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# Energy Consumption Optimization Analysis of LNG Receiving Station Based on Genetic Algorithm

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**Abstract:** In response to the problem of high energy consumption in LNG receiving stations, based on literature research, numerical simulation combined with genetic algorithm optimization methods were used to establish a calculation model and ASPEN HYSYS steady-state simulation model for the LNG receiving station equipment, each unit process and the overall receiving station process. The various parameters in the LNG receiving station will have a certain impact on the overall energy consumption of the LNG receiving station. Combined with the operating requirements of the LNG receiving station site under different working conditions, and considering the coupling effect of multiple factors, the technology of optimizing the operating parameters of the LNG receiving station to reduce energy consumption is selected, and the adjustable decision-making parameters and their range of changes are selected, and the constraints are set according to the actual situation and Establish the energy optimization objective function of the LNG receiving station process system, and evaluate and analyze the energy consumption indicators of the optimized process system.

**Keywords:** LNG receiving station; energy saving optimization; genetic algorithm.

## 1. Introduction

As the use of renewable energy increases, governments and industries around the world are transitioning from hydrocarbon fuels, and the NG and LNG industries have played an important role in the transition. Asia's imported LNG accounts for 60% of global imports [1] and is the fastest growing market. In addition, natural gas has the potential to meet 30% of global primary energy demand by 2025, and will reach 35% by 2035 [2].

Genetic Algorithms (GA) is an evolutionary optimization method based on a random search algorithm.In recent years, it has been applied in the engineering field as a goal-oriented optimization algorithm. Genetic algorithms provide new ideas for non-deterministic optimization of complex systems. Genetic algorithms are also a commonly used algorithm in energy planning projects. When solving complex combinatorial optimization problems, they often achieve better optimization results faster than some traditional optimization algorithms. The GA algorithm initializes the result of a possible solution, then applies GA operators for selection, crossover and mutation operators, calculates an evaluation function for each candidate solution, and uses GA operators to regenerate new results after the survival of the fittest, and continues to work until the requirements are met. Objective function results. In the process, multi-objective genetic algorithms are usually used for optimization, and operating parameters are selected as decision variables, costs related to energy consumption and completion time, and objective functions.

In terms of combining genetic algorithms with natural gas, Soldo[3] combined BP neural network with genetic algorithm GA for short-term gas load forecasting, Szoplik[4], Azadeh[5], etc., Rodger[6], Gorucu[7], etc. , Azadeh [8] et al., Eynard [9] et al., Kizilaslan [10] et al. developed and used ANN for natural gas prediction, and successfully realized the prediction of component content to provide reference for natural gas transportation and application. Izadyara[11] et al., Askari[12] et al., Thomas[13] et al. also considered the GA method for natural gas prediction models. The hybrid model is more accurate than a single model, and the genetic algorithm is used in conjunction with other optimization models. , the matching degree and optimization effect have been significantly improved. May [14] used total energy consumption and idle period energy consumption as energy efficiency indicators, established a multi-objective model of energy efficiency scheduling, and switched machine energy modes to improve efficiency. Sangick [15] optimized the cascade Rankine cycle natural gas liquefaction process to recover cold energy by applying genetic algorithm, and the process conditions leading to the maximum net generated power can be found by changing the process parameters. Moon [16] et al. proposed a liquefied natural gas (LNG) cold energy recovery plant optimization model based on genetic algorithm, which improved the net power performance of the cascade Rankine cycle by 58.4%.

## 2. LNG Receiving Station Optimization Model Establishment

Based on the operation process of the LNG receiving station, numerical simulation methods are used to establish calculation models and ASPEN HYSYS steady-state simulation models for the LNG receiving station equipment, each unit process and the overall receiving station process.

### 2.1. Establishing process simulation model based on HYSYS

The LNG receiving station simulation model is a full-process model of the LNG receiving station established based on the actual process flow of the LNG receiving station and the operating procedures of the LNG receiving station. According to the process category, it can be divided into LNG storage tank unit, BOG processing unit, LNG high and low pressure external transmission system, LNG high and low pressure SCV vaporization unit, LNG high and low pressure

IFV vaporization unit, seawater pump unit and fuel gas treatment unit, among which LNG high and low pressure SCV The vaporization unit, LNG high and low pressure IFV vaporization unit, seawater pump unit and fuel gas treatment unit are all established in the sub-process of HYSYS software. The LNG receiving station simulation model is shown in Figure 1.

