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A Total Productivity PCA Model for Assessment and Improvement of Electrical Manufacturing Systems

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Abstract: This study presents a framework for assessment of electrical manufacturing systems based on a total machine productivity approach and multivariate analysis. Furthermore, the total model is developed by Principle Component Analysis (PCA) and validated and verified by Numerical Taxonomy (NT) and non-parametric correlation methods, namely, Spearman correlation experiment and Kendall Tau. To achieve the objectives of this study, a comprehensive study was conducted to locate the most important economic and technical indicators which influence machine performance. These indicators are related to machine productivity, efficiency, effectiveness and profitability. Six major electrical machinery sectors are selected according to the format of International Standard for Industrial Classification of all economic activities (ISIC). Then, a comparative study is conducted through PCA among the electrical machinery sectors by considering the six sectors. This in turn shows the weak and strong points of electrical machinery and apparatus manufacturing sectors with respect to machine productivity. Furthermore, PCA identified which machine indicators have the major impacts on the performance of electrical machinery sectors. The modeling approach of this study could be used for ranking and analysis of other electrical sectors. This study is the first to introduce a total productivity model for assessment and improvement of total machine performance in electrical manufacturing sectors.

Key words: PCA, machine indicators, productivity, numerical taxonomy, electrical sectors

INTRODUCTION

Machines play an important role in the overall performance of electrical manufacturing systems. In fact, machine productivity is correlated with the overall performance of a electrical manufacturing system. Major factors influencing the overall productivity of an industrial organization are identified as technology, machinery, management, personnel and rules and procedures[1,2]. The machine factor is mainly concerned with machine condition or status in a specified period. Preventive maintenance, repair, machine layout and calibration influence machine condition. Machine condition is measured through simple productivity models and indicators. Moreover, most productivity indicators about machine are defined in terms of availability; operating time, repair time, down time, etc.

This study has identified major productivity indicators, which impact machine performance in electrical machinery and apparatus manufacturing systems. The six major electrical manufacturing sectors are selected according to International Standard for Industrial Classification for all economic activities (ISIC) format. The total productivity model considers not only the traditional productivity view but also it must consider other views such as efficiency, effectiveness and profitability. Effectiveness is defined as actual output to planned output, efficiency is defined as actual output to actual input and profitability is defined as total revenue to total cost. Furthermore, this study considers the four views of machine productivity, which are: 1) traditional productivity, 2) efficiency, 3) effectiveness and 4) profitability. In this study, all of the four views are referred to as machine productivity. By referring to a selected number of productivity indexes, the industrial organizations are ranked and analyzed by Principal Component Analysis (PCA). The validity of the model is verified and validated by Numerical Taxonomy (NT) approach. It should be mentioned that Data Envelop Analysis (DEA) was first selected as the verification tool, but several indexes could not be considered due to the unique structure of DEA. The four-digit ISICs of electrical machinery and apparatus manufacturing systems are listed as follows[2-6]:

ISIC	Industry
3110	Manufacture of electric motors, generators and transformers
3120	Manufacture of electricity distribution and control apparatus
3130	Manufacture of insulated wire and cable

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3140 Manufacture of accumulators, primary cells and primary batteries
3150 Manufacture of electric lamps and lighting equipment
3190 Manufacture of other electrical equipment n.e.c.

