A Principal Criteria Searching Approach Based Leanness Assessment Method Considering Industrial Diversity

[1]Geng Cui, [2]Fei Xie and Cunrong Li*
Department of Industrial Engineering
School of Mechanical and Electronics Engineering
Wuhan University of Technology
122 Luoshi Road, Hongshan District, Wuhan City, P. R. China, 430070
CuiGengWHUT@hotmail.com, Richard_xiefei@163.com, cunrong_li@163.com

***Corresponding author (cunrong_li@163.com)**

Abstract

Nowadays leanness implementation was more and more widely applied in production organizations to eliminate various kind of waste and reduce overall cost of business firms. During the implementation process, the incorrect choices of implementation areas may result in high cost but no obvious improvement, even the appearance of employee dissatisfaction. In this study, a leanness assessment method based on principal criteria searching approach was established. Principal Component Analysis was used to assess and improve lean performance throughout the entire organization, qualitative factors were considered as well as quantitative factors based on fuzzy logic. Throughout the identification of key leanness factors of an specific industry, a comprehensive assessment model corresponding to the characteristics of that industry was established. Finally a case study of a Chinese special purpose vehicle manufacturing organization was presented, the results show that the correlation among 15 different leanness factors and 8 principal indicators mainly contributed to the leanness performance, thus the overall measurement of leanness performance of several workshops could be achieved.

Keywords

Leanness assessment, Lean manufacturing, Principal criteria, Performance measurement and Systematic decision.

1. Introduction

Lean production (LP) has long been recognized as one of the most effective for both manufacturing and service organizations. It originated from Toyota production system and gradually evolved into a famous management philosophy. The keynote of lean production is to eliminate 7 kinds of wastes (non-value added process) in a production system: waiting time, correction of defects, over processing, over motion, over handling, over production, excess inventory. The underutilization of the employees' creativity was considered as the eighth waste recent days. As more and more organizations applied lean production method to gain powerful competitive advantages in the globalized marketplace, the objective assessment of overall lean performance is strongly demanded for organizations, especially business firms. Certain approaches for leanness measurement were contributed by researchers, and various kinds of leanness assessment tools were developed. In this study, a leanness assessment method based on the characteristics of production organizations has been proposed, which overcomes the problem that the previous models have not considered the applicability of different type of production organizations. The conceptual model was firstly developed including both quantitative and qualitative criteria, then the critical criteria were selected out through principal component analysis, which transfer the original model to a new model with less criteria included but reflect the characteristics of the production organization. Finally a comprehensive assessment model was developed. The uniqueness of this study is that dimensionality reduction theory was applied as an attempt to make the assessment criteria more accordingly, thus to overcome the drawbacks of previous studies.

2. Literature review

Nowadays lean production mode was taken as a kind of advanced management model and has been widely applied in various fields, which aims to eliminate the eight kinds of waste in the manufacturing process, thus reduce cost and improve economic benefits. As lean management being increasingly applied in the management of business firms, various kind of leanness assessment tools were developed, which made the overall measurement of the performance of lean practices an reality.

2.1 Leanness criteria

Though lean production originated from Toyota production system, the conception itself was somehow proposed by International Motor Vehicle Program in Massachusettes Institute of Technology. As lean production was defined as a management method to reach a state in which the cost of production organizations is greatly reduced, various approaches were applied in practice such as just-in-time (JIT), total quality management (TQM), total preventive maintenance (TPM), human resources management. It is believed that leanness level of an organization is affected by a variety of factors due to the complexity of the production system itself. In many researches, literature retrieval was adopted to determine the criteria included in the leanness assessment models. Gopalakrishnan N. A. and Gurumurthy (2016, *IJOPM*) analyzed existing reviews on lean in a domain, then described the current situation in various aspects of lean research and indicated the potential future research directions in the domain of leanness assessment. Narpat R. S. and Kuldip S. S. (2018, *JMTM*) reviewed various literature and revealed how the themes and approaches of leanness assessment evolved during last 2 decades, in addition, the idea was pointed out that more and more factors were considered in the leanness assessment together with the increasingly application of lean production in some other functional areas such as finance, administration supplier management and customer management. Fatma P. and Karen M. L. (2014, *IJPR*) conducted a comprehensive literature review to determine the leanness indicators include 62 quantitative indicators of 7 dimensions and 51 qualitative indicators of 5 dimensions. Subsequently a leanness evaluation approach named Leanness Assessment Tool (LAT) was proposed based on fuzzy logic. Netland T. H. and Ferdows K. (2015, *POM*) developed a grounded theory through analyzing empirical data to explain the pattern of change in a plant's performance during lean implementation. The result showed that the pattern approximately follow S-curve shape: the performance first improved slowly, then grew rapidly, finally decline.

