EFFICIENCY EVALUATION OF INDIAN PLASTIC MANUFACTURING UNITS USING SLACK BASED DATA ENVELOPMENT ANALYSIS

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ABSTRACT

Performance measurement of any industry is very crucial in order to cope with the competition, the efficiency analysis is considered as one of the most valuable and essential tools for the same. In this paper, the efficiency is tested for plastic using Data Envelopment Analysis (DEA), which is an important raw-material for many industries. Though the profit after sales of plastic industries exhibits fixed random effects over the years, none of the independent variables are statistically significant. Data Envelopment Analysis has varied applications in measuring comparative efficiency of decision-making units. One of the prime applications is used to measure the efficiency of the manufacturing companies considering discretionary and non-discretionary inputs and to find out the lacks of each unit to increase their performance. This paper calculated the technical efficiency of the 28 plastic manufacturing units of India from 2018-20. The non-parametric DEA approach is used for compute the efficiency score. Furthermore, the results classify the numerous firms according to their performance and identify the "best." Similarly, efficiency methodologies evaluate performance compared to the most efficient organizations. Slag based efficiency analysis is used to evaluate the performance of plastic manufacturing firms. The model considers the profit after tax deduction as an output and raw material, employee benefits, power fuel and lease rent as input variables respectively. By planning their inputs and outputs in conjunction with efficiency that their competitors have attained, plastic manufacturing firms can emulate the efficiency of their competitors. The firms which are more efficient would surely get more global orders and can gain competitive advantage over their competitors.

KEYWORDS: Data envelopment analysis; efficiency; plastic manufacturing units; Discretionary variables

MSC: 62P30

RESUMEN

El desempeño de toda industria es crucial para lidiar con la competencia, analizar la eficiencia es considerada como una de las herramientas más valiosas y esenciales para ello. En este paper, se prueba la eficiencia para el plástico usando Análisis Envolvente de Datos (Data Envelopment Analysis, DEA), lo cual es muy importante materia prima de la industria. Aunque las ganancias de las ventas de la industria del plástico exhiben efectos fijos a través de los años , ninguna de las independientes variables es estadísticamente significante. Data Envelopment Analysis tiene variadas aplicaciones en la medición comparativa de la eficiencia de las unidades de toma de decisión. Una de las primeras es usada para medir la eficiencia de las compañías manufactureras considerando entradas discrecionales y no-discrecionales para hallar las elasticidades de cada unidad para incrementar el desempeño. En este paper se calculó la técnica eficiencia de 28 unidades manufactureras de unidades del plástico en India durante 2018-20. El no-paramétrico DEA fue usado para computar de la eficiencia de su score. Además , los resultados clasifican las numerosas firmas de acuerdo a su habilidad para identificar el “mejor”. Similarmente, metodologías de eficiencia evalúan el desempeño comparando con las más eficientes organizaciones. Basado en el análisis “Slag-efficiency” se evaluó el desempeño de las firmas. El modelo considera las ganancias , deducidos los impuestos como una salida y la materia prima, beneficios de los empleados, combustible usado, y las rentas como “input variables”. Planeando sus inputs y outputs en conjunción con la eficiencia que obtuvieron sus competidores, las firmas pueden emular la de sus competidores. Las firmas más eficientes de seguro obtendrán más órdenes globales y obtener competitiva ventaja sobre sus competidores.

PALABRAS CLAVE: Análisis Envolvente de Datos; eficiencia; unidades manufactureras de plástico; Discrecionales variables

