Enabling Intelligent Life-cycle Health Management for Industry Internet of Things (IIOT)

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NDE and SHM in the Age of Industry 4.0

LEONARD J. BOND and NORBERT G. MEYENDORF

ABSTRACT

Condition based maintenance is now routinely applied to rotating machinery, with data transmitted wirelessly and reviewed automatically, to give a prognostic or remaining life estimate. The challenge is implementing integrated NDE/SHM strategies for structural assessment. However, advances in computer and communications technology, the internet of things and management of big data are starting to offer the digital infrastructure which can be combined with new sensor systems to enable SHM/prognostics to be applied to structural materials. Some challenges and opportunities which assess and demonstrate how NDE and SHM can potentially be revolutionized in the age of Industry 4.0 are outlined.

INTRODUCTION

There is increasing use of new materials and advanced manufacturing processes, including various composites and additively manufactured materials, to meet a diverse array of engineering challenges and opportunities [1]. At the same time these materials present new challenges with the need to maintain, and even improve quality, reliability and safety for many items at the time of manufacture and in-service. To meet these needs a variety of trends have emerged: within NDE there have been advances to move beyond detection of smaller and smaller discrete defects to include understanding of "allowables," those local material variations which do not impact performance, and which are random manufacturing material or fabrication anomalies, such as local grain size variation, and small voids in additive material or other inhomogeneity’s in composites. At the time of fabrication there is seen to be a need to provide tools to enable Material State Awareness (MSA), which looks beyond discrete defects to a mapping of a materials local properties. With aging systems and periodic inspections there has been interest to move beyond data given through NDT/NDE assessment to incorporate it in prognostics for the prediction of a remaining safe or service life [2].

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In looking at life cycle management for many engineering systems there is a trend to move beyond periodic inspections with the deployment of structural health monitoring (SHM). There has however been a separation between activities using periodic NDE and measurements performed with in-service SHM systems. The resulting data are commonly not well integrated. There must be a cultural change in the NDT/operations community so that when a defect is found or an accident occurs the response is not to just reduce the inspection interval.

To enhance life cycle management and looking at these two complementary approaches what is the state of the art and where are the NDT/NDE and SHM communities going to ensure system reliability and safety? Conventional NDT is a mature technology, in large part controlled by codes and standards, which has a diverse range of capabilities [3]: it is in large part practiced in a community which is conservative and often seen as resistant to rapid change. Globally it is a large range of activities which has a market size that was recently reported as being expected to be worth $21.20 Billion by 2025 [4]. New processes, such as additive manufacturing and increased use of composites, complicate inspection and new technologies, such as phased array and x-ray computed tomography, as well as various advanced implementation strategies are now capable of generating enormous data sets. Effectively managing assets, combined with manipulation and use of such data sets, is challenging.

There is also activity using structural health monitoring (SHM). This has been talked about for more than 40 years and in many areas adding such capability as a retrofit is hard and even in new equipment and structures for many potential application areas it has yet to be implemented. The global SHM market size is slowly growing and is expected to reach $4.34 billion by 2025 [5]: There seem to be investments in infrastructural development and government regulations are driving some deployments with mandating implementation of sensors and data acquisition systems to monitor structure health and these trends are expected to augment the market. The increasing age of existing bridges and dams and a rising focus on infrastructural advances including construction of new bridges, dams, buildings, and stadiums are also providing a push to the market. That said, although there have been many decades of work in SHM and yet there has been only relatively limited progress made in terms of industrial deployment [6].

This paper highlight some challenges and opportunities for items fabricated using additive manufacturing and composites that bring NDE and SHM together. The community is at a point where addressing big data needs for NDE and SHM has the potentiality to revolutionize asset life management in the age of Industry 4.0.

**PROACTIVE MANAGEMENT OF MATERIALS DEGRADATION**

So what are the trends to move beyond “find and fix” using periodic NDE to more integrated management approaches to tracking and managing structural degradation (aging)? More than a decade ago the nuclear power community, specifically through the US Nuclear Regulatory Commission, started to look at issues related to life and license extension of nuclear power plants, to address the issue of moving beyond “reactive management of materials degradation,” and “the inspect find and fix mentality.” To manage these aging assets two processes were envisioned: implementation of actions to mitigate or eliminate the susceptibility to material
degradation and implementation of effective inspection, monitoring, and timely repair of degradation [7]. These concepts sought to bring together processes that operated through a systems life cycle, from initial design and fabrication, through inspections and on into service, with both periodic inspections and continuous monitoring (AKA SHM). The concepts that relate to Prognostics and Proactive Management of Materials Degradation (PMMD) were developed and both active and passive components were considered. This nascent program included an assessment of the then state of the art for NDE, monitoring and prognostics, as well as an outline for a path forward. At about the same time a variety of groups were looking at the issues that relate to "managing aging structures" with names such as material damage prognostics [8], and these programs were all in addition to those for rotating machinery and condition based maintenance [9].