2.2 Assessment modelling

Fatma P. and Karen M. L. (2014, *IJPR*) proposed a leanness assessment tool to reveal the weak link of organizations in lean production, both quantitative and qualitative indicators were considered. Vinodh S. and Vimal K.E.K. (2012, *IJAMT*) developed a thirty criteria based conceptual model for lean assessment. The criteria were determined through expert evaluation methods, scoring and some fuzzy methods were applied in order to overcome the drawbacks such as ambiguity and vagueness in previous researches. Olethe O. and Konstantinos S. (2016) applied system dynamics in leanness assessment to disclose the interactions between lean practices and their improvements. A case study was presented to expound the change regulation of several aspects during lean practice. Hosseini Nasab H. *et al.* (2012, *JCP*) pointed out an approach to determine leanness level by artificial neural network model, thus the success possibility of lean production implementation could be measured. The major leanness criteria were identified through literature review and experts' experience. Vinodh S. and Balaji S. R. (2011, *IJPR*) designed a leanness measurement model and developed a computerized decision support system to eliminate the drawback of manual computation. The application of such system help identify the weaker area of an organization via computation of three major indexes. Ali A. *et al.* (2015, *ISA*) proposed a comprehensive approach based on several methods including fuzzy cognitive map and some other analysis to evaluate leanness degree of organizations. The impact of each leanness criteria was finally determined for lean strategy. Vinodh S. and Suresh K. C. (2011, *IJPR*) carried out a multi-grade fuzzy approach based leanness measurement model, which could identify the areas for leanness improvement by the computation of leanness index. Ateekh U. R. *et al.* (2018, *IEEE ACCESS*) proposed a multi criteria lean performance score approach to analysis strategies effectiveness and identify potential improvement opportunities.

Although there are various methods in the field of leanness assessment at present, some limitations still exists. First, most researchers tried hard to achieve the overall measurement of lean performance of organizations, mainly through including as many leanness factors as possible in the conceptual model. However, in practice because of the differences in production organizations, the weight of leanness indicators vary in a wide range. For example, process industries such as chemical industry, pharmaceutical industry and metal industry prefer total productive maintenance (TPM), for a series of specific equipment were usually applied in such industries, whose condition greatly affects the product quality. As for discrete industries such as machinery industry and electronics industry, production line arrangement, layout and process are more important, hence standardization and just in time (JIT) were widely used. So, the need of identifying leading leanness indicators related to characteristics of particular industry become significant.

3. Research methodology

The methodology followed during this study is shown in Figure 1. Firstly, the leanness criteria included in the assessment model should be determined. In previous researches, in order to ensure the objectivity and integrity of the measurement index, literature review method was widely used. Another common approach is expert evaluation method. Then principal component analysis was applied to identify the major factors related to the characteristics of particular production organization based on statistical data. Subsequently a conceptual model including the main influencing factors was developed, and then the leanness index was computed, thus identification of the weak link of the lean performance in production organization became possible.

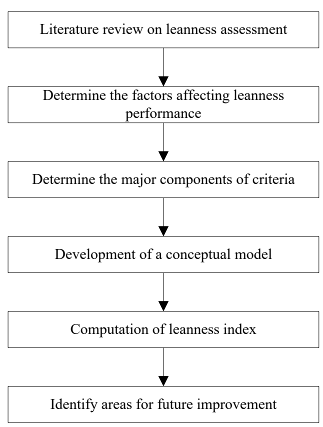

Figure 1. Research methodology

3.1 Leanness criteria

The leanness assessment conceptual model could be divided into 3 levels: qualitative criteria were included as well as quantitative criteria in the first level. For each type of criteria, the second level consists of several lean dimensions. The third level consists of lean attributes, the j_{th} attribute of dimension i is marked as D_{ij} . The structure of the conceptual model is shown in Figure 2.

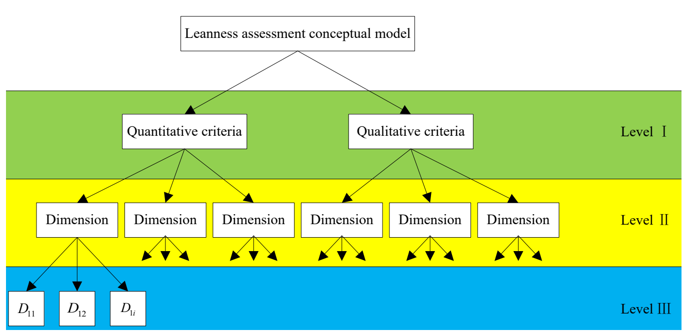

Figure 2. Structure of the conceptual model

As in practice, for different production industries, the productive factors managers mainly care of were always not the same. Hence, there is a need to converge multiple leanness criteria into a few comprehensive criteria, that is the principal component. Each principal component can reflect most of the information of the original variable. Therefore, the modified model can more accurately express the characteristics of the production system. Principal component analysis was applied to identify the comprehensive criteria.

