Approaches to Realize Materials / Damage State Characterization for the Digital Twin

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ABSTRACT

The concept of a Digital Twin is a digital representation of system that includes integrating the evolved state from the time of manufacture to enable improved life management. For the Department of the Air Force (DAF), some the aircraft types in DAF inventory have detailed digital models and for others the models are in the process of being developed. In addition, the ability to track the use of each aircraft on tail-by-tail basis as described in MIL STD 1530D is known as Individual Aircraft Tracking (IAT). This data is frequently captured by flight data recorders and associated instrumentation. Other features that are regularly tracked, although at differing levels of fidelity, include modifications, repairs, maintenance, and usage on an individual aircraft basis.

However, one attribute that is not tracked as well is the characteristics of any damage or changes in material properties that evolve as a function of manufacturing and/or in-service use. A comprehensive awareness of the damage and/or material state as it evolves would enhance any analysis routines applied to a digital twin for life management. Current practice for in-service aircraft is to determine the knowledge of the damage state from teardowns of retired assets and can be limited to visible assessments to determine size and location of flaws. Therefore, improved and expanded knowledge of the damage and/or material state of an operational aircraft would enable a higher fidelity digital twin representation rather than approximated knowledge of possible damage from a limited number of tear downs and other destructive characterization methods. In manufacturing, more sophisticated damage/materials assessment tools can be used, but typical responses indicate exceedances have occurred. The diagnostics of the magnitude of an exceedance frequently requires additional measurement methods and analysis before the exceedance can be dispositioned by a Materials Review Board or equivalent entity.

To realize the capability of damage characterization of operational aircraft, the Materials State Awareness (MSA) Branch of the Materials and Manufacturing Directorate of the Air Force Research Laboratory (AFRL) initiated efforts to enable flaw characterization. The technical approach includes the integration of heuristics, model-based, and data assisted methods to simplify the diagnostics from the nondestructive evaluation (NDE) of complex structures. This approach addresses the ill-posed inverse problem to size detected flaws for their integration into digital twins for accurate representation of structures in an as-flown and as-maintained condition, with the extra benefit of accelerating disposition of any indications.

1.0 BACKGROUND

The concept of using digital representations of aircraft for both improved manufacturing and life management is a concept that has been explored to various degrees of effort over the past few decades. A significant investment by the US Department of Defense (DoD) was the Defense Advanced Research Projects Agency (DARPA) Structural Integrity Prognosis System (SIPS) program in the early 2000s which sought to use data from sensors integrated with physics-based models to enhance life management [1]. While the program had several successes, a missing link was the inability of NDE-based methods to size flaws, such as fatigue cracks, to enable improved accuracy of models by integrating evolving damage states. Subsequent DAF projects addressing digital twins included the desired input of flaw size typically labeled as “damage state awareness” [2]. To date, the only method to obtain accurate flaw dimensions in length, depth, and width is to perform destructive characterization, such as metallography, from teardowns of existing structures.

The inability to size flaws with statistical metrics of accuracy using NDE-based methods is a function of the complexity encountered when assessing assembled aerospace components and other DOD structures. Laboratory-based methods have shown potential, but additional factors must be including in the determination of the size of a flaw from the NDE signal response, a process called inversion. When more factors affect the flaw response than the size of the flaw alone, this process becomes an ill-posed inversion as there are more unknowns than can be directly measured from the NDE assessment.

The sources of variability that can affect the NDE response in additional to flaw size include the NDE equipment, the structure being interrogated, and the nature of the flaw. Variations in NDE equipment are typically addressed by a calibration process against a flaw with a known size. However, changes in the NDE sensor performance over time can occur, as well as small changes in sensor configuration. The latter is prevalent in a limited number of situations, such as higher frequency eddy current inspections of rotating engine components where small changes in coil tilt inside the sensor can impact the magnitude of the response from a shallow crack even when within bounds of calibration [3].

