Machine-Learning and Artificial Intelligence for Improving Automated Fiber Placement Rate and Quality

Waruna Seneviratne, PhD
Director ATLAS, Sr. Research Scientist

WICHITA STATE UNIVERSITY
NATIONAL INSTITUTE FOR AVIATION RESEARCH

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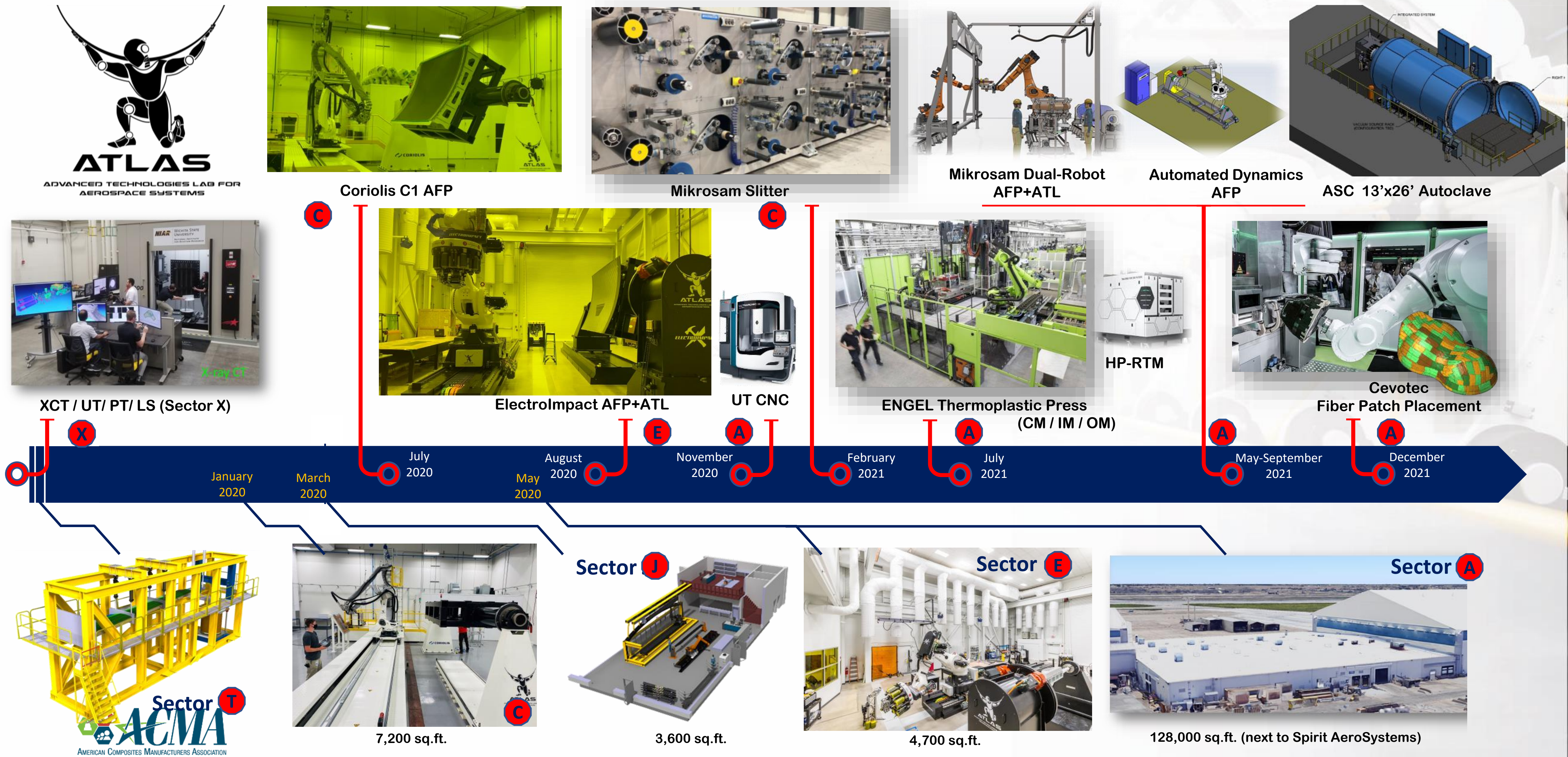
- Future
  - Create a pipeline of "industry-ready" future engineers for advanced manufacturing processes
  - Machine learning and artificial intelligence
  - Advanced materials and processes
- Present
  - Work with industry solving current manufacturing problems
  - Exposure to industry challenges
- Past
  - Develop workforce training programs for advanced manufacturing technologies
  - Create new job opportunities for current workforce

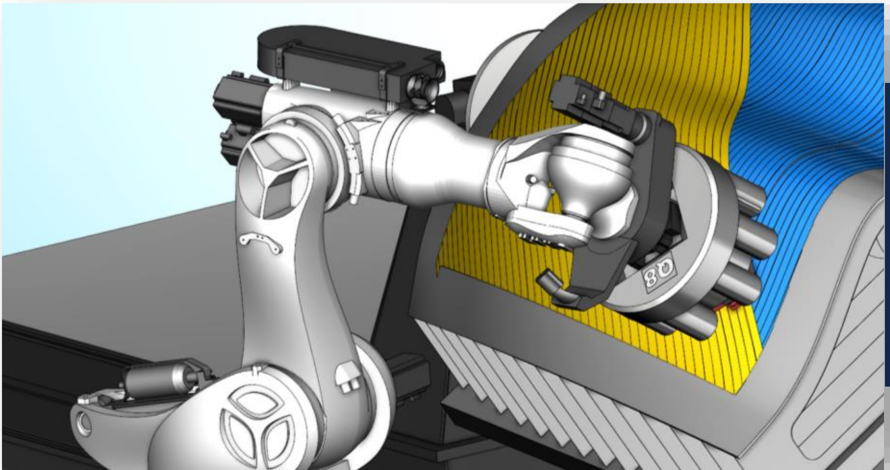
Advanced Manufacturing Technologies with Automation & Artificial Intelligence



https://www.wichita.edu/research/NIAR/Laboratories/atlas.php

Background

- Productivity and quality benefits from automated fiber placement (AFP) are becoming more attractive for complex composite components that historically were only possible to build by hand.
- Although AFP has significantly improved the production rates/quality, there are still challenges since the process requires integration of multiple disciplines such as robotics, nondestructive inspection (NDI), and process modeling.
- Quality assurance through inspections and process controls are essential to ensure that material is laid up and processed according to specification with appropriate consolidation and with no process-induced defects.
    - This manual inspection process that can consume 20-70 percent of the production time diminishes the benefits of automation to improve the production rate.
    - In addition, manual inspection processes have deficiencies such as operator/training/environment dependency and inconsistencies.



