PROCEEDINGS OF SPIE

SPIEDigitalLibrary.org/conference-proceedings-of-spie

Nuclear weapon prediction based on the verhulst method of comprehensive weighting and LS-SVM equidimensional information supplement

Hongyi Duan , Jianan Zhang

Hongyi Duan , Jianan Zhang , "Nuclear weapon prediction based on the verhulst method of comprehensive weighting and LS-SVM equidimensional information supplement," Proc. SPIE 12635, Second International Conference on Algorithms, Microchips, and Network Applications (AMNA 2023), 126350S (8 May 2023); doi: 10.1117/12.2678905

Event: International Conference on Algorithms, Microchips, and Network Applications 2023, 2023, Zhengzhou, China

Nuclear weapon prediction based on the verhulst method of comprehensive weighting and LS-SVM equidimensional information supplement

Hongyi Duan *[a], Jianan Zhang *[b]
[a] Faculty of Electronic and Information Engineering, Xi'an Jiaotong University, Xianning road 710049, CHINA
[b] Shanghai University of Finance and Economics University, Yangpu District 310110, CHINA
[*] Co-first authors: 2213611582@stu.xjtu.edu.cn (Duan Hongyi)
3628750954@qq.com (Zhang Jianan)

ABSTRACT

In this paper, to predict the nuclear weapons, we first introduce evaluation indicators that affect the possession of nuclear weapons, economic indicators, scientific and technological indicators, and establish a TOPSIS evaluation model improved by the optimal assignment method to predict countries with evaluation values less than 20, as countries that will possess nuclear weapons in the next 100 years. Then, in view of the fact that the number of nuclear weapons is calculated in years and changes over time, and considering the global consensus to limit the number of nuclear weapons from 2022 when the Treaty on the Prohibition of Nuclear Weapons and other policies come into force, it is decided to build a Verhulst prediction model with saturation based on the LS-SVM algorithm, and finally to improve the accuracy and reasonableness of the model by using the metabolic data processing method of equal-dimensional neutrosophic recurrence prediction. By predicting the number of nuclear weapons, countries can make reasonable plans for future nuclear weapons production and hope to reach a global consensus, which will help to solve the nuclear crisis.

Keywords: TLS-SVM improved Verhulst, Combination weighting

1. BACKGROUND AND INTRODUCTION

Generally, Nuclear weapons were born in 1945, which is the use of atomic nuclear fission or fusion reaction instantaneous release of enormous energy, producing an explosive effect, and has the effect of large-scale destruction and damage of weapons [1], including atomic bombs, neutron bombs, hydrogen bombs, etc. Its explosive yield is approximately equal to tens of thousands to hundreds of thousands of tons of TNT. The radiation range and explosion damage are enough to cover a city. During the Cold War, the arms race between the Soviet Union and the United States led to the birth of a large number of nuclear weapons, and nuclear shadows loomed over all mankind, and many people believe that these manufactured nuclear weapons are capable of destroying the earth many times, which requires a prediction of the number of nuclear weapons and their destructive power in the future. The number of nuclear weapons and their destructive power need to be predicted and assessed.[2]

2. IMPROVED TOPSIS EVALUATION MODEL BY OPTIMAL EMPOWERMENT METHOD

After careful reflection, economic, scientific technological and position indicators are used for evaluation.The optimal assignment method is to multiply the weights calculated by the AHP method and the weights calculated by the entropy method v_{j_2} by the combination coefficients θ_1, θ_2 to obtain the weights of the optimal assignment method for the index V_m [3]

$$V_m = \theta_1 v_{j_1} + \theta_2 v_{j_2} \, (j = 1,2,3,\cdots,n) \tag{1}$$

Deviation of the combined weight vector v_0 from the weight vector v_k determined by the kth evaluation method.

