Cross Sensitivity Reduction of Gas Sensors Using Genetic Algorithm Neural Network

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ABSTRACT

Infrared absorption method in analyzing gas components is a traditional spectrum analyzing method of gas. Nevertheless, the distribution of the absorption spectrum of a certain kind of gas intercrosses with another's, which means that the absorption peaks of two kinds of gases are near very close. So, when those kinds of gases aforementioned are mixed together, the spectrum analysis will have the cross sensitivity. In this paper, the genetic neural network algorithm is adopted to recognise the patterns of the mixed gases with three components in the simulation recognition. The genetic algorithm decreases the cross sensitivity of the gas sensor. Especially the staged-sectional method is used to increase the recognition accuracy of various over-limit value.

Keywords: infrared gas sensor, cross sensitivity, genetic neural network, staged-sectional method

1. INTRODUCE

The industrial pollution sources such as the smoke and the automobile tail gas, and the urban air polluted heavily by the above pollution sources are all composed of the mixed gases, which will have the spectrum overlap inevitably. The cross sensitivity will influence seriously the accuracy of the pattern recognition of the mixed gases and the measurement precision of the concentration of each component. So, the infrared gas sensor based on the optical absorption principle has the problem of cross sensitivity. The traditional method uses the light circuit designed detailedly and chooses the component with excellent performance such as the narrow band filter to decrease the cross sensitivity. So the structure of the system is very complicated and the cost is high. In this paper, the combination of the genetic neural network with the infrared gas sensor based on the optical absorption principle is proposed, and the cross sensitivity is decreased greatly. So the system structure is simplified and the cost is decreased. The staged-sectional method is adopted for the importance of the over-limit values of various gases in practice, and increases the recognition precision, meeting the practical requests.

2. INFRARED GAS SENSOR

The principle of the infrared gas sensor is to measure the transmitted infrared light intensity of the gas to recognise the component of the gas, according to that different gas molecules absorb the infrared radiation of different wavelength. The system is shown schematically in the Fig.1. The infrared light emitted from the infrared light source transmits the collimation lens, interference filter, infrared window to the measure cell. After being absorbed by the mixed gases in the cell, the transmitted infrared light reach the focusing lens and is measured by the infrared detector.
The absorbed infrared light intensity is described by the Lanbert- Beer law:

$$I = I_0 e^{-\varepsilon c l}, \tag{1}$$

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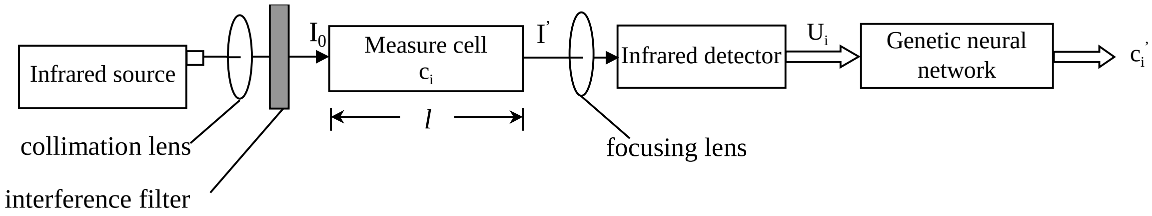

Fig1 The structure scheme of the infrared gas sensor

Where I_0 is the incident light intensity, I the absorbed infrared intensity, c the gas concentration absorbing infrared light, *l* the length of the measure cell. ε is the absorption coefficient, related to the wavelength of the absorbed infrared light and a certain kind of gas, and dependent of temperature and pressure. The transmitted infrared light intensity is as the following:

$$I' = I_0\left(1 - e^{-\varepsilon c l}\right), \tag{2}$$

Where I' is the transmitted light intensity. Apparently, when *l* and ε are given, the infrared light intensity measured by the infrared light detector is only relative to the gas concentration c. So the output voltage U of the detector is corresponding to the gas concentration c, and the relationship between U and c is shown schematically in Fig.2. Then the component and the concentration of the different kinds of gases can be recognised by the output voltage of the detector.

