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Hybrid Patterns Recognition of Control Chart Based on WA-PCA-PSO-SVM

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Abstract

Based on the analysis of the defect of traditional model, this paper proposes a new control chart pattern recognition model, which includes Wavelet Analysis (WA), Principal Component Analysis (PCA), Particle Swarm Optimization (PSO) and Support Vector Machine (SVM). WA is good to eliminate noise control chart anomaly pattern recognition of the adverse effect. PCA eliminates the redundant information of data between SVM and reduces the input dimension and computational complexity. PSO algorithm optimizes the parameters of SVM and the establishment of the optimal control chart anomaly pattern classifier can solve the problem optimal parameters of SVM. The simulation results show that the model is feasible, the results are reliable. This algorithm improves the control chart abnormal state average recognition accuracy and be used in the machining process real-time monitoring.

Keywords: ***c****ontrol chart; pattern recognition; wavelet analysis; principal component analysis; support vector machine*

1. Introduction

With the development of global economy, client’s demand for production is complexity, multiformity and personalized. In order to satisfy the client’s requirement and guarantee the normal operation of the machine, it is necessary to carry out the real-time monitoring of control system process. The abnormal situation and fault can be detected and prevented in time. The control chart is a kind of tool to reflect the processing quality whether the process is normal and improve enterprise detection quality by the state of the control chart. Therefore, control chart pattern recognition has become a hot issue in industrial manufacturing research.

Because of the impact of factors such as "man, machine, material, method, ring, measurement", the time series data with the quality descriptive characteristics represent non-stationary and nonlinear, similarity and dynamics in the production process. Traditional control chart is analysised and identified by person’s experiments. And now many intelligent algorithms have been developed. Ebrahimzadeh *et al.*, [1] regarded statistical features as the efficient characteristic of the patterns. Yang *et al.*, [2] proposed EWMA sign chart for detecting deviation from the process target. The classification based on statistics is aimed at linear system model, so the control chart

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recognition accuracy is quite low. Expert system needs constantly to update expert database [3], judge rules are very complicated and practically poor.

Neural network is applied to control chart pattern recognition effectively and gain higher recognition accuracy. El-Midany *et al.*, [4] used the Artificial Neural Networks (ANNs) to recognize set of subclasses of multivariate abnormal patterns, identify the responsible variable(s) on the occurrence of abnormal pattern and classify the abnormal pattern parameters. But the neural network is modeled based on empirical risk minimization principle, the adjusted network speed is slow and the generalization ability is poor. Ebrahimzadeh *et al.*, [5] adopted a suitable combination of the modified imperialist competitive algorithm to cluster the input data and several neural networks are used to classifier module. Its own defects are difficult to overcome, such as, network topology result is difficult to determine, quality online control reliability [6] is difficult. Recently, Du *et al.*, [7] proposed that support vector machines (SVM) is used to recognize for on-line recognition of concurrent CCPs. But original SVM demonstrate poor performance for imbalanced. Xanthopoulos and Razzaghi [8] proposed weighted support vector machines (WSVM) for automated process monitoring and early fault diagnosis, which better solves the intelligent methods such as neural networks with problems and becomes the control chart pattern recognition to the main research article. But its difficulty is the main parameter selection [9].

At present, the existed control chart recognition can not satisfy with the command of real-time monitoring. Their correct rate of recognition is low. The hybrid patterns recognition of control chart is proposed in this paper. Wavelet transform (WA) is adopted to eliminate the "noise" firstly. And then the key feature information of control chart samples is extracted to descend classifier complexity using the principal component analysis (PCA). Finally support vector matching (SVM) classifier because of its excellent small sample learning is used to construct control chart. Meanwhile, SVM is optimized by the particle swarm optimization algorithm.

This paper is organized as follows. In Section 2, Control chart pattern primitive type and recognition principle are given. In Section 3, hybrid patterns recognition of control chart based on intelligent algorithm is presented, including WA, PCA and SVM. The simulation results and applications are also presented in Section 4 and Section 5, respectively. Finally, our work of this paper is summarized in the last section.

