

New immune multiobjective optimization algorithm and its application in boiler combustion optimization

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Abstract: In order to meet the requirements of combustion optimization for saving energy and reducing pollutant emission simultaneously, an immune cell subsets based multiobjective optimization algorithm (ICSMOA) is proposed. In the ICSMOA, the subset division operator and the immunological tolerance operation are defined. Preference can be easily addressed by using the subset division operator, and the distribution of the solutions can be guaranteed by the immunological tolerance operation. Using the ICSMOA, a group of Pareto optimal solutions can be obtained. However, by the traditional weighting method (WM), only one solution can be obtained and it cannot be judged as Pareto optimal or not. In contrast to the solutions obtained by the repeatedly performed WM, the simulation results show that most solutions obtained by the ICSMOA are better than the solutions obtained by the WM. In addition, the Pareto front obtained by the ICSMOA is not as uniform as most classical multiobjective optimization algorithms. More optimal solutions which meet the preference set by the decision-maker can be obtained and they are very useful for industrial application.

Key words: combustion optimization; multiobjective optimization; immune cell subsets

With the emphasis on environmental protection, how to reduce NO_x emissions of power plants has attracted more and more attention. Accordingly, the problem of boiler combustion optimization can be described as the problem of simultaneously improving boiler efficiency and limiting pollutant emissions. Most factors affecting the efficiency and the emissions are similar, but some of them have conflicts.

In order to solve the combustion optimization problem, several optimization methods have been proposed. However, most of them solve the optimization problem as a single objective problem by the weighting method (WM)^[1-2] and few attempts have been made to take it as a multiobjective problem. Although some multiobjective algorithms are used in the boiler combustion optimization, they all adopt the existing classical multiobjective algorithms^[3-4] and they do not take the specificities of the boiler combustion into consideration.

In recent years, with the development of the theory of life

science and artificial intelligence, several computational models of the immune system have been proposed^[5-9]. The immune algorithm is a new direction for multiobjective optimization. In view of the specificities of the boiler combustion optimization problem, a novel multiobjective optimization algorithm named the immune cell subsets based multiobjective optimization algorithm (ICSMOA) is proposed in this paper.

1 Related Background

1.1 Multiobjective optimization

Generally, a multiobjective optimization problem can be described as^[10]

$$\begin{aligned} \min f(X) &= (f_1(X), f_2(X), \dots, f_n(X)) \\ \text{s. t.} \\ g_p(X) &\geq 0 \quad p = 1, 2, \dots, l \\ h_q(X) &= 0 \quad q = 1, 2, \dots, m \end{aligned} \quad (1)$$

where $X = [x_1, x_2, \dots, x_r] \in \Omega$ is the decision vector, and Ω is the feasible region.

Because there are at least two objectives, usually there is no absolutely exclusive optimal solution. The notion of “optimal” is transformed into “Pareto optimal”. The formal definitions are described as follows^[10].

Definition 1 $\forall X_i, X_j \in \Omega$, if $\forall t \in 1, 2, \dots, n, f_t(X_i) \leq f_t(X_j)$ together with $\exists s \in 1, 2, \dots, n, f_s(X_i) < f_s(X_j)$, we say that X_i dominates X_j , marked as $X_i < X_j$.

Definition 2 $\forall X_i, X_j \in \Omega$, if $\exists t \in 1, 2, \dots, n, f_t(X_i) < f_t(X_j)$ together with $\exists s \in 1, 2, \dots, n, s \neq t, f_s(X_i) > f_s(X_j)$, we say that X_i has nothing to do with X_j , marked as $X_i \circ X_j$.

Definition 3 $X_i \in \Omega$ is said to be a Pareto optimal solution iff $\neg \exists X_j \in \Omega, \text{ s. t. } X_j < X_i$.

1.2 Immunology background

From the viewpoint of information processing, the immune system is a parallel adaptive system. It has characteristics such as learning, self-organization, and distribution, etc^[11]. The immune algorithm has become an important research field of artificial intelligence since the last decade. At present, the main mechanism of the artificial immune system used for optimization is clone selection and immune network theory, while the other principles are seldom used. Using the new immune mechanism to establish a new multiobjective optimization algorithm is the main purpose of this paper, which is suitable for engineering applications.

