Artificial Intelligence Tools for Failure Event Data Management and Probability Risk Analysis for Failure Prevention*

Jeffrey T. Fong
Mathematical and Computational Sciences Division, NIST, Gaithersburg, MD 20899, and
Department of Mech. Engineering & Mechanics, Drexel University, Philadelphia, PA 19104

Pedro V. Marcal
MPave Corp., Julian, CA 92036

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Abstract

Over the last thirty years, much research has been done on the development of failure event databases and fatigue modeling of crack growth in pressure vessels and piping. According to a USNRC report (NUREG/CR6674, 2000), results of a fatigue crack growth model showed that "cracks initiate rather early in the *(nuclear power)* plant life. There is about a 50-percent probability of initiating a fatigue crack after only 10 years of operation. Over this 10 years, about 50 percent of these initiated cracks are predicted to grow to become leaking cracks."

To improve processing of failure event reporting and more timely risk assessment of critical structures and components, we applied a computer linguistic concept (Schank, 1972) and a natural language toolkit (Lopez, 2002) to develop a software code named ANLAP. This tool will automatically extract statistical data from failure event reports with linkage to fatigue modeling codes for life estimation and risk assessment of aging structures and components.

Introduction

Over the last thirty years, much research has been done on the development of failure event databases and risk-informed fatigue modeling of crack growth in aging structures such as pressure vessels and piping in powerplants, and bridges (see, e.g., Fong, et al. [1]).

For instance, in the case of an aging bridge as shown in Figure 1, information in a bridge failure event database [2, 3, 4] is used to guide the development of a bridge flaw inspection database and a crack-growth model [1]. This model, as conceptually represented in Figure 1, be it deterministic or stochastic, needs specific input from a total of five databases, namely, Failure Event Database-1, Flaw Detection, Location & Sizing Database-2, Material Property Database-3, Deterministic or Probabilistic Damage and Remaining Life Estimation Model Parameter Database-4, and Loading/Constraints Database-5, in order to predict the remaining fatigue life of an aging structure.

It is well-known that the prediction of a crack-growth model [1] is not an exact science. As shown in Figure 2, a fatigue crack growth modeling result by Khaleel, et al. [5, p.9.7] for a surge-line elbow of a typical nuclear powerplant in the United States showed that

> *" . . . cracks initiate rather early in the plant life. There is about a 50-percent probability of initiating a fatigue crack after only 10 years of operation.*
>
> *" . . . Over this 10 years, about 50 percent of these initiated cracks are predicted to grow to become through-wall or leaking cracks.*
>
> *" . . . The frequency of through-wall cracks increases significantly over this 10-year period and then remains relatively constant over the remainder of the 60-year plant life."*

