Preventive maintenance for the heated hold-up tank

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Final report of team CQFD on task 3.1.3

The aim of this task is to propose a an application of our numerical optimal stopping procedure to the example of the heated hold-up tank. The partners involved are INRIA CQFD. People involved are B. de Saporta (CQFD) with the collaboration of H. Zhang (CQFD).

1 Context

A complex system is inherently sensitive to failures of its components. One must therefore determine maintenance policies in order to maintain an acceptable operating condition. Optimizing the maintenance is a very important problem in the analysis of complex systems. It determines when it is best that maintenance tasks should be performed on the system in order to optimize a cost function: either maximize a performance function or conversely minimize a loss function. Moreover, this optimization must take into account the random nature of failures and random evolution and dynamics of the system.

The example considered here is the maintenance of the heated hold-up tank, a well know test case for dynamic reliability, see e.g. [9, 16, 17, 26]. The system consists of a tank containing a fluid whose level is controlled by three components: two inlet pumps and one outlet valve. A thermal power source heats up the fluid. The failure rate of the components depends on the temperature, the position of the three components monitors the liquid level in the tank, and in turn, the liquid level determines the temperature. The main characteristic of this system is that it can be modeled by a stochastic hybrid process, where the discrete and continuous parts interact in a closed loop. As a consequence, simulating this process and computing related reliability indices has been a challenge for the dynamic reliability community. To our best knowledge, optimization of maintenance policies for the heated hold-up tank has not been addressed yet in the literature.

The only maintenance operation considered here is the complete replacement of all the failed components and the system restarts in its initial equilibrium state. Partial repairs are not allowed. Mathematically, this problem of preventive maintenance corresponds to a stochastic optimal stopping problem as explained by example in the book of Aven and Jensen [2]. It is a difficult problem because of the closed loop interactions between the state of the components and the liquid level and temperature. A classical approach consists in using condition-based maintenance (CBM) to act on the system based on its current state and before its failure. One can for example calculate the remaining useful life (RUL) of the system and the preventive replacement is carried out when the deterioration level exceeds a certain threshold or enters in a certain state [25, 12]. Our approach also takes into account the current state of the process, but our decision rule is not based on damage accumulation nor does it correspond to hitting some threshold. Instead, it involves a performance function that reflects that the longer the system is in a functioning state the better.

The dynamics of the heated hold-up tank can be modeled by a piecewise deterministic Markov process (PDMP), see [26]. Therefore, our maintenance problem boils down to an optimal stopping problem for PDMP's. PDMP's are a class of stochastic hybrid processes that has been introduced by Davis [4] in the 80's. These processes have two components: a Euclidean component that represents the physical system (e.g. temperature, pressure, ...) and a discrete component that describes its regime of operation and/or its environment. Starting from a state x and mode m at the initial time, the process follows a deterministic trajectory given by the laws of physics until a jump time that can be either random (e.g. it corresponds to a component failure or a change of environment) or deterministic (when a magnitude reaches a certain physical threshold, for example the pressure reaches a critical value that triggers a valve). The process restarts from a new state and a new mode of operation, and so on. This defines a Markov process. Such processes can naturally take into account the dynamic and uncertain aspects of the evolution of the system. A subclass of these processes has been introduced by Devooght [9] for an application in the nuclear field. The general model has been introduced in dynamic reliability by Dutuit and Dufour [10].

2 Approach

The objective and originality of this paper is twofold. First, we propose an optimization procedure for a well-known benchmark in the dynamic reliability literature. The tank model was first introduced by [1] where only one continuous variable (liquid level) is taken into account, and then in [15] and [16] where the second variable (temperature) is introduced. They have tested various Monte Carlo approaches to simulate the process to compute reliability and safety indices. In [24], the authors have used the same system to present continuous cell-to-cell mapping Markovian approach (CCCMT) still to simulate the process. The simulation of the holdup tank example has been and is still widely studied in the literature (not exhaustive) [23, 3, 11, 22, 14, 8]. Here we go one step further and not only propose to simulate the tank process but also we optimize it.

Second, even though PDMP's have been recognized as a powerful modeling tool for dynamic reliability problems [9, 10], there are very few numerical tools adapted to these processes. Our aim is to further demonstrate the high practical power of the theoretical methodology described in [7], by applying it to the tank benchmark. In [7], the authors have proposed a numerical algorithm to optimize PDMP's and have studied its theoretical properties. This optimization procedure was first applied to an example of maintenance of a metallic structure subject to corrosion, without closed loop interactions or deterministic jumps. In addition, the system has only one continuous variable and the cost function is simple and does not depend on time, see [8]. In this paper, we adapt the numerical procedure proposed in [7] to the more challenging heated hold-up tank problem with two continuous variables, deterministic jumps when these variables hit some given boundaries and closed loop interactions between continuous and discrete variables. Furthermore, we consider a cost function that depends on both continuous variables as well as on the running time.

3 Results

The numerical method described in [7] has been applied to a well known test case of dynamic reliability to approximate the value function of the optimal stopping problem and an ϵ-optimal stopping time for a piecewise-deterministic Markov process, that is the maintenance date for the tank. The quantization method proposed can sometimes be costly in computing time, but has a very interesting property: it can be calculated off-line. Moreover it depends only on the dynamics of the model, and not on the cost function chosen, or the actual trajectory of the specific process one wants to monitor. The calculation of the optimal maintenance time is done in real time, making our procedure applicable in practice. The optimal maintenance time is updated at the changes of mode and has a conditional threshold form, which allows scheduling maintenance services in advance.

If one only changes the reward function g without changing the dynamics of the tank, one just has to run the optimization part of the algorithm, and not the quantization grids. This can be done in real time. If one wants to change the dynamics of the system, or add some components, one has to rewrite the simulation code for the system, and with this new code re-run the quantization grids, which can be quite long. However, the general methodology is valid for a wide class of piecewise deterministic Markov processes and not at all specific to the tank.

The method has been implemented on the heated hold-up tank. The main characteristic of this system is that it can be modeled by a stochastic hybrid process, where the discrete and continuous parts interact in a closed loop. The optimization problem under study has no analytic solution.

However, our method is based on a rigorous mathematical construction with proof of convergence. In addition, simple comparisons between no motoring and our policy also prove its practical validity with a significant improvement of the performance of the system (the mean performance is increased by 156% and the top events are almost always avoided).

4 Dissemination of results

This work was presented in a conference [6] and published in an international peer-reviewed journal [5].

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