Remaining Life Prognostics for an Army Ground Vehicle System

Richard Heine[1] and Donald Barker[2]

[1] *United States Army Materiel Systems Analysis Activity*
Logistics Analysis Division, Reliability Branch
392 Hopkins Road, APG, MD 21005-5071, USA
richard.heine@us.army.mil

[2] *Department of Mechanical Engineering*
University of Maryland, College Park, MD 20742
dbarker@calce.umd.edu

ABSTRACT

Reliability is a key parameter for the development of safe and effective military vehicles with a reasonable life cycle cost. One innovative technology that is being promoted in the Department of Defense is the use of Health and Usage Monitoring Systems and remaining life prognostics to improve reliability and availability. The feasibility of using data collected from a limited set of existing and simple add-on sensors to make fatigue damage estimations on a complexly loaded component within a military wheeled vehicle system was investigated. Methods for identifying the critical inputs for fatigue estimation are evaluated and compared. A baseline physics of failure analysis was performed on an example component to evaluate the proposed HUMS algorithms and demonstrate the accuracy of resulting fatigue predictions. *

1 INTRODUCTION

In a fiscally conscious environment, reliability is always a critical consideration in the design and manufacture of products. For many items designed to be used over a long time span, operation and support represents a larger proportion of the total cost than procurement. Reliability directly affects the logistics burden associated with a particular piece of equipment and is a major driver for operations and support cost. This is the case for many military vehicles, but military vehicle designers have additional incentive to design reliable equipment. Failure of components or subsystems results in inconvenience for civilian users of products, but soldier safety and effectiveness are often dependent on the operability and performance of their vehicles. Maintaining operation of the critical functions and subsystems is essential to the completion of the difficult and dangerous missions assigned to military personnel.

Even though reliability is typically assigned a high level of importance during the development and selection of Army equipment, the Government Accountability Office reports that some major systems still have reliability issues (Anonymous, 2003), (Brannon, 2010). One technology that is being promoted in the Department of Defense is the inclusion of Health and Usage Monitoring Systems or HUMS within a vehicle platform (Rabeno and Bounds, 2009). HUMS can be practically defined as a system of sensors, processors and algorithms that give an indication of remaining component life. These systems monitor the usage of individual vehicles and record the effect of the environmental factors on specific components. Remaining life prognostics is the process of converting the usage data into predictions of the probability of failure for components. The resulting predictions can be processed and provide information to operators, maintainers, and mission planning personnel as to which components should be serviced, what repair parts are likely to be needed at a maintenance facility, and which vehicles have the lowest probability of failure during a mission. With good management, this information can be used to increase availability and reliability, while decreasing overall maintenance and system cost.

An often overlooked ancillary benefit of a successful health and usage monitoring system is that it can provide an indication of what the past usage of the vehicle has been. During the development of a military vehicle system, designers often must use generalized, qualitative descriptions to predict usage and load inputs. Specific information on previous generation vehicles is often unavailable or infeasible to attain. Testing of these systems is based on estimations of previous vehicle usage and worst-case scenarios because more realistic estimates are unavailable. Data collected for critical components from a HUMS over the lifetime of multiple vehicles would provide the information necessary to make statistically significant estimations of the likely usage of next generation vehicles.

The concept of a HUMS is not particularly novel. The costs associated with development and purchasing, along with the detailed information of the system necessary to perform health and usage monitoring, typically limit application to critical components within expensive systems that are subjected to relatively simple environmental and loading conditions and operated over long time spans. Many of these applications have been for large static systems with a limited number of relevant loading conditions such as manufacturing and power facilities (Li and Ray, 1995), (Jarrell and Bond, 2006), bridges (Gandhi *et. al*., 2007), elevator systems (Yan and Lee, 2005), and computer servers (Schuster and Gross, 2004). Applications of HUMS to military vehicles have been primarily on fixed-wing aircraft (Anonymous, 2004), (Hunt and Hebden, 2001), (Martin *et. al*., 1999), (Mourna and Steffen, 2006), (Trammel *et. al*., 1997) and rotorcraft (Bechhoefer and Bernhard, 2004), (Ellerbrock *et. al*., 1999), (Evans, 2002), (Gordon, 1991).

