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An Integrated SVM and Fuzzy AHP Approach for Selecting Third Party Logistics Providers

Abstract. *The selection of third party logistics (3PL) providers is an important issue for enterprises to outsource their logistics business. In this paper, a new integrated model is put forward for selecting 3PL providers based on support vector machine (SVM) and fuzzy analytic hierarchy process (FAHP). In the first stage, the support vector machine (SVM) is used to classify the primary 3PL provider samples into four types which are excellent, good, medium and bad respectively. Then we can obtain the excellent samples which are the candidates for the second stage selection. In the second stage, the FAHP is used to evaluate the selected excellent samples in the first stage, so we can obtain the sorting results for the excellent samples and the optimal samples. The results of the case study show that the model is reasonable and effective and it can provide an important reference for enterprises to select 3PL providers.*

Streszczenie*. W artykule przedstawiono nowy zintegrowany model umożliwiający przyśpieszenie selekcji dostawcy 3PL (third party logistics). Model wykorzystuje metodę SVM (suport vector machine) i FAHP (fuzzy analytic hierarchy proces). (****Zintegrowana metoda selekcji dostawcy 3PL wykorzystująca mechanizm SVM i FAHP****)*

Keywords: Third party logistics (3PL), Providers Selection, Support vector machine (SVM), Fuzzy analytic hierarchy process (FAHP)
Słowa kluczowe: dostawca – provider, SVM – support vector machine, FAHP – fuzzy analytic hierarchy process)

Introduction

Logistics management is an important content for the operation of the enterprise. Logistics plays a significant role in integrating the supply chain of industries. In order to concentrate on their main business, enterprises often outsource their logistics to a third-party logistics provider. So they can not only save the cost of logistics enterprises related, but also enhance their flexibility and adaptability. Therefore, how to choose the most suitable third-party logistics provider becomes an important problem for enterprises.

Recently, many researchers have extensively discussed the relevant topics of 3PL from different perspectives. Mohan (1998) applied factor analysis method to analyze four selection factors on how to choose a right third party logistics provider based on a questionnaire survey which studied 163 third party logistics enterprises, including the perceived performance of logistics providers, the perceived ability of logistics providers, price and external environment[1]. Penny（2002）put forward an index system of third-party logistics provider selection including environmental facilities, customer service, warehousing and storage, financial status, customer relationship management, transportation, leadership and technical staff, geography, education and training, value-added service, etc[2]. Su & Chen (2006) used grey evaluation method to evaluate the supply chain partners[3]. Yue & Li (2007) studied the logistics supplier selection based on the analytic hierarchy process (AHP) and data envelopment analysis (DEA)[4]. Liu & Wang (2009) proposed an integrated fuzzy approach for provider evaluation and selection in third-party logistics[5]. Liao & Kao (2011) applied an integrated fuzzy TOPSIS and MCGP model to select suppliers[6]. Li et al. (2011) proposed an indicator system and established a compound quantification model based on centralized quantification values, a comparison method based on the synthesis effect, and a 3PL supplier selection model[7]. Support vector machine (SVM) was put forward by Vapnik (Vapnik, 2000) and this method has the advantages of small sample learning, and can accurately separate the sample set[8]. Support vector machines(SVM) are a set of related supervised learning methods used for classification and regression. They belong to a family of generalized linear classifiers. In recent years, SVM has been widely used in pattern recognition, regression estimation, function approximation, text categorization, time series prediction, financial sequence analysis, and successfully solved a series of decision-making problems[9,10]. Mao (2009) proposed a new analog circuit fault diagnosis method combining the SVM with principal component analysis (PCA)[11]. Tian & Liu(2009) used SVM classification algorithm to solve the incompatible problems of flood disaster assessment indexes. It provided a new way to evaluate the flood disaster assessment and improve precision[12].

In the present paper, we propose an integrated support vector machine (SVM) and fuzzy AHP method for provider selection. Because the selection of 3PL providers is a complex, nonlinear decision-making problem with features like small sample, nonlinearity and fuzziness, SVM is adopted for selection and evaluation of logistics. Together with FAHP, a two-stage SVM-FAHP optimization evaluation model is established in this paper. A specific case for application will be shown.

