c. Take the error E and the error change EC, the flue gas flow G_i and temperature T_i at the inlet as the input variables of the FLC, and take the appropriate transformation factor K_{in} & K_{out} into the fuzzy quantity;

d. According to the fuzzy algorithm, the fuzzy output $\tilde{V}$, $\tilde{Q}_{NH3}$, $\tilde{H}$ is calculated;

e. Obtain the exact descent speed of activated carbon maintained height of charcoal layer, and gas flow according to fuzzy decision-making.

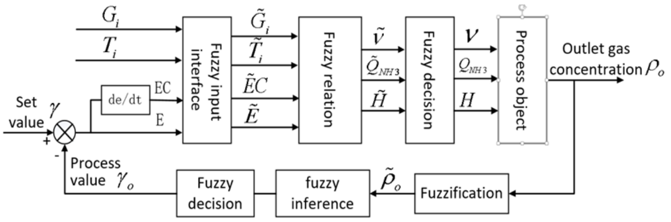

Figure 1: Block diagram of fuzzy control in desulfurization tower

For the desulfurization system, only the theoretical control method and part of the operational experience can be obtained [9]. Therefore, the pre-established fuzzy rules may be rough and cannot meet all the requirements of the working conditions. For example, the desulfurization tower is designed as a multi-tower parallel desulfurization based on the total amount of flue gas. According to the technical requirements, the load of each tower may be inconsistent, and the addition of new activated carbon will also change the desulfurization curve, so concentration of flue gas at the exit cannot meet the requirements [10]. In order to obtain a better control effect, the control rules must be corrected, and the structure of fuzzy adaptive is shown in Figure 2.

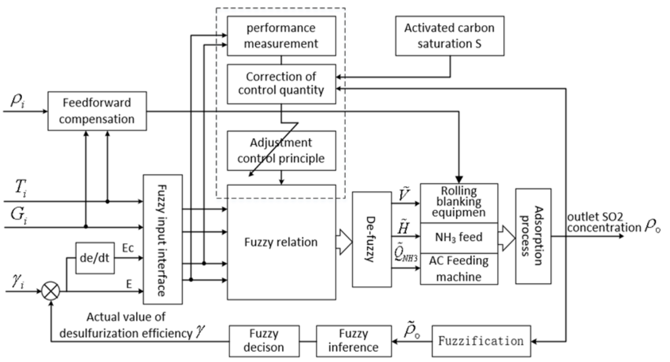

Figure 2: Fuzzy control block diagram modified by rule

Adaptive level algorithm steps are:

1) Performance measurement

The rule correction requires multiple cycles to complete, and the sampling value of the outlet flue gas is obtained in each sampling period [11]. The error E and the variation EC are calculated as the input of the FLC, and the correction amount P(nT), T of the output characteristic is calculated as the sampling period according to E and EC. The performance measurement rules described by linguistic variables are Table 1.

The errors E(nT), EC(nT), and P(nT), which is the output of discourse domain, is determined as:

E(nT) = { -6, -5, -4, -3, -2, -1, -0, +0, +1, +2, +3, +4, +5, +6};
P(nT) = EC(nT) = { -6, -5, -4, -3, -2, -1,0, +1, +2, +3, +4, +5, +6};

Table 1: The adjustment rules determined by E and EC

P E E	NB	NM	NZ	PZ	PS	PM	PB
NB	PB	PB	PB	ZE	ZE	ZE	ZE
NM	PB	PB	PM	ZE	ZE	ZE	ZE
NS	PB	PM	PS	ZE	ZE	NS	AW
ZE	PM	PM	PS	ZE	NS	NS	ZE
PS	ZE	PS	ZE	ZE	NS	NM	NB
PM	ZE	ZE	ZE	NS	NM	NB	NB
PB	ZE	ZE	ZE	NM	NB	NB	NB

