InfoSymbioticSystems/DDDAS

and Large-Scale-Big-Data & Large-Scale-Big-Computing for Smart Systems



CFD2030 Workshop AIAA/SciTech January 6-7, 2018

Frederica Darema, Ph.D., SES
Director AFOSR

Integrity ★ Service ★ Excellence



QUO VADIMUS Timely Confluence across 4 axes New Opportunities

AF Motivation; applies to broader drivers - other DOD, civilian/etc

New Capabilities through

DDDAS-Dynamic Data Driven Applications Systems

- Unifying High-End with Real-Time/Data-Acquisition&Control Large-Scale-Big-Data (Large-Scale-Dynamic-Data)
- "Big Data" + Ubiquitous Sensing&Control (2nd Wave of big-data) Large-Scale-Big-Computing
- From the exa-scale to the sensor-scale/controller-scale Multi-core Technologies
- Will be driven by sensor/controller and mobile devices

Timeliness&Opportunities - Examples



AF S&T Horizons – 10, 20, ... 40 yrs + beyond

Technology Horizons

Inherently Intrusion-Resilient Cyber Networks (and Systems)

Trusted, Highly-Autonomous Decision-Making Systems

Fractionated, Composable, Survivable, Autonomous Systems

Hyper-Precision Aerial Delivery in Difficult Environments

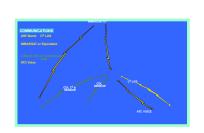


Command & Control (C2); IntellSurveilRecon (ISR)

C2&ISR "targeted as center of gravity threatening integrated and resilient global operations"

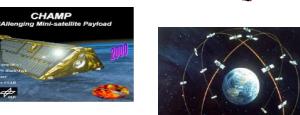
Autonomy Horizons

- Mission/Scenario Planning & Decision Making
- VHM, Fault /Failure Detection, Replanning
- Situational Awareness, Multi-Sensing & Control
- ... (other) Horizons...
- Energy Horizons
- Beyond Horizons





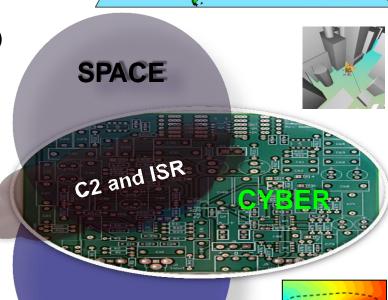
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Research for New Air Force Capabilities

"excellence in science and transformative capabilities for the Air Force"

complex |

PROBLEM: Increasingly we deal with systems-of-systems and systems/environments that are | heterogeneous | multimodal | multiscale |

dynamic

INVESTMENT STRATEGY

Pursue excellence in science through disciplinary and multidisciplinary research, to develop new methods for end-to-end systems capabilities, applied to key Air Force challenges for transformative impact to the Air Force

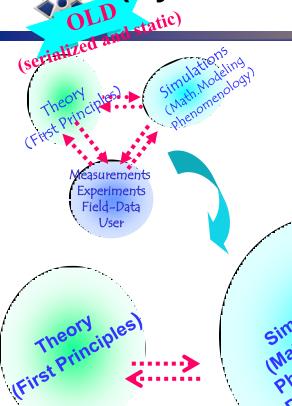


NEW METHODS - Paradigm Changing

- enable more accurate and faster modeling capabilities for analysis, prediction, & operational support
- enable decision support capabilities with the accuracy of full scale models
- support adaptive multimodal instrumentation and fault tolerance in instruments/sensors failures
- exploit ubiquitous embedded sensing & control for new test & evaluation methods

AF CAPABILITY: understand, design, manage & optimize systems-of-systems across life-cycle

The DDDAS Paradigm (Dynamic Data Driven Applications Systems)



InfoSymbiotic Systems

<u>DDDAS</u>: ability to dynamically incorporate additional data into an executing application, and in reverse, ability of an application to dynamically steer the measurement(instrumentation) processes

"revolutionary" concept enabling design, build, manage, understand complex systems

Simulations (Math.Modeling)
Phenomenodeling)
DesignModeling

Dynamic Integration of Computation & Measurements/Data Unification of

Computing Platforms & Sensors/Instruments
(from the High-End to the Real-Time,to the PDA)
DDDAS – architecting & adaptive mngmnt of sensor systems

Challenges:

Application Simulations Methods
Algorithmic Stability
Measurement/Instrumentation Methods
Computing Systems Software Support

Experiment
Measurements
Field-Data
(on-line/archival)
User

F. Darema

Dynamic
Feedback & Control
Loop

ed for Public P Synergistic, Multidisciplinary Research



Advances in Capabilities through DDDAS and Fundamental Science and Technology

- DDDAS: integration of application simulation/models with the application instrumentation components in a dynamic feed-back control loop
 - speedup of the simulation, by replacing computation with data in specific parts of the phase-space of the application and/or
 - > augment model with actual data to improve accuracy of the model, improve analysis/prediction capabilities of application models
 - > dynamically manage/schedule/architect heterogeneous resources, such as:
 - networks of heterogeneous sensors, or networks of heterogeneous controllers
 - > enable ~decision-support capabilities w simulation-modeling accuracy
- unification from the high-end to the real-time data acquisition
- Increased Computat'n/Communic'n capabilities; ubiquitous heterogeneous sensing/control
- **❖ DDDAS** is more powerful and broader paradigm than Cyber-Physical Systems





DDDAS for new capabilities for Air Force Emerging Technological Horizons and Beyond

- Increasingly we deal with systems-of-systems, and systems/environments that are complex, heterogeneous, multimodal, multiscale, dynamic
- Need methods and capabilities
 - not only for understanding, and (optimizing) design...
- ... but also manage/optimize systems' operational cycle, evolution, interoperability

 DDDAS-based methods for across the life-cycle of systems
- DDDAS beyond traditional modeling/simulation approaches and use
 - beyond the traditional instrumentation approaches and use
- DDDAS enables:
 - more accurate and faster modeling capabilities for analysis and prediction
 - decision support capabilities with the accuracy of full scale models
 - dynamic/adaptive and more efficient/effective management of heterogeneous resources; ability to compensate for instrumentation faults
- Program Investment Strategy
 - Select key AF areas & apply DDDAS for end-to-end systems capabilities
 - "Excellence in Science and Transformative Impact to the Air Force"



Fundamental Challenges and Timeliness

- Application modeling methods to support dynamic data inputs
 - multi-modal, multi-scale, multi-fidelity models/simulations
 - dynamically invoke/select multiple scales/modalities/components
 - interfacing with measurement systems
- Algorithms tolerant to perturbations from dynamic data inputs
 - handling data uncertainties, uncertainty propagation, quantification
- Measurements
 - multiple modalities/fidelities, space/time distributed, data management
- Systems Software methods supporting such dynamic environments
 - dynamic/adaptive execution on heterogeneous/multi-hierarchical environments {from the high-end/mid-range to real-time platforms-- beyond Clouds(Grids) computation, communication, storage; programming models, run-time/OS, ...}

Timeliness -- Confluence across 4 emerging

DDDAS-Dynamic Data Driven Applications Systems

- Unifying High-End with Real-Time/Data-Acquisition&Control
- Large-Scale-Big-Data (Large-Scale-Dynamic-Data)
- "Big Data" + Ubiquitous Sensing&Control (2nd Wave of big-data)
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Impact to Civilian Sector Areas of prior and present Multiagency DDDAS Efforts

- Physical, Chemical, Biological, Engineering Systems
 - Chemical pollution transport (atmosphere, aquatic, subsurface), ecological systems, molecular bionetworks, protein folding..
- Medical and Health Systems
 - MRI imaging, cancer treatment, seizure control
- Environmental (prevention, mitigation, and response)
 - Earthquakes, hurricanes, tornados, wildfires, floods, landslides, tsunamis, ...
- Critical Infrastructure systems
 - Electric-powergrid ms. water supply systems, transmitted works and vehicles (air, ground, ur

"revolutionary" concept enabling to design, build, manage and understand complex systems

NSF/ENG Blue Ribbon Panel (Report 2006 – Tinsley Oden)

"DDDAS ... key concept in many of the objectives set in Technology Horizons"

Dr. Werner Dahm, (former/recent) AF Chief Scientist

Large-Scale Con ... onments

List of Projects/Papers/Workshops in www.1dddas.org

(+ DDDAS Conference Series - August2016, 2017,...)