Immune cells are the cells which participate or have some relationship with immune responses. From generation to maturation and entering the immune cycle, immune cells have to experience complex changes. According to different

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characteristics in development, immune cells can be divided into different subsets^[12].

The artificial immune cell model is built based on the life-cycle of immune cell which mainly includes immunological tolerance, clone, mutation, memory, death and other processes^[13]. Inspired by the theory of immune cell subsets, we propose a new multiobjective optimization algorithm IC-SMOA based on the immune cell model.

2 Description of ICSMOA

For convenience of description, we give some notations in advance. C is the abbreviation for a cell, and in the algorithm it means a candidate solution. CS is the abbreviation for a cell subset. MC is the abbreviation for a memory cell, and in the algorithm it is used to represent a Pareto solution. MCS is the abbreviation for a memory cell subset. The sizes of decision variables and objectives are denoted as dec and obj, respectively.

2.1 Operator definition

In this paper, we follow the naming rules of the immune cell theory, but the meanings are newly defined. The operators in the ICSMOA are defined as follows.

Definition 4 (subset division operator) Inspired by B cell and T cell subset theory, we design the subset division operator to divide the cells into subsets.

Before subset division, the objectives are sorted according to preference. The first objective is the most preferred objective. The second objective is the second-most preferred objective. And the remaining objectives are sorted by analogy.

Usually, the number of the subsets is set as obj + 1. The first subset contains the cells which perform best at the first objective, and the second subset consists of the cells which have the best value according to the second objective. Similarly, until the No. obj subset is built up by the cells which perform best at the No. obj objective and the remaining constitutes No. obj + 1 subset. The subset division satisfies:

- 1) $CS_1 + CS_2 + \dots + CS_k = \text{cell_set}$;
- 2) $\forall i \neq j, i \leq k, j \leq k, CS_i \cap CS_j = \emptyset$.

Definition 5 (affinity maturation operation) In this paper, affinity means the similarities between the cells. We define them as the number of cells within the neighborhood of the cell, and the radius of the neighborhood is adaptive within the implementation of the algorithm.

$$\text{aff}(C_i) = \sum_j \text{sig}(C_i, C_j) \quad (2)$$

$$\text{sig}(C_i, C_j) = \begin{cases} 1 & \text{dis}(C_i, C_j) < \text{set_limit_R} \\ 0 & \text{dis}(C_i, C_j) \geq \text{set_limit_R} \end{cases} \quad (3)$$

With affinity maturation operation, each non-dominated solution of every subset is judged if it is a non-dominated solution of the whole cell group. When the answer is true, it will enter the memory cell set.

$$\text{mature}(C_i) = \begin{cases} 1 & C_i \in \text{Pareto}(\text{Pareto}(CS_1) + \dots + \text{Pareto}(CS_k)) \\ 0 & C_i \notin \text{Pareto}(\text{Pareto}(CS_1) + \dots + \text{Pareto}(CS_k)) \end{cases} \quad (4)$$

Theorem 1 Non-dominated solutions of the set composed of non-dominated solutions of each subset are equivalent to the non-dominated solutions obtained from the original cell set, i. e. ,

If $\text{cell_set} = CS_1 + CS_2 + \dots + CS_k$,

and $CS_i \cap CS_j = \emptyset, i \neq j$, then

$\text{Pareto}(\text{cell_set}) = \text{Pareto}(\text{Pareto}(CS_1) + \dots + \text{Pareto}(CS_k))$

Proof

“ \Rightarrow ”

Assume $x \in \text{Pareto}(\text{cell_set})$, and

$x \notin \text{Pareto}(\text{Pareto}(CS_1) + \dots + \text{Pareto}(CS_k))$

1) $x \notin \text{Pareto}(\text{Pareto}(CS_1) + \dots + \text{Pareto}(CS_k))$

$\Rightarrow \exists y \in \text{Pareto}(\text{Pareto}(CS_1) + \dots + \text{Pareto}(CS_k)), y < x$

and

$y \in \text{Pareto}(\text{Pareto}(CS_1) + \dots + \text{Pareto}(CS_k))$

$\Rightarrow y \in \text{cell_set}$

2) $x \in \text{Pareto}(\text{cell_set}) \Rightarrow \neg \exists y \in \text{cell_set}, y < x$.