3.2 Quantitative analysis of qualitative criteria

For the criteria of the assessment model, the qualitative criteria need to be converted into quantitative criteria. Firstly 5 linguistic variables were set: Excellent, Good, Fair, Poor, Worst. Since each qualitative leanness criteria involves fuzzy determination, a set of fuzzy intervals were developed for approximating linguistic variables, the intervals were listed in Table 1.

Table 1. Fuzzy intervals and linguistic variables

Performance rating	
Linguistic variables	Fuzzy interval
Worst	(0,20)
Poor	(20,40)
Fair	(40,60)
Good	(60,80)
Excellent	(80,100)

3.3 Conformance processing of assessment criteria

The assessment criteria could be divided into 2 categories: positive criteria, which has positive effect on the leanness index, such as sales per employee, customer satisfaction, supplier relationship. Negative criteria, which has negative effect on the leanness index, the higher the value of such criteria, the worse the performance rating of the leanness level. For example, defect rate, average set time per unit, the customer complaint rate. Therefore, it is necessary to conformance processing the negative criteria, thus make all the criteria conformable. The original criteria is C, the processed criteria is C^*, the conformance processing could be achieved by following equation:

$$C^* = \frac{1}{C}$$

3.4 Establish original variable matrix

Assume that there are n dimensions consisted of m criteria in the original conceptual model. t sets of statistical data for all the criteria. Then a $t \times m$ matrix could be developed:

$$X = (X_{ij})_{m \times t} = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1m} \\ X_{21} & X_{22} & \cdots & X_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ X_{t1} & X_{t2} & \cdots & X_{mt} \end{bmatrix}$$

Where: X_{ij} represents the index value of the j_{th} criteria of the i_{th} sample.

3.5 Standardization of sample values

Due to the difference in dimension and magnitude of each relevant indicator in the assessment model, in order to improve the comparability of the indicators, the standardization of the original variable matrix is needed. Z-Score normalization method was applied in this research, which process the data standardization based on mean and standard deviation of raw data, thus the original variable matrix was transformed into a normalized matrix, the formulas were as follows:

$$Y_{ij} = \frac{X_{ij} - \overline{X}_j}{S_j} \tag{1}$$

$$\overline{X}_j = \frac{1}{n}\sum_{i=1}^{n} X_{ij} \tag{2}$$

$$S_j^2 = \frac{1}{n-1}\sum_{i=1}^{n}(X_{ij} - \overline{X}_j)^2 \tag{3}$$

$$(i = 1,2,...,m; j = 1,2,...,t)$$

Where: X_{ij} represents the index value of the j_{th} criteria of the i_{th} sample.

3.6 Computation of principal components

The correlation coefficient matrix could be calculated as:

$$R = [r_{ij}]_{m\times m} = \frac{X^{'}X}{t-1} \tag{4}$$

Where: $X^{'}$ represents the transposed matrix of standard matrix X .

Thus, The eigenvalues and corresponding eigenvectors of matrix R is calculated, the eigenvalues λ_i could be calculated by $|R - \lambda I| = 0$, which is more clearly expressed as follows:

$$\begin{bmatrix} r_{11}-\lambda_1 & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22}-\lambda_2 & \cdots & r_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{mm}-\lambda_m \end{bmatrix} = 0$$

Where: λ_i represents theeigenvalues of matrix R, λ is a $m \times 1$ matrix, I is a $m \times m$ identity matrix.

The eigenvalues λ_i indicates the role of each component in evaluating objects, the more high the value, the greater the contribution. Based on λ, the related eigenvectors $L_n = l_{n1} + l_{n2} + \ldots + l_{nm}$ could be obtained, which forms an orthogonal matrix a. For the n_{th} principal component F_n : $F_n = l_{n1}X_1 + l_{n2}X_2 + \ldots + l_{nm}X_m$, the principal component matrix could be calculated by:

$$F = Xa^T \tag{5}$$

3.7 Determine the number of principal components

The contribution rate of n_{th} principal component is expressed as: $\frac{\lambda_n}{\sum_{i=1}^{m}\lambda_i}$, The order of principal components is arranged in descending order according to their work efficiency, the Cumulative variance contribution rate of first n principal components is expressed as: $\frac{\sum_{i=1}^{n}\lambda_i}{\sum_{i=1}^{m}\lambda_i}$, the determination of principal components was based on the contribution rate of first principal component. First, a percentile threshold value $b\%$ was set, then compare the contribution rate of first principal component with $b\%$. If the contribution rate of first principal component is greater than $b\%$, the first principal component is the only one considered criteria in the assessment model. If the contribution rate of first principal component is less than $b\%$, the first n principal components should be included, which satisfy the condition: $\frac{\sum_{i=1}^{n}\lambda_i}{\sum_{i=1}^{m}\lambda_i} \geq b\%$.

