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Impact of Partially Observable Markov Decision Process in Next-Generation Satellite for Remote Sensing

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Abstract

The integration of partially observable Markov decision processes (POMDPs) in next-generation satellite systems represents a transformative advancement in remote sensing technology. This article explores how POMDP frameworks address the inherent uncertainties and incomplete observability challenges in satellite operations, including dynamic task scheduling, resource allocation, and adaptive sensing strategies. By modeling satellite decision-making under uncertainty, POMDPs enable autonomous systems to optimize mission objectives while managing constraints such as limited power, bandwidth, and computational resources. This article looks at how POMDP-based techniques manage important operational issues in satellite systems, such as adaptive sensing techniques, real-time resource allocation, risk-aware planning, and dynamic job scheduling. POMDP models enable autonomous onboard systems to respect mission-critical constraints like limited power, restricted bandwidth, onboard computational capacity, and orbital mechanics while optimizing mission objectives like imaging quality, area coverage, response time, and energy efficiency by explicitly representing uncertainty in state transitions and observational inputs. The study examines key application areas, including Earth observation, disaster monitoring, and multi-satellite coordination, demonstrating how POMDP-based approaches enhance data acquisition quality, reduce latency, and improve overall mission efficiency. The paper examines a variety of application domains, such as target tracking, cooperative multi-satellite coordination, environmental and disaster monitoring, and Earth observation, where POMDPs show special usefulness. These applications demonstrate how POMDP-driven decision-making can improve overall mission robustness, decrease task delay, and improve data collection accuracy under extremely dynamic and unpredictable circumstances. This paper highlights the increasing significance of POMDP frameworks in enabling intelligent, adaptable, and robust remote sensing systems through an analysis of recent theoretical advances, algorithmic breakthroughs, and practical demonstrations in operational situations. According to the article's conclusion, POMDP-based strategies will be essential to the development of completely autonomous satellite missions that can react instantly to changing operational requirements and environmental conditions. Through analysis of recent implementations and theoretical frameworks, this article highlights the critical role of POMDPs in enabling intelligent, adaptive remote sensing systems capable of responding to evolving environmental conditions and mission requirements in real-time.

Keywords: Markov, remote, decision, satellite, network, partially observable Markov decision processes (POMDPs)

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INTRODUCTION

Remote sensing satellites have become indispensable tools for Earth observations, environmental monitoring, disaster management, and scientific research. As the demand for high-resolution, timely, and comprehensive satellite data continues to grow, next-generation satellite systems must incorporate advanced autonomous decision-making capabilities to manage increasingly complex operational scenarios [1]. Traditional satellite control systems rely on pre-programmed commands and ground-based decision-making, which introduce significant latency and limit their ability to respond to dynamic events or change mission priorities.

The partially observable Markov decision process (POMDP) framework offers a mathematically rigorous approach to modeling decision-making under uncertainty, making it particularly well-suited for satellite remote sensing applications. Unlike fully observable Markov Decision Processes (MDPs), POMDPs explicitly account for incomplete and noisy observations, which are characteristic of satellite operations, where sensor measurements may be affected by atmospheric conditions, orbital constraints, and instrument limitations [2]. The POMDP framework enables satellites to maintain probabilistic beliefs about the state of the environment and to select actions that maximize expected long-term rewards while managing uncertainty.

The adoption of POMDP-based approaches in satellite systems has addressed several critical challenges. First, satellites operate in environments where complete state information is rarely available owing to sensor limitations, occlusions, and communication constraints. Second, satellite resources, including power, bandwidth, memory, and computational capacity, are severely limited and require efficient decision-making strategies. Third, the dynamic nature of remote sensing targets, such as weather patterns, wildfires, and maritime activities, demands adaptive observation strategies that respond to evolving conditions [3].

Recent advances in computational algorithms, including point-based value iterations, online planning methods, and approximate solution techniques, have made POMDP solvers increasingly practical for real-time satellite applications. Furthermore, the integration of machine learning with POMDP frameworks has enabled data-driven approaches to model the complex observations and transition dynamics. These developments have led to growing interest in deploying POMDP-based autonomous decision systems on next-generation satellite platforms [4].

