

Integrated Vehicle Health Monitoring on a Truck

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ABSTRACT

There have been few practical integrated vehicle health monitoring systems for ground vehicles. One of the challenges of this application is the high dynamics of the engine/transmission, the non-fixed ratio of the transmission, and the drivetrain in general. Further, because of the drivetrain differential, there is no fixed ratio from the input of the differential to the drive wheels. The paper covers the development of a vibration-based vehicle health monitoring system for a truck and some results of a 1000-mile test run on the system. The demonstration system integrates a decision analysis process to determine when to acquire data and tach-from-vibration (TFV) processing to reconstruct zero crossing data when the ratio from a tachometer to a shaft under analysis is unknown.

1. THE OPERATIONAL NECESSITY FOR IVHMS ON A TRUCK

Initially, the move for an integrated vehicle health management system (IVHMS) in the automotive industry (Holland, 2007) was focused on improved customer experience. Holland additionally emphasizes that the IVHMS will need to deliver value at an affordable price. Benedettini et. al (2009) highlight the benefits, drivers, and barriers to the adoption of IVHMS. However, neither paper reports on an implemented system. This demonstration highlights the feasibility/performance of a system on a mission-critical vehicle.

For some high asset value vehicles or vehicles that perform critical missions, condition monitoring using IVHMS provides data to ensure availability. Expanding on that functionality allows both monitoring of the vehicle and how the vehicle is being operated. Providing comprehensive vehicle health monitoring can:

- Record how the vehicle is driven. This, in turn, gives maintenance and operations personnel data on potential exceedances, such as RPM, temperature, speeds, or angle of pitch/bank, which may require maintenance.
- Evaluate how the vehicle is operated and give feedback on the driver's performance. This feedback is an essential contribution to safety management systems and reduces the rate of mishaps.
- Measure the performance and mechanical performance of the engine, starter, and cooling system.
- Provide drivetrain diagnostics of transmission, transfer case, differentials, portal hubs, brakes, and wheel alignment. This removes unscheduled maintenance event to improve availability.

In the short term, IVHMS data allows for a move from reactive/unscheduled maintenance events to scheduled or on condition maintenance. Knowledge of the vehicle state, in turn, allows for improved operational readiness and availability, ultimately allowing for: more revenue opportunities or a smaller fleet. After a controlled introduction to service, there is the potential to move from scheduled to on condition maintenance practices. This can reduce maintenance costs while maintaining or improving vehicle reliability.

Practically speaking, this demonstration considered the environment in which the vehicle runs. The test vehicle, an HMMWV (High Mobility Multipurpose Wheeled Vehicle), was driven on a test course designed for life testing. While realistic, the course represents the operations constraints of driving off-road, typically at lower speeds, making acquisitions and the resulting analysis difficult.

The HMMWV platform itself is an all-wheel-drive truck. The power plant is a 6.2L turbocharged diesel engine using an automatic transmission with an overdrive. Transmission power goes through a two-speed transfer case through forward and rear differentials, which drive the wheels through portal hubs. Portal hubs are a drive technology where the axle tube is above the wheel hub. This gives increased ground clearance and allows

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the half shafts to drive the same power to the wheels at reduced torque.

The goal of the demonstration was to enable comprehensive vehicle monitoring, including the engine/cooling system/starter, transmission/transfer case, differential/portal hub/wheel bearing, and brakes. Additionally, the system was designed to automatically: download data, process the data, report exceedances/component health in an operational users/maintainer, and calculate the remaining useful life of a component.

2. SYSTEM ARCHITECTURE FOR THE IVHMS

The HMMWV has no electronics/OBD2 capability. Additionally, even if present, many OBD2 sensors do not have the bandwidth necessary to detect mechanical faults. Unlike the system architecture presented in Shafi (2018), this system provided the integration of vibration, temperature, speed, GPS, etc., and analog sensors needed to support IVHMS functionality.

Given the operational requirements of the HMMWV, the installed system needed to survive the harsh environment of being attached to the truck's drivetrain. This included high temperature, water immersion, shock, vibration, and a high EMI/EMC environment. Additionally, the system needed to be mounted near monitored components and not interfere with the existing functionality or lower the components' reliability.

This system implemented an edge processing based sensor system architecture (Figure 1). The system has three buses. Bus 1, which covers the drive train, has sensors on the portal hubs, differentials, transmission, transfer case, and a transmission tachometer. Bus 2 was the engine bus, which monitored the alternator, engine, geared fan (for cooling), and the starter and engine tachometer interface. Bus 3 was the truck's analog interface, used to gather data on the engine, transmission and transfer case RPM, and outside air temperature. Provisions for exhaust gas temperature, turbocharger pressure, and oxygen temperature were designed but not implemented (usually, this type of data would be available on CAN or the OBD2). The power and management of the system came from the Onboard Control Unit (OBCU). The OBCU has an inertial measurement unit (IMU) to calculate positional attitude and rates and GPS for ground speed/positional information.

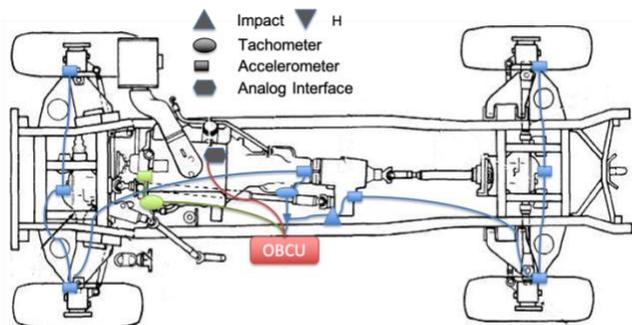


Figure 1 Bused System of IVHMS on a Truck

The data buses are attached to each sensor as a daisy chain. Each sensor was an edge processing design allowing for data sharing. For example, when the OBCU determines that it can perform an analysis, the sensors (typically accelerometers) receive configuration and are commanded to acquire data. The tachometer sensor calculates zero-cross data published on the data bus. Accelerometer sensors then use their vibration data, configuration, and tachometer zero-cross data and calculate the components' condition indicators (CIs). Vecr (2005) gives insight into the data processing flow and CI generation.

