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A randomized point-based value iteration POMDP enhanced with a counting process technique for optimal management of multi-state multi-element systems

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ABSTRACT

Optimal decision-making for systems in the presence of uncertainty poses a significant challenge in many fields of research and for many applications. While Markov Decision Process (MDP) is a capable probabilistic framework to incorporate uncertainties in system behavior, measurement randomness arising from imperfect inspections is disregarded in those models. Additionally, the decision-making problem for multi-state multi-element systems has exponential time complexity with respect to the number of system elements. This paper introduces a new decision-making framework for such systems that incorporates element-level decision variables and their consequences at the system-level of an asset. The framework employs a Partially Observable MDP (POMDP) with a randomized point-based value iteration solution strategy to capture system forecasting uncertainty as well as randomness in inspection measurements. The capability of the framework to handle large-scale optimization problems for element-level decision-making in multi-element systems is considerably enhanced via a counting process state reduction technique that is introduced and integrated into the POMDP model. The application of the proposed framework is demonstrated for long-run decision-making regarding maintenance, rehabilitation, and repair of a bridge system with realistic settings. Based on numerical results, it is concluded that the proposed framework composed of POMDP and the counting process techniques provides an efficient yet accurate approach for the optimal management of multi-state multi-element systems.

1. Introduction

Optimal decision-making for management of systems in the presence of uncertainty poses a significant challenge in many fields of research and for many applications. Infrastructure systems management, robotics science, and image processing are among such fields. The Markov Decision Process (MDP) is a well-developed probabilistic framework in which periodical observations can be incorporated for optimal decision-making. According to Markovian characteristics, the condition state of an element at each time is dependent only upon its condition state at the most previous time. Implementing this feature within dynamic programming and cost-optimization procedures, optimal decisions are identified for perfectly observed condition states. For instance in transportation systems management, many U.S. state departments of transportation (DOTs) take advantage of an MDP-based platform called AASHTOWare [5]) (formerly known as PONTIS [4]) for management of bridges. This framework accounts only for the forecasting uncertainty of the time-dependent behavior of the system. However in reality, observations of the condition state of the system made through inspection instruments are accompanied with systematic and random errors. Therefore to achieve reliable solutions, measurement uncertainty has to be dealt with in the decision-making framework. In the context of civil engineering, Madanat and Ben-Akiva [28] incorporated this uncertainty source into an MDP framework and called the approach Latent Markov Decision Process (LMDP). However more commonly, the framework is referred to as Partially Observable Markov Decision Process (POMDP) [30,12]. POMDP establishes a more realistic decision-making framework through which inspection observations provide an estimate of the current condition state as opposed to the error-free evaluations assumed in the case of MDPs.

Based on the history of observations and the actions taken, Bayes rule is utilized for updating the probability distribution of the true condition states (belief state). For decision-making in this case, rather than two consecutive time steps (which is the case in MDP frameworks), the optimal decisions for each time epoch

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depends on the entire history of the selected decision variables and observations. This procedure results in a more realistic model at the expense of an exponential increase in the complexity and computational cost of the framework compared to the conventional (fully observed) MDPs. To overcome the runtime hurdle of this approach, a number of approximate discretization techniques such as hierarchical clustering were employed [29]. As an alternative approach, some algorithms provide the exact solution, while reducing the runtime considerably by determining the belief state domains with similar optimal strategies [30,12]. These domains can be defined by solving sets of linear programming problems [13,21] with polynomial time-complexities. Using this procedure, POMDP provides a robust framework for decision-making under noisy observations.

POMDP has gained many applications in diverse fields, such as pavement and bridge management [18], system maintenance [1,41,15], robotics science [31,35,36], assistive technologies [10,23], and computer vision [31]. However, its application becomes prohibitive for systems where the size of the state and/or action space becomes large. For example in the bridge management problem by Ellis et al. [18], the bridge system was considered as a single element with five general condition states. This issue was addressed by Spaan and Vlassis [40] through development of a steady-state randomized point-based value iteration solver for POMDPs called Perseus. In this approach, instead of investigating the entire belief space, a set of likely belief state points is determined through random walks. As a fast POMDP solver, Perseus has been used for small scale decision-making problems e.g. bridge management [32,33], robotics [34,11] and image processing [14,25]. For instance, Papakonstantinou and Shinozuka [32] applied Perseus framework for an infinite-horizon decision-making of a single corroding wharf deck with 332 states (with different deterioration rates). However, as they also reported the major limitation of this framework is still the required computational demand and memory space for large state-space problems.

