ABSTRACT

In the Army mechanical fatigue subject to external and inertia transient loads in the service life of mechanical systems often leads to a structural failure due to accumulated damage. Structural durability analysis that predicts the fatigue life of mechanical components subject to dynamic stresses and strains is a compute intensive multidisciplinary simulation process, since it requires the integration of several computer-aided engineering tools and considerable data communication and computation. Uncertainties in geometric dimensions due to manufacturing tolerances cause the indeterministic nature of the fatigue life of a mechanical component. Due to the fact that uncertainty propagation to structural fatigue under transient dynamic loading is not only numerically complicated but also extremely computationally expensive, it is a challenging task to develop a structural durability-based design optimization process and reliability analysis to ascertain whether the optimal design is reliable. The objective of this paper is the demonstration of an integrated CAD-based computer-aided engineering process to effectively carry out design optimization for structural durability, yielding a durable and cost-effectively manufacturable product. This paper shows preliminary results of reliability-based durability design optimization for the Army Stryker A-Arm.

INTRODUCTION

Given the explosive growth in computational technology, computer-aided engineering (CAE) has long been used to analyze and evaluate product design. However, various uncertainties in an engineering system often prevent CAE from being directly used for some design applications. Through the use of experimental validation and probabilistic methods, CAE can become an integral part of the process of engineering product analysis and design. This paper presents an advanced CAE methodology for qualitative, reliable, durable, and cost-effective product design under conditions of uncertainty. The methodology is composed of four key elements: CAE technology, experimental validation, uncertainty quantification, and an uncertainty-based design method [1-5], as shown in Fig. 1.

Figure 1. Reliability-Based CAE Methodology

CAE technology, such as simulation techniques, enables the exploration of many different designs without building expensive prototype models. But to become an integral part of the design process, CAE must inevitably take account of engineering uncertainty. Engineering uncertainty can be categorized within three general types: physical uncertainty, model uncertainty, and statistical uncertainty [6]. Physical input uncertainties include geometric dimensions, material properties, and loads. A simulation (or mathematical) model introduces modeling uncertainty, for example from approximations in numerical algorithms, in addition to any inherent physical uncertainty in the structure. It is not possible to completely eliminate model uncertainty. Instead it may be more practical to minimize modeling uncertainty through experimental validation. Moreover, while modeling physical uncertainty, a lack of statistical information may lead to statistical uncertainty, such as uncertainty of the distribution type and its parameters, which could be modeled using Bayesian probability or possibility or evidence theory [7,8]. In fact, any uncertainty is minimal given sufficient statistical information, an advanced CAE methodology can be developed to include experimental validation and reliability-based design. As a result, a
A high fidelity model and analysis can be created that accounts for physical and model uncertainties.

Mechanical fatigue subject to external and inertia transient loads in the service life of a mechanical system often leads to structural failure due to accumulated damage [9]. A structural durability analysis that predicts the fatigue life of a mechanical component subject to dynamic stresses and strains is an intensive and complicated multidisciplinary simulation process, since it requires the integration of several CAE tools and considerable data communication and computation. In particular, uncertainties in geometric dimensions and material properties due to manufacturing tolerances result in the indeterministic nature of fatigue life for the mechanical component. The main objective of this research is thus to demonstrate the possibility of an advanced CAE methodology for structural durability based on experimental validation and reliability-based design optimization. Such a methodology should supply the framework for ascertaining whether modeling and simulation of the given problem is feasible and a simulated optimal design is reliable. This paper shows the preliminary results of a reliability-based durability design optimization for the Army Stryker A-Arm.

EXPERIMENTAL VALIDATION OF MECHANICAL FATIGUE

CAD and Finite Element (FE) Model

As shown in Fig. 4, the computer-aided design (CAD) model for the US Army Stryker A-Arm is developed with Pro/Engineer simulating a real Stryker A-Arm component with a high level of fidelity. For the purposes of structural design analysis using the University of Iowa’s Design Sensitivity and Optimization Tool (DSO) [4], the CAD model of the A-Arm was imported into MSC/PATRAN via IGES and its geometry was recreated using parametric cubic solids and surfaces. How the parametric cubic geometry is utilized for design parameterization will be explained more fully below. Then a finite element model is created in PATRAN for use as part of both flexible dynamic analysis and durability analysis. For FE modeling, ASTM A513 and A304 8620H materials are used to model plate and solid, respectively. Details of the FE model are listed in Table 1.

