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Gray wolf optimizer with bubble-net predation for modeling FCCU main fractionator

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Abstract: FCCU main fractionator is a complex system with multivariable, nonlinear and uncertainty. Its modeling is a hard nut to crack. In this work, the gray wolf optimization with bubble-net predation (GWO_BP) is proposed for solving this complex optimization problem. In order to enhance the global search ability and accelerate the convergence speed, the bubble-net predation of whale search scheme is applied to update the head wolf position. And the improved Lévy flight is used to update the positions of wolfpack for overcoming the disadvantage of easily falling into local optimum. The GWO_BP is compared with basic GWO, PSO with some typical test functions and the parameter estimation of FCCU main fractionation model. The experiment results show the effectiveness of the GWO_BP.

Keywords: Gray Wolf Optimizer, bubble-net predation, Lévy flight, FCCU main fractionator, Modeling

Introduction

Fluid catalytic cracking is one important part of the petroleum refining processes. The heavy oil is reacted in a lifting tube having a temperature of about 500°C in the presence of a molecular sieve catalyst. The hydrocarbons of the born can be separated into cracking gas, high octane gasoline and diesel. It is one of the important measures to convert heavy oil into light oil. The catalytic cracking main fractionation column is a master device that achieves product separation during catalytic cracking, which is an important part of catalytic cracking. Therefore, establishing a precise main fractionator model has a great significance to improve oil product quality¹. The catalytic crack process is full of uncertainty, complexity, nonlinearity and coupling among variables etc^{2,3}. It is very difficult to obtain an accurate mathematical model by traditional modeling methods, they have been unable to meet its requirements of building a high-precision mathematical model^{4,5}. The modeling problem of complex system can be transformed into a complex optimization problem. Researchers found that intelligent optimization algorithms can solve

the complex optimization problems^{6,7}. Intelligent optimization algorithms have no strict requirements for optimization problems, and easy to operate and implement.

With the development of artificial intelligence technique, intelligent optimization algorithms are also used in petroleum industry modeling⁸. Li et al. (2004) applied Tabu Search to solve chemical industry optimization problems, and obtains the global optimal solution in specific constrained optimization problems by setting different parameters⁹. Tao et al. (2007) proposed a RNA genetic algorithm to estimate the parameters of a heavy oil thermal cracking model and a FCCU main fractionator¹⁰. Li et al. (2014) adopted particle filter technique to improve the RBF neural network's learning speed and expression capability for modeling complex industrial processes with satisfactory accuracy¹¹. Li et al. (2020) used Grey Wolf Optimizer to optimize multi-classification Twin Support Vector Machine to explore concealed reservoirs¹². Hu et al. (2021) used a normal distribution function to improve the search mode of drosophila optimization algorithm to predict the oil pipeline energy consumption¹³.

Inspired by the preying activity of gray wolf, GWO is proposed in 2014¹⁴. GWO has strong search performance, few parameters and easy implementation. However, the basic GWO still has some defects, such as premature convergence, easy to fall into local optimum and so on. In order to overcome the defects of basic GWO, researchers have put forward various GWOs. Malik et al. (2015) used the weighted average of to update the position of wolf pack and improve the diversity of GWO population¹⁵. Kamboj et al. (2015) combined GWO with PSO in an equal way to optimize the single region constraint problem, which improved the convergence accuracy¹⁶. Min et al. (2016) balanced the local search and global search of GWO by improving the nonlinear convergence factor¹⁷. Yao et al. (2016) used the "greedy strategy" in differential evolution to eliminate the poorer new individual positions in the wolves for the UAV three-dimensional route planning problem¹⁸. Gupta et al. (2018) proposes a modified version of GWO by incorporating Random walk for leading wolves to optimize the search ability for prey by wolf pack¹⁹. Wang et al. (2019) used differential evolution and elimination mechanisms to update the Wolf pack, further speeding up the convergence rate and improving the convergence accuracy²⁰. Akash et al. (2019) performed an experiment of embedding β -Chaotic sequence in monotonically decreasing linear mechanism of GWO to avoid falling into local optimization²¹. Nadimi-Shahraki et al. (2020) used the dimension learning hunting search strategy to improve GWO, so that each wolf constructs a neighborhood, and the adjacent information is shared among wolves, which alleviated the lack of population diversity, the imbalance between development and exploration and the premature convergence²². Liu and Wang (2021) proposed a GWO with RNA cross operation to improve the global optimization ability and changed the adaptive parameter to balance the exploration and development ability²³. In this work, in order to overcome the shortcomings of basic GWO, we combine whale search scheme and improved Lévy flight to propose

the novel gray wolf optimizer (GWO_BP), and adopt to estimate the parameters of the Flowed Catalytic Cracking Unit (FCCU) main fractionator model.