In looking at what is needed for PMMD in essence the problem of prediction of remaining safe life for an aging passive component or structure could be easily solved if needed data were available with sufficient accuracy. Given data the conceptual strategy outlined in Figure 1 could potentially be followed and implemented. The challenge in implementing such a life management approach is that current NDT/NDE and SHM, as well as details of the operational environment and damage progression models are simply not available, and the available data are not easily integrated. In terms of the missing information the initial state of individual components, structures and systems are typically not known with adequate precision, and in many cases the investigator is looking at existing infrastructure, which may already be decades old and an operational environment has not traditionally been monitored for an individual component or structure. Damage progression models have also traditionally been empirical (e.g. Paris Law) and it would be difficult to incorporate the missing information into life management tools, even if it were available. The situation is further complicated by the uncertainty in available input data, and even if uncertainty can be limited there is variability to take into account, and clearly statistical processes are needed [10].

The question still remains: what is the status of the material models and the various NDE and SHM modalities needed for full implementation of a prognostic approach to SHM? Clearly various measurements are needed throughout the items life cycle. There is a continuum which goes from those made during manufacturing, including in-process measurements, to final item acceptance tests and then post-production NDE

Figure 1: Conceptual model for life models (after R.B. Thompson [10])
for damage assessment and repair validation, all integrated within a life cycle
management processes that brings together and utilizes the various data. In looking at
these capabilities there have been various assessments of the maturity of diagnostic
and prognostic technologies which have been published [e.g. 6, 11,12,13] and key
findings of these two assessments are summarized in the information given in Tables 1
and 2. It is seen that for rotating machinery CBM is well established, and in many
cases effectively deployed. The challenges increase when it comes to local damage
assessment, particularly when large components or structures are involved. The initial
challenges are obtaining and placing robust sensors with adequate sensitivity to the
desired parameters, system robustness in the operating environment, the data
structures used together with instrumentation to detect, gate and transmit data
reliability over extended periods of time.

Subsequent issues to consider in providing systems SHM and prognostic systems
which have been identified by NASA [14] include:

- **Uncertainty management**: How can the information from multiple uncertainty
  sources be properly captured and processed?
- **Autonomic control reconfiguration**: How can local prognostic information be
  translated into changes at the controller level such that controller objectives are
  satisfied in the long term?
- **Integration**: How should information from different, interacting subsystems be
  combined and processed?
- **Validation and verification of prognostics**: How can the proper operation of
  prognostic algorithms be validated, especially on new systems?
- **Post-prognostic reasoning**: How can the information from a prognostic
  reasoner be turned into an action, also factoring in other considerations such as
  logistics information, mission information, and fleet management?

<table>
<thead>
<tr>
<th>Type of SHM</th>
<th>Availability of standards</th>
<th>Type of measurement</th>
<th>Applications to real systems</th>
<th>Numbers of sensors for coverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Machine condition monitoring</td>
<td>Many</td>
<td>Mainly passive</td>
<td>• Multiple</td>
<td>Increasing²</td>
</tr>
</tbody>
</table>
| Global monitoring large structure (e.g. bridges)  | Some                      | Mainly passive      | • Increasingly common but not
|                                                  |                           |                     | mature                        |
|                                                  |                           |                     | • Many trials                 |
| Large area monitoring for local damage. Full     | Limited                   | Mainly active       | • A few commercial application |
| coverage typically requires multiple systems      |                           |                     | • Many trials                 |
| Localized damage detection, for example, cracks   | Limited                   | Mainly active       | • A few specialist applications |
| and corrosion                                    |                           |                     | • Many trials                 |

¹ Large structures are using multiple sensors, point measurements e.g. optical fibers, acoustic emission and imaging e.g. video cameras and vibration signature extraction. Large numbers of sensors needed for large areas – each sensing local region.