The relevancy of the techniques and processes developed for these applications to a military ground vehicle is limited. These examples are exposed to environments and loading conditions that have significantly less variation than those of a typical ground vehicle. In order to address all the relevant load cases on a ground vehicle system, robust engineering models are needed to calculate damage accumulated. Use of air and rotorcraft techniques on a military ground vehicle is also a challenge due to the fact that the life cycle costs associated with these applications justify the development of complicated HUMS. The development and unit cost of a HUMS applied to a military land vehicle would need to be much less. The cost to develop a military ground vehicle system is often several orders of magnitude less than that of an aircraft, so expenditures for the development of a HUMS would have to be reduced by a relative proportion. In addition, cost of the HUMS could not be a significant portion of the total vehicle cost. Redesign of components or replacement of the entire system may be a preferred alternative if the unit cost of a HUMS is prohibitive.

Recently, work has been performed to address some of the inherent challenges in applying HUMS and remaining life prognostics to ground vehicle systems. HUMS for sensors and actuators for the commercial auto industry (Barone *et. al*., 2006), (Ng *et. al*., 2006) and rotating components within the turbine engine of an M1 Abrams tank (Greitzer and Pawlowski, 2002) have been a focus of ongoing research. To address terrain induced fatigue, a general set of algorithms for the application of a HUMS to a military ground vehicle was developed (Heine and Barker, 2007), (Heine and Barker, 2008). Durability and fatigue testing are often performed based on an anticipated usage on primary, secondary and off-road terrains because the loading on many of the components changes significantly for each terrain type. These algorithms take advantage of the similarity of damage rates within each terrain type to estimate fatigue damage accumulated on individual components. One of the major advantages of this system is that a very simple set of sensors and algorithms provide damage estimates for multiple components. This effectively spreads the developmental and unit cost of the HUMS across many components. Accuracy of fatigue damage predicted from the recommended terrain identification algorithms for sample components varied by a factor of 2.9 to 6.8 of the damage predicted by high fidelity fatigue models. These results are within the typical error of fatigue estimates for similar components subjected to widely varying vibration inputs, but accuracy was shown to be highly dependent on identifying a fatigue damage per exposure time scale factor that is representative for all conditions within a terrain type. This requires significant testing on multiple courses that would represent the full range of scenarios that a military vehicle would encounter.

The desire for a more accurate fatigue estimate and the ability to minimize required algorithm training data may justify more complex algorithms for critical or safety related components. A model was developed that used vibratory inputs from an accelerometer to make component fatigue predictions on a military wheeled vehicle system (Heine and Barker, 2009). While this type of model requires significantly more computational power, it could work in concert with terrain identification algorithms to provide enhanced fatigue damage predictions and minimize the algorithm training data necessary. Accuracy of fatigue damage predicted from the recommended algorithms for a sample component was shown to vary within a factor of 1.0 to 1.4 of the damage predicted by a high fidelity fatigue model. While these were significant gains in accuracy, the algorithms developed apply only to the special cases of simply loaded components where the measured acceleration has a waveform similar to the measured strain. More computationally intensive algorithms may be required to perform remaining life prognostics on more complexly loaded components.

The objective of this research is to investigate the feasibility of using data collected from a limited set of existing and simple add-on sensors to make fatigue damage estimations on a complexly loaded component of a military wheeled vehicle system. Methods for identifying the critical inputs for fatigue estimation are evaluated. While this research was meant to develop principles generally applicable to HUMS and remaining life prognostics for a multiaxial case, in order to better illustrate the principles, a demonstration vehicle and component were chosen. A baseline physics of failure analysis was performed on the demonstration component to evaluate whether the proposed HUMS algorithms are appropriate and to demonstrate the accuracy of the resulting fatigue predictions.

2 DEMONSTRATION VEHICLE AND COMPONENT

An eight wheeled Army vehicle similar to the one shown in Figure 1 was utilized as the demonstration vehicle for this research. Data were collected from candidate sensors for the HUMS. These included accelerometers on the sprung mass of the vehicle, Global Positioning Satellite (GPS) data, J1708 bus data, and suspension position via the built-in Height Management System (HMS) sensor. Data from a triaxial strain gauge rosette was also collected on an example component over multiple courses at the Yuma Proving Ground. Course data collected were separated into distinct sets that could be used for training and testing of algorithms. Each set included at minimum one test course described as primary, secondary and off road.

