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Performance Assessment and Optimization of the After-Sale Networks

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***Abstract*—**The after–sales activities are nowadays acknowledged as a relevant source of revenue, profit and competitive advantage in most manufacturing industries. Top and middle management, therefore, should focus on the definition of a structured business performance measurement system for the after-sales business. The paper aims at filling this gap, and presents an integrated methodology for the after-sales network performance measurement, and provides an empirical application to automotive case companies and their official service network. This is the first study that presents an integrated multivariate approach for total assessment and improvement of after-sale services.

***Keywords*—**Data Envelopment Analysis (DEA), Principal Component Analysis (PCA), Automotive companies, After-sale services.

I. Introduction

P. Gaiardelli, N. Saccani, L. Songini, verified after-sale service's performance evaluation system in 2007, and expressed that in today's competitive market companies must focus on customer instead of production so after-sale services can be main income source and play a strategic role for them[1]. Every organization, particularly in dynamic complex environments, needs an evaluation system for recognizing its activity's quality and utility [2] P. Gaiardelli, N. Saccani , L. Songini(2007) surveyed the after-sale service network performance evaluation of automotive industry and expressed that after-sale activities are an income source and competitive advantage benefit for almost production industries[1,3]. The role of after-sale service performance evaluation in permanent customer oriented industries has been verified as well [3, 4]. Hong at al showed that data envelopment analysis (DEA) can be used to evaluate efficiency of system Integration projects [5].

DEA was introduced as an effective mathematic model in operation research (OR) category for organization's efficiency evaluation by Charnes, Cooper, and Rhodes (1978), and since then hundreds of articles have been published in this field all over the world. DEA analysis model has been developed for decision making unit's evaluation [2].

More over in DEA approach, a set of factors are evaluated simultaneously and decision making units collect some of them as efficient ones and constitute efficiency frontier, using them. In this evaluation criterion of deficiency does not resulted from a comparison to a given standard level or a definite function from. This criterion's basis is other decision making units which are active in the same conditions and evaluate potential performance as a performance indicator in their evaluation of different organizations which they include decision – making units too[6].

Researchers have applied DEA method in service quality evaluation [7]. This study presents an integrated DEA-PCA model for assessment and optimization of sale and after-sale services of individual business units of Iran Khodro Corporation.

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II. DEA

The original fractional CCR model (1) evaluates the relative efficiencies of n DMUs (j = 1…n), each with m inputs and s outputs denoted by *x1j, x2j,…, xmj* and *y1j, y2j,…, ysj* respectively. This is done so by maximizing the ratio of weighted sum of output to the weighted sum of inputs:

$$Max\theta = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}}$$

$$\text{s.t.} \quad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} V_i x_{ij}} \le 1 \quad j=1,\dots,n,\ \ r=1,\dots,s \qquad (1)$$

$$u_r, v_i \ge 0,\ \ i=1,\dots,m,\ \ r=1,\dots,s$$

In model (1), the efficiency of DMUo is θo and *ur* and *vi* are the factor weights. However, for computational convenience the fractional programming model (1) is re-expressed in linear program (LP) form as follows:

$$Max\theta = \sum_{r=1}^{s} u_r y_{ro}$$

$$\text{s.t.} \quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \quad j=1,\dots,n, \qquad (2)$$

$$\sum_{i=1}^{m} v_i x_{io} = 1$$

$$u_r, v_i \ge \varepsilon, \quad i=1,\dots,m, \quad r=1,\dots,s$$

Where ε is a non-Archimedean infinitesimal introduced to ensure that all the factor weights will have positive values in the solution. The model (3) evaluates the relative efficiencies of n DMUs (j = 1,…, n), respectively, by Minimizing inputs when outputs are constant. The dual of linear program (LP) model for input oriented CCR is as follows [8]:

$$Min\theta$$

$$\text{s.t.} \quad \theta \; x_{io} \ge \sum_{j=1}^{n} \lambda_j x_{ij}, \quad i=1,\dots m,$$

