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Optimization of Operating Conditions for ES-SAGD Process Using Reinforcement Learning

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Summary

The Expanding Solvent Steam-Assisted Gravity Drainage (ES-SAGD) is an enhanced thermal recovery process in which hydrocarbon solvents are co-injected with steam to further reduce bitumen viscosity and improve thermal efficiency compared to conventional SAGD. Previous ES-SAGD studies have primarily relied on empirical approaches, where a limited number of pre-defined solvent types and concentrations are manually tested and compared. Such static strategies restrict the ability to adapt injection conditions in response to developing reservoir states. Despite evidence that optimal solvent selection and concentration vary over the operation period, the dynamic nature of ES-SAGD operations has not been fully exploited.
To address these limitations, this study proposes a reinforcement learning framework for the dynamic optimization of operational conditions in ES-SAGD. The agent interacts with a reservoir simulator to autonomously learn the time dependent solvent injection strategies that maximize net present value (NPV). The optimization strategy is developed based on feedback from simulation results, enabling adaptive control under complex reservoir conditions.

Method / Workflow

The problem is formulated as a Markov decision process in which the agent selects injection actions, including solvent type and concentration, at 6-month time intervals over a 10-year operation period. The simulation environment integrates CMG STARS with Python and provides reservoir state information and economic indicators to the Actor-Critic based agent (Fig. 1). The discrete action space includes 13 combinations: four solvents (C1, C3, C5, C7) at three concentrations (1, 3, 5 vol.%) and continuous steam injection. The reward function separates intermediate net present value for local rewards from maximum net present value for global reward, allowing the agent to pursue both short-term and long-term optimization objectives.
Three cases of scenarios are defined and evaluated: SAGD, ES-SAGD, and RL-ES-SAGD cases. The SAGD case uses only steam injections for over 10 years. The ES-SAGD case involves co injection of steam and a fixed solvent type at a constant concentration. The RL-ES-SAGD case dynamically optimizes solvent injection strategies through a deep reinforcement learning. All cases are compared using key performance metrics including maximum net present value (maxNPV), oil recovery factor (RF), cumulative steam-oil ratio (cSOR), and reduction in carbon dioxide emissions. Metrics are evaluated at the point of maximum NPV in each case.

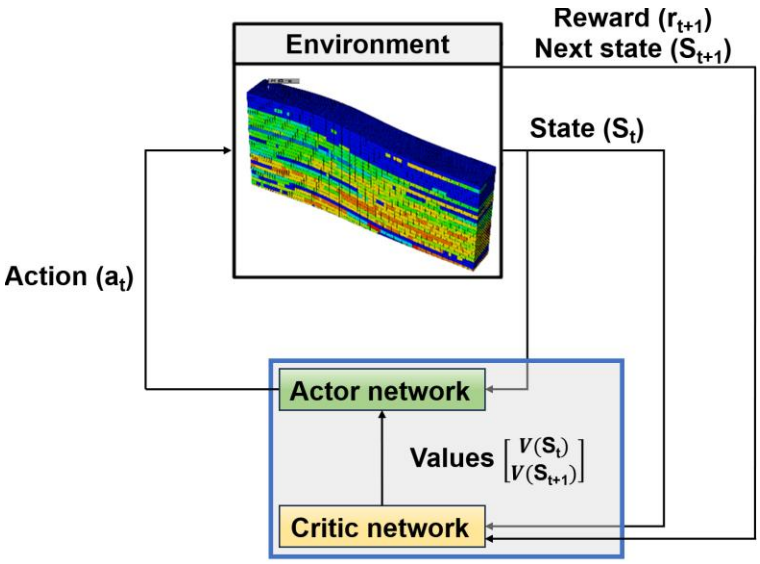


Fig. 1 Deep Reinforcement Learning Framework (Using Actor-Critic algorithm)

Results

Through deep reinforcement learning, the agent successfully learned a dynamic injection strategy over the operation period. Initially, heavier solvents such as C7 and C5 were selected, then gradually shifted to lighter solvents such as C3 and C1 at lower concentrations during the later stage of operation (Fig. 2). This time dependent behavior emerged as a response to changing reservoir conditions. RL-ES-SAGD case achieved higher NPV, improved oil recovery and thermal efficiency (Fig. 3). These results demonstrate that reinforcement learning can effectively optimize solvent injection strategies in ES-SAGD by capturing the sequential dependencies between actions and reservoir state development.