Figure 1: Army Wheeled Vehicle

The primary failure mechanism for the example component was multiaxial fatigue due to a combination of terrain and powertrain induced loading inputs. Two legs of the triaxial strain gauge rosette labeled Strain 1 and Strain 2 were generally attributed to terrain induced loading through the suspension system. The leg labeled Strain 3 was attributed to torque produced through the drivetrain. Since time histories of the strain data were determined to be non-proportional, uniaxial fatigue models were deemed unsuitable for an accurate fatigue estimate. A high-fidelity, critical plane based multiaxial fatigue analysis was performed using commercially available software on the strain data measured on the example component for each course. Results of the fatigue analysis were verified anecdotally based on failure rates.

3 DIRECT STRAIN MODEL

Strain measurements are desirable as an input to fatigue damage estimation models. However, the common method of measuring strain with adhesively bonded, electric resistance wire strain gauges is fraught with difficulties. This type of strain gauge is sensitive to temperature variations, and bonding can be an issue if the gauge is expected to last the life of the component. A preferable approach would be to use more rugged sensors to predict strain on the critical component. Use of sensors already integrated within the vehicle is an ideal source from which to estimate strain. These sensors typically have high reliability due to their use in other vehicle subsystems and the cost of integrating them within the HUMS is minimal in comparison with the cost of adding an additional sensor. Sensors such as accelerometers and GPS units are robust, easy to apply and make a good alternate source if the integrated sensors do not provide data suitable for predicting strain. In order to evaluate the candidate sensors based on their ability to make fatigue damage estimations on a complexly loaded component, two statistics are compared.

3.1 Normalized Cross-Correlation

Cross-correlation is a standard method for estimating the degree to which two signals are correlated. The cross-correlation (r_{xy}) of two series x(i) and y(i) is defined in equation 1 where $\bar{x}$ and $\bar{y}$ are the means of the corresponding series and d is the time lag.

$$r_{xy} = \frac{\sum_i \left[(x(i) - \bar{x})(y(i-d) - \bar{y}) \right]}{\sqrt{\sum_i (x(i) - \bar{x})^2} \sqrt{\sum_i (y(i-d) - \bar{y})^2}} \qquad (1)$$

The cross-correlation can be normalized by the auto-correlation which is simply the value of the cross-correlation of a signal with itself under no time shift. A normalized cross-correlation value of 1 would signify that the two signals were identical. Normalized cross-correlation were calculated for each of the courses with no time shift. Due to general vehicle symmetry and the interrelated nature of various systems, it was hypothesized that a signal on another part of the vehicle may give a good indication of the strain at the critical area. Thus, the maximum normalized cross-correlation was also calculated within a time shift of 0.5 seconds. The average normalized cross-correlation for the training courses with zero and a maximum of 0.5 second lag are listed in Table 1. The candidate sensor with maximum values of average normalized cross correlation for the strains attributed to terrain induced loading (Strain 1 and Strain 2) and the drivetrain torque (Strain 3) were selected for fatigue damage estimations and are labeled in bold font. Including a delay made relatively minor changes to the average cross-correlation values, although the 0.5 second lag did result in the selection of a different input channel for Strain 3.

A linear scale factor and offset for each of the training data sets were calculated such that the maximum and minimum values measured for the candidate sensor matched maximum and minimum of the measured strains. The mean scale factor and offset across all the training data sets was then utilized to test the accuracy of the fatigue predictions. It was previously demonstrated that scaling based on fatigue life was more accurate than maximum excursion for a uniaxial fatigue case, but for a multiaxial case the equations were indeterminate (Heine and Barker, 2009). Life predictions were made based on candidate sensor strain predictions utilizing the same fatigue analysis software and equations used in the high fidelity fatigue estimates. Results from the training data sets were labeled 1-5 and the testing data sets were labeled A-D for the scaled candidate sensors. Values were plotted and compared to the high fidelity fatigue model results in Figure 2.

