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Research Article

An Information Granulated Based SVM Approach for Anomaly Detection of Main Transformers in Nuclear Power Plants

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The main transformer is critical equipment for economically generating electricity in nuclear power plants (NPPs). Dissolved gas analysis (DGA) is an effective means of monitoring the transformer condition, and its parameters can reflect the transformer operating condition. This study introduces a framework for main transformer predictive-based maintenance management. A condition prediction method based on the online support vector machine (SVM) regression model is proposed, with the input data being preprocessed using the information granulation method, and the parameters of the model are optimized using the particle swarm optimization (PSO) algorithm. Using DGA data from the NPP data acquisition system, two experiments are designed to verify the trend tracing and prediction envelope ability of main transformers installed in NPPs with different operating ages of the proposed model. Finally, how to use this framework to benefit the maintenance plan of the main transformer is summarized.

1. Introduction

The development of the nuclear industry has slowed or even stalled for many years [1]. Without the breakthrough of new technology, an important issue to promote and even maintain the development of nuclear power is to reduce the operating and maintenance costs on the premise of ensuring safe operation reliability [2].

The main transformer is an important equipment to generate power in a nuclear power plant (NPP), which is directly connected to generators. It increases the voltage from the generator output voltage to the highest transmission voltage to supply electricity to the transmission grid, while the generator is disconnected; it is used to power auxiliary systems from the grid [3]. Compared to power transformers in other industries, main transformers are generally operated at a rated temperature and therefore age more quickly, as they are usually operated continuously at a constant load to produce more electricity [4].

Due to its importance in generating electricity and vulnerability, NPPs generally have strict and even conservative maintenance management for the main transformer. The management of main transformers is mainly based on preventive maintenance, supplemented by certain corrective maintenance [5]. In preventive maintenance, there are strict rules and standards for periodic inspection, test, inspection, and monitoring. To some extent, regular maintenance means redundancy. Redundant maintenance not only increases the cost but may even cause damage to equipment, and the reliability of equipment is reduced due to excessive maintenance [6].

Gases in oil-immersed transformers are proven to be a useful tool to identify fault types including thermal and electrical disturbances [7]. According to the criteria of the IEC/IEEE standards, dissolved gas analysis (DGA) techniques are commonly used to detect internal faults in uninterrupted power services. Available gases from chromatographic analysis of the insulation oil could contain concentrations of dissolved carbon monoxide (CO), carbon dioxide (CO_2), nitrogen (N_2), hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_2), and ethane (C_2H_6). Composition of the dissolved gases, rates of generation, and specific content ratios can be used to indicate the conditions of the transformers [8]. There are many recognized dissolved gas analysis techniques for judging the main transformer based on DGA monitoring. In particular, these diagnostic technologies integrate the latest hardware and software architectures and get functional modules adapted to new scenarios. A new integration of an Internet of Things (IoT) architecture with deep learning against cyberattacks for online monitoring of the power transformer status help improve the guarantee of the physical layer, through the combination of approved analysis methods to obtain more accurate interpretation [9]. The new optimization model optimizes feature input and diagnostic accuracy [10]; the diagnosis results of recognized dissolved gas analysis techniques are integrated towards precise interpretation [11].

The characteristics of dissolved gas can be used as an effective indicator of the state of nuclear power main transformer, and the reasonable predicted value of dissolved gas can be used as an effective basis for judging the future state of nuclear power main transformer. In general, most forecasting methods use historical measurements to build prediction models. Scholars hope to find suitable prediction methods to improve prediction accuracy. Previous studies mainly focus on the following aspects: prediction of transformer dissolved gas concentration by combining the regression algorithm and data processing techniques like wavelet [12, 13], prediction of specific parameters related to gas concentration after correlation analysis or principal component analysis [14–16], and multiple prediction methods are combined to form a combined prediction model or a multiobjective optimization problem [17, 18]. In addition, there are many interesting applications of machine learning methods in the field of time series data prediction [19, 20]. These intelligent methods mainly consider improving prediction accuracy, as given in Table 1. In this study, it is considered that in the actual operation of the nuclear power plant transformer, the overhaul cycle is taken as the decision point of the maintenance scheme, and it is more important to reliably predict the gas concentration in the subsequent cycle than simply improving the gas concentration at the next monitoring point.

Consequently, the use of data stored in NPP's supervisory control and data acquisition system (SCADA) makes it possible to construct a system-wide monitoring system and help decide maintenance strategies relating to faults that can be indicated by DGA techniques [21, 22].

SVM, which is used as a regression model, adopts the principle of structural risk minimization, can effectively solve regression problems with limited samples, nonlinear and high dimensions, and has strong generalization ability [23, 24].

This study proposes an SVM-based condition prediction approach using a nonlinear autoregressive network of SVM to estimate the condition of the main transformer. The NPP SCADA system collects DGA data. DGA data can be preprocessed by the information granulated fuzzy method. The SVM prediction model can be trained with these processed DGA data. The trained SVM model is used to predict the dissolved gases of the high value of the main transformer for the next few outage cycles. The PSO algorithm is used to optimize the parameters of the SVM regression model. The predicted value is compared with the actual condition value recorded in the system.

The structure of this study is as follows: the second section presents the framework and introduces the predictive maintenance strategy for the main transformer based on SVM. The third section introduces the prediction model based on SVM in detail. The fourth section introduces the case study, and the fifth section summarizes the conclusion.

2. Predictive-Based Maintenance Management Framework

The disadvantage of periodic health evaluation is that the time interval between two consecutive maintenance activities is not always sufficient to identify emerging issues prior to failure, while frequent periodic maintenance results in the maintenance of healthy transformer components, increasing maintenance costs and the possibility of human error. Critical components in the main transformer may have regular maintenance with relatively high frequency, which may lead to excessive maintenance, while the less important component may have regular maintenance with too low frequency, which may bring more corrective maintenance.

Maintenance management expresses a strategy to find the balance between the cost of maintenance activities and the benefits of the increased asset value.