Variations in structures are much more challenging to manage, especially over a typical life cycle of a DoD asset. Local changes in boundary conditions, such as surface stresses at faying surfaces of fastened joints, can impact ultrasonic waves propagating in a structure to the extent that a flaw may not be detected [4]. Similar changes in coating thickness and composition can affect the detection of surface breaking flaws. As changes in structural configuration, especially as a function of as-modified, as-repaired, as-maintenance, and as-used, is not tracked to the level where it will affect the NDE sensing modality response from a flaw, the ability to model and understand the effect of these variations are hard to quantify.

Another source of variation is flaw morphology. As an example, fatigue cracks are often represented by simple electric discharged machine (EDM) notches in test articles and in simulations. However, real fatigue cracks have morphology changes along the surface as well as tortuosity in how they propagate unevenly in differing materials. Similar behavior can be found for other types of flaws, such as corrosion pits or delaminations in composites. An example of the sources of variations is shown in Figure 1 that describes the 22 factors that can affect an ultrasonic interrogation of a two-layer structure with proper coupling between the layers, such as the presence of sealant [5].

2.0 APPROACH

Previous presentations have addressed the use of advanced analytics to enhance the detection of flaws in complex structures [6]. As a brief review, the approaches for very complex data include using heuristics, model-based methods, and enhanced data analytics. The latter approach includes the use of ground truth for training algorithms to analyze data or allows algorithms to train themselves. For relatively simplistic applications for detection, such as determining if a delamination is present, heuristic approaches have shown to work well [7]. Here, the focus is on using established methods to evaluate the NDE data that goes beyond standard image analysis methods that mimic techniques used by inspectors. For example, for ultrasonic data, this extends beyond C-scan image analysis to include A-scan and B-scan analyses to detect attributes of the structural response to discriminate between benign internal features, such as ply-drops, and real flaws. In addition to heuristics, model-based methods can use forward models to predict the anticipated response from a NDE signal and search for it when it is not readily detectable above other signal features using correlation functions or other signal processing methods. Lastly, if large data sets are present, enhanced data analytics can be used that develop statistical classification and/or regression statistical models to detect flaws.

