Energy Conversion and Management 196 (2019) 311–319

Contents lists available at ScienceDirect

Energy Conversion and Management

journal homepage: www.elsevier.com/locate/enconman

Production optimization and energy saving of complex chemical processes using novel competing evolutionary membrane algorithm: Emphasis on ethylene cracking

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ARTICLE INFO

Keywords:
Multi-objective optimization
Evolutionary membrane algorithm
Production optimization
Energy saving
Emission reduction
Complex chemical processes

ABSTRACT

As a relatively high energy-consuming in China, the chemical process is important and has potential to be optimized for energy saving, economic benefits and environmental protection. Multiple goals can be coordinated using multi-objective optimization algorithms. In order to improve the exploration and exploitation abilities in optimizing multiple objectives, a constrained competing evolutionary membrane algorithm is proposed. The proposed algorithm takes advantages of the distributed and parallel computing mode of the membrane computing. Populations are evolved independently in each membrane and share information between membranes based on competing communication rules. Meanwhile, the skin membrane archives global elitist solutions and serves as guidance for inner evolution processes. Finally, the optimization experiments on the ethylene cracking process, as an important production of complex chemical processes, prove that the proposed algorithm can provide enough selection for decision makers with well-distributed and converged candidate solutions. Furthermore, the solutions lead the ethylene cracking process to reach the coordinated optimum ethylene or propylene production, oil consumption reduction and carbon dioxide emission reduction. In average, the optimization solutions bring about reduction of 2697.58 tons of feed oil and 8281.57 tons of carbon dioxide emission.

1. Introduction

The increasing developments in various fields expedite multiple needs in reality. In January 2016, the 17 Sustainable Development Goals (SDGs) of the 2030 Agenda for Sustainable Development came into force officially [1]. Around the world, people try to realize sustainable development through effective measures imposed on production and living activities. Optimization, serving as one of the measures, has gained much attention [2].

Based on the IEA data of global energy & carbon dioxide (CO_2) status report [3], the energy consumption around the world grew by 2.3% in 2018, and the global energy-related CO_2 emissions grew 1.7%. According to the statistical annual report on national economic and social development of China in 2018 [4], the total energy consumption in 2018 was 4.64 billion tons of standard coal equivalent, increased by 3.3% compared to that in 2017, wherein the crude oil consumption increased by 6.5%. Meanwhile, the carbon dioxide (CO_2) emission decreased by 4.0%.

As demonstrated in Fig. 1, there were data about energy consumption constitutes in 2015 of major countries, reserved by the International Energy Agency (IEA) [5]. Among the industry sector, the chemical and petrochemical industry serves as a pillar industry in China, and the ethylene cracking process consumes more than half of the total energy in the chemical and petrochemical industry [6].

With reference to the research by the IEA [7], effective measures can help to improve energy efficiency, which contributes to emission reduction of worldwide greenhouse gases, compared with other measures like renewable energy resources investment. Therefore, it is essential for China to conduct efficient optimization, so as to raise the production and energy efficiency of processes, escape from unnecessary waste, and in turn, bring about production and energy efficiency improvements of the whole industry in China [8].

The varying needs in processes with multiple objectives to be satisfied push the fast and continuous development of the multiple-

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https://doi.org/10.1016/j.enconman.2019.05.101
Received 4 March 2019; Received in revised form 25 May 2019; Accepted 28 May 2019

Nomenclature

C	the carbon dioxide emission
c_j	the carbon dioxide emission coefficient
cd_i	the crowding distance of each variable
$Cycle_{crack}$	the cracking cycle
E_j	the energy resource
f_i	objective function
$F_{naphtha}$	the flow of feedstock naphtha
G	the number of generation
I_c	the convergence metric
I_{GD}	the general distance
I_i	the maximum iteration time
I_S	the spacing metric
m	number of objectives
n	number of decision variables
N	the population size
N_E	the number of elementary membranes
N_M	the number of middle-layer membranes
N_{EO}	the number of objects in elementary membranes
N_{MO}	the number of objects in middle-layer membranes
o_s	objects in each membrane/region as the candidate solution
P	real Pareto optimal solution set
p_c	the crossover rate
p_m	the mutation rate
p	number of equality constraints
q	number of inequality constraints
$P_{ethylene}$	the production yield of ethylene
$P_{propylene}$	the production yield of propylene
R_c	the communication rate
S_C	objects selected in each membrane to be communicated
S_{dd}	objects that are deleted in the competing communication procedure
S_{Ei}	objects in the *ith* elementary membrane
S_{Mi}	objects in the *jth* middle-layer membrane
S_S	objects in the skin membrane
T_w	the wall temperature in the tube
x	decision vector
y	objective vector
x_i	the *i*th decision variable
y_i	the *i*th objective