Impact of DDDAS in AirForce Systems

"from the nanoscale to the terra- and extra-terra-scale"

Materials modeling; Structural Health Monitoring – Environment Cognizant - Energy Efficiencies; Autonomic Coordination of U(A/G)S Swarms;

Co-operative Sensing for Surveillance - Situational Awareness Space Weather and Adverse Atmospheric Events; CyberSecurity; Systems Software

Multidisciplinary Research

Drivers: advancing capabilities along the Key Areas identified in Technology Horizons, Autonomy Horizons, Energy Horizons, Global Horizons Reports

DDDAS ... key concept in many of the objectives set in Technology Horizons

● □ Autonomous systems	• □ Spectral mutability
 Autonomous reasoning and learning 	 □ Dynamic spectrum access
• □ Resilient autonomy	 □ Quantum key distribution
• □ Complex adaptive systems	 Multi-scale simulation technologies
■ V&V for complex adaptive systems	 Coupled multi-physics simulations
 □ Collaborative/cooperative control 	• □ Embedded diagnostics
• □ Autonomous mission planning	 Decision support tools
• □ Cold-atom INS	 Automated software generation
• □ Chip-scale atomic clocks	 ■ Sensor-based processing
• □ Ad hoc networks	Behavior prediction and anticipation
■ Polymorphic networks	• □ Cognitive modeling
• □ Agile networks	• □ Cognitive performance augmentation
■ Laser communications	• ☐ Human-machine interfaces
□ Frequency-agile RF systems	



Large-Scale-Big-Data



Emerging scientific and technological trends/advances

- > ever more complex applications systems-of-systems
- increased emphasis in complex applications modeling
- increasing computational capabilities
- increasing bandwidths for streaming data
- increasing sources of data



(heterogeneous, distributed, multi-time-scales)

- > Sensors Sensors EVERYWHERE... (data intensive Wave #2)
 - Swimming in sensors and drowning in data LtGen Deptula (2010)
 Analogous experience from the past:
 - "The attack of the killer micros(microprocs)" Dr. Eugene Brooks, LLNL (early 90's)

about microprocessor-based high-end parallel systems

then seen as a problem – have now become an opportunity - advanced capabilities

Back to the present and looking to the future:

■ "Ubiquitous Sensing – the attack of the killer micros sensors) – 2nd wave"

Dr. Frederica AFOSR (2011, LNCC)

<u>challenge</u>... Ubiquitous Sensing such resources

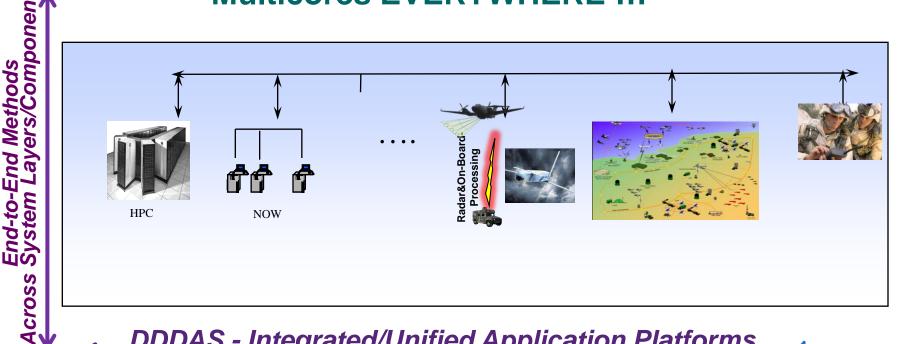
important component of BIG DATA -- Wave #2! - ... capabilities

→ Large-Scale-Big-Data



Integrated Information Processing Environments from Data-Computation-Communication to Knowledge-Decision-Action

Multicores EVERYWHERE !!!



DDAS - Integrated/Unified Application Platforms

Adaptable Computing and Data Systems Infrastructure spanning the high-end to real-time data-acquisition ontromanifesting heterogeneous multilevel distribut system architectures - softw

Technological Advances for exascale

overlapping multicore needs - por

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Large-Scale **Big-Computing f-**



Examples of Areas of DDDAS Impact to the AF "from the nanoscale to the terra- and extra-terra-scale"

Materials modeling; Structural Health Monitoring – Environment Cognizant - Energy Efficiencies; Co-operative Sensing for Surveillance - Situational Awareness; Autonomic Coordination of U(A/G)S Swarms; Cognition Space Weather and Adverse Atmospheric Events; CyberSecurity; Systems Software



Development of a Stochastic Dynamic Data-Driven System for Prediction of Material Damage

J.T. Oden (PI), P. Bauman, E. Prudencio, S. Prudhomme, K. Ravi-Chandar - UTAustin

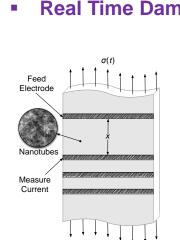
Goal: Dynamic Detection and Control of Damage in Complex Composite Structures

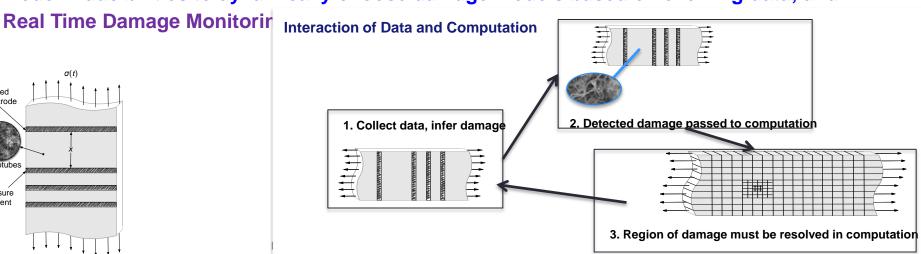
Results achieved:

- Through DDDAS new capabilities have been developed for prediction of material damage
- For example can predict on-set of damage before is observed experimentally and predict the evolution of the damage.

Methodology:

- Dynamic Data: direct and indirect measurements of damage in materials
- Reliable predictive computational models: Finite element solution of continuum damage models
- Handling uncertainties: Bayesian framework for uncertainty quantification and Bayesian Model Plaucibilities to dynamically choose damage models based on evolving data; and



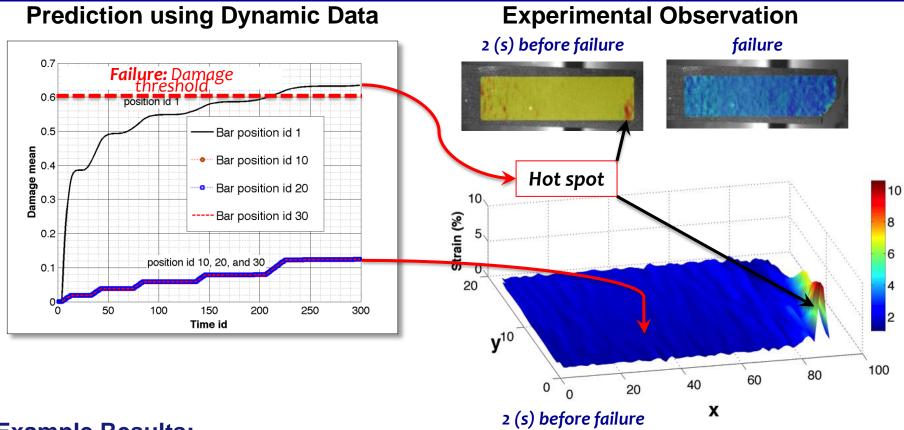




Development of a Stochastic Dynamic Data-Driven System for Prediction of Material Damage