Model based on support vector machine and fuzzy analytic hierarchy process

Support vector machine model

Support vector machine (SVM) is used to solve nonlinear of sample decision in high dimension feature space and find a separating hyper-plane of all the samples effectively (Vapnik, 2000). The undivided linear sample cannot be classified in the living space, but the theory proved that if the set of points is mapped to an appropriate higher-dimension space, this kind of sample can easily be separated. So we mainly solve the following two questions: how the set of points is mapped to a high dimension space and how to separate the undivided linear set in the high dimension space. Mapping refers to selecting the appropriate kernel function which can map the sample set to a high dimension space. The next thing is to find a separating hyper-plane which can break up these points without error. After such a process a nonlinear point set can be rightly separated.

SVM is determined by the minority samples around the hyper-plane rather than others. And the nearest samples to the hyper-plane are the support vector. SVM has the following advantages: good generalization ability, simple structure, fast learning, etc. The basic thought of SVM is shown in Figure 1. Circles and squares stand for two kinds of samples, and OSH is optimal hyper-plane. H1 and H2 consist of the samples which are nearest to the optimal hyper-plane. The distance between the samples which are nearest to the optimal hyper-plane and the optimal hyper-plane is called the classification interval.

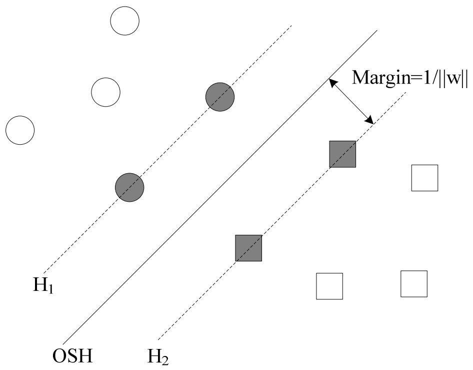

Fig.1. Optimal classification line schematic diagram

To optimal hyper-plane, the classification hyper-plane should meet the following two requirements (Zhang, 2001) : (a) It can divide samples into two categories, (b) It also can maximize the classification interval[13].

Suppose that the training sample set is $\{(x_i, y_i), i = 1,2,\cdots,l\}$. Samples contain two kinds of data. When sample i belongs to the first class, $y_i = 1$; when sample i belongs to the second class, $y_i = -1$. Learning problems refers to constructing a decision-making function, enabling it to separate two kinds of data (Luo, 2009)[14].

Nonlinear classification hyper-plane:

(1) $$\omega \bullet \varphi(x) + b = 0$$

Decision-making function:

(2) $$f(x) = sign(\omega \bullet \varphi(x) + b)$$

The optimal hyper-plane problem solving is described as follows:

(3) $$\begin{aligned} &\min_{\omega,b} \frac{1}{2}\omega^T\omega + C\sum_{i=1}^{l}\xi_i \\ &s.t. \quad y_i(\omega^T \bullet \varphi(x_i) + b) \geq 1 - \xi_i \\ &\qquad \xi_i \geq 0, i = 1,2,...,l \end{aligned}$$

Using Lagrange method to convert it into its dual problem:

(4) $$\begin{aligned} &s.t. \quad \sum_{i=1}^{l} y_i\alpha_i = 0 \\ &\qquad 0 \leq \alpha_i \leq C \quad i = 1,2\cdots,l \end{aligned}$$

The decision-making function is:

(5) $$f(x) = sign(\sum_{i=1}^{l} y_i\alpha_i^* K(x, x_i) + b^*)$$

where $K(x_i, x_j)$ is the kernel function; α is Lagrange multiplier, and C Punishment control parameters.

The optimal solution is

(6) $$\begin{aligned} &\alpha^* = (\alpha_1^*, \alpha_2^*, \cdots, \alpha_l^*) \\ &b^* = y_j - \sum_{i=1}^{l} y_i\alpha_i K(x_i, x_j) \end{aligned}$$

From Hilbert-Schmidt's study, as long as the Mercer conditions are satisfied, the symmetrical functions can be a kernel function. Commonly used kernel functions are: Polynomial kernel function $K(x_i, x_j) = [(x_i + x_j) + c]^d, c \geq 0$; Radial Basis Function (RBF) $K(x_i, x_j) = \exp(-\frac{|x_i - x_j|}{\sigma^2})$; Sigmoid kernel function $K(x_i, x_j) = \tanh[v(x_i, x_j) + c], c < 0$.