Table 1. A classification of SHM Techniques [after 6]
### Table 2: An assessment of the state of maturity for diagnostic and prognostics technologies [11,12,13]

<table>
<thead>
<tr>
<th>Diagnostic/Prognostic Technology for:</th>
<th>AP(^{(a)})</th>
<th>A(^{(b)})</th>
<th>I(^{(c)})</th>
<th>NO(^{(d)})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic Machinery (motors, pumps, generators, etc.)</td>
<td>D&amp;P</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Complex Machinery (helicopter gearboxes, etc.)</td>
<td></td>
<td>D&amp;P</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Metal Structures</td>
<td></td>
<td>D</td>
<td>P</td>
<td></td>
</tr>
<tr>
<td>Composite Structures</td>
<td></td>
<td>D</td>
<td>P</td>
<td></td>
</tr>
<tr>
<td>Electronic Power Supplies (low power)</td>
<td></td>
<td>D</td>
<td>P</td>
<td></td>
</tr>
<tr>
<td>Avionics and Controls Electronics</td>
<td></td>
<td>D</td>
<td>P</td>
<td></td>
</tr>
<tr>
<td>Medium Power Electronics (radar, etc.)</td>
<td></td>
<td>D</td>
<td>P</td>
<td></td>
</tr>
<tr>
<td>High Power Electronics (electric propulsion, etc.)</td>
<td></td>
<td>D</td>
<td>P</td>
<td></td>
</tr>
<tr>
<td>Instrument Calibration Monitoring (NPP)</td>
<td></td>
<td>D</td>
<td>P</td>
<td></td>
</tr>
<tr>
<td>Active Components (NPP)</td>
<td></td>
<td>D</td>
<td>P</td>
<td></td>
</tr>
<tr>
<td>Passive Components (NPP)</td>
<td></td>
<td>D</td>
<td>P</td>
<td></td>
</tr>
</tbody>
</table>

(a) AP = Technology currently available and proven effective  
(b) A = Technology currently available, but V&V not completed  
(c) I = Technology in process, but not completely ready for V&V  
(d) NO = No significant technology development in place

The status for deployment can be further seen by looking at various recently reported aero-space examples of advances in CBM/SHM commercial systems:

- In January 2018, Avitas Systems, a GE Venture, collaborated with Limelight Networks, Inc. for its next-generation, automated inspection platform [15].
- In July 2019 Honeywell’s Forge helps with predictive maintenance across components in 11 ATA chapters, including avionics, APUs, mechanical, electrical, hydraulic and environmental systems. The tool supports six models, Boeing 737s, 747s, 777s and 787s and Airbus A320s and A350s. For landing gear, Forge tracks hard landings and, when available, sensor data on temperatures in wheels and brakes [16].
- Rolls-Royce says its health-monitoring systems touch upon 70% of an airline’s direct operating costs [17].

For the aero-space community aircraft and engine health-monitoring solutions are at the heart of predictive maintenance and the “on-condition” maintenance model. Looking further ahead, the next generation of aircraft may incorporate structural sensors to warn of impending damage or weakness in wings and fuselages. OEMs are reported as already using a variety of such sensors in testing and research and have proved the viability of embedding strain gauges into materials such as carbon fiber [18]. One example of a deployed system has been reported for the F-35 structural prognostics and health management system [19] which has two corrosion sensors installed on each aircraft. In addition there are between 10 and 13 strain gages
installed and recording time histories, together with over 150 operational parameter time histories.

Various papers which analyze IVHM systems for PHM in the aviation and automotive industries show there are three elements used: (i) sensors, (ii) transfer of data from asset and (iii) use of the data. It has been found in a recent assessment, illustrated with Figure 2, that many of the most advanced units are in the automotive industry, and even then capability is less that those envisioned by the SAE [20].

When put in the context of integrate system life cycle management the various IVHM systems are not shown to be giving data to be integrated with that from NDE. So how are the gaps between the two communities to be bridged? Starting from an NDE assessment when looking at an engineering component in terms of the relationships between a crack that could cause failure and acceptance criteria these are shown in schematic form in Figure 3 [2]. As an example for high stress items, such as a turbine disc, an acceptance criteria for an ultrasonic inspection can be defined as an reflector signal equivalent to the response from a flat bottom hole (FBH). Performance of inspections would then typically be assessed in terms of a POD (probability of detection curve) and say a 90% POD with 95% confidence.
Critical crack size for unstable

SAFETY MARGIN

Crack size limit for fitness for purpose

BASIC SAFETY

Recording Threshold

Recording Threshold

Structural and other noise

DEFECT SIZE

Fig 3. Schematic showing relationship between crack size and NDT acceptance criteria [after 2, 21]

A largely open question then becomes, how does data from any SHM system correlate with the nominal the NDE levels defined in Figure 3. Particularly with some monitoring technologies what is the detected defect size, and the confidence with which the SHM system is performing. For example acoustic emission (AE) can tell an operator that something is cracking, and potentially give a location, but size information is lacking. With many guided wave systems changes can be detected, and as with AE a location can be given, but type and size of degradation can be much more difficult to determine, without either addition and separate NDT measurements or a model based inversion.

