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Integrated model for dynamics and reliability of intelligent mechatronic systems

T. Kaul, T. Meyer & W. Sextro
Mechatronics and Dynamics, Faculty of Mechanical Engineering, University of Paderborn, Paderborn, Germany

ABSTRACT: Intelligent mechatronic systems are able to autonomously adapt system behavior to current environmental conditions and to system states. To allow for such reactions, complex sensor and actuator systems as well as sophisticated information processing are required, making these systems increasingly complex. However, with the risk of increased system complexity also comes the chance to adapt system behavior based on current reliability and in turn to increase reliability. The adaptation is based on switching selecting an appropriate working point at runtime. Multiple suitable working points can be found using multi-objective optimization techniques, which require an accurate system model including system reliability. At present, modeling of system reliability is a laborious manual task performed by reliability modelling experts. Despite actual system reliability being highly dependent on system dynamics, pre-existing system dynamics models and the resulting reliability model are at best loosely coupled. To allow for closer interaction among dynamics and reliability model and to ensure these are always synchronized, advanced modeling techniques are required. Therefore, an integrated model is introduced that reduces user input to a minimum and that integrates system dynamics and system reliability.

1 INTRODUCTION

The development of intelligent mechatronic systems leads to systems with advanced functionality at the cost of increasing complexity. To cope with the increased failure risk due to complexity, reliability is a main objective during development, necessitating comprehensive reliability models. However, among the capabilities of intelligent systems is the adaptation of system behavior at runtime. This can be used to increase reliability, leading to so-called reliability adaptive systems. These systems react on their own reliability. If reliability is lower than specified, an inherently more reliable operating point is selected while decreasing system performance. However, powerful software tools are required to facilitate the development process for reliable intelligent systems.

In this paper, a novel methodology for automated model based transformation of a dynamic model into a system reliability model is introduced. These two models are then used to quantify system performance and system reliability and are used as objectives in multi-objective optimization. Bayesian Networks are used to represent system reliability. An automated transformation algorithm allows autonomous generation of a model of system reliability with respect to changes in the dynamic model. These can either be structural changes to the system itself or changes in parameters. During multi-objective optimization, user-selected parameters are changed and system performance and reliability is evaluated by the optimization algorithm to find suitable working points.

The prevailing load on a component is crucial for its degradation and therefore for its lifetime. In turn, system reliability is highly influenced by loads on individual system components. To compute the load on components, the model of system dynamics is simulated and evaluated. A topological modeling approach was chosen for the model of system dynamics and component degradation models are added to compute component lifetime for current loads. By integrating component degradation models into the model of system dynamics, the complete system model is formed. The system model is automatically transformed into Bayesian networks as model of system reliability.

Model-based multi-objective optimization is a suitable approach to determine working points for mechatronic systems in case of conflicting objectives. In this case, the required objective functions contain a model of system behavior which is simulated and evaluated during each function call for a parameter set given by the multi-objective optimization algorithm. In order to allow for reliability-based behavior adaptation, a reliability-related objective function, which is based on the reliability-model, must be included. The reliability model strongly depends on dynamic system behavior, which is influenced by the currently evaluated optimization parameter. Thus, an update of the reliability model during each objective function call is necessary.

The remainder of this paper is organized as follows: Sec. 2 introduces the current state of research regarding integrated modeling. Secs. 3 and 4.2 introduce the selected application example. The integrated model is detailed in Sec. 4 before the transformation algorithm is introduced in Sec. 5. The step to system reliability is fulfilled in Sec. 6 to form an objective function in Sec. 7. The paper ends with a short conclusion in Sec. 8.

2 MODELING SYSTEM DYNAMICS AND RELIABILITY

Intelligent mechatronic systems can autonomously adapt system behavior to current environmental conditions and system states, which leads constantly changing system behavior with varying dynamic loads. Combining this autonomous response to possibly unknown environmental conditions and the high complexity, it becomes clear that advanced modelling methods based on multi-domain description languages, e.g. MODELICA, VHDL-AMS, LARES or Matlab/Simulink, are required.

