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Title: **A Robust Structural Health Monitoring Technique for Airframe Structures**

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ABSTRACT

Next generation technology of integrated health management systems for air-transportation structures will combine different single SHM methods to an overall system with multiple abilities considering different stages of damage initiation and propagation. The fundamental configuration of the proposed SHM technique will involve the idea of an integrated passive/active monitoring and diagnostic system extended by numerical modules for lifetime prediction. The overall system is capable of providing real-time load monitoring and damage estimation on a global structure level as well as precise damage diagnostics on a local level. This robust diagnostic technique provides quantifiable damage location and size estimation that account for the uncertainties induced by the environments or the system itself continuously during flight. Finally, efficient prediction and prognostic methods are integrated with monitoring and diagnostic outputs to provide real time estimation of possible damage scenarios, residual strength, and remaining useful life of the damaged structure. From this result information is gained which allow appropriate preventative actions on the monitored structure. To achieve those objectives, a built-in sensor/actuator network is employed and numerical simulation methods of damage estimation and propagation are developed and applied. The goal of this work is to integrate all these single techniques and subsystems into an integrated structural health management system for composite airframe structures. The system design, data exchange between the different subsystems, and the performance of each module is presented.

INTRODUCTION

Structural design of air transportation systems includes many goals: light weight for fuel efficiency, stiffness and strength for an appropriate dynamic performance. Another major task is the improvement of the safety of those systems by inspecting for system and component failure.

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At the same time the downtime of the transportation system due to inspection should be dramatically reduced by nearly continuous monitoring of the structure.

One of the most critical concerns is the presence of undetectable damage, which may be introduced during the manufacturing process as well as in-service events, such as impact loads or fatigue. The presence of any degradation, which is not easily detectable by visual inspection, may significantly reduce the mechanical properties of a component, in particular strength and stiffness. Due to this fact, the design of air transportation systems and associated maintenance practice must take this concern seriously into consideration in practice.

Due to the increasingly high demands for safety and low cost maintenance, the use of a built-in real-time structural health management (SHM) system for aircraft health monitoring is becoming more and more attractive. Unlike traditional NDE systems, the SHM system is designed to apply to a specific structure with a built-in network of sensors and actuators.

Although many well-established diagnostic techniques and prognostic methods have been proposed in the literature during the last decade, each single SHM technology aims at observing very specific properties of structures or systems. Due to this fact, the performance of a single SHM technology is subjected to inherent limitations of the applied methodology and may only cover single aspects of structural health monitoring. In an effort to improve the overall performance of SHM systems and to merge interactively the capabilities and advantages of the several single methods, research effort is conducted to link and to integrate different SHM technologies to a complete system for the purpose of an Integrated Vehicle Health Management (IVHM) as required for next-generation air and space transportation systems. The goal of IVHM is to develop validated technologies and techniques for automated detection, diagnosis and prognosis to enable early detection and mitigation of adverse events during flight. Adverse events include those that arise from system or component faults or failures due to damage, degradation, or environmental hazards that occur during service of vehicles. The capabilities of the IVHM systems will comprise rapid detection and diagnosis of adverse events, estimation of severity and remaining useful life (RUL) for the affected systems. The gained health information will be distributed to other subsystems as real-time automated reasoning and decision making systems.

The integration of monitoring and diagnostics with damage prediction and prognostics into a single health management (SHM) system is still a very challenging technical task and the subject of the current research. In particular, the exchange and the transfer of health data between the different subsystems as well as an efficient interaction to achieve optimal performance need to be explored in detail and receive immerged attention. The details of data flow and linkage between the subsystems are illustrated by the flowchart of Figure 1.

After final completion, the proposed SHM system will be capable to diagnose automatically in real-time the health condition of a structure as well as provide an estimate of the residual strength and remaining useful lifetime to optimize the performance and off-service schedule of the transportation system.

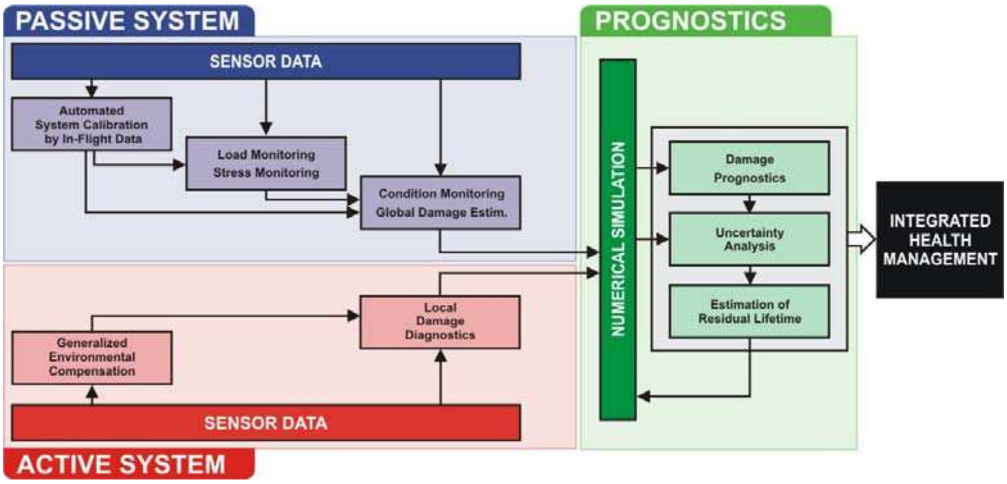

Figure 1. Flowchart of the interactive SHM system.

Accordingly, the SHM system relies on a network of sensors and actuators to be integrated with the structure and be equipped with a diagnostic capability for detecting damage and a prognostic capability to predict the residual life of the damaged structures in service.

