Formulating Partially Observable Markov Decision Processes (POMDP) for Satellite-Based Pavement Monitoring

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***Abstract*—In this paper, we analyze a POMDP framework used to assess costs associated with monitoring and repair of pavement conditions. We provide a thorough summary of related works which introduce various aerial surveillance methods and models for assessing pavement distress. We discuss a foundational paper which formulates the problem in a POMDP framework, and introduce our implementation of the POMDP framework. We provide a comparison of our results after implementing the POMDP framework and using two POMDP solvers, SARSOP and QMDP, to the original formulation. Finally, we provide suggestions for improving the model to reduce ambiguity and we demonstrate the effectiveness of this improved model using a comparison of belief simplex plots.**

***Index Terms*—Annual Distress Survey, Satellite Based Imagery, POMDP, SARSOP, QMDP**

I. Introduction

The assessment and management of pavement conditions play a critical role in the efficient operation and maintenance of transportation infrastructure. Traditional methods depend largely on ground-based monitoring, which is expensive and resource-intensive. The evolution of data collection technology, particularly the integration of low-cost sensors and advanced remote sensing technologies, presents new opportunities to enhance the efficiency and cost-effectiveness of pavement condition assessments [1]. However, the use of such technologies introduces significant uncertainties in the data collected, primarily due to the indirect nature of the condition assessment methods [1].

This paper uses a framework of a Partially Observable Markov Decision Process (POMDP) to model the problem of assessing pavement condition and provides an analysis of several POMDP solving methods for the problem. By conducting a detailed study, this research evaluates the performance of previous methods from [1] against conventional methods, highlighting its potential to reduce errors significantly in pavement condition assessments. Furthermore, the study explores multiple POMDP solvers, providing a deeper understanding of their impact on the predictive outcomes of pavement conditions.

II. Background and Related Work

A. Partially Observable Markov Decision Processes

Partially Observable Markov Decision Processes (POMDPs) extend the classical framework of Markov Decision Processes (MDPs) to scenarios where the agent's perception of the environment's state is limited or noisy. A POMDP models decision making under uncertainty by incorporating observations that provide indirect information about the true state of the system [2].

A POMDP is formally defined by the tuple $(\mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{R}, \mathcal{O}, \Omega, \gamma)$ where [2]:

- $\mathcal{S}$ is a finite set of states.
- $\mathcal{A}$ is a finite set of actions.
- $\mathcal{T} : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to [0, 1]$ is the transition probability function, where $\mathcal{T}(s, a, s')$ represents the probability of transitioning to state s' from state s after taking action a.
- $\mathcal{R} : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$ is the reward function, which specifies the immediate reward received after taking an action a in state s.
- $\mathcal{O}$ is a finite set of observations.
- $\Omega : \mathcal{S} \times \mathcal{A} \times \mathcal{O} \to [0, 1]$ is the observation probability function, where $\Omega(s', a, o)$ gives the probability of receiving observation o after taking action a and reaching state s'.
- $\gamma \in [0, 1)$ is the discount factor, which models the present value of future rewards.

B. Belief State

Due to the uncertainty about the actual state, a POMDP utilizes a *belief state*, a probability distribution over $\mathcal{S}$, to represent the agent's knowledge about the current state. The belief state is updated based on the observation history and the actions taken, using Bayesian updating [2].

C. Solution Methods

Solving a POMDP involves finding a policy that maximizes the expected discounted reward over the belief states. This is computationally challenging due to the need to maintain and update a continuous belief space. Common approaches to solving POMDPs include SARSOP and QMDP. These solution methods are discussed in detail in the following section.

1) SARSOP: SARSOP, or *Successive Approximations of the Reachable Space under Optimal Policies*, is an advanced point-based algorithm for solving POMDPs. It focuses on the subset of belief states that are most relevant to achieving high rewards, which it determines by iteratively refining a lower and upper bound on the optimal value function [3]. The algorithm employs a sampling-based approach to efficiently approximate the reachable belief space, thus focusing computational resources on areas of the belief space that significantly affect optimal policy decisions [3]. By pruning less relevant parts of the belief space, SARSOP manages to find near-optimal solutions with reduced computational overhead compared to exhaustive methods [3].

