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Multi-objective operation optimization of ethylene cracking furnace based on AMOPSO algorithm

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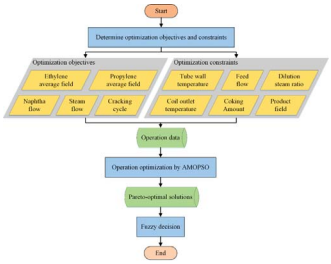
HIGHLIGHTS

- An AMOPSO algorithm is proposed and developed based on dynamic AHP.
- The algorithm is applied to the operation optimization of ethylene cracking furnace.
- Two cases are studied including the fixed cracking cycle and the non-fixed cracking cycle.
- The coil outlet temperature of the optimization strategy changes with the cracking days.

GRAPHICAL ABSTRACT



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ABSTRACT

The objective of this article is to research and design a multi-objective operation optimization strategy and comprehensive evaluation method of solutions, to efficiently solve the multi-objective operation optimization problem of ethylene cracking furnace. An adaptive multi-objective particle swarm optimization (AMOPSO) algorithm is proposed and developed based on dynamic analytic hierarchy process (AHP). The algorithm adopts fuzzy consistent matrix to select the global best solution, which ensures the right direction of particle evolution. Furthermore, the evolution state is measured to adjust the weight and learning coefficients adaptively. The proposed method is applied to the operation optimization of ethylene cracking furnace. Two cases are studied including the fixed cracking cycle with four objectives and the non-fixed cracking cycle with five objectives. According to the preferences, decision makers can select the appropriate operation optimization conditions from alternative Pareto optimal solutions by the results of fuzzy evaluation. A feasible solution is provided for the multi-objective operation optimization of ethylene cracking furnace.

1. Introduction

Petrochemical industry is one of the pillar industries promoting global economic development, and ethylene is an important precursor for the petrochemical industry (Yu et al., 2015). Ethylene, one of the important basic chemical raw materials, occupies a pivotal position in the petrochemical industry and even the entire national economy. The operating level of ethylene preparation device has become an important symbol to measure the development level of the industrialization and modernization of a country or region. Furthermore, the operating level and optimization situation of ethylene cracking furnace directly affect not only the quality and yield of ethylene products, but the chemical products of its downstream device, and even the production operations of the whole petrochemical industry (Tarafder et al., 2005).

At present, the design and development of cracking furnace

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structure is basically the same, except the differences in the structural design, arrangement and shape of the furnace tube. In order to achieve the design principles of "high-temperature, low hydrocarbon partial pressure, short residence time" and the target of high yield and high selectivity, almost all types of cracking furnace develop toward the direction of reducing tube pass, shortening length and narrow diameter, adopting branch adjustable tube to increase specific surface area, seeking higher temperature resistance materials, and others.

CBL series cracking furnace (Li et al., 1999) developed by Sinopec and SL type cracking furnace (Li, 2006) jointly developed by Sinopec and Lummus Corporation, both have inherited the advantages of internationally advanced large-scale cracking furnace, which includes great processing capacity, lower investment and operation costs, longer running cycle, security, stability, overall running well, easy to maintain, and others. Currently, this type cracking furnace is more convenient for practical application of ethylene plant operator in China. Therefore, this article adopts such domestic widely used SL-type cracking furnace as the research object to study the operation optimization method of the ethylene cracking furnace process.

Many scholars have made extensive researches on ethylene cracking furnace. Masoumi et al. (2006) reviewed the progress of cracking furnace modeling, optimization and control, and pointed out the existing technical problems. Ghashghaee and Karimzadeh (2011) and Berreni and Wang (2011) studied the multivariable process modeling and dynamic nonlinear optimization methods of the steam cracking furnace. Keyvanloo et al. (2012) applied genetic algorithm in optimizing the operation of the main products of ethylene cracking furnace. They made a comparative study with the dynamic model, and proposed an operating optimization strategy. Zamostny et al. (2012) studied steam cracking process modeling based on semi-empirical and semi-mechanistic modeling method, improving the yield of major products. Shang and Geng (2010) and Geng and Zhu (2008) established the key variables predictive model and product yield soft measurement model of the ethylene cracking furnace. They adopted radical basis function (RBF) neural network, and then solved the soft measurement model based on particle swarm optimization. Chen and Yu (2008) studied the chaotic particle swarm optimization algorithm, and applied it to the neural network soft measurement modeling process of the ethylene yield to get a better generalization performance. Gao et al. (2008) studied the multi-objective optimization problem of cracking process based on multi-objective genetic algorithms and sequential quadratic programming (SQP), and optimized ethylene yield and propylene yield by adjusting the operation condition per two days. Li et al. (2007) studied the multi-objective optimization problem based on hybrid particle swarm optimization algorithm and improved the yield of diene. Geng and Zhu (2005) proposed a method for identifying different oil cracking performance based on dynamic kernel clustering methods. Depending on characteristics of different oil, they established the optimal operating mode of ethylene production process, and made a dynamic adjustment of cracking furnace operating conditions to achieve good effects. Wang and Tang (2013) employed multi-objective parallel differential evolution with competitive evolution strategies to maximize the yields of ethylene and propylene. Nabavi et al. (2009) and Rangaiah et al. (2011) studied the operation and design optimization of an industrial liquefied petroleum gas cracker for multiple objectives. In addition, many relevant developments and applications of moo for modeling and solving a variety of challenging case studies in different areas of petrochemical engineering can be found in the book edited by Rangaiah and Bonilla-Petriciolet (2013).

The multi-objective problem in operation process requires comprehensive consideration of multiple optimization objectives and constraints, such as a conflict between the selectivity of ethylene and propylene, coke and running cycle, etc. Most previous studies mentioned above, however, are limited to weigh the two objectives of ethylene yield and propylene yield. Therefore, it needs to study the multi-objective optimization algorithms, and design the multi-objective optimization functions and constraints of ethylene cracking furnace production process, to guide the optimization operation conditions of the actual running of the cracking furnace.

Particle Swarm Optimization (PSO) algorithm (Kennedy and Eberhart, 1995) is an intelligent optimization algorithm presented by Kennedy in 1995. It was initially proposed as a single-objective optimization algorithm. Because the single-objective algorithm cannot meet the needs of multi-objective optimization, it is necessary to develop a multi-objective optimization algorithm. The intelligent algorithms of biological evolution have implied parallelism. Based on this point, a multi-group solution can be obtained in one evolution. Ideally suit for solving multi-objective optimization problem, such algorithms have been widely used in many fields, such as electricity, energy and industrial control (Ma and Hu, 2006; Gong et al., 2008; Fang et al., 2008).

Reyes-Sierra and Coello (2006) comprehensively summed the various multi-objective particle swarm optimizers (MOPSO), and presented that the development of PSO algorithm from single-objective to multi-objective required solving the following three questions: 1) how to establish a set of non-dominated solutions; 2) how to select the best particle during the search process; 3) how to maintain the diversity and uniform distribution of the solutions along the Pareto front. Around these three issues, many scholars have conducted intensive study and discussion. Coello et al. (2004) selected the personal best solution in a random manner, and selected the global best solution of deflection roulette according to the predefined network. Hu and Eberhart (2002) selected the personal best particle by calculating the distance between the particle swarms, and successively optimized each objective. But it is more sensitive to the optimization sequence of objective function. Tsai et al. (2010) directly replaced personal best solution with the specific optimal solution. Branke and Mostaghim (2006) introduced the concept of archive. They established an independent archive for each particle, and randomly selected personal best solution from the archive. Coello et al. (2004) adopted the one by one comparison approach by generation, and used adaptive network and the solution distribution deletion strategy of the congestion degree to maintenance the archive capacity. Villalobos-Arias et al. (2005) adopted the archive index of non-dominated solutions to select global best solution. Wang and Qian (2008) randomly selected a set of solutions from non-dominated solutions as the best particles, and Chen et al. (2009) used dynamic weighted method to select multi-objective best particles. But their selected global best particles are random with lack of objectivity.

By the summarized above, we can find that there exist several problems in multi-objective particle swarm optimization. 1) The evolution parameters, such as the swarm evolution weight, learning factor and so on. They often are set with fixed values, even for the so-called adaptive PSO parameters which also only used an iteration number function, rather than the adaptive adjustment based on the true state of swarm evolution. 2) For personal best update, it was lack of a good theoretical basis, and cannot guarantee the distribution, rationality and effectiveness of optimal solution selection in theory. 3) For the swarm topology, it often used a fixed topology or a random topology, without giving full play to the respective strengths of much neighborhood and little neighborhood in solving complex problems.

