Towards a Dynamic Data Driven System for Structural and Material Health Monitoring

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Abstract. This paper outlines the initial motivations and implementation scope supporting a dynamic data driven application system for material and structural health monitoring as well as critical event prediction. The dynamic data driven paradigm is exploited to promote application advances, application measurement systems and methods, mathematical and statistical algorithms and finally systems software infrastructure relevant to this effort. These advances are intended to enable behavior monitoring and prediction as well as critical event avoidance on multiple time scales.

1 Introduction

During the last two decades, great strides have been achieved in many aspects of computational sciences and engineering. Higher-fidelity mathematical models, higher-order approximation methods, and faster solution algorithms have been developed for many applications. Computing speed and networking communications barriers have also been shattered by hardware manufacturers. As a result, the potential of modeling and simulation for reducing design-cycle time and enhancing system performance is recognized today in almost every field of engineering. However, for many complex structural systems, even the most elaborate computational models remain bound to be imperfect for many reasons. These include the limited means currently available for realistically modeling a number of phenomena governing the behavior of the system of interest or some of its components. They also include the fact that for most cases, stimulus conditions (initial, boundary, and loading) are typically acquired only after the actual systems are placed in service. This hinders the potential of modeling and simulation, and forces designers to impose empirical safety factors for allowable performance limits. This practice often leads to over-designed, inefficient and expensive products that may be unsafe in the presence of unforeseen critical conditions. The Dynamic Data Driven Application Systems (DDDAS) paradigm is uniquely opportune for exploiting maturing computational and sensor networking technologies to compensate for model deficiencies and unforeseen

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system evolution and stimulus conditions, mitigate the effect of design imperfections on long-term as well as short-term system safety, and enable informed decision for maintenance planning and crisis management.

Our overall goal is to enable and promote active health monitoring, failure prediction, aging assessment, informed crisis management, and decision support for complex and degrading structural engineering systems based on dynamic-data-driven approaches. The specific objectives are: (i) To investigate, design, implement, illustrate and assess a DDDAS for health monitoring, failure prediction, and crisis management at various time-scales of degrading structural systems. (2) To build a test-bed and exercise it to guide the development of the desired DDDAS, and validate with experiments a representative set of its underlying approaches and methodologies. (iii) To exploit the above test-bed and design a series of educational experiments that can serve as pillars for educational exploitation of the DDDAS concept.

The research themes associated with these specific objectives are driven by the following representative application scenarios: (S1) Apply the DDDAS concept off-line to obtain material characterizations and construct an initial model of the structural system of interest (S2) Exploit dynamic operational data to update regularly, on-line, the current model. (S3) Apply the DDDAS concept to perform on-line crisis management. (S4) Apply the DDDAS concept to assist off-line crisis management and maintenance planning.

Our project will draw experiences and technologies from our previous efforts on a data-driven environment for multiphysics applications (DDEMA) [1].

2 Approach

Scenario S1 outlined above is representative of the problem of collecting and exploiting data to develop a behavioral model for a system prior to its usage. Scenarios S2 to S4 cover a time-scale that ranges from very short as in catastrophic failure induced (e.g. by flutter manifesting in less than 2 seconds), to very long as in a failure induced (e.g. by a slowly accumulating damage due to cyclic load manifesting in months or years of platform operation).

Figure 1 captures the various application scenarios of the envisioned DDDAS and displays a road map of the corresponding research activities as follows. Material characterization will provide behavior models to the damage detection schemes (path 1); on-line processing and prognosis procedures will be updated by sensor-originating dynamic data (path 2); in turn, these procedures will modify the damage detection schemes (path 3) which will either provide feedback directly to the system if an imminent crisis is detected (path 4); otherwise, they will update off-line high performance modeling and simulation procedures and request long-term prognosis of slow evolving but accumulating damage (path 5). This can then enable on-demand rather than routinely scheduled maintenance.