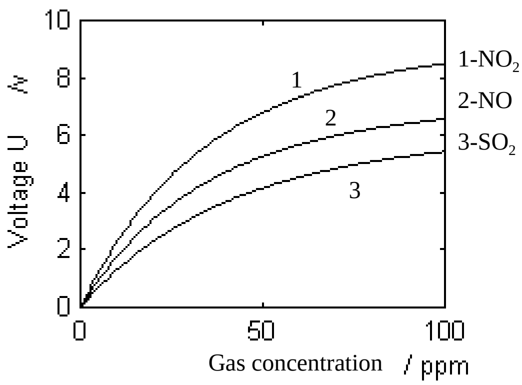

Fig 2 Relationship between voltage and concentration

When the mixed gases having n components are measured, interference filters with different central wavelengths are chosen to recognise the components of the mixed gases. The infrared detector outputs the voltages U_i (i =1, 2, ⋯ n) corresponding to the every component. Traditional double wavelength method is used because it could eliminate the influences of emitting light intensity change of the light source and the performance change of the detector. Because the filter has a definite wavelength band, so the transmitted absorption spectrum often has the overlap, especially when the absorption spectrum of the mixed gases is near close. For example, the absorption spectrum range of 6.03 μ m～6.45 μ m of NO_2 is very close to that of 4.46 μ m～6.38 μ m of NO, shown schematically in Fig.3, so the transmitted light intensity is not relative to a certain kind of gas, but is the result of synthesizing absorption of various gases. This is the phenomenon of cross sensitivity. Then, the recognition accuracy of the gas concentration is very poor by measuring the output voltage of the infrared detector. In this paper, the genetic neural network is adopted to do the data fusion to solve this problem. Data fusion is done by inputting U_i to the neural network, and can decrease the cross sensitivity and the recognition error. So the output concentrations c_i' corresponding to various gas components are obtained.

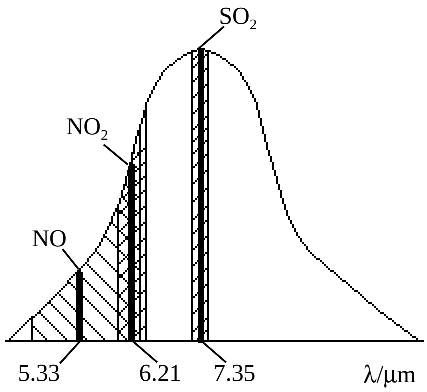

Fig 3 The optic spectrum of the transmitted lights of SO_2, NO_2, NO through the SO_2 interference filters

** λ is the wavelength of the absorbed infrared

3. GENETIC NEURAL NETWORK

For a complex problem, it is a hard work to optimize the weights of the neural network. The conventional algorithm is that of Back-Propagation (BP) of the error. This method is a kind of partial searching algorithm and its calculating rate is relatively slow. It also converges easily on a partial minimum. To this problem, the traditional optimization methods have no resolutions yet. The genetic algorithm is a global optimization method and has special superiority in solving this kind of complex problem[1-6]. In the condition of the definite network topology, the genetic neural network optimizes the weights of the network and improves the performance of the neural network greatly compared with the BP neural network. In this paper, a multi-group parallel genetic neural network with simulated annealing method is used and is superior to the normal genetic neural network.

3.1 BP neural network

An error back propagation (BP) network is used, which is made up of three layer of units, shown schematically in Fig.4. The bottom layer is the input layer, the middle layer is the hidden layer, and the top layer is the output layer. The output of units in the input layer equals to its input, viz. o_i=i_i; the units in the middle hidden layer and the output layer use the nonlinear function as the activation functions, and the operation characteristics are as the following respectively:

$$\mathrm{net}_{pj} = \sum \omega_{ij} o_{pi}, \tag{3}$$

$$o_{pj} = f_j(\mathrm{net}_{pj}), \tag{4}$$

where p figures the present specimen of the input, w_{ji} is the connection weight of the unit i in the hidden layer with the unit j in the output layer, O_{pi} is the present input of the output units and O_{pj} is its present output, f_j is the nonlinear differentiable non-descending function which is often adopted as S function:

$$f_j(x) = 1/(1+e^{-x}), \tag{5}$$

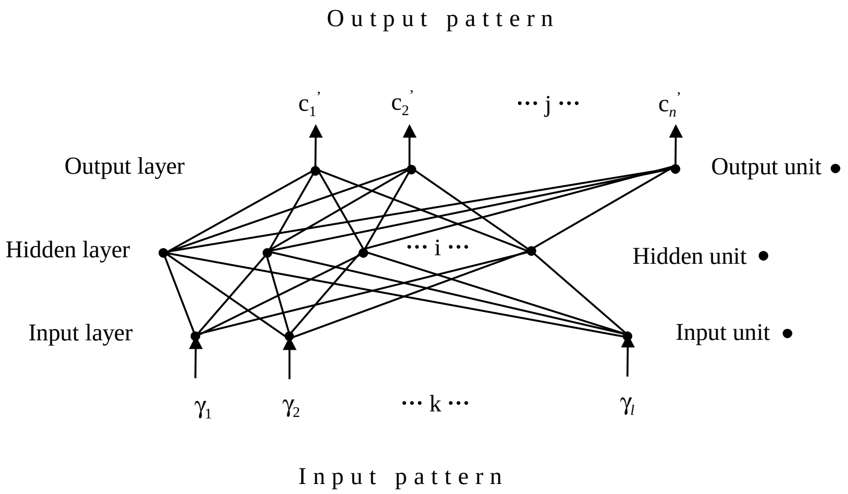

Fig 4 The model of BP network

3.2 Combination of genetic algorithm and neural network

Genetic neural network combines the genetic algorithm with the neural network. It means that the values of weights ω are obtained by using the genetic algorithm. The structure of the genetic neural network is shown schematically in Fig. 5.

The training course of the genetic neural network used in this paper is as the following[8]:

a) Definition of multi-group: Define the number of units in the input layer, the hidden layer and the output layer *l, m and n* respectively, and then the size of multi-group N ($N= l\times m+ m\times n$). N values of the weights ω_{ji} and ω_{jk} of the neural network are given randomly and encoded with real number to establish the original multi-group.

b) Training of BP neural network: Decode each individual i.e. the weight of the network. The learning specimen composed of the input specimen U_i and output specimen i.e. expected output c_i is used to train the neural network and the relevant output c_i' of the network is obtained.

c) Calculation of adaptability: Adaptability is used to estimate the performance of each individual in the multi-group which has been decoded in the *b)* step, and the estimation rule could be the reciprocal of the square sum of error between the output of the network and the expected output of the learning specimen, learning rate, etc.

d) Seed selection: The probability of multiplying offspring of each individual is chosen according to the value of the adaptability.

e) Cross and mutation: New generation of multi-group is obtained according to the cross probability P_c and the mutation probability P_m adjusted actively self-adaptedly.

f) Simulated anneal: The mechanism of the simulated anneal accepts new individuals created by the cross and the mutation according to *Metropolis* rule. Not only the fine individuals, also the inferior ones are accepted, and the probability of accepting the inferior ones decreases with the annealing temperature decreasing.

g) Constructing the BP neural network newly: Return to the *b)* step until the convergence condition (viz. arithmetic termination condition) is satisfied. This condition is a definite evolution epoch number of multi-group and the deviation of the adaptability which is the difference between the adaptability and its excellent target value.

