Preprints, 9th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes
September 2-4, 2015. Arts et Métiers ParisTech, Paris, France

Advantages of reliability-adaptive system operation for maintenance planning ⋆

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Abstract: Intelligent mechatronic systems offer the possibility to adapt system behavior to current dependability. This can be used to assure reliability by controlling system behavior to reach a pre-defined lifetime. By using such closed loop control, the margin of error of useful lifetime of an individual system is lowered. It is also possible to change the pre-defined lifetime during operation, by adapting system behavior to derate component usage. When planning maintenance actions, the remaining useful lifetime of each individual system has to be taken into account. Usually, stochastic properties of a fleet of systems are analyzed to create maintenance plans. Among these, the main factor is the probability of an individual system to last until maintenance. If condition-based maintenance is used, this is updated for each individual system using available information about its current state. By lowering the margin of error of useful lifetime, which directly corresponds to the time until maintenance, extended maintenance periods are made possible. Also using reliability-adaptive operation, a reversal of degradation driven maintenance planning is possible where a maintenance plan is setup not only according to system properties, but mainly to requirements imposed by maintenance personnel or infrastructure. Each system then adapts its behavior accordingly and fails according to the maintenance plan, making better use of maintenance personnel and system capabilities at the same time. In this contribution, the potential of maintenance plan driven system behavior adaptation is shown. A model including adaptation process and maintenance actions is simulated over full system lifetime to assess the advantages gained.

Keywords: Adaptive systems, Reliability analysis, Availability, Adaptive control, Maintenance, Self-optimizing systems, Self-optimizing control, Stochastic Petri-nets

1. INTRODUCTION

Availability is the key to cost efficient operation of fleets of systems. To achieve good availability, maintenance has to be scheduled such that usable lifetime is maximized, while unexpected failures are avoided. Unexpected failures not only inhibit system usage, they also severely compromise efficiency of maintenance itself. The system might have to be recovered and repair teams might be busy, both contributing to long maintenance times. However, unexpected failures can occur at any time, necessitating a probabilistic approach to maintenance planning. A trade-off between the probability of an unexpected failure, usable lifetime before maintenance and the number of repair teams has to be found.

While this is purely reacting to degradation, reliability-adaptive systems offer the possibility to adapt system behavior to its degradation in order to reach pre-defined maintenance intervals. This way, maintenance can be planned according to system usage requirements or the availability of repair teams, implicitly taking system degradation into account.

In the remainder of this paper, state of the art maintenance strategies are discussed in Sect. 2. Afterwards, one possible implementation of such reliability-adaptive system behavior (Sect. 3) is introduced before appyling this approach to a clutch system as example system (Sect. 4). Sect. 5 goes into details about the reliability of this clutch system, before Sect. 6 introduces a Petri-net used to evaluate system reliability over long time spans and availability of a fleet of systems. Since this is limited and only partially suitable for reliability-adaptive systems, a more complex lifetime simulation model is introduced in Sect. 7. The results of these models and ideas for further work are discussed in Sect. 8. The paper ends with a brief Conclusion in Sect. 9.

2. MAINTENANCE STRATEGIES

In order to keep availability high while keeping the number of unexpected failures low, system usage and maintenance have to be taken into account simultaneously. A simple approach that can be considered to be common knowledge is to use condition based maintenance by assessing the current condition of the system and conducting maintenance if necessary. This increases mean time to failure by scheduling maintenance as late as current system degradation al-

⋆ This research project is funded by the German Federal Ministry of Education and Research (BMBF) within the Leading-Edge Cluster Competition "its OWL" (intelligent technical systems OstWestfalen-Lippe) and managed by the Project Management Agency Karlsruhe (PTKA). The authors are responsible for the contents of this publication.

lows, without impairing availability by scheduling maintenance early enough to avoid unexpected failures. However, maintenance scheduling becomes even more complex than for traditional time- or usage-based maintenance, since spontaneous reactions might be required.

