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## FINANCIAL EARLY WARNING DYNAMIC EVALUATION MODEL BASED ON SUPPORT VECTOR MACHINE

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## МОДЕЛЬ ДИНАМІЧНОЇ ОЦІНКИ РАНЬОГО ПОПЕРЕДЖЕННЯ ФІНАНСОВОЇ КРИЗИ НА ОСНОВІ МЕТОДА ОПОРНИХ ВЕКТОРІВ

**Purpose.** The issue of bankruptcy prediction and taking corresponding effect-reduction measures has become an important research topic in the field of economy. The article mainly studies the issue how to improve the support vector machine (SVM) based on prediction effect of the financial crisis early-warning model.

**Methodology.** In view of the improved method of the kernel function exported Riemannian geometry structure, the financial crisis early-warning system based on the support vector machine (SVM) algorithm has been developed.

**Findings.** The improved SVM model can effectively reduce the number of support vectors so that the model can feature better capacity for generalization, and provide a more accurate classification for unknown samples. The improved SVM model has increased the classification accuracy for the original training and testing sample set.

**Originality.** An actual analysis on an improved algorithm for kernel function has been conducted based on the data information, according to the zoom level of data information adjustment feature mapping, giving the expression of the algorithm of Riemann measures on the polynomial kernel function. There has been no other literature describing the related study yet.

**Practical value.** For the financial crisis early warning issue, provided its scale is not large, and in consideration of the enterprise's actual interests, it is often worthwhile to pursue a better prediction effect. In this case, the application of the SVM model with an improved kernel function is a good solution.

**Keywords:** *support vector machine (SVM), kernel function, enterprise early warning*

**Introduction.** The issue of providing early warning before an enterprise goes bankruptcy and taking the corresponding effect reduction measures has become an important research topic in the field of economy. Financial crisis refers to the following situations: a listed company or an enterprise in a certain period of time due to various aspects and reasons, has encountered significant setback, problems or the internal financial situation which causes out of control problems, making its financial status in danger or in the state of emergency [1]. This study considers the actual situation of domestic listed companies and the related regulations and provides special treatment carried out on the standard to distinguish whether a company has financial crisis or not. The earliest financial crisis early warning model abroad started from the single variable bankruptcy research. Then, scholars began to do a lot of research on the financial crisis early warning, and put forward different financial early warning models one after another successively [2].

Despite different classification methods applied to the establishment of the financial crisis model, most of the research mainly focuses on the use of certain statistical methods or artificial intelligence methods [3–4]. The multivariate linear discriminant analysis

method can make classification of companies into the categories that are already known, and come to the conclusion of five financial proportions that basically can fully explain the state of the company which goes bankrupt [5]. The multivariate model has overcome the inevitable problems that a traditional single variable model is hard to avoid, such as different forecast results obtained for the same company due to different proportions [6]. Logistic regression (Logit Model) predicts the financial crisis of a company, with the conclusion that the Logit model is more reasonable than the multivariate analysis, and that the scale of the company is a very influential input variable [7–8]. A decision Tree method is applied to the research of financial crisis prediction [9]. Later, with the rise of the artificial intelligence method, a Neural Network (NN) method becomes the most widely applied machine learning algorithm in this field, which has also been applied to the financial crisis prediction of the company [10].

The expression form of such modified methods in the polynomial kernel function is given in this paper. Moreover, the implementation idea of the modified algorithm in Matlab is designed. The input index set of the financial crisis warning model is designed. Through the statistics and support vector machine (SVM) pre-treatment technology, layers of screening on samples

are performed, and then, the support vector classification machine is applied to make financial crisis prediction on the samples, thus, an improvement is made. Finally, the testing results are compared and evaluated.