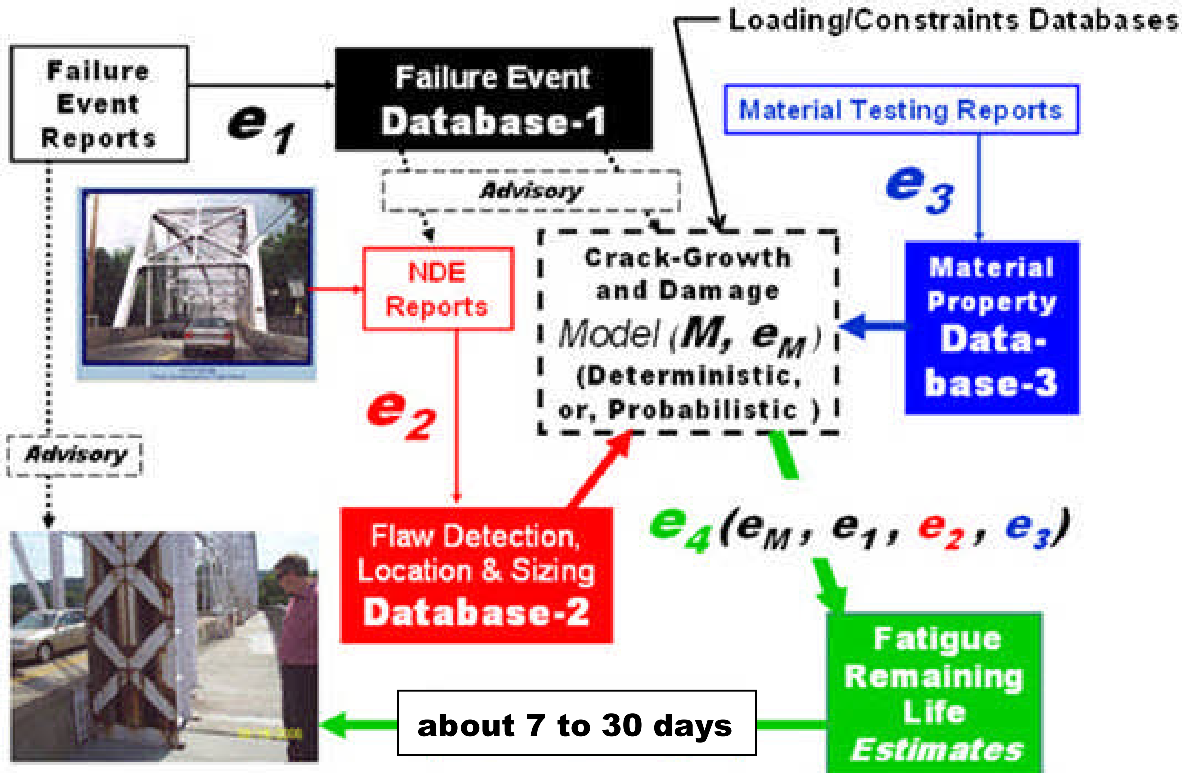

Figure 1 A conceptual representation (after Fong and Marcal [2] and Fong, Ranson, Vachon, and Marcal [3]) of the information flow plus the uncertainties and potential errors associated with and inherent in (1) Failure Event Database-1 (Uncertainty-1, or, e_1), (2) Flaw Detection, Location & Sizing Database-2 (Uncertainty-2, or, e_2), (3) Material Property Database-3 (Uncertainty-3, or, e_3), (4) Deterministic or Probabilistic Damage Models (Uncertainty-M, or, e_M) and Remaining Life Estimates (Uncertainty-4, e_4), and (5) Loading/ Constraints databases, Photo at the upper left corner is from the 100-year-old Jonathan Hulton Bridge, built in 1909, of Pittsburgh, PA, courtesy of reference [4]. Photo at the lower left corner by Fong during a visit to the bridge in 2006.

The report [5, p.10.1] concluded that

> *". . . it is recognized that there are uncertainties in these calculated failure probabilities and core damage frequencies.*
> *" . . . Sources of the uncertainties come from assumptions made in the fracture mechanics and probabilistic risk analysis models themselves and from the inputs to the models."*   *[Note: Words in red are altered by authors for emphasis.]*

In other words, engineers dealing with failure probability or time-to-failure predictions need to formulate their models with stochastic variables to account for the uncertainties mentioned in Ref. [5]. Furthermore, engineers need to include in their analysis models as many source uncertainties as possible to account for the input to the models such that estimates of the so-called remaining life of an aging structure can be given with uncertainty for risk assessment.

As a follow-up of the above observation, we present in this paper (1) a new approach to periodic inspection of aging structures based on stochastic modeling, and (2) an application of a recently-developed artificial intelligence (AI) tool to probabilistic fracture mechanics models for remaining life prediction. A remark on human-machine partnership using AI is also included.