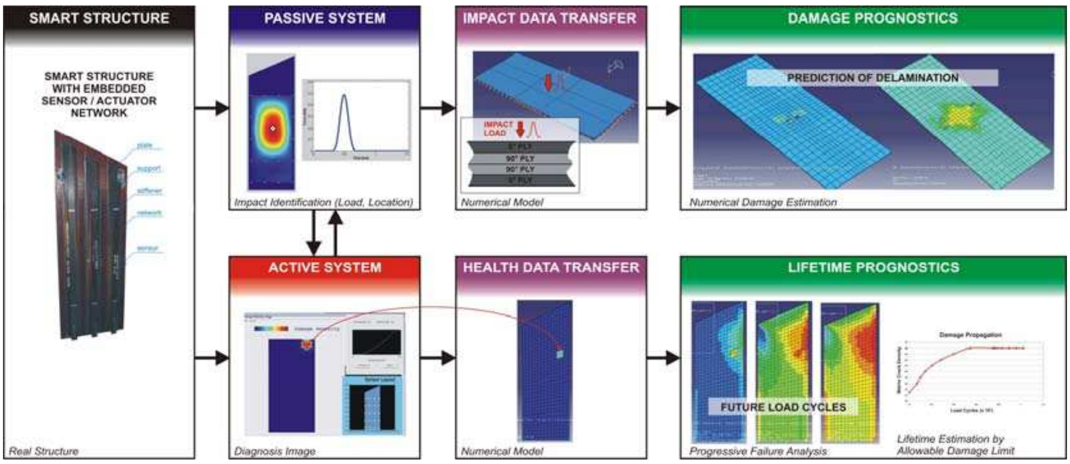

Figure 2. Capabilities and flow of structural health data interactive SHM system.

By merging all the afore-mentioned single techniques and subsystems an integrated structural health management system for composite airframe structures is obtained having unique capabilities of interactive monitoring, detection and prediction.

After a short introduction of the embedded network technology, each major SHM subsystem is briefly described along with interfaces to the linked subsystems. The current state of work and open questions are discussed. However, the focus of attention for this contribution will be on the passive system with prediction of impact-induced damage.

PASSIVE AND ACTIVE MODE OF EMBEDDED SENSING NETWORKS

Structural health monitoring techniques require the use of built-in sensors in a network to monitor external conditions and structural integrity. In general, there are two types of sensor-based diagnostic and monitoring systems: *passive sensing* (e.g. [1-3]) and *active sensing* (e.g. [4-8]). In the majority of cases, piezoelectric sensors are employed to build sensing networks. Piezoelectric sensors are active transducers, which can act for both the collection of measurement data at certain points of the structure and the generation of controlled diagnostic signals.

A passive system is useful to monitor changes in the environment, such as loads and impacts, but it is extremely difficult to locate damage or cracks with high reliability and good resolution. However, innovative passive technologies may have the capability to provide information on a global structure level about the existence and rough location of damage, which might be considered within a global condition monitoring process. Since no actuators are needed here (only operational excitation is used) a limited hardware is sufficient to operate the system. For the proposed SHM system, the passive network technology will mainly be used to acquire real-time sensor data for impact monitoring as one crucial SHM subsystem.

Re-examination and interrogation in order to locate and characterize damage, as well as to estimate the residual life of structures, becomes possible within an active sensing approach. In principle, an active system allows damage to be interrogated by injecting controlled diagnostic signals (i.e. guided Lamb waves) into the structure. With the known inputs, the changes in local sensor measurements are associated with the introduction of damage in the structure. Here, the active sensing approach compares the sensor data before and after an event to interrogate the structural condition. Therefore, it is most effective to detect damage and local defects in structures. Although these techniques have been demonstrated to be a promising method for reliable damage diagnostics, active systems have the disadvantage that extensive hardware and power supply is needed to operate the system. Additionally, the installation of active networks may not be feasible on the entire structure and usually only monitoring of structural hot-spots is performed.

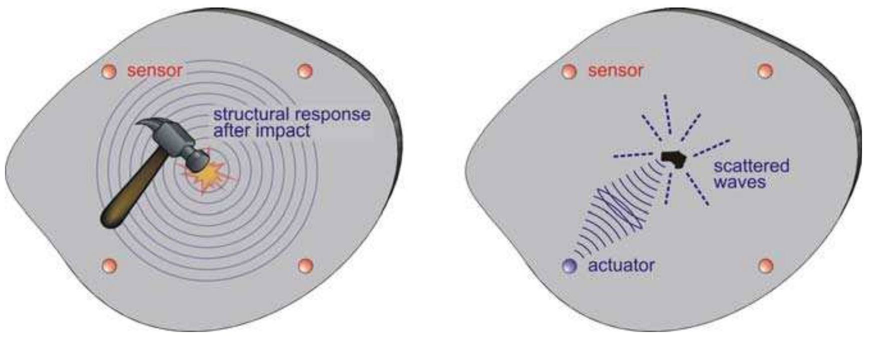

Figure 3. Passive (left) and active sensing networks (right).

Current research, as described in this contribution, aims to link the two sensing technologies in effective way which allows to merge interactively the capabilities and advantages of the two sensing technologies. The passive technology constantly monitors the structure and associated algorithms will provide real-time capabilities [7],

[8] for global impact and condition monitoring. After detection of a severe impact event, data of impact location and impact force history will be submitted to a damage prediction module where numerical simulation is used to estimate the impact damage by failure analysis.

The active technology provides the damage diagnostics and will afterwards interface with numerical prognosis module for estimation of remaining useful lifetime.

In summary, the uniqueness of this approach is an interactive global-local diagnostics by integration of passive sensor data as well as active sensor data provided by locally built-in actuators in the structure. The overall system will be capable of providing real-time load monitoring on a global structure level as well as precise damage diagnostics on a local level. For this purpose, structural health data will be exchanged between the subsystems and numerical models are continuously updated with occurring degradation.

IMPACT MONITRORING BY PASSIVE SENSING NETWORKS

Real-time impact monitoring is an important key approach for structural health management. For this purpose, a passive sensing network based on built-in sensor technology is employed to acquire local sensor data of structural response due to impact events. However, passive sensing approaches rely on numerical models to reconstruct meaningful information as impact location and impact load history from the point-wise sensor data.

Generally speaking, recovering external impact loads using structural response data works on the principle of an inverse problem (see Figure 4). While the phenomenon of interest (impact location and force history) may not be measured directly, there exists some other variable that can be observed (sensor data of structural response), which is related to the event of interest through the use of a data-derived computer model. Depending on its mathematical representation, the properties of the adopted model, and the sensor network configuration (number and location of sensors) the resulting inverse problem may be subjected to the difficulties of ill-posedness. According to Hadamard [9], the ill-posed properties of the resulting inverse problem appear in terms of stability, existence, and uniqueness of the solution and may cause serious errors in the identification results. The effect of ill-posedness for the problem of impact monitoring has been studied in [10], in particular with a view to influence of the sensor network configuration.

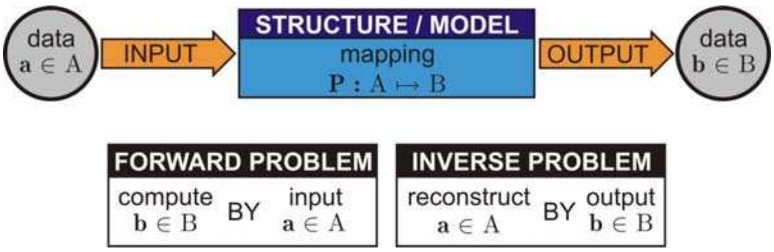

Figure 4. Schematic of inverse problems.

