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DYNAMIC MODELING AND WEAR-BASED REMAINING USEFUL LIFE PREDICTION OF HIGH POWER CLUTCH SYSTEMS

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ABSTRACT

A model-based technique is presented for Remaining Useful Life (RUL) prediction of highly dynamic, high power dry clutch systems by combining physics-based simulation and wear prediction models. Primary load and engagement shear drivers (i.e. torque, speed, clutch surface temperature) are modeled using a first principle approach. An extension of Archard's law is presented in which life usage is predicted using multiple stochastic models to determine a wear coefficient for each applicable wear mechanism. These models consider the physical wear process, including debris particle and protective layer formation, using parameters such as surface roughness, particle size, and surface temperature. These stochastic variables are evaluated in a probabilistic framework, using statistical methods such as Monte Carlo and importance sampling, which considers both measurement and modeling uncertainty. Confidence interval prognostic results are provided to predict the RUL of the clutch throughout its limited life in near-real time.

Keywords: Abrasive, Adhesive, Oxidative, Wear Particles, Clutches, Contact Mechanics, Dynamic Modeling, Heat Transfer Analysis, Statistical Analysis, Failure Analysis, Life Prediction Methods, Preventive Maintenance, Condition Monitoring.

NOMENCLATURE

A – Area
a_S - Smoothing constant
b – Damping Coefficient
C_d – Drag Coefficient
C_p – Specific Heat
F –Force
h – Convective Coefficient
H – Material Hardness
I – Inertia
K – Wear Coefficient
L – Length/Sliding Distance
m – Mass
p – Pressure
P – *Perimeter*
q – Volumetric Flow
Q – Thermal Energy
R – Radius
T – Torque
V – Volume
W – Contact Load
α – Contact angle
β – Bulk Modulus
ρ – Density
μ – Friction Coefficient
ω – Rotational Speed

INTRODUCTION

The fundamental purpose of propulsion coupled drive train systems is to provide and direct mechanical power to lift and vectoring thrust elements. Gas turbine engines, gearboxes, rotor assemblies, fans and other rotating members are subject to finite design lives and susceptible to life limiting damage. Furthermore, the drive train and clutch systems of modern military systems are highly dynamic and carry a potential for high load densities. This paper describes an approach that was developed to predict the remaining useful life of high power clutch systems that are used in such extreme applications.

Traditionally, the reliability of critical mechanical components was estimated statistically and a conservative safe life removal interval (time or usage) for operational units was specified. Historical evidence, however, indicates that the actual usage of military systems often differs greatly from its intended use and estimated operating environment. Thus, the unfortunate reality of statistical-based preventative removals is that significant useful life is lost and premature failures continue to occur in the field. The former problem represents an opportunity for maintenance and support cost savings to be recouped while the latter represents a significant safety improvement to be achieved. The current evolution of diagnostic and prognostic techniques, coupled with the development of advanced monitoring systems, provides a clear path towards prognostics and health management and the realization of reduced life cycle costs, increased readiness, and improved safety.

Model-based prognostics methods have proven especially appropriate for fatigue-related failures in shafts, gear teeth, and ball bearings. These methods typically implement mathematical models that can be used to simulate steady state and transient performance under various commanded conditions, loads, and operational regimes. In the case of drive train systems, these models should be dynamic in order to simulate the transient interaction between speeds, loads, and power sources. These dynamic simulation models enable the identification of diagnostic indicators, which are the necessary inputs for the prognostic health management (PHM) system.

Military clutch systems have been identified as a good candidate for PHM due to the high load density and torque demands placed on these critical subsystems. Furthermore, the authors have identified clutch wear and fatigue to be key life drivers based on past experience. Figure 1 depicts the general approach that has been developed to monitor and predict clutch plate wear during operation. This model-based method incorporates physics-based models, stochastic variables, statistical sampling techniques, virtual temperature sensing, uncertainty characterization, and probabilistic wear forecasting for remaining useful life prediction.

PHYSICAL CLUTCH MODELING

As with any model-based approach, the physics-based model plays a central role in the overall PHM architecture. The developed physical model of the drive train represents the dynamic behavior of the system and can be used to (1) simulate system response (to generate fault progression data for validation of the developed approach) and (2) enable temperature prediction at the clutch plate interface. Drive trains are inherently dynamic; and thus, evaluating transient engagement signatures requires incorporation of appropriate dynamic models within the context of the failure progression approach. This section describes the modeling of a clutch sub-system that was performed using the Simulink modeling environment. A lumped parameter approach was adopted and the developed Simulink model can be seen in Figure 2.

Dynamic Clutch Model

The clutch model was developed based on four distinct operating regimes that are typical of an actual clutch assembly (fully disengaged, engaging, fully engaged, and disengaging). These regimes were further classified into two operational modes: locked operation (fully engaged) and unlocked operation (fully disengaged, disengaging, and engaging). From a modeling standpoint, the transition from one mode to another is the most challenging. As such, consideration to both dynamic and static friction was needed to produce a high-fidelity model [1].

As part of the developed model, equations for frictional torque were used to determine both the operational mode of the system and the amount of torque transmitted across the clutch ($T_{Transmit}$). Kinetic friction was used to determine the amount of transmitted torque ($T_{Transmit}$):

$$T_{Transmit} = T_{kf} = \frac{2}{3} R F_n \mu_k \qquad (1)$$

where R is the radius of the clutch plates, F_n is the normal force applied, and μ_k is the coefficient of kinetic friction. The static friction, T_{sf}, calculated by replacing μ_k with μ_s in Equation 1, is used to determine if the system is locked or unlocked. If the transmitted torque is less than the static friction of the plate, then the clutch will be locked. However, if the transmitted torque surpasses T_{sf}, the clutch will slip.

The equations of motion of the system are described according to the two operational regimes. For the unlocked case, the clutch motion is described as:

$$\left[I_1 \dot{\omega}_1 + b_1 \omega_1 \right] = T_{in} - T_{Transmit} \qquad (2)$$

$$\left[I_2 \dot{\omega}_2 + \omega_2 b_2 \right] = T_{Transmit} \qquad (3)$$

where I is inertia, $\dot{\omega}$ is rotational acceleration, b is damping coefficient, ω is the rotational speed, and T_{in} is the torque delivered to the system (from the engine). In these equations, the driving plate is represented as component 1 and the driven plate is represented as component 2. For the locked condition, the two plates rotate together and their inertias are combined, resulting in an equation of motion of:

$$(I_1 + I_2)\dot{\omega} = T_{in} - (b_1 + b_2)\omega \qquad (4)$$

This first principle's approach allows the primary load and engagement shear drivers to be modeled and enables accurate simulation of clutch operation.

