Challenges with Adopting New Material and Process Technologies: An Open Manufacturing Approach

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Briefing prepared for IWSHM

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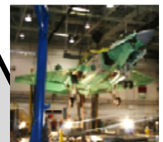
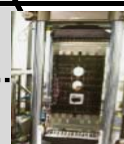
Typical DoD Qualification/Certification Approach

Building Block Test Structure Required for Certification

size scale





		Specimen Count	Cost ($M)	Time (Yrs)
Analysis validation	**Full-scale article**	2-3	100-125	4
	Components	10-30	10-20	3
Design-value development	**Sub-components**	25-50	10-35	3
	Elements	2000-5000	10-35	3
Material property evaluation	**Coupons**	5000-100,000	8-15	2

Comprehensive understanding of manufacturing variation at different scales is needed

Current Approach Does Not Capture Impact of Manufacturing Variability Across Size Scales

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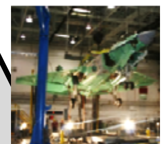
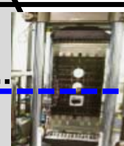
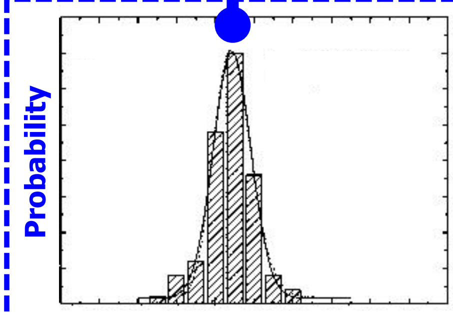




- **Collect statistically valid populations of properties for small size specimens**
- **Base larger scale structure designs on <u>measured material character</u>**



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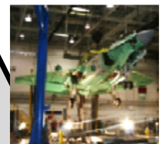

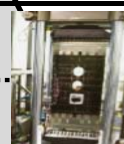

Effects of scale-up are not captured until the sub-component / component level testing

Redesign/Rework Iterations result in budget escalation and schedule delays

Impact: Contemporary platforms reuse traditional approaches to reduce the cost and risk of qualifying new technology

Comprehensive understanding of manufacturing variation at different scales is needed

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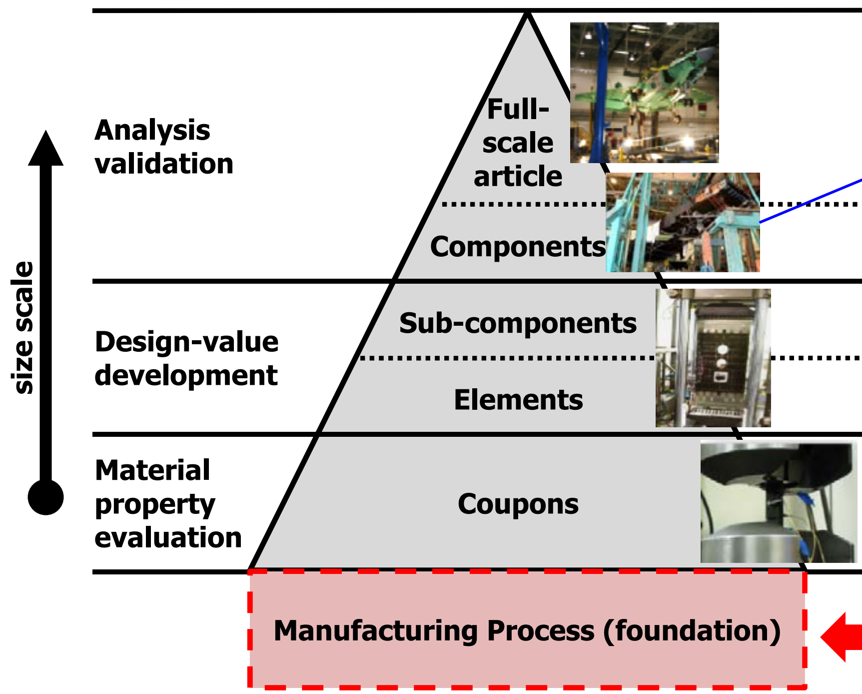

