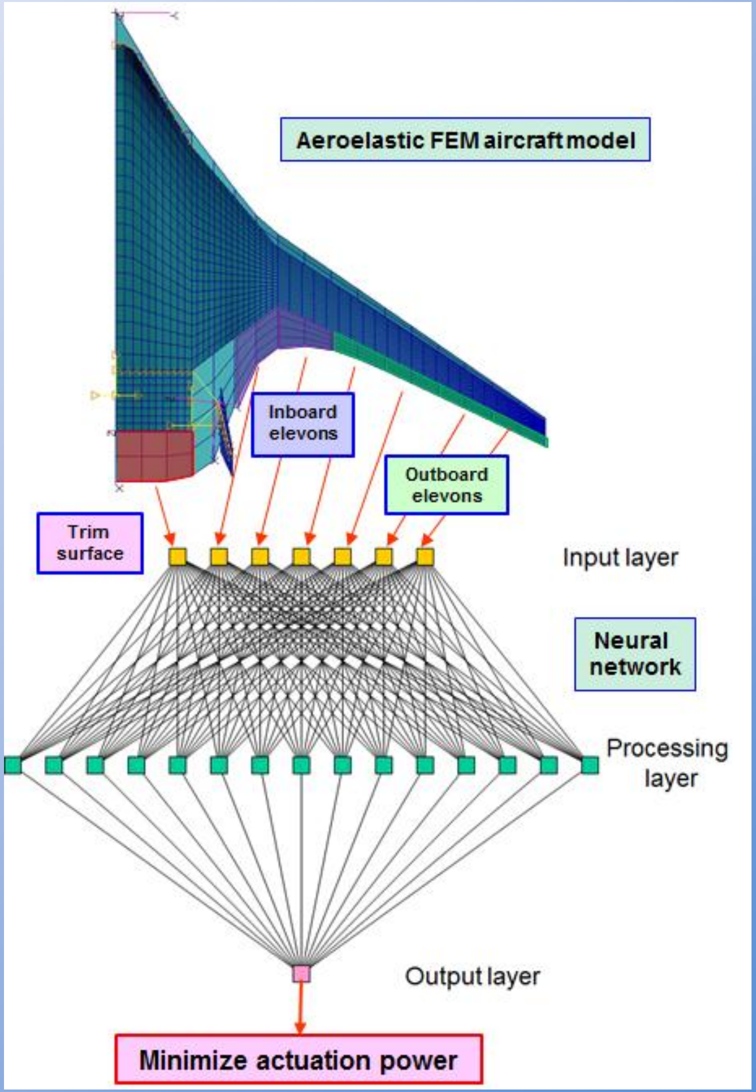
- Problem Statement:
  - Hybrid Wing Body aircraft feature multiple control surfaces
  - Very large control surface geometries can lead to large hinge moments, high actuation power demands, and large actuator forces/moments
  - Due to the large number of control surfaces, there is no unique relationship between control inputs and aircraft response
  - Different combinations of control surface deflections may result in the same maneuver, but with large differences in actuation power

Boeing OREIO HWB Concept



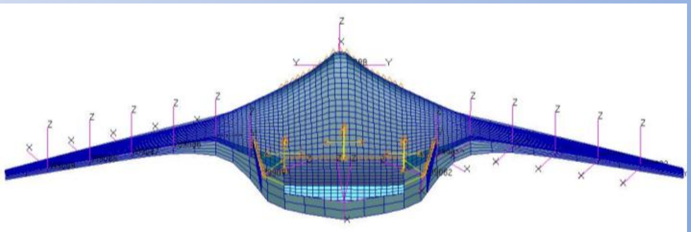
Innovation Cont'd

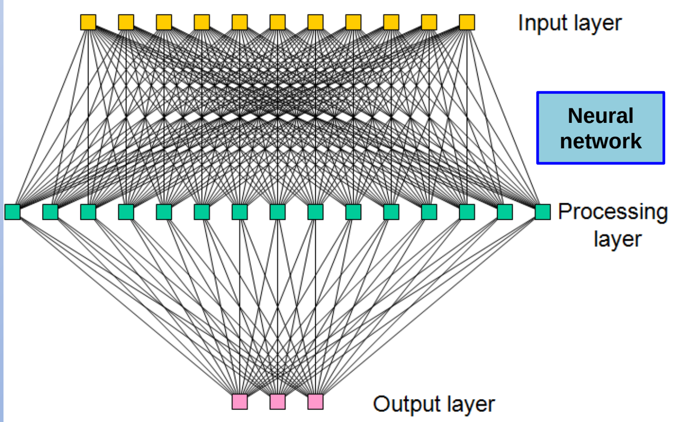
- Proposed Solution
  - Apply artificial intelligence methods to the HWB control allocation problem
  - Use artificial neural networks (ANN) to develop innovative control surface schedules
  - Fully flexible aeroelastic finite element model for complete structural and aerodynamic vehicle representation
  - Reduce actuation power
  - Minimize hinge moments and actuator loads
  - Minimize structural loads



Project Team

- NASA Langley Research Center
  - Frank H. Gern (PI), Dan D. Vicroy, Michael R. Sorokach
  - Project management
  - Aeroservoelastic finite element modeling
- Virginia Polytechnic Institute and State Univ.
  - Rakesh K. Kapania, Joseph A. Schetz, Sameer Mulani, Rupanshi Chhabra
  - Finite element analysis
  - Neurocomputing and actuation power optimization
- Boeing Research and Technology
  - Norman H. Princen, Derrell Brown
  - Actuator dynamics, control surface geometry, effectiveness, and deflection limits
  - Provide wind tunnel and flight test data





Technical Approach

- Main Objective:
  - **Develop a proof-of-concept process showing that Neurocomputing can be applied to minimize actuation power!**
- Key Accomplishments
  - Established complete process for single DOF maneuver
  - Developed suitable aeroelastic model
  - Generated aeroelastic trim database
  - Trained neural network using training database
  - Optimized neural network using genetic algorithm
  - Quantified optimization results

