Adaptive Control of Actuator Lifetime

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Abstract—The harder an actuator is pushed to its performance limits, the shorter its lifetime becomes. Existing actuator controllers are typically designed to optimize performance and robustness, without considering the operational lifetime of the actuator. However, it is often desirable to trade off performance for extended lifetime in order to reduce vehicle maintenance cost and improve vehicle safety and mission readiness.

We present two adaptive control algorithms for managing the performance and lifetime of motors in electromechanical actuators. The first algorithm provides tracking control of a desired motor lifetime by adapting the motor performance level. The second algorithm provides adaptive trade-off between motor performance and lifetime based on vehicle mission needs. Simulation results are presented to show the effectiveness of these control algorithms.

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1. INTRODUCTION

Existing actuator controllers are typically designed to maximize actuator performance while providing sufficient stability margins. However, extracting high performance from an actuator results in decreased operational lifetime due to higher temperature and stress on the actuator components. This hidden cost of high performance control must be considered in future controller designs, as increasing emphasis is placed on vehicle safety, reliability and maintenance cost.

The current state-of-the art in machinery health diagnostics and prognostics consists of (i) detection and localization of the fault and (ii) estimation of the remaining life (time to failure) of the faulty component [1]. The health prognostics usually provide short-term life prediction, as it is triggered by the detection of abnormal behaviors that indicate there is already noticeable damage in the component. There have also been efforts to integrate prognostics with control. The objective is to extend the component lifetime by changing control strategies or changing the system's operating point when a fault is detected [2].

Our work is focused on *long-term* life prediction and control. We assume a new machinery component is initially damage-free and estimate its remaining life by modeling the accumulation of damage during its operation. The machinery controller incorporates the remaining life as a controlled parameter and applies a consistent control strategy that keeps the machinery on track to achieve the desired long-term life.

In our previous work, we developed a control algorithm that enforces desired motor lifetimes in electromechanical actuators by imposing a hard constraint on the motor current [3,4]. However, this approach can produce undesirable actuator performance characteristics associated with saturation-type nonlinearity. In this paper we present two new algorithms for actuator motor lifetime control that significantly improve upon the previous method.

The two new control algorithms provide tracking control of a motor's desired lifetime and adaptive lifetime/performance trade-off, respectively, without the use of hard constraints [5]. Both methods utilize a conventional optimal controller designed to only minimize the motor's position/velocity tracking error and the magnitude of the control effort (i.e., magnitude of motor current). Because motor lifetime is related to motor current, motor lifetime can be indirectly regulated by adjusting the relative weighting between minimizing the position/velocity tracking error and minimizing the magnitude of the control effort. The new algorithm for motor lifetime tracking control automatically adjusts the relative weighting to find a balance between position/velocity tracking performance and control effort that results in the desired motor lifetime. Similarly, the

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algorithm for adaptive lifetime/performance trade-off adjusts the relative weighting based on the vehicle's mission attributes. The basic concept is to optimize actuator motor usage by emphasizing motor performance (expending lifetime) when a vehicle maneuver is critical, while relaxing performance (extending lifetime) when a maneuver is not critical. In our implementation of adaptive lifetime/performance trade-off, the weighting factors are adjusted using a set of fuzzy logic rules that takes into account the priority of the actuation task, the motor's present performance, and the remaining motor lifetime relative to the desired lifetime.

In the following sections, we present methods for estimating the remaining lifetime of an actuator motor and describe the adaptive lifetime control algorithms in detail.

2. PREDICTION OF MOTOR LIFETIME

The primary failure modes of brushless DC (BLDC) motors are winding insulation failure and bearing failure. In this section, we use heuristic methods to develop analytic models for estimating the life expectancy of the motor winding and bearing. These two components are assumed to be initially damage-free and the objective is to predict the time at which the first sign of fault would occur.

2.1. Motor Winding Lifetime Prediction

The life expectancy of motor winding insulation is a function of the winding temperature; different classes of insulation material offer different temperature ratings. For example, BLDC motors commonly use class F winding insulation, which provides an average life expectancy of approximately 20,000 hours at 155ºC. The average life expectancy of winding insulation is reduced approximately by half for every 10ºC rise in temperature [6]. Because of the strong influence of temperature on insulation life, most servo motors provide an embedded thermal switch to prevent thermal damage. Aside from mechanisms to reduce bearing wear (e.g., improve motor-load alignment, maintain proper lubrication, reduce electrically induced bearing currents), the best way to prolong motor life is to control its winding temperature.

A typical insulation life expectancy versus temperature curve is shown in Fig. 1. Such manufacturer specification allows us to calculate the expected remaining life of the insulation when the motor operates at a constant temperature (e.g., constant duty operation). However, no formula exists for calculating the remaining life when the winding temperature is varying. We use a heuristic method based on applying Fig. 1 and the assumption that damages incurred at different temperatures are linearly additive. For example, suppose class F insulation (which has a life of 20,000 hours at 155ºC) is operated for 10,000 hours at 155ºC, the insulation would lose 10,000/20,000 = 50% of its original

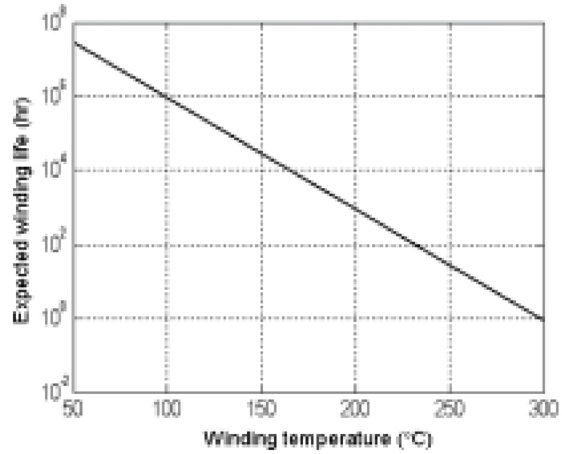

Figure 1 – Typical winding insulation life versus temperature curve.