In Cassady and Kutanoglu (2005), an integrated approach for planning maintenance actions of production equipment and production scheduling is presented. While this takes two main parameters of system availability into account, increasing lifetime of production equipment e.g. by derating is not considered. Taking this one step further is Aravinthan and Jewell (2013), where the maintenance cost of a power grid is optimized while keeping reliability within specifications and costs within budget. However, derating is only used to compensate deviations of hazard rate of individual components within one system. Scheduling maintenance based on current condition of a fleet of systems, where maintenance actions might be conducted on one or more systems at a time, but not on all, is not considered.

Multiple systems are considered in Griffith et al. (2012). A structural health monitoring approach to determine damages to blades, i.e. cracks, of individual wind turbines in a wind farm is combined with a maintenance program in which damaged turbines are derated to slow crack growth, while accepting a decrease in production. This way, the overall production until maintenance is lower than for a healthy turbine, but higher than for a non-derated turbine failing early. However, the derating is not automated and it is only designed as means to stop the evolution of existing faults, not to determine suitable system behavior over the whole lifetime.

Reliability-adaptive system operation allows for such an automated adaptation according to current reliability.

3. RELIABILITY-ADAPTIVE OPERATION

The main requirement to allow for reliability-adaptive operation, as it is introduced in Rakowsky (2005), is to make system behavior dependent on current system reliability. This can only be achieved if at first, the current reliability is known and secondly if system behavior can be changed during operation.

The field of reliability estimation is well researched with many examples of successful online-estimation using e.g. condition monitoring techniques. See e.g. Nandi et al. (2005) for electrical motors, Lu et al. (2009) for wind turbines or Jardine et al. (2006) for a general overview focussed on methods suitable for condition-based maintenance. Our approach builds on this but adds a behavior adaptation control loop. The basic idea of closed loop control has been introduced in Meyer et al. (2013a), but an additional modification, which allows for more robust control, was introduced in Meyer and Sextro (2014). Since then, further modifications were conducted to facilitate setup of the control loop while keeping its robustness. Due to space constraints, these cannot be explained in detail, but are used in the remainder of this paper. The basic setup and behavior of the control loop is unchanged and as published in Meyer and Sextro (2014).

This control loop is comprised of two stages: An inner behavior adaptation loop and an outer reliability control loop. The inner loop is based on the work done by Krüger et al. (2013). System behavior is controlled by evaluating current system objectives and setting a newly determined working point accordingly. To determine suitable working points, multiobjective optimization is used. Several possible points are obtained, from which the control algorithm then chooses using a so-called α-parameterization. Reliability can be controlled by including a reliability-related objective in the multiobjective optimization problem. Then, the working point chosen is a trade-off among reliability and other performance objectives, which are impaired if reliability needs to be increased.

The reliability control loop does this by computing suitable values for the α-parameterization, which serves as input to the lower behavior control loop, according to currently desired remaining useful lifetime and currently estimated remaining useful lifetime. As set point, a desired remaining useful lifetime is required. This can be assumed to be linearly falling with $RUL_{des}\left(t=0\right) = 100\%$ and $RUL_{des}\left(t=t_{failure}\right) = 0\%$. However, this set point can also be used to change system behavior. If the desired lifetime $t_{failure}$ is changed during operation, the setpoint needs to be adapted accordingly, resulting in changed system operation.

In prior publications on the same topic referenced herein, a single plate dry clutch system was used as example.

4. APPLICATION EXAMPLE

In keeping with prior publications, the single plate dry clutch system is re-used as application example. A clutch system, as used in many automotive applications, was chosen since it is a well known system of which one component is wearing due to friction, and where the interdepency of usage and wear directly affects system lifetime. In Meyer et al. (2013a) it was shown that for quick clutch engagement, low wear but high accelerations, i.e. low comfort, is obtained, whereas for slower clutch engagement the acceleration process is more comfortable, but clutch wear is increased. The working point selected is always a compromise between these two objectives and can be changed at runtime, as for each actuation cycle, the actuation trajectory can be selected individually. This way, an adaptation of the behavior and in turn an adaptation of the degradation is possible.

