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Controlling the Remaining Useful Lifetime using Self-Optimization

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Self-optimizing mechatronic systems offer possibilities well beyond those of traditional mechatronic systems. Among these is the adaptation of the system behavior to the current situation. To do so, they are able to choose from different working points, which are pre-calculated using multiobjective optimization and are thus Pareto-optimal with regard to the chosen objective functions. In this contribution, a method is presented that allows to continuously control the system degradation by adapting the behavior of a self-optimizing system throughout its complete lifetime. The current remaining useful lifetime is estimated and then related to the spent lifetime and the desired useful lifetime. Using this information, a reliability-related objective is prioritized using a closed-loop control, which in turn is used to determine the working point of the self-optimizing system. This way, the desired useful lifetime can be achieved.
To exemplify the setup of the controller structure and to demonstrate the adaptation of the system behavior, a dynamic model of a clutch system is used. It can be seen that the closed loop controller is able to correct for external perturbations, such as changed requirements, as well as changed system parameters. This way, the modeled system is able to achieve the desired lifetime reliably.

1. Introduction

Self-optimizing mechatronic systems are able to autonomously adapt their behavior if the user requirements or operating conditions change (Gausemeier et al., 2013). To this end, the current situation is monitored and the objectives of the system are determined. Using model based multiobjective optimization, for which a model of the dynamical behavior of the system is used, optimal system configurations are calculated before operation of the system. To adapt the system behavior during operation, the self-optimizing system selects among these optimal system configurations.
In order to use self-optimization to ensure that the requirements regarding reliability of the system are met, a suitable selection process has to be implemented. To adapt the system behavior advantageously with regard to system reliability, it has to be possible to lower work load or wear on critical components by selecting appropriate optimal system configurations. Thus it is also necessary to include system degradation in the objective functions used for the multiobjective optimization.
To control the remaining useful lifetime, the whole system history has to be taken into account as well. If it was to be included in the model used for the model based multiobjective optimization, the optimization process would take disproportionally long, effectively rendering this approach impossible. Thus a process to take the system history into account separately during operation is required. For this, our presented self-optimization based remaining useful lifetime controller can be used.

2. Controlling the Remaining Useful Lifetime

One strategy to increase the productive lifetime of a system is a precise maintenance strategy. The aim is to increase uptime and reduce downtime to achieve higher availability. With the further development of sensor technologies and sensor fusion techniques, a lot of sensor data to determine the current health state of a component or subsystem is accessible. Based on the current data and the system history, the

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remaining useful lifetime can be estimated. For the estimation of the remaining useful lifetime, many methods, subdivided into statistical approaches, model-based approaches and artificial intelligence approaches, are readily available (Jardine, 2006). Given this remaining useful lifetime estimation, maintenance can be conducted condition-based in order to use the respective component as long as feasible with regard to e.g. product quality, concerning machine tools, or system safety in general. Increasing the availability and reliability of a system is mainly done during the development phase of a system. A first approach to influence the maintenance of a system during runtime is presented by so called self-maintaining systems. These systems are equipped with functional redundancies and therefore are able to reconfigure in the case of a failure (Umeda, 1992). This reconfiguration prolongates the availability by recovering the original function, but is not able to adapt the system to unforeseen situations.
Only few approaches focus on controlling the reliability of the system during the operating phase. An approach to control the safety and reliability of a system is suggested in (Wolters, 2005). This approach uses reliability characteristics like the probability of failure, failure rate, etc. to control the system's failure behavior. In order to influence the system, operating parameters or strategies are changed.
The concept of Reliability-Adaptive Systems is presented by (Rakowsky, 2005). These systems should fulfill two main requirements: Firstly, the capability of quantifying the current system reliability and secondly, the capability of influencing the system behavior. For the influence, different aspects are mentioned. One option is to control the reliability in the sense of a closed loop control; another option is to enhance the preventive maintenance by estimating the maintenance point in time more precisely.
Both mentioned approaches are not trying to control the remaining useful lifetime directly. A multi-objective optimization approach concerning the reliability within an optimization objective is not considered. Controlling the reliability opens up the possibility to fulfill desired maintenance intervals while at the same time, in contrast to condition-based maintenance, utilizing the system up to its full potential.