Process Flow

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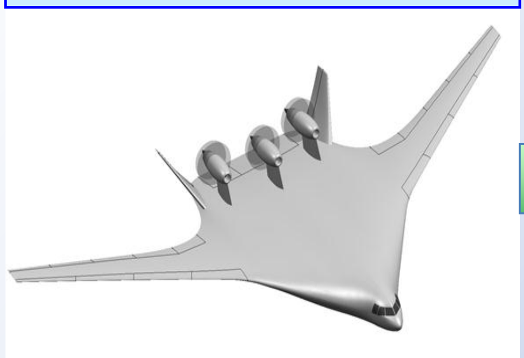
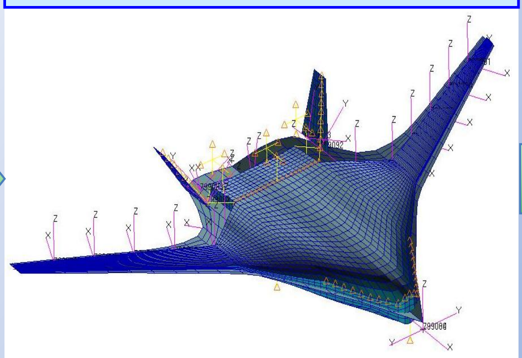
- Developed a complete semi-automatic process from design concept to optimized control surface schedule

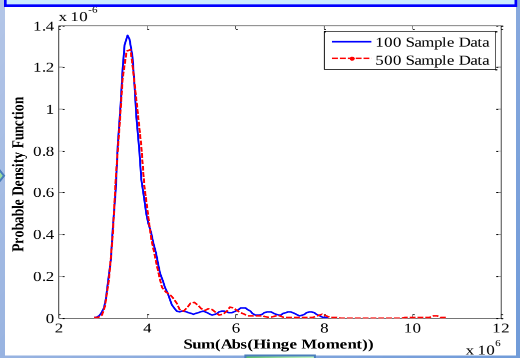
HWB Concept



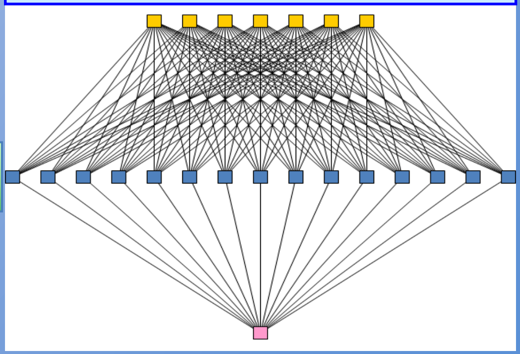
Nastran FEM



Aeroelastic Trim Data



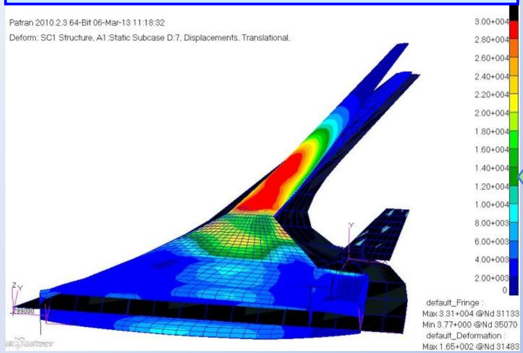
Neural Network



Optimized CS Schedule

	Input Parameters	
	AELINK Coefficients	Control Surface Deflections
AOA	0.1417	0.1320
Elevator	0.2225	0.1368
Rudder	0.1927	0.2671
Inboard 1	-0.2224	0.1012
Inboard 2	-0.2222	-0.3630
Outboard 1	0.2217	0.3360
Outboard 2	0.2223	0.3296
Outboard 3	0.2197	0.3134
Outboard 4	0.2193	0.1882

Validation: Nastran FEM



Aeroelastic Model

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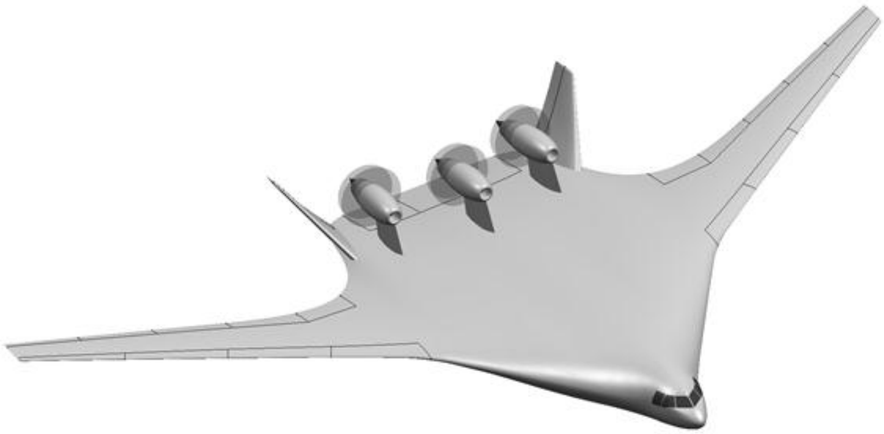
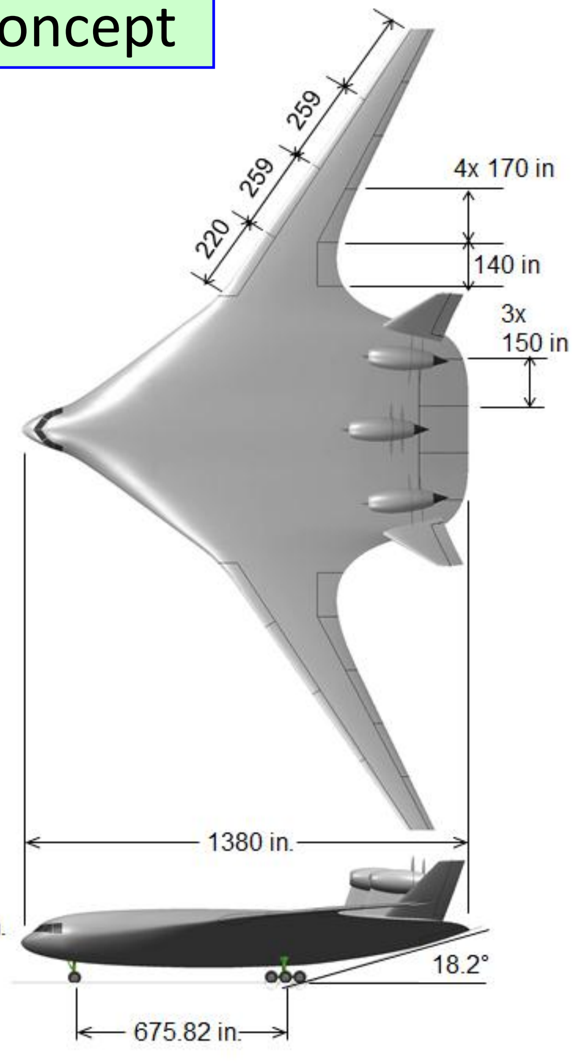
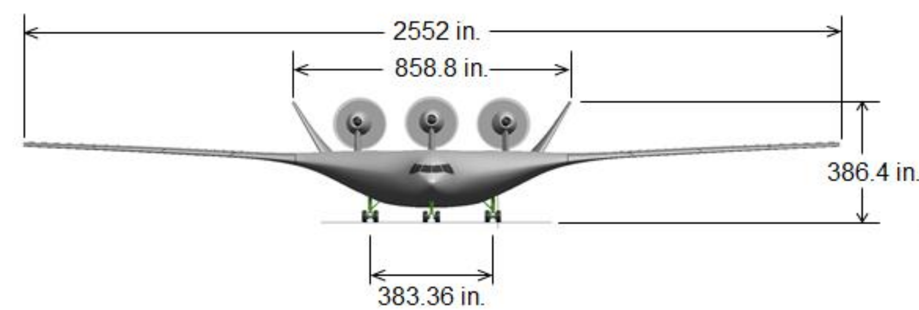
Boeing OREIO Hybrid Wing Body Concept

