



Benchmarking Scheme for Retail Stores Efficiency

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Abstract

The Indian retail sector is changing at a faster rate. At the same time the consumers' preference is also changing and the retailers need to take note of this and prepare for new and innovative strategies to tackle the situation. On the other hand there is rapid growth of retailing in recent years and upcoming many new firms in India has necessitated for benchmarking. So retail firms are very much concern about the available resources and their optimum utilization with respect to consumers' need and preference. The paper deals with study of benchmarking in retailing and compares the performance of some selected retail stores. This study is an application of Data Envelopment Analysis (DEA) to assess the relative efficiency of the retail stores. The analysis has found that only sales cannot increase the efficiency of a retail store.

Keywords: Benchmarking, Data envelopment analysis, Retail store

1. Introduction

In India, retail sector is emerging at a faster rate. It has significant impact on nation's economic growth. Most of the retail sector is in unorganized form. Now-a-days many retail chains have come up, such as shoppers' stop, Food world, Subhiksha etc. It is due to organized retailing, customer can get wide range of products in one place having comfort and convenience. Benchmarking is most important in case of organized retailing. The performance of retailing depends upon the performance of its retail stores. So it is necessary to measure their performance and benchmark them accordingly.

India's retail sector, which includes sales of products ranging from groceries to clothes to cell phones, will surge to \$ 607 billion in 2010 from \$ 330 billion last year. The high projected growth and low penetration of modern retailing in India make the country the most attractive destination in the world for international retailer. India has always been one of the world's largest markets in term of population. Recent changes in the shopping habits of India's more than 300 millions middle class consumers will most likely keep retail industry growth running at about 10% a year for the next five years. The economy of our country resides on more than 10 million tiny retail shops. But a growing number of Indians are shopping at modern retail chains. In this year hundred of malls and large retailers have sprouted up all over the country (www.srcg.com)

Benchmarking has been defined as a continuous, systematic process for evaluating the products, services and work processes of organizations that are recognized as best practices for the purpose of organizational improvements (Spendolini, 1992). Companies have adopted this approach for improving specific business processes that is helpful for increasing market share leading to high profit. Benchmarking concept is used by many leading companies like Xerox Corporation, American Express, etc. to excel in their respective industries in a global scale (Camp, 1998). It is also useful for small and medium size firm. In marketing the concept is used extensively (Churchill & Peter 1999, Kottler, 2004). It has not been an academic study conceptualizing benchmarking efforts. This paper attempts to fill this gap and add our understanding of benchmarking and its applicability in retailing research and practice.

2. Literature review

Benchmarking is most popularly adopted by organizations to understand how well they are performing relative to their competitors. It is also used to identify what management practices are worthwhile to apply in one's own firm in order to achieve desired performance goals. Benchmarking has been defined as "the search for industry best practices that lead to superior performance" (Camp, 1989) but it can also regarded as the constant search for reference points due to the rapid state of change on all fronts (eg. technology, human resources skill, consumer tastes, etc.). The benchmarking process consists of investigating practices and establishing metrics where practices are interpreted as the processes that are employed and metrics are the quantified result of instituting practices (Camp 1989). Companies have to create close relationships with their upstream and downstream partners due to acute competition. The traditional relationship is no

more effective in this competitive era (Bowersox et al., 2000). As a company may belong to many supply chains, few areas of logistic decisions and market access are under their direct control. The emerging trend of supply chain collaborations has been quickly adopted in many companies. For example, the pilot project of collaborative planning, forecasting and replenishment (CPFR) scheme helps Wal-Mart and its supplier to improve stock levels, reduce lead-times, slash on hand inventory create more consistent orders and smooth production cycles (Parks 2001). For its substantial benefits, the trend of adopting collaborative practices such as CPFR will continue to increase in the coming decade. Internal and external metrics are monitored to enable the chain members to assess the progress of performance improvements (Stewart, 1997). An integrated performance is required by all members to facilitate their performance status along the supply chain (Lapid, 2000). The participating members become committed only if their individual performance is clearly linked to collaborative performance (Lambert & Pohlen, 2000). They also need a collaborative benchmarking that provides ideas of improvement based on comparisons between their collaborative performance against customers and competitors' requirements (Boyson et al., 1999; Cox et al., 1997, Watson, 1993). Previous research on benchmarking often emphasizes on internal performance metrics. It has paid little attention to the importance of collaborative metrics that span inter companies. It is limited to an individual company as a part of supply chain. A new relationship amongst independent and related members of the supply chain requires a new type of benchmarking that involves more than one company (Cox et al., 1997; Gunasekaran, 2002). This would make it relevant to study benchmarking that involves more than one company. A new scheme is required to help companies to identify clearly what areas need improvement and the use of benchmarking to provide direction of improvement.

This paper aims to conceptualizing a benchmarking scheme that assists the chain members to understand the supply chain performance involved among them. It can be used to compare the performance not only with the best in class practice but also with customer expectations in order to reinvent key levers used to enhance performance. This research moves away from intra company level to the inter company level and thereby provides an approach to the study of benchmarking in supply chain. Data Envelopment analysis (DEA) technique is proposed for benchmarking.