<table>
<thead>
<tr>
<th>Table 1. Aspects of FE Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>No of Nodes</td>
</tr>
<tr>
<td>No of Elements Quadrilateral</td>
</tr>
<tr>
<td>4 Node Solid</td>
</tr>
<tr>
<td>8 Node Solid</td>
</tr>
<tr>
<td>Rigid Bar</td>
</tr>
<tr>
<td>Total No of Element</td>
</tr>
</tbody>
</table>
Validation of Dynamics Model

As shown in Fig. 6, the dynamics model for the US Army Stryker is developed with DADS to simulate a real Stryker model. To achieve high fidelity of the dynamics model, the DADS model goes through an experimental validation to generate the input of dynamic analysis and validate the output of the dynamic analysis. As indicated by Fig. 7, the validation includes the mass/inertia properties; tire/suspension characterization; acceleration, displacement, dynamic strain; and “wind up” between axles.

Validation of Dynamics Analysis

As shown in Figs. 9 and 10, the dynamic strain and time histories for the US Army Stryker are computed from the dynamic simulation. A power spectral density (PSD) curve of dynamic strain is used to compare testing data with simulation results, in addition to a statistical comparison, such as mean, root mean square, skewness, and kurtosis of dynamic strain.
Validation of Durability Analysis

Durability analysis is carried out using the Durability Analysis And Reliability Workspace (DRAW) program developed at the University of Iowa [10]. The fatigue life computation consists of two primary computations, preliminary analysis and refined analysis, as shown in Fig. 11. A preliminary durability analysis is executed to estimate the fatigue life of the Army Stryker A-Arm and to predict the critical regions that experience a low fatigue life. For this preliminary durability analysis, the fatigue life for crack initiation is calculated at all surface nodes of the component in order to predict the critical regions. More accurate fatigue life is calculated at those critical nodes in the mechanical component that experience a short life span. The critical region on the A-Arm is clearly shown in Fig. 12. Dynamic stress used for the durability analysis can be obtained from either a hardware prototype experiment in which mounting sensors or transducers are placed on the physical component, or from numerical simulation. In the former case, the dynamic stress is obtained by converting the strains that is measured from the strain gauges into stresses. Then using simulation, a stress influence coefficient (SIC) [10] obtained from a hybrid quasi-static finite element analysis (FEA) using ANSYS is evaluated. Then the SIC are used with dynamic analysis results, including joint reaction and external forces, accelerations, and angular velocities, to superpose the dynamic stress history. This history is then used to compute the crack initiation fatigue life of the component.

Figure 11. Computation Process for Fatigue Life

Without prior knowledge of the fatigue failure shown in Fig. 3, the most critical region is found in the front solid at the location of the actual failure.

Figure 12. Fatigue Life Contour

DESIGN OPTIMIZATION TO DURABILITY

Since damage accumulation leads to structural fatigue failure of the A-Arm, a durability design optimization for the Army Stryker A-Arm is carried out to improve its fatigue life and minimize weight. The critical region where mechanical fatigue failure occurs is now considered for design change during the design optimization process. The integrated design optimization process involves (a) design parameterization [11], (b) design sensitivity analysis
Design parameters of the Stryker A-Arm are carefully defined to include a consideration of geometric and manufacturing restrictions.

**DESIGN PARAMETERIZATION**

As shown in Fig. 4, the Stryker A-Arm is composed of a front and rear solid parts connected by plate parts. While carrying out the design optimization, the front solid design maintains a symmetric geometry, and thus design parameterization is made to yield a symmetric design for the front solid part, as shown in Figure 9 and Table 2. In particular, the fourth and fifth design parameters shown in Fig. 14 are considered as crucial to the design, in order to increase fatigue life. By improving the fillet design of the front solid part with $b_4$ and $b_5$, the fatigue life could increase significantly without adding material. In addition, the width of reinforcing plate and the widths and heights of the (left/right) tubes are parameterized as designs as shown in Fig. 15. It is hoped that these parameters may be changed so as to reduce the weight of the component without reducing its fatigue life. Thus, ten shape designs are defined for the entire A-Arm shape design. Three sizing parameters are defined as the thicknesses of reinforcing plates, left tube, and right tube as shown in Fig. 15.