Control System Modeling

In order to correctly simulate the dynamic operation of the clutch, a control system was also included in the model. This included a physical model of the actuator that is used to move and clamp the clutch plates, as well as some simple control loops to mimic operational commands to the system. The actuation system was modeled using a servo-cylinder and its accompanying hydraulics. This modeling approach was adapted from [2] and a schematic is shown in Figure 3. The servo-valve supplies a flow rate based on plunger position, orifice area, and pressure differences. The equations for flow rate are given below. If the plunger is positioned to open the supply line, the fluid will flow into the cylinder at a rate calculated from the equation:

$$q_1 = C_d A_o \sqrt{\frac{2 \cdot |p_s - p_1|}{\rho}} \tag{5}$$

where q_1 is the volumetric flow rate, C_d is the drag coefficient, ρ is the density of the fluid, A_o is the orifice area (a function of the plunger position, x_v), p_s is the supply pressure, and p_1 is the hydraulic pressure created in the servo-valve chamber. Alternatively, if the plunger is positioned to expose the supply line, fluid will flow out of the cylinder at a rate calculated from the equation:

$$q_1 = -C_d A_o \sqrt{\frac{2 \cdot |p_1 - p_0|}{\rho}} \tag{6}$$

where p_o is the reservoir pressure. Finally, if the plunger is positioned in a neutral position, with both lines closed, there will be no flow in or out of the system. Assuming negligible pressure loss in the line ($q_1 = q_2$), the change in pressure ($\dot{p}_2$) on the pressure side of the piston can then be quantified using the equation:

$$\dot{p}_2 = \frac{\beta}{V_o + A \cdot x}\left[q_2 - A \cdot \dot{x}\right] \tag{7}$$

where β is the bulk modulus of the fluid, V_0 is the initial volume of the pressure side of the piston, A is the cross sectional area of the piston, and x and $\dot{x}$ are the position and velocity of the piston. This pressure change has two effects, depending on the state of the system. Initially, pressure results in displacement of the clutch plate until it makes contact with its mating plate. Once contact is made and no further displacement can occur, this pressure change causes the normal force that creates the frictional torque needed to engage the system.

Both states can be solved using Newton's second law. During state 1 (displacement), the force balance can be used to compute the position of the clutch using the equation:

$$\ddot{x} = \frac{1}{m}\left[-F_s + A \cdot p_2\right] \tag{8}$$

where $A \cdot p_2$ is the hydraulic pressure force supplied by the servo-valve and F_s represents a lumped resistance, modeled here as a spring. The choice of a spring also allows simulation of clutch disengagement, where the spring forces the plates apart when the hydraulic pressure is reduced. During state 2, however, there is no displacement of the clutch plate and the normal force is calculated using the following equation:

$$F_N = -F_s + A \cdot p_2 \tag{9}$$

Modeling the system in this manner makes the clutch normal force a function of the input valve position and allows easier control of the system.

A controller was also implemented to maintain the speed of the input shaft as the clutch is engaged. This is needed because the additional inertia added by clutch-driven components causes a reduction in the shaft speed of the lumped system as the clutch engages (if constant torque is applied). A feedback controller is therefore used to control the applied input torque to the clutch so that the commanded speed is maintained throughout engagement. A PID (Proportional-Integral-Derivative) controller was used to simulate a simplified controller in the model.

VIRTUAL TEMPERATURE AND THERMAL MODELING

It is well known that wear is highly dependent on the interface temperature of the surfaces. As such, a critical component of this wear monitoring strategy is the accurate, reliable estimation of interfacial clutch temperatures. A technique for inferring, or "virtually sensing", temperature is therefore very important, as there are currently no practical means for taking this measurement. A physics-based temperature module was included in the Simulink model to enable reliable, autonomous temperature sensing. Data driven approaches, such as neural network and regression techniques, can also be implemented and fused with the physics-based virtual sensor for increased performance, but were not performed here.

Thermal modeling techniques are based on the physics of heat transfer and the dynamics of clutch operation. The clutch surface temperature was predicted based on the governing heat transfer equations for the clutch system. The two primary thermal mechanisms affecting the temperature of the clutch plates are heat generation (caused by the slipping that occurs during engagement and disengagement) and forced convective heat transfer (caused by a cooling fan).

A simple energy balance equation was used to calculate heat generation at the clutch plate surfaces during engagement and disengagement. This approach assumes that all energy losses in the system translate directly to heat generation, which is a reasonable assumption. The final energy balance equation for heat generation is:

$$Q_{Gen} = \frac{1}{2}\left(J_1 \omega_1^{\ 2} - J_2 \omega_2^{\ 2}\right) \tag{10}$$

where J_1 and J_2 represent the lumped inertias on the driving and driven sides of the clutch (respectively) and ω represents the rotation speed of the input and output shafts. This equation is used to calculate the heat generated during slip conditions (engagement and disengagement).

Convective heat transfer was modeled as forced convection flow across parallel plates for the fully disengaged state. It was modeled as forced convection over a cylinder in cross-flow during the other three states of the system. The following equations were used for the forced convection flow across parallel plates:

$$Q_{conv} = \dot{m}_{air}\ c_{p,air}\left(T_{m,o} - T_{m,i}\right) \tag{11}$$

$$Q_{stored} - Q_{conv} = m_{plate} c_{p,plate} \frac{dT_{plate}}{dt} \tag{12}$$

$$T_{m,o} = T_{plate} - \exp\left[\frac{-P_w L}{\dot{m} c_{p,air}} h\right](T_{plate} - T_{m,i}) \tag{13}$$

where Q_{conv} represents the heat lost to convective cooling and Q_{stored} is the heat generated and stored from the previous engagement. $T_{m,i}$, $T_{m,o}$, and T_{plate} are the incoming air temperature, exiting air temperature, and plate temperature respectively. Additional parameters in the equation include the mass flow of the cooling air ($\dot{m}_{air}$), numerous specific heat terms (C_p), the convective coefficient (h), the mass of the plate (m_{plate}), the wetted perimeter (P_w), and the length of the parallel plate (L), which, in this case, is the disc diameter.