3.8 Determine the final assessment function

Compute the weighted sum of the selected n principal components:

$$F = \frac{\lambda_1}{\sum_{i=1}^{n}\lambda_i}F_1 + \frac{\lambda_2}{\sum_{i=1}^{n}\lambda_i}F_2 + \frac{\lambda_3}{\sum_{i=1}^{n}\lambda_i}F_3 + \ldots + \frac{\lambda_n}{\sum_{i=1}^{n}\lambda_i} \tag{6}$$

The value of F reflect the leanness level of the production organization, which is based on the most closely related criteria.

4. Case study

Suizhou is a major special purpose vehicle manufacturing base in China, the thriving of such industry are related to some historical issues. The industry of this city is very different from the common concepts, and the management is rather undeveloped. A lean improvement implementation team was trying to improve leanness level in several workshops throughout some lean production tools like Kanban, 5S, TQM etc. In the process of implementation, the first work was to search for the major areas need improvement at present.

4.1 Research background

The characteristic of the special purpose vehicle manufacturing in Suizhou could be described as follows:

1. Unusual supplier customer relationship. The most important raw material of such industry is truck chassis, which are mainly supplied by state-owned enterprises like Dongfeng Motor and JAC Motor, and the production of truck chassis is very strictly restricted by national policies. Under such circumstances, the output was at a low level, which resulted in the operation of special purpose vehicle manufacturing enterprises in Suizhou heavily dependent on its suppliers.
2. Inefficient management. The decision making was generally based on the general manager's experience, almost no scientific management tools were applied to support the decision. As Suizhou is a not very developed city, the lack of management talents also resulted in the poor condition of self improvement.

3. Irregular production planning. The production plan is mainly determined by orders. While the value of product per unit is high, the overall output is small, and the orders change frequently, the production planning of such enterprises were very irregular.

4.2 Conception model

The leanness assessment conceptual model is developed and is shown in Table 2. The model comprised of 6 dimensions including 15 criteria: 9 quantitative criteria of 5 dimensions and 6 qualitative criteria of 3 dimensions.

Table 2. Leanness assessment conceptual model

Dimension	Criteria	Symbol	Attribute
Quality	Defect rate	D_{11}	Quantitative
	Scrap rate	D_{12}	Quantitative
	Processes are controlled through measuring inside the process	D_{13}	Qualitative
Human Resources	Labor turnover rate	D_{21}	Quantitative
	Absenteeism rate	D_{22}	Quantitative
Delivery	Total # of orders delivered late per year/total # of deliveries per year	D_{31}	Quantitative
	Production is pulled by the shipment of finished goods	D_{32}	Qualitative
	We have helped our suppliers to improve their product quality	D_{33}	Qualitative
Customer	Customer satisfaction index	D_{41}	Quantitative
	Market share (market share by product group)	D_{42}	Quantitative
Inventory	Stock turnover rate (Inventory turnover rate)	D_{51}	Quantitative
	Total inventory/total sales	D_{52}	Quantitative
Process	Standard operating procedures are developed, published and readily available in all areas	D_{61}	Qualitative
	Non-manufacturing operations are standardized.	D_{62}	Qualitative
	We use kanban, squares, or containers of signals for production control	D_{63}	Qualitative

4.3 Establish leanness assessment matrix

The case study has been conducted in several special purpose vehicle manufacturing organizations in Suizhou to help improve management efficiency. These organizations are in the process of implementing lean manufacturing strategies like 5S, Kanban and ERP. Since the characteristic of such industry differ greatly from the common, there is a need to select the essential indicators effecting the overall leanness level. The data were from 10 workshops of several organizations.

Table 3. Original data

Leanness indicators	D_{11}	D_{12}	D_{13}	D_{21}	D_{22}	D_{31}	D_{32}	D_{33}	D_{41}	D_{42}	D_{51}	D_{52}	D_{61}	D_{62}	D_{63}
Sample 1	31.61%	11.45%	22	3.08%	1.22%	0	64	12	82%	1.16%	3.46%	48.34%	50	22	56
Sample 2	35.50%	16.07%	22	4.53%	1.47%	0.81%	60	12	80%	1.21%	4.10%	47.00%	63	31	56
Sample 3	23.22%	7.30%	68	1.79%	0.70%	0	88	38	87%	1.01%	8.42%	23.34%	32	26	69
Sample 4	26.08%	9.87%	61	1.89%	0.79%	0	84	33	87%	2.65%	6.08%	27.25%	72	25	66
Sample 5	30.96%	11.43%	22	3.37%	1.31%	0	65	19	83%	2.92%	3.30%	43.41%	39	26	52
Sample 6	32.59%	9.59%	55	2.14%	0.78%	0	77	26	85%	2.99%	5.50%	31.08%	77	25	64
Sample 7	28.70%	9.75%	55	2.23%	0.85%	0	83	33	86%	1.30%	5.41%	31.69%	64	25	64
Sample 8	31.03%	12.98%	36	2.99%	1.01%	0	74	27	84%	2.08%	4.44%	30.13%	68	28	51
Sample 9	40.74%	12.82%	34	2.77%	1.02%	0	70	21	87%	2.82%	3.74%	34.73%	67	28	51
Sample 10	38.31%	12.83%	25	4.12%	1.11%	0.25%	69	26	82%	1.89%	4.44%	34.68%	63	28	51