lifetime (i.e., we can view the insulation as 50% deteriorated). If the insulation is subsequently operated for 1000 hours at 175ºC (where Fig. 1 indicates the life expectancy of brand new insulation is 5,000 hours), we then assume that the insulation has lost an additional 1,000/5,000 = 20% of its original lifetime. Thus, the sum of the effects of operating for 10,000 hours at 155ºC plus operating for 1,000 hours at 175ºC is to lose 50% + 20% = 70% of the life of new insulation. The remaining life is then 100% – 70% = 30% of the life of new insulation. In this way, the percentage of life expended at each temperature level can be calculated and accumulated to estimate the remaining life at any time instant.

Specifically, the percentage residual (remaining) life at time instant t is calculated by

$$\%Liferes(t) = 100 \cdot \left(1 - \int_{t_o}^{t} \frac{d\tau}{Lifenew(\tau)}\right), \quad t_o \le \tau < t \qquad (1)$$

where t_o is the initial time instant and $Lifenew(\tau)$ is the life expectancy of brand new insulation corresponding to the winding temperature at time instant τ for $t_o \le \tau < t$. Note that $Lifenew(\tau)$ is obtained from the curve in Fig. 1, which can also be expressed as an exponential function of temperature as follows

$$Lifenew(\tau) = \alpha \cdot e^{-\beta \cdot T_w(\tau)} \qquad (2)$$

where $T_w(\tau)$ is the winding temperature at time instant τ, and α and β are constants. For the life expectancy curve of class F insulation shown in Fig. 1, T_w is given in units of °C, $\beta=0.0693$ (1/°C), and $\alpha=926818992.2$ (hr). The integration term in Eq. (1), which is the fractional used life at time instant t, is limited between 0 and 1, and its initial value at time instant t_o is assumed to be zero. The integral's value can be accumulated as the motor operates; thus it is not necessary to store any past temperature history.

Since the residual life in terms of absolute hours varies with the operating temperature, it is more useful to track the residual life as a percentage of the full life of new insulation. At any instant, we can convert the percentage residual life into absolute residual life-hours at the present operating temperature by

$$Liferes(t) = \frac{\%Liferes(t)}{100} \cdot Lifenew(t) \qquad (3)$$

Again, *Lifenew(t)* in Eq. (3) is the life expectancy of new insulation corresponding to the winding temperature at time instant *t*.

In addition to computing the residual lifetime at the present operating temperature, we can also compute the desired present operating temperature for achieving a desired future residual lifetime. From Eqs. (1) and (3), the relationship between the lifetime of brand new winding *Lifenew*(t) and the residual lifetime of used winding *Liferes*(t) can be written as

$$Lifenew(t) = \frac{Liferes(t)}{1 - \int_{o}^{t} \frac{d\tau}{Lifenew(\tau)}}, \quad t_o \le \tau < t \qquad (4)$$

To ensure the residual lifetime is greater than or equal to some desired value, we can rearrange Eq. (4) as the following constraint:

$$Lifenew(t) \ge \frac{Liferes^{*}(t)}{1 - \int_{o}^{t} \frac{d\tau}{Lifenew(\tau)}}, \quad t_o \le \tau < t \qquad (5)$$

where *Liferes**(t) is the desired absolute residual life-hours. This constraint requires that we operate the winding at a sufficiently low temperature such that the lifetime of brand new winding *Lifenew(t)* corresponding to this temperature would satisfy Eq. (5). After computing the required *Lifenew(t)* from Eq. (5), the winding temperature $T_w(t)$ that corresponds to *Lifenew(t)* can then be obtained from Eq. (2). This yields

$$T_w^{*}(t) = -\frac{1}{\beta} \cdot \ln\left(Liferes^{*}(t) / (\alpha(1 - \int_{o}^{t} \frac{d\tau}{Lifenew(\tau)})) \right), \; t_o \le \tau < t. \qquad (6)$$

where $T_w^{*}(t)$ is the desired present winding temperature that will yield the desired residual lifetime *Liferes**(t).

2.2. Motor Bearing Lifetime Prediction

The rated life of motor bearings is commonly specified by the bearing manufacturer in terms of the L_{10} life – the service life at which there is a 10% probability of fatigue failure under a given constant load [7]. The fatigue failure occurs in the form of metal chips breaking off from the surface of bearing races or rolling elements – a condition referred to as "spalling."

In its basic form, the L_{10} life of a motor bearing specifies the number of revolutions that can be attained before there is a 10% probability of failure. The L_{10} life can be translated into number of hours by dividing the number of revolutions by the bearing's rotational speed, and is given by

$$L_{10} = \left(\frac{C_r}{P_{eq}} \right)^3 \frac{10^6 \cdot 2\pi}{3600 \cdot \omega_r} \qquad (7)$$

where C_r is the bearing's radial load rating specified by the manufacturer (in lbf or N), P_{eq} is the equivalent radial load applied to the bearing, and ω_r is the angular speed of the motor rotor (or, the rotational speed of the bearing inner race) in rad/s. It is important to observe from Eq. (7) that a small change in applied load results in a large change in lifetime. For example, reducing the load by half results in increasing the lifetime by eightfold.

