Advanced Dynamic Validations using Integrated Simulation and Experimentation

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Guide to damage quantification

Project relevance: **Task 4.2 – Quantitative damage assessment for prediction of residual life**

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INTRODUCTION

Composite materials offer the opportunity to design structures that have a high specific strength and stiffness, i.e. light-weight structures with good strength and stiffness performance. However, composite materials are susceptible to damage. Impacts with relatively low levels of energy can cause damage to composite components that significantly degrades the structural performance of the component; but, which is not visible when the component is subject to inspection. Structural health monitoring (SHM), based on in-situ sensors, can be used to advise operators of the occurrence of such damage-inducing events and the location of the damage. While non-destructive testing (NDT), based on methods such as x-radiography, ultrasound and thermography, can be used to detect the presence and location of damage, and in some cases define its extent. However, neither SHM nor NDT provide sufficient information to allow the prediction or estimation of post-damage performance, which leads to substantial uncertainty concerning the structural prognosis, i.e., the remnant life of a damaged component. Thus, once damage has been detected there is perceived to be a high risk of a system failure. Consequently, it is common practice to repair or, more commonly, replace composite components as soon as any scale of damage is detected. This practice leads to unnecessary costs incurred through the time out-of-service for repairs and the acquisition of replacement components. In general, there are few, if any, links or coordination between the processes of design, manufacturing quality assurance, structural health monitoring, non-destructive testing, and structural prognosis. However, all of these processes can provide data that could inform decisions for life-cycle management and the hypothesis, proposed here, is that the integration of these processes into a continuum could significantly enhance the quality of these decisions.

BACKGROUND

Design models and their validation

It is common practice to optimise the structural design of composite components using computational solid mechanics models to predict the stress distribution experienced as a result of in-service loads and to minimise the levels of stress. In order to provide confidence and reduce uncertainty, it is appropriate to verify and validate the computational models employed in these processes. ASME V&V [2006] provides definitions for both the verification and validation of such models. Verification is “the process of determining that a computational model accurately represents the underlying mathematical model and its solution. Whereas validation is defined as “the process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended uses of the model.”, ASME V&V [2006] does not offer any guidance on the performance of these processes. Usually, verification is perceived to be the responsibility of the suppliers of the computer packages and algorithms that are employed to realise the computational models. The need for model validation is often ignored, or limited to the checking of strain values at a number of locations, known as ‘hot-spots’, where the model predicts high values of stress. Electrical resistance strain gauges applied to a prototype of the design are commonly used to obtain experimental values for these checks. This approach to validation is not good practice for a number of reasons. First, if the hot-spots in the prototype occur at different locations to those identified by the computational model, then they will be undetected as will the error in the model; and this is likely to lead to a high probability of failure of the final product. Second, in order to reduce weight and costs, material is often removed from designs in areas where the stress is predicted to be low or zero; however, these predictions have not been corroborated in the validation process and so there is a significant probability of product failure arising from this material removal process. Recently, Hack et al. [2010] have suggested that the validation of a computational solid mechanics model can be performed over the entire surface of a component by using strain data obtained using techniques from experimental mechanics, such as photoelasticity, interferometry, thermoelastic stress analysis, and digital image correlation. Digital image correlation [Sutton et al., 2009], which has become very popular in recent years, provides an excellent source of data for performing the more comprehensive type of validation recommended by Hack et al. [2010]. Wang et al. [2010] have shown that the data-rich maps of strain generated by digital image correlation and other experimental techniques can be represented accurately and at reduced dimensionality by using shape descriptors, which can be used for updating of numerical models and for their validation [Wang et al., 2011].