**DESIGN VELOCITY FIELD COMPUTATION**

The process of deforming shape design may be viewed as a dynamic process of deforming a continuum design, which can be described by a design velocity field over the design domain. The design velocity field can be characterized by a mapping between the undeformed and deformed designs. Since a FE method is used as the analysis tool, it is desirable to use a design velocity that can yield a regular mesh distribution after shape perturbation. This paper employs an iso-parametric mapping to compute the design velocity field for the shape design parameters defined on the CAD model. The isoparametric mapping is based on a representation of the model geometry using parametric cubic geometric entities in Patran.

**Table 2. Design Parameters**

<table>
<thead>
<tr>
<th>Type</th>
<th>Design</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shape</td>
<td>$b_1$</td>
<td>y-dimension of hole</td>
</tr>
<tr>
<td></td>
<td>$b_2$</td>
<td>x-dimension of hole</td>
</tr>
<tr>
<td></td>
<td>$b_3$</td>
<td>Height of lip around hole</td>
</tr>
<tr>
<td></td>
<td>$b_4$</td>
<td>Contour top</td>
</tr>
<tr>
<td></td>
<td>$b_5$</td>
<td>Contour bottom</td>
</tr>
<tr>
<td></td>
<td>$b_6$</td>
<td>Width of reinforcing plates</td>
</tr>
<tr>
<td></td>
<td>$b_7$</td>
<td>Width of right tube</td>
</tr>
<tr>
<td></td>
<td>$b_8$</td>
<td>Height of right tube</td>
</tr>
<tr>
<td></td>
<td>$b_9$</td>
<td>Width of left tube</td>
</tr>
<tr>
<td></td>
<td>$b_{10}$</td>
<td>Height of left tube</td>
</tr>
<tr>
<td>Sizing</td>
<td>$b_1$</td>
<td>Thickness of reinforcing plates</td>
</tr>
<tr>
<td></td>
<td>$b_{12}$</td>
<td>Thickness of right tube</td>
</tr>
<tr>
<td></td>
<td>$b_{13}$</td>
<td>Thickness of left tube</td>
</tr>
</tbody>
</table>

**DESIGN SENSITIVITY ANALYSIS FOR FATIGUE RESPONSE**

The sensitivity computational procedure for fatigue life is shown in Fig. 16. First, quasi-static loadings need to be computed consisting of inertia force and reaction force.
For this problem, there are a total of 24 quasi-static loading cases, 12 unit loads applied at 2 joints plus 12 loads for inertia forces. The 24 loading cases are applied to the A-Arm to perform FE analyses to obtain the stress influence coefficients (SICs), which are used to compute the dynamic stress history of the current design. This dynamic stress history is used to predict the fatigue life of the perturbed design. Also, continuum-based DSA of the SICs is carried out, which is then used to predict dynamic stress history of the perturbed design. This perturbed dynamic stress history is then used to predict fatigue life of the perturbed design. Finally, the design sensitivity of fatigue life is computed by taking a finite difference of original and perturbed fatigue life.

Computation of Quasi-static Loading and Stress Influence Coefficient (SIC) FE Analysis

**Quasi-Static Loading**

\[ \begin{align*}
\text{Inertia Forces due to Gross Body Motion (IFGBM)} &: f_i^\text{IFGBM} = -m^r (A^T \ddot{x} + \dddot{k} x + \ddot{k} \dot{x} + \dot{k} x + k x) \\
\text{Inertia Forces due to Elastic Deformation (IFED)} &: f_i^\text{IFED} = -m^r \left\{ (\dddot{k} \ddot{x} + \ddot{k} x) \Phi^T \Phi \right\} \\
\text{External & Joint Reaction Forces} &: f_i^\text{ER} = 1.0, \quad \text{where} \Phi \text{ is eigenmode}
\end{align*} \]