The L_{10} life in Eq. (7) is established for the conditions of constant load and constant speed. For time-varying load and speed, we will estimate the residual L_{10} life by using the same heuristics as for winding lifetime estimation; that is, we assume that the percentage of the L_{10} life lost at different conditions are linearly additive. The predicted percentage and absolute residual lifetimes of the motor bearing at time instant *t* can then be calculated, respectively, by:

$$\%L_{10res}(t) = 100 \cdot \left(1 - \int_{o}^{t} \frac{d\tau}{L_{10}(\tau)} \right), \quad t_o \le \tau < t \qquad (8)$$

$$L_{10res}(t) = \frac{\%L_{10res}(t)}{100} \cdot L_{10}(t) \qquad (9)$$

where $L_{10}(\tau)$ is the life expectancy of brand new bearing corresponding to the radial load and motor speed at time instant τ for $t_o \le \tau < t$. Note that $L_{10}(\tau)$ is obtained from Eq. (7). $L_{10}(t)$ in Eq. (9) is the life expectancy of brand new bearing corresponding to the radial load and motor speed at time instant *t*.

The method of estimating the fatigue life of bearings by summing the percentage damage incurred at each discrete load level is commonly known as Miner's rule (or Palmgren-Miner rule) [8]. Equations (8) and (9) are the continuous version of Miner's rule.

2.3. Relationships Between Motor Lifetime and Current

Motor winding temperature, and hence winding lifetime, can

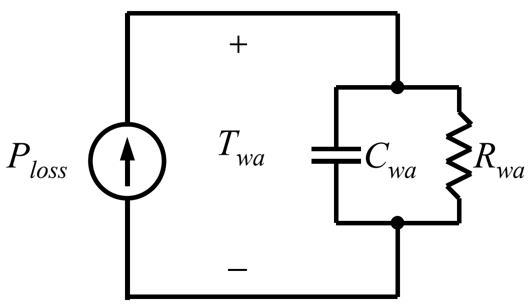

Figure 2 – Equivalent circuit for motor thermal model.

be controlled by regulating the motor current. The winding temperature can be estimated from the motor current by using the simple equivalent circuit model shown in Fig. 2 [9]. In this figure, R_{wa} is the thermal resistance from winding to ambient air, C_{wa} is the thermal capacitance from winding to ambient air, T_{wa} is the temperature difference between the winding and ambient air, and P_{loss} is the total power dissipated as heat. P_{loss} can be approximated by the total copper loss in the windings [6], which is given by

$$P_{loss} = R_m \cdot u^2 \tag{10}$$

where R_m is the motor phase-to-phase winding resistance and u is the motor current.

After T_{wa} is computed from this model, the winding temperature is simply determined from

$$T_w = T_{wa} + T_a \tag{11}$$

where T_a is the ambient air temperature which is assumed to be known.

Motor bearing lifetime can also be controlled by regulating the motor current, due to the relationship between bearing load and motor torque. Consider the motor shown in Fig. 3. In general, the bearing closer to the load side (closer to the gearbox) experiences heavier load. Thus, control of bearing lifetime will focus on bearing #2 shown in the figure.

The radial load acting on bearing #2 can be expressed by

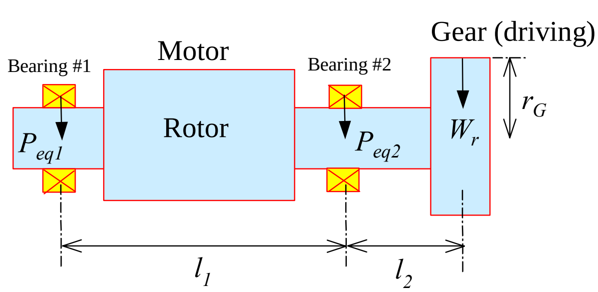

Figure 3 – Radial force acting on motor bearings.

$$P_{eq} = W_r \frac{l_1 + l_2}{l_1} \tag{12}$$

where W_r is the total radial force at the gear mesh, and l_1 and l_2 are the lengths defined in Fig. 3. The total radial force at the gear mesh is comprised of two components:

$$W_r = \sqrt{W_t^2 + W_r'^2} = \sqrt{W_t^2 + (W_t \cdot \tan(\gamma))^2} \tag{13}$$

where W_t is the tangential force at the gear mesh, W_r' is the separating force at the gear mesh, and γ is the gear pressure angle [10]. For spur gears, $\gamma = 20^\circ$, which results in

$$W_r = 1.0642 \cdot W_t = 1.0642 \cdot \frac{Trq}{r_G} \tag{14}$$

where Trq is the torque acting on the gear and r_G is the radius of the gear. Substitution of Eq. (14) into Eq. (12) yields

$$P_{eq} = cpeq \cdot Trq \tag{15}$$

where the coefficient for equivalent load is given by

$$cpeq = 1.0642 \frac{l_1 + l_2}{r_G \cdot l_1} \tag{16}$$

The torque acting on the gear can be assumed to be equal to the torque produced by the motor current, unless the external torque acting on the gear (e.g., from the load or disturbance) exceeds the torque produced by the motor current. Thus, under most conditions, Eq. (15) results in

$$P_{eq} = cpeq \cdot Trq = cpeq \cdot K_t u \tag{17}$$

where, K_t is the torque constant of the motor and u is the motor current.

3. Control of Motor Lifetime

Active control of the lifetime of a BLDC motor can be achieved by controlling the motor winding temperature and bearing load through the motor current. In this section, we present a method for tracking control of motor lifetime. This method exploits the standard linear optimal control design framework.