3.2 Coefficient of Determination of Root Mean Square

A comparison of Root Mean Square or RMS values for linearity was used previously to determine if relative magnitude of individual time segments are proportional (Heine and Barker, 2009). Relative magnitude of strain cycles are essential to calculating fatigue, so a process was developed to evaluate the linearity of the comparison. Strain and predictor channels were separated into five second blocks. RMS, denoted as z in equation 2 below, was calculated for each time sample of the strain or predictor channel (x_i) in the block.

$$z = \sqrt{\frac{1}{n}\sum_{i=1}^{n} {x_i}^2} \tag{2}$$

The coefficient of determination (R^2) was then calculated based on the RMS values (z), a least squares, linear fit of the sensor RMS blocks to the strain RMS blocks ($\hat{z}$) and the average sensor value ($\bar{z}$).

$$R^2 = 1 - \frac{\sum_i (z_i - \hat{z}_i)^2}{\sum_i (z_i - \bar{z})^2} \tag{3}$$

Resulting coefficient of determination values for each sensor are listed in Table 2 with the maximum values in bold font.

A linear scale factor and offset for each of the training data sets were calculated such that the maximum and minimum values measured for the candidate sensor matched maximum and minimum of the measured strains. The mean scale factor and offset across all the training data sets was then utilized to test the accuracy of the fatigue predictions. Life of the scaled candidate sensors were plotted and compared to the high fidelity fatigue model results in Figure 3.

4 PHYSICS-BASED STRAIN ESTIMATION

As an alternate method to utilizing statistics to blindly select from a pool of candidate sensors to estimate strain at a critical location, a physics-based estimation could be made utilizing known characteristics of the vehicle subsystems. Candidate sensors are not typically available that provide all the information desired for a highly accurate load model of critical components, nor is it feasible to run a highly complex model real-time on an inexpensive HUMS. If a basic model using a limited set of sensors can be manipulated to provide the most critical aspects of loading, a physics-based load estimation may be justifiable.

To evaluate this method on the demonstration component used in this study, it was necessary to estimate the torque applied through the drivetrain subsystem in order to predict Strain 3 and the terrain induced loads through the suspension subsystem to predict Strain 1 and Strain 2. A simplified drivetrain model was developed which utilized engine speed, vehicle speed and a simplified shift map to estimate engine load inputs. Transmission output shaft speeds, component geometries, and material properties were used to estimate the resulting reaction torques and convert load information to strain at the critical area. A simple suspension model was developed based on sprung and unsprung masses, sprung mass acceleration near the example component and unsprung mass acceleration via differentiated HMS reading. Strain predictions were implemented into the multiaxial fatigue model and compared to the high-fidelity fatigue predictions. Physics-based predictions were shown to be significantly less accurate for the example component than the estimates made based on the blind sensor selection. This may be attributable to the simplifications necessary to make the physics-based models run in real-time, the limited set of sensors, the locations from which the subsystem load predictions were made or the fidelity of the sensor data.

5 HYBRID MODELS

To investigate the poor quality of the physics-based predictions, the average normalized cross-correlation and coefficient of determination of root mean square statistics were calculated for the physics-based strain predictions to determine which subsystem model resulted in the significantly less accurate fatigue predictions. In general, the loading seen in Strain 1 and Strain 2 were attributed to the terrain induced loading through the suspension subsystem and Strain 3 was attributed to the drivetrain. Results are shown in Table 3.

Average normalized cross-correlation statistics suggest that the powertrain subsystem model was the cause of the poor predictions, while the coefficient of determination of root mean squares suggests the suspension model was the issue. Two hybrid models were developed. Hybrid Model A utilized the physics-based suspension model to predict strains 1 and 2. Strain 3 was predicted based on the average normalized cross-correlation statistic without a time lag candidate sensor. Hybrid model B utilized the physics-based powertrain model to predict strain 3 and the average normalized cross-correlation without lag statistic candidate for strains 1 and 2. Both models showed improvement over the physics-based strain estimation model, but the Hybrid B model gave the most accurate fatigue predictions. Life predictions based on the Hybrid B model were plotted and compared to the high fidelity fatigue model results in Figure 4.