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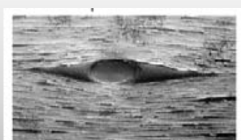
Impact: Contemporary platforms reuse traditional approaches to reduce the cost and risk of qualifying new technology

Impact of Manufacturing Parameters and Variability on material properties are never captured, understood, or controlled

Comprehensive understanding of manufacturing variation at different scales is needed

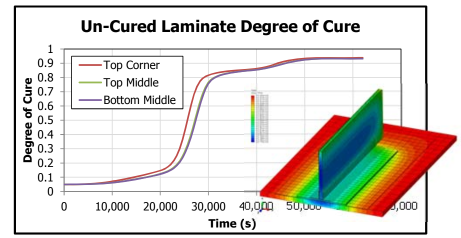
New Manufacturing Technologies: Perception is *NOT* Reality

	Perception: PROMISE	**Reality: CHALLENGE**
Metal Additive Manufacturing	 Greater component design flexibility, lower buy-to-fly ratio, no tooling required	 Current manufacturing environment does not capture process data; poor understanding and control of materials, machines, and processes
Bonded Composites	 Unitized structures; reduced cost, weight, part count, time, and labor	 Bonded parts also bolted; adhesive treated as env. sealant; quantify process control for manual process
Structural Health Monitoring	 Real time condition of structure; condition based maintenance; reduced life cycle costs	 Optical fiber at 30° to fiber Embedded systems act as defect centers; data acquisition and processing; space, weight, and power on platform

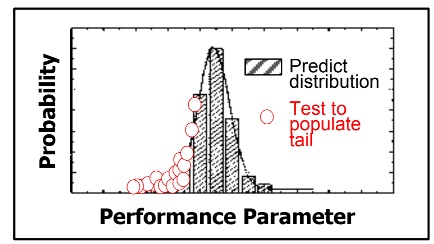
Challenges are barrier to transitioning technologies to production

Open Manufacturing Approach and Goals

Probabilistic sensing and routine data-capture capabilities that can be transferred to manufacturing environment

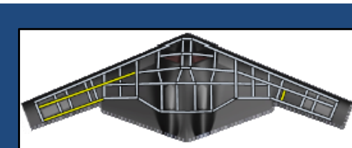


Maturing multi-physics and data-based models allow for understanding of process/microstructure/property relationships



New probabilistic frameworks and verification and validation techniques can link data sources and simulation modules to output product performance with quantified uncertainty

Location specific probabilistic description of product performance for rapid qualification