3.1 Trade-offs in Linear Optimal Control Design

Let us consider the design of a conventional motor control law for position/velocity tracking and disregard, for the moment, the problem of controlling motor lifetime. Linear optimal control theory [11, 12] provides a well-known procedure for generating linear feedback controllers that minimize a cost function of the form

$$J = \int_0^\infty \{(x(t) - x^*(t))^T \cdot Q \cdot (x(t) - x^*(t)) + u^T(t) \cdot R \cdot u(t)\}dt \quad (18)$$

where x is a vector of the states of the controlled plant (e.g., motor position and velocity), x^* is a vector of the desired states (e.g., commanded motor position and velocity), u is the control effort (e.g., motor current), and Q and R are weighting factors (or matrices containing weighting factors). The magnitude of Q indicates the importance of minimizing the tracking error, while the magnitude of R indicates the importance of minimizing the control effort when performing the control task. A motor control designer can, for example, increase Q to improve the position/velocity tracking performance at the expense of higher overall motor current. Correspondingly, increasing R will reduce the overall motor current at the expense of position/velocity tracking performance.

Given a dynamic system represented by the linear model

$$\dot{x} = A \cdot x + B \cdot u \quad (19)$$

where A and B are constant matrices, the feedback control law that minimizes the cost function of Eq. (18) is

$$u = -K \cdot (x(t) - x^*(t))^T \quad (20)$$

where K is the optimal feedback gain matrix computed from

$$K = R^{-1} \cdot B^T \cdot S \quad (21)$$

and S is the solution to the algebraic Riccati equation

$$0 = A^T \cdot S + S \cdot A - S \cdot B \cdot R^{-1} \cdot B^T \cdot S + Q \quad (22)$$

A feedback controller generated from this methodology provides guaranteed stability and is called a Linear Quadratic Regulator (LQR).

A simple guideline for selecting the Q and R weighting factors is given in [13]. It basically substitutes the reciprocals of the maximum allowable tracking errors and maximum allowable control effort into the diagonal entries of the corresponding weighting matrices [13].

3.2. Adaptive Linear Quadratic Regulator

Because reducing motor current reduces motor winding temperature and bearing load, motor lifetime can be extended by exploiting the ability to minimize motor current in the LQR design methodology. Our approach to controlling motor lifetime is based on adapting the Q and R weighting factors online according the need to increase/decrease performance and lifetime. The adaptation of Q and R is simplified by inserting a scalar variable ρ into the optimal control cost function of Eq. (18) as follows

$$J = \int_0^\infty \{(x - x^*)^T \cdot \frac{1}{\rho} \cdot Q \cdot (x - x^*) + u^T \cdot \rho \cdot R \cdot u\}dt \quad (23)$$

Thus, increasing ρ has the effect of generating LQR feedback gains that provide longer motor lifetime but poorer tracking performance. Conversely, decreasing ρ will generate LQR feedback gains that provide better tracking performance at the expense of reduced motor lifetime.

With ρ inserted into the cost function, the optimal feedback gain matrix K is then computed from

$$K = \frac{1}{\rho} \cdot R^{-1} \cdot B^T \cdot S \quad (24)$$

where S is the solution to the equation

$$0 = A^T \cdot S + S \cdot A - S \cdot B \cdot \frac{1}{\rho} \cdot R^{-1} \cdot B^T \cdot S + \frac{1}{\rho} \cdot Q \quad (25)$$

The optimal feedback gain matrix K can be computed very quickly for low-dimension problems, which allows K to be updated in real-time in response to changing values of ρ. For high-dimension problems, it is possible to pre-compute a collection of optimal K matrices corresponding to different ρ values and store the matrices in a lookup table. Interpolation from the lookup table can then be used to generate optimal K matrices online based on changing values of ρ.

3.3. Tracking Control of Desired Lifetime

To provide tracking control of desired motor lifetime, we use the following simple adaptation law for ρ.

$$\dot{\rho} = -K_p (L(t) - L^*(t)) - K_d \frac{d}{dt}(L(t) - L^*(t)) \quad (26)$$

where K_p and K_d are positive constants, $L^*(t)$ is the desired residual lifetime of the motor and $L(t)$ is the estimated residual lifetime of the weakest component (i.e., the residual lifetime of the winding or the residual lifetime of the bearing, whichever is less).

This adaptation law basically increases ρ when the estimated residual lifetime of the motor is less than the desired residual lifetime, resulting in new LQR feedback gains that increase motor lifetime and reduce motor performance. Conversely, when the estimated residual lifetime is greater than the desired residual lifetime, ρ is reduced to allow the “excess” lifetime to be used to improve motor performance. The derivative term in Eq. (26) provides damping during the adaptation process to facilitate stable convergence.

$L^*(t)$ in Eq. (26) can be in units of absolute residual life-hours or percentage residual life, as long as K_p and K_d are scaled appropriately. In our implementation, we chose to use the absolute residual life-hours. Specifically,

If $Liferes \le L_{10res}$ then $L = Liferes$

else $L = L_{10res}$

where *Liferes* is the winding's residual lifetime and L_{10res} is the bearing's residual lifetime as defined in Sections 2.1 and 2.2.

Tracking control of actuator motor lifetime based on the above algorithm was tested in simulation. Due the slow change in winding and bearing residual lifetimes, it would require many hours of motor operation (and hence extremely long simulations) for the change in residual life to become noticeable. To reduce simulation time, we significantly reduced the motor's thermal time constant in the simulation model (changing the thermal time constant from 10 minutes to 10 seconds). We also increased the motor inertia tenfold to intensify the acceleration load and thereby push the winding temperature and bearing load to much higher values than those seen in normal operation. As a result, a visible consumption of winding and bearing lifetimes can be observed for reasonable simulation times.