**Financial crisis early warning model based on support vector machine (SVM). Algorithm Thought.** As mentioned above, since the application of the support vector machine (SVM) is still in the stage of exploration and development, in the practical application, the selection of model and its parameters is often transcendental, and lacks theoretical guidance. In fact, the method of kernel function does not require knowing the specific form of the kernel mapping specifically, which makes it hard to get universal guidelines before the start of the training. To this end, a compromise idea is through an adaptive approach, based on the particularity of the problem itself, to improve the model in the process of training. In this paper the algorithm, which is in research and applied to the financial crisis early warning model, is based on the modified method of Riemannian geometry structure derived from the basis of the kernel function. Relevant information of the samples can be obtained through the training for one time, and then through the information to improve the kernel function, making it locally expand the mapping near the surface of the optimal classification, thus, expanding the hyper plane, reducing the number of support vectors, and improving the accuracy and the generalization ability, so as to achieve a better classification effect. In order to achieve such expansion, conformal mappings on the input space are adopted, which can be achieved by the conformal transformation in the kernel function.

**Zoom Level Based on the Data Information Adjustment Feature Mapping.** First of all, according to the definition of the kernel function [11], there is

$$K(x, x') = \phi(x) \cdot \phi(x').$$

Wherein,  $\phi : x \rightarrow \phi(x)$  is the mapping of the input space  $X$  to feature space  $F$ . Let us consider the geometric structure derived from such kernel function. Mapping defines a volume manifold from  $X$  to  $F$ . When the feature space  $F$  is the Euclidean space or the Hilbert space, it can derive a Riemannian measure in the input space, which is in  $X$ , for a tiny vector change  $dx$ , it can be defined by its relative length due in the feature space.

Set  $z$  is the image of  $x \subset X$  in the feature space, namely  $z = \phi(x)$ , and a tiny vector change can be mapped to

$$dz = \nabla\phi \cdot dx = \sum_i \frac{\partial}{\partial x_i} \phi(x) dx_i.$$

Wherein  $\nabla\phi = \left( \frac{\partial}{\partial x_i} \phi(x) \right)$ .

Thus, the sum of the squares of  $dz = (dz_a)$  can be expressed as

$$|dz|^2 = \sum_a (dz_a)^2 = \sum_{i,j} g_{ij}(x) dx_i dx_j.$$

Where in  $g_{ij}(x) = \left( \frac{\partial}{\partial x_i} \phi(x) \right) \cdot \left( \frac{\partial}{\partial x_j} \phi(x) \right)$ , from

which the tensor of Riemann measures  $G(x) = (g_a(x))$  can be obtained in the input space, and this is a positive definite matrix with  $n \times n$  dimension. It can be proved that this measure can be derived directly by the kernel function, namely

$$g_{ij}(x) = \frac{\partial}{\partial x_i} \frac{\partial}{\partial x_j} K(x, x') \Big|_{x'=x}.$$

Now take the Gauss radial basis kernel function, for example, through the analysis of the amplification factor after improvement  $\sqrt{g(x)}$  to study how the image of the sample point is locally amplified in the feature space. The main consideration is the amplification factor near the support vector point, such as

$$g_{ij}(x) = \frac{c^2(x)}{\sigma^2} A_{ij}.$$

Wherein  $A_{ij} = a_i a_j + \delta_{ij}$ , and  $a_i = \frac{\sigma}{c} c_i(x)$ , matrix  $A = \{A_{ij}\}$  can be written as

$$A = I + a^2 e e^T.$$

Wherein  $I$  is the unit matrix, and  $a^2 = \sum_i^n a_i^2$ ,  $e$  is the unit vector with  $n \times 1$  dimension, meeting the condition  $\left\{ e_{ij} = \frac{a_i}{a} \right\}$ , and  $e^T$  is the transpose vector of  $e$ , through the orthogonal transformation, there is clearly

$$\det|A| = 1 + a^2$$

and

$$g(x) = \det|g_{ij}| = \frac{c^{2c}(x)}{\sigma^2} \left( 1 + \sum_{i=1}^n a_i^2 \right);$$

$$\frac{d\sqrt{g(x)}}{dr} = \frac{h_i^n \exp\left(-\frac{nr^2}{2\tau^2}\right) \left[ \frac{2\sigma^2 r}{\tau^4} - \frac{2nr}{\tau^2} \left( 1 + \frac{\sigma^2}{\tau^4} r^2 \right) \right]}{\sqrt{1 + \frac{\sigma^2}{\tau^4} r^2}}.$$

Hence the following conclusions can be made:

1. When  $\tau < \frac{\sigma}{\sqrt{n}}$ , the amplification effect near the

point  $r = \tau \sqrt{\frac{1}{n - \tau^2}} > 0$  is the maximum.