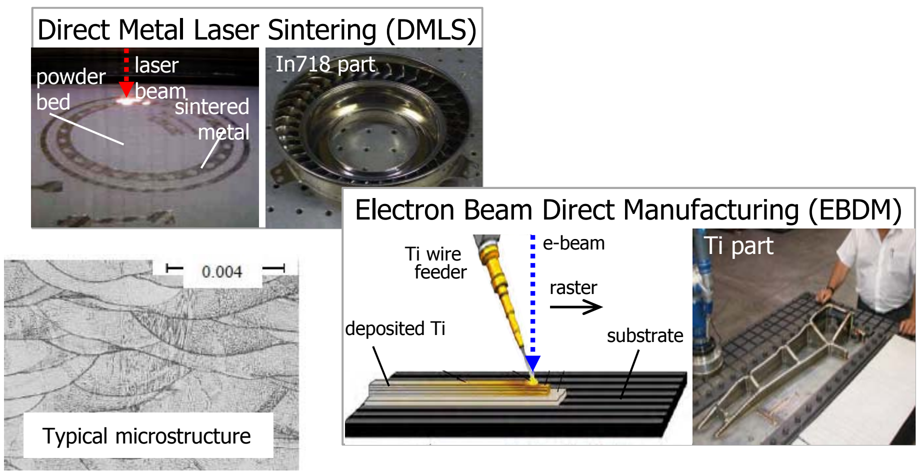


Open Manufacturing Focus Technologies

Two focus technologies chosen to apply and validate OM methodologies

Metals Additive Manufacturing

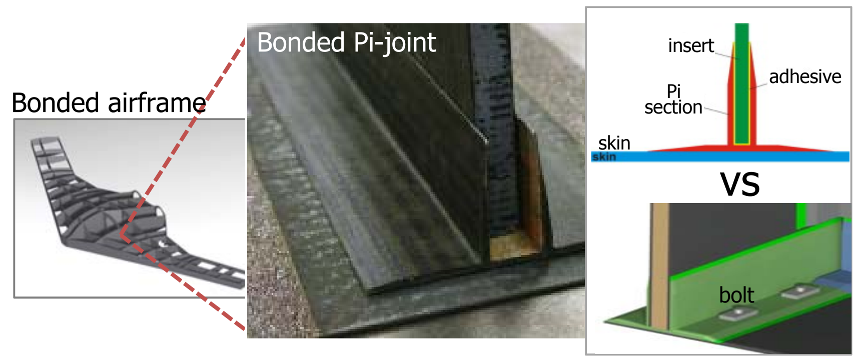
Emerging technology that is stuck with limited transition



- Reduces material usage, eliminates costly and lengthy tool development, and provides design freedom
- Cost benefits of additive manufacturing are negated by high cost of traditional "make and break" qualification
- 2 performers

Bonded Composite Structures

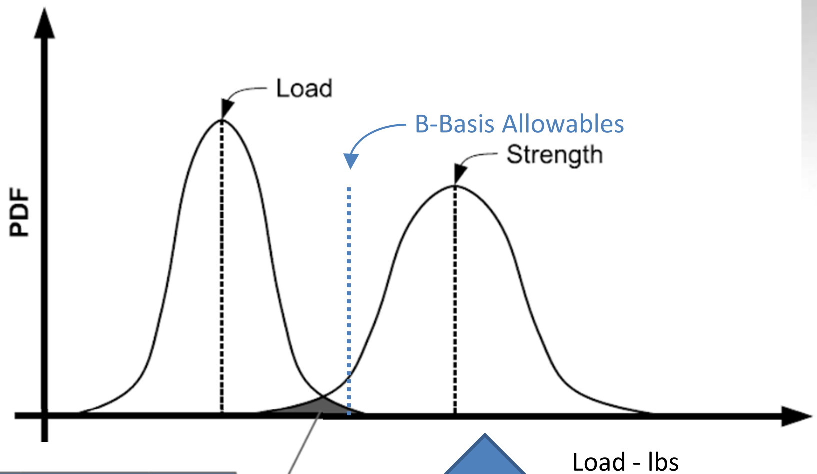
Holy grail for composite community for last 30 years

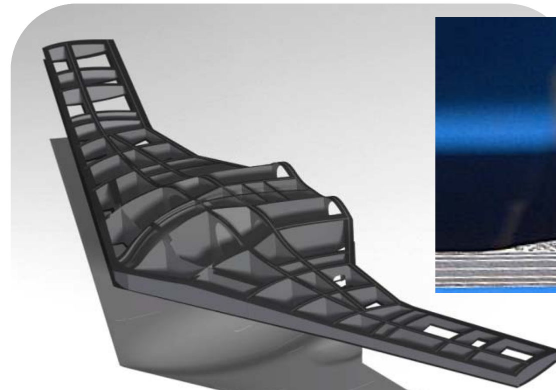


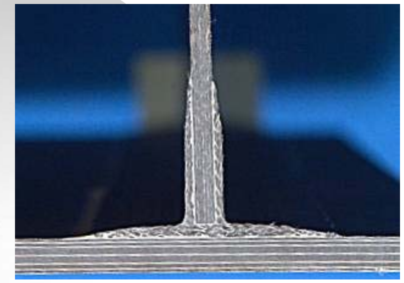
- Bonded composites allows unitized structure with lowered labor and reduced schedule
- Manufacturing process is not equipped to capture all variability
- Therefore, certifiers and designers don't have confidence that the process is well-controlled
- Bolts are added after bonding
- 1 performer