The chapter structure is as follows. The second section introduces the basic GWO. The third section proposes a novel GWO (GWO_BP), which combines the whale search scheme and improved Lévy flight. The fourth section uses the typical optimization test functions to test the GWO_BP and the basic GWO and PSO. The GWO_BP is applied to estimate the model parameter of FCCU main fractionator to verify the effectiveness and feasibility.

Basic Gray Wolf Optimizer

Grey Wolf Optimizer (GWO) is a newly intelligence optimization algorithm proposed by Mirjalili et al.¹⁴. GWO is inspired by the prey hunting activities of gray wolves. Gray wolves are social canine animals that live at the top of the food chain, and they adhere to a strict hierarchy of social dominance. There are four social hierarchies in the gray wolf population α , β , δ , ω . Where α is the leading wolf in the wolf pack, and it makes major decisions about activities in the wolves, In the GWO, α is the best fitness value in the wolves. β wolf obeys the leading wolf and helps him to make decisions. β wolf can dominate the other grades of wolves, and β is the second best solution of fitness value in GWO. δ obeys α and β in the wolf pack, and at the same time dominates the wolves of the remaining level. δ is the third best solution of fitness value. The rest of the candidate solutions are ω , ω wolves usually need to obey wolves at higher social levels. The optimization process of GWO is guided by α , β and δ , after judging the position of the prey which is the optimal solution, α , β and δ lead ω to surround the prey. Finally, the optimal value is found by iterating continuously.

GWO can divide the whole process of hunting prey into three stages, which are encircling, chasing, attacking, and finally capturing the prey, The detailed algorithm is described as follows¹⁴:

(1) Encircling prey: after the wolves lock the location of the prey, they will slowly move to the prey for encirclement. In the encirclement process, the distance between the gray wolf and the prey can be calculated by Eqs (1) and (2):

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right| \quad (1)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad (2)$$

where $\vec{D}$ indicates the distance between the wolf and prey, t is the current iteration, $\vec{X}_p(t)$ is the location of prey after the iteration t , $\vec{A}$ and $\vec{C}$ are coefficients, and can be calculated as follows:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \quad (3)$$

$$\vec{C} = 2 \cdot \vec{r}_2 \quad (4)$$

where $\vec{r}_1$, $\vec{r}_2$ are random value in [0,1]. $\vec{a}$ is the convergence factor and decreases linearly from 2 to 0 with the iteration proceeds, the definition is as follows:

$$\vec{a} = 2 - \frac{2T}{T_{\max}} \quad (5)$$

(2) Hunting: the hunting process of gray wolf population is usually guided by α wolf, β and δ assisted α wolf. Therefore, GWO assumes that α , β and δ are related to the possible positions of prey, and updates according to the positions of these three optimal solutions, the expression are as follows:

$$\begin{cases} \vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha(t) - \vec{X}(t)| \\ \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta(t) - \vec{X}(t)| \\ \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta(t) - \vec{X}(t)| \end{cases} \quad (6)$$

$$\begin{cases} \vec{X}_1 = \vec{X}_\alpha(t) - \vec{A}_1 \vec{D}_\alpha \\ \vec{X}_2 = \vec{X}_\beta(t) - \vec{A}_2 \vec{D}_\beta \\ \vec{X}_3 = \vec{X}_\delta(t) - \vec{A}_3 \vec{D}_\delta \end{cases} \quad (7)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (8)$$

(3) Attack prey: This step is the last stage of the hunting process, the wolves siege and capture the prey (obtain the optimal solution). This stage can be realized by decreasing the value of $\vec{a}$ in Eq (3). When the value of $\vec{a}$ decreases linearly from 2 to 0, the corresponding value of $\vec{a}$ also changes in the interval [-a, a]. When the random value of A is above [-1,1], the next position of the wolf may be anywhere between its current position and its prey position, when $|A| > 1$, wolves are currently moving away from position of prey to find new potential prey. Random parameter C in Eq (4) ranges from [0,2], parameter C randomly enhances ($C \geq 1$) or weakens ($C < 1$) the influence of the target wolf on the computational distance, this helps to enhance the detectability of the algorithm and avoid local optimum values.

