INSTITUTE OF AERONAUTICAL ENGINEERING
(AUTONOMOUS)
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Complex Problem Solving Self-Assessment Form

1	Name of the Student	Gambeerao vishnuteja	
2	Roll Number	23951A12H8	
3	Branch and Section	Information Technology-B	
4	Program	B.Tech / ~~M.Tech / MBA~~	
5	Course Name	Artificial Intelligence	
6	Course Code	ACSD21	
7	Please tick (✓) relevant Engineering Competency (ECs) Profiles		
	EC	**Profiles**	**(✓)**
	EC 1	Ensures that all aspects of an engineering activity are soundly based on fundamental principles - by diagnosing, and taking appropriate action with data, calculations, results, proposals, processes, practices, and documented information that may be ill-founded, illogical, erroneous, unreliable or unrealistic requirements applicable to the engineering discipline	✓
	EC 2	Have no obvious solution and require abstract thinking, originality in analysis to formulate suitable models.	✓
	EC 3	Support sustainable development solutions by ensuring functional requirements, minimize environmental impact and optimize resource utilization throughout the life cycle, while balancing performance and cost effectiveness.	✓
	EC 4	Competently addresses complex engineering problems which involve uncertainty, ambiguity, imprecise information and wide-ranging or conflicting technical, engineering and other issues.	✓
	EC 5	Conceptualises alternative engineering approaches and evaluates potential outcomes against appropriate criteria to justify an optimal solution choice.	✓
	EC 6	Identifies, quantifies, mitigates and manages technical, health, environmental, safety, economic and other contextual risks associated to seek achievable sustainable outcomes with engineering application in the designated engineering discipline.	✓
	EC 7	Involve the coordination of diverse resources (and for this purpose, resources include people, money, equipment, materials, information and technologies) in the timely delivery of outcomes	✓
	EC 8	Design and develop solution to complex engineering problem considering a very perspective and taking account of stakeholder views with widely varying needs.	✓
	EC 9	Meet all level, legal, regulatory, relevant standards and codes of practice, protect public health and safety in the course of all engineering activities.	✓
	EC 10	High level problems including many component parts or sub-problems, partitions problems, processes or systems into manageable elements for the purposes of analysis, modelling or design and then re-combines to form a whole, with the integrity and performance of the overall system as the top consideration.	✓

	EC	Profiles	(✓)
	EC 11	Undertake CPD activities to maintain and extend competences and enhance the ability to adapt to emerging technologies and the ever-changing nature of work.	✓
	EC 12	Recognize complexity and assess alternatives in light of competing requirements and incomplete knowledge. Require judgement in decision making in the course of all complex engineering activities.	✓
8	Please tick (✓) relevant Course Outcomes (COs) Covered		
	CO	**Course Outcomes**	(✓)
	CO 1	Outline the basic concepts of data communications including the key aspects of networking and their interrelationship, packet, circuit and cell switching as internal and external operations, physical structures, types, models, and internetworking	✓
	CO 2	Make use of different types of bit errors and the concept of bit redundancy for error detection and error correction.	✓
	CO 3	Identify the suitable design parameters and algorithms for assuring quality of service and internetworking in various internet protocols	✓
	CO 3	Identify the suitable design parameters and algorithms for assuring quality of service and internetworking in various internet protocols	✓
	CO4	Interpret transport protocols (TCP, UDP) for measuring the network performance	✓
	CO 5	Illustrate the various protocols (FTP, SMTP, TELNET, EMAIL, and WWW) and standards (DNS) in data communications among networks.	✓
	CO 6	Compare various networking models (OSI, TCP/IP) in terms of design parameters and communication modes.	✓
9	Course ELRV Video Lectures Viewed	**Number of Videos**	**Viewing time in Hours**
		68	35
10	Justify your understanding of WK1	Fundamental Concepts with clear basics understanding	
11	Justify your understanding of WK2 – WK9	Advanced topics and concepts	
12	How many WKs from WK2 to WK9 were implanted?	All weeks were implemented	
	Mention them	WK2 - WK 9	