Structural health monitoring

The term 'structural health monitoring' is associated with the process of implementing a strategy for damage identification in engineering infrastructure and, in particular, with online-global damage identification in structural systems [Farrar & Worden, 2007]. Damage in this context is taken to mean changes to the material and, or geometric property of a structure that adversely influences its performance. This implies a comparison between an initial, probably undamaged, state of the component or structure and a subsequent state following an event or period of service. Structural health monitoring involves obtaining measurements from a component or structure as a function of time, extracting features that are sensitive to damage from these measurements and determining the health of the structure through the analysis of these features. This analysis might be entirely empirical, employing pattern recognition techniques to compare features with databases of established signatures, for instance in the monitoring of rotating machinery using displacement, velocity or acceleration data measured at individual points. Alternatively, the analysis might be based on models of the modal behaviour of the structure and the changes associated with the development of damage, in which case inverse methods can be used to identify the location as well as existence of damage [Friswell, 2007]. At a fundamental level, damage causes a change in the material, and hence component, response to vibration; thus, the measurement of changes in natural frequency is an indicator of impact damage [Salawu, 1997], whereas changes in modal curvature can indicate delamination damage [Pandey et al., 1991]. At a more sophisticated level, the same data can be used as the basis for sensitivity-based Finite Element Model (FEM) updating [Friswell & Mottershead, 1995; Moaveni et al, 2008], or for other inverse approaches, such as the Virtual Fields Method (VFM) [Grédiac et al., 2006]. In these inverse methods, damage is quantified as local changes in stiffness although the criterion for damage identification may be changes in surface displacement, modal shape curvature or strain energy [Kumar et al., 2009].

However, structural health monitoring is largely associated with measurements acquired by sensors at individual locations from which a global estimation of the damage state is made [Sohn et al. 2003]. In this context, Farrar and Worden [2007] highlight five questions that need to be answered when describing the damage state of a system. Is there damage? Where is the damage? What kind of damage is present? How severe is the damage? How much useful life remains? One of the challenges that structural health monitoring faces is that damage occurs on a local scale and often does not significantly change the global response of the component or structure that can be monitored by sensors, which are remote from the damage site. Consequently, these five questions are increasingly more difficult to answer and many structural health monitoring systems cannot progress beyond providing answers to the first two questions.

Non-destructive testing and evaluation

Non-destructive testing and evaluation differs from structural health monitoring in that it is usually performed off-line, in the sense that the component or structure is taken out of service. This enables the possibility of employing or selecting from a wide range of techniques including ultrasonics, acoustic emission, thermal imaging, and x-radiography [Farrow & Young, 1988], as well as identification techniques based vibration analysis used in structural health monitoring. Rytter [1993] classified the information provided by these techniques into four levels as follows:

Level 1: Damage detection
Level 2: Level 1 plus location identification
Level 3: Level 2 plus extent definition
Level 4: Level 3 plus remnant life prediction

These levels are the basis for the five questions posed by Farrar & Worden [2007] for structural health monitoring, with the extent of damage being divided into severity and type of damage since both of these factors influence the remaining service life of the component or structure. In the non-destructive evaluation and testing of composite components and structures, information at levels 1 and 2 is readily available and routinely acquired to an acceptable level of reliability. In some cases, level 3 data related to the severity and type of damage can be discerned. Some recent developments in NDE have involved modelling the wave propagation for techniques, such as ultrasound, in order to generate images of the defects [Dominguez & Gibiat, 2010], rather than simply a map of the measured ultrasound signal; or, using tomography to reconstruct the geometry of a defect, from for example ultrasonic [Vavilov et al., 2010], synchrotron [Wright et al., 2010] or thermal [Kishore et al., 2011] data. However, the focus in non-destructive evaluation and testing tends to be on the detection of flaws and damage and their definition in the spatial domain. The criticality of the detected damage or flaws tends to be based on evaluations, made at the design stage, of the maximum permissible flaw.

Recently, some investigators have investigated the use in non-destructive evaluation of techniques employed routinely for quantitative stress analysis, such as electronic speckle pattern interferometry [Findeis et al., 2010; Garnier et al., 2011], digital shearography [Gryzagoridis & Findeis, 2010] and thermoelastic stress analysis [Fruehmann et al., 2010; Emery & Barton 2009]; and, in the latter case, strain maps in the vicinity of the detected damage were generated, thus enabling direct assessment of the residual fatigue life. An implicit assumption in the use of this class of techniques is that damage which induces no discernible change in the strain distribution is not of interest because such damage has not degraded the performance of the component or structure, as demonstrated by the lack of change in the stress or strain distribution. A feature of using strain maps to indicate damage is the need to introduce a load, since residual stresses are difficult to measure accurately. Webster & Thevar [2007] have developed a non-contact acoustic procedure for inducing surface strains for this purpose.