2) QMDP: The QMDP algorithm represents a simplifying approach for handling POMDPs by assuming that all uncertainty about the system state is resolved after one step. Under this assumption, the QMDP algorithm reduces the POMDP to a Markov Decision Process (MDP) at each decision step based on the current belief state [2]. This method computes the optimal action by considering the expected value of the Q-function over the current belief distribution, which significantly simplifies computations. However, QMDP tends to perform poorly in scenarios where the assumption of immediate uncertainty resolution is unrealistic, particularly in environments where observations provide limited information about the state transitions [2].

Despite these methods, solving POMDPs remains a challenge due to the “curse of dimensionality”, making the problem intractable for large state spaces or long planning horizons [2], [3]. We will address how we handled the challenges of dimensionality in section III.

D. Related Work

The authors in [1] provide a comprehensive analysis of the use of satellite-based systems for pavement monitoring within partially observable stochastic environments. Their work highlights the potential for satellites to offer a cost-effective alternative to traditional methods. The authors in [4] find that satellite and aerial imagery can be combined to provide further information for a POMDP framework.

In [1] the authors bring attention to the tradeoff between accuracy and the ability to effectively cover large areas. Viewing this trade-off through the lens of a POMDP, the authors focus on optimal life-cycle inspection and maintenance policies. They establish a foundational comparison between satellite-based observations and ground-based assessments, concluding that satellites can reduce maintenance costs by up to 6.5% for non-monitored roads, compared to annually inspected major roads [1]. Their findings are significant in showing that the use of satellite data becomes particularly valuable at a 70% accuracy level when combined with more precise systems [1]. This is in line with earlier studies that have grappled with the challenges of integrating high-uncertainty data into maintenance strategies.

This research intersects with other recent studies that have leveraged various types of remote sensing data for pavement condition assessment. For example, [5] and [6] have explored the potential of synthetic aperture radar (SAR) and high-resolution multispectral imagery, respectively, to assess road conditions at a network level. Another study uses high spatial resolution (HSR) multispectral digital aerial photography for evaluating pavement surface distress, providing a foundation for our research on satellite-based monitoring [7]. The authors demonstrated that HSR multispectral digital aerial photographs could accurately assess pavement conditions through principal component analysis (PCA) and linear regression models. Their findings revealed that the spectral response of these photographs correlates strongly with manually collected pavement distress data, achieving an impressive correlation coefficient (R^2) greater than 0.95 at a 6-inch resolution [7].

These approaches underscore the growing recognition of satellite imagery as a viable tool for large-scale infrastructure monitoring, supporting the decision-making processes in pavement management by providing critical, wide-reaching data more economically than traditional methods. These advancements and the subsequent implications for cost-efficiency align with a broader move towards more data-driven, predictive maintenance strategies in civil engineering.

III. Problem Formulation

Initially, we planned to formulate the problem exactly as done in [1]. However, preliminary implementation efforts revealed some discrepancies between the problem formulation and code implementation. These will be discussed in the following subsections where we describe the state space, action space, reward, observation space, and transition probabilities. The original source code, written in R, was obtained from the author [8]. Our intention was to transcribe this code to Julia and improve upon the methodology laid out in the original work [1].

State Space

The condition of the pavement will be described using three states based on their International Roughness Index (IRI) as done in [1]. The state space S represents the discrete condition states of the pavement, defined as follows:

$$S = \{\text{Good}, \text{Fair}, \text{Poor}\}$$

Each state reflects a specific level of pavement quality, where *Good* indicates minimal degradation, *Fair* indicates moderate degradation, and *Poor* indicates significant degradation requiring immediate attention. Initially, a uniform probability of being in any of these three states is assumed as per [1]. We will use the same state space in our problem formulation.