**Stress Influence Coefficient (SIC) FE Analysis**

**Continuum DSA of SIC**

\[ \psi' = \int_\Omega \sigma_{\text{vm,}u} \delta u \ d\Omega + \dddot{a}_{\text{in}} (\lambda) - \dddot{a}_{\text{in}} (\lambda) \]

Where: \[ \dddot{a}_{\text{in}} (\lambda) \] is design dependant (IFGBM is through mass and IFED is through mass and eigenmodes). Hence eigenmodes DSA is introduced to compute \[ \dddot{a}_{\text{in}} (\lambda) \].

**Dynamic Stress History**

\[ \sigma(t, b) = \int_0^t \psi' \ d\tau \]

**Dynamic Parameters**

\( (\ddot{\omega}, \dddot{\omega}, a, \dot{a}, \dddot{a} ) \)

Assumed no changes with small local design changes to improve the fatigue life

**Perturbed Dynamic Stress History**

\[ \sigma^p(t, b) = \sigma(t, b) + \delta \sigma \]

**Design Perturbation** \( \delta b \)

**Perturbed Life Prediction**

\[ L^p(b) = L(b) + \delta L \]

**Fatigue Life DSA**

\[ \frac{\partial L(b)}{\partial b_i} = \frac{L^p(b + \delta b) - L(b)}{\delta b_i} \]

**Original Life Prediction**

\( L(b) \)

**Figure 16. Design Sensitivity Computational Procedure for Flexible Structural Systems**

Continuum DSA of SIC

The direct differentiation method [7] is used for DSA of SICs. Since there are seven design parameters and 114 loading cases, the direct differentiation method...
requires 798 FE re-analyses to calculate the fatigue life sensitivity. To understand this approach further, consider the following form of sensitivity equation [7]

\[ a(z', z) = \ell'_{\delta u}(z) - a'_{\delta u}(z, \bar{z}), \quad \text{for all } \bar{z} \in Z \]  

(1)

In the discretized FE matrix form, this equation corresponds to

\[ [K] \{z'\} = \{F'\} - \{F''\} \]  

(2)

From the assumption that mass and inertia characteristics of the Stryker do not change significantly due to the sizing and shape design change occurred locally, the dynamic properties of the Stryker A-Arm will remain unchanged. Thus, the contribution \( \ell'_{\delta u}(z) \) from the applied load to the design sensitivity in Eq. (1) vanishes. The contribution \( a'_{\delta u}(z, \bar{z}) \) from the structural stiffness involves numerical integration over finite elements that are affected by design changes. Thus, it is possible to carry out the design sensitivity computation using FEA results at the A-Arm only, which will significantly reduce the amount of required data storage.

The solution of Eq. (2) is the design sensitivity \( \{z'\} \) of the displacement \( \{z\} \). From this design sensitivity, the design sensitivity of the stress can be calculated using a chain rule of differentiation as

\[ \frac{\partial \sigma}{\partial b_j} = \frac{\partial \sigma}{\partial z} \cdot z' \]  

(3)

Computation of design sensitivity using Eq. (3) is straightforward if \( \partial \sigma / \partial z \) is available.

RELIABILITY-BASED DESIGN OPTIMIZATION

RBDO Model for Performance Measure Approach

For the Army durability application, the following RBDO model [13-17] will be used to obtain a reliable and durable optimal design.

\[
\begin{align*}
\text{min} & \quad \text{Cost}(\mathbf{d}) \\
\text{s.t.} & \quad P(G_i(\mathbf{d}(\mathbf{X})) > 0) - \Phi(-\beta_i) \leq 0, \quad i = 1, \ldots, np \\
& \quad \mathbf{d}^l \leq \mathbf{d} \leq \mathbf{d}^u
\end{align*}
\]  

(4)

where \( \mathbf{d} = [d_1^T] = \mathbf{u}(\mathbf{X}) \in R^n \) is the design vector, \( \mathbf{X} = [X_i]^T \in R^{nr} \) is the random vector, and \( n, nr \) and \( np \) are the number of design variables, random variables, and probabilistic constraints, respectively. The design constraints are described by the probability \( P(\bullet) \) of the failure event \( G_i(\mathbf{d}(\mathbf{X})) \geq 0 \).