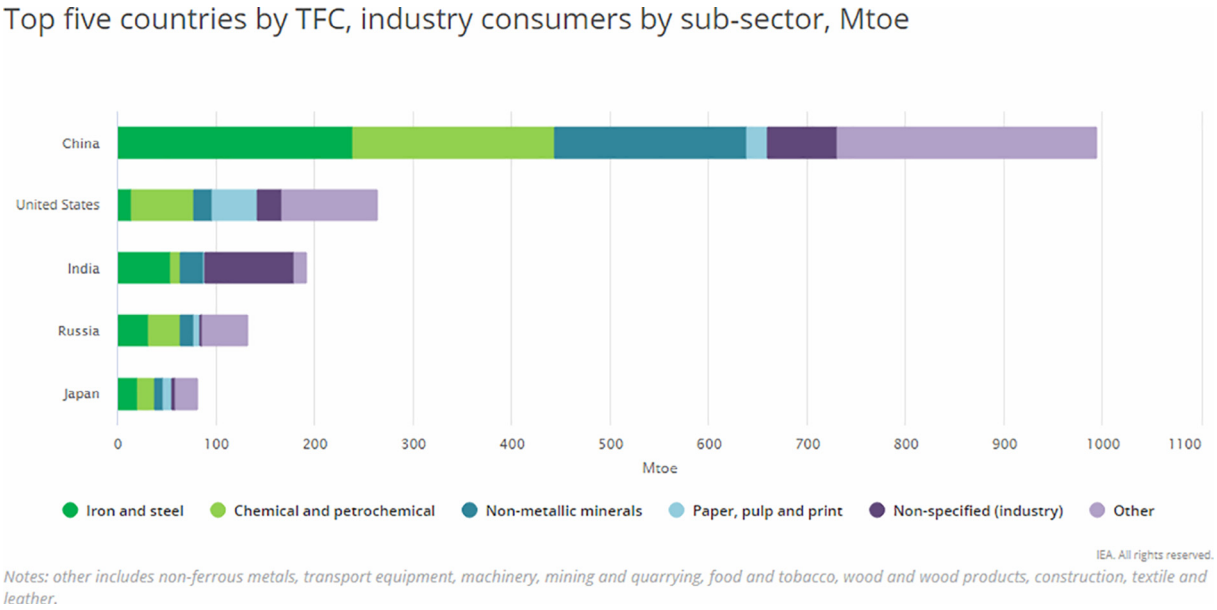

Fig. 1. Energy consumption constitute of the industry of top five countries in 2015 [5] Source: IEA (2015) Key World Energy Statistics. All rights reserved.

objective optimization. The multiple-objective optimization problem (MOP) requires optimization algorithms to be able to deal with multiple objectives simultaneously without sacrifice of any one objective, taking the form as in Eq. (1). Heuristic and intelligent algorithms search for approximate solutions as close as possible to the realistic ones. They are able to find global optimal solutions and escape from local optima. It is not necessary that the optimization problem has a definite expression, which many realistic problems could not satisfy [9].

Table 1
The Application of Optimization Algorithms on the Ethylene Cracking Process.

Optimization Method	Optimization Objectives
The multi-objective particle swarm optimization algorithm (MOPSO), Xia et al. [13]	Maximum ethylene yields and propylene yields
A self-adaptive teaching-learning-based optimization (TLBO) algorithm, Yu et al. [14]	Maximize the yields of ethylene, propylene, and butadiene
The ELM integrating affinity propagation clustering, Han et al. [15]	Energy saving and emission reduction
An adaptive multi-objective optimization algorithm (AMOPSO), Geng et al. [16]	Maximum ethylene yields and propylene yields, minimum feeds of naphtha and stream
An improved hybrid encoding non-dominated sorting genetic algorithm (MDNSGA-II), Jiang et al. [17]	The profit and energy saving
The multi-objective linear programming method, Di Somma et al. [18]	The total annual cost and primary exergy input

$$\begin{aligned}&\min f_M(\boldsymbol{x}) = [f_1(\boldsymbol{x}), ...,f_m(\boldsymbol{x})]^T\\&\text{s.t. } i_j(\boldsymbol{x}) \le 0(j = 1, 2, ...,q)\\&e_l(\boldsymbol{x}) = 0(l = 1, 2, ...,p)\\&x_i \in [x_i^{min}, x_i^{max}](i = 1, 2, ...,n)\end{aligned} \quad (1)$$

In the previous work [2], there was a review about intelligent algorithms for solving the MOPs. The algorithms have been testified with good optimization performances and widely applied to solve realistic problems of various fields, with the aim to optimize multiple objectives like production optimization, energy efficiency improvement, emission reduction or environmental protection.

Geng et al. [10] made researches on the modeling and optimization of the ethylene cracking process to realize efficient production, making use of the weighted sum method (WSM) and the chaos optimization algorithm (COA). Based on the fuzzy extreme learning machine (FELM) method, Han et al. [11] proposed a novel energy management and optimization model to optimize the ethylene process, with the result of about 15% energy-saving potential. Han et al. [12] applied a novel data envelopment analysis cross-model, based on the affinity propagation clustering algorithm to realize optimization of the pure terephthalic acid (PTA) production process and the ethylene cracking process for energy saving and carbon emission reduction. As demonstrated in Table 1, more researches about the multi-objective optimization of the ethylene cracking process are listed.

As a heuristic and intelligent algorithm, the evolutionary membrane algorithm (EMA) has been successfully applied to solve the MOP. In this paper, a constrained competing EMA (CCEMA) is proposed to strengthen its exploration and exploitation abilities in finding the solution set, which is verified by test functions. Furthermore, the optimization experiments on the ethylene cracking process, as an important production of complex chemical processes, prove that the proposed CCEMA can provide enough selection for decision makers with well-distributed and converged candidate solutions. The optimization solutions bring about reduction of 2697.58 tons of feed oil and 8281.57 tons of CO_2 emission.

The paper is organized as follows: the basic theorem about the EMA and applications in solving MOPs is described in Section 2; in Section 3, a detailed description is listed about the proposed CCEMA, whose performance is then tested on the specific ethylene cracking process as described in Section 4. Finally, a conclusion about this paper and discussion about further improvements are given in Section 5.

2. Evolutionary membrane algorithm

Membrane computing [19], also called the P system, was initiated by and named after Păun in 1998. It is inspired by the structure of biological cells, and simulates the functions and interactions of cells. The most inner membrane that doesn't involve any membrane is called an elementary membrane, while the remaining membranes are called middle membranes. All membranes divide the cell into several regions. Among the membrane structure are some objects with designed rules reacted on them to realize computation. Rules work in a non-deterministic, synchronous, and maximally parallel manner, which is a most distinguished specialty of the membrane computing. Objects are also communicated between membranes to share information.