The configuration for a sensor consists of metadata, such as:

- The sample rate and length of the acquisition for the sensor.
- The ratio from the tachometer to the shaft under analysis.
- The gears associated with that shaft, the number of teeth on a given gear.
- The bearings associated with the shaft, the bearing fault features, and processing specifics for the bearing envelope analysis.

An accelerometer sensor can generate CIs for many components in near proximity. Each sensor can process up to 10 shafts. Each shaft may have 0 to 10 gears associated with that shaft. Additionally, each shaft can have 10 bearings associated with it. Each bearing can have multiple envelope analyses. For a further discussion on bearing analysis, see Randal and Antonni, 2011.

Typically, a sensor acquires 4 to 10 seconds of data between 2500 to 100000 samples per second and processes that data in 5 to 10 seconds. Because of the distributed processing nature of the bused system, this allows the OBCU to command and acquire data when in an opportunity regime. The OBCU determines when to acquire data and which data to acquire through a Regime Recognition process.

2.1. The Purpose of Regime Recognition in IVHMS

Ground vehicles do not operate at constant speeds. Additionally, because of the variable ratios of the transmission, not all component analyses can be done simultaneously. For example, there is no shaft rate when the truck is idle. At low speed (say 13 mph), the transmission is in first gear (the input shaft rate is around 30 Hz): the overdrive is off, and there is no drive torque going through the second and third gears. The engine is turning at approximately 53% of its maximum RPM. For the portal hub and wheel bearings, the shaft rate is approximately 2 Hz. The differential is perhaps at a 6 Hz input shaft rate. While appropriate to analyze the first gear, there is not enough shaft rate to analyze most of the drivetrain or those gears that are not engaged. Therefore, we need a way to command and acquire data only for those components where it is appropriate to do analysis.

Similarly, at say, 35 MPH, the transmission could be in third gear, but the overdrive may or may not be engaged. However, the wheel shaft rate would be closer to 6 Hz, and the differential at 17 Hz would be appropriate to analyze these shafts. Clearly, analysis of the brakes can only be performed when the OBCU

senses the vehicle is braking. This type of problem requires a decision process to determine when data should be acquired and what analysis is performed on that data.

Regime recognition controls these decisions as to which sensor is to acquire data, for how long, and which components to analyze. Regime recognition defines the likely state of the vehicle. This is done by analyzing analog interface, IMU, and GPS data. The input to the regime algorithm was Yaw Rate (to determine if the vehicle was turning), Engine RPM, Transmission RPM, vehicle speed, rate of change in speed (for determining acceleration and braking), and the calculated gear ratio (ratio of the transmission input and transfer case output). There were 47 regimes, which were calculated eight times per second.

Examples of some regimes are:

- Regime 5, 18 MPH Straight, 3rd Gear, Transfer Case Low
- Regime 8, 24 MPH, Straight, 2nd Gear, Transfer Case High
- Regime 22, 42 MPH, Straight, 3rd Gear, Overdrive, Transfer Case High
- Regime 23, 42 MPH, Left Hand Turn
- Regime 39, 47 MPH, Braking

Associated with each regime is a binary flag, which controls which operations/commands can be executed, such as:

- If Engine Run time (ERT) is accrued,
- If drive time (DT) is accrued,
- If a mechanical diagnostics acquisition can be performed,
- If a Break Analysis acquisition can be performed in that regime,
- If a Wheel Alignment acquisition can be performed in that regime,
- If the wireless communications (XMIT) can be on for downloading the operations (indicating that the flight operation had terminated)

The flag masks, and their integer representation where:

Table 1 Bit Mask

BIT MASK	INTEGER
BIT 0 => XMIT ON	01
BIT 1 => ENGINE IDLE	02
BIT 2 => ACCRUE DRIVE TIME	04
BIT 3 => TCASE, LOW	08
BIT 4 => GEAR 1, TCASE HIGH	16
BIT 5 => GEAR 2, TCASE HIGH	32
BIT 6 => GEAR D, TCASE HIGH	64
BIT 7 => GEAR OD, TCASE HIGH	128
BIT 8 => COLLECT RAW DATA	256
BIT 9 => DIFF/WHEEL HUB	512
BIT 10 => WHEEL ALIGNMENT	1024
BIT 11 => ENGINE PERFORMANCE	2048
BIT 12 => BRAKE PAD ANALYSIS	4096

For example, consider that the regime algorithm returned an index of 5, which represents the vehicle state of:

- 18 MPH Straight, 3rd Gear, Transfer Case Low.

The associated flag is 14: the engine is on, the vehicle is driving and we can do an analysis of the Transfer Case (low gear ratio). That is, the bit mask flag is $2 + 4 + 8 = 14$.

Alternatively, consider being in Regime 22.

- 42 MPH, Straight, 3rd Gear, Overdrive, Transfer Case High

The flag would be: Engine is on, Driving, Gear OD, TCASE High, Diff/Wheel Hub, and wheel alignment analysis. The bit mask is then: $2 + 4 + 128 + 512 + 1024$, or a flag of 1670. If the regime returned with index 23, the flag would be 6 - accruing run time and drive time. Because the vehicle is turning, no vibration analysis is performed.

Why was no analysis was done when the vehicle was turning? Because of the differential, the outboard wheel ratio relative to the input shaft will be a bit higher than anticipated, while the inboard wheel ratio will be lower. The time synchronous average (TSA) is susceptible to errors in ratio. Errors in the TSA effectively filter the signal associated with the wheel and portal hub.