Main goal of this research is to develop and implement a machine-learning algorithm (MLA) for an in-process automated manufacturing inspection system (IAMIS) for reducing defects in automated fiber placement process

Digital Manufacturing Twin (DMT)

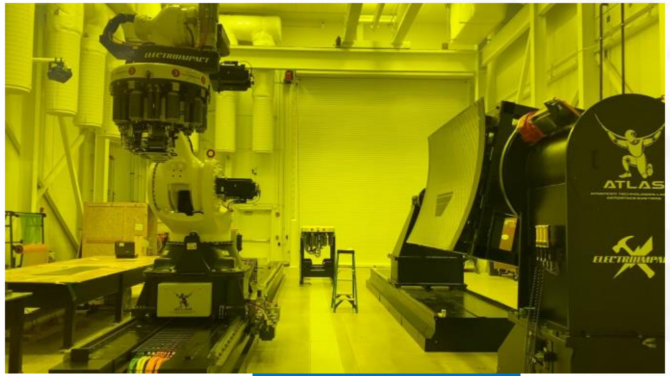
AFRL

NIAR Wichita State University National Institute for Aviation Research

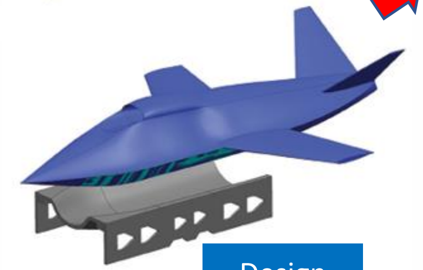
Modeling for Affordable Sustainable Composite (MASC)

CGTech VERICUT®

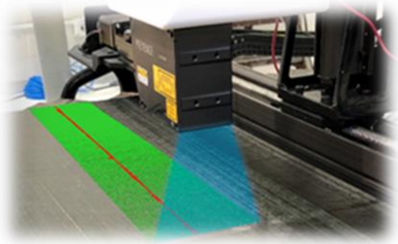
Manufacturing Simulations



Automated Manufacturing



Design



In-Process Inspections

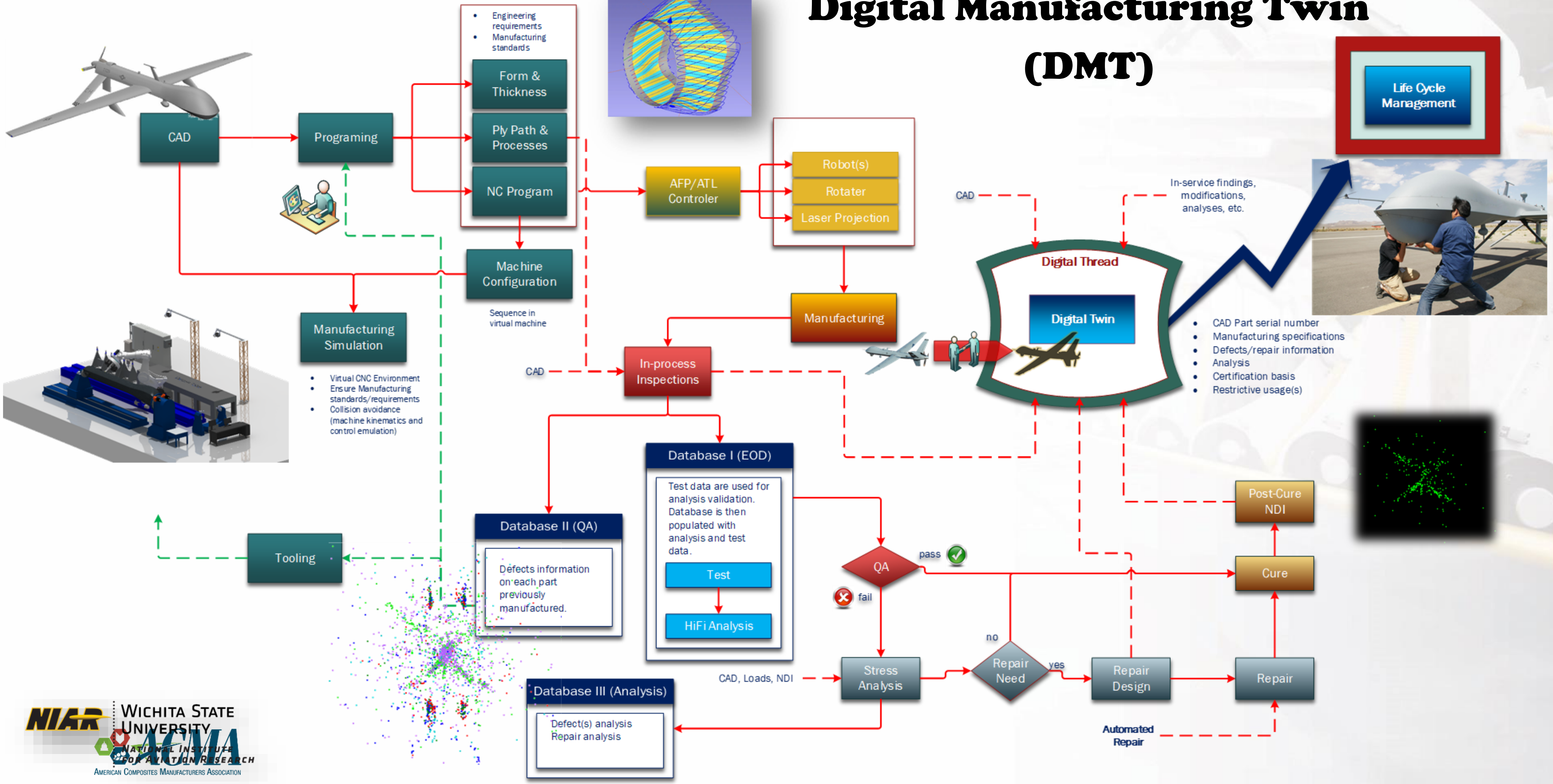
Lifecycle Management

Increase Rate, Improve Quality, and Reduce Cost

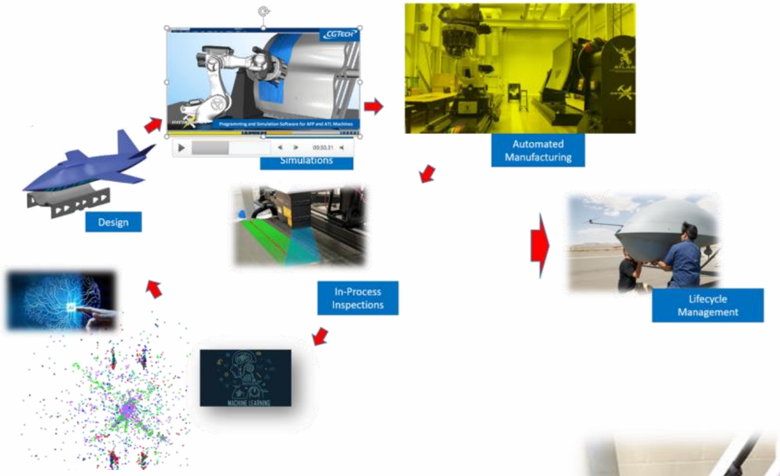
- Detecting manufacturing defects that are above certification basis through ***machine-learning algorithms*** for reducing time-consuming manual inspection processes that require interrupting the manufacturing process, and
- Using ***artificial intelligence*** for identifying manufacturing anomalies for optimizing process parameters (ex, lay down speed, heat input, compaction force, steering radii, etc.) in order to reduce manufacturing defects.

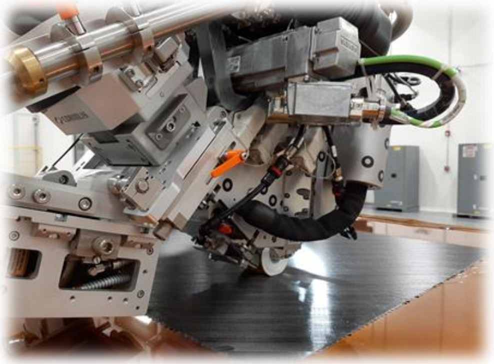
ACMA American Composites Manufacturers Association

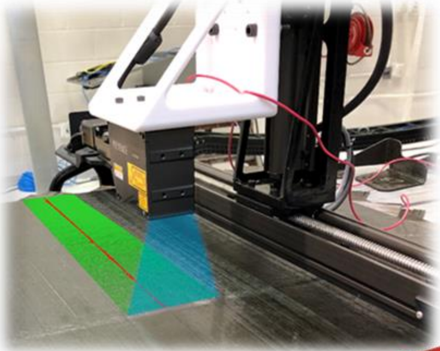
Digital Manufacturing Twin (DMT)