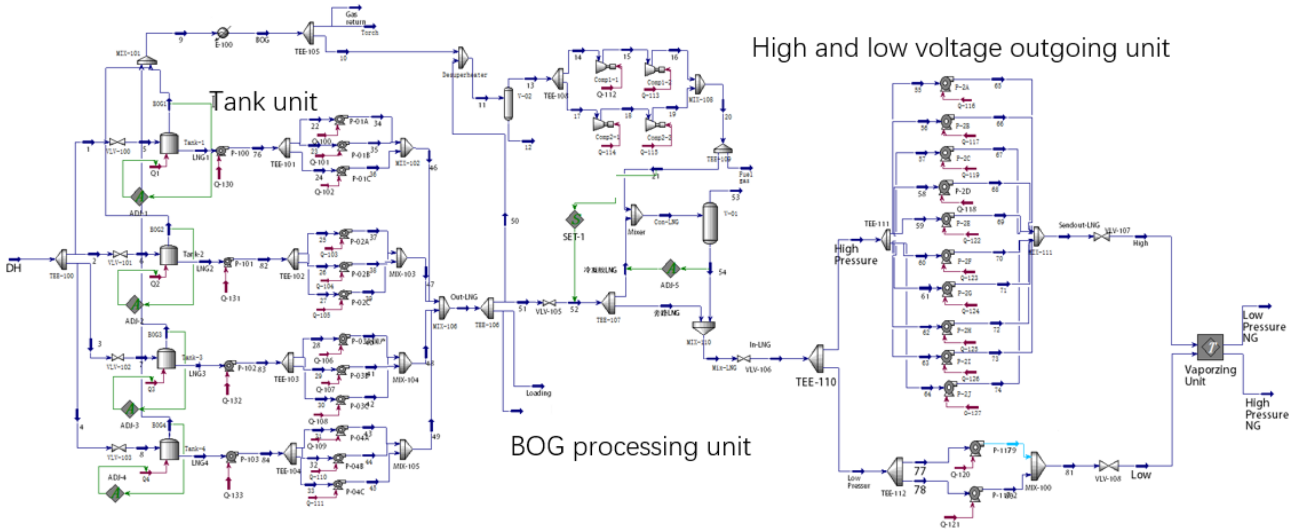



**Figure 1.** LNG receiving station process simulation model

## 2.2. Genetic algorithm optimization process

Compared with other classic optimization methods, GA has many advantages and greatly improves optimization efficiency. Genetic algorithms have obvious advantages in solving some highly discrete and nonlinear problems. The energy consumption optimization of LNG receiving stations is a relatively complex optimization problem. There are many optimization decision variables and many restrictive conditions. At the same time, the objective function is nonlinear. In existing simulation optimization, most of the optimization algorithms used are based on the gradient information of the function.

There are two main ways of exchanging data between external programs and most process simulators: ActiveX and OPC. ActiveX is a rebrand of OLE (Object Linking and Embedding), a technology developed by Microsoft that allows data exchange within programs. This technology was originally developed to allow users to edit spreadsheets within text documents, but quickly evolved to communicate between many other programs and can be used to communicate within a single computer as well as across a network. communication between. In 2011 AspenTech provided a set of ActiveX automation servers and instructions using Aspen HYSYS.

First, connect MATLAB and ASPEN HYSYS through the ActiveX ("actxserver") component of COM technology, call the ASPEN HYSYS program and pass in the data. Use MATLAB programming and genetic algorithm to optimize key parameters of the LNG receiving station. Write the objective function, decision parameters, parameters to be optimized, etc. through the HYSYS internal spreadsheet (spreadsheet) to determine the optimized objective function and target variable search space range (upper and lower limits of parameters), and establish the basis for model convergence judgment, that is, spreadsheet-node parameters Numerical judgment.

The parameters of the genetic algorithm (gaoptimset) can be set according to the number of variables and the complexity of the model. The key parameter PopulationSize represents the number of populations in each generation, Generations represents the total number of search generations, and PlotFcns represents the search for the optimal population of each generation in the form of an image. During the optimization process, HYSYS calculates the objective function, and MATLAB provides the calculation process of the genetic algorithm. The results calculated using HYSYS are returned to MATLAB for optimization analysis. During the transmission process, all individuals are converted into parameters identifiable by HYSYS, brought into the process for calculation, and returned as objective function values . The genetic algorithm optimization process is shown in Figure 2.