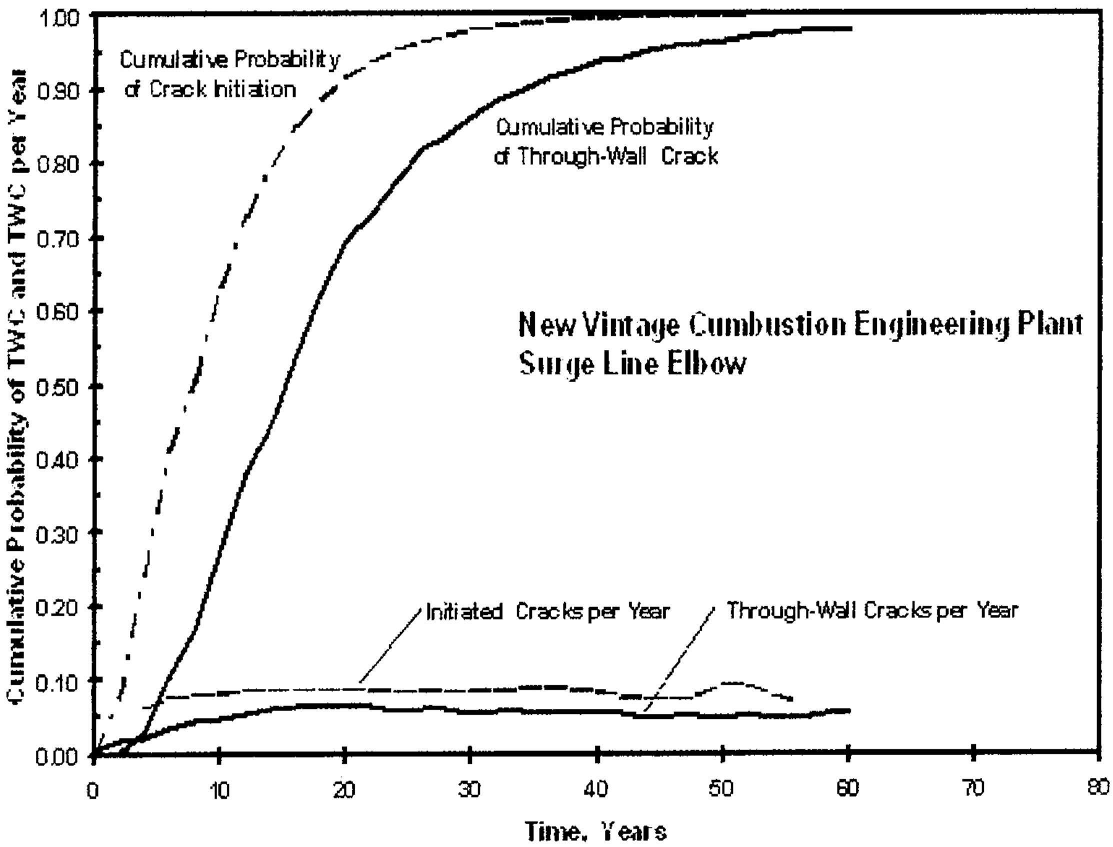

Figure 2   Calculated Probabilities of Crack Initiation and Through-Wall Crack for the Surge-Line Elbow of the Newer Vintage Combustion Engineering Plant (after Khaleel, Simonen, Phan, Harris, and Dedhia [5]).

A New Approach to Periodic Inspection of Aging Structures

To prevent catastropic failure of aging structures such as bridges, dams, high-rise buildings, pressure vessels and piping of the nation's physical infrastructure, engineers traditionally use an assortment of nondestructive tools such as ultrasonic testing, acoustic emission technique, etc. to discover cracks and conduct repairs by following a *deterministic* periodic inspection design as described in Fig. 3 (after Dowling [6, p. 491, Fig. 11.2]).

It is well-known that all of the quantities plotted in Fig. 3 contain *uncertainties* such as those reported in Ref. [5], and it is incumbent upon the engineers to devise a new approach to account for such *uncertainties*. An example of such a new approach, based on a stochastic model of fatigue crack growth using direct measurements [1], is given in Fig. 4. In particular, four new measures of *uncertainties*. are added:

(1) q_{ad} , for the detectable or initial crack length, a_d (= a_i),
(2) q_{ac} , for the critical or final crack length, a_c (= a_f),
(3) q_{Nif} , for the remaining fatigue life cycle, N_{if}, , and
(4) q_{Np} , for the number of cycles from the initial to the second inspection, N_p.

Here, the q's are the so-called tolerance intervals with formulas well-defined in the statistics literature (see, e.g., Nelson, et al. [7, pp. 178-187]).

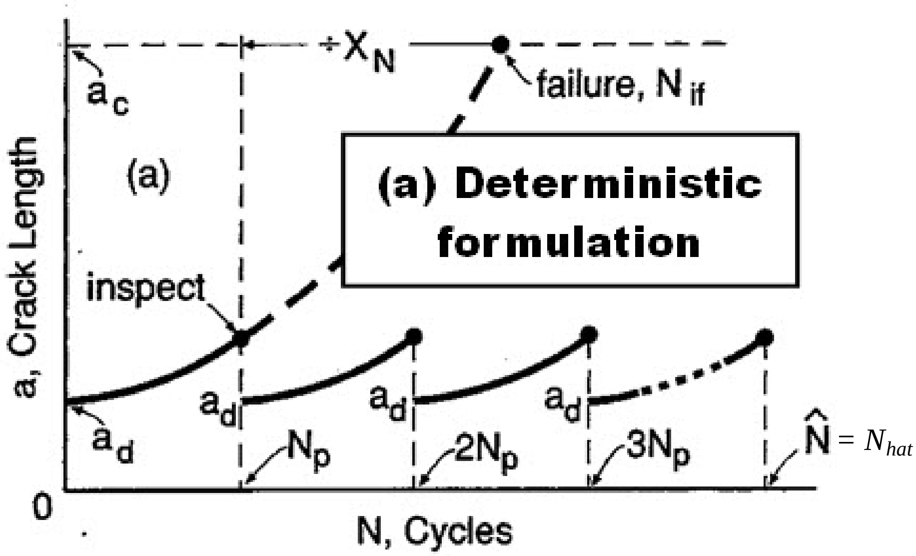

Figure 3 An application of the crack-length-based approach to fatigue (after Dowling [6, p. 491, Fig. 11.2]) is illustrated in two formulations: (a) deterministic, as shown above, and (b) stochastic, as shown in Figure 4. In each case, several plots of crack length a vs. cycle number N, appear where two types of crack lengths are defined: a_d = the minimum crack size that can be "reliably" detected by NDE, and a_c = the critical crack length that causes a structure or component to fail and is related to material properties such as K_{Ic}. Three cycle number parameters, N_{if}, N_p, N_{hat}, and a safety factor on life, X_N, are also defined: N_{if} = no. of remaining life cycle after initial detection without further inspection, N_p = no. of cycles from the initial to the 2nd inspection, N_{hat} = no. of remaining life cycles expected in service after initial inspection with the detection of a_d , and X_N = N_{if} /N_{hat} , the safety factor on life.