Benchmarking may be relevant in studying retailing phenomena by comparing the retail chains to standard set by successful retail firm in strategic domain of retailing such as retail promotion, pricing and supply chain activities. As the retailing function is playing an important role in firm's strategic decisions. It is a suggestive tool for companies to use for imitating leading firm's retailing practice. Parikh, D. (2004) study shows that layout of the store front has major impact on perceived service quality. The discrimination and expectation of customer have increased the dynamism of retail sector and the retail environment is changing more rapidly than ever before. It is characterized by identifying competition from both domestic and foreign companies, a spate of merger and acquisition, and more sophisticated and demanding customer. A successful retail enterprise has to have a vast network of people and error free processes in place (IIMB management Review Sept. 2006). Traditionally qualitative techniques are used to identify benchmark. Benchmarking experts suggest multi step approaches (Camp 1995, Camp, 1998, Spendolini 1992, Ncnair et al. 1995). Lau et al. (2001) has proposed an intelligent assessment system known as partner benchmarking assessment system which aimed for improving the current practice of partner selection, adopting the computational intelligence technologies. So the performance of the target benchmarked firm must be described. After that the firm has to decide which part to imitate. Benchmarking creates value by (PASBA, 2003):

- focusing on key performance gaps
- identifying ideas from other companies
- creating a consensus to move an organization forward
- making better decisions from a larger base of facts

Benchmarking goal should be measurable, attainable and actionable (Spendolini 1992). This has been largely conducted via qualitative procedure basically having an evaluation of best practices. For example in order to improve its retail supply chain, a company would examine their competitors to see how they handled their retail supply chain. As a result of their investigation, they would make changes to their processes that improve their response to such changes (Spendolini 1992). This type of benchmarking has become the standard practice. However, without a quantitative tool, it is difficult to determine "the best practice" which is adopted by management is really efficient in holistic sense. A company determines that their response to supply chain activities could be improved based on single process of competitor. But there may be other processes that could be altered to further enhance their efficiency.

The implementation of "best practices" has been the point of focus of most companies. It involves affecting business practices in order to emulate competitors who have an advantage. However it occurs in the absence of a robust methodology and proper measurement tool. A quantitative benchmarking tool should have the ability to analyze multiple inputs and outputs. It also provides feed back concerning areas which are needed for improvement. For example a retail firm may be very efficient in pricing policy but less efficient in supply chain activities. If this firm measured efficiency using ratio measure of pricing policy to spending on retail research, they may find that their

efficiency ratio is well above their competitors. But if that retail firm measured efficiency as a ratio between on time delivery rate to square feet of warehouse space, they may find that they are lagging behind their competitor. So benchmarking technique should provide a single measure of overall efficiency which can be compared to competitors. Hence there is a need to have a good methodology for benchmarking. The method should be able to identify a specific peer group to be used as a comparison group, which should be able to assist manager to set goal. Hence DEA technique may be represent as a balance one for quantifying benchmarking activities.

3. Concept of Data Envelopment Analysis

Farrell (1957) attempted to measure the efficiency of production in the single input and output case. Farrell's applied the model to estimate the efficiency of US agricultural output relative to other countries. But he failed to summarize all the various inputs and outputs into a single virtual input and single virtual output. Charnes, Cooper and Rhodes (1978) extended Farrell's idea and proposed a model which generalizes the single input, single output measure of efficiency of a Decision Making Unit (DMU) to a multiple input, multiple output setting. A DMU is an entity that uses inputs to produce outputs. The technique of DEA involves the use of Linear Programming (LP) to solve a set of inter related problems to determine the relative efficiency of DMUs. In retailing, a retail store constitutes a DMU.

The efficiency of a DMU is computed as:

$$\text{Efficiency} = \sum \text{weighted outputs} / \sum \text{weighted inputs}$$

DEA is an approach comparing the efficiency of organizational units such as schools, hospitals, shops, sales branch and similar instances where there is a relatively homogeneous set of units. It focuses on individual observations as represented by optimization of each observation in contrast to the focus on the averages and estimation (regression) of parameters that are associated with single optimization statistical approaches. The analysis will ensure outputs achieved from the inputs provided and will compare the group of DMUs by their strength in turning input into output. At the end of the analysis the DEA will be able to say which units are (relatively) efficient and which are (relatively) inefficient. The term 'relative' is important here which a DMU identified by DEA, as an efficient unit in a given data set may be deemed inefficient when compared using another set of data. The relatively "most efficient" units become the efficient frontier and the relative efficiency of other units is compared with the efficient frontier. An advantage of DEA is that it uses actual sample data to derive the efficient frontier that each unit in the sample is evaluated without prior information on the most important inputs and outputs in the evaluation.

3.1 Orientations in DEA

DEA has three orientations in efficiency analysis (Charnes 1994):

- Input oriented models are models where DMUs are deemed to produce a given amount of output with the smallest possible amount of input.
- Output Oriented models are models where DMUs are deemed to produce the highest possible amount of output with the given amount of input.
- Base oriented models are models where DMUs are deemed to produce the optimal mix of input and output.

4. Specification of inputs and outputs

Inputs	Outputs
1. Value of stock : X1 (in lakhs)	1. Annual sales Y1 (in lakhs)
2. Recurrent costs mainly in the form of wages: X2 (in lakhs)	2. Customer satisfaction: Y2
3. Floor space: X3 (in sq. mt.)	