Second International Conference on Algorithms, Microchips, and Network Applications (AMNA 2023),
edited by Kannimuthu Subramaniam, Arunkumar Palanisamy Muthuramalingam, Proc. of SPIE
Vol. 12635, 126350S · © 2023 SPIE · 0277-786X · doi: 10.1117/12.2678905

$$v_0 - v_k = (v_{10} - v_{1k}, v_{20} - v_{2k}, \cdots, v_{n0} - v_{nk}) \\ (k = 1,2,3,\cdots,s) \tag{2}$$

Minimize the deviation of the combined weights from the known weights and construct the optimization model in the sense of deviation and minimization of.

$$\begin{aligned} &\min \sum_{k=1}^{s} \left\| v_0 - v_k \right\|^2 \\ &= \min \sum_{k=1}^{s} \sum_{j=1}^{n} (v_{j_0} - v_{j_k})^2 = \min \sum_{k=1}^{s} \sum_{j=1}^{n} \left[\sum_{k=1}^{s} \theta_k v_{j_k} - v_{j_k} \right]^2 \end{aligned} \tag{3}$$

Using the weights obtained by the most empowering method, the TOPSIS method is improved, TOPSIS is a comprehensive evaluation ranking method that approaches the ideal solution and makes good use of raw data to distinguish between decision options [4]. The purpose of this article is to evaluate whether there will be nuclear weapons in the next 100 years. The evaluation index variables are economic indicators, technological indicators, and location indicators, and construct a data matrix $A = (a_{ij})_{m \times n}$

2.1 Step 1 will be the original matrix positive:

The so-called normalization of the original indicators is to convert all indicator types into very large new indicators. Credit rating, whether the company is in breach of contract, product return rate, company status, etc. are all very small indicators, which need to be converted into very large indicators. The conversion formula is as follows [5]

$$x_{ij} = \max\left\{x_{1j}, x_{2j}, \cdots x_{nj}\right\} - x \tag{4}$$

2.2 Step 2 normalization of the normalization matrix:

Since the data magnitude of each index is different, when using the entropy weight method to calculate its weight, it is necessary to standardize the data first and remove the magnitude. The normalization formula is as follows.

$$\tilde{z}_{ij} = \frac{x_{ij} - \min\left\{x_{1j}, x_{2j}, \cdots x_{nj}\right\}}{\max\left\{x_{1j}, x_{2j}, \cdots x_{nj}\right\} - \min\left\{x_{1j}, x_{2j}, \cdots x_{nj}\right\}} \tag{5}$$

2.3 Step 3 calculate the weighted score and ranking of each indicator:

calculate the weighted distance between each indicator object and the maximum and minimum values, the larger the score, the closer the distance between the indicator and the maximum value [6] i.e., the closer to the maximum specific formula is as follows.

$$\begin{gathered} optimal\ vector\ z_j^+ = \max_{1 \le i \le n} |\tilde{z}_{ij}|,\ worst\ vector\ z_j^- = \min_{1 \le i \le n} |\tilde{z}_{ij}| \\ D_i^+ = \sqrt{\sum_{j=1}^{m} v_j (z_{ij} - z_j^+)^2},\ D_i^- = \sqrt{\sum_{j=1}^{m} v_j (z_{ij} - z_j^-)^2},\ s_i = \frac{D_i^+}{D_i^-} \end{gathered} \tag{6}$$

2.4 Step 4 Score normalization process:

the final score will be normalized by the following formula.

$$\tilde{s}_i = \frac{s_i}{\sum_{i=1}^{n} s_i},\ \sum_{i=1}^{n} \tilde{s}_i = 1 \tag{7}$$

3. VERHULST PREDICTION MODEL BASED ON LS-SVM ALGORITHM

Considering the characteristics of gray system theory with long-term predictability and good fitting effect [7], the Verhulst model with saturation performance is used. At the same time, due to the limitations of parameter selection and initial data, the LS-SVM algorithm in statistical learning theory is used to adjust the parameters [8], and the metabolic data processing method of equal-dimensional neoteny recurrence prediction is applied to improve the prediction accuracy and rationality of the mode [9].