2. Control Chart Pattern Primitive Type and Recognition Principle

Control chart pattern recognition is a kind of multi-classification problem. The control chart pattern recognition refers to the use of certain analysis method to process and analyze the quality characteristic of time series data, mine implied condition information characteristics, status and changing trend in process. In the machine process, control chart patterns are divided into for normal mode, step abnormal mode (jump and decreased), trend abnormal mode (tendency rising and trend descending), cycle abnormal pattern and their hybrid abnormal pattern for affected by influence of many kinds of factors, as shown in Figure 1.

Control chart patterns are described with data as following:

$$y(t) = \mu + x(t) + d(t) \qquad t = 1,2,\ldots, N \tag{1}$$

where μ represents controlled condition statistic mean, $y(t)$ is time process quality, $x(t)$ is accidental factor of disturbance time t, and $d(t)$ is abnormal interference value.

For $d(t)$, all kinds of control chart patterns are as follows:

For normal mode:

$$d(t)=0 \tag{2}$$

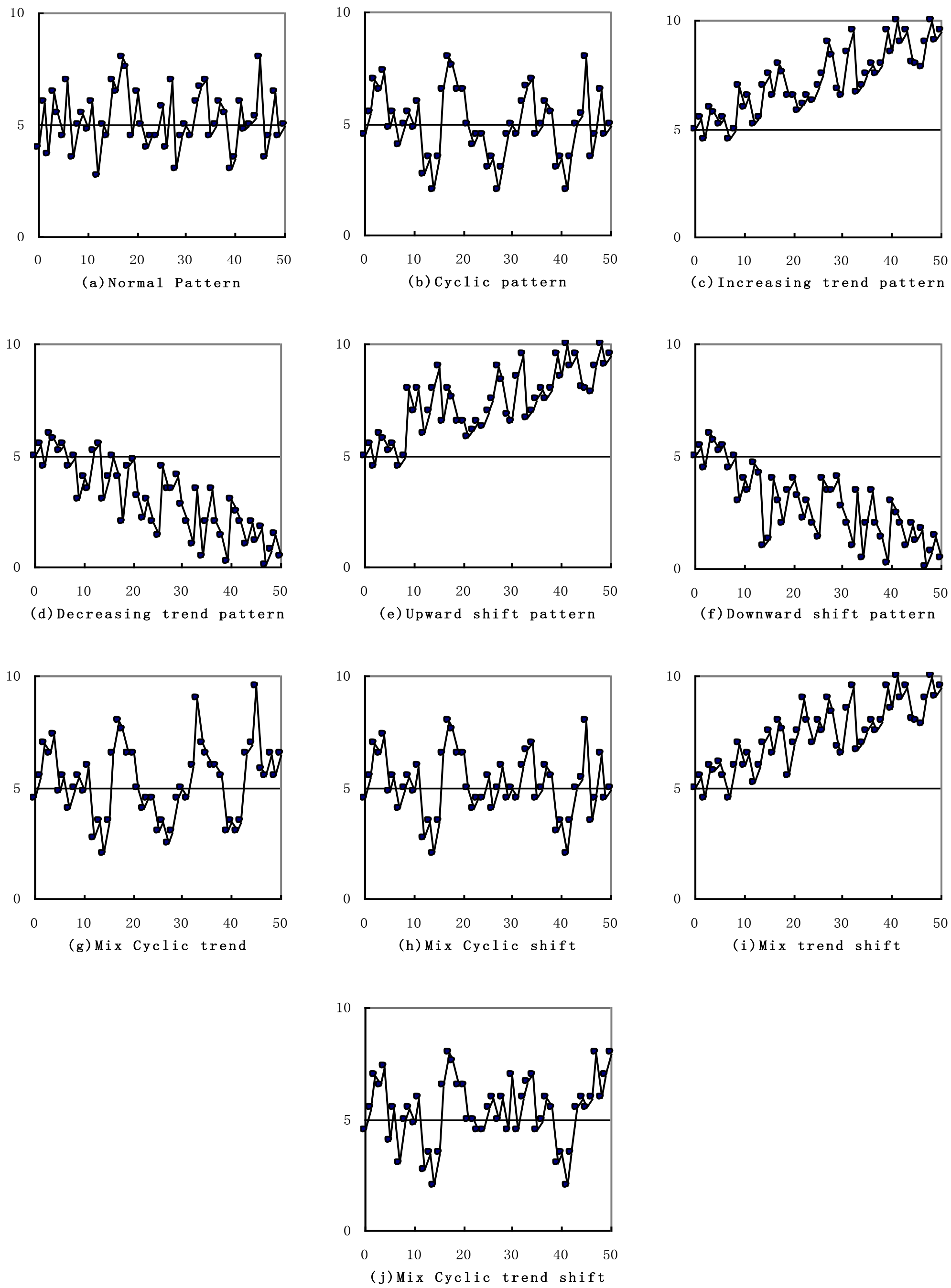

Figure 1. Ten Fundamental Patterns of Control Char

For step abnormal state mode:

$$d(t) = \pm l(t - t_0) \times \alpha \tag{3}$$

where t_0 represents happening starting point of step trend; + and -stand for gradually rise and drop respectively; $l(t- t_0)$ represents step abnormal coefficient; α represents step amplitude.

For trend abnormal state mode:

$$d(t) = \pm\gamma(t - t_0) \times \beta \tag{4}$$

where t_0 represents occurrence of trend starting point, β represents trend slope, γ represents trend abnormal coefficient.

For cycle type abnormal mode:

$$d(t) = A\sin(\frac{2\pi\sin(t - t_0)}{T}) \tag{5}$$

where t_0 represents starting point of happening cycle, A is expressed as wave amplitude, T is expressed as wave cycle length.

