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Research Article

Application of Improved NSGA-II to Multi-objective Optimization of a Coal-fired Boiler Combustion Electronical Systems in Green Food Bases

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Abstract: In this study, we have a research of a hybrid algorithm by combining BP neural network and improved Non-dominated Sorting Genetic Algorithm-II (NSGA-II) to solve the multi-objective optimization problem of a nanoscale coal-fired boiler combustion electronical systems, the two objectives considered are minimization of overall heat loss and NOx emissions from coal-fired boiler. First, Back Propagation (BP) neural network was dopted to establish a mathematical model predicting the NOx emissions and overall heat loss of the coal-fired boiler with the inputs such as operational parameters of the nanoscale coal-fired boiler. Then, BP model and the Non-dominated Sorting Genetic Algorithm II (NSGA-II) were combined to gain the optimal operating parameters which lead to lower NOx emissions and overall heat loss boiler. According to the problems such as premature convergence and uneven distribution of Pareto solutions exist in the application of NSGA-II, corresponding improvements in the crowded-comparison operator and crossover operator were performed. The optimization results show that hybrid algorithm by combining BP neural network and improved NSGA-II can be a good tool to solve the problem of multi-objective optimization of a nanoscale coal-fired boiler combustion electronical systems in green food bases, which can reduce NOx emissions and overall heat loss effectively for the nanoscale coal-fired boiler combustion electronical systems in green food bases. Compared with original NSGA-II, the Pareto set obtained by the improved NSGA-II shows a better distribution and better quality.

Keywords: Coal-fired boiler, combustion electronical systems in green food bases, green food bases, improved NSGA-II, multi-objective optimization

INTRODUCTION

In China, the requirements for environmental protection are increasingly strict, especially for coal-fired utility boiler. Coal remains the primary energy resource in China and one of the major concerns associated with coal-fired power plants is the emission of pollutants, especially for NO_2 and NO (collectively referred to as NOx). Today, NOx emission is regulated and has become an important consideration in the design and modification of coal-fired utility boiler (Liu *et al*., 2008; GB13223-2011, 2011). However, many old-designed utility boilers in China emit the NOx pollutants above the limit and have posed terrible threat to the surrounding environment, coal-fired power plants face important challenges concerning the methods and technologies to meet these new environmental requirements. In addition to the developments in the plant construction and flue gas cleaners, the control of the boiler operating conditions through combustion optimization is an important and cost-effective way to affect NOx emissions (Xu *et al*., 2006; Liang *et al*., 2006; Gao *et al*., 2011).

In recently years, many scholars applied intelligent methods to optimization of coal-fired boiler combustion (Zheng *et al*., 2009). However, it is well known that the coal-fired boiler combustion is one of the most complex problem system, NOx emission from utility boilers and the boiler efficiency are the different functions of fuel properties, boiler design and operating variables. In the combustion optimization, the conflict between low NOx emission and high boiler thermal efficiency encounters, the operation parameters suited to lower NOx emissions of coal-fired boiler always lead to a higher carbon content in fly ash and lower efficiency of the boiler, the above studies on optimization of coal-fired boiler combustion mainly focus on the single-objective optimization, for only on the emissions of NOx from the boilers or only boiler efficiency alone and can't reach both lower NOx emissions and higher efficiency of boiler, it is imperative to find a good tool for multi-objective optimization of coal-fired boiler combustion.

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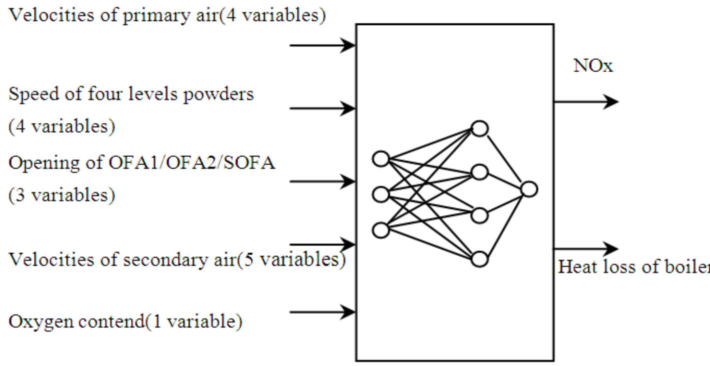

Fig. 1: BP neural network mathematical model of the coal-fired boiler

In order to get the minimum NOx emissions and maximum boiler efficiency, two objectives considered are minimization of overall heat loss and NOx emissions from coal-fired boiler. BP neural-network was proposed to model NOx emissions and overall heat loss of the coal-fired boiler, then the NSGA-II was introduced as multi-objective optimization algorithms combined with BP neural network model to obtain the Pareto-optimal solution set of the multi-objective optimization of coal-fired boiler combustion problem. According to the problems such as premature convergence and uneven distribution of Pareto solutions exist in the application of NSGA-II, corresponding improvements in the crowded-comparison operator and crossover operator were performed in this study.