Membrane computing is advantageous in the computation power with its attractive features of computation completeness and high efficiency [20]. The computation efficiency of the P system is demonstrated by its ability to produce an exponential work space in polynomial time. It has been proved that any Turing computable problems can be solved by the P system [21]. There are mainly three types of the P system: the cell-like, tissue-like and neural-like P system [22], classified by the structure and function of the cell, the cell mass or the neuron.

Applying the membrane computing in solving optimization problems has gained more and more attention in the latest years. The membrane computing optimization algorithm, abbreviated as membrane algorithm, was firstly proposed in 2004 by Nishida [23]. It has been proved that membrane algorithms, based on variant and flexible structures combining with different optimization algorithms have global search ability, high reliability, fast convergence speed and well-distributed solutions.

The flexible structure of the P system is also beneficial for solving complex real-world problems [24], such as Gao et al. [25] proposed a membrane-inspired quantum bee colony algorithm to realize multi-objective spectrum allocation, Zhao et al. [26] applied the membrane algorithm to the gasoline blending scheduling problem, Hea et al. [27] succeeded in optimizing the solid waste transportation problem. Therefore, relative researches on the membrane algorithm are important for the systematic research of the membrane computing and the optimization algorithm.

3. A constrained competing evolutionary membrane algorithm

In this paper, a constrained competing evolutionary membrane algorithm (CCEMA) is proposed, to find converged and well-distributed solution set for the multi-objective optimization of the ethylene cracking process.

According to theorems and corollaries by Paun [22], a P system with at most 6 membranes is able to realize universal computation. Therefore, the membrane structure of the CCEMA is designed as a three-layer hierarchical cell-like P system with six middle membranes, each with two elementary membranes, as shown in Fig. 2. Objects in inner membranes representing candidate solutions are coded as real numbers and communicate between neighboring membranes in a symport form.

Based on the NSGA-II (non-dominated sorting genetic algorithm) [28], a set of randomly produced initial objects are evolved according to the crossover rule, the mutation rule, and the selection rule. In the

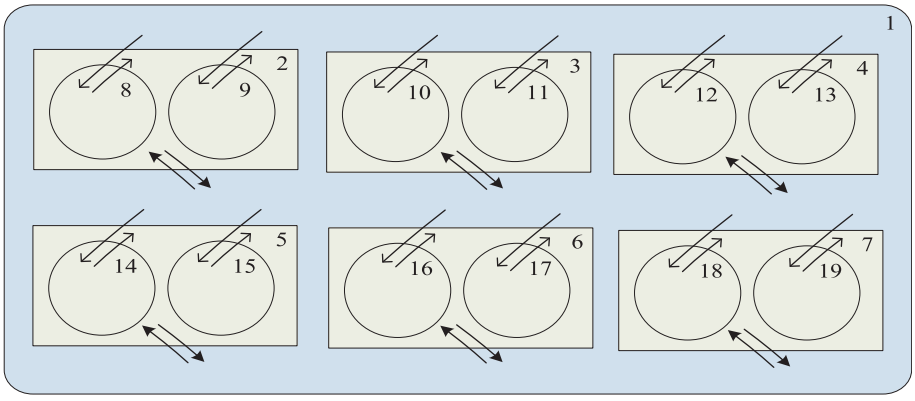

Fig. 2. The membrane structure of the CCEMA.

selection procedure, any solution that violates any one of the constraints is strictly deleted.

3.1. Communication

It is special for the CCEMA that the evolved populations share information between neighboring hierarchical membranes in a competing mode. Inspired by substance exchange in the cells, membranes communicate their best objects to the directly upper-layer membrane till the skin membrane. After the parallel evolution process in each elementary membrane, candidate solutions are sorted in the descending order by the crowding distance method [28]. Then the elitist solutions that are ranked in the first 30% with the largest distances are selected to the next-layer neighboring membrane.

The membrane that receives elitist objects from the lower-layer membranes makes these local elitists compete with its own objects. Instead of taking all objects in, the objects that are Pareto-dominated by any other object are sifted out as Eq. (2).

$$\begin{aligned} &For\ two\ variables \quad \boldsymbol{x_1} = [x_{11},\ x_{12},\ ...,x_{1n}],\\ &\boldsymbol{x_2} = [x_{21},\ x_{22},\ ...,x_{2n}]\\ &\forall\ i \in \{1,\ 2,\ ...,m\},\ f_i(\boldsymbol{x_1}) \le f_i(\boldsymbol{x_2})\\ &and\ \exists\ j \in \{1,\ 2,\ ...,m\},\ f_i(\boldsymbol{x_1}) < f_i(\boldsymbol{x_2})\\ &then\ \boldsymbol{x_2} p \boldsymbol{x_1},\ \text{i. e. } \boldsymbol{x_1}\ dominates\ \boldsymbol{x_2} \end{aligned} \tag{2}$$

Going through the competing communication procedure, the number of objects in each membrane is uncertain and different from each other, taking the form of Eq. (3). The skin membrane does not evolve the elitists but serves as an archive for global best solutions and transmits selected solutions back into inner membranes for global information exchange. All remained objects after competition join in the next iteration evolution processes. Therefore, the skin membrane contributes to the whole optimization procedure through the bidirectional communication and elitists archiving mechanism by guiding the search direction.

$$\begin{aligned} &\boldsymbol{S_E} = [S_{E1},\ S_{E2}...,S_{EN_E}]\\ &\boldsymbol{S_M} = [S_{M1},\ S_{M2}...,S_{MN_M}]\\ &S'_M = S_C \cup S_M - S_{dd}\\ &S'_S = S_C \cup S_S - S_{dd}\\ &S'_E = S_C \cup S_E - S_{dd} \end{aligned} \tag{3}$$

To sum up, the brief procedure of the proposed CCEMA can be seen in Table 2.

