

Research on Optimization for Methods Light Hydrocarbon Recovery Processes

Ning Su, Haijun He

College of Petroleum Engineering, Xi'an Shiyou University, Xi'an, Shaanxi 710065, China

Abstract: This study provides a systematic review of the fundamental principles and optimization strategies for light hydrocarbon recovery, focusing on thermodynamics-based process simulation and intelligent optimization methods. The study explores the integration of HYSYS process simulation with deep learning techniques, leveraging neural networks, genetic algorithms, and other advanced approaches to optimize process parameters, enhance recovery efficiency, and reduce energy consumption. Deep learning enables accurate prediction of key process variables and, when combined with optimization algorithms, significantly improves system performance. The synergy between HYSYS modeling and intelligent optimization offers a novel framework for enhancing the efficiency and accuracy of light hydrocarbon recovery, contributing to the advancement of smart process optimization.

Keywords: Light hydrocarbon recovery; HYSYS modeling; Deep learning; Optimization algorithms.

1. Introduction

With the acceleration of industrialization and the continuous change of energy demand structure, the high-value utilization of natural gas has become a global focus. Light hydrocarbon components in natural gas (such as ethane, propane, etc.) have gradually become important targets for optimizing energy utilization due to their advantages of high combustion calorific value and environmental friendliness. Although traditional light hydrocarbon recovery processes have achieved certain achievements in separation efficiency, with the diversity of natural gas components and the complexity of operating conditions, traditional methods can no longer meet the needs of modern industry for efficient and low-energy separation technologies.

Deng Zhi'an et al^[1] proposed a new process by utilizing the cold energy released during the gasification of liquefied natural gas (LNG) and combining three reported LNG light hydrocarbon recovery processes in the literature. They used HYSYS simulation software to simulate the process and conduct sensitivity analysis. Xiao Rongge et al^[2] integrated the direct heat exchange (DHX) light hydrocarbon recovery process with self-produced refrigerant refrigeration, expansion refrigeration, and cold box integrated heat exchange, combining it with a natural gas low-temperature helium recovery process to design a co-production process capable of simultaneously producing C3+, crude helium, and LNG. To improve the C3 product yield while reducing energy consumption, they simulated the DHX process light hydrocarbon recovery flow using HYSYS software, established a multi-objective optimization regression model with maximum C3 product yield and minimum total energy consumption through MATLAB software, and solved it using the adaptive second-generation non-dominated sorting genetic algorithm (NSGA-II)^[3]. Wang Chuanping et al^[4] implemented pressurization and cryogenic efficiency enhancement projects to achieve long-term stable production in condensate gas fields, comprehensively improving the development benefits of the gas field by increasing the recovery rate of resources such as ethane and liquefied gas in natural gas. The light hydrocarbon recovery adopted the RSV

process, with an ethane recovery rate reaching 95%.

In recent years, scholars at home and abroad have increasingly attempted to introduce thermodynamic simulation and intelligent optimization algorithms into light hydrocarbon recovery processes, aiming to achieve optimal process operation through precise model prediction and intelligent parameter regulation. This paper aims to discuss different optimization methods for light hydrocarbon recovery, firstly by constructing a process simulation platform based on HYSYS for simulation optimization, and secondly by using deep learning including BP neural networks and genetic algorithms to optimize key parameters. The combination of HYSYS and deep learning provides new ideas and technical pathways for the improvement of light hydrocarbon recovery technologies, and is conducive to enhancing the safety, stability, and production efficiency of production operations.

2. Light Hydrocarbon Recovery Process

2.1. Basic Principles of Light Hydrocarbon Recovery

The core of light hydrocarbon recovery^[5] technology lies in utilizing the phase equilibrium characteristics of different hydrocarbons under conditions such as temperature and pressure to achieve efficient separation of high-value components, thereby improving economic benefits and reducing environmental impacts. By regulating process conditions, heavy hydrocarbon components are liquefied in advance, while light hydrocarbons are separated in gaseous or liquid form, so as to purify natural gas and enhance product quality. This process not only relies on heat transfer and pressure regulation between equipment but also involves precise calculations of physical property parameters and equation of state.