$$y_{ro} \le \sum_{j=1}^{n} \lambda_j y_{rj} \qquad r=1,\dots,s \qquad (3)$$

$$\lambda_j \ge 0$$

The output oriented CCR model is as follows:

$$Max\theta$$

$$\text{s.t.} \quad x_{io} \ge \sum_{j=1}^{n} \lambda_j x_{ij}, \qquad i=1,\dots m,$$

$$\theta \; y_{ro} \le \sum_{j=1}^{n} \lambda_j y_{rj} \qquad r=1,\dots,s \qquad (4)$$

$$\lambda_j \ge 0$$

If ∑ λj = 1 (j=1, …, n) is added to model (3), the BCC model is obtained which is input oriented and its return to scale is variable [9]. The calculations provide a maximal performance measure using piecewise linear optimization on each DMU with respect to the closest observation on the frontier. The linear programming system for the BCC input-oriented model is given in expression (5), and the output-oriented model in expression (6) for more detail. [10]

$$Min\theta$$

$$\text{s.t.} \quad \theta$$

$$\theta \; x_{io} \ge \sum_{j=1}^{n} \lambda_j x_{ij}, \quad i=1,\dots m,$$

$$y_{ro} \le \sum_{j=1}^{n} \lambda_j y_{rj} \qquad r=1,\dots, \; s \qquad (5)$$

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad , \; j=1,\dots, \; n$$

$$Max\theta$$

$$\text{s.t.} \quad x_{io} \ge \sum_{j=1}^{n} \lambda_j x_{ij}, \; i=1,\dots m,$$

$$\theta \; y_{ro} \le \sum_{j=1}^{n} \lambda_j y_{rj} \qquad r=1,\dots,s \qquad (6)$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \ge 0 \qquad , \; j=1,\dots,n$$

The original DEA model is not capable of ranking efficient units and therefore it is modified by Andersen and Petersen for DEA based ranking purposes to rank efficient units [11].

For efficient units, target and real values of the input/output(s) are equal. The target value for each input/output is computed as:

$$\left(X_0, Y_0\right) \to \left(X_0 = \theta_B^0 X_0 - S^{-0}, Y_0^{\wedge} = Y_0 + S^{+0}\right) \quad (7)$$

III. PCA

PCA is a multivariate statistical technique which is used for variable reduction. Also, it is utilized for performance evaluation and ranking ([12], [13], [15], [16], [17]).

Here, the former approach of PCA will be discussed. It is assumed there are $m \times s$ variables and n DMUs and suppose $d_{jir} = y_{rj}/x_{ij}$ (i = 1…m; r = l…s) ratios of individual output to individual input for each DMUj (j = l... n). Obviously, the bigger the d_{ir}^{j} the better the performance of DMU_j in terms of the *r* th output and the *i* th input. Now let $d_k^j = d_{ir}^j$ where *k = 1, ..., p* and $p = m \times s$. Consider the following $n \times l$ data matrix composed by d_{jk}: $D = (d_1, ..., d_p)_{n \times p}$ with each row represents p individual ratios of d_k^j for each DMU and each column represents a specific output/input ratio. That is, $d_k = [d_k^1 \; d_k^2 ... d_k^n], k = 1,..., p$.

The PCA is employed here to find out new independent measures (principal components) which are respectively different linear combinations of $d_1, ..., d_p$ so that the principal components can be combined by their Eigenvalues to obtain a weighted measure of d_k^j. The PCA process of D is carried out as follows:

Step 1: Calculate the sample mean vector đ and covariance matrix S.

Step 2: Calculate the sample correlation matrix R.