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Example Results:

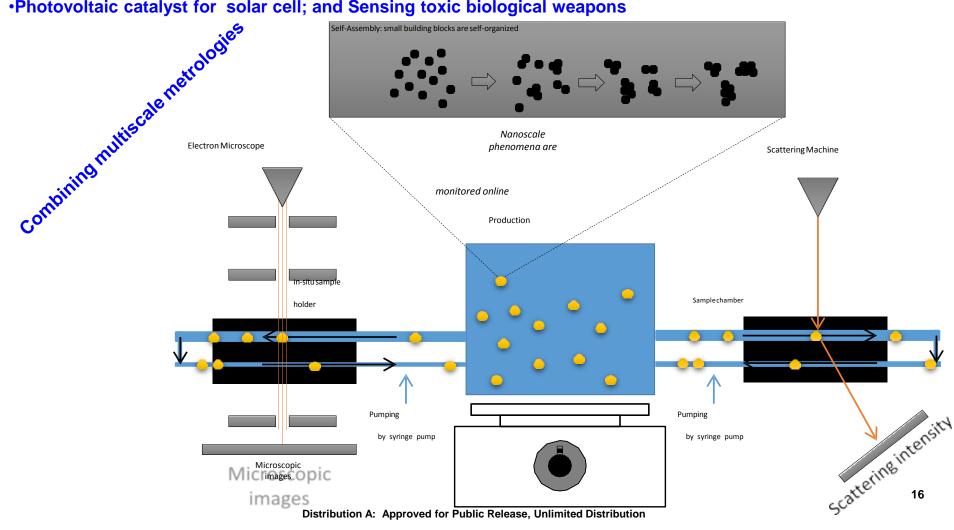
- Experimental Data: shows the spatial variation of strain 2(s) before the failure
- Prediction Using Dynamic Data: shows the computed evolution of the damage variable with time at various position
- "hot spot": is the dangerous point leading to system failure
- From the test results the hot spot can be observed few second before failure



Dynamic, Data-Driven Modeling of Nanoparticle Self-Assembly Processes Team: Ding, Park, Huang, Liu, Zhang

Many applications require nanoparticle products of precisely controlled sizes and shapes, because the functionalities of the nanoparticles are determined by their sizes and shapes.

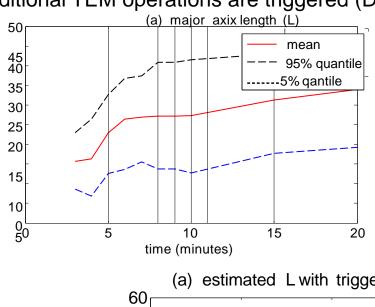
- •Nanoparticles as propellants of satellites and space craft propulsion;
- •Nanocomposites with special mechanical and electrical properties;
- •Photovoltaic catalyst for solar cell; and Sensing toxic biological weapons

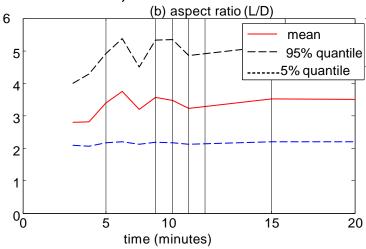


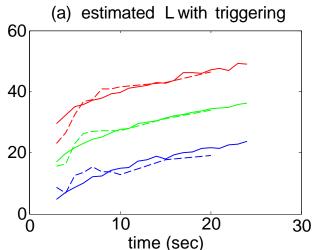


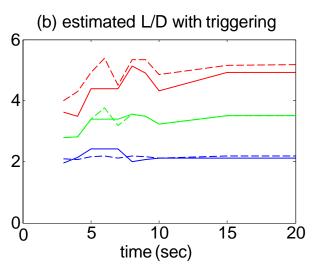
Controlled TEM Triggering

TEM triggering process initiated after t = 5 mins, controlled per the (DDDAS-based) approach. Additional TEM operations are triggered (DDDAS model driven) in between 5 and 20 minutes.





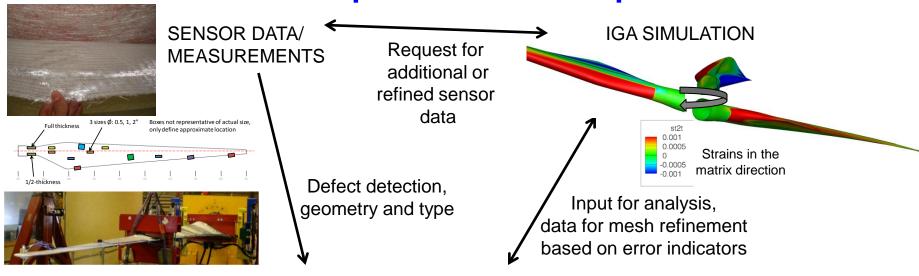




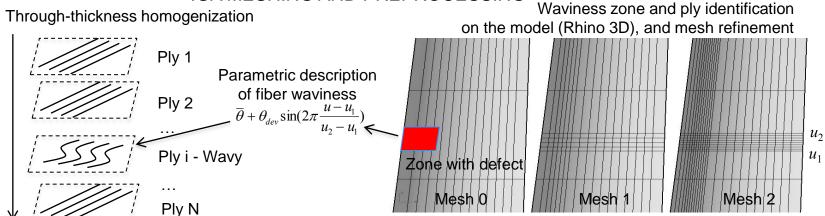


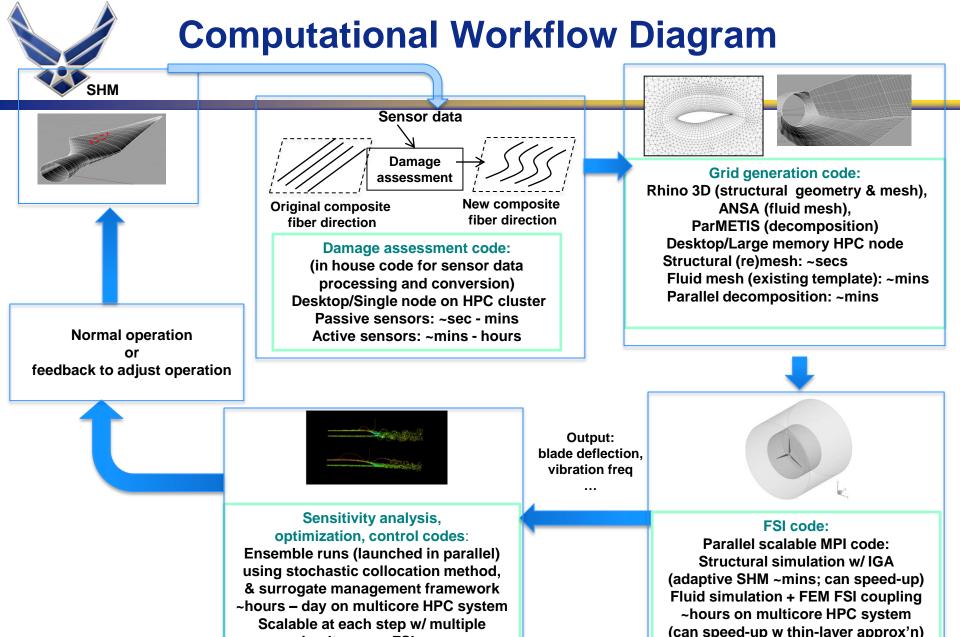
Advanced Simulation, Optimization, and Health Monitoring of Large Scale Structural Systems Y. Bazilevs, A.L. Marsden, F. Lanza di Scalea, A. Majumdar, and M. Tatineni (UCSD)

