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ENTERPRISE FINANCIAL DISTRESS PREDICTION BASED ON BACKWARD PROPAGATION NEURAL NETWORK: AN EMPIRICAL STUDY ON THE CHINESE LISTED EQUIPMENT MANUFACTURING ENTERPRISES

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As a key part of the effective prevention of the enterprise financial distress, financial distress prediction has been the attention focus in the theory study and the practical business field. According to the principle of the indicator selection, 11 financial indicators are chosen for the financial distress prediction model. In order to reduce the information redundancy, factor analysis is used to extract five common factors and therefore, the comprehensive score of each sample is obtained. Unlike the traditional ST or non-ST criteria to classify the tested samples, the enterprises are divided into three categories: health, concern, and distress. Furthermore, the prediction model based on Backward Propagation Neural Network is built, trained and tested with the five common factors as input and the enterprise financial conditions of the Chinese Listed Equipment Manufacturing Enterprises a great help for the development of Chinese transportation industry.

Keywords: financial distress prediction, factor analysis, financial category, Backward Propagation Neural Network, Chinese listed equipment manufacturing enterprises

Classifications: 03C98，97M30

1. Introduction

As a key part of the effective prevention of financial distress, enterprise financial distress prediction has been the attention focus in the theory study. Therefore, experts, scholars and practitioners have been very interested in tools that can predict financial distress which is the comprehensive result of the internal and external distress factors and refers to the precarious or emergent financial state caused by severe external setbacks and/or the internal control failures of financial activities. The financial distress prediction is designed to provide warning of the financial statements of the enterprise poor management strategies and to further improve the financial distress prediction model. Based on the analysis and summaries of home and abroad theoretical and empirical studies of the enterprise financial distress prediction of the listed equipment manufacturing enterprises, the proposed model in this study is constructed based on Backward Propagation Neural Network (BPNN) and the empirical research is conducted on the prediction model.

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2. Literature Review

2.1 Research Content

In the 1960s, many scholars from the United States and Europe began to study the enterprise financial conditions [1]. Odom and Sharda [2] first introduced the Neural Network (NN) to forecast financial distress, and built a simple three-layer forward BPNN model whose prediction accuracy rate of the testing samples was 81.81%, while the accuracy of Multiple Discriminant Analysis (MDA) was 74.28%, so they believed NNs were superior to MDA. Since then, NNs, MDA or Logit model have been used for comparative analysis [3]. Fletcher and Zhang et al. agreed that the NNs was better than Logit [4,5]; Wilson and Sharda, Leshno and Spector , Yang, et.al. , and Wu, et al. proved that NNs were superior to MDA [6-9].

The previous studies were based on specially treatment (ST) and non-ST classification. According to this "one or the other" category, the predicted ST enterprises almost have a foregone financial distress without enough adjustment time to avoid a crisis situation, which makes the model very little practical significance. In this study, a more realistic and feasible classification method is proposed to classify the financial situation of enterprises into three categories: health, concern, and distress. Therefore, the predicted financial concerned enterprises can pay attention to their internal improvements in advance. This model can help the enterprises conduct accurate and reasonable adjustments in order to avoid the potential financial predicaments.

2.2 Research Method

Starting from the definition of the financial distresses and the previous research results, this study establishes an objective and rational index system for the financial distress prediction. In order to simplify the network input and reduce the information redundancy while saving the main information, principal component factor (PCA) analysis is used to process the indicators as well as to reduce the input dimensions of BPNN. At the same time, factor analysis (FA) is used to derive the composite score of the enterprises' finance conditions and to check the distribution of the ST enterprises to determine their initial financial conditions. Then the timely data in 2009 and 2010 of the listed enterprises are analyzed. The common factors of each enterprise gotten from FA are taken as the input, and the financial conditions of each sample gotten from the above initial financial conditions as the output. The samples are trained according to the NN training algorithm using Matlab software to determine the network parameters and to construct the model and the finally test the model.