Step 3: Solve the following equation.

$$\left| R - \lambda I_p \right| = 0$$

It is obtained the ordered p characteristic roots (Eigenvalues) λ1 ≥ λ2 ≥…≥ λp with ∑ λj = p (j =1, …, p) and the related p characteristic vectors (Eigenvectors) (l1, l2,…, lp). Those characteristic vectors compose the principal components Yi.

$$Y_m = \sum_{j=1}^{p} l_{mj} \hat{x}_{ij} \quad \text{for } m = 1...3 \text{ and } i = 1...37$$

Step 4: calculate the weights (wi) of the principal components and PCA scores (zi) of each DMU (i = 1, ..., 37). Furthermore, the z vector (z1, ..., z5) where zj shows the score of jth DMUs is given by:

$$z = \sum_{j=1}^{5} w_j Y_j \qquad i = 1 ... 37$$

IV. Case Study

Iran Khodro Corporation as the biggest automotive company in the Middle East the following organizational structure for its sale and after-sale services: sale service, after-service, and business unit territorial offices. Company's important factors in this field are: B.U1 warranty's costs, B.U spare- part costs, B.U automotive sale income, customer satisfaction, Iran khodro's evaluation and industrial ministry's evaluation. Each territorial office as a B.U must maximize its profit.

Associated data of 11 Iran khodro's territorial offices over 2007 were collected.

Owing to data collection limitations, only four indicators were selected for the purpose of this study. The data in regard to manufacturing sectors are collected, and structured for a one year period. Normalized for an one- year period (2007). Furthermore, the PCA DEA model ranked the manufacturing sectors based on the four indicators selected for the case study.

This in turn shows the weak and strong points of each sector in regard to equipment. Furthermore, the model identified which equipment indicators have major impact on the performance. Model validity is identified by non-parametric correlation analysis.

Four above mentioned key indicators are: representative's quantity, warranty' costs, automotive – sale income and spare – part sale income.

First, PCA is used to rank and analyze the data. Then, the data is converted to DEA format and DEA is conducted to rank and analyze the data. The integrated model identifies weak and strong points and introduces productivity and improving factors in regard to equipment condition in each sector. Using PCA method, B.Us will be ranked. PCA is achieved through a set of well-defined steps as follows:

Normalize the indicator vectors; standardize the indicators; Evaluate the correlation matrix; Calculate eigenvalues, eigenvectors and proportion of the sample variance for all the four principal components (new variables); Evaluate principal components and aggregated weights.

The indicators are standardized and are shown in Table I.

TABLE I
STANDARDIZED MATRIX FOR THE FOUR INDICATORS

	X	Y1	Y2	Y3
BU1	1.491445	0.462952	1.287271	0.437807
BU10	0.756053	-0.264544	-0.379996	0.317391
BU11	-0.034597	-0.541685	-0.550935	-0.346999
BU2	-0.821061	-1.026682	-0.520909	-1.205094
BU3	0.913382	-0.229901	-0.266038	-0.064526
BU4	-1.726566	2.26437	2.407041	2.566443
BU5	-1.116662	1.294376	0.367128	-0.906916
BU6	0.520434	-0.4724	-0.743922	-0.51552
BU7	0.637629	-0.403115	-0.822603	-0.261512
BU8	-0.856265	-0.022045	-0.173731	-0.450576
BU9	0.236207	-1.061325	-0.603306	0.429501

In the Table II, principal component values are shown. The rank of each BU is calculated upon the principal component value and eigenvector's importance. B.U ranking is shown sixth column of Table II.

TABLE II
THE VALUES AND SCORES OF PRINCIPAL COMPONENTS

	PC1	PC2	PC3	PC4	z_i(Scores)	Rank
BU1	0.73	1.67	0.87	0.47	0.92	2
BU10	-0.46	0.76	-0.18	-0.25	-0.16	4
BU11	-0.78	-0.25	-0.21	0.00	-0.60	8
BU2	-1.20	-1.29	-0.16	0.57	-1.12	11
BU3	-0.62	0.73	0.19	-0.11	-0.24	5
BU4	4.49	-0.04	-0.56	-0.03	2.99	1
BU5	0.87	-1.43	1.01	-0.25	0.36	3
BU6	-1.12	0.12	0.10	-0.19	-0.72	10
BU7	-1.04	0.32	-0.02	-0.36	-0.63	9
BU8	-0.05	-0.98	-0.07	0.04	-0.26	6

Ranking is done based on AP complete ranking model. The results of this ranking are presented in Table III. Using spearman correlation coefficient, relationship between two obtained ranks from DEA and PCA is compared. Big correlation coefficient value (0.92) shows that these two ranking method are very similar. In following, employing DEA model, we will analysis real situation.