Gray wolf optimizer with bubble-net predation (GWO_BP)

The bubble-net predation of whales. When the basic GWO encircles the prey, it will gradually make the wolves approach the α , β , δ wolves through continuous iteration, which may reduce the population diversity and lead the algorithm falling into the local optimal values. It is unfavorable for solving the problems with multiple local optimal values. We turn our attention to the whale foraging behavior, and make use of the bubble-net predation of whales to enhance the leading wolf α .

Whales are the largest mammals in the world, and they have a unique method of foraging, called the bubble feeding method. Whales dive into the ocean about 12 meters, then create a spiral bubble around their prey, and then swim to the surface. Inspired by this foraging behavior, WOA is proposed by Mirjalili et al. (2016)²⁴. The advantages of WOA are simple operation, fewer parameters to adjust good global optimization ability and the convergence speed is fast. The bubble net predation is expressed by the following formula²⁴:

$$\vec{X}(t+1) = \vec{X}^*(t) + \vec{D}_p e^{bl} \cos(2\pi l) \quad (9)$$

where, $\vec{D}_p = |\vec{X}^*(t) - \vec{X}(t)|$ represents the length of the i th whale from its prey, that is, the distance between the i th solution and the current optimal solution; $\vec{X}^*(t)$ represents the best whale position up to now, $\vec{X}(t)$ represents the current position of the whale; b is a constant, usually b takes 1, which determines the shape of the diameter spiral; l is the random value on $[-1, 1]$, and ‘ $\cdot$ ’ represents the dot product.

In addition, the algorithm believes that whales also surround their prey, which is similar to the encirclement mechanism of GWO, the mathematical description is as follows:

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \quad (10)$$

Suppose we update the whale's position with probabilistic selective contraction encirclement mechanism of P_i and probability selection spiral model of Eq (9). WOA sets when $A < 1$, the whale attacked its prey, the mathematical model is as follows:

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A} \cdot \vec{D}, & p < P_i \\ \vec{X}(t) = \vec{X}^*(t) + \vec{D}_p e^{bl} \cos(2\pi l), & p \geq P_i \end{cases} \quad (11)$$

where, $\vec{D} = |\vec{C} \cdot \vec{X}^*(t) - \vec{X}(t)|$ is the radius of the contraction circle, and the definition of $\vec{A}$, $\vec{C}$ are as follows:

$$\begin{cases} \vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \\ \vec{C} = 2 \cdot \vec{r}_2 \\ \vec{a} = 2 - \frac{2t}{T_{\max}} \end{cases} \quad (12)$$

When WOA set to $A \geq 1$, the whale is forced to deviate from the prey, so as to find a more suitable prey, which can strengthen the exploration ability of the algorithm and make WOA to conduct global search. The mathematical model is as follows:

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A} \cdot \left| \vec{C} \vec{X}_{rand} - \vec{X}(t) \right| \quad (13)$$

where, $\vec{X}_{rand}$ is a random selection of whale locations (not a pre-optimal solution).

In GWO_BP, we will use Eqs (11-13) to replace the position update formula of α wolf.

Lévy flight of hybrid α wolf. In order to improve the population diversity and avoid falling into the local optimal solution, we use Lévy flight strategy for global detection.

Lévy flight²⁵ is a random search method that obeys Lévy distribution and Lévy flight is named after Paul Pierre Lévy, the French mathematician. The search step of Lévy flight is a short-distance and long-distance search alternately. Such a search method has good global search capabilities²⁶.

The position update equation of Lévy flight is as follows:

$$x_i(t+1) = x_i(t) + l \oplus Levy(\bar{\lambda}) \quad (14)$$

where, $\oplus$ represents point-to-point multiplication, and $l > 0$ is the step size parameter related to the scope of the optimization problem.

As the equation of Lévy flight is very complex, we use Mantegna algorithm to simulate^{27,28}. The calculation equation of step size is as follows:

$$s_p = \frac{\mu}{|\nu|^{1/\chi}} \quad (15)$$

In GWO, the value of α wolf is the closest to the optimal solution, so we add α to S_p , it is a complex process.

