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Gas Hydrate Pipeline Is Optimized: Levy Flight, Cauchy Mechanism, and Perception Probability

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Pipelines used for the hydraulic lifting of gas hydrate particles in deep-sea gas hydrates consume a large quantity of energy, so the level of efficient resource exploitation is very low and it is challenging to meet an efficient gas supply. Therefore, the article aims to optimize and analyze a process used for rigid pipe hydraulic lifting, an essential part of a deep-sea gas hydrate extraction system. First, the objective function is constructed considering the relationship between the extraction system's parameters, and a specific energy consumption is set when the deep-sea gas hydrate extraction is under consideration. Then, the range of each parameter is determined according to the extraction system's actual situation. Secondly, the improved crow search algorithm with a hybrid strategy covering dynamic perception probability, Levy flight, and Cauchy variation mechanism is employed to solve the optimization model. Finally, the improved crow search algorithm is applied to the experimental settings and compared with other optimization algorithms. The experimental results show that the proposed method, which is, the improved crow search algorithm, has a good computational efficiency, can effectively realize the optimization of the parameters of the deep-sea natural gas hydrate system, and is robust to numerical fluctuations of the parameters. Thus, the performance of the pipeline is improved and the energy consumption of the system is effectively reduced. Eventually, a theoretical reference is provided for the development of deep-sea gas hydrate. The proposed algorithm, I-CSA, can effectively deal with larger sample data and maintain high computational efficiency with fewer MAPE results when the sample sizes increase. Eventually, it is helpful for the deep exploitation and utilization of deep-sea gas hydrate.

KEYWORDS: crow search algorithm, gas hydrate, pipeline lifting, dynamic perception probability, Levy flight, Cauchy variation mechanism.

1.Introduction

The exploration and extraction of gas hydrates from deep seas have emerged as a significant research field due to their potential to serve as an alternative energy source. Gas hydrates, crystalline structures composed of gas molecules surrounded by water molecules, are found in oceanic sediments and permafrost regions. Their extraction poses many technical challenges, notably requiring optimizing hydraulic lifting processes that are critical for transporting extracted materials from a seabed to a surface. Hydraulic lifting in deep-sea extraction systems revolves around utilizing a fluid medium to create a differential pressure that aids in lifting extracted materials through a rigid pipe to a surface [1]. The efficiency and reliability of this process are paramount, given the extreme conditions and fragile nature of gas hydrates. Initial research in this domain focused on understanding the physical properties of gas hydrates and the engineering challenges associated with their extraction processes. As the field progresses, the spotlight turns towards optimizing the lifting process to minimize energy consumption and ensure the structural integrity of the hydrates during ascent.

The primary objective of the research is to enhance the efficiency and effectiveness of a hard pipe hydraulic lifting process within deep-sea gas hydrate extraction systems [8]. Globally, researchers have undertaken various studies to address the challenges associated with hydraulic lifting. They range from experimental investigations of flow behavior and hydrate disassociation risks to computational simulations to optimize pipe design and lifting parameters [3, 17]. The optimization process of deep-sea gas hydrate pipeline lifting is crucial, and pivotal for ensuring energy efficiency, operational safety, and environmental sustainability in offshore engineering. This field intersects with various disciplines, including fluid mechanics, thermodynamics, materials science, and computational intelligence. The primary research categories encompass flow assurance, pipeline material and design optimization, hydrate management, and the application of intelligent optimization algorithms.

1. Flow Assurance and Hydrate Management are fundamental in ensuring uninterrupted flow in pipelines, with a significant focus on preventing and managing gas hydrates, which can block pipelines and disrupt operations. The research includes thermodynamic and kinetic inhibitors, as well as mechanical strategies to prevent hydrate formation.
2. Pipeline Material and Design Optimization deals with material selection and structural design critical for withstanding the harsh deep-sea environment and high pressures. Innovations in materials science, such as developing corrosion-resistant alloys and flexible pipeline designs, are among the key research focuses.
3. Intelligent Optimization Algorithms research several algorithms that have gained prominence for their potential to improve decision-making processes in pipeline lifting. These algorithms include genetic algorithms (GA), particle swarm optimization (PSO), artificial neural networks (ANN), and others. They are implemented for optimizing various aspects of pipeline operation and design.

Ahmadi et al. [2] compared four artificial intelligence models for testing the equilibrium conditions of natural gas hydrates. Predicted the equilibrium pressure of the pipeline with the highest accuracy, while reducing calculation time while maintaining accuracy. The utilization of these techniques led to significant progress in pipeline optimization, which bodes well for the feasibility of such methods in the future. However, they are still prone to the problems of falling into local optimization and low convergence efficiency in practical applications, and thus still have limitations in practical applications. Thus, aiming at resolving those issues, the article mainly contributes to

1. Aiming at improving the principle of deep-sea gas hydrate extraction by devising a mathematical model and an objective function about the working parameters, and the range of the working parameters is reached.
2. A multi-strategy hybrid improved crow search algorithm is proposed for realizing the optimization of the working parameters of the natural gas hydrate extraction system.
3. Simulation tests are designed with energy consumption as an index and the effect and efficacy of the optimization are compared with different intelligent optimization algorithms to verify the rationality of the proposed algorithm.