For the rest type abnormal modes, the Eq (3)-(5) can be described by different combinations. In order to find and determine the quality improvement measures to provide more diagnostic information, WA is used to analyze the quality characteristic data decomposition, eliminate the noise, then reconstruct, and reduce the complexity of the data in this paper. The PCA is used to reduce dimension feature information processing, and eliminate the feature information redundancy information. Moreover, the quality characteristics of the time series data are a non-stationary and nonlinear, therefore machine learning algorithm SVM classifier is used to establish control chart, and SVM parameter optimization problem is solved through the PSO algorithm. So the hybrid patterns recognition of control chart framework based on intelligent algorithm is shown as in Figure 2.

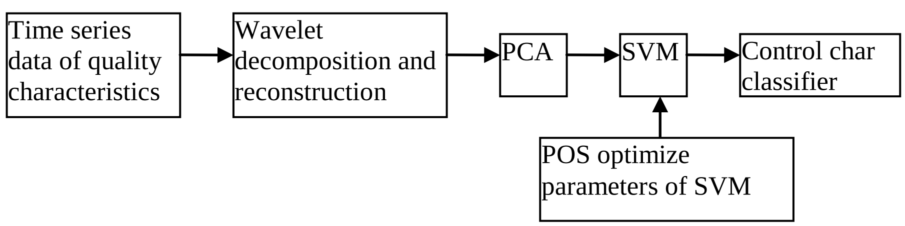

Figure 2. Control Chart Recognition Model of the Structure

3. Hybrid Patterns Recognition of Control Chart Framework

In the framework, noise of the control chart time series data is eliminate by WA, the sample dimension is reduced by PCA, collection of all point is separated by SVM, and parameters of SVM is optimized by PSO.

3.1. WA Eliminates Noise of the Control Chart Time Series Data

Set control chart for time series of time series data is $X(t)$, $t=0,1,...,N-1$, and the wavelet analysis is used to its decomposition, then decomposition scale factor for:

$$c_{j+1}(t) = \sum_{l=-\infty}^{+\infty} h(l)c_j(t + 2^j l) \tag{6}$$

According to nature of α *Trous* wavelet transform, control chart time series data detail coefficient d_j is shown as:

$$d_{j+1}(l) = c_j(t) - c_{j+1}(t) \tag{7}$$

Then control chart time sequence of resolution for L wavelet transform is shown as:

$$D = \{d_1, d_2, ..., d_L, c_L\} \tag{8}$$

where $\{d_1, d_2, ..., d_L\}$ is control chart time series signal details, $\{c_L\}$ is approximate signal of control chart time series.