To control for TSA errors associated with the differential, a novel signal processing technique, tach-from-vibe (TFV), was used (see Bechhoefer and Spence, 2018). The need for TFV analysis is needed as even differences in vehicle loading can affect the wheel diameter and ratio/shaft rate between wheels. As one needs a reasonable estimate of the shaft under analysis (under 1%), analysis was only performed when the vehicle was not turning (sensed by vehicle yaw).

A cellular modem was used to update configuration/executables remotely and download files after a mission. The modem (Bit 0, XMIT) was only allowed to be on in Regime 0: Power on, engine not turning. Hence regime also controls when data download occurs by determining the end of an operation.

The Regime flag controls the configuration and “scripts” on the OBCU. A script defines which sensors are to acquire data for an acquisition length, while the configuration defines the shaft(s), gear(s), and bearing(s) that the sensor would perform analysis on. Consider the configuration for sensor 9, the transfer case:

```
<cam id="9" type="hs-accel" desc="Transfer Case" channel="1">
  <acqcfg fg="8"><s>1.0</s><sh>S19,S20,S21</sh></acqcfg>
  <asmcnfg fg="8">
    <s i="S19" r="2.7169811320">
      <g i="G16" t="91" b="23" />
    </s>
    <s i="S20" r="1.0000000000" >
      <g i="G17" t="34" b="9" />
    </s>
    <s i="S21" r="1.7169811320" >
      <g i="G18" t="53" b="14" />
    </s>
  </asmcnfg>
```

```

<acqcfg
fg="128"><s>1.0</s><sh>S22</sh><w>W7</w></acqcfg>
<asmcnfg fg="128">
<s i="S22" r="1.0000000000" >
<g i="G19" t="34" b="9" />
</s>
<w i="W7" l="4500" h="6500" pl="4096" ol="2048">
<b i="U" s="S22" cg="0.44" bl="8.55" in="10.55" ou="8.45" />
<b i="V" s="S22" cg="0.43" bl="7.11" in="6.83" ou="5.17" />
</w>
</asmcnfg>
</cam>

```

In this example, if Regime 5 is identified, it returns a flag of 14, which includes the mask value "8" (flag 14 is 2+4+8). This configuration defines an analysis of Shaft S19, S20, and S21. Note that S19 has G16 associated with it, while S20 had gear G17 and S21, G18. The ratio from the drivetrain tach to the shaft is labeled "r" for ratio.

However, if Regime 22 is identified (TCASE high), the bit mask contains flag 128: sensor 9 would then perform analysis on S22, gear G19, and the two bearings "U" and "V" fault rates. The window, W7, defines the low and high frequencies and spectral length (pl) and overlap (ol).

The script gives the setup for the command to collect data. For example, Script 11 defines that when a regime with a mask of 128 is found (f="128), and the period since the last acquisition is greater than 1 minute (period="1M"), perform a four-second acquisition with sensor 8 (Transmission), sensor 9 (TCASE) and the drivetrain tachometer (ID is 50).

```

<script index="11" period="1M" channel="1" init="0" f="128"
desc="Perform Acquisition" actcode="ACQ">
<cam id="8" sampcode="23438" secs="4" />
<cam id="9" sampcode="23438" secs="4" />
<cam id="50" sampcode="" secs="4" />
</script>

```

For this application, there were 24 different scripts. Note that in this way, regime processing allows sensors to perform analysis on different shafts, gears, and bearings when appropriate, based on what gear the transmission is in and what speed the vehicle is traveling at.

2.2. Decision Making with Uncertainty: Regime Algorithm

Several potential algorithms can be used to determine vehicle state or regime. For this demonstration, a Bayes Classifier was implemented. As a simple example, consider the case with just two classes. Let us define $P(H_i|\mathbf{z})$ as the probability that H_i was the actual regime given a measured observation, \mathbf{z} , where \mathbf{z} is the vector of parameters as noted: yaw rate (to determine if the vehicle was turning), engine RPM, transmission RPM, vehicle speed, rate of change in speed, and the calculate gear ratio above. The correct hypothesis corresponds to the largest probability of the possible regimes. The decision rule will be to choose H_0 if:

$$P(H_0|\mathbf{z}) > P(H_1|\mathbf{z}), P(H_2|\mathbf{z}), \dots, P(H_m|\mathbf{z}) \quad (1)$$

else choose the most likely probability: $P(H_i|\mathbf{z})$. The null hypothesis $P(H_0|\mathbf{z})$ will represent the vehicle engine running or some other default case.

For illustration, consider the binary case, where the rule becomes:

$$P(H_1|\mathbf{z}) / P(H_0|\mathbf{z}) \underset{H_0}{\overset{H_1}{>}} 1 \quad (2)$$

This is the maximum *a posteriori* probability criterion, wherein the chosen hypothesis corresponds to the maximum of two posterior probabilities. Using Bayes' rules to write the criterion gives:

$$P(H_i|\mathbf{z}) = P(\mathbf{z}|H_i)P(H_i) / P(\mathbf{z}), i = 0, 1 \quad (3)$$

where $P(H_i)$ is the probability of H_i in the observation space, such that:

$$P(H_1|\mathbf{z}) / P(H_0|\mathbf{z}) = P(\mathbf{z}|H_1)P(H_1) / P(\mathbf{z}|H_0)P(H_0) \quad (4)$$

This allows the test to become:

$$P(\mathbf{z}|H_1) / P(\mathbf{z}|H_0) \underset{H_0}{\overset{H_1}{>}} P(H_0) / P(H_1) \quad (5)$$

Let us further define the log ratio $l(\mathbf{z}) = p(\mathbf{z}|H_1)/p(\mathbf{z}|H_0)$ as the likelihood ratio. Because the likelihood ratio is well behaved and everywhere continuous and differentiable, the natural logarithm of both sides can be taken. The logarithm is a monotonically increasing function so the inequality holds. Then the log-likelihood ratio becomes:

$$\ln l(\mathbf{z}) \underset{H_0}{\overset{H_1}{>}} \ln P(H_0) / P(H_1) \quad (6)$$

We want to take the log of the likelihood ratio because the probability function $P(H_i)$ is usually some exponential function, such as Rayleigh, Gaussian, etc. Taking the log linearizes the function, simplifying the problem.