Even though the literature provides a wide range of optimization algorithms implemented in this area, some problems persist such as being trapped in a local optimum and not applicable to practical problems. On the other hand, the crow search algorithm proves itself in several different areas and could provide solutions to these mentioned problems in the literature. The Crow search algorithm is implemented in high-dimensional data classification [12], optimal deployment of private 5G multi-access edge computing systems [15], semiconductor final testing scheduling problems [10], and power system state estimation [4]. In addition, a modified version of the crow search algorithm is implemented to resolve problems, for example, disease diagnosis [24], automatic clustering, feature selection [19], and optimal flexible manufacturing process planning. All indicates that the modified version of the Crow search algorithm has better results when compared with the utilization of single-form. Thus, the article combines 3 different mechanisms into the Crow search algorithm to deal with the problems, which are called dynamic perception probability, Levy flight, and Cauchy variation mechanism. Alternatively, heuristic algorithms are used in a variety of areas such as image segmentation, image classification, image restoration, and deep learning applications [23, 13, 26, 6, 20].

The main structure of the article is as follows: The introduction is presented in Section 1. Section 2 describes the working principle of the deep-sea gas hydrate extraction system, and gives the mathematical model and objective function, as well as determines the range of the parameters of the system. Section 3 presents the basic principle of the crow search algorithm and improves it based on the hybrid strategy, namely, perception probability, Levy flight, and Cauchy variation mechanism. Simulation experiments are designed in Section 4 to test the effectiveness of the proposed algorithm. Section 5 concludes the research and provides an outlook.

2. System Modeling

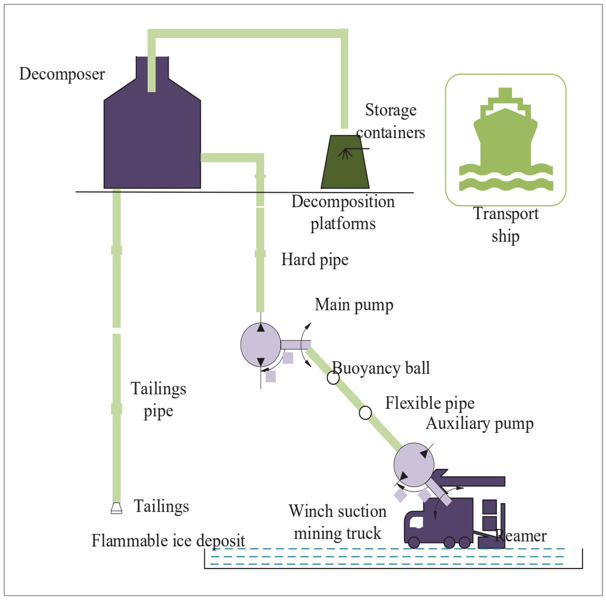
2.1 Fundamentals of Deep-Sea Gas Hydrate Extraction Systems

The distribution range of gas hydrate deposits in nature is high-latitude permafrost zones and deep seas of 300-4,000 m, and the reserves of natural gas hydrate in the deep sea account for more than 90% of the total amount of gas hydrate.

The marine storage depth is relatively shallow when compared with that of conventional oil and natural gas, so it is very promising to utilize the deep sea as a place for natural gas hydrate exploitation. Therefore, it is very promising to utilize the deep sea as a site for gas hydrate extraction. The extraction methods of gas hydrate include pressure relief, thermal stimulation, injection of chemical reagents, carbon dioxide replacement, and solid-state implementations, among which the solid-state method draws on the extraction method of deep-sea manganese nodules and combines with the working principle of the winch suction dredger. A great prospect of application is shown in Figure 1.

Figure 1

Working principle of deep sea gas hydrate extraction system.



2.2 Mathematical Modeling of the System

At present, in both academia and industry, the prevalent practice involves altering merely 1 or 2 variables while keeping the rest fixed to analyze how these adjustments impact energy use and efficiency. However, they do not accurately reflect the unpredictable variations of operational conditions in real-world scenarios, nor do they consider the comprehensive impact of simultaneous changes in variables on energy use and efficiency. In response, this study introduces a method to calculate hydraulic loss in vertical pipelines and utilizes the concept of "energy consumption ratio" (ECR) to construct a mathematical model. By adhering to theoretical guidelines and practical considerations for parameter variability, this work constructs a complex relationship between energy efficiency and consumption and the discussed parameters. This approach allows for a broader understanding of how variations in these parameters can collectively influence the system's performance, rather than examining them in isolated forms. The model aims to closely mimic actual operational conditions by considering the global impact of parameter changes, thus offering a more nuanced insight into optimizing energy efficiency and consumption in practical applications.

In the article, gas hydrate optimization is carried out in terms of transport efficiency, and the objective function measures water consumed when a unit weight of gas hydrate particles is lifted based on a unit distance in height along a vertical pipeline, called the ECR. Combined with the actual deep-sea extraction and lifting process of gas hydrate, it is possible to reduce the specific energy consumption of the pipeline. The objective function is represented based on the consumed per unit weight of natural gas hydrate particles when lifting them per unit distance along the vertical pipeline, which is called the specific energy consumption. Assuming that the total length of the lifting pipeline is denoted by L, the mass of the gas hydrate particles in the pipeline of total length is D. The mass of the gas hydrate particles in the pipeline whose total length is L defined by Equation (1):

$$M_{ghp} = \frac{\pi D_L{}^2 L \rho_s \left(\rho_m - \rho_w\right)}{4\left(\rho_s - \rho_w\right)} \ , \tag{1}$$

where M_{ghp} (kg) denotes the total mass of hydrate particles of natural gas in the pipeline. D_L(m) denotes the inner diameter of the pipeline in m. L (m) denotes the total length of the pipeline. ρ_s(kg/m^3) denotes the mineral density. ρ_m(kg/m^3) denotes the slurry density. ρ_w(kg/m^3) is the density of seawater.