For the other three states (fully engaged, engaging, and disengaging), heat transfer was modeled as forced convection across a cylinder. The equations used for analysis during these state are shown below.

$$q_{conv} = hA\left(T_{plate} - T_{m,i}\right) \tag{14}$$

$$\frac{dT_{plate}}{dt} = \frac{Q_{stored} - q_{cross}}{m_{plate} c_{p,plate}} \tag{15}$$

A is the frontal projection area of the cylinder that is exposed to cross flow air and T_{plate}, in this case, is the surface temperature of the lumped cylinder. This lumped parameter approach assumes that heat is dispersed uniformly across the clutch pack and does not consider the heat conduction that would occur axially throughout the clutch plates or radially outward towards the cooled clutch plate outer surfaces and nearby metal structures. This is a valid assumption for high performance clutch plates, which are made from very conductive materials such as carbon-carbon (C-C) composites that effectively dissipate generated heat.

MULTI-MECHANISM WEAR MODEL

Wear is generally defined as surface damage resulting from the removal of material during relative motion between a surface and another contacting body. Wear involves both physical and chemical interactions at the contact surface and is typically classified in two ways: by *mode* and by *mechanism*. A wear *mode* is a classification of the type of contact. Common wear modes include sliding, rolling, erosion, and impact wear. A wear *mechanism* is a classification of the process by which material is removed from the contact surface. The most common wear mechanisms are: adhesive, abrasive, surface-fatigue, corrosive, and thermal. It is important to note that these wear mechanisms are not mutually exclusive; two or more wear mechanisms frequently occur together. A difficulty often encountered when developing wear prediction models is that most of the models focus only on an individual wear mechanism, which is usually not a good assumption for practical applications. Therefore, it is imperative that the relevant wear mechanisms, and their interdependencies, are thoroughly understood and that any corresponding models are capable of accounting for each mechanism and interaction. In the case of drive train clutch systems, it is likely that adhesive wear will be the dominant wear mechanism. Abrasive wear, however, is also a concern and has an effect on the formation of protective surface layers due to the comminuting of abrasive wear particles [4],[5]. Oxidation could also play a substantial role, depending on the severity of interfacial temperatures.

Two important characteristics were desired for the developed clutch wear modeling approach. First, a modular architecture that is flexible and facilitates updating or augmenting of the approach was desired. This flexibility allows consideration of multiple wear mechanisms. In the case of high performance clutch plates, for example, the flexibility should exist to not only model adhesion or abrasive wear but also oxidation, which is necessary due to the vulnerability of carbon-carbon composites to oxidize at high temperatures. A second important focus of the wear modeling approach is the use of statistical variables. Due to the inherently stochastic nature of wear, it is more appropriate to model certain parameters and material properties, such as hardness, surface roughness, and contact area, by using distributions of values. Modeling wear in this manner provides the most robust capability for monitoring wear at the clutch plate surfaces. The developed approach is shown in Figure 4.

Numerous models exist for calculating and predicting wear. Two important research sources for this effort were Stolarski's [7] probabilistic approach, which addresses the inherent uncertainty of wear prediction, and Stott's [8] protective layer model. Stott's model addresses the physical wear process with greater complexity and accuracy by accounting for the interdependency of multiple wear mechanisms. This is accomplished by modeling the competitive processes of the breakdown/formation of the protective surface layers. Elements of each method were adapted for use within this effort.

One of the fundamental models for adhesive wear is Archard's Law [6], which postulates that wear is proportional to material hardness, contact pressure, and relative surface velocities. Specifically, Archard's Law is described as follows:

$$V_{Wear} = K\left(\frac{WL}{3H}\right) \tag{16}$$

where V_{Wear} is wear volume, H is material hardness, W is the contact load, L is the sliding distance, and K is the proportionality constant or wear coefficient. While Archard's Law has been adapted or expanded numerous times as researchers seek a greater understanding of sliding wear, it remains a standard in predicting wear under general sliding conditions. Often, adaptations of Archard's Law focus on experimental or theoretical derivations for the wear coefficient, K, which is considered the most critical term in Archard's equation. Although K was initially intended to represent the probability of adhesive wear, it has since been used to model abrasive and oxidative wear in various adaptations of Archard's sliding wear theory. This flexibility allows the use of Archard's Law to generate separate models for each wear mechanism or a single model to represent all wear mechanisms.

One example of a more complex, physics-based wear model is Quinn's extension of Archard's model for oxidative wear, which includes a specific equation for determining the wear coefficient [9]. According to Quinn, K_{oxid} can be calculated as follows:

$$K_{oxid} = \frac{d \cdot \beta}{\upsilon \cdot f^2 \xi_c^2 \rho_o^2} \tag{17}$$

where d is the sliding distance, υ is the sliding velocity, f is the fraction of oxygen in the oxide, β is the oxidation rate constant, ξ_c is the critical thickness of the oxide layer, and ρ_0 is the density of the oxide. The oxidation rate constant can be calculated using:

$$\beta = \beta_0 e^{(-Q/RT)} \tag{18}$$

where 'β_0' is the Arrehenius constant, Q the activation energy for oxidation under dry sliding, and T is the temperature during contact [10]. Some of these values are obviously hard to quantify, but this serves as a good example of adapting the wear coefficient of Archard's Law for additional wear mechanisms.