Based on the China disclosure system of listed enterprises' annual reports, the deadline for the listed companies to publish their annual report is on April 30 of the next year. Therefore, a listed enterprise's annual report of the year *(t-1)* and ST decision in the year *t* happen almost simultaneously. That means an enterprise's annual report information of the year *(t-1)* can decide whether the enterprise will be in the special treatment due to "the financial anomalies". Therefore, it's not practical to predict whether the enterprise will be in the ST in the year *t* by using the information of year *(t-1)*. In order to avoid this problem, this research uses a listed enterprise's year *(t-2)* annual financial report to predict its financial condition in year *t*. For example, the 2009 financial data of an enterprise will predict its financial condition in 2011, which will improve business-related measures of an enterprise to avoid the problems next year. This method plays an important role in the early prevention and can help managers and supervisory staff to make the scientific and effective decisions.

3. Construction of Evaluation Index System

The construction of this index system is made in the following principles: (1) *Systematical design*. (2) *Scientific feasibility*. (3) *Expansibility*. (4) *Independence*. (5) *Objectivity* [10]. Meanwhile, with the financial crisis evaluation system from domestic and foreign scholars [11] and the data availability and the special financial situations of Chinese enterprises into the consideration, the following 11 indicators are selected as the evaluation index system of a listed enterprise's financial distress prediction model as shown in Table 1.

Table 1

Evaluation index system of financial distress prediction model

Index	Indicator	Unit	Property
Solvency	1Current ratio	Times	Forward
	2 Quick ratio	Times	Forward
		100%	Moderate
Profitability	4 Profit rate to net worth(average weighed)	100 %	Forward
	5 Net profit margin	100 %	Forward
	6 Earning per share	Yuan	Forward
	7 Return on total assets ratio	(%)	Forward
Asset management	8 Inventory turnover	100 %	Forward
	9 Total asset turnover	Time	Forward
	10 Fixed asset turnover	100 %	Forward
	11 Accounts receivable turnover	100 %	Forward

4. Empirical Study

4.1 Feasibility of BPNN

Artificial neural networks (ANNs) are a brain-like intelligent information processing system intending to mimic the human brain structure and function [12]. BPNN, with the incomparable superiorities [13], is one of the most widely used ANN model [14], and the most effectively applied NN model [15].

4.2 Data Process and Analysis

Based on the China disclosure system of listed enterprises' annual reports, the deadline for the listed companies to publish their annual report is on April 30 of the next year. Therefore, a listed enterprise's annual report of the year (t-1) and ST decision in the year t happen almost simultaneously. That means an enterprise's annual report information of the year (t-1) cannot decide whether the enterprise will be in the special treatment due to "the financial anomalies". Therefore, it's not practical to predict whether the enterprise will be in the ST in the year t by using the information of year (t-1). In order to avoid this problem, a listed enterprise's year (t-2) annual financial report is used to predict its financial condition in year t. For example, the financial data of an enterprise in 2009 will predict its financial condition in 2011, which will improve business-related measures of an enterprise to avoid the problems next year. Based on the industry representation and the asset size, 100 valid samples are selected in the latest data of 2009 and 2010 and SPSS18.0 is used to standardize the raw data. For the financial status of the 15 testing samples, see Table 7. The currence relation derived from past values is not utilized for the estimation of future data values or the testing samples.

As the correlation of indicators between the variables increases the probability of information overlap [16], there is unnecessary trouble in the statistical analysis. Factor analysis is very effective to increase the accuracy and decrease the variable correlation [17]. Under the premise of the least lost information, factor analysis minimizes the original data base to several types of composite variables. These variables in this basic structure are named common factors. In order to get the common factors among the indicators, we process the samples using the principal component analysis of the factor analysis [18].

The samples are tested in KMO and Bartlett's Test using SPSS18.0.The KMO value which is 0.571, greater than 0.5, is proper for the principal component analysis; the accompanied probability of the Bartlett's Test which is 0.000, less than the significant level of 0.05, rejects the null hypothesis of the Bartlett's Test. That is, the sample data are proper for the principal component analysis [19] as shown in Table 2.