6 RESULTS

In order to compare the accuracy of various models, a representative usage made up of the available terrain types was necessary. Requirements documents indicate a predicted usage in terms of primary, secondary and off-road courses for each variant of the demonstration vehicle. Durability tests for army combat vehicles are commonly 20,000 miles in length. Predictions of the fatigue damage accumulated over a 20,000 mile test following the expected terrain profile for the most common variant were made based on the testing data sets A-D for each model. Results are listed in Table 4. As a point of comparison, the most accurate terrain identification models resulted in 20,000 mile damage accumulated of 1.79 to 3.00 for similar components (Heine and Barker, 2007), (Heine and Barker, 2008)

Normalized cross-correlation without time lag provided the closest estimate to the high-fidelity strain-based damage of the direct strain estimate models. Allowing a maximum time shift of 0.5 seconds made no difference in the selection of sensors for strains 1 and 2, but the time shift led to the selection of the instant fuel economy calculations rather than the left side, axle 3 HMS sensor for strain 3 predictions. Close review of the instant fuel economy data showed that the data was clipped at a maximum value. When this data was scaled based on the maximum excursion, all of the clipped cycles were equivalent to the maximum strain cycle. This led to the significant under-prediction of life seen in Figure 2 and the over-prediction of damage seen in Table 4. Although this was not readily apparent from the cross-correlation data alone, the R^2 RMS showed significantly higher correlation between strain 3 and axle 3 HMS sensor data. If a direct strain model is selected for a component, it would be advisable to calculate both statistics in order to select the most appropriate candidate sensors. An alternate method of determining the scaling and offset based on fatigue rather than the maximum excursion may also improve fatigue predictions for the direct strain models.

The physics-based model developed required significantly more computational power and had poor predictive capabilities due to the limited ability of the suspension model developed to predict strains 1 and 2. When the normalized cross-correlation without time lag model for predicting strains 1 and 2 was combined with the powertrain model for predicting strain 3 in the Hybrid B model, the damage estimate over the 20,000 mile endurance test was much improved. This demonstrates that the use of a physics-based model can improve fatigue damage predictions if the component monitored justifies the additional computational load. Failure of the suspension model is attributed to the lack of quality sensor data at the critical locations necessary to make a high fidelity strain prediction. Sensor data may not be of the quality required to make accurate predictions in current vehicles, but inclusion of higher quality sensors at critical locations may be justifiable for future vehicles designed for use with HUMS and remaining life prognostics.

Table 1: Average Normalized Cross-Correlation with Strain

Channel	Strain 1 Average Normalized Cross-correlation with, without lag	Strain 2 Average Normalized Cross-correlation with, without lag	Strain 3 Average Normalized Cross-correlation with, without lag
Battery Voltage	0.01, 0.01	0.01, 0.01	0.01, 0.01
Engine Temperature	0.01, 0.01	0.01, 0.01	0.01, 0.01
Engine Speed	0.01, 0.01	0.02, 0.02	0.03, 0.03
Instant Fuel Economy	0.16, 0.13	0.05, 0.04	**0.36**, 0.31
Percent Accelerator Pedal Position	0.09, 0.08	0.03, 0.03	0.23, 0.20
Percent Engine Load	0.07, 0.07	0.03, 0.03	0.14, 0.13
Transmission Oil Temperature	0.01, 0.01	0.01, 0.01	0.01, 0.01
Transmission Output Shaft Speed	0.02, 0.02	0.02, 0.02	0.06, 0.05
Fuel Rate	0.08, 0.07	0.03, 0.02	0.22, 0.19
Vehicle Speed	0.04, 0.03	0.02, 0.02	0.07, 0.06
Sprung Accel Front Left Side	0.14, 0.07	0.10, 0.05	0.14, 0.05
Sprung Accel Rear Left Side	0.19, 0.19	0.17, 0.16	0.12, 0.10
Sprung Accel Rear Right Side	0.22, 0.21	0.19, 0.18	0.15, 0.13
HMS Axle 1 Left Side	**0.33, 0.32**	0.27, 0.26	0.36, 0.32
HMS Axle 1 Right Side	0.21, 0.17	**0.33**, **0.31**	0.21, 0.17
HMS Axle 3 Left Side	0.32, 0.30	0.30, 0.28	0.36, **0.35**
HMS Axle 3 Right Side	0.18, 0.18	0.30, 0.29	0.16, 0.16

