

## Quantitative Recognizing Dissolved Hydrocarbons with Genetic Algorithm-Support Vector Regression

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### Abstract

*Online monitoring of dissolved fault characteristic hydrocarbon gases, such as methane, ethane, ethylene and acetylene in power transformer oil has significant meaning for condition assessment of transformer. Recently, semiconductor tin oxide based gas sensor array has been widely applied in online monitoring apparatus, while cross sensitivity of the gas sensor array is inevitable due to same compositions and similar structures among the four hydrocarbon gases. Based on support vector regression (SVR) with genetic algorithm (GA), a new pattern recognition method was proposed to reduce the cross sensitivity of the gas sensor array and further quantitatively recognize the concentration of dissolved hydrocarbon gases. The experimental data from a certain online monitoring device in China is used to illustrate the performance of the proposed GA-SVR model. Experimental results indicate that the GA-SVR method can effectively decrease the cross sensitivity and the regressed data is much more closed to the real values.*

**Keywords:** *patterson recognition, sensor array, genetic algorithm, support vector regression, hydrocarbon gases,*

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### 1. Introduction

Power transformers are essential and costly equipments in power system [1, 2]. Once faults happened in larger power transformers, it would interrupt the power supply and bring huge economic loss. Therefore, many related researchers have being dedicated to how effectively detect transformer incipient faults [3-5] Hydrogen, carbon monoxide, methane, ethane, ethylene and acetylene are the main fault characteristic gases dissolved in transformer oil. Online monitoring of these dissolved gases can forecast the potential fault types of power transformers and their development trend early [6, 7]. Then the loss caused by transformer accident and fault will be reduced minimally.

Presently, gas sensor array has been widely used in a large variety of technological fields, such as inflammable [8] explosive [9] and toxic gas detection [10, 11] environmental pollution monitoring [12] food, cosmetics and drink analysis [13, 14], industrial control [15], and so on. With the advantages of simple manufacture technique, low maintenance cost, high gas response, rapid response and recovery time, long service life and stability, semiconductor tin oxide based gas sensing array provides an ideal platform for online monitoring of dissolved fault characteristic gases in power transformer oil [2, 5]. However, due to same chemical composition and similar molecular structure among the four hydrocarbon gases, cross-sensitivity is inevitable [3, 5]. Therefore, it needs to take appropriate pattern recognition technologies for further quantitative recognizing of these characteristic gases.

In the past few years, pattern recognition approaches are mostly focused on artificial neural network (ANN) models [16], including generalized regress neural network, back propagation neural network and radial basis function neural network. However, ANN suffers from several weaknesses, such as slow convergence rate, falling into local minim, over fitting and requirement of a larger amount of training data. Different from the principle of empirical risk minimization in ANN, based on the structural risk minimization principle support vector machine (SVM) has excellent performances such as global optimization, generalization ability and

accuracy, especially in the situation of small sample [16]. And SVM has been receiving increasing attention and successfully used in many fields, including fault diagnosis [17], housing price forecasting [18], patent classification [19], particle identification, digital images identification, bankruptcy prediction and so on.

Meanwhile, how to choose appropriate SVM parameters ( $\sigma$ ,  $\varepsilon$  and  $C$ ) has a great influence on SVM precision. Based on the Darwinian principle of survival of the fittest, genetic algorithm is a fast searching technique with less time consuming and can obtain the optimal solution well. Thus, the genetic algorithm is applied to select appropriate parameters  $\sigma$ ,  $\varepsilon$  and  $C$ . This study proposes a genetic algorithm-support vector machine model for pattern recognition of sensor array, which can lower the cross-sensitivity and further quantitatively detect the real gaseous contents of methane, ethane, ethylene and acetylene dissolved in transformer oil. The rest of this paper is organized as follows. Section 2 introduces the theory and model of support vector regression. Parameters selection of SVM based on genetic algorithm is introduced in Section 3. Section 4 testifies the pattern recognition performance of the proposed model with online monitoring data collected from a certain running power transformer in China. And conclusions are drawn in the last section.