In making a decision in a binary hypothesis-testing problem (e.g., Regime 0 vs. Regime 1), there are four possible outcomes:

- Say H_0 , and it is true that the AC is in regime 0;
- Say H_1 , and it is true that the AC is in regime 1;
- Say H_1 , but the AC is in regime 0; and
- Say H_0 , but the AC is in regime 1.

An error occurs when either the third or fourth conditions are chosen. The third condition is a type I error, and the fourth condition is a type II error. The goal of the regime algorithm is to minimize both type I and type II errors. The Bayes classifier can be shown to do this (Fukinaga, 1990)

We assumed that the measured parameters, \mathbf{z} , have a Gaussian distribution. The default case is the hypothesis H_0 , defined as

the mean of the parameter vector space, \mathbf{m}_0 , representing the parameters for regime 0. The probability distribution function of the parameter vector, \mathbf{z} , given H_0 , is then:

$$P(\mathbf{z}|H_0) = \frac{1}{n\sqrt{2\pi}|\Sigma_0|} \exp\left[-\frac{1}{2}(\mathbf{z}-\mathbf{m}_0)^T \Sigma_0^{-1}(\mathbf{z}-\mathbf{m}_0)\right] \quad (7)$$

While the alternative hypothesis is:

$$P(\mathbf{z}|H_1) = \frac{1}{n\sqrt{2\pi}|\Sigma_1|} \exp\left[-\frac{1}{2}(\mathbf{z}-\mathbf{m}_1)^T \Sigma_1^{-1}(\mathbf{z}-\mathbf{m}_1)\right] \quad (8)$$

Where Σ_i is the covariance of the regime parameters. The normalized distance squared between the measured parameters \mathbf{z} and any \mathbf{m} :

$$d^2 = (\mathbf{z} - \mathbf{m})^T \Sigma^{-1}(\mathbf{z} - \mathbf{m}) \quad (9)$$

Substituting the distance function into the log-likelihood ratio test gives:

$$\frac{H_1}{H_0} \left(\frac{1}{2}(d_0^2 - d_1^2) + \frac{1}{2} \ln l(|\Sigma_0|/|\Sigma_1|) \right) > \ln \left(\frac{P_0}{P_1} \right) \quad (10)$$

Where $|\Sigma|$ is the determinant of the covariance. This states that if the normalized distance squared between \mathbf{z} and \mathbf{m}_0 (plus a threshold offset represents the log ratio of the test's probabilities. It is assumed that P_0 is equally likely with P_1 , such that the offset is $\ln(1) = 0$). Hence, if the normalized distance between \mathbf{z} and \mathbf{m}_1 is greater, then accept the alternate hypothesis, H_1 .

In this demonstration, where there are 46 regimes, we conduct 45 tests against the null hypothesis. If after completing the 45 tests, where each test is negative, one cannot reject the null hypothesis (e.g., the vehicle is in regime 0). If there are positive test values, we select the maximum test value: accepts the alternative hypothesis representing the maximum likely regime the vehicle is in. For a more detailed analysis, see Fukinaga, 1990.

3. SIGNAL PROCESSING TECHNIQUES FOR THE IVHMS

A tach from vibration processing was implemented because the exact ratio for many components was unknown due to the drivetrain differentials. A tachometer signal is reconstructed from the vibration data itself at the sensor to solve this problem. That is because the vibration signals from rotating equipment are sinusoidal, and they are, by definition, synchronous with signals associated with the shaft rotation. However, the measured vibration is the superposition (i.e., addition) of many signals in the time domain. For example, consider a portal hub with an input shaft, an output shaft, and a gear pair. The input shaft turns at 30 Hz and has a 12-tooth gear, and the output shaft has a 23-tooth gear with a rotational speed of 15.65 Hz. The gear mesh frequency is 360 Hz (30 * 12). The gear mesh frequency will have sidebands because any shaft imbalance is modulated onto the gear mesh. This can be shown using the trigonometric identity:

$$\cos(a) \times \cos(b) = \frac{1}{2} [\cos(a + b) + \cos(a - b)] \quad (11)$$

In this example, $\cos(a)$ is 360 Hz, and $\cos(b)$ is 30 Hz and 15.65 Hz shaft. Additionally, if the shaft is bent or bowed, there will be a 2x shaft vibration component. Other manufacturing defects, such as the gear not being mounted perpendicular to the shaft or not centering the shaft on the gear (e.g., eccentricity), will result in different frequency tones.

We used an ideal bandpass filter to recover only those signals associated with the desired component and create an analytic signal in one functional procedure. This is followed by using a jitter reduction model to remove noise (jitter) from the reconstructed tachometer signal not associated with changes in the machine rate.

Recovering rotational information from vibration data involves estimating the rotation rate of a component under analysis based on the transmission tachometer. A known gear mesh frequency for the input shaft can be estimated from this information. A range of frequency encompassing the estimated gear mesh frequency is found based on the variance in the measured shaft rate. The actual gear mesh frequency is extracted from the overall vibration data by filtering around this range even though its magnitude may be significantly smaller than the average overall vibration spectrum. Once the gear mesh frequency signal is determined, the actual shaft rate of the component of interest can be found. This may be accomplished using the following pseudo-code:

- Define the Sample Rate = sr. The number of data points, n, of vibration data equals $sr \times$ acquisition length in seconds, then:
- Calculate the next larger radix-2 length for the FFT: $nRadix = 2^{\text{ceil}(\log_2(n))}$.