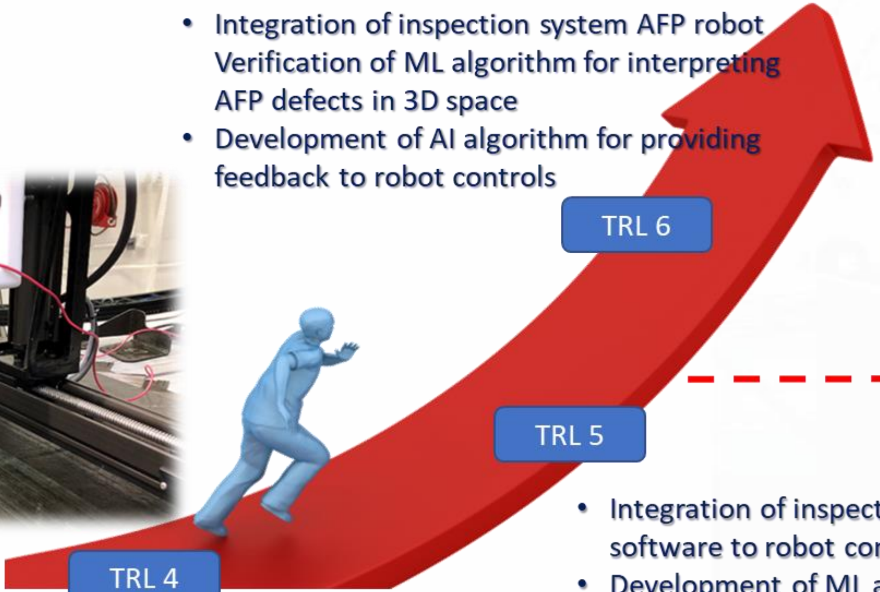


Road Map for DMT









TRL 7

- Demonstration of system capability for DMT
- Demonstration of EoD interrogation
- DOE for PoD on 3D part
- Demonstration of AI algorithm for process optimization

TRL 6

- Integration of inspection system AFP robot Verification of ML algorithm for interpreting AFP defects in 3D space
- Development of AI algorithm for providing feedback to robot controls

Manufacturing Environment

Laboratory Environment

TRL 5

- Integration of inspection system and software to robot controls
- Development of ML algorithm for interpreting AFP defects
- Development of AI algorithm for providing feedback to robot controls

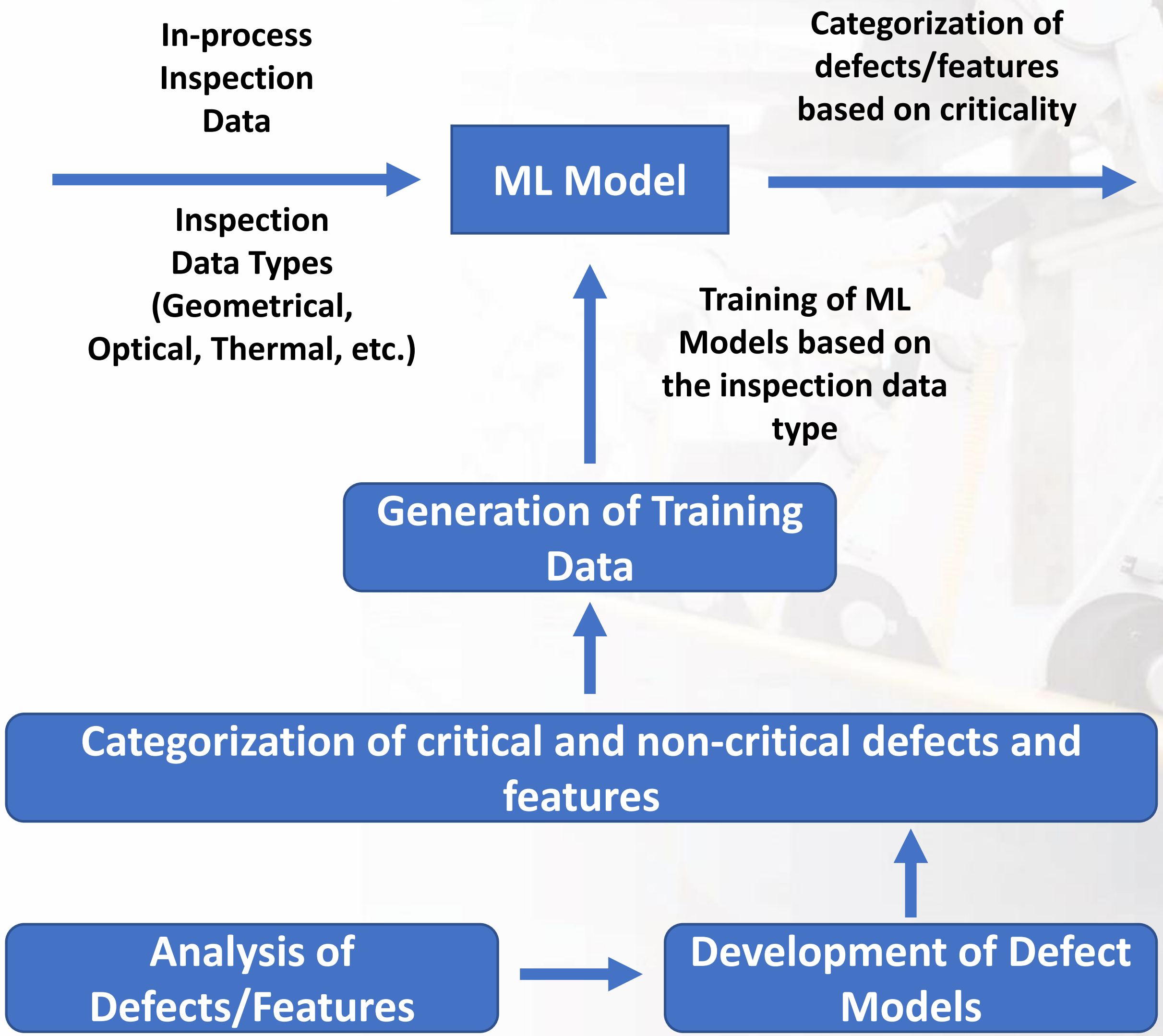
TRL 4

- Manual inspections for detecting AFP defects
- Software for converting point cloud into a defect map
- DOE for PoD on flat panels

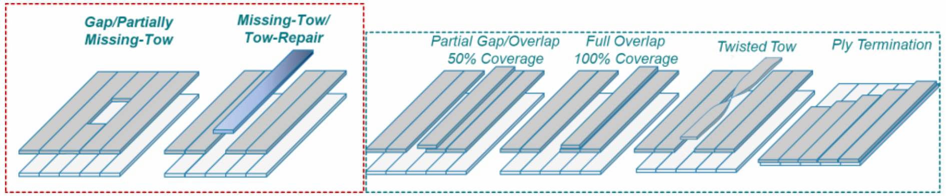
ACMA
American Composites Manufacturers Association

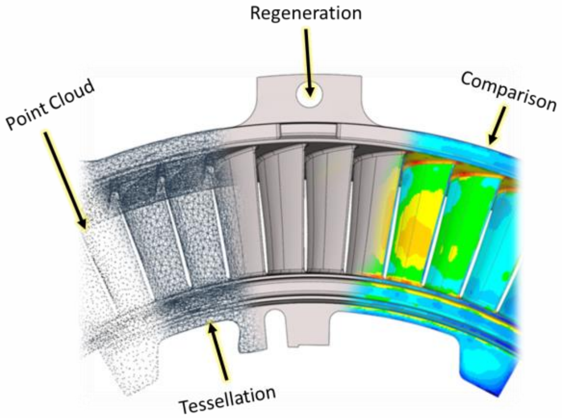
Machine Learning Model

- Use Existing Machine Learning Architectures and Frameworks.
- Develop a methodology to generate large amounts of training data.
- Develop optimal parameters for machine learning model training.
- Train ML models to categorize critical defects/features