In Schallert (2011) the implementation of MODELICA-libraries for simulation as well as for reliability and safety analysis of aircraft onboard electric power systems is introduced. Reliability and safety analysis is done by evaluating automatically Generated Fault Trees (FTA) or Reliability Block Diagrams (RBD).

Bestory et al. (2007) describe electronic circuit behavior and degradation models in VHDL-AMS and perform statistical reliability analysis using Monte-Carlo-Simulations with respect to component degradation over lifetime.

The two previously introduced methods are restricted to electrical systems and therefore not suitable for integrated modeling of mechatronic systems as desired in this paper.

Walter et al. (2009) introduce the LAnguage for REconfigurable Systems (LARES) to model dynamic behavior and reliability of fault-tolerant systems. While originally developed to model computer systems, it can also be used to evaluate reliability of self-optimizing mechatronic systems (Meyer et al. (2013)). A major drawback is that dependencies between current system behavior and failure rates need to be defined externally and are not computed automatically.

The three approaches do not provide an automatic synchronization between dynamics and reliability to model the influence of dynamic loads on component lifetime. This aspect as well as the restriction on electronic systems limit the use of these methods in multi-objective optimization problems of mechatronic systems in the design phase.

3 APPLICATION EXAMPLE

A single plate dry clutch system was chosen as application example since it is a well-known system of which one component is wearing due to friction, and where the interdepency of usage, i.e. actuation strategy, and wear directly affects system lifetime. 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. In the model setup shown in Figure 1 and used for experiments, engine and driven system are represented by brushed DC motors. They are connected to the clutch plate drive shafts by toothed belts, which are not shown in Figure 1. To engage the clutch, both plates are pressed against each other by the force F_N, thus transmitting torque from the driving motor to the input plate, to the output plate and in turn applying this torque to the driven 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.

Those interested in further details are asked to refer to Meyer et al. (2013), Meyer and Sextro (2014).

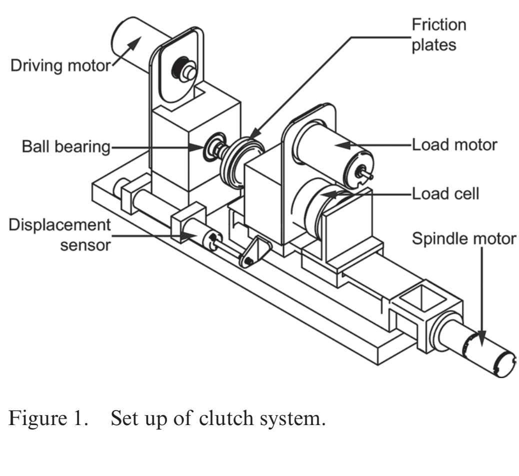

Figure 1. Set up of clutch system.

4 INTEGRATED MODEL

For combined evaluation of reliability and performance of the system, the component lifetime models are integrated with a model of system dynamics, thus forming the system model. In Figure 2, the structure of the integrated model is shown. The proposed system model is intended to allow without limitations for evaluation of dynamic system behavior and controller synthesis as well as evaluation of system component reliability $R_C(t)$. The transformation algorithm described in Sec. 5 then combines system component reliabilities $R_C(t)$ and system model structure identified by the transformation algorithm to allow evaluation of system reliability $R_S(t)$. Hence, system reliability $R_S(t)$ can be used as reliability oriented objective function in a multi-objective optimization problem, where it is combined with additional objective functions to take system dynamics into account.

4.1 *Dynamic model*

The dynamic model serves two purposes. Firstly, it is used to assess system dynamics and performance and to design controllers. This can be combined with multiobjective optimization where the optimization algorithm varies e.g. controller parameters. Secondly, and also the main purpose within the scope of this paper, it is used to determine dynamic loads, e.g. forces transmitted through a joint, for inclusion in component lifetime models.

The dynamic model uses a topology-oriented modeling approach, where dynamic behavior is directly mapped to the corresponding system component and dynamic loads for each relevant system component can be obtained. Topology-oriented modeling contains generalized multidomain components, e.g. mechanical, electrical, electronic, hydraulic, that can be parametrized to match real technical subsystems. Those components are reusable and can be used to modularize models according to real system structure.