Accelerate the manufacturing innovation timeline for these high impact processing technologies to unlock design and higher performance opportunities

Why We Need to Quantify Manufacturing Process Reliability

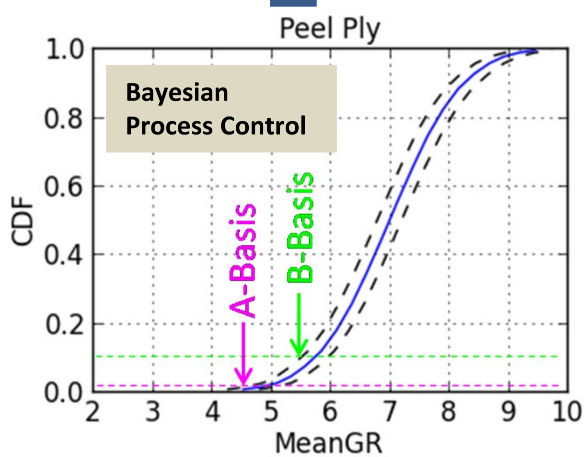






Intersection is Structural Failure

BPC



Traditional Calculation:

Strength ~ $F_{(G, E, T, M)}$

G: Geometry
E: Environment
T: Mfg Tolerances
M: Material Properties

TRUST Enables:

Strength ~ $F_{(G, E, T, M \& P)}$

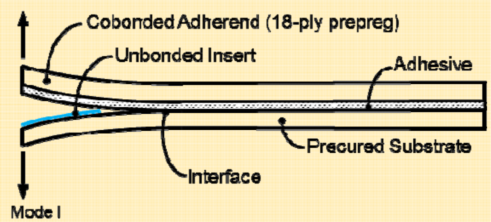
P: Process Control

Transition Reliable Unitized Structures (TRUST) Approach

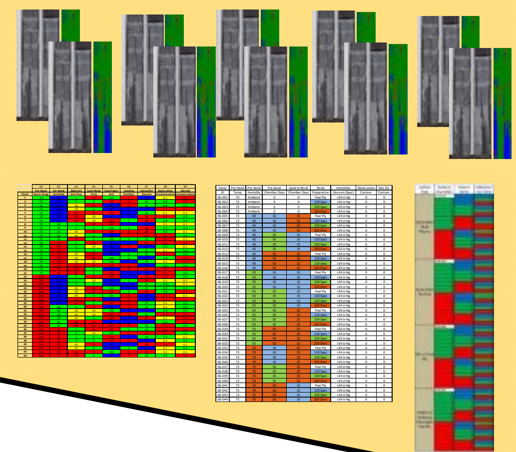
- Capture shop floor variability into informatics database that informs probabilistic Bayesian Process Control (BPC) model
- BPC model determines critical process parameters, predicts bond quality, and computes confidence to ultimately quantify bonding process

Test Data is Foundation of BPC Model

Discriminate bond performance by DCB:

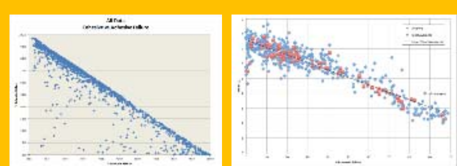


Rigorously populate informatics database:



- Process baseline and 3 DOE test matrices
- Over 500 parameters tracked per test coupon
- Over 1500 individual coupons tested for initial database

Determine model by forward and reverse stepwise regression



$$f(DCB) = \beta_0 + \beta_1 x_{SurfPrep} + \beta_2 x_{PrepBondTime} + \beta_3 x_{OutTime} + \beta_4 x_{Contamination} + \beta_5 x_{PBT} x_{humidity} + \beta_6 x_{OT} X_{Humidity} + \beta_7 x_{SP} x_{PBT} + \beta_8 x_{SP} x_{OT}$$