Fig. 4 shows a simulation case in which the motor winding is the weaker component. Thus, adaptation of ρ is focused on regulating the winding residual lifetime. In this example, the motor is commanded to follow a high frequency sinusoidal position trajectory (shown in Fig. 5) while the actuator is under constant external load. During actuator operation, step changes in the desired motor residual lifetime are commanded. As can be seen from Fig. 4, the adaptive control algorithm increases ρ when longer residual lifetime is needed, resulting in decreased winding temperature at the expense of larger position tracking error. When the residual lifetime exceeds the desired value, ρ is then decreased to bring the motor back to its original level of high performance. It is interesting to note that low desired residual lifetime cannot always be achieved, because it may

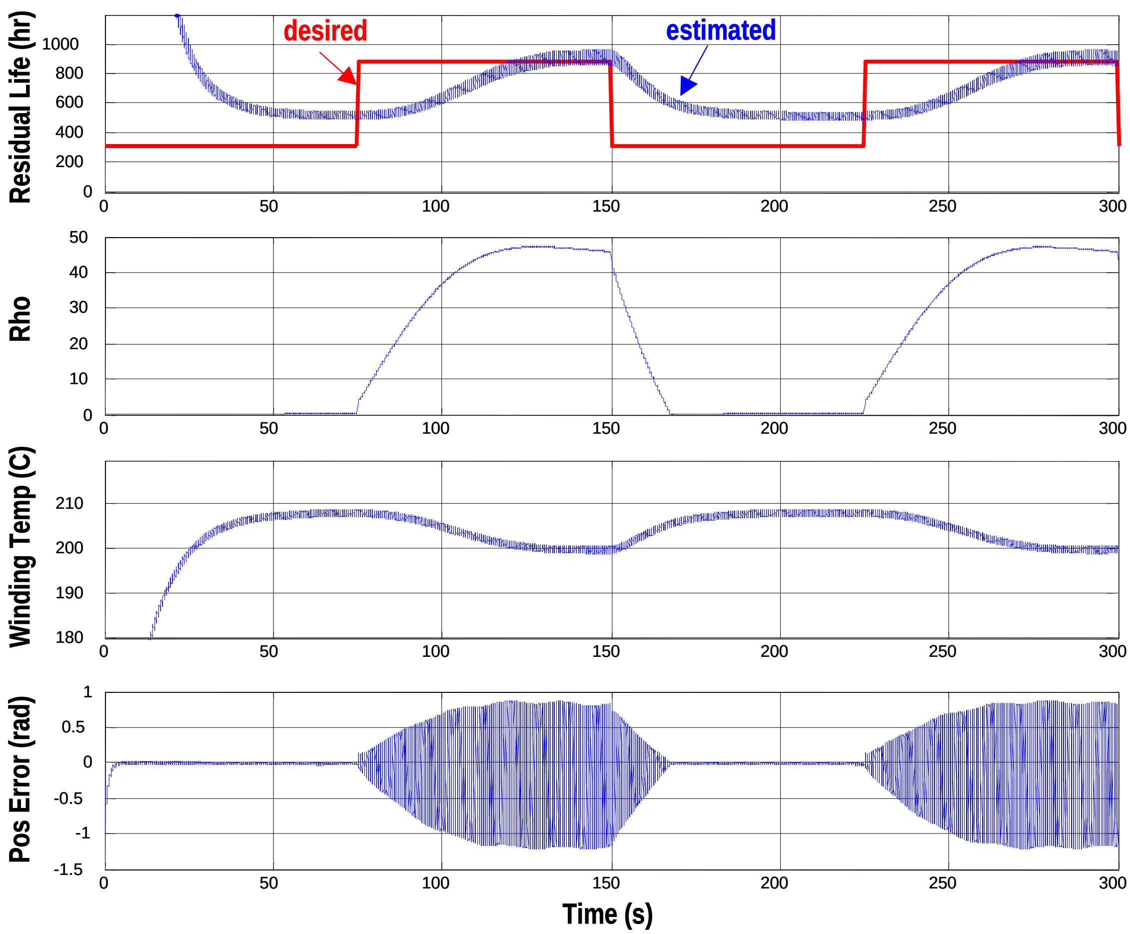

Figure 4 – Tracking control of motor winding lifetime using adaptive Linear Quadratic Regulator.

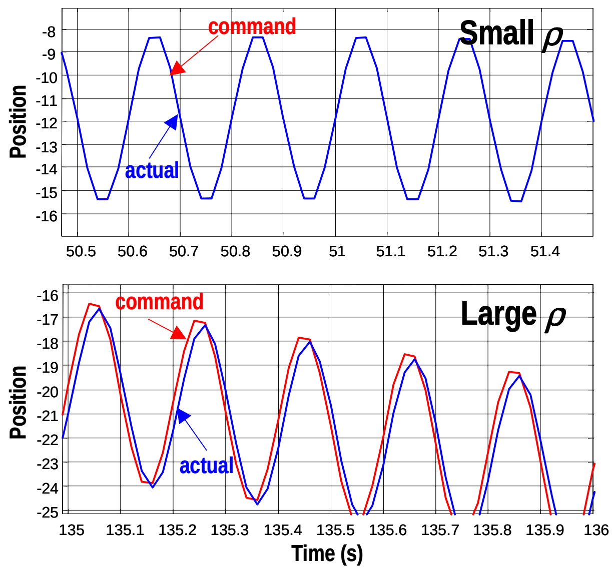

Figure 5 – Motor position response during tracking control of motor winding lifetime.

require a performance level that exceeds the bandwidth of the digital controller or the output current limit of the motor drive.

Fig. 5 shows the motor position response corresponding to instances of small ρ value and large ρ value. Note that the time scale in Fig. 5 provides an expanded view of the position errors manifested at different time intervals in Fig. 4.