5. Data source and methodology

The data for this study is collected from 25 retail stores of Sambalpur district of Orissa with a structured questionnaire and interviewing customers and retailers. The customer satisfaction is calculated as number of customer visiting to the particular retail store twice or more than twice. The DEA model is utilized to evaluate the data considering the above inputs and outputs.

5.1 Interpretation

As mentioned above (Table-3) eleven retail stores are best performers as they have the maximum efficiency score i.e. 100 percent. These eleven retail stores are regarded as efficient stores. The mean score of 25 DMUS is 0.871. The lowest relative efficiency score is 0.40 for DMU 6. The relative efficiency score of nine retail stores i.e. (DMU-1, DMU-2, DMU-3, DMU-9, DMU-13, DMU-14, DMU-22, DMU-23 and DMU-25) are falling in the range from 80 to 100 percent. Three retail stores are falling in the relative performance range of 60 to 70 percent.

5.2 Input and output slacks

Suppose the DMU A is the most efficient, we can set Performance Targets for the inefficient firms to enable them to reach 100 % relative efficiency. Since the DMU A has operated under similar environment and hence using its performance as benchmark is realistic. We are not assigning unrealistic targets.

Input Target: The input target for an inefficient unit say DMU B is the amount of input which shall be used by the inefficient DMU to produce the same level of output so as to make the DMU efficient one.

$$\text{Input Target} = \text{Actual Input} * \text{Efficiency}$$

Input Slack: For inefficient firms, Input target will be smaller than actual input. The difference between actual input and input target is usually called the Input Slack.

Input Slack for an inefficient DMU = Actual Input – Input Target

Input Slack can also be expressed in percentage.

$$\text{Input Target} = \frac{\text{Input Slack}}{\text{Actual Input}} * 100$$

Using a similar logic, we can compute *Output Targets* and *Output Slacks*.

$$\text{Output Target} = \frac{\text{Actual Output}}{\text{Efficiency}}$$

$$\text{Output Slack} = \text{Output Target} - \text{Actual Output}$$

$$\text{Output Target Percentage} = \frac{\text{Output Slack}}{\text{Actual Output}} * 100$$

The output slack and the input slack of all the 25 DMUs are calculated and shown in Table-4 and Table-5 respectively. The corresponding Input Target and Output Target can be calculated using the above formula described.

6. Sensitivity analysis

The sensitivity analysis has taken a variety of forms in the DEA literature. One part of this literature studies the responses when DMUs are deleted or added to the set being considered or when outputs or inputs are added to the set being considered or when outputs or inputs are added or withdrawn from consideration. Analytically oriented treatments of this topic are not lacking but most of this literature has taken the form of simulation studies, as in Banker et al. (1996). As in statistics or other empirically oriented methodologies, there is a problem involving degrees of freedom, which is compounded in DEA, because of its orientation to relative efficiency. In the envelopment model, the number of degrees of freedom will increase with the number of DMUs and decrease with the number of inputs and outputs. A rough rule of thumb which can provide guidance is as follows:

$$n \geq \max\{m \times s, 3(m + s)\}$$

Where n = number of DMUs, m = number of inputs and s = number of outputs

6.1 Sensitivity analysis of CCR-DEA result

The sensitivity of DEA efficiency can be verified by checking whether the efficiency of a DMU is affected appreciably. The detailed is given in Table-9.

1. If only one input or output is omitted from DEA analysis.
2. Dropping one efficient DMU at a time from DEA analysis.

For our study the robustness test of the DEA results obtained is done in two ways:

- Initially the **input** “wages” is dropped from the analysis and technical efficiency of DMUs is calculated, then input “floor space” is dropped, similarly the **outputs** “sales” is dropped one by one.
- At the second level the efficient units “DMU₄” and “DMU₁₆” is dropped one by one and technical efficiency is calculated.
- Dropping the input “X2” and “X3” one by one there is no significant change in TE score of DMUs. Efficient units remain efficient.

- The deviation in efficiency score is observed when the output “sales” is dropped from the analysis. DMU₁₁ and DMU₁₂ is becoming inefficient when “sales” is not considered. This is an indication that sale is an important output for such retail stores.
- When DMU₄ and DMU₁₆ dropped one by one – No change in the technical efficiency score of other efficient units.
- The above two-step analysis shows the robustness of DEA-CRS results.

7. DEA with VRS scale assumption

The second analysis is made with variable return to scale assumption, the efficiency of all the DMUs are calculated using output oriented model. The efficiency score of each DMU is calculated using output oriented model. The result is tabulated in Table-8. The input slack and output slack is displayed in Table-9 and Table-10. The input Target and Output Target are displayed in Table-11 and Table-12 respectively.

7.1 Comparison between various rankings

In the Table-14, the DMUs with efficiency score of unity will be referred as efficient unit, any technical efficiency score less than unity will be referred as inefficient unit. It is observed from the above results that, when CRS model is used fourteen DMUs i.e. DMU₁-DMU₃, DMU₅-DMU₉, DMU₁₃, DMU₁₄, DMU₂₀, DMU₂₂, DMU₂₃ and DMU₂₅ is emerging as inefficient units and calls for performance improvements. The benchmarking units for DMU₁ are DMU₄, DMU₁₁, DMU₁₂ and DMU₁₅. So DMU₁ shall refer these units for performance improvements. Similarly in VRS model only ten units are coming out as inefficient units i.e. DMU₁, DMU₅-DMU₉, DMU₄, DMU₂₀, DMU₂₂ and DMU₂₅ and the corresponding benchmarking units are mentioned in the last column of table-2. Each inefficient unit can find their respective benchmarking units and take necessary steps to become efficient unit. Moreover, further analysis is possible to find how much weightage shall be attached to each benchmarking units by individual inefficient DMUs and improvement target on each parameters for individual inefficient DMUs.