Experiments are conducted of the CCEMA on test functions ZDT1 ~ 4 [29], and DTLZ1 [30] to verify its optimization performance, using the convergence metric I_C [31], the spacing metric I_S [32], and the general distance I_{GD} [32]. The statistical results of these indexes are compared with those of a few classical optimization algorithms like the NSGA-II [28], SPEA2 (strength Pareto evolutionary algorithm) [33], MOEA/D (multi-objective evolutionary algorithm based on decomposition) [34], as shown in Table 3. On the other hand, the optimization results are compared with the ideal Pareto front as depicted in Figs. 3–6 to demonstrate the approximation extent.

It can be seen from the results that the CCEMA is able to produce solutions that are converged and well-distributed. Due to the intrinsically parallel computing mode, the competition mechanism and the elitists archiving in the skin membrane, the exploration and exploitation abilities of the CCEMA is proved to be good.

4. Production optimization and energy saving of the ethylene cracking process

In implementing the CCEMA, it is convenient to be used since the algorithm does not have many parameters to be adjusted except for the population size, which can be enlarged with the increasing problem complexity based on experience.

In this paper, the proposed CCEMA is applied to solve the multi-objective optimization of the ethylene cracking process (as depicted in Fig. 7), a major production and energy-consuming process of the chemical and petrochemical industry, so as to realize effective production and efficient energy saving.

4.1. Ethylene cracking process model

Based on the improved Kumar kinetics model [10], the cracking process model is established including first order and second order reactions, the heat transfer model, the mass balance, the energy balance and the momentum balance equations. Taking a real-world SL-I cracking furnace for example, whose structure parameters are given in Table 4 and its feedstock characteristics parameters in Table 5.

4.2. Constrained multi-objective optimization

Under the initial operation conditions as in Table 6, experiments are carried out on the ethylene cracking process to realize simultaneously objectives of maximum ethylene production yield, maximum propylene production yield, and maximum cracking cycle. The minimum use of the feedstock oil and the maximum yields of primary products helps to reach goals of effective production and efficient energy saving. The optimized variables are selected as the oil flow, dilution steam ratio, and coil outlet temperature (COT) due to their significance on affecting the production process [16]. The COT is assumed to be adjusted every ten days, which in practical production is reflected on adjusting the CIT and the fuel combustion.

There are also constraints that must be satisfied for reasonable production as shown in Eq. (4). In this paper, these constraints are dealt

Table 2
The pseudo-code of the CCEMA.

Input parameters: the number of each layer membrane N_E, N_M, the number of initial objects in each layer membrane N_E, N_M, the maximum iteration step I_i, the maximum generation number G, the crossover rate p_c, the mutation rate p_m, and the communication rate R_c.

Output results: the global best solutions archived in the skin membrane S_s, and the corresponding objectives f_i, $1 \le i \le m$.

Step 1. Initialization
Produce randomly initial objects in the predefined variables range for each inner membrane.

Step 2. Evolution in membranes
On the basis of the NSGA-II, objects are evolved in inner membranes, except the skin membrane, simultaneously in a parallel computing mode.

Step 3. Communication between membranes

a. Sort and select the front 30% best objects according to the crowding distance method.

b. The selected objects are communicated from the elementary membranes to the surrounding upper middle-layer membranes and compete with existing objects in the upper membranes. During the competition procedure, the Pareto-dominated objects are eliminated.

c. In the same way, the selected best objects in the middle-layer membranes are communicated to the skin membrane.

Especially, due to the independent evolution procedure in each membrane, objects in different membranes are different. Meanwhile, the competing communication procedure leaves each membrane with different number of objects, which may increase the gap between membranes.

Step 4. Skin membrane archiving and guidance
Serving as an archive, the skin membrane does not take part in the evolution procedure but the communication procedure. All best objects communicated from inner membranes are archived in the skin membrane, and they are also sorted and selected the front 30% elitists to communicate back to inner membranes. These communicated elitists compete with objects in inner membranes to sift out those Pareto-dominated and join in the next iteration evolution procedure. Therefore, the skin membrane also acts as guidance for evolution in inner regions.

Step 5. Termination condition judgment
If the iteration step reaches the maximum number, the algorithm terminates and the archived elitists in the skin membrane S_s are output as the problem solution set.

Table 3
Performance comparison between CCEMA and other algorithms (mean and standard deviation values of 30 runs, mean (std)) (*the bold denotes the best result).

