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Research Article

An Empirical Study of Hybrid DEA and Grey System Theory on Analyzing Performance: A Case from Indian Mining Industry

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India, which has long been recognized as a well-endowed nation in natural mineral resources, is a major minerals producer. According to the report of Indian Ministry of Mines 2013, Indian mining and metals sector ranked the fourth among the mineral producer countries, behind China, United States, and Russia and had in fact led the economy into recovery from the global financial crisis. Since this industry has turned into a significant issue, this paper attempts to rank the performance of 23 Indian mining and metal companies and to evaluate and measure the productivity change of these sectors during different time periods (2010–2014). Besides, the authors would like to choose one advanced model of MPI to see the performance of these companies in the past-present period and the 4-year future period (2015–2018) by using forecasting results of Grey system theory. The results revealed that from the past to future period the National Mineral Development Corporation, Hindalco Industries Limited, and Coal India always keep their highest best rankings among 23 DMUs regarding performance scores. This study contributes better insights of Indian mining industry as it is the core of the economy.

1. Introduction

India is a growing economy, and its mineral and energy demands are likely to grow fast [1]. As one of the world's leading mineral producers, India is endowed with a rich resource base of several metallic, nonmetallic, and fuel minerals that offer huge opportunities to both domestic and global players for investment. India's mineral policy is also aimed at attracting foreign investment and encouraging foreign technology and foreign participation in exploration mining for high value. Report of Indian Ministry of Mines (2012-2013) revealed that the country's mining and metals sector has contributed to lead the national economy into recovery out of the period time of global financial crisis of 2007–2009. The total value of mineral production during 2012-2013 has been estimated at rupees (Rs.), 2006 billion reflecting an increase of around 11.83%, while the sector's share in the total gross domestic product (GDP) has remained flat at 2% over the last 15 years. In addition, financially, this sector has performed reasonable well in the last few years, as reflected in the volume and profit growth of some large mining companies, namely Coal India, National Mineral Development Corporation, and Manganese Ore India.

Since around the turn of the century, the country is a leading producer of certain key minerals such as iron ore and bauxite; thus, it is considered as a key segment of Indian economy [2]. In the year 2013, mining industry provides daily direct employment to about 1 million people and is largely fragmented into small scale operational mines. The number of small mines in India was 3,108 in 2012-2013 as against 3,236 in the previous year. However, during this period of time, the public sector or Government-owned Corporation continued to play a dominant role in mineral production accounting for 67.7%, while small mines, mostly from the private sector, continued to be operated manually either as proprietary or as partnership ventures.

Previous studies on measuring productivity of Indian coal mining activity have shown a steady increase and performance of the different companies also depends on the state of technology and economic efficiency of the regions

Kulshreshtha and Parikh [3]. This study attempts to analyze performance of Indian mining activity in the various coal producing companies across the country from 2010 to 2014. The objective is to derive performance measures for the different mining companies into adopting a right approach to policy decisions to improve performance.

One way to propose productive efficiency is the ability to combine inputs and outputs in optimal proportions at their prevailing prices, under a behavioural assumption for the decision making units (DMUs), for example, cost minimisation, revenue maximisation, and so forth [4]. A nonparametric approach to frontier analysis, the DEA, is used in this paper in order to distinguish between well-performing companies of coal mining and the inefficient ones. With DEA methodology, the author evaluates the enterprises' performance by classifying input and output data to propose productive efficiency. Moreover, Grey system theory is also used in this study for the purpose of forecasting companies' productivity for the next four years (2015–2018) concisely.

Super SBM method is also applied in this study to rank companies' performance and this method is followed by Malmquist nonradial and Malmquist radial models. DEA can be applied to measure the productivity of multiple input and output decision-making units, whereas the DEA-based Malmquist productivity index can be used as a tool for measuring the productivity change of coal mining sectors during different time periods (2010–2014). At the same research procedure, the author also aims to test significant differences between MPI models and Malmquist nonradial and radial models to choose which model is effective for evaluating companies' performance in recent years and future time.

2. Literature Review

The study of Kulshreshtha and Parikh [5] was an attempt that has been made to do an in-depth analysis of the productivity growth in the Indian coal sector during the period 1980–1992. Total factor productivity was calculated from the output and input indices for Coal India Ltd. Results of the analysis indicated that the labor productivity increase of around 37.6% was achieved. Study of the individual subsidiaries indicated that companies with larger share of underground mines have shown slower growth in productivity. The underutilization of capital, surplus labor, power shortages in the underground mines, inability to adapt to modern technologies, and a pricing structure of coal were the reasons of poor performance of Coal India Ltd.