The distance transported per unit of time for gas hydrate particles of mass M_{ghp} is denoted by m, and the head loss is defined by

$$Loss_{head} = L\rho_w g G_m \vartheta \ , \tag{2}$$

where G_m g (m/s^2) denotes the hydraulic gradient and the gravitational acceleration, respectively. The slurry flow rate ϑ is shown in Equation (3).

$$\vartheta = 0.25\pi D_L{}^2 v_s \ , \tag{3}$$

where v_s denotes the slurry conveying speed. Then, the ECR is defined by

$$E_{ecr} = \frac{Loss_{head}}{M_{ghp} g v_s} \ . \tag{4}$$

Equations (2)-(4) lead to Equation (5):

$$E_{ecr} = \frac{\rho_w G_m}{\rho_s C_p} \ , \tag{5}$$

where C_p represents the concentrated volume of particles, and the hydraulic gradient G_m is delineated by Equation (6)

$$G_m = 1.8416\left(\frac{v_s}{\sqrt{gD_L}}\right)^{2.7736} C_l C_d \frac{d_p}{D_L}\frac{\rho_s-\rho_w}{\rho_w} + \frac{f v_s^2}{2gD_L} + C_l\left(\frac{\rho_s-\rho_w}{\rho_w}\right) , \tag{6}$$

where f denotes the friction coefficient whose score is taken as 0.0206, C_l denotes the local concentration transported by the pipeline, C_d represents the drag coefficient, which is taken as 0.44 for turbulent flow with a large Reynolds number, d_p characterizes the particle size.

E_{ecr} represents a function of pipe diameter D_L, slurry conveying speed v_s, particle size d_p, mineral density ρ_s, and volume concentration C_p Equation (6) is the objective function to be optimized in the article.

2.3 Determination of Ranges of Operating Parameters

1 Pipe diameter, D_L, and size are relatred to the flow rate ϑ and slurry conveying speed v_s. If the pipe diameter is too small, the conveying flow of a pipeline is small, and the conveying capacity is limited. If the flow rate is unchanged and the pipe diameter is too large, it will reduce the speed of slurry conveying. If it is lower than the critical flow rate,

the system cannot work properly. Therefore, the pipe should cooperate with the slurry pump. If the size is too large and is not conducive to deployment in the ocean, the pipe diameter of the vertical pipeline for energy requirement value has little impact. For example, an increase in the pipe diameter greater than 0.3 m cannot reduce energy consumption. Therefore, the size of the pipe diameter D_L is taken to be 0.2~0.3 m since the gas production capacity of medium-sized natural gas wells (3-10×10^4 m^3/d) is considered.

2 Slurry conveying speed v_s designates the particles in the vertical pipeline slurry transporting upward. The slurry flow rate must be greater than the settling speed of the particles. When taking into account the hydraulic conveying process itself is not completely stable and the existence of the wind and waves, vibration, or the movement of the ship itself and other external reasons, the slurry conveying speed should be at least 3 to 4 more times than the settling speed to ensure the reliability of the system because the system and the main pump are connected. As the system and the main pump connected to the hose are close to the level, it should also limit the slurry conveying speed greater than the critical speed. The slurry conveying speed $v_s \geq 1.534\text{m/s}$ is selected by considering the flow rate.

3 Particle size d_p in the system of hydraulic conveying represents the vertical pipeline elevation of coarse particles. To prevent the rapid reduction of the resistance coefficient leading to the end of the settlement velocity increases, the requirements of the particle size and pipe diameter ratio need to be $d_p / D_L \leq 0.2$. If the particle size is too small flocculation phenomenon may appear. Thus, the particle size d_p needs to be between 10~40 mm.

4 Mineral density ρ_s is measured based on the longitudinal wave velocity of sonic logging. The saturation degree of marine gas hydrate is estimated to change from 10% to 50%, the density of pure gas hydrate is 930 kg/m^3, and the density of seafloor sediment is 1450 kg/m^3, so the mineral density ρ_s can be considered to be between 1190-1398 kg/m^3.

5 Volume concentration C_p is measured according to the experience of hydraulic coal transportation based on developed experience in the industry for hundreds of years. Hydraulic coal transportation usually ranges from 30% to 40%, the concentration of natural gas hydrate slurry should not be more than 40% and $C_p \leq 40\%$ is taken.

3. Proposed Methodology

3.1 Crow Search Algorithm (CSA)

The crow search algorithm is a heuristic optimization method that mimics the behavior of crowns. Crows will steal food by observing where the other birds hide their food, if a crow finds the thief, it will move to hiding places to avoid being a future victim. Crows use their own experiences to predict the pilferer's behavior. The crow's overall flight area is the searching space, and the crow's hidden food represents the quality of the algorithm function score. We briefly provide the steps of the crow search algorithm (CSA) below.

1 Determine the crow population size N_c (how many crows are in the population) and the algorithm's maximum iteration number, $Iter_{max}$. Then, initialize the crows' positions within a d-dimensional space (representing the optimization variables for the problem at hand) in a random manner.

