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Automated plan assessment in cognitive manufacturing

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ABSTRACT

In a cognitive factory setting, product manufacturing is automatically planned and scheduled, exploiting a knowledge base that describes component capabilities and behaviors of the factory. However, because planning and scheduling are computationally hard, they must typically be done offline using a simplified system model, and are thus unaware of online observations and potential component faults. This leads to a problem: given behavior models and online observations of possibly faulty behavior, how likely is each manufacturing process plan to still succeed? In this work, we first formalize this problem in the context of probabilistic reasoning as *plan assessment*. Then we contribute a solution which computes plan success probabilities based on most likely system behaviors retrieved from solving a constraint optimization problem. The constraint optimization problem is solved using well-optimized off-the-shelf solvers. Results obtained with a prototype show that our method can guide systems away from plans which rely on suspect components.

1. Introduction

As the market demands for customized and variant-rich products, the industry struggles to implement production systems that demonstrate the necessary flexibility while maintaining cost efficiency comparable to highly automated mass production. A main cost driver in automated production is the human workforce needed for setup steps, the development of processes, and quality assurance. These high labor costs can only be amortized by very large lot sizes. For small lot sizes as found in prototype and highly customized production, human workers are still unchallenged in flexibility and cost. Therefore, to facilitate the emergence of mass customization at prices only highly automated systems can achieve, levels of flexibility similar to the flexibility of human workers must be reached.

Future technical systems are expected to act robustly under high uncertainty, reliably handle unexpected events, quickly adapt to changing tasks and own capabilities. A key technology for the realization of such systems is automated planning combined with self-diagnosis and self-assessment. These capabilities can allow the system to plan its own actions, and also react to failures and adapt the behavior to changing circumstances. Cognitive architectures try to achieve such capabilities for industrial applications by implementing solutions inspired from human and animal cognitive behavior [1]. Research within the German cluster "Cognition for Technical Systems" (CoTeSys) [2] tries to understand human cognition to make its performance accessible for technical systems.

In a scenario of cognitive manufacturing, a factory generates the manufacturing process plans for numerous individualized products during night for manufacturing the next day. A factory knowledge base, describing component capabilities and behavior, serves as model basis for the factory's intelligent capabilities such as planning. During night enough time is available to generate complex plans. Still, relevant parts of the knowledge have to be selected [3] from the knowledge base, as planning/scheduling on the whole knowledge base would be intractable. The question is: can it be guaranteed that the plan works given the behavioral knowledge of the system?

Planning and scheduling finishes at a deadline the next day (e.g. 8 am). However, partial observations can be made after that deadline, especially during execution of the plans. In the light of this new information, it might become clear that success for certain plans cannot be guaranteed anymore (e.g., if a plan operates a component intensely which has been observed to be prone to failure).

The two problems illustrated above lead to the same problem of evaluating manufacturing process plans in the face of information that was not available or not used for their generation. In the first case, a sparse model without behavior knowledge was used due to problem hardness. In the second case, it's observations which where not available at planning/scheduling time. In both cases, planning and scheduling are complex tasks (even on the sparse model), which prohibit quick reformulation of whole plans, only slight modifications are possible.

In this work, we are interested in the probability of plan success, i.e. that it achieves its goal, or plan failure. We want to provide a

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criterion upon which an AI decision component or a human operator can decide to (a) continue with a plan, (b) stop it because it probably will not succeed or (c) gather more information. We call the problem of computing this probability the *Plan Assessment Problem*. In this work, we do not address planning and/or scheduling problems. We assume a given cognitive architecture which provides typical AI capabilities such as planning [4]. This work is based on prior work presented in [5,6]. It combines concepts from these works and extends them by (a) a formal definition of the plan assessment problem as a probabilistic reasoning problem within the domain of cognitive manufacturing and (b) elaborating ideas on how focussed plan assessment models which model behavior of multiple, different products can be created.

The rest of our article is organized as follows: in the next section, we introduce our example scenario for the CoTeSys cognitive factory. We then precisely analyse all aspects of the plan assessment problem in Section 3 and discuss related work in Section 4. In Section 5 we describe in detail the modeling formalisms used to create planning and plan assessment models. Plan assessment with *hybrid* discrete/continuous models based on hybrid automata is shortly explained in Section 6. Then in Section 7 we show how belief state approximations can be computed and introduce our approach to estimating the success probability using soft-constraint optimization. Section 8 is concerned with our restricted prototype implementation of plan assessment, followed by the results obtained with it.