Conflict exists.

Thus $x \in \text{Pareto}(\text{cell_set}) \Rightarrow$

$x \in \text{Pareto}(\text{Pareto}(CS_1) + \dots + \text{Pareto}(CS_k))$.

“ \Leftarrow ”

Assume $x \in \text{Pareto}(\text{Pareto}(CS_1) + \dots + \text{Pareto}(CS_k))$, and

$x \notin \text{Pareto}(\text{cell_set})$

1) $x \notin \text{Pareto}(\text{cell_set}) \Rightarrow \exists y \in \text{cell_set}, y < x$

2) $x \in \text{Pareto}(\text{Pareto}(CS_1) + \dots + \text{Pareto}(CS_k))$

$\Rightarrow y \notin \text{Pareto}(CS_m), m = 1, 2, \dots, k$

$\Rightarrow y \notin \text{cell_set}$.

Conflict exists.

Thus $x \in \text{Pareto}(\text{Pareto}(CS_1) + \dots + \text{Pareto}(CS_k))$

$\Rightarrow x \in \text{Pareto}(\text{cell_set})$.

This completes the proof of theorem 1.

Definition 6 (clone operator) Clone means asexual reproduction, thus a group of identical cells can be descended from a single original ancestor. In the ICSMOA, the clone size of each source cell is determined by the affinity and the preference of the objective. The cell with lower affinity and greater preference will be reproduced more times.

Assuming that $(C_{11}, \dots, C_{1i}; \dots; C_{k1}, \dots, C_{ki})$ are the cells for the clone, preference proportion for objective j is set as $\text{prefer}(j)$, M_j is the modified coefficient, and then the clone size of cell C_{js} is

$$M_{js} = \text{int} \left(\frac{M_j \prod_{i=1}^{i_j} \text{aff}(C_{ji})}{\text{aff}(C_{js}) \text{prefer}(j)} \right) \quad (5)$$

After clone proliferation, all the cells have to experience hyper-mutation. In this paper, the mutation proportion is set as 100%.

Definition 7 (immunological tolerance operation) Based on the immune cell model, the process of immunological tolerance operation is outlined in Fig. 1. If the new immune cell can pass the immunological tolerance, it will be regarded as a mature cell. According to Ref. [14], a great deal of new generated anti-self-reactive cells are not cleared immediately, instead, receptor editing occurs in most cases. And as a result of receptor editing, anti-self-reactive cells can be conver-

ted to non-self-reactive cells. Inspired by this, a random number is generated to determine the anti-self-reactive cells to undergo receptor editing or die immediately.

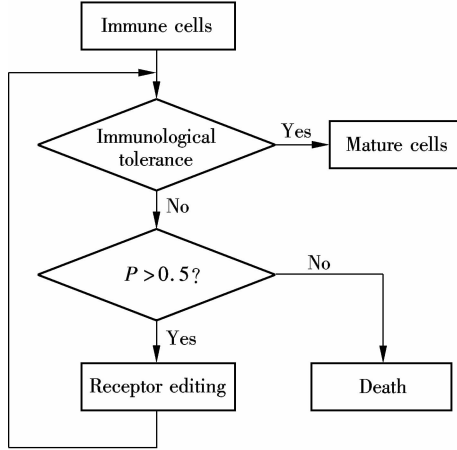


Fig. 1 Flowchart for processing immunological tolerance

The central tolerance operation can be described as

$$\text{central_tole}(C_i) = \begin{cases} 1 & \text{neighbor_count}(C_i) < \text{set_limit} \\ 0 & \text{neighbor_count}(C_i) \geq \text{set_limit} \end{cases} \quad (6)$$

If the number of cells around the new generated cell is under the set limit, the cell will survive. With the examination of central tolerance, new cells cannot be much concentrated, so that better distribution of the candidates can be guaranteed.

The peripheral tolerance operation can be described as

$$\text{peri_tole}(C_i) = \begin{cases} 1 & C_i < C_{\text{source}} \text{ or } C_i \circ C_{\text{source}} \\ 0 & \text{others} \end{cases} \quad (7)$$

The new cell after mutation is compared with the clone source. If it is not inferior to the clone source, it will survive. If the new cell is dominated by the clone source, there will be no possibility for it to be a non-dominated solution, and there will be no need to preserve it for the next generation. In this way, the computational complexity of the next generation can be decreased.