2 Assess each crow's fitness score employing the fitness function, which then serves as the foundational memory. This memory of converted positions is documented within the $\boldsymbol{M}$ variable setting.

3 Suppose that crow i moves to another location during the flight. Then, 2 scenarios exist.

Scenario 1: at the t-th iteration, crow i does not find the tracked crow j while traveling to the memorized hiding place $M_{i,}^{t}$ then the position of crow i at the t+1-th iteration will be updated as follows [21, 18]:

$$\boldsymbol{X}_i^{t+1} = \boldsymbol{X}_i^t + R_1 \cdot f_s \cdot \left(\boldsymbol{M}_i^t - \boldsymbol{X}_i^t \right), \tag{7}$$

where X_i^{t+1} and X_i^t denote the positions of crow i at t+1-th and t-th iterations, respectively. $R_1 \in [0,1]$ denotes a random number. f_s denotes the flight step of a crow.

Scenario 2: At the t-th iteration, crow i have a perception probability P of determining the tracked crow j while traveling to the memorized hiding place M_i^t, then crow i will move to a random location within the search range at t+1-th iteration.

To combine 2 scenarios, the position of crow i at t+1-th iteration is updated as follows [22].

$$X_i^{t+1} \begin{cases} X_i^t + R_1 \cdot f_s \cdot \left(M_i^t - X_i^t \right), R_1 \geq P \\ Random\ location\ , R_1 < P \end{cases} \tag{8}$$

4 To assess each crow's updated fitness score and compare it with the available score stored in memory if the fitness score at the new location surpasses that in memory, the position is deemed valid, prompting an update to reflect this improvement. Conversely, if the new position does not offer a better fitness score, th e crow remains stationary, maintaining its current location as follows:

$$M_i^{t+1} = \begin{cases} X_i^{t+1}, & f\left(X_i^{t+1}\right) > f\left(M_i^t\right) \\ M_i^t, & f\left(X_i^{t+1}\right) \leq f\left(M_i^t\right) \end{cases} \tag{9}$$

5 Continue to iterate, repeat steps (3) and (4) until the iteration stopping condition is met and the optimal value is the output.

3.2 Improvements to CSA

To make the CSA converged and optimized better, the article adopts a hybrid improvement strategy including dynamic perception probability, Levy flight, and Cauchy variation mechanism for improving the performance of the CSA.

3.2.1 Dynamic Perception Probability

In the improved CSA, the fixed perception probability, P, requires a prior configuration. A higher P value increases the likelihood of crows being detected, prompting them to leave their current spot in favor of new ones. Conversely, a smaller P value inclines crows towards a localized search approach, highlighting a preference for exploring nearby areas. Such a static P score does not effectively balance the exploratory capabilities in the algorithm's initial and subsequent phases. To enhance algorithm efficiency, the dynamic perception probability of each iteration is advocated. The article introduces a method for calculating probabilities dynamically, which significantly boosts the algorithm's efficacy. The presented innovative approach for dynamic probability adjustment aims to optimize search efficiency throughout the algorithm's execution.

$$P = P_{\max} - P_{\max} \frac{t^3}{Iter_{\max}^3}, \tag{10}$$

where t and $Iter_{max}$ denote the previous iteration and maximum iteration numbers, respectively, and P_{max} denote the maximum perceptual probability.

The dynamic probability of perception P satisfies the convex decreasing curve, and the score of P is kept in a relatively large range at the beginning of the iteration, and gradually decreases with the iteration process, to realize the balance between the global and local search capability of the algorithm.

3.2.2 Levy Flight

In the CSA framework, crows adjust their locations randomly if $R_1 < P$, which means that when lacking guidance from superior solutions, it will lead to indiscriminate updates. To address this, the article incorporates the Levy flight approach into the crows' updating mechanism. The Levy flight employs a heavy-tailed probability distribution for its movements, facilitating both extensive and intensive searches due to its varied step lengths characterized by its high randomness. Effective local exploration is achieved with shorter steps, whereas longer strides enable the transition across different areas, broadening the search scope. Following the integration of the Levy flight concept, modifications to the method of updating the crows' positions have been implemented accordingly. More up-to-date Levy flight implementations can be found in [25, 11, 23].

$$X_i^{t+1} = \begin{cases} X_i^t + R_1 \cdot f_s \cdot \left(M_i^t - X_i^t \right), R_1 \geq P \\ X_i^t \cdot \left[1 + \text{Levy}(\lambda) \right], R_1 < P \end{cases}, \tag{11}$$

where denote the Levy(λ) flight step [7]:

$$\text{Levy} = \frac{\mu}{|\eta|^{1/\beta}}, \tag{12}$$

where β takes values in the range (0, 2) and is usually taken as 1.5. μ and η follow normal distributions with zero mean and σ^2 variances, $\mu \sim \left(0, \sigma_\mu^2\right), \eta \sim \left(0, \sigma_\eta^2\right)$, σ_μ and σ_η satisfy Equation (12) [16]:

$$\begin{cases} \sigma_{\mu} = \left\{ \dfrac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\times 2^{(\beta-1)/2}} \right\}, \\ \sigma_{\eta} = 1 \end{cases} \quad (13)$$

where $\Gamma(\cdot)$ denotes the gamma function.