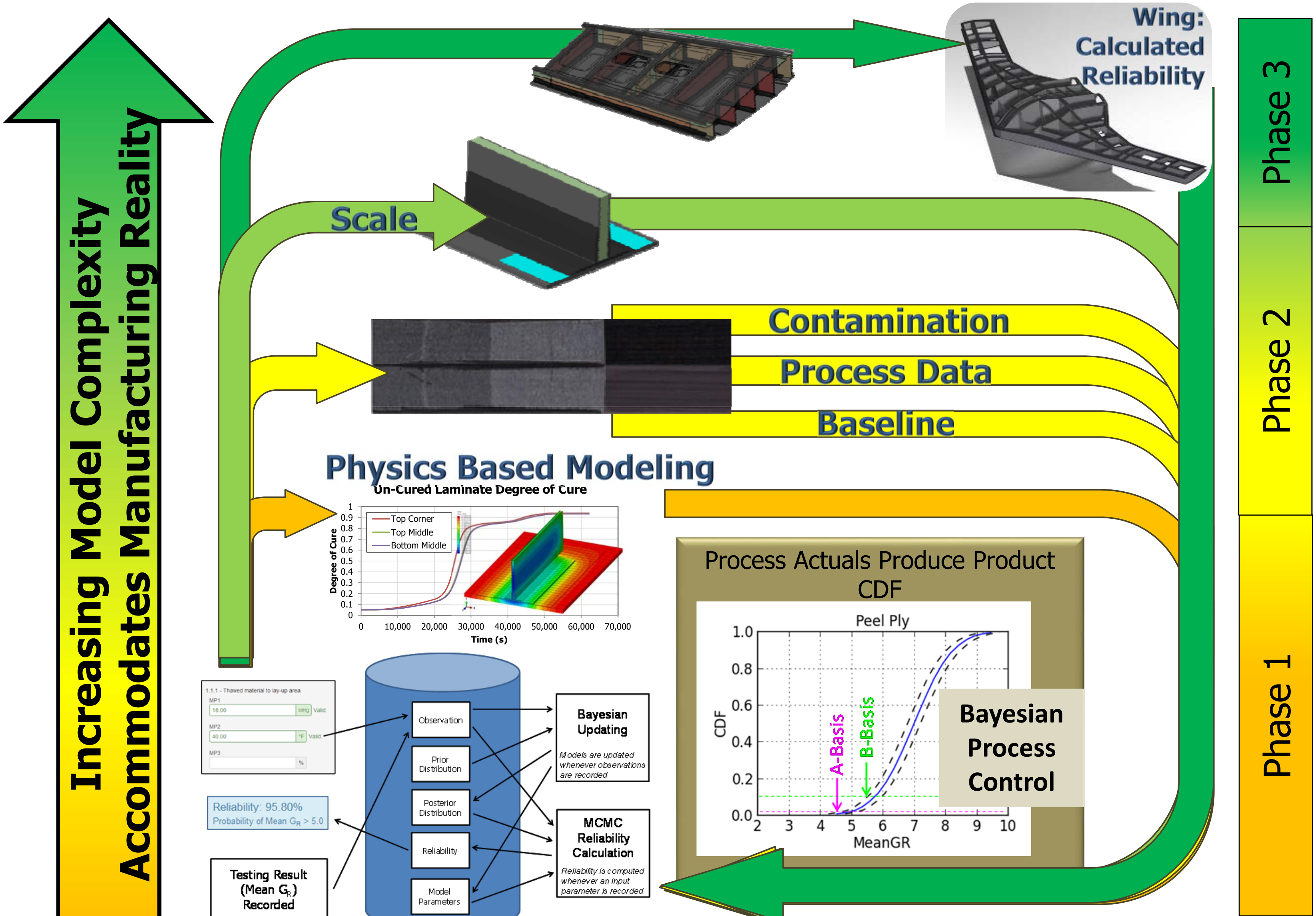
Leverage tribal knowledge of important parameters and test regression model