Action Space

The action space A encompasses the various maintenance and inspection actions that can be applied to the pavement sections. The authors in [1] define the action space to be made of the following four actions:

$$A = \{\text{Do Nothing}, \text{Minor Repair}, \text{Major Repair}, \text{Reconstruction}\}$$

However, in the source code [8], the authors define the action space to be much larger encompassing inspection actions paired with the maintenance actions, which were mentioned to be in the observation space Ω. For example, "MS" in Figure 1 is defined as the Minor Repair - Satellite Inspection action.

```
actions = c("DN", "DS", "DA", "MN", "MS",
            "MA", "JN", "JS", "JA", "RN")
```

Fig. 1. R code for defining POMDP actions from [8].

We modified our initial Julia code to reflect this new action space as part of our efforts to reproduce the authors original results in [1]. In III, we will propose modifications to improve the model.

Transition Probabilities

In our analytical framework, the states are assumed to have stationary transition dynamics (i.e., the transition from one state to another is independent of time and rate of pavement deterioration) and the impact on condition derived from the application of each possible maintenance action a is defined by a transition probability matrix [1]. These matrices describe the probability that the system will transition from an initial state s to a final state s' after the application of a maintenance action a. That is, T is a set of conditional transition probabilities, $T(s' \mid s, a)$ for the state transition $s \to s'$ [1].

The foundation of the transition model is based on the Colorado Department of Transportation (CDOT) pavement condition dataset, which encompasses field performance data from the years 2013 to 2018. This dataset includes detailed records of pavement conditions and the maintenance actions applied. Data was categorized based on maintenance interventions into *no action*, *minor repair* (such as crack sealing, chip seal, ultrathin overlays), and *major repair* categories. The pavement conditions were quantified using the International Roughness Index (IRI), a reliable measure of pavement smoothness and an indicator of service quality perceived by vehicle users. Based on the Federal Highway Administration's criteria, three discrete states were defined: good (IRI $<$1.51 m/km), fair (IRI between 1.51 and 2.68 m/km), and poor (IRI $>$ 2.68 m/km) [9].Year-over-year IRI changes were analyzed and transitions were aggregated within these states. For instance, with no maintenance, 74% of sections initially in good condition remained so, 25% transitioned to fair, and 1% deteriorated to poor, demonstrating the critical impact of maintenance actions on pavement longevity. For the reconstruction maintenance action, the transition probability matrix is defined as follows: with a 100% probability, sections in any initial state (good, fair, or poor) fully return to a good condition, with no chance of remaining in or reverting to fair or poor states [1].

$$T(1) = \begin{pmatrix} 0.74 & 0.25 & 0.01 \\ 0 & 0.82 & 0.18 \\ 0 & 0 & 1.00 \end{pmatrix}$$

$$T(2) = \begin{pmatrix} 0.86 & 0.14 & 0 \\ 0.62 & 0.35 & 0.03 \\ 0 & 0 & 1.00 \end{pmatrix}$$

$$T(3) = \begin{pmatrix} 0.94 & 0.06 & 0 \\ 0.86 & 0.13 & 0.01 \\ 0 & 0.50 & 0.50 \end{pmatrix}$$

$$T(4) = \begin{pmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}$$

Rewards (R) and Discount Factor (γ)

A 25-year analysis period used a discount factor (γ) of 0.95 to reflect the time value of money, aligning with common discount values (0.95–0.98) for infrastructure projects seen in [10]. No penalty costs apply when pavement conditions are good. However, when pavement conditions are fair or poor, the penalty reward is estimated based on the increase in operating costs drivers pay per year due to poor conditions of the road [11]. This penalty is based on annual average daily traffic estimated by [11]. The costs are assumed by [1] to increase by 1.5 or 2 times with each deteriorating level of road condition (e.g. fair to poor). The reward values, while not mentioned specifically in [1], were acquired from the source code used [8] and can be viewed in Table I. According to [1], the costs associated with the different actions are roughly based on $1,000 per lane-km.