Multivariate techniques: *Principal Component Analysis* (PCA) is widely used in multivariate statistics such as factor analysis. It is used to reduce the number of variables under study and consequently ranking and analysis of decision-making units (DMUs), such as industries, universities, hospitals, cities, etc[1,2,7- 9]. The objective of PCA is to identify a new set of variables such that each new variable, called a principal component, is a linear combination of original variables. Second, the first new variable y1 accounts for the maximum variance in the sample data and so on. Third, the new variables (principal components) are uncorrelated. PCA is performed by identifying eignestructure of the covariance or singular value decomposition of the original data. Here, the former approach will be discussed. It is assumed there are p variables (indexes) and k DMUs and suppose $X = (x_1 ... x_p)_{k\times p}$ is a k×p matrix composed by x_{ij}'s defined as the value of jth index for ith DMU and therefore $x_m = (x_{1m} ... x_{km})^T \, (m = 1...p)$. Furthermore, suppose $\hat{X} = (\hat{x}_1 ... \hat{x}_p)_{k\times p}$ is the standardized matrix of $X = (x_1 ... x_p)_{k\times p}$ with $\hat{x}_{ij}$'s defined as the value of jth standardized index for ith DMU and therefore $\hat{x}_m = (\hat{x}_{1m} ... \hat{x}_{km})^T$. PCA is performed to identify new independent variables or principal components (defined as Y_j for, $j = 1...p$) which are respectively different linear combination of $\hat{x}_1 ... \hat{x}_p$. As mentioned, this is achieved by identifying eignestructure of the covariance of the original data. The principal components are defined by a k × p matrix $Y = (y_1 ... y_p)_{k\times p}$ composed by y_{ij}'s are shown by[10-11]. The eigenvectors $(y_{1j} ... y_{kj})\ (j = 1...p)$ are calculated and the components in eigenvectors are respectively the coefficients in each coresponding Yi. The weights and PCA score are estimated as follows:

$$Y_m = \sum_{j=1}^{p} l_{mj} \hat{x}_{ij} \quad \text{for} \quad m = 1...p \text{ and } i = 1,...,k$$

$$w_j = \lambda_j / \sum_{j=1}^{p} \lambda_j = \lambda_j / p \qquad j = 1...p$$

$$z_i = \sum_{j=1}^{p} w_j Y_j \quad i = 1...k$$

Numerical Taxonomy approach is capable of identifying homogeneous from non-homogeneous cases. Furthermore, a group of DMUs by given indexes is divided to homogeneous sub-groups[1,2, 12]. It also ranks the DMUs in a particular group.

Total productivity model: To achieve the objectives of this study, a comprehensive study was conducted to locate the most important economic and technical indicators (indexes) which influence machine performance. These indicators are related to machine productivity, efficiency, effectiveness and profitability[13-26]. Standard factors such as down time, time to repair, mean time between failure, operating time, value added and production value were considered as parameters influencing the indicators. The data is collected from the annual reports of Iran Statistic Center, which is the authorized body to collect the manufacturing data according to ISIC formats.

Iranian electrical machinery sectors are classified as 4-digit ISIC format. A comparative study is conducted among electrical machinery sectors through PCA by the selected indicators.

The total productivity approach is based on ten indicators identified in this study. The ten indexes are categorized into four classes. The first class reflects availability of machine and is measured by indexes number 1, 2 and 3. Availability is defined as the probability that a system is operating satisfactorily at any point in time and considers only operating time and down time, thus excluding idle time. It is simply operating time over operating time plus down time. Maximum time is defined as maximum allowable time dedicated to a machine per period. Administrative time is a fixed time due to preventive maintenance, adjustment, etc. Available time is defined as maximum time minus administrative time. Inefficient time is maximum time minus available time and includes repair time, idle time due to lack of plan, material, labor, etc. Operating time is available time minus down time. Down time is obtained by integration of inefficient time and administrative time. The second class deals with machinery stoppage due to lack of good plans, preventive maintenance and material, etc (indexes number 4 and5). The third class represents random failures (indexes number 6, 7 and 8). The last class which is composed of indexes number 9 and 10 reflects availability in relation to value added and production value. Currency unit per time unit measures indexes number 9 and 10. The selected machinery indexes (indicators) are listed as follows:

Table 1: Standardized matrix for the electrical manufacturing sectors

Sector code	$\hat{x}_1$	$\hat{x}_2$	$\hat{x}_3$	$\hat{x}_4$	$\hat{x}_5$	$\hat{x}_6$	$\hat{x}_7$	$\hat{x}_8$	$\hat{x}_9$	$\hat{x}_{10}$
3110	0.093	0.284	0.332	0.360	0.332	0.166	0.093	-0.055	0.024	0.125
3120	-0.013	0.393	0.739	0.553	0.424	0.070	-0.013	-0.263	1.778	1.882
3130	-0.343	-0.129	0.393	0.018	-0.038	-0.246	-0.343	-0.525	0.320	-0.030
3140	1.096	-0.034	-1.932	-0.597	0.051	0.991	1.096	1.320	-0.927	-0.848
3150	-1.706	-1.776	-0.182	-1.608	-1.870	-1.803	-1.706	-1.421	-0.313	-0.361
3190	0.873	1.262	0.651	1.274	1.100	0.821	0.873	0.944	-0.882	-0.769