$$\begin{aligned} f = \beta_0 + {} & \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \\ & \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 + \beta_{10} x_{10} + \beta_{11} x_{11} + \beta_{12} x_{12} + \\ & \beta_{13} x_1^2 + \beta_{14} x_2^2 + \beta_{15} x_3^2 + \beta_{16} x_4^2 + \beta_{17} x_5^2 + \\ & \beta_{18} x_6^2 + \beta_{19} x_7^2 + \beta_{20} x_8^2 + \beta_{21} x_9^2 + \beta_{22} x_{11}^2 + \beta_{23} x_{12}^2 + \\ & \beta_{24} x_1 x_2 + \beta_{25} x_1 x_3 + \beta_{26} x_2 x_3 + \beta_{27} x_5 x_6 + \\ & \beta_{28} x_8 x_9 + \beta_{29} x_8 x_{10} + \beta_{30} x_9 x_{10} + \beta_{31} x_{11} x_{12} + e \end{aligned}$$

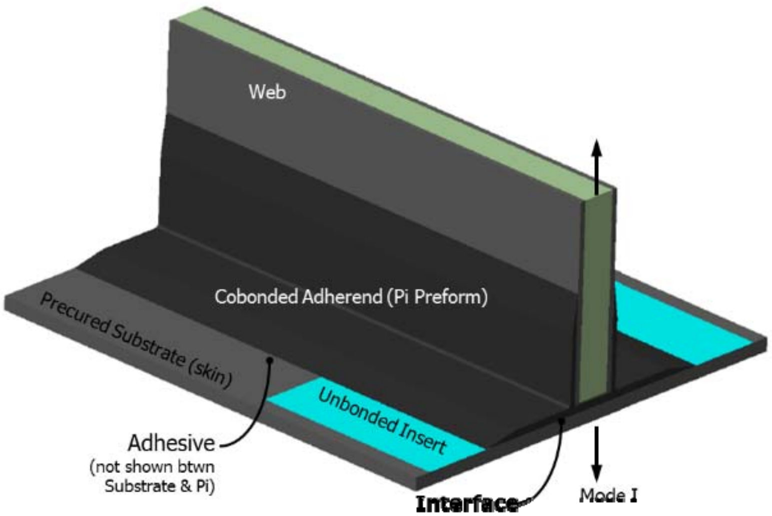
where

x_1: Pre-Bond Room Temperature
x_2: Pre-Bond Room Humidity
x_3: Adhesive Out Time
x_4: Sand-To-Bond Time
x_5: Sandpaper Grit
x_6: Sanding Duration
x_7: Cure Cycle Vacuum
x_8: Hand Lotion Contamination
x_9: Skin Oil Contamination
x_{10}: Cure Cycle Ramp Rate
x_{11}: Cure Cycle Hold Temperature
x_{12}: Cure Cycle Hold Time

BPC Model Requires Iterative Learning at Increasing Scale

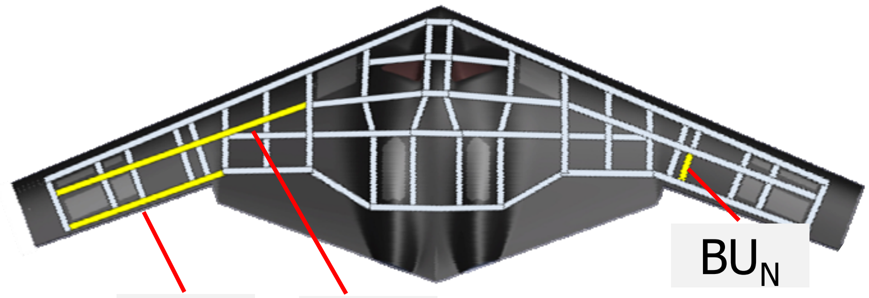


Advancing BPC to Pi-CB and Bond Units



Pi-CB specimens enable adaptation and scale up of DCB regression model to validate predicted against actual bond performance

$$\boxed{f(PiCB) = K * f(DCB)}$$



Bond Unit: Defined as homogenous, discrete section bonded with:

- Single pi, adhesive, peel ply batch
- Common out times
- Identical processing parameters