In this study, an adaptive maintenance scheduler (AMS) framework is proposed for certain maintenance management of main transformers. The AMS framework considers the time window of an outage interval, which exists between an indication of impeding failure from DGA inspection and the eventual faults. In the framework, the history data extracted from SCADA are preprocessed by the information granulated method; new sampling data are updated into the data preprocessing module only impacting the latest cycle. Then, granulated data are obtained to train the SVM regression model for real-time update of the prediction model. The output of the prediction model would be the basis for the experts' diagnosis module, which also provides decision-making support to maintenance personnel. The overall logic of the AMS framework is shown in Figure 1.

According to the AMS framework and the SVM-based condition prediction approach, it would help the maintenance personnel to decide the maintenance plan. The diagnostic expert system can receive the prediction of the DGA parameter values, judging from the DGA characterization, to find any anomalies or faults that could occur in the main transformer in the next fuel duration. These insights can be passed on to maintenance decision makers to decide the maintenance program for the next outage, which may involve some additional tests, parts/component replacement, and disassembly inspection. Thus, the execution frequency of certain programs can be increased or decreased during continuous validation.

As longer the transformer operates, according to the monitoring data generated and the online trained SVM regression network of the individual transformer, the network structure would be more adaptive for each unique transformer

Table 1: Comparison of prediction methods of typical transformer dissolved gas and sequence data in recent years.

Method	Dataset	Features
ANN + wavelet [12]	A GE transformer located in Brazil, 176 samples in 7 months	Robustness, improved precision prediction; the need for retraining for new measurements.
LSSVM + wavelet + PSO [13]	Data from several electric power companies in China; 11 samples in 3 months for case 1; 7 samples in 2 months for case 2	With limited samples, performs better generalization performance and stable forecasting capability
LSSVM + GRA + EMD + GWO [14]	A transformer in the State Grid Corporation of China sampled every 3 days during 9 January 2012 and 3 July 2012	Improved prediction accuracy, strong generalization ability, and robustness.
KPCA + FFOA + GRNN [15]	A substation installed in Shandong Province, daily sampled data from October 2010 to May 2012	Improved prediction accuracy, the need for retraining for new measurements.
GRA + GP [16]	8 different datasets between 1992 and 2011 for a transformer	Removing irrelevant and redundant features, improved prediction accuracy.
RBFNN/BPNN/LSSVM + GM [17]	7 samples in 7 months for case 1; 8 samples in 8 months for case 2; 10 samples in 10 months for case 3 for a transformer	Improved accuracy and stability
SVR/RT/GMDH/RBF/ANFIS/ESN/ KRIDGE/CFNN/FFNN [18]	1639 samples in 6 months in a power transformer	Improved prediction accuracy and wide adaptability
HIFI [19]	Solar irradiation dataset	Improved precision, strong generalization performance
SVM-based distribution system [20]	Photovoltaic unit dataset	Improved accuracy and time-saving

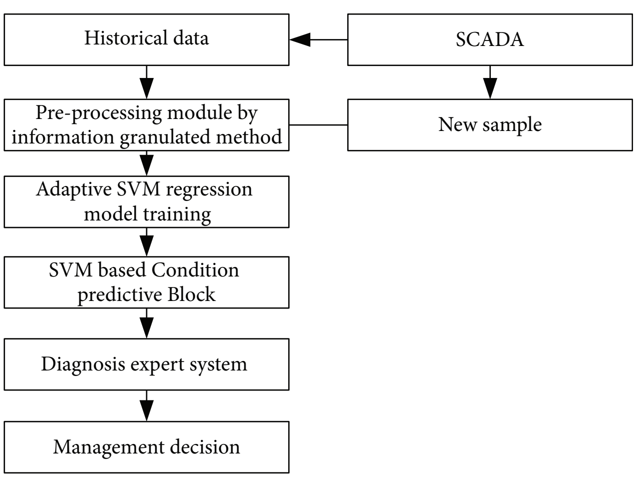

Figure 1: AMS framework for main transformer maintenance management.

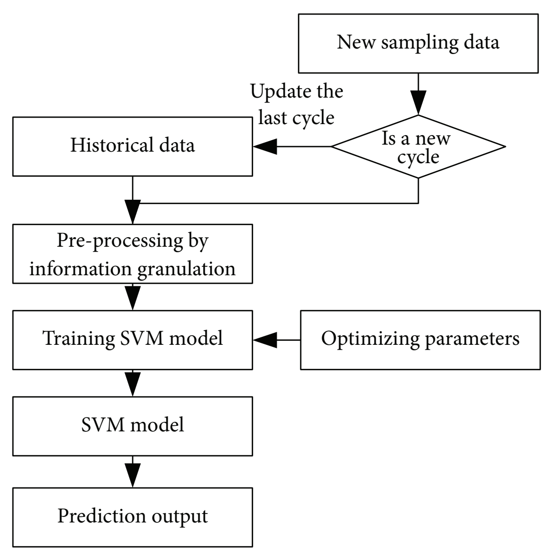

Figure 2: Information granulated SVM-based condition prediction process.

to adapt to the differences generated in the design, installation, and operation of the individual transformers.

3. Information Granulated SVM-Based Condition Prediction Approach

According to the main transformer preventive maintenance management framework introduced in the second paragraph, how to use historical data and newly sampled data to predict the future state is very important, which is also the role of the method proposed in this study. The flowchart of the information granulated SVM-based condition prediction approach is shown in Figure 2. Historical data stored in the SCADA system are preprocessed to obtain representative data of each cycle. Then, determine whether the new sampling data are in a new cycle, if it is, preprocess directly; if not, update the last cycle dataset of historical data and then preprocess the updated dataset. The preprocessed data are used to train the SVM regression model.

3.1. Information Granulation Method. The information granulation method was first introduced into time series mining and explored the nature and mining algorithm of time series by studying different granularity divisions of time series on the time axis [25].

The timeline information granulation of time series is divided into several subsequences, according to the changing characteristics of the time series in a certain way, and the subseries in each time window is regarded as an information granulation. Then, the subseries in the time window is described effectively.

The choice of time window width is an important factor affecting information granulation. Another is the information granulation membership function. Membership function reflects the rules of information granulation for the original time series data.

The main task of fuzzification is to establish a fuzzy particle P, in which the fuzzy particle is established according to the fuzzy set G that can describe the original information, and its essence is to determine the membership function A of G, where $A = P(G)$.

Commonly used fuzzy particles have the following basic forms: triangle, Gaussian, and parabolic [26].