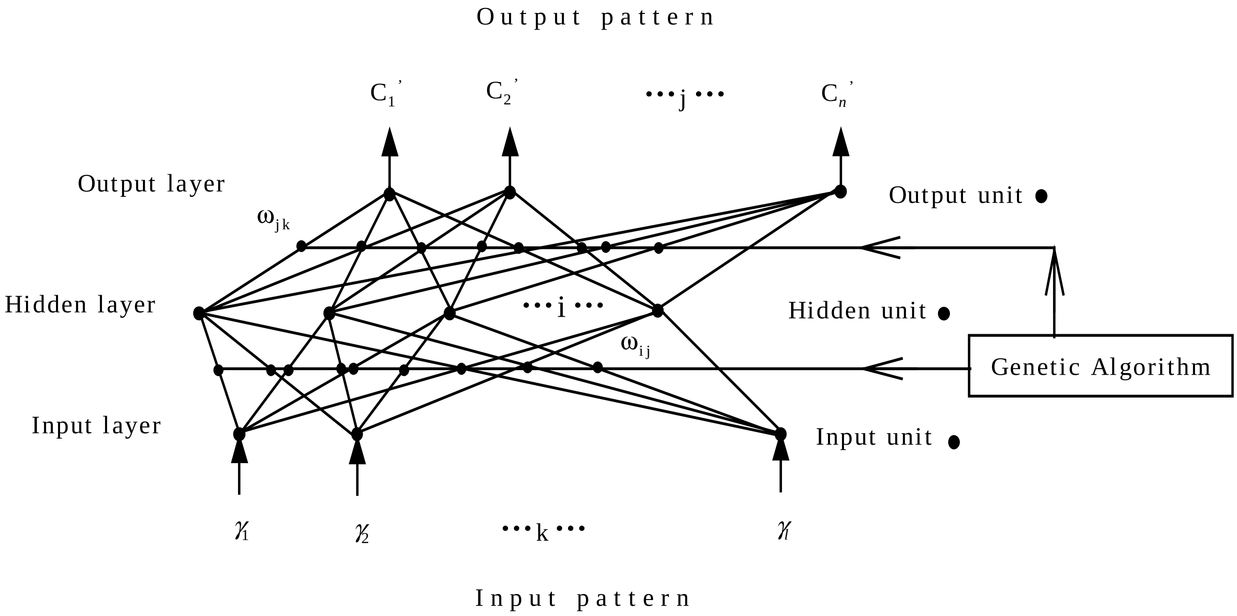

Fig 5 The model of the genetic neural network

4. PATTERN RECOGNITION OF THREE KINDS OF GASES USING GENETIC NEURAL NETWORK

4.1 Pattern recognition system of the mixed gases

The recognition system of the mixed gases patterns i.e. the species of the gas and the concentration is shown in Fig. 1. The pattern recognition of three kinds of gases—SO_2, NO_2, NO is taken for example. In order to eliminate the influence of emitting light intensity change of the light source and the performance change of the detector, double wavelength method is used in calibration. A referenced filter is used, and its absorption wavelength is different from that of various gases filters, so the spectrum lines don't overlap. Four interference filters are fixed on a rotating dragging bracket in Fig. 1, and their central wavelengths are of the peak spectrum lines of infrared absorption of three kinds of gases and the peak spectrum line of the reference filter respectively: SO_2— $(7.35\pm0.8)\ \mu m$, NO_2— $(6.21\pm0.8)\ \mu m$, NO— $(5.33\pm1.5)\ \mu m$, referenced light — $(10\pm0.8)\ \mu m$.

4.2 Obtain of learning specimen

The genetic neural network must be trained by the learning specimen before it is used to recognise the mixed gases pattern. The learning specimen is obtained by the calibration experiment. Three kinds of gases with different concentration values $\{c_{SO2}, c_{NO2}, c_{NO}\}$ are injected into the measure cell. The transmitted infrared intensities of 4 filters with different central wavelengths are detected by the detector, the outputs of the detector are U_{SO2}, U_{NO2}, U_{NO}, U_R. U_R is corresponding to the transmitted intensity of the referenced light. The voltage ratios of $\gamma_{SO2}=U_{SO2}/U_R$, $\gamma_{NO2}=U_{NO2}/U_R$ and $\gamma_{NO}=U_{NO}/U_R$ are used as the input specimen in the learning specimen $\{\gamma_{SO2}, \gamma_{NO2}, \gamma_{NO}\}$, while the corresponding concentration values as the expected output specimen. The sets of specimen in different concentration values $\{\gamma_{SO2}, \gamma_{NO2}, \gamma_{NO}\}$ and $\{c_{SO2}, c_{NO2}, c_{NO}\}$ are obtained. One set of specimen is obtained once the concentration of each component is changed. 182 sets of specimen are prepared from the referenced experiment data[9-11], and they form a specimen base. Some of them is used for training of the network, and some for testing of the network.

4.3 The parameters of genetic neural network

- the number of nodes in the input layer *l* —3
- the number of nodes in the hidden layer *m* —15
- the number of nodes in the output layer *n* — 3
- the size of multi-group — 90
- the evolution epoch number (namely the iterative number of times) —500 epoch
- initial value of cross probability P_c— 0.8, initial value of mutation probability P_m— 0.05. Both of P_c and P_m are adjusted using dynamic self-adaptation technology.
- initial temperature of simulating anneal — 6, and decreased annealing temperature — 0.09
- BP training times — to train BP network 50 times with selected excellent individual in the multi-group.
- the adaptability is the reciprocal of the square sum of error between the output of the network and the expected output of the learning specimen.

4.4 Training and testing of genetic neural network

35 sets of specimen as the inputs of the network are chosen from the specimen base to train the network. The optimized weights are obtained after the training ends. Then the network could be used to recognise the gas pattern. Nevertheless, it must be tested for the request of accuracy. Several specimens can be chosen from the surplus 147 sets of specimen as the testing specimen. The input specimen in the testing specimen is the input of the network. The output is the concentration of each component of three kinds of gases, and is compared with the expected output in the testing specimen. If the error of comparison result could satisfies the request of accuracy, the network could be used to recognise the practical pattern.