2. When  $\tau \geq \frac{\sigma}{\sqrt{n}}$ , as  $\frac{d\sqrt{g}}{dr} \leq 0$  is true to any  $r$ ,

therefore, at  $r = 0$ , i.e. the support vector, the amplification effect is the maximum.

To sum up, take  $\tau = \frac{\sigma}{\sqrt{n}}$  nearby, so that the amplification factor can be amplified to the maximum at the support vector, and the amplification is local.

**Financial Crisis Prediction Model.** After the selection of the samples used in the prediction experiment and determination of the time difference, let us consider the main process of the model and the experimental design. Fig. 1 shows the framework of the modified kernel function model.

*Step 1:* in order to prevent the influence of the singular value existing in some data on the classification accuracy; the percentile method is adopted for the first step of pretreatment to the sample. First of all, through the SPSS statistical software to perform descriptive statistical analysis, we exclude the sample points outside of 5 and 95 % quantile. After removing the outliers outside of 5 and 95 % quantile, there are 124 remaining samples, including 42 from a ST company, 82 from the other Non ST companies.

*Step 2:* standardization (dimensionless). Let us standardize the samples, remove three standard deviation samples. The processing results are 106 remaining samples, in which 36 are from a ST company, 70 from the other non ST companies.

*Step 3:* select the training set and the testing set. In order to use the support vector machine (SVM) classification, the samples need to be classified, and divided into a training set and a testing set. The training set is used to perform the modeling training on the support vector machine (SVM), and the testing set tests the prediction effect. We randomly select 75 samples from 106 samples for the training set, in which the ST company has 25 samples, non ST companies have 50 samples. The remaining 11 ST company samples and 20 non ST company samples are for the testing set.

*Step 4:* normalization. Based on the past experience, the normalization of the sample data can improve the classification performance of the support vector machine (SVM). This article selects (0–1) for the normalization, making all items of indexes of the samples between 0 and 1.

*Step 5:* model building. In this experiment, in consideration of the excellent properties of the Gauss radial basis kernel function, we choose it as the core used in the prediction model. The experiment is mainly divided into several groups. For details please refer to Table 1.

In the first set of the experiments, we adopt the RBF kernel function, with the default parameter ( $C = 1$ ,  $g = 1/Dim$ ), where Dim represents the dimension of the input samples, in the experiment Dim = 19.

In the second set of the experiments, we adopt the RBF kernel function, with the default parameter, perform the parameter optimization, and obtain the optimal parameter.

In the third set of the experiments, we use the default parameter modified kernel function, namely, under the condition of the original RBF kernel function and the default parameters, modify the kernel function and perform the quadratic model building.

In the fourth set of the experiments, we use the optimal parameter modified kernel function, namely, under the condition of the original RBF kernel function and the optimal parameter, modify the kernel function and perform the quadratic model building.

In the fifth set of the experiments, we adopt the SVM method combined with the principal component analysis, which has the advantages of reducing the theoretical dimensions of the sample and, thus, reducing the computational complexity, we discuss its effect on the financial crisis early warning model in this paper and compare with the modified kernel function algorithm.