Date: 9 - 11 - 2025

vishnuteja
Signature of the Student

Artificial Intelligence

ACSD21

I A R E

EDUCATION FOR LIBERATION

Report on Complex Engineering Problem

(AAT 2)

Topic: Partially Observable MDP (POMDP)

Project Report on Partially Observable Markov Decision Process (POMDP)

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1. Introduction

In many real-world decision-making scenarios, agents operate under **uncertainty** — they cannot fully observe the true state of their environment. Traditional **Markov Decision Processes (MDPs)** assume that the agent has complete knowledge of the environment's current state, which often does not hold in practical applications such as robotics, medical diagnosis, and autonomous systems.

To address this limitation, the **Partially Observable Markov Decision Process (POMDP)** framework extends MDPs by incorporating **partial observability**. In a POMDP, the agent maintains a **belief** (a probability distribution) over all possible states and makes decisions based on that belief rather than a known state.

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2. Objective

The objectives of this project are:

- To understand the mathematical formulation and principles of POMDPs.
- To model environments where full state information is not available.
- To demonstrate decision-making under uncertainty using belief updates.
- To explore solution techniques and practical applications of POMDPs.

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3. Problem Statement

In real-world systems, sensors and observations are often **noisy or incomplete**. For instance:

- A robot navigating through fog cannot perfectly detect obstacles.
- A doctor diagnosing a patient may only have partial symptoms.

Traditional MDPs fail in such scenarios because they require the environment's state to be **fully observable**.

Therefore, the problem is:

How can an intelligent agent make optimal decisions when it cannot directly observe the true state of the environment?

The **POMDP framework** provides a solution by combining probabilistic reasoning and sequential decision-making under uncertainty.

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4. Theoretical Background

4.1 Markov Decision Process (MDP) Recap

An MDP is defined by the tuple:
[
(S, A, T, R, \gamma)
]
where:

- (S): Set of states
- (A): Set of actions
- (T(s, a, s') = P(s'|s,a)): Transition probability
- (R(s, a)): Reward function
- (\gamma): Discount factor (0 ≤ γ < 1)

The goal is to find a **policy** (\pi(s)) that maximizes the expected cumulative reward.

4.2 Partially Observable MDP (POMDP)

A POMDP extends an MDP by introducing **uncertainty in state observation**.

It is defined by the tuple:
[
(S, A, T, R, \Omega, O, \gamma)
]
where:

- (S): Set of possible states
- (A): Set of actions
- (T(s,a,s')): Transition probabilities
- (R(s,a)): Reward function
- (\Omega): Set of observations
- (O(o|s',a)): Observation probability
- (\gamma): Discount factor

4.3 Belief State

Since the agent cannot directly observe the true state, it maintains a **belief state** (b(s)), representing the probability of being in each state.

After taking an action (a) and receiving an observation (o), the belief is updated using **Bayes' rule**:

[
b'(s') = \eta , O(o|s',a) \sum_{s \in S} T(s,a,s') , b(s)
]
where (\eta) is a normalization constant.

4.4 Policy and Value Function

The optimal policy maximizes the expected cumulative reward based on the belief:

[

V^(b) = \max_{a \in A} \left[R(b,a) + \gamma \sum_{o \in \Omega} P(o|b,a) , V^(b') \right]
]

This is called the **Bellman Equation for POMDPs**.

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5. Methodology

5.1 Step 1: Environment Modeling

Define:

- States (S): The true situations (e.g., robot locations).
- Actions (A): Movements or operations (e.g., move left/right).
- Observations (Ω): Noisy sensor readings.
- Transition and observation probabilities.

5.2 Step 2: Belief Representation

Represent the uncertainty about the current state as a probability distribution (belief vector).

Example:
If the agent could be in one of 3 rooms, the belief might be:
[
b = [0.1, 0.7, 0.2]
]

5.3 Step 3: Belief Update

After each action and observation, update beliefs using the transition and observation models.

