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DOI
10.1016/j.ifacol.2024.10.076

Publication date
2024

Document Version
Final published version

Published in
IFAC-PapersOnLine

Citation (APA)
Dhyani, A., Wang, Y., Verbeke, M., Pissoort, D., & Reppa, V. (2024). A POMDP model-based online risk mitigation method for autonomous inland vessels. *IFAC-PapersOnLine*, *58*(20), 335-340. https://doi.org/10.1016/j.ifacol.2024.10.076

Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 58-20 (2024) 335–340

A POMDP model-based online risk mitigation method for autonomous inland vessels ⋆

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Abstract: Autonomous surface vessels (ASVs) increasingly gain appeal in the maritime industry for their high efficiency and improved navigational capabilities. However, risks originating from various internal and external factors such as faults, traffic, harsh weather conditions, etc., can affect their guidance and control capabilities and impact nominal vessel operations. The existing risk mitigation methods mainly focus on the vessel's guidance system and do not consider unsafe actions due to the control system. In this paper, we propose a new method based on a partially observable Markov decision process (POMDP) model for the online risk mitigation of autonomous inland vessels. The POMDP model-based method utilizes information about situational awareness to assist the vessel's planning and control system in real-time decision-making during hazardous situations, thereby ensuring that the vessel remains in a minimum-risk condition. Based on the identified risk-influencing factors (RIFs), the transition probabilities are updated by a Bayesian belief network (BBN). A case study of an autonomous inland vessel navigating in a confined waterway is presented to demonstrate the capability of the proposed method.

Keywords: Risk mitigation, Fail-safe, Fail-operational, Partially observable Markov decision process, Autonomous surface vessels.

1. INTRODUCTION

The escalating demand for cargo transport and the imperative to reduce carbon emissions puts substantial pressure on existing transportation systems. New challenges including increasing road congestion, soaring transportation costs, and frequent accidents require effective solutions. Autonomous inland vessels present an attractive potential solution to many of these challenges, thanks to an extensive network of underutilized rivers and canals. Promoting inland transportation not only promises to alleviate road congestion but can also contribute to reducing road fatalities. Their economic viability though, stemming from reduced crew requirements, presents a compelling case for their implementation. It is crucial to recognize that the implementation of autonomous vessels is not without safety challenges. Rigorous safety measures must be undertaken to ensure their safe integration into the existing inland waterways infrastructure.

Hazard identification and risk assessment analysis are essential steps in the design of engineering systems to ensure their safe and reliable operation. In the context of autonomous vessels, the use of techniques such as systems theoretic process analysis (STPA) has been widely explored in the literature for safety assessment and verification (Wróbel et al. (2018) and references therein). Additionally, providing the analysis results as inputs to the control system during system operation can further enhance the decision-making capabilities of autonomous vessels (Thieme et al. (2023)). Arguably, one of the most critical decision-making tasks is to identify a hazardous situation and prevent an accident by bringing the system to a minimum-risk condition (MRC). According to DNV GL, an MRC is defined as *"a temporary as-safe-as-possible state that the vessel enters when it experiences situations which, if continued, involves operating outside the safe operating envelope"* (DNV (2018)). These situations can arise from unsafe actions taken during vessel operation, originating from factors such as sensor faults, commu-

⋆ The research leading to these results has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 955768 (MSCA-ETN AUTOBarge) and grant agreement No. 101096923 (SEAMLESS Project). This publication reflects only the authors' view, exempting the European Union and the granting authority from any liability. Project websites: https://etn-autobarge.eu/, https://www.seamless-project.eu/.

10.1016/j.ifacol.2024.10.076

nication delays, or harsh weather conditions, and can potentially disrupt nominal operations. In this context, Bremnes et al. (2020) performed hazard identification for autonomous underwater vehicles and utilized the results for constructing a dynamic Bayesian network for risk-based decision-making. In Utne et al. (2020), a framework for the online risk modeling and control of autonomous ships, called supervisory risk control, is proposed. Risk is evaluated during the operation by a Bayesian belief network (BBN), which is designed based on the results of STPA hazard analysis. One of the limitations of using a risk variable in decision-making (like in Bayesian-based approaches) for control stems from the quantification, which will inevitably lead to loss of information (Rothmund (2023)). Furthermore, it can lead to a scenario with very low consequences receiving the same risk value as a very unlikely but high-consequence scenario .