Regarding the parameters to compare, several parameters in this paper are selected for comparison. Firstly, we compare their overall classification accuracy in the training set and the testing set, which reflects the classification effect of the support vector machine (SVM). Secondly, considering that the modified algorithm can reduce the number of support vectors theoretically and, thus, ensure the generalization capacity of the model, we examine the number of the support vector of the classification plane. We correlate whether there is significant reduction before and after the modification. For parameter optimization, this ex-

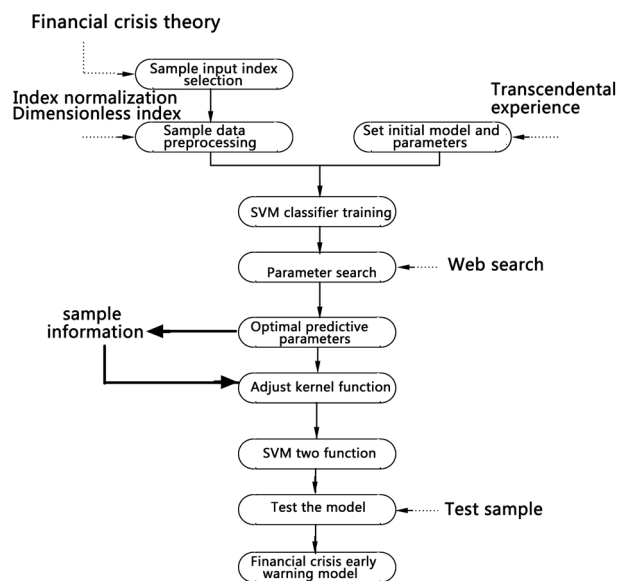


Fig. 1. Modified SVM Financial Crisis Prediction Model

Table 1

Experimental Group Parameter Setting

Group	Kernel Function Type	The Initial Parameter C	The Initial Bandwidth g	Parameter Optimization	Kernel Function Modification	PCA Integration
1	Gauss RBF Kernel	1	1/Dim	No	No	No
2	Gauss RBF Kernel	1	1/Dim	Yes	No	No
3	Gauss RBF Kernel	1	1/Dim	No	Yes	No
4	Gauss RBF Kernel	1	1/Dim	Yes	Yes	No
5	Gauss RBF Kernel	1	1/Dim	Yes	Yes	Yes

periment selects the traditional Grid Search 5-Folds Cross Validation method, and displays the optimization process and the final optimal classification accuracy.

To modify the kernel function algorithm for the experiment, in consideration of different values that the parameter  $T$  takes, it is generally believed that when the value of  $T$  takes the theoretical optimal, the amplification effect is the best; hence the experiment verifies whether this theory is true for the financial crisis. The specific parameters are shown in Table 2.

**Experiment and analysis. Experiment.** The aforementioned model being run in the Matlab software, the experimental results obtained are as follows.

1. The first set of the experimental results are in Table 3.

2. Regarding the second set of experiments, the optimal parameter, and the optimal parameter. The training images and results are shown in Fig. 2 and Table 4, and Experimental Optimization 3D Figure is shown in Fig. 3.

3. Regarding the third set of experiments, on the basis of the default parameters and, we perform the modification of the kernel function. The results are in Table 5.

4. In the fourth set of experiment, on the basis of the optimal parameters, we perform the modification of the kernel function. The results are as follows in Table 6.

**Experimental Analysis.** After obtaining the results of the four sets of experiments respectively, ac-

ording to the classification accuracy, we perform the horizontal comparison, analysis and evaluation of each experiment (Table 7).

Comparing the first and the second set of the experiments, on the basis of the parameter optimization, one can see that the number of support vectors in the second set of the experiments shows small reduction; in addition, regarding the classification accuracy, related to the default parameter settings, it has been greatly modified. This has proved the importance of the parameter optimization. Comparing the first and third sets of the experiments, it can be found that on the basis of the default parameters the modification of the kernel function can significantly reduce the number of support vectors and improve the classification accuracy of two categories. In particular, when the value of parameter  $T$  is the optimal value theoretically, the classification effect of the modified model is the best. Whether the value of  $T$  is too large or small, it significantly affects the scaling degree of the feature mapping. If the amplification degree is too large, it will make the space set amplified globally, resulting in the loss of the significance of modification; however, if the amplification degree is too small, it will make the magnified area discontinuous, hence, the effect is not ideal. Considering the second and the fourth set of the experiments, the same conclusion can be obtained. Therefore, the parameters optimization can be performed first, and then according to the result of the parameter optimization, we make adjustment on the kernel function.