In addition, Hockenhull presents several other wear coefficient models for the sliding contact of metallic surfaces [11]. The three models presented here consider the cases of wave formation, wave removal, and chip formation. The wave removal model represents a case similar to adhesive wear, where hard asperities are broken off the surface. The chip formation model represents the removal of larger chips from the surface. Hockenhull refers to Challen and Oxley [12] in finding the wear rate for the wave removal model, which uses Archard's fundamental law for material removal. Using this approach, the wear coefficient can be obtained using the material hardness and the asperity contact angle, which is essentially a surface roughness parameter. For the adhesive model:

$$\frac{K}{3H} = \frac{\sin^2\alpha + \frac{1}{2}\sin 2\alpha}{2k(1+\sin 2\alpha)} \tag{19}$$

where α is the asperity contact angle and k can be related to H using the following equation:

$$k = H/(3 + 31/2) \tag{20}$$

The wear coefficient for the chip removal model is:

$$\frac{K}{3H} = \frac{1}{k\left\{\left[1+2(\frac{1}{4}\pi-\varphi)\right]\cot\varphi-1\right\}} \tag{21}$$

where k is again found using H and φ is a surface parameter found using an additional lubrication parameter, f, and α.

As shown by these various models, the wear coefficient, K, may be modeled in various ways, depending on the particular wear mode and mechanism. These models consider the physical wear process, including debris particle and protective layer formation, as well as surface roughness, surface temperature and other important considerations. As this wear modeling approach matures, these tailored wear models may be adapted for use within the overall wear model. Alternatively, elements of these models may be incorporated for determining a "fused" wear coefficient. Regardless, these models illustrate the diversity of opinions on wear modeling and justify the implementation of a modeling approach that is modular and adaptable, allowing for improvements as better models become available.

REMAINING LIFE PREDICTION

In the case of fault-to-failure prediction, the time (or engagements) remaining before the current health state progresses to functional failure is desired. The time to reach this region is determined by tracking and projecting the path of the wear predictions using a statistical trending method. One such method, double exponential smoothing (DXS), was employed here to effectively track and project wear. Other methods, such as Kalman filters, could also be applied.

DXS employs an exponentially weighted averaging function that can forecast future values of a vector based on past observations. These past observations are weighted using an exponential function. DXS is represented mathematically by:

$$\begin{aligned} S_T &= a_s y_T + (1-a_s)S_{T-1} \\ S^{[2]}{}_T &= a_s S_T + (1-a_s)S^{[2]}{}_{T-1} \end{aligned} \tag{22}$$

$$\hat{y}_{T+\tau}(T) = \left(2+\frac{a_s\tau}{(1-a_s)}\right)S_T - \left(1+\frac{a_s\tau}{1-a_s}\right)S^{[2]}{}_T \tag{23}$$

where a_S is the smoothing constant and S_T and $S^{[2]}{}_T$ are the smoothing statistics. As part of the developed approach, DXS forecasts are made one time unit into the future and smoothing statistics are updated and used to make the next prediction. This process is repeated until the predicted wear approaches the wear limit of the component. This piece-wise approach allows the algorithm to capture the non-linear characteristics of failure progression.

UNCERTAINTY ESTIMATION

In any modeling effort, uncertainty plays an important role. In applications such as wear modeling, this role is even more critical as several physical parameters, such as surface roughness, must be determined by reasonable estimates or experimentally determined relationships. In this effort, uncertainty is considered in each step of the process and takes two primary forms: 1) measurement uncertainty and 2) modeling uncertainty, as seen in Figure 4. Measurement uncertainty, which is dictated by the accuracy of the sensor, manifests itself as error propagation. Capturing this propagation is important to quantifying the uncertainty in the final prediction. Modeling uncertainty appears as a residual difference between the validated model and the actual system. This is a consequence of a limited capability to exhaustively model all of the system's physical characteristics, as well as inherent system non-linearities and random system variations. These variations exist and can be accounted for by analyzing actual system data and quantifying the variability of the monitored system variables.

Statistical Wrappers

Monte Carlo methods provided a practical means for reaching an accurate wear prediction within the developed probabilistic framework for propulsion and drivetrain clutch systems. Monte Carlo (MC) methods refer to statistical simulation techniques used to predict the behavior of an engineering system. MC methods employ system modeling and random combinations of system parameters to perform this analysis. Unlike MC simulation, conventional simulation starts with system modeling involving discrete differential equations. These relationships are then solved algebraically to determine the unknown states of the system. In performing MC simulations, however, the system is assumed to be a stochastic process, and random number simulation is therefore applicable. The following steps describe a common methodology used in Monte Carlo simulations:

1. Generate a model of the system consisting of relevant parameters
2. Generate a set of random values for each model parameter
3. Evaluate model with the random values
4. Evaluate the behavior of the system with statistical analysis

5. Study the efficiency of the simulation and its convergence [13]

Monte Carlo simulations assume that the evolution of a physical system can be described by probability density functions (PDFs). Because Monte Carlo theory is dependent on random numbers and emphasizes the importance of randomness and chance, *sampling* of the PDF is important. One common sampling technique is variance reduction, which, when coupled with Monte Carlo simulation can improve the statistical efficiency of the simulator and decrease the number of samples needed to generate an estimate within a desired error tolerance. As mentioned, simulations are used to estimate the performance measure of a stochastic model. Variance reduction methods are used to make sure this estimator is unbiased. One such variance reduction technique, importance sampling, is especially useful for Monte Carlo Simulation. Importance sampling reduces the variance of the PDF by choosing a new density that gives more importance to the region closer to the mean. Importance sampling chooses a nonrandom representative set that is biased towards conformations that are significantly populated at equilibrium. Using this technique, PDF values are carefully selected so that mean values are closer to the design point than the actual PDF. This results in an increase in the number of failures, which increases simulation efficiency. This is important for near real-time systems where processing time is a concern.

WEAR MODELING RESULTS

The operational data and virtual temperature predictions generated by the Simulink model (described previously) were used to validate the model-based clutch fault progression module. A number of fault progression data sets were generated to simulate plate material loss by increasing the distance that the clutch plates must be moved before engaging. Parameter uncertainties were then estimated and coupled with simulation data for use within the developed probabilistic methodology. Operational sensor, wear coefficient, and material property uncertainties were estimated from past experience. Virtual temperature model uncertainty was calculated from a sensitivity analysis using factorial Design of Experiment (DOE) methodology, as discussed next.

