# A Method of Supply Chain Performance Evaluation Based on Principal Component Analysis 

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#### Abstract

Supply chain performance evaluation is an important topic and many researchers focus on investigating the methods to evaluate the performance of supply chain as reasonable as they can. In this paper, the fundamental principle of principal component analysis was introduced, which followed by the practical operating process. Then, the advantage of the method was indicated. Subsequently, the model is obtained by empirical analysis, using the statistical software SPSS. At last, some empirical results, supported the new method's validity, bring this paper into close.


Keywords: supply chain; performance; principal component analysis

## I. Introduction

With the development of social, the competition is not only the competition between the enterprises ,but between the supply chains. In order to enable the supply chain develop healthily and evaluate the operating performance of the supply chain systematically, we need to consider all aspects of supply chain operating conditions, which need evaluate the efficiency of enterprises with multiple indicators. But it is difficult for our study, because of the relations between different indicators. What's more, the information reflected from the indicators has a certain degree of overlap.

There are many methods of supply chain performance evaluation, such as neural network, balanced scorecard and so on. In this paper, I will consider supply chain performance by principal component analysis. The method is an objective method which is not dependent on the judgments of experts. So we can rule out the interference and influence of human factors in the evaluation process.

## II. Basic principles of principal component analysis

Principal component analysis is a method to simplify the complex relationship between various variables. We use principal component analysis to reduce the high-dimensional to the low with the principle of minimum information loss. In the study, many indicators must be considered for analyzing and researching the problem comprehensively and systematically. These indicators reflect the characteristics of our study from different aspects. However, there are
information- overlaps in some degree. In other words, there is correlation between the indicators, which brings us a lot of difficulties. Principal component analysis makes the study more convenient and the result more clear.
The steps of principal component analysis:
Standardizing the original data: Standardize the original data with Z-score algorithm. Let

$$
\begin{equation*}
\mathrm{y}_{i j}=\frac{x_{i j}-\bar{x}_{j}}{S_{j}} \tag{1}
\end{equation*}
$$

Solving the correlation coefficient matrix between the indicator data:We get the correlation coefficient matrix by computing the correlation coefficient between every two Indicator variables in normalized matrix;

Solving the Eigenvalues and Eigenvectors of correlation coefficient matrix;

Computing the variance proportion and cumulative variance proportion of principal component: variance proportion:

$$
\begin{equation*}
\omega_{j}=\frac{\lambda_{j}}{\sum_{j-1}^{p} \lambda_{j}} \tag{2}
\end{equation*}
$$

cumulative variance proportion:

$$
\begin{equation*}
\omega=\sum_{j=1}^{m} \omega_{j} \tag{3}
\end{equation*}
$$

Computing the load capacity of principal component; Solving principal components;

## III. Application research of the supply chain performance evaluation based on principal component analysis

## Data sources

The text data (in table I) include 18 groups of samples with 16 Indicators.

## Process of principal component analysis

First, in order to get the correlation coefficient matrix, we deal with the indicators of supply chain performance evaluation by factor analysis with the software of SPSS13.0. Known from the correlation coefficient matrix, we should emove the three variables: V8, V15, V16.Thus, there is significant correlation between the other indicators. Now, I
mark the indicators as follows:Return on capital of supply chain( x 1 ), Inventory days of supply chain ( x 2 ) , Cash