3. Example System

The example system used within this paper is a single plate dry clutch. This type of clutch is commonly utilized in passenger vehicles to connect an internal combustion engine to the drivetrain. The basic outline of the clutch system is shown in Figure 1. It consists of two friction plates with coefficient of friction μ, of which the input plate is connected to the engine while the output plate is connected to the driven system, e.g. a gearbox. The input and the output plates are rotating at speeds ω_1 and ω_2 respectively. To engage the clutch, both plates are pressed against each other by the force F_N, thus transmitting torque from the input plate to the output plate and in turn applying this torque to the driven system.

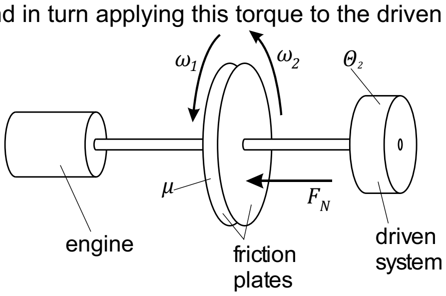

Figure 1: Clutch system

3.1 Modeling the System Dynamics

The torque $T_F(t)$, that can be transmitted by a clutch with effective radius r_{eff}, is calculated as follows:

$$T_F(t) = F_N(t) \cdot \mu\big(\Delta\omega(t)\big) \cdot r_{eff} \tag{1}$$

The force $F_N(t)$ is the actuation force. The clutch is fully disengaged with $F_N = 0\ \mathrm{N}$ and is fully engaged with $F_N = F_{N,max}$. The coefficient of friction $\mu(\Delta\omega)$ depends on the difference in revolutionary speed of the two clutch plates $\Delta\omega(t) = \omega_1(t) - \omega_2(t)$. The first plate is assumed to rotate at a constant speed, $\omega_1 = \mathrm{const.}$, whereas the second plate's dynamics have to be taken into account. These are given by:

$$\dot{\omega}_2(t) = \frac{1}{\Theta_2} \cdot \big(T_F(t) - d_2 \cdot \omega_2(t)\big) \tag{2}$$

All masses of the driven system are merged into the moment of inertia Θ_2. The second plate and the driven system are damped with parameter d_2.

The coefficient of friction is given by (Popov, 2010):

$$\mu(\Delta\omega) = \mu_0 \cdot \frac{2}{\pi} \cdot \arctan\left(\frac{\Delta\omega}{\widehat{\omega}}\right) \approx \begin{cases} -\mu_0 & \text{if } \Delta\omega \leq -0.1 \\ \mu_0 \cdot 10 \cdot \Delta\omega & \text{if} -0.1 < \Delta\omega < 0.1 \\ \mu_0 & \text{if } \Delta\omega \geq 0.1 \end{cases} \tag{3}$$

The parameters of the system are not based on a real clutch but chosen arbitrarily. They are as follows: $\omega_1 = 1\,\frac{\mathrm{rad}}{\mathrm{s}}$, $\Theta_2 = 1\,\frac{\mathrm{kg}}{\mathrm{m}^2}$, $d_2 = 10\,\frac{\mathrm{N \cdot m \cdot s}}{\mathrm{rad}}$, $r_{eff} = 1\ \mathrm{m}$, $F_{N,max} = 100\ \mathrm{N}$, $\mu_0 = 1$.

3.2 Estimating the Remaining Useful Lifetime

The most vulnerable components of the clutch system are the friction plates, which transmit torque by means of dry friction, which in turn induces wear. A model-based approach has been selected to estimate the remaining useful lifetime which is based on the assumption that clutch plate wear is proportional to the energy dissipated through friction E_f (Fleischer, 1973). For each actuation cycle k with time span $t = t_0 \dots t_0 + t_r$, where t_r is the duration of the actuation cycle, the wear w is:

$$w(k) = p_f \cdot E_f(k) = p_f \cdot \int_{t_0}^{t_0+t_r} P_f(t)\mathrm{d}t \ = p_f \cdot \int_{t_0}^{t_0+t_r} T_F(t) \cdot \Delta\,\omega(t)\mathrm{d}t \tag{4}$$