As wear is a mechanical abrasion process, it can be modelled quite well. The basic outline of the clutch system is shown in Fig. 1. Due to repeated usage, this introduction is kept very brief. Those interested in further details are asked to refer to Meyer et al. (2013a); Meyer and Sextro (2014). The clutch system 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. 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.

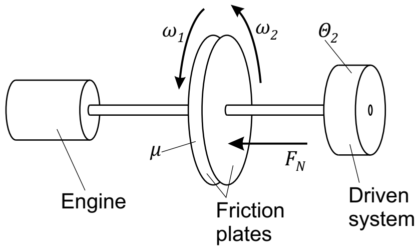

Fig. 1. Basic structure of clutch system.

The dominating failure mode is the inability to transmit torque due to worn out clutch plates. Other failure modes, e.g. actuator or sensor defects, broken mechanical parts or failures in control units, are by far less probable and for this reason are neglected entirely.

In Meyer et al. (2013a) it was shown that using multi-objective optimization techniques, a control trajectory for the actuation force $F_N(t)$ can be computed to actuate the clutch system. The required objective functions are included in a full model of system dynamics. For the clutch system, objective functions are energy dissipated in clutch system, which in turn corresponds to wear of clutch plates, and comfort of vehicle passengers taking human perception into account.

A model-based approach has been selected to estimate the remaining useful lifetime of the friction plates. It is based on an assumption as in Fleischer (1973) that clutch plate wear is proportional to friction energy E_f. For each actuation cycle i, wear w_i is:

$$w_i = w_{i-1} + p_f \cdot \Delta E_{f,i}. \tag{1}$$

For our test setup, the proportionality factor was determined to be $p_f = 4.37 \cdot 10^{-4} \frac{\text{mm}}{\text{J}}$ for normal wear behavior. Due to e.g. errors in manufacturing or materials, it might deviate, thus requiring a changed operating point in order to fulfill the specified lifetime. Remaining useful lifetime can be modelled by taking w_{max} into account, which is the known thickness of clutch plates.

5. RELIABILITY OF CLUTCH SYSTEM

In order to determine the effect that continuous control of system behavior and system reliability has on actual system reliability, simulations of the system model introduced in Sect. 4 were used. As was shown, the main component regarding reliability is the pair of clutch plates themselves. With each actuation cycle, it wears according to (1).

It is now assumed that the coefficient of wear p_f included in (1) is individual for each pair of clutch plates, e.g. due to manufacturing tolerances. For this, a normally distributed perturbation factor z is introduced:

$$p_f = z \cdot p_{f,0},$$
$$z \sim \mathcal{N}(1, \sigma_z^2)$$

with variance $\sigma_z = 0.1$ and $p_{f,0} = 4.37 \cdot 10^{-4} \frac{\text{mm}}{\text{J}}$ being the nominal wear rate. Reliability of the full clutch system was then evaluated by taking 200 samples of z and simulating the full system lifetime for a system with reliability controlled operation and for a basic system which uses a fixed nominal working point.

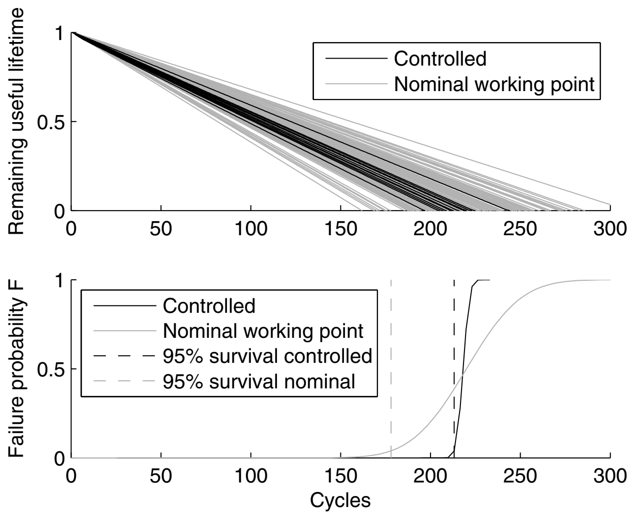

Fig. 2. Remaining useful lifetime of system with constant working point or with reliability adaptive behavior adaptation and resulting failure probability $F(t)$.