Kasap et al. [6] conducted a study which aimed to examine the effects of noncontrollable factors as well as input parameters on the efficiency performances of eight enterprises within Turkish Coal Enterprises (TCE) from 2005 to 2007. For each enterprise, the outputs included the production sold and the total income; the controllable inputs consisted of investment expenditure, overburden stripping, and number of staff and the noncontrollable inputs consisted of total reserve and low heat values. Considering the noncontrollable inputs as a result of the analyses conducted with three-stage DEA model, it was determined that the average efficiency value of Turkish Coal Enterprises increased from 87.5% to 92.3%.

In the study of Xue et al. [7], the authors used an input-oriented model to measure the energy consumption productivity change from 1999 to 2008 of fourteen industry sectors in China as decision-making units. The results showed that there are only four sectors that experienced effective energy consumption throughout the whole reference period. The other ten sectors experienced inefficiency in some two-year time periods and the productivity changes were not steady. The data envelopment analysis-based Malmquist productivity index provided a good way to measure the energy consumption and can give China's policy makers the information to promote their strategy of sustainable development.

Fang et al. [4] attempted to compare the technical efficiency performance of listed coal mining companies in China and the US using CCR and BCC models in the advanced DEA linear programming. The results showed that the level of relative efficiency in Chinese coal mining enterprises, regardless of total technical efficiency or decomposed pure technical and scale efficiency, is much lower than that in American coal firms.

In the study of Tsolas [8], the author presented DEA model combined with bootstrapping to assess performance in mining operations. Since DEA-type indicators based on nonparametric production analysis are simply point estimates without any standard error, the author provides a methodology to assess the performance of strip mining operations by means of a DEA bootstrapping approach. Although omitting undesirable output resulted in biased performance estimates, these findings were based on sample specific results and indicate that this bias is not statistically significant.

3. Methodology

3.1. Research Process. In this study, the author attempts to measure productive efficiency of 23 listed companies in India covering the period time from 2010 to 2014. The data are collected from the websites of Bombay Stock Exchange and Money Control that contain the financial data of individual Indian mining companies and these pages are currently considered as one of the India's number one financial portal [9–11]. In our study consideration, we skip some mining companies for which financial data have not been found on the websites. The selected companies chosen for this research are listed in Table 1. These mining sectors are named Decision Making Unit from DMU1 to DMU23, respectively.

Zhu [12] emphasized that levels of employees, assets, and equity may actually increase revenue and profit levels. Moreover, according to the study of T.-Y. Chen and L.-H. Chen [13], the elements of profitability; relative market position; change in profitability and cash flow; and growth in sales and market share, total expenditure, equity capital, net income, net profit, and EPS (earnings per share) are considered as key factors that contribute directly to the performance of companies. Table 2 presents in detail real stock market data collected

Table 1: List of mining companies of India.

Category	Name of Companies	Type	Sector	Financial index symbols
Section 1: Companies listed on the website of Bombay Stock Exchange				
DMU1	Hindustan Copper Limited	Government owned	Mining and smelting	BSE: 513599; NSE: HINDCOPPER
DMU2	J & K Mineral Development	State-owned enterprise	Minerals and metals	BSE: 526371; NSE: NMDC
DMU3	National Aluminium Company	Government owned	Aluminium metal	BSE: 532234; NSE: NATIONALUM
DMU4	Manganese Ore India	State-owned enterprise	Manganese ore	BSE: 533286; NSE: MOIL
DMU5	Oil and Natural Gas Corporation	Public sector rise	Mining and oil	BSE: 500312; NSE: ONGC
DMU6	National Mineral Development	State-owned enterprise	Minerals and meta	BSE: 526371; NSE: NMDC
DMU7	Sterlite Industries	Public company	Metal and mining	BSE: 500900; NYSE: SLT
DMU8	Hindalco Industries	Public company	Mining and metals	BSE: 500440; NSE: HINDALCO
DMU9	Hindustan Zinc Limited	Public company	Mining and smelting	BSE: 500188; NSE: HINDZINC
DMU10	Sesa Sterlite Limited	Public limited	Mining	BSE: 500295; NSE: SESAGOA
Section 2: Companies listed on the website of Money Control				
DMU11	Gujarat Mineral Development	State-owned enterprise	Mining and smelting	BSE: 532181; NSE: GMDCLTD
DMU12	Rohit Ferro Tech	Public company	Mining and minerals	BSE: 532731; NSE: ROHITFERRO
DMU13	Indian Metals & Ferro Alloys	Public company	Mining and minerals	BSE: 533047; NSE: IMFA
DMU14	Maithan Alloys	Public company	Mining and minerals	BSE: 590078; NSE: MAITHANALL
DMU15	Impex Ferro Tech	Public company	Mining and minerals	BSE: 532614; NSE: IMPEXFERRO
DMU16	Ferro Alloys Corporation	Public company	Mining and minerals	BSE: 500141; NSE: FERROALLOY
DMU17	Coal India	State-owned enterprise	Mining and minerals	BSE: 533278; NSE: COALINDIA
DMU18	20 Microns	Public company	Mining and minerals	BSE: 533022; NSE: 20 MICRONS
DMU19	Facor Alloys	Public company	Mining and minerals	BSE: 532656; NSE: FACORALLOY
DMU20	Associated Stone Industries	Public company	Mining and minerals	BSE: 502015; NSE: ASOCSTONE
DMU21	Sandur Manganese and Iron Ores	Public company	Mining and minerals	BSE: 504918; NSE: SANDUR
DMU22	Nagpur Power Industries	Public company	Mining and minerals	BSE: 532362; NSE: NAGPUR
DMU23	Resurgere Mines and Minerals	State-owned enterprise	Mining and minerals	BSE: 533017; NSE: RMMIL