The step length calculation formula is as follows which has been suggested by Yang²⁹:

$$s = 0.01 * s_p * (X_p(t) - X_\alpha(t)) \quad (16)$$

where, μ and ν Obey normal distribution, $\mu \sim N(0, \sigma_\mu^2)$, $\nu \sim N(0, \sigma_\nu^2)$, $\sigma_\nu = 1$, The equation of σ_μ is as follows:

$$\sigma_{\mu} = \left\{ \frac{\Gamma(1+\chi)\sin(\pi\chi/2)}{\chi \cdot \Gamma[(1+\chi)/2] \cdot 2^{(\chi-1)/2}} \right\}^{1/\chi} \quad (17)$$

where, the value of χ is usually 1.5.

The GWO_BP. From the discussed as above, the flowchart of GWO_BP is shown in Fig. 1, and the procedure of GWO_BP are as follows:

- Step 1: Set the control parameters of the algorithm. They are the population size S , the maximum number of iterations $T_{\max}$, the dimension of variables to be optimized $\dim$, the sum of upper ub and lower bounds lb in space, and initial population randomly.
- Step 2: Calculate the fitness of all individuals in the population, sort by fitness, that is, α = the individual with the best fitness, β = the individual with the second fitness, δ = the individual with the third fitness ranking.
- Step 3: Calculate the convergence factor a according to Eq (5). Calculate A , C according to Eqs (3) and (4). α wolf has the best fitness value, so in order to improve the convergence speed and global search ability, this paper replaces the position update Eqs (6-8) of the leading wolf with the whale spiral bubble predation Eqs (11-13). β, δ, ω wolves update the position according to the original GWO Eqs (6-8).
- Step 4: Update the position of the wolf pack according to the Lévy flight equation of the mixed-head wolf position in Eq (14).
- Step 5: Update $\vec{a}$, A , C .
- Step 6: Determine whether the number of iterations reaches the maximum $T_{\max}$ or satisfy other algorithm termination conditions. If satisfied, output the current optimal solution, otherwise, return to step 2 and continue.

Fig 1. Flow chart of GWO_BP

Experimental results

Test function optimization. In order to verify the effectiveness of GWO_BP, twelve test functions in Tables 1-3 are selected for the numerical optimization. $f_1 - f_4$ in Table 1 are unimodal functions, they only have one extreme point, which are mainly used to test the accuracy of the local search and the development ability of the algorithm; $f_5 - f_8$ are multimodal functions, the feature of these functions are that they have multiple local minima, so they also suitable for detecting the global search ability of the algorithm, that is, the detectability of the GWO_BP: whether it has the ability to jump out of the local optimum and search for the global optimum; $f_9 - f_{12}$ are fixed-dimension multimodal functions, they are also the multimodal functions but the dimension of these functions are fixed.

Function name	Function	Rang	Dim	$F_{\min}$
Sphere	$f_1(x) = \sum_{i=1}^n x_i^2$	$x_1, x_2 \in [-100, 100]$	30	0
Schwefel 2.22	$f_2 = \sum_{i=1}^n x_i + \prod_{i=1}^n x_i$	$x_1, x_2 \in [-10, 10]$	30	0
Schwefel 1.2	$f_3(x) = \sum_{i=1}^n (\sum_{j=1}^i x_j)^2$	$x_1, x_2 \in [-100, 100]$	30	0
Schwefel 2.21	$f_4(x) = \max_i \{ x_i , 1 \leq i \leq n\}$	$x_1, x_2 \in [-100, 100]$	30	0

Table 1. Unimodal benchmark functions.

Function name	Test functions	Rang	Dim	$F_{\min}$
Schwefel	$f_5(x) = \sum_{i=1}^n -x_i \sin(\sqrt{ x_i })$	$x_1, x_2 \in [-500, 500]$	30	-418.9829*n
Rastrigin	$f_6 = \sum_{i=1}^n [x_i - 10 \cos(2\pi x_i) + 10]$	$x_1, x_2 \in [-5.12, 5.12]$	30	0
Ackley	$f_7(x) = \sum_{i=1}^n -20 \exp(-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^n x_i^2}) - \exp\left(\frac{1}{n} \sum_{i=1}^n \cos(2\pi x_i)\right) + 20 + e$	$x_1, x_2 \in [-32, 32]$	30	0
Griewank	$f_8 = \frac{1}{4000} \sum_{i=1}^n x_i^2 - \prod_{i=1}^n \cos(\frac{x_i}{\sqrt{i}}) + 1$	$x_1, x_2 \in [-600, 600]$	30	0