The same trend is apparent in the use of modal analysis for damage identification, where data from accelerometers and strain gauges is routinely used, whereas recent work has employed non-contact optical techniques, such as deflectometry [Kim et al., 2009] and digital image correlation [Sztefak & Olsson, 2009] in thin laminates modelled as plates or shells. The use of optical techniques with their low robustness to environmental conditions, shifts the focus of modal based damage assessment from structural health monitoring, i.e. in-service or online, to non-destructive evaluation and testing, i.e. offline requiring removal from service.

These trends towards the use of non-contact optical methods of measuring deformation and, or strain raises the possibility of providing more comprehensive Level 3 information about the severity and type of damage, as well as enabling the prediction of remnant life, i.e., Level 4 data, based on the measured strain distribution associated with the damage.

INTEGRATED LIFE MONITORING

Hypothesis

There is a common requirement in both the validation of computational solid mechanics models and damage assessment, which is the need to compare one state with another and to identify the differences. In the validation process, the physical reality is the baseline and the extent to which it is represented by a computational model is the required output of the comparison. In damage assessment, the undamaged or virgin state of the component or structure is the baseline and the extent to which subsequent states deviate from it is the required output. Recent work, outlined above, has shown that the use of maps of surface strain, obtained from non-contact optical techniques, can enhance non-destructive evaluation and testing. The same maps of surface strain form the basis of the validation procedure suggested by Hack et al. [2010]. Thus, it is proposed here that the maps of surface strain acquired using non-contact optical techniques should be used to create a continuum of structural integrity assessment for composite components that will enable risk-quantified design and life-cycle management, as shown schematically in Figure 1.

Rationale

It is appropriate to consider the validity of a computational solid mechanics model in the same way as a scientific theory. This implies that it cannot be proved correct using evidence, but evidence can demonstrate its inappropriateness or falsity [Popper, 1959]. A single piece of evidence could invalidate a model but it cannot provide reasonable grounds for acceptance. Thus, it is unreasonable to utilise measured strain data from a single location or even a small number of locations to validate a computational solid mechanics model of an engineering component or structure. Equally, no amount of measurement data will prove the validity of a model; however a large body of evidence will increase the degree of belief in the model [Audi, 2011] and increase the probability that the model is appropriate or correct. In the light of this logic, it would seem obvious that current practices for validating computational solid mechanics models, based on the strain value at a small number of locations, are inadequate; however, until now, this obviousness has been over-powered by two arguments: (1) the cost of experimental data and (2) the lack of methodologies for quantitative comparisons.

Electrical resistance strain gauges are relatively cheap and easy to install compared with the resources required to perform full-field deformation or strain measurements on prototypes using non-contact optical methods such reflection photoelasticity or moiré. However, the advent of digital image correlation and, to a lesser extent, thermoelastic stress analysis has made it very simple, and relatively cheap in the former case, to obtain surface strain information for a complete component or structure.

It is relatively easy to compare data from a small number of strain gauges with the strain data predicted by a model at the corresponding locations. The comparison of data-rich maps of strain data from experiments and simulations can be complicated, computationally intensive and cumbersome to interpret due to the different size, resolution and orientation of the datasets. Whereas, the reduced dimensionality achieved by the representation of strain maps using shape descriptions provides a straightforward, quantitative means of comparing maps that is invariant to scale, rotation and translation.

The same advances in measurement technology have driven the trends in non-destructive evaluation and testing. In addition, the representation of a strain map using a feature vector, containing a small set of shape descriptors, is also an enabling technology for the performance of quantitative comparisons of undamaged and damaged states [Patki, 2010], which is at the core of the process of non-destructive evaluation and testing. The use of feature vectors involves reducing maps of strain that may contain strain data at 10^5 or 10^6 locations or pixels to a set of less than 10^2 shape descriptors. The reduced dimensionality enables a quantitative comparison, or correlation, of two feature vectors representing strain distributions from a model and an experiment, or from virgin and damaged states, using simple measures such as a Pearson correlation coefficient, cosine similarity or Euclidean distance [Patki, 2010; Hack et al., 2011]. For an identical pair of feature vectors, the Pearson coefficient and cosine similarity will be unity whereas the Euclidean distance will be zero. The deviation of these measures from unity, or zero in the case of Euclidean distance, provides a quantitative measure of the difference between the feature vectors and the strain distributions that they represent. Of course, experimental measurements will contain uncertainties that will cause apparent differences, and so these uncertainties will need to be quantified using calibration techniques [Patterson et al., 2007]. Usually, the quantification of uncertainties associated with these processes will represent an improvement in their quality and rigour, which will enhance the subsequent decision-making process.

