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Dynamic energy efficiency optimization research of gas hydrate dissociation by combined method of thermal stimulation and depressurization

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ABSTRACT

This work constructs an innovative dynamic energy efficiency optimization model of methane hydrate dissociation by thermal stimulation method base on artificial intelligence predictive control of heat injection strategy. Model can divided into two parts, firstly, the prediction of hydrate decomposition rate of each time step is realized via the supervised learning neural network prediction part of the model. The optimization of the energy consumption of hydrate decomposition by thermal stimulation under different gas recovery situations is realized by the deep reinforcement learning-based policy optimization part of the model. Take the lowest injection/recovery energy consumption ratio as the optimization objective, take the injection temperature and heat injection rate (per unit time step) as optimized variables. Implement evaluation and execution for each time step, updating and correcting the prediction errors of successive time steps to achieve dynamic optimization of energy efficiency. The application results of the model showed that under the premise of the same deposits conditions and the same injected heat, the recovery time of the model optimization group decreased by 38% compared with the control group; while under the same deposits conditions and recovery time, the energy consumption of the model optimization group decreased by 40% compared with the control group.

Keywords: natural gas hydrate, thermal stimulation, energy efficiency, deep reinforcement learning, dynamic optimization

NONMENCLATURE

Abbreviations	
NGH	Natural Gas Hydrate
ANN	Artificial Neural Network
RL	Reinforcement Learning
Symbols	
R_t	Total reward of the current time step
ξ_1, ξ_2, ξ_3	The weight factor of the reward
E_{Rec}	Combustion heat of recovered methane
E_{Inj}	Enthalpy of injected heat water
P_{TM}	The punishment term for recovery efficiency
PE_{Inj}	The punishment term of total injected enthalpy
PT_{Tol}	The punishment term of total exploitation time
E_{π}	Expected value of the maximum long-term cumulative reward
γ	Discount factor.
$R(s_t, a_t)$	Instant rewards of At
$\max_{a} Q(s_{t+1}, a_{t+1})$	Estimation of the maximum Q value that can be obtained in the next timestep.

1. INTRODUCTION

Thermal stimulation is an important gas production technique for producing gas from NGH deposits. The energy efficiency is a key parameter to evaluate the performance of methane recovery, the higher energy efficiency of heat injection can effectively reduce the exploitation cost and make the method better applied in engineering practice. The exploitation of NGH is a dynamic and long-term process. How to determine the key parameters to improve energy utilization in dynamic exploitation process, such as heat injection temperature, heat injection rate and heat injection duration, has not been well studied, and there is still a lack of effective dynamic optimization model. Therefore, this paper proposes an energy efficiency optimization model based on ANN and RL algorithm. The optimization effect of the model will be reflected in the following two scenario:

Scenario I. improvement of exploitation efficiency, i.e. under the same conditions of the total amount of injected enthalpy as in the control group, the purpose of reducing the time of NGH exploitation is achieved through the dynamic control of the heat injection variables during the exploitation process.

Scenario II. improvement of energy efficiency , i.e. under the same conditions of the total exploitation time as in the control group, the purpose of reducing energy consumption of NGH exploitation is achieved.

2. METHODOLOGY

2.1 Numerical simulation

The geometric model of the numerical model is taken from the experimental device of methane hydrate decompression and thermal injection decomposition. The initial conditions for the numerical model were set by referring to the gas hydrate decomposing experiment of us[1], and it was assumed that the hydrate was evenly distributed in the quartz sand deposits. The system flow and wettability properties were estimated based on the experimental quartz sand mercury intrusion porosimetry results. The main system parameters used in the numerical simulation are shown in Table 1.

Table 1. System parameters

Parameter	Value
Deposit density ρ_R	2600 Kg/cm3
Deposit specific heat capacity C_R	1000 J·Kg-1 K-1
Deposit intrinsic permeability K	6.24×10-13 m2
Deposit Porosity φ	0.4534
Critical fluid mobile porosity φ_C	0.05
Boundary thermal conductivity λ_B	0.15 W·m-1·K-1
Wet deposit thermal conductivity λ_{RW}	3.1 W·m-1·K-1
Dry deposit thermal conductivity λ_{RD}	1.0 W·m-1·K-1
Gas composition	100% CH4
Gas density ρ_G	227 Kg/cm3
Gas specific heat capacity C_G	2391 J·Kg-1 K-1
Hydration number N_H	5.75
Hydrate density ρ_H	920 Kg/cm3
Relative permeability model parameters	S_{irA} :0.05 n_A :4 S_{irG} :0.15 n_G :6
Capillary pressure model parameters	λ :0.45 S_{irA} :0.04 P_0 :10^5Pa S_{mxA} :1.0

2.2 Energy efficiency optimization model

The energy efficiency optimization model is construct based on the reinforcement learning DQN algorithm. Therefore, based on the concept of reinforcement learning, the dynamic process of NGH dissociation by thermal stimulation in depressurized deposits is decomposed into a series of sub-processes (1 minute = 1timestep). The aim of energy efficiency optimization is achieved through the dynamic control of three thermal injection action variables in each time step. In each time step, according to the current state of NGH decomposition and the circumstance of heat water injection(St), the agent chooses the action combination(At) within the threshold value to imposing on the deposits(environment), then the agent gets feedback information(quantity of NGH decomposition Rt and updated state St+1) from the deposits. After learning from the feedback information, the agent will take a new evaluated heat injection combination At+1 imposing on the deposits, as showed in figure 1.