Partially observable Markov decision processes (POMDPs), on the other hand, can directly model the effect of decisions taken on the system's state by incorporating them as "actions" in their framework. Furthermore, unlike the static structure of Bayesian networks, POMDPs offer a dynamic modeling approach that enhances their ability to assess risks more effectively. However, this approach to risk modeling for ASVs remains unexplored in the literature, as the number of states and associated properties in a POMDP model can rapidly proliferate. This could significantly increase the computational cost of real-time evaluation, which stands as a key consideration favoring the adoption of Bayesian networks (Rothmund (2023)). Furthermore, determining the transition probabilities for the POMDP model is also a challenge. To address these limitations, in this work, we propose a POMDP model-based method for providing risk mitigation support to the guidance and control system of an autonomous inland vessel. Based on real-time observations, the proposed method prompts the vessel into a safe state, i.e., a state with minimum risk. The POMDP model is constructed by using the results of the STPA method for hazard analysis. It computes a safe control strategy (SCS) by complementing various unsafe control actions with specific recovery control actions. The state-transition probabilities within the POMDP model are derived from the results of a BBN, which updates the probabilities as new inputs are received. The ability of BBNs to calculate conditional probabilities is well known and results from their effective mapping of the cause-and-effect relationships among the variables.

Compared to previous works that focused on hazards affecting the guidance system of an ASV (see, e.g., Utne et al. (2020); Blindheim et al. (2023)), one of the main contributions of this work is to propose a risk mitigation method for the control system of an ASV. The proposed method provides an updated control strategy, leading to the vessel modifying its control action and/or the path followed. Furthermore, to the best of the authors' knowledge, the application of Markov decision processes for risk mitigation of ASVs has not been explored in the literature so far, although it has been applied in other domains, such as mobile robotics and EMI resilience (e.g., see Zacharaki et al. (2021); Gonzalez-Atienza et al. (2023)). Finally, to address the computational issue in solving the POMDP model online, we propose employing a Monte Carlo tree search (MCTS) planning algorithm, which has a computational complexity that is independent of the state or observation space dimension (Coulom (2006)). The basic idea behind employing MCTS in POMDP is to estimate long-term rewards using random simulation by focusing on the most viable region in the search space.

The remainder of this paper is organized as follows: In Section 2, the ASV risk mitigation problem is formulated. In Section 3, the proposed method is described by first modeling the BBN for computing the POMDP state-transition probabilities and then constructing the POMDP model. In Section 4, a case study is presented for an autonomous vessel in an inland waterway scenario. Finally, the conclusions are reported in Section 5.

2. ASV RISK MITIGATION PROBLEM

We consider an inland vessel of automation level 3, as per the CCNR definition of automation level, where the vessel's autonomous system is primarily responsible for navigation. However, the human operator *"will be receptive to requests to intervene and to system failures and will respond appropriately"* (CCNR (2022)). The main objective of the POMDP model-based method is to provide risk mitigation support in the form of an SCS. The SCS is updated to avoid two hazardous situations, namely, *collision with another vessel* and *grounding of the vessel while navigating in shallow water.*

Firstly, we define the states of the vessel, categorized into three sets: the safe states S_s, the unsafe states S_u, and the recovery states S_r. The safe states S_s refer to vessel states where there are no hazardous situations involved or the vessel is in an MRC. On the other hand, unsafe states S_u correspond to states with a high risk of a hazardous situation. The recovery states S_r correspond to the intermediary set of states resulting from applying a corrective measure to eliminate the hazardous situation. Similarly, we also define three sets of actions performed by the vessel's control system, namely the safe (A_s), unsafe (A_u), and recovery (A_r) control actions. A_s is defined as the set of actions that constitute the vessel control system's "control responsibilities", and ensure that the vessel stays in a safe state. When the control system executes an unsafe action from A_u, it increases the level of risk as the system transitions to an unsafe state. Finally, A_r corresponds to the recovery control actions applied to bring the system from an unsafe state to a safe state. In this work, we define the safe control action as:
A_{s_1} : Provide the rudders and thruster (R & T) commands for the steering and propulsion of the vessel to execute the planned path.