Implementation

The flow chart in figure 1 consists of two major portions. The upper half, down to and including the validation process, is from ASME V&V [2006] and lays out a procedure for the verification and validation of computational solid mechanics models. ASME V&V does not provide a methodology for performing the quantitative comparison that is at the heart of the validation process and which leads to a decision on the acceptable agreement or otherwise of the simulation and experiment results. Here, it is proposed that this comparison can be performed by representing both sets of results using feature vectors based on orthogonal shape descriptors; and that their similarity can be quantified using a Pearson correlation coefficient. The decision on the acceptability of agreement would be based on the deviation of the Pearson coefficient from unity and the level of uncertainty in both the experiment results, established via a calibration, and the simulation results, established via the verification process.

A successful validation of the computational solid mechanics model would permit progress into the lower half of the flow chart in figure 1. The first step would be the optimisation of the design, based on the design parameters. The strain distribution predicted by the Finite Element Analysis (FEA in Figure 1) of the final design would become a baseline for future comparisons. The second step would be the production of components or structures based on the final design. It is proposed here, that part of the quality assurance procedure for new components would be an Experimental Strain Analysis (ESA in Figure 1) of each component using one, or more, non-contacting optical methods while the component is subject to a load induced by a transducer, such as that proposed by Webster & Thevar [2007]. A quantitative comparison would be performed of the feature vectors representing the strain distributions obtained from the FEA of the final design and from the ESA on the new component. The first fundamental axiom of structural health monitoring is that all materials have inherent flaws or defects [Worden et al., 2007] and, hence, perfect correlation would not be expected between these strain distributions. The decision on acceptability of the new component would be based on its structural prognosis, i.e. the remnant life, given the flaws and defects present in it. This prognosis could be calculated based on the measured strain distribution. If the prognosis is acceptable then the new component goes into service; however, if it is unacceptable, then the component enters a repair cycle that involves assessing its viability for repair and then either scrapping or repairing it. Following repair, ESA is performed again and a quantitative comparison made with the results from FEA on the final design, as for the new component.

When the prognosis for a new component is acceptable, then the feature vectors representing the strain distribution from the FEA of the final design and from the ESA of the new component are lodged in a database for future use as baseline comparisons. The new component enters service either with or without structural health monitoring. At the moment it is not envisaged that non-contact optical techniques of strain measurement could be utilised in structural health monitoring because of their low level of robustness in service environments. However, the validated model produced via the processes described above will be of value in the analysis performed as part of structural health monitoring, particular for the implementation of inverse methods.

After a period in service, the length of which could be decided based on the earlier structural prognosis, or following a damage-inducing event detected by a structural health monitoring system, the 'used component' would be subjected to a further ESA as the basis for a non-destructive evaluation. The resultant strain distribution would be represented by a feature vector and a quantitative comparison performed against the feature vectors lodged in the database. Comparison against the post-manufacture data will allow the degradation of the component in use to be assessed, while comparison against the FEA results for the final design will permit its deviation from the ideal state to be quantified. In either case the measured strain distribution from the used state can be used to predict the structural prognosis and decision made on its acceptability. If it is unacceptable then the repair process can be initiated; however, if it is acceptable then the component can be returned to service and the new data lodged in the database. A used component with an acceptable prognosis continues around the service cycle until sufficient damage is accumulated to make the repair cycle appropriate. Throughout this process a database is being populated that describes the condition of the component in terms of feature vectors that accurately represent the strain distribution in the component at the various stages of its life.