TABLE I
REWARD VALUES ASSOCIATED WITH MAINTENANCE ACTION - INSPECTION ACTION PAIRS

Maintenance-Action pair	Good	Fair	Poor
DN	0	-34	-48
DS	-0.03	-34.03	-48.03
DA	-0.10	-34.10	-48.10
MN	-25.00	-72.00	-98.00
MS	-25.03	-72.03	-98.03
MA	-25.10	-72.10	-98.10
JN	-175.00	-297.00	-398.00
JS	-175.03	-297.03	-398.03
JA	-175.10	-297.10	-398.10
RN	-1050.00	-1084.00	-1098.00

Observations

As described in II, in a POMDP we have only the observations, not the true underlying state of the system. The different inspection strategies (no inspection, satellite-based, annual surveys) represent different methods through which the system (e.g., pavement conditions) can be observed [1]. The observation model links the true states of the system to the observations received. For each true state, the observation matrix describes the probability distribution over possible observations. For example, with no inspection, the observation is always "unknown", represented as an equal probability (e.g., [1 1 1]) across all potential true states because no informative observation is made [1].

For satellite-based inspections, the observation probabilities vary based on the outcomes from pixel brightness analysis, making these probabilities contingent on both the actual state of the pavement and the result of the inspection technology used [1]. The observation matrix for satellite-based pavement inspections is constructed from histograms of pixel brightness across different pavement conditions [1]. These conditions are classified into five distinct levels based on the digital number (DN) values: very low, low, medium, high, and very high. This classification is achieved by dividing the DN value range into five classes, where [1]:

- Values below 1% of those in fair condition are categorized as very low.
- Values above 99% are categorized as very high.
- Values in between are equally divided into low, medium, and high categories.

Observation probabilities O^{so}, where s indicates the state and o the observation level, are calculated by estimating the area under the curve for each state within a specific DN range. For instance, O^{so}_{12} represents the probability of observing a low pixel brightness value given that the pavement is in good condition. These probabilities are organized into a matrix format as shown below:

$$O(2) = \begin{bmatrix} O^{so}_{11} & O^{so}_{12} & O^{so}_{13} & O^{so}_{14} & O^{so}_{15} \\ O^{so}_{21} & O^{so}_{22} & O^{so}_{23} & O^{so}_{24} & O^{so}_{25} \\ O^{so}_{31} & O^{so}_{32} & O^{so}_{33} & O^{so}_{34} & O^{so}_{35} \end{bmatrix}$$

Consistent with [1], this matrix forms the basis for the satellite-based inspection system, allowing for differentiated responses based on observed pavement conditions.

Annual distress surveys are used to estimate IRI. Therefore, the same methodology which discretized IRI values into three distinct states can be applied for the observation space when an annual distress survey is performed [1]. This results in a 3x3 matrix which reflects 90% accuracy for the ground based observations. The other 10% is divided between the remaining states to account for variations in measurement techniques, devices, and data processing methods that differ between surveys [1].

$$O(3) = \begin{bmatrix} 0.90 & 0.08 & 0.02 \\ 0.05 & 0.90 & 0.05 \\ 0.02 & 0.08 & 0.90 \end{bmatrix}$$

The authors introduce another observation matrix, the "emission probability matrix (O)", which when compared with the previously defined O(2), can be used to determine the level of accuracy for the satellite based observations [1].

$$O'(2) = \begin{bmatrix} p & \frac{1-p}{2} & \frac{1-p}{2} & 0 & 0 \\ 0 & \frac{1-p}{2} & p & \frac{1-p}{2} & 0 \\ 0 & 0 & \frac{1-p}{2} & \frac{1-p}{2} & p \end{bmatrix}$$

In $O'(2)$, the p value is bounded $0 \leq p \leq 1$ and is used to study the effect of observation uncertainty by tuning that value [1]. The comparison between $O'(2)$ and $O(2)$ is used to perform a quantitative evaluation of how the value of satellite information changes with accuracy improvements [1]. We will not perform this value analysis as part of our work as our primary objective is improving the POMDP model.