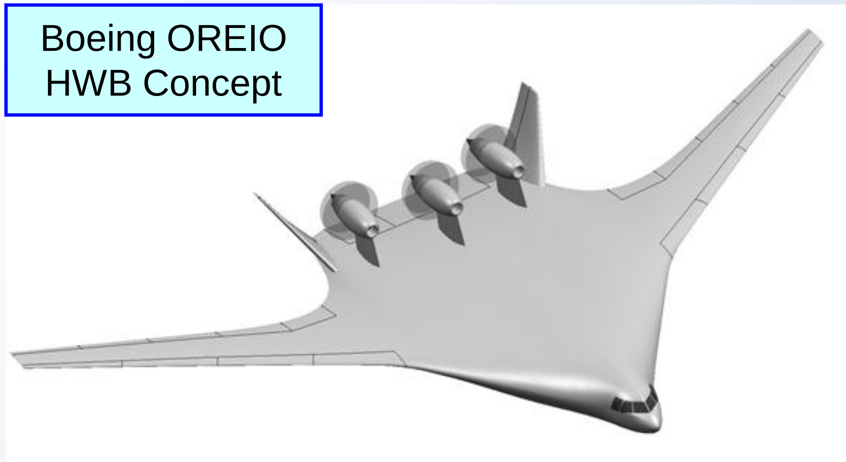


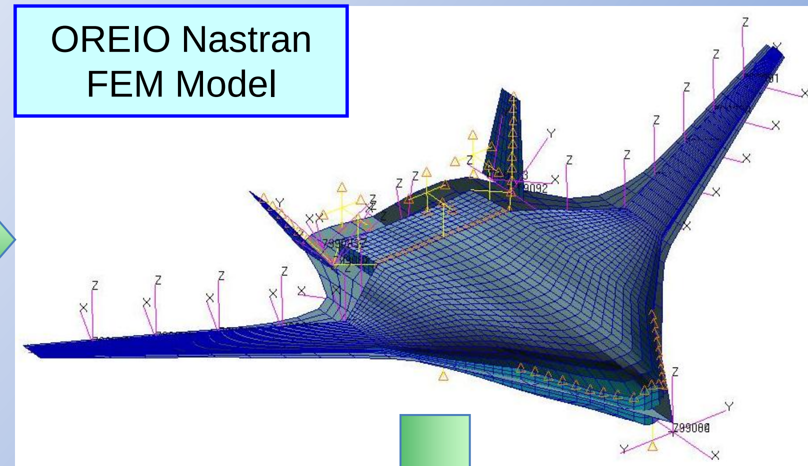


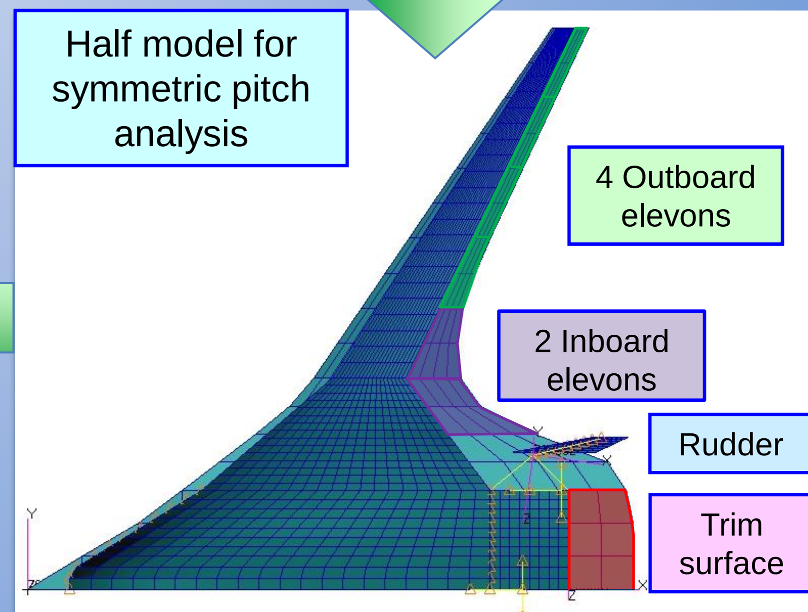
OREIO = Open Rotor Engine Integration on an HWB (Non-proprietary configuration)
Wing span 212.7ft, TOGW 475,800lb
NASA-CR-2011-217303