Definition 8 (receptor editing operator) The receptor editing operator disposes of the cells which have not passed the affinity test. It maps the cells to the surroundings of the cell which has the lowest affinity. We take a two-dimensional condition as an example to describe the problem simply.

The schematic diagram is shown in Fig. 2. As for a high dimensional condition, we suppose that cell B has the lowest affinity and cell A_i is the cell for receptor editing, and then the coordinate of the new cell D_i can be described as follows:

Coordinate of B : (B^1, B^2, \dots, B^d) ;

Coordinate of A_i : $(A_i^1, A_i^2, \dots, A_i^d)$;

Coordinate of D_i : $(D_i^1, D_i^2, \dots, D_i^d)$.

The range of each dimension is $(\text{down}^j, \text{upper}^j)$, $j \in 1, 2, \dots, d$,

$$D_i^j = \begin{cases} B^j - \frac{B^j - A_i^j}{B^j - \text{down}^j} R^{1/2} & A_i^j < B^j \\ B^j + \frac{A_i^j - B^j}{\text{upper}^j - B^j} R^{1/2} & \text{others} \end{cases} \quad (8)$$

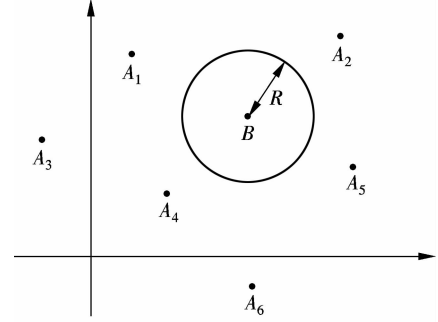


Fig. 2 Schematic figure for receptor editing

Definition 9 (redundant memory cell removal operator)

Redundant memory cell removal operator is executed in the case that memory pool size exceeds the set limit. The redundant cells are removed one by one according to preference and affinity.

2.2 Running mechanism of the algorithm

With the operators described in section 2.1, the running mechanism of the ICSMOA is designed and shown in Fig. 3. Except for the first generation, the immune cell set contains three parts: new generated cells obtained from the central tolerance, mature cells obtained from the peripheral tolerance and memory cells obtained from the former generation. New cell sets are divided into subsets, and the non-dominated set of each subset is regarded as the clone source. We design the clone source in this way to guarantee the quantity of the clone source which is helpful for subsequent searching.

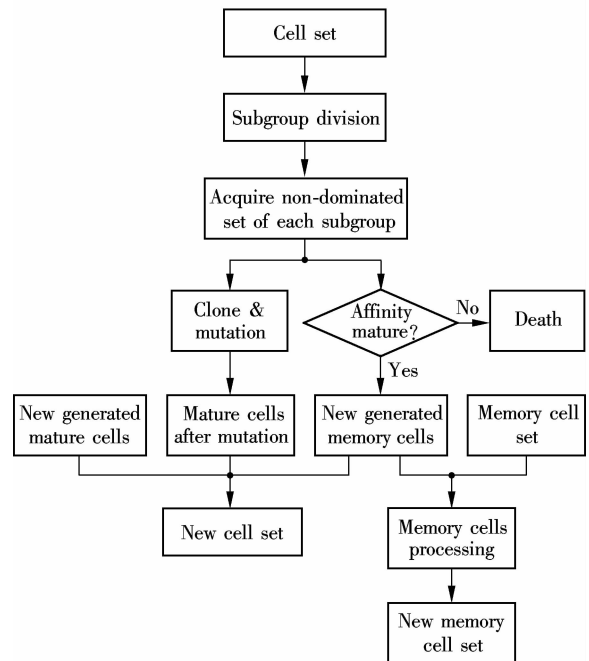


Fig. 3 Running mechanism of ICSMOA

Fig. 4 is the flowchart for processing the memory cells. First, the new generated memory cells are combined with the former memory cells. Then the non-dominated set of the combo is found, and the redundant memory cell removal operation is executed if needed.