DISCUSSION

The developing demand for a sustainable society places tremendous pressures on the engineering profession to create more sustainable machines, devices, and structures. One important consideration in meeting this demand is the design of engineering artefacts with low levels of embedded energy and lower life-cycle energy requirements. In general, this will imply designs that utilise less material and are lighter in weight; but at the same time offer no less, and probably better, reliability and safety. These two groups of design constraints are in conflict with one another, since, in general, conservative designs use an excess of material to provide a high level of safety and reliability. The underlying premise in the work described here is that less conservative designs can be created with higher levels of confidence and hence reliability and safety comparable to existing designs, though the use of comprehensively validated computational solid mechanics models. And, further to that, the extension of the quantitative comparison methodology, at the core of the validation process, to the evaluation of strain maps from virgin and damaged, or used, artefacts enables a new approach to managing the life cycle of composite components. The new approach would provide the potential to reduce the frequency of replacements, extend service periods by tailoring maintenance to the usage experienced by the artefact, and perhaps to allow additional conservatism to be removed from designs as a consequence of this more detailed monitoring of structural integrity.

The common purpose of a computational solid mechanics model of an engineering artefact is to allow predictions to be made about the performance of the artefact in a range of conditions that it is expected to experience in service. Such models are based on observations of the behaviour of the material of the artefact enshrined in constitutive laws and of the response of simple structures to loading conditions encapsulated in the principles of equilibrium of forces and compatibility of displacements. A computational model uses these principles and constitutive laws as building blocks to create a sophisticated simulation of the behaviour of an engineering artefact. In simple terms, the manner in which these blocks are connected together has a very strong influence on the validity of model. Hume [1748] suggested that observational evidence will never support any hypothesis about the unobserved; however, a more pragmatic approach is to follow the philosophy propounded by Popper [1959] that observation evidence cannot prove a hypothesis to be correct, but it can demonstrate its inappropriateness or falsity. In the case of computational solid mechanics models, it is viable to conduct a limited number of experiments in order generate ‘observational evidence’ for a selected load case or a set of loading cases. However, the usual intention is to use the model to predict the performance of an engineering artifact beyond these observed loading cases to all of the loading cases likely to be encountered by the artifact in service. It is too costly to conduct experiments for all of these loading cases, and so, the model provides a cost effective means to examine the structural prognoses associated with them. However, it is only effective, if it is believed that the predictions are accurate, and indeed, that they are accurate. It is not possible to prove that a model is accurate for unobserved cases, but it is viable to assess its accuracy for observed cases, i.e. to validate it. The use of a greater body of evidence for this validation will lead to a greater level of belief in the model than when a single or smaller level of observation is employed. This process in itself will not render the model more appropriate or less false; however the process of conducting the data comparisons involved in validation will tend to lead to refinements in the model either because of the modellers professionalism or at the begat of their managers.

Usually, structural analyses of engineering artefacts are multi-dimensional involving the spatial and temporal domains as well as a domain incorporating the loading and boundary conditions. The advent of non-contact optical methods of strain analysis such as digital image correlation means that it is almost as straightforward to acquire strain data over the entire spatial domain, or a very large portion of it, as it is from a single point, or set of points, using strain gauges. Hence, it seems reasonable to extend the body of evidence used in the validation of computational solid mechanics models by using strain data from the majority of the spatial domain. Of course, if this can be repeated at multiple locations in the temporal and boundary condition domains, then confidence in the model would be improved, but for significant additional costs. Thus, it is concluded that the validity of computational solid mechanics models should be treated in a manner similar or analogous to scientific models, i.e. recognising that observational or experimental data cannot prove its validity but an increasing body of evidence can increase the level of belief and confidence in the model. It is also concluded that use of non-contact optical strain techniques to obtain maps of strain over the surface of an engineering artefact can support such a validation process, and also provide an opportunity to refine a model thereby increasing its accuracy.