4. Performance/Lifetime Trade-off

The adaptive LQR methodology described above enables a motor to achieve the desired residual lifetime by sacrificing position/velocity tracking performance. However, a motor controller must balance the need for extended lifetime with the need for good performance. In this section, we present a method that provides adaptive trade-off between motor performance and lifetime based on vehicle mission needs.

4.1. Adaptive Performance/Lifetime Trade-off

Actuator performance demand may vary throughout different phases of a vehicle's mission. For example, actuator performance during flight over friendly territory is not as critical as during combat maneuvers. By emphasizing actuator motor performance (expending life) when a vehicle maneuver is critical while relaxing performance (extending lifetime) when a maneuver is not critical, motor usage can be optimized to achieve extended life while meeting critical performance demands.

Our goal is to construct a supervisory control function that adaptively adjusts motor performance/lifetime trade-off based on mission needs. Following the same approach as the lifetime tracking control algorithm, the supervisory control function can use the ρ value to regulate the performance/lifetime trade-off. The general adaptive behaviors that we would like to achieve are as follows:

1. Increase ρ (extend motor lifetime) if the actuation task has low priority and the present performance is adequate

2. Increase ρ if the motor's residual lifetime is short and performance is adequate

3. Decrease ρ (increase motor performance) if the actuation task has high priority and the present performance is poor

These behaviors can be naturally implemented using fuzzy logic rules. As a result, we constructed a set of fuzzy logic rules that adjusts ρ based on (i) the priority of the actuation task, (ii) the position tracking performance, and (iii) residual lifetime of the motor. In our implementation, the priority of an actuation task is defined as a number between 0 and 10, where 10 represents the highest priority; the position tracking performance is judged simply by the present position error of the motor; and the residual lifetime of the motor is judged by comparing actual winding temperature or actual bearing load to the desired winding temperature or desired bearing load corresponding to the desired residual life. It is possible to use other criteria to judge the quality of position tracking performance and the adequacy of residual lifetime. Refinement of these criteria is a subject for future work.

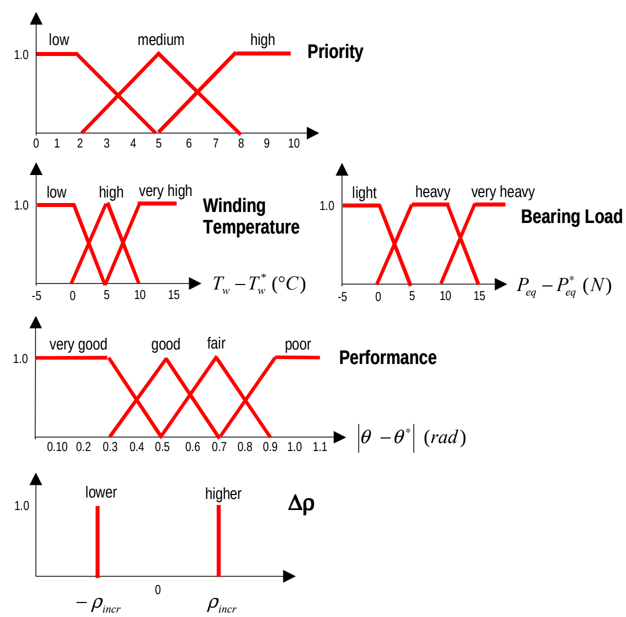

Figure 6 – Fuzzy membership functions used in decision rules for adapting performance/lifetime trade-off.