Advanced materials are changing the needs and implementation of NDE, particularly when composites and powder metals are considered. A critical question for composites and additively manufactured parts is the impact of manufacturing anomalies, given that the response of such features has little direct correlation in terms of echo size measured with ultrasonics to the reflection from a flat bottom hole (FBH) and then, particularly for composites, damage on design allowables or manufacturing acceptable features, with criteria for types and acceptable “anomalies. Figure 4 considers the case of a composite. An equivalent figure for a powder metal part can address the QA/QC from the powder through to the part [22].

The next issue when considering NDE and SHM is then the evolution of damage and the challenge of what and when degradation can be detected in-service. A schematic for the evolution of stress corrosion cracking developed by Staehle, is shown as Fig 5 [11,23]. Probably 95% of the life of a part is in phases 1-4. It is only in phase 5 when there is relatively rapid growth that NDT can usually be expected to find the cracks. This then leaves two questions: (i) what is the in-service performance of NDT and (ii) at what point in a life cycle do SHM techniques start to detect damage and how much remaining life is there at that point?
Figure 4. Schematic showing impact of both design anomalies and damage on a composite

Figure 5. Schematic for the evolution of stress corrosion cracking [11,23]

THE NDE-SHM INTERFACE

In many ways, materials damage prognosis and PMMD are analogous to other damage tolerance approaches, with the addition of in-situ local damage and global state awareness capability and much improved damage predictive models [7, 8]. But how do we bring the data together? There are fundamental differences in data structure between NDE and SHM in monitoring passive (structural components). As illustrated in Figure 6 on line monitoring sensors provide data as a function of time at discrete locations, whereas NDE provides data sets at discrete times.
On-line monitoring sensors provide data as a function of time at discrete locations

Figure 6: Illustration of the fundamental differences between NDT and SHM data faced by the community [2].

Current SHM has limited coverage and flaw sizing to give an acceptable POD is still research. In addition SHM seeks to provide much broader coverage and R&D is seeking to demonstrate flaw sizing capability. NDT/NDE is seeking more efficient inspections, particularly for hard to access structure. Both SHM and NDE are needed and it is the data fusion which may well be considered to be the biggest challenge.

There are also a range of activities to advance Condition-Based Maintenance (CBM) and System Life Cycle Management. Various groups have sought to look at trends relating to the application of MSA to condition-based maintenance and system life cycle management [24]. A workshop was structured around three focal topics: (1) advances in metrology and experimental methods, (2) advances in physics-based models for assessment, and (3) advances in databases and diagnostic technologies.

Merging NDT data and engineering analysis (CAD) into digital twins, together with moves from focusing on discrete defect detection and characterization to material state awareness (MSA), combined with increasing use of models and model assisted probability of detection (MAPOD) are all providing major challenges. There are opportunities to improve designs, achieve enhanced performance while at the same time maintaining quality, safety and reliability all in the context of life cycle management, and moves to give prognostic capabilities [2].

PATH FORWARD

As already stated condition based maintenance for rotating machinery is well established and being effectively deployed for a diverse range of systems, from jet engines, to pumps and wind turbines. What has been largely missing has been the "structural" part of health monitoring!

To address the passive structure and structural components in many engineering systems the requirement there is a need to get smarter with the sensing and to look to combine both NDE and SHM. For example sol-gel
transducers can be applied in a sparse array to give continuous local NDE measurements for thickness gages on piping systems in a refinery [25] and guided waves for long-range ultrasound can be used to detect global changes in other regions. Both sensing technologies can be implemented with either wired or wireless data transmission. Combining these technologies can give nearly complete and continuous of high temperature piping, without the requirement to remove insulation that is needed for periodic inspections. The use of integrated NDE and SHM as tools with integrated approaches to life cycle management, do appear to be on the cusp of major changes. Data volumes can now start to be managed in near-real-time.

When working to bring together NDE and SHM approaches, and prognostics with life cycle management, a first step is to improve initial component NDE assessments [26]. Stressors need to be understood: such as temperature, stress, and corrosion, and effects on defects or anomalies. Good material damage models are needed. In service it is then all about being smart about the what, when, where and how to make measurements for the sensing! In the integrated approach to life assessment it is then important to identify and understand measurement sensitivities to critical parameters and relating them to life cycle, particularly early damage and bringing together of system that measure operational parameters and the NDE/SHM data.