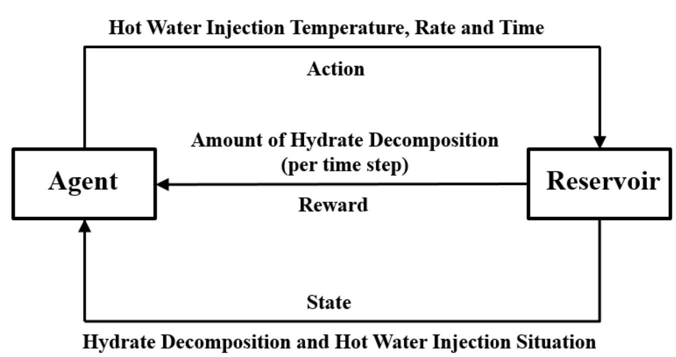


Figure 1. Schematic diagram of interaction between agent and deposits

In such a continuous interaction process, the agent will obtain the maximum long-term cumulative reward as target, through continuous learning and trial, to find an optimal strategy π*, which reflects the agent's understanding of the deposits and the process of knowledge accumulation. the optimal strategy π* can be expressed as:

$$\pi^* = \arg\max \mathrm{E}_\pi \left\{ \sum_{k=0}^{\infty} \Upsilon^k R_{t+k} \,|\, s_t = s \right\}, \quad (1)$$
$$\forall s \in S, \forall t \geq 0$$

Therefore, according to the optimization purpose of the model, the reward function obtained by each time step agent is defined as Rt, the Rt can be expressed as:

$$\mathrm{R_t} = \xi_1 \cdot \mathrm{E_{Rec}} + \xi_2 \cdot \mathrm{E_{Inj}} + \xi_3 \cdot \mathrm{P_{Tm}} + \mathrm{PE_{Inj}} + \mathrm{PT_{Tol}} \quad (2)$$

The amount of methane recovered by the agent interacting with the environment at each time step is obtained by an artificial neural network (ANN). The neural network is composed of the input layer, the hidden layer of ReLU transfer function and the output layer. The information is transmitted forward and the error is transmitted backward to form a closed loop of parameter adjustment.

Through the forward and back propagation training of the loop, the optimal ANN weight parameters, and the minimum loss are ultimately obtained. The functional relationship between the state variable, the action variable and the NGH decomposition quantity is also obtained.

Experimentally verified numerical simulation results of NGH decomposition via heat water injection combined with depressurization are taken as the training conditions of the ANN. Therefore, the specific input and output parameters of the ANN, the value space of heat injection action variables and the updating formulas of state variables are given in table 2.

Table 2.ANN Parameter list

Parameters	Input/ Output	Types	Value Space/ Updating Formula
Injection Enthalpy IEt (J)	Input	Action Value	[84476,126280,168060, 209850, 251670,293530,335450]
Injection Rate IRt (ml/min)	Input	Action Value	[5,10,20,30,40,50]
Injection Time ITt (s)	Input	Action Value	[10,20,30,40,50,60]
Total Injection Enthalpy TIEt (J)	Input	State Value	$\mathrm{TIE_t = TIE_{t-1} + IE_t * IR_t * IT_t}$
Total Injection Volume TIVt (J)	Input	State Value	$\mathrm{TIV_t = TIV_{t-1} + IR_t * IT_t}$
Duration of Depressurization TDt (S)	Input	State Value	$\mathrm{TD_t = TD_{t-1} + 60}$
Hydrate Remain Quality HRQ t (g)	Input	State Value	$\mathrm{HRQ_t = HRQ_{t-1} - H_{dec}}$
Hydrate Decomposition Quality Hdec, t (g)	Output	Target Value	$\mathrm{H_{dec}}$

Couple the trained ANN into the deep reinforcement learning part of the energy efficiency optimization model. This part is based on the deep Q-learning algorithm, a state-action function $Q(\mathrm{s}_t, a_t)$ is usually used to help the agent iterate. The update formula can be written as:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \mathrm{a}\begin{bmatrix} R(s_t, a_t) \\ + \Upsilon \max_a Q(\mathrm{s}_{t+1}, a_{t+1}) - Q(s_t, a_t) \end{bmatrix} \quad (3)$$

After repeated iterative update of ANN parameters, the agent acquires the optimization strategy and finally finds out the optimal thermal action combination within each time step.

3. RESULTS AND DISCUSSION

After adjustment, determine the amount of NGH decomposition forecast ANN structure as the first hidden layer of 64 neurons and the 2nd of 32 neurons.Aafter Adam optimization algorithm to optimize, as showed in figure 2, the training and validation error are at 5e-4 level, the results of the 200 randomly selected ANN predicted values are very close to the train values, indicating that the ANN model fits well and has high reliability.