8. Reviewing the Long Term Prospects of Each Retail Store

The long term prospects of each retail stores can not be ascertained from its historical sales alone. Historical sales may not reflect the potential of the market of a retail store which better management could exploit. Once the retail efficiency and sales of a retail store are known we can judge its long-term prospects by means of “Efficiency versus Sales Matrix” depicted in (figure-2). Efficiency and sales of all the DMUs are taken into account. According to the Efficiency Sales matrix DMUs, 4,10,12,13,14,15,16,17,18,22,23,24,25 are regarded as star performers. DMUs-2, 3, 11, 9, 19 and 21 are mentioned as question mark (?). Here more investment is required to revive them. DMUs- 6, 7, and 8 are denoted as sleeper. The rest DMUs are under dog category. They are the lowest performing unit relative to others.

9. Strength and Weakness of DEA

9.1 Strengths of DEA

- DEA can handle multiple input and multiple output models.
- DEA identifies the possible peers as role models who have an efficiency score of 1 and sets improvement targets for them.
- By providing improvement targets DEA acts as an important tool for benchmarking
- The possible sources of inefficiency can be determined using DEA

9.2 Weaknesses of DEA

As DEA is deterministic rather than stochastic DEA produces results that are particularly sensitive to measurement errors. If an input of a DMU is understated or the output is overstated then the organization can become the outlier that significantly distorts the shape of frontier and reduces the efficiency score of nearby organization.

DEA score is sensitive to input and output specifications and the size of the sample. Increasing the size of the sample will tend to reduce the average efficiency score, as more DMUs provide greater score for DEA to find similar comparison partners. Conversely too small DMUs relative to the number of inputs and outputs can artificially inflate the efficiency score.

10. Conclusion

The paper presents applications of DEA to determine relative efficiency of retail stores. The paper presents applications of DEA to determine relative efficiency of retail stores. The sales of DMUs-2, 3, 11, 9 19 and 21 can be increased. So proper attention should be given to this DMU

The management has to think of about DMUs 6, 7, and 8 because of their low efficiency and poor sales. It is interesting if one can take the non-discretionary inputs like location, manager’s experience and others to measure the

benchmarking. Retailers must be aware about good customer service, so that they not only enhance, attract and retail customer but also customer delight can be achieved which is an asset to the company.

References

- Balaji, Chetan., Tuli, Rajnish., & Srivastave, Nidhi, V. (2005). *Retail Management*, Oxford University Press, New Delhi.
- Bowersox, D.J., Closs, D.J., Stank, T.P., & Keller, S.B. (2000). How supply chain competency leads to business success. *Supply Chain Management Review*, 4 (4) 70 – 77.
- Boyson, S., Corsi, T.M., Dresner, M.E., & Harrington, L.H. (1999). *Logistics and the Extended Enterprise: Benchmarks and Best Practices for the Manufacturing Professional*, Wiley: New York.
- Camp, Robert, C. (1989). *Benchmarking: the search for Industry Best practices that Lead to Superior Performance*. ASQC Quality Press: Milwaukee.
- Camp, Robert, C. (1995). *Business Process Benchmarking*, ASQ Quality Press, Milwaukee, WI.
- Camp, Robert, C. (1998). *Global Cases in Benchmarking*, ASQ Quality Press, Milwaukee, WI.
- Charnes, A., Cooper, W.W., and Rhodes, E. (1978). Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research*, 1.3, 429-444.
- Charnes, A., Cooper, W.W., Lewin, A.Y., and Seiford, L.M. (1994). *Data Envelopment Analysis: Theory, Methodology and Application*, Kluwer Academic Publishers, Boston.
- Churchill, Gilbert, Jr., and Peter paul, J. (1999). *Marketing: Creating Value for Customers*, (2nd ed.). McGraw Hill, Boston.
- Cox, J.R.W., Mann, L., & Samsom, D. (1997). Benchmarking as a mixed metaphor: disentangling assumptions of competition and collaboration. *Journal of Management Studies*, 34 (2), 285-314.
- Gunasekaran, A. (2002). Editorial benchmarking in logistics. *Benchmarking: An International Journal*, 9 (4), 324 -325.
- Kottler, Philip. (2004). *Marketing Management*, (11th ed.), Prentice Hall of India, pvt. Ltd., New Delhi.
- Lambert, D.M., & Pohlen, T.L. (2001). Supply Chain metrics. *International Journal of Logistics Management*, 12 (1) 1– 19.
- Lapide, L. (2000). True measures of supply chain performance. *Supply Chain Management Review*, 4 (3), 25-28.
- Lau, H.C.W., Lee, W.B. and Lau, P.K.H. (2001). Development of an intelligent decision support system for benchmarking assessment for business partners. *Benchmarking: An International Journal*, 8(5), 376-95.
- Ncnair, C.J., Kathleen, H.J., Leibfried, Carol, J. Mc Nair. (1995). *Benchmarking: A tool for continuous improvement*, John Wiley & Sons, NY.
- Parikh, Darshan. (2006). Profiling Internet Shoppers: A study of Expected adoption of Online shopping In India. *IIMB Management Review*, Vol. 18, No. 3, pp. 221-231.
- Parikh, D. (2004). *Measuring Retail Service Quality: An Empirical study in a Developing Country*. in the proceedings of COSMAR-2004, Indian Institute of Science, Bangalore.
- Parks, L. (2001). Wal-Mart gets onboard early with collaborative planning. *Drug Store News*, 23 (2), 14.
- PASBA. (2003). Procurement and Supply Chain Benchmarking Association. [Online] Available: <http://www.pasba.com/benchmarking> (Retrieved from 21st October, 2007).
- Spendolini, M.J. (1992). *The Benchmarking Book*, American Management Association, New York.
- Stewart, G. (1997). Supply Chain operations reference model (SCOR): the first cross-industry framework for integrated supply chain management. *Logistics Information Management*, 10 (2), 62-67.
- Watson, G.H. (1993). *Strategic Benchmarking*, Wiley, New York, NY.