Several models and techniques (e.g. [4-6]) have been proposed in the literature to identify impact events from passive sensor data. Park and Chang [7] have proposed an advantageous methodology which is based on a linear system identification model. This auto-regressive model with exogenous input (ARX) is a linear finite difference model which represents the dynamic response of a linear elastic structure by a parametric approach as given by equation (1).

$$\varepsilon(k) = \sum_{i=1}^{n} a_i\, \varepsilon(k-i) + \sum_{j=1}^{m} b_j\, f(k-j) \tag{1}$$

Here, $\varepsilon(k)$ and $f(k)$ are a sequence of strain and impact force values at discrete time instances. The parameters a_i and b_j are the ARX parameters of the model while n and m represent the order of the model, respectively. A training step is needed to find appropriate ARX parameters based on the physical behavior of the structure. For this purpose, sets of training data in terms of impulse response are generated and ARX parameters are derived.

For the inverse reconstruction of the impact force history the ARX model need to be inverted. One striking feature of ARX based methods is that the inversion can be performed analytically as shown by Park [7]. Due to this fact, real-time capabilities of impact monitoring module are achieved. Furthermore, this method can be applied to complex structures with uncertain properties and boundary conditions. On the other hand, the proposed ARX model has inherent assumptions of linearity. Non-linear structural behavior as occurring on time-variant structures (e.g. damage propagation) may not be represented correctly. For these cases, a model update or the utilization of another set of ARX parameters might be necessary to capture appropriately the current condition of the structure. Hence, a feed-back of the current health status received from active diagnostics is needed to involve the latest structural condition.

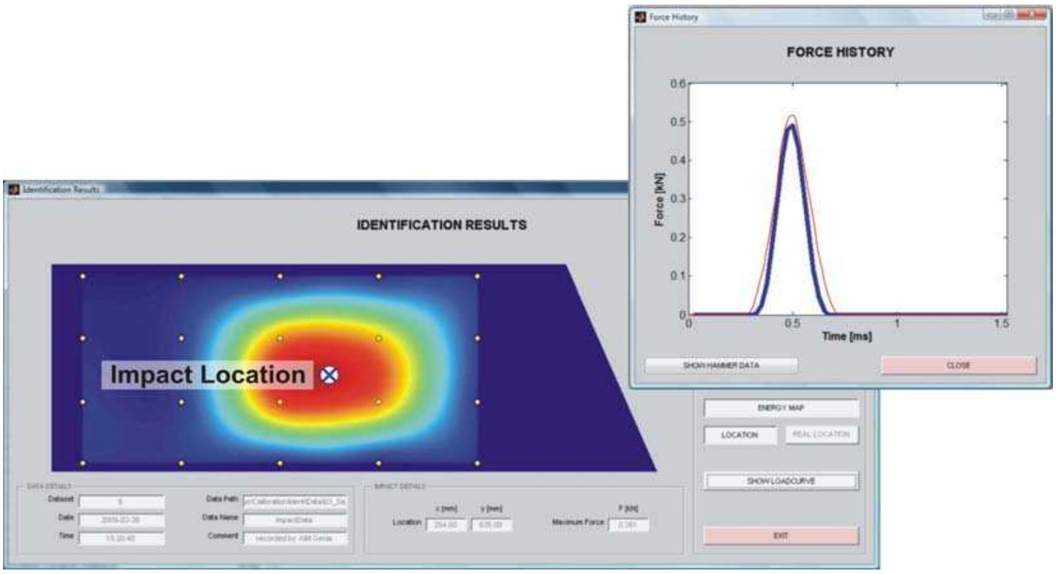

Figure 5. Results of impact monitoring on the example of a composite stiffener panel (left: impact location and energy map, right: impact force history).

Figure 5 illustrates the results of the impact monitoring system on the example of a stiffener panel manufactured by Boeing Company (also see Figure 12). The proposed method identifies the impact location as well as the impact the load-time history in real-time. As a comparison, the impact force was directly measured by utilization of a modal hammer (red curve) and reconstructed by the described ARX approach (blue curve). As can be seen, the results are in a good agreement.

Stability of ARX Models for Impact Monitoring

One significant difficulty in parametric identification of ARX models is an appropriate assumption for the model order n (see equation (3)) to construct the regression vector. In fact, an incorrect choice for the model order n will lead, in general, to difficulties in terms of model accuracy.

Selecting a value for n to large is called over-parameterization and may lead to unstable ARX estimates in the majority of cases. On the other, selecting a value n to small will lead to mismatch between measured data and model output. In this case, errors of approximation may be large. A heuristic approach for estimation of an appropriate model order can be found in [7].

In order to evaluate the model order for a given structure a stability map for the estimated ARX parameter can be compiled. Apparently it can be expected that almost identical or similar impact events will only lead to slight changes for the estimated ARX parameters. Such a stable behavior can only be found for appropriate model orders n. In all other cases, the model might be subjected to instability and, hence, slight changes in the input/output data leads to large differences in the computed ARX parameters (fluctuations).

Practically, a large number of input/output data will be recorded based on impacts at the same location and with similar amplitudes (impact force). For each set of I/O data an estimation of ARX parameters is performed and results are collected in a stability map (see Figure 7). For stable model orders n straight lines for the ARX parameter are obtained. Figure 7 shows a typical result on the example of the before-mentioned composite stiffener panel. A model order n=3 (left) will show stable ARX models while a 5th order model (right) leads to strong parameter fluctuations. As a result of extensive experimental tests, it has turned out that model order n=3 is the most appropriate assumption for the considered class of structures.