In this article, we provide an adaptive multi-objective PSO (AMOPSO) algorithm based on dynamic AHP. In AMOPSO-AHP, the best particles are selected based on dynamic consistent judgment

matrix. According to the real-time dynamic of the current evolution solution, the best solution is determined objectively to ensure its objectivity. In the evolution process, weights and other important parameters are adjusted adaptively via particles evolution state, in order to ensure the distribution and diversity of the objective solution. Furthermore, we research the coordination and balance strategy between the different objectives. Against the multi-objective operation optimization problem of ethylene cracking furnace, we seek to meet the multi-objective operating conditions, rather than just limited to the yield optimization of ethylene and propylene. What's more, the feasible optimization strategies are given under two cases of fixed and non-fixed cracking cycle.

The remainder of this article is organized as follows. In Section 2, after introducing some basic concepts about the AHP based on fuzzy judgment matrix, we provide the AMOPSO-AHP algorithm based on AHP, and give a performance verification. We carry out the multi-objective operation optimization of the ethylene cracking furnace in Section 3. Finally, we present our conclusions and discuss possible paths of future research in Section 4.

2. AMOPSO-AHP algorithm

2.1. AHP method based on fuzzy judgment matrix

The fuzzy analytic hierarchy process is a comprehensive index evaluation method with broader application (Sun and Lin, 2002; Gu et al., 2006). Its core is to establish the fuzzy consistent judgment matrix. The nine scales method is a commonly used method to establish the consistent judgment matrix. But in the actual applications it is vulnerable to the constraints of subjective and objective conditions. For example, the importance of the schemes represented by nine scales often results in inconsistent problems. It makes decision-maker easily disturbed by many factors when selecting optimal scheme. Because these factors consist of different categories and levels, their structures are quite complex and easily lead to inconsistency of the synthesized judgment matrix. Even worse, it is a waste of time to determine main characteristic roots of the judgment matrix which does not have satisfaction consistency. Therefore, this article uses three scales method to construct fuzzy consistent judgment matrix, which can better ensure consistency and synthesis of judgment matrix.

The scheme to be evaluated can be described by the following data matrix:

$$C = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_m \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1n} \\ b_{21} & b_{22} & \cdots & b_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & \cdots & b_{mn} \end{bmatrix} \tag{1}$$

where m is the number of c, the schemes to be evaluated, and n represents the number of b, the scheme attributes. An importance comparative analysis is made on the various attributes of each scheme respectively, where $e_{i,j}^l$ represents the importance indicator, and its value is as Eq. (2):

$$e_{i,j}^l = \begin{cases} 0 & b_{jl} \text{ is more important than } b_{il} \\ 0.5 & b_{jl} \text{ is as important as } b_{il} \\ 1 & b_{il} \text{ is more important than } b_{jl} \end{cases} \tag{2}$$

where $i, j \in \{1, 2, \cdots, n\}$ and $l \in \{1, 2, \cdots, m\}$. Taking $E_i^l = \sum_{i=1}^n e_{i,j}^l$, we can get each element of fuzzy consistent judgment matrix by Eq. (3):

$$A^l = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mm} \end{bmatrix} \tag{3}$$

where

$$a_{i,j} = \frac{E_i^l - E_j^l}{2^\alpha n} + 1 \tag{4}$$

α represents sensitive factor, whose value range is {0, 1, 2, 3}, and the specific value is determined according to the actual situation. Combined the characteristics of fuzzy consistent judgment matrix, the weight of each group is calculated by the multiplied square root method:

$$w_i^l = \left(\prod_{j=1}^n a_{i,j}^l \right)^{1/n} \tag{5}$$

The effectiveness value of the parameter $b_{i,j}^l$ is obtained by normalization:

$$w_i^{*l} = \frac{w_i^l}{\sum_{l=1}^m w_i^l} \tag{6}$$

The comprehensive evaluation function of the i-th scheme to be evaluated is as follows:

$$y_i = \sum_{j=1}^n w_j^l b_{i,j} \tag{7}$$

2.2. AMOPSO algorithm based on AHP

The practical applications usually take multiple targets into account. The multi-objective problem is a broader practical problem. The optimization problem of multiple targets in a given area is called multi-objective optimization problem. Generally, for n targets containing D-dimensional variable, the multi-objective optimization problem can be described as:

$$\min \; y = \left(f_1(x), f_2(x), \cdots, f_n(x)\right)$$

$$S.t.: g(x) \le 0$$

where, $x = (x_1, x_2, \cdots, x_D)$ represents decision vector, y represents objective vector, and $g(x)$ represents constraint conditions.

The objective function $f(x)$ is non-dominated, if $f(y) \ge f(x)$ for each other vector and there exists at least one objective vector making $f_i(y) > f_i(x)$ established, otherwise it is dominated.

In most cases, the best solution in single-objective optimization problem does not exist in multi-objective optimization problem. And there are only the Pareto optimal solutions. The Pareto optimal solution is only an alternative non-inferior solution or satisfactory solution. In general, multi-objective optimization problem has a number of Pareto non-inferior solutions, which is a reasonable solution set of multi-objective optimization problem. In practical applications, decision-makers need to select one or multiple solutions form Pareto optimal solutions as the optimal solution of multi-objective optimization problem, according to the understanding extent of the problem and personal preferences. Therefore, multi-objective optimization algorithms need to achieve the following objectives:

1) Approximation of solution set: most problems cannot find the analytic solutions of the Pareto front, which hopes to obtain the solution set as close to real Pareto frontier.

2) Uniformity of solution set: the obtained solution set is hoped to distribute along the Pareto front as uniformly as possible.
3) Representativeness of solution set: the solution set is hoped to try to cover all areas, especially the limit area of the edge.

2.2.1. Adaptive adjustment of weights and learning factor

Each particle of PSO represents a possible solution, which has two characteristic parameters of position and velocity. It usually takes the function value corresponding to location coordinates as the adaptive value of the particle, to evaluate the merits of current particle position. Firstly, algorithm randomly initializes a group of particles within the optimization range. And then it updates the position and velocity by tracking the personal best position and the global best position, which stops and outputs the final search result when finds the satisfactory solution or reaches the maximum optimization number. The updating formula of its velocity and position is as follow (Wang and Tang, 2013):

$$V_i = w*V_i + C_1*rand()*(pbest_i - x_i) + C_2*rand()*(gbest_i - x_i) \tag{8}$$

$$x_i = x_i + V_i \tag{9}$$

where, $V_i = [V_i^1, V_i^2, \cdots, V_i^D]$ is the velocity of particle i, indicating the next step advancing direction and step of the particles; $x_i = [x_i^1, x_i^2, \cdots, x_i^D]$ is the current position of particle i; $pbest_i$ and $gbest_i$ represent the optimal position of the current particle and the optimal position of the whole swarm respectively; w is called weight, mainly used in trade-off for global and local search capability; C_1 and C_2 are acceleration factor, representing the velocity change amount approaching to local and global; $rand()$ is a random number between 0 and 1.

In the evolutionary process of particle swarm, the weight represents the global and local search capability. When the weight is large, the particles are easy to carry out global traversal; when the weight is small, the particles have stronger local search capability. The learning factor represents self-recognition and social learning ability of the current particles. When personal learning factor is larger, the particles have better local search ability, but easy to fall into local optimum; when global learning factor is larger and vice versa. Therefore, according to the state of the particles evolution, adaptive adjustment of weights and learning factor allows particles better convergence to the global optimum. In this article, the evolutionary factor is used to measure the state of the swarms (Zhan et al., 2009).

The dynamical adjustment steps of evolutionary factor are as follows:

1) Calculate the average of the euclidean distance of each particle with other particles as Eq. (10)

$$d_i = \frac{1}{N-1}\sum_{j=1,j\neq i}^{N}\sqrt{\sum_{k=1}^{D}(x_i^k - x_j^k)^2} \tag{10}$$

2) When the distance of the global best solution is defined as d_g, the evolutionary factor is defined as Eq. (11)

$$f = \frac{d_g - d_{min}}{d_{max} - d_{min}} \tag{11}$$

where d_{max} and d_{min} are the maximum value and the minimum value of d_i, respectively.