To estimate the remaining useful lifetime, all actuation cycles need to be taken into account. To do so, the sum of $w(i)$ from cycle $i = 1$ until the current cycle $i = k$ is calculated. The remaining useful lifetime RUL for the next cycle $k+1$ can then be estimated by taking the maximum amount of wear w_{max} of the clutch into account. This results in the following relation:

$$RUL(k+1) = 1 - \left(\frac{\sum_{i=1}^{k} w(i)}{w_{max}}\right) \tag{5}$$

With this formula, several minor aspects of clutch wear are neglected in favor of short simulation times, e.g. the influence of temperature on the proportionality factor p_f, which we assume to be $p_f = 1$.

3.3 Multiobjective Optimization

A control trajectory for the actuation force $F_N(t)$ has to be computed to actuate the clutch system. For this, multiobjective optimization techniques are employed, which attempt to minimize user defined objective functions by adapting system parameters. Typically, it is not possible to minimize multiple objective functions at once, but instead as one function's value is lowered, another function's value rises. This leads to the so-called Pareto front, which consists of all optimal compromises between multiple objective functions. To each point on the Pareto front, system parameters are given in the Pareto set. To compute Pareto front and –set, a genetic algorithm which comes with the Matlab global optimization toolbox has been used.

The required objective functions are included in the model of the system dynamics outlined in section 3.1. For our system, the objective functions are f_1, which represents the power loss in the clutch P_f and in turn corresponds to the wear rate of the clutch plates, as has been described in section 3.2, and f_2, which represents e.g. comfort of vehicle passengers:

$$f_1 = \int_{t_0}^{t_0+t_r} P_f(t)^2\mathrm{d}t = \int_{t_0}^{t_0+t_r} \big(T_F(t) \cdot \Delta\omega(t)\big)^2\mathrm{d}t \tag{6}$$

$$f_2 = \int_{t_0}^{t_0+t_r} \big(\dot{\omega}_2(t)\big)^2\mathrm{d}t \tag{7}$$

To compute the values of these objective functions, the dynamical model of the system is simulated over the period $t = t_0 \dots t_0 + t_r$ using trajectories for $F_N(t)$ as simulation input.

The duration of the actuation cycle and the shape of the trajectory are the optimization parameters. To include these in the optimization procedure, we subdivided the trajectory into 16 sections with equal durations. For the trajectory to begin with a completely disengaged clutch and end with a completely engaged clutch, $F_N(t_0) = 0\ \mathrm{N}$ and $F_N(t_0 + t_r) = F_{N,max}$ are assumed. The optimization parameters are then the total duration of the actuation cycle t_r and the shape computed by using 15 intermediate values $F_N\left(t_0 + \frac{i}{16} \cdot t_r\right)$, $i = 1 \dots 15$. Linear interpolation is used between these values. This way, the Pareto front shown in Figure 2 is obtained. A short total duration of the actuation cycle yields low energy losses but high accelerations, as opposed to a long duration, which yields inverse results. Each trajectory is a trade-off between these two objectives.