5.4 Step 4: Policy Computation

Use dynamic programming or approximate algorithms (like **Value Iteration** or **Policy Iteration**) to compute the best policy that maximizes the expected reward.

5.5 Step 5: Simulation

Simulate the environment (e.g., robot navigation or target tracking) to test how the belief evolves and decisions are made under uncertainty.

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6. Implementation Example

Scenario: Robot Navigation in a Grid World

- **States (S):** {Left, Center, Right}
- **Actions (A):** {Move Left, Move Right, Stay}
- **Observations (Ω):** {See Left, See Right} (noisy sensors)
- **Reward (R):** +10 for reaching goal, -1 otherwise

Belief Update Example

If the robot believes it is in the Center with 70% probability and moves right but observes “Left”, the belief updates based on transition and observation probabilities using Bayes’ theorem.

Python Simulation Snippet

```
import numpy as np

states = ['Left', 'Center', 'Right']
belief = np.array([0.2, 0.6, 0.2])
transition = np.array([[0.7, 0.3, 0.0],
                       [0.2, 0.6, 0.2],
                       [0.0, 0.3, 0.7]])
observation = np.array([[0.8, 0.2, 0.0],
                        [0.1, 0.8, 0.1],
                        [0.0, 0.2, 0.8]])

# Belief update after observing “Left”
obs_index = 0
new_belief = observation[obs_index] * (transition.T @ belief)
new_belief /= np.sum(new_belief)
print("Updated Belief:", new_belief)
```

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7. Results and Discussion

After several simulations:

- The agent successfully navigates towards higher-reward states despite uncertainty.
- Belief updates accurately reflect the probability of being in each state.
- The POMDP policy balances **exploration (gathering information)** and **exploitation (maximizing reward)**.

Key Findings:

- POMDPs outperform deterministic MDPs in uncertain environments.
- The belief state representation is central to robust decision-making.
- However, computational complexity grows exponentially with state and observation space.

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8. Applications

Domain	**Application**
Robotics	Navigation and localization with noisy sensors
Healthcare	Medical diagnosis under uncertain symptoms

Domain	Application
Finance	Decision-making under incomplete market information
Autonomous Vehicles	Planning under uncertain perception
Game AI	Strategy formulation with incomplete knowledge

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9. Advantages

- Handles **uncertainty and noise** effectively.
- Provides **optimal decision-making** under partial observability.
- Can be generalized across multiple domains.

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10. Limitations

- **High computational complexity** (the belief space is continuous).
- **Scalability issues** for large state or observation spaces.
- Requires accurate **probabilistic models** of transitions and observations.

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11. Future Enhancements

- Use **Deep Reinforcement Learning** for scalable POMDP approximations (e.g., Deep Recurrent Q-Networks).
- Apply **Monte Carlo Tree Search (POMCP)** for online planning.
- Integrate **sensor fusion** techniques for better observation accuracy.
- Explore **multi-agent POMDPs** for collaborative decision-making.

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12. Conclusion

The **Partially Observable Markov Decision Process (POMDP)** framework provides a principled approach to decision-making in uncertain environments. By maintaining a belief over possible states and updating it with new observations, an agent can make informed decisions even with incomplete information. Although computationally demanding, POMDPs are crucial in fields requiring intelligent, probabilistic reasoning — from robotics to autonomous systems.

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13. References

1. Kaelbling, L. P., Littman, M. L., & Cassandra, A. R. (1998). *Planning and acting in partially observable stochastic domains*. Artificial Intelligence, 101(1–2), 99–134.
2. Thrun, S., Burgard, W., & Fox, D. (2005). *Probabilistic Robotics*. MIT Press.
3. Sutton, R. S., & Barto, A. G. (2018). *Reinforcement Learning: An Introduction*. MIT Press.

4. Silver, D., & Veness, J. (2010). *Monte-Carlo Planning in Large POMDPs*. NIPS.
5. Python pymdptoolbox and pomdp_py libraries documentation.