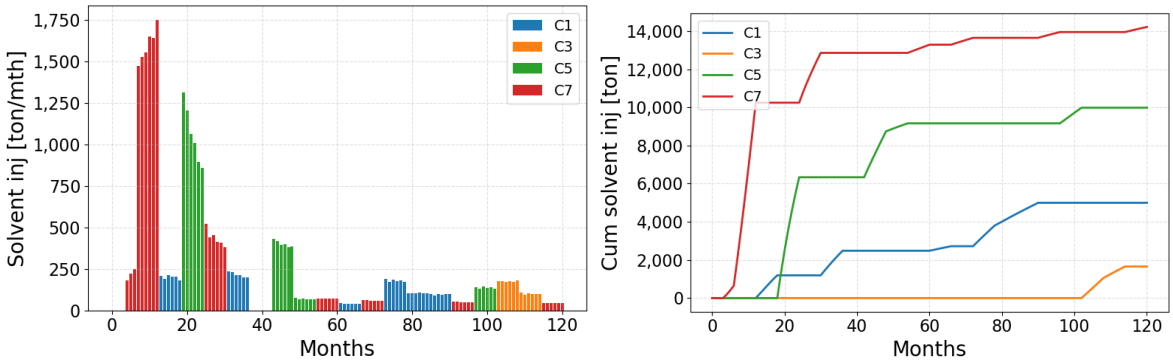


Fig. 2 Solvent injection policy for RL-ES-SAGD

Case	Solvent type	Solvent concentration [vol.%]	Elapsed months to maximum NPV (Year)	cSOR [m3/m3]	CDOR [m3/d]	RF [%]	CO2 emission compared to SAGD [%]	maxNPV [$MM]
SAGD	-	-	33 (2.8)	2.5	172	65	0	46.6
ES-SAGD	C1	1	26 (2.2)	2.7	370	61	7	24.1
		3	26 (2.2)	2.9	386	60	16	23.8
		5	25 (2.1)	2.8	429	58	13	24.9
	C3	1	38 (3.2)	2.1	144	68	-13	48.9
		3	25 (2.1)	2.7	438	59	7	28.5
		5	25 (2.1)	2.7	436	59	6	29.1
	C5	1	36 (3.0)	2.3	159	67	-3	44.5
		3	25 (2.1)	2.7	434	59	7	27.9
		5	25 (2.1)	2.7	433	59	7	28.0
	C7	1	41 (3.4)	2.1	113	69	-15	49.7
		3	33 (2.7)	2.2	201	66	-11	45.0
		5	41 (3.4)	2.1	115	69	-15	50.6
RL-ES-SAGD	Change depending on time		39 (3.3)	2.0	112	67	-16	51.0

Fig. 3 Comparison of productivity metrics across all cases

Novel/Additive Information

This study presents a simulation integrated reinforcement learning framework that addresses key limitations of conventional empirical approaches to ES-SAGD optimization. The proposed method enables an Advantage Actor-Critic(A2C) based agent to learn adaptive injection strategies through interaction with a reservoir simulator. By capturing the sequential nature of the decision process, where early injection choices influence the development of reservoir conditions, the framework identifies long term dependencies between actions and system response. This allows dynamic policy learning without exhaustive scenario testing and demonstrates the potential of reinforcement learning for optimizing feedback driven recovery processes.

Acknowledgements

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