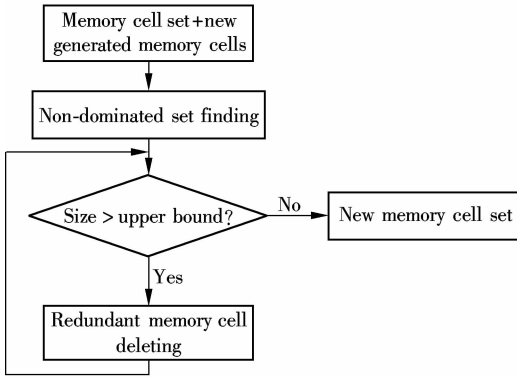


Fig. 4 Flowchart for processing memory cells

2.3 Analysis of ICSMOA

Unlike the existing MOAs, the ICSMOA can be characterized as follows:

1) Immune cells are divided into subsets, and the Pareto optimal set is correspondingly divided into several subsets. On the one hand, the computational complexity of obtaining a non-dominated set can be reduced to some extent. On the other hand, we can easily express the preference.

2) We define two new operators, immunological tolerance and receptor editing. The experimental results show that they are very useful in diversity preservation and keeping the algorithm from prematurity.

3) The affinity value is set as the cell number in the neighborhood, and the bounds of the neighborhood is adjustable. On the one hand, there is no need to compute Pareto rank which is time-consuming. On the other hand, it is very effective in preventing the algorithm from falling into the local optimal solutions.

4) The clone size is determined by the preference and the affinity; thus more preference optimal solutions can be obtained.

3 Simulation

The boiler combustion system is a complex multi-input and multi-output nonlinear system. The emissions of the boiler is associated with fuel characteristics, boiler load and various operating parameters, so it is difficult to establish an analytical function model and we have to establish a model through the black-box method to meet the requirements of optimization. In this paper, we adopt the SVM (support vector machine) algorithm to establish the statistical boiler combustion model since it has good performance even if when a small amount of samples are provided.

3.1 Boiler combustion system modeling based on LSSVM

The SVM algorithm uses the principle of minimizing the structural risk to ensure the promotion of the model, and it is effective in solving the problem of generalization^[15]. The LSSVM (least squares support vector machine) is an exten-

sion of the standard SVM. The LSSVM uses equality constraints instead of inequality constraints in the SVM. Correspondingly, the nonlinear equations required to be solved become the linear equations. So the LSSVM has advantages in computational speed and it is more suitable for online application^[16].

1) Input and output of the LSSVM

Here we use the data provided in Ref. [17]. The data are obtained from a 300 MW pulverized coal fueled boiler. According to the result in Ref. [18], the RBF function $\exp(-\|x - x_i\|^2 / 2\sigma^2)$ is used as the kernel function. In order to express the relationships between the parameters, a three-level LSSVM model is established as shown in Fig. 5.

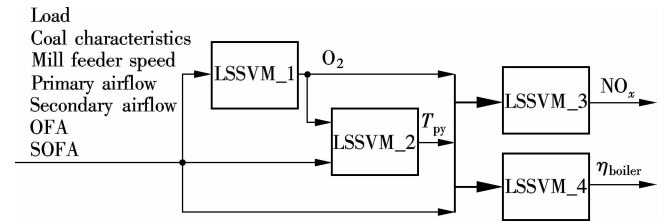


Fig. 5 LSSVM model for NO_x emission and boiler efficiency

2) Parameter searching of LSSVM

We use the method proposed in Ref. [19] for parameter searching. The boundaries of C and σ^2 are set as $[1, 1000]$ and $[0.001, 10]$, respectively. Parameters of each LSSVM are shown in Tab. 1.

Tab. 1 Optimized parameters of LSSVM

LSSVM	C	σ^2
1	912.1	5.026
2	798.3	5.023
3	724.2	10.000
4	685.6	9.980

3) Training results

We select the last one as the test sample and the others as training samples, and the training results are shown in Fig. 6. It is clear that the output of the LSSVM is very close to the real value. The biggest relative error is below 1%.