Control chart time sequence $X(t)$ can be made by detail signal and approximate signal reconstruction:

$$X(t) = c_0(t) = c_L(t) + \sum_{j=1}^{L} d_j(t) \tag{9}$$

Therefore, the control and reconstruction of chart time series decomposition through the WA can effectively eliminate the control chart time series data of the "noise".

3.2. PCA Reduces Time Series Data Dimension of Control Chart

After eliminating the noise of time series data, these data are multicollinearity and repetition of them is serious. PCA points to control chart data dimension reduction processing, with a few key features describe the original data information, as far as possibility to reduce the sample dimension and improve the control chart pattern recognition accuracy and efficiency. The steps of reduction dimensionality of PCA are described as following:

Firstly, normalize feature data of the original control chart. In this way, adverse impact on them between feature data range of big or small bring can be eliminated:

$$y_{ij} = \frac{x_{ij} - \overline{x_j}}{s_j} \in Y \tag{10}$$

where s_j represents characteristics, $\overline{x_j}$ represents mean characteristics.

Secondly, calculate characteristics of the covariance matrix S:

$$S = \frac{1}{N}[Y - \overline{Yl}][Y - \overline{Yl}]^T \tag{11}$$

Thirdly, solve characteristic value of S and the corresponding U value according to the characteristic equation $(\lambda l - S)U = 0$.

At last, the number of principal component m can be got when the cumulative contribution rate is more than 85%, according to the characteristic value size, and the sort of principal component variance contribution cohorts. The principal component can input support vector machine for learning.

3.3. Support Vector Machine Classify the Control Chart

The goal of SVM in the classification of control chart is a statistical learning method based on structural risk minimization principle, its classification goal to the control chart is to find an optimal hyperplane and try to make this plane which can satisfy the classification of the restrictions need separate classification data collection of all point, and make point as far as possible and the hyperplane farthest distance.

The classification problem to two kinds of control chart, the original control chart time series data are mapped into a high dimensional feature space classification through the nonlinear mapping function, and the optimal separating hyperplane is:

$$f(x) = w \cdot \varphi(x) + b = 0 \tag{12}$$

where w is weight vector and b is threshold. In order to make structure risk minimization, the optimal classification plane should satisfy the constraint conditions:

$$y_i \cdot (w \cdot \varphi(x) + b) \geq 1 \tag{13}$$

Introducing non-negative slack variable, to improve the learning method of classification generalization ability, classification problem is transformed into:

$$\min \ \frac{1}{2} w \cdot w + C \sum_{i=1}^{n} \xi_i \tag{14}$$

Constraint conditions are for:

$$y_i \cdot (w \cdot \varphi(x) + b) \geq 1 - \xi_i, \xi_i \geq 0, i = 1,..., n \tag{15}$$

where C is error penalty factor. By Lagrange multiplier algorithm, the optimization problem is transformed into dual form:

$$\min \ \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j (\varphi(x_i) \cdot \varphi(x_j)) + \sum_{i=1}^{n} a_i \tag{16}$$

At the same time, it can satisfy

$$\sum_{i=1}^{n} \alpha_i y_i = 0, 0 \leq \alpha_i \leq C \tag{17}$$

where the corresponding point when $\alpha_i > 0$ are called support vector.

The kernel function Eq.(12) is transformed into:

$$\min \ \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j k(x_i, x_j) + \sum_{i=1}^{n} a_i \tag{18}$$

where $k(x_i, x_j)$ is the kernel function.

The most optimal separating hyperplane of SVM

$$f(x) = sign \ (\sum_{i,j=1}^{n} \alpha_i y_i k(x_i, x) + b) \tag{19}$$

SVM can solve two classification problems. However, control chart recognition is a kind of multi-classification problem, therefore, control chart classifier must be constructed through the combination strategy. We adopt the directed acyclic graph to combine two classes of SVM together, structural control chart classifier, and construct the concrete structure as shown in Figure 3.