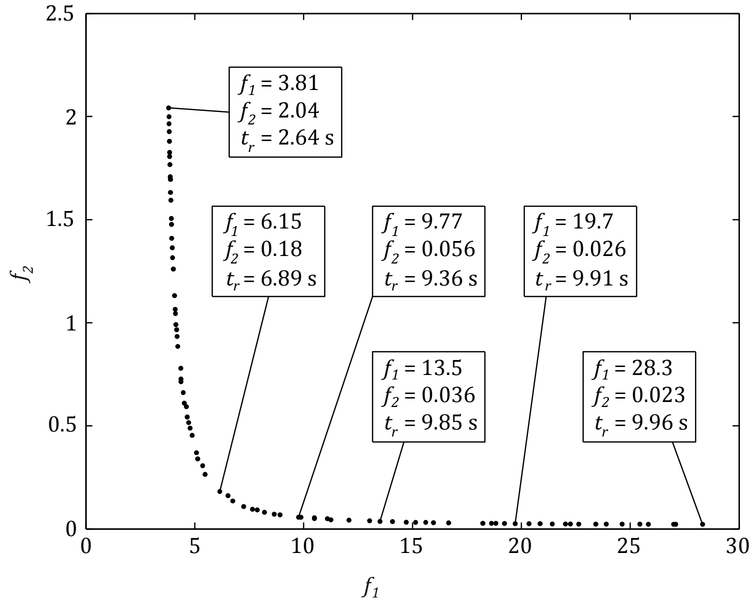

Figure 2: Pareto front for the clutch system with several selected points

4. Closed-loop controller for the Remaining Useful Lifetime

The proposed controller structure is shown in Figure 3. The model of the clutch system, the RUL estimation and the optimization look up, which contains Pareto front and Pareto set as results from the multiobjective optimization, are known from section 3. What is required furthermore are the controller and the generation of the RUL trajectory. The controller is a discrete closed-loop controller, which calculates the system input parameters for the k^{th} cycle using data from cycles $1 \dots k-1$.

Based on the current system requirements, a trajectory for the remaining useful lifetime is calculated. It begins with $RUL_{des}(0) = 100\,\%$ and ends with $RUL_{des}(k_{max}) = 0\,\%$ and has to be strictly monotonically decreasing. It can be altered during operation in order to adapt the system behavior.

The difference in desired remaining useful lifetime and achieved remaining useful lifetime is calculated from this trajectory and the estimated remaining useful lifetime known from Eq (5). The controller then determines the required values for the system objectives f_1 and f_2. Using the pre-calculated optimization results, the system parameters t_r (actuation cycle duration) and $F_N(t)$ (actuation trajectory) are known. These are used for the next actuation of the clutch system, which is modeled using Eqs (1), (2) and (3).

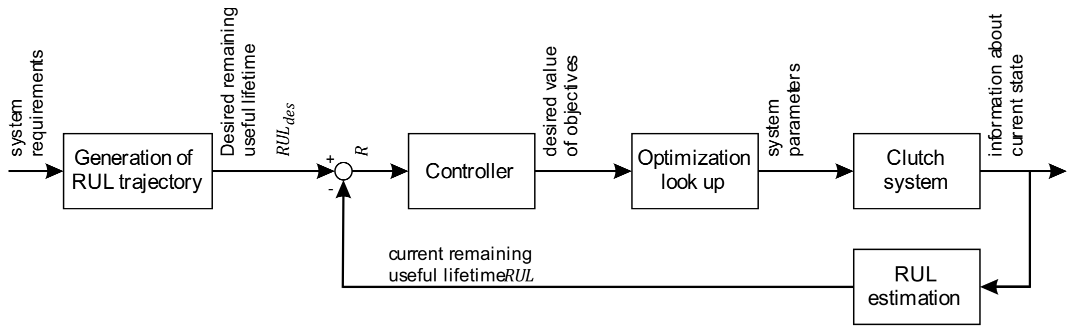

Figure 3: Structure of the system with self-optimization based controller for the remaining useful lifetime.

4.1 Implementation of the controller

The control error $R(k) = RUL(k) - RUL_{des}(k)$ is used as controller input. To compute the controller signal, which is the value of one objective, a discrete PID controller is used:

$$f_1(k) = P \cdot R(k) + I \cdot \sum_{i=1}^{k} R(i) + D \cdot \big(R(k-1) - R(k)\big) \quad (8)$$

This way, for the next actuation cycle, the desired value of the objective $f_1(k)$ is known. The closest known point is selected from the pre-calculated Pareto front, which also sets $f_2(k)$. With the corresponding data from the Pareto set, the system parameters actuation duration and the actuation trajectory are known.
The parameters P, I and D have to be adapted to the system. For our clutch system, they were determined empirically ($P = 3750$, $I = 10$, $D = 650$).