[1] Business Unit

TABLE III
RESULTS OF DEA AND PCA

DMU	Efficiency - DEA	Rank	Zpca	Rank
BU1	1.00	2	0.92	2
BU10	0.90	4	-0.16	4
BU11	0.60	10	-0.60	8
BU2	0.36	11	-1.12	11
BU3	0.77	6	-0.24	5
BU4	1.00	1	2.99	1
BU5	0.96	3	0.36	3
BU6	0.62	9	-0.72	10
BU7	0.68	7	-0.63	9
BU8	0.64	8	-0.26	6
BU9	0.89	5	-0.55	7
Correlation between DEA & PCA				0.92

In the Table I, Required data for B.U analyzing with DEA approach are given. The efficiency marks are presented in Table's last column.

TABLE IV
ACTUAL INPUTS AND OUTPUTS DATA AND SCORES OF EFFICIENCY

	Inputs	Outputs			VRS Efficiency
MU	Warranty' costs (x)	Representatives quantity(y1)	Automotive – sale income annual (y2)	Spare – part sale income annual (y3)	
U1	66,000,00	80	5,410,000,0	154,355,111	1
U2	136,900,0	37	1,760,600,0	56,991,584	0.36399
U3	75,815,00	60	2,275,000,0	124,585,268	0.77082
U4	236,295,0	132	7,670,000,0	280,504,833	1
U5	158,691,0	104	3,552,900,0	74,662,575	0.96026
U6	84,341,00	53	1,310,500,0	97,857,945	0.61915
U7	81,604,00	55	1,151,700,0	112,911,285	0.68054
U8	139,176,0	66	2,461,300,0	101,706,738	0.64488
U9	91,809,00	36	1,594,300,0	153,862,898	0.88695
U10	79,013,00	59	2,045,000,0	147,218,895	0.89770
U11	100,268,0	51	1,700,000,0	107,845,031	0.60000

As Table IV. Is shown, $B.U_1$ and $B.U_4$ are ore efficient than others and $B.U_2$ has the least efficiency. For identifying the strength and weakness points, calculations are done based on equation 7 and for deficient unit's ideal values. These results are shown in Table V.

TABLE V
OUTPUT TARGETS FOR INEFFICIENT DMUS

DMU	Warranty' costs	Representatives quantity	Automotive – sale income annual	Spare – part sale income annual
BU2	1369000000	101.64949	4836867381959.61	156572042686.422
BU3	7581500000	82.99703	5540255732699.10	161625786229.601
BU5	1586910000	108.30343	3699915804633.14	81727396257.6296
BU6	8434100000	85.60047	5447579269568.35	158050681594.067
BU7	8160400000	84.76472	5617082063478.08	165914113779.506
BU8	1391760000	102.34447	3816673499515.55	157713978192.233
BU9	9180900000	87.88084	5752513520655.33	173473689292.855
BU10	7901300000	83.97355	5582696673419.65	163994774224.867
BU11	1002680000	90.46382	5864773657476.73	179739877364.136

V. CONCLUSION

The integrated approach of this study introduces a set of well-defined machine indicators and utilizes an integrated PCA DEA model to assess and rank manufacturing unit. Also, Big correlation coefficient (0.92) shows high similarity between these methods. Ultimately efficient and deficient units are identified and strength and weakness points of deficient units are calculated. In summary, this paper presents a unique standard methodology for assessment and ranking in Iran khodro individual Business units based on integrated PCA DEA model.

The results of such studies would help policy maker sand top managers to have better under standing of their sectors with respect to equipment condition .Also, designers and engineers could identify weak and strong points in regard to equipment .The framework presented in this paper may be used by top managers to compare the machine performance of various units with in a manufacturing organization .This may be accomplished by defining the target units(say n DMUs) and ranking them with respect to the indicators discussed in this paper. Therefore, they will have standard and scientific results about the standings of all Business units. Second, the most important indicators will be identified which will help managers improve weak points in respect to machine conditions. Third, the modeling approach may be extended to include external units(competitors)to identify standings and weak and strong factors in the big picture.