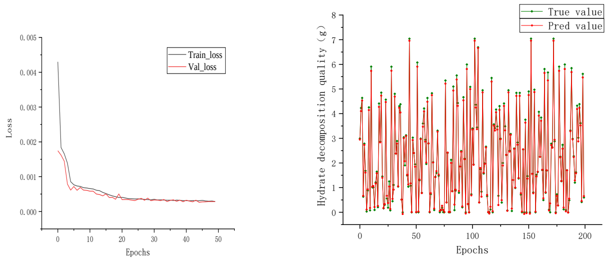
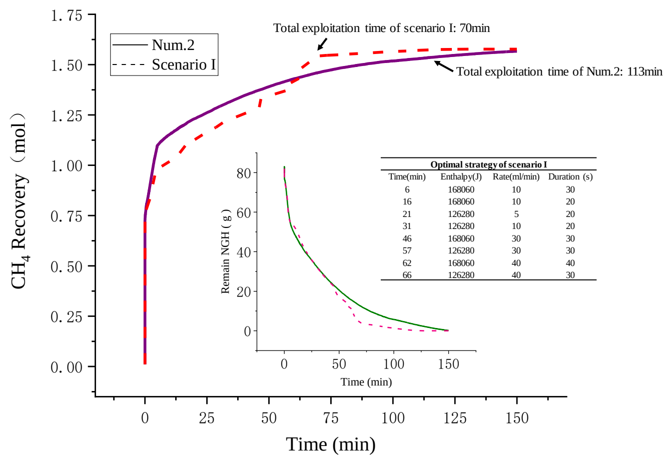


Figure 2. Comparison diagram of training error and prediction error of ANN model

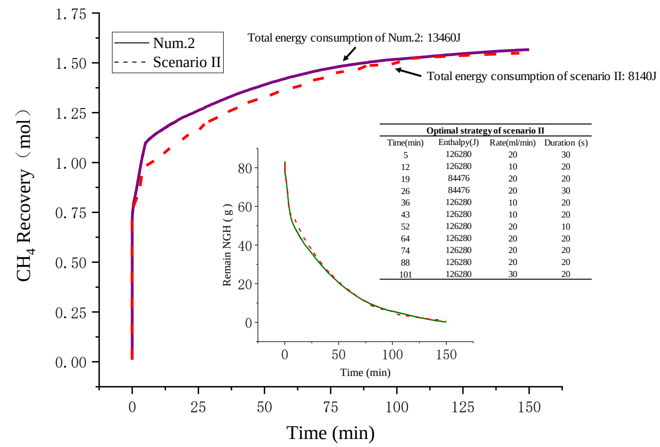
Set the total enthalpy injected and the exploitation time of the control group as the scene threshold conditions, and the remaining 5% of the NGH mass as the exploration end conditions, the agent was set to interact with the deposits environment for 5000 times.



Time(min)	Enthalpy(J)	Rate(ml/min)	Duration (s)
6	168060	10	30
16	168060	10	20
21	126280	5	20
31	126280	10	20
46	168060	30	30
57	126280	30	30
62	168060	40	40
66	126280	40	30

Figure 3. CH4 recovery curve of scenario I compared with the control group.

After iterative calculation, the optimal control strategy under the pre-set scenario was obtained. The comparison between the CH4 recovery curve under the optimal strategy control and the CH4 recovery curve of the control group was presented in figure 3 and 4. In the scenario of improvement exploitation efficiency, the recovery time of NGH was shortened from 113min to 70min, and the recovery time decreased by 38% after model optimization. Besides, in the scenario of improvement of energy efficiency, the total energy of injected heat water decreased from 13460J to 8140J, the energy consumption decreased to 60%.



Time(min)	Enthalpy(J)	Rate(ml/min)	Duration (s)
5	126280	20	30
12	126280	10	20
19	84476	20	20
26	84476	20	30
36	126280	10	20
43	126280	10	20
52	126280	20	10
64	126280	20	20
74	126280	20	20
88	126280	20	20
101	126280	30	20

Figure 4. CH4 recovery curve of scenario II compared with the control group.

4. RESULTS AND DISCUSSION

Aiming at the optimization of the consumption of injected heat in the NGH joint exploitation of thermal stimulation and depressurization, this paper proposes a dynamic energy efficiency optimization model based on deep learning and reinforcement learning. Take the injection temperature, rate and duration of time step as optimized variables, and (1) improving the efficiency of exploitation, (2) saving the injection energy were taken as optimization targets as reward functions. After adjusting the reward coefficient according to different exploitation demands, the model can be independently learned to achieve the required engineering objectives. Finally, under the condition of satisfying the pre-set scenario, the recovery time decreased by 38% and the energy consumption decreased by 40%.

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[1] Datong Yi, 2018. Experimental Study on the Decomposition Characteristics and Mechanism of Natural Gas Hydrate Formed in Silica Sands. MS Thesis, ChongQing Univ.