3.2 Boiler combustion optimization based on ICSMOA

We select the secondary airflow, OFA, SOFA as decision variables, and the NO_x emissions and the boiler efficiency as two objectives. The ICSMOA is performed under some conditions. Here, we select the conditions which have the extreme values of the NO_x emissions or the boiler efficiency; i. e., conditions 2, 5 and 18. The original values of the NO_x emissions and the boiler efficiency under these conditions are shown in Tab. 2^[17].

Tab. 2 Values of NO_x emissions and η_{boiler} in conditions 2, 5 and 18

Condition	NO _x emission concentration/(mg · Nm ⁻³)	η_{boiler} /%
2	716.05	89.15
5	906.05	91.91
18	552.00	90.41

Running results are shown in Fig. 7. We also use the solution of the WM in Ref. [1] for comparison. Running results of the ICSMOA are a group of Pareto solutions and the circles are the Pareto front obtained by the ICSMOA.

It is obvious that most WM solutions are under the Pareto

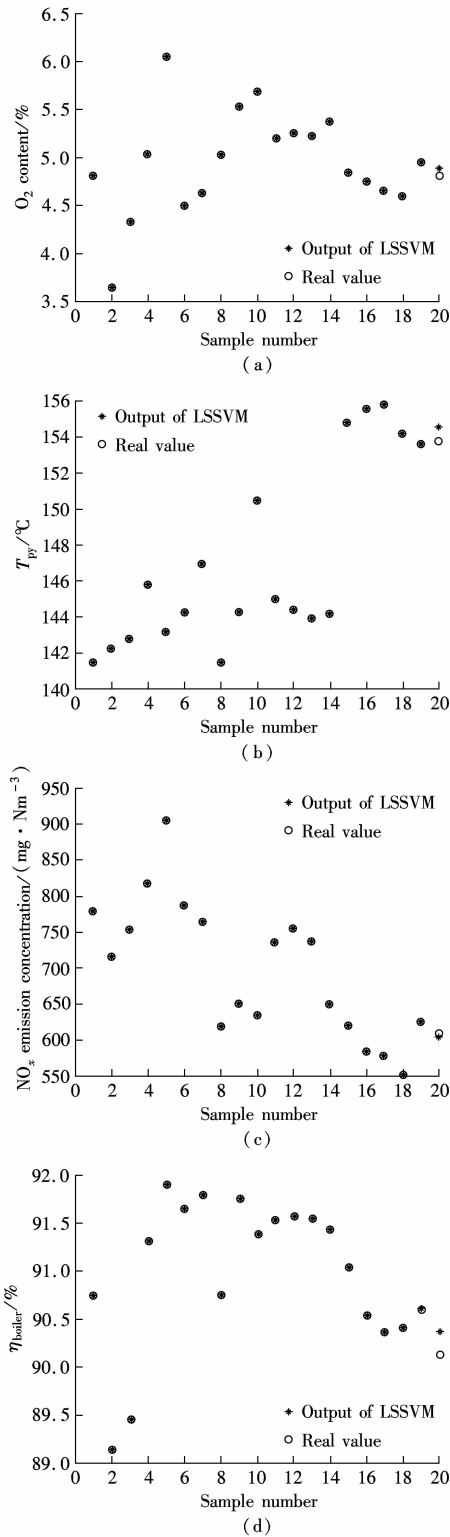


Fig. 6 Comparisons of real values and LSSVM regression values. (a) O_2 content; (b) T_{py} ; (c) NO_x emission; (d) η_{boiler}

front and very few of them are barely in the Pareto front. The reason is that the solutions of the WM are obtained through an objective optimization method which can only provide one solution at a time. And we cannot judge whether the solution is Pareto optimal or not. Multiple stars in Fig. 7 are the repeatedly performed solutions of the WM.

From Fig. 7(a) we can see that the NO_x emission and the boiler efficiency can be optimized at the same time when optimization space exists. But in condition 5, the decrease

of NO_x emissions is accompanied by the decrease in efficiency. Similarly, in condition 18, the boiler efficiency increases with the increase in NO_x emissions. The reason is that there are conflicts between the two objectives. So, when there is no optimization space, the objectives must be considered comprehensively. There is no absolute optimization for both the two objectives.