Table I Quantization table of Sampled data

|  | Table I Quantization table of Sampled data |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| indicator | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| Return on capital of supply chain | 0 | 0.96 | 0.94 | 0.967 | 0.925 | 0.846 | 0.654 | 0.991 | 0.983 |
| Inventory days of supply chain | 0.853 | 1 | 0.853 | 0.603 | 0.873 | 0.631 | 0.539 | 0.561 | 0.763 |
| Cash turnover ratio | 0.067 | 0.071 | 0 | 0 | 0.175 | 0.18 | 0.065 | 0.481 | 0.105 |
| Customer sales growth | 0 | 0.849 | 0.689 | 0.501 | 0.613 | 0.709 | 0.891 | 0.981 | 0.815 |
| Effective Lead | 0.625 | 0 | 0.25 | 0.75 | 0.25 | 0.5 | 0.375 | 0.375 | 0.375 |
| Time Flexibility | 1 | 0.259 | 0.331 | 0.389 | 0.35 | 0.901 | 0.528 | 0.711 | 0.115 |
| Ratio of being target cost | 0.5 | 0.5 | 1 | 0.5 | 1 | 0.5 | 0.5 | 0.5 | 0 |
| Sales rate of new product | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Holding costs of supply chain | 0.535 | 0.359 | 0.529 | 1 | 0.41 | 0.771 | 0.32 | 0.309 | 0.051 |
| Final assembly point of product | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 |
| Information sharing rati | 0.511 | 0.561 | 0.538 | 0.553 | 0.475 | 1 | 0.527 | 0.611 | 0.244 |
| Team participation | 0.609 | 0.7 | 0.698 | 0.803 | 0.683 | 1 | 0.413 | 0.221 | 0.223 |
| Total cycle time of order | 0.969 | 0.7 | 0.735 | 0.78 | 0.703 | 0.43 | 1 | 0.325 | 0.261 |
| Customer recognition of flexibility | 1 | 0.14 | 0.093 | 0.083 | 0.096 | 0.205 | 0.07 | 0.021 | 0.005 |
| Customer Value Rate | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Customer retention | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

Continued

| indicator | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| Return on capital of supply chain | 0.99 | 0.981 | 1 | 0.991 | 0.919 | 0.995 | 0.997 | 0.993 | 1 |
| Inventory days of supply chain | 0.735 | 0.907 | 0.781 | 0.093 | 0.939 | 0.41 | 0 | 0.411 | 0.339 |
| Cash turnover ratio | 1 | 0.413 | 0.071 | 0.071 | 0.344 | 0.995 | 0.997 | 0.993 | 1 |
| Customer sales growth | 0.97 | 1 | 0.963 | 0.963 | 0.813 | 0.961 | 0.971 | 0.957 | 0.948 |
| Effective Lead | 0 | 0.25 | 0.191 | 0.311 | 0.88 | 0.061 | 0.25 | 0.25 | 0.269 |
| Time Flexibility | 0.093 | 0 | 0.151 | 0 | 0.061 | 0.109 | 0.217 | 0.061 | 0.07 |
| Ratio of being target cost | 0.5 | 0.5 | 0.5 | 0 | 0 | 0.5 | 0 | 0 | 0 |
| Sales rate of new product | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Holding costs of supply chain | 0.048 | 0.191 | 0.191 | 0 | 1 | 0.411 | 0.221 | 1 | 1 |
| Final assembly point of product | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 |
| Information sharing rati | 0 | 0.248 | 0.239 | 0.211 | 0 | 0.247 | 0 | 0 | 0 |
| Team participation | 0 | 0.223 | 0.227 | 0.225 | 0 | 0.301 | 0.225 | 0.22 | 0.211 |
| Total cycle time of order | 0.329 | 0.491 | 0.485 | 0 | 0.095 | 0.271 | 0.327 | 0.325 | 0.331 |
| Customer recognition of flexibility | 0 | 0.021 | 0.003 | 0.002 | 0.003 | 0.003 | 0.003 | 0.005 | 0.004 |
| Customer Value Rate | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |


| Customer retention | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |

turnover ratio(x3),Customer sales growth(x4), Effective Lead(x5),Time Flexibility(x6),Ratio of being target $\operatorname{cost}(\mathrm{x} 7$ ),

Holding costs of supply chain(x8), Final assembly point of product(x9),Information sharing ratio(x10), Team participation(x11), Total cycle time of order(x12), Customer
recognition of flexibility(x13).
Second, we choose five factors for reaching $85 \%$ of cumulative variance proportion. Then, the cumulative variance proportion accounts to $86.631 \%$ which reflects the information of original variables better. The eigenvalues, variance proportion and cumulative variance proportion are listed in table II.