MATHEMATICAL MODEL OF NOX EMISSIONS AND BOILER HEAT LOSS

Brief description of the boiler: The boiler is a 300 MWe, tangentially fired dry bottom boiler with double furnaces, equipped with indirect-fired coal-storage pulverizing system and exhaust pneumatic convey system, four DTM350/600 drum ball mill, four exhaust fans, 32 powders, using horizontal and louver type concentrated diluted pulverized coal burner. The Maximum Continuous Rating (MCR) of the boiler is 1025 t/h of superheated steam at 538°C. The boiler had four levels of primary air nozzles (A, B, C, D) and five levels of secondary air nozzles (AA, AB, BC, CD, DE), two levels of over-fire air nozzles (OFA1,OFA2), a level Separated Over-Fire Air nozzles (SOFA).

BP model of NOx emissions and boiler heat loss: As BP neural network has good nonlinear mapping ability, the paper introduced the BP neural network to establish mathematical model of the coal-fired boiler combustion characteristics, which is used to evaluate the NOx emissions (at 6 vol% O_2 dry) from the boiler and the overall heat loss of boiler. Moreover, the model can be employed as the objective functions in the later multi-objective optimization of coal-fired boiler combustion.

On the basis of test data of the 300 MWe boiler[3], BP neural network mathematical model of the coal-fired boiler combustion characteristics under the steady-state operation conditions was established, 17 parameters closely related to the NOx emissions and the overall heat loss from the boiler were selected as the input variables: Four levels primary Air average velocities (A-D), four levels Average speed of the powders (A-D), five levels secondary Air Average velocities (AA-DE), three Opening percent of the over-Fire Air nozzles (OFA1/OFA2/SOFA) and the oxygen content in the exhaust gas from the boiler. The output of the BP model are NOx emissions and the overall heat loss from the boiler, thus the BP neural network has 17 neurons with input layer, two output neuron in the output layer, according to a large number of simulation, we finally select 21 neurons in the hidden layer for the BP model show as in Fig. 1.

Improved NSGA-II:

Disadvantage of NSGA-II: In the application of the NSGA-II to coal-fired boiler multi-objective optimization problem, we found that the distribution of the obtained Pareto-optimal solution set is not very satisfactory, a large number of the solutions often concentrated in some regions, this phenomenon of premature convergence of NSGA-II is the same mechanism as the conventional genetic algorithm[15], Since the NSGA-II was developed from genetic algorithm. Although the elitist strategy used in NSGA-II accelerated the speed of optimization, but it also reduced the diversity of the population, NSGA-II crowded-comparison operator also has its own defects , i.e., the density of information is estimated that only limited with a non-dominated individuals concentrated and therefore cannot reflect the density of individuals around, thus the diversity of solutions set obtained by the NSGA-II in the coal-fired boiler multi-objective optimization problem is still not ideal.

In the NSGA-II crowded-comparison operator, the crowding-distance of individual i is calculated as follows:

$$D_i^d = \frac{1}{r}\sum_{m=1}^{r}\frac{f_{i+1}^m - f_{i-1}^m}{f_m^{\max} - f_m^{\min}} \tag{1}$$

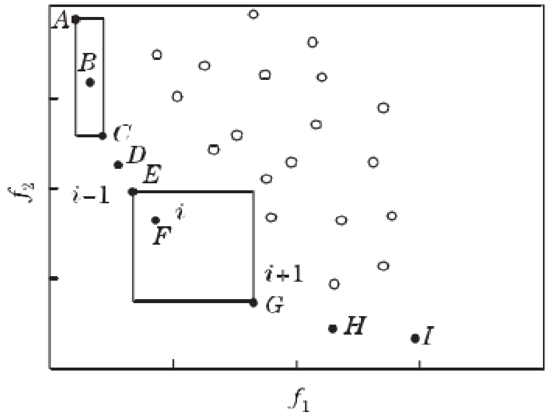

Fig. 2: Individual crowding-distance schematic

where, r is the number of objectives, f_{i+1}^{m}, f_{i-1}^{m} are the value of the i+1 and i-1 individuals m^{th} target respectively, f_{m}^{max}, f_{m}^{min}, are the minimum and maximum values of the m^{th} target.