Table 2. Multimodal benchmark functions

Function name	Test functions	Rang	Dim	$F_{\min}$
Kowalik	$f_9(x) = \sum_{i=1}^{11} \left[a_i - \frac{x_i(b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4} \right]^2$	$x_1, x_2 \in [-5, 5]$	4	0.00030
Hartman 3	$f_{10}(x) = -\sum_{i=1}^4 c_i \exp(-\sum_{j=1}^3 a_{ij}(x_j - p_{ij})^2)$	$x_1, x_2 \in [1, 3]$	3	-3.86
Shekel 7	$f_{11}(x) = -\sum_{i=1}^7 [(X - a_i)(X - a_i)^T + c_i]^{-1}$	$x_1, x_2 \in [0, 10]$	4	-10.4028
Shekel 10	$f_{12}(x) = -\sum_{i=1}^{10} [(X - a_i)(X - a_i)^T + c_i]^{-1}$	$x_1, x_2 \in [0, 10]$	4	-10.5363

Table 3. Fixed-dimension multimodal benchmark functions

Parameter Setting. We compare the GWO_BP with the basic GWO and PSO. The parameter values of the three optimization algorithms are shown in Table 4.

GWO_BP	GWO	PSO
$S = 30$	$S = 30$	$S = 30$
$T_{\max} = 500$	$T_{\max} = 500$	$T_{\max} = 500$
$\alpha = 1$		$\alpha = 0.2$
$\beta = 1.5$		$\beta = 0.5$
$p_i = 0.5$		
$b = 1$		

Table 4. Parameter setting

Each algorithm is run 30 times for the 12 test functions to calculate the optimal value, mean value and variance.

The results of the three algorithms are shown in Table 5.

Test function	GWO_BP			GWO			PSO		
	F_b	$\bar{F}$	F_v	F_b	$\bar{F}$	F_v	F_b	$\bar{F}$	F_v
f_1	3.39e-272	1.34e-201	0	3.54e-31	1.89e-27	5.19e-27	3.19e-6	0.0010256	0.0002591
f_2	1.41e-130	2.63e-105	1.44e-104	1.16e-17	8.33e-17	5.15e-17	0.0033293	0.025077	0.025181
f_3	1.47e-235	1.04e-175	0	4.29e-8	6.11e-6	8.83e-6	22.5641	76.8104	29.6565
f_4	5.94e-125	7.21e-95	3.94e-94	6.49e-8	7.79e-7	9.31e-7	0.73877	1.1871	0.27429
f_5	-11029.776	-11116.73	5.75e-8	-6573.7406	-5906.67	0.41465	-7792.1445	-5401.569	1395.7081
f_6	0	0	0	0	11.8383	3.5676	33.852	55.271	12.4957
f_7	8.88e-16	8.88e-16	0	7.55e-14	1.037e-13	1575e-14	0.0033485	0.29308	0.57525
f_8	0	0	0	0	0.0042187	0.0086354	1.4178e-6	0.0092825	0.008039
f_9	0.00030644	0.0017249	0.005068	0.0003075	0.003824	0.0075286	0.00050106	0.0008804	0.0001414
f_{10}	-3.8628	-3.8628	2.19e-15	-3.8628	-3.8628	0.001398	-3.8628	-3.8628	2.65e-15
f_{11}	-5.0832	-5.0604	0.019028	-10.4028	-10.4012	0.0007519	-10.4029	-8.1837	3.0366
f_{12}	-10.5364	-10.5364	3.5134	-10.536	-10.2039	1.4811	-10.5364	-9.1866	2.569

Table 5. The Optimization Results of GWO_BP, GWO and PSO

Results and discussion. In order to obtain accurate mathematical model in FCCU main fractionator model, a hybrid grey wolf optimizer was developed. The method was tested on several functions. The results showed that this method achieves the best results in most test functions. The theoretical global value is obtained for functions f_6 and f_8 . For unimodal functions $f_1 \sim f_4$, the test results of GWO_BP are several orders of magnitude higher than GWO and PSO.