Test Functions	EMACM	NSGA-II	SPEA2	MOEA/D
I_c of **ZDT1**	4.87E−3 (1.56E−3)	1.77E−3 (1.41E−3)	**1.23E−3 (8.19E−5)**	1.51E−2 (4.40E−2)
I_s of **ZDT1**	**3.18E−5 (4.07E−5)**	7.32E−3 (8.02E−4)	3.17E−3 (3.54E−4)	1.43E−1 (3.89E−1)
$I_{GD}$of **ZDT1**	**1.89E−4 (8.17E−5)**	4.62E−3 (2.15E−4)	3.88E−3 (3.77E−5)	1.15E−1 (1.32E−1)
$I_C$of **ZDT2**	6.13E−3 (1.06E−3)	1.34E−3 (1.18E−3)	**8.11E−4 (5.97E−5)**	4.28E−0 (5.20E−0)
$I_S$of **ZDT2**	**6.27E−5 (7.64E−5)**	7.31E−3 (6.51E−4)	3.33E−3 (2.21E−4)	2.25E−2 (1.16E−2)
$I_{GD}$of **ZDT2**	**2.14E−4 (8.44E−5)**	4.77E−3 (1.63E−4)	3.88E−3 (3.22E−5)	4.66E−0 (5.18E−0)
$I_C$of **ZDT3**	3.91E−3 (1.19E−3)	3.05E−3 (2.14E−3)	**2.86E−3 (1.30E−4)**	1.18E−2 (2.29E−2)
$I_S$of **ZDT3**	**4.10E−5 (6.89E−5)**	7.63E−3 (1.87E−3)	3.64E−3 (5.02E−4)	7.82E−2 (1.12E−1)
$I_{GD}$of **ZDT3**	**1.49E−4 (7.51E−5)**	9.36E−3 (1.03E−2)	4.73E−3 (4.73E−3)	2.72E−1 (2.30E−1)
$I_C$of **ZDT4**	1.98E−3 (9.91E−4)	2.46E−3 (1.46E−3)	**1.97E−3 (6.47E−4)**	1.26E−1 (2.76E−1)
$I_S$of **ZDT4**	**6.84E−5 (1.02E−4)**	7.32E−3 (6.86E−4)	3.10E−3 (2.50E−4)	1.89E−1 (5.27E−1)
$I_{GD}$of **ZDT4**	**1.78E−4 (1.31E−4)**	4.84E−3 (4.14E−4)	4.23E−3 (3.91E−4)	3.19E−1 (3.53E−1)
$I_C$of **DTLZ1**	**6.87E−3 (3.42E−3)**	3.66E−2 (1.20E−3)	7.03E−2 (2.97E−1)	1.54E−2 (1.68E−3)
$I_S$of **DTLZ1**	**5.20E−5 (5.83E−5)**	2.14E−2 (2.08E−3)	2.88E−1 (1.51E+0)	7.15E−3 (1.24E−2)
$I_{GD}$of **DTLZ1**	**1.88E−4 (1.09E−4)**	2.68E−2 (1.65E−3)	1.95E−2 (2.43E−4)	2.68E−2 (4.01E−2)

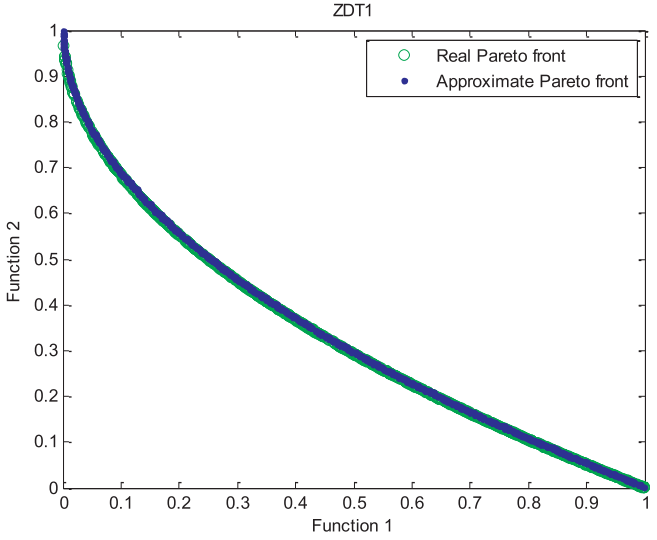

Fig. 3. Approximation of CCEMA to the real front on ZDT1.

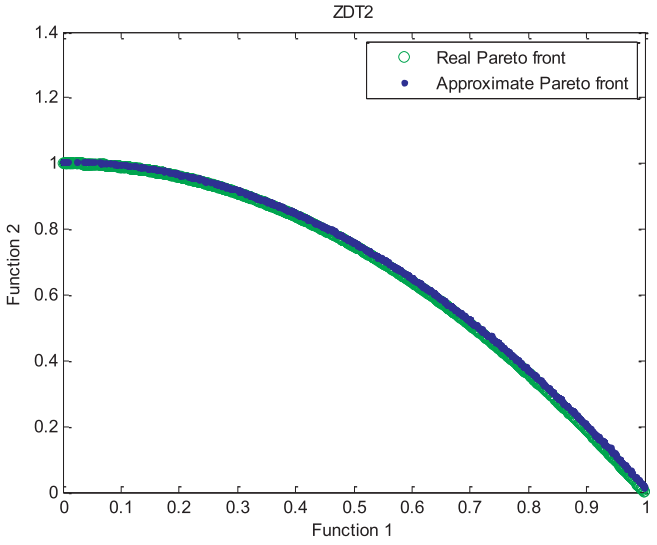

Fig. 4. Approximation of CCEMA to the real front on ZDT2.

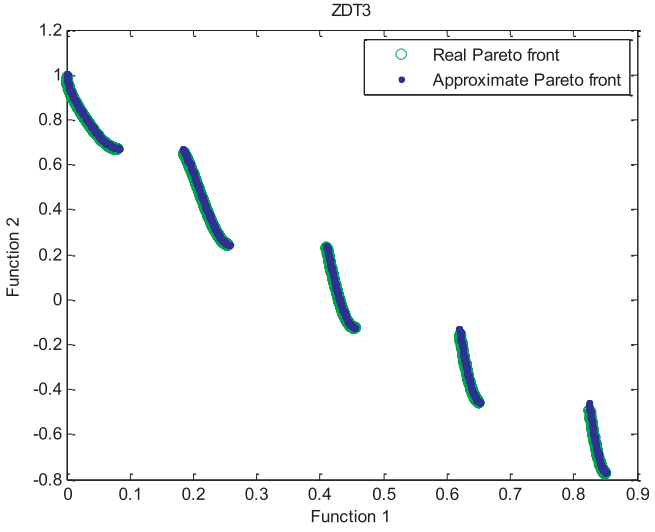

Fig. 5. Approximation of CCEMA to the real front on ZDT3.