Fuzzy Analytic Hierarchy Process (FAHP)

Analytic hierarchy process (AHP) is a decision making method that combines qualitative and quantitative methods. AHP decomposes the complex issues into target layer, decision criteria layer and scheme layer. The method was first proposed by Saaty. The advantage of this method is that it can make decision process mathematical by using less of the quantitative data.

When constructing the judgment matrix, traditional AHP has a defect that the subjective qualitative problems will be transformed into a precise value of quantitative problems. However, in practical problems, the evaluation of research subjects is often complex and uncertain. This will result in a gap between the analysis and the actual situation. In this case, the idea of fuzzy mathematics is applied to the AHP to solve practical problems in fuzzy uncertainty (Buckley, 1985; Lu, 2008)[15,16].

In this paper, we adopted one triangular fuzzy number to show the relative importance, and then calculated the fuzzy weight according to the triangular fuzzy number. Membership functions of the triangular fuzzy number are:

(7) $$U_{A(x)} = \begin{cases} (x-a)/(b-a), a \leq x \leq b \\ (x-c)/(b-c), b \leq x \leq c \\ 0 \ \ , \ others \end{cases}$$

The A_{ij} represents the element $A_{ij} = (a_{ij}, b_{ij}, c_{ij})$ of A matrix, a_{ij} is the pessimistic assessment of the relative importance of i and j index. b_{ij} is the average assessment of the relative importance of i and j index. c_{ij} is the optimistic assessment of the relative importance of i and j index. The triangular fuzzy number above can solve the subjective, fuzzy and uncertain characteristics of human mind. The formula of the triangular fuzzy is as follows:

(8) $$A_{ij} = (a_{ij}, b_{ij}, c_{ij}), \quad \begin{cases} a_{ij} = \min(a_{ij}^1, ..., a_{ij}^n) \\ b_{ij} = \sqrt[n]{\prod_{k-1}^{n} b_{ij}^k} \\ c_{ij} = \max(c_{ij}^1, ...c_{ij}^n) \end{cases}$$

The method of fuzzy weighted geometric average calculation which was put forward by Buckley to calculate the triangular fuzzy matrix of the fuzzy weighted index was adopted in this paper (Buckley,1985; Lu,2008). This method can satisfy the consistency and regularization requirements.

(9) $$\tilde{Z}_i = [\tilde{a}_{i1} \otimes ... \otimes \tilde{a}_{in}]^{1/n}$$

(10) $$\tilde{W}_i = \tilde{Z}_i \otimes (\tilde{Z}_1 \oplus ... \oplus \tilde{Z}_n)^{-1}$$

Here $\tilde{a}_1 \otimes \tilde{a}_2 \cong (\alpha_1 \times \alpha_2, \beta_1 \times \beta_2, \gamma_1 \times \gamma_2)$; $\oplus$ is addition of one triangular fuzzy number; $\otimes$ is the multiplication of triangular fuzzy number; $\tilde{W}_i$ is the fuzzy weighted vector of each index.

Steps of using SVM-FAHP

The steps for the SVM-FAHP are as follows:

Step 1: Establishing the index system of 3PL provider selection.

Step 2: Data collection for the training samples and the test samples. The one-to-one multi-classification algorithm is used to obtain the excellent samples which are the candidates for the FAHP.

Step 3: Assessment of the excellent enterprises by the FAHP model.

Step 4: Layer simple sequencing and Composite total sequencing for the assessment samples.

Step 5: Sorting the excellent enterprises according to the weight calculated so that the most suitable one can be chosen.

Application example and results

The LinJin Co., Ltd (LJCL) is a large manufacturer in China. In recent years, facing the market competition, LJCL determines to outsource its logistics business, reduce its cost of logistics and achieve its competitive advantage in the market. Based on market investigation and combining with actual situation of LJCL, the index system is established and shown in Figure 2. The index system is divided into one criteria layer and one sub-criteria layer. It is comprehensive and covers five internal and external aspects, that is, service level, technical level, cost level, operating efficiency, financial situation respectively.