## 2. The Theory of SVR

The support vector regression (SVR) is to map nonlinear sample vectors into a high-dimensional feature space, where the nonlinear regression problem is transformed into a linear problem and the curse of dimensionality problem would be solved. The SVR estimates a structural risk minimization function  $f(x)$  according to a given training data  $T = \{(x_i, y_i), i = 1, 2, \dots, l\}$ , where  $x_i = [x_{i1}, x_{i2}, \dots, x_{id}]^T$ ,  $x_i \in R^d$  is the input vector with a  $d$ -dimensional column vector,  $y_i \in R$  denotes the corresponding output value for simple  $i$  and  $l$  is the total number of data set. The SVR function is defined as follows,

$$f(x) = \omega^T \varphi(x) + b \quad (1)$$

Where  $w^T$ ,  $\varphi(x)$  and  $b$  denotes the weight vector, a set of nonlinear transformations and the bias term, respectively.  $L_\varepsilon$  is called the  $\varepsilon$ -insensitive loss function,

$$L_\varepsilon = |y - f(x)| = \begin{cases} 0 & |y - f(x)| \leq \varepsilon \\ |y - f(x)| - \varepsilon & |y - f(x)| > \varepsilon \end{cases} \quad (2)$$

If the difference between the target  $y$  and the regression estimates value  $f(x)$  is less than  $\varepsilon$ , the loss equals zero, otherwise the loss equals value beyond  $\varepsilon$ . The goal of SVR is to find the coefficients  $\omega^T$  and  $b$  by minimizing the following regularized risk function, which is defined as,

$$\min \psi(w, \xi, \xi^*) = \frac{1}{2} w w^T + C \sum_{i=1}^l (\xi_i + \xi_i^*) \quad (3)$$

Where  $C$  denotes a punishment coefficient to measure the structural risk, and  $\frac{1}{2} w w^T$  is the regularization term.  $\xi_i$  and  $\xi_i^*$  are two positive slack variables introduced to represent the distance from actual values to the corresponding boundary values of the  $\varepsilon$ -tube. Equation (2) is subjected to the constrains,

$$\begin{cases} y_i - \omega^T \varphi(x_i) - b \leq \varepsilon + \xi_i \\ \omega^T \varphi(x_i) + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \quad i = 1, 2, \dots, l \end{cases} \quad (4)$$

The Lagrangian function can turn the SVR algorithm into a convex quadratic optimization problem and the local optimal solution is certainly the global optimal one. By introducing the

Lagrangian function its dual optimization problem is:

$$\begin{cases} \min[-\frac{1}{2}\sum_{i=1}^l\sum_{j=1}^l(a_i - a_i^*)(a_j - a_j^*)K(x_i, x_j) - \varepsilon\sum_{i=1}^l(a_i + a_i^*) + \sum_{i=1}^ly_i(a_i + a_i^*)] \\ \text{st. } \sum_{i=1}^l(a_i - a_i^*) = 0, 0 \leq a_i \leq C, 0 \leq a_i^* \leq C \end{cases} \quad (5)$$

Where  $a_i$  and  $a_i^*$  represent the Lagrangian multipliers, and  $K(x_i, x_j)$  is the kernel function. By  $a_i$  and  $a_i^*$  calculated, an optimal desired weight vector of the regression is obtained, that is:

$$w = \sum_{i=1}^l(a_i - a_i^*)K(x_i, x_j) \quad (6)$$

Hence, the SVR function is:  $f(x) = \sum_{i=1}^l(a_i - a_i^*)K(x_i, x_j) + b$

Where:

$$b = \frac{1}{N_{NSV}}\{\sum_{0 < a_i < C}[y_i - \sum_{x_i \in SV}(a_i - a_i^*)K(x_i, x_j) - \varepsilon] + \sum_{0 < a_i^* < C}[y_i - \sum_{y_j \in SV}(a_i - a_i^*)K(x_i, x_j) + \varepsilon]\} \quad (7)$$

Radial basis function (RBF), polynomial basis function and sigmoid function are the most common kernel functions used in SVR algorithm. Fewer free parameters needed than that in polynomial basis function and sigmoid function, there is only one variable in RBF. Moreover, SVR constructed with RBF has more excellent nonlinear forecasting performance. Thus, the RBF kernel function has become a more prior option for SVR, and this study applied the RBF kernel function, showed as following equation:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \quad (8)$$

$C$ ,  $\varepsilon$  and  $\sigma$  are three major hyper-parameters, which need to be chosen priori by users appropriately.