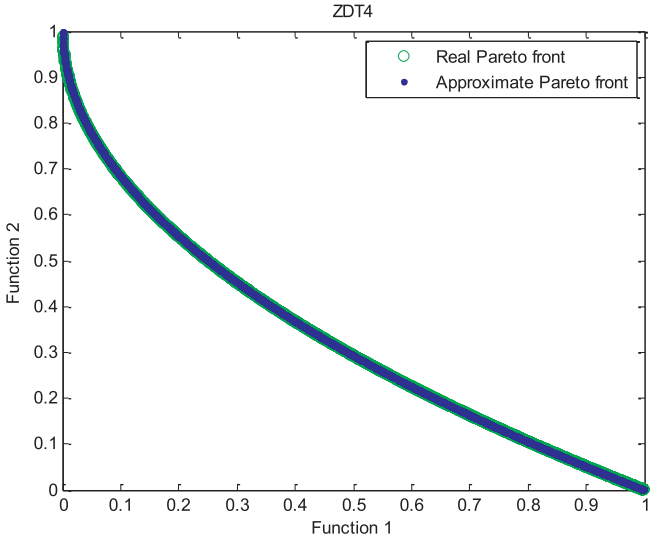

Fig. 6. Approximation of CCEMA to the real front on ZDT4.

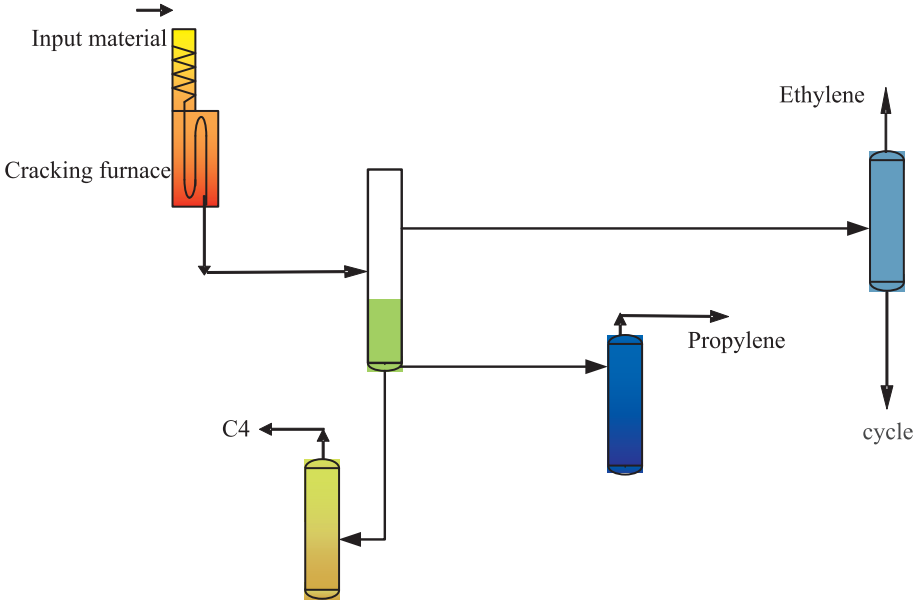

Fig. 7. A simplified schematic diagram of the ethylene cracking process.

Table 4
Structural parameters of the SL-I cracking furnace.

Structural parameters	
Furnace tube group	6
Tube pass	2
Arrangement	16/8
Length (m)	13.681/14.921
Tube pitch (m)	0.112/0.154
Inner diameter (m)	0.051/0.073
Outer diameter (m)	0.063/0.086

Table 5
Feedstock characteristics parameters.

Feedstock	naphtha
Paraffinic hydrocarbons	0.6561
Cycloalkanes	0.2639
Aromatic hydrocarbons	0.08
Average relative molecular mass (g/mol)	95.1722
Relative density (g/cm^3)	0.7021

Table 6
Initial Operation Conditions.

Operation Conditions	
Oil flow (kg/h) (per single tube)	890.625
Dilution steam ratio (D_R)	0.60
Coil inlet temperature (CIT) (K)	875
Coil outlet temperature (COT) (K)	1122
Coil outlet pressure (COP) (kPa)	178
Coking thickness (cm)	0

with using dead penalty method, which eliminate those candidate solutions that violate one of the required constraints.

$$
\begin{aligned}
&F_{low} \le F_{naphtha} \le F_{up}\\
&D\_R_{min} \le D\_R \le D\_R_{max}\\
&COT_{low} \le COT \le COT_{up}\\
&T_w \le T_{up}\\
&P_{ethylene_{min}} \le P_{ethylene} \le P_{ethylene_{max}}\\
&P_{propylene_{min}} \le P_{propylene} \le P_{propylene_{max}}\\
&Cycle_{crack_{min}} \le Cycle_{crack} \le Cycle_{crack_{max}}
\end{aligned}
\tag{4}
$$

4.3. Experimental setup

Experiments are conducted by a computer with the setup of the 2.40 GHz Intel Core 2, the CPU E4600, the 2.00 G RAM, and the WIN10 32 bit operating system. The MATLAB tool is used here for running the CCEMA [35]. The parameters are set up as follows: $N_E = 12$, $N_{EO} = 10$, $N_m = 6$, $N_{MO} = 15$, max_iteration = 20, generations = 100, crossover_rate = 0.8, mutation_rate = $1/n$

Theoretically, working in a maximally parallel mode, the worst time complexity of the CCEMA is $O(GmN_{max}^2)$ (N_{max} denotes the maximal population size of all membranes). Even in the serial working mode, the complexity is $N_E * O(mN_{EO}^2) + N_M * O(mN_{MO}^2)$. As usually set, there is $(N_E * S_E + N_M * S_M) \approx N_{NSGA-II}$.

4.4. Optimization result

After taking several runs of experiments, the set of solutions with the most visually converged and well-distributed solution is chosen as the experimental result. Because the true Pareto front of the multi-objective optimization problem of the ethylene cracking process is unknown, the best 30% of all non-dominated solutions from the CCEMA based on the crowding distance sorting were selected. The resulting trends of optimization objectives are shown in Fig. 8. It can be seen from the Pareto front of the optimized objectives that the proposed CCEMA is able to get converged and well-distributed solutions that are located in reasonable ranges.