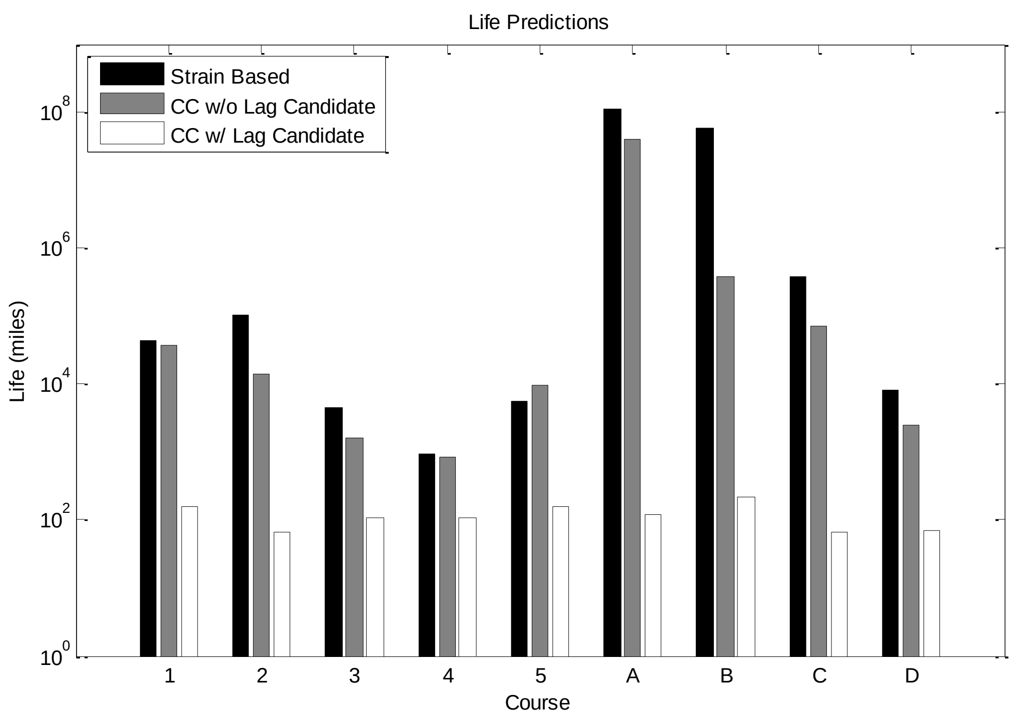

Figure 2: Life Estimate Using Cross-Correlation (CC)

Table 2: Coefficient of Determination of RMS with RMS Strain

Channel	Strain 1 Average R^2 RMS	Strain 2 Average R^2 RMS	Strain 3 Average R^2 RMS
Battery Voltage	0.01	0.00	0.01
Engine Temperature	0.01	0.03	0.03
Engine Speed	0.04	0.04	0.06
Instant Fuel Economy	0.03	0.01	0.07
Percent Accelerator Pedal Position	0.02	0.01	0.03
Percent Engine Load	0.10	0.06	0.07
Transmission Oil Temperature	0.03	0.04	0.02
Transmission Output Shaft Speed	0.05	0.05	0.16
Fuel Rate	0.03	0.01	0.04
Speed	0.04	0.05	0.14
Sprung Accel Front Left Side	0.15	0.10	0.01
Sprung Accel Rear Left Side	0.17	0.12	0.03
Sprung Accel Rear Right Side	**0.18**	**0.13**	0.05
HMS Axle 1 Left Side	0.10	0.11	0.16
HMS Axle 1 Right Side	0.09	0.12	0.10
HMS Axle 3 Left Side	0.11	0.11	**0.19**
HMS Axle 3 Right Side	0.03	0.04	0.06