First stage of 3PL providers selection

(1) Collection of sample set

According to the market survey and the collected information, there are fifty 3PL companies selected. The index data are obtained by expert evaluation. The first 40 samples of them are used as the training set, and the remaining 10 as the test set. The training sets are divided into four grades. The first 10 samples are excellent, the second 10 are good, the third 10 are medium and the rest 10 are bad for the 40 samples. A training set is used for learning. The remaining 10 test set with 3 excellent, 3 good, 2 medium and 2 poor is used to test the classification accuracy of SVM.

(2)Solve the problem

The training purpose is to enable SVM to identify excellent, good, medium and bad. One-to-one multi-classification algorithm is used.

Step1. Divide all the samples (40) into excellent (top 10) and non-excellent (remaining 30), mark the excellent ones with 1, and non-excellent with -1. Input all the samples and obtain the function χ_1, which is used for distinguish excellent from non-excellent.

Step2. Divide the non-excellent samples (30) into good (top 10) and non-good (remaining 20), mark the good ones with 1, and non-good ones with -1. Input all the samples and obtain the function χ_2, which is used for distinguish good from non-good.

Step3. Divide the non-good samples (20) into medium (top 10) and non-medium (remaining 10), mark the medium ones with 1, and non-medium ones with -1. Input all the samples and obtain the function χ_3, which is used for distinguish medium from non-medium.

The multi-classification model is established based on the above process and parameters nsv1, nsv2, nsv3, alpha1, alpha2, alpha3, bias1, bias2, bias3 are calculated

(3)The first selection by SVM

Through various ways to survey the actual market situation and make every criteria quantitative according to the index system established above, we obtained 30 samples data of 3PL providers.

Firstly, input the 30 group data to the function whose parameters are nsv1, alpha1, bias1. We can find that the top 7 output 1, and the others output -1, so the top 7 belong to excellent. Input the 23 groups data marked by -1 to the function whose parameters are nsv2, alpha2, bias2. We can find that the top 8 output 1, and the remaining 15 output -1, so the top 8 belong to good. Input the 15 groups data marked by -1 to the function whose parameters are nsv3、alpha3、bias3. We can find that the top 8 output 1, and the remaining 15 output -1, so the top 8 belong to medium.

The results show that sample 1 to sample 7 among the 30 samples is excellent, and they are also the excellent solutions for the first stage. Meanwhile, they are selected as the input for the second stage.

Second stage of selection by FAHP

Through analyzing five aspects of the 3PL providers including customer service level, technical level, cost level, operation efficiency and financial situation, we compute the index weights by fuzzy judgment matrix methods. The mainly steps are as follows.

(1) Establishing triangular fuzzy positive reciprocal matrix $\tilde{M}$

$$\tilde{M}=\begin{bmatrix} (1,1,1) & (1/5,1/4,1/3) & (1/7,1/5,1/3) & (1/5,1/3,1/2) & (1/7,1/5,1/3) \\ (3,4,5) & (1,1,1) & (1,1,2) & (1,3,5) & (3,4,5) \\ (3,5,7) & (1/2,1,1) & (1,1,1) & (1/7,1/5,1/3) & (2,3,5) \\ (2,3,5) & (1/5,1/3,1) & (3,5,7) & (1,1,1) & (3,4,5) \\ (3,5,7) & (1/5,1/4,1/3) & (1/5,1/3,1/2) & (1/5,1/4,1/3) & (1,1,1) \end{bmatrix}$$

Computing the index fuzzy weight matrix $\tilde{W}$

The $\tilde{M}$ is divided into 3 matrix L, M and U as follows.

$$L=[l_{ij}]=\begin{bmatrix} 1 & 1/5 & 1/7 & 1/5 & 1/7 \\ 3 & 1 & 1 & 1 & 3 \\ 3 & 1/2 & 1 & 1/7 & 2 \\ 2 & 1/5 & 3 & 1 & 3 \\ 3 & 1/5 & 1/5 & 1/5 & 1 \end{bmatrix},$$

$$M=[m_{ij}]=\begin{bmatrix} 1 & 1/4 & 1/5 & 1/3 & 1/5 \\ 4 & 1 & 1 & 3 & 4 \\ 5 & 1 & 1 & 1/5 & 3 \\ 3 & 1/3 & 5 & 1 & 4 \\ 5 & 1/4 & 1/3 & 1/4 & 1 \end{bmatrix},$$

$$U=[u_{ij}]=\begin{bmatrix} 1 & 1/3 & 1/3 & 1/2 & 1/3 \\ 5 & 1 & 2 & 5 & 5 \\ 7 & 1 & 1 & 1/3 & 5 \\ 5 & 1 & 7 & 1 & 5 \\ 7 & 1/3 & 1/2 & 1/3 & 1 \end{bmatrix}.$$