With regard to A_{s_1}, the following states of the vessel are of interest:

(1) Safe states:
 (a) S_{s_1} : The navigational plan is successfully obtained
 (b) S_{s_2} : Vessel follows the desired path
(2) Unsafe states:
 (a) S_{u_1} : Vessel does not follow the desired path
 (b) S_{u_2} : Vessel violates the safety margin
 (c) S_{u_3} : Vessel enters a shallow water-depth area

Table 1. Unsafe control actions (A_u) originating from the control responsibility A_{s_1}

Control responsibility provided	**Control responsibility not provided**	**Control responsibility provided too early /too late**
A_{u_1}: R&T commands provided based on incorrect vessel's navigational states, leading to the vessel being unable to follow the planned path.	A_{u_2}: R&T commands are not provided as the vessel's navigational states are unknown	A_{u_3} : R&T commands are provided too late as the guidance system provides a path update too late
A_{u_4} : R&T commands provided cannot be followed due to insufficient available power	A_{u_5} : R&T commands are not provided as there are no feasible path options	
A_{u_6} : R&T commands are provided without considering the effect of external disturbance, such as wind, water depth, etc., leading to the vessel being unable to follow the planned path.		

(d) S_{u_4} : Desired control is not achieved / collision or grounding risk is not averted

(3) Recovery states:
(a) S_{r_1} : Updated control action corrects the vessel's path and averts the risk
(b) S_{r_2} : A human supervisor corrects the vessel's path

When the action A_{s_1} is executed, it leads the vessel to the safe state S_{s_2}. Subsequently, by performing an STPA, the unsafe actions (A_u) which could potentially lead the vessel to an unsafe state, are identified. Unlike traditional hazard analysis methods, STPA's systems thinking approach can help in capturing emerging risks from complex interactions between various system components (Leveson and Thomas (2018)). These actions are described as shown in Table 1. Finally, the recovery control actions (A_r) are defined, which constitute the set of possible control strategies to direct the vessel to an MRC. These actions correspond to either the fail-safe or fail-operational actions and must be selected based on the vessel's assessment of the existing risk. Based on class guidelines recommended by classification societies such as DNV (DNV (2018)), ClassNK (ClassNK (2020)), and similar fallback strategies proposed in the literature (for example in Bolbot et al. (2023)), a total of six recovery control actions are identified, as mentioned below:

(1) A_{r_1} : Limp home
(2) A_{r_2} : Fault-tolerant control strategy is selected
(3) A_{r_3} : Keep position (DP control strategy is selected)
(4) A_{r_4} : Human supervision is requested
(5) A_{r_5} : Move away from the quay and other vessels
(6) A_{r_6} : Vessel's speed is reduced

These actions can be further categorized as follows:

(1) Fail-operational strategies: A_{r_2}, A_{r_4}, and A_{r_6}
(2) Fail-safe strategies: A_{r_1}, A_{r_3}, and A_{r_5}

The fail-operational strategies provide path planning and control updates that enable the vessel to maintain operations, albeit with possibly reduced performance. In contrast, the fail-safe strategies guide the vessel to a safe state and cease its operations. The selection of the SCS is performed by the proposed risk-mitigation scheme, which is described in the next section.