After obtaining the evolutionary factor, the algorithm can evaluate the evolutionary state of the particles and adaptively adjust the evolutionary weight and learning factors of the particles. The adopted weight coefficient changes in the range [0.4, 0.9], and learning factors dynamically adjust in the range [0.5, 2.5] with the dynamic change of the evolutionary factor. The adjustment method is as follows.

$$w = \frac{1}{1 + 1.5e^{-2.6f}} \tag{12}$$

$$C_1 = \frac{1}{0.2 + 0.2e^{2.2f}} \tag{13}$$

$$C_2 = \frac{1}{0.1 + 1.9e^{-1.85f}} \tag{14}$$

When the sum of C_1 and C_2 is greater than 4, it needs to standardize their values:

$$C_i^* = \frac{4C_i}{\sum_{i=1}^{2} C_i} \tag{15}$$

2.2.2. The updating and maintenance strategies of external archive

The selected best particles of MOPSO have a greater impact on the search results. This article selects the personal best based on the domination relations and random manner of the solution. When the evolutionary solutions of the particles dominate the personal best of the current particles, and then the solutions are selected as the personal best of the current particles; when they are not mutually dominated, the personal best particles are randomly selected to be updated, otherwise the personal best particles keep unchanged to ensure the non-domination and uniformly distribution of the solutions.

MOPSO is an iterative approximation process of the real Pareto front of the multi-objective function. For the overall swarm, the obtained solutions constituted of non-dominated solutions in Pareto optimal solutions set are non-dominated for all current and past swarms. Using AHP, the algorithm can give a better objective evaluation on multiple non-dominated targets. In order to take full advantage of the evolutionary information obtained in evolutionary process, the decision-making analysis based on fuzzy consistent judgment matrix selects the lower comprehensive effectiveness as the global best solution to ensure the objectivity and effectiveness of the selection.

The reasonable updating and maintenance strategy of external archive can guarantee the Pareto front obtained in the swarm evolution process to have good distribution and diversity. This article maintains and updates external archive by the sorting strategy of the congestion degree.

The congestion degree is defined as the sum of the side length of different objective function adjacent points in the maximum cube where the calculation point exists but other points not contained. By definition it can be found that the definition represents the distribution of the solutions. The greater congestion degree represents the better distribution of the solutions, otherwise the poor distribution. Therefore, when external archive updates and maintains, the particles having great congestion degree is to be retained, and the relatively small is to be deleted, to ensure the distribution and diversity of the solutions.

The calculation steps of the congestion degree are as follows:

- Step 1: Initialization: All the congestion degrees of the solutions in current external archive are 0; the size of the solution set is L; the objective number is M, and the current objective number is $i=1$.
- Step 2: Taking $j = 1$, sort the j-th objective in descending order, and set the congestion degrees of the first and the last particle

are infinitely large.
- Step 3: Beginning from the second particle, calculate the congestion degree distance, according to Eq. (16).

$$Dis[i] = Dis[i] + \frac{f_{i+1}^m - f_{i-1}^m}{\max(f^m) - \min(f^m)} \tag{16}$$

- Step 4: Judge whether the current calculation particle is larger than $L-1$, and if so, skip to Step 5, otherwise skip to Step 3.
- Step 5: Taking $j = j + 1$, judge whether the current objective number is larger than M, and if so, stop, otherwise skip to Step 2.
- Step 6: Taking $i = i + 1$, judge whether the current particle number is larger than L, and if so, stop, otherwise skip to Step 2.

According to the selection of particle parameters and the updating strategy of external archive discussed above, AMOPSO based on AHP can be obtained as follows:

- Step 1: Initialization: swarm size, maximum iteration number and other parameters, the position and velocity of the initial swarm, as well as the initial personal best of the swarm evolution.
- Step 2: Calculate the objective function value of the initial swarm.
- Step 3: According to fuzzy consistent judgment matrix, give an objective assessment of the particle state, and select the global best particle to guide the swarm evolution direction.
- Step 4: Calculate the evolutionary factor of swarm, and adaptively adjust the swarm evolution weight, learning factors and other parameters.
- Step 5: Carry out the velocity and position updating and evolutionary iterations according to Eqs. (8) and (9).
- Step 6: According to the updating strategy of personal best solution, update the personal best solution and global best solution.
- Step 7: Judge whether the current particle is the last particle, and if not, skip to Step 5.
- Step 8: Judge whether the end condition is satisfied, and if so, end and output the results, otherwise skip to Step 4.

2.3. Algorithm performance verification

2.3.1. Verification function and performance indicators

In order to verify the effectiveness of the proposed algorithm, the known standard multi-objective functions ZDT1, ZDT2, ZDT3 and ZDT4 (Deb et al., 2002) of the Pareto front are used for experimental study. The specific expressions of functions and the distribution of solutions are as shown in Table 1. In order to compare the authenticity of the obtained Pareto front by algorithm, and the diversity and distribution of the solutions, we use two performance indicators of convergence degree and spread to measure algorithm performance.

The convergence degree is defined as:

$$\gamma = \frac{1}{N}\sum_{y\in Y} \min\left\{\left|y - y'\right|, y' \in Y'\right\} \tag{17}$$

where, y is the non-inferior solution set P, N is the size of the non-inferior solution set, and y' is the real non-inferior solution set P^*. The size of the convergence degree characterizes the approximation extent of the obtained Pareto solution set and the real Pareto front. The value is smaller, and the approximation extent of its real Pareto front is better.

Spread is defined as

$$\Delta = \frac{d_f + d_l + \sum_{i=1}^{N-1}\left|d_i - \bar{d}\right|}{d_f + d_l + (N-1)\bar{d}} \tag{18}$$

where, d_i is the distance between the adjacent solutions in solution set, $\bar{d}$ is the average of d_i, d_f and d_l are the distance between the boundary solutions and between real the most extreme solutions in solution set. The size of spread characterizes the distribution of the obtained solution set along the Pareto front. The value is smaller, and the distribution of solution set along the Pareto front is more uniform.

2.3.2. Comparative analysis of algorithms

In order to verify the solving effectiveness and superiority of the algorithm, the proposed algorithm is given a comparative analysis with other existing multi-objective algorithms, including NSGA-II (Deb et al., 2002), PESA-II (Corne et al., 2001), NSPSO (Li, 2003), MOPSO (Coello et al., 2004), RM-MEDA (Zhang et al., 2008), AEPSO (Chen et al., 2009), TV-MOPSO (Tripathi et al., 2007), PSO-IMOCA (Wu and Xu, 2012) and ADRMOPSO (Ni et al., 2015).

The comparison algorithm parameters are set as follows. NSGA-II, PESA-II, NSPSO, MOPSO, RE-MEDA and AEPSO are set according to Chen et al. (2009). The swarm size of MOPSO is 50, and the number of iterations is 500 times. The swarm size of other algorithms is 100, and the number of iterations is 250. TV-MOPSO and PSO-IMOCA are set according to Wu and Xu (2012). TV-MOPSO swarm size is 50, and the number of iterations is 500, and the weight linearly decreased from 0.9 to 0.4. The warm size of PSO-

Table 1
Benchmark of multi-objective functions.

Function	Expression	Pareto solution set
ZDT1	$\min f_1(x) = x_1$ $\min f_2(x) = g(x)[1 - \sqrt{x_1/g(x)}]$ $g(x) = 1 + 9\left(\sum_{i=2}^{N} x_i\right)/(N-1)$	where, $n=30$; the test function is convex and continuous Pareto front; the Pareto solution set is $\{x\|g(x) = 1\}$; that is $x_1 \in [0, 1]$, $x_i = 0$, $i = 2, 3, \cdots n$;
ZDT2	$\min f_1(x) = x_1$ $\min f_2(x) = g(x)[1 - (x_1/g(x))^2]$ $g(x) = 1 + 9\left(\sum_{i=2}^{N} x_i\right)/(N-1)$	where, $n=30$; $x_i \in [0, 1]$; the test function is non-convex and continuous Pareto front non-convex continuous Pareto frontier surface; the Pareto solution set is $\{x\|g(x) = 1\}$; that is $x_1 \in [0, 1]$, $x_i = 0$, $i = 2, 3, \cdots n$;
ZDT3	$\min f_1(x) = x_1$ $\min f_2(x) = g(x)[1 - \sqrt{x_1/g(x)} - \frac{x_1}{g(x)}\sin(10\pi x_1)]$ $g(x) = 1 + 9\left(\sum_{i=2}^{N} x_i\right)/(N-1)$	where, $n=30$; $x_i \in [0, 1]$; the test function is continuous in variable space, but due to the introduction of the sine function, the Pareto front surface becomes convex and discontinuous; the Pareto solution set is $\{x\|g(x) = 1\}$; that is $x_1 \in [0, 1]$, $x_i = 0$, $i = 2, 3, \cdots n$;
ZDT4	$\min f_1(x) = x_1$ $\min f_2(x) = g(x)[1 - \sqrt{x_1/g(x)}]$ $g(x) = 1 + 10(n-1) + \sum_{i=2}^{N}[x_i^2 - 10\cos(4\pi x_i)])$	where, $n=10$; $x_i \in [0, 1]$; the test function has 21^9 local Pareto front, which can be well used for the test of multi-mode problems; the Pareto solution set is $\{x\|g(x) = 1\}$; that is $x_1 \in [0, 1]$, $x_i = 0$, $i = 2, 3, \cdots n$;

Table 2
Comparison of convergence γ.