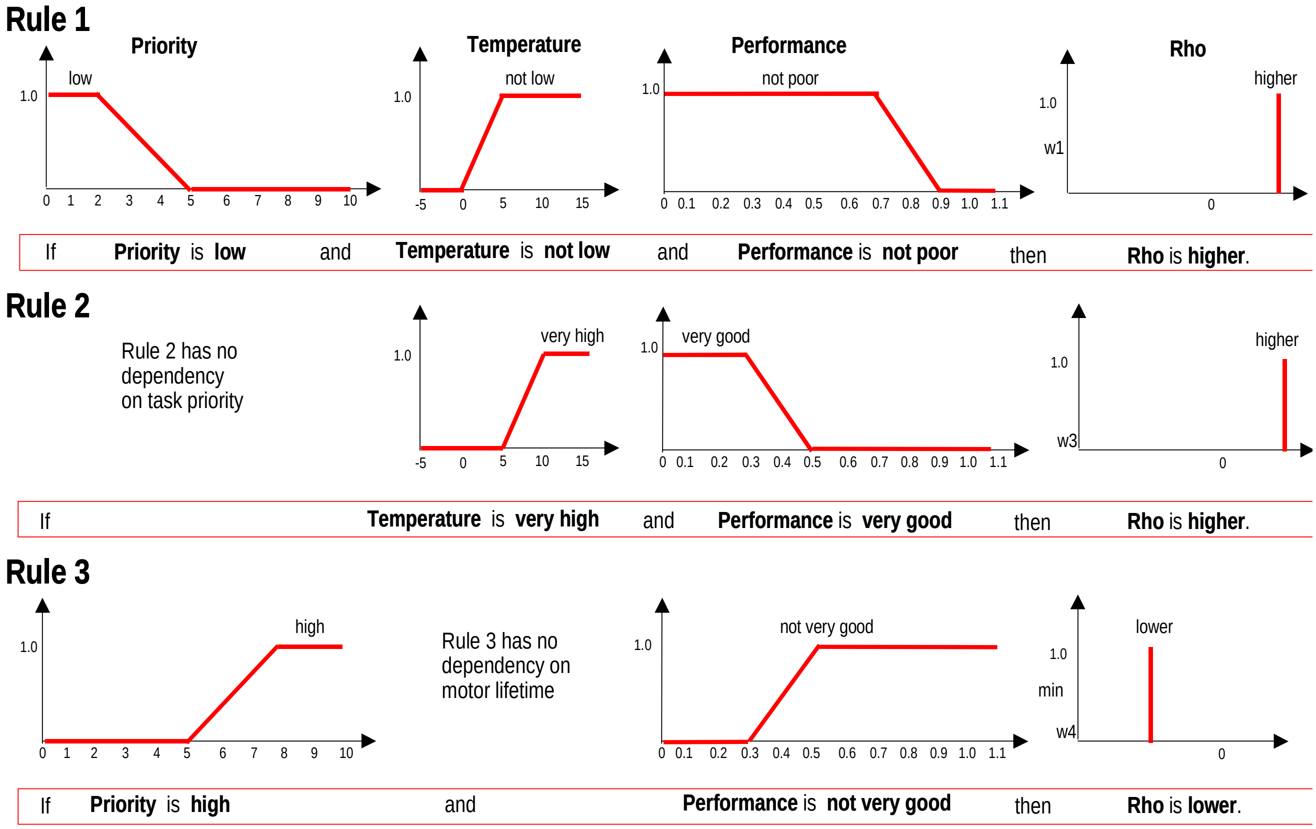

Figure 7 – Representative fuzzy rules for adapting ρ value.

Our fuzzy supervisory control function uses only 8 rules. The membership functions that describe the input and output variables of the fuzzy rules are shown in Fig. 6 and some representative rules are shown in Fig. 7. An explanation of the fuzzy inference procedure can be found in [14]. Only the residual lifetime of the weakest component is considered when evaluating the adequacy of the motor's residual lifetime. For example, if the winding residual lifetime is less than the bearing residual lifetime, then any rule that has a dependency on motor lifetime will evaluate a clause related to winding temperature (e.g., "winding temperature is very high"); otherwise these rules will evaluate an equivalent clause related to bearing load (e.g., "bearing load is very heavy"). A block diagram of the actuator control system with adaptive performance/lifetime trade-off function is shown in Fig. 8.

4.2. Simulation Results

Actuator control incorporating the adaptive performance/lifetime trade-off function has been tested in simulation. Fig. 9 shows a simulation case in which the actuation task has a priority of 2 (low priority) and successive step increases in desired motor lifetime were commanded. The motor winding is the weaker component in this case; thus the adaptive trade-off is focused on motor performance versus winding lifetime.

For low priority tasks, the trade-off favors providing long lifetime unless the performance becomes unacceptably poor. In the initial phase in Fig. 9, the residual lifetime is well above the desired value and the performance belongs in the "very good" category. After a step increase in desired residual lifetime, the adaptive trade-off function increases ρ to continue to keep the residual lifetime well above the new desired value; it can afford to keep the residual life well above the desired value because the resultant degradation in performance is still very acceptable for a low priority task. After another step increase in desired residual lifetime, ρ is further increased to meet the demand. However, the adaptive trade-off function will no longer maintain a large margin of residual lifetime above the desired value, because doing so would push the performance into the "poor" category.

Fig. 10 shows a simulation case in which step changes in task priority were commanded. The actuation task initially has a priority of 8 (high priority), which demanded good performance at the cost of accepting a low residual lifetime. When the task priority is lowered to 2, the performance/lifetime trade-off emphasis shifts to providing long lifetime, and ρ is thereby increased to push the residual lifetime above the desired value. As the task priority is raised to 8 again, lifetime is sacrificed to support the renewed need for good performance.