Application of Artificial Intelligence (AI) Tools to Fatigue Damage Modeling and Remaining Life Estimation

As shown in Fig. 1, the formulation of a stochastic crack-length-based periodic inspection design (Fig. 4) addresses only two uncertainties, i.e., e_2 and e_M, of the complete modeling effort in predicting the remaining life of an aging structure. In this section, we introduce a recently-developed artificial intelligence (AI) tool named ANLAP [8, 9] to automate the human-dependent input process associated with the other two uncertainties, namely, e_1 and e_3, which correspond to the failure event reports and material property testing, respectively. As shown in Ref. [8], ANLAP was developed by adopting the early works of Schank [10, 11] and a recent work of Lopez and Bird [12], and is coded in Python [13, 14].

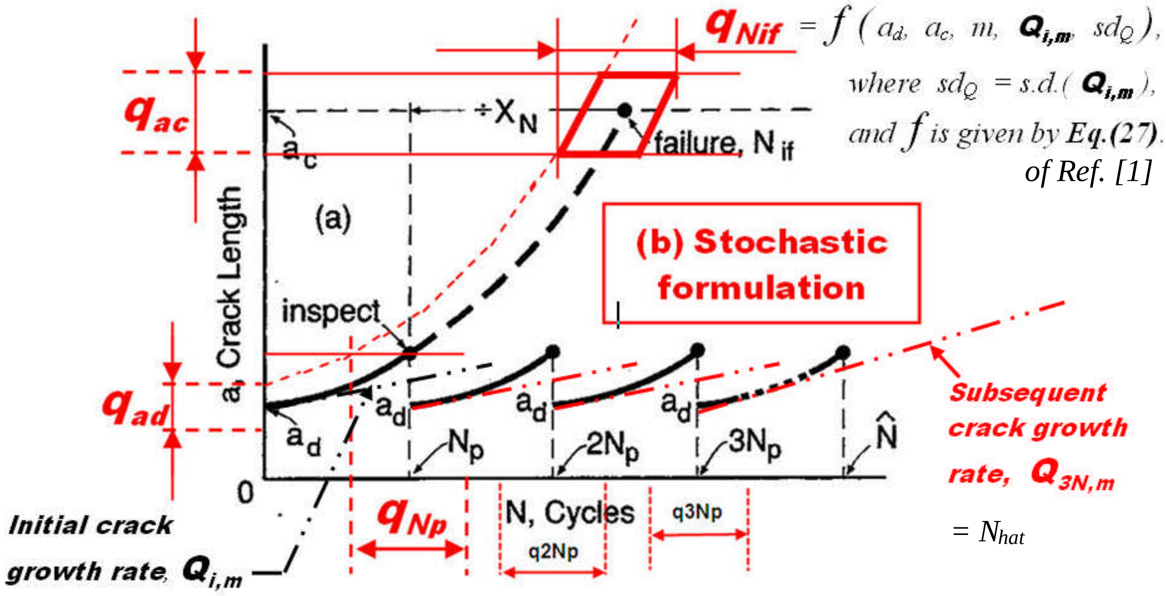

Figure 4 An application of the crack-length-based approach to fatigue (after Dowling [6, p. 491, Fig. 11.2]) using a stochastic formulation as defined by Fong, et al. [1] (see Sect. VI of [1] using Eqs. (19) through (22) and Conditions S-1 through S-6 in that paper [1]). In this case, several plots of crack length a vs. cycle number N, appear where two types of crack lengths are defined: a_d = the minimum crack size that can be "reliably" detected by NDE, and a_c = the critical crack length that causes a structure or component to fail and is related to material properties such as K_{Ic}. Three cycle number parameters, N_{if}, N_p, N_{hat}, and a safety factor on life, X_N, are also defined: N_{if} = no. of remaining life cycle after initial detection without further inspection, N_p = no. of cycles from the initial to the 2nd inspection, N_{hat} = no. of remaining life cycles expected in service after initial inspection with the detection of a_d, and $X_N = N_{if} / N_{hat}$, the safety factor on life. Furthermore, as defined by Fong, et al. [1, Section VII], four new measures of uncertainties are added: (1) q_{ad}, for the detectable or initial crack length, a_d (= a_i), (2) q_{ac}, for the critical or final crack length, a_c (= a_f), (3) q_{Nif}, for the remaining fatigue life cycle, N_{if}, and (4) q_{Np}, for the number of cycles from the initial to the second inspection, N_p, where the q's are the so-called tolerance intervals with formulas well-defined in the statistics literature (see, e.g., Nelson, et al. [7, pp. 178-187]).