DDDAS Loop for Detected In-plane Waviness



IGA MESHING AND PREPROCESSING



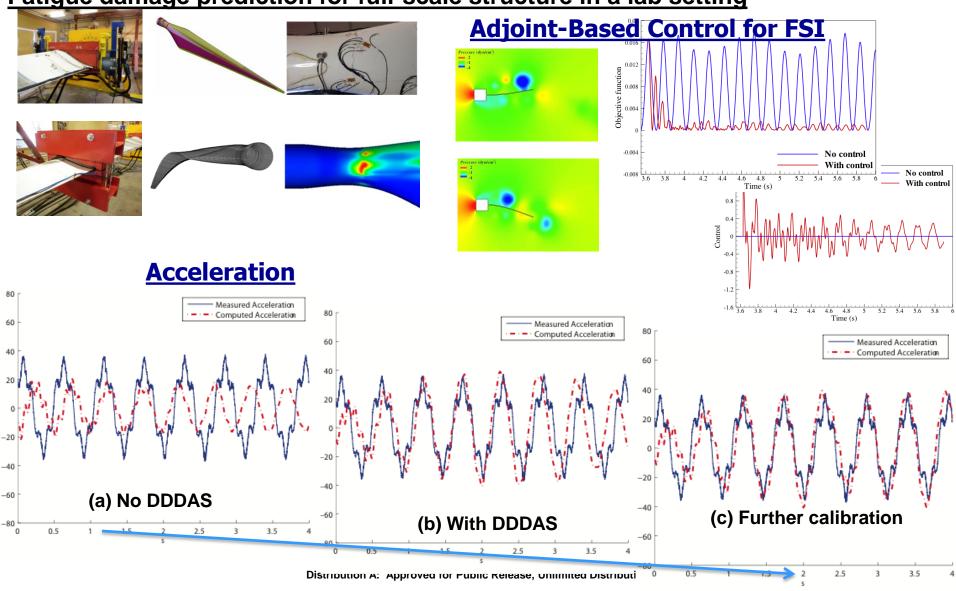


simultaneous FSI runs



Advanced Simulation, Optimization, and Health Monitoring of Large Scale Structural Systems Y. Bazilevs, A.L. Marsden, F. Lanza di Scalea, A. Majumdar, and M. Tatineni (UCSD)

Fatigue damage prediction for full-scale structure in a lab setting





Advanced Simulation, Optimization, and Health Monitoring of Large Scale Structural Systems Y. Bazilevs, A.L. Marsden, F. Lanza di Scalea, A. Majumdar, and M. Tatineni (UCSD)

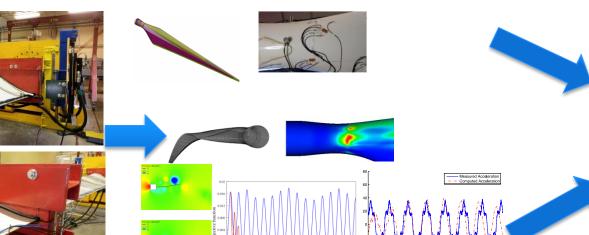
Using the DDDAS paradigm the project has developed:

- new multiscale laminated-composite fatigue damage model data-based dynamic calibration
- new algorithm for numerical fatigue testing and failure prediction for laminated composite structures driven by dynamic accelerometer data
- new formulation and algorithm for adjoint-based control in coupled fluid-structure interaction
- new software based on isogeometric analysis for modeling complex geometry and material layout, including measured defects, for large-scale composite structures

Results:

new capability to dynamically update advanced fatigue damage models in full-scale structural simulations with the goal to predict the remaining fatigue life of a structure

Fatigue damage prediction for full-scale structure in a lab setting



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Prediction of fatigue damage in real operating conditions...



and sheltering of structures from excessive damage



Dynamic Data-Driven Methods for

Self-Aware Aerospace Vehicles

D Allaire, L Mainini, F Ulker, M Lecerf, H Li, K Willcox (MIT); G Biros, O Ghattas (UT Austin);
J Chambers, R Cowlagi, D Kordonowy (Aurora)

A self-aware aerospace vehicle; dynamically adapt to perform mission cognizant of itself and its surroundings and responding intelligently.



Approach and objectives

- > infer vehicle health and state through dynamic integration of sensed data, prior information and simulation models
- > predict flight limits through updated estimates using adaptive simulation models
- re-plan mission with updated flight limits and health-awareness based on sensed environmental data

Research Goal: multifidelity framework using DDDAS paradigm

- draws on multiple modeling options and data sources to evolve models, sensing strategies, and predictions
- dynamic data inform online adaptation of structural damage models and reduced-order models
- dynamic guidance of sensing strategies
- dynamic, online multifidelity structural response models&sensor-data, for predictions w sufficient confidence

Results: dynamic health-aware mission re-planning with quantifiable benefits in reliability, maneuverability and survivability.

Methodologies

- statistical inference for dynamic vehicle state estimation, using machine learning and reduced-order modeling
- adaptive reduced-order models for vehicle flight limit prediction using dynamic data
- on-line management of multi-fidelity models and sensor data, using variance-based sensitivity anal
- quantify the reliability, maneuverability and survivability benefits of a self-aware UAV





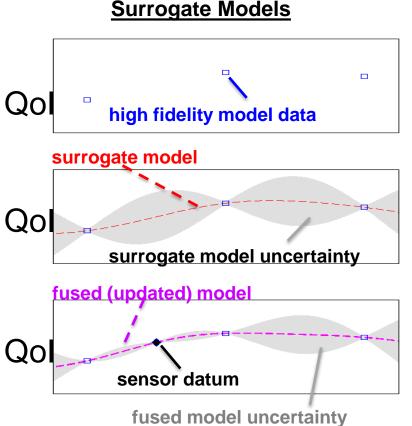
Dynamic Data-Driven Methods for Self-Aware Aerospace Vehicles



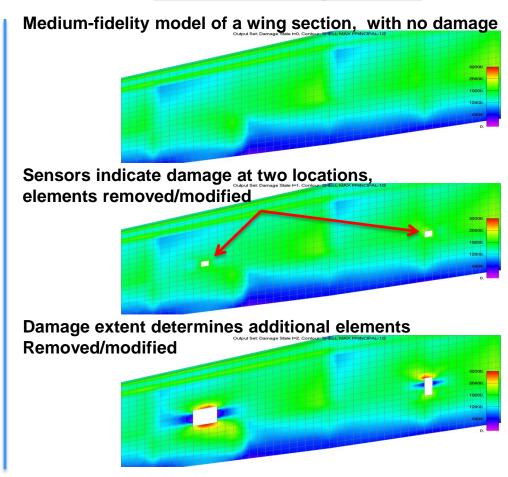
K. Willcox (MIT); G. Biros, O. Ghattas (UT Austin); J. Chambers, D. Kordonowy (Aurora).