The approach described above is not common practice in engineering, in part because of the relative novelty of non-contact optical methods of strain measurement and, in part, because there is no recognised methodology for comparing data-rich maps of strain data, which maybe in different spatial coordinate systems, at different orientations, and different spatial resolutions. It is proposed that image decomposition leading to the representation of strain maps using orthogonal shape descriptors is a key enabling technology. A small number of orthogonal shape descriptors can be employed to accurately represent a detailed map of strain on the surface of an engineering artefact with a data compression of three or four orders of magnitude, i.e., from 10^5 or 10^6 data points to less than 10^2 shape descriptors. This level of data compression renders a quantitative or statistical comparison of the datasets relatively straightforward using existing measures. Patki [2010] examined the relative performance of the Pearson correlation coefficient, cosine similarity and Euclidean distance in providing a measure of the similarity between two feature vectors containing shape descriptors that represented the strain distributions in damaged and undamaged laboratory specimens manufactured from a composite laminate. He found that there was little to differentiate between these similarity measures, and so any of them could be chosen to suit a particular situation. The issue of what constitutes an acceptable level of similarity is a matter for further investigation. Two identical strain maps perfectly represented by a feature vector obviously would give a Pearson correlation coefficient and a cosine similarity of unity, and a Euclidean distance of zero. However, the representation of the strain maps by the feature vector will never be perfect and so the process of image decomposition will introduce an uncertainty. This uncertainty is relatively straightforward to assess by reconstructing the strain map from its feature vector and calculating the average percentage difference between the reconstructed and original strain values. Two nominally identical strain maps from a simulation and an experiment will also possess a level of uncertainty associated with the processes by which they were acquired. For the simulation results, this uncertainty could be established via the verification process. Whelan et al. [2008] and more recently Sebastian and Patterson [2010] have demonstrated how the minimum measurement uncertainty in a full-field non-contact optical strain measurement system can be evaluated as part of a calibration process employing a reference material.

The capability to make a quantitative comparison of two data-rich maps of strain, arising from the requirements of a rigorous validation process, creates an opportunity to create an innovative approach to non-destructive evaluation. The core principle of non-destructive evaluation is the comparison of the actual or expected condition of a virgin or undamaged artefact with that of a damaged or used artefact. Almost any material performance characteristic, which can be measured and correlated to the effect of damage on structural integrity, has been investigated as a potential non-destructive technique for damage evaluation in composites, including ultrasound, temperature, and x-ray. However, it is believed that the strain induced in an artefact by a simple, repeatable loading condition is the most directly related to the structural integrity, because the structural failure is a function of the strain induced by the loads in service. Therefore the approach pioneered by, for example, Emery et al. [2010], Findeis et al. [2010], Fruehmann et al. [2010] offer tremendous potential and should be combined with the quantitative comparison methodology based on image decomposition and a similarity measure, as for the validation process. Patki [2010] has demonstrated the feasibility of this approach using digital image correlation to acquire strain data from impact-damaged laminates subject to a tensile load. This approach has the advantages relative to conventional non-destructive evaluation techniques of enabling automated decision-making based on the quantified level of similarity. Such a decision might be based on the remnant life of the artefact, or the structural prognosis and this approach has the additional advantage of yielding experimental data that can be used to seed the calculation of the remnant life, i.e. Level 4 information in Rytter's [1993] classification. When an artefact is inspected using this approach on completion of the manufacturing process, as part of a quality assurance procedure, two comparisons can be performed. First and immediately, a comparison with the results from the simulation of the final design provides a confirmation of manufacturing quality; and the second, at some point in the future, with the results from a post-service inspection. These two comparisons form the first links in a continuous chain of comparisons that extend from the original physical prototype and its simulation results, through a quality assurance procedure, to subsequent periodic maintenance inspections until the end of the artefact's useful life. The ability to track the progressive changes in the structural performance of an engineering artefact in this way has the potential to disrupt the conventional approaches to life-cycle management of critical engineering infrastructure. For instance, service periods can be tailored based on the structural prognosis for an individual part derived from the strain-driven non-destructive evaluation; instead of being based on the time required for the initiation of the minimum detectable flaw. It would be preferable to combine the new approach with a structural health monitoring strategy that can alert the operator to an unexpected damage-inducing event, such as an bird-strike, and trigger an additional inspection. The capability to calculate remnant life also allows an account to be maintained of the proportion of the design life expired during a particular period of service, which could be used to charge for use or rental of the artefact. This would be of use in the aerospace and rail industries where infrastructure is often rented to operators by manufacturers who remain responsible for its maintenance. The capability to evaluate remnant life also would allow composite components to remain in service after the detection of damage providing the structural prognosis is appropriate, which would reduce the number of replacement components required and hence reduce operating costs as well as contributing to sustainability. These advantages are more relevant to applications involving high cost, low volume parts for which it is worthwhile contemplating the 100% inspection regime implied by the approach and its inherent costs both in terms of time for the inspections but also equipment and skilled labour to conduct them.