1. INTRODUCTION

Technology is an indispensable component of our life and in the globalizing economy, it is important that companies retain their market position in accordance with changing circumstances. In order to make India self-reliant and curb the unemployment issue, in May 2020 government has conceptualized “Atmanirbhar Bharat” program to create new jobs in manufacturing sector and establish the country as a manufacturing hub (Al-Faraj et al.,1993). As per Business Standard (Banker et al.,1986) post COVID-19 as many of the international companies are planning to shift their manufacturing in India and this would embark manufacturing as an emergent sector in India. Many industries namely automotive, construction, electronics, healthcare, textiles, and FMCG are supported by plastics manufacturing industry as plastic is considered to be a vital raw material or semi-finished good for them. Plastic industry in India is one of the biggest in the world and holds the first position with production volume at 16 MMTPA (Million Metric Ton Per Annum) in Year 2017 (FY2017) and expecting 26 MMTPA by 2021. Indian plastic manufactures are actively searching opportunities in the global market. The COVID-19 pandemic is encouraging many developed countries to consider India and other developing countries as possible alternatives destination of setting up manufacturing plants. As per the Kearney a Global Consulting firm suggested the for India the efficiency improvement and the innovation are two very important factors in order to cope up with the global competition. Measurement of the performance of plastic manufacturing sectors is essential in this context (Banker et al., 1984). Companies measure their products, services, and processes against those of other organizations through benchmarking. Benchmarking is the process of identification and learning from the best practices (Johnson and Misic, 1999) and one of the valuable approaches to achieve and cope up with the competition (Elmuti, 1998). Efficiency can be achieved by effective use of inputs, which are influenced by various factors like production techniques, technological innovation management skills and labour (Ertay et al., 2006). Plastic manufacturing industry is always received lots of attention from the researches in conducting research on various aspects related to plastics like environmental impact, recycling, exports, adopting new technologies and policy decisions. After reviewing the literature, very few researches have been conducted on efficiency measure of plastic industry.

Authors have conducted research on Data Envelopment Analysis (DEA) approach to measure the efficiency of plastic manufacturing by calculating the relative efficiencies of a group of homogenous Decision-Making Units (DMUs), using multiple uncompensated inputs to achieve multitudinous uncompensated outputs. One of the pioneers of DEA work was conceptualized by (Charnes et al., 1978), explaining DEA as an efficient methodology used to measure the relative effectiveness of a group of homogeneous DMUs by using linear programming technique. DEA can be used in many real-life contexts, including school systems, health units, farming production, military logistics and many other applications. DEA approach was first used for measuring technological operation only and was applied in the proposition of constant returns to scale. Further, (Banker et al.,1986) advances DEA approach using variable returns for scale activity and altered (Charnes et al., 1985) linear programming model for the calculation of technical efficiency and scale return. DEA measures the technical effectiveness of the DMUS of an organization, and using DEA, technical efficiency can be determined by the maximization of the output relative to the DMUs input quantity or the minimization of the input subject to the output.

It is critical to specify the inputs and outputs that will be examined for the research in order to use DEA. Additionally, it is important to evaluate the use of convenient inputs and outputs in order to avoid drawing conclusions that are deceptive. The goal of this paper is to utilise DEA to evaluate the relative efficiency of plastics manufacturers. This method compares and analyses the efficiency of enterprises based on their own inputs and outputs. Following data processing, it will be clear which organisations are already efficient and which are not. The goal of this study to accomplish two things: (1) To identify the most convenient inputs and outputs for measuring the performance of firms. (2) To allow for the establishment of a rating of efficient enterprises amongst themselves.

The purpose of this study is to calculate the technical efficiency score and identify the elements that influence technical efficiency in a plastic manufacturing company in India for the period 2018-2020 using the slack-based DEA approach. The model considered profit after tax deduction as an output and raw material, Employee benefits, power fuel and lease rent as input variables respectively. The model identified the total efficiency of plastic manufacturing and this would guide the plastic manufacturing firms by planning their inputs and outputs in a manner so that they can achieve the efficiency as per their competitors. The firms which are more efficient would surely get more global orders and can gain competitive advantage over their competitors. In this study, we have calculated the efficiency of 28 plastic manufacturing organizations of India measured for the period 2018–2020 using input and output slacks as well as considering discretionary and non-discretionary input variables. Some of the main highlights of this paper are listed below:

- The efficiency of plastic manufacturing companies was measured using DEA approach considering discretionary and non-discretionary inputs to find slacks of each unit to increase their performance.
- Lease rent (non-discretionary inputs), raw material, power, employee benefits have been considering as an input variable.
- Profit after sales has been consider as an output variable, it exhibits fixed random effects over the years.