Data Incorporation Examples

Companyata Madala



Structural Damage Models



Dynamic Data-Driven Methods for Self-Aware Aerospace Vehicles D Allaire, K Willcox (MIT); G Biros, O Ghattas (UT Austin); J Chambers, D Kordonowy (Aurora)

Decision-making needs are informed by current quantity of **Quantities of Interest** interest estimates **Dynamically evolving DDDAS process:** -Infer-Predict-Plan-Act-**Mission Plan Flight Limits Vehicle State** Models Adaptive Structural Response Planning Models Information Fusion Models Models Models provide current estimates of the Environmental data inform Models drive adaptive sensing quantities of interest planning models Sensors Sensors: structural health, Sensors: IMS/GPS. stress/strain, pressure temperature Quantities of interest drive adaptive sensing

- •Confident estimation of vehicle state in offline phase, time-sensitive estimation of vehicle state in online phase
- Onboard damage model updated using sensed structural data/state
- •Efficient algorithms scale well on GPU and manycore architectures
 - Update estimates of flight limits via adaptive reduced-order models
 - •Progressively fuse higher fidelity information with current information as more time and resources become available
 - Sensitivity analysis for dynamic online management of multifidelity models & sensors for vehicle state & flight limit

PREDICTION

NFERENCE

Dynamic environmental data inform online adaption of reduced-order models for mission planning Multifidelity planning approaches using reduced-order models Quantification of reliability, maneuverability, survivability

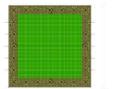


Dynamic Data-Driven Methods for

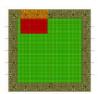
Šelf-Aware Aerospace VehiclesD Allaire, L Mainini, F Ulker, M Lecerf, H Li, K Willcox (MIT); G Biros, O Ghattas (UT Austin); J Chambers, R Cowlagi, D Kordonowy (Aurora)

An offline/online DDDAS approach 18" x 18" Panel Test case: composite panel on a UAV

Offline: develop libraries of panel strain information, under different load/damage scenarios under uncertainty. Develop data-driven reduced-order models to map from sensed strain to damage state, capability state, and mission decision-making.



information



estimation

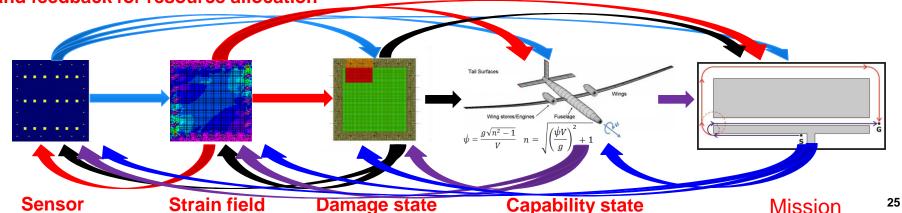


Example damage scenarios caused by ply delamination. Red and orange indicate delamination sites.

25decision-making

Online: information management strategy for dynamic sensor and model-based data acquisition, damage and capability state updates, and dynamic mission re-planning.

Arrows represent mapping capabilities from sensor data to mission decision-making, and feedback for resource allocation

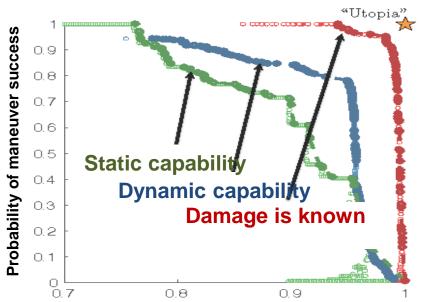


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Dynamic Data-Driven Methods for Self-Aware Aerospace Vehicles D Allaire, L Mainini, F Ulker, M Lecerf, H Li, K Willcox (MIT); G Biros, O Ghattas (UT Austin); J Chambers, R Cowlagi, D Kordonowy (Aurora)

Trade-off curves for evasive maneuver flight scenario decision strategies



Using the dynamic data through the DDDAS approach increases both vehicle utilization and probability of maneuver success

Average fraction of vehicle capability utilized

Highlights of improvements achieved in this project:

- High-fidelity offline evaluation takes \sim 5-10 seconds per maneuver per damage case. To evaluate a flight envelope over 100 damage cases and 50 maneuvers takes ~7-14hrs
- Online classification using the damage library takes ~100-300 microseconds The DDDAS method yields a speed up of a factor of ~50,000-100,000
- **Decision support for maneuver**
- Work transitioned to Aurora Flight Sciences



PROGNOSIS

STANFORD MECHANICAL

Slides Courtesy C. Farhat

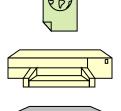




Pilot Display of Crisis

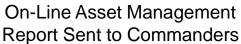
Real-Time On-Board Sensing and Processing

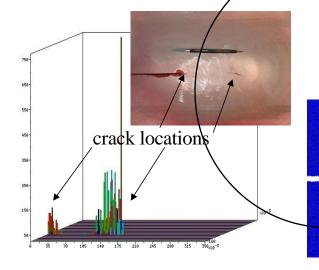




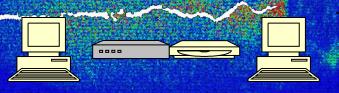
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Real-Time On-Board **Prognosis and Processing**





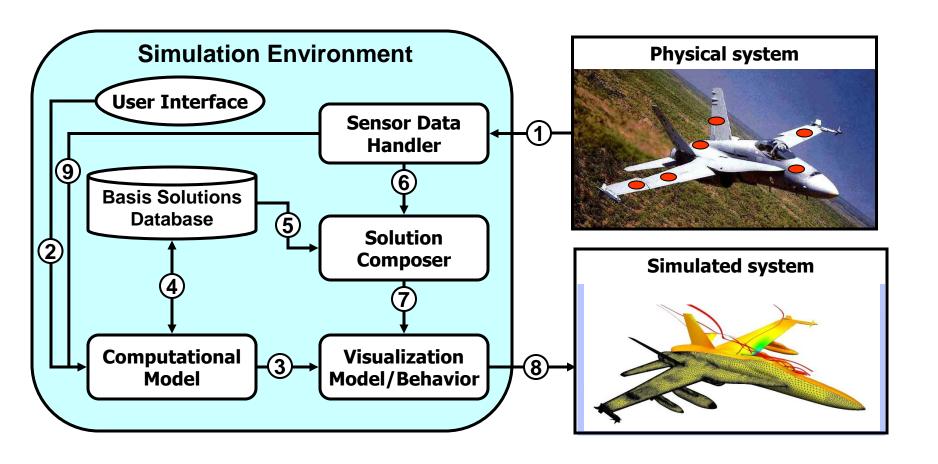
High-Performance Off-Line Prognosis by Modeling and Simulation



Detailed **Prognosis** Results

Real-Time Support for supersonic/hypersonic multiphysics simulation-based paltform management: Flutter, Temperature & Softening of Skin Material Degredation etc.