The selection of these parameters plays an important role in the performance of SVR model. In the past few years trial-and-error method was widely used to obtain the optimal SVR parameters. With the development of modern evolutionary theories, genetic algorithm, immune algorithm and simulated annealing algorithm have gained growing attentions. In this paper, the genetic algorithm (GA) is employed to optimize the SVR parameters to yield the highest regression performance. The optimization method based on GA is described detailedly in next sections.

### 3. Parameters Selection of SVR based on GA

#### 3.1. The Theory of GA

Genetic algorithm (GA) is an efficient global optimum intelligence procedure based on the theory of genetic evolution and natural selection. GA applies the idea of survival of the fittest, which is inspired by the biological processes of inheritance, mutation, genetic crossover and natural selection. The key feature of GA is the introduction of population and chromosome. First, an initial population is generated randomly, in which each individual is denoted by a chromosome. In view of the genetic operations such as selection, crossover and mutation, the initial solution population evolves into next generation. Each evolutionary population is coded by strings and evaluated by the fitness function. This evolutionary procedure should proceed until stop conditions are satisfied.

Selection, crossover and mutation are three major operations in GA. Selection operation is to pick the individual according to the fitness value, where individual with higher (lower) fitness value has a higher (lower) probability inherited to the next generation. In this case, the individual fitness value is constantly close to the global optimal solution. Crossover operation is to select two individuals from the groups and exchange in a bit with a greater probability. Crossover operation produces the offspring, which inherits the basic chromosome information of the parent. Mutation operation is applied to determine whether a chromosome should be

mutated in the next generation. The mutation operation could further search problem space and avoid local convergence. After the mutation operation, new chromosomes are obtained.

### 3.2. Parameters Optimization of SVR based on GA

Based on the Darwinian principle of survival of the fittest, GA can obtain the global optimum optimal solution after a series of iterative computations. In this model, the chromosome of GA should include parameter  $\sigma$ ,  $\varepsilon$  and  $C$ . Thus, each chromosome is consisted of three segments, which represents the value of Kernel function parameter  $\sigma$ , insensitive loss parameter  $\varepsilon$  and penalty parameter  $C$ , respectively. If the number of chromosomes is too large, the learning speed of GA is quite slow and it is usually too hard for convergence. The initial population of the GA is made up of 30 chromosomes in this study. Figure 1 shows the flow diagram of optimizing the SVR parameters with GA, which is described in detail below:

Step 1: Coding and Initialization. GA is initialized with a population of random binary encoding of parameter  $\sigma$ ,  $\varepsilon$  and  $C$ .

Step 2: Evaluation of the fitness function. The training subsets are used to calculate the fitness values of a population of GA-SVR. In this paper the k-fold cross validation is applied to evaluate the fitness function value. In k-fold cross validation process, one of the training subsets is taken as validation set in turn, and others are taken as training set. The above procedure is repeated k times, so that each subset is used once for testing. The fitness function is defined as  $\frac{1}{l} \sum_{i=1}^l \left| \frac{y_i - y'_i}{y_i} \right|$ , where  $y_i$ ,  $y'_i$  and  $l$  represents the actual value, validation value and the number of subsets, respectively.

Step 3: Selection, crossover and mutation operation. In the study, the roulette wheel scheme is adopted to select excellent chromosomes. The chromosomes that survive to the next generation are employed for crossover and mutation operations. Genes of two chromosomes are selected to crossover randomly and the probability of exchanging genes to create new chromosomes in each pair is 80%. The mutation operation is performed to alter binary code to avoid local convergence, and in this model each gene undergoes a mutation operation with a fixed probability 3%.