Algorithm	PI	ZDT1	ZDT2	ZDT3	ZDT4
NSGA-II	*M*	0.03348	0.07239	0.11450	0.51305
	V	0.00475	0.03168	0.00794	0.11846
PESA-II	*M*	0.00105	0.00074	0.00789	9.98254
	V	0.00000	0.00000	0.00011	20.1340
NSPSO	*M*	0.00642	0.00951	0.00491	4.95775
	V	0.00000	0.00000	0.00000	7.43601
MOPSO	*M*	0.00133	0.00089	0.00418	7.37429
	V	0.00000	0.00000	0.00000	5.48286
RM-MEDA	*M*	0.02121	0.02919	0.04418	53.7033
	V	0.00002	0.00017	0.00014	5.37964
AEPSO	*M*	0.00100	0.00078	0.00462	0.49800
	V	0.00000	0.00000	0.00000	1.93606
TV-MOPSO	*M*	0.00120	0.00083	0.00670	–
	V	0.00000	0.00000	0.00000	–
PSO-IMOCA	*M*	0.00110	0.00079	0.00130	–
	V	0.00000	0.00000	0.00000	–
ADRMOPSO	*M*	0.00094	0.00057	0.00389	0.43050
	V	0.00000	0.00000	0.00000	0.10942
AMOPSO-AHP	*M*	0.00042	0.00041	0.00045	0.00040
	V	0.00000	0.00000	0.00000	0.00000

IMOCA is 50, space size is 20, the archive is 100, and the number of iterations is 500. ADRMOPSO is set according to Ni et al. (2015). The warm size of ADRMOPSO is 200, and the number of iterations is 125. The swarm size of the proposed AMOPSO algorithm is 50, and the number of iterations is 500.

As the above parameters, the number of function evaluation times for all algorithms is 25,000, so their operating results are comparable. According to the above parameters configuration, the above algorithms for each multi-objective test function independently run 30 times. Tables 2 and 3 show the results comparison of the convergence degree and spread of the various algorithms after running, where the performance indicator (PI) *M* represents the mean, and *V* represents the variance. The results of NSGA-II, PESA-II, NSPSO, MOPSO, RM-MEDA and AEPSO are from the literature Chen et al. (2009), the results of TV-MOPSO and PSO-IMOCA are from literature Wu and Xu (2012), and ADRMOPSO results are from the literature Ni (2015). The "–" indicates specific values are not given by related literatures.

Tables 2 and 3 show that for all multi-objective optimization test functions, from the perspective of the performance comparison of the convergence, the proposed multi-objective optimization algorithm is superior to other algorithms. Its best solution set is closer to the real Pareto front, having a better convergence. For the distribution indicator, the search results for most of the test functions are better than other algorithms, having good distribution. In practical optimization problem, the best particles are selected in accordance with the fuzzy consistent AHP, which makes the algorithm have a good consistency and comprehensiveness and well take the preferences of different decision-makers into account.

Table 3
Comparison of spread Δ.

Algorithm	PI	ZDT1	ZDT2	ZDT3	ZDT4
NSGA-II	*M*	0.39031	0.43077	0.73854	0.70261
	V	0.00187	0.00472	0.01971	0.06465
PESA-II	*M*	0.84816	0.89292	1.22731	1.01136
	V	0.00287	0.00574	0.02925	0.00072
NSPSO	*M*	0.90695	0.92156	0.62072	0.96462
	V	0.00000	0.00012	0.00069	0.00156
MOPSO	*M*	0.68132	0.63922	0.83195	0.96194
	V	0.01335	0.00114	0.00892	0.00114
RM-MEDA	*M*	0.38590	0.36560	0.81103	0.76447
	V	0.00057	0.00531	0.00404	0.00415
AEPSO	*M*	0.55743	0.51901	0.55182	0.80367
	V	0.00142	0.00095	0.00087	0.07078
TV-MOPSO	*M*	0.02100	0.02100	0.01540	–
	V	0.00004	0.00007	0.00001	–
PSO-IMOCA	*M*	0.02350	0.02330	0.01600	–
	V	0.00001	0.00001	0.00001	–
ADRMOPSO	*M*	0.27625	0.29862	0.47952	0.51247
	V	0.00104	0.00136	0.00617	0.04182
AMOPSO-AHP	*M*	0.47715	0.34931	0.71642	0.19511
	V	0.00207	0.00093	0.00021	0.00042

In order to compare the results of different algorithms for multi-objective function optimization, the many times optimized results are repeatedly superimposed to show the iterative process of algorithms. The results compare the spread and distribution of different multi-objective optimization algorithm. It can be seen from Fig. 1, that the convergence and Pareto solution distribution of the proposed multi-objective optimization algorithm outperform other algorithms.

The other algorithms to select the best particles are random. They select the best particles in the way of selecting the global best solution, and donot give an objective evaluation on the solutions. Their obtained solutions cannot represent the real weigh optimal solution of the problem. The proposed algorithm is to select the best particles after objective evaluation according to the fuzzy consistent judgment matrix, which can be used to select the final weigh solutions, having a certain rationality and feasibility.

3. Multi-objective operation optimization of ethylene cracking furnace

Taking an SL-I type naphtha cracker as a study, we develop multi-objective operation optimization of ethylene cracking furnace process based on the established mechanism model of cracking product yield (Geng et al., 2012). The model includes calculating process, and provides the solving method of kinetics model, heat transfer model and balance equations, as well as the compromising adjustment solution of the primary reaction coefficients. The details can be found in Geng et al. (2012).

Fig. 2 shows the schematic structure of the article used SL-I type cracking furnace. The convection section from top to bottom is feed preheating section (FPH-I), boiler watering preheating section (BWPH), feed preheat section (FPH-II), the upper mixing preheater (UMPH), dilution steam super heater (DSSH), ultra-high pressure steam super heater (HPSSH-I and II), and the lower mixing preheater (LMPH).

The radiant section consists of the reaction tube group and furnace. The furnace tubes arrangement of SL-I type cracking furnace consists of a big group of four tubes and a small group of eight tubes, and the furnace tube of each group is 2–1 type. The furnace tubes of radiant section using two-way branch adjustable tube, the structure of tube diameter and tube pass is shown in Fig. 3. Table 4 lists the structural parameters of furnace tubes and the hearth. Table 5 lists the operational conditions of the studied SL-I type cracking furnace. The selected cracking oils are shown in Table 6.

By using the proposed AMOPSO algorithm, the full cycle average yields of ethylene and propylene are selected as two goals to solve the optimization of the operating conditions. This optimization process is under certain operating conditions. In the actual industry, the selectivity control of ethylene and propylene yield is completed mainly through the regulation of temperature, which is reflected directly by the measurement of the coil outlet temperature (COT). In the cracking process, the decline in COT will make the average yield of ethylene decrease and propylene yield increase, and its impact on yield is more obvious. Therefore, we select COT as an operating variable of optimization. Meantime, feedstock flow and DSR are also considered. According to the