In addition, the parallel coordinates of all objectives are plotted in Fig. 9, wherein each line of different colors denotes a solution, and all lines form the whole solution set. It is evident that the three objectives are conflicted with each other under the synergic effects of operation

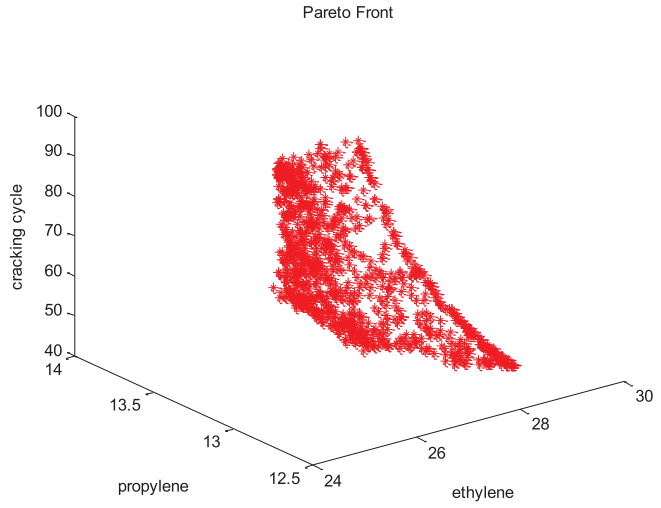

Fig. 8. The Pareto front of optimized objectives of the ethylene cracking process.

variables. For example, the increase of COT leads to the increase of the ethylene yield but the decrease of the propylene yield. The increase of the oil flow makes the ethylene yield decrease and the propylene yield increase. These trends are in accordance with the practical variation trends, testifying the rationality of the optimized results.

The optimization results are compared with the original values of the cracking model, with the statistical data of the optimized objectives given in Table 7.

The conflicted objectives are not able to reach the desired extreme results simultaneously, if one objective reaches the optimum value, the other one or more objectives may not get the desired values. The archived solution set is sorted according to the crowding distance method, with the first front solutions given in the Table 8. Moreover, optimization results of the oil flow of each solution are listed.

When one single solution is needed to be decided, the preferences of decision makers need to be considered. Imitating the decision making process, a set of solutions are chosen based on the primary production consideration of the ethylene yield, as in Table 9. These solutions are chosen for certain preference, and the whole solution set involves more information for selection based on different considerations of decision makers.

According to the carbon dioxide emission factors of different energy resources as shown in Table 10 [36], the CO_2 emission can be reduced along with the decrease of the energy resources consumption.

In the ethylene production process, the primary energy is the crude oil, whose carbon dioxide emission coefficient is 3.07. In the actual production of the ethylene production, its carbon emission can be estimated as Eq. (5) [37].

$$C = \sum (E_j \times c_j) \tag{5}$$

wherein C is the carbon dioxide emission, E_j is the input energy resource j, c_j is related carbon emission factor. Therefore, the reduced carbon dioxide emission amount of optimal solutions in the Table 8 and part of Table 11 are calculated as in Table 11. It can be seen from the optimization results that, in average, the optimization solutions bring about reduction of 2697.58 tons of feed oil and 8281.57 tons of CO_2 emission.

As a whole, the multi-objective optimization experiments of the proposed CCEMA produce fronts that are converged with uniform distribution, covering as many as possible solutions in the predefined variables ranges, making the CCEMA promising in solving MOPs. The optimization results also meet with constraints requirements and are reasonable for practical production, providing enough selection for decision makers to choose the preferred solution set.

5. Conclusion

In this paper, a novel CCEMA is proposed to improve the optimization performances for better solving the MOP. The intrinsically parallel computation features and the competition mechanism in communication leads the CCEMA to be able to find globally converged and distributed elitists.

Experiments of the CCEMA on the ethylene cracking process testify

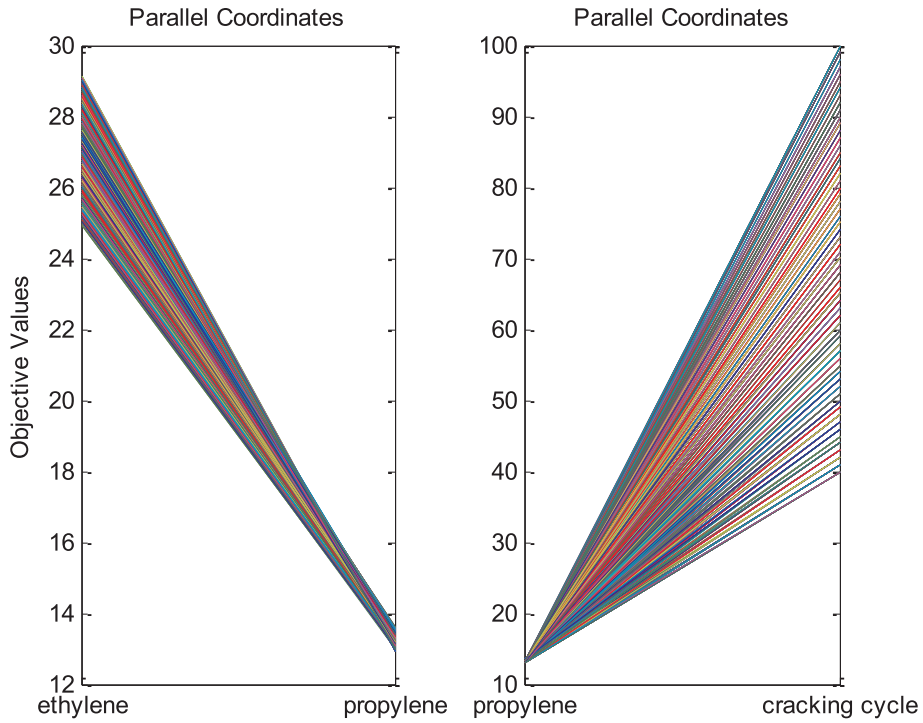

Fig. 9. The parallel coordinates plot of all optimized objectives.