3. RISK MITIGATION METHOD

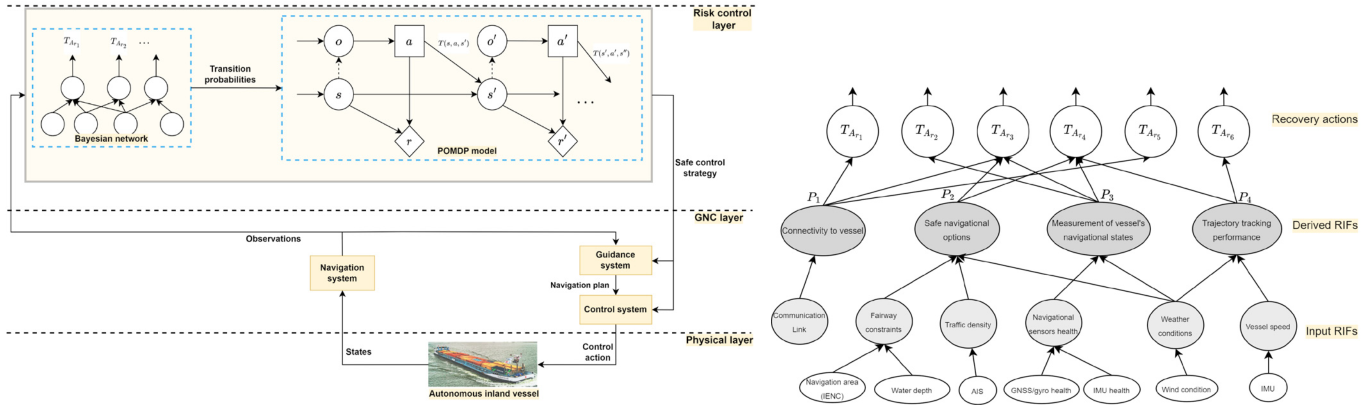
Figure 1a provides an overview of the proposed risk mitigation scheme for ASVs. The vessel's control system can execute any one of the unsafe actions (A_u) identified in Table 1. These unsafe actions form part of the set of actions of the POMDP model, along with the set of recovery control actions (A_r). Additionally, the states of the vessel are used to construct the states of the POMDP model. The transition probabilities for the model are calculated starting with the calculation of risk probabilities, which are derived from various input sources of the BBN. The output of the POMDP model is the SCS corresponding to the hazardous situation encountered. The overall steps involved in the proposed risk mitigation method are summarised in Algorithm 1. The steps 1–3 of the algorithm, which involve the BBN, are detailed next.

Algorithm 1 Computation of the safe control strategy (SCS) for risk mitigation.

Input: Observations O, Rewards R, Discount factor γ, Initial belief b_0, Maximum Iterations
Bayesian Belief Network:
1: Compute the probabilities of input RIFs based on the BBN inputs.
2: Compute the probabilities of the derived RIFs ($\mathrm{P_{D\text{-}RIF}}$) using equation (1).
3: Calculate the state transition probabilities T_{A_r}, based on their identified dependencies with the derived RIFs and using statistical data or expert knowledge.
POMDP Model Initialization:
4: Initialize the state space $\mathcal{S}$, action space $\mathcal{A}$, and the observations O.
5: Set the initial parameters, including the rewards R, transition probabilities T, discount factor γ, and initial belief b_0.
MCTS Algorithm:
6: Initialize the tree with the current belief as the root node.
while no. of iterations < Maximum Iterations, **do**
7: Select the optimal node using the UCB formula, given by equation (2).
8: Expand the selected node by adding a child node.
9: Simulate a random playout from the child node.
10: Backpropagate the result of the playout through the tree.
end while
11: Select the action a having the highest expected reward at the root node.
SCS Calculation:
12: Compute the SCS by using equation (3).
Output: SCS $\in \{A_{r_1}, \ldots, A_{r_6}\}$

3.1 Bayesian Belief Network (BBN)

A BBN is a graphical method that employs a directed acyclic graph for probabilistic reasoning. It comprises various nodes representing the variables of interest, for which the respective probabilities are computed using Bayesian reasoning. We use the BBN to compute the transition probabilities for the POMDP model based on inputs from various metrological and communication sources, such as onboard sensors, AIS, electronic navigational charts (ENC), metocean services, sensor monitoring modules, etc. The first layer of the BBN consists of the variables or nodes representing the input risk-influencing factors (RIFs), which can be directly computed from the aforementioned sources. Each of the input RIFs has the states



(a) (b)

Fig. 1. (a) Proposed online risk mitigation scheme for autonomous inland vessels. For the Bayesian network, the observations comprise the inputs for determining the input RIF probabilities (see Table 2 for the list of input sources). Further, the POMDP model receives as observations the noisy states of the vessel. The output of the risk mitigation scheme is a Safe Control Strategy (SCS), selected from the set of possible recovery control actions A_r.(b) Proposed structure of the BBN for computing the POMDP model's transition probabilities.

mentioned in Table 2 and is associated with a risk probability. In this work, we consider six input RIFs, namely, the communication link, fairway constraints, traffic density, navigational sensor health, weather conditions, and vessel speed. In addition to quantitative information such as sensor measurements, the risk probabilities can also be estimated using available qualitative information, including existing regulations and expert judgment (Fenton and Neil (2018); Utne et al. (2020)). However, a detailed discussion of their calculation lies outside the scope of this work.