4. Simulation Results and Application

Simulation data are produced by Eq.1, each kind of sample sizes are for 500, each kind of samples are chosen from 400 samples as the training sample randomly to compose training set, and the 100 remaining samples are used for testing set. The sample is pretreated in the method.

$$y^{'}(t) = \frac{y(t) - y_{\min}}{y_{\max} - y_{\min}} \tag{20}$$

After pretreatment of data wavelet decomposition, the "noise" is eliminated, and then reconstructs the wavelet to get useful data without "noise". The reconstructed data are analysis by PCA.

It is known that the first principal component contribution rate reaches 52.061%, which represents the most important control chart each pattern recognition factor. The cumulative contribution rate of former eight principal components is 89.41%, which shows that the eight principal components can reflect the characteristics of the original sample distribution, i.e., choose the eight principal components as the input of the SVM. Obviously, PCA not only reduces the data dimension, but also reduces the computational complexity and SVM classifier structure.

Ten fold interactive test methods and PSO algorithm are used to optimize parameter C and σ based on SVM (using radial basis kernel function). PSO algorithm parameter is set as followed: particle swarm size for 10, $c1 = c2 = 2$, the number iterations are 500, and finally get the optimal parameter $C = 6.258$, $\sigma = 0.1965$.

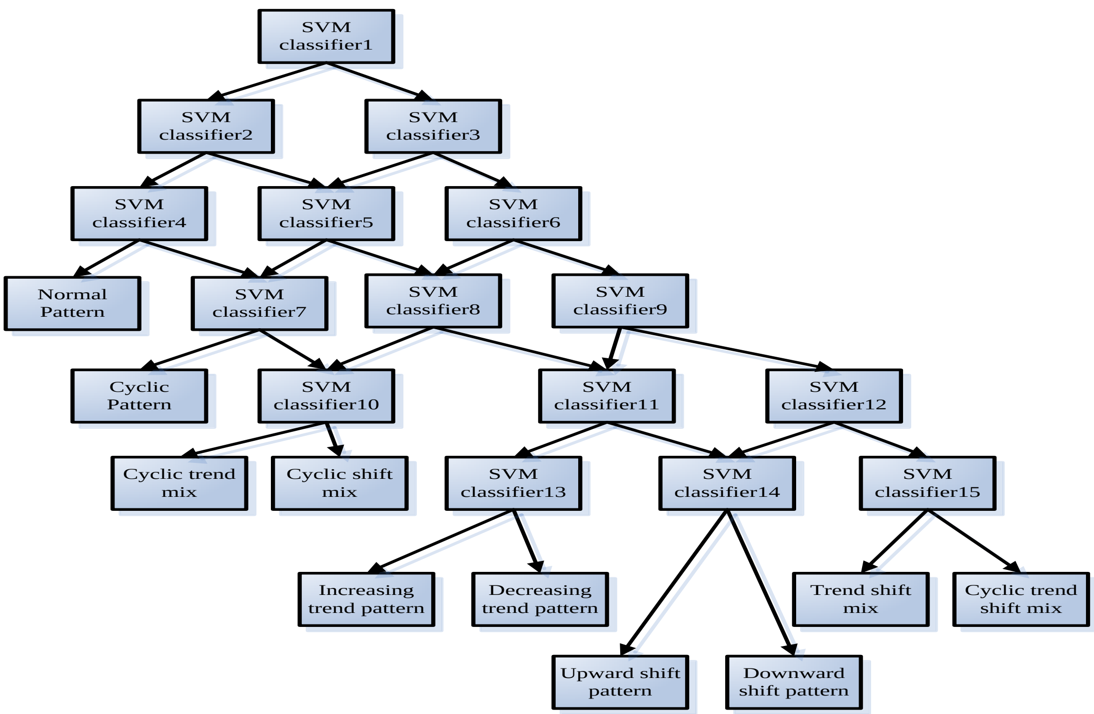

Figure 3. The Multi-classification of Network Intrusion Detector Structure

The PCA features sample is input as SVM, PSO algorithm parameters as to establish optimal control chart pattern classifier, and through the DAG construct control chart pattern classifiers. In order to further evident WA - PCA - PSO - SVM establishment quality control chart pattern recognition model, this study also chooses other identification model contrast test: WA - PCA - PSO - BPNN, PCA - SVM, WA - SVM, WA - PCA - SVM. This research is to control chart recognition model which is applied to a company motor enameled wire production process. Identification of the results are shown as: when the input to 2l, 23 sample data, identify a step down trend rise and often mode, the input to 25 and 26 sample, identify the trend rise anomaly pattern. WA - PCA - PSO - SVM results and Figure 4 mean control charts are compared. It is known that the recognition results basically consistent with actual situation, which shows that the WA - PCA - PSO - SVM control chart pattern recognition model is applied to processing abnormal state recognition and it is feasible.