Table 7
The Statistical Multi-objective Optimization Results Under Non-fixed Cracking Period.

Optimization Objectives	Ethylene Yield (avg. %)	Propylene Yield (avg. %)	Cracking Cycle (day)
Before Optimization	27.54	13.14	63
Maximum Ethylene Yield	28.52	13.02	50
Minimum Ethylene Yield	25.21	13.08	85
Maximum Propylene Yield	26.86	13.60	54
Minimum Propylene Yield	25.70	13.00	89
Maximum Cracking Cycle	27.05	13.13	90
Minimum Cracking Cycle	28.51	13.02	50

Table 8
Sorted Multi-objective Optimization Solution Set.

Objectives				
Solutions	Ethylene Yield (avg. %)	Propylene Yield (avg. %)	Cracking Cycle (day)	Oil Flow (kg/h) (per single tube)
Original	27.54	13.14	63	890.63
Sorted Solution 1	28.38	13.04	53	748.22
Sorted Solution 2	26.83	13.22	73	861.19
Sorted Solution 3	28.09	13.07	59	764.42
Sorted Solution 4	26.89	13.50	53	641.35
Sorted Solution 5	27.82	13.10	66	776.62
Sorted Solution 6	28.47	13.03	51	746.70
Sorted Solution 7	27.75	13.11	68	780.15
Sorted Solution 8	27.27	13.13	82	803.90
Sorted Solution 9	28.14	13.07	58	767.46
Sorted Solution 10	27.91	13.09	64	772.66
Sorted Solution 11	28.06	13.07	61	756.25
Sorted Solution 12	26.94	13.14	87	801.19
Sorted Solution 13	28.31	13.05	54	756.12
Sorted Solution 14	28.18	13.07	56	780.15
Sorted Solution 15	27.69	13.11	69	787.21

Table 9
Preferred Multi-objective Optimization Solution Set.

Objectives				
Solutions	Ethylene Yield (avg. %)	Propylene Yield (avg. %)	Cracking Cycle (day)	Oil Flow (kg/h) (per single tube)
Original	27.54	13.14	63	890.63
Preferred Solution 1	28.52	13.02	50	741.35
Preferred Solution 2	28.51	13.02	50	741.59
Preferred Solution 3	28.51	13.02	50	747.44
Preferred Solution 4	28.47	13.03	51	746.69
Preferred Solution 5	28.47	13.03	51	743.91
Preferred Solution 6	28.45	13.03	51	752.31
Preferred Solution 7	28.42	13.03	52	746.69
Preferred Solution 8	28.42	13.03	52	746.72
Preferred Solution 9	28.42	13.03	52	746.69
Preferred Solution 10	28.41	13.04	51	767.46
Preferred Solution 11	28.38	13.04	53	748.22
Preferred Solution 12	28.35	13.04	53	756.25
Preferred Solution 13	28.35	13.04	54	741.65
Preferred Solution 14	28.35	13.04	54	741.60
Preferred Solution 15	28.31	13.05	54	756.12

Table 10
The common carbon dioxide emission factor (Ton CO_2/Ton).

Energy Resource	Carbon Dioxide Emission	Energy Resource	Carbon dioxide emission
Raw coal	2.07	Kerosene	3.08
Cleaned coal	2.49	Diesel	3.16
Coke	3.04	Liquefied petroleum gas	3.17
Crude Oil	3.07	Natural gas	2.84
Fuel oil	3.24	Coke oven gas	7.71
Gasoline	3	Other coal gas	5.92

that the proposed algorithm is able to find reasonable solutions with relatively good performances of convergence, uniformity and distribution. The solution set but not a single solution is offered to decision makers for further selection according to different preferences. Either a set of sorted solutions, or a preferred solution or a few preferred solutions can be decided. In average, the optimization set of solutions bring about reduction of 2697.58 tons of feed oil and 8281.57 tons of CO_2 emission.

The flexible membrane structure and free design of evolution and communication rules make the CCEMA extensible to more optimization problems. In the future, we will make a deep research on the improvement of the CCEMA in solving many-objective optimization problems with more than three objectives, on both test functions and other

Table 11
The reduced amount of carbon dioxide emission after MOP.

Optimum Objectives	Oil Flow (kg/h) (per single tube)			Total reduced CO_2 emission (Ton)
	Before Optimization	After Optimization	Total Reduced Consumption (Ton)	
Optimum Ethylene Yield	890.63	741.35	2866.18	8799.16
Optimum Propylene Yield	890.63	593.79	6155.27	18896.69
Optimum Cracking Cycle	890.63	808.59	2835.30	8704.38
Sorted Solution 1	890.63	748.22	3663.92	11248.25
Sorted Solution 2	890.63	861.19	757.43	2325.32
Sorted Solution 3	890.63	764.42	3247.13	9968.69
Sorted Solution 4	890.63	641.35	6413.48	19689.37
Sorted Solution 5	890.63	776.62	2933.25	9005.08
Preferred Solution 1	890.63	741.35	3840.68	11790.87
Preferred Solution 2	890.63	741.59	3834.50	11771.92
Preferred Solution 3	890.63	747.44	3684.00	11309.86
Preferred Solution 4	890.63	746.69	3703.29	11369.10
Preferred Solution 5	890.63	743.91	3774.81	11588.67
Average Oil Flow	890.63	785.78	2697.58	8281.57

chemical processes like the PTA production process.

Declaration of Competing Interest

None.

Acknowledgements

This work is partly funded by the National Key Research and Development Program of China (2017YFC1601800), the National Natural Science Foundation of China (61603025 and 61533003) and Fundamental Research Funds for the Central Universities (XK1802-4).

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