The index fuzzy weight matrix $\tilde{W}=(\tilde{w}_1,\ \tilde{w}_2,\ \tilde{w}_3,\ \tilde{w}_4,\ \tilde{w}_5)$ is computed as follows.

$$\tilde{w}_i=\left(\frac{\left(\prod_{k=1}^{5} l_{ik}\right)^{1/5}}{\sum_{j=1}^{5}\left(\prod_{k=1}^{5} u_{jk}\right)^{1/5}}\quad \frac{\left(\prod_{k=1}^{5} m_{ik}\right)^{1/5}}{\sum_{j=1}^{5}\left(\prod_{k=1}^{5} m_{jk}\right)^{1/5}}\quad \frac{\left(\prod_{k=1}^{5} u_{ik}\right)^{1/5}}{\sum_{j=1}^{5}\left(\prod_{k=1}^{5} l_{jk}\right)^{1/5}}\right),$$

$$\tilde{W}=(\tilde{w}_1,\tilde{w}_2,\tilde{w}_3,\tilde{w}_4,\tilde{w}_5)=\begin{bmatrix} 0.0276 & 0.0516 & 0.1023 \\ 0.1776 & 0.3503 & 0.6852 \\ 0.0966 & 0.2012 & 0.3712 \\ 0.1478 & 0.2941 & 0.6380 \\ 0.0543 & 0.1027 & 0.1880 \end{bmatrix}.$$

(3) Computing the normalization weights $W_i(i=1,2,3,4,5)$

The normalization weights $W_i(i=1,2,3,4,5)$ can be computed by normalizing the fuzzy weight $\tilde{W}$ by geometry average method. Let $\tilde{W}_i = (\tilde{w}_{il} \times \tilde{w}_{im} \times \tilde{w}_{iu})^{1/3}$, then we can compute the normalization weights W_i , $W_i = \tilde{W}_i / \sum_{j=1}^{5} \tilde{W}_j$ $(i=1,2,3,4,5)$. That is, $W_1 = 0.0526$, $W_2 = 0.3495$, $W_3 = 0.1933$, $W_4 = 0.3029$, $W_5 = 0.1017$.

The comparison matrix for service level(A), technical level(B), cost level(C), operation efficiency(D) and financial situation(E) can be established respectively. The weight of each criterion by geometric average fuzzy weight calculation method can be calculated. The results of all index weights are shown in Table 1.

Table 1. The weights of 3PL providers index system

A:w_1 =0.0526	I_1 : w_{11} =0.1550 I_2 : w_{12} =0.3915 I_3 : w_{13} =0.3975 I_4 : w_{14} =0.0560
B: w_2 =0.3495	I_5 : w_{21} =0.5973 I_6 : w_{22} =0.0679 I_7 : w_{23} =0.3348
C: w_3 =0.1933	I_8 : w_{31} =0.5860 I_9 : w_{32} =0.4140
D: w_4 =0.3029	I_{10} : w_{41} =0.6348 I_{11} : w_{42} =0.2593 I_{12} : w_{43} =0.1059
E: w_5 =0.1017	I_{13} : w_{51} =0.2685 I_{14} : w_{52} =0.6275 I_{15} : w_{53} =0.1040

According to the data of the 7 excellent samples, the samples evaluation scores are calculated by the weighted method. That is,

$S_1 = 66.1207$, $S_2 = 67.2280$, $S_3 = 69.6905$, $S_4 = 69.7883$, $S_5 = 66.8707$, $S_6 = 70.3667$, $S_7 = 68.0050$.

Since $S_6 \succ S_4 \succ S_3 \succ S_7 \succ S_2 \succ S_5 \succ S_1$, the rank of the samples is $6 \succ 4 \succ 3 \succ 7 \succ 2 \succ 5 \succ 1$. The results are shown in Table 2.