The dynamic model is simulated and evaluated for a *characteristic maneuver*. The characteristic maneuver is used as basis of system and controller design and needs to represent common usage of the system at hand as good as possible, as it is the environmental model the system is designed for. If using automated multiobjective optimization, the system is simulated for the characteristic maneuver during each objective function call. By reusing this characteristic maneuver to determine component reliability, user input is reduced.

4.2 *Component lifetime models*

The proposed integrated model builds a model of system reliability from individual component reliability models. Those models contain an estimation of useful lifetime based on the dynamic load on the component that is highly influenced by current dynamic system behavior and is thus crucial for component degradation. Thus for each component that is considered in system reliability analysis, a lifetime model is required in order to compute component lifetime based on current system dynamic behavior. Lifetime models are annotated to the corresponding component in the dynamic model.

Lifetime modeling is exemplarily shown for the friction plates of the clutch system. Additionally required lifetime models can be deducted from literature, e.g. for ball-bearings (DIN ISO (2003)), resistive displacement sensors (Department of Defense (1995)), micro controllers (Department of Defense (1995)), and are not shown in detail.

As basis of the model, the assumption from Fleischer (1973) that clutch plate wear is proportional to friction energy E_f is used. Friction energy is dependent on the currently selected parameters

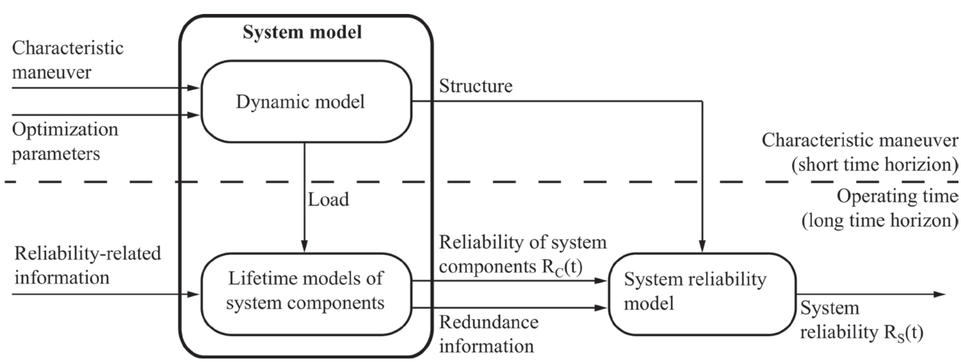

Figure 2. Structure of integrated model.

p, which determine the behavior of the system. For each actuation cycle k, wear Δw_k is:

$$\Delta w_k = p_f \cdot \Delta E_f\left(p_k\right) \tag{1}$$

with coefficient of wear p_f. The maximum bearable wear w_{max} for the number of bearable cycles k_{max} is given by:

$$w_{max} = \sum_{k=1}^{k_{max}} \Delta w_k\left(p_k\right). \tag{2}$$

It is assumed that e.g. errors or tolerances in manufacturing or materials mainly alter the coefficient of wear p_f included in (1), which is then individual for each pair of clutch plates. For this, a normally distributed perturbation factor z is introduced:

$$p_f = z \cdot p_{f,0}, \qquad z \sim \mathcal{N}(1, \sigma_z^2) \tag{3}$$

with variance $\sigma_z = 0.1$. For our test setup, the proportionality factor was determined to be $p_{f,0} = 4.37 \cdot 10^{-4}\ mm \cdot J^{-1}$ for normal wear behavior and maximum bearable wear $w_{max} = 5\ mm$ was measured Reliability of the full clutch system is then evaluated by taking 100 samples of z and simulating the full system lifetime until maximum bearable wear w_{max} is reached. The number of bearable cycles k_{max} is used to calculate friction plate lifetime T_{clt}. It is assumed that cycle time T_{cycle} is known and that all clutch cycles are directly performed in sequence:

$$T_{clt} = \sum_{k=1}^{k_{max}} T_{cycle,k} \tag{4}$$

For each sample of z, an individual lifetime T_{clt} is obtained. All are then fitted to a distribution to obtain reliability $R_{clt}(t)$ of the friction plates for operating time t.