The nominal working point was chosen such that for $z = 1$, $k_{des} = 220$ cycles of usable lifetime were obtained. The set point for the reliability-adaptive system was also determined to give $k_{des} = 220$ cycles of usable lifetime.

For each sample of z, an individual lifetime was obtained, as can be seen in Fig. 2. The mean time to failure for systems with nominal working point is approximately the same as for reliability controlled systems and it is close to the desired lifetime. However, variance differs greatly.

Fig. 3 shows that for an arbitrary value of the perturbation factor z, the resulting time to failure of the system with static nominal working point is changed almost linearly. Thus for z being a normally distributed stochastic variable, the resulting time to failure is *approximately* normally distributed as well. However, for a reliability controlled system, a small perturbation (approximately $z \in (0.8, 1.2)$) is compensated for and a constant time to failure is achieved. Only for very large deviations $z \gg 1$ or $z \ll 1$, the time to failure is influenced as well. So despite

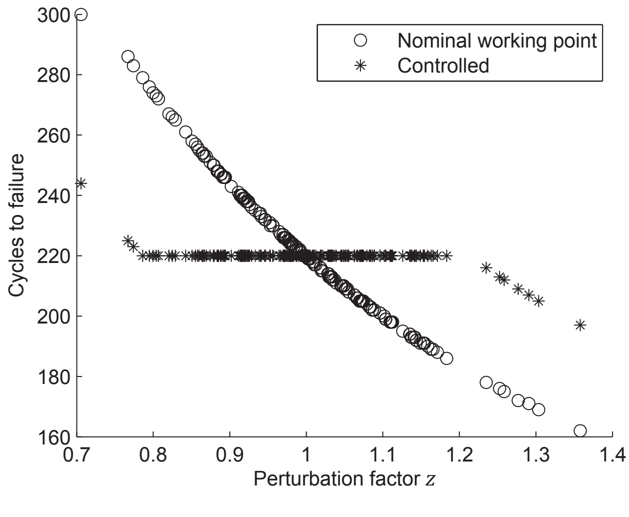

Fig. 3. Relationship of perturbation factor to resulting time to failure.

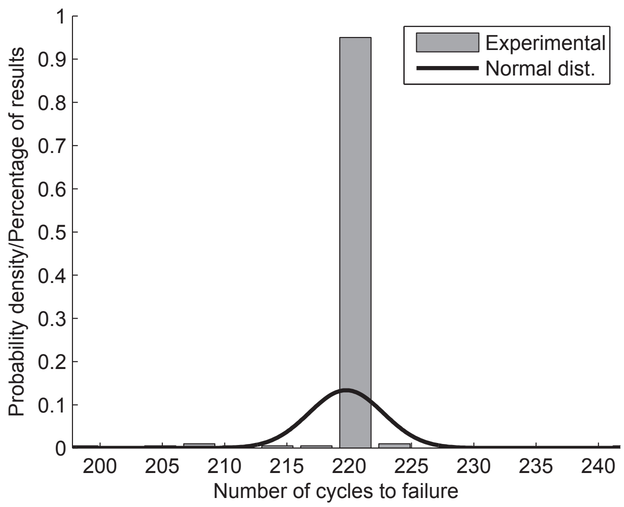

Fig. 4. Experimentally achieved distribution of cycles until failure of clutch system and fitted normal distribution.

a normally distributed perturbation factor z, the time to failure is not normally distributed as well. Due to lack of a suitable distribution function, time to failure of the reliability controlled system is still assumed to be normally distributed. As Fig. 4 shows, this is a *pessimistic* assumption; normally distributed results would give less spot-on results than were actually achieved. For this reason, it is *safe* to use the normal probability distribution.