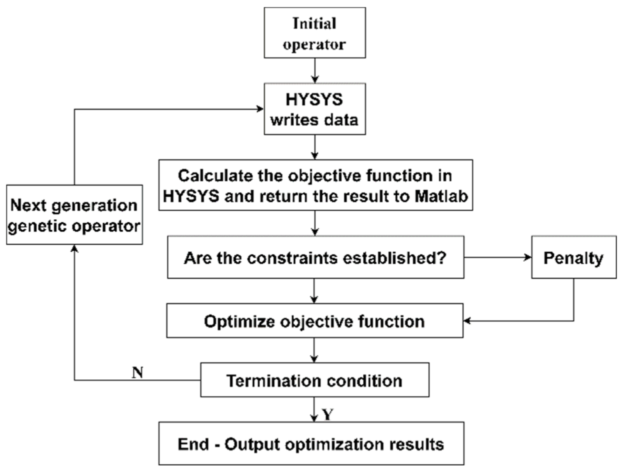



**Figure 2.** Genetic algorithm flow chart

## 2.3. Process parameter optimization objective function decision variable analysis

The process operation modes of LNG receiving stations are divided into three categories: IFV independent operation (discharging + 0 discharge), SCV independent operation (discharging + 0 discharge), and IFV and SCV joint operation (discharging + 0 discharge). Mathematical models for process parameter optimization in six operating modes were established respectively. Minimizing the total energy consumption of the LNG receiving station was the optimization goal, and parameters that had a greater impact on the LNG receiving station and were controllable were selected as decision variables for optimization.

#### 2.3.1. IFV independent operation mode (unloading + 0 unloading)

According to the simulation model of IFV independent operation mode, in this operation mode, its energy-consuming equipment is the LNG tank pump, BOG compressor, LNG high-pressure external pump and seawater pump. According to the analysis of factors affecting energy consumption in IFV independent operation mode, it was found that the process parameters (controllable factors) tank pressure, BOG compressor outlet pressure, and IFV seawater inlet and outlet temperature difference will affect the energy consumption of the LNG receiving station system.

The seawater flow of each IFV is controlled by adjusting the manual control valve on the seawater inlet pipeline of the seawater pump. By adjusting the seawater flow, the NG outlet temperature is adjusted so that the NG outlet temperature reaches the terminal demand output temperature. When the seawater flow in the IFV is too low, the PID interlock can be used to automatically close the gasifier inlet LNG pipeline valve and interlock to close the NG outlet valve, thereby selecting the IFV seawater temperature as the decision variable. The corresponding constraints are determine according to the process operating procedures of the LNG receiving station. The constraints under IFV independent operation conditions are:

LNG tank pressure constraints:

$$118kPa \le P_T \le 125\ kPa \tag{1}$$

BOG compressor secondary outlet pressure:

$$720kPa \le P_c \le 885\ kPa \tag{2}$$

IFV seawater flow:

$$5880t/h \le m \tag{3}$$

#### 2.3.2. SCV independent operation mode (unloading + 0 unloading)

According to the simulation model of SCV independent operation mode, in this operation mode, its energy-consuming equipment is LNG tank pump, BOG compressor, LNG high-pressure external pump, LNG low-pressure external pump, SCV fuel gas, SCV blower and fuel gas Heater etc. According to the analysis of factors affecting energy consumption in SCV independent operation mode, it was found that the process parameters (controllable factors) tank pressure, BOG compressor outlet pressure and SCV outlet NG temperature will affect the power consumption, gas consumption and overall energy consumption of the LNG receiving station system. Consumption.

The temperature signal of the SCV vaporizer is sent to the temperature controller by the temperature sensor. The temperature-controlled LNG flow input in the LNG receiving station controls the opening of the LNG flow valve so that the temperature reaches the output temperature. The corresponding constraints are determined according to the process operating procedures of the LNG receiving station. The constraints are:

LNG tank pressure constraints

$$118kPa \le P_T \le 125\ kPa \tag{4}$$

BOG compressor secondary outlet pressure:

$$720kPa \le P_c \le 885\ kPa \tag{5}$$

SCV outlet NG temperature:

$$10℃ \le \Delta t_w \le 25℃ \tag{6}$$

#### 2.3.3. SCV+IFV combined operation mode (discharging + 0 discharging)

According to the simulation model of SCV and IFV joint operation mode, in this operation mode, its energy-consuming equipment is LNG tank pump, BOG compressor, LNG high-pressure export pump, LNG low-pressure export pump, seawater pump, SCV fuel gas, SCV blower and fuel gas heater, etc. According to the analysis of factors affecting energy consumption in the joint operation mode of SCV and IFV, it is found that the process parameters (controllable factors) tank pressure, BOG compressor outlet pressure and SCV outlet NG temperature will affect the power consumption, gas consumption and gas consumption of the LNG receiving station system. Overall energy consumption.