The main shortcoming of MDP-based frameworks, while providing a strong tool for optimal decision-making, is the poor adaptation to a portfolio of joint elements [27]. An example follows to further elaborate this point. Let's consider a bridge system consisting of multiple components among which deck, superstructure and substructure components contribute to the overall safety of the bridge. Optimal planning for such a system requires the consideration of these components and the combinations of their states. As a result, the state and action size of the decision-making problem increases exponentially as the number of components increases. For a bridge system composed of 10 elements each having 10 condition states and 5 possible maintenance, rehabilitation and repair (MR&R) actions, the total number of states and action combinations in the decision-making framework would be 10^{10} and 5^{10}, respectively. The difficulty of handling this problem and the extremely significant required computational cost are prohibitive for any decision-making platform. Due to the extremely large number of states and actions in such problems, many available models have applied MDP for optimal decision-making through state generalization and condensation (e.g.; [18,17,27]). In these studies, the condition state of the system or a subsystem composed of a group of elements typically represents an average condition of their constituent parts. Likewise, the actions corresponding to these states are general for all elements within the subsystem or the system itself [27]. Although such techniques reduce the size of the problem and therefore the computational cost, they may introduce large approximations for the assignment of element-level optimal strategies.

This paper introduces a new comprehensive decision-making framework for the management of systems comprised of multiple elements, in a way that optimal strategies are provided at the element-level and uncertainty sources both in the system performance and inspected measurements are incorporated. The proposed method integrates a randomized point-based value iteration approach to solve Partially Observable MDP problems with a new counting process state reduction technique that enables tackling large scale decision-making problems. The concept behind the counting process is that elements of a system can be grouped based on significant attributes that influence the outcomes of the analysis; for management of bridges, these attributes can be structural features and deterioration performance of the elements, and consequences of different damage states. Using this methodology, the optimization problem in POMDP deals with the quantity of elements in each of the condition states for each element type rather than dealing with all combinations of the condition states of elements. This enhances the ability to handle larger optimization problems for multi-state multi-element systems. However it should be mentioned that the proposed integration of the counting process technique with POMDP introduces a number of approximations and loss of accuracy to the original problem. These include, for example, loss of spatial information about elements and correlations in elements' rate of deterioration, and assignment of the same action to elements in the same condition state.

The proposed framework is applied to a case study bridge system with realistic settings composed of four girders and a concrete deck. The elements of the bridge are under time-dependent deterioration due to the combined effects of aging, demand loads, and other environmental stressors. Furthermore, measurement randomness associated with commonly used inspection techniques are considered to account for the uncertainties in the estimation of the condition states of bridge elements.

The rest of this paper is organized as follows: In Section 2, the applied POMDP-based framework is presented. Section 3 explains the counting process technique and discusses its effectiveness in reducing the number of states. Furthermore, expressions are derived for POMDP matrices based on the new definition of the condition states. In Section 4, the application of the framework is demonstrated for the example bridge system, and the numerical results are provided and discussed next in Section 5. Finally, the conclusion section summarizes the features of this framework and its application for multi-state multi-element systems.

2. POMDP framework

In a discrete MDP, the time variant behavior of a system element is predicted through Markov chains. A Markov chain consists of a transition probability matrix that defines the conditional probability of the true condition state of the utility at time t given the state at time $t-1$

$$P(X_t|X_{t-1}, X_{t-2}, \ldots, X_0) = P(X_t|X_{t-1}) \tag{1}$$

where $P(.)$ denotes the probability and X_i stands for the condition state at time i. For each of the possible condition states at time $t-1$, a probability mass function (PMF) is provided in the Markov chain to describe the likelihood of the condition states for the next time period. A graph-based representation of a 5-state Markov chain is depicted in Fig. 1 where PMF values are shown on the graph edges. The goal of the MDP is to choose among a set of actions such that a predefined objective function is optimized. Each considered action requires a transition probability matrix describing the probabilistic impact of the action on the condition states, as well as the reward associated with that action. Defining the objective function as the expected accumulated reward at each of the decision-making times, the MDP framework can be mathematically described as