Table 2

Model Evaluation Standard

Name of Evaluation Criteria	Description	Observation Experiment Group
Cross validation overall classification accuracy	Result of the cross validation parameter optimization	2,4,5
Classification accuracy of the training set	Correct classification number of the training set / Total number of samples of the training set	1, 2, 3, 4, 5
Classification accuracy of the testing set	Correct classification of the testing set / Total number of samples of the testing set	1, 2, 3, 4, 5
Total number of support vectors	Total number of support vectors after the completion of training and modification	1, 2, 3, 4

Table 3

The Classification Accuracy of the First Set of the Experimental Model

Experimental Group	Total Number of Support Vectors	Classification Accuracy of the Training Set	Classification Accuracy of the Testing Set	Optimal Accuracy of the Cross Validation
1	51	66.6667 % (50/75)	64.5161 % (20/31)	Null

Table 4

Classification Accuracy of the Second Set of the Experimental Model

Experimental Group	Total Number of Support Vectors	Accuracy of the Training Set	Accuracy of the Testing Set	Optimal Accuracy of the Cross Validation
2	48	78.6667 % (59/75)	83.8710 % (26/31)	78.6667

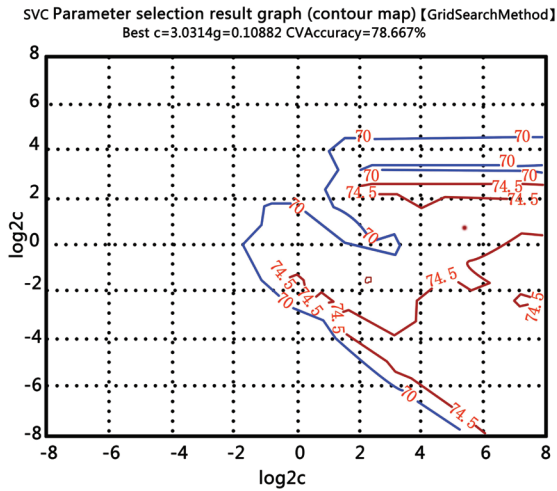


Fig. 2. The Second Group of Experimental Parameter Optimization Result

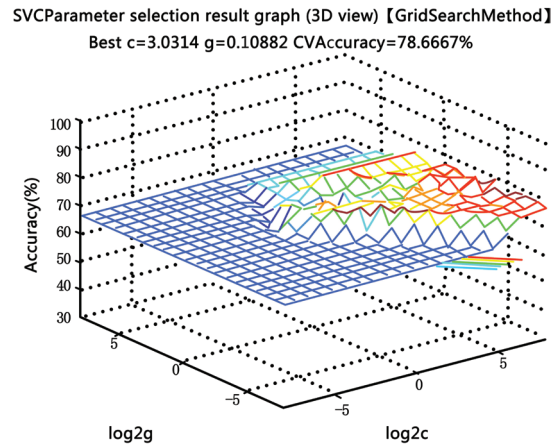


Fig. 3. The Second Group of Parameters of Experimental Optimization 3D Figure

Table 5

Classification Accuracy of the Third Set of the Experimental Model

Experimental Group	Parameter <i>T</i> Value	Total Number of Support Vectors	Classification Accuracy of the Training Set	Classification Accuracy of the Testing Set
3	0.1	40	78.6667 % (59/75)	67.7419 % (21/31)
	2.06758 (Optimal in the theory)	24	86.6667 % (65/75)	90.3226 % (28/31)
	5	16	92 % (69/75)	35.4839 % (11/31)