The information granulation method is applied to preprocessed monitored dissolved gas concentration values, which can reduce the real-time calculation amount of the system. Moreover, the predicted values formed after the processing can better represent the state of the main transformer in the next fueling cycle.

3.2. SVM Regression. The SVM regression model can be described as follows: setting training dataset as $(x_1, y_1), (x_2, y_2), \ldots, (x_l, y_l)$, in which $x_i \in R^N$ is a vector of N dimensions, $y_i \in R$

The model $M(x)$ (or the learning machine) is found through training and learning to satisfy $y_i = M(x_i)$, for training sample set and prediction dataset: $x_{l+1}, x_{l+2}, \ldots, x_m$.

The model can also obtain a satisfactory corresponding output value y_i, finding an optimal functional relation $y = f(x)$ reflecting sample data. Optimal here refers to the "best" (minimum cumulative error) fitting of the sample dataset by the function relation calculated according to a specified error function.

The problem of finding the optimal regression hyperplane is transformed into solving the following quadratic convex programming problem:

$$\min \frac{1}{2}\|\omega\|^2 + C\sum_i (\xi_i + \xi_i^*). \tag{1}$$

Constraint can be described as follows.

$$y_i - (\omega \cdot x_i) - b \le \varepsilon + \xi_i, \tag{2}$$

$$(\omega \cdot x_i) + b - y_i \le \varepsilon + \xi_i^*, \tag{3}$$

where $\xi_i, \xi_i^* \ge 0$.

By mapping, the nonlinear regression function determined by the SVM method is described as

$$f(x) = \sum_{i=1}^{L} (\alpha_i - \alpha_i^*) K(x, x_i) + b, \tag{4}$$

where $K(x, x_i)$ is the kernel function, and $\alpha_i - \alpha_i^*$ and b are the parameters to determine the optimal hyperplane [27].

The weights would be obtained by training the SVM regression model with preprocessed data described in Section 3.1.

3.3. Optimization Method. The effect of SVM is mainly related to the kernel function and the penalty parameter. To get the best fitting function, we need to optimize the parameters. The grid search [28], genetic algorithm [29], and particle swarm optimization are regular methods to search for optimal solvers in a complex space of the SVM model [30].

PSO is an evolutionary computational algorithm to solve nonlinear optimization problems. In PSO, a number of simple entities, called particles, are placed in the search space for a problem or function, and each evaluates the objective function at its current location. Each particle then determines its movement through the search space by combining some aspects of the history of its own current and best locations with those of one or more members of the swarm, with some random perturbations. The next iteration occurs after all particles have been moved. Eventually, the swarm as a whole, like a flock of birds collectively foraging for food, is likely to move close to an optimum of the fitness function [31]. Formula 5 denotes the moving direction of particle swarm, and formula 6 denotes the example position of iterative update after moving. Particle swarm optimization would be used to optimize the parameters in the SVM model. Each particle represented a potential solution, including regularization parameter c and kernel parameter a.

$$\begin{aligned} v_i^d(t+1) = {} & w v_i^d(t) + c_1 r(t)\left(p_i^d(t) - x_i^d(t)\right) \\ & + c_2 r(t)\left(p_g^d(t) - x_i^d(t)\right), \end{aligned} \tag{5}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1). \tag{6}$$

In the training and testing process of the SVM model, its goal is to minimize the deviation between the real value and the predicted value of the test sample. Therefore, the fitness function can be defined as

$$\text{Fitness} = \frac{1}{k}\sum_{i=1}^{k}\frac{1}{m}\sum_{j=1}^{m}\left(f\left(x_{ij}\right) - y_{ij}\right)^2. \tag{7}$$

4. Experiment and Analysis

In order to satisfy the decision support process of NPP main transformer maintenance management, the AMS framework and the proposed SVM-based condition prediction approach are applied. First, the application data of the algorithm are introduced. Two experiments were designed based on the actual operating data. The first experiment applied the SVM model optimized by PSO to the data after information granulation, which had good tracking performance and fast convergence performance. The second test is used to verify that the prediction

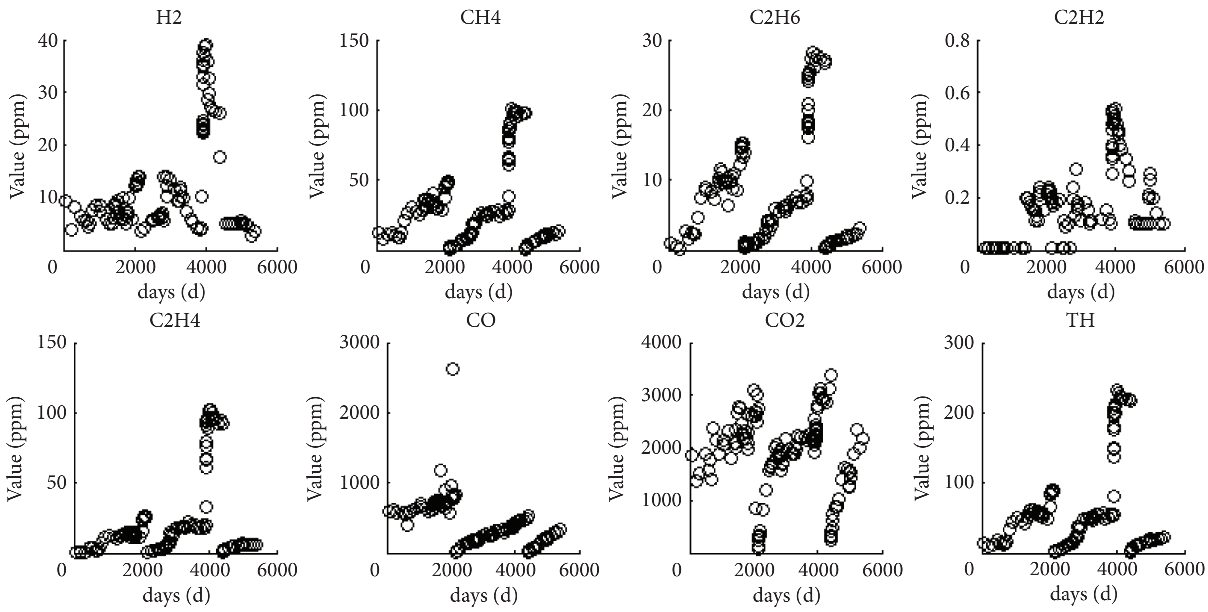

Figure 3: DGA inspection data of a main transformer phase A.

method proposed in this study has a good envelope ability for the performance of the main transformer of nuclear power plant with different operating periods in the next cycle.