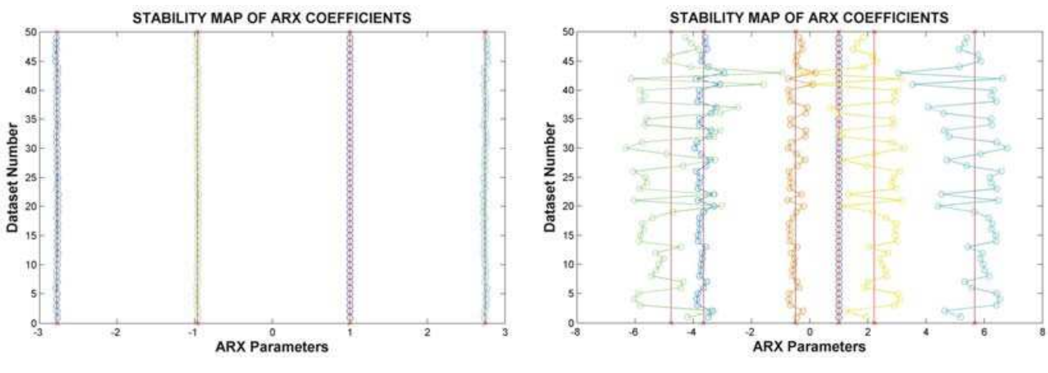

Figure 7. Stability map of ARX models for different model orders n
(left: n=3, right: n=5).

Automated System Calibration

In order to improve and to speed up the necessary training step for the ARX model Markmiller and Chang [8] recently proposed the utilization of a structural model based on Finite Element methods to obtain numerically the necessary impulse responses of the structure. Figure 7 shows the two-stage approach in a schematic.

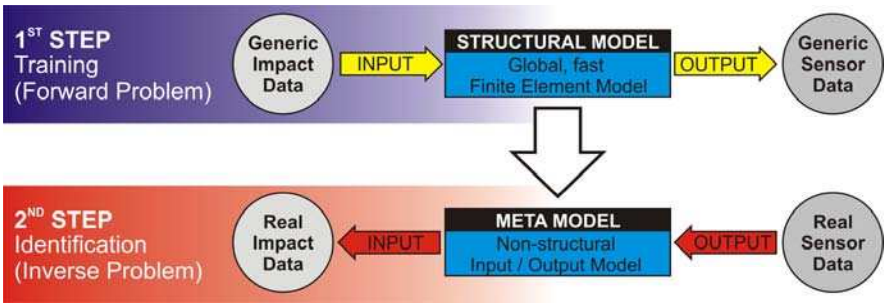

Figure 7. Training of ARX models by numerical simulation.

Apparently, the quality of the training process strongly depends on the accuracy of the Finite Element model employed during the training process. Stated another way, without having a reliable simulation model at hand, the training step of finding appropriate ARX parameters may lead to incorrect results. Thus, the calibration of the numerical model and the sensor / model relations is of immense importance.

The calibration of the sensor/model relation involves usually extensive experimental testing which might be difficult, time-consuming, and expensive for large-scale structures. Even with a view to future large sensor networks - having potentially thousands of sensors in a network - a reliable and efficient calibration technique is strongly required.

A promising alternative to extensive experimental lab tests is to extract the necessary dynamic properties for the numerical model from the structure response collected by the passive network during operation (operational data / in-flight data) or noise tests [11]. Here, the challenge appears in the reliable extraction of needed system properties (system identification) from sensor data only (dynamic response) while the ambient input (dynamic excitation) is not or not completely known. In contrast, commonly applied procedures of system identification are based on input/output relations. Nevertheless, the key target of both approaches is the same, namely to get knowledge either of frequency response or impulse response functions of the system under consideration. The obtained data are either used to update the numerical model in terms of model calibration or provide a direct basis for the training process.

In general, the methodology of output only system analysis – as core for automated sensor / model calibration – is based on three foundations: (1) long-term measurements with appropriate sampling rate by the passive sensing, (2) averaging in order to reduce measuring noise and random effects, and (3) power spectral density estimate. Following the assumption that the natural (operational) excitation of a flexible structure is characterized by continuous energy supply with a broad spectrum, one can expect energy to concentrate around modal frequencies. Hence, a power spectral density estimate will lead to the according frequency response function that can be utilized for a subsequent model updating process or direct training step.

Figure 8 shows an example for the reconstruction of frequency response functions by output-only analysis as part of the proposed calibration method.

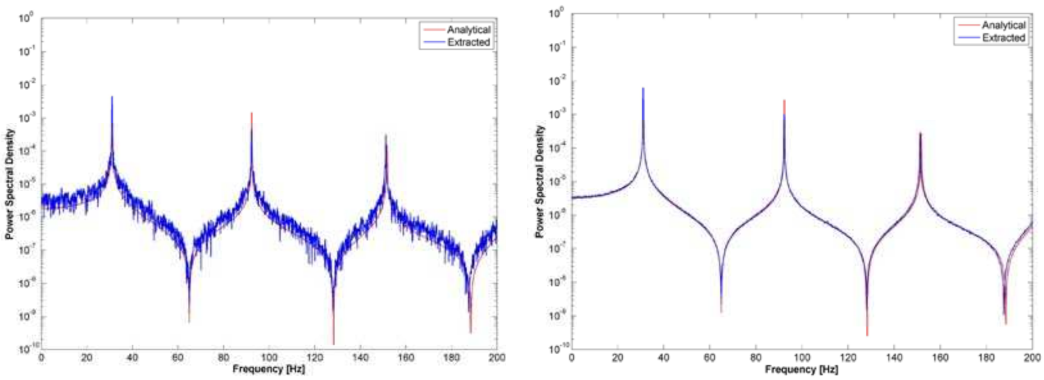

Figure 8. Extracted vs. analytical frequency response for the example of a beam-type structure (left: after 200 sec measuring time, right: after 2000 sec measuring time).

DAMAGE PREDICTION AFTER IMPACT DETECTION BY PASSIVE SENSING NETWORKS

To accomplish the goal of a SHM system with immediate capabilities for damage prediction after an adverse impact event, the results of impact monitoring will be linked with numerical failure analysis. Once the impact load history is known by the impact monitoring system, an appropriate FEM model for the structure is employed to obtain the stresses during the impact event. The damage will then be estimated from the stresses using appropriate failure criteria. In this research, criteria for matrix cracking and delamination have been considered and implemented.

As commonly acknowledged, transverse low velocity impact on laminated composites mainly induces intra-ply matrix cracking and inter-ply delaminations. The occurrence of cracks is primarily due to the inter-laminar transverse shear stress and transverse in-plane stress. In contrast, delamination growth at the interface is governed by the state of stresses of the constraining plies or ply groups having different orientations.

Analytical models for estimation of impact damage have been developed by Choi [12] taking into account matrix cracking and delamination. According to Choi delamination growth in composite laminates due to low velocity impact occurs only in cases: (1) the ply group next to the concerned interface has failed due to matrix cracking or (2) the stresses governing the delamination growth mechanisms through the thickness of the upper and lower ply groups of the interface reach a critical value.