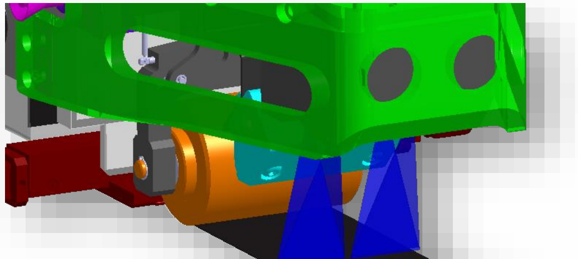


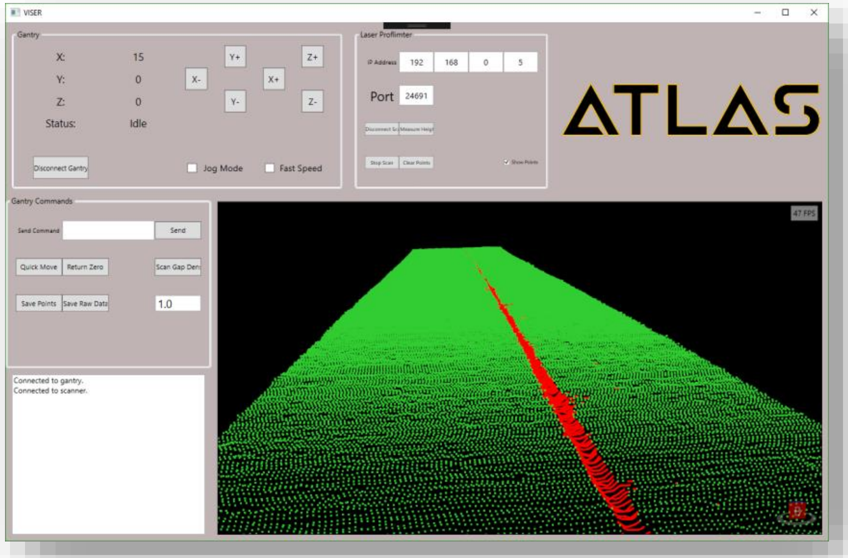
In-Process Inspections

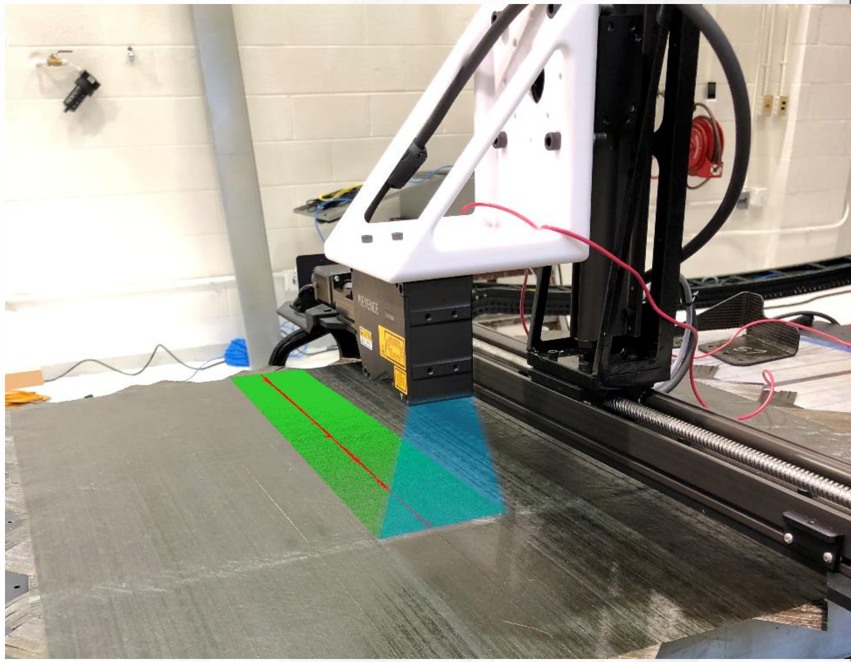


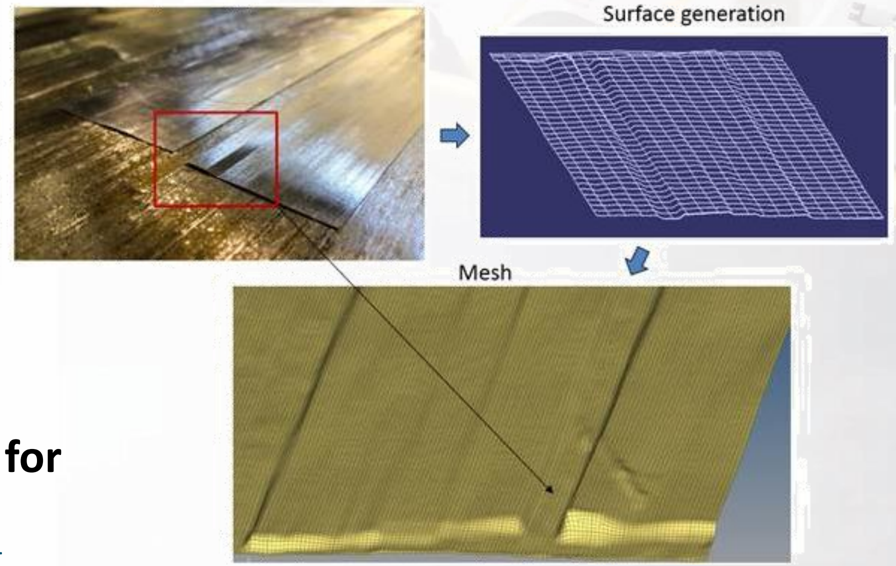


Laser Profilometry



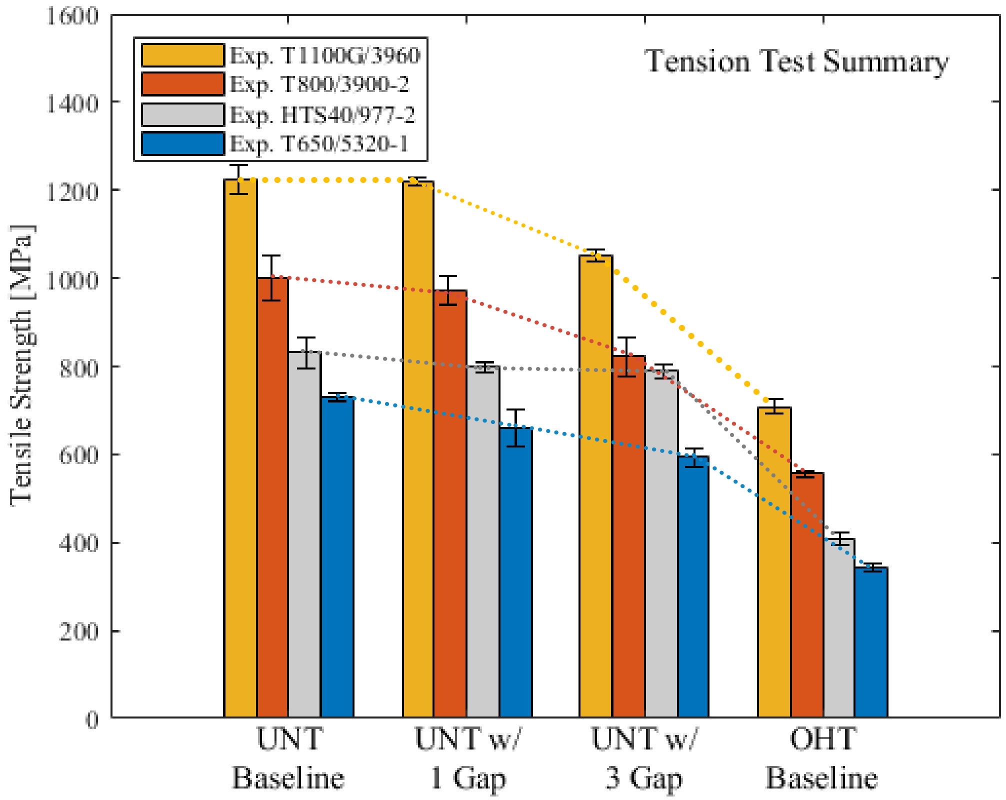




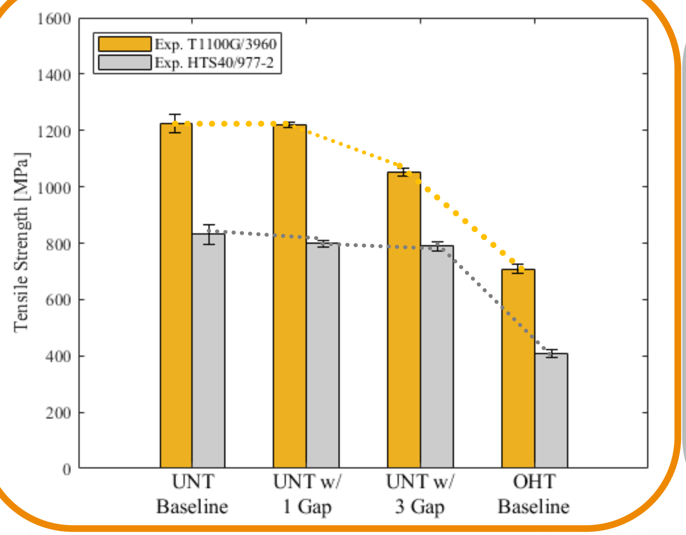


- **Custom feature-recognition algorithm**
- **Integrated machine learning database for advanced recognition and analysis**

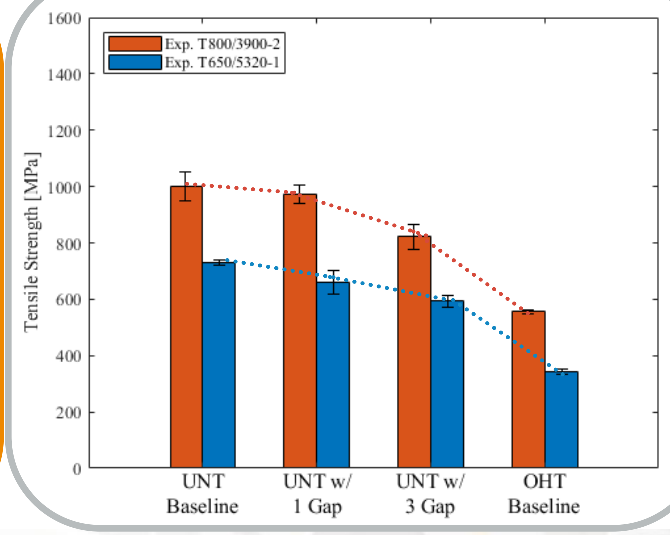
Database I (EoD) - Strength Knockdowns for Margin of Safety



AFP Manufactured Strength Knockdown



Hand Layup Strength Knockdown



- *1 AFP Gap Tensile Strength Knockdown ~ 0 - 4%*
- *3 AFP Gap Tensile Strength Knockdown ~ 5 - 14%*