According to the crowding-distance, the NSGA-II population diversity conservation strategy as: If the population size is N, the size of current non-dominating set is M and $M>N$; According to Eq. (1) to calculate the population of M non-dominant individuals crowding-distance (two end points of individuals were assigned infinity), then Sort these M individuals According to the crowding-distance from small to large, Finally, the number of M-N individuals which has the minimum crowding-distance were removed from the population one-time, so as to achieve the purpose of pruning.

The above diversity maintain strategy has two defects:

- Shown as Fig. 2, individuals with solid black A-I are non-dominated individuals, due to the crowding distance of the C, D, E are smaller, If you remove all the small individual C, D, E at once, big gap occurs between the individual B and F, Thus affecting the distribution of solutions.
- For individual B, because large difference in the one-dimensional target and very small difference in another dimension to the target, which lead to the crowding-distance of B is also smaller. For individual F, due to the difference in each dimension objectives are less, the crowding-distance of F is also larger than B, thus individual B is removed, In fact, the distribution of B is better than that of F.

Improved NSGA-II: For the above-mentioned defects of the NSGA-II, crowded-comparison operator and crossover operator for NSGA-II has been improved.

Improvement of crowded-comparison operator: Reference to the literature[16], the concept of Dynamic Crowding-Distance (DCD) was introduced, two improvements were made as following to the crowded-comparison operator:

- In the process of population maintenance, after each removal of an individual, recalculation of the remaining population crowding-distance of each individual were performed.
- The i^{th} Individual Dynamic Crowding-Distance (DCD) is calculated according to Eq. (2):

$$D_i^{dd} = D_i^{d} / log\ (1/V_i) \tag{2}$$

Of which: D_i^{d} is calculated according to Eq. (1); V_i is calculated according to Eq. (3) as follows:

$$V_i = \frac{1}{r}\sum_{m=1}^{r}(|\ f_{i+1}^{m} - f_{i-1}^{m}\ | - D_i^{d})^2 \tag{3}$$

where, V_i is the variance of crowding-distances of the individuals that are the neighbors of the i^{th} individual.

Improvement of the crossover operator: SBX crossover operator was adopted in initial NSGA-II, cross-point position was received randomly and the genetic codes of two parent individuals on both sides of the crossing point were exchanged. In this study, the arithmetic crossover operator to improve the crossover operator of NSGA-II.

Let x_i^t and x_j^t are the real value codes of the corresponding decision variables for the two individuals at the t^{th} generation respectively, The crossover procedure for finding the offspring solutions x_i^{t+1} and x_j^{t+1} from parent solutions x_i^t and x_j^t is given below:

$$\begin{cases} x_i^{t+1} = ax_i^t + (1-a)x_j^t \\ x_j^{t+1} = bx_j^t + (1-b)x_i^t \end{cases} \tag{4}$$

where, a, b are the uniformly distributed random number between 0 to 1, compared with the SBX operator, improved operator has better global search ability and maintain the population diversity better.

Polynomial mutation: The probability of creating a solution y_i^{t+1} near to the parent is higher than the probability of creating one distant from it. The shape of the probability distribution is directly controlled by an external parameter η_m and the distribution remains unchanged throughout the iterations. Like in the SBX operator, the probability distribution can also be a polynomial function, instead of a normal distribution:

$$y_i^{t+1} = x_i^{t+1} + (x_i^{(U)} - x_i^{(L)})\ \delta_i \tag{5}$$

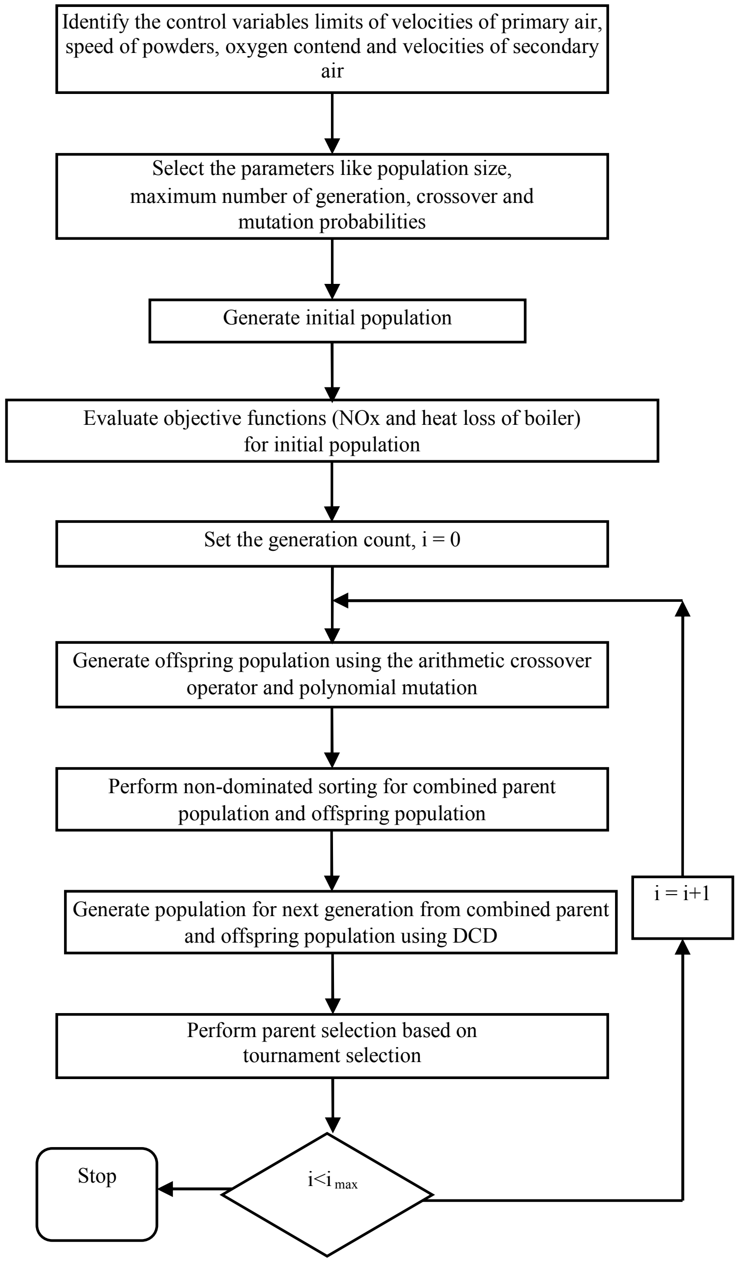

Fig. 3: Flowchart for improved NSGA-II algorithm

where, the parameter δ_i is calculated from the polynomial probability distribution, superscript U and L represents the upper and lower limit for the corresponding variables:

$$P\ (\delta_i) = 0.5\ (\eta_m + 1)\ (1 - |\delta_i\ |)\ \eta_m$$

$$\delta_i \begin{cases} = (2r_i)]^{1/\eta m - 1} - 1, \text{if } r_i < 0.5 \\ = 1 - [2\ (1 - r_i)]^{1/\eta m + 1}, \text{if } r_i \geq 0.5 \end{cases} \quad (6)$$

For handling the bounded decision variables, the mutation operator is modified for two regions:

$[x_i^{(L)}, x_i]$ and $[x_i, x_i^{(U)}]$[17]

Implementation of algorithm: Figure 3 explains the implementation of improved NSGA-II algorithm for the multi-objective coal-fired combustion problem.

The controlled elitism strategy and the DCD approach have been incorporated into the NSGA-II, obtaining an improved optimization algorithm. It is described in the following steps:

Step 1: Identify the control variables limits of the boiler operational parameters like velocities of primary air, speed of powders, oxygen contend and velocities of secondary air for the multi-objective optimization of a coal-fired boiler combustion problem.

Step 2: Select the parameters like number of population, maximum number of generation, crossover and mutation probabilities.

Step 3: Generate initial population.

Step 4: Evaluate objective functions (i.e., *NOx* and Heat loss of the boiler) by the BP model in above section for initial population.

Step 5: Set the generation count.

Step 6: Perform the arithmetic crossover operator and polynomial mutation for the set of individuals.

Step 7: Perform non-dominated sorting (i.e., sorting the population according to each objective function value in ascending order of magnitude).

Step 8: Calculate DCD between the solutions based on the algorithm discussed in above Section.

Step 9: Perform selection based on tournament selection[11] thereby a higher fitness is assigned to individuals located on a sparsely populated part of the front.

Step 10: Increment the generation count and repeat the steps from 6 to 9 until the count reaches the maximum number of generation.