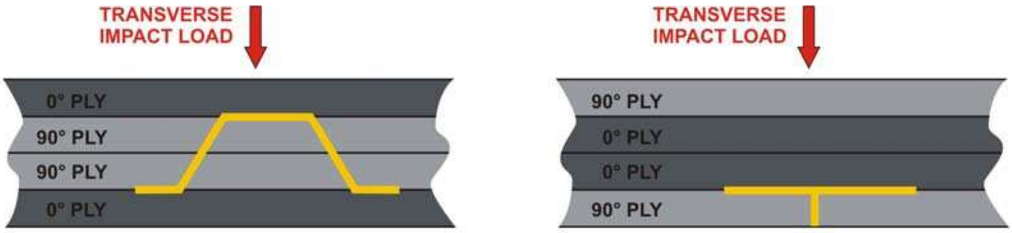

Figure 9. Impact-induced damage of matrix cracking and delamination.

The initial mode of impact damage is induced by matrix cracking of the laminate. Due to this fact, an appropriate model for matrix cracking is needed to simulate this initial type of local degradation. Accordingly, the failure criterion of matrix cracking derived by Hashin [13] was adopted and modified for thin laminated composite. In the case of thin laminate structures, where the stress component σ_{zz} is negligible, the occurrence of matrix cracking can be estimated by the following stress criterion

$$\left(\frac{\sigma_{yy}}{Y_t}\right)^2 + \left(\frac{\sigma_{yz}^2 + \sigma_{xz}^2 + \sigma_{xy}^2}{S^2}\right) \geq 1 \tag{2}$$

Here, Y_t denotes the transverse tensile strength and S denotes the transverse shear strength. Subsequently, if matrix cracking occurs in either n-th layer or (n+1)-th layer, having different material orientation, the criterion of Choi [12] for impact-delamination growth is evaluated

$$D_a \left[{}^{\langle n \rangle}\!\left(\frac{\sigma_{yz}}{S}\right)^2 + {}^{\langle n+1 \rangle}\!\left(\frac{\sigma_{xz}}{S}\right)^2 + {}^{\langle n+1 \rangle}\!\left(\frac{\sigma_{yy}}{Y}\right)^2 \right] \geq 1 \tag{3}$$

The equation is stated in an orthonormal coordinate system where the x-direction is the fiber direction of the ply and the z-direction is the normal direction to the ply. Therefore, the stresses σ_{yz} and σ_{xz} represent interlaminar shear stresses while σ_{yy} is the transverse stress in a ply. Again, Y denotes the transverse strength. The factor D_a is an empirical constant which is material dependent and has to be determined by appropriate experiments.

For practical simulation of impact-induced damage the commercial Finite Element package ABAQUS has been utilized. First, the stresses for the failure analysis are computed by numerical simulation using the outputs of the impact monitoring module as impact location and impact force history. For this purpose, it is crucial that the passive SHM system for impact monitoring is able to accurately identify the impact event from the sensor measurements. In the next step, the described damage model is applied and evaluated on basis of UMAT subroutines linked with ABAQUS. As a result, the potential damage after an adverse impact event is obtained and appropriate action can be taken. In order to estimate the effect for the future performance of the structure a computational prognosis tool can be triggered (see next section) to estimate the residual strength of the structure under the in situ environmental condition.

Since the impact-damage prediction by numerical simulation requires considerable computation resources even for large and complex structures the application of a database technology is recommended. This database contains precomputed results for impact damage scenarios that will be interpolated for the actual impact data. This procedure ensures near real-time capabilities for the impact-damage prediction module of the SHM system and allows rapid decisions of the health management system. A systematic methodology to create and to handle the required database technology and application within the SHM system will be subject of future work.

As an example for impact-damage prediction a flat composite panel will be considered. The dimensions and the material of the structure are chosen according to the afore-mentioned stiffener panel (see Figure 12). A symmetric ply lay-up (layers: $[45|90_2|-45|0|45|-45|0_2|45|-45|45|0|-45]_s$) is assumed based on unidirectional carbon fiber composite material.

The input for the numerical analysis as impact location and impact force history was gained from the impact monitoring module by passive sensing data. Figure 10 shows the Finite Element model with applied impact force according to the identification result.

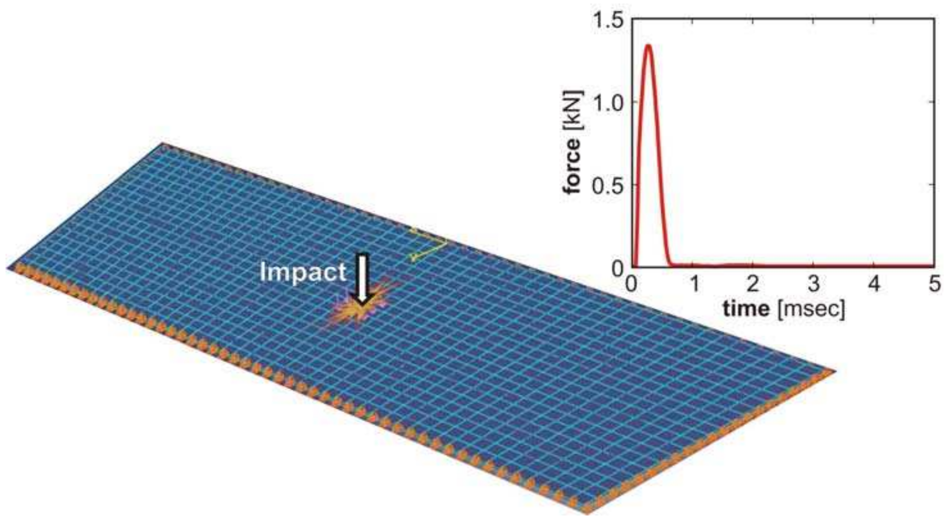

Figure 10. Finite Element model for analysis of impact-induced damage and impact load history.

Figure 11 depicts the results of the impact damage analysis by two different states of damage evolution occurring during the impact event. First, the initiation of delamination is shown. Beginning from this damage state the delamination is propagating as shown in the lower image. The figure clearly highlights the location of the damage where a disbond took place along the lower 0°/45° interface of adjacent layers. As expected, the location of degradation corresponds to the impact location.

A fundamental validation of the predicted impact damage by experiments can be found in [8]. Here, impact tests were performed on different composite specimens where appropriate damage was caused. The impact force histories were reconstructed as demonstrated before and damage was predicted by numerical analysis. As a comparison, the damage size was indicated by ultrasound images taken after the impact test.