Table 1. Data of Inputs and Outputs

DMUs	(I)Value of stock	(I)wage	(I)Floor Space	(O)Sales	(O)Customer Satisfaction
1	40	13	288	47	45
2	65	8	200	37	35
3	35	9	387	31	50
4	40	13	382	62	50
5	60	17	360	47	45
6	45	12	268	12	30
7	48	10	277	19	33
8	50	9	213	31	36
9	65	11	299	16	70
10	60	16	282	62	75
11	37	11	286	31	80
12	43	25	321	47	80
13	80	14	254	62	50
14	99	14	304	47	65
15	40	12	275	62	33
16	54	7	243	55	35
17	65	11	227	56	45
18	60	12	225	55	50
19	43	7	220	35	50
20	60	14	275	42	35
21	40	6	285	30	45
22	55	9	256	45	55
23	50	10	260	50	60
24	45	8	211	42	55
25	55	10	243	40	50

Table 2. Descriptive Statistics

INPUTS				OUTPUTS	
	X1	X2	X3	Y1	Y2
Min.	99	25	387	62	80
Max.	35	6	200	12	30
Mean	53.36	11.52	273.64	42.52	50.28
S.D	14.291	3.889	48.853	14.128	14.349
Sum	1334	288	6841	1063	1257

The efficiency scores and weights are presented in table-3 after running it through DEA solver pro.5.0

Table 3. Efficiency Score and Weights of each Decision Making Unit (Output oriented DEA, Scale Assumption: CRS)

DMU	Efficiency	Wx1	Wx2	Wx3	Wy1	Wy2
1	0.886	1.78E-02	4.84E-03	1.23E-03	1.36E-02	8.02E-03
2	0.828	0	4.20E-02	4.36E-03	1.96E-02	7.86E-03
3	0.876	0.015138	6.79E-02	0	1.58E-02	1.02E-02
4	1	0.025	0	0	1.61E-02	0
5	0.636	1.29E-02	0.017599	1.37E-03	1.36E-02	8.06E-03
6	0.400	0	0	9.31E-03	3.92E-03	3.18E-02
7	0.462	0	0.181967	1.23E-03	4.70E-03	2.76E-02
8	0.683	0	3.78E-02	5.27E-03	0.021035	9.66E-03
9	0.873	0	1.00E-01	1.51E-04	0	1.43E-02
10	1	8.95E-03	0.012177	9.51E-04	9.38E-03	5.58E-03
11	1	0	0	3.50E-03	1.47E-03	1.19E-02
12	1	0.016549	0	8.98E-04	1.17E-02	5.65E-03
13	0.989	0	0	3.98E-03	1.50E-02	1.41E-03
14	0.803	0	6.83E-03	3.78E-03	2.77E-03	1.34E-02
15	1	0.025	0	0	1.61E-02	0
16	1	1.12E-02	5.67E-02	0	1.82E-02	0
17	1	2.04E-03	0	3.82E-03	1.79E-02	0
18	1	2.66E-03	2.34E-03	3.61E-03	1.82E-02	0
19	1	0	0.133127	3.10E-04	8.67E-03	1.39E-02
20	0.651	6.40E-03	0	4.18E-03	2.07E-02	3.74E-03
21	1	4.77E-03	0.134886	0	1.34E-02	1.33E-02
22	0.909	0	0.115811	2.25E-04	8.68E-03	1.11E-02
23	0.985	1.14E-02	2.18E-02	8.79E-04	1.18E-02	6.81E-03
24	1	3.69E-03	0.104271	0	1.03E-02	1.03E-02
25	0.800	0	1.77E-02	4.41E-03	1.37E-02	9.06E-03
Mean	0.871	0.007	0.0423	0.002	0.012	0.008

Table 4. Summary of output slack (Output Oriented DEA, Scale Assumption: CRS)