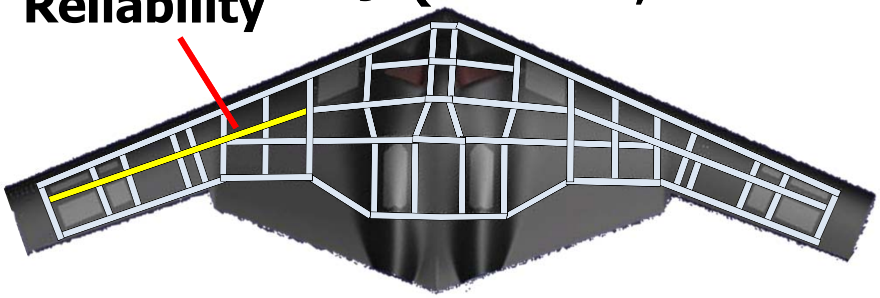
A wing will have different spatially predicted process reliabilities:

- For BU_1, BU_2…BU_N

The Bond Unit enables spatial reliability predictions

Improving BPC Reliability Model

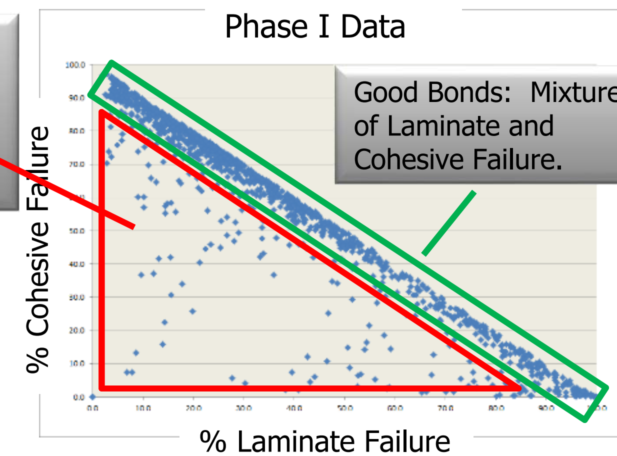
Bond Unit Reliability **≈ ƒ (Baseline, Process Perturbations, Contamination & Scale)**



Calculate Wing Process Reliability
- Translate process variables to product reliability
- Update models for process variables
- Quantify effect of contamination
- Reduce inherent variability

Characterize Bad Bonds
- Analyze data for manufacturing process parameters that create bad bonds.
- Characterize the bonding surface to identify appropriate bond preparation.

Bad Bonds: These exhibit high percentage of Interfacial Failure.
- **Need To Understand the Process Variables that Cause This.**

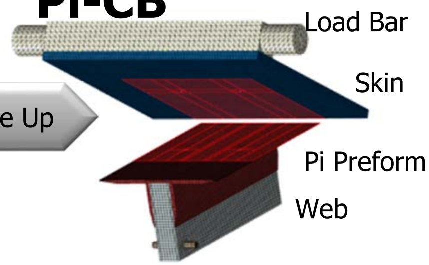


Good Bonds: Mixture of Laminate and Cohesive Failure.