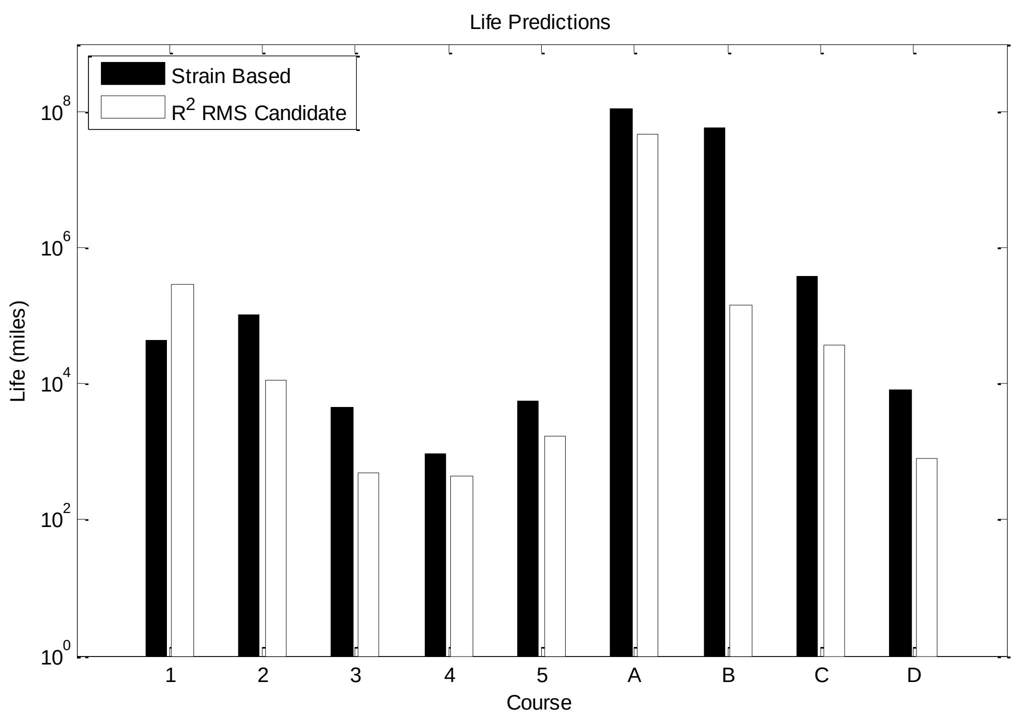

Figure 3: Life Estimate Using Coefficient of Determination of Root Mean Square

Table 3: Physics-Based Comparison

Estimator	Strain 1 Average	Strain 2 Average	Strain 3 Average
Average Normalized Cross-Correlation with Lag	0.03	0.03	0.15
Average Normalized Cross-Correlation without Lag	0.03	0.03	0.14
R^2 RMS	0.14	0.10	0.07

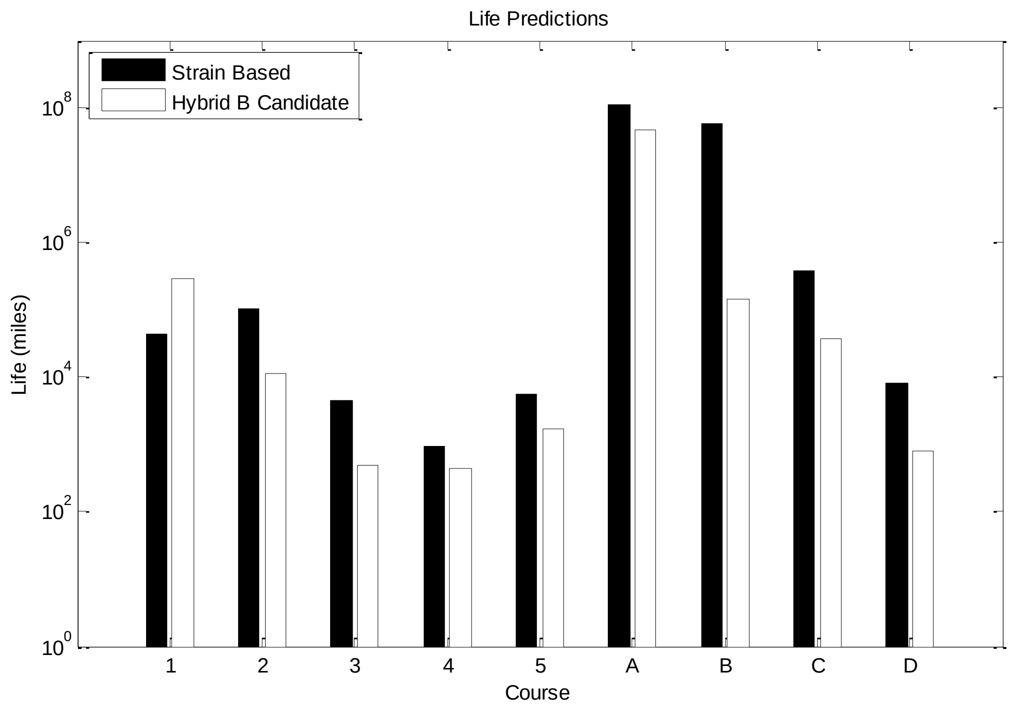

Figure 4: Life Estimate Using Hybrid B Model

Table 4: 20,000 Mile Endurance Test Damage

Model	20,000 Mile Damage Accumulated
High Fidelity Strain	0.75
Normalized Cross-Correlation without Time Lag	2.57
Normalized Cross-Correlation with Time Lag	216.44
R^2 RMS	7.80
Physics-Based	0.00
Hybrid A	0.21
Hybrid B	1.28