5. Results

Figure 4 shows simulation results of a system model as outlined in section 3.1. To adapt the working point, the controller described in section 4 is used. In order to achieve good controller performance, the actual value, which in this case is the RUL, needs to be known as precisely as possible. For a real clutch system e.g. the thickness of the friction pad could be measured; however in the model, the estimation of the obtained RUL is conducted according to section 3.2. .The desired RUL, which serves as input for the closed loop controller, linearly decreases over the span of 500 actuation cycles. As can be seen, the adaptive system starts out with the working point $(f_1, f_2) = (19.7, 0.026)$, $t_r = 9.91$ s but adapts its behavior within approximately ten cycles to $(f_1, f_2) = (13.5, 0.36)$, $t_r = 9.85$ s, both of which are also highlighted in Figure 2. After this, the working point is not changed much. Note that the controller values are continuous, whereas the working points available in Pareto front and Pareto set are discrete. Due to this, the system might continuously switch between two working points that are close to the one desired working point which is not available. As can be seen, deviations between desired and obtained RUL are very low.

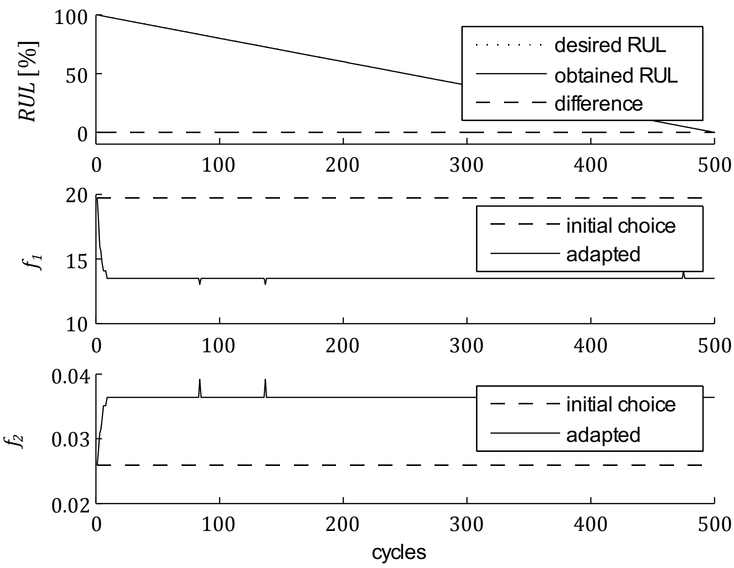

Figure 4: System behavior adaptation from an arbitrary starting point

Such behavior could also be obtained by selecting an appropriate working point in the first place. However, this is limited to the goals known during development, an adaptation during runtime is not possible.
If the desired remaining useful lifetime changes, e.g. because of extended maintenance intervals, the system behavior has to be adapted, as is shown in Figure 5. At cycle 200, due to an external event, the desired remaining useful lifetime RUL_{des} is increased from 500 cycles to 600 cycles. The static system is not able to fulfill these changed requirements, whereas the adaptive system can do so easily by adapting the working point to $(f_1, f_2) = (9.77{,}0.056)$, $t_r = 9.36$ s.
In another scenario, the system deteriorates more quickly than was anticipated, e.g. due to manufacturing tolerances or due to changed working conditions. In Figure 6, the system deterioration per cycle has been increased from cycle 200 onwards by altering $p_f = 2$ in Eq (3). The adaptive system is able to adapt its behavior to these changed operating conditions by selecting $(f_1, f_2) = (6.15, 0.18)$, $t_r = 6.89\ s$ and to meet the required number of cycles. The static system fails early and does not fulfill the reliability requirements.

6. Conclusion and Outlook

A novel strategy to actively control the remaining useful lifetime of mechatronic systems by using self-optimization has been introduced. To this end, Pareto optimal working points, which are computed by

using a multiobjective optimization algorithm and a model of the dynamic behavior of the system, are used. The proposed controller selects the current working point based on the estimated remaining useful lifetime of the system and the desired remaining useful lifetime. By using this controller, either a pre-determined desired remaining useful lifetime can be ensured even though the system deteriorates differently than was anticipated during development or the desired remaining useful lifetime can be changed during runtime, e.g. to better comply with maintenance intervals.
A model of a clutch system is used to exemplify the setup of this controller. The results of simulations of the clutch system show that the desired remaining useful lifetime can be achieved reliably. In this work, a basic controller that was parameterized empirically was used. We assume that it is possible to apply more advanced controller design techniques, however this was beyond the scope of this paper. Also systems with more than two optimization objectives, which are able to not only adapt their behavior based on the system reliability but also, at the same time, on other requirements, demand further investigation.
The controller performance depends heavily on the precision of the estimation of the obtained RUL. It might prove necessary to include stochastic information about this in a future revision of the controller.