** Data from only AFP manufactured materials/panels*

Normalized Strength Knockdown [%]	T1100G/3960		HTS40/977-2		T800/3900-2		T650/5320-1	
	Exp.	COV	Exp.	COV	Exp.	COV	Exp.	COV
UNT 1 gap	-0.30%	0.80%	-3.93%	0.48%	-2.60%	3.40%	-10.00%	6.00%
UNT 3 gap	-14.10%	1.50%	-4.97%	3.19%	-17.70%	5.40%	-18.90%	3.40%
OHT	-42.10%	2.10%	-50.91%	3.30%	-44.30%	1.10%	-53.30%	3.10%

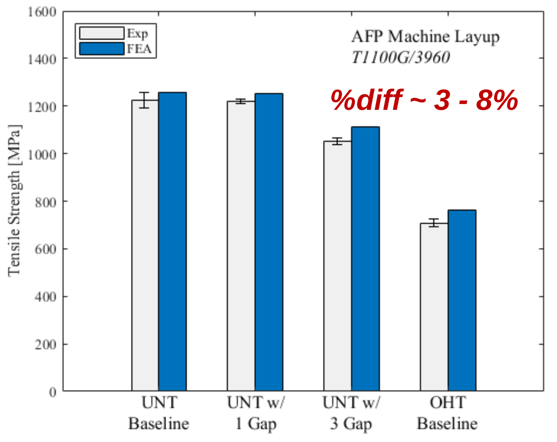
AFP Layup *Hand Layup*

Largest Knockdown

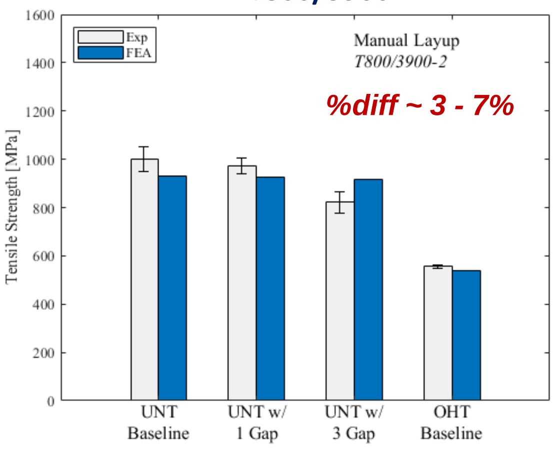
Smallest Knockdown

Database I (EoD) - High-Fidelity Analysis of AFP Features

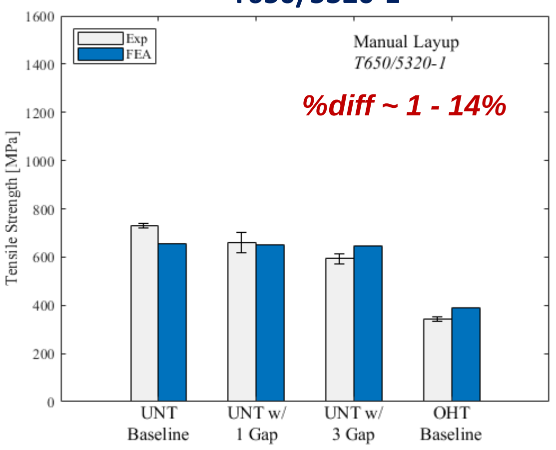
T1100G/3960



T800/3900-2

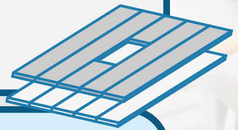


T650/5320-1



Exp. Strength Knockdowns (for 3 material systems)