The statistical description of the constraint violation is characterized by the cumulative distribution function \( F_{G_i}(\bullet) \) as

\[ P(G_i(\mathbf{X}) \geq 0) = 1 - F_{G_i}(0) \leq \Phi(-\beta_i) \]  

(5)

where

\[ F_{G_i}(0) = \int_{G_i(\mathbf{X}) > 0} \cdots \int f_X(x)dx_1 \cdots dx_n, \quad i = 1, \ldots, np \]  

(6)

In Eq. (6), \( f_X(x) \) is the joint probability density function of all random variables. Its evaluation requires a reliability analysis where multiple integrations are involved, as shown in Eq. (6). Some approximate probability integration methods have been developed to provide efficient solutions, such as the first-order reliability method (FORM) [18,19], or the asymptotic second-order reliability method (SORM) [20,21] with a rotationally invariant measure as the reliability. FORM often provides adequate accuracy and is widely used for design applications. Those reliability methods require a transformation \( T \) [22,23] from the original random parameter \( \mathbf{X} \) to the standard normal random parameter \( \mathbf{U} \). The performance function \( G(\mathbf{X}) \) in \( X \)-space can then be mapped onto \( G(T(\mathbf{X})) = G(\mathbf{U}) \) in \( U \)-space.

The probabilistic constraint in Eq. (5) can be expressed as a performance measure through the inverse transformation of \( F_{G_i}(\bullet) \) as [15-17]

\[
\begin{align*}
G_{p_i}(\mathbf{d}(\mathbf{X})) &= F_{G_i}^{-1}(1 - \Phi(-\beta_i)) \\
&= F_{G_i}^{-1}(\Phi(\beta_i)) \leq 0
\end{align*}
\]  

(7)

where \( G_{p_i} \) is the \( i \)th probabilistic constraint. In Eq. (7), the probabilistic constraint in Eq. (4) can be replaced with the performance measure, which is referred to as the performance measure approach (PMA) [15-17]. Thus, the RBDO model using PMA can be redefined as

\[
\begin{align*}
\text{minimize} & \quad \text{Cost}(\mathbf{d}) \\
\text{subject to} & \quad G_{p_i}(\mathbf{d}(\mathbf{X})) \leq 0, \quad i = 1, 2, \ldots, np \\
& \quad \mathbf{d}^l \leq \mathbf{d} \leq \mathbf{d}^u
\end{align*}
\]  

(8)

Reliability Analysis Model of PMA

Reliability analysis in PMA can be formulated as the inverse of reliability analysis in the reliability index approach. The first-order probabilistic performance measure \( G_{p,\text{FORM}} \) is obtained from a nonlinear optimization problem in \( U \)-space, defined as

\[
\begin{align*}
\text{maximize} & \quad G(\mathbf{U}) \\
\text{subject to} & \quad \|\mathbf{U}\| = \beta_i
\end{align*}
\]  

(9)
where the optimum point on the target reliability surface is identified as the most probable point (MPP) \( \mathbf{u}_{\beta_{\text{MPP}}} \), with the prescribed reliability \( \beta_i = \| \mathbf{u}_{\beta_{\text{MPP}}} \| \). The Karush-Kuhn-Tucker (KKT) necessary condition of Eq. (9) is defined as

\[
\mathbf{u}_{\beta_{\text{MPP}}}^* = -\beta_{\text{MPP}} \nabla G(\mathbf{u}_{\beta_{\text{MPP}}}^*) / \| \nabla G(\mathbf{u}_{\beta_{\text{MPP}}}^*) \| \tag{10}
\]

Any general optimization algorithm can be employed to solve the optimization problem in Eq. (9). However, an enhanced hybrid mean value (HMV+) first-order method is well suited for PMA due to its stability and efficiency [17,24].