4.1. The Main Transformer Description. A nuclear power plant generator, 24 kV voltage through the main transformer increased to 500 kV, and connected to the 500 kV power grid, the main transformer is three single-phase transformers, each phase capacity is 410 MVA. DGA is sampled once every 3 months regularly. Sampling intervals can sometimes be uneven, depending on condition values or work schedules. 158 time-marked sampling data from the transformer were collected in this study, where sampled time spans 13 operating cycles, since the service reactor was connected to the grid, with the longest time span of 5387 days. The dataset is shown in Figure 3.

DGA data can be information granulated considering outage cycles to generalize the high and median values of features for each outage cycle. The SVM prediction model can be trained with these processed feature data. The trained SVM model is used to predict the DGA high value of the main transformer in the next outage cycle, and the condition is compared with the actual condition value recorded in the system. The PSO optimization algorithm will be used to optimize the parameters of the SVM prediction model.

4.2. SVM-Based Model. The time granularity (the width of the time window) used in this study is an outage period that is not evenly distributed in the absolute sense. The data should be divided according to the characteristics of the sampling interval after learning. The best practice is manual assisted marking.

4.3. Experiment 1 (Middle Age). This experiment is designed to test the prediction ability of the proposed method on the condition of the main transformer of the nuclear power plant which has been in operation in the middle age under strict and conservative maintenance management.

This experiment aims to test the prediction ability of the proposed method for the main transformer operating state of nuclear power plant, which is operated under strict and conservative maintenance management. In this experiment, the proposed SVM-based model applied to data preprocessing, parameter optimization, regression prediction, and prediction accuracy is analysed.

4.3.1. Features Preprocessing. Figure 3 shows the phase A DGA monitoring value of a main transformer, where abscissa is the number of days for which the nuclear power plant is connected to the grid, and the ordinate is the concentration of the monitored gas concentration, in μL/L PPM. The title of each subplot shows the corresponding gas, where TH is the sum of hydrocarbon gases. The concentration of CO and CO_2 is obviously not of the same order as that for other gases.

The data in Figure 3 indicate that the eight characteristic gas concentrations are in a certain periodic distribution during the period, that is, more than 5000 days from the day that the nuclear power plant was connected to the grid, which is related to the existing regular maintenance activities. Once several fuel cycles have been performed, the main transformer is reexamined and these disposal activities can significantly change the gas concentration. As shown in Figure 3, the process of developing characteristic gas changes can be missed due to a too long sampling interval, resulting in abrupt changes in the data. When the triangle membership function is used for the estimation of high, median, and low value estimations, the low value may cause the

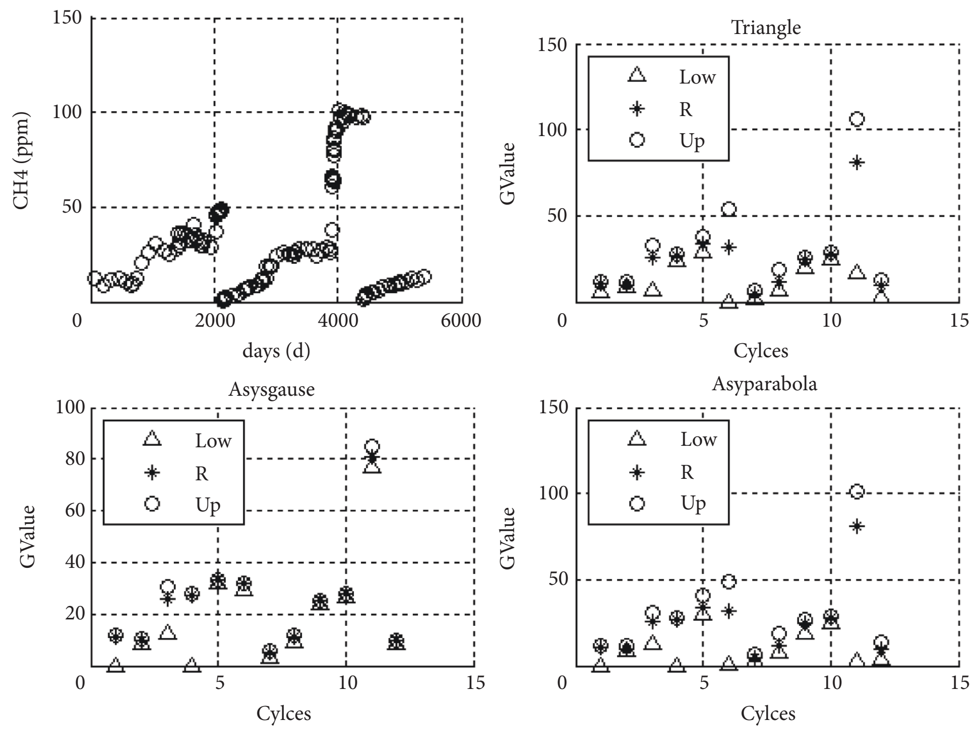

Figure 4: CH_4 concentration and information granulated by a refueling cycle as time window with three different membership functions.