If this component lifetime model is used as part of a multi-objective optimization problem, the operating parameters p are used as optimization parameters, denoted as p_{opt}, thus giving $R_{clt}(p_{opt}, t)$. However, current dynamic system behavior strongly depends on the chosen parameter set p_{opt} that is varied during optimization.

The lifetime models require parameters given by user input (e.g. parameters of friction plates lifetime model: $p_{f,0}$, w_{max}, z and σ_z^2) and dynamic loads on the components that are automatically obtained from simulation of system dynamics model (dissipated friction energy $E_f(p_{opt})$, which is influenced by optimization parameters p_{opt}). The estimation of useful lifetime of a system component under current conditions is used to compute reliability $R_C(t)$ for a given component-specific distribution, e.g. Weibull distribution for reliability of machine elements $H(t)$:

$$H(t) = e^{-(\lambda \cdot t)^{\beta}} \tag{5}$$

with scale parameter λ, shape parameter β and operating time t. Respectively, an exponential reliability distribution is assumed for electronic components with $\beta = 1$. The scale parameter λ of the introduced distributions depends on component lifetime and is thus automatically computed by lifetime models. The Weibull shape parameter β is assumed to be constant for certain types of machine elements (Bertsche (2008)) and is set as default value for predefined lifetime models. The parametrization of reliability distributions of standardized system components, e.g. ball-bearings, is well-known and can be taken from literature (Bertsche (2008)).

4.3 *Bayesian networks and system reliability*

Now that lifetime of each component is known, they need to be combined to compute system reliability. The synthesis of a model of system reliability is based on two pieces of information taken from the system model: the *structure* of the dynamic model to identify causal dependencies in functionality between system components and the *reliability of system components*. These two aspects directly refer to the chosen model of system reliability—Bayesian Networks. The automatic transformation will be described in Sec. 5.

Bayesian Networks are Directed Acyclic Graph (DAG) models with nodes representing a set of stochastic variables $\nu = \{X_1, X_2, ..., X_n\}$ that are endowed with distributions. A directed graph model is fully defined for a given DAG and Conditional Probability Distributions (CPDs) for every node. Each stochastic variable of $\{X_1, X_2, ..., X_n\}$ represents a set of a finite number of possible states. A variable can only have one of its states at a time. Variables can be endowed with individual probability distributions, e.g. Weibull (Zaidi et al. (2012)) or Exponential for use as reliability model. Bayesian Networks set up for ν specify a unique joint probability distribution $P(\nu)$ given by the product of all CPDs:

$$P(\nu) = \prod_{i=0}^{n} P(X_i \mid Pa(X_i)) \tag{6}$$

where X_i represents node i and $Pa(X_i)$ is the set of its parents. If the variables $\{X_1, X_2, ..., X_n\}$ are discrete, they can be represented by a Conditional Probability Table (CPT), which lists the probability that the child node C takes on each of its different states for each combination of states of its parent nodes $P(C \mid Pa(C))$ (Nielsen and Jensen (2009)). The probability table of a root node K (nodes without parents) is reduced to an unconditional probability table $P(K)$ that includes only a priori probabilities.

Bayesian Networks can be seen as causal networks to be used for reasoning about relevance and causal analysis for propagation of beliefs throughout the network. Therefore, they can be used to model the causal dependencies in functionality in a technical system, e.g. is a failure of system component A relevant for functionality of a system component B?

In a system reliability model, the set of variables ν represent a set of system components of the monitored technical system. In a first approach it is assumed for all system components to have binary states: true *tr* representing a component in *operable state* and false *fa* representing a component *failure*. Bobbio et al. (2001) show a multi-state variable approach to allow for modeling multiple failure modes of a system component. This approach takes advantage of compact reliability modeling when using Bayesian Networks.