In the joint operation mode, the total energy consumption of the LNG tank pump, BOG compressor, LNG high-pressure export pump, LNG low-pressure export pump, seawater pump, SCV fuel gas, SCV blower and fuel gas heater is the lowest. For the optimization objective, the storage tank pressure, BOG compressor outlet pressure and SCV outlet NG temperature are used as optimization variables. The objective function is:

LNG tank pressure constraints:

$$118kPa \le P_T \le 125\ kPa \tag{7}$$

BOG compressor secondary outlet pressure:

$$720kPa \le P_c \le 885\ kPa \tag{8}$$

IFV seawater flow:

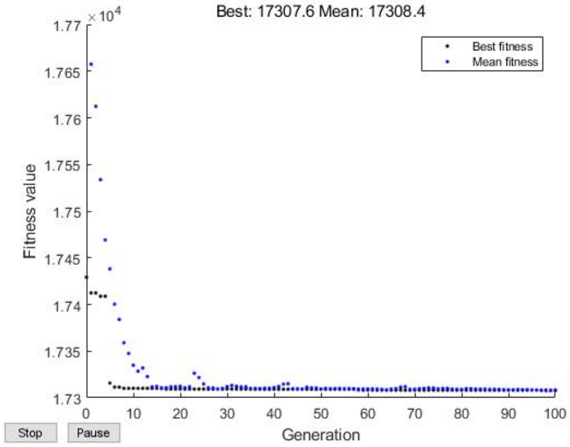
$$5880t/h \le m \tag{9}$$

SCV outlet NG temperature:

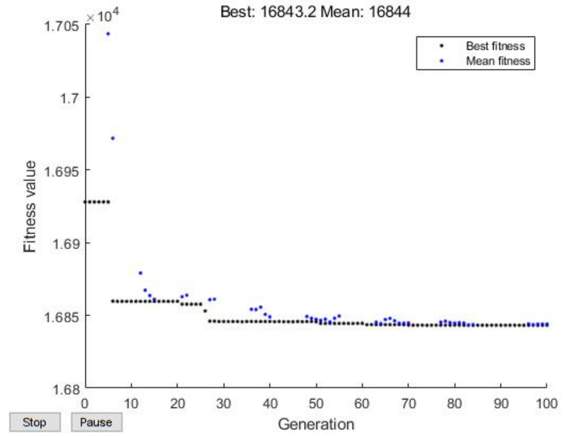
$$10℃ \le \Delta t_w \le 25℃ \tag{10}$$

## 3. Analysis of Process Parameter Optimization Results

Based on the above three basic working conditions, the genetic algorithm is used to call HYSYS through MATLAB, with controllable parameters as decision variables and the lowest energy consumption as the objective function for optimization. The abscissa in the figure represents the genetic algebra (generation), the ordinate represents the fitness value (i.e. objective function). The black dot represents the fitness value of the optimal individual, and the blue dot represents the average fitness value. The following results are obtained:




(a) Unloading IFV operates independent




(b) 0 unloading IFV operates independently

**Figure 3.** IFV independent running genetic algorithm energy consumption optimization results

Under the unloading IFV working condition, as the number of genetic generations increases, the blue points and black points gradually decrease and then stabilize around 43 generations. Under the 0 unloading IFV independent operating condition, the blue points and black points tend to stabilize after 80 generations. It coincides with the blue dot, indicating that the genetic algorithm has searched for the optimal result and found the global optimal solution. According to the optimized parameter comparison, under the unloading condition, the BOG compressor secondary outlet pressure is mainly reduced by increasing the storage tank pressure and the BOG compressor primary outlet pressure. Different IFV seawater input flow rates have different increases and decreases. Adjust to the same range to reduce the overall energy consumption of the LNG receiving station. During the unloading period of IFV independent operation, after parameter optimization, the overall energy consumption of the LNG receiving station was reduced by 1102kW, about 6%; under 0 unloading conditions, the outlet pressure of the first-stage compressor was increased, which reduced the energy consumption of the BOG compressor and started If IFV is not used, each IFV uses seawater flow on average, and the overall energy consumption is reduced by 808.44kW, about 4.58%.