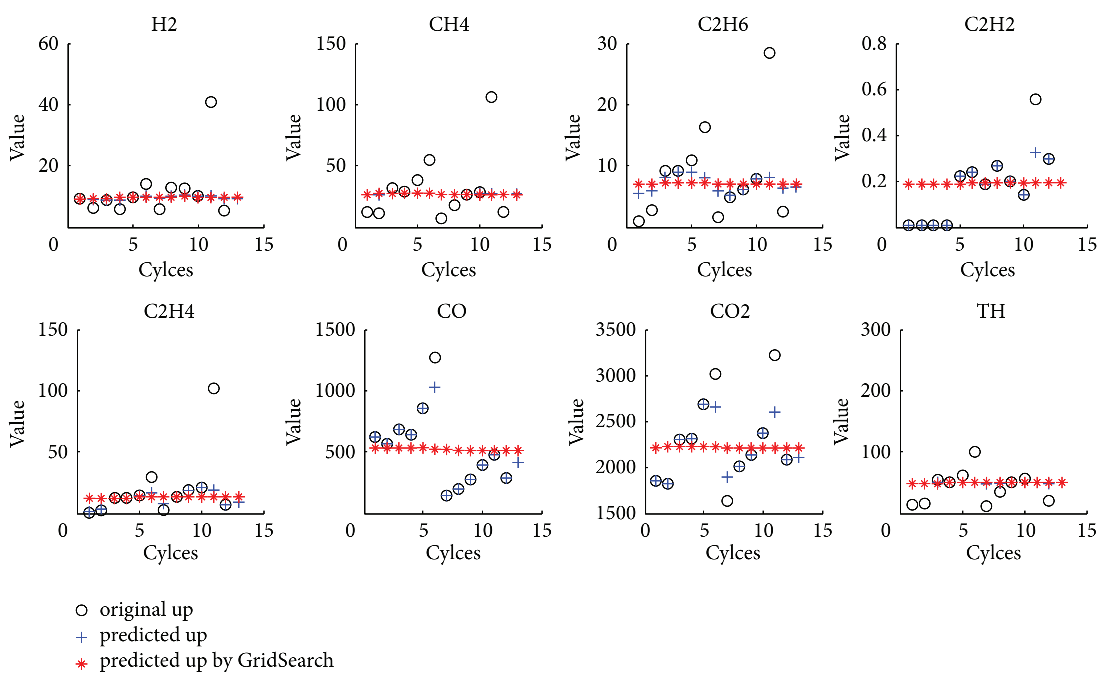

Figure 5: Original vs. predicted value by the SVM model and grid search optimized SVM model.

phenomenon that the low value is negative, which is impossible in the actual situation. Here, the point with the low value is negative and is set to zero.

The appropriate membership function can help the granulated information reasonably summarize the monitoring values in the time window. The granulation effect of each membership function shows that the granulation result of the triangular membership function, as shown in Figure 4, has a greater enveloping ability and a stronger ability to cover extreme observation values that may be missing due to insufficient sampling frequency. This enveloping purpose is consistent with the conservative safety view of nuclear power.

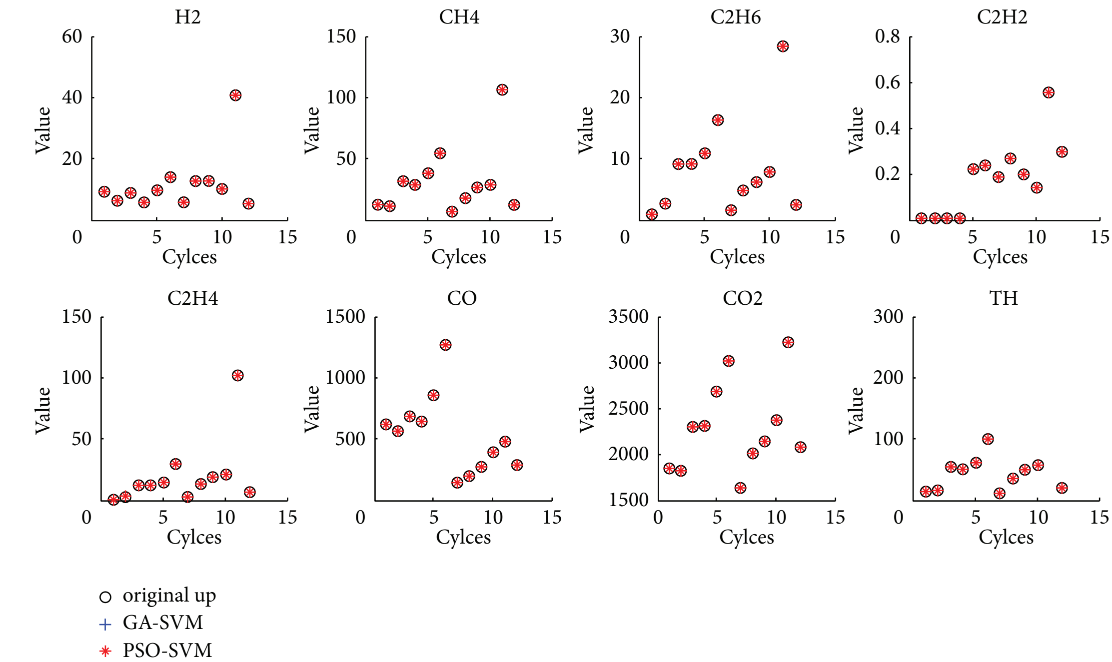

FIGURE 6: The predicted value of the GA-SVM/PSO-SVM regression model based on the high value obtained by the information granulation of DGA condition monitoring (set as Up) vs. Up.