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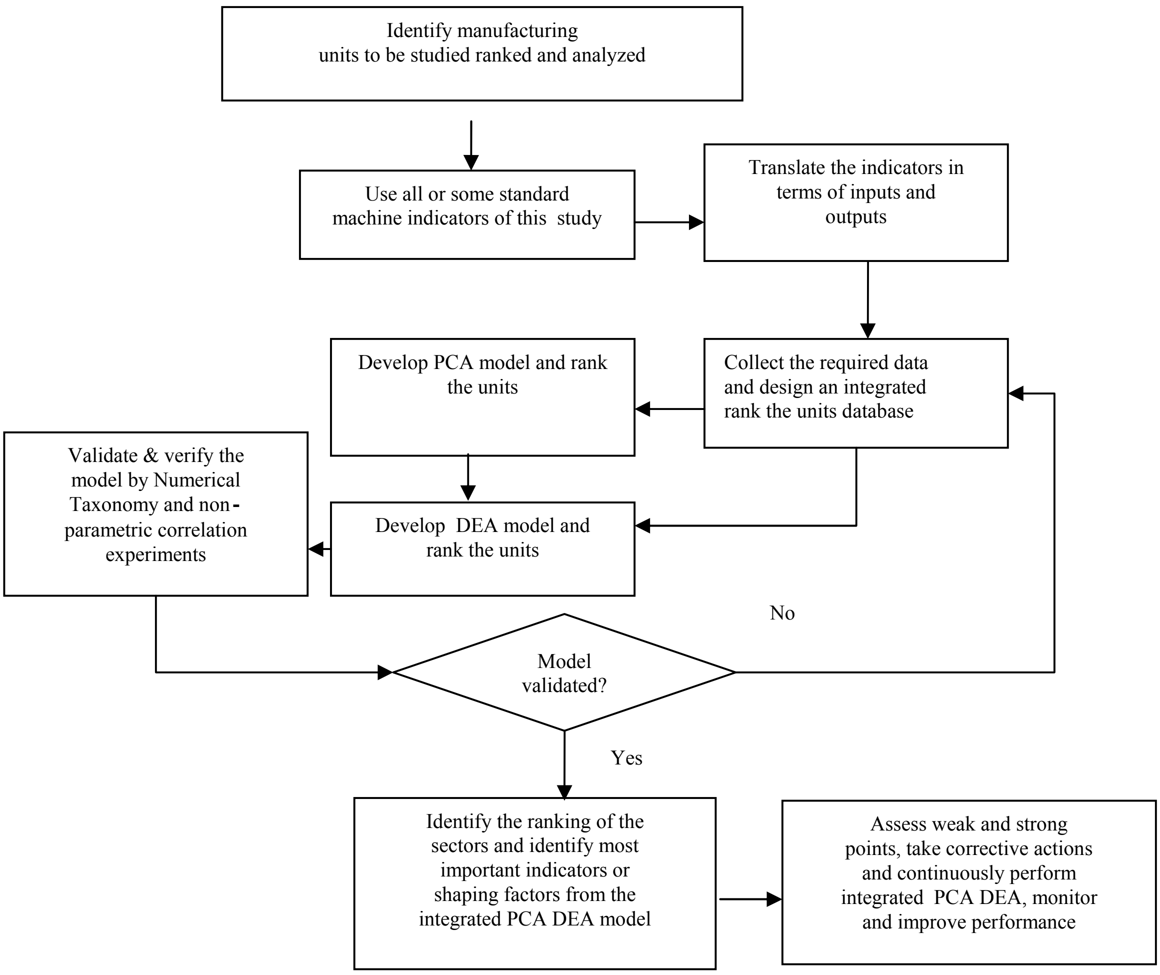

Fig. 1The integrated PCA DEA model for assessment of manufacturing systems based on machine performance