As shown in Figure 1b, these inputs are further mapped within the BBN into the derived RIFs, namely, connectivity to the vessel, safe navigational options, measurement of vessel's navigational states, and trajectory tracking performance. This structure of the BBN is inspired by the work in Utne et al. (2020), where the modeling is done based on the causal factors identified through STPA. The derived RIFs' risk probabilities are computed under the assumption of the independence of input RIFs, using

$$\mathrm{P}_{\text{D-RIF}} = \prod_{i=1}^{k} {}^{k}\mathrm{P}_{\text{I-RIF}}, \tag{1}$$

where $\mathrm{P}_{\text{I-RIF}}$ represents the probabilities associated with the input RIFs calculated by using the BBN inputs, and k is the number of nodes in the input layer connected to the derived layer node. Finally, these risk probabilities are mapped to the output layer of the BBN, where the nodes correspond to the recovery actions A_r. An edge exists between the nodes in these two layers if the corresponding recovery action can lead to a transition to a safe state for the derived RIF.

3.2 Partially observable Markov decision process (POMDP) modeling

In this section, we describe the finite-state, discrete POMDP model, which is constructed to represent the states crucial for the risk mitigation of an ASV. The POMDP framework facilitates sequential decision-making in an environment characterized by noise and uncertainty, where only a partial view of the system's state is available.

Table 2. The input RIFs with their states and the corresponding input sources of the BBN

Input risk-influencing factors (RIFs)	**States**	**Input sources**
Communication link	Healthy, Broken (0.05, 0.9)	Communication channel
Fairway constraints	Low , Moderate, Strict (0.1, 0.55, 0.9)	ENC, Bathymetry data
Traffic density	Low, Medium, High (0.1, 0.55, 0.9)	AIS
Navigational sensors health	Reliable, Unreliable (0.05, 0.9)	Sensor monitoring module
Weather conditions	Light, Moderate, Rough (0.1, 0.55, 0.9)	Onboard sensors, Radio/satellite-based services
Vessel speed	Low, Medium, High (0.1, 0.55, 0.9)	Onboard sensor (e.g. IMU)

Instead of having access to precise state information, the model can deal with potentially imperfect observations. The model is defined as a tuple $\mathcal{P} = \langle \mathcal{S}, \mathcal{A}, T, R, \Omega, O, \gamma \rangle$, where $\mathcal{S}$ denotes the state space of the POMDP model given by $\mathcal{S} = \{s_1, s_2, \ldots, s_n\}$, for n vessel states. The state space is further partitioned into the previously identified set of states, such that $\mathcal{S} = \{S_u, S_r\}$. To simplify the modeling of the POMDP, we only consider the unsafe and recovery states, since only these states are involved in the risk mitigation process. An action space can be defined as a finite set, given by $\mathcal{A} = \{a_1, a_2, \ldots, a_m\}$, with m representing the total number of actions. It corresponds to the actions performed by the vessel control system that lead the vessel to another state. To highlight the new state resulting from performing a specific action, a similar partitioning of the action space is performed such that $\mathcal{A} = \{A_u, A_r\}$. Further, T represents the transition function, which comprises the probability of transitioning to a state given the current state and an action, defined as $T : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \rightarrow [0, 1]$. R represents the reward function used to favor certain actions over others, defined as $R : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \rightarrow \mathbb{R}$. O is the finite set of observations, and Ω is an observation function that is used to capture the uncertainty in determining the current state, defined as $\Omega : \mathcal{S} \times \mathcal{A} \times O \rightarrow [0, 1]$. Finally, $\gamma \in [0, 1]$ is the discount factor used to consider the importance of future rewards. The initialization of the aforementioned properties of the POMDP model forms steps 4-5 of Algorithm 1.