Table 2: Financial results of Indian mining companies in 2014 (Rs. million; except EPS).

DMUs	Expenditure (I)	Equity capital (I)	Net sales (O)	Net profit (O)	EPS (O)
DMU1	(11,509.50)	4,626.10	14,888.80	2,864.20	3.10
DMU2	(44,371.50)	3,964.70	120,582.00	64,200.80	16.19
DMU3	(63,713.80)	12,886.20	67,808.50	6,423.50	2.49
DMU4	(45,283.10)	16,777.10	59,672.30	15,018.80	8.95
DMU5	(44,371.50)	3,964.70	120,582.00	64,200.80	16.19
DMU6	(581,698.70)	42,777.60	838,889.30	220,948.10	25.83
DMU7	(183,682.30)	3,361.20	189,210.30	15,772.70	4.69
DMU8	(261,823.40)	2,064.80	278,509.30	14,133.30	7.09
DMU9	(74,591.10)	8,450.60	136,360.40	69,046.20	16.34
DMU10	(277,294.00)	2,965.00	285,365.30	10,760.90	3.67
DMU11	7,974.50	636.00	12,896.70	4,391.30	13.81
DMU12	25,934.50	1,137.80	25,503.00	(2,284.90)	(20.08)
DMU13	11,682.10	259.80	12,433.40	391.20	15.06
DMU14	7,840.30	145.60	9,551.10	113.10	7.83
DMU15	7,341.60	816.00	6,875.00	(548.60)	(7.47)
DMU16	5,947.70	185.30	6,326.30	313.60	1.69
DMU17	7,250.90	63,163.60	3,142.50	150,085.40	23.76
DMU18	2,773.80	169.10	2,902.30	1.30	0.04
DMU19	2,734.80	195.50	2,401.10	(282.60)	(1.42)
DMU20	1,121.40	66.30	1,307.40	100.70	7.60
DMU21	2,575.40	87.50	2,959.10	383.70	43.85
DMU22	38.20	131.00	15.40	(8.40)	(0.64)
DMU23	370.70	1,988.70	0.70	(588.40)	(2.96)

from the websites of Bombay Stock Exchange and Money Control. Collected data are derived as two classes: inputs and outputs. Data inputs consist of the capital expenditure and equity capital indices; and the outputs consist of the indices of net sale or income from operations, net profit, and basic EPS after extraordinary items.

In last sections, we have mentioned information about introduction, motivation, selection of companies, and selection attributes of these firms. After the setting stages, we go to the analysis stage at which research models are applied. In performing evaluation by ranking, super SBM is employed. GM(1, 1) is used for forecasting the parameters that can then be used for future estimated ranking among mining companies. On the other side, Malmquist nonradial and radial models are applied to demonstrate performance evaluation. However, we need to see whether significant differences exist between these models and then Wilcoxon can handle this task. Again, GM(1, 1) in the previous section is utilized to see future trends. Finally, we could easily analyze the efficiency change based MPI.

3.2. Models of Data Envelopment Analysis (DEA). The DEA pioneered by Charnes et al. [14] and developed by Banker et al. [15] and Fare et al. [16] is a mathematical programming approach which characterises the relationship among multiple inputs and multiple outputs by envelopment of the observed data to determine the best practice frontier for production. DEA involves the use of linear programming methods to construct a nonparametric piecewise surface or frontier over the data. Efficiency measures are then calculated relative to this surface which can be perceived as the production possibility frontier.