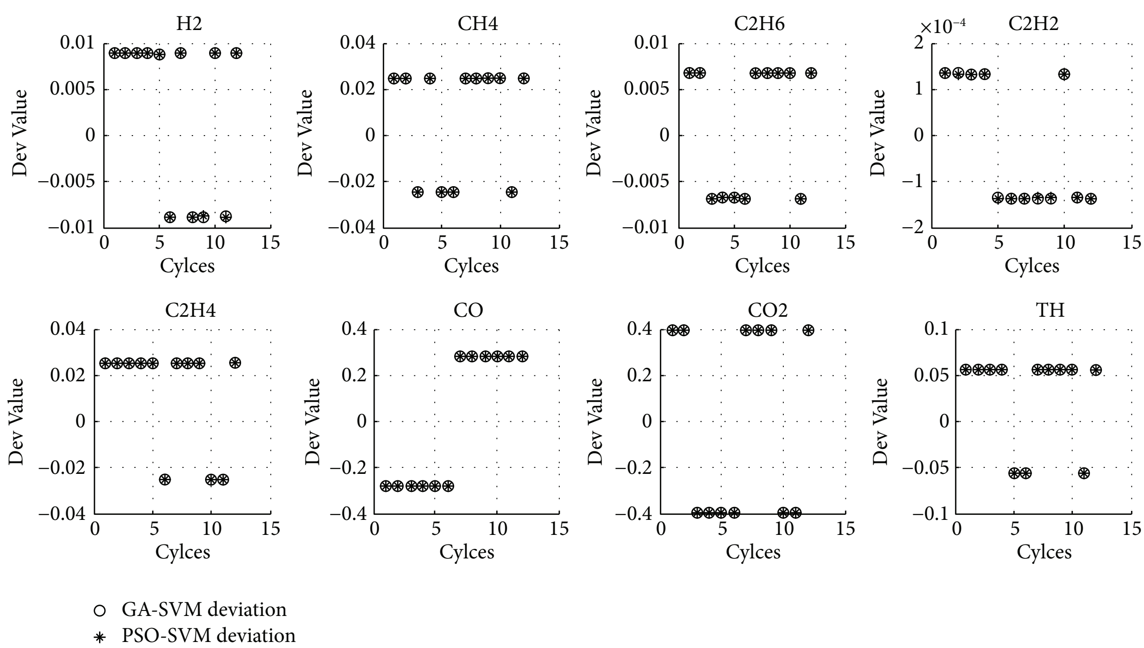

FIGURE 7: The deviation between the predicted value by the GA-SVM/PSO-SVM regression model and the high value obtained by information granulation.

4.3.2. SVM Regression Model. In the process of modelling SVM regression, the training data are normalized and processed to [100, 500], and reasonable c and g values are set according to experience and operation time.

Figure 5 shows the comparison between the high value of gas concentration processed by the information granulation method and the predicted value of the SVM regression model and the predicted value of the SVM regression model optimized by grid search, which illustrates that the SVM regression model has great deviation when applied for the high value predication on granulated DGA data. Moreover, an inappropriate optimization method is detrimental to finding appropriate parameters, as the SVM model optimized by grid search demonstrates.

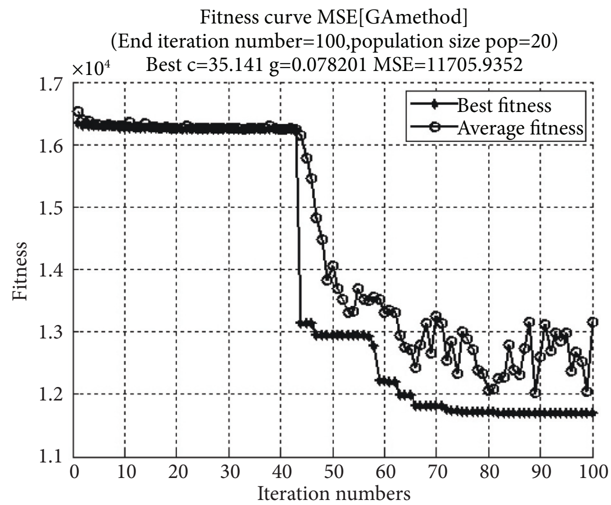

Figure 8: GA-SVM optimization process of CO data.

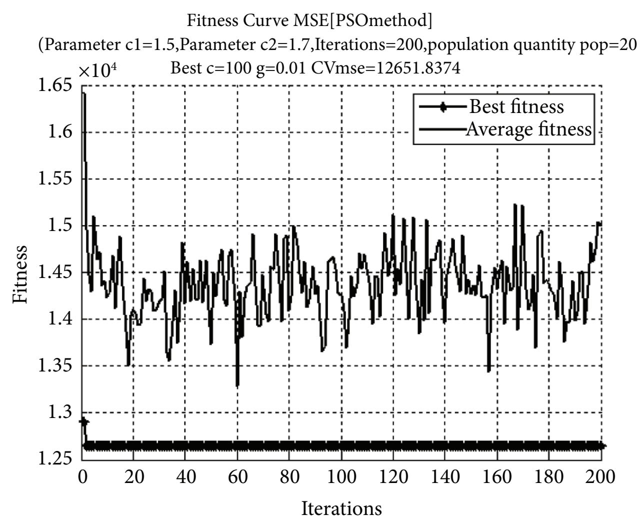

Figure 9: PSO-SVM optimization process of CO data.

4.3.3. Optimized SVM Regression. The parameters of the SVM regression model were optimized by the genetic algorithm (GA-SVM regression model) and the particle swarm optimization algorithm (PSO-SVM regression model). The maximum number of evolutions is set as 200, and the maximum number of populations is set as 20. The maximum range of parameters c and g is set as [0, 100].

Figure 6 shows the comparison between the high value of the gas concentration processed by the information granulation method and the predicted value of the SVM regression model optimized by the genetic algorithm and the predicted value of the SVM regression model optimized by PSO. The parameter optimization of the SVM regression model for DGA condition monitoring of the main transformer by the genetic algorithm and PSO has certain trend tracking ability.

Figure 7 shows the deviation between the values predicted by GA-SVM and PSO-SVM and the high values obtained by the information granulation method, indicating that the two prediction models have good trend tracking ability for historical data.

In Figures 8 and 9, the CO monitoring data are taken as an example to illustrate the convergence process when GA and PSO optimization algorithms are used, respectively. Compared to GA-SVM, the PSO-SVM model converges to the global optimal solution faster and is more effective for parameter optimization than GA-SVM in the granulated DGA predication application.

4.3.4. Model Prediction Accuracy Analysis. Figure 10 shows the comparison of the predicted gas concentration values for the 13th fuel cycle using the SVM, GA-SVM, and PSO-SVM models with the actual monitored values, illustrating that PSO-SVM has stronger and accurate envelope ability than the SVM and GA-SVM models.