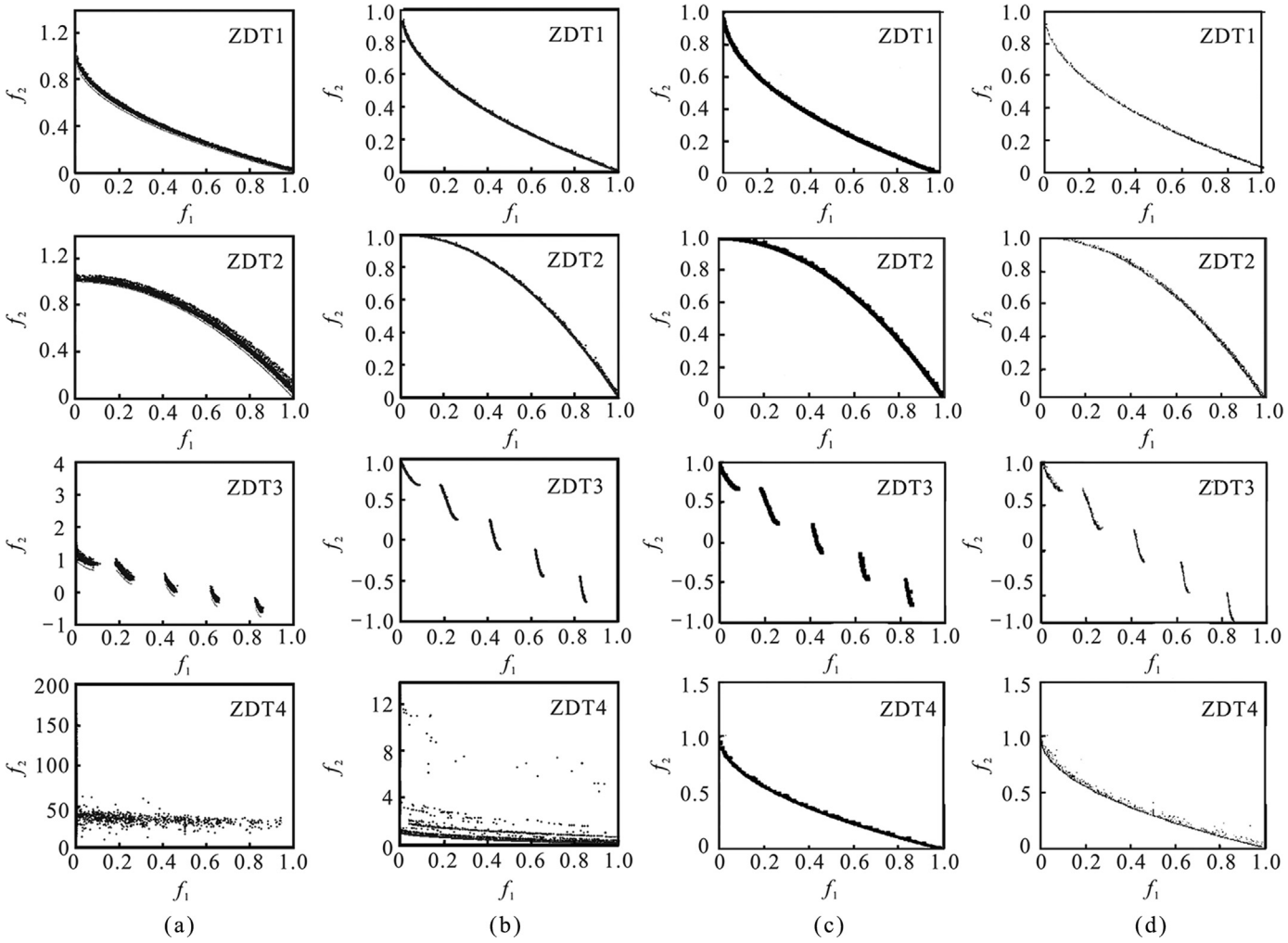

Fig. 1. Comparison of different algorithms: (a) RM-MEDA, (b) AEPSO, (c) ADRMOPSO, and (d) AMOPSO.

cracking cycle fixed or not, we explore the optimization strategies in both cases. Comprehensively considering the actual production situation, we set here that the cracking cycle is as important as the average yields of ethylene and propylene, more important than the feed amounts of the naphtha and the steam.

3.1. Case 1: The fixed cracking cycle

The multi-objective optimization problem of ethylene cracking furnace is described as follows.

Optimization objectives:

$$Max\ f_1 = \frac{1}{N}\sum_{i=1}^{N} Yi_{ethy} \tag{19}$$

$$Max\ f_2 = \frac{1}{N}\sum_{i=1}^{N} Yi_{prop} \tag{20}$$

$$Min\ f_3 = Q_{Naphtha} \tag{21}$$

$$Min\ f_4 = Q_{Steam} \tag{22}$$

$$\text{Constraints:}\begin{cases} Yi_{ethy} \geq L_{ethy} \\ Yi_{prop} \geq L_{prop} \\ T_w \leq T_u \\ Q_l \leq Q_{Naphtha} \leq Q_u \\ DSR_l \leq DSR_i \leq DSR_u \\ COT_l \leq COT_i \leq COT_u \\ NPFM \\ I_l \leq i \leq I_u \end{cases} \tag{23}$$

where, Yi_{ethy} and Yi_{prop} are ethylene and propylene yield of the i-th day; N is the number of the days of the cracking cycle; $Q_{Naphtha}$ and Q_{Steam} are the flows of naphtha and steam; L_{ethy} and L_{prop} are the lower bound of ethylene and propylene yield; T_w and T_u are the tube wall temperature and its upper limit; Q_l and Q_u are the lower and upper limit of feedstock flow; COT_l and COT_u are the lower and upper limit of COT; DSR_l and DSR_u are the lower and upper limit of DSR; NPFM is the mechanistic model of full cycle ethylene cracking furnace process established by Geng et al. (2012) (considering coking); I_l and I_u are the lower and upper limit of cracking cycle. During the optimization process, the amount of coke in furnace tube is taken as the basis to determine whether cracking have ended, i.e., when the diameter satisfy the following formula, the cracking process is considered end.

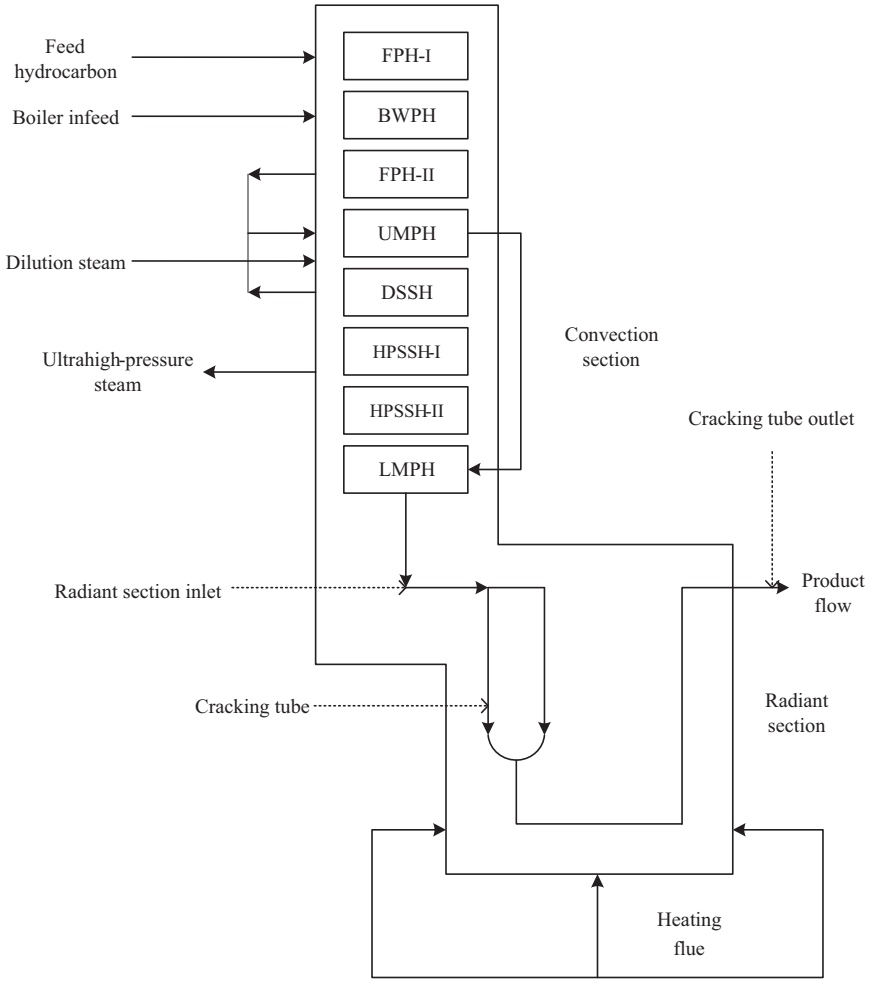

Fig. 2. Schematic structure of SL-I cracking furnace.