Throughout the decision-making process, a posterior distribution over the potential states is maintained and continually updated by utilizing the actions taken and observations gathered, referred to as the belief state $b(s)$. In the MCTS algorithm, a tree of possible actions and the resulting observations is constructed, guided by the Upper Confidence Bound (UCB) formula given by

$$\mathrm{UCB} = \bar{X}_j + C\sqrt{\frac{2\ln N}{n_j}}, \tag{2}$$

where $\bar{X}_j$ represents the average reward of the $j-$th node in the tree, N is the total number of simulation runs, n_j is the number of visits to the node j, and C is the exploration parameter. By using this formula for action selection, the MCTS algorithm balances exploration and exploitation to build a tree that represents the possible outcomes and their respective values. Finally, an optimal action is selected based on the maximum expected reward and forms the SCS, calculated as

$$\mathrm{SCS} = \arg\max_{a\in A_r} R(b', a) + \gamma \sum_{s'\in\mathcal{S}} V(b'(s'))T(s, a, s'), \tag{3}$$

where $V(b'(s'))$ represents the value function at the belief state b'. The vessel's guidance and control systems can adapt to the identified SCS by switching between various operation modes. The design of the switching logic, however, lies beyond the scope of this work. The MCTS algorithm and the SCS calculation process are outlined in steps 6–12 of Algorithm 1.

4. CASE STUDY: RISK MITIGATION FOR AN INLAND WATERWAY SCENARIO

In this section, a case study is conducted to illustrate the proposed method tailored to the safety challenges faced by autonomous inland vessels navigating through constrained waterways. The considered scenario is detailed next.

4.1 Description of the scenario

In this case study, we will only focus on the occurrence of the unsafe control action A_{u_1}. We explore a scenario where this action originates due to a fault in the onboard GNSS sensor, a fault that is diagnosed by the vessel's sensor monitoring module (see e.g., Dhyani et al. (2024)). Concurrently, rough weather conditions and moderate nearby traffic prevail. All other conditions are assumed to be in a moderate or medium state. The BBN processes these inputs to produce the corresponding output risk probabilities, as detailed in Table 3. Further, to determine the transition probabilities for the given scenario, we utilize the output risk probabilities computed by the BBN. Given that the probabilities P_3 and P_4 are notably high and P_2 is significantly greater than zero, this suggests a scenario with reduced safe navigational options, substantial uncertainty in the measurement of navigational states, and low trajectory tracking performance. Consequently, based on our knowledge of the scenario, we assign high probabilities to actions A_{r_2}, A_{r_3}, A_{r_4}, and A_{r_6}, leading to a risk-mitigated state (S_{r_1}/S_{r_2}). Regarding the rewards structure, transitions to fail-safe vessel states resulting from

Table 3. Input RIFs and derived RIFs risk probabilities for the BBN

Input RIFs	**State**	**Risk Probability**
Communication link	Healthy	0.05
Fairway constraints	Moderate	0.55
Traffic density	Medium	0.55
Navigational sensors health	Unreliable	0.9
Weather conditions	Rough	0.9
Vessel speed	Medium	0.55
(P_1, P_2, P_3, P_4)		(0.05,0.2722,0.81,0.495)

Table 4. The transition probabilities and rewards for the POMDP model for the given scenario

Current state s	**Action** a	**Next state** s'	R	T
S_{u_1}	A_{r_1}	S_{r_1}	+5	0.55
	A_{r_1}	S_{u_2}	-5	0.225
	A_{r_1}	S_{u_3}	-5	0.225
	A_{r_2}	S_{r_1}	+10	0.75
	A_{r_2}	S_{u_2}	-5	0.125
	A_{r_2}	S_{u_3}	-5	0.125
S_{u_2}	A_{r_3}	S_{r_1}	+5	0.9
	A_{r_3}	S_{u_4}	-10	0.1
	A_{r_4}	S_{r_2}	+3	0.95
	A_{r_4}	S_{u_4}	-10	0.05
	A_{r_5}	S_{r_1}	+5	0.75
	A_{r_5}	S_{u_4}	-10	0.25
S_{u_3}	A_{r_4}	S_{r_2}	+3	0.95
	A_{r_4}	S_{u_4}	-10	0.05
	A_{r_6}	S_{r_1}	+10	0.85
	A_{r_6}	S_{u_4}	-10	0.15
any state	any action	same state	-1	-

fail-safe control actions (A_{r_1}, A_{r_3}, A_{r_5}) are assigned lower rewards compared to those leading to a fail-operational state. Further, a state transition on taking the action A_{r_4} is allocated a smaller reward than for the rest of the fail-operational control actions. This approach is adopted to discourage excessive dependence on remote or onboard crew intervention. Finally, a transition that results in the vessel remaining in the same state in the subsequent time step incurs a minor penalty to promote proactive risk mitigation. The resulting transition probabilities and reward values are mentioned in Table 4.