Table 1: TOPSIS scoring results of the possibility of a country possessing nuclear weapons

Country	TOPSIS Score	Rank	Country	TOPSIS Score	Rank
United States	0.0748	1	Japan	0.0197	11
China	0.055	2	South Korea	0.0177	12
United Kingdom	0.0258	3	Iran	0.0171	13
India	0.0257	4	Iraq	0.0169	14
France	0.0256	5	Serbia	0.0169	15
Russia	0.0242	6	Libya	0.0168	16
North Korea	0.0241	7	Syrian Arab Republic	0.0167	17
Israel	0.0231	8	Germany	0.0165	18
South Africa	0.023	9	Italy	0.0121	19
Pakistan	0.0229	10	Brazil	0.0113	20

Let:

$$X^{(0)} = (x_1^{(0)}, x_2^{(0)}, \cdots x_n^{(0)})$$

denote the original data sequence, do the accumulation to generate:

$$x_k^{(1)} = \sum_{j=1}^{k} x_j^{(0)} \ (k = 1, 2, 3, \cdots n)$$

and get:

$$X^{(1)} = (x_1^{(1)}, x_2^{(1)}, \cdots x_n^{(1)})$$

The whitening equation of is given by:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b\left(x^{(1)}\right)^2 \tag{8}$$

(In formula (8), there is $x \in R$)

where a and b are the gray parameters and t is the time. Using:

$$Z_k^{(1)} = \frac{1}{2}(x_k^{(1)} + x_{k-1}^{(1)}) \ (k = 2, 3, \cdots n)$$

for the immediate mean values to generate

$$Z^{(1)} = (z_2^{(1)}, z_3^{(1)}, \cdots z_n^{(1)})$$

and replacing $\frac{dx^{(1)}}{dt}$ in the differential equation with the original data series $x_k^{(0)}$ approximation, the Verhulst gray difference equation is obtained as follows.

$$x_k^{(0)} = -az_k^{(1)} + b(z_k^{(1)})^2 \tag{9}$$

For n time series, the above equation can form a system of equations:

$$X_k^{(0)} = -az_k^{(1)} + b(z_k^{(1)})^2$$

with least squares estimation to solve the solution of the whitening equation as:

$$x_{k+1}^{(1)} = \frac{\hat{a}\, x_1^{(1)}}{\hat{b}\, x_1^{(1)} + (\hat{a} - \hat{b}\, x_1^{(1)})e^{ak}}$$

and taking the initial value $x_1^{(1)}$ as the initial value of the original series $x_1^{(0)}$, the time response series is:

$$x_{k+1}^{(1)} = \frac{\hat{a}\, x_1^{(1)}}{\hat{b}\, x_1^{(0)} + (\hat{a} - \hat{b}\, x_1^{(0)})e^{ak}}$$

which leads to the original data fit value as

$$x^{(0)}(k+1) = x^{(1)}(k+1) - x^{(1)}(k) \tag{10}$$

In order to improve the predictive power of the gray Verhulst model, the paper investigates the problem of building the gray Verhulst model using the viewpoint of statistical learning theory. By constructing a gray Verhulst type LS-SVM with background value sequence and original sequence as training samples in two ways, the Verhulst model in one-dimensional sample space is transformed into an LS-SVM model in two-dimensional feature space[10] and then the problem of estimating the gray parameters of the Verhulst model is transformed into a problem of estimating the regression coefficients of the LS-SVM model. The establishment of the gray Verhulst model and parameter estimation in the small sample regime are realized, which can effectively improve the generalization of the Verhulst model and provide higher prediction accuracy than the traditional parameter estimation methods [4].

With a training sample

$$\{(x_i, y_j)\}_{i=1}^{l},\ x_i \in R^n,\ y_i \in R$$

a nonlinear mapping $\varphi(x)$ is used to move the sample from the original space

mapped to a high-dimensional feature space Z of dimension k, in which the support vector machine model, i.e., the optimal linear regression function, is constructed [5, 6].