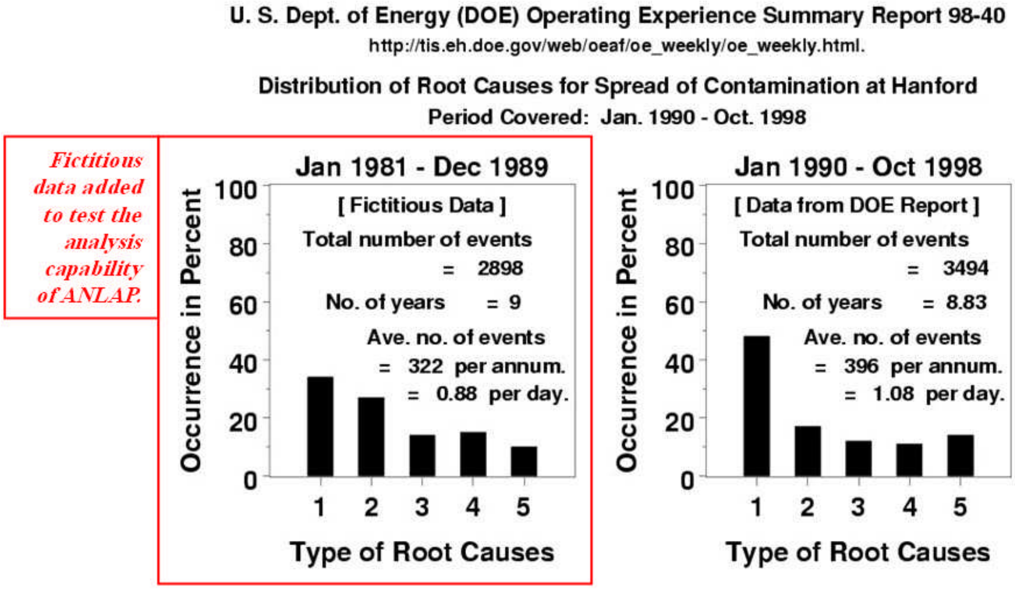

Figure 5 A typical output of using an artificial intelligence tool named ANLAP [8, 9] to read a failure event report and extract critical information with statistical graphics and analysis as input to probabilistic fracture mechanics damage and remaining life estimation models.

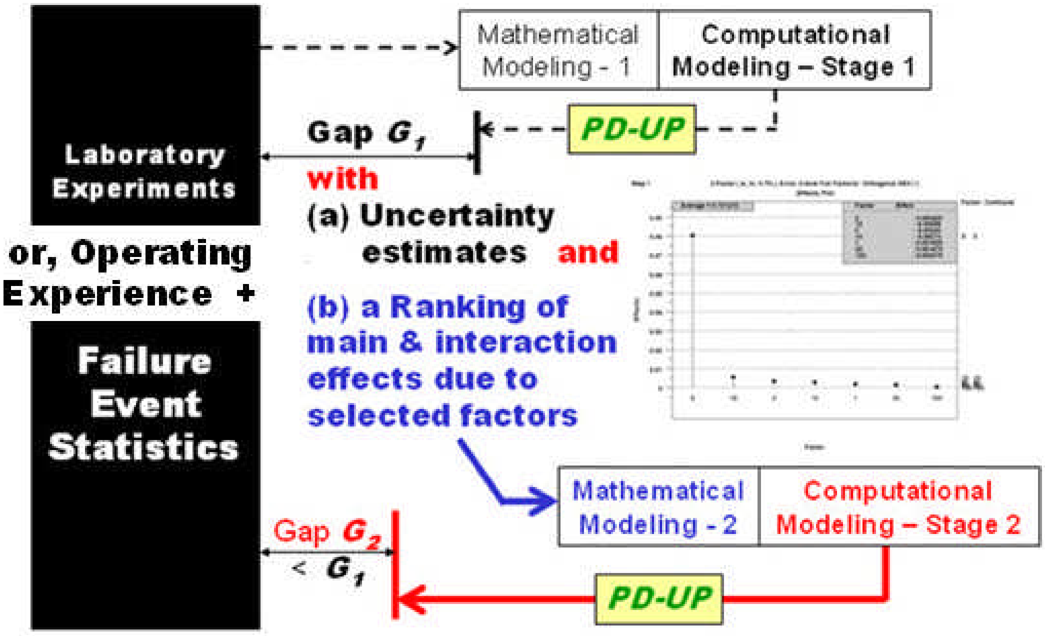

Figure 6 A schematic representation of a two-stage refinement of mathematical and computational models, where the stage-1 gap, G_1, between facts (laboratory experiments, operating experience, or failure event statistics) and predictions are computed using an uncertainty estimation plug-in, PD-UP, as formulated by Fong, et al. [18], such that a ranking of the relative importance of uncertainty-contributing factors becomes available to guide the modeler in obtaining an "improved" stage-2 model (i.e., gap $G_2 < G_1$).