When implementing the POMDP model and solver in Julia [12] using the source code in [8], we found that an assumption was made to fit the problem into a POMDP model. The observation matrix define above, $O(2)$, which corresponds to pixel brightness in the satellite imagery, is also being used for all maintenace actions that are paired with the "No Inspection" action. In the source code [8], any maintenance action paired with a no inspection action has the following observation matrix:

$$O_{No\_Inspection} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Similarly, in the source code [8], the following observation matrix was used for the actions relating to *Annual Distress Survey*:

$$O_{Annual\_Distress\_Survey} = \begin{bmatrix} 0.90 & 0.08 & 0.02 & 0 & 0 \\ 0.05 & 0.90 & 0.05 & 0 & 0 \\ 0.02 & 0.08 & 0.90 & 0 & 0 \end{bmatrix}$$

It is not immediately clear how this impacted the performance of the POMDP, if at all. However, we intend to improve the formulation by removing this ambiguity in the observation space. There is no clear reason for assuming that every No Inspection action should have a pixel brightness corresponding to Very Low. Since Pixel Brightness was only used for measuring satellite imagery, it does not make any sense to assign a pixel brightness observation to a No Inspection action. Furthermore, due to the observation in the source code [8] being defined as

```
observations = c("VL", "L",
                 "M", "H", "VH")
```

there is no way for the code to tell apart the differences in between the different inspection methods.

Adapted Problem Formulation

We propose improvements to the model from [1] which can be used to reduce ambiguity in the problem definition and reduce inconsistencies between the written paper and the accompanying source code [8].

We use the same state space as [1], however, we simplify the action space to clearly indicate which action is being taken. This decouples the actions from inspection types. We also propose removing "Do Nothing" as an action, as "No Inspection" sufficiently captures the same transition, observation, and reward dynamics.

$$S = \{\text{Good}, \text{Fair}, \text{Poor}\}$$

$$A = \{\text{No Inspection}, \text{Satellite Inspection}, \text{Annual Distress Survey}, \text{Minor Repair}, \text{Major Repair}, \text{Reconstruction}\}$$

We slightly modify the transition matrices such that they match our refined action space. T_{all_others} now represents the transition probabilities for actions which do not modify the road conditions (i.e. No Inspection, Satellite Inspection, Annual Distress Survey). The other transition matrices are associated with a pavement modification action. Most notable for complete reconstruction, we assume the transition probability to "Good" state is 100%.

$$T_{all\_others} = \begin{pmatrix} 0.74 & 0.25 & 0.01 \\ 0 & 0.82 & 0.18 \\ 0 & 0 & 1.00 \end{pmatrix}$$

$$T_{minor\_repair} = \begin{pmatrix} 0.86 & 0.14 & 0 \\ 0.62 & 0.35 & 0.03 \\ 0 & 0 & 1.00 \end{pmatrix}$$

$$T_{major\_repair} = \begin{pmatrix} 0.94 & 0.06 & 0 \\ 0.86 & 0.13 & 0.01 \\ 0 & 0.50 & 0.50 \end{pmatrix}$$

$$T_{reconstruction} = \begin{pmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}$$

For the observations, given that we programmed this in Tabular format [13] in Julia [12], we expanded the observation matrices used. We have simply combined all the original matrices provided in [1]. By combining them into the same size, we make the matrices clear for the packages being used [13], ascertaining an accurate policy from the model.

$$O_{No\_Inspection} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

$$O_{Sat\_Insp} = \begin{pmatrix} 0 & p & \frac{1-p}{2} & \frac{1-p}{2} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1-p}{2} & p & \frac{1-p}{2} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{1-p}{2} & \frac{1-p}{2} & p & 0 & 0 & 0 \end{pmatrix}$$

$$O_{ADS} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0.9 & 0.08 & 0.02 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.05 & 0.9 & 0.05 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.02 & 0.08 & 0.9 \end{pmatrix}$$

Due to the change in $\mathcal{A}$, we also require a change in $\mathcal{R}$. The rewards, shown below in Table II, were obtained from simplifying the reward differences between actions in Table I.