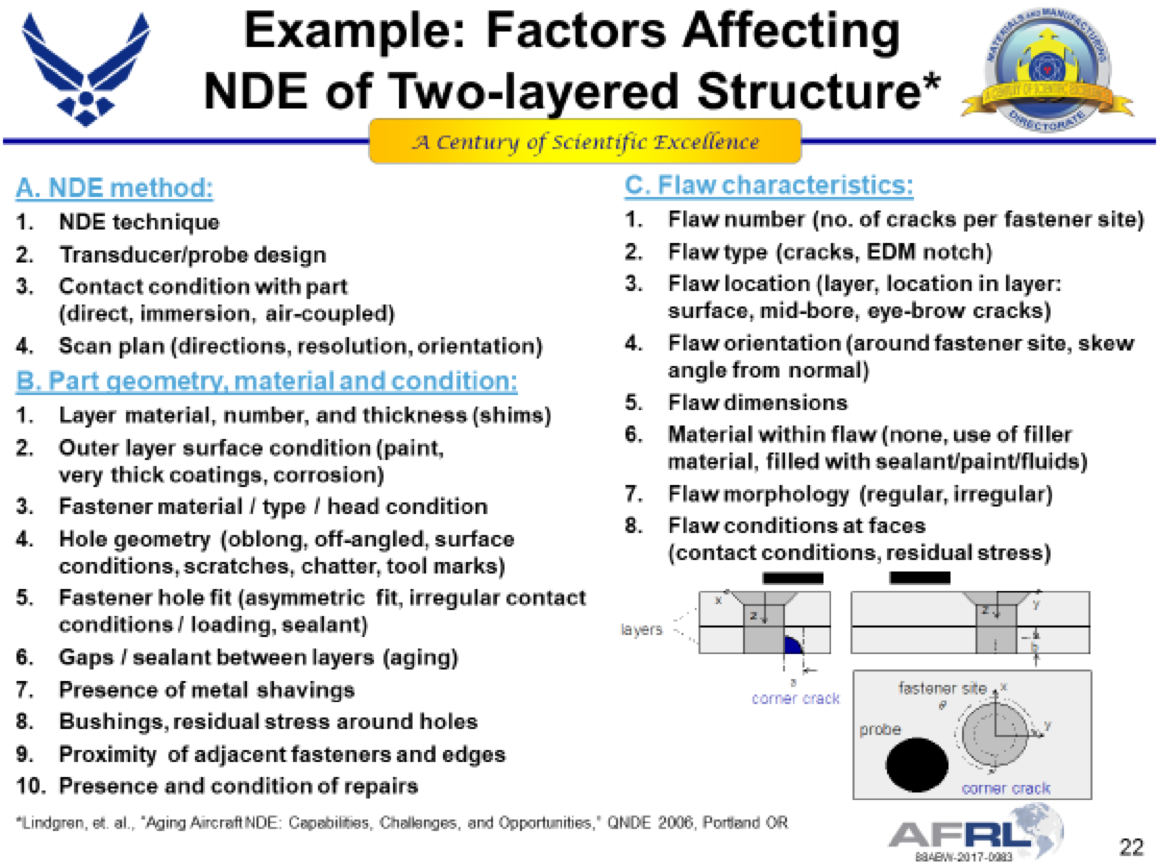

Figure 1:Twenty-two factors that can affect an ultrasonic interrogation of a two-layer structure with proper coupling between the layers.

While these techniques are sufficient to enhance detection, materials and/or flaw characterization requires more sophisticated method that combines at least two of the above approaches. Using both forward and inverse models can extract additional information regarding the attributes of the response from a feature of interest. This requires a model calibration step to ensure the model is configured for the structure being evaluated. The models can be used to perform localized sensitivity analysis as a function of one or more parameters, enabling equivalent look-up data sets to align attributes of a response to what is anticipated from the feature of interest. However, to ensure the full robustness of this approach, the simulations need to be enhanced by data from representative test articles, ideally harvested from actual parts. The data sets acquired for these test articles facilitate validation of the simulations to assess benign features that do not necessarily indicate damage but are features that can be used to ensure the model is tuned to assist in characterizing the damage. This approach combines model-based methods and enhanced data analytics. For some applications, these two approaches can be further refined by heuristics for well-understood assessment scenarios, or when alternative features are present that can be used as triggers for specific functions in the model-based, data analytics, or combined approaches.

3.0 RESULTS

The initial focus of this work has been on sizing fatigue cracks in rotating components of turbine engines. This application was selected as the first demonstrator of flaw/material characterization due to the high level of geometric control that minimizes the variability of the structure being assessed. Therefore, the model-based methods could focus on variability in the inspection equipment and in the flaw itself, in this case a fatigue crack. To further simplify the inspection scenario, flat sections of the component were selected. NDE data for these applications are collected using a scanning system that can spatially register the data as a function of location on the component.

Once collected, noise and clutter are removed from the data. Some of the noise could be simple electrical and/or thermal noise, while other sources include attributes of the data collection process, such as probe tilt. In addition to the use of conventional high pass and/or low pass filter, some of the noise sources need to be addressed by refining and calibrating the simulations used for the forward and inverse modeling processes. A general diagram of the process is shown in Figure 2 [8].