From the tachometer measurement and the gearbox configuration (i.e., the shaft ratio from the shaft measured by the tachometer to the shaft under analysis), calculate meta statistics such as the approximate rotation rate of the shaft under analysis (i.e., the first moment), the variation (i.e., the second moment) in the approximate rotation rate, and the estimated known gear mesh frequency (based on the number of teeth of gear on the shaft under analysis).

- From the estimated known gear mesh frequency and the variance in the estimated shaft rotation rate, calculate the low bandwidth index and the high bandwidth index (*below*, *bwhigh*), encompassing the gear mesh frequency of interest.
- Take the zero-padded FFT of the vibration data.
- Zero the FFT from zero to *below*, and from *bwhigh* to $nRadix$.
- Take the inverse FFT to generate the analytic signal.
- Calculate the unwrapped argument of the generated analytical signal from 1 to n time series. (The argument is the arctangent of the imaginary part of the analytic signal to the real part. Note that the value can only go from 0 to π and $-\pi$ to 0. One is interested in the cumulative rotation of the analytic signal in time. Hence as the signal exceeds $-\pi$ to some small positive number, 2π is added. That is, if at

index i the value is -0.03π , and the next value calculated at index $i + 1$ is 0.03π , the saved (unwrapped) value is 2.03π .)

- Normalize the time series of radians by the number of teeth of the gear (assuming first-order harmonics).
- Interpolate the number of indexes for every 2π radians. The value 2π radians is one zero-cross. Hence, the interpolation gives the exact index of the zero-cross of the shaft.
- Normalize to "tachometer" zero-crossing index by the Sample Rate (sr), which provides the zero cross time and from which the rotation rate for the component under analysis is calculated.

A process may be used in which developing the analytic signal using an ideal bandpass filter is completed in a single functional process. The analytic signal is defined for the real-valued signal $x(t)$, as determined:

$$X(f) = F\{x(t)\} \quad (12)$$

where F is the Fast Fourier Transform, and where:

$$X_a(f) = X(f), \quad f = 0 \quad (13)$$

$$X_a(f) = 2X(f), \quad f > 0 \quad (14)$$

$$X_a(f) = 0, \quad f < 0 \quad (15)$$

$$x_a(t) = F^{-1}(X_a(f)) \quad (16)$$

$X(f)$ is the Fourier transform of $x(t)$, and f is measured signal frequency (Bechhoefer, Spence, 2018)

3.1. Analysis Algorithms

Vibration-based diagnostics provide condition indicators (CIs) representative of a component's health. This health, in turn, was used to estimate the remaining useful life (RUL) of the component. The flow of the analysis follows the example configurations above. The OBCU commands a tachometer and accelerometers to acquire data when the regime flags are appropriate (as noted, the tach signal could come from the vibration signal itself). This data is used to generate a Time Synchronous Average (TSA). The TSA is then used for shaft and gear analysis. The TSA removes variation in the shaft rate and acts as a filter for signals that are non-synchronous to the shaft under analysis. The resulting time-domain signal is operated on the generate condition indicators (CIs) for that shaft. There are 12 CIs for each shaft, such as shaft order 1 (magnitude of the first shaft harmonics, e.g., SO1), phase, higher harmonic order, TSA RMS, TSA peak to peak, and other statistics (Figure 2).

If there is a gear(s) associated with the shaft, further analysis is performed on the TSA itself and the spectrum of the TSA. Some analyses are classified as gear specific, which used the number of teeth on the gear under analysis (FMO, the AM/FM analysis, for example). Other non-gear-specific analyses are also performed, such as the residual or the energy operator (a time/frequency analysis). It should be noted that there are many implementations of gear analysis (Vecer, Bechhoefer et al 2020). There is no single analysis that works for every gear fault type. In this implementation, the system generated 18 CIs for each gear (Figure 3).

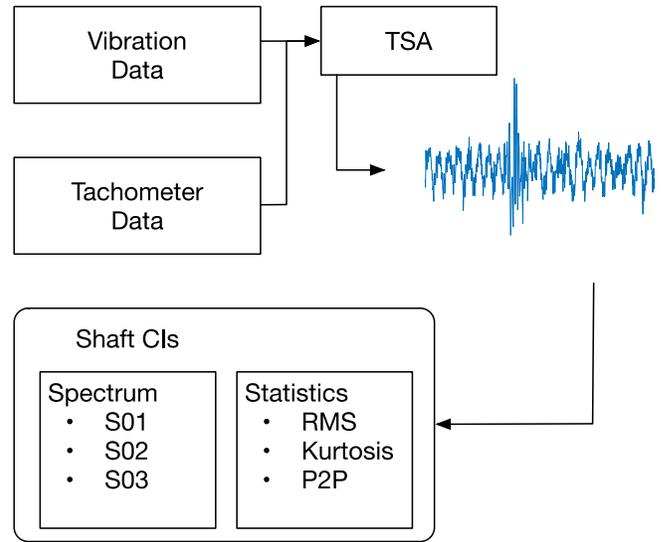


Figure 2 Shaft Analysis Processing

Bearing analysis is a separate processing flow. Bearings, as they are designed to be greased, have non-Hertzian contact. Typically, we observe a 1% slip in the calculated motion of the bearing components. Some bearings, when under thrust, will have changed their contact angle and pitch diameter, resulting in an increased fault rate by a 2 to 3%. (Hamrock, Dowson, 1981). The point being is that the analysis is asynchronous.