7 CONCLUSIONS

In order to utilize HUMS and remaining life prognostics to obtain the desired improvements in reliability and availability on military ground vehicles within a reasonable cost, durable sensors that provide loading information for fatigue sensitive components are critical. Strain is often the desired input for fatigue calculations, but most common sensors used to measure strain including adhesively bonded electric resistant wire strain gauges, are neither rugged nor reliable enough for a military ground vehicle environment. In addition, the sensors need to provide data for many of the components on a vehicle. Components susceptible to fatigue damage that should be monitored using a HUMS are not clearly recognized during the design of a vehicle system, so sensors that indicate loading to a wide variety of components are preferred. Use of sensors already integrated within the vehicle is an ideal source from which to estimate strain due to their high reliability and minimal additional cost. Add-on sensors such as accelerometers and GPS units are robust, easy to apply and make a good alternate source for strain estimates. For many modern military vehicles, the combination of integrated and add-on sensors make a large group of candidates available for use in a HUMS, but the best indicators of strain may not be clearly identifiable. A method is needed to identify and select sensors that provide inputs suitable for fatigue damage models.

Two statistics were evaluated based on ability to identify data that provides accurate fatigue predictions for a complexly loaded component on a military wheeled vehicle. Normalized cross-correlation without time lag provided the most accurate fatigue estimate of the direct strain calculations. Allowing for time shift was shown to have a minor effect on the ranking of candidate components, but calculation of the coefficient of determination of root mean square statistics as an additional means of comparison are recommended for identifying the best candidate sensor.

As an alternate method to utilizing statistics to select sensors that indicate strain on a component, a physics-based estimation can be made from the sensor data available and known characteristics of the vehicle subsystems. More complex physics-based subsystem loading models and geometry data were shown to improve the fidelity of fatigue predictions, but quality sensor data at critical locations is essential. Generally an improvement in the accuracy of fatigue predictions was demonstrated as the HUMS and remaining life prognostics algorithms increase in complexity. Selection of the model to be used on a specific component requires a balance of the accuracy needed with the developmental and computational cost.

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NOMENCLATURE

d	time delay
R^2	coefficient of determination
r_{xy}	cross correlation
$x(i)$	generic sample of series x
$\bar{x}$	mean of series x
$y(i)$	generic sample of series y
$\bar{y}$	mean of series y
z	Root Mean Square (RMS)
$\hat{z}$	least square linear fit of RMS
$\bar{z}$	Average sensor value

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Richard Heine received his PhD in Mechanical Engineering from the University of Maryland in 2008 based on his research regarding the role of on-board sensors in remaining life prognostic algorithm development for military ground vehicles. He currently is a Physics of Failure team lead in the Reliability Branch of the Army Materiel Systems Analysis Activity. In this position, he uses analytical techniques and Physics of Failure to assess and improve the reliability of military equipment. He is a member of the ASME, SAE and IEST where he recently received the Maurice Simpson Technical Editors Award for his paper on “Acceleration-Based Remaining Life Prognostics for Terrain-Loaded Components on an Army Vehicle System.”

Professor Donald B. Barker (Ph.D. Engineering Mechanics, UCLA) has been working in the general areas of experimental mechanics, fracture mechanics, fatigue, dynamic material response, and electronic packaging since joining the faculty of the University of Maryland faculty in 1976. He is one of the co-founders of the University of Maryland CALCE Center which is a industry/university cooperative research center concerned with assessing, mitigating, and managing the risks associated with the design, manufacture and fielding of electronic products and systems. Dr. Barker's research involves analyzing, characterizing and modeling the failure mechanisms in electronic components and assemblies and the integration of design tools into a concurrent engineering environment. This research is leading to practical approaches for microelectronic package design and the implementation of reliability prediction methodologies, based on physics of failure concepts. Dr. Barker is a senior member of IEST.