5. Conclusions

It is very important for process quality control to perform intelligent identification of control chart anomaly model. According to the lower control chart recognition correct rate, we propose that a novel control chart intelligent recognition model, including wavelet analysis, principal component analysis, and particle swarm optimization algorithm and support vector machine. Wavelet transform is adopted to decompose and reconstruct the data and eliminate the "noise" in the data. And control chart sample key feature information is extracted to descend classifier complexity by principal component analysis. Particle swarm optimization algorithm for SVM is used to construct control chart classifier. The simulation results show that this algorithm can accurately describe the change rule of control chart and improves the control chart pattern recognition rate, and recognition results are consistent with the actual production conditions.

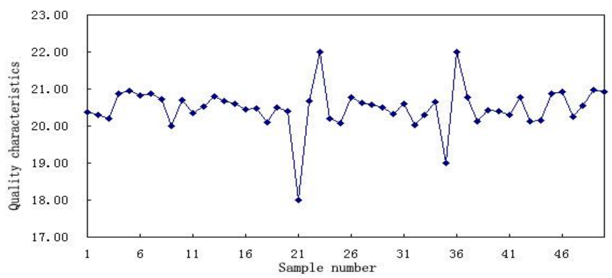

Figure 4. Mean Control Charts of Enameled Wire Production Process

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References

[1] A. Ebrahimzadeh, J. Addeh and V. Ranaee, "Recognition of control chart patterns using an intelligent technique", Applied Soft Computing, vol. 13, no. 5, **(2013)**, pp. 2970–2980.

[2] S.-F. Yang, J.-S. Lin and S. W. Cheng, "A new nonparametric EWMA Sign Control Chart", Expert Systems with Applications, vol. 38, no. 5, **(2011)**, pp. 6239–6243

[3] Y. J. Liu, J. Y. Li, B. Yang and X. J. Liu, "Optimal Control Based on Schur Complement for Trajectory Tracking of Robotic", [J], ICIC Express Letters, vol. 5, no. 8, **(2011)**, pp. 2901-2906.

[4] T. T. El-Midany, M. A. El-Baz and M. S. Abd-Elwahed, "A proposed framework for control chart pattern recognition in multivariate process using artificial neural networks", [J], Expert Systems with Applications, vol. 37, no. 2, **(2010)**, pp. 1035–1042.

[5] A. Ebrahimzadeh, J. Addeh and Z. Rahmani, "Control chart pattern recognition using K-MICA clustering and neural networks", [J], ISA Transactions, vol. 51, no. 1, **(2012)**, pp. 111–119.

[6] J. Addeh, A. Ebrahimzadeh, M. Azarbad and V. Ranaee, "Statistical process control using optimized neural networks: A case study", [J], ISA Transactions, 2013, http://dx.doi.org/10.1016/j.isatra\, vol. 07, no. 018. **(2013)**.

[7] S. Du, D. Huang and J. Lv, "Recognition of concurrent control chart patterns using wavelet transform decomposition and multiclass support vector machines", [J], Computers & Industrial Engineering, vol. 66, no. 4, **(2013)**, pp. 683–695

[8] P. Xanthopoulos and T. Razzaghi, "A weighted support vector machine method for control chart pattern recognition", [J], Computers & Industrial Engineering, vol. 70, **(2014)**, pp. 134-149.

[9] P.Das and I. Banerjee, "An Hybrid Detection System of Control Chart Patterns Using Cascaded SVM and Neural Network–based Detector", [J], Neural Computing and Applications, vol. 20, no. 2, **(2011)**, pp. 287-296.