For further evaluations, it is necessary to schedule maintenance actions. A basic approach is to schedule these based on a given system survival probability, which can be chosen arbitrarily. If 5% of early failures can be tolerated, the results shown in table 1 are achieved. The failure probability along with times until maintenance are also indicated in Fig. 2.

Table 1. Comparison of stochastic properties of reliability controlled system and of system with fixed nominal working point.

	Reliability controlled	Nominal working point
k_{des}	220 cycles	220 cycles
k_{MTTF}	219.76 cycles	221.69 cycles
$\hat{\sigma}_{MTTF}$	2.98	23.95
$k\,(F = 5\%)$	213.10 cycles	178.02 cycles

6. PETRI-NET MODEL FOR SYSTEM OPERATION

In order to assess the effect of reliability-controlled operation over long time spans, a reliability model is required. An almost-exhaustive overview over suitable methods can be found in Malek et al. (2007). While several established methods such as Petri-nets can be used to model repairable systems, they do not offer the possibility of interactions among several systems and the maintenance scheme. Despite their evident shortcomings, Petri-nets were chosen as state-of-the-art method for modelling repairable systems.

The Petri-net model as shown in Fig. 5 is based on Schneeweiss (1992) and consists of two parts: an arbitrarily chosen number of $n = 8$ clutch systems and one repair team. The clutch systems *Sys_i* are each modelled having 3 states: operating, in maintenance and failed. These are

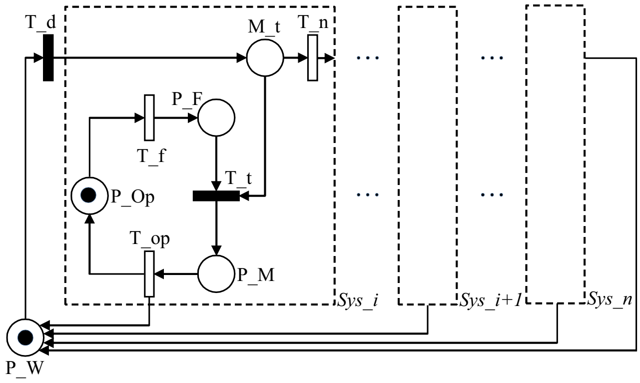

Fig. 5. Petri-net model for repairable clutch system

represented by the places P_Op, P_M and P_F in the Petri-net model. T_op is a timed transition parameterized to fire after 29 cycles according to results from Sect. 5. The transition T_f contains the stochastic properties of each clutch system, namely the normally distributed nominal lifetime with certain variance according to table 1.

The part of the Petri-net model referencing the repair team is located around the clutch system models and implies the maintenance strategy for the fleet. In this strategy the clutch systems under surveillance of the repair team are ordered in series and thus prioritized according to the availability of maintenance. This approach is necessary due to prioritize arcs in Petri-nets in presence of a conflict between more than one possible transitions. This leads to a decreasing availability of the clutch systems remote in the line of the repair team. The repair team is available for the current clutch system in place M_t for a short time of 1 cycle defined in timed transition T_n. It is assumed that the repair team has only a brief look at each system to detect a failure, which always takes the same time.

The Petri-net model is used to determine system reliability for a fleet of $n = 8$ clutch systems as introduced in Sect. 4. They are maintained by one repair team, that restores a system in case of failure. The Petri-net model is evaluated using the timed net evaluation tool TimeNET.

This approach is limited to evaluating static stochastic properties such as mean time to failure of systems. With reliability-adaptive systems, these might change for individual systems or even for the full fleet of systems. It is still suitable for validation of the more complex models introduced in the following section.