The probability tables $P(A)$ for a system component A and conditional table $P(B \mid A)$ for a system component B in a Bayesian Network as system reliability model as shown in Figure 3 represent system component reliability $R_A(t)$ and $R_B(t)$ as well as causal failure propagation represented by binary table entries. It is still assumed that both components have binary states and B conditionally fails when a failure of A occurs. Thus, B eventually fails on his own account with $1 - R_B(t)$ when is in operable state.

Considering (6), the joint probability distribution of the Bayesian Network $P(A,B)$ can be computed that could be interpreted as system reliability $R_S(t)$. The Bayesian Network as set up above represents system and component reliability $R_C(t)$ and $R_S(t)$ only at a particular operating time t.

System reliability $R_S(t)$ has to be evaluated over system lifetime T_S, which is radically different from simulation time dynamic model and from the duration of the characteristic maneuver T_{cm}.

4.4 *Simulation*

The introduced system model combines two aspects of a technical system, dynamics and reliability, that are observed on different time scales. Dynamic system behavior typically contains high-frequency signals, e.g. system response to an excitation, that require a sufficiently small sampling step size to observe relevant aspects. To this end, the horizon of simulation time of the characteristic maneuver T_{cm}, e.g. T_{cycle} in Sec. 4.2 is limited due to increasing data size and duration of simulation for small sampling step sizes $t_{s,dyn}$. However, system and component reliability $R_S(t)$ and $R_C(t)$ with operating time of the system t are sampled with greater step size $t_{s,rel}$.

The lifetime of technical systems typically ranges in $10^6 h$ in contrast to the the duration of the characteristic maneuver T_{cm} in the range of seconds or minutes. Thus, dynamic system behavior cannot be sampled with greater step size, because $t_{s,rel} > T_{cm}$. To cope with this challenge, the order of simulation is as follows: first the dynamic model within the system model is evaluated using sample step size $t_{s,dyn}$ to obtain dynamic loads for the characteristic maneuver. The dynamic load data is then used as input to component lifetime models. Based on component lifetime and parameters of the distribution function, component reliability $R_C(t)$ is computed and t is sampled with step size $t_{s,rel}$. The component reliabilities $R_C(t)$ and the causal structure of the system, the DAG, are used to transform the Bayesian Network into a model for system reliability, that is also evaluated for t sampled with step size $t_{s,rel}$.

4.5 *Implementation*

The system model as shown in Figure 2 is implemented in Matlab/Simulink. For modeling and evaluating Bayesian Networks as model of system reliability, Bayes Net Toolbox (BNT) (Murphy et al. (2001)) is used. Despite Matlab/Simulink following a signal-flow oriented modeling approach, with careful modeling, the system topology can be represented as well. To achieve this, customized subsystems are used to represent system components that contain a model of dynamic component behavior.

However, Matlab/Simulink was chosen because of the accessibility of toolboxes, e.g. BNT to evaluate Bayesian Networks and the possibility to implement an algorithm for automatic transformation of reliability models out of dynamic models.

4.6 *System component reliability*

The results of a simulation of the clutch system as introduced in Sec. 3 is shown in Figure 4. It is carried out for a characteristic maneuver, which represents an actuation cycle of the clutch system as described in detail in Sec. 4.2, after which the component lifetime models are parametrized. Transformation into a full system model is omitted.

The following ten system components are taken into account for reliability evaluation: driving and load motor (M_{in}, M_{out}), friction plates (Clt), four

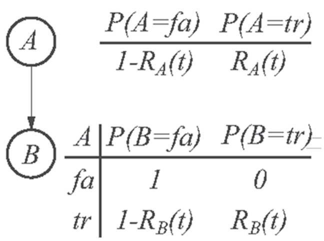

Figure 3. Simple Bayesian Network with CPTs used as system reliability model.