In summary, it has been demonstrated that diagnostic load monitoring by passive sensing data with a link to impact damage prediction has great potential for the development of next-generation health management systems. In particular, the fundamental option to achieve real-time capabilities is beneficial for fast trigger of other subsystems and immediate action of decision-making subsystems controlling the complete health management system.

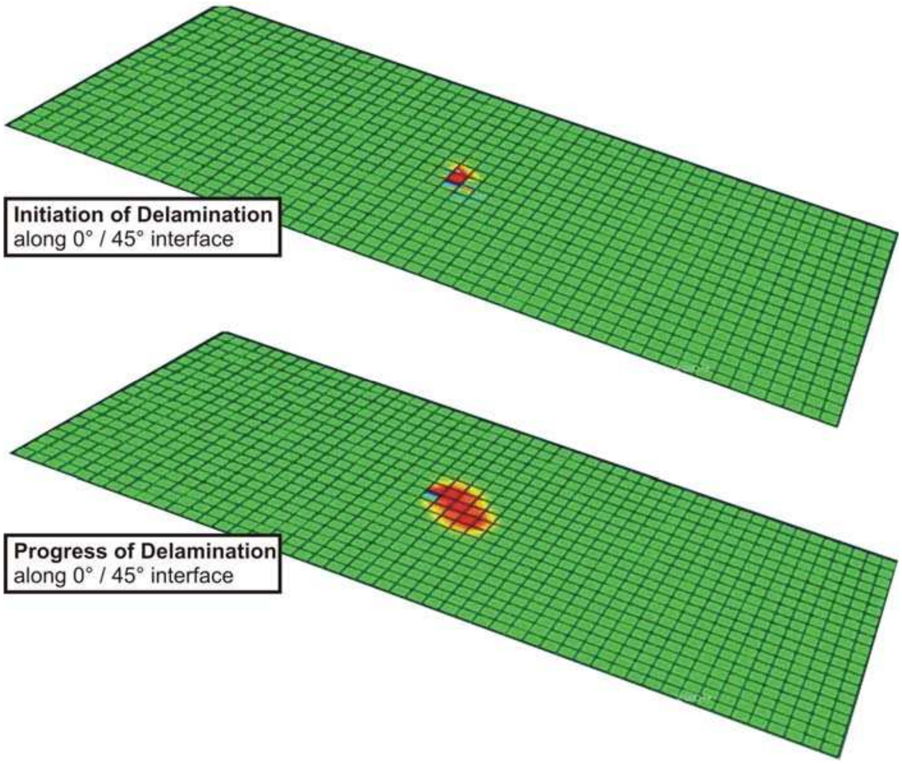

Figure 11. Prediction of impact-induced delamination on a composite plate.

However, for composite design with integrated health management the effect of damage on the residual life of a structure must be known. Accordingly, a prognostic capability must be included in the SHM system in order to provide predictive capabilities for the residual strength and remaining useful lifetime of structures. This SHM capability is another subject of current work and will be described in the following.

ACTIVE SENSING FOR DAMAGE DIAGNOSIS AND LIFE-TIME PROGNOSTICS

One of the major advantages sensing networks based on piezoelectric transducers is that it can be used for an active and passive mode. In the active mode, each piezoelectric element in the sensor network can be used as both a transmitter and a receiver so that more comprehensive information about the structure and the damage can be retrieved.

The fundamental principle of damage diagnosis by active sensing is based on the controlled injection of diagnostic waves into the structure under observation. It is widely acknowledged that the utilization of guided Lamb waves is one of the most promising approaches in this area which is increasingly applied in various engineering fields. Some of the fundamental advantages over other methodologies are the capabilities to inspect large structures and the entire cross-section area without disassembling the system under inspection. A comprehensive review of the current state for the guided Lamb wave technique can be found in [14].

The acousto-ultrasound (AU) technique based on Lamb waves has been demonstrated by Chang and his associates (e.g. [15], [16]) to be very sensitive and effective in detecting of local damage [15-17] in thin to moderate thick structures which is ideally for aircraft structure application. Advanced diagnostic images similar to ultrasonic images have been developed to identify the location of damage and to estimate its extent.

Although, the damage diagnosis by active sensing has attracted much research effort during the last years and extensive studies have been conducted, still some fundamental difficulties and open questions exist that require pursuing the research efforts. In the following, two questions with particular relevance for the proposed interactive SHM system haven been taken out and will be discussed.

Compensation of Environmental Effects

An active diagnosis system allows damage to be interrogated by injecting controlled diagnostic signals into the structure. With the known inputs, the changes in local sensor measurements (compared to baselines of a pristine state) are associated with the introduction of damage in the structure.

In general, a set of baseline data will be collected from all actuator / sensor paths on the intact structure. The signals will change if any local degradation occurs. To quantify the change in the signals due to damage, the post-damage signal can be subtracted from the original (baseline) signal before there was damage. The remaining difference is called scatter signal that is used to quantify the amount of change in the signal of a particular actuator-sensor path. After data normalization (e.g. taking path length into account) of the scatter signal amplitude, the ratio between signal scatter and signal baseline within a certain time window [t_0, t_1] provides an indicator for structural alteration, as shown by equation (4).

$$\mathrm{SER} = \left[\frac{\int_{t_0}^{t_1} \|S_{SC}(\omega_0, t)\| dt}{\int_{t_0}^{t_1} \|S_B(\omega_0, t)\| dt} \right]^n \tag{4}$$

Compiling this information for each sensing path creates the basis for the diagnostic image. Diagnostic imaging which highlights the region where significant changes in sensor-actuator signals occur has been demonstrated to be a beneficial tool for locating damage and potentially quantify the damage.