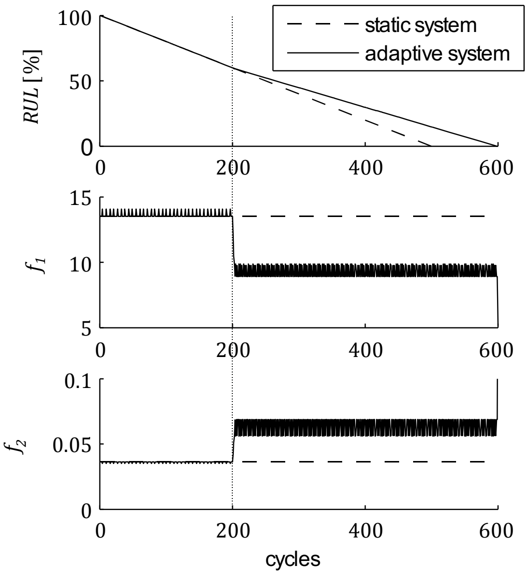

Figure 5: At 200 cycles, the requirements are changed to a desired RUL of 600 cycles

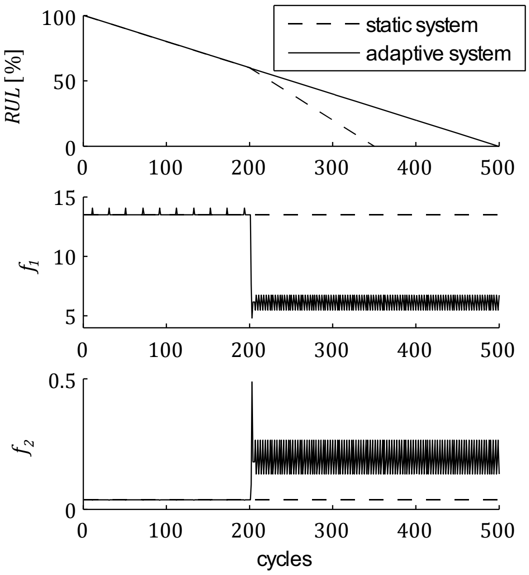

Figure 6: At 200 cycles, the wear of the clutch plates is increased by factor 2, prompting the static system to fail early

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References

Fleischer, G., 1973: Energetische Methode der Bestimmung des Verschleißes (*Energetic method to determine wear*, in German). Schmierungstechnik, 4(9), 269-274.

Gausemeier, J., Rammig, F., Schäfer, W., Sextro, W. (Eds.), 2013: Dependability of Self-Optimizing Mechatronic Systems. Springer, Berlin, Heidelberg, Germany.

Jardine, A., Lin, D., Banjevic, D., 2006: A review on machinery diagnostics and prognostics implementing condition-based maintenance, Mechanical systems and signal processing, 20, 1483–1510.

Popov, I., 2010: Contact Mechanics and Friction. Springer, Berlin, Heidelberg, Germany.

Rakowsky, U.K., 2005: An Introduction to Reliability-Adaptive Systems. Advances in Safety and Reliability, Vol. II, Proc. of the European Safety & Reliability Conference, 2005, 1633-1636.

Umeda, Y.; Tomiyama, T.; Yoshikawa, H., 1992: A design methodology for a self-maintenance machine. First Int. Conf. on Intelligent Systems Engineering, 19-21 Aug 1992, 179-184.

Wolters, K.; Söffker, D., 2005: An Approach to Affect the Probability of Failure by Changed Operation Modes. In: Advances in Safety and Reliability, Vol. II, Proc. of the European Safety & Reliability Conference, Tri City, Poland, June 27 - 30, 2005, 2047-2051.