2. REVIEW OF LITERATURE

The 1980s reforms resulted in increased in the Indian economy's growth and productivity, particularly in the manufacturing sector. Industry can only thrive if it is more efficient and effective than its competitors. Efficiency is accomplished by effective input utilization, which is based on a variety of factors such as manufacturing techniques, technical innovation, management skills, and labour. Additionally, the environment constraint can be considered. By implementing the DEA approach, detailed insights into operational and environmental performance can be shared, including a broad identification of inefficiency causes. This strategy promotes resource efficiency and also assists inside the reduction of carbon footprints (Rebolledo-Leiva et al., 2021). Enhancing the efficiency of water resource management is essential to promoting. The data envelopment analysis method (DEA) is used to evaluate the financing efficiency of emerging industries of China, the tobit analysis method is used to identify low and high efficiency industries like the bio-pharmaceutical industry, the energy-saving and environmental protection industry have the highest efficiency level, and the high-end equipment manufacturing industry and the new energy industry have the lowest level of financing efficiency (Chen and Wang, 2020). Financial system stability is not only supported by the banking sector, but also the role of insurance companies that operate efficiently. The efficiency level of general insurance companies experiencing a upward trend as per the non-parametric data envelopment analysis (DEA) approach and the only factor which determines the efficiency level of insurance companies are the cost ratio (Abin et al., 2022).

It is very challenging to measure efficiency for various sectors, in such situations DEA is the most popular technique for measuring the efficiency of manufacturing sectors (Ertay et al., 2006). To measure the efficiency, the maximum of the ratio of weighted inputs and output is analyzed (Bolandnazar et al., 2014), and inefficient units are compared with those units which are showcasing better performance (Liu, 2008). (Thanassoulis, 2001) explained that in DEA the resources are mentioned as "inputs" and conclusions as "outputs". The identification of inputs and the outputs is very crucial and tough in assessing the efficiency of the DMUs. The inputs should be selected taking into consideration all resources that influence the output, as well as the output should reflect all beneficial outcomes for which the DMUs should be evaluated. Depending on the direction of the impact, every one of the environmental factors that explain the conversion of resource to results should be expressed in the input or output.

Basically, DEA model are of two types, input or output oriented. Output oriented measures the efficiency without increasing output and input oriented without decreasing any inputs. It overcomes the limitation of allowing number of inputs and outputs as it allows multiple inputs and outputs simultaneously though in regression analysis multiple inputs and outputs are possible but not possible to give any benchmarking and the feedback for the improvement (Cooper, 2000, 2001). Application of DEA was used by (Al-Faraj et.al.,1993) to appraise the relative efficiency of the DMUs (bank branches). The objective is to efficiently utilize the resources in order to improve the services. This would help to identify the unproductive branches and list out the reasons for the same and on the basis of the decision can be taken to continue or discontinue the inefficient branches. A model developed by (Elmuti, 1998) based on used widely among researchers to check the technical efficiency. It is a mathematical technique that utilizes linear programming (LP) to ascertain the efficiency level of a collection of functionally similar decision-making units (DMUs). (Köksalan and Tuncer, 2009) used DEA to compare the relative efficiencies of nine production lines in an electronics industry in Bangladesh. The efficiency of 1007 manufacturing firms for the total annual sales, total annual cost, annual of raw material cost, annual expenditure on electricity and number of permanent full-time workers are utilized as input variables and total annual sales is used as output variable.

Low productivity in hotel industry is one of the major concerns, DEA method was used to measure and benchmark productivity of hotels (Nimisha and Dharmaraj, 2016). The factors used to measure DEA can be implemented to measure the quantitative factors and provide the information and empower the managers in their decision-making (Borenstein et al., 2014). The two-stage DEA method was used to measure the technical efficiency of plastic manufacturing firms in Malaysia. The input factors are the labour, training expenses, educational level, wage rates, information and communications technology expenses, firm size and sales is considered as the only output factor (Moharir and Kumar, 2019). The empirical results of DEA help to suggest that there is a strong role for RandD and need to reduce the production time in order to improve the manufacturing performance among major automobile producers producing is larger volume (Leachman et al., 2005). DEA is also used for wafer fabrication industry in Taiwan to evaluate the efficiency, as per the analysis it is recommended to introduce the new technology to improve its technology change effect (Chen and Chen,2009). (Farooq and Brien, 2010) illustrated how DEA can be used in supply chain operations to assist an organization in selecting a manufacturing technology that otherwise meets its own requirements, but also the interests of its constituent supply chain. Six input variables are considered in this framework: labour, higher absenteeism, style change, total machines, and overall number of malfunctioning machines; and three output variables are used to evaluate efficiency: production quantity, production duration, and quality. The discrete events simulation technique for a period of two years considering diverse scenarios for manufacturing system was studied by (Sofianopoulou, 2006), efficiency of each scenario was measured DEA approach.

3. RESEARCH METHODOLOGY

Authors' focus was to measure the efficiency on the basis of variable returns to scale of 28 plastic manufacturing units considering three consecutive years data from 2018 - 2020. The efficiency was contemplated by the extent to which a DMU can maximize the output from its selected combination of inputs.