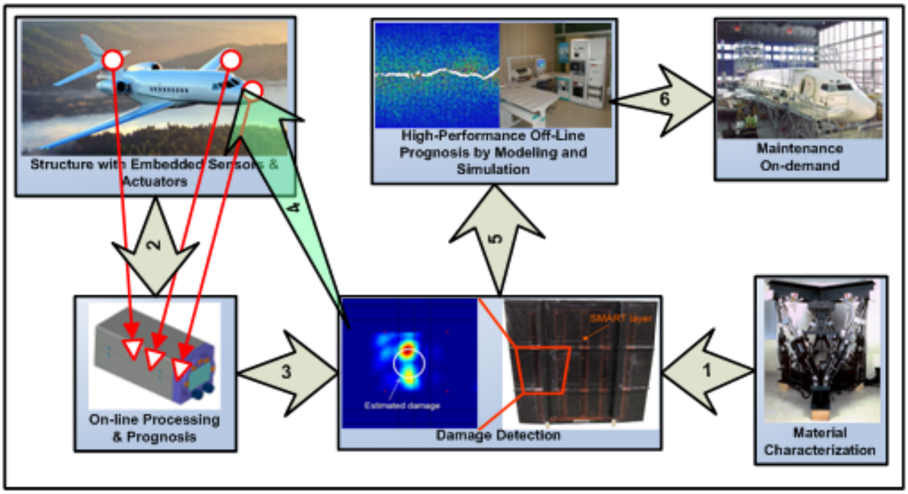

Fig. 1. Data flow within the main activities associated with our approach

2.1 Dynamic-Data-Driven Inverse Material State Characterization

An essential element of our approach is the data-driven computation of a constitutive theory/model that accounts for multiphysics loading conditions. This approach consists of the following parts.

A. Mechatronicaly Automated Data Acquisition. Data-streams of experimentally controlled continuous system behavior in the form of stimulus-response pairs of all observables will be generated. This will be done with the aid of an extended multi-degree of freedom mechatronic loading systems [2, 3]. While the system imposes preprogrammed displacement controlled loading paths to the appropriated specimens, sensors measure both the controlled displacements and rotations as well as the corresponding reaction forces and moments along with the additional multi-field state variables (i.e. temperature). These sensors generate the data-streams upon which all subsequent energy based evaluations are made. Of particular interest to DDDAS in general, is the opportunity we have to use our system in a manner which demonstrates that the modeled behavior can be used to adjust an experimental procedure.

B. Inverse Modeling of Dissipative Behavior. Analytical representations will be constructed such that they can accurately reproduce a subset of the acquired data via successive dynamic adaptation with the help of optimization technology. This will be accomplished by the employment of an energy density dissipation potential called dissipated energy density function (DEDF) that is a function of the strain and temperature states of the material. Aerodynamically induced heat can further contribute to the damage behavior of aerospace composite structures and therefore, the coupled influence of temperature with mechanical deformations cannot be neglected any longer and will be integrated in the formalism. The DEDF corresponds to the energy lost into the material system for the creation of micro-cracking damage and therefore it represents a scalar physical quantity associated with material health [2, 4, 5]. Its gradient with respect to strains yields the corresponding constitutive relations that determine the stresses. An approximation of the DEDF for a material system will be constructed as a sum of appropriately selected basis functions that depend only on the local strain and temperature state of the material in the structure. The coefficients that are weighting these basis functions are the unknowns to be determined with the aid of the experimental data. Minimizing the error between the analytically computed dissipated energy and the experimentally measured one by NRLs mechatronic systems reduces this problem to a data-driven inverse global optimization problem with appropriate inequality constraints. Solving this problem by any global optimization technique produces the sought-after coefficients and fixes the form of the DEDF.

C. Degrading Behavior Simulation. The derived constitutive models derived will be utilized to simulate the response of any system that uses the characterized materials. To achieve this, the identified degrading behavior model will be introduced into our AERO-S structural code [6, 7]. AERO-Ss separation of material and geometric encoding makes this effort very feasible as we have already demonstrated for single physics applications [2, 3, 4, 5].

D. On-line Extensions. The material characterization procedures described above are essentially off-line activities. Online exploitation of damage accumulation models, damage tracking criteria and algorithms will also be developed based on the amount and rate of dissipated energy in a fashion similar to the one developed for metal fatigue.

2.2 Sensor Network Architectures and Protocols

Any prediction based on the approach outlined above depends, among others, on the performance of the sensor network providing the data. In the context of coupling the simulation of a structure to a sensor network monitoring the structure, some problems take on a special significance and need to be addressed.