One example of a deployed life management system is that for the F-35 where it is reported that 150 operational parameters are recorded, with data combined with that from a relatively small number of strain gages and two corrosion sensors [19]. It is not however clear how NDE data are integrated into assessments.

An example from the NDE side which illustrates the challenges presented by big data is axle inspection for a high speed train. Systems have now been developed for both wheel and axle inspections. For one axle there is 1.6 GByte of data obtained with 7 transducers. There are 32 axles per train and six inspections per year. The estimated life for a wheel set is 10 years and with a conservative estimate this gives 3 TByle of data, just for the axles for each train. Data volumes can be increased if inspection frequency is increased and it is reported that Deutsche Bahn reduced inspection intervals from 250,00 to 60,000 km following an accident in Cologne [27].

The leap forward will be when the digital twin is merged with NDE data, that from ongoing SHM, operational parameters, all to give a reliable and prognostic prediction, in reasonable time. When assessing the state of the internet of things it is being projected that software agents and advanced sensor fusion will occur in a physical world web over the next decade. The evolution of both industrial revolutions and NDE are illustrated with Figure 7. The internet of things will enable continuous monitoring of manufacturing processes, as additive manufacturing increasingly presents unique parts to be inspected and monitored [27].

The implementation of advanced and integrated life-cycle NDE and SHM have the potential for prognostics and the economic advantages which that can bring, as shown in Figure 8.
<table>
<thead>
<tr>
<th>Industrial Revolution</th>
<th>1st</th>
<th>2nd</th>
<th>3rd</th>
<th>4th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mechanization.</td>
<td>Mass Production.</td>
<td>Automation</td>
<td>AI-machine learning systems</td>
<td></td>
</tr>
<tr>
<td>Replacement of muscle power</td>
<td>Assembly lines, Electrical energy</td>
<td>Electronic control and data processing</td>
<td>Learning and decision-making mechanisms</td>
<td></td>
</tr>
</tbody>
</table>

**NDT/NDI**

<table>
<thead>
<tr>
<th>1st</th>
<th>2nd</th>
<th>3rd</th>
<th>4th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Using human senses to assess “quality.”</td>
<td>Enhancing detectability - e.g. penetrant and human senses for surface breaking cracks</td>
<td>Using physical effects - e.g. radiation, fields and waves to detect defects and measure material properties</td>
<td>Use cyber-physical systems (cloud computing, Internet of Things, modeling)</td>
</tr>
<tr>
<td>Random (and not uniform) inspections.</td>
<td>100% manual inspection of selected safety critical parts</td>
<td>Manual and automated testing</td>
<td>Continuous monitoring of manufacturing processes &amp; components during services</td>
</tr>
<tr>
<td></td>
<td></td>
<td>100% inspection of large quantities of parts</td>
<td>Large volume data files</td>
</tr>
</tbody>
</table>

**CONCLUSIONS**

The community is at a point where addressing big data needs for NDE and SHM has the potentially to revolutionize asset life management in the age of Industry 4.0. The adoption of prognostics has the potential to provide an economic framework that can support use of advanced NDE and SHM. PHM is best implemented and sold during the installation: its always cheaper to implement a PHM system in the beginning (e.g., when starting a new design/process) rather than after the fact. Determining the level of performance required for the PHM system in the beginning can help to determine how varying levels of maintenance and downtime will impact production and profitability. Tying reduced maintenance costs and productivity increases to PHM can help demonstrate the value of implementing a PHM system from the start. [20]
The technical challenges are not negligible and require systematic and interdisciplinary attention:

- **Sensing**: what to measure and how to measure it
- Better sensor materials
- Data interrogation, communication and integration
- Large volumes of data (may be real time) — big data and data fusion
- Signal to noise - Extracting signals from noise in signals (to give early detection) and managing drift in sensors (aging)
- Stability of measurement systems/sensors over time
- System integration and deployment on real-world hardware
- **Quantification of uncertainty** — (ill-posed problems)
- Phenomena of aging and degradation — effects of stressors — understanding
- Aging damage models
- Health sensors/NDE/NDI — sensors for SHM — smart components (self-diagnostic)
- Data integration with process models
- Predictive/prognostic models — symbiotic systems
- Probabilistic analysis — risk informed in-service inspection (ISI)
- Integration of prognostics into plant operation — O&M
- Cost-of-ownership — and life cycle management
- Development of tools for early damage characterization
- Move from SHM to true prognostics, at system level.
- Fully integration of NDE/SHM into engineering and product life cycle — design for inspectability and monitoring.

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**REFERENCES**