Modeling of FCCU main fractionator

Description of FCC unit main fractionator. With the gradual development of national economy, heavy oil catalytic cracking has become a very important problem in today's industrial production^{30,31}. The FCC fractionation system is mainly composed of main fractionator, overhead oil and gas condensation cooling system, diesel stripper, recycle tank and its interrupted reflux. In the typical split flow system process, the high-temperature reaction oil vapor mixture at $450^\circ\text{C} \sim 510^\circ\text{C}$ comes out from the top of the reactor, entrains a small amount of catalyst powder, enters the desuperheating section of the lower section of the main fractionator, contacts with the 250°C oil slurry countercurrent on the baffle for heat exchange, desuperheates and washes the entrained catalyst powder, and then enters the main body of the fractionator. In the main fractionator, the oil vapor mixture condensed to the saturated state is separated.

Process modeling. We apply GWO_BP to parameter estimation of FCCU main fractionator model. The schematic diagram of the main fractionator is shown in Figure 18 in the paper of Zhong et al³². The factors that affect the dry point are the top temperature, top pressure, top heat discharge and other related parameters, while the factors that affect the pour point are the top load change, top pressure change, first and second heat discharge. The change of heat discharge is realized by the change of flow or the change of temperature, so we set the controlled variables are the top temperature y_1 , the crude gasoline dry point y_2 , pour point of light diesel oil y_3 ; control quantity is circulating flow u_1 , first medium flow u_2 , second middle flow u_3 . 100 input and output data are used for parameter modeling; The dynamic model of FCCU main fractionation column process is as follows:

$$y_1(z^{-1}) = \frac{a_{11}(1) + a_{11}(2)z^{-1}}{1 + b_{11}z^{-1}} z^{-d_{11}} u_1(z^{-1}) + \frac{a_{21}(1) + a_{21}(2)z^{-1}}{1 + b_{21}z^{-1}} z^{-d_{21}} u_2(z^{-1}) \quad (18)$$

$$y_2(z^{-1}) = \frac{a_{22}(1) + a_{22}(2)z^{-1}}{1 + b_{22}z^{-1}} z^{-d_{22}} u_2(z^{-1}) + \frac{a_{32}(1) + a_{32}(2)z^{-1}}{1 + b_{32}z^{-1}} z^{-d_{32}} u_3(z^{-1}) \quad (19)$$

$$y_3(z^{-1}) = \frac{a_{33}(1) + a_{33}(2)z^{-1}}{1 + b_{33}z^{-1}} z^{-d_{33}} u_3(z^{-1}) \quad (20)$$

Due to the coupling between y_1 and y_2 , Zhong et al. established the model of the main fractionation column of the FCCU based on the field data of typical FCC reactions. Therefore, parameters of FCCU dynamic mathematical model provided by Zhong et al. are used³².

GWO_BP and GWO are used to estimate the model parameters in the main fractionator and the algorithms parameter setting is shown in Table 4. The modeling results are shown in Fig. 2, Fig. 3 and Fig. 4.

The model error formula is as follows:

$$e_i = \frac{1}{N} \sum_{k=1}^N |y_i(k) - \hat{y}_i(k)|, \quad i = 1, 2, 3 \quad (21)$$

Where N is the number of samples, $\hat{y}_i$ is the model output, y_i is the model actual output. The adjustable range of $y_1 \sim y_3$ is 0.0 ~ 0.8, and the allowable error range is within 0.1. The output error of GWO_BP and GWO are shown in the Table 6.

Figure 2. Modeling result graph of y_1

Figure 3. Modeling result graph of y_2

Figure 4. Modeling result graph of y_3

Table 6 The output error

Methods	e_1	e_2	e_3
GWO_BP	0.01292	0.00487	0.01009
GWO	0.03548	0.01629	0.07486

Conclusions

To realize the advanced control of product quality in a refinery is to establish a high precision dynamic model of complex industrial process. In this work, by combining bubble-net predation of whales and Lévy flight, a novel GWO algorithm (GWO_BP) is proposed for parameter estimation of FCC main fractionator model. Compared with basic GWO, the experimental results reveal that the model predictive outputs of GWO_BP are in better agreement with the actual experimental data.

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Author Contributions

X. J. W carried out the implementation and wrote the manuscript. C.L. S., N. W and H.Y. S. conceived the idea and supervised this work. All authors provided critical feedback and helped shape the research, analysis.

Additional Information

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