DMU	Y1	Y2
1	0	0
2	0	0
3	0	0
4	0	0
5	0	0
6	0	0
7	0	0
8	0	0
9	14.00211	0
10	0	0
11	0	0
12	0	0
13	0	0
14	0	0
15	0	0
16	0	0
17	0	0
18	0	0
19	0	0
20	0	0
21	0	0
22	0	0
23	0	0
24	0	0
25	0	0

Table 5. Summary of Input Slack (Output oriented DEA, Scale Assumption CRS)

DMU	X1	X2	X3
1	0	0	0
2	16.324	0	0
3	0	0	144.738
4	0	0	0
5	0	0	0
6	9.660	1.545	0
7	0.187	0	0
8	0.831	0	0
9	26.002	0	0
10	0	0	0
11	0	0	0
12	0	0	0
13	7.406	1.657	0
14	38.585	0	0
15	0	0	0
16	0	0	0
17	0	0	0
18	0	0	0
19	0	0	0
20	0	6.84E-02	0
21	0	0	0
22	1.927	0	0
23	0	0	0
24	0	0	0
25	1.811	0	0

Table 6. Sample of Input targets (Output Oriented DEA, Scale Assumption: CRS)

DMU	X1	X2	X3
1	40	13	288
2	48.675	8	200
3	35	9	242.261
4	40	13	382
5	60	17	360
6	35.339	10.454	268
7	47.812	10	277
8	49.168	9	213
9	38.997	11	299
10	60	16	282
11	37	11	286
12	43	25	321
13	72.593	12.342	254
14	60.414	14	304
15	40	12	275
16	54	7	243
17	65	11	227
18	60	12	225
19	43	7	220
20	60	13.931	275
21	40	6	285
22	53.072	9	256
23	50	10	260
24	45	8	211
25	53.188	10	243

Table 7. Sample of Output Targets (Output Oriented DEA, Scale Assumption: CRS)

DMU	Y1	Y2
1	53.04351	50.78634
2	44.6684	42.25389
3	35.36968	57.04786
4	62	50
5	73.79437	70.65418
6	29.94191	74.85478
7	41.04716	71.29243
8	45.36486	52.68177
9	32.31924	80.13742
10	62	75
11	31	80
12	47	80
13	62.64504	50.5202
14	58.51027	80.91846
15	62	33
16	55	35
17	56	45
18	55	50
19	35	50
20	64.43963	53.69969
21	30	45
22	49.49447	60.49324
23	50.74141	60.88969
24	42	55
25	49.96905	62.46131

Table 8. Result of Sensitivity Analysis

DMU	Eff.	Dropping (X2)	Dropping (X3)	Dropping (Y1)	Dropping DMU-4	Dropping DMU-16
1	0.886	0.871	0.812	0.758	0.886	0.886
2	0.828	0.767	0.709	0.777	0.828	0.886
3	0.876	0.786	0.876	0.625	1	0.876
4	1	1	1	1		1
5	0.636	0.630	0.582	0.570	0.636	0.636
6	0.400	0.400	0.342	0.195	0.400	0.400
7	0.462	0.435	0.460	0.313	0.462	0.462
8	0.683	0.651	0.630	0.616	0.683	0.683
9	0.873	0.836	0.854	0.232	0.873	0.873
10	1	1	1	1	1	1
11	1	1	1	0.543	1	1
12	1	1	1	0.705	1	1
13	0.989	0.989	0.708	0.989	0.989	0.989
14	0.803	0.794	0.638	0.633	0.803	0.803
15	1	1	1	1	1	1
16	1	1	1	1	1	
17	1	1	1	1	1	1
18	1	1	1	1	1	1
19	1	1	1	1	1	1
20	0.651	0.651	0.555	0.644	0.651	0.651
21	1	1	1	1	1	1
22	0.909	0.807	0.903	0.766	0.909	0.952
23	0.985	0.927	0.976	0.842	0.985	0.985
24	1	1	1	1	1	1
25	0.800	0.771	0.756	0.702	0.800	0.800

Table 9. Efficiency Score and Weights of each Decision Making Unit (Output oriented DEA, Scale Assumption: VRS)

DMU	Efficiency	W_{x1}	W_{x2}	W_{x3}	W_{y1}	W_{y2}
1	0.886	1.54E-02	5.76E-03	1.23E-03	1.35E-02	0.0081
2	1	0	5.75E-02	1.26E-02	2.68E-02	2.05E-04
3	1	4.13E-02	8.94E-02	0	1.82E-02	8.72E-03
4	1	0.025	0	0	1.61E-02	0
5	0.758	0	0	0	2.13E-02	0
6	0.405	0	0	1.11E-02	0	3.33E-02
7	0.484	0	0.117	0	1.60E-02	0.021072
8	0.699	5.29E-03	0	2.43E-02	0.032258	0
9	0.875	0	0.1	0	0	1.43E-02
10	1	8.95E-03	0.0122	9.51E-04	9.38E-03	5.58E-03
11	1	0	0	3.50E-03	1.47E-03	1.19E-02
12	1	0.0165	0	8.98E-04	1.17E-02	5.65E-03
13	1	0	0	3.59E-03	1.49E-02	1.54E-03
14	0.880	0	4.00E-02	0	8.00E-03	9.60E-03
15	1	0.025	0	0	1.61E-02	0
16	1	1.12E-02	5.67E-02	0	1.82E-02	0
17	1	2.04E-03	0	3.82E-03	1.79E-02	0
18	1	2.66E-03	2.34E-03	3.61E-03	1.82E-02	0
19	1	0	0.133	3.10E-04	8.67E-03	1.39E-02
20	0.677	0	0	0	2.38E-02	0
21	1	4.77E-03	0.135	0	1.34E-02	1.33E-02
22	0.966	0	6.53E-02	0	1.02E-02	9.87E-03
23	1	8.78E-03	2.30E-02	8.19E-04	1.22E-02	6.51E-03
24	1	3.69E-03	0.104271	0	1.03E-02	1.03E-02
25	0.831	0	4.67E-02	9.05E-04	9.42E-03	1.25E-02
Mean	0.898	0.007	0.039	0.002704	0.014	0.0074