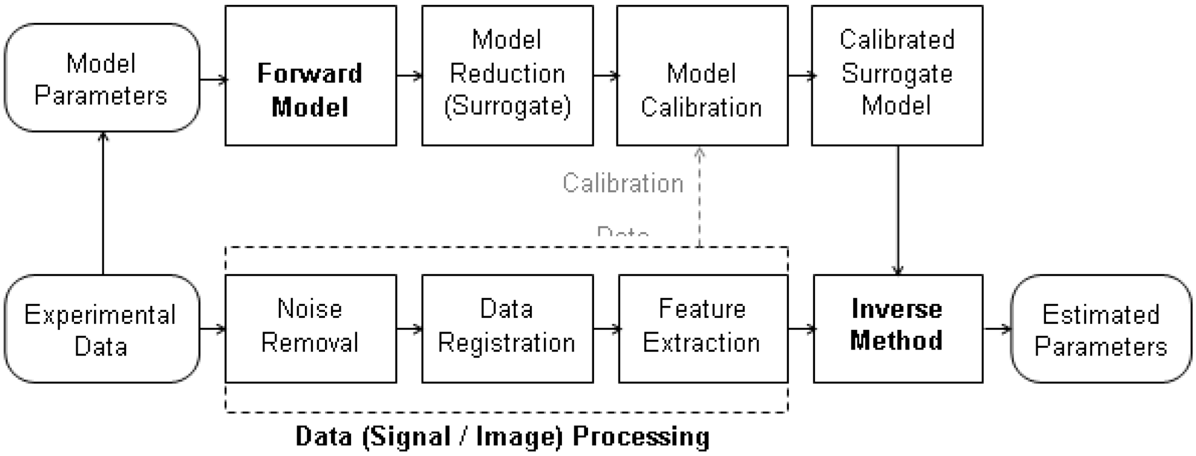

Figure 2: General inversion process for parameter estimation.

Using this general approach, the depth of very shallow cracks in the propulsion component could be determined. For multiple representative examples, the crack sizing was sufficiently accurate to provide a diagnostic tool that would greatly simplify and accelerate the disposition of any indications when implemented into a production process. However, additional complications arise due to sub-surface features that provide NDE responses similar to fatigue cracks. An eddy current scan from a test sample that contains indications from both surface breaking cracks grown by fatigue and sub-surface features is shown in Figure 3. These features were quantified by using a serial sectioning technique to accurately measure the length and depth of the cracks and sub-surface features [9]. As an example of the characterization capability, one of the indications labeled number 3 is from a sub-surface feature. Using NDE-based inversion, it was estimated to be at a depth of 32 micrometers from the sample surface. For high frequency eddy currents used for this assessment, this is considered quite deep. The serial sectioning, performed in 1.3 micrometer increments, indicate the measured depth of the sub-surface future to be at 39 micrometers of depth. The overall volume of this feature was estimated to be 0.0020 mm^3 from the eddy current measurements. The actual volume for the serial sectioning indicated the total volume was 0.0045 mm^3. While this error seems to be substantial, it is quite an achievement to obtain any estimate of size for a sub-surface feature at this depth with high frequency eddy current testing. Additional work is planned to enhance this characterization capability using information from serial sectioning.

The next challenge to be addressed for propulsion applications is geometry that is non-planar. Initially this will evaluate cracks located along radii. For these applications, the eddy current sensor is not sufficiently small to enable it to be completely conformed to the radius, especially for multi-element sensors typically used for propulsion component assessments. This can be a challenge as cracks can be in the radius, in the flaw section next to a radius, or in the transition zone from the flat section to the radius. An example of a representative component and the eddy current response, including a crack indication, is show in Figure 4 [10].