The negative indicators includes: $D_{11}, D_{12}, D_{21}, D_{22}, D_{31}, D_{52}$. These criteria need conformance processing, the processed value is obtained by equation: $C^* = \frac{1}{C}$. Where C^* represents the processed criteria value while represents the original value. Since there are 0 values in the sample of indicator D_{31}, the conformance processing formula of this indicator was changed to $C^* = 1 - C$. The processed value was shown as follow:

Table 4. Processed data

Leanness indicators	D_{11}	D_{12}	D_{21}	D_{22}	D_{31}	D_{52}
Sample 1	3.1636	8.7336	32.4675	81.9672	1	2.0687
Sample 2	2.8169	6.2228	22.0751	68.0272	0.9919	2.1277
Sample 3	4.3066	13.6986	55.8659	142.8571	1	4.2845
Sample 4	3.8344	10.1317	52.9101	126.5823	1	3.6697
Sample 5	3.2300	8.7489	29.6736	76.3359	1	2.3036
Sample 6	3.0684	10.4275	46.7290	128.2051	1	3.2175
Sample 7	3.4843	10.2564	44.8430	117.6471	1	3.1556
Sample 8	3.2227	7.7042	33.4448	99.0099	1	3.3190
Sample 9	2.4546	7.8003	36.1011	98.0392	1	2.8794
Sample 10	2.6103	7.7942	24.2718	90.0901	0.9975	2.8835

The processed data play a positive role in the model, the higher the value, the well the leanness level. Based on the statistical data, the original matrix was obtained as follow, some data have been rounded off.

$$\begin{bmatrix}
3.1636 & 8.7336 & 22 & 32.4675 & 81.9672 & 1 & 64 & 12 & 0.82 & 0.0116 & 0.0346 & 2.0687 & 50 & 22 & 56 \\
2.8169 & 6.2228 & 22 & 22.0751 & 68.0272 & 0.9919 & 60 & 12 & 0.80 & 0.0121 & 0.0410 & 2.1277 & 63 & 31 & 56 \\
4.3066 & 13.6986 & 68 & 55.8659 & 142.8571 & 1 & 88 & 38 & 0.87 & 0.0101 & 0.0842 & 4.2845 & 32 & 26 & 69 \\
3.8344 & 10.1317 & 61 & 52.9101 & 126.5823 & 1 & 84 & 33 & 0.87 & 0.0265 & 0.0608 & 3.6697 & 72 & 25 & 66 \\
3.2300 & 8.7489 & 22 & 29.6736 & 76.3359 & 1 & 65 & 19 & 0.83 & 0.0292 & 0.0330 & 2.3036 & 39 & 26 & 52 \\
3.0684 & 10.4275 & 55 & 46.7290 & 128.2051 & 1 & 77 & 26 & 0.85 & 0.0299 & 0.0550 & 3.2175 & 77 & 25 & 64 \\
3.4843 & 10.2564 & 55 & 44.8430 & 117.6471 & 1 & 83 & 33 & 0.86 & 0.0130 & 0.0541 & 3.1556 & 64 & 25 & 64 \\
3.2227 & 7.7042 & 36 & 33.4448 & 99.0099 & 1 & 74 & 27 & 0.84 & 0.0208 & 0.0444 & 3.3190 & 68 & 28 & 51 \\
2.4546 & 7.8003 & 34 & 36.1011 & 98.0392 & 1 & 70 & 21 & 0.87 & 0.0282 & 0.0374 & 2.8794 & 67 & 28 & 51 \\
2.6103 & 7.7942 & 25 & 24.2718 & 90.0901 & 0.9975 & 69 & 26 & 0.82 & 0.0189 & 0.0444 & 2.8835 & 63 & 28 & 51
\end{bmatrix}$$

The initial matrix needs to be standardized, thus to eliminate the effects of differences in dimensions and magnitude of different indicators. By formula (1) and formula (2) , the mean value and standard deviation of the j_{th} criteria was computed.