$$f(x) = \omega^T \phi(x) + b \tag{11}$$

According to the principle of structural risk minimization, the LS-SVM algorithm can be expressed as the following optimization problems:

$$\min_{\omega,b,\xi}\left(\frac{1}{2}\|\omega\|^2 + \frac{\lambda}{2}\sum_{i=1}^{l}\xi_i^2\right)$$

subject to

$$y_i = \omega^T \varphi(x_i) + b + \xi_i$$

In the formula, ξ_i is the error term and λ is the adjustment factor. When λ is infinite, the obtained solution is the least square solution

To estimate the parameters, first transform the equation into:

$$X^{(0)} = -Z^{(1)} + b(Z^{(1)})^2$$

Further, we let:

$$Y = X^{(0)}, X = [-Z^{(1)}, (Z^{(1)})^2]$$

Among them, we have:

$$Y = [X_2^{(0)},\ \ X_3^{(0)}, \cdots\cdots, X_m^{(0)}]^T$$
$$Z = [Z_2^{(1)},\ \ Z_3^{(1)}, \cdots\cdots, Z_m^{(1)}]^T$$

Thus, the estimation of parameters can be transformed into the problem of constructing the optimal linear regression function in the sample space, which is equivalent to solving the following planning problems:

$$\min_{\omega,\xi}\left(\frac{1}{2}\|\omega\|^2 + \frac{\lambda}{2}\sum_{k=2}^{l}\xi_k^2\right)$$

subject to:

$$y_k = \omega^T x_k + \xi_k (k = 2,3,\cdots,n)$$

Therefore, we introduce the following Lagrange function and solve:

$$L(\omega,\xi,a) = \frac{1}{2}\|\omega\|^2 + \frac{\lambda}{2}\sum_{k=2}^{l}\xi_k^2 - \sum_{k=2}^{n} a_k(\omega^T x_k + \xi_k - y_k)$$

According to Kuhn-Tuk optimization conditions, there are:

$$\frac{\partial L}{\partial \omega} = 0, \frac{\partial L}{\partial \xi_k} = 0, \frac{\partial L}{\partial a} = 0$$

Eliminate, the problem comes down to:

$$(\omega + \frac{\Gamma}{\lambda})a = y$$

According to Mercer condition, the linear kernel function is defined as:

$$k(x_i, x_j) = x_i^{\ T} x_j$$

Substitute the above formula and use the least square method to find the Lagrange multiplier a^*, then ccording to:

$$\omega = \sum_{k=2}^{m} a_k x_k$$

The coefficient of the optimal linear regression function can be estimated as:

$$\hat{\omega} = (\hat{a}, \hat{b})^T = \sum_{k=2}^{m} a_k^* x_k$$

Using the data provided by the topic for the nine countries that have nuclear weapons to date, a Verhulst model based on the LS-SVM algorithm is used to predict the change in the number of nuclear weapons in the next 100 years for the nine countries and the total number of nuclear weapons worldwide, and an error analysis is performed on the prediction results. The results were then visualized in order to visualize the trend of the number of nuclear weapons.

The predicted number of nuclear weapons in the next 100 years for the nine countries that have nuclear weapons at present is obtained from the prediction results of the Verhulst model improved by the equal-dimension and new-information incremental prediction method. Some results are shown in the following table:

Table 2: Table of Forecast Results of the Number of Nuclear Weapons in the Next 100 Years

Year	US	Russia	China	France	UK	Pakistan	India	Isael	North Korea
2023	3743	4398	354	289	196	166	160	91	22
2024	3748	4411	356	289	200	169	165	92	26
2025	3756	4418	359	288	201	171	173	92	29
2026	3768	4456	360	286	202	171	174	93	35
2027	3786	4458	365	285	205	174	179	93	38
2028	3796	4459	368	284	208	176	185	95	40
2029	3810	4468	369	284	211	181	189	93	46
2030	3816	4487	372	284	209	181	195	95	41
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
2121	3241	3671	559	210	171	359	340	122	36
2122	3239	3663	561	212	171	359	342	121	35
2123	3235	3650	562	210	170	359	343	122	35

4. ERROR ANALYSIS

Relative error test:

$$\mu(k)=\frac{\left|y^{(0)}(k)-y^{v(0)}(k)\right|}{y^{(0)}(k)}$$

where $y^{v(0)}(k)$ is the predicted value, if the error indicator is less than 0.2, it is considered to meet the general requirements; if the error is less than 0.1, it is considered to meet the higher requirements [11].