Aeroelastic Model Cont'd







- Fully flexible aeroelastic FEM Model
- 8 independently actuated control surfaces
- Control surface linkage coefficients (AELINK) randomly generated for aeroelastic trim database
- Generate stability and control derivatives and hinge moments
- Each solution is a trimmed condition

Neural Network Training Data

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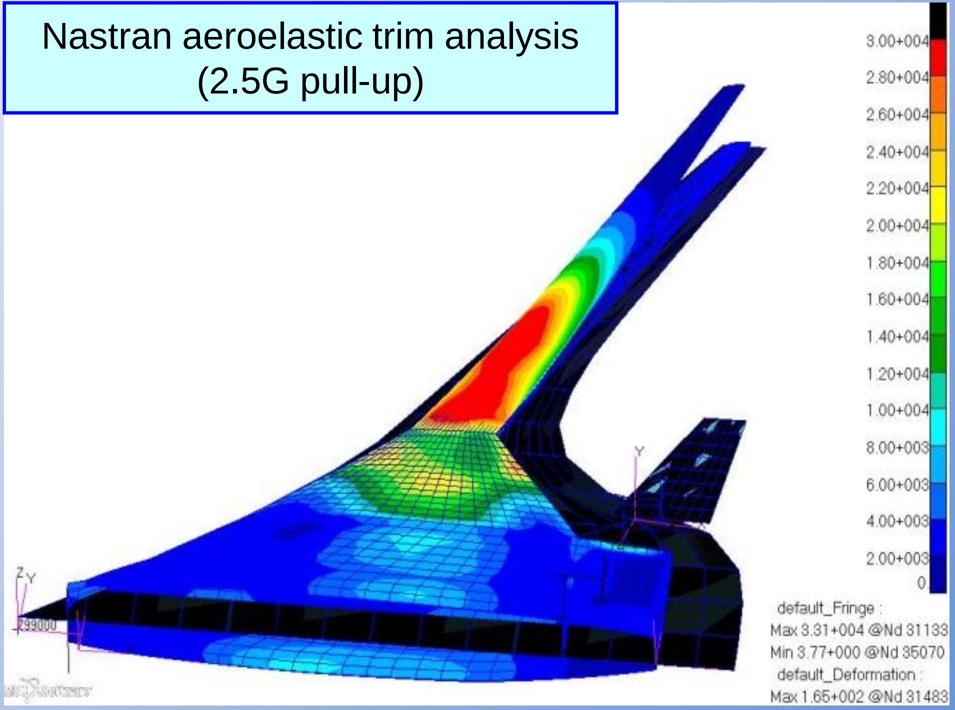
- Test case: 2.5G symmetric pull-up
  - High wing loading, large deformations
  - Structural flexibility not negligible
- Symmetric halfmodel
- All control surfaces are active
  - 7 trailing edge elevons, 1 rudder
- Run Nastran aeroelastic TRIM solution (SOL 144)
  - Random sets of control surface linkage coefficients (AELINK)
  - Up to 2500 runs (runtime: ≈ 5sec/run)



Nastran aeroelastic trim analysis (2.5G pull-up)

- Store linkage coefficients, control surface deflections and hinge moments in aeroelastic trim database
- Figure of merit: Absolute hinge moment sum
  - ≈ proportional to actuation power
  - Hinge moment x deflection = actuation energy
  - Hinge moment x deflection rate = actuation power

Neural Network Training Data

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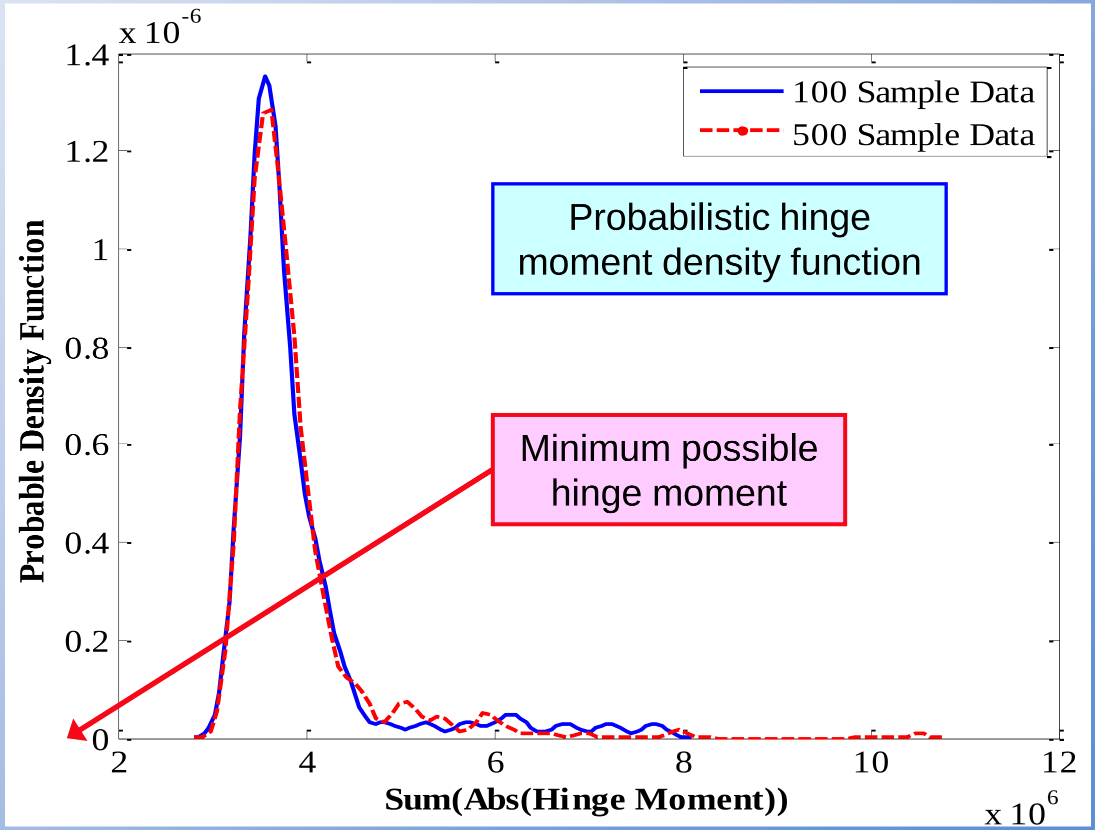
- Check database suitability for neural network training
  - Probabilistic density function of hinge moment data
  - Data is distributed evenly enough for neural network training
- Training database contains
  - Hinge moments for each individual control surface
  - AELINK control surface linkage coefficients
  - Control surface deflections
  - Up to 2500 trimmed maneuver data sets
- Use neural network to find the best possible minimum