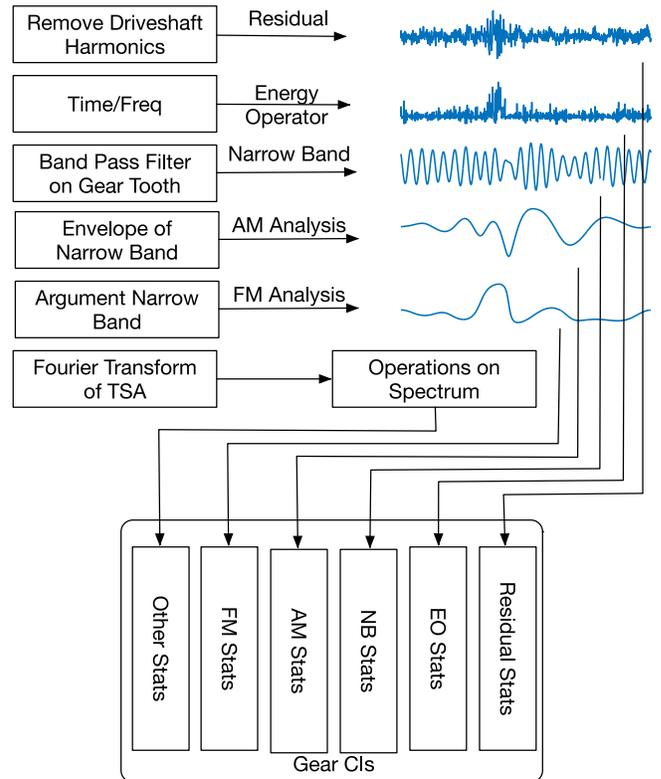


Figure 3 Gear Analysis Processing

Additionally, the analysis must consider the non-stationarity of the shaft. The vibration data is resampled instead of being

synchronously averaged (Bechhoefer, Van Hecke 2013). Bearing analysis uses this speed-corrected signal for envelope analysis, which takes the spectrum of the demodulated and envelopes (absolute value of the Hilbert transform) and the vibration data (Figure 4).

The bearing analysis process returns eight CIs for each bearing, including the cage, ball, inner and outer race energies, the 1/rev spectral energy, the whip/whorl energy (for journal bearing analysis), the kurtosis of the spectrum and temperature.

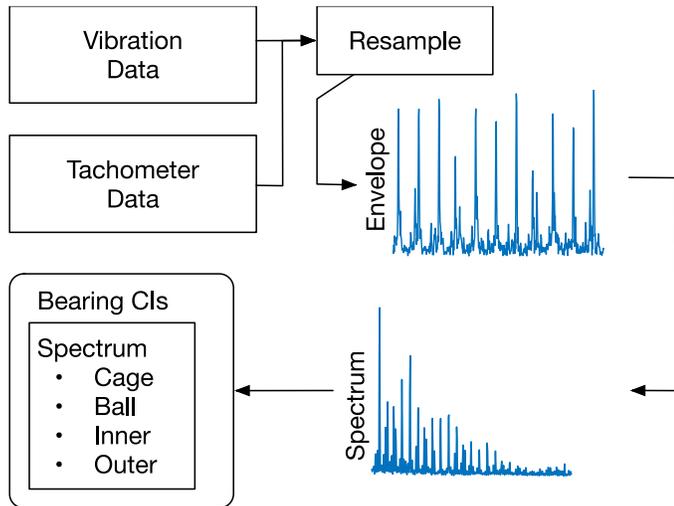


Figure 4 Bearing Processing

4. ALERTING AND RUL ESTIMATION

RUL, or Remaining Useful Life, is a prognostic based on a fracture mechanics model. RUL calculation requires four inputs to calculate an RUL.

- An estimate of the current component health.
- An estimate of when it is appropriate to do maintenance, e.g., the threshold.
- An estimate of the future component load.
- A component degradation process model takes the current component health and the estimated future load and calculates the time/cycles to when it is appropriate to do maintenance.

The estimate of the current component health is based on hypothesis testing. In the context of a hypothesis test, it is observed that all condition indicators (CIs) have a PDF. Any operation on the CI to define a health index (HI) is then a function of distributions. The HI function in this application is the weighted norm of n CIs (e.g., the normalized energy of n CIs), where the weights are determined by the Jacobian (the inverse covariance):

$$HI = 0.35 /_{critical} \sqrt{Y^T Y} \quad (17)$$

where Y is the whitened, normalized (by the Cholesky decomposition of the Jacobian) array of CIs, and *critical*, is the

critical value of the test. The critical value is calculated from the inverse cumulative distribution function (ICDF) for a given probability of false alarm in a hypothesis test. For Eq. (17), the ICDF is the Nakagami where η is the number of CIs in the array and $= n$, and $\omega = \eta / (2 - \pi/2) * 2$. See Bechhoefer, E., Xiao L., Zhang 2021 for details and proof. A normalized HI > 0.35 for a component indicates that the Null Hypothesis is rejected. That is, the component is no longer nominal. Maintenance is not recommended until the HI > 1. These threshold values have been tested by numerous helicopters, wind turbines, and seeded fault testing on 60+ gearboxes. The level of damage for an HI of 1.00 is typically moderate visible damage.

For this demonstration, the design reliability is typical "six-nines," e.g., the probability of failure of the part under design loads is less than 10^{-6} per hour. For the damaged part, the reliability may be reduced to three-nines or a probability of failure of 10^{-3} . Thus, the appropriateness of repairing the faulty component can be seen as an action to restore the designed reliability of the system. From a maintainer perspective, then:

- HI reflect the current components damage, where the probability of exceeding an HI of 0.35 is the PFA.
- A warning (yellow) alert is generated when the HI is greater than or equal to 0.75. Therefore, maintenance should be planned by estimating the RUL until the HI is 1.0.
- An alarm (red) alert is generated when the HI is greater than or equal to 1.0. Continued operations could cause collateral damage.
- This threshold setting model ensures that the probability of a false alarm is exceedingly small when the HI reaches 1. From numerous installations and seeded fault tests in practice, a bearing at HI 1 has easily seen physical damage.