Step 4: Termination judgement. The same procedures from Step 2 to Step 3 are repeated until stop conditions are satisfied.

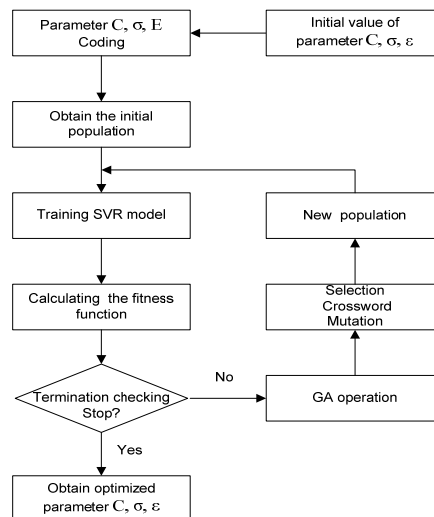


Figure 1. The Flow Diagram of Optimizing the SVR Parameters with GA

### 3.3. SVR Model based on GA

On the basis of SVR and GA theory discussed above, we are now in a position to formulate a procedure for pattern recognition of the gas sensor array. The structure diagram of GA-SVR procedure is shown in Figure 2. At first, the data set is divided into training subset and

testing subset. Based on GA optimization, a trained SVR model with optimized parameters is obtained. And then the testing subset is used to check the regression performance of the model.

As seen in Figure 2, the idea of this procedure is very clear, and all programs are compiled on the Matlab platform in this paper.

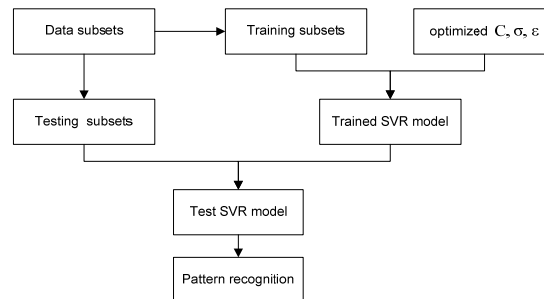


Figure 2. The Structure Diagram of GA-SVR Procedure Structure

#### 4. Engineering Application

This study applied the GA-SVR model to investigate the pattern recognition performances of the gas sensor array. We employed the dissolved gas data of a certain 220 kV power transformer from Henan province, China, as an example. Figure 3 (a) presents the structure chart of a gas sensor array, which is consisted of six  $\text{SnO}_2$  based sensors. As shown in Figure 3 (b) the gas sensor array is installed in the power transformer drain valve to sensing dissolved  $\text{H}_2$ ,  $\text{CO}$ ,  $\text{CH}_4$ ,  $\text{C}_2\text{H}_2$ ,  $\text{C}_2\text{H}_4$  and  $\text{C}_2\text{H}_6$ , respectively. Figure 3 (c) and (d) represents the onsite control box of the online monitoring device and the running power transformer, respectively.



Figure 3. The Photographs of (a) Gas Sensor Array, (b) Transformer Drain Valve, (c) Onsite Control Box and (d) Power Transformer

Table 1 demonstrates the online monitoring data obtained in every ten days. As known to all that offline gas chromatography (GC) data have been recognized as a standard for dissolved gas-in-oil analysis (DGA) [Error! Bookmark not defined., Error! Bookmark not defined., Error! Bookmark not defined.]. So in this paper the offline data are also measured by a gas chromatograph for further comparison. As shown in Table 1, the testing data are

divided into training samples and testing sample.

Data normalization is necessary in order to improve the learning speed and stability of the model. The process of standardization is as follows:

$$x'_{ij} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}}$$

Where  $x'_{ij}$ ,  $x_{ij}$ ,  $x_{max}$  and  $x_{min}$  denote the normalized data, initial data, the maximum and minimum values of the initial data, respectively. After standardization the value of  $x'_{ij}$  is between 0 and 1.