Slides Courtesy C. Farhat

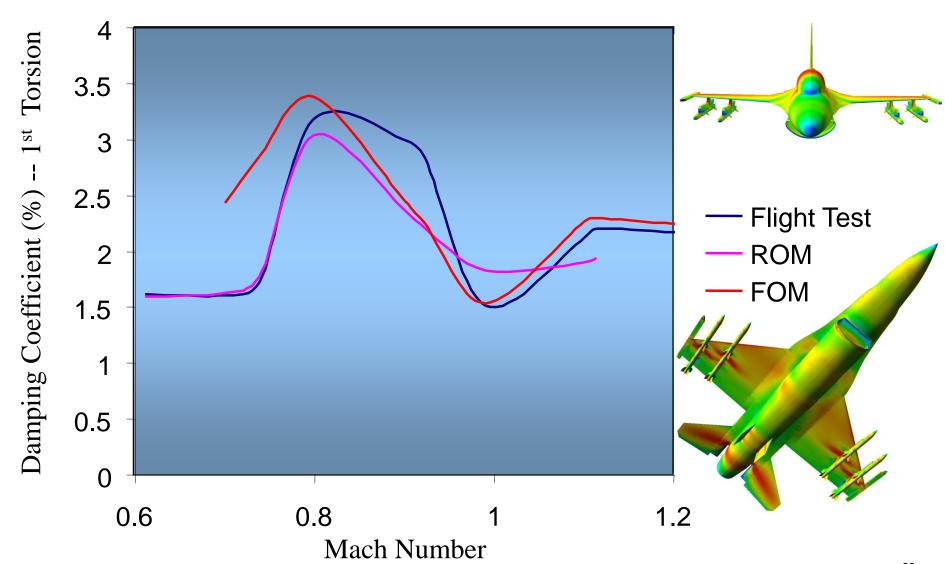




VALIDATION

STANFORD MECHANICAL ENGINEERING

Slides Courtesy C. Farhat

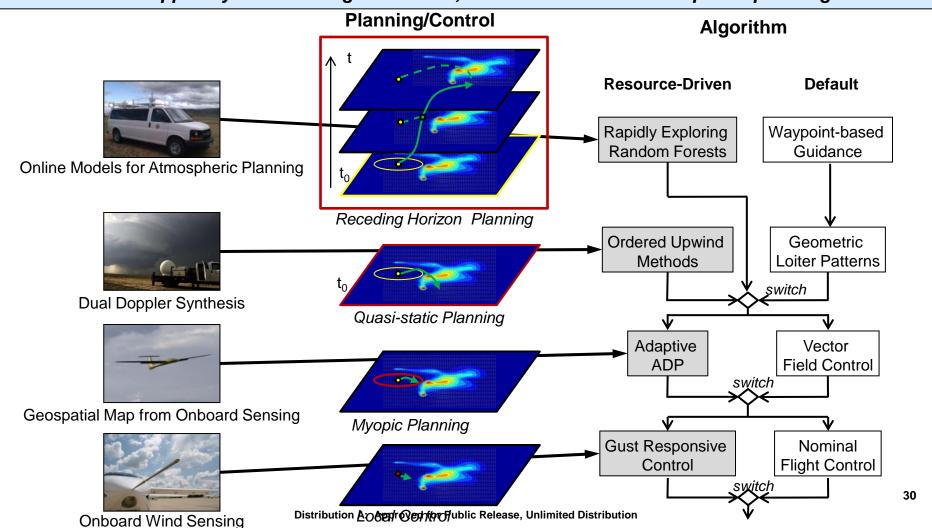




Energy-Aware Aerial Systems for Persistent Sampling and Surveillance

E. W. Frew, Brian Argrow- U of Colorado-Boulder; Adam Houston – U of Nebraska-Lincoln)
Chris Weiss - Texas Tech University

Energy efficient flight planning through dynamically integrated multilevel models and information sources local aircraft energy and wind states; spatio-temporal wind fields; dual-Doppler synthesis of regional winds; on-line models for atmospheric planning.

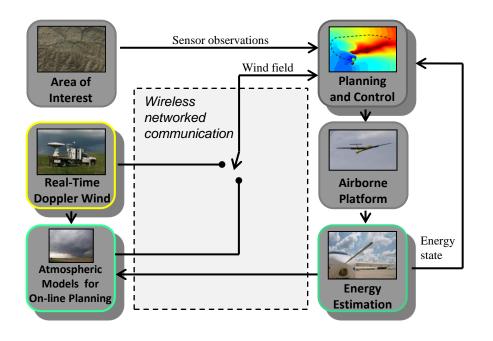




Energy-Aware Aerial Systems for Persistent Sampling and Surveillance



E. W. Frew, Brian Argrow- U of Colorado-Boulder; Adam Houston – U of Nebraska-Lincoln) Chris Weiss - Texas Tech University



This effort will develop, assess, and deliver new Air Force capabilities in the form of energy-aware, airborne, dynamic data-driven application systems (EA-DDDAS) that can perform persistent sampling and surveillance in complex atmospheric conditions.

Features of the EA-DDDAS span the four key DDDAS technology frontiers

- Decision-making over different application modeling layers that include
 - local aircraft energy and wind states
 - spatio-temporal wind fields
 - dual-Doppler synthesis of regional winds
 - on-line models for atmospheric planning.
- •Mathematical algorithms that provide high degree of autonomy with control loops closed over multiple spatial and temporal scales.
- •New measurement systems and methods whereby disparate information sources are assimilated by online models; mobile sensors are targeted to relevant measurements in real time; and data processing rates are throttled in response to computation resource availability.
- •Net-centric middleware **systems software** that connects multiple systems with computation and control resources dispersed over wireless communication networks.



Dynamic Modality Switching Aided Object Tracking using an Adaptive Sensor Matthew Hoffman, Anthony Vodacek (RIT)

- Create capabilities to enhance persistent aerial vehicle tracking in complex environments where single imaging modality is insufficient, and full spectral imaging yields inordinate amounts of data
- Approach and objectives
 - Use the DDDAS framework to allow the tracker to dynamically control the sensor to specify modality and location of data collection and this data to reduce uncertainty in target location
 - Develop algorithms to optimize the use of small amounts of hyperspectral data and evaluate performance in simulated scenes using realistic noise and a moving platform
 - Begin development of real data testing scenes

Methodology

- Tracker leverages DOTCODE framework from previous AFOSR funding
- Simulation study leverages existing Digital Imaging and Remote Sensing Image Generation (DIRSIG) scenes of a cluttered urban area
- Real data collection leverages multispectral WASP Lite sensor at RIT







Multispectral Wasp Lite scene with moving vehicles



Dynamic Modality Switching Aided Object Tracking using an Adaptive Sensor Matthew Hoffman, Anthony Vodacek (RIT)

 Object tracking through particle filtering approach – uses Gaussian Sum Filter (GSM needed to handle noise in observing turning vehicles – uses an ensemble of vehicle models)

New adaptive image processing methods for both the targets and the background

Introduced new cascaded **Data Acquisition & Filtering** target detection, combining: MHT Data Association Gaussian Sum Filer **Target Detection/ Background Modeling** NDVI vegetation detection Nonlinear SVM roads classifier **Target Movement Model** Spectral matching to target • Adaptive, multi-model ensemble Linear SVM/HoG vehicle classifier

Processing

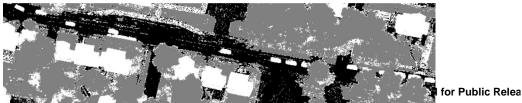
- SIFT Keypoint Registration
 - Homography Estimation

Sensor Control & Data Acquisition

- Modality Selection
- Region of interest determination

Vegetation and **road** classification (bottom) of image





Object tracking through targeted feature matching











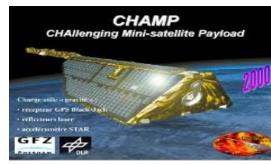
Transformative Advances in DDDAS with Application to Space Weather Modeling Dennis Bernstein (PI), Amy Cohn, James Cutler, Aaron Ridley – U of Michigan

Scientific Motivation

Unknown changes to the atmospheric density degrade the accuracy of GPS and impede the ability to track space objects

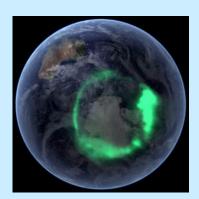
Project Scope and Objectives

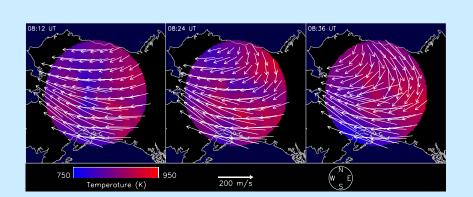
- Apply DDDAS concepts and methods to space weather monitoring
- Key goals are input estimation and model refinement to facilitate higher-accuracy data assimilation
- Input reconstruction is used to estimate atmospheric drivers that determine the evolution of the ionosphere-thermosphere
- Model refinement is used to improve the accuracy of atmospheric models
- DDDAS supported by space physics modeling and mission planning and analysis
- DDDAS-based accurate prediction of important quantities: NO, Neutral Density, PhotoElectron Heating, Eddy Diffusion Coefficient Estimate