Virtual Temperature Uncertainty

Uncertainty estimation is critical to the developed probabilistic approach. As such, techniques are needed to determine the uncertainty of model-determined values. As an alternative to real-time simulation techniques, such as Monte Carlo Simulation, a sensitivity analysis was implemented to determine virtual temperature model uncertainty. This approach reduces the processing necessary for near real-time implementation by predetermining uncertainty values using experimentation. The basic idea of the approach can be captured with the following equation:

$$\Delta T = \delta T / \delta P_1 * \Delta P_1 + \delta T / \delta P_2 * \Delta P_2 + \ldots + \delta T / \delta P_N * \Delta P_N \quad (24)$$

As seen, temperature (T) uncertainty is calculated using (1) the uncertainty of each parameter (ΔP) and (2) the sensitivity (or effect) that each critical model input has on temperature (δT/δP). Sensitivity parameters are determined using experimentation and Design of Experiments (DOE) analysis.

The DOE strategy is widely used in many engineering and design problems because it allows experimenters to develop an organized and structured experimental plan. The primary benefits of the DOE approach are simpler end-effect determination, easier interpretation of experiment results and possible data transformations, and higher confidence in design drivers. DOE also ensures maximum cost and time efficiency since a factorial design can be implemented to allow simultaneous consideration of multiple variables. There are four basic stages of DOE: project breakdown, experiment planning, experiment conduction, and result analysis. A well-known DOE example is the Taguchi method for test matrix design. Stat-Ease, Inc. Design-Expert Version 6.0.3 was used to perform the DOE evaluation.

Using the structure and methods in the DOE process, a statistical analysis was conducted to identify the effect that the different model inputs have on temperature. These effects were captured with a sensitivity coefficient, $\delta T/\delta p_i$, for each critical model input. This analysis was conducted after generating sufficient training data from the Simulink model to determine each primary effect and interaction. An interaction would be one in which two or more effects combine to produce a new or emerging effect. Central to this approach, the sensitivity, or effect coefficient, of each variable is calculated using a regression estimate of the given data. The sum of squares for each effect is calculated (similar to Yates [14]) and is summed as the regression progresses.

The advantage to using DOE is that a reduced number of experiments can be used to produce the most meaningful information about the model or system and the input parameters. Design methods, such as factorial design, are used to plan experimental schedules that vary input parameters between different levels. A factorial design setup with N input parameters requires 2^N experiments to fully explore the effects of the parameters. Five model parameters were selected for consideration in the analysis (coefficient of friction, specific heat, convective coefficient, ambient air temperature, and speed differential) and, as a result, 32 experiments (2^5 experiments) were required to identify the parameter effects and the temperature prediction uncertainty. Based on the DOE analysis, the effect coefficient for each model input was identified and combined with their uncertainties to estimate the uncertainty in the temperature prediction. These effects can be seen in Table 1.

Stochastic Wear Results

For the initial effort, only the wear coefficient for adhesive wear was implemented. However, the algorithms were constructed in a modular fashion to allow for future updates to incorporate abrasive and oxidative wear coefficient models. Normal parameter distributions were assumed and PDFs were created for each wear model input. An example of these parameter distributions can be seen in Figure 5.

A Monte Carlo simulation was then used to solve Archard's wear equation, using 500 simulations, to produce an estimate of the lost wear volume from the surface of the plates. An example of the resulting probabilistic output can be seen in the bottom right corner of Figure 5. This process was repeated for each simulated engagement-disengagement cycle.

Figure 6 is an example of the results obtained for a series of engagements at various speeds. In the figure, confidence bounds are also included and appear as dashed lines around the mean prediction (solid line). These values are a result of the Monte Carlo simulation. An important characteristic of this approach is the ability to predict wear using the actual usage of the clutch. As seen in the figure, changes in the operation of the clutch result in different wear rates.

An example of the RUL predictions for this data set can be seen in Figure 6. In the figure, a forecast is performed at ~1400 engagements (current time). The mean wear (solid line) and 2-sigma confidence bound (dashed line) represent the probabilistic wear predictions described in the previous section. The lines to the right of the current time represent the predicted wear progression of the clutch using the DXS routine. The error bounds (dashed line) represent a fusion of the uncertainty in the current health and past RUL error predictions. As seen, a conservative estimate of clutch wear (using the upper bound) results in failure at about 1800 engagements. Statistical methods, such as Monte Carlo simulation, could be used to generate a full distribution at each point, but this was not performed in the current effort.

Demonstration of Model-Based Clutch Fault Progression Module

A demonstration of the model-based clutch fault progression module was also created to illustrate the operation of the module. The Graphical User Interface (GUI) of the demo, depicted in Figure 7, was constructed using MATLAB's *GUI Design Environment (GUIDE)*. The demo operates using the developed SIMULINK clutch model and wear prediction algorithms. As seen, the demo shows (1) raw operational data (friction torque and speed differential) and virtual temperature prediction from the SIMULINK model, (2) statistical and uncertainty information used in the Monte Carlo Simulation, and (3) wear prediction and fault-to-failure prediction results. The GUI allows the user to step through a clutch fault progression (selected from the *File* menu) using the *Engagement Number* slider bar. The user can also launch a number of additional screens from the main GUI, including the SIMULINK model, a description of the wear modeling approach, and contact/data rights information. Information regarding the data set and data simulation is also provided (far left). The ability to convert the predictions from 'number of engagements remaining' to a 'remaining useful operational time' is planned by allowing the user to enter the planned usage of the component (the *Upload Usage* button), but is not active at this time.

CONCLUSIONS

An overall architecture was developed for Remaining Useful Life (RUL) prediction in highly dynamic, high-power dry clutch systems. This architecture integrates a physics-based model of the system with a stochastic, modular approach to wear modeling. Debris particle formation, protective layer development, surface roughness, particle size, and surface temperature are considered, as well as uncertainty due to both measurement error and modeling error. Within the developed approach, Monte Carlo methods replace the traditional deterministic analysis and are used to capture these stochastic variables within a probabilistic framework. Sampling methods, such as importance sampling, are also treated and confidence interval prognostic results are provided to predict the RUL of the clutch throughout its limited life in near-real time.

This stochastic, modular wear monitoring approach was initially validated using a computer model within

Simulink. A number of fault progression data sets were generated to simulate plate material loss by increasing the distance that the clutch plates must be moved before engaging. The model demonstrated a good ability to follow the seeded progression of cumulative wear. The next step in the validation process for this approach is to perform wear testing and run the model with actual failure progression data.