Table 2

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.571
Bartlett's Test of Sphericity Approx.	Chi-Square	1139.152
	df	55
	Sig.	.000

4.3 Selection and Analysis of Common Factors

In the total variance table of PCA (Table 3.):

Table 3

Total Variance Explained

Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	Variance (%)	Cumulative variance (%)	Total	Variance (%)	Cumulative variance (%)	Total	Variance (%)	Cumulative variance (%)
1	3.105	28.224	28.224	3.105	28.224	28.224	2.570	23.368	23.368
2	2.073	18.846	47.069	2.073	18.846	47.069	2.532	23.023	46.391
3	1.396	12.689	59.758	1.396	12.689	59.758	1.411	12.825	59.216
4	1.083	9.844	69.602	1.083	9.844	69.602	1.095	9.954	69.169
5	1.047	9.519	79.121	1.047	9.519	79.121	1.095	9.952	79.121
6	.736	6.695	85.816						
7	.566	5.145	90.961						
8	.515	4.686	95.648						
9	.337	3.062	98.710						
10	.105	.953	99.664						
11	.037	.336	100.000						

There are five factors whose eigenvalues are greater than 1, namely, the common factors. The cumulative variance contribution rate of their eigenvalues reaches 79.121%. Based on the gravel figure (Fig. 1), namely, the scree test, the two lines converge on about the fifth factor, the scree line rises suddenly at around the fifth factor. Therefore, it is reasonable to reserve these five factors [20]:

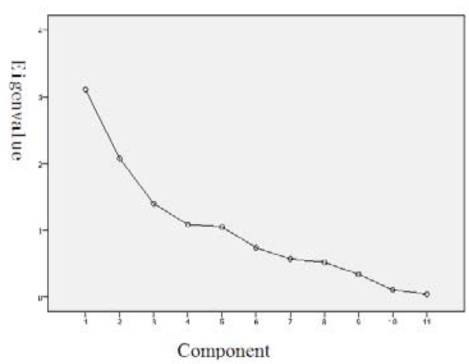

Fig. 1 Gravel figure of the principle component analysis

The following conclusions can be got from the rotated component matrix out of SPSS (See Table 4.). Different indicators are chosen to explain the five different factors.

Table 4

Rotated Component Matrix

actor	Indicator		Zscore				
	Name	Code	Compo-nent 1	Compo-nent 2	Compo-nent 3	Compo-nent 4	Compo-nent 5
1	Return on total assets ratio	X9	<u>0.919</u>	0.201	0.108	0.053	0.071

	Profit rate to net worth(average weighed)	X1	<u>0.844</u>	0.041	0.018	0.04	-0.012
	Earning per share	X2	<u>0.725</u>	0.071	0.248	-0.165	0.198
	Net profit margin	X6	<u>0.638</u>	0.033	-0.259	0.126	-0.119
2	Quick ratio	X4	0.027	<u>0.966</u>	0.072	-0.022	0.025
	Current ratio	X3	0.055	<u>0.948</u>	0.005	-0.057	0.136
	Asset-liability ratio	X5	-0.235	<u>-0.796</u>	0.146	-0.022	0.17
3	Total asset turnover	X11	0.117	-0.099	<u>0.847</u>	-0.173	0.178
	Fixed asset turnover	X8	-0.053	0.074	<u>0.725</u>	0.405	-0.263
4	Accounts receivable turnover	X7	0.065	-0.057	0.01	<u>0.916</u>	0.117
5	Inventory turnover	X10	0.051	0.015	0.013	0.101	<u>0.935</u>

Based on the component score coefficient matrix out of the SPSS (See Table 5.), the five common factor scores are calculated as follows.

Table 5

Component Score Coefficient Matrix

Zcore	Component				
	1	2	3	4	5
Profit rate to net worth(average weighed)	.346	-.057	-.025	.014	-.066
Earning per share (Yuan)	.276	-.033	.147	-.182	.125
Current ratio (Time)	-.069	.388	.016	-.030	.130
Quick ratio (Time)	-.079	.399	.070	.000	.026
Accounts receivable turnover (Times)	.000	-.005	-.051	.840	.104
Asset-liability ratio (%)	-.043	-.305	.092	-.041	.158
Net profit margin (%)	.278	-.046	-.215	.113	-.138
Return on total assets ratio (%)	.353	.005	.035	.024	.004
Inventory turnover	-.054	.058	.519	.338	-.276
Fixed asset turnover	-.043	.013	-.045	.092	.864
Total asset turnover	.013	-.037	.603	-.209	.113

$$F_1 = 0.346\times X_1 + 0.276\times X_2 - 0.069\times X_3 - 0.079\times X_4 - 0.043\times X_6 \\ +0.278\times X_7 + 0.353\times X_8 - 0.054\times X_9 - 0.043\times X_{10} + 0.013\times X_{11} , \tag{1}$$