Table 10. Result of Input slack (Output Oriented DEA, Scale Assumption: VRS)

DMU	X1	X2	X3
1	0	0	0
2	1.55E-03	0	0
3	0	0	1.13E-02
4	0	0	0
5	0	1	78
6	6.080	1.720	0
7	5.242	0	16.299
8	0	0.146	0
9	28	0	13
10	0	0	0
11	0	0	0
12	0	0	0
13	0	0	0
14	45.551	0	24.432
15	0	0	0
16	0	0	0
17	0	0	0
18	0	0	0
19	0	0	0
20	5.714	0	0
21	0	0	0
22	7.116	0	18.613
23	0	0	0
24	0	0	0
25	5.834	0	0
Mean	4.142	0.115	6.014

Table 11. Summary Output of Output slack (Output Oriented DEA, Scale Assumption: VRS)

DMU	Y1	Y2
1	0	0
2	0	0
3	0	0
4	0	0
5	0	15.638
6	4.039	0
7	0	0
8	0	0.658
9	12.714	0
10	0	0
11	0	0
12	0	0
13	0	0
14	0	0
15	0	0
16	0	0
17	0	0
18	0	0
19	0	0
20	0	1.762
21	0	0
22	0	0
23	0	0
24	0	0
25	0	0
Mean	0.670	0.722

Table 12. Result of Input Targets (Output Oriented DEA, Scale Assumption: VRS)

DMU	X1	X2	X3
1	40	13	288
2	64.998	8	200
3	35	9	386.988
4	40	13	382
5	60	16	282
6	38.919	10.28	268
7	42.757	10	260.700
8	50	8.854	213
9	37	11	286
10	60	16	282
11	37	11	286
12	43	25	321
13	80	14	254
14	53.448	14	279.567
15	40	12	275
16	54	7	243
17	65	11	227
18	60	12	225
19	43	7	220
20	54.285	14	275
21	40	6	285
22	47.884	9	237.386
23	50	10	260
24	45	8	211
25	49.166	10	243
Mean	49.218	11.405	267.625

Table 13. Result of Output Targets (Output Oriented DEA: Scale Assumption VRS)

DMU	Y1	Y2
1	52.988	50.733
2	37	35
3	31	50
4	62	50
5	62	75
6	33.639	74.000
7	39.253	68.177
8	44.327	52.135
9	31	80
10	62	75
11	31	80
12	47	80
13	62	50
14	53.392	73.84
15	62	33
16	55	35
17	56	45
18	55	50
19	35	50
20	62	53.428
21	30	45
22	46.567	56.916
23	50	60
24	42	55
25	48.138	60.173
Mean	47.612	57.496

Table 14. Comparison between Various Ranking

DMU	Crste	vrste	Scale Efficiency	Benchmarking Units (CRS)	Benchmarking Units (VRS)
1	0.886	0.886	0.998	4,11,12,15	4,10,11,12,15
2	0.828	1	0.828	16,17,24	
3	0.876	1	0.876	4,11,24	
4	1	1	1		
5	0.636	0.758	0.840	10,11,15,24	10
6	0.400	0.405	0.988	10,11	11,24
7	0.462	0.484	0.956	11,19,24	11,23,24
8	0.683	0.699	0.977	17,18,24	2,18,24
9	0.873	0.875	0.998	11,21	
10	1	1	1		
11	1	1	1		
12	1	1	1		
13	0.989	1	0.989	17,18	
14	0.803	0.880	0.912	10,11,24	10,11,23
15	1	1	1		
16	1	1	1		
17	1	1	1		
18	1	1	1		
19	1	1	1		
20	0.651	0.677	0.962	10,15,18	10,13,15
21	1	1	1		
22	0.909	0.966	0.940	16,21,24	16,23,24
23	0.985	1	0.985	4,11,15,24	
24	1	1	1		
25	0.800	0.831	0.963	10,18,24	10,11,23,24
Mean	0.871	0.898	0.968		

Note: crste = technical efficiency from CRS DEA; vrste = technical efficiency from VRS DEA;
scale efficiency = crste / vrste