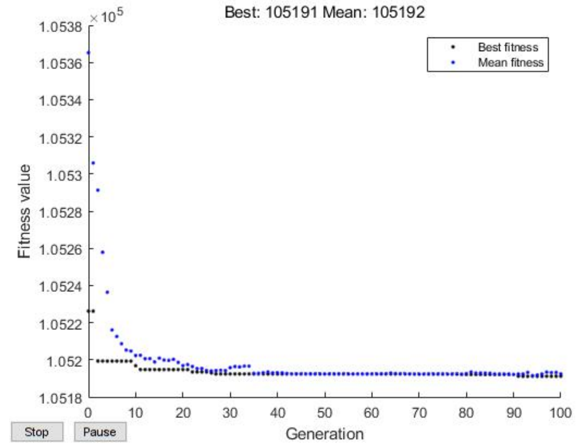
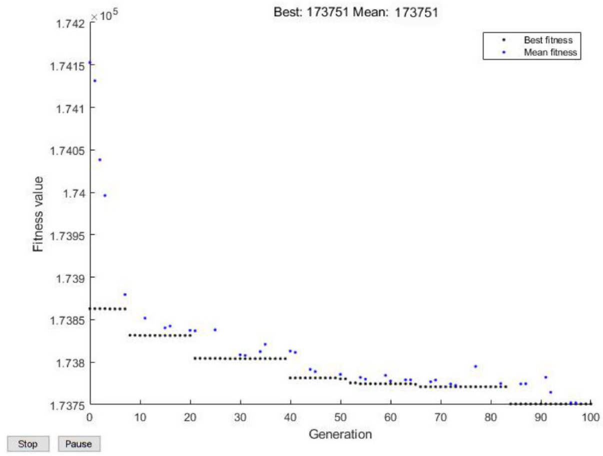
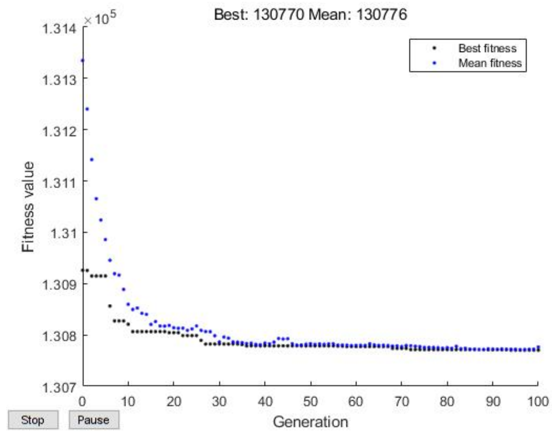



**Figure 4.** SCV independent running genetic algorithm energy consumption optimization results

It can be seen from Figure 4 that as the number of iterations of the genetic algorithm increases, the objective function (minimum energy consumption) first decreases and then becomes stable, that is, the optimal solution is found. Under the 0 unloading condition of SCV joint operation, the black point and the blue point coincide with each other after 43 generations. After optimizing the parameters, the storage tank pressure decreases, the BOG compressor primary outlet pressure increases, the secondary outlet pressure decreases, and the SCV outlet As the temperature rises, the overall energy consumption of the LNG receiving station decreases by 4138kW, a decrease of approximately 3.934%.




(a) Joint operation of IFV and SCV unloading




(b) IFV, SCV0 unloading joint operation

**Figure 5**. Energy consumption optimization results of genetic algorithm jointly run by IFV and SCV

It can be analyzed from Figure 5 that as the number of iterations of the genetic algorithm increases, the objective function (minimum energy consumption) first decreases and then becomes stable, that is, the optimal solution is found. Under the joint operation of IFV and SCV with 0 unloading conditions, the black point and the blue point coincide with each other after 84 generations. After optimizing the parameters, due to the increase in BOG flow during unloading, the secondary outlet pressure of the BOG compressor increases, and IFV The seawater flow rate is slightly reduced, the SCV outlet temperature is reduced by 1-3°C, and the overall energy consumption of the LNG receiving station is reduced by 8201kW, a reduction of approximately 4.72%. Under the joint operation of IFV and SCV with zero discharge, the black point and the blue point coincide with each other after 76 generations. After optimizing the parameters, the BOG compressor outlet pressure increases, the IFV seawater flow rate increases significantly, and the SCV outlet temperature decreases. This fuel gas flow reduction reduces the overall energy consumption of the LNG receiving station by 5754kW, a reduction of approximately 4.4%.