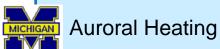




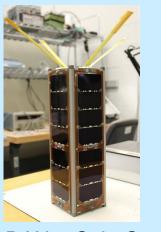
Space Debris







Wind Field Estimation

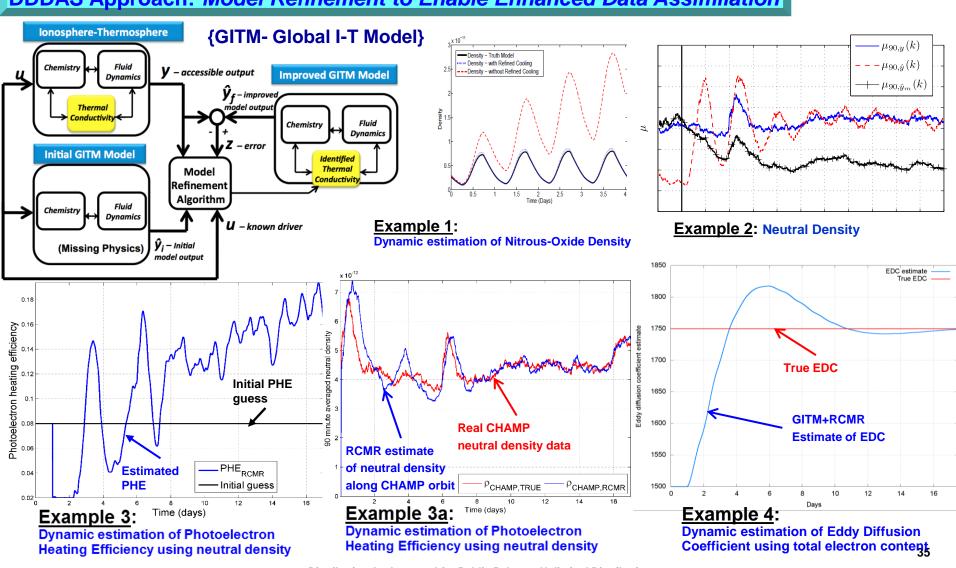


RAX-2 CubeSat



Transformative Advances in DDDAS with Application to Space Weather Modeling Dennis Bernstein (PI), Amy Cohn, James Cutler, Aaron Ridley – U of Michigan

DDDAS Approach: Model Refinement to Enable Enhanced Data Assimilation





Real-time Assessment and Control of Electric-Microgrids (YIP - Project) Nurcin Celik, University of Miami

Motivation: predict/mitigate power outage (case study: effects in an AF Base)

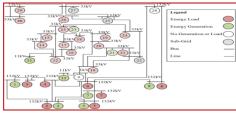
- How should a real-time diagnosis and forensics analysis be performed automatically?
- Did it occur because of an accidental failure or malicious and possibly ongoing attack?
- A wide spread disturbance or just a localized outage of a few minutes?
- How should the AFB microgrid respond to this abnormality (or catastrophe)?
- What actions should be taken to secure the AFB power supply?



quick responsive and corrective actions via autonomous control







Approach:

- Dynamic Data Driven Adaptive Multi-scale Simulations framework (DDDAMS)
- new algorithms and instrumentation methods for RT data acquisition and timely control

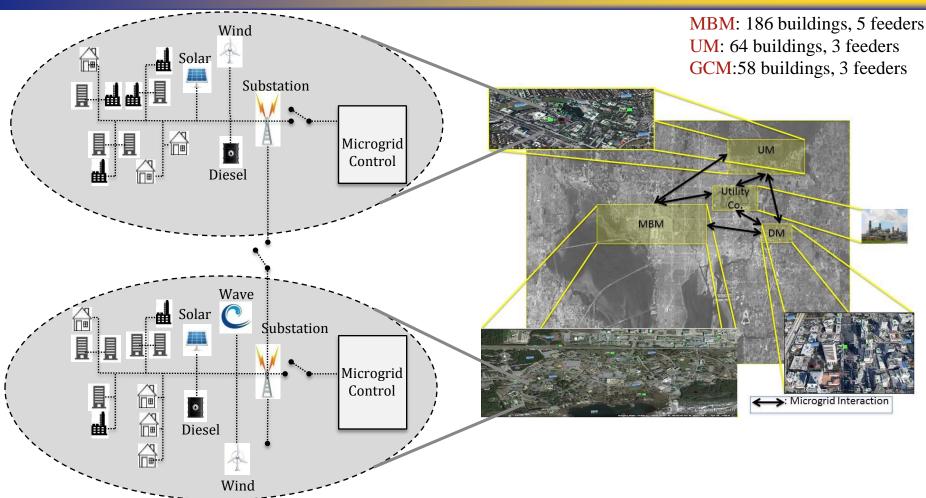
Challenges:

- Large number of variables, nonlinearities and uncertainties
- Intense and time-critical information exchange
- High processing requirements for massive information loads
- Synchronization between the distributed sensor and decision networks



Real-time Assessment and Control of Electric-Microgrids

(YIP - Project)
Nurcin Celik, University of Miami



- To ensure that primary electrical needs are satisfied while total cost is minimized
- To maintain MGs' stability and security by
 - Meeting requested demands within each individual MG
 - Searching for neighboring MGs for back-up



Experiments on Self-Healing Microgrids

The proposed DDDAMS approach is tested on MGs that do not share energy in the following cases:

- **Scenario A:** A major hurricane completely wipes out power to GCM for 48 hrs
- **Scenario B:** A terrorist attack within the borders of UM forces MBM to isolate from the local utility for 2 hrs until the threat is cleared (damage on UM link will require 6 hrs to repair)

Demand Satisfaction

	Caonaria	MBM Loads		UM Loads			GCM Loads			
	Scenario	Cr	Pr	NCr	Cr	Pr	NCr	Cr	Pr	NCr
No Sharing	A	100%	100%	100%	100	100%	100%	4 <u>6</u> %	0%	0%
	В	97.6%	79%	66.4%	45 <u>.</u> 2%	4%	0 %	10 %	100%	100%
Sharing	A	100%	10 %	95.7%	10 0%	93.2%	27.9%	100%	0 6	0 %
	В	98.6%	94%	66.4%	97%	41.1%	6%	99%	52.1 %	26%

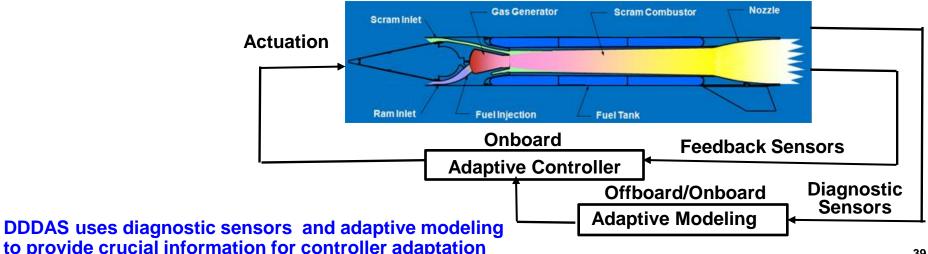
Cr: Critical Pr: Priority NCr: Non-critical



An example of other possible future scope of work **Estimation and Control of Highly Inaccessible Dynamics** in Complex Systems

- Major challenges for understanding, characterization, performance optimization, adaptive control in real-world natural&engineered systems and their applications are due to a combination of:
 - high degree of non-linearity; very high dimensionality of the parameter space;
 - epistemic and aleatoric uncertainty; and hard constraints on states and control inputs
- Examples include: turbulent flows for complex and adaptive aircraft configurations; combustion in jet engines and scramjets; instabilities in structures; and programmable metamaterials (e.g. solitons/breathers; quantum information devices)
- Measurements are difficult to attain, and models alone do not afford the fidelity needed, in highly unstable (&inaccessible) regions
- Dynamic Data-Driven Application Systems (DDDAS) based methods
 - combine estimation and control techniques with real-time computation and data
 - dynamically couple an executing model with the instrumentation, allow targeted collection of data and compensate for data sparsity in the measurement or the solution phase space

Highly Complex System (Scramiet)



Examples of Sci&Tech Highlights of Outcomes/Results/Achievements through DDDAS

Materials modeling - Structural Health Monitoring

- Demonstrated that DDDAS-based materials modeling can model regions of instabilities leading to exploitation of new properties in materials
- Have demonstrated that DDDAS models can predict the onset of damage prior to being detected experimentally

Self -Cognizant and Environment -Cognizant UAS Mission Planning

 Demonstrated that DDDAS methods allow decision support in real-time with accuracy of large scale simulation – e.g.: DDDAS method yields a speed up of a factor of ~50,000-100,000 - online classification using the damage library takes ~100-300 microseconds.