5. STAGED-SECTIONAL METHOD INCREASING RECOGNITION ACCURACY

Normally, it is difficult that a device has a large measure range as well as the high resolution. In order to realize the measure of the various gases in the large range listed in table 1 with high resolution at two over-limit values (TLV-TWA and TLV-STEL), the staged-sectional method is proposed in this paper. TLV-TWA in the table 1 expresses the average of maximum gas concentration, human being could stay in this condition safely for a long time. TLV-STEL expresses the average of maximum gas concentration in 15 minutes during 8 hours of work time. Human being could not stay more than 15 minutes and more than four times in one day where the gas concentration lies between STEL and TWA. IDLH expresses the maximum gas concentration, human being could escape from the dangerous place in 30 minutes without gas mask and the health is not endangered heavily. The key of this recognition problem in practical measure does not lie in whether the recognition result of 10ppm is 10.03ppm or 15ppm, but in the recognition accuracy of two over-limit values TLV-TWA and TLV-STEL.

The staged-sectional method has two stages: first recognition and sectional recognition. The flow chart is shown in Fig.6.

(1) First recognition

The data values of the learning specimen cover with the maximum gas concentration, and the difference between the expected concentration values is large. So the allowable error $\Delta c'$ could be large in the first recognition.

(2) Section distinguish of the first recognition result

When the first recognition result is near the over-limit value V_{oj} and in the range of ($V_{oj} - \Delta c'$, $V_{oj} + \Delta c'$) (j =1, 2), the sectional recognition of the gas concentration is necessary. Otherwise, the first recognition result is as the final result.

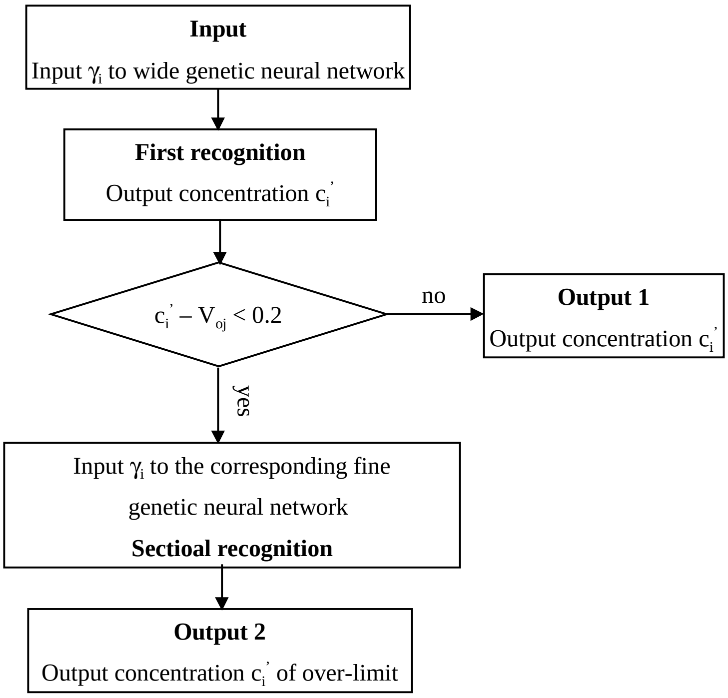

Fig 6 The flow chart of staged-sectional recognition

(3) Sectional recognition

New network (i.e. fine network) should be used in the sectional recognition. The learning specimen is chosen near the over-limit value V_o. The difference between the expected concentration values $\Delta c_m'$ is far less than the allowable error $\Delta c'$. It can be known from the table 1 that different kinds of gases have different over-limit values V_o. Three kinds of gases have 6 different over-limit values, so there are 6 fine networks in the sectional recognition.

Table 1 Characteristics of SO_2, NO_2, NO

Concentration c (ppm) / Gas	TLV-TWA	TLV-STEL	IDLH
SO_2	2	5	100
NO_2	3	5	20
NO	25		100

6. SIMULATION RECOGNITION RESULT

6.1 First recognition result

First recognition is done using the genetic neural network to the whole range of concentration of three kinds of gases in table 1. The first recognition results $\{c'_{SO2}, c'_{NO2}, c'_{NO}\}$ of the 7 groups testing specimen are listed in table 2. Thus it can be seen that the genetic neural network can recognise the gas component and the concentration values. The first recognition results of the over-limit value of TLV-TWA of SO_2 2ppm and the over-limit value of TLV-STEL of SO_2 5ppm are listed in the 1st row and 2nd row of the first recognition, the absolute errors of these results are 0.39ppm and 017ppm respectively.