Neural Networks Background

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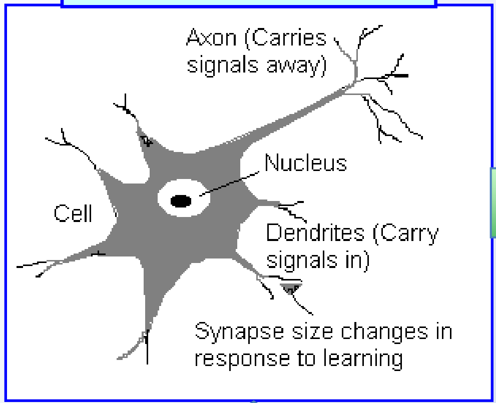
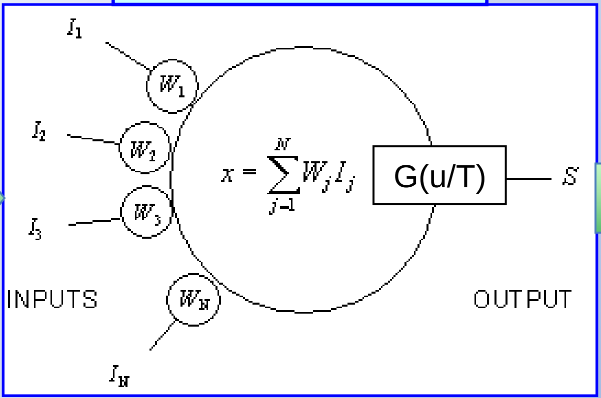
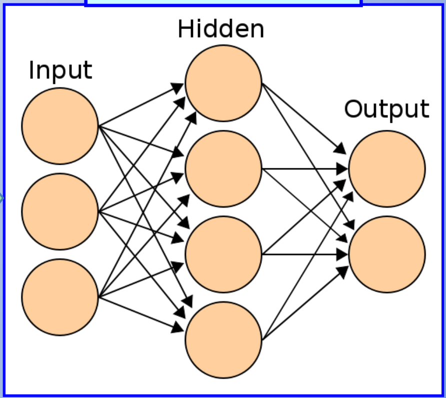
Biological Neuron[2]



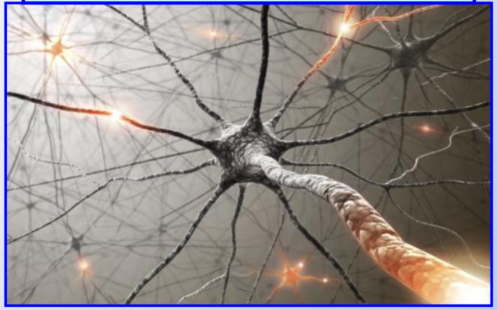
Artificial Neuron[2]



Simple ANN[3]



Human brain contains ≈86-100 billion neurons[1]



- Artificial Neural Networks (ANN) are inspired by the functionality of biological nervous structures.
- Training the ANN is accomplished by adjusting the synaptic weights at the neurons, i.e. numerical optimization of a nonlinear function.
- Optimization generally achieved through simulated annealing or genetic algorithms.
- Neural networks have successfully been applied to a wide variety of multidimensional engineering optimization problems.

Image credits: [1]iDesign, Shutterstock
[2]http://ulcar.uml.edu/~iag/CS/Intro-to-ANN.html
[3]http://digital-mind.co/post/artificial-neural-network-tutorial

Neural Network Architecture

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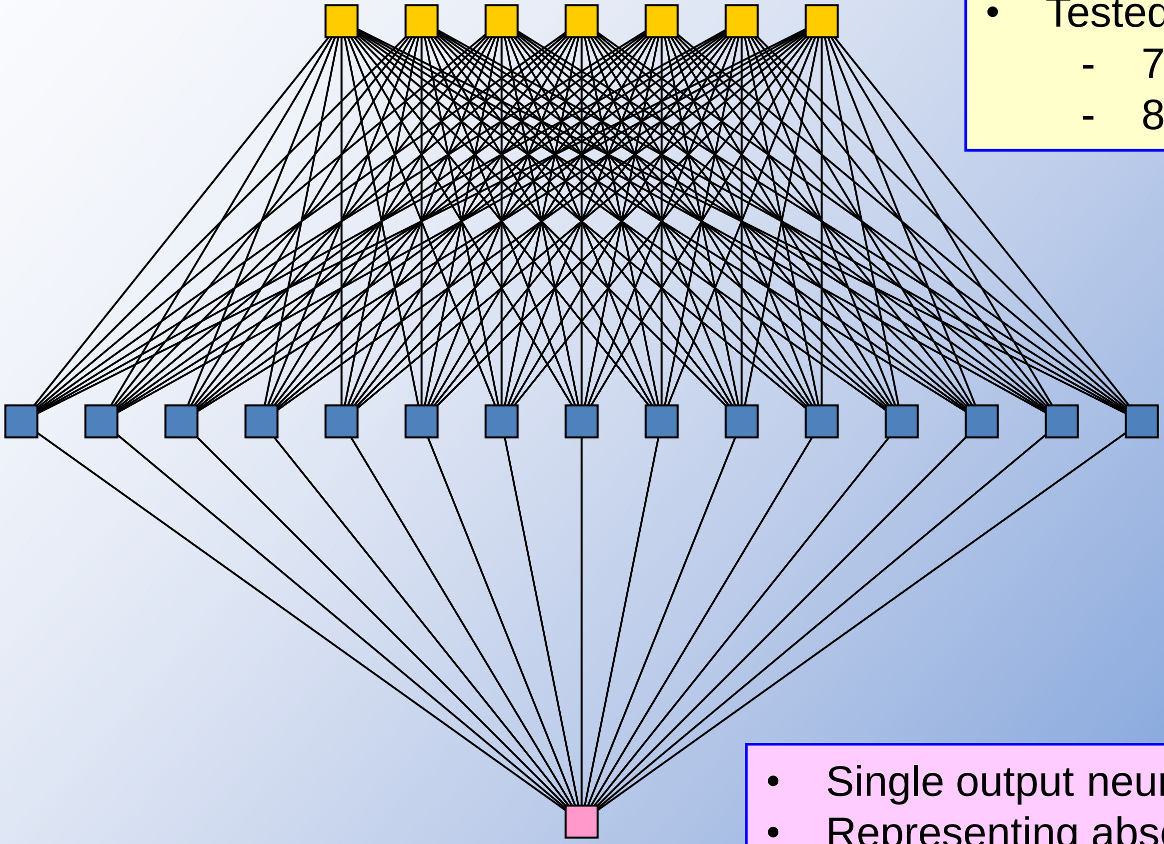
- ANN implemented in Matlab neural network toolbox