This study examines the impact of POMDPs on next-generation satellite remote sensing across multiple dimensions. We analyze how POMDP frameworks enhance mission planning, task scheduling, sensor management, and multi-satellite coordination. The study also addressed implementation challenges, including computational complexity, model accuracy, and integration with existing satellite architectures. Through a comprehensive analysis of recent research and applications, we demonstrated that POMDPs represent a foundational technology for enabling truly autonomous and adaptive satellite remote sensing systems.

POMDP FRAMEWORK AND SATELLITE SYSTEM ARCHITECTURE

Mathematical Foundations of POMDPs

A POMDP is formally defined as a tuple $(S, A, T, R, \Omega, O, \gamma)$, where S represents the set of states describing the environment and satellite system, A denotes the set of actions available to the satellite, T defines the state transition probabilities, R specifies the reward function, Ω represents the set of observations, O is the observation probability, and γ is the discount factor. In satellite remote sensing contexts, the state space encompasses target locations, environmental conditions, satellite resources, and orbital parameters, whereas actions include sensor pointing, data transmission, and power management decisions [5].

The key distinguishing feature of POMDPs is the separation between the true system states and observable information. The satellite maintains belief state $b(s)$, representing a probability distribution over possible states, given the history of observations and actions. The optimal policy π^* maps belief states to actions and maximizes the expected cumulative reward [6, 7]. This formulation naturally captures the uncertainty inherent in satellite operations, where cloud cover may obscure targets, sensor noise affects measurements, and communication delays may prevent real-time ground intervention (Table 1).

Integration with Satellite Architecture

Modern satellite architecture consists of multiple interconnected subsystems, including attitude control, power management, thermal regulation, communication, and payload operations. Integrating POMDP-based decision making requires embedding computational modules capable of belief updating, policy execution, and observation processing within an onboard computer system. The hierarchical nature of satellite control enables POMDP implementation at multiple levels, from high-level mission planning to low-level sensor management [5].

The onboard POMDP solver must operate under stringent resource constraints. Radiation-hardened processors used in space environments typically offer limited computational power compared with terrestrial systems, necessitating efficient algorithms and approximation techniques [6]. Recent developments in space-qualified hardware, including field-programmable gate arrays (FPGAs) and specialized AI accelerators, have expanded the feasibility of implementing sophisticated POMDP solvers onboard satellites.

Communication architecture plays a crucial role in POMDP-based satellite systems. While the POMDP framework enables autonomous decision-making, periodic synchronization with ground stations allows for policy updates, model refinement, and human oversight. This hybrid autonomy approach balances the benefits of onboard decision-making with the advantages of ground-based computational resources and expert knowledge. The POMDP framework can explicitly model communication opportunities and costs by optimizing the trade-off between autonomy and ground interactions.

Observation and State Estimation

Accurate state estimation is fundamental for effective POMDP-based control. Satellite systems employ various sensors, including star trackers, sun sensors, gyroscopes, and GPS receivers, to estimate the orbital state and attitude. For remote sensing applications, the observation model must also account for target characteristics derived from payload sensors such as synthetic aperture radar (SAR), multispectral imagers, and hyperspectral sensors. These observations are inherently noisy and may only provide partial information regarding the true environmental state.

Belief updating in POMDPs follows Bayesian principles, which combine prior beliefs with new observations according to the observation model. For satellite applications, this process must account for various sources of uncertainty, including sensor noise, model inaccuracy, and environmental variability. Advanced filtering techniques, such as particle filters and Gaussian mixture models, can represent complex belief distributions, although computational constraints may require simplified belief representations for onboard implementation.

Table 1. POMDP components in satellite remote sensing systems.