On-line dynamic techniques that monitor the health of the routing infrastructure of the network, bypass failed areas, and always guarantee information delivery as long as the network remains connected will be investigated. We already have developed distributed techniques for discovering failed areas, or “holes”, in a sensor network and building routes around them [8].

Regarding the data integrity we intend to investigate how to tune sensor misbehavior detection system, as too many false positives may remove valuable sensor resources from the network, while too many false negatives may pollute the data generated and veer the simulation off track. Unlike other sensor network settings, the availability of a powerful simulator in our scenarios can greatly aid the discovery and correction of node misbehavior.

Relative to the coupling between sensors and simulation technology, our goal is to define a narrow interface between the sensor network and the simulator, exploiting our knowledge of models of how the system should behave in order to compress away predictable information and focus only on the deviations between the simulation predictions and the actual readings. We are constrained by the fact that the nodes have very limited computational power, so it is not possible for them, individually or in groups, to run the full simulation model.

To achieve this goal, an approach where the simulation computes reduced-order models that are appropriate for making predictions over a certain time period for small groups of collocated sensors (sensor clusters) will be followed. These models are transmitted to the sensor clusters and then independently checked by distributed regression within the cluster. No communication with the base station is necessary as long as the local models fit the data. The communication between the sensor network and the simulation is reduced to the periodic transmission of reduced-order models from the simulation and of deviant sensor readings from the nodes. Even if reduced-order models are difficult to obtain for some applications, general data aggregation and summarization techniques can be exploited to the same effect, though not with the same efficiency [9]. These approaches can be used to define narrow interfaces between the simulation and the sensor network and can form the basis of a software infrastructure that serves well data-driven application systems.

2.3 Modeling Approaches and Solution Algorithms

The application problems targeted by this research effort are not linear time-invariant. Hence, constructing reduced order models (ROMs) can be challenging. Some nonlinear model order reduction techniques have already been developed and encountered some success. However, these techniques are in general either applicable only to weakly nonlinear systems, or they are reliable only for input signals close to the training input. Furthermore, they are not usually robust with respect to large parameter changes, whether the parameter is geometrical, material, or related to the surrounding of the structural system for example, the Mach number of a cruising aerospace vehicle [10]. Reconstructing a ROM each time a problem parameter is varied cannot be performed today anywhere close to near real-time, and therefore defeats the purpose of using a ROM in the first place. Alternatively, a ROM can be rapidly adapted to a parameter change. Previous approaches for adapting a proper orthogonal decomposition (POD) basis to address a parameter variation include the global POD method [11, 12] and the direct interpolation of the basis vectors [10] with poor results.

Two approaches for adapting a ROM will be investigated. The first approach aims at short time-response or on-line predictions where changes in the material properties of the structure slightly before the onset of the short-term instability and a couple of seconds later can be neglected. The objective is to rapidly adapt a ROM trained at a particular set of stimulus conditions to another set of loading conditions. For such applications, a suitable combination of a sensitivity approach and the method of “subspace angle interpolation” [13] will be investigated. We expect that the combination of this approach with sensitivity analysis and a precomputing strategy will lead to an effective approach for adapting in near-real-time a given ROM to changes in multiple parameters. The second approach aims at off-line medium time-response problems where fast but not necessarily near-real-time processing is required. It is based on the re-use of Krylov subspaces for the solution of near-by problems [14].

We have recently developed a family of Parallel Implicit Time-integration Algorithms (PITAs) for accelerating the numerical processing of ROMs in order to achieve near-real-time predictions [15, 16]. In [16], it was shown that for linear but otherwise complex structural dynamics problems, the latest PITAs can converge in two to three iterations and speed-up the total processing of a ROM by a factor equal to six using 25 processors. Hence, the objective of a PITA is not to deliver a high parallel efficiency, but to reduce as much as possible the CPU time of a problem that offers little opportunities for parallelism. We are attempting to extend the PITA methodology to nonlinear structural dynamics problems. Furthermore, in order to get closer to near-real-time response, we are also attempting to investigate two complementary approaches for improving the CPU performance of the PITA methodology. The first approach consists in investigating an alternative to propagating the jumps of the solution on the coarse time-grid in order to reduce the computational overhead of this time-parallel methodology. The second approach consists in exploiting the DDDAS context and initializing the seed values of the solution by sensor-provided data.