# 4. Summary

This article connects MATLAB to ASPEN HYSYS through ActiveX components, calls the HYSYS program and passes in data. Use MATLAB programming and genetic algorithm to optimize key parameters of the LNG receiving station. According to the LNG receiving station conditions, six operating conditions are established: IFV independent operation (unloading + 0 unloading), SCV independent operation (unloading + 0 unloading), and IFV and SCV joint operation (unloading + 0 unloading). The process parameter optimization mathematical model under six operating modes takes the minimum total energy consumption of the LNG receiving station as the optimization goal, and adjusts four decision-making parameters such as seawater flow, storage tank pressure, BOG compressor pressure, and SCV outlet NG parameters. Optimized, the energy consumption of LNG receiving stations is reduced by 3.2%-6% under different working conditions.

# References


[1] KIM Y, BLANK S. US shale revolution and Russia: shifting geopolitics of energy in Europe and Asia [J]. Asia Europe Journal, 2014, 13(1): 95-112.

[2] MOZAKKA M, SALIMI M, HOSSEINPOUR M, et al. Why LNG Can Be a First Step in East Asia's Energy Transition to a Low Carbon Economy: Evaluation of Challenges Using Game Theory [J]. Energies, 2022, 15(17).

[3] SOLDO B. Forecasting natural gas consumption [J]. Applied Energy,, 2012, 92: 26-37.

[4] SZOPLIK J. Forecasting of natural gas consumption with artificial neural networks [J]. Energy Policy, 2015, 85: 208-20.

[5] AZADEH A, ZARRIN M, RAHDAR BEIK H, et al. A neuro-fuzzy algorithm for improved gas consumption forecasting with economic, environmental and IT/IS indicators [J]. Journal of Petroleum Science and Engineering, 2015, 133: 716-39.

[6] RODGER J A. A fuzzy nearest neighbor neural network statistical model for predicting demand for natural gas and energy cost savings in public buildings [J]. Expert Systems with Applications, 2014, 41(4): 1813-29.

[7] F. G F G P G. Artificial neural network modeling for forecasting gas consumption [J]. Energy Sources, 2004, Vol.26(NO.3): 299-307.

[8] AZADEH A, ASADZADEH S M, GHANBARI A. An adaptive network-based fuzzy inference system for short-term natural gas demand estimation: Uncertain and complex environments [J]. Energy Policy, 2010, 38(3): 1529-36.

[9] EYNARD J, GRIEU S, POLIT M. Wavelet-based multi-resolution analysis and artificial neural networks for forecasting temperature and thermal power consumption [J]. Engineering Applications of Artificial Intelligence, 2011, 24(3): 501-16.

[10] KARLIK R K B. Comparison neural networks models for short term forecasting of natural gas consumption in Istanbul [Z]. 2008 First International Conference on the Applications of Digital Information and Web Technologies Ostrava, Czech Republic. 2008

[11] IZADYAR N, ONG H C, SHAMSHIRBAND S, et al. Intelligent forecasting of residential heating demand for the District Heating System based on the monthly overall natural gas consumption [J]. Energy and Buildings, 2015, 104: 208-14.

[12] ASKARI S, MONTAZERIN N, ZARANDI M H F. A clustering based forecasting algorithm for multivariable fuzzy time series using linear combinations of independent variables [J]. Applied Soft Computing, 2015, 35: 151-60.

[13] THOMAS NG S, SKITMORE M, WONG K F. Using genetic algorithms and linear regression analysis for private housing demand forecast [J]. Building and Environment, 2008, 43(6): 1171-84.

[14] MAY G, STAHL B, TAISCH M, et al. Multi-objective genetic algorithm for energy-efficient job shop scheduling [J]. International Journal of Production Research, 2015, 53(23): 7071-89.

[15] LEE S. Multi-parameter optimization of cold energy recovery in cascade Rankine cycle for LNG regasification using genetic algorithm [J]. Energy, 2017, 118: 776-82.

[16] JEONG M, CHO E-B, BYUN H-S, et al. Maximization of the power production in LNG cold energy recovery plant via genetic algorithm [J]. Korean Journal of Chemical Engineering, 2021, 38(2): 380-5.