OPTIMIZATION RESULTS OF THE IMPROVED NSGA-II

The optimization objectives of the multi-objective optimization of coal-fired boiler combustion include the minimum of NOx emissions from boiler and the minimum of overall heat loss.

In the process of optimization with the NSGA-II algorithm, the premises include maintain the stability of the boiler load, the same coal injected into the boiler. Moreover, In order to ensure accuracy and reasonableness of the optimal results, there are also some constraints must be taken into account, those constraints include:

- Upper and lower limits of the optimization variables, the range of optimization variables are: primary air velocity of 25~30 m/sec, the secondary air in the AA~DE levels were 25~40 m/sec, OFA dampers opening as 0~100%, oxygen to optimize rang of 3 to 6.5%, the speed of powders ranges from 300~500 rpm.
- Oxygen in the exhaust flue gas is the function of all levels air velocities (include A~D primary air, AA~DE secondary air and OFAs).
- The load of the boiler is the function of A~D speed of powders and the efficiency of the boiler.

In order to compare the optimization results of NSGA-II and improved NSGA-II, the same parameters were selected by NSGA-II and improved NSGA-II as follow: population size = 50, Crossover probability = 0.4, Mutation probability = 0.05, Maximum number of generation = 500. The Pareto-optimal set of multi-objective optimization on the coal-fired boiler obtained by NSGA-II and improved NSGA-II are illustrated by Fig. 4.

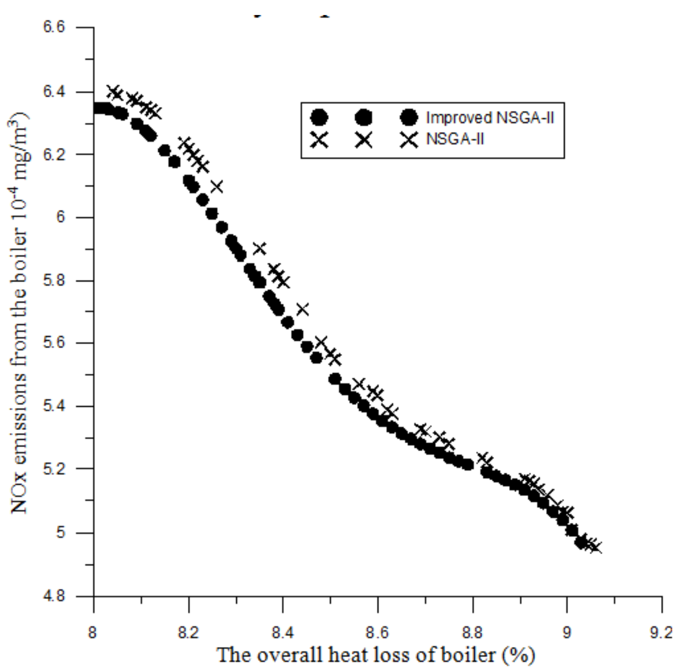

Fig. 4: Pareto-optimal set of multi-objective optimization of a coal-fired boiler combustion

Compared to the data of literature 3, if the boiler operated under the conditions of the Pareto-optimal solutions, the overall heat loss can be decreased by 0.3~1.0% and the NOx emissions can be reduced by 30~40%, in all conditions of the Pareto-optimal solutions, NOx emissions from the boiler are all within the national standard of 650 mg/Nm^3 in China, which demonstrated good results of the NSGA-II applied to the problem of multi-objective optimization of coal-fired combustion. Shown as Fig. 4, distribution of Pareto-optimal set obtained by NSGA-II is not satisfied: most of solutions concentrated in the region of lower NOx, solutions in this region show a higher overall heat loss of the boiler and there are many overlapped solution. However, compared to the Pareto-optimal set of obtained by initial NSGA-II, distribution of the Pareto-optimal set obtained by improved NSGA-II is more uniform, better Pareto solutions are obtained by improved NSGA-II.

CONCLUSION

The aim of this study is to obtain a set of well distributed Pareto solutions on the problem of multi-objective optimization of coal-fired boiler combustions. According to the problems such as premature convergence and uneven distribution of Pareto solutions exist in the application of NSGA-II, corresponding improvements in the crowded-comparison operator and crossover operator were performed in this study. The optimal results show that hybrid algorithm by combining BP neural network and improved NSGA-II can be a good tool to solve the problem of multi-objective optimization of a coal-fired combustion, which can reduce NOx emissions and overall heat loss effectively for the coal-fired boiler. Compared with initial NSGA-II, the Pareto set obtained by the improved NSGA-II shows a better distribution and better quality.

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