$$\overline{X}_j = [3.2192 \quad 9.1518 \quad 40.0000 \quad 37.9382 \quad 102.8761 \quad 0.9989 \quad 73.4000 \quad 24.7000 \quad 0.8430 \quad 0.0200 \quad 0.0489 \quad 2.9909 \quad 59.5000 \quad 26.4000 \quad 58.0000]$$

$$S_j = [0.5552 \quad 2.0860 \quad 18.0247 \quad 11.6559 \quad 24.8954 \quad 0.0026 \quad 9.4304 \quad 8.7693 \quad 0.0250 \quad 0.0080 \quad 0.0154 \quad 0.7002 \quad 14.5392 \quad 2.4585 \quad 7.0553]$$

X_{ij} the index value of the j_{th} criteria of the i_{th} sample in the standardized matrix was calculated as $Y_{ij} = \dfrac{X_{ij} - \overline{X}_j}{S_j}$. The standardized matrix was as follow:

$$\begin{bmatrix}
-0.1001 & -0.2005 & 22 & 32.4675 & 81.9672 & 1 & 64 & 12 & 0.82 & 0.0116 & 0.0346 & 2.0687 & 50 & 22 & 56 \\
-0.7245 & -1.4041 & 22 & 22.0751 & 68.0272 & 0.9919 & 60 & 12 & 0.80 & 0.0121 & 0.0410 & 2.1277 & 63 & 31 & 56 \\
1.9586 & 2.1797 & 68 & 55.8659 & 142.8571 & 1 & 88 & 38 & 0.87 & 0.0101 & 0.0842 & 4.2845 & 32 & 26 & 69 \\
1.1081 & 0.4697 & 61 & 52.9101 & 126.5823 & 1 & 84 & 33 & 0.87 & 0.0265 & 0.0608 & 3.6697 & 72 & 25 & 66 \\
0.0195 & -0.1932 & 22 & 29.6736 & 76.3359 & 1 & 65 & 19 & 0.83 & 0.0292 & 0.0330 & 2.3036 & 39 & 26 & 52 \\
-0.2716 & 10.4275 & 55 & 46.7290 & 128.2051 & 1 & 77 & 26 & 0.85 & 0.0299 & 0.0550 & 3.2175 & 77 & 25 & 64 \\
0.4775 & 10.2564 & 55 & 44.8430 & 117.6471 & 1 & 83 & 33 & 0.86 & 0.0130 & 0.0541 & 3.1556 & 64 & 25 & 64 \\
0.0063 & 7.7042 & 36 & 33.4448 & 99.0099 & 1 & 74 & 27 & 0.84 & 0.0208 & 0.0444 & 3.3190 & 68 & 28 & 51 \\
-1.3771 & 7.8003 & 34 & 36.1011 & 98.0392 & 1 & 70 & 21 & 0.87 & 0.0282 & 0.0374 & 2.8794 & 67 & 28 & 51 \\
-1.0967 & 7.7942 & 25 & 24.2718 & 90.0901 & 0.9975 & 69 & 26 & 0.82 & 0.0189 & 0.0444 & 2.8835 & 63 & 28 & 51
\end{bmatrix}$$

4.4 Computation of principal components

According to formula (4), the correlation coefficient matrix was computed.