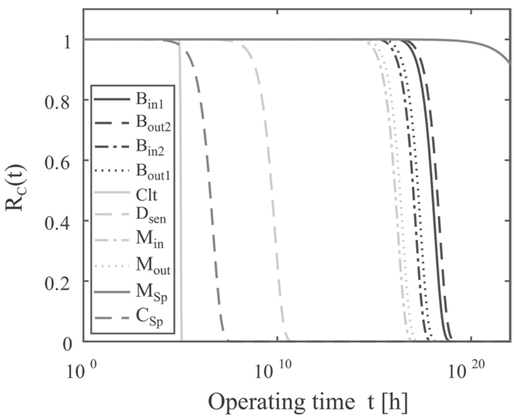

Figure 4. Reliability of system components of clutch system.

identical ball bearings with two bearings on each shaft connected to the friction plates for drive side (B_{in1}, B_{in2}) and load side B_{out1}, B_{out2}), displacement sensor (D_{sen}), spindle motor (M_{Sp}) and spindle motor controller (C_{Sp}). These components are endowed with lifetime models as introduced in Sec. 4.2.

The simulation confirms the assumption made in Sec. 4.2 for worn out clutch plates $R_{Clt}(t)$ to be the most probable failure mode.

The four identical ball bearings used in the assembly differ in reliability according to their load. The bearings B_{in1} and B_{out2} are stressed by a constant radial force F_r due to the required belt tension that is applied by the belt tensioning force F_{belt}. The normal force F_N applied to the friction plates to close the clutch stresses only the bearings nearest to the friction plates B_{in2} and B_{out1} due to the arrangement of bearings on drive and load shaft. However, the radial force F_r appears to be less crucial to bearing reliability ($R_{B_{in1}}(t)$ and $R_{B_{out2}}(t)$) than the axial load due to normal Force F_N for $R_{B_{in2}}(t)$ and $R_{B_{out1}}(t)$.

To automatically construct the system model from a topology-oriented dynamic model that was augmented with reliability information and lifetime models, a dedicated transformation is required.

5 TRANSFORMATION ALGORITHM

The transformation algorithm is used to synthesize a model of system reliability from the system model introduced in Sec. 4. The system component reliabilities $R_C(t)$ parametrize a Bayesian Network, whose structure is identified by performing a *Causal Dependency Analysis* on the dynamic model, which includes the system topology.

5.1 *Preliminary assumptions*

To allow for an automatic transformation of the dynamic model into reliability, in addition to the parametrization of the system model (Sec. 4.1 and 4.2), some assumptions regarding the structure of the system and its functions are required.

Reliability evaluation of complex mechatronic systems may take subsystems as one component into account, while the dynamic model must simulate dynamics of components inside a subsystem as well. To setup a reliability model with desired granularity, all components to be taken into account must be tagged accordingly. Only tagged components are used for reliability evaluation, e.g. the clutch system components named in Sec. 4.6. Despite this, loads used for parametrization of lifetime models are computed using the full dynamic model, thus taking the internal subsystem dynamics into account.

In the current implementation of the integrated model, redundant components appear only once in system dynamics model. The order of component redundancy is implemented as a component parameter along with m-out-of-n redundancy—a redundant system with n components requires at least m of its components to fulfill its function (Birolini (2007)).

A main user input is the definition of the *system failure* the system reliability is evaluated for. The system failure is defined as the negation of the *main function* of the system. In other words, we assume that a system is likely to fail if the main function cannot be fulfilled due to component failure. The main function can be broken down into subfunctions, thus forming the function structure (Pahl et al. (2007)). For fulfilling each subfunction, one or more individual components are required. This relationship is not included in dynamic model and a true function or component structure cannot directly be derived from its topology. However, it is possible to annotate the main function to one required component and to derive a functional component structure from there.

The basic structure of a mechatronic system as shown in Figure 5 can be formulated for each function of a system. It shows all required components and signal flows connecting the components for a certain function. The flows of energy, information and material represent the different kinds of signals used in mechatronic systems (Gausemeier et al. (2003)). An interruption of any of the signal flows, e.g. caused by a component failure, leads to a malfunction of the system. Thus, we assume each component to be essential for the main function and each component failure or failure of redundancy structure to lead to system failure. This functional component structure can be created using causal depency analysis.