2. Metal machining and assembly example

Part of the CoTeSys cognitive factory test-bed is a customized and extended Flexible Manufacturing System (FMS) based on the iCim3000 from Festo AG (see Fig. 1b). The system consists of conveyor transports and three stations: storage, machining (milling and turning), and assembly.

The following scenario will serve as basis for examples throughout the article. In the cognitive factory, a planner creates plans for a toy maze and a toy robot arm. The maze consists of an alloy base plate and an acrylic glass cover fixed by metal pins (see Fig. 1a), the robot arm (see Fig. 1c) consists of alloy parts, joints and servos. The robot is configurable regarding the number of joints and their orientation as well as in the choice of a manipulator. A single joint consists of two metal brackets and a servo motor. In the example laid out, some CNC (Computerized Numerical Control) cutting operations are done on each of the brackets, later sets of two brackets are assembled with a servo. Cabling is not considered in this scenario and has to be done manually as a last step. A scheduler assigns the necessary resources. The two product plans, i.e. two sequences of (action, time)-pairs, look like shown in Fig. 4. A rough visualization of the complete schedule is shown in Fig. 3.

Errors can be detected in the plant using a vibration sensor at suspicious components. In our situation, the machining station is suspicious, because its cutter can go blunt during operation. A blunt cutter is very likely to break, leading to flawed products (see Fig. 1a). However, not every vibration means that a component is faulty. Some components generate random vibrations, e.g., the assembly station. Furthermore, with some probability, vibrations in one station can trigger signals in sensors of nearby stations. In our example, the vibrations of the assembly station and conveyor belts can trigger sensor signals of the machining station sensor. The plan assessment must be able to cope with these kinds of ambiguities. Our approach can deal with them by finding most probable explanations for what happened in the past.

A vibration is detected at $t_2 = 520$ s, while the machining station is cutting a bracket for the robot arm and the maze is being

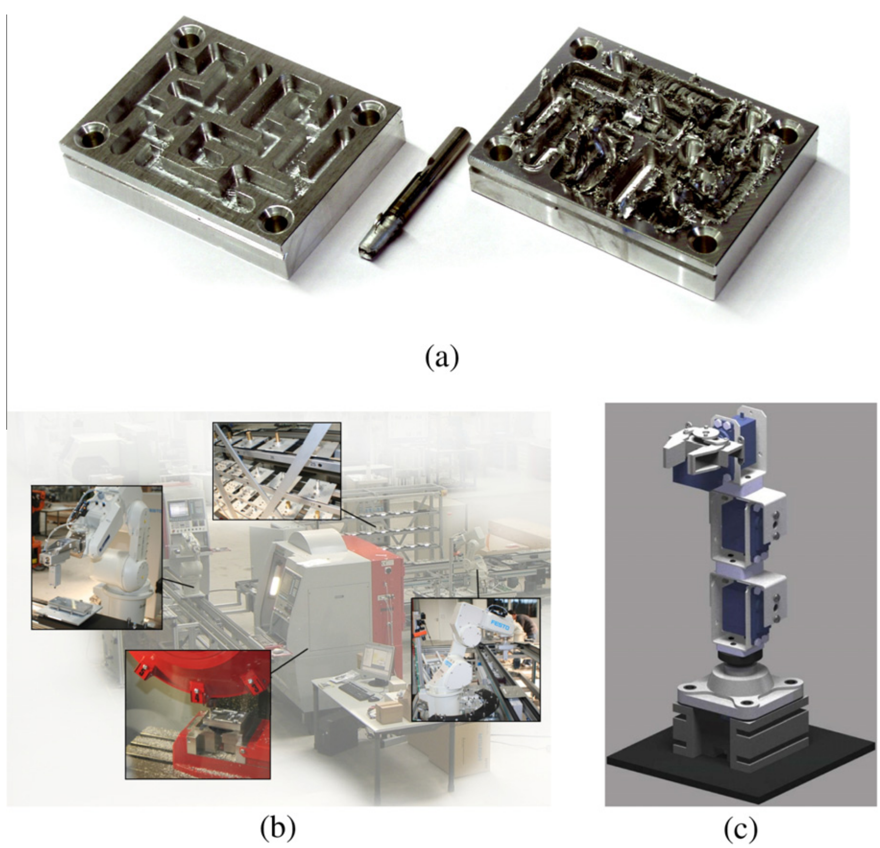

Fig. 1. (a) Effects of cutter deterioration until breakage in machining. (b) The hardware setup used for experimentation, showing storage, transport, robot and machining components. (c) The robotic arm product. Images ©Prof. Shea TUM PE.