$$\begin{bmatrix}
1.0000 & 0.8346 & 0.7421 & 0.7816 & 0.6794 & 0.3686 & 0.7534 & 0.6703 & 0.4906 & -0.2999 & 0.7971 & 0.6793 & -0.4487 & -0.4280 & 0.7945 \\
0.8346 & 1.0000 & 0.8433 & 0.8829 & 0.8658 & 0.5566 & 0.8372 & 0.7541 & 0.6759 & -0.1437 & 0.8605 & 0.7630 & -0.4056 & -0.5340 & 0.8331 \\
0.7421 & 0.8433 & 1.0000 & 0.9597 & 0.9747 & 0.4354 & 0.9642 & 0.8745 & 0.8148 & -0.0041 & 0.8978 & 0.8964 & 0.0712 & -0.2984 & 0.8833 \\
0.7816 & 0.8829 & 0.9597 & 1.0000 & 0.9496 & 0.5974 & 0.9260 & 0.7941 & 0.8621 & 0.0608 & 0.8237 & 0.8363 & -0.0304 & -0.4889 & 0.8598 \\
0.6794 & 0.8658 & 0.9747 & 0.9496 & 1.0000 & 0.5404 & 0.9583 & 0.8834 & 0.8308 & 0.0468 & 0.8823 & 0.9194 & 0.0655 & -0.3583 & 0.8168 \\
0.3686 & 0.5566 & 0.4354 & 0.5974 & 0.5404 & 1.0000 & 0.5427 & 0.4863 & 0.6958 & 0.3595 & 0.2084 & 0.4439 & -0.1092 & -0.7185 & 0.2045 \\
0.7534 & 0.8372 & 0.9642 & 0.9260 & 0.9583 & 0.5427 & 1.0000 & 0.9569 & 0.8391 & -0.0328 & 0.8728 & 0.9345 & 0.0130 & -0.3240 & 0.7866 \\
0.6703 & 0.7541 & 0.8745 & 0.7941 & 0.8834 & 0.4863 & 0.9569 & 1.0000 & 0.7658 & 0.0027 & 0.8358 & 0.9432 & -0.0109 & -0.1587 & 0.6393 \\
0.4906 & 0.6759 & 0.8148 & 0.8621 & 0.8308 & 0.6958 & 0.8391 & 0.7658 & 1.0000 & 0.2876 & 0.6018 & 0.7842 & 0.0689 & -0.3113 & 0.5425 \\
-0.2999 & -0.1437 & -0.0041 & 0.0608 & 0.0468 & 0.3595 & -0.0328 & 0.0027 & 0.2876 & 1.0000 & -0.2748 & 0.0080 & 0.4050 & 0.0022 & -0.2315 \\
0.7971 & 0.8605 & 0.8978 & 0.8237 & 0.8823 & 0.2084 & 0.8728 & 0.8358 & 0.6018 & -0.2748 & 1.0000 & 0.8965 & -0.1970 & -0.1360 & 0.8515 \\
0.6793 & 0.7630 & 0.8964 & 0.8363 & 0.9194 & 0.4439 & 0.9345 & 0.9432 & 0.7842 & 0.0080 & 0.8965 & 1.0000 & -0.0107 & -0.0955 & 0.6509 \\
-0.4487 & -0.4056 & 0.0712 & -0.0304 & 0.0655 & -0.1092 & 0.0130 & -0.0109 & 0.0689 & 0.4050 & -0.1970 & -0.0107 & 1.0000 & 0.1865 & -0.0780 \\
-0.4280 & -0.5340 & -0.2984 & -0.4889 & -0.3583 & -0.7185 & -0.3240 & -0.1587 & -0.3113 & 0.0022 & -0.1360 & -0.0955 & 0.1865 & 1.0000 & -0.4100 \\
0.7945 & 0.8331 & 0.8833 & 0.8598 & 0.8168 & 0.2045 & 0.7866 & 0.6393 & 0.5425 & -0.2315 & 0.8515 & 0.6509 & -0.0780 & -0.4100 & 1.0000
\end{bmatrix}$$

Then, the eigenvalues λ_i was calculated as:

$$\lambda_1 = 9.6768, \lambda_2 = 1.9934, \lambda_3 = 1.6222, \lambda_4 = 0.7773, \lambda_5 = 0.4274, \lambda_6 = 0.2196, \lambda_7 = 0.1794,$$
$$\lambda_8 = 0.0824, \lambda_9 = 0.0216$$

In this research, percentile threshold value $b\%$ was set to 85%, the Cumulative contribution rate of first 3 principal components was 86.6155%, hence, the number of principal components in the evaluation method is three.

Table 5. Principal components

principal components	eigenvalues		
	eigenvalues	contribution rate	cumulative contribution rate
1	9.6768	64.5119%	64.5119%
2	1.9934	13.2892%	77.8011%
3	1.6222	10.8144%	86.6155%

4.5 Determine the final assessment function

The eigenvectors respectively corresponding to the selected three principal components L_1, L_2, L_3 were as follow.

$$L_1 = \begin{bmatrix} 0.2637 \\ 0.2973 \\ 0.3115 \\ 0.3120 \\ 0.3119 \\ 0.1835 \\ 0.3135 \\ 0.2887 \\ 0.2665 \\ -0.0129 \\ 0.2899 \\ 0.2927 \\ -0.0367 \\ -0.1357 \\ 0.2729 \end{bmatrix}, \quad L_2 = \begin{bmatrix} -0.2898 \\ -0.1492 \\ 0.0435 \\ 0.0708 \\ 0.0942 \\ 0.3213 \\ 0.0539 \\ 0.0620 \\ 0.2883 \\ 0.6116 \\ -0.2068 \\ 0.0518 \\ 0.4807 \\ -0.0372 \\ -0.1815 \end{bmatrix}, \quad L_3 = \begin{bmatrix} -0.1226 \\ -0.1737 \\ 0.1452 \\ -0.0479 \\ 0.0873 \\ -0.4913 \\ 0.0955 \\ 0.1706 \\ -0.0238 \\ -0.0637 \\ 0.2146 \\ 0.2174 \\ 0.3807 \\ 0.6306 \\ 0.0609 \end{bmatrix}$$

Thus, the final assessment function could be obtained.

$$F = 0.6451F_1 + 0.1329F_2 + 0.1081F_3$$

Table 6 shows the weight of each leanness indicator in each of the three principal components. It could be concluded that the major indicators in principal component 1 were D_{13}, D_{21}, D_{22}, D_{32}. While the major indicators in principal component 2 were D_{42} and D_{61}, principal component 3 were D_{61} and D_{62}.