A common problem associated with data collection in failure event databases, NDE databases, and material property databases, is the proliferation of technical reports written in natural languages. In Ref. [8], we describe an application of an Automatic Natural Language Abstracting and Processing (ANLAP) tool to reduce uncertainty e_1 of a failure event report database. A typical output of ANLAP in extracting a page out of a DOE 1998 Nuclear Facility Operating Experience Weekly Report is given in Fig. 5.

Using Python as a "wrapper" of computer script languages such as ANLAP [9], and DATAPLOT [15, 16] that does statistical data analysis and design of experiments [17, 18], we show in Fig. 6 a typical modeling refinement exercise, where a computer plug-in named PD-UP [18] allows a user to rank the relative importance of a large number of factors and their interactions in order to produce a "better" model. In Fig. 7, we illustrate an application of ANLAP in estimating the uncertainty e_3 of a material property database by displaying the results of an investigation [19, 20] on the static crack initiation toughness, K_{IC}, of a high-strength steel.

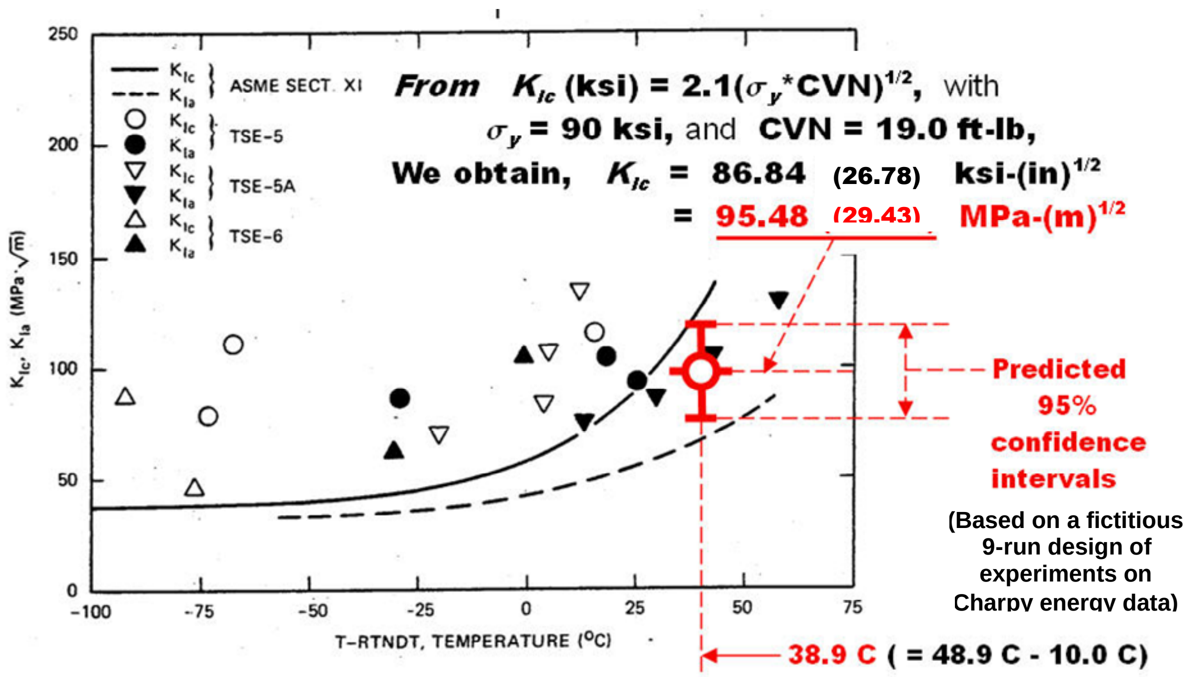

Figure 7 Plot of an estimated static crack initiation toughness (K_{Ic}) value with an expression of uncertainty (error bar in red) based on fictitious design-of-experiments(DOE)-generated results at 120 °F (48.9 °C), in a K vs. (T - RTNDT) diagram where K_{Ic} and K_{Ia} data from three thermal shock experiment (TSE) test cylinders, TSE-5, 5A, and 6, and ASME Section XI K_{Ic} and K_{Ia} curves over a broad range of temperature shift, (T - RTNDT), were plotted by Cheverton et al [19] and reported by Interrante, et al. [20] and Fong, et al. [1]. Note that all experimental data or design curves are for comparable steels having a room temperature yield strength of about 90 ksi (620.6 MPa) (after Interrante, et al. [20]).