TABLE II
PROPOSED REWARD VALUES

Maintenance-Action pair	**Good**	**Fair**	**Poor**
No Inspection	0.00	-34.00	-48.00
Satellite Inspection	-0.03	-34.03	-48.03
Annual Distress Survey	-0.10	-34.10	-48.10
Minor Repair	-25.00	-72.00	-98.00
Major Repair	-175.00	-297.00	-398.00
Reconstruction	-1050.00	-1084.00	-1098.00

IV. SOLUTION APPROACH

We aim to provide a baseline comparison between SARSOP and QMDP solvers for this problem formulation. We will assess the two solvers individually using the same problem formulation defined in III and [1]. We created a belief simplex [14] and plotted it [15] in order to evaluate the policies created by each method in section V.

V. RESULTS

Comparison of QMDP

Figures 2 and 3 are belief simplex plots generated from the outputs of the QMDP solver. Figure 2 is the belief simplex from the POMDP model matching [1]. Figure 3 is the belief simplex generated from our proposed improved model.

Observations from the plots indicate that when the belief probability of the system being in a "Poor" state is high, the strategy favors a "Reconstruction" action, denoted by green dots. This decision suggests a preference for comprehensive rebuilding measures in response to adverse conditions. Conversely, the prevalence of black dots, representing the "No Inspection" action, in regions associated with a higher belief in the "Good" state, underlines a strategy of minimal intervention, assuming stability and reduced likelihood of deterioration.

The dominance of the *No inspection* action in the decision-making process across the belief space is a focal point in both our proposed model and the model from [1]. The QMDP approach simplifies the decision process by focusing on immediate reward maximization through a single look-ahead step. This characteristic results in a substantial portion of the belief space opting for passive actions like "No Inspection" when the probability of being in a "Good" state is elevated.

The consistent behavior observed under the QMDP policy across different model configurations might suggest a certain robustness in its application to this type of decision problem. Nonetheless, this also highlights a significant limitation of the QMDP framework, particularly its inability to account for multi-step consequences and long-term strategic planning [16]. Such limitations are especially pronounced under varying assumptions about state transitions and the associated costs, pointing to the necessity for more sophisticated decision-making frameworks that can accommodate longer-term planning and uncertainty in complex infrastructural management systems.

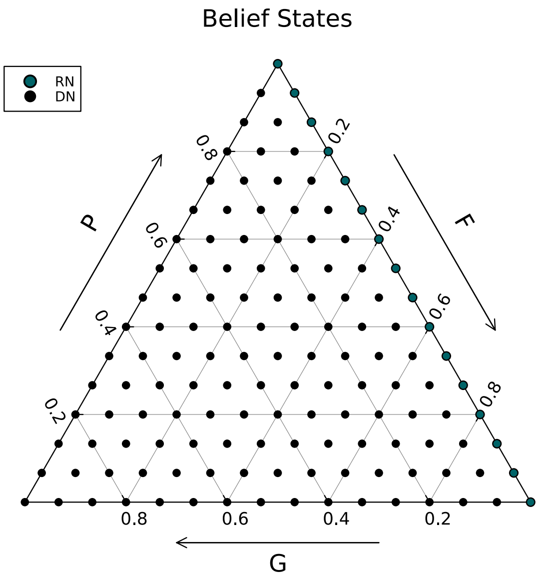

Fig. 2. Belief simplex output from the implementation based on [1] using the QMDP solver.