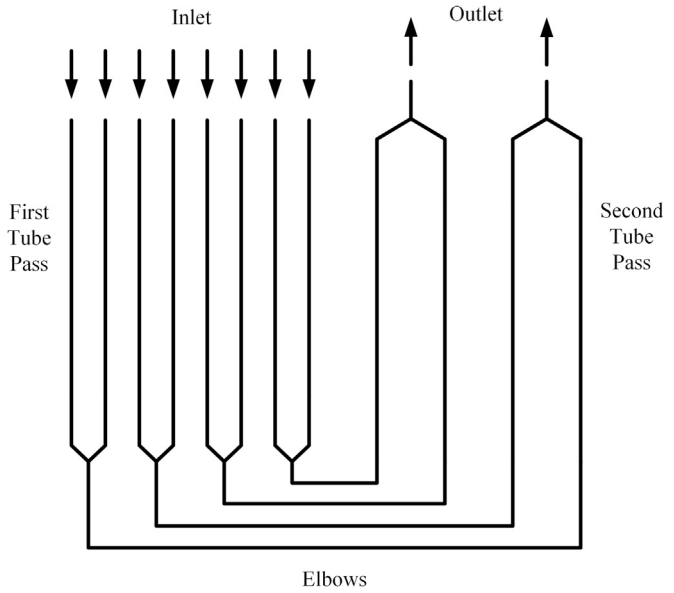

Fig. 3. The radiation tubes structure of SL-I cracking furnace.

Table 4
Structural parameters of SL-I cracking furnace.

Structural parameter	Value
Tube pass	2
Arrangement	16/8
Inner diameter (m)	0.051/0.073
Outer diameter (m)	0.063/0.086
Length (m)	13.68/14.92
Tube pitch (m)	0.112/0.154
Furnace structure	
Furnace height (m)	13.66
Furnace depth (m)	3.56
Furnace width (m)	18.94
Bottom burners	48
Sidewall burners	36
Fuel gas composition (volume fraction %)	
Hydrogen	10
Methane	80
Ethane	5
Propane	5

$$d_i \le \frac{1}{4}d \tag{24}$$

where, d_i and d are the tube inner diameter of the i-th day and before cracking. First in accordance with full cycle ethylene cracking furnace model calculate the ethylene and propylene yield, tube wall temperature, heat flux and the coking amount of the i-th day. Under the original conditions, the cracking cycle is 63 days. So we fix the cycle, and use AMOPSO algorithm for solving the multi-objective optimization problem of Eqs. (19)–(23) to determine whether meet the end conditions of the cracking. Finally output the values of the objective function.

As shown in Fig. 4, although there are four objectives, the

Table 5
Operational conditions of cracking furnace.

Condition	Value
Feedstock flow (kg/h) (single tube)	890.625
Dilution steam ratio (DSR)	0.60
Coil inlet temperature (CIT) (K)	875
Coil outlet temperature (COT) (K)	1122
Coil outlet pressure (COP) (kPa)	178

Table 6
Oil character parameters.

Oil character	Parameter	Oil character	Parameter
The relative density	0.7021	ASTM distillation range (K)	
PONA		10%	55.9
Paraffinic hydrocarbons	0.6561	30%	73.2
Cycloalkanes	0.2639	50%	91.6
Aromatic hydrocarbons	0.08	70%	111.8
The average molecular weight (g/mol)	95.1722	90%	140.5

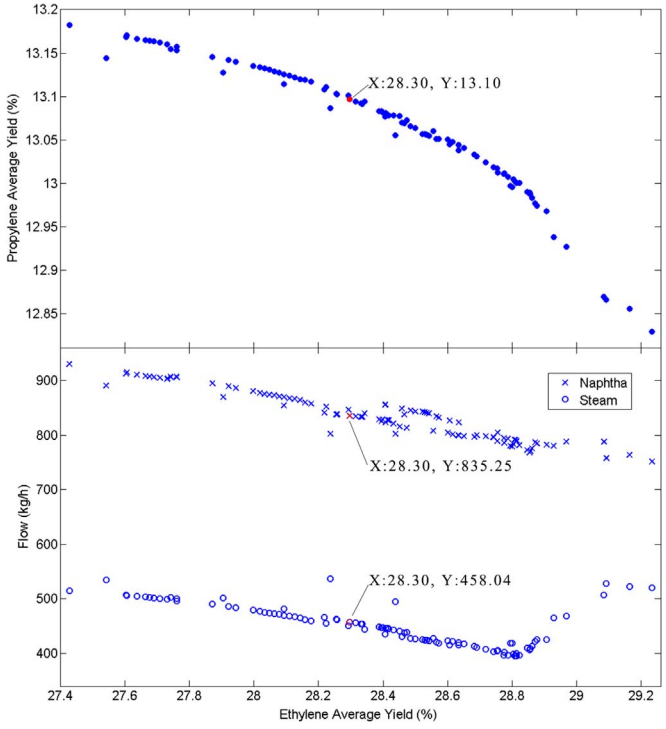

Fig. 4. Pareto solutions distribution under fixed cracking cycle.

Pareto solutions have the satisfactory distribution, which verifies the effectiveness of the proposed algorithm and guarantees the rationality of the optimization operation. The marked values are the selected optimal solution.

Fig. 5 is the COT change with the cracking days, rather than the changeless of the actual operation. At the beginning of the cracking, the coking amount in furnace tube is less, and energy transfer efficiency high, which make COT in the low temperature meet the required cracking heat. With the progress of the cracking reaction, coke thickness gradually increases, and the heat transfer efficiency decreases. In order to ensure a higher yield of ethylene and propylene, COT need gradually increase, which is the reasons for adjusting to improve COT in the latter part of cracking.

Figs. 6 and 7 show the ethylene and propylene yield trends with the number of cracking days before and after. Before the

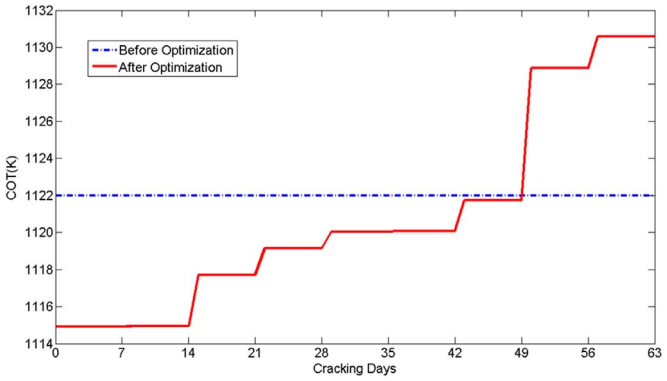

Fig. 5. COT trend with cracking days under fixed cracking cycle.

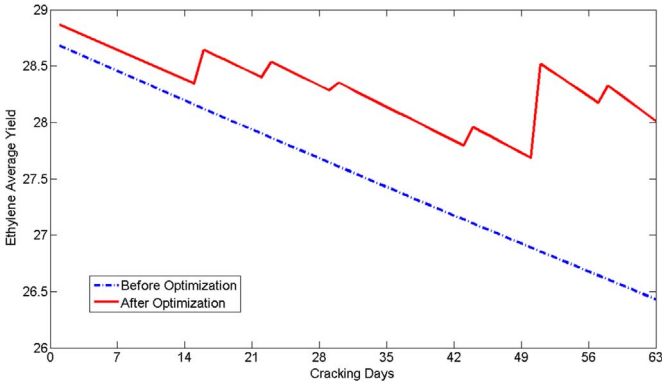

Fig. 6. Ethylene yield trend under fixed cracking cycle.

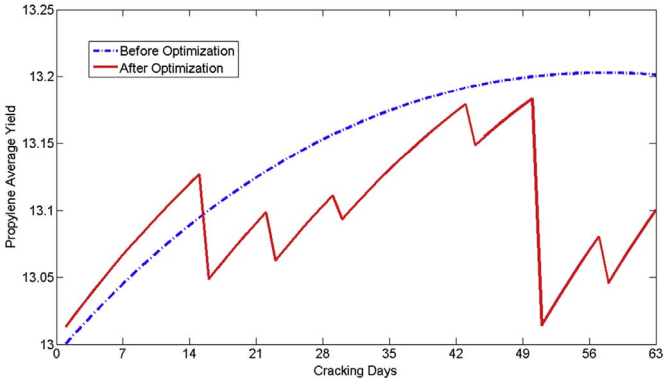

Fig. 7. Propylene yield trend under fixed cracking cycle.

optimization, because COT remains unchanged during the entire cracking process, the ethylene yield gradually decreases, and propylene yield shows a growing trend. After the optimization, the yields of ethylene and propylene change more smoothly, beneficial to ensure product quality.

As shown in Table 7, we can find that the optimization operation within the reasonable adjustment range achieved good

Table 7
Comparison of result before and after optimization under fixed cracking cycle.