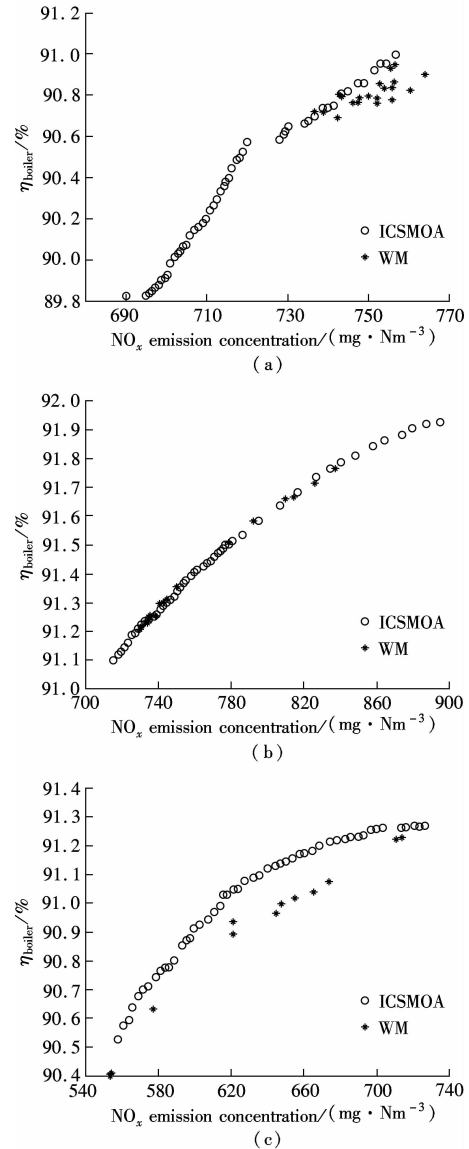


Fig. 7 Optimization results of NO_x emission and boiler efficiency. (a) Condition 2; (b) Condition 5; (c) Condition 18

It should be pointed out that the Pareto front obtained by the ICSMOA is different from that by SPEA2, NSGA-II and most classical MOAs. The classical MOAs pursued for the distribution of Pareto front is uniform, no matter what the preference is. The output of the ICSMOA has added the preference factor, so abundant preferred solutions can be output to meet the requirements of the decision-makers.

As for condition 2 and condition 5, since the NO_x emission is higher than the government regulations regarding it, we prefer the solutions of a lower NO_x emission. The results show that there are abundant solutions with lower NO_x emission whereas the solutions in the higher NO_x district are very sparse. As for condition 18, because the NO_x emission is

less than the government regulations prescribe, the efficiency is relatively low. Under this condition, the solutions with higher efficiency are preferred.

4 Conclusion

The simulation shows that if there is optimization space, the increase in the boiler efficiency and the decrease in the NO_x emission are not contradictory. However, when there is no optimization space, the boiler efficiency and the NO_x emission will be increased or decreased simultaneously.

The simulation results show that the ICSMOA is an effective method for boiler combustion optimization when compared with the WM. Multiple Pareto solutions can be found in a single run by the ICSMOA while only one solution can be obtained by the WM. Compared with the solutions obtained by the repeatedly performed WM, the Pareto solutions obtained by the ICSMOA are better.

On the other hand, the distribution of the Pareto front obtained by the ICSMOA is not the same as that obtained classical MOAs since we use the preference factor in the searching process, so more solutions which meet the preference set by the decision-maker can be obtained and they are very useful for industrial applications.

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一种新的免疫多目标优化算法及其在锅炉燃烧优化中的应用

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摘要:为了综合考虑锅炉燃烧优化问题中锅炉效率与 NO_x 排放 2 个目标,提出了一种新的基于免疫细胞亚群的多目标优化算法 ICSMOA. 算法定义了亚群划分算子与免疫耐受算子,亚群划分可以很方便地表达偏好,免疫耐受则能保证解的分布性. ICSMOA 的运行结果为一组 Pareto 最优解,而传统的加权法的运行结果为一个不能判断 Pareto 占优与否的解. 与多次运行加权法获得的结果相比,所提算法的运行结果优于加权法. 另外,运行 ICSMOA 所获得的 Pareto 前沿不同于经典的多目标优化算法,它可以输出更多的满足决策者偏好的解,从而更适用于工业应用.

关键词: 燃烧优化; 多目标优化; 免疫细胞亚群

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