There are a number of technology gaps to be bridged prior to a full implementation of the flow-chart in figure 1. It is necessary to induce a strain distribution in an engineering artefact in order to be able to evaluate it by experiment. This is relatively straightforward in a laboratory but in an industrial environment a non-contact loading scheme would be preferable as it would be substantially more straightforward than connecting a loading mechanism, which in some applications might be impractical or impossible. In traditional non-destructive evaluation testing thermal loading is used in active thermography but has significant limitations. An alternative would be to use acoustic impulses such as proposed by Webster & Thevar [2007]. Most non-contact optical methods of measuring surface strain distributions require some form of surface preparation. The most versatile measurement approach is probably digital image correlation, which generally, requires a speckle pattern to be created on the surface of interest; although some investigators have used the surface texture [Lopez-Crespo, 2008]. Other techniques, such as thermoelastic stress analysis and electronic speckle pattern interferometry, in theory do not require an surface preparation, but in practice a uniform surface colour allows a higher quality result to be obtained than is possible with an untreated surface. Wang et al [2011] tailored Zernike moments to provide appropriate shape descriptors for a tensile tie-bar with a central hole; while Patki and Patterson [2010] combined Zernike moments with a Fourier transform in an attempt to create a general orthogonal shape descriptor that is capable of describing strain distributions containing discontinuities associated with holes, cut-outs and other geometric features. The Fourier-Zernike shape descriptor is computational expensive and while it was found to be capable of describing the strain distribution around a hole and around damage in a composite tie-bar, there is scope for further improvement to obtain a more accurate representation. Sebastian [2011] has demonstrated that Tchebichef moments combined with the Fourier transform are substantially more computationally efficient than the Fourier-Zernike shape descriptor and marginally more accurate. The comparison of feature vectors representing two strain distributions is relatively straightforward using a variety of distance measures; however the use of a distance measure as a quality indicator in the validation process or as a damage indication has not established. Further work is needed to develop appropriate indicators that can be universally accepted across a range of industries. Finally, our current understanding of the failure mechanisms in composites is insufficient to allow reliable remnant life calculations to be made, even with a detailed knowledge of the structural status of the artefact of interest.

All of the technology gaps discussed above have been bridged in the laboratory or for idealised cases, so the research and development required is to move them up various technology readiness levels. These are not insignificant challenges; however, when they are overcome, the methodology enabled and summarised in figure 1 will have the potential to become a disruptive technology, in the sense that it could transform the market by offering considerable competitive advantages to first adopters.

CONCLUSIONS

A new approach to the use of non-contact optical methods of strain measurement in the life-cycle management of composite components is proposed. This technology when combined with image decomposition methodologies has the potential to become a 'disruptive technology' for industries where the composite components are employed in safety critical roles and, or low volumes. A methodology for the deployment of these methods of experimental strain analysis (ESA) has been elucidated and is summarised in figure 1. It can be concluded that:

(1) Numerical models should be treated in the same manner as scientific theories so that evidence from a single or small number of locations cannot prove but only disprove their validity. A large body of evidence, such as provided by full-field maps of surface strain can increase the degree of belief and confidence in a model and increase the probability of its appropriateness or correctness.

(2) The use of experimental strain analysis, based on non-contact optical methods, can provide the large body of evidence required to convincingly test the validity of a computational solid mechanics model, and thus lower the probability of unexpected failure in service.

(3) Damage assessment can be divided into two modes: online evaluation, known as structural health monitoring, and offline evaluation, known as non-destructive evaluation or testing. In each case, there is a hierarchy of damage identification starting from damage detection (level 1) and rising through location identification (level 2) and extent definition (level 3) to remnant life prediction (level 4).

(4) The use of experimental strain analysis, based on non-contact optical methods, could raise the level of damage identification achieved to level 4 and, thus, allow the efficient and effective management of the life-cycle of engineering assets.