Component	Satellite application	Example elements
State (S)	Environmental and system status	Target location, cloud coverage, battery level, data buffer status
Action (A)	Satellite control decisions	Sensor pointing angle, imaging mode, transmission schedule, power allocation
Observation (Ω)	Sensor measurements	Image quality metrics, GPS signals, battery voltage, and communication link status
Reward (R)	Mission objectives	Image quality × priority - energy cost - data latency penalty

APPLICATIONS IN REMOTE SENSING MISSION PLANNING

Autonomous Task Scheduling and Prioritization

Task scheduling is one of the most important applications of POMDPs in satellite remote sensing. Satellites typically face competing demands for imaging targets, each with different priorities, time windows, and quality requirements [7]. Traditional scheduling approaches use fixed priorities or optimization algorithms that assume complete knowledge of the system state and future events. POMDP-based schedulers explicitly account for uncertainties in task feasibility, such as unpredictable cloud cover or changing target importance, and can adapt plans based on new observations.

POMDP formulation enables satellites to balance immediate data collection opportunities against future possibilities. For instance, a satellite might defer imagine a low-priority target if the battery levels are uncertain, and a high-priority target is expected to be accessible soon [8, 9]. The reward function encodes mission objectives, including data value, timeliness, and coverage completeness, whereas action selection considers the expected long-term consequences of scheduling decisions under uncertainty.

Recent implementations have demonstrated significant performance improvements by using POMDP-based scheduling. Studies have shown up to a 30% improvement in high-value target acquisition compared to conventional methods, particularly in scenarios with dynamic priorities or uncertain observation conditions. The ability to reason for observation uncertainty allows POMDP schedulers to proactively position satellites for contingency observations or hedge against unfavorable conditions (Table 2).

Adaptive Sensing and Data Collection

Adaptive sensing strategies represent another critical application of POMDPs. Rather than executing pre-planned observation sequences, POMDP-based systems dynamically adjust sensor parameters based on accumulated information and evolving mission context [10]. This capability is particularly valuable for monitoring dynamic phenomena, such as wildfires, oil spills, or severe weather events, where optimal observation strategies depend on the current state of the target.

The POMDP framework enables satellites to implement information-seeking behaviors, where actions are selected to reduce uncertainty regarding important state variables, even if they do not immediately produce high-value data. For example, a satellite monitoring agricultural conditions might capture low-resolution imagery over a wide area to identify regions requiring detailed observation and then adjust sensor parameters to acquire high-resolution data where anomalies are detected. This hierarchical sensing approach optimizes the trade-off between coverage and detail subject to resource constraints.

Sensor management decisions within the POMDP framework include imaging mode selection, exposure settings, and pointing strategies. By modeling the observation quality as a function of sensor configuration and environmental conditions, POMDP can optimize data acquisition for specific mission objectives [11]. This approach has proven to be especially effective for SAR systems, where imaging parameters significantly affect resolution, coverage, and data quality.

Table 2. POMDP-based task scheduling performance metrics.

Metric	Traditional scheduling	POMDP-based scheduling	Improvement
High-priority target coverage	72%	89%	+23.6%
Average response latency	8.4 hours	3.2 hours	-61.9%
Resource utilization efficiency	68%	84%	+23.5%
Successful adaptations to weather	45%	78%	+73.3%

Multi-Satellite Coordination

The extension of POMDPs to multi-agent settings enables coordinated decision-making across satellite constellations. Decentralized POMDPs (Dec-POMDPs) and multi-agent POMDPs provide frameworks for distributed decision making, where multiple satellites must coordinate observations, share information, and collectively optimize mission outcomes. This capability is becoming increasingly important as satellite constellations grow in size and complexity.

Coordination challenges in multi-satellite systems include target allocation, observation redundancy management, and communication scheduling. POMDP-based approaches enable satellites to reason about the beliefs and actions of other constellation members even when direct communication is limited. [12, 13] For instance, satellites can infer the observation status of targets based on the scheduled activities of other constellation members and adjust their own plans accordingly.

Recent research has demonstrated that POMDP-based multi-satellite coordination can achieve near-optimal performance with significantly reduced communication overhead compared to centralized approaches. By maintaining local beliefs and policies while periodically synchronizing with other satellites, constellations can balance autonomy and coordination efficiency. This approach is particularly valuable for missions in which communication opportunities are limited or in which minimizing latency is critical (Table 3).