3.2.3 Cauchy Variation Mechanism

Within the CSA algorithm, the method for updating positions among crow populations is standardized and singular, devoid of any mutation mechanism [27]. This absence could lead to homogeneity within the population, hindering the algorithm's capacity to escape local optima once trapped. To counteract this, it is essential to introduce a degree of mutation in individual crows, thereby maintaining population diversity. The Cauchy distribution emerges as an ideal choice for introducing perturbations. More up-to-date research can be found in [23]. In the study, it is applied to adjust crow positions, facilitating variations and enhancing the algorithm's capability to overcome local optima while preserving population heterogeneity. The perturbation is implemented by employing the standard Cauchy distribution function defined in Equation (14)

$$F(\alpha) = \frac{1}{\left(\alpha^2+1\right)\pi}, \alpha \in (-\infty, +\infty). \quad (14)$$

When the position of the crow is perturbed the obtained new position is calculated as follows:

$$\hat{\boldsymbol{X}}_i^{t+1} = \boldsymbol{X}_i^{t+1} \times \left[1 + F(\alpha)\right]. \quad (15)$$

According to Equation (15), utilizing the Cauchy distribution to adjust the position of the crow effectively amounts to a renewed exploration of its available location. If this new position proves superior, it supersedes the former; otherwise, the original stance is maintained. This process, facilitated by the Cauchy modification, guarantees the population's variety and boosts the algorithm's proficiency in escaping local optimum.

3.3 The Steps of the Improved CSA Process

By introducing the dynamic perception probability, Levy flight strategy, and Cauchy variation mechanism into the CSA algorithm, the improved CSA (I-CSA) algorithm is obtained. Figure 2 depicts it and the steps of the algorithm are as follows:

Step 1: Initialize the crow population position, crow memory, initial perception probability, initial flight step size, and maximum number of iterations.

Step 2: Calculate the fitness score of each crow and determine the current optimal position.

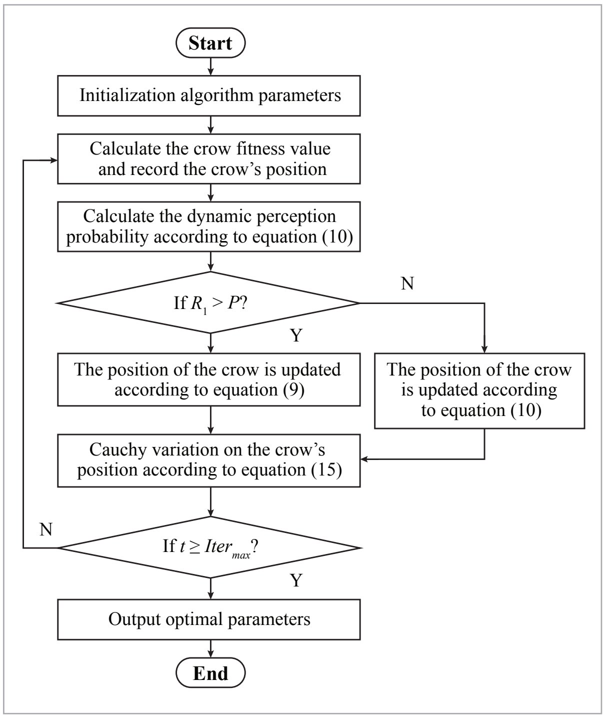
Step 3: Calculate the dynamic probability of sensing and determine whether the generated random number is greater than the current probability of sensing. If yes, use Equation (9) to update the crow's position. Otherwise, use Equation (10) to update the crow's position.

Step 4: Perform Cauchy variation on the crow's location according to Equation (15).

Step 5: Calculate the fitness score of the new location of the crow and update the memory according to Equation (9).

Step 6: Judge the maximum number of iterations, if it is reached to a set number, output the optimal position and its fitness value; otherwise, repeat steps 2 to 6 until the termination condition is met.

Figure 2
The workflow of CSA.



4. Experimental Analysis

4.1 Experimental Environment and Data Sources

In this study, the investigative setting is anchored within a deep-sea gas hydrate exploration lab's mining system. Adjustments can be made to the slurry's flow rate, particle size, and volume concentration to meet specific requirements. The pipeline's inner diameter remained unchanged, owing to the extensive array of testing instruments encircling it, which made swapping pipelines of varying inner diameters a challenging endeavor. Due to the storage challenges associated with natural gas hydrate particles, substitutes in the form of bituminous coal particles were employed, given their similar density. The experimental results are presented based on the data collected from actual experiments.

Table 1
Hardware environment of the experiment.

Settings	Parameters
CPU	Intel peon E5-2678 v3 @ 2.SGHz* 12
GPU	GeForce RTX 2080 Ti 11 GB
Memory	64GB
Hard disk capacity	2TB
Operating System	Windows 10
Calculation software	Matlab 2023A

4.2 Calculation Settings

Table 2 presents the parameters of the operating system, which is converted to international standard units.

Table 2
System operating parameters.

Parameters	Value
D_L	0.3
v_s	[1.534, +∞]
d_p	[0.01,0.04]
ρ_s	1197.4
C_p	(0,0.04]

The Uniform Crossover and Roulette Wheel Section methods are used, with an allowable error of convergence of 1.00E-10, and the number of judgments on the allowable error of convergence is 100 times. The convergence error is compared with the allowable convergence error, if the convergence error is larger than the allowable convergence error, then the corresponding independent variables are recalculated. If the convergence error is smaller than the convergence allowable error, the computation ends with the output of the optimal result and the score of the corresponding independent variable.