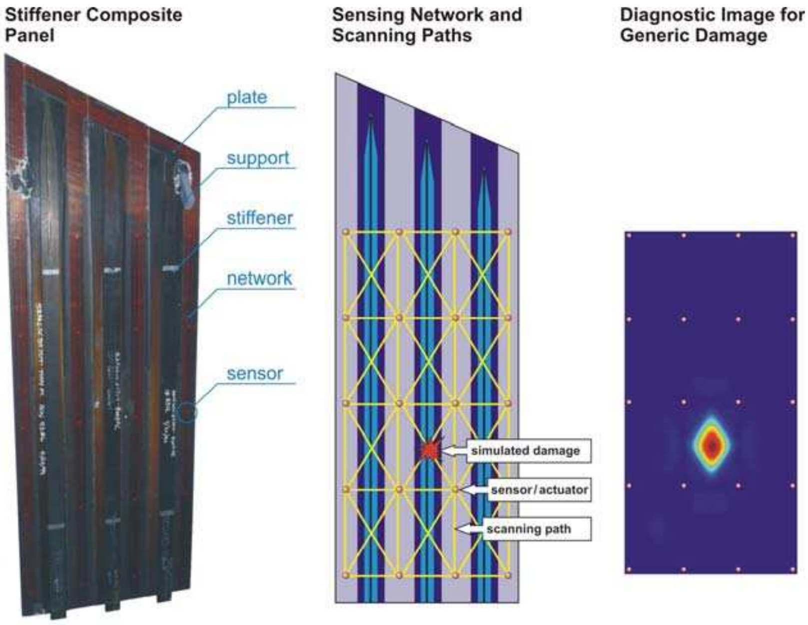

Figure 12. Example of damage diagnosis by guided lamb waves on the example of a stiffener composite panel with generic damage

However, the acousto-ultrasound technique is not only sensitive to structural alterations as induced by damage, it also sensitive to the change of environmental condition as temperature or load. Those environmental effects can corrupt the sensor signals and, thus, the scatter energy ratio in such a way that an accurate prediction of location and size of the damage will not be possible in the majority of cases.

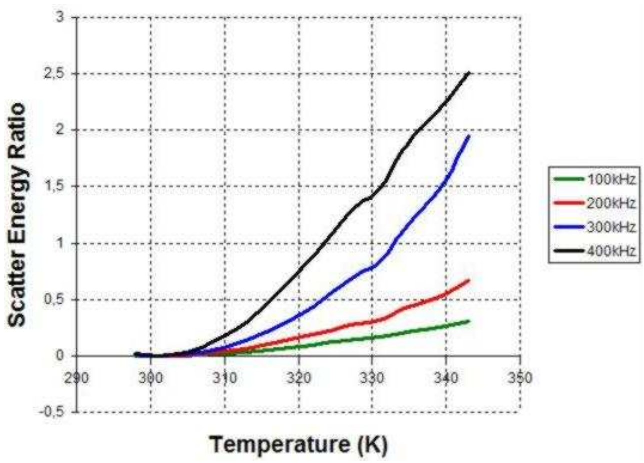

Figure 13. Example for the influence of different environment temperatures to the scatter energy ratio for different scanning frequencies (100 kHz … 400 kHz).

Current approaches try to overcome these difficulties by utilization of large sets of different baseline data for different environmental conditions to compensate environmental effects on damage diagnosis. Moreover, interpolation techniques are applied to provide baseline data for all possible conditions. However, interpolation in heterogeneous data may be a source for severe errors in damage diagnosis, in particular, if based on a small number of experimental sets of baseline data. On the other hand, the acquisition of a large database for the necessary baseline data might be time-consuming and inefficient even for large structures.

In an effort to improve the current compensation technique research is conducted to develop a method with minimum of necessary baseline data to compensate for the environmental effects on sensor signal. The method to be developed will be based on the physics that causes the environment-induced changes in the diagnostics signals. For this purpose, the physics of wave propagation under certain environmental conditions need to be studied and simulated by numerical analysis.

However, direct relationships between the signal changes and environmental conditions are still quite difficult to establish, and such a relationship may change with sensor/actuator location and structural geometry, etc., making it difficult to quantify and to compensate the environmental effects in a real application. Currently, numerical tools based on Finite Element methods are developed to achieve reliable simulation for the wave propagation of Lamb waves in structures of practical complexity. The simulation is based on the application of spectral elements within an explicit time integration scheme. This methodology was presented recently by Chang and his associates in [17] and turns out to be promising as a fundamental basis for environmental compensation.

Preliminary results of the numerical analysis show a dominant influence to the signal by temperature-induced property changes for the adhesive layer of sensor network. Exemplarily, Figure 14 compares simulation results for Lamb wave propagation in a thin aluminum plate-structure for a temperature change of 75 K.

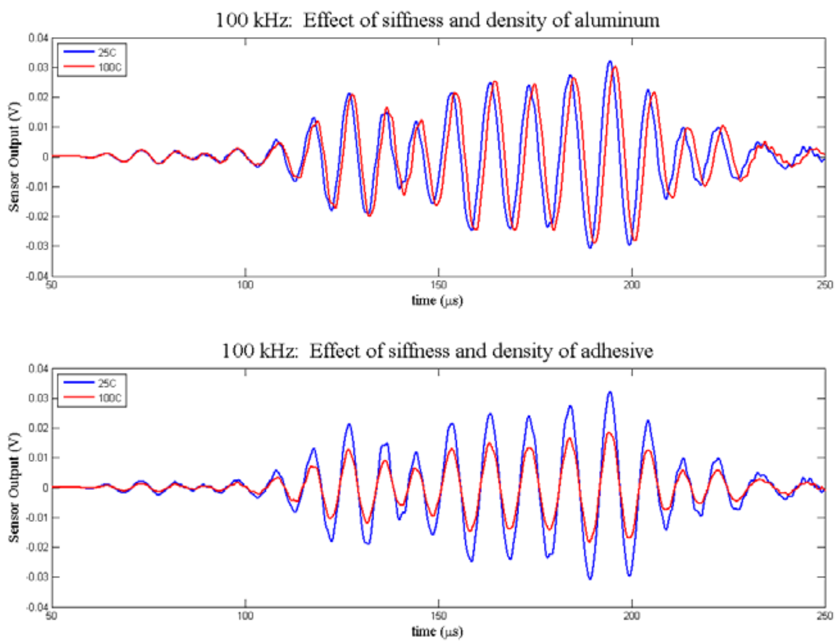

Figure 14. Numerical simulation of Lamb wave propagation in a thin aluminum plate subjected to different temperatures as environmental effect.

Prognostics of Remaining Useful Lifetime (RUL)

After the damage diagnosis by the active sensing system, the current health status of the structure shall be submitted to the prognostic module of the interactive SHM system for prognostics. Prognostic models are widely available for predicting damage growth and estimating residual strength and remaining useful lifetime (RUL) of structures made of metals or composites. In order to yield accurate predictions of damage growth and residual strength, one key issue is to create a proper link between the diagnostic outputs and prognostic inputs. The error in detection and extraction of health data can significantly affect the accuracy of the life-time prediction by the prognostic tools. Therefore, the extraction of health data from the diagnostic results is of immense importance. In particular, the differentiation between the different failure modes is crucial and future research need to be conducted to overcome these difficulties. Figure 15 shows the transfer of health data from diagnosis to the prognostics module by utilization of calibrated diagnostic images and interpolation techniques.