	Ethylene average yield	Propylene average yield	Naphtha flow	Steam flow
Before optimization	27.54	13.14	890.63	534.38
After optimization	28.30	13.10	835.25	458.04
Change rate	+2.76%	−0.30%	−6.22%	−14.29%

results. The ethylene yield significantly increased with lower naphtha and steam flows, while ensuring the propylene yield without excessive reduction, which consist with the set optimization objectives to a great extent.

Multi-objective optimization results provide a decision-making range for decision-makers, which makes decision-makers understand the impact of the decision variables on different targets by the Pareto front. After obtaining the Pareto front, it needs to have decision-making evaluation on the solutions. This article uses fuzzy consistent matrix method for compromise solution scheme of various targets, according to the preference to select the satisfactory solution. According to satisfaction of each sub-goal, define the fuzzy subset: {very poor, poor, middle, good, very good}, assuming the same preference of different objectives. The fuzzy satisfaction function (Abido, 2006) is defined as

$$\mu_i = \begin{cases} 1 & F_i \geq F_{i\ \max} \\ \dfrac{F_i - F_{i\ \min}}{F_{i\ \max} - F_{i\ \min}} & F_{i\ \min} < F_i < F_{i\ \max} \\ 0 & F_i \leq F_{i\ \min} \end{cases} \tag{25}$$

$$\text{Ethylene yield satisfaction function: } \mu_i = \begin{cases} 1 & F_i \geq 29.23 \\ 0.55F_i - 16.20 & 27.43 < F_i < 29.23 \\ 0 & F_i \leq 27.43 \end{cases} \tag{26}$$

$$\text{Propylene yield satisfaction function: } \mu_i = \begin{cases} 1 & F_i \geq 13.18 \\ 2.83F_i - 37.35 & 12.83 < F_i < 13.18 \\ 0 & F_i \leq 12.83 \end{cases} \tag{27}$$

$$\text{Naphtha flow satisfaction function: } \mu_i = \begin{cases} 1 & F_i \geq 929.57 \\ 0.01F_i - 4.21 & 751.16 < F_i < 929.57 \\ 0 & F_i \leq 751.16 \end{cases} \tag{28}$$

$$\text{Steam flow satisfaction function: } \mu_i = \begin{cases} 1 & F_i \geq 536.75 \\ 0.01F_i - 2.80 & 395.40 < F_i < 536.75 \\ 0 & F_i \leq 395.40 \end{cases} \tag{29}$$

Five solutions from the Pareto non-inferior solutions are chosen to have optimization decision-making evaluation, specifically as shown in Table 8. Strategy 3 is the optimal solution, which has been shown above; the other strategies are alternate in the optimal solution set. By fuzzy evaluation of Pareto solutions, decision-makers can choose their satisfactory Pareto solution and corresponding decision-making scheme according to the preference information.

Fig. 8 is operation optimization results in the cracking cycle with the number of cracking days. Strategies 1–5 respectively correspond to the optimization strategies 1–5 in Table 8. In practice it is unrealistic to make frequent adjustment of the operation conditions every day. So this article is based on an adjustment cycle of 7 days. Of course, it also can set the adjustment period of the operation conditions according to the actual needs of the factory, making a phased regulation of COT operation to guide the procedure.

3.2. Case 2: The non-fixed cracking cycle

The multi-objective optimization problem of ethylene cracking furnace is described as follows.

Optimization objectives:

$$Max\ f_1 = \frac{1}{N}\sum_{i=1}^{N} Yi_{ethy} \tag{30}$$

$$Max\ f_2 = \frac{1}{N}\sum_{i=1}^{N} Yi_{prop} \tag{31}$$

$$Min\ f_3 = Q_{Naphtha} \tag{32}$$

$$Min\ f_4 = Q_{Steam} \tag{33}$$

$$Max\ f_6 = N \tag{34}$$

$$\text{Constraints: } \begin{cases} Yi_{ethy} \geq L_{ethy} \\ Yi_{prop} \geq L_{prop} \\ T_w \leq T_u \\ Q_l \leq Q_{Naphtha} \leq Q_u \\ DSR_l \leq DSR_i \leq DSR_u \\ COT_l \leq COT_i \leq COT_u \\ NPFM \\ I_l \leq i \leq I_u \end{cases} \tag{35}$$

Compared with the previous optimization operation, we donot fix the cycle here, and add an optimization objective of maximizing cracking cycle. Then we use AMOPSO algorithm for solving the multi-objective optimization problem of (Eqs. (30)–35) to determine whether meet the end conditions of the cracking. Finally output the values of the objective function and cracking cycle.

As shown in Fig. 9, the addition of the cycle objective makes the Pareto solutions distribution effect still acceptable.

Fig. 10 is the COT change with the number of cracking days. Figs. 11 and 12 show the ethylene and propylene yield trends with the number of cracking days before and after. Table 9 is the comparison of results. The case is substantially identical to the fixed cycle, however, in order to extend the cracking cycle, the other optimization objectives are tradeoff.

Because of the change of cracking cycle, the variation ranges of optimization objectives have changed. Fuzzy satisfaction functions, which generate corresponding adjustments, are as follows.

$$\text{Ethylene yield satisfaction function: } \mu_i = \begin{cases} 1 & F_i \geq 28.80 \\ 0.34F_i - 9.91 & 25.89 < F_i < 28.80 \\ 0 & F_i \leq 25.89 \end{cases} \tag{36}$$

Table 8
Fuzzy decision of Pareto solutions under fixed cracking cycle.

Fuzzy evaluation				Average yield		Flow		Strategy
E	P	N	S	E	P	N	S	
Very poor	Very good	Very poor	Very poor	27.43	13.18	929.57	515.19	1
Middle	Good	Poor	Middle	28.14	13.12	863.69	465.42	2
Middle	Middle	Middle	Middle	28.30	13.10	835.25	458.04	3
Very good	Poor	Very good	Middle	28.93	12.94	780.15	465.29	4
Very good	Very poor	Very good	Very good	29.09	12.87	757.50	528.14	5

Note: E, P, N and S denote ethylene, propylene, naphtha and steam, respectively.

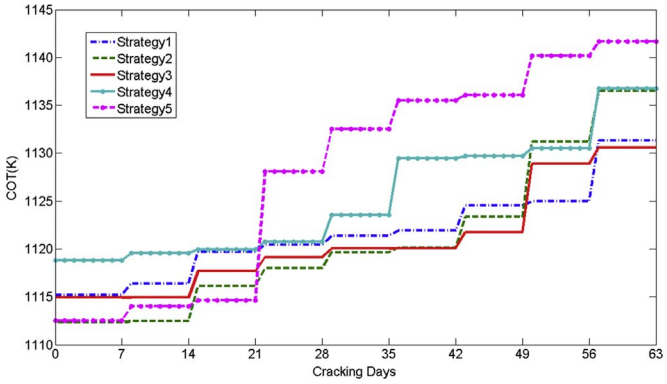

Fig. 8. Optimization stratagy of COT under fixed cracking cycle.

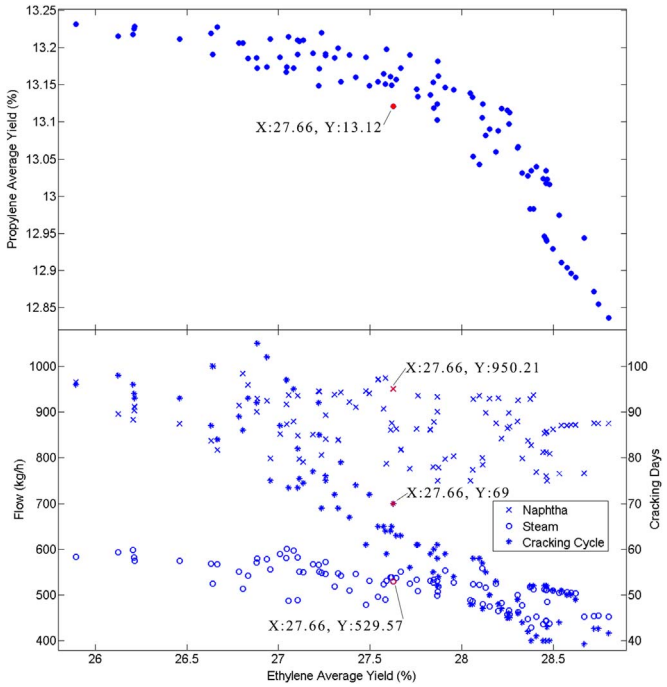

Fig. 9. Pareto solutions distribution under non-fixed cracking cycle.

