

Paper:

Probabilistic Planning for Predictive Condition Monitoring and Adaptation Within the Self-Optimizing Energy Management of an Autonomous Railway Vehicle

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Self-optimizing mechatronic systems are a new class of technical systems. On the one hand, new challenges regarding dependability arise from their additional complexity and adaptivity. On the other hand, their abilities enable new concepts and methods to improve the dependability of mechatronic systems. This paper introduces a multi-level dependability concept for self-optimizing mechatronic systems and shows how probabilistic planning can be used to improve the availability and reliability of systems in the operating phase. The general idea to improve the availability of autonomous systems by applying probabilistic planning methods to avoid energy shortages is exemplified on the example of an innovative railway vehicle.

Keywords: self-optimizing systems, dependability, probabilistic planning, energy management

1. Self-Optimizing Systems and Dependability

Technical systems and machines are designed to fulfill tasks for humans. The spectrum of tasks and the quality of task fulfillment is continuously improved by technical progress. The quality of task fulfillment can be measured in various dimensions, depending on the current area of applications. Examples for such dimensions are: timeliness, resource consumption, processing accuracy (e.g., in case of machining tools), or comfort and driving pleasure (in case of vehicles). The close integration of electro-mechanical systems, electronic and information technology in mechatronic systems [1] opens new paths to further improvement: the availability of information and communication technology enables systems to adapt their behavior to changing environmental settings and user preferences. We use the term self-optimization to characterize such systems.

Self-optimizing systems are able to adapt their objectives autonomously [2]. This includes modifying the relative weighting or ranking of the objectives. Adapting the objectives must result in an adaptation of the system

behavior. For this purpose, the identified objectives are transformed into a corresponding optimization problems. The solutions of the optimization problems indicate the suitable behavior adaptations. This is realized by adapting parameters (e.g., changing a control parameter) or the structure of the system (e.g., replacing the current controller). Hence, a self-optimization process is defined as an iterative sequence of three actions.

Situation Analysis: Situations include the system's state and all observations about its environment.

Determination of Objectives: The relevant objectives are ranked and weighted. Objectives can be also transformed into side conditions.

Behavior Adaptation: The determination of objectives results in a formulation of optimization problems which determine appropriate adaptation of the system behavior. This adaptation is implemented by changing control parameters or replacing controller variants.

According to Laprie [3] dependability encompasses four attributes: safety, reliability, availability and confidentiality. These attributes are integrated in the system of objectives and may increase the dependability under consideration of the application and current situation. Regarding dependability, self-optimizing mechatronic systems comprise both: on the one hand, the risk of unforeseen failures, due to their complexity and inherent non-deterministic behavior; on the other hand, the chance of developing new dependability concepts by using the paradigm of self-optimization.

An important factor in the dependability of many mechatronic systems is the assurance of sufficient energy supply. This paper introduces a multi-level dependability concept for self-optimizing mechatronic systems applied during the operating phase and shows how planning can be used to implement a pro-active and risk-avoiding behavior. This method is especially promising to ensure sufficient energy supply and thus improve the availability of mechatronic systems. A first version of the approach

has been introduced in [4].

The next section introduces the multi-level dependability concept for self-optimizing mechatronic systems. Subsequently, the importance of the energy storage for the dependability of mechatronic systems is motivated. The fourth section introduces our application example, the autonomous railway vehicle RailCab. In Section 5 a planning concept for mechatronic systems is explained and that is extended to a probabilistic planning procedure that is integrated in the dependability concept (Section 6). Simulation results are presented in Section 7. The last section presents the conclusion.

2. Related Work

2.1. Planning for Mechatronic System

Although planning is a promising method, it is hardly used in mechatronic systems. One reason is a significant difference in the system models. Most planning approaches model system activities as discrete sequence of states and activities [5]. In mechatronic systems, the continuous trajectories of system activities are important. One possibility is the usage of planning models based on hybrid automata [6], which integrate discrete change between modes and continuous evolution of state variables. Maier and Sachenbacher introduce an application to mechatronic systems in manufacturing [7]. Considering the long planning horizon required in the RailCab system, the information about the future environment is not precise enough to derive the differential equations required for the definition of hybrid automata. Hence, a hybrid planning architecture was developed [8, 9]. The hybrid planning integrates planning and simulation in order to react to unavoidable plan deviations. The just-in-case planning introduced in this paper is an important building block within this architecture.

2.2. Probabilistic Planning

There are various planning algorithms which consider random variables in the state description and action effects. Examples of such planning algorithms are Paragraph [10], Probapop [11], and Weaver [12]. These planning systems do not support the consideration of an objective function, which is required to implement the self-optimization process. Weaver has the most advanced representation of environmental influences. It includes exogenous events and a probabilistic model of their influence towards the action results and dynamically constructs a Bayes Network to calculate the joint probability distribution of the plan. Nevertheless, Weaver does not include external knowledge about the environment and is restricted to a priori knowledge included in the action definition.

Thus, all these planning approaches clearly lack the ability to adapt themselves to changing environmental circumstances. The approach presented in this contribution uses a distributed system of expert agents and provides an

integration of up-to-date information about the environment. Furthermore, the basic concept of the presented approach to apply a probabilistic plan analysis to determine threshold values enables the integration of arbitrary deterministic planning concept (e.g., state space search like in the example or meta-heuristics) to provide the original and alternative plans.

2.3. Stochastic Dynamic Programming

Stochastic Dynamic Programming (SDP) based on Markov Chains (MC) can be considered as an approach for planning under uncertainty. SDP for instance is applied in optimal control problems for hybrid vehicles [13] and electric vehicles with hybrid energy storages [14]. Besides a position independent determination of the control strategy, Johanneson et al. [13] suggest to consider a position dependent Markov Chain, similar to the suggested agent based approach. Nevertheless, there are some major difference regarding the presented approach and SDP. Result of an SDP is an (optimal) policy, which defines for every possible state from the state space a corresponding action which is to be chosen for that case. The policy selects actions in such a way, that the expected costs (e.g., fuel consumption [13] or energy losses [14]) of all actions in a finite or infinite horizon are minimized. Here a problem arises regarding the integration with the dependability concept introduced in the next section: it is not possible to specify a threshold that defines the acceptable probability of a failure. Thus, to integrate a SDP into the dependability concept a cost model has to be chosen that results in a corresponding failure probability of the optimal policy. The selection of such a cost model is not a trivial problem. Furthermore, the simulation results in Section 8 show that the planning procedure introduced in this contribution reduces the failure probability already if a small number of alternative plans are added. This feature enables the implementation as an anytime algorithm and the reliability of the system can be improved with limited exploration of the state space and thus in limited calculation time. In contrast, SDP usually analyze the complete state space to generate a policy, thus it is not possible to use intermediate results. Online planning approaches with partial exploration of the state space exists for similar problem models such as partially observable Markov decision processes [15]. Nevertheless, the consideration of a threshold probability for failure is even more difficult to consider in these approaches.

3. Predictive Condition Monitoring

To reduce the risks and exploit the potentials of self-optimization a predictive condition monitoring policy was developed. The policy comprises the design phase, the operating phase and the maintenance phase (cf. [16]). The main element of the policy in the operating phase is the Multi-Level Dependability Concept (MLDC) depicted in **Fig. 1**. The MLDC monitors the system state and