4.3 Experimental Results

To test the effectiveness of the proposed algorithm, 3 experiments are designed to test its performance and compare it with the particle swarm optimization (PSO) algorithm, genetic algorithm (GA), and unimproved crow search algorithm in each experiment. The experiments are divided into the following 3 parts:

1. Experiments on the ECR of the algorithm solution under different sample capacity conditions;
2. Experiments on the error comparison between the ECR of the simulation test and that of the actual system under different sample capacity conditions; and
3. Experiments on the comparison of the algorithm's computational efficiency under different sample capacity conditions.

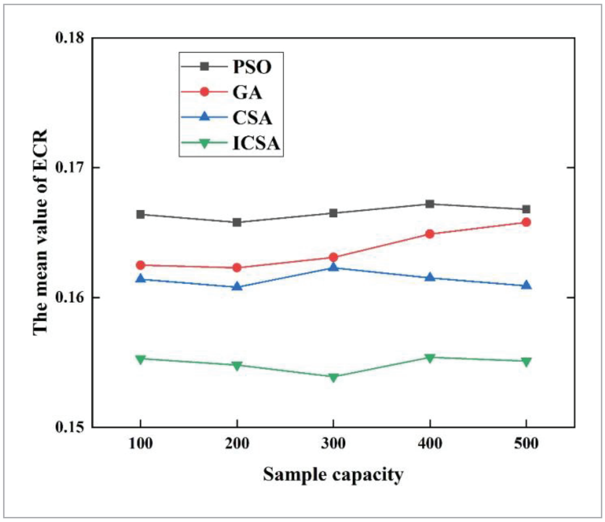
4.4 Experiments on the ECR of the Algorithm Solution Under Different Sample Capacity Conditions

The experimental data containing 100, 200, 300, 400, and 500 groups were randomly generated in MatLab 7.0 according to the parameter settings presented in Table 1, and then I-CSA was implemented to find the optimized outcomes and calculate the mean of the ECR, and the results are shown in Figure 3 to compare PSO, GA, and CSA algorithms.

Figure 3 depicts that the average of the ECR attained by the intelligent optimization algorithm fluctuates within a certain range as the sample capacity increases since calculation results conform to a certain distribution law. Figure 3 depicts the results of PSO and GA by comparing those of CSA. The CSA has a higher precision in optimization search due to its simpler structure. Moreover, the proposed algorithm, I-CSA, has a further improvement in the optimization performance, which makes the average of the ECR much lower than that of other algorithms. Therefore, the I-CSA can effectively decrease the ECR and advance the mining efficiency.

Figure 3

The calculation results of the mean value of ECR.



4.5 Experiments on the Error Comparison Between the ECR of the Simulation Test and That of the Actual System Under Different Sample Capacity Conditions

To test the performance of the proposed algorithm in practical applications, its optimized output operating parameters are applied in practice, the results are compared with the results of the simulation, and the error is calculated. The results are compared with those of PSO, GA, and CSA and the Mean Absolute Percentage Error (MAPE) is presented in Table 3.

Table 3

The MAPE (%) of the obtained results.

Sample capacity	PSO	GA	CSA	ICSA
100	26.45	25.55	12.93	4.50
200	44.54	26.85	16.69	5.16
300	51.45	43.99	10.18	8.05
400	38.97	23.13	18.58	4.91
500	66.11	35.41	18.23	5.31

Table 3 summarizes the ECR attained by the intelligent optimization algorithm in the practical application of the operating parameters that deviate from the simulation results, which is because the marine environment such as seawater density and pressure is quite different from the experimental ones. Found that the simulation results of the PSO and GA have a large deviation from the actual results, and the MAPE of both of them varies in the range of 20% to 70% when all sample sizes are considered, which is insufficient for the accuracy of practical application. On the other hand, the optimization accuracy of the CSA is relatively higher, and the error between the optimization and the actual results can be controlled within the range of 10%~20%. The optimization accuracy of the I-CSA is higher, and the error can be reduced to less than 10%, with good optimization accuracy, thus its results are more in line with the actual situation, which can be effectively applied to the exploitation of deep-sea gas hydrate.

4.6. Experiments on the Comparison of the Algorithm's Computational Efficiency Under Different Sample Capacity Conditions

To check the computational efficiency of different algorithms, the computational time of I-CSA is compared with those of the PSO, GA, and CSA when different sample sizes are implemented. Figure 4 depicts the outcomes.

Figure 4

The results of computational efficiency.