Table 1. The Testing Dissolved Hydrocarbon Gases Data (online/offline)

Testing date	CH <sub>4</sub> (μL/L)	C <sub>2</sub> H <sub>2</sub> (μL/L)	C <sub>2</sub> H <sub>4</sub> (μL/L)	C <sub>2</sub> H <sub>6</sub> (μL/L)	Data type
2012-11-10	23.2/20.9	0/0	53.4/49.3	10.5/9.5	Training
2012-11-20	24.6/21.8	0/0	57.1/52.9	11.3/10.2	Training
2012-11-30	27.3/24.7	0/0	61.9/57.3	13.2/11.8	Training
2012-12-10	21.5/19.1	0/0	49.7/46.1	9.70/8.70	Training
2012-12-20	25.4/22.7	0/0	57.8/53.4	11.8/10.7	Training
2012-12-30	26.8/24.1	0/0	52.3/48.5	12.5/11.3	Training
2013-01-10	27.9/25.0	0/0	64.1/59.7	13.7/12.4	Training
2013-01-20	32.5/28.8	0/0	74.5/68.9	15.1/13.7	Testing
2013-01-30	28.7/25.9	0/0	65.6/61.1	13.9/12.5	Testing
2013-02-10	29.5/26.1	0/0	68.2/63.3	14.1/12.7	Testing
2013-02-20	31.2/27.8	0/0	71.8/66.5	14.6/13.1	Testing

In the SVR stage, firstly the free parameters  $\sigma$ ,  $\epsilon$  and  $C$  are optimized by GA. Then, the obtained optimal parameters are utilized to train SVM model. The testing data are used to examine the performance of the model. Given the idea of investigating the regression performance of the model, we take CH<sub>4</sub> gas as an example to state the pattern recognition procedure. For training model the input  $x_i = (x_{i1}, x_{i2}, x_{i3}, x_{i4})$  is a four-dimensional vector, which denotes the online monitoring data of CH<sub>4</sub>, C<sub>2</sub>H<sub>2</sub>, C<sub>2</sub>H<sub>4</sub> and C<sub>2</sub>H<sub>6</sub>, respectively. The offline value of CH<sub>4</sub> gas is performed as the out put  $y = f(x)$ . When inputting the online monitoring data into trained model, we get the regression value of CH<sub>4</sub> gas.