2) Correction of control amount

According to the performance of measuring, the amount of output correction for each sampling period is measured. Combined with the G_i, ν, ρ_i and the evaluation value of the activated carbon ξ saturation obtained by the interval sampling, which are detected at the inlet. It can be obtained that the control amount is:

$$\begin{cases} v(nT) = a_1 V[(n-1)T] + a_2[(n-1)T] + a_3 M[(n-1)\rho] + a_4 P_i(nT) + a_5 T_i(nT) \\ H(nT) = b_1 H[(n-1)T] + b_2[(n-1)T] + b_3 M[(n-1)\rho] + b_4 P_i(nT) + b_5 T_i(nT) \\ Q_{NH3}(nT) = c_1 H[(n-1)T] + c_2[(n-1)T] + c_3 M[(n-1)\rho] + c_4 P_i(nT) + c_5 T_i(nT) \end{cases}$$

Thereinto *a1, a2, ... a5, b1, b2, ..., b5, c1, c2, ..., c5* is correction factor, T is the sampling period (s), P_i is correction amount of FLC output, T_i is the flue gas temperature at the inlet, $\rho[(n-1)]$ is evaluation of saturation of the activated carbon of n-1 cycles.

3) Amended control rules

Denote R by fundamental fuzzy relationship, it is R' after correction. ΔR is correction amount of the fuzzy relationship. Then it can be expressed as $R' = R + \Delta R$. Set rule correction function is:

$$\Delta R = f(E, EC, G_i, T_i, \Delta H, \Delta V, \Delta L)$$

In the formula, ΔH, ΔV and ΔL are the incremental changes of the rule of increment ν of feed rate per unit time, height of carbon layer H and feed rate of NH_3, respectively. Considering the inherent lag of the system, set $E(kT-dT), \Delta E(kT-dT), \Delta EC(kT-dT), UH(kT-dT), UN(kT-dT), UL(kT-dT)$ before d samples and dT is the lag time length. Suppose the process performance at the sampling moment has the greatest influence, then the control quantity at (k-d)T is $u(kT-dT) + Pi(kT)$.

$\tilde{E}, \widetilde{EC}, \tilde{U}, \tilde{V}$ are the variables being after fuzzified. For one of the outputs, the control rules Before and after the modification are written by fuzzy relationship matrix form:

$$\tilde{R}1(kT) = \tilde{E}(kT-dT) \times \Delta\tilde{E}(kT-dT) \times \tilde{U}(kT-dT)$$
$$\tilde{R}2(kT) = \tilde{E}(kT-dT) \times \Delta\tilde{E}(kT-dT) \times \tilde{V}(kT-dT)$$

The method of rule correction is:

$$\tilde{R}(nT+T) = (\tilde{R}(nT) \text{but not } \tilde{R}1(nT)) \text{else } \tilde{R}2(nT)$$

After written a logical relationship:

$$\tilde{R}(nT+T) = (\tilde{R}(nT) \cap \tilde{R}1(nT)) \cup \tilde{R}2(nT)$$

E is obtained by sampling and EC by calculating, after fuzzification and the correction, fuzzy relation matrix R integrates fuzzy control quantity $\tilde{u}(kT)$, and then an accurate control quantity $u(kT)$ is obtained by de-fuzzifier. After many sampling calculations, the rules are amended, it gradually meets the accuracy requirements of the control object.

After constant looping correction, new rules with new conditions are added to the fuzzy rule base, and rules with different preconditions will be replaced. The output correction $P_o(nT)$ is an important factor that affects the performance of closed-loop control. A common method is to store the performance indicators, which are designed according to the controlled process, in tabular form in the memory of the controller. Correction amount is obtained by looking up the table. This approach is easy to implement, the disadvantage is that the versatility and flexibility of the controller are greatly reduced. In this paper, genetic algorithm is used to update and optimize the data of the performance index table.