Table II Eigenvalues and variance proportion

| Component | Initial Eigenvalues |  |  |  | Extraction Sums of Squared Loadings |  |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: |
|  | Total | \% of Variance | Cumulative \% | Total | \% of Variance | Cumulative \% |
|  | 5.750 | 44.230 | 44.230 | 5.750 | 44.230 | 44.230 |
| 2 | 2.117 | 16.285 | 60.516 | 2.117 | 16.285 | 60.516 |
| 3 | 1.296 | 9.972 | 70.488 | 1.296 | 9.972 | 70.488 |
| 4 | 1.106 | 8.511 | 78.999 | 1.106 | 8.511 | 78.999 |
| 5 | .992 | 7.632 | 86.631 | .992 | 7.632 | 86.631 |
| 6 | .728 | 5.600 | 92.231 |  |  |  |
| 7 | .377 | 2.904 | 95.135 |  |  |  |
| 8 | .276 | 2.127 | 97.262 |  |  |  |
| 9 | .221 | 1.703 | 98.965 |  |  |  |
| 10 | .081 | .623 | 99.587 |  |  |  |
| 11 | .029 | .220 | 99.808 |  |  |  |
| 13 | .013 | .099 | 99.906 |  |  |  |

Table III Component Matrix

|  | Component |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 | 2 | 3 | 4 | 5 |
| X1 | -. 756 | . 396 | . 459 | . 154 | . 040 |
| X2 | . 487 | . 342 | . 068 | -. 318 | . 653 |
| X3 | -. 661 | -. 281 | -. 220 | . 345 | -. 115 |
| X4 | -. 873 | . 325 | . 104 | . 084 | -. 094 |
| X5 | . 419 | -. 605 | . 477 | -. 349 | . 051 |
| X6 | . 839 | -. 088 | -. 041 | . 074 | -. 389 |
| X7 | . 584 | . 623 | -. 048 | . 291 | . 221 |
| X8 | . 202 | -. 550 | . 627 | . 256 | . 164 |
| X9 | . 107 | -. 479 | -. 101 | . 639 | . 314 |
| X10 | . 774 | . 392 | . 278 | . 054 | -. 348 |
| X11 | . 779 | . 255 | . 328 | . 255 | -. 227 |
| X12 | . 796 | . 161 | -. 167 | . 291 | . 197 |
| X13 | . 794 | -. 345 | -. 417 | -. 133 | -. 061 |

Third, input the data of Component Matrix to SPSS, and compute the Eigenvalues according to Transform/Compute,
in which input

$$
\mathrm{z}_{i j}=a_{i j} / \sqrt{\lambda_{j}}
$$

(4)

The result is listed in table IV.
Table IV Eigenvector matrix

|  | Z1 | Z2 | Z3 | Z4 | Z5 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | -0.315 | 0.272 | 0.403 | 0.146 | 0.040 |
| 2 | 0.203 | 0.235 | 0.060 | -0.302 | 0.656 |
| 3 | -0.276 | -0.193 | -0.193 | 0.328 | -0.115 |
| 4 | -0.364 | 0.223 | 0.091 | 0.080 | -0.094 |
| 5 | 0.175 | -0.416 | 0.419 | -0.332 | 0.051 |
| 6 | 0.350 | -0.060 | -0.036 | 0.070 | -0.391 |
| 7 | 0.244 | 0.428 | -0.042 | 0.277 | 0.222 |
| 8 | 0.084 | -0.378 | 0.551 | 0.243 | 0.165 |
| 9 | 0.045 | -0.329 | -0.089 | 0.608 | 0.315 |
| 10 | 0.323 | 0.269 | 0.244 | 0.051 | -0.349 |
| 11 | 0.325 | 0.175 | 0.288 | 0.242 | -0.228 |
| 12 | 0.332 | 0.111 | -0.147 | 0.277 | 0.198 |
| 13 | 0.331 | -0.237 | -0.366 | -0.126 | -0.061 |