$$F_2 = -0.057\times X_1 - 0.033\times X_2 + 0.388\times X_3 + 0.399\times X_4 - 0.005\times X_5 \\ -0.305\times X_6 - 0.046\times X_7 + 0.005\times X_8 + 0.058\times X_9 + 0.013\times X_{10} - 0.037\times X_{11} , \tag{2}$$

$$F_3 = -0.025\times X_1 + 0.147\times X_2 + 0.016\times X_3 + 0.070\times X_4 - 0.051\times X_5 \\ +0.092\times X_6 - 0.215\times X_7 + 0.035\times X_8 + 0.519\times X_9 - 0.045\times X_{10} + 0.603\times X_{11} , \tag{3}$$

$$F_4 = 0.014\times X_1 - 0.182\times X_2 - 0.030\times X_3 + 0.840\times X_5 - 0.041\times X_6 \\ +0.113\times X_7 + 0.024\times X_8 + 0.338\times X_9 + 0.092\times X_{10} - 0.209\times X_{11} , \tag{4}$$

$$F_5 = -0.066 \times X_1 + 0.125 \times X_2 + 0.130 \times X_3 + 0.026 \times X_4 + 0.104 \times X_5 + 0.158 \times X_6 - 0.138 \times X_7 + 0.004 \times X_8 - 0.276 \times X_9 + 0.864 \times X_{10} + 0.113 \times X_{11} \quad (5)$$

The composite score F, that is, the sum of the product of each factor and its contribution out of the total variance table is

$$F = F_1 \times 0.28224 + F_2 \times 0.18846 + F_3 \times 0.12689 + F_4 \times 0.09844 + F_5 \times 0.09519 . \quad (6)$$

4.4 Specific Classification of Enterprise Financial Conditions

Based on the F value of the enterprises and the ST or non-ST condition as the reference, the intervals of F value are divided and the final classifications are determined as in Table 6.

Table 6

Financial Condition Classification of Enterprises

Intervals of F Value	Financial Condition	Number of Enterprises	ST Enterprises	Proportion of ST Enterprises
(-∞,-0.2)	Distress	19	16	84.2%
(-0.2,0.13)	Concern	54	16	29.6%
(0.13,+∞)	Health	27	1	3.7%

As can be seen, when F is greater than 0.13, the very small proportion of ST enterprises can be ignored. Therefore, it can be regarded as a health condition interval; when F is between -0.2 and 0.13, the proportion of ST enterprises is much smaller than the proportion of distressed enterprises but can not be ignored. Therefore, it can be regarded as a concern condition interval; when F is smaller than -0.2, ST enterprises account for a large part. Therefore, it can be regarded as a distress condition interval. In summary, based on the analysis above, the financial condition of the enterprises can be divided into three categories, i.e. distress, concern, and health.

5 Empirical Analysis

Since five common factors represent the 11 original data indicators, the number of the input nodes of BPNN is five. In this study, the enterprise financial status can be divided into three situations: health, concern, and distress which can be represented by the available state values (1,0,0), (0,1,0), and (0,0,1).So the number of the output nodes of this network is 3. Referring to Formula (7) , the number of the hidden nodes is 7. In training, the learning rate is 0.05, the required training accuracy is 0.0001, and the training times are 4000.

$$n = n_i + 0.618 \times (n_i - n_o) , \quad (7)$$

where n_i is the number of the input nodes, n_o the number of the output nodes, n the number of the hidden nodes.

85 enterprises from the Chinese listed equipment manufacturing enterprises are selected as the training samples, 15 as the testing samples.

Matlab7.11 is used and the programs are shown in the appendix. The prediction results of the enterprise financial distress based on BPNN are shown in Table 7.

Table 7

Prediction Results of the Enterprise Financial Distress Based on BPNN

Financial Condition	Number of Enterprises	Correctly Predicted Enterprises	Accuracy
A	3	3	1
B	10	9	0.9
C	2	2	1
Total	15	14	0.93

The training results show that the error is relatively small and the results are satisfactory, which means that BPNN is very appropriate to predict the financial distresses of the Chinese listed equipment manufacturing enterprises.

6 Conclusions

A financial distress prediction model based on BPNN is constructed to study the Chinese listed the Chinese listed equipment manufacturing enterprises and the empirical study is carried out. The main features of this study are as follows.