DCB

Scale Up

Pi-CB

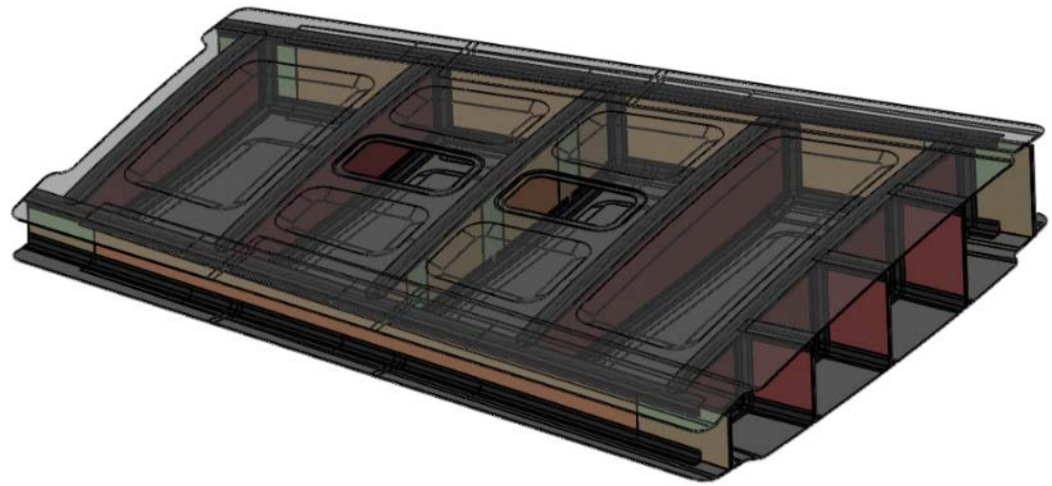


Validate Model's Ability to Predict Complex Structure
- Develop & implement geometry factors from DCB to Pi-CB.
- Validate reliability model on Pi-CB across broad process & contamination Parameters.

Exercising BPC Model on Real Structure

Component Wing Box

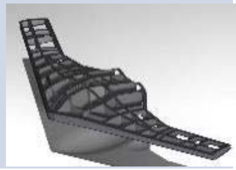
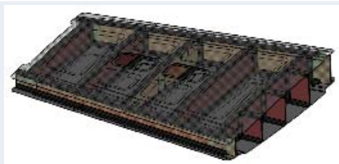
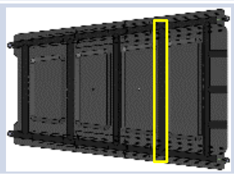
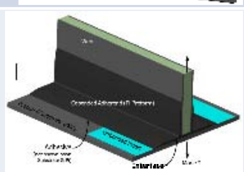
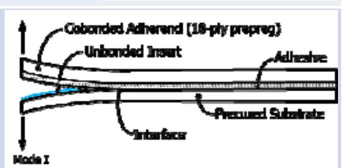
- AFP skins
- Sandwich ribs / spars
- MTM45-1 / IM7
- Pi-joined assembly

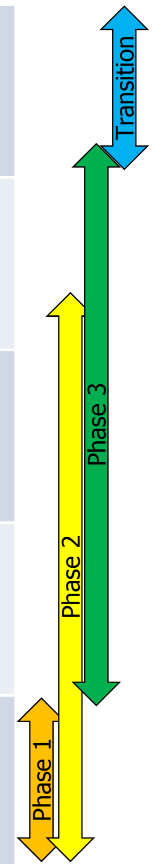


The Objectives

- Design:
    - Incorporate Pi-CB's into a three dimensional article
- Build:
    - Bring BPC to a three dimensional article
    - Incorporate manufacturing / process complexities
    - Move out of the ISO 7 clean room, & explore associated realities
    - Find unknown unknowns!
- Test:
    - Extract Pi-CB's from article for evaluation.

Scaling Up BPC Model with Less Data

	Nominal Size, inches	Bayesian Model	# Samples (P1/P2/P3)
Bonded Wing 	>> 109 x 44 x 15	TBD	0/0/0
Comp’t Box 	~109 x 44 x 15	TBD (Phase 3)	0/1/5
Bond Unit 	≥12.0 x 8.0 x 6.0	$f(BU) = f(\pi CB) + \beta_{10} x_{Scale}$	0/13/65
Pi-CB Specimen 	12.0 x 8.0 x 6.0	$f(\pi CB) = f(DCB) + \beta_9 x_{\pi}$	0/147/50
DCB Coupon 	9.0 x 1.0 x 0.3	$f(DCB) = \beta_0 + \beta_1 x_{SurfPrep} + \beta_2 x_{PrepBondTime} + \beta_3 x_{OutTime} + \beta_4 x_{Contamination} + \beta_5 x_{PBT} x_{humidity} + \beta_6 x_{OT} X_{Humidity} + \beta_7 x_{SP} x_{PBT} + \beta_8 x_{SP} x_{OT}$	1500/1600/250



Projected

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