4.2 Simulation results

In this subsection, we present the results of the POMDP model-based simulation and testing. The model is initialized at the unsafe state S_{u_1} (Root node), resulting from taking the unsafe action A_{u_1}, and the simulation runs until one of the terminal states is reached. The observations are modeled as states with an additional noise component by considering a 5% probability of receiving a false observation. Further, the initial belief is set as the state S_{u_1} with a 90% probability. The discount factor is selected to be equal to 0.95, and the number of particles utilized by the MCTS algorithm is selected as 100.

We test the proposed method for a total duration of 20 epochs. Each epoch constitutes 1000 simulation runs performed to compute the Monte Carlo decision tree starting from the given initial state. After each epoch, the belief of states and the search tree are updated. As a result, the safe actions are identified for the given scenario. In total, the process ends in a single epoch ten times,

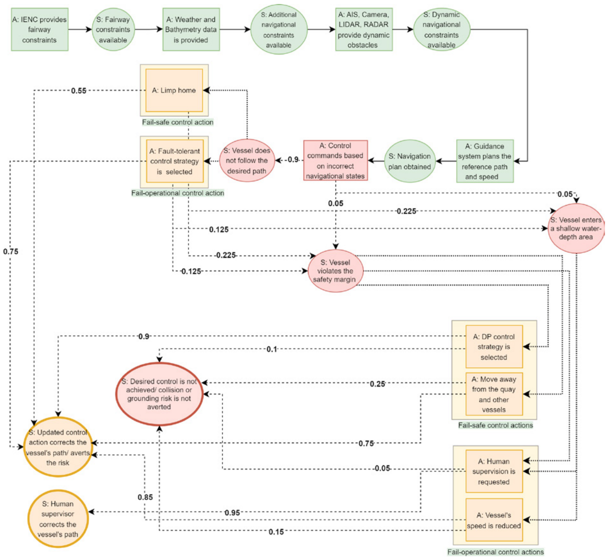


Fig. 2. POMDP model for the given scenario

whereas in the rest of the cases, it took two epochs to reach a terminal state. Following are the resulting state-action pairs obtained during the testing phase.

(1) $S_{u_1} \longrightarrow A_{r_2} \longrightarrow S_{r_1}$ (10 times, 1 epoch long).
(2) $S_{u_1} \longrightarrow A_{r_2} \longrightarrow S_{u_3} \longrightarrow A_{r_6} \longrightarrow S_{r_1}$ (4 times, 2 epochs long).
(3) $S_{u_1} \longrightarrow A_{r_2} \longrightarrow S_{u_2} \longrightarrow A_{r_3} \longrightarrow S_{r_1}$ (1 time, 2 epochs long).

As shown above, in all 20 epochs of testing, a safe state is ultimately reached. The algorithm thereby identifies the following SCSs for the hazardous situations considered:

(1) S_{u_2} : Keep position (DP control strategy is selected) (A_{r_3})
(2) S_{u_3} : Vessel's speed is reduced (A_{r_6})

The SCS will vary based on incoming observations, assigned rewards, and transition probabilities.

5. CONCLUSIONS

In this paper, a POMDP model-based method for the online risk mitigation of autonomous inland vessels is introduced. Firstly, the hazards impacting the vessel's control capabilities, which can lead to collision or grounding, were identified. Furthermore, in the proposed method, by integrating the identified unsafe control actions with recovery (fail-safe and fail-operational) actions within a sequential decision-making framework, an SCS that leads to an MRC was obtained. Following the provided strategy thereby improves the ASV's planning and control system's capability to navigate complex and uncertain maritime environments. Case study results for an autonomous inland vessel navigating in a constrained waterway are presented to demonstrate the capability of the proposed method in calculating an SCS and mitigating the risk of a hazardous situation. A limitation of the proposed method is that it relies on expert knowledge for determining the state transition probabilities from the computed risk probabilities. Future research will explore data-driven state transition modeling while incorporating safety constraints.

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