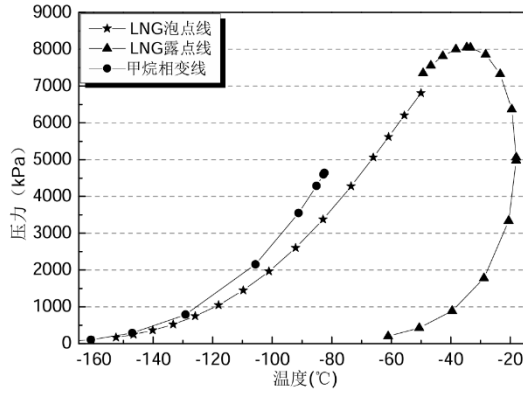


Figure 1. Pressure and Temperature Equilibrium Curve Diagram of Methane and LNG

2.2. Main Methods of Light Hydrocarbon Recovery

The main processes for light hydrocarbon recovery from natural gas are classified into solvent absorption separation process, solid adsorption separation process, low-temperature phase change separation process, and membrane permeation separation process^[6].

Solvent absorption method achieves separation by establishing a gas-liquid two-phase system, relying on the difference in solubility of hydrocarbon components in medium oils (such as naphtha-diesel mixed solvents). However, this process faces bottlenecks such as high system complexity and poor operational economy, and is gradually being replaced by new low-temperature technologies^[7].

Adsorption method^[8] enriches light hydrocarbons through the selective adsorption properties of porous materials, offering advantages such as compact equipment and low infrastructure costs. However, its industrial applicability has obvious limitations due to the constraints of adsorption kinetics for key components like ethane.

Low-temperature condensation process realizes gradient condensation separation by precisely controlling the pressure-temperature field, based on the differences in critical phase change parameters of each component^[9]. With its process stability and energy efficiency advantages, it has become the mainstream technical solution in the industry.

Membrane separation technology^[10] uses the difference in permeation characteristics of components in asymmetric membrane structures as the separation driving force, achieving molecular-level sieving through transmembrane pressure differences. Although this technology has a high maturity in industrial applications, its large-scale promotion is restricted by the strict requirements for the chemical stability and mechanical strength of membrane materials.

3. Light Hydrocarbon Recovery Optimization

3.1. Optimization Based on Thermodynamics and Process Simulation

This study uses HYSYS process simulation software as the

process modeling platform, and simulates and calculates the multi-component equilibrium in natural gas based on the Peng-Robinson equation of state. By setting reasonable process parameters such as temperature, pressure, and flow rate, a light hydrocarbon separation process model under real operating conditions is established.

As early as 1960, foreign countries had patents for light hydrocarbon separation from LNG. In the United States, separating C2+ light hydrocarbons from LNG has become an important means to adjust the calorific value of natural gas to meet national gas standards. According to existing processes, China has optimized the heat exchange network and distillation column system of the process using process energy integration optimization technology, and proposed an LNG light hydrocarbon separation process integrating a low-temperature heat exchange network with the light hydrocarbon separation process^[11].

The P-R state equation is as follows:

$$P = \frac{RT}{V-b} - \frac{a \times \alpha}{V(V+b) + b(V-b)} \quad (1)$$

Among them:

$$\alpha = [1 + (0.37464 + 1.54226\omega - 0.26992\omega^2)(1 - T_r^{0.5})] \quad (2)$$

$$a = 0.45724R_g^2T_c^2 / P_c \quad (3)$$

$$b = 0.0778RT_c / p_c \quad (4)$$

Where: a 、 b 、 α represent gas-related constants; P_c represents the critical pressure, Pa; T_c represents the critical temperature,; T_r represents the comparison temperature, K; P_r represents contrast pressure, Pa; V represents molar volume, m³/mol; R represents the molar gas constant, with a value of 8.3145 kJ; ω represents the eccentricity factor.

Due to the multi-component nature of LNG, specific mixing rules should be used when applying the P-R equation:

$$a = \sum_{i=1}^n \sum_{j=1}^n x_i x_j a(T)_{ij}, a(T)_{ij} = (1 - k_{ij}) \sqrt{a(T)_i a(T)_j} \quad (5)$$

$$b = \sum_{i=1}^n x_i b_i \quad (6)$$

Where: k_{ij} represent the interaction parameters of i-j molecular pairs, x_i represent the molar fraction of component i.

By adjusting parameters such as α , a , and b in the state equation, it is ensured that the model can accurately predict the phase equilibrium state under different operating conditions.