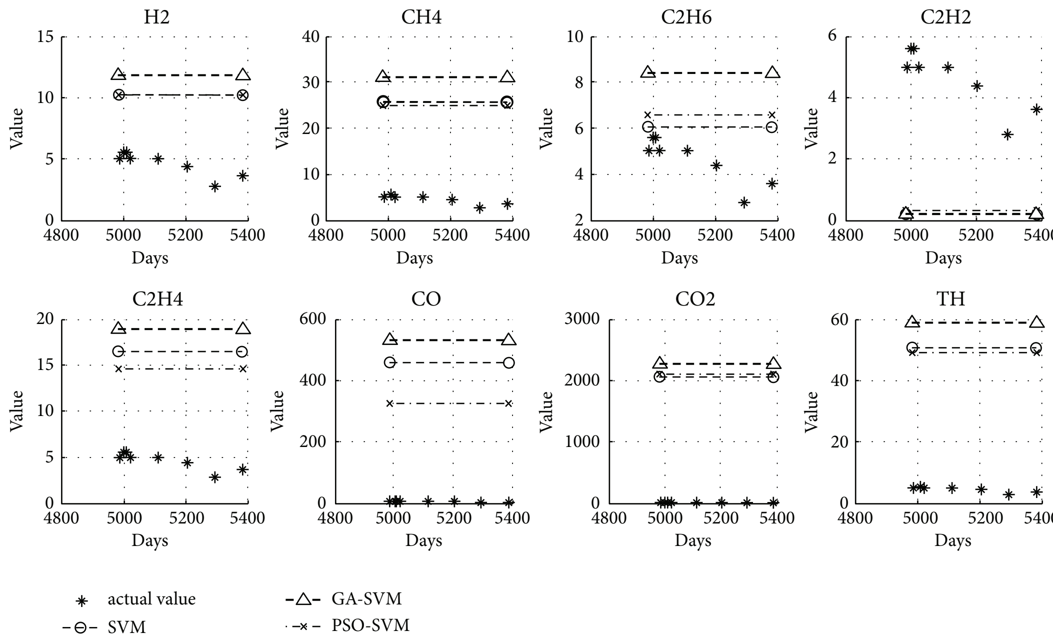

FIGURE 10: The monitored gas concentration values during the 13th refueling cycle compared to the values predicted by different models.

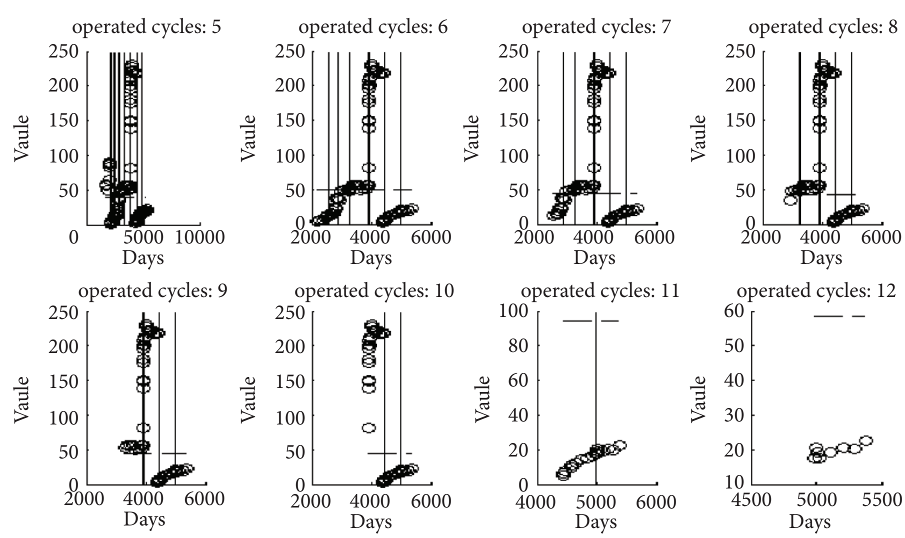

FIGURE 11: Actual value vs. predicted high value by PSO-SVM with different refueling cycle operation history for the main transformer taking TH as an example.

Thus, a PSO-SVM model is applied to predict the DGA high value of the main transformer for maintenance plan during outage.

4.4. Experiment 2 (NPP's Different Ages). This experiment uses the historical data of the main transformer operation condition described in experiment 1 to test the predictive capacity of the PSO-SVM model to the operation condition of the main transformer with different operating cycles for the next few refueling periods.

When the reactor is operated at different ages, the subsequent predictions of the SVM regression model trained on the running history data are shown. The separation line parallel to the y-axis in Figure 11 is the first sampling time after refueling. Therefore, the envelope abilities of the results predicted by the model for subsequent refueling cycles are shown in Figure 11.

When the reactor enters a long operating life, sufficient historical data can help the model make effective predictions that can cover DGA conditions in subsequent refueling cycles even when the main transformer is in a more complex environment.

5. Conclusion

This study presents a framework to predict and judge the condition of the main transformer in a nuclear power plant, including an online training SVM regression model to predict the condition of the main transformer.

To carry out fast online training, a refueling cycle is used as a time window with granulate information to preprocess the monitoring data without affecting the condition judgment.

The PSO algorithm is used to optimize the parameters of the SVM regression model in this study, which makes the training model converge quickly and track the trend well.

On the basis of the data preprocessing of information granulation, a particle swarm optimization algorithm is used to train the model and the model is used to predict the future condition. In this framework, the prediction results can be used as input into maintenance decisions during subsequent refueling overhauls. The practicability of the model is verified by experiment 1. In experiment 2, the tracking ability and prediction ability of the model in reactors of different ages are analysed and verified. Under the established maintenance strategy, this model can provide the beneficial support for the maintenance decision of the main transformer entering the mature operation reactor for a subsequent outage and support the establishment of the maintenance management framework.

Although the monitored data applied in the model are not frequent, the DGA analysis tool has been gradually installed in the main transformers; the amount of monitoring data generated online in real time would be enormous. Calculation efficiency obtained by applying the distributed computing mode of the proposed information granulation processing method to deal with online DGA monitoring value initially would become a significant advantage. Meanwhile, the granulation data may also lose some internal indications that have not been found in the original monitoring values, which may also affect the detection of potential problems as a compromise.

Data Availability

The data used to support this study are included in within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] M. Schneider, "World Nuclear Industry Status Report," 2021, https://www.worldnuclearreport.org/-World-Nuclear-Industry-Status-Report-2021.html.

[2] B. Christiane, E. Arne, and F. Gianluca, *Load-following Operating Mode at Nuclear Power Plants (NPPs) and Incidence on Operation and Maintenance (O & M) Costs—Compatibility with Wind Power Variability*, 2010.

[3] V. Agarwal, N. J. Lybeck, and B. T. Pham, "Diagnostic and prognostic models for generator step-up transformers," Technical report, Chicago, Ill, USA, 2014.