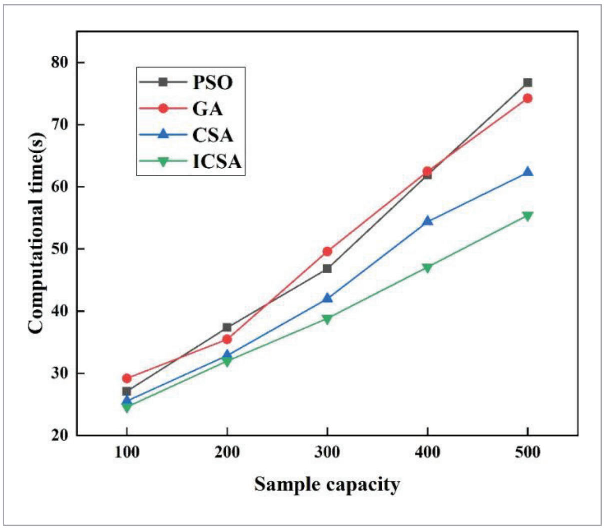


Figure 4 depicts that as the sample size grows, the computational burden also increases, so the computation time of the intelligent optimization algorithm also grows. The PSO and GA are more complex due to their structural deficiencies. When the sample size increases, the computational time grows more rapidly for the PSO and GA. In contrast, the computational time increases slightly slower for CSA, which is due to the simplicity of its computational process. However, the 3 algorithms still have shortcomings due to falling into local optimum and having low efficiency in optimization. Nevertheless, after using dynamic perception probability, Levy flight, and the Cauchy variation mechanism the shortcomings are eliminated and optimization efficiency is significantly improved by the I-CSA. In addition, the proposed algorithm can effectively deal with larger sample data and maintain a high computational efficiency.

5. Conclusion

In the manuscript, an I-CSA-based optimization method for natural gas hydrate pipeline lifting is proposed to optimize the natural gas hydrate pipeline lifting process. Firstly, a mathematical model of energy loss and pipeline lifting-related parameters is constructed, and the objective function and parameter ranges are given. Subsequently, the CSA is improved based on the hybrid strategy of dynamic perception probability, Levy flight, and Cauchy variation mechanism, and the proposed I-CSA realizes the optimization of the working parameters of the system. Finally, experiments are designed to test the performance of the proposed algorithm, and the experimental results show that the proposed I-CSA algorithm can effectively reduce the energy consumption of the system, and reduce the computational burden, thus the actual error grows relatively small, the computational efficiency is high, and the performance increases. So, a better performance for practical applications is probable as a reference for the natural gas extraction work.

Considering that the unstable flow in a pipeline causes a large impact on the energy consumption ratio, the next step is to investigate the optimization of the optimal operating parameters in various types of deep-sea environments and to design the corresponding estimation model for assessing the mining revenue.

Declaration of Conflicting Interests

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References

1. Abbasi, A., Hashim, F. Prediction of Hydrate Formation Conditions in the Subsea Pipeline with a Genetic Algorithm, International Conference on Technology, Informatics, Management, Engineering & Environment (TIME-E), 2015, 133-136. https://doi.org/10.1109/TIME-E.2015.7389761
2. Ahmadi, M., Chen, Z.-X., Clarke, M., Fedutenko, E. Comparison of Kriging, Machine Learning Algorithms, and Classical Thermodynamics for Correlating the Formation Conditions for CO_2 Gas Hydrates and Semi-Clathrates, Journal of Natural Gas Science and Engineering, 2020, 84, 103659. https://doi.org/10.1016/j.jngse.2020.103659
3. Akhnafovich, S. R., Flusovich, Y. I., Rashitovich, K. A., Frilovna, S. G. Engineering Calculation of Inductor Parameters for Gas Pipelines, International Conference on Electrotechnical Complexes and Systems (ICOECS), 2019, 1-5. https://doi.org/10.1109/ICOECS46375.2019.8949982