Table 6

Classification Accuracy of the Fourth Set of the Experimental Model

Experimental Group	Parameter <i>T</i> Value	Total Number of Support Vectors	Classification Accuracy of the Training Set	Classification Accuracy of the Testing Set
4	0.1	30	86.6667 % (65/75)	35.4839 % (21/31)
	2.06758 (Theoretical Optimal)	30	89.3333 % (67/75)	90.3226 % (28/31)
	5	18	93.3333 % (70/75)	87.0968 % (27/31)

Table 7

The Horizontal Comparison of Classification Accuracy of Five Sets of the Experimental Models

Experimental Group	Parameter <i>T</i>	Total Number of Support Vectors	Classification Accuracy of the Training Set	Classification Accuracy of the Testing Set	Optimal Accuracy of the Cross Validation
1	NA	51	66.6667 % (50/75)	64.5161 % (20/31)	NA
2	NA	48	78.6667 % (59/75)	83.8710 % (26/31)	78.6667 %
	0.1	40	78.6667 % (59/75)	67.7419 % (21/31)	NA
3	2.06758	24	86.6667 % (65/75)	90.3226 % (28/31)	NA
	5	16	92 % (69/75)	35.4839 % (11/31)	NA
	0.1	30	86.6667 % (65/75)	35.4839 % (11/31)	NA
4	2.06758	30	89.3333 % (65/75)	90.3226 % (28/31)	NA
	5	18	93.3333 % (70/75)	87.0968 % (27/31)	NA
5	NA	45	90.6667 % (68/75)	90.3226 % (28/21)	82.6667 %

**Conclusion.** In this paper, a kind of modified method of the kernel function for support vector machine (SVM) is studied, whose core idea is to apply the information of the data itself to zoom in the most core

feature mapping locally. The mapping measure concept is expressed on the polynomial kernel function and the corresponding financial crisis early warning model is constructed. By the empirical comparison

with the traditional SVM financial crisis model, the feasibility and effect of this modified method in the field of the financial crisis early warning is analyzed and evaluated.

Through the experiments, the following conclusions are obtained: firstly, the modified SVM model can effectively reduce the number of support vector, allow better generalization capacity for the model, so as to make more accurate classification for unknown samples. Secondly, the modified SVM model has improved the classification accuracy for the original training sample and testing sample set. Finally, due to the need for secondary training of the modified SVM model, there is a potential problem that the algorithm is too complicated, and the additional computational complexity is worthy of in-depth study. However, the financial crisis early warning problem, due to the scale of the problem, is not large in consideration of the actual interests of the enterprise; it is often worth applying to pursue a better prediction effect. In this case, the application of the kernel function of the SVM model is a pretty good solution.

**Acknowledgments.** This paper presented Anhui Province Education Department Provincial Quality Engineering Project “Accounting Professional Comprehensive Reform Pilot” phase achievement, Project No. 2014ZY081.

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**Мета.** Важливою темою досліджень в області економіки є раннє попередження банкрутства підприємства і вживання відповідних заходів зі зниження впливу. У даній роботі, в основному, досліджується питання про те, як покращити метод опорних векторів (SVM), заснований на ефекті прогнозування моделі раннього попередження фінансової кризи.

**Методика.** З урахуванням удосконаленого способу функції ядра, що експортується риманою геометричною структурою, побудована система раннього попередження фінансової кризи на основі алгоритму SVM.

**Результати.** Покращена модель SVM дозволяє ефективно зменшувати число опорних векторів так, щоб модель мала кращу здатність до узагальнення, забезпечувала точнішу класифікацію для невідомих зразків. Покращена модель SVM підвищила точність класифікації для первинного навчання й тестування вибірки.

**Наукова новизна.** Проведено конкретний аналіз удосконаленого алгоритму для функції ядра на основі інформаційних даних, у відповідності до рівня масштабування інформаційних даних з можливістю регулювання відображення. Отримано вираз алгоритму мір Рімана на функцію поліноміального ядра. На даний момент не існує іншої літератури з описом подібних досліджень.