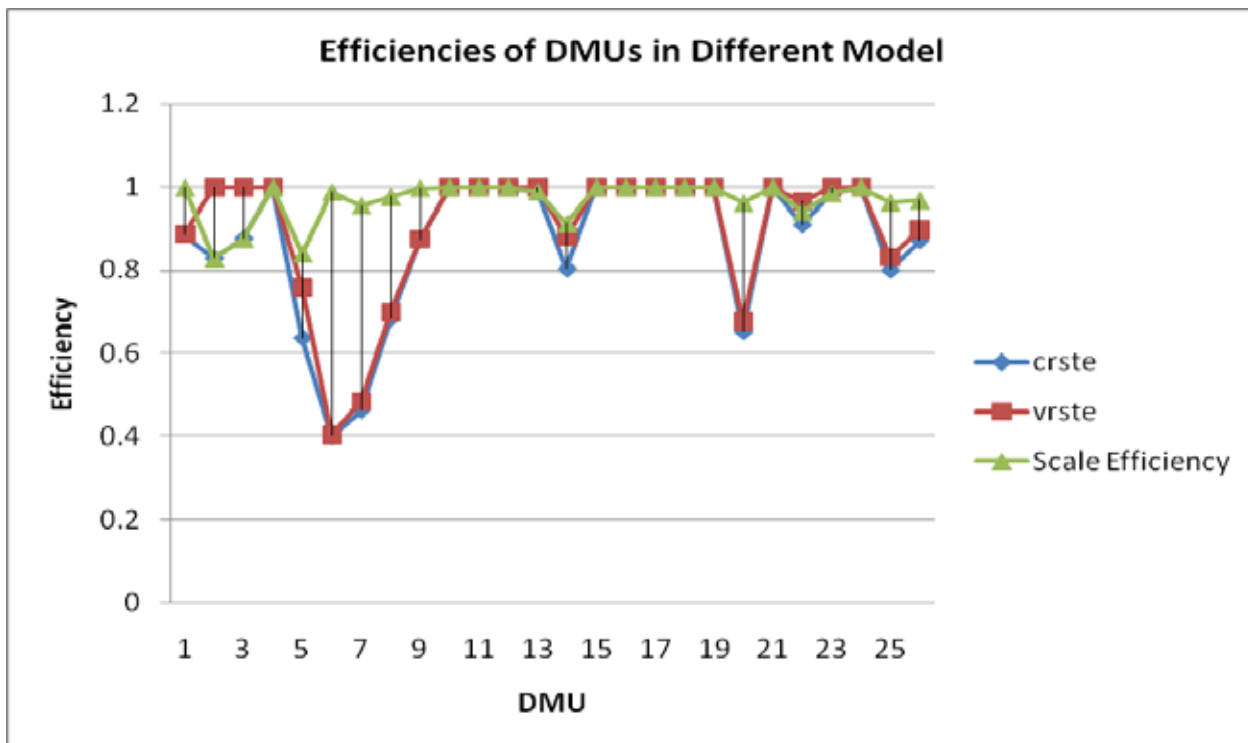


Figure 1. Efficiency of DMUs in Different Model

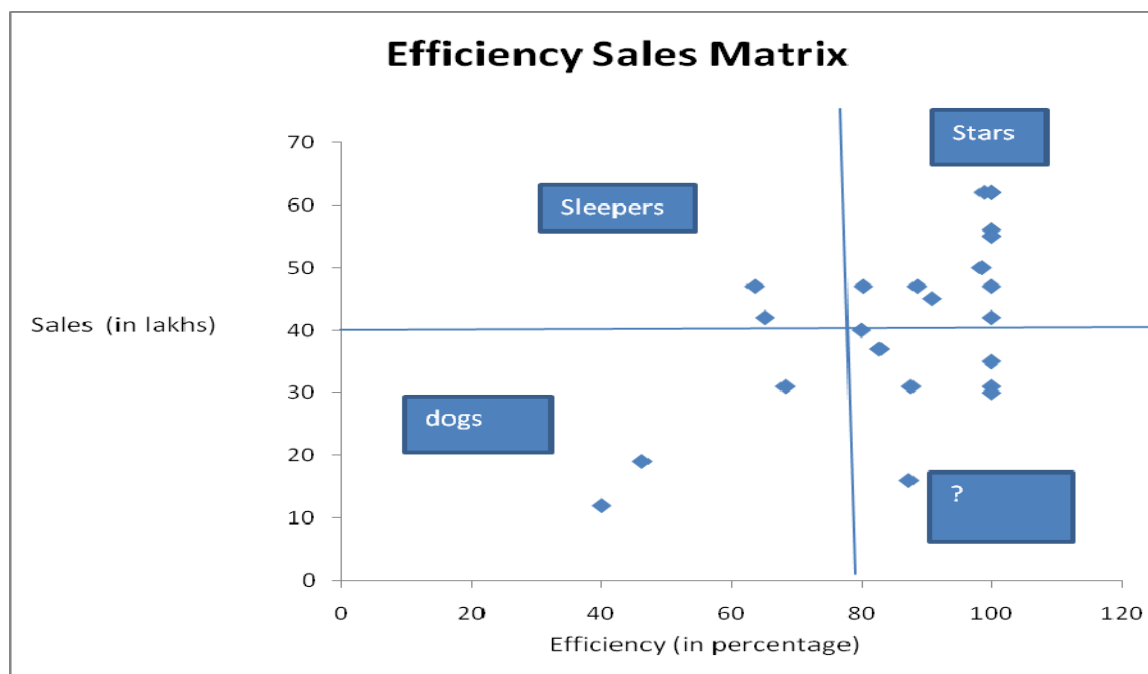


Figure 2. Efficiency Sales Matrix