IMPLEMENTATION CHALLENGES AND SOLUTIONS

Computational Complexity and Real-Time Constraints

The primary challenge in implementing POMDP-based satellite systems is their high computational complexity. Exact POMDP solution algorithms have an exponential time complexity in the size of the state, action, and observation spaces, making them intractable for realistic satellite applications. The continuous nature of many satellite state variables, such as orbital position and attitude, further complicates this problem by creating infinite state and observation spaces.

To address these challenges, approximate solution methods have been developed. Point-based value iteration (PBVI) algorithms focus computational effort on reachable belief points rather than the entire belief space, thereby significantly reducing complexity while maintaining solution quality. Online planning approaches, such as Monte Carlo tree search (MCTS) and partially observable Monte Carlo planning (POMCP), generate policies on demand by simulating future trajectories from the current belief state, enabling real-time decision-making with limited computational resources.

Hierarchical decomposition is another powerful approach to managing complexity. By structuring satellite decision-making into multiple levels, from long-term mission planning to immediate sensor control, the overall POMDP can be decomposed into smaller and more tractable subproblems [13]. High-level policies set goals and constraints for lower-level controllers, whereas feedback from low-level execution informs high-level belief updating and replanning.

Recent advances in deep reinforcement learning have enabled neural-network-based POMDP policies that can be trained offline and executed efficiently onboard satellites [14]. Deep recurrent Q-networks (DRQN) and other architectures can learn observation-to-action mappings that implicitly

Table 3. Multi-satellite coordination scenarios using POMDP.

Coordination task	Key challenges	POMDP solution approach	Outcome metrics
Disaster monitoring	Rapid coverage, dynamic targets	Dec-POMDP with shared belief	40% faster complete coverage
Maritime surveillance	Large area, sparse events	Information-sharing POMDP	65% better detection rate
Weather tracking	Temporal continuity, handoffs	Coordinated observation policy	55% improved prediction accuracy
Communication relay	Link availability, data priority	Joint optimization of POMDP	35% higher throughput

represent belief states through recurrent connections. Although these approaches sacrifice the interpretability and convergence guarantees of traditional POMDP solvers, they offer practical solutions for complex, high-dimensional problems.

Model Accuracy and Uncertainty Quantification

The POMDP solution quality depends critically on the accuracy of the underlying models, including transition dynamics, observation probabilities, and reward functions [15]. In satellite applications, these models must capture complex physical phenomena, such as atmospheric effects on imaging, solar panel degradation over time, and target behavior patterns. Model inaccuracy can lead to suboptimal or even harmful decision-making.

Robust POMDP formulations address model uncertainty by optimizing the worst-case performance or by explicitly representing uncertainty in the model parameters [16]. These approaches sacrifice performance under nominal conditions to guarantee acceptable behavior across a range of possible model variations. Robust formulations provide valuable safety margins for satellite systems operating in poorly characterized environments or with degraded components.

Data-driven approaches to model learning leverage historical mission data to estimate the POMDP parameters. Inverse reinforcement learning can infer reward functions from expert demonstrations, whereas maximum likelihood estimation and Bayesian methods can learn transition and observation models from operational data [17]. Online learning techniques enable continuous model refinement during mission execution, adaptation to changing conditions, and component aging.

The validation and verification of POMDP-based satellite systems present unique challenges. The stochastic nature of POMDP policies means that the system behavior varies across executions, complicating traditional testing approaches. Simulation-based verification using high-fidelity satellite models can assess performance across diverse scenarios, whereas formal verification techniques can provide guarantees of critical safety properties.

Integration with Existing Satellite Infrastructure

Deploying POMDP-based systems on operational satellites requires careful integration with the existing flight software, communication protocols, and ground systems. Many satellites use layered control architectures, in which high-level planning, mid-level control, and low-level execution are separated into distinct software modules. POMDP-based decision making can be implemented at the planning layer while leveraging existing low-level controllers for reliable execution [18].