7. LIFETIME-SIMULATIONS OF RELIABILITY-ADAPTIVE SYSTEMS

To evaluate system reliability not only using stochastic properties, but also including the feedback from maintenance planning to system behavior that reliability-adaptive systems allow, a simulative approach is chosen. In this, simulations of a basic model as introduced in Sect. 4 and in Meyer and Sextro (2014) are run. To compare simulation accuracy to the Petri-net model introduced in Sect. 6, both models were used with the same parameters. If a failure occurs, and the repair team is available, the system is restored to as-good-as-new condition. Repair teams are accustomed to changing clutch plates, have all tools at hand, always order new spare parts in advance and thus always require the same amount of time, which is equivalent to precisely 29 cycles. After 10000 cycles, a boundary value for availability can be estimated. The theoretical threshold is $A_{max} = \frac{MTTF}{MTTF+MTTR}$ with the mean time to failure $MTTF$ being the nominal lifetime, i.e. 220 cycles, and the mean time to repair $MTTR$ being precisely 29 cycles. This gives $A_{max} = 88.4\%$.

Table 2 shows a comparison of evaluation results from both models. Results for systems with static nominal working point were almost identical, while those for reliability controlled systems differ. This is mostly due to divergence of assumed probability distribution to real distribution of failures. While in the Petri-net model normally distributed parameters were assumed, this assumption does not take the effect of reliability controlled operation into account. With this, instead of having normally distributed times to failure, most systems fail as specified with a low number of systems reaching higher life times or failing early, as can be seen in Fig. 4.

To further evaluate the gain of reliability controlled operation including an adaptive maintenance scheme, a fleet of 56 clutch system models is simulated in parallel. A basic maintenance strategy is implemented: If either a system fails or if the pre-defined time until maintenance is reached, and a maintenance team is available, the system is restored to as-good-as-new conditions. Maintenance is conducted on a first-come-first-serve basis. For both types of systems, the time until maintenance is set to the 95% survival threshold, i.e. 178 cycles for static systems and 213 cycles for reliability controlled systems.

In simulations, the fleet of 56 non controlled systems is able to reach an availability of approx. 85.9%, while the fleet of 56 reliability controlled systems is able to reach 88.0%. The simulated availability and the boundary values are illustrated in Fig. 6. While this might not seem like a big gain, the fleet of non controlled systems required the usage of 8 maintenance teams for this, while the fleet of controlled systems only required 7 teams.

This model does not make use of the possibility to adapt system behavior to the current number of available maintenance teams, which would require a more sophisticated maintenance strategy in the first place. This would need to supervise all systems and create maintenance slots with teams available to compensate for predicted early failures by extending the lifetime of other systems. Deliberately creating maintenance slots is possible by adapting desired system lifetime to e.g. fail later, in turn leaving enough time before failure for servicing of another system.

Table 2. Comparison of results from Petri-net model and from simulation model.

	Petri-net model	Simulation model
Nominal working point		
k_{MTTF}	220 cycles	221.69 cycles
$\hat{\sigma}_{MTTF}$	23.95	23.95
Availability	80.15%	81.47%
Reliability controlled		
k_{MTTF}	220 cycles	221.69 cycles
$\hat{\sigma}_{MTTF}$	2.98	2.98
Availability	83.94%	85.17%

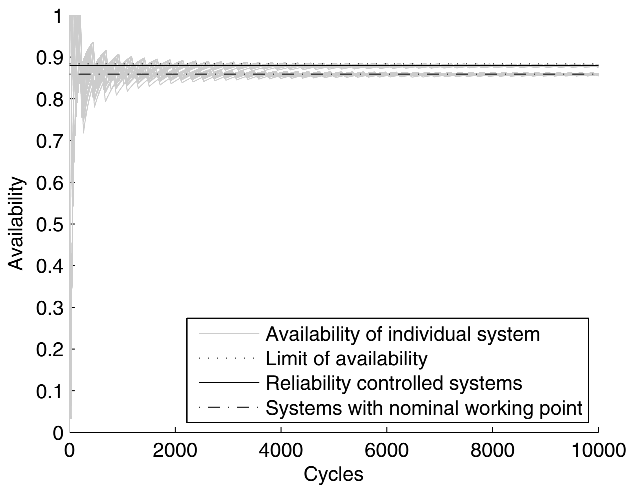

Fig. 6. Availability of individual systems, of fleet of 56 reliability controlled systems and of fleet of 56 systems with nominal working point.