The HI value does not define a probability of failure for the component nor that the component fails when the HI is 1.0. Instead, defining maintenance at an HI of 1 initiates a proactive policy to change operator behavior. The desire is to reduce the cost and time associated with component failure by performing maintenance prior to the generations of collateral or cascading faults. For example, by performing maintenance on a bearing before the bearing sheds extensive material, costly gearbox replacement can be avoided, and the reliability of the gearbox can be restored to its design requirements.

The RUL is defined as the time from the current HI until the HI is greater than or equal to 1. The RUL model was based on a high cycle fatigue, assuming Mode 1 fracture mechanics:

$$\frac{da}{dN} = D(\Delta K)^m \quad (18)$$

where

- da/dN is the rate of change in the half crack length per cycle
- D is a material constant
- m is the crack growth exponent for steel is 4.

Substituting in ΔK :

$$\frac{da}{dN} = D \left(2\sigma(\pi)^{1/2}\alpha \right)^m a^{m/2} \quad (19)$$

Inverting and integrating to get N , the number of cycles gives:

$$N = \int_{a_0}^{a_t} a^{-m/2} / D \left(2\sigma(\pi)^{1/2}\alpha \right)^m da \quad (20)$$

By taking a as a_0 to get the crack growth rate, the constants cancel out, leaving:

$$N = -dN/da \cdot a_0 - a_f (a_0/a_f)^{m/2} / m/2 - 1 \quad (21)$$

Setting m to be 4, this gives:

$$N = -dN/da \times a_0 \times \ln(1/a_0) \quad (22)$$

We substitute the measured component health (the HI) for a_0 , which is proportional to damage. The guidance is to perform maintenance when the HI is 1, Eq. (21), then define the RUL estimate.

5. RESULTS

The system was designed to monitor 40 Shafts, 37 Gears, 36 Bearings, the brakes, and the starter.

Component modifications (seeded faults) took place after the system installation on the vehicle. These modifications were intended to change the "known good" state of the vehicle to a compromised state of condition to validate the system performance. These modifications included:

- Rotor warpage by generating high heat during hot braking events and degraded brake pads
- Right rear and left front brake pads ground to minimal coverage
- Degreasing of the rear prop shaft u-joint axle yoke caps to simulate a bad rear differential
- Replacement of a known good starter motor with a known worn starter motor
- Misalignment condition for all four tires at toe-in 0.25"
- Installation of a faulty front differential



Figure 5 Example of Monitored Components.

5.1. Detection of Damaged Rotors

The brake rotors were monitored to detect warping. The rotors under usage get hot and deform, resulting in an upward trend on the HI. The damage feature resulted from an increasing 1/Rev modulation of the rotor. Figure 6 below shows the rotor trend before any modification of components, during the damage propagation phase, and post-repair.

The rotor damage propagated due to wear and was replaced when the HI was greater than 1 (intermediate maintenance event in Figure 6). The effects of the brake pad replacement with known good brake pads are seen as a drop in the HI. The Time Synchronous Average (TSA) and TSA Peak to Peak condition indicators were used for the HI.

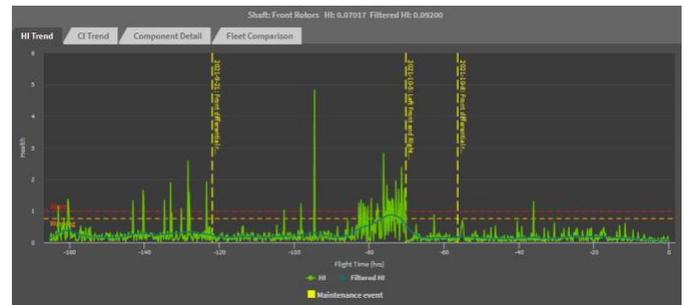


Figure 6 Example Propagating Front Rotor Fault

5.2. Brake Pads Wear

In conjunction with the rotors viewed as a 1/Rev issue due to warping, the brakes were evaluated using the envelope analysis to quantify energy associated with high-frequency noise from metal-on-metal contact. The envelope window selected was 2.5 to 6.5 kHz.

Beyond viewing the condition indicators on the user interface, the raw data was analyzed. Before any brake pad changes, a raw spectrum can be seen below is relatively low. After the left front brake pad material was removed to simulate pad damage, the raw data confirms the wear with much greater broadband energy (Figure 7).

It is evident from the spectrum that the brake pad wear does increase the measured energy. This analysis can be refined with more data, and the sensitivity can be improved. For example, the envelope window that was initially selected was likely too low to capture "chatter" from the brake pad wear. Additional analysis of raw data would result in a better CI, resulting in an improved display on the user interface.

For example, it was seen that both Cage Energy and Whirl condition indicators for the front brake pads both show a significant change in energy at the time the brake pads were replaced on the vehicle. Note that Cage and Whirl have similar, fractional 1/Rev rates. Whirl is usually associated with mechanical looseness and wear.

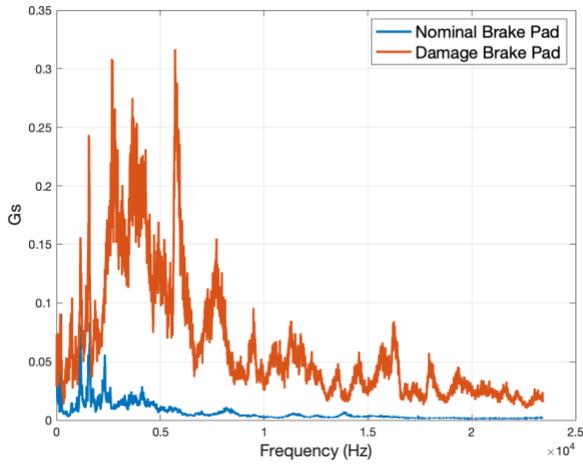


Figure 7 Effect of Data on Spectrum of Brake Pad

5.3. Rear Differential Damage

The rear differential was replaced with a used differential where the worn output bearing and race were sanded/damaged. The worn rear differential was left installed on the vehicle longer than anticipated due to data analysis issues with the rear differential sensor. After the 1,000-mile durability testing was complete, the field service representatives (FSRs) operated the HMMWV on the outer paved portion of the test route, so regimes associated with the differential acquisitions could be achieved. The prior differential acquisition had occurred on the highlighted data point shown in Figure 8, preceding the start of durability testing.