Human-Machine Partnership in Structural Health Monitoring

As shown in Refs. [1, 21, 22] and Fig. 8, the use of Python in the development of AI tools such as ANLAP to manage uncertainties in the "health" state of an aging structure using a stochastic model, leads naturally to the design of an internet-based aging-structure health monitoring system.

Such a system, clearly, depends on the availability of very fast computing speed, large computing memory, sophisticated database technology, and transparent computer coding practice for modular debugging. When properly designed and implemented, such systems are capable of assisting engineers in giving early warning signs of rapidly degrading structure.

However, those warning signs need interpretation by humans, whose experience and judgment are invaluable in weeding out "false" signals. AI tools with a human partnership are, therefore, more reliable and cost-effective in managing an aging structure.

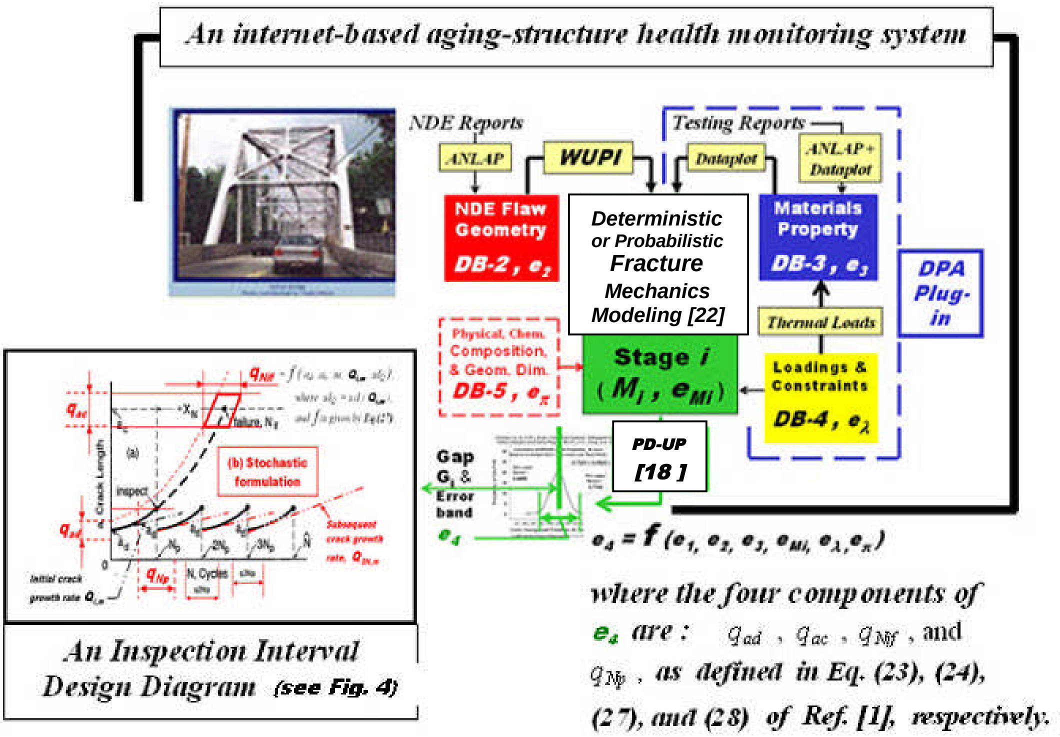

Figure 8 A schematic design of the internet-based aging-structure health monitoring system involving the use of ANLAP [8, 9](to manage e_1, WUPI [1] to manage e_2, DPA [21] to manage e_3, and PD-UP [18] to manage e_M for a stochastic fracture mechanics-based crack growth model [22]. Note that in this web-based computational exercise, the five source uncertainties,

$$\boldsymbol{e_1}, \boldsymbol{e_2}, \boldsymbol{e_3}, \boldsymbol{e_\lambda}, \boldsymbol{e_\pi},$$

are being combined with the model uncertainty, e_M, in a functional relationship, f, with the result uncertainty, $\boldsymbol{e_4}$, being given by four uncertainty components, q_{ad}, q_{ac}, q_{Nif}, and q_{Np}, of the inspection interval design diagram (see Fig. 4 and Ref. [1]).

Concluding Remarks

In this paper, we describe an uncertainty-based methodology, using a Python-coded artificial intelligence (AI) tool, ANLAP [8], and its linkage with a statistical analysis tool, DATAPLOT [15, 16], for managing the "health" of an aging structure so as to minimize the chances of a catastropic failure.