**Практична значимість.** Для питання раннього попередження фінансової кризи, якщо його масштаб не великий, а також з урахуванням реальних інтересів підприємства, часто буває доцільно добиватися кращого прогнозуючого ефекту. У цьому випадку застосування моделі SVM з покращеною функцією ядра є хорошим рішенням.

**Ключові слова:** метод опорних векторів (SVM), функція ядра, раннє попередження банкрутства підприємства

**Цель.** Важной темой исследований в области экономики является раннее предупреждение банкротства предприятия и принятие соответствующих мер по снижению воздействия. В данной работе, в основном, исследуется вопрос о том, как

улучшить метод опорных векторов (SVM), основанный на эффекте прогнозирования модели раннего предупреждения финансового кризиса.

**Методика.** С учетом усовершенствованного способа функции ядра, экспортируемой римановой геометрической структурой, построена система раннего предупреждения финансового кризиса на основе алгоритма SVM.

**Результаты.** Улучшенная модель SVM позволяет эффективно уменьшать число опорных векторов так, чтобы модель имела лучшую способность к обобщению, обеспечивала более точную классификацию для неизвестных образцов. Улучшенная модель SVM повысила точность классификации для первоначального обучения и тестирования выборки.

**Научная новизна.** Проведен конкретный анализ усовершенствованного алгоритма для функции ядра на основе информационных данных, в соответствии с уровнем масштабирования ин-

формационных данных с возможностью регулировки отображения. Получено выражение алгоритма мер Римана на функцию полиномиального ядра. На данный момент не существует другой литературы с описанием подобных исследований.

**Практическая значимость.** Для вопроса раннего предупреждения финансового кризиса, если его масштаб не велик, а также с учетом реальных интересов предприятия, часто бывает целесообразно добиваться лучшего прогнозирующего эффекта. В этом случае применение модели SVM с улучшенной функцией ядра является хорошим решением.

**Ключевые слова:** метод опорных векторов (SVM), функция ядра, раннее предупреждение банкротства предприятия

*Рекомендовано до публікації докт. техн. наук В. В. Гнатушенком. Дата надходження рукопису 28.07.15.*

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## SELF-ADAPTIVE OPTIMIZED MARKET PREDICTION MODEL BASED ON GREY MODEL

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## САМОАДАПТИВНА ОПТИМІЗОВАНА МОДЕЛЬ ПРОГНОЗУВАННЯ РИНКУ НА ОСНОВІ СІРОЇ МОДЕЛІ

**Purpose.** Market prediction refers to prediction of internal rules and future development trends of various market indexes and factors based on exploration and in-depth research of various factors influencing market demand and supply changes through scientific theories and systematic model algorithms. This paper analyses optimization results of the traditional prediction algorithms and the intelligent prediction algorithms.

**Methodology.** In order to analyse differences between the results obtained by prediction algorithms and practical situations, it is necessary to unify the model analysis parameters. The model predicting the grey system is applicable to predicting situations with an index variation trend. The time sequence model is suitable to data with certain trend and periodical changes.

**Findings.** It has been found that the neural network and model and the support vector model have no requirements of data, so they are suitable to any situations. And when the market demand changes show index changes, the dynamic pricing and inventory control optimization model based on the grey prediction model is of vital guiding significance towards planning of commodity sales.

**Originality.** Through simulation, the predicted value of models is close to the final optimization target earnings.

**Practical value.** The following fact has been also considered: when market demand changes tend to show index changes, the dynamic pricing and inventory control optimization model based on the grey prediction model can guide the planning of commodity sales.

**Keywords:** grey model, self-adaptive optimization, model prediction, specific power function

**Introduction.** Market prediction refers to prediction of internal rules and future development trends of various market indexes and factors based on exploration and in-depth research of various factors influencing market demand and supply changes through scien-

tific theories and systematic model algorithms [1]. Based on the rules of market supply and demand changes, it provides reliable guidance and bases for operation decision-making of enterprises. Prediction can help improve the scientific level of management and reduce the blindness of decision-making. Therefore, the purpose of market prediction is actually to