$\mathrm{F} 1=-0.315 \mathrm{X} 1+0.203 \mathrm{X} 2-0.276 \mathrm{X} 3-0.364 \mathrm{X} 4+0.175 \mathrm{X} 5$
$+0.350 \mathrm{X} 6+0.244 \mathrm{X} 7+0.084 \mathrm{X} 8+0.045 \mathrm{X} 9+0.323 \mathrm{X} 10$ $+0.325 \mathrm{X} 11+0.332 \mathrm{X} 12+0.331 \mathrm{X} 13$
$\mathrm{F} 2=0.272 \mathrm{X} 1+0.235 \mathrm{X} 2-0.193 \mathrm{X} 3+0.223 \mathrm{X} 4-0.416 \mathrm{X} 5$ $-0.060 \mathrm{X} 6+0.428 \mathrm{X} 7-0.378 \mathrm{X} 8-0.329 \mathrm{X} 9+0.269 \mathrm{X} 10$ $+0.175 \mathrm{X} 11+0.111 \mathrm{X} 12-0.237 \mathrm{X} 13$
$\mathrm{F} 3=0.403 \mathrm{X} 1+0.060 \mathrm{X} 2-0.193 \mathrm{X} 3+0.091 \mathrm{X} 4+0.419 \mathrm{X} 5$ $-0.036 \mathrm{X} 6-0.042 \mathrm{X} 7+0.551 \mathrm{X} 8-0.089 \mathrm{X} 9+0.244 \mathrm{X} 10$ $+0.288 \mathrm{X} 11-0.147 \mathrm{X} 12-0.366 \mathrm{X} 13$
$\mathrm{F} 4=0.146 \mathrm{X} 1-0.302 \mathrm{X} 2+0.328 \mathrm{X} 3+0.080 \mathrm{X} 4-0.332 \mathrm{X} 5$ $+0.070 \mathrm{X} 6+0.277 \mathrm{X} 7+0.243 \mathrm{X} 8+0.608 \mathrm{X} 9+0.051 \mathrm{X} 10$ $+0.242 \mathrm{X} 11+0.277 \mathrm{X} 12-0.126 \mathrm{X} 13$
$\mathrm{F} 5=0.040 \mathrm{X} 1+0.656 \mathrm{X} 2-0.115 \mathrm{X} 3-0.094 \mathrm{X} 4+0.051 \mathrm{X} 5$
$-0.391 \mathrm{X} 6+0.222 \mathrm{X} 7+0.165 \mathrm{X} 8+0.315 \mathrm{X} 9-0.349 \mathrm{X} 10$
$-0.228 \mathrm{X} 11+0.198 \mathrm{X} 12-0.061 \mathrm{X} 13$
So, the expression of $F$ is obtained.

$$
\begin{align*}
& F=\lambda_{1} F_{1} / \sum_{i=1}^{m} \lambda_{i}+\cdots+\lambda_{m} F_{m} / \sum_{i=1}^{m} \lambda_{i}  \tag{10}\\
& =0.442 F_{1}+0.163 F_{2}+0.1 F_{3}+0.085 F_{4}+0.076 F_{5}
\end{align*}
$$

It is observed that $\mathrm{X} 4, \mathrm{X} 11, \mathrm{X} 12$ have higher load on the
We can know from table 5 that F1 retain 44.2\% information of original indicators, which is more similar to the composite score than other four principal components. The coefficient of customer sales growth is the largest, which reflects that the stimulation of consumption is closely
first principal component. They are customer sales growth, team participation and total cycle time of order respectively.F1 shows sales factor.

X 7 has a higher load on the second principal component. X 7 is ratio of being target cost. F2 shows achievement factor.
$\mathrm{X} 1, \mathrm{X} 8, \mathrm{X} 13$ have higher load on the third principal component. They are return on capital of supply chain, holding costs of supply chain and customer recognition of flexibility respectively.F3 shows market factor.

X3, X5, X9 have higher load on the forth principal component. They are cash turnover ratio, effective Lead and final assembly point of product respectively.F4 shows operation factor.

X2, X6, X10 have higher load on the fifth principal component. They are inventory days of supply chain, time Flexibility, and information sharing ratio respectively.F5 shows effectiveness factor.