- *1Gap ~ 1 – 10%*
- *3Gap ~ 14 – 18%*
- *OHT ~ 40 – 44%*

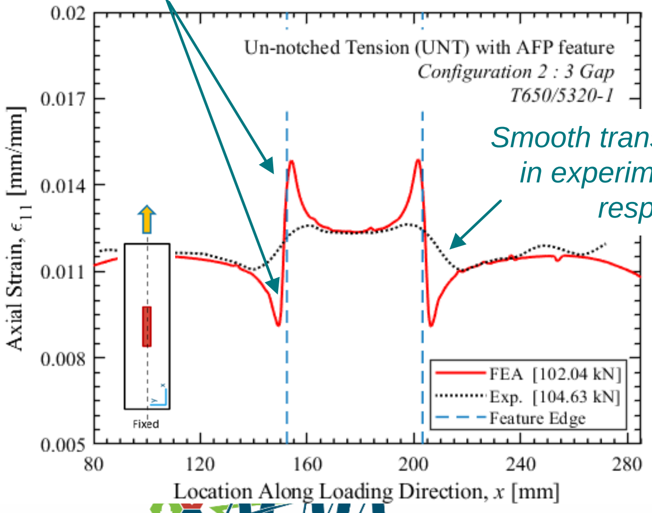


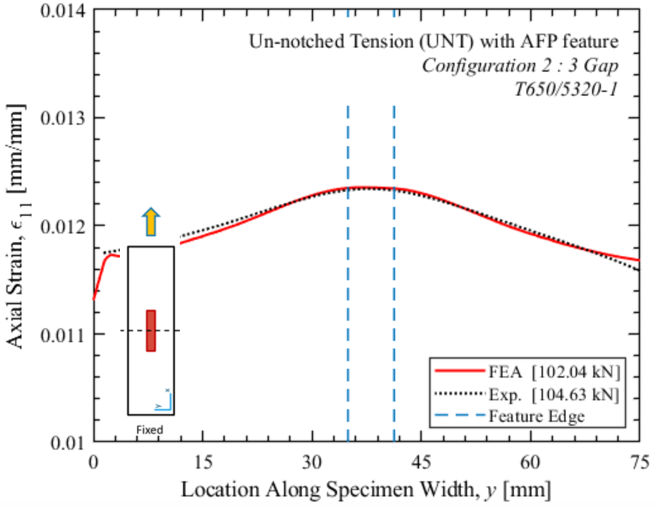
FEA Strength Knockdown (for 3 material systems)

- *1Gap ~ 1 – 3%*
- *3Gap ~ 1 – 12%*
- *OHT ~ 39 – 42%*

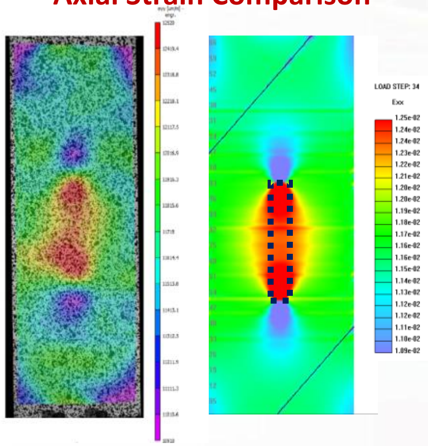
Due to discrete jump in material properties in FE gap model

Smooth transition in experimental response





3 Gap Configuration
Axial Strain Comparison

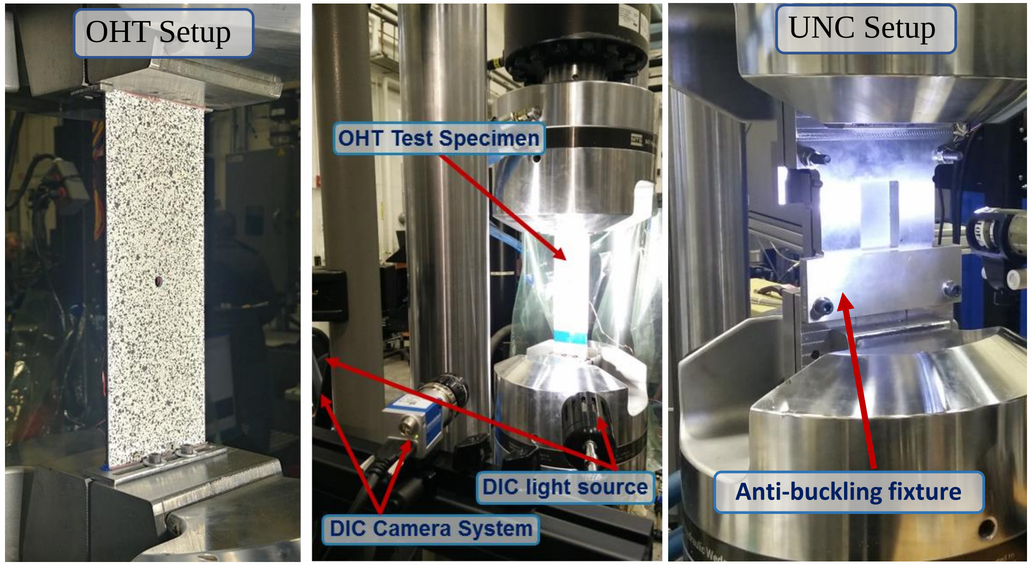


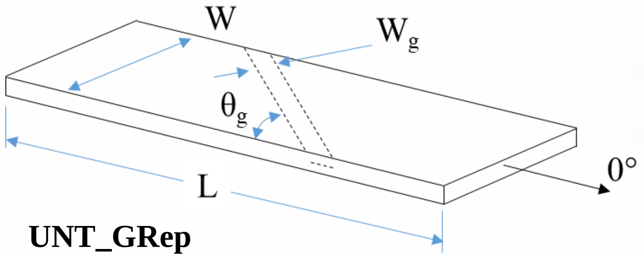
Exp. **FEA**

- *Static strength predictions compared well with experiments*
- *T1100G/3960 and T800/3900-2 displayed best correlation for strength data (within 8%)*
- *All models correlated very well for stress strain responses*
- *"Resin-block" approach successful; axial strain along centerline length & width matched that of DIC/exp. data*

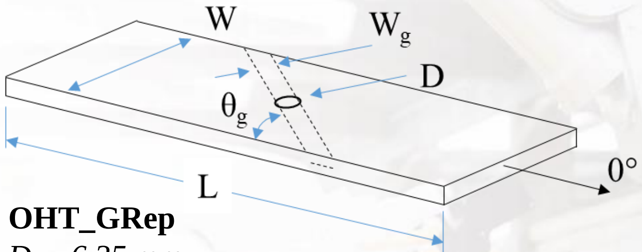
Axial strain comparison for 3Gap configuration – DIC vs FEA

Database III (Analysis) - Automated Repair



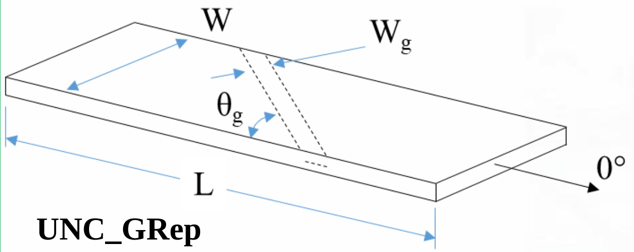


UNT_GRep
$[45/90/-45/0]_{2s}$
L = 355.6 mm
W = 76.2 mm
W_g = 6.35 mm
θ_g = -45°

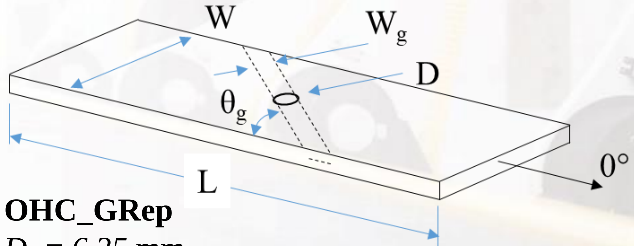


OHT_GRep
D = 6.35 mm

Gap-Repair: Tension



UNC_GRep
$[45/90/-45/0]_{2s}$
L = 304.8 mm
W = 76.2 mm
W_g = 6.35 mm
θ_g = -45°



OHC_GRep
D = 6.35 mm

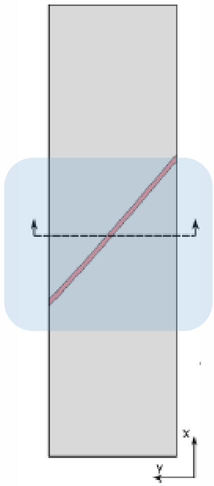
Gap-Repair: Compression

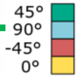
Missing Tow in Ply level #7 (-45°)