- 7 or 8 Input Neurons
- Tested different input parameters
  - 7 AELINK coefficients
  - 8 Control surface deflections

- Tested different numbers of Hidden Neurons (120-300)
- Tested two hidden layer transfer functions with similar results
  - log sigmoid (log-sig)
  - hyperbolic tangent sigmoid (tan-sig)

- Single output neuron
- Representing absolute hinge moment sum

Neural Network Training

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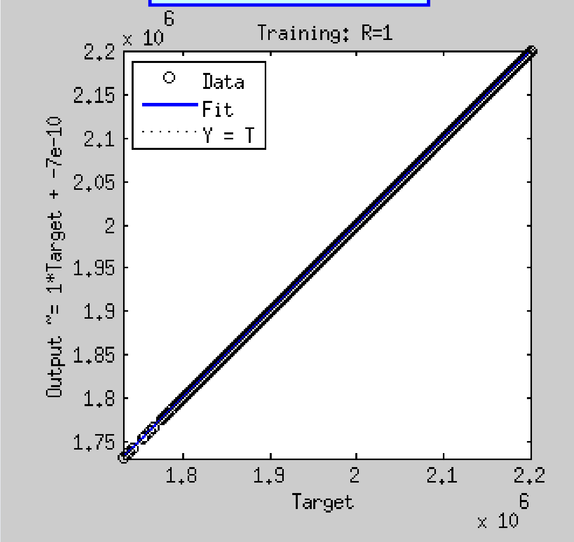
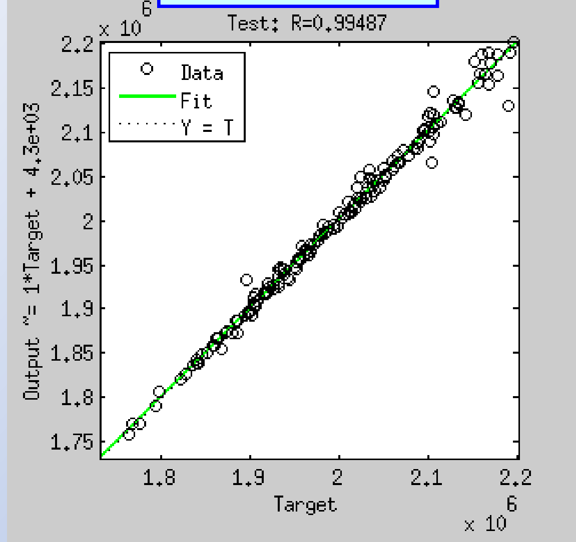
- ANN trained through backpropagation using Genetic Algorithm

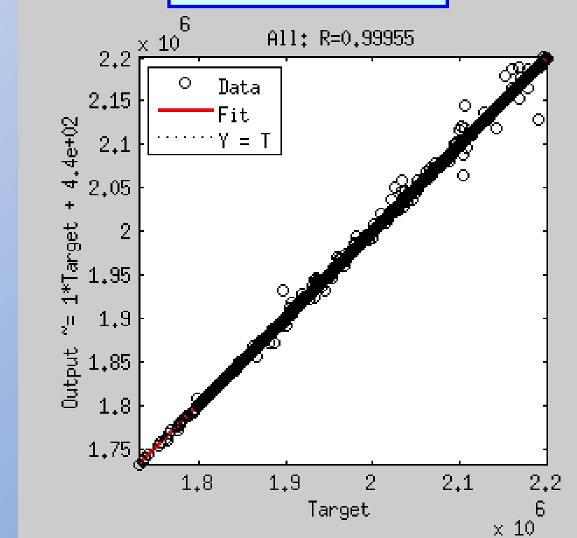
Training



Test



Full Data Set



- Input Param.: Control Surface Deflections
- Output Param.: Absolute Sum of Hinge Moments
- Data Samples: 1782
- Number of Neurons : 300
- Hidden Layer Transfer Function : Log-Sig

- Data subset used for NN training
- Testing using remaining data
- Excellent fit for complete data set
- **"Neural Network has successfully learned Nastran!"**