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FIGURE CAPTIONS

Figure 1 – Stochastic, Modular Wear-Modeling Architecture

Figure 2 – Dynamic Clutch Model in Simulink

Figure 3 – Schematic of Servo-cylinder and hydraulic system

Figure 4 – Overall Wear Modeling Approach

Figure 5 – Wear Model Parameter Distributions

Figure 6 – Example wear prediction results (left plot) and forecast/RUL prediction

Figure 7 – Model-based Clutch Fault Progression Module Demonstration

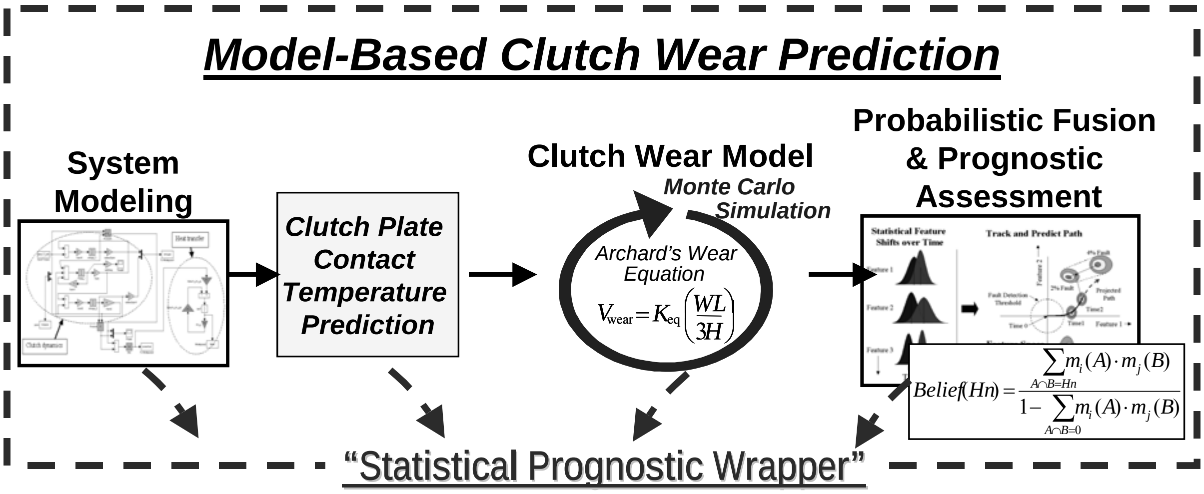

Figure 1 – Stochastic, Modular Wear-Modeling Architecture