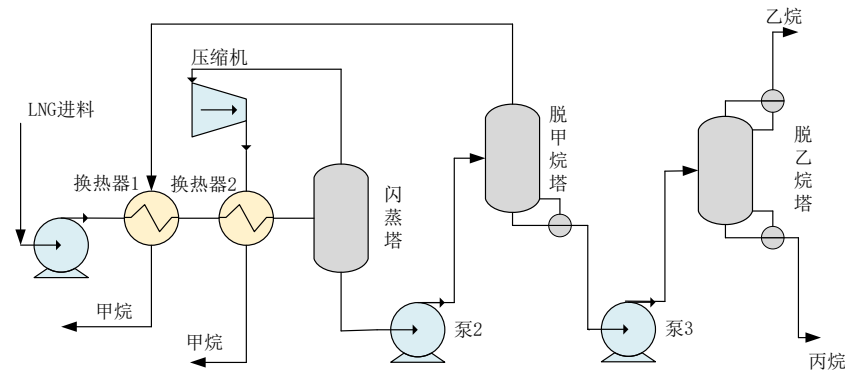


Figure 2. Flow Chart of LNG Light Hydrocarbon Separation

As shown in Figure 2, Aspen Plus process simulation software was used as a tool to obtain optimal operating conditions through integrated optimization of the heat exchange network and distillation column system^[12].

(1) During the LNG feedstock and product gas recovery process, efficient energy utilization in the process was achieved by optimizing the heat exchanger configuration, enabling complete reliquefaction of the two separated methane gas streams. The simulation results show that maximizing the use of cooling capacity can be achieved by reasonably controlling the top pressure of the demethanizer. First, the top pressure of the demethanizer is controlled: when the feed conditions are fixed, an initial pressure value for the demethanizer is selected, and the top pressure is changed in a fixed step size. With pressure changes, calculations are performed for parameters such as the molar fraction of methane, ethane recovery rate, and energy consumption per unit of C3+, to analyze the impact of demethanizer pressure changes on the entire process.

(2) Sensitivity analysis of equipment parameters was conducted for key equipment including compressors, flash tanks, and pumps, to analyze their respective impacts on the overall process performance through parameter analysis, providing data support for subsequent intelligent optimization.

(3) Optimization analysis of the entire process was carried out, including exergy analysis. According to the second law of thermodynamics, the exergy value of a system in a specific state is defined as the maximum useful work that can be output when the system undergoes a reversible process from that state to the environmental reference state. Exergy analysis systematically evaluates the perfection of energy conversion processes in process units by integrating the first law of thermodynamics (energy conservation) and the second law (entropy increase principle), focusing on examining the distribution characteristics of exergy loss and the potential for exergy efficiency improvement.

3.2. Parameter Optimization Based on Intelligent Optimization Algorithms

Deep learning techniques have demonstrated significant advantages in the field of process industry modeling. In this study, a data-driven model for the light hydrocarbon recovery process was established by constructing multi-layer neural network architectures, including multi-layer perceptrons (MLP), convolutional neural networks (CNN), and recurrent neural networks (RNN). Compared with traditional mechanism-based modeling methods, this data-driven model can effectively characterize the complex non-linear mapping

relationships in the process, achieving a significant improvement in prediction accuracy. Among them, backpropagation (BP) neural networks^[13], as a typical artificial intelligence algorithm, realize iterative optimization of network parameters through gradient descent. Their non-linear approximation capability, generalization performance, and robustness have made them widely used in the prediction and optimization of industrial process parameters. Zhang Zibo et al^[14], constructed a key parameter prediction model for light hydrocarbon recovery units based on BP networks, achieving accurate prediction of dry gas production and stable light hydrocarbon production with a relative error of 3.81%. Liu Miao'er et al^[15], optimized the initial weights of BP networks using genetic algorithms (GA), reducing the average prediction error of operating parameters in natural gas liquefaction units from 9.64% to 5.17%, verifying the effectiveness of intelligent algorithms in industrial optimization.

The BP neural network architecture adopted in this study includes three basic structural units: an input layer, hidden layers, and an output layer. Its computational process comprises two core stages: forward propagation and error backpropagation. As shown in Figure 3, it is a topological structure diagram with multiple inputs and outputs. By establishing a process model for the light hydrocarbon recovery unit and combining it with actual production data for network training, genetic algorithms were finally used for global optimization of process parameters. The main steps include data processing, neural network parameter setting, and model establishment.