Optimization Results

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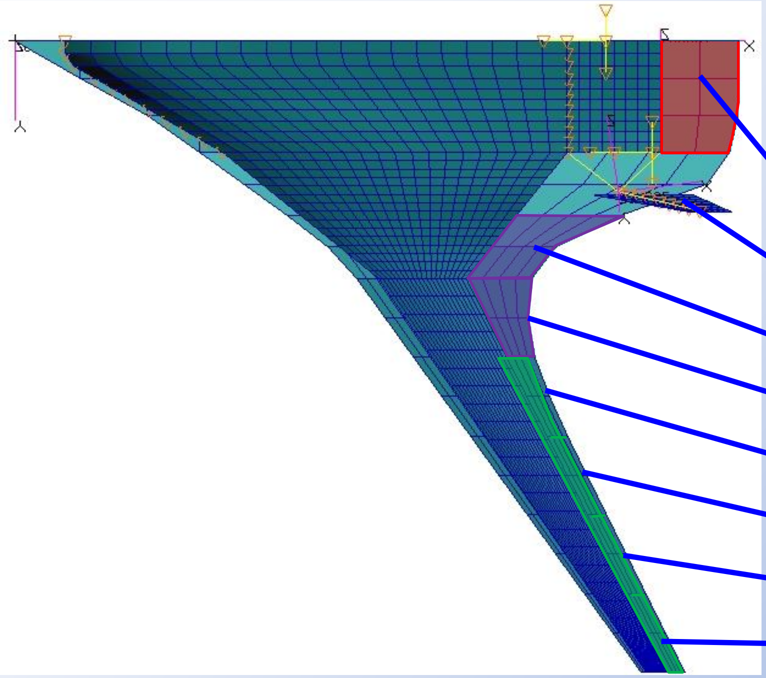
- Control Surface Deflections (degrees)



	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

- Optimum solution depends on input parameter
  - Two different control surface schedules
  - Underlines problem of non-unique control surface schedules for same maneuver!

Optimization Results

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- Absolut Sum of Hinge Moments (lb-in)

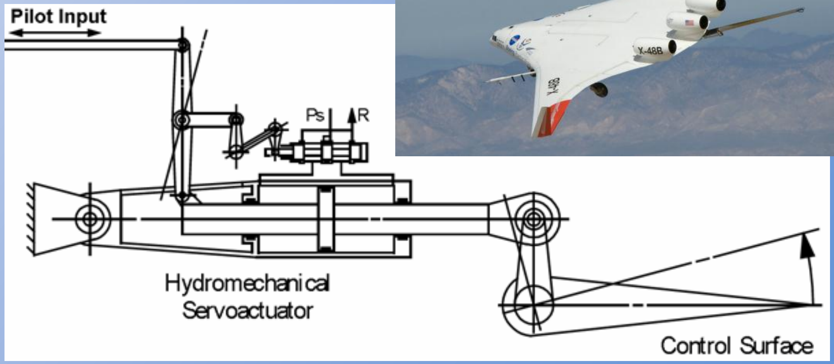
	Input Parameters	
	AELINK Coefficients	Control Surface Deflections
Minimum from Aeroelastic Trim Data Set	1.7309e+06	1.7309e+06
Neural Network	**1.6579e+06**	**1.5418e+06**
Nastran Validation (SOL 144 Using NN AELINK Coefficients)	1.6600e+06	1.5418e+06
% Error	0.1242%	5.7791e-14%
Improvement over best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

- Using control surface deflections results in lower hinge moment sum
- More than 12% improvement over best Nastran SOL 144
- For both cases: exact match between Neural Network prediction and Nastran validation!

Boeing Actuator Dynamics Analysis

- Developed for BWB-450-1L full scale airplane piloted low speed flight dynamics simulation
- Validated through X-48 wind tunnel and flight testing
- Implemented in Matlab/Simulink
- Tool has been modified for OREIO actuator dynamics analysis
- Model suitable for
  - actuator sizing
  - actuator dynamics
  - actuator stiffness/damping
  - control surface geometry
  - control surface effectiveness
  - deflection limit analysis
- Results will be used for transition from hinge moment analysis to actuation power calculations (Phase II)

Boeing Actuator Model and X-48B Blended Wing Body Demonstrator



Potential Impact of the Innovation

- Reducing actuation power is an enabler for ultra efficient commercial transport aircraft and therefore directly impacts the National Aeronautics Challenges
- Research applies to three of the six ARMD Strategic Thrust areas
  - Innovation in Commercial Supersonic Aircraft
  - Ultra-Efficient Commercial Transports
  - Transition to Low-Carbon Propulsion
- Approach reduces power requirements, hinge moments, structural loads, and therefore overall vehicle weight
- Process suitable to exploit full potential of multiple distributed control surfaces
- Process is easily applicable to other innovative and unconventional configurations

Boeing/NASA HWB Concept

Potential Impact of the Innovation

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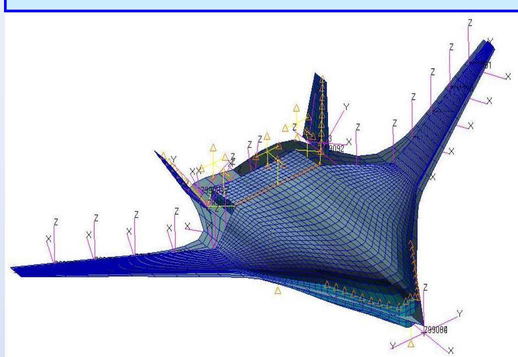
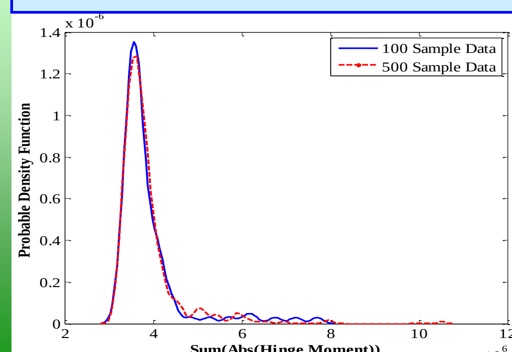
- Process is configuration independent and can be applied to any vehicle type!
  - Builds on aeroelastic models that usually already exist in a conceptual or preliminary design structural sizing effort
  - Does not require to setup a Nastran SOL 200 optimization problem (which can be very tedious and time consuming)
  - Only interface between FEM analysis and neural network optimizer is aeroelastic trim database (can be generated via Nastran batch routine)
- These benefits even outweigh the benefits in reduced computational time!