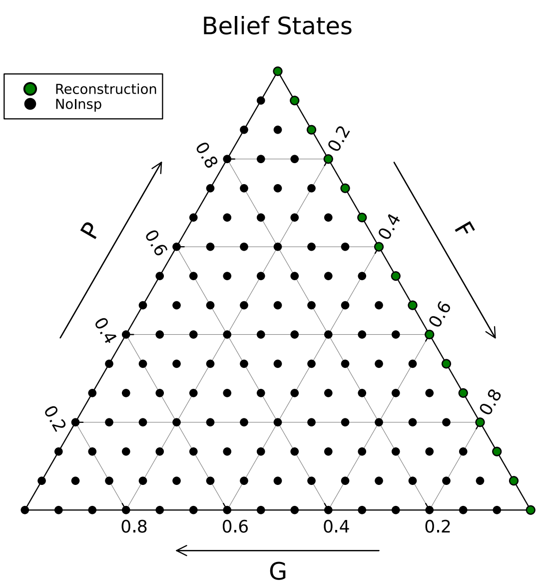

Fig. 3. Belief simplex output from our proposed improved model using the QMDP solver.

Comparison of SARSOP

Figures 4 and 5 are belief simplex plots generated from the outputs of the SARSOP solver. Figure 4 shows the output from the POMDP model that matches [1]. Notable in this plot is the inspection action - maintenance action pairing in the plot legend. Because of the coupling between the two types of actions, the belief simplex is confusing to interpret. For example, the plot shows that if you are relatively confident that the state is “Poor”, then the best action is a satellite inspection with no planned maintenance action, which is an overly obtuse way of recommending satellite inspection.

Figure 5 shows the output of our proposed improved POMDP model. We represent the action space with a more concise definition such that the recommendation for satellite inspection is decoupled from a maintenance action. It is our belief that this makes the recommendations based on belief states more clear and usable.

The SARSOP solver, in our proposed model and the model in [1], appear to heavily favor the use of satellite inspection over annual distress surveys. This is understandable when there is a high confidence that the state is “Good” given that a distress survey is more costly than satellite inspection given in the reward structure defined in II. If confidence is high that the condition is “Good”, then there is no need to perform a more costly information gathering action if a less costly alternative is available.

The original POMDP model and our improved model both heavily favored inspection actions - specifically satellite based inspections. Another interesting note is that major and minor repairs are heavily favored over reconstruction in both models. These are likely the result of the reward structures defined in Tables I and II. The rewards heavily penalize a full reconstruction effort which explains why a SARSOP model would avoid these high penalties, instead favoring actions with reduced penalties. This aligns with the literature [1], [5], [4], that discusses the high costs associated with allowing roadways to fall into disrepair and instead advocates for pre-emptive corrective action to prevent further degradation as a cost saving measure for state agencies.

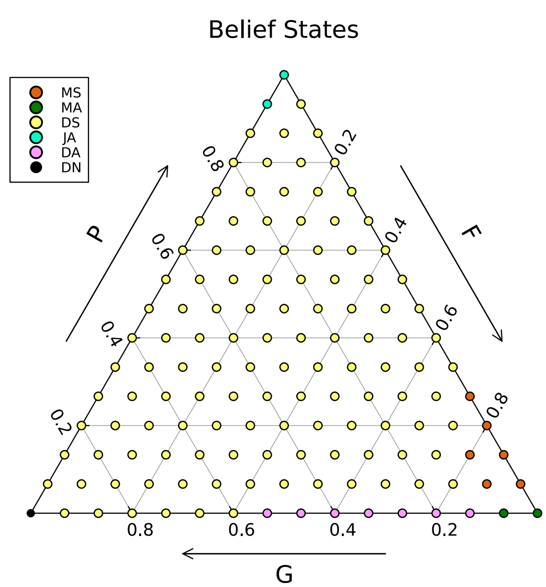

Fig. 4. Belief simplex output from the implementation based on [1] using the SARSOP solver.