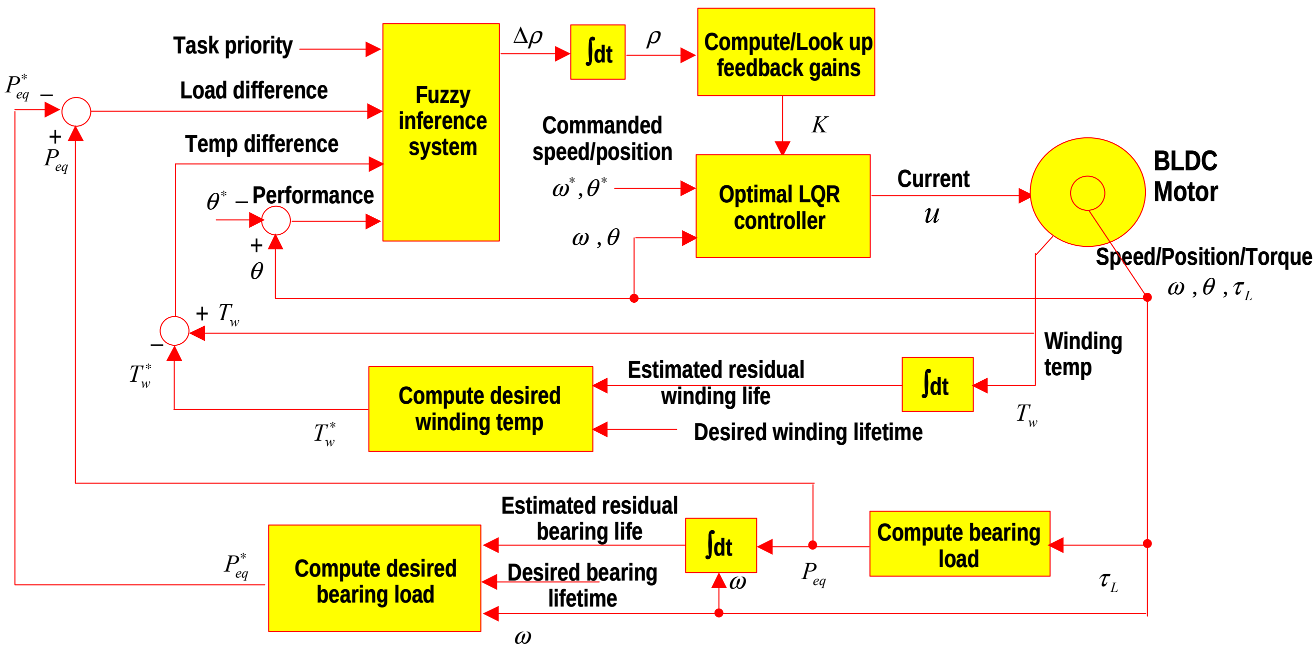

Figure 8 – Actuator control system block diagram showing integration of standard LQR control with adaptive performance/lifetime trade-off function.

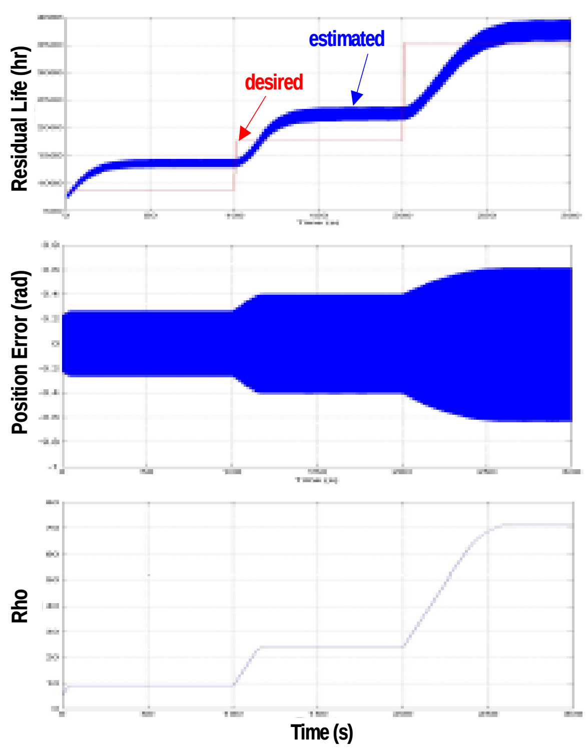

Figure 9 – Simulation of adaptive performance/lifetime trade-off with successive step increases in desired residual lifetime.

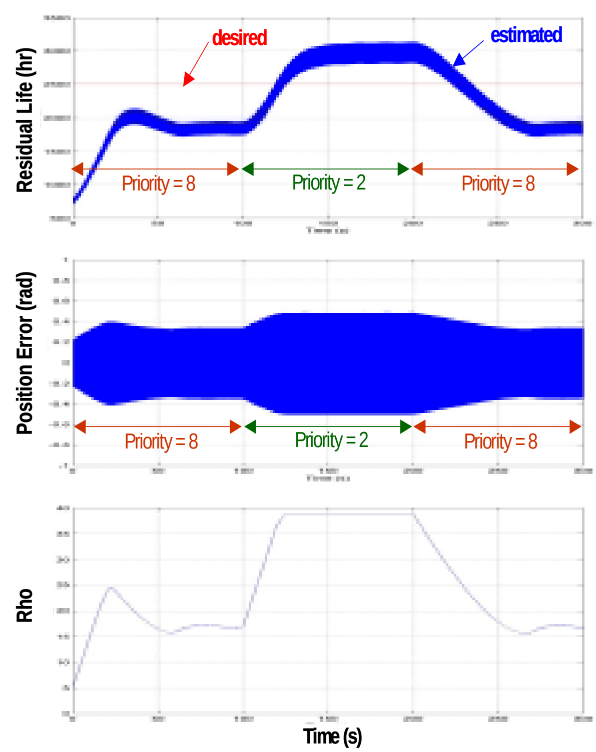

Figure 10 – Simulation of adaptive performance/lifetime trade-off with step changes in task priority.

5. CONCLUSION

We presented a new machinery control concept that incorporates the desired machinery lifetime as a controlled parameter. The ability to actively control machinery lifetime will reduce maintenance cost and improve system safety and reliability. The application of this concept to actuator motor control was explored.

Two adaptive methods for motor lifetime control were discussed. The first method provides tracking control of a desired motor lifetime by adapting the motor performance level. The second method provides adaptive trade-off between motor performance and lifetime based on mission needs. Both control methods exploit the Linear Quadratic Regulator (LQR) design methodology by tuning the weighting factors in the optimization cost function to achieve the desired performance/lifetime objective. Stability of the resultant motor lifetime controllers is guaranteed due the inherent stability property of LQR design.

The use of fuzzy logic rules in performance/lifetime adaptation provides a high degree of flexibility in implementing intelligent trade-off behaviors. Different measures of machinery performance and measures of criticality of residual life can also be incorporated into the fuzzy rules.

Whether accurate lifetime control can be achieved is critically dependent on the accuracy of the models used in estimating residual life. In our derivations, we have used lifetime models established by winding and bearing manufacturers for constant operating conditions (i.e., constant temperature, constant load), and extrapolated these models for use in variable operating conditions by assuming that the damages incurred at each of the operating conditions are linearly additive. It is very likely that this assumption of linearly additive damage is too simplistic. Deriving an accurate damage model through physics-based modeling and experimental verification is a key area for future work.

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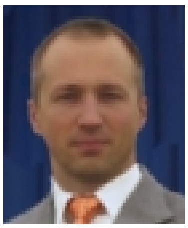

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