[4] G. W. Alexander, S. L. Corbin, and W. J. Mcnutt, "Influence of design and operating practices on excitation of generator step-up transformers," *IEEE Transactions on Power Apparatus and Systems*, vol. 85, pp. 901–909, 1966.

[5] H. Cai, "Practical application of condition based maintenance of main transformer in qinshan nuclear power Co., Limited," in *Proceedings of the Annual Meeting of China Nuclear Society*, Beijing, China, 2009.

[6] Y. Zhang, *Research on Life Cycle Maintenance Decision of Power Transformer Based on Operation State and Life Assessment Diss*, Chongqing University, Chongqing, China, 2014.

[7] M. Duval, "A review of faults detectable by gas-in-oil analysis in transformers," *Electrical Insulation Magazine IEEE*, vol. 18, pp. 8–17, 2002.

[8] M. Duval and A. Depabla, "Interpretation of gas-in-oil analysis using new IEC publication 60599 and IEC TC 10 databases," *Electrical Insulation Magazine IEEE*, vol. 17, pp. 31–41, 2002.

[9] E. Mahmoud, M.-Q. Tran, M. Karar, D.-E. A. Mansour, L. Matti, and M. M. F. Darwish, "Effective IoT-based deep learning platform for online fault diagnosis of power transformers against cyberattacks and data uncertainties," *Measurement*, vol. 190, 2022.

[10] S. S. M. Ghoneim, M. Karar, L. Matti, and M. M. F. Darwish, "Enhancing diagnostic accuracy of transformer faults using teaching-learning based optimization," *IEEE Access*, vol. 99, 2021.

[11] S. A. Ward, A. El-Faraskoury, M. Badawi et al., "Towards precise interpretation of oil transformers via novel combined techniques based on DGA and partial discharge sensors," *Sensors*, vol. 21, 2021.

[12] F. H. Pereira, F. E. Bezerra, S. Junior et al., "Nonlinear autoregressive neural network models for prediction of transformer oil-dissolved gas concentrations," *Energies*, vol. 11, 2018.

[13] H. Zheng, Y. Zhang, J. Liu, H. Wei, J. Zhao, and R. Liao, "A novel model based on wavelet LS-SVM integrated improved PSO algorithm for forecasting of dissolved gas contents in power transformers," *Electric Power Systems Research*, vol. 155, pp. 196–205, 2018.

[14] Z. Bing, G. Jiang, F. Zhang et al., "Prediction model for dissolved gas concentration in transformer oil based on modified grey wolf optimizer and LSSVM with grey relational analysis and empirical mode decomposition," *Energies*, vol. 13, 2020.

[15] J. Lin, G. Sheng, Y. Yan, J. Dai, and X. Jiang, "Prediction of dissolved gas concentrations in transformer oil based on the KPCA-FFOA-GRNN model," *Energies*, vol. 11, 2018.

[16] S. X. Lu, G. Lin, M. J. Li, C. H. Wei, and J. K. Wang, "Grey relational analysis using Gaussian process regression method for dissolved gas concentration prediction," *International Journal of Machine Learning and Cybernetics*, vol. 10, pp. 1313–1322, 2019.

[17] C. Liu, H. Zhang, Z. Xie et al., "Combined forecasting method of dissolved gases concentration and its application in condition-based maintenance," *IEEE Transactions on Power Delivery*, vol. 34, pp. 1269–1279, 2019.

[18] A. Peimankar, S. J. Weddell, T. Jalal, and A. C. Lapthorn, "Multi-objective ensemble forecasting with an application to

power transformers," *Applied Soft Computing*, vol. 68, pp. 233–248, 2018.
[19] M. Abdel-Nasser, K. Mahmoud, and M. Lehtonen, "HIFA: promising heterogeneous solar irradiance forecasting approach based on kernel mapping," *IEEE Access*, vol. 9, pp. 144906–144915, 2021.
[20] K. Mahmoud, M. Abdel-Nasser, and M. Lehtonen, "Low-computational voltage-assessment approach considering fine-resolution simulations for distribution systems with photovoltaics," *IEEE Systems Journal*, vol. 15, no. 4, pp. 5321–5331, 2021.
[21] T. K. Saha, "Review of modern diagnostic techniques for assessing insulation condition in aged transformers," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 10, pp. 903–917, 2003.
[22] T. Nagpal and Y. S. Brar, "Expert system based fault detection of power transformer," *Journal of Computational and Theoretical Nanoscience*, vol. 12, no. 7, pp. 208–214, 2015.
[23] H. Yu and S. Kim, *SVM Tutorial—Classification, Regression and Ranking*, Springer, Berlin, Germany, 2012.
[24] S. U. Gao-Li and F. P. Deng, "Introduction to model selection of SVM regression," *Bulletin of Science and Technology*, vol. 22, 2006.
[25] L. A. Zadeh, "Toward a theory of fuzzy information granulation and its centrality in human reasoning and fuzzy logic," *Fuzzy Sets and Systems*, vol. 90, no. 2, pp. 111–127, 1997.
[26] W. Lu, *Research on Time Series Analysis and Modeling Method Based on Granular Computing*, Dalian University of Technology, Dalian, China, 2015.
[27] U. Thissen, R. Van Brakel, A. P. De Weijer, W. J. Melssen, and L. M. C. Buydens, "Using support vector machines for time series prediction," *Chemometrics and Intelligent Laboratory Systems*, vol. 69, no. 1–2, pp. 35–49, 2003.
[28] L. Chao, S. Q. Yin, M. Zhang, Y. Zeng, and J. Y. Liu, "An improved grid search algorithm for parameters optimization on SVM," *Applied Mechanics and Materials*, vol. 644-650, pp. 2216–2219, 2014.
[29] C. Zheng and L. Jiao, "Automatic parameters selection for SVM based on GA," *Intelligent Control and Automation*, vol. 2, pp. 1869–1872, 2004.
[30] C. J. Tu, L. Y. Chuang, J. Y. Chang, and C. H. Yang, "Feature selection using PSO-SVM," *IAENG International Journal of Computer Science*, vol. 33, pp. 111–116, 2007.
[31] Y. H. Shi and R. C. Eberhart, "Empirical study of particle swarm optimization," in *Proceedings of the Congress on Evolutionary Computation IEEE*, Washington, DC, USA, August 2002.