Considering the clutch system, the main function could be formulated as "transmit torque via friction plates". The main function of the clutch system is annotated to the friction plates, which connect drive and load side of the test rig.

5.2 *Causal dependency analysis*

Causal Dependency Analysis is carried out to identify the structure of Bayesian Network. The causal dependencies between functional components are explored by tracing the topology of dynamic model. It is traced from the component with annotated main function to each component that has a direct or indirect connection through other components to this root component.

The Causal Dependency Analysis for clutch system starting from the friction plates (Clt) as main functional component is shown in Figure 6. A simplified graph is used to illustrate the signals between the tagged components in system dynamic model.

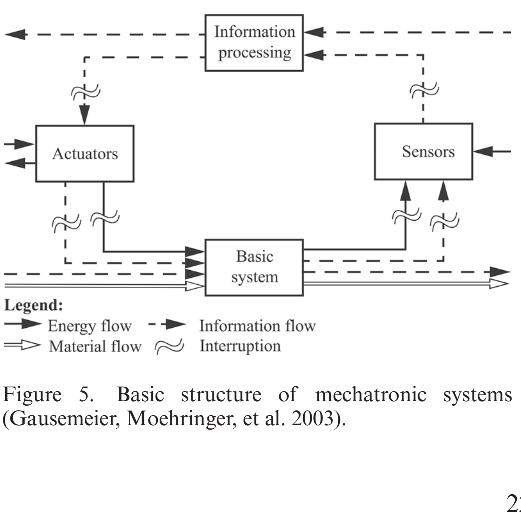

Figure 5. Basic structure of mechatronic systems (Gausemeier, Moehringer, et al. 2003).

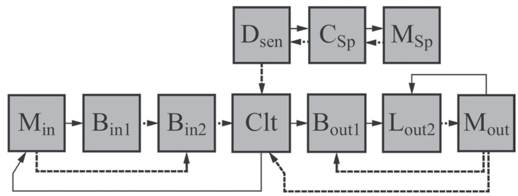

Figure 6. Simplified graph of system dynamics model with traced signals.

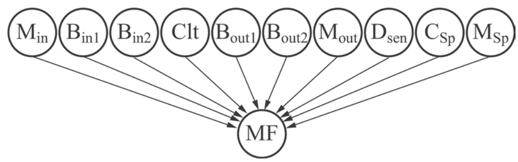

Figure 7. Graph of Bayesian Network as reliability model for clutch system.

The highlighted paths (dashed line) show the signals traced by the dependency analysis. It turns out that every tagged component is required for main function of the system.

5.3 *Synthesis of system reliability model*

In the Bayesian Network, nodes are set up for all identified components and annotated functions. The components are used as root nodes of the network with attached binary probability tables $P(C)$ as introduced in Sec. 4.3. Those tables $P(C)$ are filled with a priori probabilities $R_C(t)$ for operable state and $1 - R_C(t)$ for failed state.

The functions of the evaluated system are also introduced as nodes endowed with the states *true* and *false*. The Conditional Probability Tables (CPTs) assigned to those nodes are filled with Boolean expressions to model the causal dependency between components and functions. Those CPTs can be seen as truth tables that model a logical disjunction of the relation of components and functions. Thus, a parallel structure of the Bayesian Network as shown in Figure 7 is evoked.

The clutch system features only one annotated function that can be seen as root node MF. The nodes connected in parallel to the root node refer to the identified components with relevance for the main function of the system.

6 EVALUATING SYSTEM RELIABILITY

The evaluation of the Bayesian Network shown in Figure 7 as a model of system reliability for node MF gives its joint probability distribution $P(MF)$. The joint probability for node MF to be in operable state *true* is interpreted as system reliability and is used equivalently in the following sections:

$$P(MF = true) \Leftrightarrow R_S(t). \quad (7)$$

The results of the evaluation of the Bayesian Network using the BNT are shown in Figure 7. The Bayesian Network is evaluated piecewise for $t = \{t_1, t_2, ..., t_m\}$ as for system component reliability $R_C(t)$ to obtain a reliability curve over operating time.