Enriched Performance Measure Approach (PMA+)

The enriched PMA (PMA+) has been proposed to enhance numerical efficiency while maintaining stability in the RBDO process [16]. PMA+ is an extension of PMA by integrating three key ideas: as a way to launch RBDO at a deterministic optimum design, as a probabilistic feasibility check, and as a fast reliability analysis under the condition of design closeness. The overall design procedure in PMA+ for RBDO is to obtain the deterministic optimum design efficiently, and then carry out reliability-based design optimization. The feasibility of probabilistic constraints in RBDO can be identified by using the MV first-order method that provides an allowable degree of accuracy for the purpose of constraint violation. Once the feasibility status of probabilistic constraints is identified by the MV first-order method, a refined reliability analysis is performed using the enhanced hybrid mean value (HMV+) first-order method to evaluate \( \varepsilon \)-active and violate constraints. The MV first-order method based feasibility check for probabilistic constraints substantially improves the numerical efficiency of the RBDO process. During RBDO iterations, sufficient information is generated while evaluating the cost and probabilistic constraints, and updating the design. Some of this information could be reused to evaluate probabilistic constraints efficiently at the next design iteration using the condition of design closeness. In other words, under the condition that two consecutive designs in the RBDO design iterations are close enough, the reliability analysis can be efficiently carried out by starting from the MPP obtained at the previous iteration, instead of at the mean value point of the current design iteration. This fast reliability analysis method is integrated with the HMV+ method to evaluate probabilistic constraints efficiently.

CONCLUSION

With the successful completion of this effort a reliability-based durability design optimization process will have been demonstrated. The design of the Stryker A-arm will be significantly improved when simulation results for the new design show increased fatigue life together with a reduction (or at least no significant increase) in the weight of the component. The process will exercise the integration of CAE technologies with experimental validation, uncertainty quantification, and an uncertainty-based design.

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REFERENCES


**CONTACT**

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**DEFINITIONS, ACRONYMS, ABBREVIATIONS**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>L</td>
<td>Crack initiation fatigue life</td>
</tr>
<tr>
<td>W</td>
<td>Weight for design optimization</td>
</tr>
<tr>
<td>d</td>
<td>Design parameter; $d = [d_1, d_2, \ldots, d_n]^T$</td>
</tr>
<tr>
<td>$g(d)$</td>
<td>Design constraint of design parameters</td>
</tr>
<tr>
<td>$X$</td>
<td>Random vector; $X = [X_1, X_2, \ldots, X_n]^T$</td>
</tr>
<tr>
<td>$x$</td>
<td>Realization of $X$; $x = [x_1, x_2, \ldots, x_n]^T$</td>
</tr>
<tr>
<td>$G(X)$</td>
<td>Constraint of random parameters</td>
</tr>
<tr>
<td>$U$</td>
<td>Independent and standard normal random parameter</td>
</tr>
<tr>
<td>$u$</td>
<td>Realization of $U$; $u = [u_1, u_2, \ldots, u_n]^T$</td>
</tr>
<tr>
<td>$P_f$</td>
<td>Probability of failure</td>
</tr>
<tr>
<td>$f_X$</td>
<td>Probability density function of $X$</td>
</tr>
<tr>
<td>$\mu$</td>
<td>Mean of random vector $X$; $\mu = [\mu_1, \mu_2, \ldots, \mu_n]^T$</td>
</tr>
<tr>
<td>$\beta$</td>
<td>Reliability index</td>
</tr>
<tr>
<td>$K_f$</td>
<td>Fatigue-strength reduction factor</td>
</tr>
<tr>
<td>$K_i$</td>
<td>Stress intensification factor</td>
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<tr>
<td>$q$</td>
<td>Notch sensitivity factor</td>
</tr>
<tr>
<td>$X$</td>
<td>Random or fuzzy variable; $X = [X_1, X_2, \ldots, X_n]^T$</td>
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<td>Most probable point (MPP) for reliability</td>
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<td>Parametric coordinates for MPP search</td>
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<tr>
<td>$T$</td>
<td>Transformation matrix from $X$ space to $U$ space</td>
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