Repair Tow in Ply level #8

AFP Gap/Repair Distribution

Ply #	Stacking Sequence	Note
1	45	
2	90	
3	-45	
4	0	
5	45	
6	90	
7	-45	AFP Gap/Missing tow
8	0	
REPAIR TOW	-45	0.25" Repair Tow
9	0	
10	-45	
11	90	
12	45	
13	0	
14	-45	
15	90	
16	45	

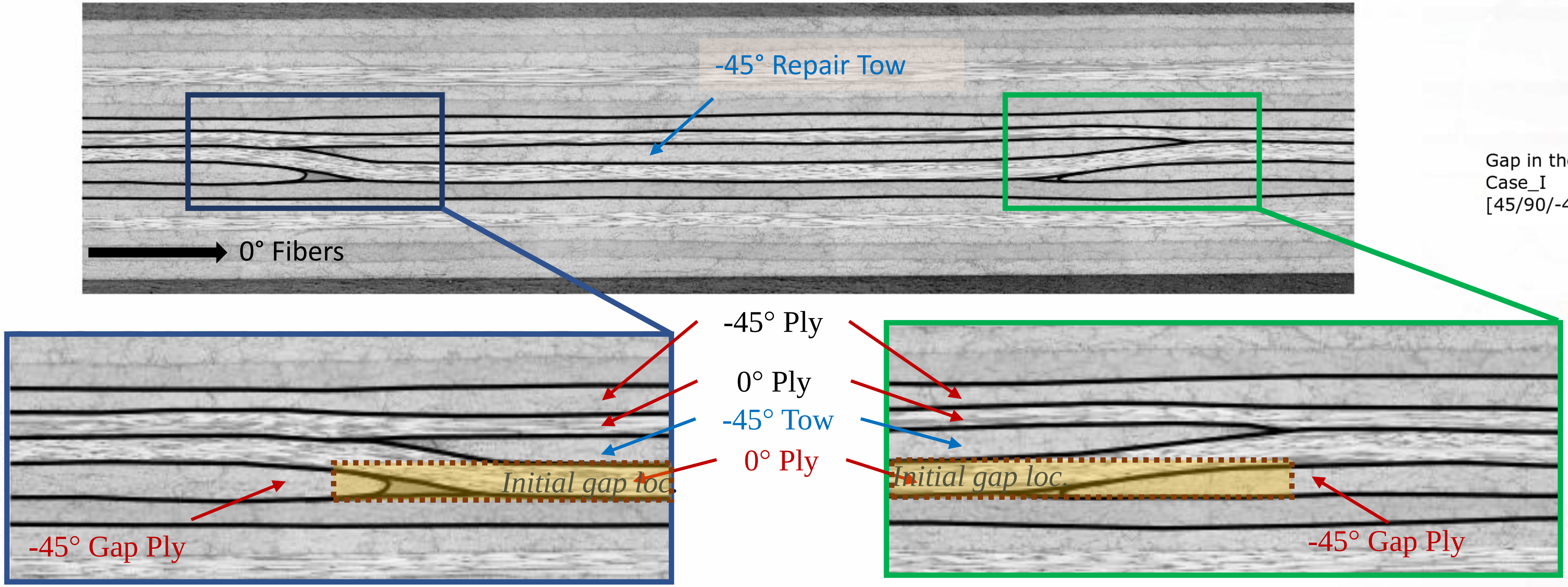


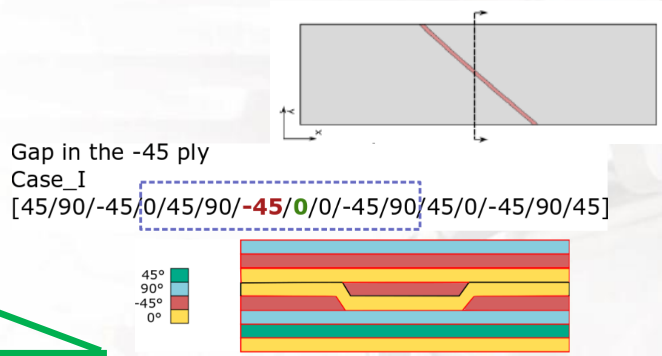


Gap in the -45 ply
Case_I
[45/90/-45/0/45/90/**-45**/**0**/0/-45/90/45/0/-45/90/45]

Gap in -45° to induce out-of-plane waviness in 0° Ply

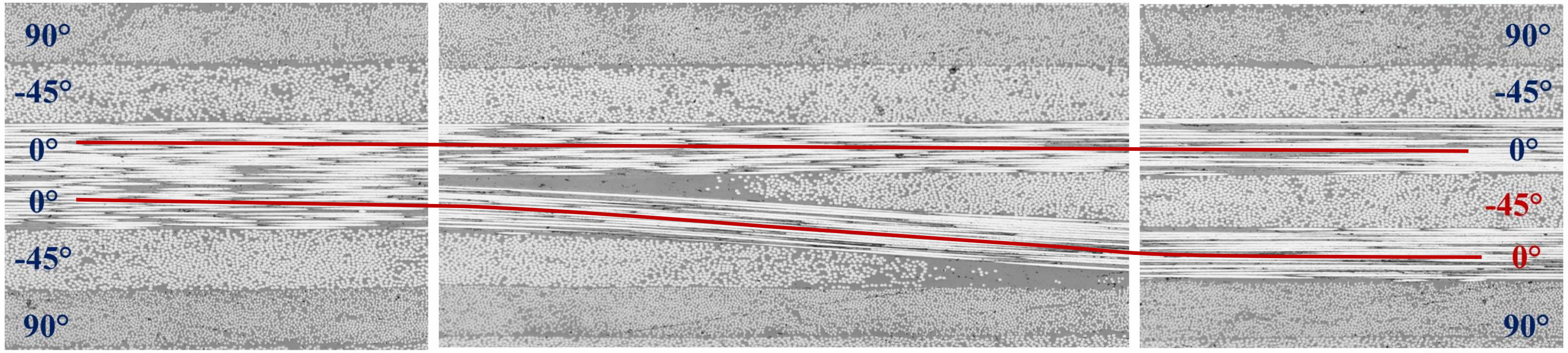
AFP Gap Repair - Photomicrographs





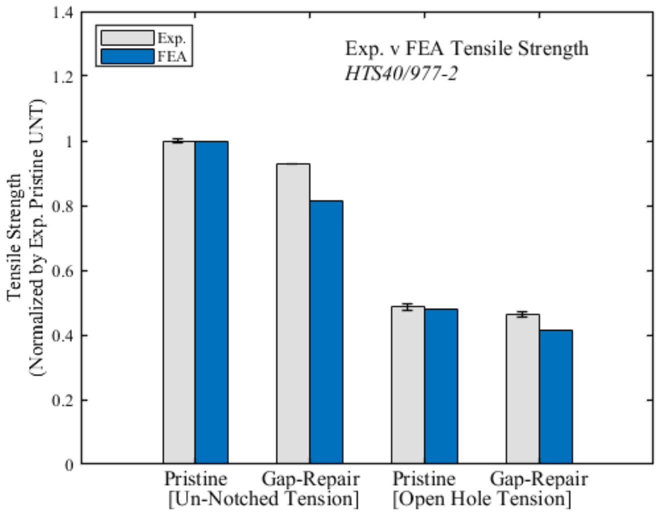
- *Gap/Missing tow in -45° ply induces adjacent 0° ply to contour into the vacant region.*
- *0° creates out of plane wrinkle.*
- *Wrinkle stabilized by the repair tow (-45°) placed on top of 0° ply*
- *Smooth transition seen within repair distribution region with limited resin rich regions.*
- *Local V_f generally maintained in gap region*