8. ADVANTAGES AND CHALLENGES OF RELIABILITY-CONTROLLED SYSTEM OPERATION

It was shown that using reliability-adaptive operation, reliability of individual systems can be increased due to lowering the variance of time to failure, while keeping the mean time to failure approximately constant. This allows prolonged maintenance intervals without increasing the number of early failures. Availability of individual systems and of a fleet of systems is improved. As application example, a fleet of 56 reliability-controlled clutch systems with dominating failure mode *no torque transmitted due to worn out clutch plates* was used. In simulations, this fleet could *almost* achieve the theoretically achievable availability. Compared to systems operating at a fixed nominal working point, a lower number of maintenance teams was required.

Reliability adaptive systems offer new possibilities regarding maintenance planning, since behavior adaptation driven by maintenance planning is not addressed in current maintenance strategies. The approach presented within this paper is not as sophisticated as possible and does not take requirements of individual systems into account. These could be, for example, extended maintenance intervals to allow returning to the workshop, shortened maintenance intervals due to changed requirements during usage or prioritization of systems which, due to secondary properties, are more important than others. Close interaction of maintenance planning, system degradation and system behavior poses new challenges for modelling reliability.

The common approach is to evaluate stochastic properties of systems and to use these to construct a reliability model of several systems including maintenance. This fails if interactions from one system to another and from maintenance plans to system behavior lead to changes in stochastic properties, such as mean time to failure or the number of early failures. In this paper, simulations are used to cover these aspects. However, these required great computing power [1], are complex to setup and limited in

[1] Each simulation in this paper required about 1000h of CPU time.

interactions due to implementation complexity. Methods that allow reliability evaluations of reliability-adaptive systems would need to allow modelling system behavior, system degradation and maintenance without the simulative approach. While LARES was used successfully to model adaptive systems (see Meyer et al. (2013b)), it is currently limited to the limitations imposed by Markov Chains. Several other projects such as AltaRica[2] seem to be promising, yet most of these modelling techniques are based on classification of the system into *discrete states.* For reliability-adaptive systems, the classification proves troublesome since it is in general not desirable to have hard thresholds to distinguish whether a system is usable or whether it fulfills certain requirements. Also system behavior is not based on states, but instead on continuous adaptation. Methods that allow for modelling of reliability including continuous behavior, which are suitable for modelling reliability-adaptive systems, are, to the best of our knowledge, not yet available.

9. CONCLUSION

Using a clutch system as application example, it was shown that reliability-adaptive system operation offers new ways to increase system reliability and availability. For this, reliability of classical systems with pre-defined static working point were compared to reliability-adaptive systems using a Petri-net model. Since this has some serious limitations, an additional simulation model was implemented. It models a a fleet of clutch system models which are simulated over a time span that covers multiple maintenance actions. A basic maintenance strategy that makes use of the possibilities of reliabilty-controlled operation was implemented within this model. In these simulations, all individual systems were used alike and no priorities were implemented in the maintenance strategy. The systems differed from one another due to a stochastic model parameter, which affects wear rate and leads to changed times to failure.

It can be observed that reliability-controlled system operation yields higher availability, while keeping mean time to failure of all systems constant. This is mainly achieved by using longer maintenance intervals, which are possible without increasing the number of early failures. Due to the complex interaction of all systems and the maintenance strategy, current maintenance strategies are not suitable as are current modelling techniques. Suggestions for further work in the fields of maintenance planning and of modelling techniques that allow these interactions are made.

ACKNOWLEDGEMENTS

The authors would like to thank the Paderborn Center For Parallel Computing (PC^2) for providing access to the OCuLUS cluster for running simulations and the System and Software Engineering group at Technische Universität Ilmenau for providing access to TimeNet for modelling and analyzing Petri-nets.

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