First, for data preprocessing, real-time historical data collected by the distributed control system (DCS) was aligned using a sliding window method for time-series data. Aiming at operational disturbances such as raw material gas quality fluctuations and abnormal heat transfer temperature differences, outlier detection was performed using the 3σ criterion to eliminate abnormal samples under non-normal production conditions, data anomalies, and missing data. The dataset was finally divided into training, validation, and test sets at a ratio of 6:2:2. The training dataset was used for model training, the validation dataset was used to verify the model's generalization ability during training to avoid overfitting, and the test dataset did not participate in the training process but was used to test the model's performance. Next, for network parameter configuration, the Sigmoid function was selected as the activation function for the hidden layers, which serves as the core mechanism for neural networks to achieve complex mapping capabilities. The optimal number of hidden layer nodes was determined through a trial-and-error method,

mean squared error was used as the loss function, and an adaptive learning rate optimizer was set for parameter updates. Finally, for model validation, the generalization ability of the model was evaluated based on the test set, and the prediction performance was verified using dual indicators of mean absolute percentage error (MAPE) and coefficient of determination (R^2). The ultimately constructed GA-BP hybrid optimization model has demonstrated good engineering applicability in the optimization of light hydrocarbon recovery process parameters.

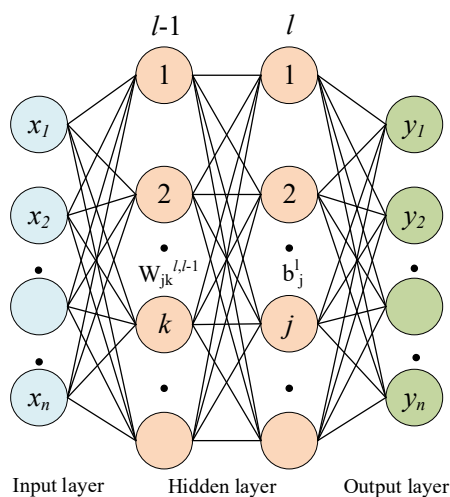


Figure 3. Structure of BP Neural Network

4. The Combination of HYSYS Modeling and Deep Learning Optimization

In the optimization of light hydrocarbon recovery processes, HYSYS, as a powerful process simulation tool, can accurately simulate the process flow and predict the system performance under different operating conditions. Deep learning can learn complex nonlinear relationships from the simulation data of HYSYS, establish a data-driven prediction model, and be used to optimize process parameters. The combination of the two can achieve more efficient and intelligent process optimization.

(1) Model establishment: Based on the designed light hydrocarbon recovery process flow, select the corresponding equipment models and state equations, and establish the corresponding simulation process in HYSYS software. Conduct sensitivity analysis and exergy analysis, including changes in parameters such as the top pressure of the methane removal tower, the top pressure of the ethane removal tower, and heat exchangers, and their impact on overall energy consumption and light hydrocarbon recovery rate.

(2) Algorithm optimization: Build a thermodynamic simulation platform using HYSYS software and use Matlab software as the parameter optimization platform. Achieve process parameter optimization through cross-platform data interaction between the two software^[16]. First, establish the objective function, set the multi-objective function to maximize light hydrocarbon recovery rate and minimize energy consumption, and determine the constraints based on parameter analysis in the simulation. Then, solve the objective function, write the algorithm, determine the number, dimension, and iteration times, and use the simulation results to determine the range of values for each variable, and start iterative calculation^[17].

(3) Through iterative calculation, the optimal solution set is obtained. The optimal solution set is an intermediate scheme that meets the lower total energy consumption and higher light hydrocarbon recovery rate of the entire process.

5. Summary

This paper systematically studies the optimization methods of light hydrocarbon recovery process, focusing on the in-depth research of the combination of thermodynamic process simulation based on HYSYS and intelligent optimization algorithms.

(1) Light hydrocarbon recovery can not only increase the economic value of natural gas products, but also reduce the hydrocarbon dew point and enhance the safety of transportation.

(2) Through mechanism modeling with HYSYS software, the thermodynamic characteristics of the light hydrocarbon recovery process can be accurately simulated. The phase equilibrium of light hydrocarbon separation can be calculated using the state equation to improve the simulation accuracy. By establishing a data-driven model with neural networks, complex nonlinear relationships can be effectively learned, enhancing the prediction ability of key parameters in light hydrocarbon recovery. Combining optimization methods such as genetic algorithms can further improve process parameters, increase recovery rate and reduce energy consumption.

(3) By using HYSYS as a process simulation tool and combining it with intelligent optimization algorithms, intelligent optimization of the light hydrocarbon recovery process can be achieved. This method has a faster calculation speed and better parameter configuration compared to traditional optimization strategies.

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