Ground system integration involves the development of interfaces for policy uploads, telemetry monitoring, and operator oversight. Although POMDP-based systems enable autonomous operation, human operators require visibility into system beliefs, planned actions, and reasoning processes. Explainable AI techniques can provide intuitive representations of POMDP decision making, helping operators understand and trust autonomous behavior.

Software verification and validation processes for space systems are rigorous and time-consuming, and require extensive testing and documentation [19, 20]. POMDP-based systems must satisfy these standards while incorporating machine learning or other adaptive components. A hybrid architecture that combines POMDP-based planning with formally verified safety monitors offers a path to meet certification requirements while enabling advanced autonomy.

The transition from research prototypes to operational deployment requires addressing failure modes and contingency planning. POMDP-based systems must include fallback modes to ensure safe operation when computational resources are insufficient or when the model assumptions are violated [21]. Graceful degradation strategies allow satellites to revert to simpler control modes while maintaining critical functions during anomalies (Table 4).

Table 4. Implementation approaches for satellite POMDP systems.

Implementation aspect	Approach	Key technologies	Maturity level
Onboard computation	FPGA-accelerated solvers	Point-based value iteration, POMCP	Prototype testing
Model learning	Deep learning from mission data	Recurrent neural networks, variational autoencoders	Research phase
Multi-satellite coordination	Distributed belief propagation	Decentralized POMDP, message passing	Simulation validation
Ground integration	Policy updates and monitoring	Web-based interfaces, telemetry analysis	Operational deployment

CONCLUSION

The integration of POMDPs in next-generation satellite remote sensing systems represents a paradigm shift from reactive ground-commanded operations to proactive autonomous decision-making. This article demonstrated that POMDP frameworks provide a principled mathematical foundation for addressing the fundamental challenges of satellite operations, including incomplete observability, resource constraints, dynamic environments, and complex mission objectives. The ability of POMDPs to explicitly model uncertainty and optimize long-term performance under partial observability makes them uniquely suited to the satellite remote sensing domain.

The key findings from this analysis highlight the substantial performance improvements enabled by POMDP-based approaches. In task scheduling applications, POMDP methods achieve up to 30% improvement in high-priority target acquisition compared with traditional approaches, with particularly strong performance in uncertain environments. Adaptive sensing strategies based on POMDPs demonstrate superior information-gathering efficiency, optimizing the trade-off between coverage and resolution, while managing resource constraints. Multi-satellite coordination using decentralized POMDP frameworks enables constellation-level optimization with reduced communication overhead, achieving near-optimal performance, even with limited inter-satellite links.

However, significant challenges remain for realizing the full potential of POMDP-based satellite systems. Computational complexity continues to constrain the scale and sophistication of problems that can be addressed in real-time onboard satellites. Although approximate solution methods and hierarchical decomposition techniques have expanded feasibility, further algorithmic advances and specialized hardware acceleration are needed to support complex missions. Model accuracy represents another critical concern, as the POMDP solution quality depends fundamentally on the fidelity of the transition, observation, and reward models. Robust formulations and online learning approaches offer pathways to manage model uncertainty, but systematic approaches to model validation and refinement remain active research areas.

Integration with the existing satellite infrastructure presents practical challenges that must be addressed for operational deployment. Flight software architectures, communication protocols, and ground system interfaces must evolve to support POMDP-based autonomy, while maintaining safety and reliability standards. The development of explainable AI techniques for POMDP decision-making is essential for operator acceptance and effective human-machine teaming.

The convergence of POMDP frameworks with emerging technologies, including deep reinforcement learning, edge computing, and advanced sensor systems, promises to unlock new capabilities in satellite remote sensing. As computational resources continue to advance and algorithmic techniques mature, POMDP-based approaches will enable increasingly sophisticated autonomous behaviors from coordinated constellation operations to adaptive multimodal sensing. The continued evolution of this technology will be essential for meeting the growing demand for timely, high-quality Earth observation data in applications ranging from climate monitoring to disaster response to national security.

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