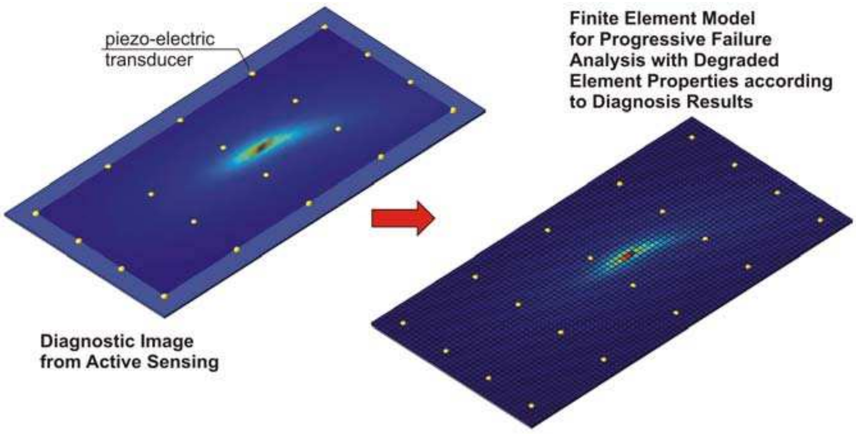

Figure 15. Example of health data transfer from diagnostics module to Finite Element model for progressive failure analysis to estimate the RUL

By collecting the data of degradation by damage diagnosis and determining or predicting the loading spectra during operation an estimate of the sustained damage can be made. This running estimate of the damage accumulation can be recorded and reconciled with future results of damage diagnosis at less frequent intervals, e.g. during maintenance procedures. With these estimates either *damage tolerance* or *safe-life* philosophy can be applied, as appropriate for the particular case, to estimate remaining useful lifetimes.

The damage tolerance approach assumes that a crack or flaw exists in a part and then determines the impact that a flight spectrum will have on the growth of the crack size. Safe-life methodologies are based on extensive service history and can determine the remaining lifetime of a part where no crack or flaw is expected to exist.

By utilization of database techniques, an update of the RUL estimate after occurrence of a specified trigger event (i.e. impact) can be achieved near real-time and will be submitted to the decision-making module.

Figure 16 shows an example for the life-time estimation after damage diagnosis. A progressive failure analysis model, originally derived by Chang and his associates (e.g. [18]) for the simulation of damage in bolted composite joints, was adopted and extended. A set of failure criteria was selected to predict the damage during the evolution of load history. The model was implemented as a user defined subroutine in the commercial Finite Element package ABAQUS/Standard.

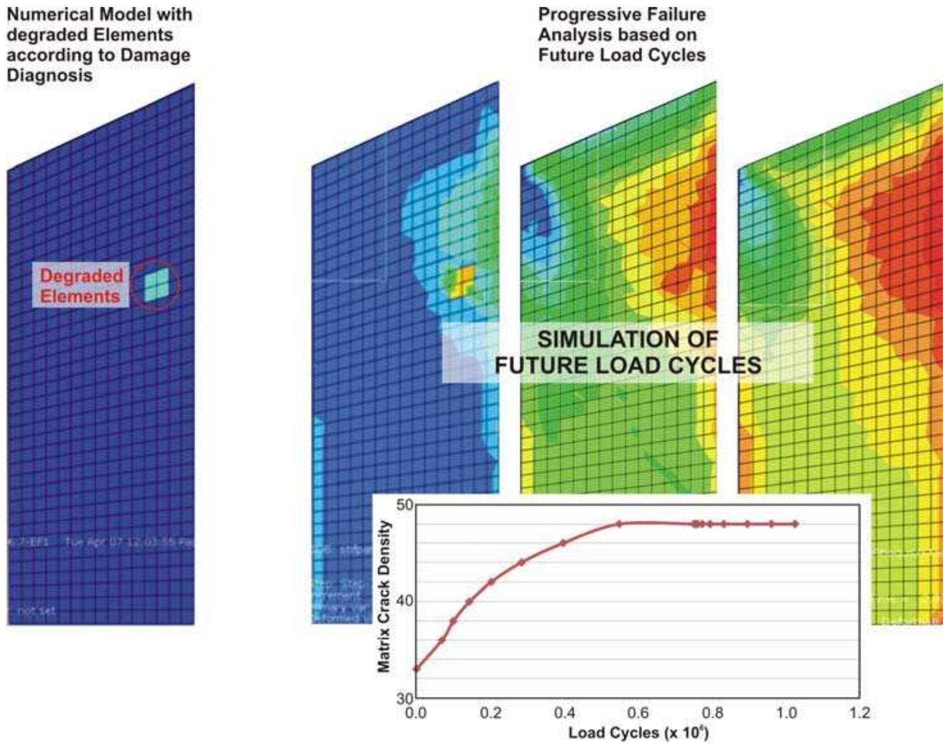

Figure 16. Example for the estimate of RUL by progressive failure analysis.

CONCLUSIONS

Next generation SHM technology will link different key technologies as impact monitoring by passive sensing, numerical prediction of impact-induced damage, diagnosis of structural damage by active sensing, and prognostics of remaining useful lifetime to an interactive system for integrated vehicle health management. One of the striking features of the proposed system is the continuous exchange of health data between the different subsystems to update the structural models and to feed the real-time automated reasoning and decision making systems with various health data.

The contribution has reported the current state of the development of an interactive SHM system in terms of system design, basic functionalities of the single SHM subsystems and data exchange between the modules. Some typical examples have demonstrated the fundamental capabilities of the proposed system and open questions as well as future needs and developments have been discussed.

In summary, the following capabilities are merged within a unique system for integrated vehicle health management:

1) Both impact location and impact force history can be identified in real-time by impact monitoring based on passive sensing data. An automated procedure for system calibration will be implemented.
2) The impact characteristics will be submitted subsequently to a damage prediction module to estimate the occurrence and severity of impact-induced damage.
3) After an adverse event, active diagnosis is performed to acquire the current health status of the structure. Environmental effects on the diagnosis results are compensated by updated baseline data. For this purpose, the propagation of diagnostic waves under environmental conditions is simulated and evaluated.
4) Health data from active sensing is passed to the prognostics module where numerical simulation of progressive failure under future load conditions is performed. The remaining useful lifetime will be estimated by consideration of an allowable damage/degradation limit.
5) A global health management interface controls the system and data flow interactively and provides real-time reasoning and decision-making capabilities.

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