## Discussion

Compute the result by putting the Standardized data into F1, F2, F3, F4, F5 and F, which be ranked in table V.
related to supply chain performance. And this coincides with the current policy.

F2 retain $16.3 \%$ information of original indicators. The coefficient of ratio of being target cost is the largest, which reflects that the supply chain performance is closely related
to the ability of task.
We can also draw the appropriate conclusions from the contribution rate of other Principal components and the
coefficient of each indicator. And we can control the supply chain accordingly.

Table V Composite Score Table

|  | F1 |  | F2 |  | F3 |  | F4 |  | F5 |  | F |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 1.842 | 1 | -0.335 | 15 | 0.241 | 17 | 0.819 | 11 | 0.521 | 10 | 0.893 | 1 |
| 2 | 0.547 | 7 | 0.723 | 3 | 0.773 | 9 | 1.156 | 9 | 0.765 | 5 | 0.593 | 6 |
| 3 | 0.795 | 4 | 0.711 | 4 | 0.936 | 4 | 1.277 | 4 | 0.833 | 2 | 0.733 | 2 |
| 4 | 0.880 | 3 | 0.044 | 13 | 1.434 | 1 | 1.195 | 6 | 0.638 | 6 | 0.690 | 5 |
| 5 | 0.745 | 5 | 0.681 | 5 | 0.808 | 7 | 1.276 | 5 | 0.824 | 3 | 0.692 | 4 |
| 6 | 1.002 | 2 | 0.605 | 6 | 1.383 | 2 | 0.658 | 13 | -0.233 | 18 | 0.718 | 3 |
| 7 | 0.665 | 6 | 0.376 | 9 | 0.644 | 14 | 1.157 | 8 | 0.496 | 12 | 0.556 | 7 |
| 8 | 0.203 | 8 | 0.331 | 11 | 0.779 | 8 | 1.130 | 10 | 0.278 | 14 | 0.339 | 8 |
| 9 | -0.131 | 11 | 0.558 | 8 | 0.760 | 10 | 0.047 | 18 | 0.349 | 13 | 0.140 | 11 |
| 10 | -0.479 | 16 | 0.363 | 10 | 0.203 | 18 | 1.184 | 7 | 0.778 | 4 | 0.028 | 14 |
| 11 | -0.099 | 10 | 0.816 | 2 | 0.695 | 12 | 0.387 | 16 | 0.607 | 7 | 0.238 | 10 |
| 12 | 0.011 | 9 | 0.867 | 1 | 0.734 | 11 | 0.344 | 17 | 0.508 | 11 | 0.287 | 9 |
| 13 | -0.422 | 14 | 0.130 | 12 | 0.636 | 15 | 0.787 | 14 | 0.208 | 15 | -0.019 | 15 |
| 14 | -0.153 | 12 | -0.481 | 18 | 1.248 | 3 | 0.618 | 15 | 1.056 | 1 | 0.112 | 12 |
| 15 | -0.381 | 13 | 0.564 | 7 | 0.654 | 13 | 0.811 | 12 | 0.142 | 16 | 0.069 | 13 |
| 16 | -0.577 | 18 | -0.159 | 14 | 0.443 | 16 | 1.289 | 3 | 0.127 | 17 | -0.117 | 18 |
| 17 | -0.477 | 15 | -0.353 | 16 | 0.899 | 5 | 1.338 | 2 | 0.588 | 8 | -0.020 | 16 |
| 18 | -0.487 | 17 | -0.380 | 17 | 0.899 | 5 | 1.356 | 1 | 0.542 | 9 | -0.031 | 17 |

## V. Conclusion

PCA eliminates the overlap between indicators, and evaluate supply chain performance excellently with fewer indicators. We can know which indicators are more important than the others according to diverse contribution rates. Moreover, we can point out the advantages and disadvantages of our supply chain by the rank of principal components. Thus, it is clear for the future direction of effort. Above all, it is feasible for us to evaluate supply chain performance Based on Principal Component Analysis.

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## Appendices and References Available Upon Requests