(1) Innovation in the classification of enterprise financial conditions. That is, divide the financial conditions into three categories: health, concern, and distress. This can help the enterprises to take the preventive measures as early as possible, to make more scientific and rational decisions, and to avoid the financial crisis.

(2) Reduction of the overlapped and redundant index information. PCA is used to identify the common factors maximally reflect the information of the index system. The selected five common factors are the linear combinations of the original 11 indicators, but not relevant.

(3) As the indicator variables chosen for this study can be obtained from public audited annual report of the listed companies, the method is quite feasible. Meanwhile, as the annual report and ST decisions of the enterprises are released almost at the same time, it's not practical to predict whether the enterprise will be specially treated in the year *t* by using the information of year *(t-1)*. This research used a listed enterprise's year *(t-2)* annual financial report to predict its financial condition in year *t*, which can increase the scientific nature and the practicality of the training model.

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Appendix

Programs for the enterprise financial distress prediction based on BPNN in Matlab

```
p=[
0.0273      -0.27266    -0.83974    -0.17833    -0.12363
0.59849     0.88428     -0.27288    -0.22094    -0.23278
0.4341      -0.61392    -0.26055    -0.20656    -0.06129
0.11049     -0.29599    -0.32439    -0.28368    0.05482
0.32925     0.2068      0.17148     -0.32978    0.00424
0.11079     -0.6657     0.22326     -0.16376    -0.09896
0.37951     -0.61279    2.95207     -0.90161    2.68686
0.11896     -0.56809    -1.20409    0.00493     -0.45024
-0.06138    0.11573     -0.30057    -0.28876    -0.01598
-0.60458    0.14903     1.27431     -0.25652    -0.11523
0.69643     1.11095     0.9452      -0.62937    0.48397
-0.68261    2.25353     0.24287     0.05865     0.21655
0.1016      -0.33287    -0.279      -0.27825    -0.02232
0.7783      0.25494     -1.50256    0.36145     -1.00344
-0.0153     0.26674     -0.63087    -0.23901    -0.27906
0.55702     0.1342      -0.81492    -0.11911    1.02667
-0.14808    -0.58515    -0.6191     0.20841     -0.65757
0.27806     0.04896     -0.5629     -0.27835    -0.0831
-0.09343    1.24763     -0.49208    -0.10909    -0.38085
-0.51218    -0.07917    -0.38877    -0.21177    -0.05504
-0.52154    0.98137     -0.76865    0.24358     -0.70449
0.12729     -0.8689     -0.82206    -0.1333     -0.16839
-0.72186    -0.60552    -0.05899    0.00123     -0.29007
-0.12445    -0.06509    -0.45127    -0.11562    -0.18567
-0.17387    -0.11417    -0.39366    0.03675     -0.46224
0.6045      0.35195     -0.62518    -0.04864    -0.22042
-0.05358    -0.79954    -0.66687    7.39972     0.36569
-0.48461    -0.59201    1.80955     0.88139     0.04834
-0.60897    -0.43289    -0.08895    -0.08822    -0.29824
0.15515     0.24191     1.25594     0.20781     -0.79116
-0.76859    -0.34739    -0.7423     -0.14511    -0.26061
-0.14729    -0.67205    0.29574     -0.30644    0.60281
-0.40655    0.20227     0.32286     0.12884     -0.40883
0.2179      1.13919     -0.66322    -0.21614    -0.18636
```