Grade ratio deviation test: Firstly, the grade ratio is calculated from the reference series

$$\lambda(k)=\frac{y^{(0)}(k-1)+c}{y^{(0)}(k)+c}$$

where c is the constant that makes all the grade ratios fall into the tolerable coverage ($e^{-\frac{2}{m+1}}, e^{\frac{2}{m+1}}$), and then the corresponding grade ratio deviation can be found by using the development coefficient a

$$\rho(k)=1-\left(\frac{1-0.5\alpha}{1+0.5\alpha}\right)\lambda(k)$$

if $\left|\rho(k)\right|$ is less than 0.2, the general demand can be reached; if it is less than 0.1, it can be considered to reach the higher demand.

Testing the model using the two indicators mentioned above, the following results were obtained.

Table 3: Prediction error analysis results

Country	Relative Error	Stage Ratio test	Country	Relative Error	Stage Ratio test
United States	0.1812	0.1561	Pakistan	0.0723	0.0986
Russia	0.1621	0.1123	North korea	0.2001	0.1987
CHina	0.0212	0.0112	Israel	0.1123	0.0879
India	0.0431	0.0543	France	0.0976	0.1201
United Kingdom	0.0321	0.0352			

5. CONCLUSION

The innovative method adopted in this paper has well predicted the future situation of nuclear weapons. Compared with the traditional time series model prediction, the fitting degree and accuracy are higher, which has important practical value for the control of the scale of nuclear weapons in the future.

REFERENCES

[1] Zhao Xuegong. Nuclear Weapons and American Policy towards the Korean War [J]. Historical Research, 2006(01):136-156+192.

[2] Tian Jingmei, Huside. Treaty on the Non-Proliferation of Nuclear Weapons: Differences and bridging [J]. Modern International Relations,2006(10):1-5.

[3] Guo Jinyu, Zhang Zhongbin, Sun Qingyun. The research and application of the analytic hierarchy process [J]. Chinese journal of safety science, 2008 (5): 148-153. The DOI: 10.16265 / j.carol carroll nki issn1003-3033.2008.05.018.

[4] Yu Xiaofen, Fu Dai. Statistics and Decision,2004(11):119-121.

[5] Shen Zhidong. Construction of State-owned Enterprise Performance Evaluation System by AHP [J]. Audit Research,2013(02):106-112.

[6] Xu Zeshui, Da Qingli. Study on the method of multiple attribute decision making performance [J]. Journal of management science in China, 2002 (02): 85-88. The DOI: 10.16381 / j.carol carroll nki issn1003-207 - x. 2002.02.018.

[7] Liu Sifeng, CAI Hua, Yang Yingjie, Cao Ying. Research progress of Grey correlation analysis Model [J]. Systems Engineering Theory & Practice,2013,33(08):2041-2046.

[8] Yuhong Wang, Dexian Huang, Dongjie Gao, Yihui Jin. Nonlinear predictive control based on LS - SVM technology [J]. Control and decision, 2004 (4): 383-387. The DOI: 10.13195 / j.carol carroll d. 2004.04.23. Wangyh. 005.

[9] Zhang Zhaofei, Luo Jianjun, Xu Binghua, Ma Weihua. Metabolic adaptive multiple parameters based on the theory of the grey prediction method [J]. Journal of Shanghai jiaotong university, 2017 ploidy (8): 970-976. The DOI: 10.16183 / j.carol carroll nki jsjtu. 2017.08.011.

[10] Long Wen, Liang Ximing, Long Zuqiang, Li Zhaohui. Short-term Load prediction of LSSVM based on Optimized parameters of improved ant Colony Algorithm [J]. Journal of Central South University (Science and Technology),2011,42(11):3408-3414.

[11] Fang Chen, Yong Wei. A new kind of data transformation and its effectiveness to improve the accuracy of grey prediction [J]. Statistics and Information Forum,2012,27(04):27-30.