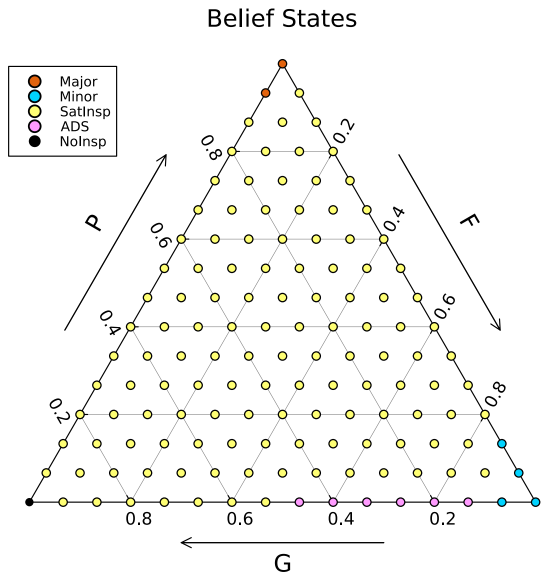

Fig. 5. Belief simplex output from our proposed improved model using the SARSOP solver.

Comparison Against [1]: Original R Code vs. Our Julia Implementation

When we ran the original R source code [8] to create the belief simplex from Figure 7 in [1], the code produced different results than the plot published in [1]. This is another discrepancy we found between the published work and the source code. Figure 7b in [1] shows that with a high probability of the road condition being "Poor", that the preferred action is to survey. Given the problem formulation, this does not make sense as the best policy when there is a high confidence that the road is in bad condition. The proper response should be a maintenance action because repairs would be needed if the road conditions were in this state.

VI. Future Work

In our modified problem formulation in III, we assume that all reconstructions leave the roads in a Good state with 100% certainty. In reality, it is possible that the reconstruction is completed with defects. These transition probabilities may need altering based on road defects in new construction. This enhancement could be added with additional information on the success rate of reconstruction efforts.

Additionally, it is possible that road conditions are not adequately described by only three discrete states. Future models could be discretized into four or more states and analyze the model outcomes. It is also possible to introduce a transition model allowing us to directly predict the IRI and obtain the best policy. This approach would however require an online POMDP solver.

Furthermore, our analytical framework currently assumes that the transition dynamics between states are stationary—that is, the likelihood of transitioning from one state to another does not change over time. A similar assumption was also considered in [1]. This assumption does not account for the varying rates of pavement deterioration that can occur due to environmental factors, traffic loads, and maintenance quality. Introducing dynamic transition probabilities that adjust based on observed deterioration rates and other influencing factors could significantly enhance model accuracy and decision-making effectiveness in pavement management.

VII. Conclusion

Directly reproducing the results from [1] proved to be slightly more challenging than expected. The inconsistency in the way the actions were described in the paper versus the implementation in the source code [8] was the first hurdle. The second was the use of pixel brightness in the observation matrix for any action that included a "No Inspection" survey action. As shown in V, we were able to get very close to the results of [1].

Though we were able to get similar results for the cost associated with the different states as represented in V, we still felt there was an opportunity to improve the model. Our proposed model in III reduces ambiguity related to the actions and observations, increasing the likelihood that the model can be adopted and used to further improve modeling of road conditions and the associated cost of repairs.

VIII. Contribution and Release

All three authors were instrumental in completing this project. Aritra served as our resident Julia expert, leading the implementation of the POMDP model in Julia. Lorin and Istiakur worked primarily on analyzing the model defined in the original paper, experimenting with Julia plotting packages, and writing the final report. All authors were involved in evaluating the potential shortcomings of the original model and brainstorming ways to improve it.

Acknowledgment

We would like to thank the authors in [1] for allowing us to build on their prior work and offering support and encouragement along the way. Similarly, we acknowledge the Colorado Department of Transportation (CDOT) who assisted in the data collection process. The contents of this paper do not necessarily reflect the official views or policies of CDOT.

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