4) Genetic algorithm optimization

According to the fuzzy subsets of E and EC, the performance measurement table is encoded into 49 independent GA sets. N is the number of cells of the performance indicator. Each GA set contains 7 randomly generated individuals, and assign the same fitness value for each individual. At each sampling moment, perform optimization and iteration on the individual containing a set of sub-collections of the current activation rule and selects crossover and sorting according to the selection criteria. When the best relevant individuals are obtained according to the fitness function, the corresponding parameters in the performance index table are modified, and other GA individuals and subsets and their corresponding performance index are maintained. At each sampling moment, do the following for different GA sets:

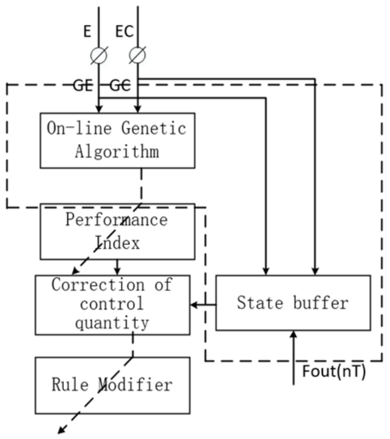

Figure 3: Genetic algorithm optimization

1）Using genetic algorithm, the cell indexed by $X_{i,j}$ Which is activated at sampling time nT-mT, is called again at the current sampling moment. The best individual is obtained by calculating fitness of each individual in the corresponding set.

2）Update Performance Indicators Table: When one Performance $X_{i,j}$ is activated again, the individual of highest fitness is used to replace the original and a new modification $P'(nT)$ is obtained;

3）Modify basic fuzzy control rules: Invoke cells X, indexed by E(nT) and CE(nT) and select modification values generated by individuals in the individual set with the highest fitness to infer modification $Pi(nT)$ of lower simple fuzzy logic.

3.2 Introduce feedforward compensation

The disturbances, such as flow rate and concentration, associated with inlet flue gas status, can be measured and its disturbance to the system is significant. Consider adding feedforward to the closed-loop control to improve the control effect.

Select the typical interference amount, such as ρ_i , G_i and T_i as the feedforward input. The control amount is superimposed on the variable speed rolling mill speed, and adjust the descent speed of activated carbon.

The multivariate linear regression and least square method are used to fit the feedforward model. The fitting relationship model obtained is:

$$\mathbf{x_1} = -\frac{\boldsymbol{Y + \xi_1 x_2 + \xi_2 x_3 + \xi_3 x_4}}{\boldsymbol{\xi_5}}$$

Table 2: Calculation result of multiple linear regression

Model variable	Unstandardized Coefficients	Proof test value
Constant	-15.879	-41.945
ρ_i	-0.213	-65.444
G_i	0.382	82.410
T_i	0.763	423.151

By measuring the change of the relevant variables, the variable v is used to make up the interference compensation of the control effect of the Desulfurization efficiency, ensuring the stability of the concentration of sulfide in the outlet flue gas so as to improve the robustness. It should be noted that feedforward compensation is not always activated during system operation.

4. PROGRAM IMPLEMENTATION

Hierarchical system includes: process control layer and human-computer interaction monitoring layer. The switch logic control of the process control completion system controls loop performance evaluation, parameter optimization and continuous process control. The human-machine interaction monitoring layer provides interactive access for the monitoring system, which configures control parameters, to complete the system data monitoring, data recording and analysis reports and so on. Taking the PLC's data capacity and the difficulties to achieve the algorithm into account. The high-level language or special software can be adopted to complete the algorithm in the host computer. OPC and PLC are adopted to establish data exchange. Figure 4 shows the execution sequence of each function block.

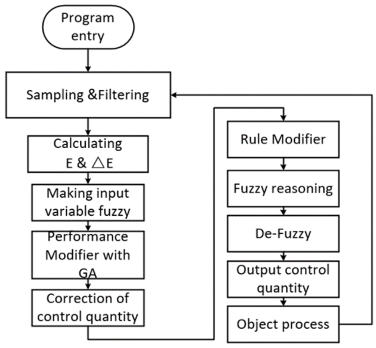

Figure 4: Flow chart of control algorithm

5. CONCLUSIONS

This paper analyzes the characteristics of desulfurization rate control of activated carbon desulfurization adsorption tower. An adaptive FLC is designed according to the characteristics of dry desulfurization adsorption tower t of activated carbon. A method using genetic algorithm to optimize its performance is proposed, and the implementation in S7-400PLC is briefly described. Experimental results show that the adaptive FLC has better control effect for uncertain control objects.

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