3.1 Data and Variables

Data about select 28 plastic manufacturing organizations was obtained from Prowess database, which is the part of Centre for Monitoring Indian Economy (CMIE). CMIE is an independent consortium, the idea of its conceptualization is to deliver information the form of databases and research reports.
Appendix A is comprised of detailed list of select plastic manufacturing companies. In DEA approach the choice of input and output variables are very important and crucial (Venkateswarlu and Subramanyam, 2015). Authors have deliberated on several criteria's for deciding inputs and outputs. Firstly, they considered the availability of factual data, secondly for guaranteeing the validity of the research the literature survey is used and lastly the expert opinion from managers was considered (Banker and Morey,1986).
Researchers do not consider same set of performance criteria even though they are focussing on the same practical scenario. Criteria selection is reliant on numerous factors like availability of data, profession and background of decision makers including this the managerial rankings is also one of the deciding factors (Verma et al., 2016). The authors of this study considered all necessary criteria when selecting the inputs. Studies have examined various output measures, including sales revenue, operating results, value added, profit, and market share. The authors included sales as such an output variable in this study because that reflects the firm's objectives (Sigala, 2004). Based on literature survey and availability of the data, the authors estimated the input variables specifically employee benefits, raw material, power expenses. The rule based on which the number of DMUs are selected is reliant on number of input and output variables considered and it must be twice the sum of inputs and outputs (Charnes et al., 1985 and Farrell, 1957). As authors have considered 4 inputs and 1 output which give the total as 5 and, in the study, authors have considered 28 DMUs, which is much more than twice of total inputs and outputs.

3.2 Envelopment Model for Plastic Industry

Mathematical programming approach to estimate the optimum production used DEA to limit and to assess the relative utility of the various DMUs with related types of inputs and outputs. To calculate the productivity of the DMU against other DMUs that work within the same ecosystem was the fundamental goal of DEA. The constraint in this analysis is a necessity for all DMUs to be above or below the efficiency limit. As a consequence, while productive DMUs have an efficiency value of 1, and inefficient DMUs have a value that is less than 1. The difference between 1 and the efficiency value means, the same amount of output with lower input can be achieved. DEA assigns weights for the input and output of a DMU to ensure maximum performance and efficiency. It has been achieved through the weighting of the relative importance of the input and output variables that reflects their significance in this particular DMU. Mathematically, there are number of variants of DEA models are available for checking the efficiency. In some models' inputs or outputs are deemed controllable or part thereof that may be constant returns to scale (Model 1) or variable returns to scale (Model 2). Mathematically, DEA model can be presented as:

$$
\begin{aligned}
&\min \theta_0 \\
&\textit{Subject to} \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{io}, \qquad i = 1,2,\dots, m \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \ge y r_o, \qquad r = 1,2,\dots., s \\
&\lambda_j \ge 0, \qquad \forall j = 1,2,\dots, n
\end{aligned}
$$

(1)

$$\min \theta_0$$

Subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io}, \qquad i = 1,2,\ldots,m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y r_o, \qquad r = 1,2,\ldots., s$$

$$\sum_{j=1}^{n} \lambda_j = 1, \qquad \forall j = 1,2,\ldots,n$$

$$\lambda_j \geq 0, \qquad \forall j = 1,2,\ldots,n$$

(2)

Let discretionary and non-discretionary variables are denoted by D and ND respectively. In the discretionary models, all resources are considered under the control of the management. In any truthful business situation, there are many non-discretionary inputs which are not in the control of a management. For example, consider lease rent of plastic manufacturing industry which is one of the inputs. It will not be possible for the industry owners to decrease or increase the lease rent which is entirely depends upon the size of the manufacturing plant for its utilization in order to improve efficiency.

$$\min \theta_0$$

Subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io}, \qquad i \in D$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io}, \qquad i \in ND$$

$$\sum_{j=1}^{n} \lambda_j y_j \geq y_o, \qquad r = 1,2,\ldots., s$$

$$\sum_{j=1}^{n} \lambda_j = 1, \qquad \forall j = 1,2,\ldots,n$$

$$\lambda_j \geq 0, \qquad \forall j = 1,2,\ldots,n$$

(3)

The following generic model (4) is used to measure the efficiency of the proposed work. Let. s_i^- and s_r^+ represents input and output slacks. The slack based DEA model with discretionary and non-discretionary inputs can be written as:

$$\min \; \theta - \varepsilon\left(\sum_{i\in D} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

Subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io}, \quad i \in D$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io}, \quad i \in ND$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro},$$

$$\sum_{j=1}^{n} \lambda_j = 1, \qquad \forall j = 1,2,\ldots,n$$

$$\lambda_j \geq 0, \qquad \forall j = 1,2,\ldots,n$$

(4)

The model (4) assesses the efficiency of the input-output (x_{i0}, y_{ro}) by estimating the minimum factor θ. $\varepsilon > 0$ is used for handling the slack values. It may be noted that θ is not associated non-discretionary inputs, as these are the uncontrollable variables which are fixed exogenously. The non-discretionary inputs neither contributed directly in the efficiency measures being improved in objective function nor they effect the efficiency by virtue of their presence in constraints.

4. RESULT AND DISCUSSION

To evaluate the relative efficiency of the plastics manufacturing companies we have taken four inputs out of which three are discretionary in nature namely raw materials, stores and spares (Input 1), Power, fuel (including wheeling charges paid by electricity companies) and water charges (Input 2), Employee Benefit Expenses (Input 3), and Lease rent (Input 4) is considered as non- discretionary and profit after tax deduction as only output variable. In our sample manufacturing units, there are some differences. Descriptive statistics of inputs and outputs variables are given for the three year 2018-20 in Table 1. The value of standard deviation clearly explains that there is a noticeable variation in the selected inputs and outputs across the plastic manufacturing units.

Table1: Descriptive statistics from 2018-2020

Parameters	Year 2018		Year 2019		Year 2020	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Sales	2119.2581	3474.86503	2265.9063	3966.95786	1898.2606	2533.36715
Profit after Tax	14.4037	34.682933	13.1778	35.57589	-69.4889	120.6043
Lease rent	7.8065	12.24315	8.4286	14.88830	8.7143	14.09454
Raw Material	1244.3226	2182.22674	1385.4375	2420.47633	1161.6758	1438.69873
Power	88.3548	131.14789	107.8750	159.32777	100.2515	136.38661
Employee Benefits	126.0323	170.17647	144.9063	178.42706	150.2909	200.33520

The method of panel least squares considering profit after tax as dependent variable and others as independent variables gives R^2 as 0.2798 with employee benefits, power and fuel costs, raw material and lease-rent have significant contribution. Panel regression with fixed effects give R^2 as 0.7455 with neither

significant dependent variables nor the slope is significant. The Haussmann test (χ^2= 9.523, p-value = 0.040) excludes the random effects on panel data.
The fixed effect panel regression for the data set with Profit after tax as dependent variable is

$$Porfit = 81.195 - 0.189Emp - 0.348\ Power + 0.019\ Raw - 2.327lease\_rent$$
$$R^2 = 0.7455.$$

Table-2: Efficient scores plastic manufacturing units from the year 2018-2020 (DEA) Table-3: Efficient scores plastic manufacturing units from the year 2018-2020 (SFA)

DMU1	1	1	1	DMU15	0.32353	0.1818	1
DMU2	0.06353	0.05112	0.04713	DMU16	0.11546	0.06318	0.01635
DMU3	1	1	1	DMU17	1	1	0.14129
DMU4	1	1	0.18964	DMU18	0.78809	0.43132	0.13174
DMU5	0.63331	0.53679	0.18577	DMU19	0.29601	0.34244	1
DMU6	0.90135	0.38054	0.42909	DMU20	1	1	1
DMU7	0.27086	0.26905	0.22434	DMU21	1	1	0.07681
DMU8	1	1	0.05859	DMU22	0.68963	0.57231	0.184
DMU9	1	0.33617	0.85894	DMU23	1	1	1
DMU10	0.0336	0.67349	0.4447	DMU24	0.67882	0.23721	0.42934
DMU11	0.61606	1	0.02925	DMU25	1	0.71536	0.37382
DMU12	0.21557	0.21696	1	DMU26	1	0.93594	0.1999
DMU13	1	1	0.15509	DMU27	1	1	0.75977
DMU14	1	0.85492	0.3851	DMU28	1	1	1

Table-3: Efficient scores plastic manufacturing units from the year 2018-2020 (SFA)