-0.04581	-0.53664	-0.71297	0.08417	-0.56493
0.15266	-0.25949	-0.13176	-0.24959	0.00962
0.43083	-0.34449	-0.23871	-0.25835	-0.27325
-0.01931	-0.67752	-0.34785	-0.24625	0.06119
-1.27242	-0.78946	-0.64334	-0.00623	-0.27515
0.58694	1.14057	0.01435	-0.2672	0.02339
-0.04243	-0.15168	-0.68685	-0.09422	-0.4108
-1.3669	-0.81215	0.42681	-0.09371	0.56921
0.1283	-0.52685	2.12768	-0.08089	-0.20227
-0.17539	-0.52533	0.26632	-0.29894	0.08349
0.32385	-0.4771	0.47116	-0.30787	0.06615
-1.67488	-0.38205	-0.644	-0.27752	0.05745
-0.51065	-0.35157	-0.52959	0.18839	-0.47535
-0.52154	0.98137	-0.76865	0.24358	-0.70449
0.03113	-0.72105	-0.45618	-0.07927	-0.34297
-0.38177	-0.86337	-0.22975	0.00646	-0.25749
0.16517	-0.28608	-0.47117	-0.19963	-0.26055
-0.5387	-0.25459	-0.70084	-0.09285	-0.38461
-0.01291	0.22714	-0.45967	-0.0976	-0.32112
-0.07874	-0.63714	-0.25887	-0.28987	-0.00419
-0.20133	0.48466	-0.56771	-0.08232	-0.067
-0.14618	-0.65976	0.38962	-0.13251	0.03923
0.40741	0.23759	-0.01036	-0.18328	-0.1539
3.14803	-0.14208	-3.75262	1.20807	-1.86872
-1.3669	-0.81215	0.42681	-0.09371	0.56921
0.76436	-0.86104	3.56198	-1.11435	1.10578
-0.65787	-0.52693	-0.49243	-0.19175	-0.01474
1.30518	1.90544	-0.48514	-0.01067	-0.31761
-0.45218	-0.56545	-0.04881	0.18624	-0.48526
-10.3191	0.17651	-0.00577	-0.33958	0.70199
0.37196	0.11426	0.19274	-0.20455	-0.21346
-2.07475	-1.01897	-0.15203	0.06243	-0.17493
0.3021	-0.45947	-0.34152	-0.38105	0.07614
0.10234	0.09885	-0.5865	-0.21088	-0.03417
0.63405	2.24586	0.32293	-0.29239	0.19778
0.71303	-0.37391	0.66926	-0.71312	0.92737
0.22067	0.16599	-0.21991	-0.22077	-0.24629
-0.12693	-0.70667	0.36508	-0.25915	0.15873
1.09808	0.14147	-0.65352	0.55749	4.46241
0.74347	0.10328	-0.07153	-0.32175	-0.18027

```
1.85652    0.36245    -0.0679    -0.23865   0.17615
-0.04455   -0.85369   0.18647    -0.22295   -0.0933
0.40003    0.48257    -1.23805   -0.05786   -0.36611
0.08999    -0.78771   0.7382     -0.307     0.20065
1.62916    0.10618    0.40753    -0.76167   0.17503
0.67777    1.89916    0.65583    -0.07201   0.23465
-0.28204   -0.25829   -1.09592   -0.1371    -0.39091
-0.24275   -0.21972   -0.85807   -0.14137   -0.19444
-0.76726   4.81815    -0.14499   -0.30099   0.38163
-2.02138   0.08047    -0.64905   0.37338    -0.4944
-1.12346   -1.13741   -0.17597   -0.16146   0.01487
];
t=[
0    1    0
……
0    1    0
];
p_test=[
0.29628    0.55219    -0.54322   0.41355    -0.83319
0.35983    -0.56026   -0.81189   -0.0446    -0.27241
0.14373    -0.41797   -0.1411    0.56676    -0.25521
0.08143    0.05893    -0.59584   -0.10843   -0.32216
-0.06898   -0.06732   4.69852    2.58148    -2.26961
-1.00237   -0.37986   -0.09843   -0.01095   -0.21207
0.03287    0.1888     -0.30398   -0.21616   -0.1927
-0.29943   -0.34842   -0.35277   -0.24121   -0.11218
-1.4943    -0.50793   -0.06839   0.62902    -0.79424
-0.11437   -0.73957   -0.26519   -0.31795   0.17662
-0.5567    -0.16595   -0.92322   -0.1547    -0.27425
0.1283     -0.52685   2.12768    -0.08089   -0.20227
-0.51218   -0.07917   -0.38877   -0.21177   -0.05504
-0.68532   -0.57558   -0.77484   -0.21593   -0.0965
-0.13303   3.56256    -0.04665   -0.16739   0.01123

];
p=p'; t=t'; p_test=p_test'; [P,pps]=mapminmax(p); [T,tps]=mapminmax(t);
net=newff(P,T,11); net.trainParam.epochs=4000; net.trainParam.goal=0.0001;
net.trainParam.lr=0.05; net=train(net,P,T);

P_test=mapminmax('apply',p_test,pps); an=sim(net,P_test); BPt=mapminmax('reverse',an,tps)
```