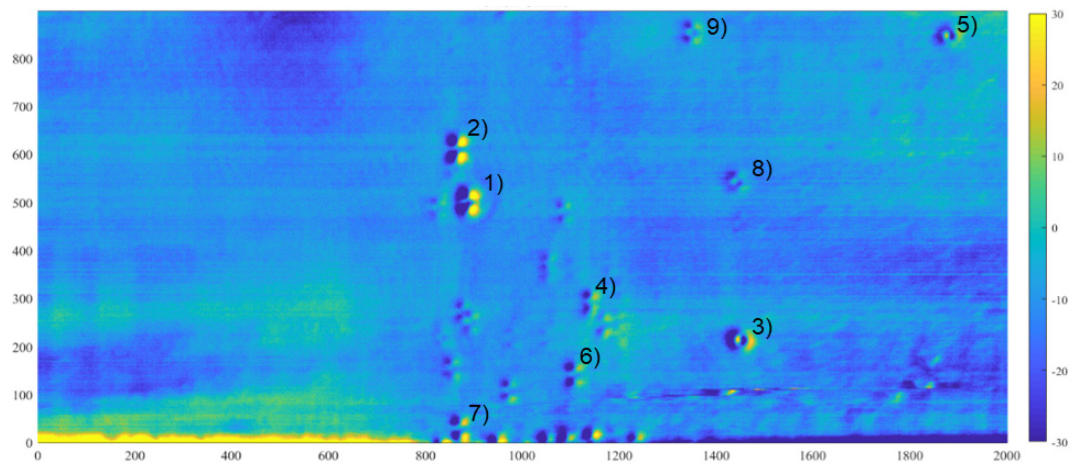

Figure 3: Eddy current (vertical) response from nickel-based superalloy region with surface breaking and possible sub-surface features. Indication #3 is a sub-surface feature characterized by eddy current and serial sectioning.

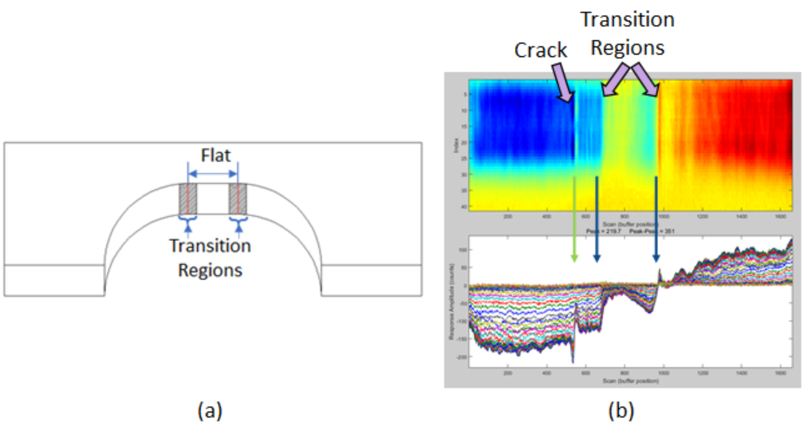

Figure 4: (a) Elongated radius test specimens. (b) Example 6 MHz eddy current response with flaw indication and flat-to-curved transition regions.

For full characterization of flaws at these locations, additional effort is required to enhance the spatial resolution and fitting of the volume element simulation software to enable analysis of these types of indications. For smaller features of interest, the flaw response can approach the magnitude of the response from the geometric change in the radius. As these signals can be superimposed, methods to discriminate between these two classes of indications are being developed that leverage the ability to perform rapidly multiple parameter sensitivity studies in the virtual domain. A consideration for this approach is the requirement of collecting spatially registered data, which in this case consists of the full impedance plane of the eddy current signal. The accuracy of the spatial registration and the sampling rate at which the data is collected depends on the desired accuracy of the flaw characterization.

Similar flaw sizing capabilities are being developed for aircraft structural applications. The initial application being explore addresses bolt-hole eddy current (BHEC) where the eddy current sensor is placed into a fastener hole after the fastener is removed. The intent is to detect fatigue cracks that nucleate and grow at the faying surface between layers. This application has the benefit of geometric constraints of the fastener hole, though these structural elements are known to have more variability that propulsion components due to fastener hole skew, elongation, and other variations, such as being drilled twice into a figure eight-like geometry for match drilled repairs. Due to the increased complexity, the inversion process includes elements of all three types of algorithms, namely heuristics, model-based, and enhanced data analytics.

The heuristic component of the algorithms mimics the decision-making process of an inspector to determine if a feature is an indication. BHEC procedures typically are used for safety critical inspection to justify the increased aircraft disassembly required to remove fasteners. Therefore, the procedure to identify a crack is mature. Enhancements in signal interpretation to enable characterization when geometric complexity is present are being developed. Model-based methods address more complex attributes of the signal interpretation, such as compensated time-dependent calibration noise of a typical bolt-hole eddy current inspection shown in Figure 5. This calibration phenomena must be integrated into models to mitigate the effect of the noise in determining the depth of the fatigue crack into the structure at the fastener hole. Additional factors that must be addressed include other equipment variables, such as the impact of band-pass filters, some of which are built into the equipment and cannot be removed, and differential and absolute eddy current coil metrics, such as rotation and tilt.