Table 6. weight of principal components

Principal Components	D_{11}	D_{12}	D_{13}	D_{21}	D_{22}	D_{31}	D_{32}	D_{33}	D_{41}	D_{42}	D_{51}	D_{51}	D_{61}	D_{62}	D_{63}
1	0.2637	0.2973	0.3115	0.3120	0.3119	0.1835	0.3135	0.2887	0.2665	-0.0129	0.2899	0.2927	-0.0367	-0.1357	0.2729
2	-0.2898	-0.1492	0.0435	0.0708	0.0942	0.3213	0.0539	0.0620	0.2883	0.6116	-0.2068	0.0518	0.4807	-0.0372	-0.1815
3	-0.1226	-0.1737	0.1452	-0.0479	0.0873	-0.4913	0.0955	0.1706	-0.0238	-0.0637	0.2146	0.2174	0.3807	0.6306	0.0609

4.6 Leanness assessment results

Through substituting sample data into the final assessment function, the final assessment result of each sample and rank of the sample assessment result could be achieved.

Table 7. Assessment results

Sample	principal component 1	principal component 2	principal component 3	comprehensive outcome	rank
1	80.9827	26.6644	51.3151	158.9623	9
2	69.6145	30.7835	61.3344	161.7324	8
3	142.7523	26.8462	64.8697	234.4681	3
4	128.3527	44.7364	76.2894	249.3786	1
5	79.5516	21.7185	50.3765	151.6466	10
6	119.8629	46.2978	75.7182	241.8788	2
7	120.4042	39.5729	71.6706	231.6477	4
8	95.9854	40.0353	69.0304	205.0511	5
9	92.3303	39.1057	66.7690	198.2051	6
10	84.6620	35.3956	64.5567	184.6142	7

It could be concluded from table 7 that the leanness level of the 10 workshops, which also indicated the principal part need for improvement. For example, sample 5 scored low on the third principal component, it showed that the corresponding workshop was at a low level on production process management, the manager should immediately focus on improving the production process in leanness implementation, thus the leanness level of the production organization could be most effectively promoted.

The leanness assessment result also showed the key criteria affecting leanness level in Suizhou special purpose vehicle manufacturing industry. As the principal component 1 shared the highest contribution rate, the most important lean indicators for Suizhou special purpose vehicle manufacturing industry is D_{13} : Processes are controlled through measuring inside the process, D_{21} : Labor turnover rate, D_{22} : Absenteeism rate, D_{32} : production is pulled by the shipment of finished goods. In fact, the main contents of the industry are welding, cutting, bending, and other low skilled jobs, which are accomplished mainly manual labour. And since the production characteristics could be expressed as: multispecies, small amount and high value of single product, the production was mainly driven by orders. It showed that the assessment result is consistent with reality, and the rationality of the method is verified.

5. Conclusion

The establish of a scientific assessment system, making the assessment of lean level no longer depends on subjective evaluation. Also, such method help managers find key factors for lean implementation, thus the best improvement effect at a certain cost could be achieved. As previous studies mainly focus on measuring the leanness level of organization from the perspective of integrity, the general model does not take full account of the differences in production industries. In this research, a leanness assessment method based on principal components analysis was proposed, the key leanness factors of a production industry are reflected through production related data, thus the drawback that the previous models have not considered the applicability of different type of production organizations was overcame.

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Biographies

Cunrong Li is a Professor, and Director of Master of Mechanical Engineering and Master of Industrial Engineering in the Department of Industrial Engineering at the Wuhan University of Technology, Wuhan, China. He earned B.S. in Mechanical & Electronics Engineering from Wuhan University of Technology, China, Masters in Mechanical Engineering from Wuhan University of Technology, China and PhD in Mechanical Engineering from Wuhan University of Technology, China. He was a visiting scholar at University of Liverpool and Louisiana State University. He has published journal and conference papers. Dr Li has completed research projects with Bhaba R. Sarker, Louisiana State University, KKB Hon, University of Liverpool, S. S. Guo, Wuhan University of Technology, M. Z. Yang, Wuhan University of Technology. His research interests include Production Planning & Control, Flexible/Cellular Manufacturing Systems, Material Handling, Scheduling, Location Theory, JIT Inventory Systems, Warehouse Logistics and Distribution, Lean Manufacturing, Supply Chain Management, Manufacturing Automation.

Geng Cui is a postgraduate student at the Wuhan University of Technology. In 2015, he received the B.Eng. in Industrial Engineering from Wuhan University of Technology, Hubei, China, and currently studying in the graduate school at Wuhan University of Technology with a Industrial Engineering major for a engineering master's degree.

Fei Xie is a postgraduate student at the Wuhan University of Technology. In 2015, he received the B.Eng. in Manufacturing and Automation from Wuhan Huaxia University of Technology, Hubei, China, and in 2017 the M.Eng. in Mechanical Engineering from Wuhan University of Technology.