Table 2: Correlation matrix for the machinery indicators

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}
x_1	1.00									
x_2	0.832	1.00								
x_3	-0.270	0.309	1.00							
x_4	0.644	0.960	0.562	1.00						
x_5	0.849	0.995	0.273	0.946	1.00					
x_6	0.996	0.862	-0.209	0.689	0.884	1.00				
x_7	1.00	0.832	-0.270	0.644	0.849	0.996	1.00			
x_8	0.975	0.724	-0.419	0.505	0.731	0.949	0.975	1.00		
x_9	-0.276	0.028	0.545	0.186	0.064	-0.206	-0.276	-0.450	1.00	
x_{10}	-0.197	0.096	0.525	0.238	0.126	-0.132	-0.197	-0.363	0.983	1.00

Table 3: Eigenanalysis for the six electrical manufacturing sectors

Variable	Eigenvalue (λ_j)	Weight (w_j)	Eigenvectors		
			l_{1p}	l_{2p}	l_{3p}
1	6.156	0.616	0.393	0.090	0.164
2	2.960	0.296	0.375	-0.194	-0.169
3	0.853	0.085	-0.025	-0.499	-0.551
4	0.026	0.003	0.318	-0.316	-0.308
5	0.005	0.000	0.377	-0.196	-0.091
6	-0.001	0.000	0.396	0.045	0.170
7	0.001	0.000	0.393	0.090	0.164
8	0.000	0.000	0.372	0.202	0.139
9	0.000	0.000	-0.085	-0.509	0.463
10	0.000	0.000	-0.054	-0.508	0.497

Table 4: The scores of principal components for the electrical sectors

Sector code	y_1	y_2	y_3	z_i (PCA scores)	Rank
3110	0.4482	-0.4626	-0.2474	0.392	4
3120	0.1316	-2.6161	1.0477	0.945	2
3130	-0.6548	-0.4956	-0.2909	-0.282	5
3140	1.7343	2.5604	1.1102	0.404	3
3150	-4.4151	0.9773	-0.3222	-3.034	6
3190	2.7559	0.0366	-1.2973	1.575	1

a_1: Availability
a_2: Operating time to maximum time
a_3: Available time to maximum time
a_4: Inefficient time to available time
a_5: Inefficient time to operating time
a_6: Down time to available time
a_7: Down time to operating time
a_8: Down time to inefficient time
a_9: Value added to operating time
a_{10}: Production value to operating time

The ten indexes must be normalized and have same order to be used in PCA. Indexes a_4 and a_8 have opposite order than the rest of the indexes. To alleviate this problem, a_4 and a_8 are subtracted from 1 and all the ten indexes from now on are referred to as x_j for j = 1...10. The indexes are standardized and are shown in Table 1. They are standardized through predefined mean and standard deviation for each index.

The correlation matrix shows the values of linear correlation between indexes x_1 to x_{10} (Table The eigenvalues and proportion of the sample variance for the 10 indicators (principal components) are presented in Table 3. It is noted that first three principal components y_1, y_2 and y_3 account for 99.5 percent of the sample variance. Therefore, the coefficients of the first three principal components are presented in the last three column of Table 3. It should be noted that the coefficients are retrieved from the eigenvectors for the respective principal components. The values of principal components and consequently their aggregated weights are presented in Table 4.

Model validation: To verify the results of PCA, a numerical taxonomy approach is employed and described next. First, the summary of numerical taxonomy analysis is described. Second, the ranking of the two approaches are analyzed by Spearman correlation technique. The distance matrix is computed and the values of vector d are shown in Table 5. As noted, d_is represent the smallest value in each row of the distance matrix for each DMU. By computing the lower and upper limits of di [1.146, 4.061], it is observed that all DMUs are within the range of dis. Therefore cluster analysis is not required to identify homogenous DMUs. The values of f_is for homogenous DMUs and their ranks are presented in Table 6.