(5) The use of experimental strain analysis, both for the validation of the model utilised in the design process and for damage assessment of manufactured and used components, provides an opportunity to create a continuous process of risk and life quantification throughout the life cycle of a component or structure. This has benefits in terms of optimised designs with lower embedded energy and in-service energy requirements, extended service, the enhanced options to repair rather than replace. All of these outcomes have positive cost implications.

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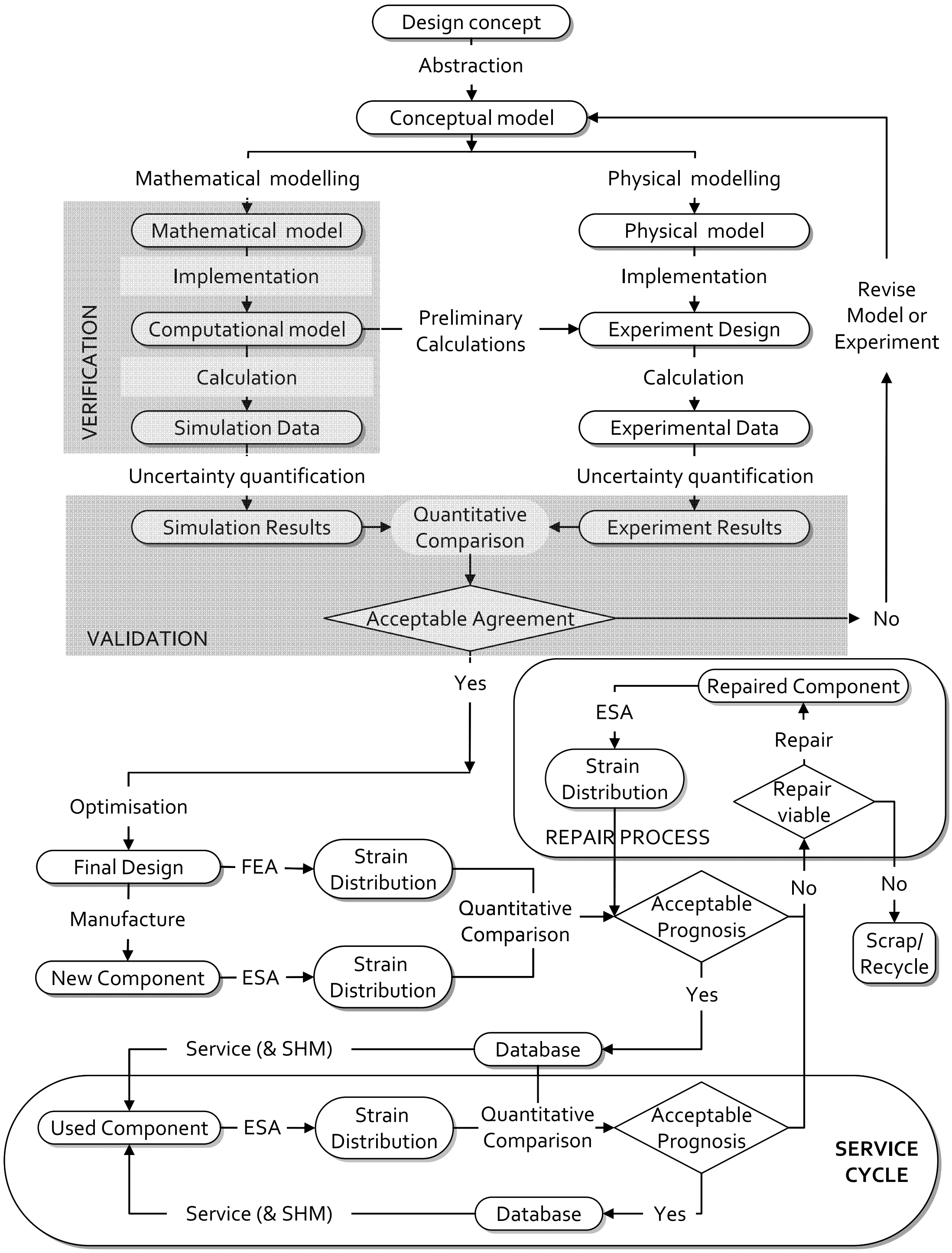

Figure 1 – Flow-chart for design and life monitoring of a component, developed from design flow chart in ASME V&V 10-2006.