If system component reliabilities $R_C(t)$ (Fig. 4) are compared to system reliability $R_S(t)$ (Fig. 8), the results appear to be as expected. According to (6), the whole system is more likely to fail than its individual components at any point in time.

Full system reliability can now be formulated as objective function to be optimized together with any pre-existing performance objective functions.

7 RELIABILITY-RELATED OBJECTIVE FUNCTION

To formulate a reliability-related objective function for use in multi-objective optimization, optimization parameters p_{opt} have to be chosen in system dynamics model, e.g. controller or component geometry parameters, which influence both system dynamics and system reliability $R_S(t)$ as shown in Figure 8. The use of lifetime model parameters, such as shape parameter b of distribution functions, as optimization parameters is not feasible as these model failure characteristics and are part of the reliability-related objective function.

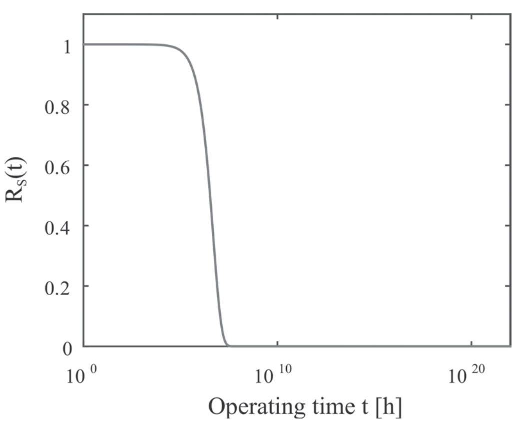

Figure 8. System reliability of clutch system.

The objective function is formulated as minimization problem for the probability of system failure $1 - R_S(p_{opt}, t_i)$ for a certain operating time t_i:

$$\min_{p_{opt}}[1 - R_S(p_{opt}, t_i)]. \quad (8)$$

As intermediate step towards minimization of failure probability, dynamic loads on system components are reduced by having the optimization algorithm choose adequate optimization parameter values p_{opt} which in turn extend component lifetime.

Objective functions that cover system performance are highly system-specific and are not within the scope of this paper. For the clutch system, a cost-function was already formulated to evaluate system performance (Meyer et al. (2013), Meyer and Sextro (2014)). It was found that accelerations, i.e. passenger comfort, as performance objective and wear as reliability objective contradict one another. Working points which yield high comfort also lead to high wear, whereas low wear can only be achieved if inferior comfort is accepted.

8 CONCLUSION

The proposed integrated model for dynamics and reliability of mechatronic systems can be used in early design phases to ensure reliability as well as performance objectives. The influence of component changes, control strategies and controller parameters on dynamic system behavior and system performance can be evaluated at the same time as their influence on system reliability.

The integrated system model allows for close interaction among dynamic and reliability model and eliminates user input while synchronizing the two models. It models the interdependency between dynamic system behavior and component degradation to allow for identification of critical components according to reliability aspects. Synchronization between dynamic and reliability model is carried out repeatedly when solving multi-objective optimization problem. Based on the system model, a transformation algorithm was developed to synthesize Bayesian Networks as a model of system reliability from system dynamics model. The evaluation of system and component reliability requires preliminary parametrization, but can be used afterwards without further user input. Thus, solving a multi-objective optimization problem of complex mechatronic systems including a reliability-related objective is possible.

The combination of integrated system model and multi-objective optimization methods allows the computation of several working points and operating strategies, of which intelligent mechatronic system can make use to adapt system behavior according to their current situation.

With the current transformation algorithm, a flat hierarchy is created for the DAG used in reliability evaluation, making it hard to grasp the model structure and validate it manually. This could be overcome if the topology of the dynamic model was found in the DAG as well. This way, reliability models for subsystems would directly be included in the reliability model of the full system.

The limitation of Matlab/Simulink to a signal flow oriented modeling approach means that including the system topology is up to the user and prone to errors. This could be overcome by using a native topology oriented modelling environment, which would then be augmented by our transformation algorithm.

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