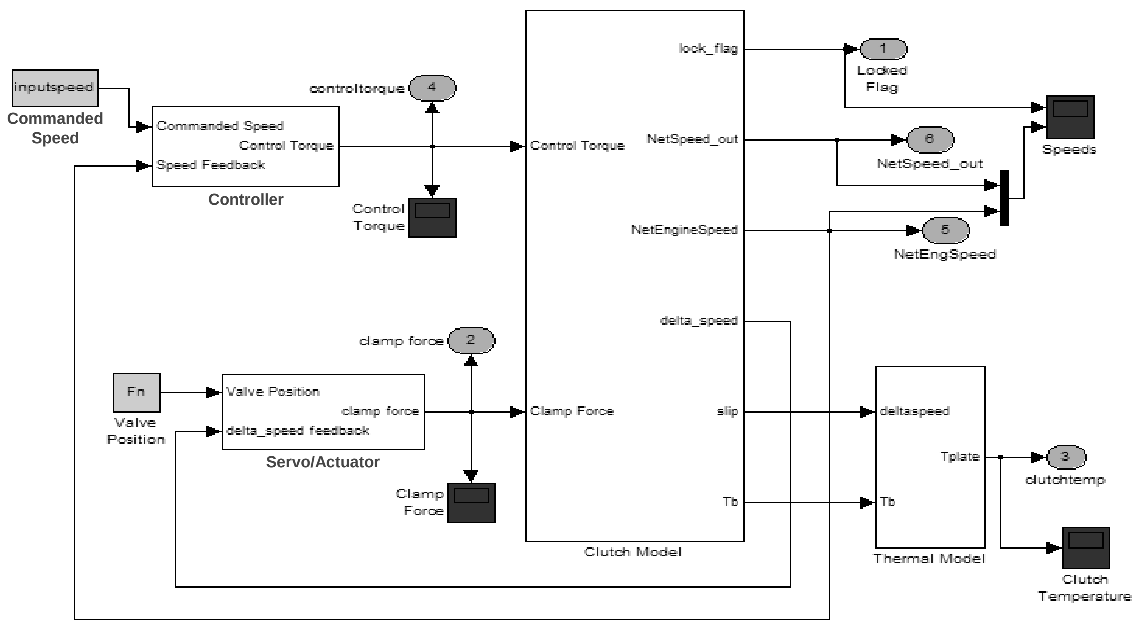

Figure 2 – Dynamic Clutch Model in Simulink

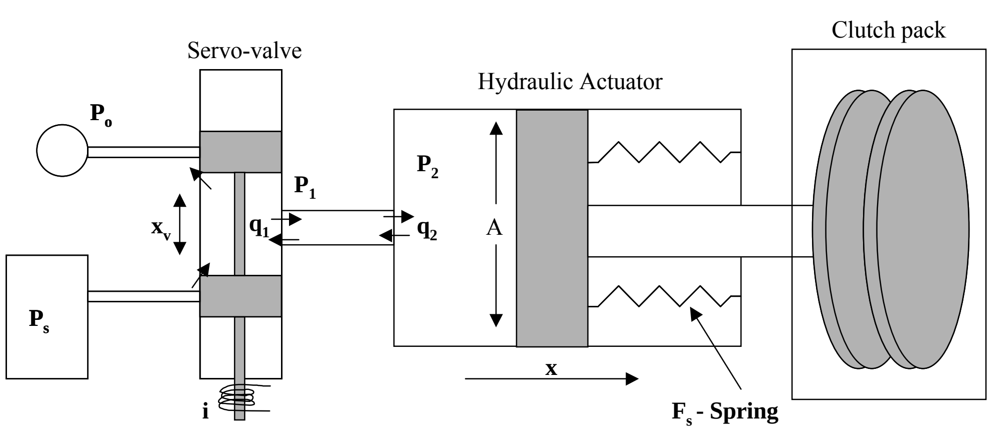

Figure 3 – Schematic of Servo-cylinder and hydraulic system

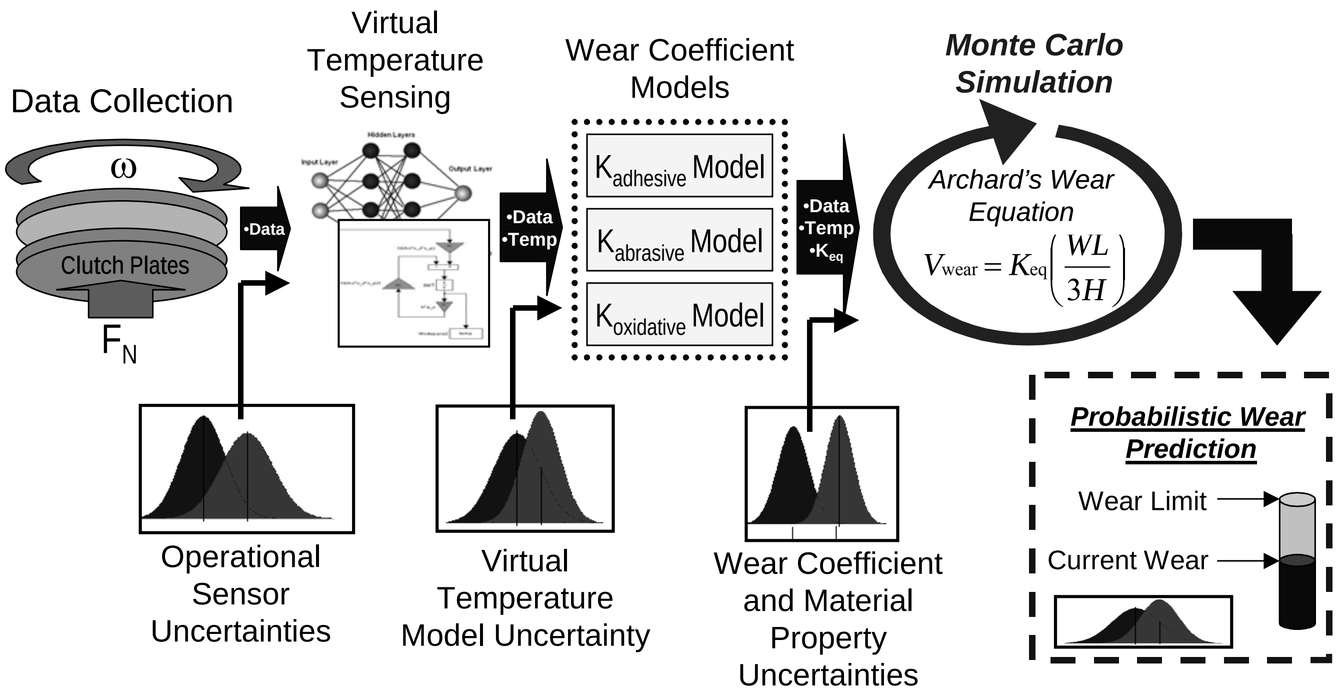

Figure 4 – Overall Wear Modeling Approach

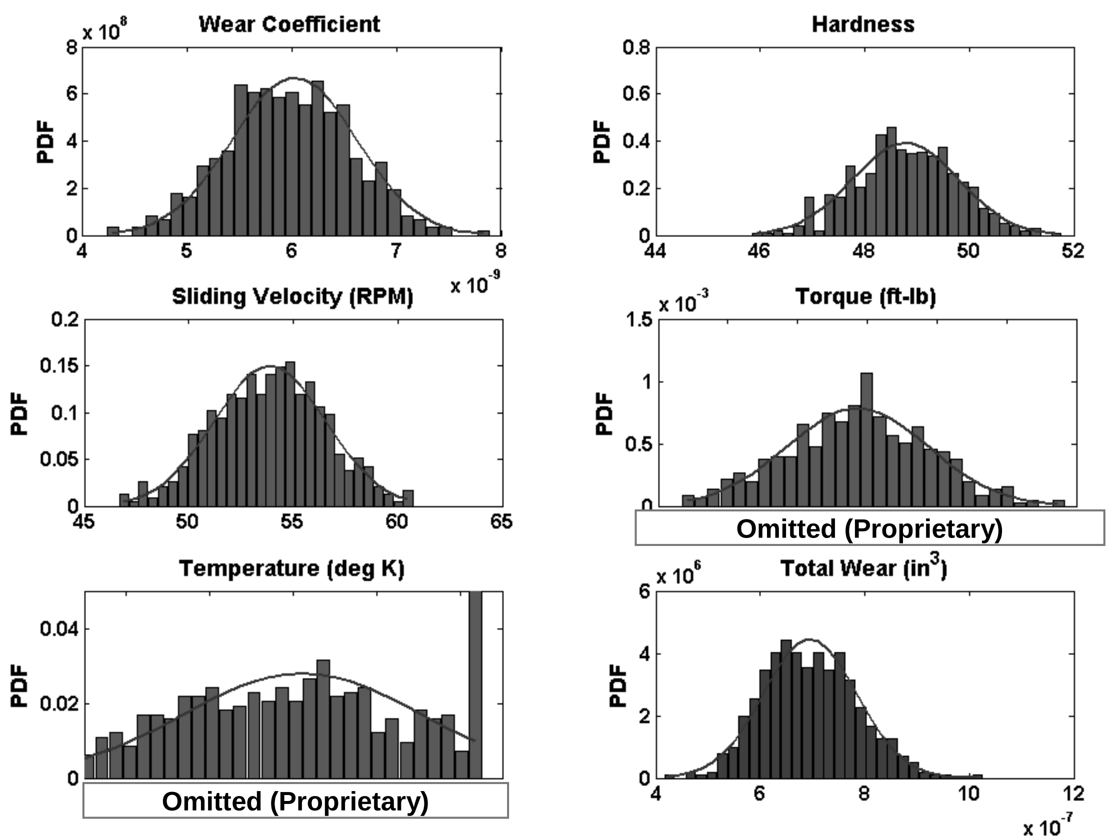

Figure 5 – Wear Model Parameter Distributions

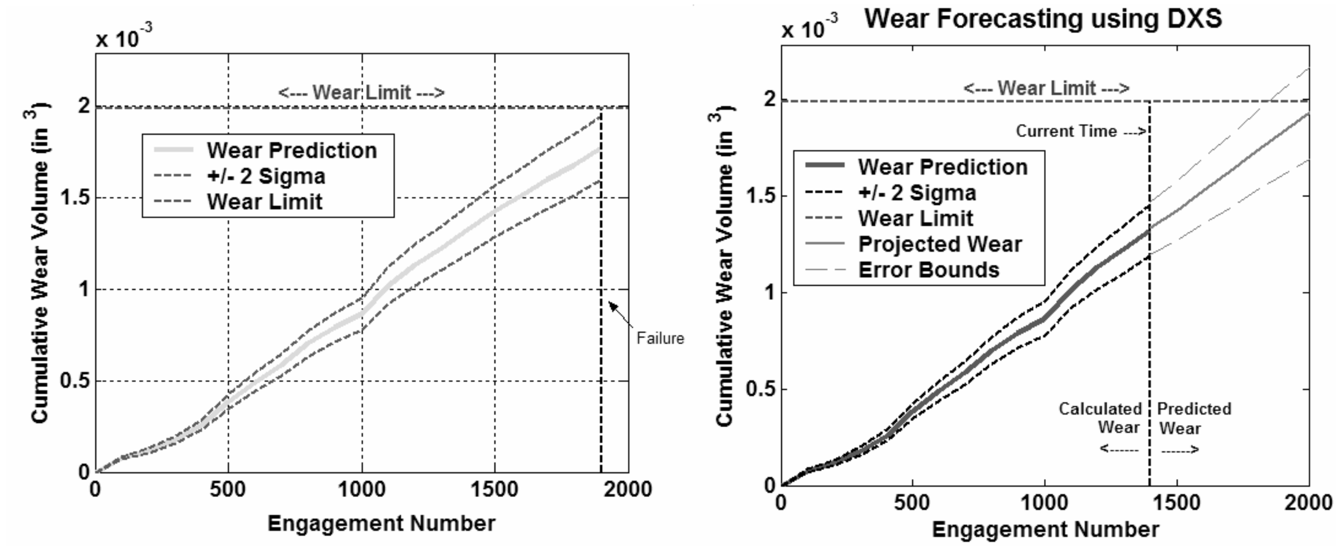

Figure 6 – Example wear prediction results (left plot) and forecast/RUL prediction (right plot) for engagements at various RPMs

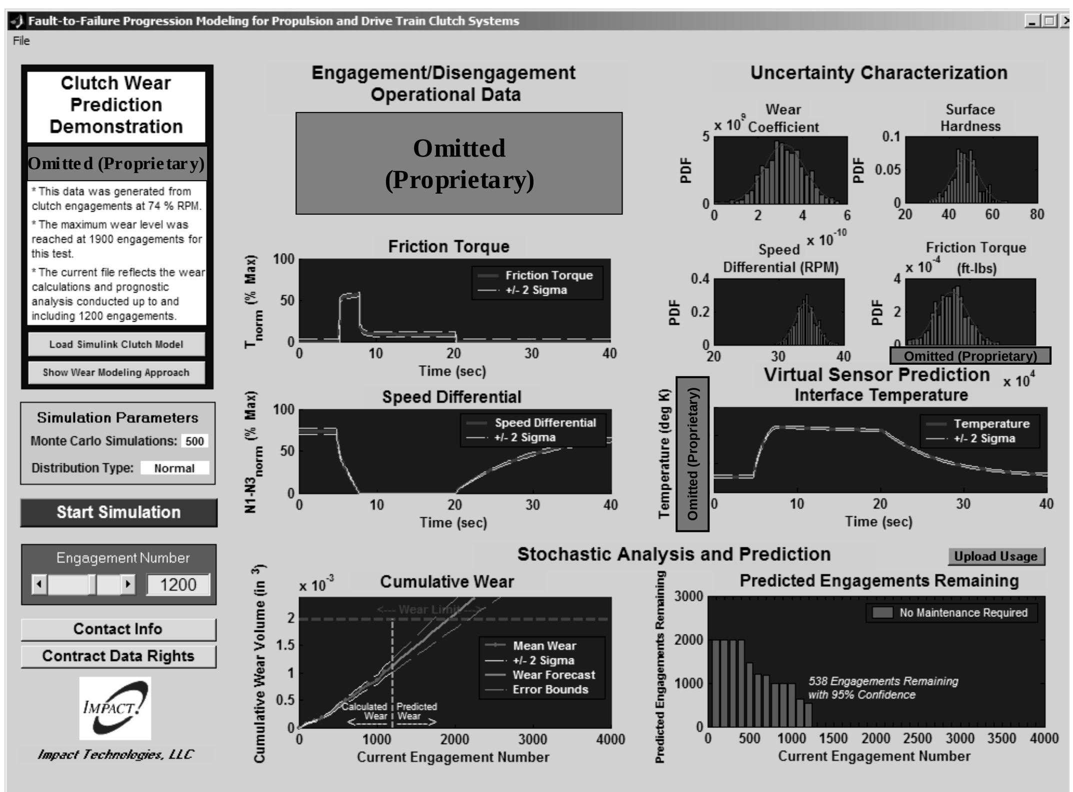

Figure 7 – Model-based Clutch Fault Progression Module Demonstration

Parameter	Input Parameter Descriptions	Parameter Effect
$\delta T/\delta\mu$	Coefficient of Friction at the Clutch Plate Interface	194.38
$\delta T/\delta C_{p,air}$	Specific Heat of the Cooling Air	~0
$\delta T/\delta h_{air}$	Convection Coefficient due to the Cooling Air over the Clutch Plates	~0
$\delta T/\delta T_{m,i}$	Ambient Air Temperature at the Clutch Plates	40
$\delta T/\delta(\Delta N)$	Speed Differential between the Clutch Plates	935.88

Table 1 – DOE Parameters for Virtual Temperature Uncertainty