Table 5: The results of distance matrix for the electrical sectors

Sector code	di	Selected sector
3110	1.146	3130
3120	2.542	3110
3130	1.146	3110
3140	3.557	3110
3150	4.061	3130
3190	2.597	3110

Table 6: Taxonomy values of the homogenous process for the electrical sectors

Sector code	f_i	Rank
3110	0.444	2
3120	0.334	1
3130	0.541	4
3140	0.646	5
3150	1.001	6
3190	0.462	3

The f_is show the values of taxonomy for each sector. As mentioned, values of f_is range between 0 and 1 with 1 the worst and 0 best scores. Considering the scores of PCA and Taxonomy in Table 7 ranks the sectors (DMUs). This table also reports the non-parametric test of relationship (Spearman) between PCA rankings and Taxonomy rankings, which result in the rejection of H_o at 0.01 level. Also, the Kendall's Tau test of correlation verifies this finding at the same level of significance. There is a direct relationship between PCA and Taxonomy in terms of data set presented for the four-digit ISIC code. Hence, the results of PCA are verified by Numerical Taxonomy.

Table 7: Test of correlation between PCA and Taxonomy for the electrical sectors

Sector code	PCA rank (U)	Taxonomy rank (V)	Spearman $(U-V)^2$
3110	9	9	0
3120	2	1	1
3130	4	2	4
3140	1	3	4
3150	7	7	0
3190	6	6	0
Result of tests of correlation between PCA and Taxonomy		Total	0
$r_s = 0.6$ & $\tau = 0.5$ Reject at 0.01			

CONCLUSION

Verifying and validating the PCA rankings by Taxonomy approach may further analyze the PCA results. It was shown that 2 principal components with weights w_1 =62 % and w_2= 30% compose about 92% of the sample variance. Therefore, by increasing the first and second components the ranking may be greatly improved. Furthermore, the sectors in the bottom of the ranking may enhance their performance by improving the first and second principal components. The first and second principal components are further analyzed by referring to their coefficients (eigenvectors). Also, sectors 3150 and 3190 show the worst and best ranks respectively, with respect to the selected machine indicators.

It should be noted that the p aggregated weights ($\tilde{w}_m$) for $m = 1...p$ show the importance of each indicator and is computed as follows:

$$\tilde{w}_m = \sum_{j=1}^{p} w_j l_{mj}$$

Applying the above formulation to our problem, the 10 machinery indicators $\tilde{w}_m$ are evaluated and shown in Table 8. It is observed that 1) inefficient time to operating time 2) operating time to maximum time and 3) inefficient time to available time are the most important indicators respectively. Moreover, economic indicators, namely, value added to operating time and production value to operating time are at the bottom of the rankings (aggregated weights). The first three indicators are influenced by the two independent characteristics, operating time and down time. In other words, it can be expected that the system performance

Table 8: Aggregated weights for each of the ten machinery indicators

$\widetilde{w}_1$	$\widetilde{w}_2$	$\widetilde{w}_3$	$\widetilde{w}_4$	$\widetilde{w}_5$	$\widetilde{w}_6$	$\widetilde{w}_7$	$\widetilde{w}_8$	$\widetilde{w}_9$	$\widetilde{w}_{10}$
0.2295	0.2742	0.0853	0.2633	0.2813	0.2440	0.2295	0.1827	0.1372	0.1600

can be enhanced by improving the machine operating time and down time. In fact, it is proven that economic factors do not play an important role in system performance due to machine condition. Furthermore, machine performance in electrical manufacturers is affected by technical factors rather than economic factors. This is an important finding since traditionally it is believed that economic indicators such as value added and production value are the shaping factors in the performance of such systems.

In summary, this study presents a unique standard methodology for assessment and ranking of electrical sectors based on machine productivity and PCA. The structure and approach of this study could be applied for other electrical manufacturing sectors. The results of such studies would help policy makers and top managers to have better understanding of their sectors with respect to machinery condition. Also, designers and engineers could identify weak and strong points in regard to machinery. Moreover, the modeling approach of this study may be used for continuous assessment and improvement of machine status in electrical machinery and apparatus manufacturing systems.

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