DMUs	Efficiency			DMUs	Efficiency		
	2018	2019	2020		2018	2019	2020
DMU1	0.9684	0.9740	1.0000	DMU15	0.3280	0.1307	1.0000
DMU2	0.0456	0.1807	0.0899	DMU16	0.1043	0.0863	0.1059
DMU3	0.9740	1.0000	0.9980	DMU17	0.9910	1.0000	0.2142
DMU4	1.0000	0.9790	0.2610	DMU18	0.7881	0.4818	0.3698
DMU5	0.5050	0.4548	0.1686	DMU19	0.3129	0.3032	1.0000
DMU6	0.9014	0.2771	0.4291	DMU20	0.9970	0.9950	0.9510
DMU7	0.2458	0.1002	0.1580	DMU21	0.9640	1.0000	0.0529
DMU8	0.9830	1.0000	0.0018	DMU22	0.6032	0.3353	0.7168
DMU9	1.0000	0.4437	0.8448	DMU23	0.9410	0.9610	0.9530
DMU10	0.2829	0.5973	0.4908	DMU24	0.6114	0.2894	0.5800
DMU11	0.7992	1.0000	0.0868	DMU25	1.0000	0.7002	0.7465
DMU12	0.3697	0.3694	0.9810	DMU26	0.9760	0.9347	0.5690
DMU13	0.9110	0.9230	0.2113	DMU27	1.0000	1.0000	0.6032
DMU14	0.9210	0.3694	0.3125	DMU28	0.9570	0.9560	0.9970

Table-4: Percentage reduction in inputs and keeping no change in output forinefficient plastic manufacturing units from the year 2018- 2020 under SBM model

	Profit after Tax (Output)%tages			Power (Input)%tages			Raw Material (Input)%tages			Employee Benefits (Input)%tages		
	2018	2019	2020	2018	2019	2020	2018	2019	2020	2018	2019	2020
DMU1												
DMU2	10.2	10.1	73.2	93.6	98	69		95	70	94	95	69
DMU3							93.63					
DMU4					87			81			89	
DMU5			20	54.8	82	12		81	8	37	81	8
DMU6				9.86	67	56	36.67	57	63	37	57	56
DMU7				72.6	78	29	24.39	78	29	73	78	29
DMU8		11.7			94		72.66	96			94	
DMU9					14			14			14	
DMU10	10.6			96.4	56	44		56	52	97	56	66
DMU11	20	62.77	1.00	38.3	98	1.00	98.98	9	1.00	38	97	1.00
DMU12	83			78.4		10	88.97		10	78		10
DMU13		16.0			84		97.22	86			84	
DMU14		10			61			62			61	
DMU15	24			68		82			82	72		82
DMU16	24.4	12.1		88	99	45	67.65	98	45	88	98	45

DMU17		19			86		98.43	92			86	
DMU18	17.3	12.9		21	87	80		96	89	21	87	80
DMU19				70.4		66	70.61		66	82		77
DMU20							70.40					
DMU21		16.05			92	65		93	48		92	27
DMU22				31.9	84	39		82	39	30	82	39
DMU23							30.06					
DMU24	13.6		34.75	50.3		82			76	50		76
DMU25		37.7			63	47	32.12	67	47		63	47
DMU26		12.7	98.51		80	95		91	95		80	95
DMU27					24			24			24	
DMU28				33.5			-1.88			34		

We have used the base method oriented as we have done percentage reduction in input and keeping no change in output variable and non- discretionary input variable. We have run the DEA analysis using the MS EXCEL Solver. Table 3 is a summary of the data and the efficiency scores calculated by DEA for the three years combined from 2018-20.

Whenever the inputs and outputs of an effective DMU are compared to other DMUs, a score referred to as the relative efficiency score is calculated. Efficiency-score 1.0 DMUs are deemed to be effective and would be included in the efficiency frontier. In this paper, we have calculated efficiency using DEA method for three years individually from 2018 to 2029 and also calculated combined efficiency for three years. Some of the DMUs which are having efficient score as 1.0 in the individual years, may or may not have efficient score of 1.0 when we considered for three years as combined.

In many of the times some DMU performed good and having efficiency score as 1.0 but when it would be considered with other years it may or may not performed good. In Table 3 like DMU3 in 2018 is efficient with efficiency score 1 but when calculated for combined 3 years DMU3 is no more efficient, as the efficiency which is calculated by DEA method is the relative efficiency not the absolute efficiency.