Nastran FEM

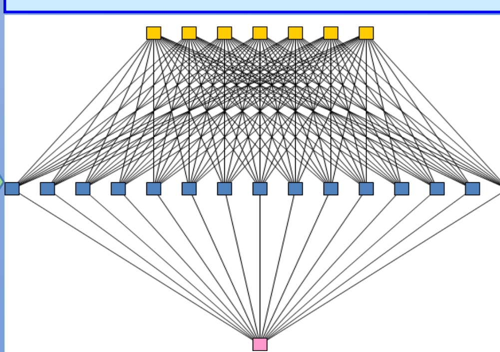


Process Interface

Aeroelastic Trim Data



Neural Network



Potential Impact of the Innovation

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- Process can easily be applied to other vehicles!
- Low Boom Supersonic Vehicles
  - Very difficult to trim even for cruise conditions, more challenging for maneuvering
  - Extremely thin airfoils require detailed structural models and aeroservoelastic models for realistic analysis
  - Beyond the scope of traditional flight controls models
- Distributed Electrical Propulsion (DEP)
  - Robust transition control across pitch, roll, yaw while achieving high cruise aerodynamic efficiency
  - Distributed concentrated masses
  - High structural flexibility
  - Significant configuration changes in flight

NASA Low Boom Supersonic Transport Concept

Greased Lightning DEP Demonstrator

LEAPTech DEP General Aviation Concept

Distribution/Dissemination

- Planned Publications
  - Parametric Finite Element Model for Hybrid Wing Body Structural Optimization and Aeroservoelastic Analysis, AIAA SciTech Conference, January 5-9, 2015, Orlando, FL.
  - An Artificial Intelligence Based Process for Actuation Power Optimization on Tailless Aircraft, AIAA SciTech Conference, January 5-9, 2015, Orlando, FL.
- Projects Suitable for Technology Infusion
  - Distributed Electrical Propulsion (DEP)
  - High-Speed System Level Tools and Methods Development (Supersonics Research)
  - Environmentally Responsible Aviation (ERA)
  - Fixed Wing (FW)

Next Steps

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- Update FEM to full aeroservoelastic model
  - Incorporate Boeing Phase I actuator and control surface sizing
  - Include actuator dynamics for full aeroservoelastic FEM
  - Switch to full model for arbitrary/asymmetric maneuver analysis (engine out, dynamic overswing, sideslip)
- Apply Phase I process to complete maneuvers (e.g. pull-up 1g→2.5g)
  - Quasi-steady approach, compute deflection schedule for each g increment
  - Calculate actuation energy
  - Compare with conventional control surface schedule
  - Additional figures of merit (stresses, deformations, structural loads, weight)
- Switch from quasi-steady approach to full dynamic model
  - Develop state space model from Nastran aeroservoelastic analysis
  - Apply neurocomputing approach to dynamic state space model
  - Compare results and show potential of ANN process
- Develop neurocomputing process into a full user friendly tool
  - Can easily be leveraged into other projects (e.g. supersonics, DEP, etc.)
  - Compliance with NASA software development process
  - Provide Nastran batch wrapper, documentation, manual, validation, GUI, etc.

Conclusions

- Developed a proof-of-concept process to apply artificial intelligence to minimize actuation power
- Applied neural network optimization to fully aeroelastic finite element flight controls model
- Accomplished >12% improvement over best Nastran solution
- Process is independent of vehicle configuration
- Significantly reduced processing and setup time (no Nastran optimization required)
- Laid all the necessary ground work for a successful Phase II project

Backup Slides

Project Schedule

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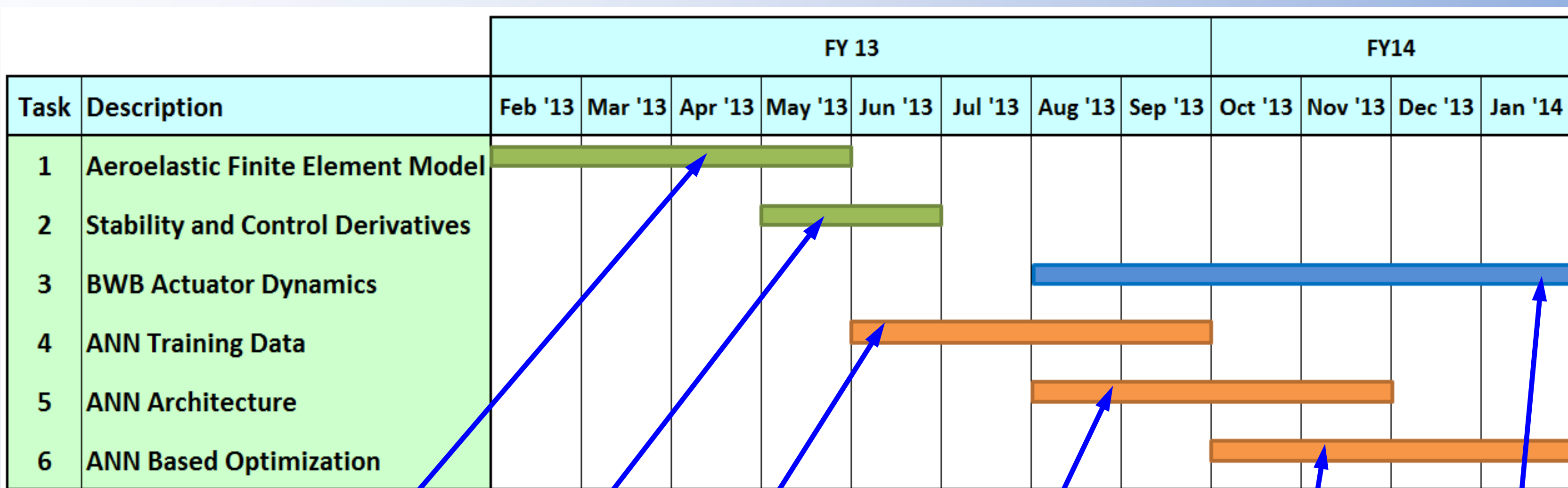
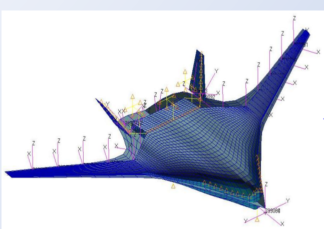
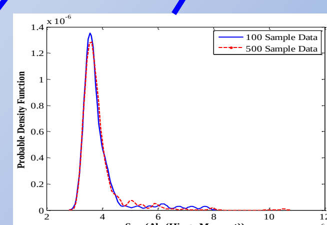
- All work tasks were successfully completed







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