Differential acquisitions occurred while the vehicle was traversing on a paved surface in a straight line at sufficient speeds. Effects of the damaged rear differential were seen in the data. The rear differential pinion, rear differential pinion bearing, rear differential drive bearing, rear differential ring gear, rear axle bearing, and the rear shaft output bearing jumped to the 'alarm' state. These components being in the 'alarm' state show the effects of the worn rear differential installed on the vehicle.



Figure 8 Example Damaged Rear Differential Pinion

There were numerous acquisitions with the worn rear rear differential installed. Where the data points drop back down to a healthy level signifies the worn rear differential was replaced.

The filtered health indicator is included in the health indicator view. The filtered health indicator value is calculated from the last acquisition and reassessed whether the component is in the alarm, warning, or healthy state. It is used for RUL calculation. The rear shaft output bearing filtered health indicator is still in the alarm state, which drives the component icon red.

Similarly, the Rear Differential Half Shafts damage was also detected. In general, seeded faults, such as the replacement of the nominal differential with a known damage gearset, allow for rapid validation of the condition monitoring techniques. Unfortunately, this does not allow for a fault progression and testing of remaining useful life (RUL, see Figure 9).



Figure 9 Half Shaft Damage, Output Bearing Example

5.4. Starter Motor Wear

The starter was monitored with a 100% duty cycle sensor that recorded CIs over an "epoch," or analysis time of 5 minutes. The challenge with this analysis is that the truck was started seldom. In general, the truck ran for eight hours a day. Hence, successful analysis required the system to report the "start" event and not the energy associated with idle or driving. As noted, reporting is driven by the script, which depends on the current regime. We have not yet developed a good start regime. The results showed both the start event and some idle events.



Figure 10 Starter Damage Progression

It was found that the X-Magnitude and X-Axis RMS condition indicators were good indicators (Figure 10). The first maintenance event showed when the worn starter was installed.

This worn starter resulted in an upward trend that continued until the worn starter motor was replaced. This was a complex problem as one needed to record data associated with the engine start and not other conditions of operations. Research is continuing on how best to design an appropriate regime to capture the start event.

5.4.1. Wheel Alignment/Misalignment

The HMMWV BF Goodrich 37x12.5R16.5L tire has 34 lugs on the tread; therefore, the signal of interest is in the 34th and 68th harmonics, or 1st and 2nd harmonics of the tire tread lug count. We performed tach from vibration processing on the data through post-test analysis of the raw data to determine an analysis approach. The ratio of the 2nd harmonic to the 1st harmonic, the Energy Operator Kurtosis, the FM0 (Figure of Merit 0), and the Sideband Level Factor analysis showed favorable results. Much of the data acquired during durability testing was taken at slower speeds. It is expected that the results would be more remarkable when the data is gathered at higher speeds or data acquired on paved roads.

The following are alignment study results obtained when comparing the misaligned condition acquisitions against the aligned condition acquisition. Note that data is not available for comparison on the right rear tire.

Table 2 Left Front Tire CIs

Analysis	Misaligned	Aligned
G2	0.87402	0.26031
Energy Operator	8.2874	5.3553
Figure of Merit 0	52.0857	51.9092
Sideband Level Factor	10.33004	7.4753

Table 3 Right Front Tire

Analysis	Misaligned	Aligned
G2	0.97675	0.4239
Energy Operator	8.9424	7.5664
Figure of Merit 0	100.09	28.73282
Sideband Level Factor	24.514	13.1556

Table 4 Left Rear Tire

Analysis	Misaligned	Aligned
G2	1.1134	0.24531
Energy Operator	6.3999	5.3472
Figure of Merit 0	94.5	15.7416
Sideband Level Factor	8.593	4.3605

The aligned results for all four of these analyses are lower than those seen from the misaligned calculations. This will require additional research to optimize CIs specific for this fault feature. Continued research into a dedicated alignment analysis will continue.

6. CONCLUSION

The study demonstrated an IVHMS system with both seeded and natural faults. The system, through regime recognition, was able to automate data collection, analysis, and fault reporting. In addition to drivetrain diagnostics, the system was able to generate automated exceedance events which could support a safety management system. The drive data monitoring allowed for mission replay, facilitating asset protection, training, and mission awareness.

In general, this system development would not have been successful without the ability to update configuration via the cellular modem remotely. While initial testing was conducted on typical urban roads and highways, real-world operations conducted on unimproved roads and trails occur at much lower vehicle speeds: it was challenging to get into a regime to collect data on the test track. Over time, regimes were shifted to lower speed to acquire data more often. The changes to configurations were made quite often as we learned how the vehicle was operated. Again, these updates were made remotely using the system's cellular modem.

The integrated vehicle health monitoring system (Foresight MX) was initially developed for helicopters. In aviation, there is always a cool-down period for that asset after the flight, which allows time for IVHMS to download data. For a ground vehicle, the end of an operation is when the vehicle is shut down. Hence, for ground vehicle application, a system will need to hold up voltage or use its battery to support data download. Adding a hold battery is a future improvement that we are currently working on.

Another observation was that TFV processing requires processing a large FFT on an embedded system. Where typical sensor processing was 6 to 15 seconds, TFV processing time was closer to a minute. The large FFT needed for TFV requires double precision math, which is slow on most embedded processors. Future systems will incorporate a more powerful double-precision processor to reduce the time required for processing.

The success of the application resulted in a follow-on study for a higher asset value ground vehicle. In this next study, the functions of the IVHMS will be expanded to look at compressor and engine performance health.

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