4. Andic, C., Ozturk, A., Turkay, B. A Robust Crow Search Algorithm-Based Power System State Estimation, Energy Reports, 2023, 9(Suppl. 11), 490-501. https://doi.org/10.1016/j.egyr.2023.09.075
5. Avalos, O., Haro, E. H., Camarena, O., Díaz, P. Improved Crow Search Algorithm for Optimal Flexible Manufacturing Process Planning. Expert Systems with Applications, 2024, 235, 121243. https://doi.org/10.1016/j.eswa.2023.121243
6. Bhandari, A. K., Rahul, K. A Context-Sensitive Masi Entropy for Multilevel Image Segmentation Using Moth Swarm Algorithm. Infrared Physics & Technology, 2019, 98, 132-154. https://doi.org/10.1016/j.infrared.2019.03.010
7. Deng, B. An Improved Honey Badger Algorithm by Genetic Algorithm and Lévy Flight Distribution for Solving Airline Crew Rostering Problem, IEEE Access, 2022, 10, 108075-108088. https://doi.org/10.1109/ACCESS.2022.3213066
8. Feng, Z., Wu, L., Jin, S. SVM-Based Identification Method for Hydrate Blockage in Natural Gas Pipelines, International Conference on Mechanical, Control and Computer Engineering (ICMCCE), 2019, 394-3943. https://doi.org/10.1109/ICMCCE48743.2019.00094
9. Gil, M., Akbari, E., Rahimnejad, A., Ghasemi, M., Gadsden, S. A. Solution of Optimal Reactive Power Dispatch by Lévy-Flight Phasor Particle Swarm Optimization. Intelligent Systems with Applications, 2024, 23, 200398. https://doi.org/10.1016/j.iswa.2024.200398
10. Hu, W., Liu, M., Dong, M., Liu, T., Zhang, Y., Cheng, G. A Greedy-Based Crow Search Algorithm for Semiconductor Final Testing Scheduling Problem, Computers & Industrial Engineering, 2023, 183, 109423. https://doi.org/10.1016/j.cie.2023.109423
11. Ivanov, V. V., Dlugach, J. M. Radiative Transfer of Excitation: Lévy Flights and Self-Similarity. Journal of Quantitative Spectroscopy and Radiative Transfer, 2024, 323, 108999. https://doi.org/10.1016/j.jqsrt.2024.108999
12. Jiang, H., Yang, Y., Wan, Q., Dong, Y. Feature Selection Based on Dynamic Crow Search Algorithm for High-Dimensional Data Classification, Expert Systems with Applications, 2024, 250, 123871. https://doi.org/10.1016/j.eswa.2024.123871
13. Ke, Q., Zhang, J., Wei, W., Połap, D., Woźniak, M., Kośmider, L., Damaševĭcius, R. A Neuro-Heuristic Approach for Recognition of Lung Diseases from X-Ray Images. Expert Systems with Applications, 2019, 126, 218-232. https://doi.org/10.1016/j.eswa.2019.01.060
14. Liang, Y., Wang, R., Qu, G., Zhou, Z., Liu, Y., Yan, W. A Cauchy Perturbation Cuckoo Search Particle Filtering Algorithm for Remaining Useful Life Prediction of Lithium-Ion Battery Considering Capacity Regeneration. International Journal of Electrochemical Science, 2023, 18(10), 100304. https://doi.org/10.1016/j.ijoes.2023.100304
15. Lin, C.-C., Deng, D.-J., Hsieh, L.-T., Pan, P.-T. Optimal Deployment of Private 5G Multi-Access Edge Computing Systems at Smart Factories: Using Hybrid Crow Search Algorithm, Journal of Network and Computer Applications, 2024, 227, 103906. https://doi.org/10.1016/j.jnca.2024.103906
16. Liu, Y., Cao, B. A Novel Ant Colony Optimization Algorithm with Lévy Flight, IEEE Access, 2020, 8, 67205-67213. https://doi.org/10.1109/ACCESS.2020.2985498
17. Prasad, N. T., Murthy, K. N. V. V., Sandhya, C. S., Gobichandhru, D., Ramesh, S., Ramadass, G. A. Experimental Investigations on In-Situ Properties Measurement of Gas Hydrate Systems, OCEANS - Chennai, 2022, 1-6. https://doi.org/10.1109/OCEANSChennai45887.2022.9775293
18. Rai, K., Kamble, M. Incubation of a Metaheuristic Searching Approach for Intrusion Detection into a New Constrained Crow Search Algorithm, IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), 2023, 1-9. https://doi.org/10.1109/SCEECS57921.2023.10063120
19. Ranjan, R., Chhabra, J. K. Automatic Clustering and Feature Selection Using Multi-Objective Crow Search Algorithm. Applied Soft Computing, 2023, 142, 110305. https://doi.org/10.1016/j.asoc.2023.110305
20. Ranjbarzadeh, R., Caputo, A., Tirkolaee, E. B., Ghoushchi, S. J., Bendechache, M. Brain Tumor Segmentation of MRI Images: A Comprehensive Review on the Application of Artificial Intelligence Tools. Computers in Biology and Medicine, 2023, 152, 106405. https://doi.org/10.1016/j.compbiomed.2022.106405
21. Shirke, S., Udayakumar, R. Evaluation of Crow Search Algorithm (CSA) for Optimization in Discrete Applications, International Conference on Trends in Electronics and Informatics (ICOEI), 2019, 584-589. https://doi.org/10.1109/ICOEI.2019.8862669
22. Sumanth, K., Priya, M. V. New Crow Search Algorithm for Economic Load Dispatch Resolution vs.

the Time-Proven BAT Algorithm, International Conference on Artificial Intelligence and Knowledge Discovery in Concurrent Engineering (ICECONF), 2023, 1-4. https://doi.org/10.1109/ICECONF57129.2023.10083563

23. Yu, F., Guan, J., Wu, H., Chen, Y., Xia, X. Lens Imaging Opposition-Based Learning for Differential Evolution with Cauchy Perturbation. Applied Soft Computing, 2024, 152, 111211. https://doi.org/10.1016/j.asoc.2023.111211
24. Zamani, H., Nadimi-Shahraki, M. H. An Evolutionary Crow Search Algorithm Equipped with Interactive Memory Mechanism to Optimize Artificial Neural Network for Disease Diagnosis. Biomedical Signal Processing and Control, 2024, 90, 105879. https://doi.org/10.1016/j.bspc.2023.105879
25. Zhang, B., Liu, W., Cai, Y., Zhou, Z., Wang, L., Liao, Q., Fu, Z., Cheng, Z. State of Health Prediction of Lithium-Ion Batteries Using Particle Swarm Optimization with Lévy Flight and Generalized Opposition-Based Learning. Journal of Energy Storage, 2024, 84, Part A, 110816. https://doi.org/10.1016/j.est.2024.110816
26. Zhao, D., Qi, A., Yu, F., Heidari, A. A., Chen, H., Li, Y. Multi-Strategy Ant Colony Optimization for Multi-Level Image Segmentation: A Case Study of Melanoma. Biomedical Signal Processing and Control, 2023, 83, 104647. https://doi.org/10.1016/j.bspc.2023.104647
27. Zhu, J., Lv, H., Hao, B., Peng, J. Non-Convex High Order Total Variation with Overlapping Group Sparsity Denoising Model Under Cauchy Noise, IEEE Access, 2021, 9, 49901-49911. https://doi.org/10.1109/ACCESS.2021.3069500