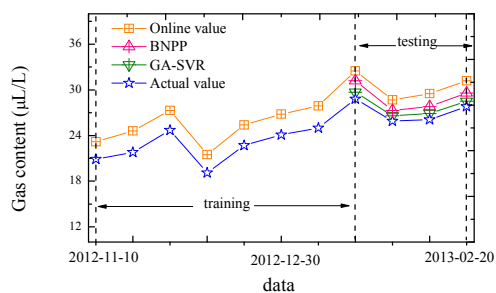


Figure 4. Pattern Recognizing Values of C<sub>2</sub>H<sub>4</sub> Gas Sensor

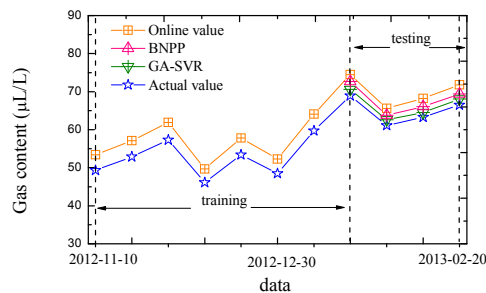


Figure 5. Pattern Recognizing Values of CH<sub>4</sub> Gas Sensor

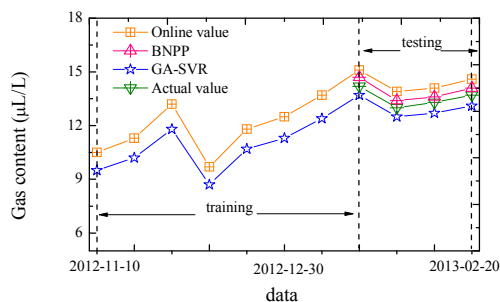


Figure 6. Pattern Recognizing Values of Gas

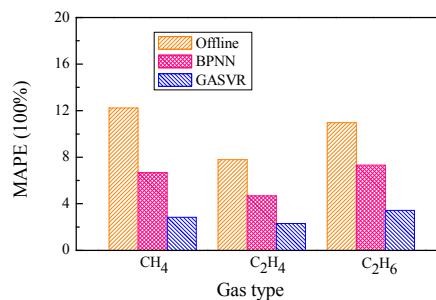


Figure 7. Comparison of MAPE Values for

## Sensor Array

C<sub>2</sub>H<sub>6</sub> Gas Sensor

In order to further verify the superior regression performance of the SVR model based upon GA, expanded artificial intelligence model is also carried out in terms of BP neural network. The examining results of CH<sub>4</sub>, C<sub>2</sub>H<sub>4</sub> and C<sub>2</sub>H<sub>6</sub> and their evaluation performances are shown in Figure 4-6 and Table 2.

A mean absolute percentage error (MAPE) is used to evaluate the regression accuracy, which is defined as follows:

$$\text{MAPE} = \frac{1}{N} \sum_{h=1}^N \left| \frac{y_h - y'_h}{y_h} \right| \times 100\%$$

Where  $y_h$  and  $y'_h$  represent the actual and recognizing values, respectively, N is the number of testing points.

Table 2. The original and pattern recognizing values of CH<sub>4</sub>, C<sub>2</sub>H<sub>4</sub> and C<sub>2</sub>H<sub>6</sub> (online/offline/BPNN/GA-SVR)

Testing date	CH <sub>4</sub> (μL/L)	C <sub>2</sub> H <sub>4</sub> (μL/L)	C <sub>2</sub> H <sub>6</sub> (μL/L)
2013-01-20	32.5/28.8/31.2/29.7	74.5/68.9/72.7/70.6	15.1/13.7/14.7/14.2
2013-01-30	28.7/25.9/27.3/26.6	65.6/61.1/63.8/62.6	13.9/12.5/13.4/13.1
2013-02-10	29.5/26.1/27.8/26.9	68.2/63.3/66.1/64.5	14.1/12.7/13.6/13.3
2013-02-20	31.2/27.8/29.6/28.5	71.8/66.5/69.4/68.1	14.6/13.1/14.1/13.7

From Figure 4-7 and Table 2, it can be clearly noted that both GA-SVR and BNPP has effective pattern recognizing performance for online monitoring sensor array, which could restrain the cross-sensitivity of gas sensor array and further quantitatively recognize the content of dissolved CH<sub>4</sub>, C<sub>2</sub>H<sub>2</sub>, C<sub>2</sub>H<sub>4</sub> and C<sub>2</sub>H<sub>6</sub> gas. As lower MAPE observed in Figure 7 the GA-SVR procedure has much more superior pattern recognition performance for CH<sub>4</sub>, C<sub>2</sub>H<sub>2</sub>, C<sub>2</sub>H<sub>4</sub> and C<sub>2</sub>H<sub>6</sub> gas, respectively, when compared with BPNN. Therefore, we can safely draw a conclusion that the SVR model based upon GA performs excellent recognizing performance than BPNN, and it presents a promising artificial intelligence method used in online monitoring device to further quantitative recognizing of the fault characteristic gases dissolved in transformer oil.

## 5. Conclusion

In this study, a hybrid pattern recognition approach of support vector regression (SVR) and genetic algorithm(GA) is proposed to reduce the cross-sensitivity of gas sensor array and further recognize the gas content. Compared with original online monitoring data and BNPP recognized data, the presented GA-SVR procedure exhibits more excellent pattern recognition performance. A satisfactory recognizing performance has been achieved for methane, ethane, ethylene and acetylene. These results indicate that the proposed GA-SVR can be a promising candidate used in online monitoring system to handle the cross-sensitivity of the four fault characteristic hydrocarbon gases. However, a subsequent work needs to be supplemented in the future study to handle all fault characteristic gases dissolved in transformer oil.

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