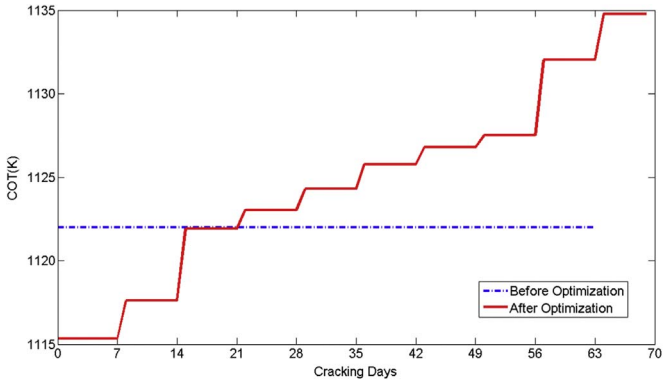

Fig. 10. COT trend with cracking days under non-fixed cracking cycle.

$$\text{Propylene yield satisfaction function:}\mu_i = \begin{cases} 1 & F_i \geq 13.23 \\ 2.49F_i - 33.05 & 12.84 < F_i < 13.23 \\ 0 & F_i \leq 12.84 \end{cases} \quad (37)$$

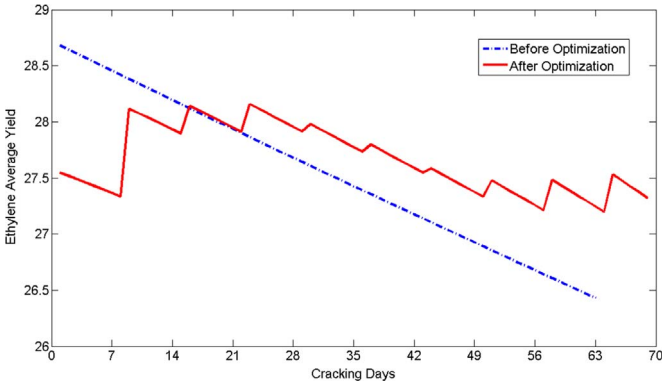

Fig. 11. Ethylene yield trend under non-fixed cracking cycle.

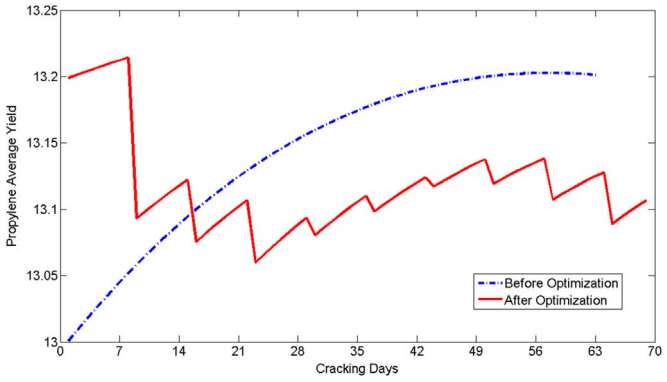

Fig. 12. Propylene yield trend under non-fixed cracking cycle.

Table 9
Comparison of result before and after optimization under non-fixed cracking cycle.

	Ethylene average yield	Propylene average yield	Naphtha flow	Steam flow	Cycle
Before optimization	27.54	13.14	890.63	534.38	63
After optimization	27.66	13.12	950.21	529.57	69
Change rate	+0.44%	−0.15%	+6.69%	−0.90%	+9.52%

$$\text{Naphtha flow satisfaction function:}\mu_i = \begin{cases} 1 & F_i \geq 999.77 \\ 0.01F_i - 3.00 & 750.00 < F_i < 999.77 \\ 0 & F_i \leq 750.00 \end{cases} \quad (38)$$

$$\text{Steam flow satisfaction function: } \mu_i = \begin{cases} 1 & F_i \geq 601.26 \\ 0.01F_i - 2.49 & 428.86 < F_i < 601.26 \\ 0 & F_i \leq 428.86 \end{cases} \quad (39)$$

$$\text{Cracking cycle satisfaction function:}\mu_i = \begin{cases} 1 & F_i \geq 105 \\ 0.02F_i - 1.61 & 40 < F_i < 105 \\ 0 & F_i \leq 40 \end{cases} \quad (40)$$

Five solutions from the Pareto non-inferior solutions are chosen to have optimization decision-making evaluation, specifically as shown in Table 10. Strategy 3 is the optimal solution, which has been shown above; the other strategies are alternate in the optimal solution set. By fuzzy evaluation of Pareto solutions, decision-makers can choose their satisfactory Pareto solution and

Table 10
Fuzzy decision of Pareto solutions under non-fixed cracking cycle.

Fuzzy evaluation					Average yield		Flow		Cycle	Strategy
E	P	N	S	Cycle	E	P	N	S		
Poor	Good	Poor	Very poor	Very good	26.94	13.16	923.80	579.03	102	1
Middle	Good	Poor	Poor	Good	27.22	13.15	944.10	550.82	85	2
Middle	Good	Very poor	Middle	Middle	27.66	13.12	950.21	529.57	69	3
Good	Good	Good	Poor	Poor	28.11	13.11	800.12	559.00	57	4
Very good	Middle	Very good	good	Very poor	28.67	13.04	765.85	495.94	42	5

Note: E, P, N and S denote ethylene, propylene, naphtha and steam, respectively.

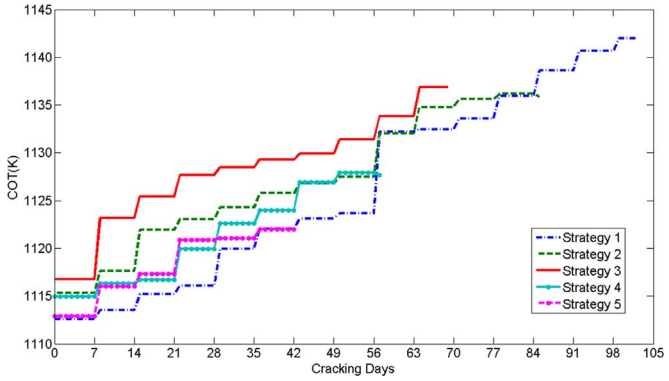

Fig. 13. Optimization stratagy of COT under non-fixed cracking cycle.

corresponding decision-making scheme according to the preference information.

Fig. 13 is COT optimization operation results in the cracking cycle with the number of cracking days. Strategies 1–5 respectively correspond to the optimization strategies 1–5 in Table 10.

By the two cases mentioned above about multi-objective of ethylene cracking furnace, the proposed method can give constructive guidance and reference about optimization operation under the conditions of fixed and non-fixed cracking cycle. Basically, higher ethylene yield means lower propylene yield and less naphtha flow under the fixed cycle, while longer cracking cycle means lower ethylene yield and higher propylene yield, which requires decision makers to make choices based on the actual production conditions and demands.

4. Conclusions

This article proposes an AMOPSO-AHP algorithm based on fuzzy consistent matrix, which takes advantage of the solutions in the obtained non-dominated solution set to make fuzzy consistent decisions in the optimization process. The global best solution is selected for guidance of global particles search, and the swarm evolutionary state is measured in the optimization process. The process adaptively adjusts the swarm evolutionary weight, learning factors and other parameters. Finally, the proposed algorithm is applied in the standard multi-objective test functions and compared with other multi-objective algorithms. The result shows that the proposed algorithm has better optimization effect.

Against the multi-objective operation optimization problems of ethylene cracking furnace, this article gives full consideration to the conflict and operating constraints of multiple objectives of product yield, coking thickness and running cycle, and designs the multi-objective optimization strategy and comprehensive evaluation methods of solutions for ethylene cracking furnace production process. The optimization conditions of cracking furnace operation are explored to guide the process optimization operation. The experimental results show that the proposed method provides a viable solution for the operation optimization of the ethylene cracking furnace.

In addition, the multi-objective operation optimization process of ethylene cracking furnace in this article is a steady-state or static optimization. The further study of the dynamic or online multi-objective optimization method and optimal control scheme of ethylene cracking process will be based on this method to guide the multi-objective operating optimization of real-time ethylene production process, which is the direction of further efforts in the future.

In our further studies, we will try refining the importance of multiple objectives to approach the ideal solutions. Moreover, considering the factors of economic, environment, and other aspects, we will improve our optimization strategies by a comprehensive analysis of the effects of the total production, operating costs, energy saving, and emission reduction.

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