In the Table 3 the percentage reduction in inputs and keeping no change in non-discretionary input variable and output for inefficient plastic manufacturing units combined from 2018-2020 under SBM model, for example DMU3 is efficient in 2018 with efficiency score of 1.0 but when we considered efficiency of all the three years DMU3 is no more efficient, with (efficiency = 0.97172). In some cases, inefficient DMUs are performing better than the efficient DMUs. Overall performance is not the only criteria to differentiate between efficiency and inefficiency of DMUs as efficient is the relative not the absolute (Li and Zhu, 2008). In order to make this DMU efficient we have to put three slacks' weights for inputs like we have to reduce input 1(raw material) from 118.2(million) to 114.8(million), input2(power fuel) from 10.7(million) to 10.4(million) and input3(employee benefits) from 23.3(million) to 22.6(million). In this illustration, DMU3 does not have any slacks in the outputs. As a consequence of the results in Tables 2 and 3, it can be concluded that the efficiency scores produced via DEA without determinants differ from one another, which is consistent with the results obtained using the SFA method (Reinhard et al., 2000).

5. CONCLUSION

As per the business standard, India is holding only 1% share in the $1 trillion global plastic exports market as compare to China with huge share of 10 per cent. After COVID-19 Indian plastic exporters are aggressive to get more share in the global market. The Indian government is not keeping any stone unturned to persuade investors. The plastics exporters in India have witnessed increase in orders from countries like United States, Japan but due to nationwide lockdown it was very difficult to fulfils these orders.

This paper calculated the technical efficiency of the 28 plastic manufacturing units of India from 2018-20. The non-parametric DEA approach is used for compute the efficiency score. Furthermore, the results classify the different firms as according their performance by identifying the "best." Likewise, efficiency techniques measure performance in comparison to the most efficient firms. The performance of plastic manufacturing firms is assessed using a slag-based efficiency study. The model considered profit after tax deduction as an output and raw material, Employee benefits, power fuel and lease rent as input variables respectively. The model identified the total efficiency of plastic manufacturing and this would guide the plastic manufacturing firms by planning their inputs and outputs in a manner so that they can achieve the efficiency as per their competitors. The firms which are more efficient would surely get more global orders and can gain competitive advantage over their competitors.

6. RESEARCH GAPS AND FUTURE RESEARCH DIRECTIONS

This section of the publication addresses our findings in light of the study's identified research gaps and future research directions. The topic of data envelopment analysis is a more commonly used technique for determining efficiency. During the COVID lockdown there is huge opportunity exists in the manufacturing sector specifically in plastic due to huge demand of surgical gloves, disposal items and other health and hygiene related items like sanitizer bottles etc. The results from the analysis highlight the substantial opportunities that exist to further research in DEA related to plastic manufacturing industries. An initial insight is that DEA research related to plastic manufacturing to date has attracted research efforts in specific areas. A number of research themes were not identified as being prominent during the pandemic period which should be prioritised for future research. DEA research needs to be targeted at better understanding how manufacturers can be utilizes the efficiency skills to improve their output and compete with their competitors. In addition, the maturity levels of plastic manufacturing organizations in India in terms of utilizing DEA are still only in the early stages. The successful implementation of DEA to support policy development requires exploration of DEA among key users

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Appendix-1

S.No.	Name of the Plastic Company
1	Bharathi Polymers India Pvt. Ltd.
2	Bilcare Ltd.
3	C G-P P I Adhesive Products Ltd.
4	Dalmia Laminators Ltd.
5	Duropack Ltd.
4	Emmbi Industries Ltd.
5	Essel Propack Ltd.
6	Ganpati Plastfab Ltd.
7	Gujarat Craft Inds. Ltd.
8	Hindustan Adhesives Ltd.
9	Hitech Corporation Ltd.
10	I T W India Pvt. Ltd.
11	Indra Industries Ltd.
12	Innovative Tech Pack Ltd.
13	Jai Corp Ltd.
14	Jauss Polymers Ltd.
15	Jumbo Bag Ltd.
16	M P L Plastics Ltd.
17	Manjushree Technopack Ltd.
18	O K Play India Ltd.
19	Pearl Polymers Ltd.
20	Pithampur Poly Products Ltd.

21	Polycon International Ltd.
22	Polyspin Exports Ltd.
23	R D B Rasayans Ltd.
24	Raj Packaging Inds. Ltd.
25	Rishi Techtex Ltd.
26	Sah Polymers Ltd.
27	Salguti Industries Ltd.
28	Shree Rama Multi-Tech Ltd.