Table 2. Evaluation value and sorting results

Sample No.	Scores	Sorting results
1	66.1207	7
2	67.2280	5
3	69.6905	3
4	69.7883	2
5	66.8707	6
6	70.3667	1
7	68.0050	4

From Table 2, we can find the 6th logistics provider obtained the highest score. Thus the best 3PL provider is the 6th logistics provider. So the LJCL's optimal 3PL provider is the 6th logistics provider.

Conclusions

Along with the development of information technology, logistics outsourcing has become an important tool to promote the core competitiveness of enterprises. The importance of 3PL provider selection has been intensified. The SVM-FAHP method is proposed in this study. The method separates 3PL provider selection into two stages. SVM is used in the first stage to classify all the enterprises to be selected. Then fuzzy AHP is adopted to evaluate the excellent enterprises which were selected in the first stage. Compared with the traditional method, the model based on SVM-FAHP can improve the selection efficiency and reduce the computational cost during decision-making process and the cost of information collection. SVM ensures the accuracy of classification since SVM can learn from small sample accurately. The FAHP model can solve the uncertainty problem effectively when converting the qualitative case to quantitative ones. The example study shows that the SVM-FAHP model is feasible and effective. The research can provide decision-making for enterprises to select 3PL providers. Future studies can apply the proposed method to other areas of decision-making.

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REFERENCES

[1] Menon M. K., Miehael A. M., Kenneth B.A., Selection criteria for providers of third–Party logistics services: an exploratory study, *Journal of Business Logisties*, 19(1998),No.1,121-137
[2] Penny M. S., Measuring the performance of suppliers: An analysis of evaluation processes, *Journal of Supply Chain Management*, 38(2002), No.1, 29-43
[3] Su J. N., Chen J. H., Multilevel gray evaluation method applies in supply chain logistics partner selection, *Operations Research and Management Science*, 15(2006), No. 3, 66-70
[4] Zhang Z. H., A probe on logistics strategic partner selecting model with preference DEA based on AHP, *Journal of Chinese Market*, (2007),No.8, 66-67
[5] Liu H. T., Wang W. K., An integrated fuzzy approach for provider evaluation and selection in third-party logistics, *Expert Systems with Applications*, 36(2009),No 3, 4387-4398
[6] Liao C. N., Kao H. P., An integrated fuzzy TOPSIS and MCGP approach to supplier selection in supply chain management, *Expert Systems with Applications*, 38(2011),No.9, 10803-10811
[7] Li F. C., Li L., Jin C. X., Wang R. J., Wang H., Yang L. L., A 3PL supplier selection model based on fuzzy sets, *Computers & Operations Research*, 39(2012),No.8, 1879-1884
[8] Vapnik, V. The Nature of Statistical Learning Theory, Springer-Verlag, New York(1995).
[9] Chi-wei, H., Chih-jen, L., A Comparison of Methods for Multiclass Support Vector Machine, *IEEE Transacatutions on Neural Networks*,13(2002),No. 2, 415-425
[10] Gold, C., Sollich, P., Model selection for support vector machine classification, *Neurocomputing*, 55 (2003), No.1, 221-249
[11] Mao X. B., Li C. X., Application of PCA-SVM in fault diagnosis for analog circuit, *Computer Measurement & Control* ,17(2009),No.7, 1250-1253
[12] Tian J. F., Wu L., A Model of Flood Disaster Evaluation Based on SVM, *Journal of Chinese Hydrology*, 29(2009), No. 1, 66-68
[13] Zhang X. G., Statistical learning theory and support vector machines, *Acta Automatic Sinica*, 26(2001), No. 1, 32-42
[14] Luo Z. M., Zhou J. Z., Zhang Y. C., Wu S.Y., Partners optimum decision-making of virtual research center based on support vector machine and fuzzy analytic hierarchy process, *Computer Integrated Manufacturing System*, 15(2009), No.11, 2266-2272
[15] Buckley J. J., Fuzzy analytic hierarchy, *Fuzzy Sets and Systems*, 17(1985), No.3, 233-247
[16] Lu G. Y., Zhu Z. Q., Li H., Xiong Y., Rock mass classification method in highway tunnel based on fuzzy analytic hierarchy process, *Journal of Chinese Central-South University*, 39(2008),No.2,368-374

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