2.4 Systems Software Technology

Figure 2 presents an abstract architecture that has both off-line and on-line functionality and remains consistent with the tenets of our project. It consists of the following main components: a sensor subsystem,a narrow interface between the sensor subsystem and the sensor data reduction and/or preparation subsystem, a user interface, a full order model (FOM) solver with the ability to construct ROMs, a ROM database, a ROM adaptor that composes appropriate on-line models based on sensor inputs, and a behavior visualizer. This architecture is capable of addressing both the off-line and on-line modes of operations as they were described earlier. In particular, the path defined by the sequence

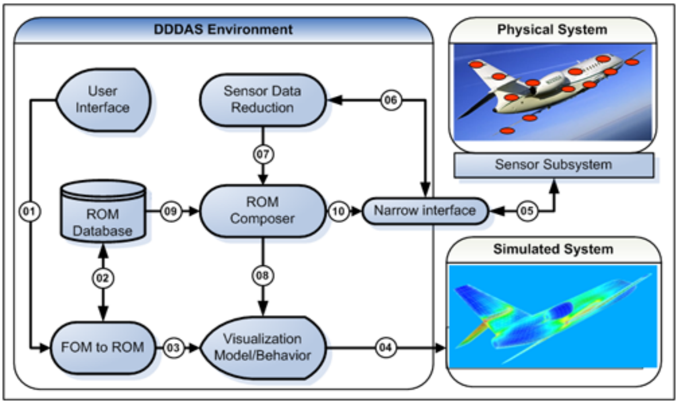

Fig. 2. Generic DDDAS architecture

[01,02,03,04]in Figure 2 can be executed off-line and can be used for computing and storing ROMs. Similarly, the path [05,06,07&09,08,04] can be used for ROM-based and sensor-driven simulations for decision support. Finally, the path [09,10,05] implements the model-based effects on the sensor network. Some software components in this architecture will dynamically select and optimize their distribution at run-time via mobile "middleware" as shown for DDEMA [1].

2.5 Test-Bed Article Integration and Demonstration

A general test-bed infrastructure of both wired and wireless sensor networks will be selected for building the prototype in the study. For a wired network system, the "SMART" layer approach [17] will be adopted. Passive sensors such as strain and temp sensors will be embedded along with active piezoelectric sensors/actuators into the layer. The layer will be customized fit into the configuration of the wing, which will be made of graphite epoxy prepreg commonly used in aircraft structures. Sensor network strips will be embedded inside composites or mounted on the inner surface of the wing during curing process as shown in Figure below so the composite and layer were integrated during the fabrication.

For the study of short-term response, the composite wing will be subjected to a foreign object impact by a hammer or a drop weight at the structures. Upon impact, the same sensor networks will be activated automatically to characterize the impact event and determine if active sensing is needed to interrogate the severity of the impact damage to create diagnostic images. The estimated damage image will be imported into a finite element simulation code to determine the effect of such damage on the residual strengths of the structure.

Finally, for the study of long-term time scale, the composite wing will be subjected to repetitive flight conditions determined by repetitive combinations of angle of attack and speed in order to induce and to assess the long-term degradation. Sensors will be reporting strains and temperature data for a multiple missions over long period of time. Tracking of the strain-temperature condition will be accomplished by appropriate database utilization along with corresponding dissipated energy density evaluations. After each emulated mission is completed, the final distribution of dissipated energy density will be assessed and used to derive the current softened distributions of the material properties (at the areas where this is applicable), to be used as startup conditions for the next emulated flight. This process will be repeated for various emulated flights and the computed material softening distributions as a result of slowly accumulating damage will be compared with the correlated values of damage index evaluated from the short-term (or medium time) health monitoring technique that will be employed.

3 Conclusions

In this paper, we have described an outline for the motivational drivers, some technical issues and the approach for developing a DDDAS for material and structural health monitoring along with critical event prediction across heterogeneous time-scales. Both the main research activities of the project and their interrelationship as well as an abstract architecture of the system have been described. The general application area for such a system is the area of design and maintenance of aerospace platforms.

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