Algorithmic Advances in UQ

Demonstrated effectiveness of PCQ in a broader class of systems than gPC;
 developing further improved UQ methods based on the DDDAS paradigm

Improved sensing approaches

• Demonstrated that intelligent deployment of mobile sensors provides improved efficiencies – e.g. one mobile sensor (DDDAS model driven) vs 7 stationary sensors

Cybersecurity

Demonstrated theoretical basis for resilient software security.



Summary and QUO Vadimous

Key strategies and directions

- Transformational Research Dynamic Data-Driven methods for Adaptive, Agile, Autonomic systems; end-to-end capabilities
- Responsive to AF needs, Transformational Impact to the AF and other sectors
- Impact to civilian sector applications

Expansion Opportunities

- Expanding interactions with AFRL, ONR/NRL, ARO/ARL
- Expanding collaborations and leverage other Agencies' efforts
- Expanding international collaborations
- Expanding/leveraging industry partnerships

(1998- ... precursor Next Generation Software Program)

SystemsSoftware - Runtime Compiler - Dynamic Composition - Performance Engineering

(2000 - Through NGS/ITR Program)

Pingali, Adaptive Software for Field-Driven Simulations

(2001 - Through ITR Program)

Biegler - Real-Time Optimization for Data Assimilation and Control of Large Scale Dynamic Simulations

Car - Novel Scalable Simulation Techniques for Chemistry, Materials Science and

Knight - Data Driven design Optimization in Engineering Using Concurrent Integrated Experiment and Simulation

Lonsdale - The Low Frequency Array (LOFAR) - A Digital Radio Telescope

McLaughlin - An Ensemble Approach for Data Assimilation in the Earth Sciences

<u>Patrikalakis</u> – Poseidon – Rapid Real–Time Interdisciplinary Ocean Forecasting: Adaptive Sampling and Adaptive Modeling in a Distributed Environment

Pierrehumbert - Flexible Environments for Grand-Challenge Climate Simulation Wheeler- Data Intense Challenge: The Instrumented Oil Field of the Future

(2002 - Through ITR Program)

<u>Carmichael</u> – Development of a general Computational Framework for the Optimal Integration of Atmospheric Chemical Transport Models and Measurements Using Adjoints

<u>Douglas-Ewing-Johnson</u> - Predictive Contaminant Tracking Using Dynamic Data Driven Application Simulation (DDDAS) Techniques

Evans - A Framework for Environment-Aware Massively Distributed Computing

Farhat - A Data Driven Environment for Multi-physics Applications

Guibas - Representations and Algorithms for Deformable Objects

Karniadakis - Generalized Polynomial Chaos: Parallel Algorithms for Modeling and

Propagating Uncertainty in Physical and Biological Systems

Oden - Computational Infrastructure for Reliable Computer Simulations

Trafalis - A Real Time Mining of Integrated Weather Data

(2003 -Through ITR Program)

Baden - Asynchronous Execution for Scalable Simulation in Cell Physiology

Chaturvedi- Synthetic Environment for Continuous Experimentation (Crisis Management

Droegemeier-Linked Environments for Atmospheric Discovery (LEAD)

Kumar - Data Mining and Exploration Middleware for Grid and Distributed Computing Machiraju - A Framework for Discovery, Exploration and Analysis of Evolutionary Data

Mandel - DDDAS: Data Dynamic Simulation for Disaster Management (Fire Propagation) Metaxas- Stochastic Multicue Tracking of Objects with Many Degrees of Freedom

Sameh - Building Structural Integrity

{Sensors Program: Seltzer - Hourglass: An Infrastructure for Sensor Networks}

(2004 - Through ITR Program)

Brogan - Simulation Transformation for Dynamic, Data-Driven Application Systems (DDDAS) Baldridge - A Novel Grid Architecture Integrating Real-Time Data and Intervention During Image Guided Therapy

Floudas-In Silico De Novo Protein Design: A Dynamically Data Driven, (DDDAS), Computational and **Experimental Framework**

Grimshaw: Dependable Grids

Laidlaw: Computational simulation, modeling, and visualization for understanding unsteady bioflows Metaxas - DDDAS - Advances in recognition and interpretation of human motion: An Integrated

Approach to ASL Recognition

Wheeler: Data Driven Simulation of the Subsurface: Optimization and Uncertainty Estimation

(2005 DDDAS Multi-Agency Program - NSF/NIH/NOAA/AFOSR)

Ghattas - MIPS: A Real-Time Measurement-Inversion-Prediction-Steering Framework

for Hazardous Events

How - Coordinated Control of Multiple Mobile Observing Platforms for Weather

Forecast Improvement

Bernstein - Targeted Data Assimilation for Disturbance-Driven Systems: Space

weather Forecasting

McLaughlin - Data Assimilation by Field Alignment

Leiserson - Planet-in-a-Bottle: A Numerical Fluid-Laboratory

Chryssostomidis - Multiscale Data-Driven POD-Based Prediction of the Ocean

Ntaimo - Dynamic Data Driven Integrated Simulation and Stochastic Optimization for Wildland Fire Containment

Allen - DynaCode: A General DDDAS Framework with Coast and Environment Modeling

Douglas - Adaptive Data-Driven Sensor Configuration, Modeling, and Deployment for

Oil, Chemical, and Biological Contamination near Coastal Facilities

Clark - Dynamic Sensor Networks - Enabling the Measurement, Modeling, and Prediction of Biophysical Change in a Landscape

Golubchik - A Generic Multi-scale Modeling Framework for Reactive Observing

Williams - Real-Time Astronomy with a Rapid-Response Telescope Grid Gilbert - Optimizing Signal and Image Processing in a Dynamic, Data-Driven Application System

Liang - SEP: Intergrating Multipath Measurements with Site Specific RF **Propagation Simulations**

Chen - SEP: Optimal interlaced distributed control and distributed measurement with networked mobile actuators and sensors

Oden - Dynamic Data-Driven System for Laser Treatment of Cancer

Rabitz - Development of a closed-loop identification machine for bionetworks

(CLIMB) and its application to nucleotide metabolism

Fortes - Dynamic Data-Driven Brain-Machine Interfaces

McCalley - Auto-Steered Information-Decision Processes for Electric System Asset Management

Downar - Autonomic Interconnected Systems: The National Energy

Sauer- Data-Driven Power System Operations

<u>Ball</u> - Dynamic Real-Time Order Promising and Fulfillment for Global Make-to-Order Supply Chains

Thiele - Robustness and Performance in Data-Driven Revenue Management Son - Dynamically-Integrated Production Planning and Operational Control for the Distributed Enterprise



* projects, funded through other sources and "retargeted by the researchers to incorporate DDDAS"

* ICCS/DDDAS Workshop Series, yearly 2003 - todate other workshops organized by the community...

•2 Workshop Reports in 2000 and in 2006, in www.cise.nsf.gov/dddas & www.dddas.org