Table 2 The first recognition result compared with the sectional recognition result of SO_2

Staged-Sectional recognition	Testing specimen	Recognition result of network c_i' and expected output c_i					
		SO_2		NO_2		NO	
		c'_{SO2}	c_{SO2}	c'_{NO2}	c_{NO2}	c'_{NO}	c_{NO}
First recognition	1	1.61	2.0	3.25	4.0	10.59	10.0
	2	4.83	5.0	9.729	10.0	11.59	10.0
	3	5.04	5.25	10.25	10.5	11.67	10.0
	4	17.22	17.0	4.291	4.25	24.99	25.0
	5	86.62	85.0	20.02	20.0	52.00	52.5
	6	88.86	87.5	22.70	22.5	99.332	100.0
	7	96.07	100.0	24.29	25.0	99.418	100.0
Sectional recognition	1	1.96	2.0	3.86	4.0	9.874	10.0
	2	4.97	5.0	10.06	10.0	10.22	10.0
	3	5.271	5.25	10.61	10.5	10.28	10.0
	4	16.99	17.0	4.308	4.25	25.47	25.0
	5	85.98	85.0	20.26	20.0	52.49	52.5
	6	89.50	87.5	22.76	22.5	98.893	100.0
	7	97.991	100.0	20.192	21.25	86.31	85.0

6.2 Sectional recognition result

The sectional recognition method is to divide the large measure range into several sections and recognise in different sections respectively. The sectional recognition is used especially for the over-limit values of TLV-TWA and TLV-STEL, and the data of the learning specimen are chosen near the over-limit value. Because the difference between two over-limit values of SO_2 is not very large, one fine network is established for the sectional recognition of two over-limit values. After sectional recognition, the absolute errors of the recognition results of the over-limit values of TLV-TWA and TLV-STEL are decreased to 0.04ppm and 0.03ppm respectively, less 4 times than the absolute error of the first recognition results. So these results demonstrate that cross sensitivity has been decreased and the recognition precision has been enhanced. The over-limit values of other two kinds of gases NO_2 and NO can also be recognised precisely using the sectional recognition method.

7. CONCLUSION

(1) The genetic neural network is used to decrease the cross sensitivity of infrared gas sensor and the request to the wavelength band of the filter, so the cost of the optic system could be cut down.
(2) The staged-sectional method increases the recognition accuracy of two over-limit values of TLV-TWA and TLV-STEL.

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REFERENCES

1. J.David Schaffer, Richard A. Caruana, Larry J.Eshelman, "Using genetic search to exploit the emergent behavior of neural networks, " *Physica D*, **42**, pp. 244-248, 1990.
2. H.D.Schaffer, et al, "Combinations of genetic algorithm and neural networks, " in: D.Whiteley, H.D.Schaffer eds, *A survey of the state of the art combination of genetic algorithms and neural network*, IEEE Computer Society Press, pp. 1-37, 1992.
3. D.H.Ackley, M.L.Littman, *Interactions between learning and evolution*, Artificial life Ⅱ, Addison Wesley Pub. pp. 487-509,1992.
4. D.J.Montana, L.Davis, "Training feedforward neural networks using genetic algorithm, " Proc. of 11th IJCAI, San Mateo, pp. 762-767, 1989.
5. G.F.Miller, et al, "Designing neural network using genetic algorithm, " Proc. of 3rd Conf. On GA, Arlingtion, 379-384, 1989.
6. Berna Dengiz, Fulya Altiparmak, Alice E Smith, " Local search genetic algorithm for optimal design of reliable networks, " *IEEE Transactions on Evolutionary Computation*, **1**, pp. 179-188, 1997.
7. D.Goldberg, *Genetic algorithm in search optimization and machine learning*, Addison Wesley Pub., Massachusetts, 1989.
8. Haoyang Wu, " Paralleling genetic algorithm of colonies based on the modulated annealing mechanism, " Software transaction, to be pulished.
9. L.S.Rothman, " AFGL atmospheric absorption line parameters compilation: 1980 version, " *Applied Optics*, **20**, pp. 791-795, 1981.
10. L.S.Rothman, A.Goldman, J.R.Jillis, R.R.Gamache, H.M.Pickett, R.L.Poynter, N.Husson, A Chedin, "AFGL trace gas compilation: 1982 version, " *Applied Optics*, **22**, pp. 1616-1627.
11. L.S.Rothman, R.R.Gamache, A.Barbe, A.Goldman, J.R.Gillis, L.R.Brown, R.A.Toth, J.-M.Flaud, C.Camy-Peyret, " AFGL atmospheric absorption line parameters compilation: 1982 edition, " *Applied Optics*, **22**, pp.2247-2256.

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