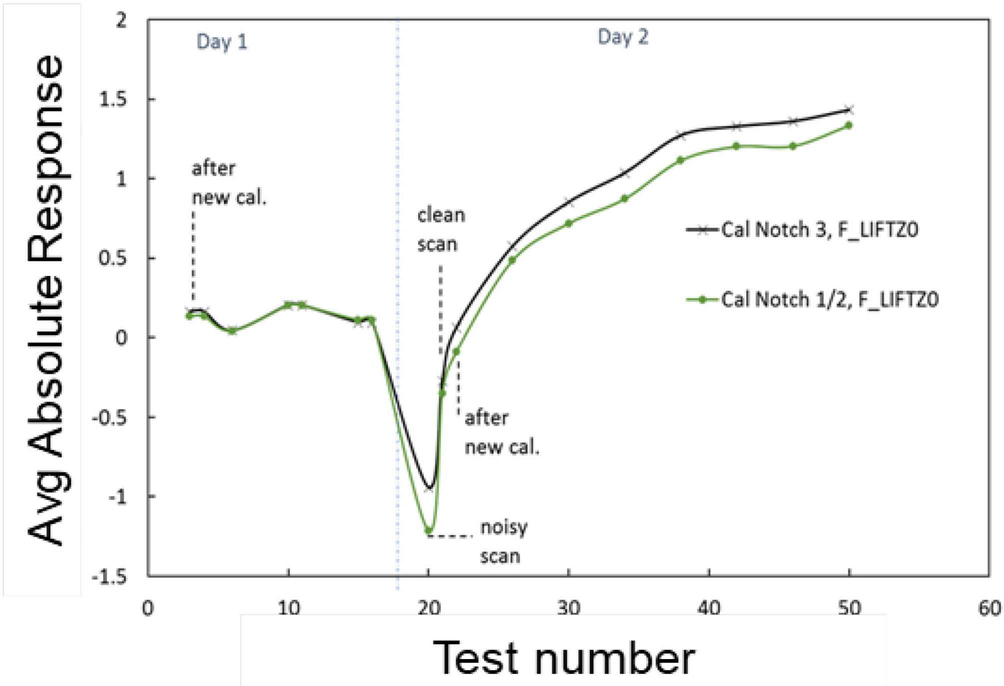

Figure 5: Compensated time-dependent calibration noise.

Once the equipment variables are fully addressed and appropriate compensation is built into the models, the variability of the flaw in question can be addressed by similar model tuning methods to account for changes in signal due to through wall cracks, corner cracks, crack aspect ratio, and crack morphology. The integration of these factors into the model-based inversion has been proven to size the depth of cracks using bolt hole eddy current data to an accuracy of 8.5% of actual depth for multiple crack sizes in multi-layered aluminum laboratory test samples [6]. These test samples do not have fastener hole variability and current efforts are addressing factors such as fastener hole skew, out-of-roundness, and oblongness.

To evaluate the effect of the fastener hole to fastener hole variability, a relatively large test matrix is being prepared as simulation tools have not tackled this challenge to date. Thus, large data sets will be required to assist in validating simulation, plus the data can be evaluated by enhanced data analytics (EDA). These methods are effectively statistical classifiers and or statistical regression techniques. The ability to train these algorithms, even when using supervised approaches, is highly dependent on the magnitude and quality of the data being used.

Recent work illustrated the impact of data quantity and signal to noise ratio (SNR) on the ability of a supervised neural network-based diagnostic [6]. The study used a synthetic data set and introduced Gaussian noise at different percent levels at different number of data points used to train the EDA algorithm. The neural network used for this study was a multi-layered perceptron with four layers and 50 layers in each hidden layer.

The results of this evaluation are show in Figure 6. The plot illustrates the log of the mean square error of the neural network as a function of SNR for differing number of data points in each data set. The SNR varies from an infinite value to one that is very poor of only 10 to 1. The number of data points in each data set varies from 50 up to 14,000. The outcomes are presented in standard box plots with the outliers indicated by red indices for each set of numbered data points.