In addition to introducing a new approach to periodic inspection of aging structures, we also touched upon the concept of a dialog-box design for an uncertainty analysis plug-in, which effectively allows the engineer to come to grips with uncertainty issues without being over-burdened by the mathematical rigor that comes with any attempt at probabilistic modeling.

As a concluding remark, the following quote from the "Introduction" of a book by Giurgiutiu [23] best summarizes our thoughts on the timeliness and societal impact of a need for developing an uncertainty-based and risk-informed approach to managing aging structures:

> *"The United States spends more than $200 billion each year on the maintenance of plant, equipment, and facilities.*
>
> *"Maintenance and repairs represents about a quarter of commercial aircraft operating costs.*
>
> *"Out of approximately 576,600 bridges in the U.S. National inventory, about a third are either 'structural deficient' and in need of repair, or 'functionally obsolete' and in need of replacement,*
>
> *"The mounting costs associated with the aging infrastructure have become an on-going concern. Structural health monitoring systems installed on the aging infrastructure could ensure increased safety and reliability."*

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Biographical Sketches of Co-Authors

Jeffrey T. Fong

Dr. Fong was educated at the University of Hong Kong (B.Sc., engineering, 1955), Columbia University (M.S., engineering mechanics, 1961), and Stanford (Ph.D., applied mechanics and mathematics, 1966). He worked for 8 years (1955-63) as a design and construction engineer at Ebasco, Inc., New York, New York, and more than 40 years (1966 - present) as a researcher, consultant, and project leader with the title of Physicist at the U.S. National Institute of Standards and Technology (NIST), Gaithersburg, Maryland. He also spent a year (1975-76) with the Office of the Chairman, U.S. Nuclear Regulatory Commission (NRC) as a ComSci Fellow and Consultant on the WASH-1400 report.

Dr. Fong's technical expertise and research interests are in applied mechanics, computational modeling, finite element method (FEM), fluid-structural interactions, wave propagation, fire-structure interactions, fatigue and fracture, thermodynamic theory of materials with microstructures, biotechnology, nanotechnology, nondestructive testing, uncertainty analysis, and risk-informed engineering practice. His current research is on uncertainty analysis of finite element simulations and the development of Python-based uncertainty estimation *plug-ins* for interpreting small-sample experimental and numerical simulation data in support of risk-informed engineering design decisions and structural failure prevention.

In 2006, Dr. Fong was appointed adjunct research professor of structures and statistics at the Mechanical Engineering and Mechanics Department of Drexel University, Philadelphia, PA, and has been invited to teach two courses entitled "Finite Element Method Uncertainty Analysis," and "Experimental Design for Engineers." Dr. Fong is a registered professional engineer in the State of New York, (1962) and United Kingdom (1968), and has published more than 100 technical reports and journal papers in the engineering, materials science, and applied mathematics literature, and edited 15 conference proceedings. He has received numerous awards including Fellow of the ASTM International, Fellow of the American Society of Mechanical Engineers (ASME), ASME Distinguished Lecturership (1988-92), and ASME Pressure Vessels & Piping Medal (1993).

Pedro V. Marcal

Pedro V. Marcal began his career as a Lecturer at the Imperial College of Science and Technology, London University in 1963 and a Professor in the Division of Engineering, Brown University (1967-1974). He founded the MARC Analysis Research Corp. in 1971, the software company that developed and marketed the Marc general purpose program. This program was and continues to be used widely in Industry for nonlinear analysis. He then became President of Phoenics North America in 1992. The appointment was a major opportunity to learn about fluid flow and CFD. In 1995, he established PVM Corp. and embarked on the development of the General Purpose Finite Element Program for Multi-Physics that is known as FEVA. In 2004, he established the MPACT Corp. to develop CAD-centric FEA software to foster widespread adoption of the Finite Element Method.

Dr. Marcal is active in ASME and was made a Fellow in 1975. He served as Chairman of the Pressure Vessel and Piping Division and was awarded the Pressure Vessel Medal, 1989 for research work in Nonlinear Finite Element Analysis. Dr. Marcal is the author of over 80 scientific papers on Finite Element Analysis, Fatigue and Fracture and AI. He has helped organize many scientific meetings on Computational Structural Mechanics. Dr. Marcal's technical expertise and research accomplishments are widely known in the areas of finite element method (FEM), artificial intelligence applications, nonlinear mathematics and mechanics, FEM code development, and the use of Python as a wrapper for numerous computing codes such as Fortran, C++, Dataplot, Excel, Abaqus, Ansys, LsDyna, Nastran, TrueGrid, Mathematica, Matlab, etc. He was the developer of two nonlinear FEM codes (MARC, MPACT) and one artificial intelligence code (ANLAP), the latter of which is capable of extracting information from material testing or failure event reports written in English or Japanese as indexed data for instant input to FEM or statistical analysis codes.