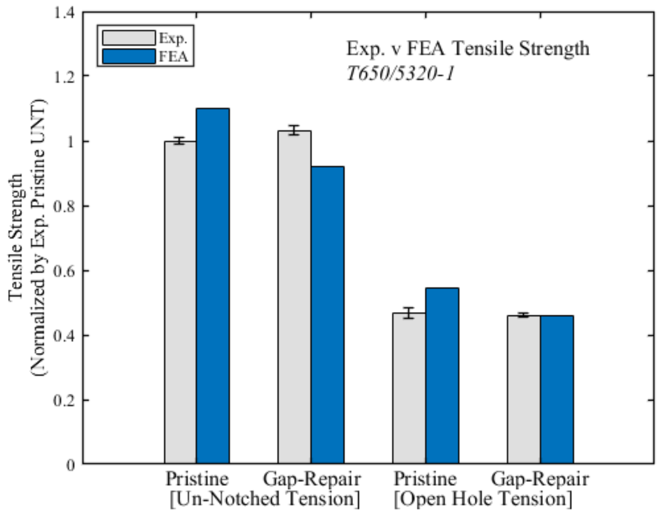
Repair region - local transition zone:



Gap-Repair Strength Results

Exp. vs FEA - TENSIONS CONFIGURATION

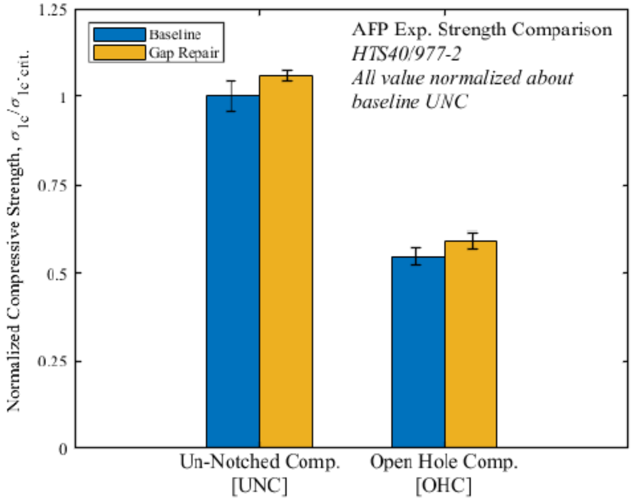


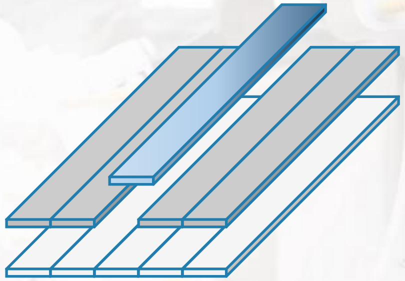


Failure Strength [Normalized by UNT Exp.]	HTS40/977-2			T650/5320-1		
	Exp.	FEA	%diff	Exp.	FEA	%diff
UNT	1.0000	0.9962	-0.4%	1.0000	1.0091	9.9%
UNT Gap Repair	0.9293	0.8158	-12.2%	1.0320	0.9186	-11.0%
OHT	0.4866	0.4798	-1.4%	0.4674	0.5432	16.2%
OHT Gap Repair	0.4626	0.4145	-10.4%	0.4610	0.4598	-0.3%

- *Strength predictions for HTS40/977-2 material showed better correlation;*
  - *% Difference between for FEA vs Exp. less than 12%*
  - *Displayed a consistent trend of under prediction across the configurations*
- *A general trend of over prediction was seen in the T650/5320-1 material for baseline specimens; Results still within 16%*

Exp. - COMPRESSION CONFIGURATION





TENSION TEST RESULTS:

- *UNT-Repair Strength knockdown:*
  - *T650/5320-1* *Increase of (+3%)*
  - *HTS40/977-2* *Knockdown of (-7%)*
- *OHT-Repair configuration for both materials had knockdown in the range of (-1 to -2)%*

COMPRESSION TEST RESULTS:

- *HTS40/977-2 displayed a consistent increase in strength for repair specimens (ranging from +6 to +8%)*
- *T1100G/3960 saw knockdown up to (-6%)*

Summary

- The proposed IAMIS integrated robot controls enhanced with ML and AI framework improves manufacturing rate and quality, while reducing overall manufacturing cost, impacting the following key performance parameters (KPPs) associated with AFP:
  - ***Versatility*** – Human error associated with various levels of operator experience will be eliminated. In addition, MLA incorporated into the system will reduce recurring defects (improve quality) in part and reduce scrap rate (reduce overall cost).
  - ***Time to Deploy*** – IAMIS eliminates the need for costly and time-consuming secondary inspection processes that cause more than 20 percent of the manufacturing time (increase manufacturing rate).
  - ***Total Cost of Ownership*** – Lightweight low-cost inspection system can be incorporated to an AFP system with MLA to manufacturer quality parts with low scrap rate at a higher efficiency. Elimination of secondary inspection step not only save time, but also the cost of equipment, programming, and operators.

Acknowledgement

NIAR System Development & Analysis Team

- Upul Palliyaguru
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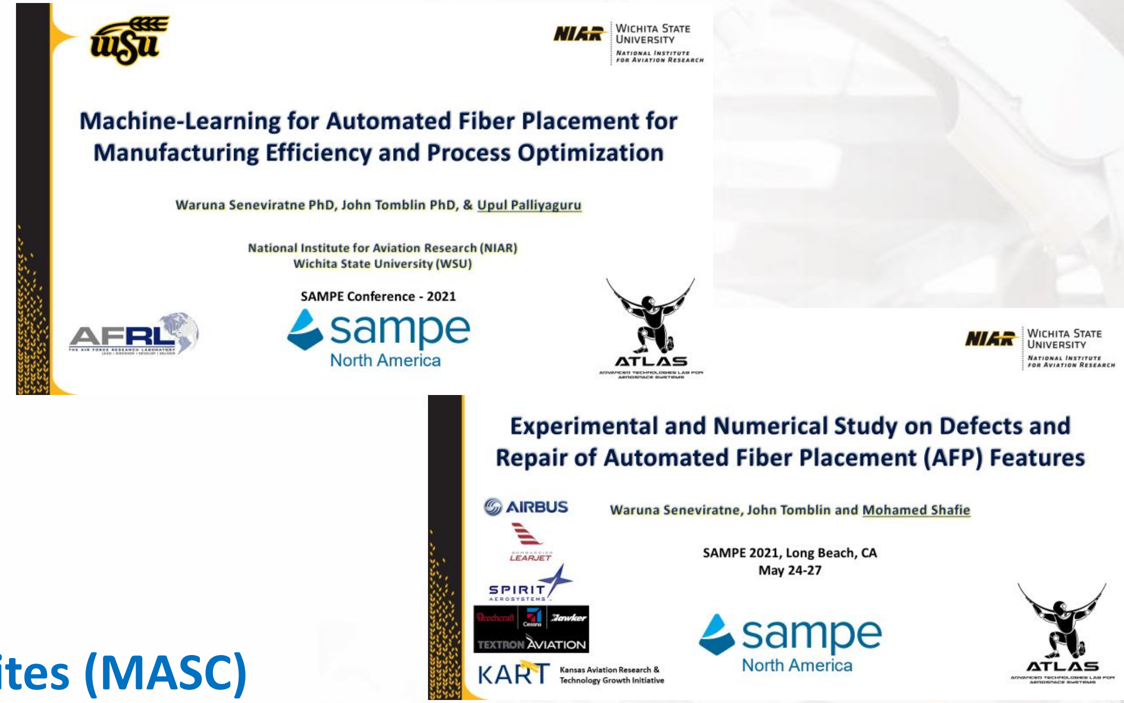

AFRL - Modeling for Affordable Sustainable Composites (MASC)
Contract No. FA8650-19-c5212

- *Dr. David Mollenhauer (Program Manager)*

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Contract No. N00014-21-1-2506

- *Dr. Anisur Rahman (Program Manager)*