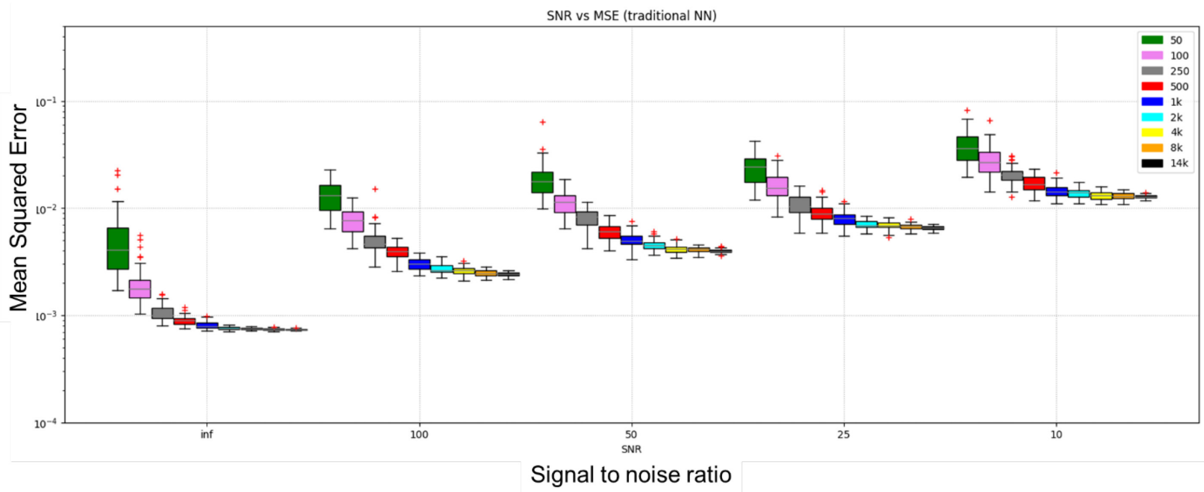

Figure 6: Multi-layer perceptron results illustrating mean square error as a function of data quantity and SNR.

It is clear from this data set is that the improved SNR and larger data sets results in a lower value for the mean squared error. This outcome is intuitively anticipated as it is expected that more data with higher fidelity will result in improved outcomes. However, this example highlights some of the challenges of using EDA for NDE data analysis. Even with the highest level of SNR, the smaller data sets have outliers that are considerably deviant for the mean values. When considering the impact of safety of systems, these outliers are the equivalent of a large, missed flaw that could impact the safety of a system. It is important to recall that it is not the smallest flaw that can be detected, but the largest flaw that could be missed that impacts the safety of a system. This is especially true in aviation where single load path structures are expected to have an extraordinarily low risk of failure.

This data sensitivity study demonstrates two critical issues that need to be considered when applying EDA algorithms to NDE data. The first is the number of data points required to enable improved performance of EDA methods. The second issue is the ability to address outliers and nuances in data that can be indicators of flaws. The concern is the tendency of statistical methods to ignore such features when using large data sets.

As seen in Figure 6, even large data sets with high SNR can have outliers that exceed the anticipated statistical distribution.

4.0 SUMMARY

The development of the various approaches to realize NDE-based flaw/materials characterization in military aircraft frequently required a combination of multiple analysis methods. Research and development efforts completed to date indicate that at least two of the three primary analysis methods, namely heuristics, model-based, and enhanced data analytics, need to be integrated to provide results with an acceptable level of accuracy and precision for engineering applications. Progress to date has demonstrated the capability to determine the length and depth of cracks in propulsion components where the geometry variance is very low due to the high precision tolerances required for these applications. For structural applications, a broader implementation of the analytical tools is required to account for the looser geometric tolerances. Initial results for BHEC have shown promise, though additional development is required to address all possible parameters. Future work will include the use of EDA to help address large data sets required to explore all the possible sources of variance in the NDE responses. Quantifying the damage state is a critical element to enable higher fidelity analysis using digital twin analysis methods. The ability to tailor these capabilities becomes a function of the identified variables that affect NDE-based measurements.

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