The Malmquist index evaluates the efficiency change of a DMU between two time periods. It is defined as the product of "catch-up" and "frontier-shift" terms. The catch-up term is related to the degree of efforts that the DMU attained for improving its efficiency, while the frontier-shift term reflects the change in the efficient frontiers surrounding the DMU between the two time periods 1 and 2. We denote DMU_0 at the time periods 1 and 2 by (x_0^1, y_0^1) and (x_0^2, y_0^2), respectively. We employ the following notation for the efficiency score of DMU $(x_0, y_0)^{t_1}$ measured by the frontier technology t_2. $\delta^{t_2}((x_0, y_0)^{t_1})$ ($t_1 = 1, 2$ and $t_2 = 1, 2$).

Then, the catch-up effect is measured by the following formula:

$$C = \frac{\delta^2\left((x_0, y_0)^2\right)}{\delta^1\left((x_0, y_0)^1\right)}. \tag{1}$$

The frontier-shift effect is described as

$$F = \left[\frac{\delta^1\left((x_0, y_0)^1\right)}{\delta^2\left((x_0, y_0)^1\right)} \times \frac{\delta^1\left((x_0, y_0)^2\right)}{\delta^2\left((x_0, y_0)^2\right)}\right]^{1/2}. \tag{2}$$

Malmquist index (MI) is the product of C and F; that is, *Malmquist index = (catch-up) × (frontier-shift)* or MI = $C * F$ or

$$\text{MI} = \left[\frac{\delta^1\left((x_0, y_0)^2\right)}{\delta^1\left((x_0, y_0)^1\right)} \times \frac{\delta^2\left((x_0, y_0)^2\right)}{\delta^2\left((x_0, y_0)^1\right)}\right]^{1/2}. \tag{3}$$

(C); (F); (MI) > 1 indicates progress in relative efficiency from period 1 to period 2, while (C); (F); (MI) = 1 and (C); (F); (MI) < 1 indicate the status quo and regress in efficiency, respectively.

(*Note that DEA efficiency is considered a distance measure in the literature as it reflects the efficiency of converting inputs to outputs [16]*).

We can develop the *output-oriented MI* as well by means of the *output-oriented radial* DEA models. The output-oriented models take all output slacks into account but no input slacks. This is explained below—*within score in output-orientation (O-V):*

$$\begin{aligned} \delta^s\left((x_0, y_0)^s\right) &= \min_{\theta,\lambda}\theta \\ \text{subject to } x_0^s &\geq X^s\lambda \\ \left(\frac{1}{\theta}\right) y_0^s &\leq Y^s\lambda \\ L \leq e\lambda &\leq U \\ \lambda &\geq 0. \end{aligned} \tag{4}$$

Intertemporal score in output-orientation (O-V):

$$\begin{aligned} \delta^s\left((x_0, y_0)^t\right) &= \min_{\theta,\lambda}\theta \\ \text{subject to } x_0^t &\geq X^s\lambda \\ \left(\frac{1}{\theta}\right) y_0^t &\leq Y^s\lambda \\ L \leq e\lambda &\leq U \\ \lambda &\geq 0. \end{aligned} \tag{5}$$

The radial approaches suffer from one general problem, that is, the neglect of slacks. In an effort to overcome this problem, Tone [17, 18] has developed the *nonradial measures of efficiency and super-efficiency slack-based measure (SBM) and super SBM*. Using these measures, we develop here the nonradial and slacks-based MI. In the *output-oriented* case, we solve the following LPs.

SBM-O

$$\begin{aligned} \delta^t\left((x_0, y_0)^s\right) &= \frac{\min_{\lambda,s^+} 1}{\left(1 + \left((1/q)\sum_{i=1}^{q} s_i^+\right)/y_{i0}^s\right)} \\ \text{subject to } x_0^s &\geq X^t\lambda \\ y_0^s &= Y^t\lambda - s^+ \\ L \leq e\lambda &\leq U \\ \lambda \geq 0, &\quad s^+ \geq 0, \end{aligned} \tag{6}$$

where the vector $s^+ \in R^q$ denotes the output-slacks.

Table 3: Forecasted values of outputs of all DMUs from 2015 to 2018.

DMUs	Outputs (Rs. millions, except EPS)											
	(O) Net sale				(O) Net profit				(O) EPS			
	'15	'16	'17	'18	'15	'16	'17	'18	'15	'16	'17	'18
DMU1	15,846.62	16,855.90	17,929.47	19,071.42	3498.10	3736.30	3990.72	4262.47	3.78	4.04	4.32	4.62
DMU2	117,408.21	119,022.55	120,659.08	122,318.12	63524.04	62444.81	61383.92	60341.05	16.02	15.75	15.48	15.22
DMU3	72,203.19	74,912.73	77,723.95	80,640.67	4512.24	3659.75	2968.31	2407.51	1.77	1.44	1.17	0.95
DMU4	69,654.52	79,310.72	90,305.56	102,824.62	15882.79	16630.55	17413.51	18233.34	9.46	9.91	10.37	10.86
DMU5	117,408.21	119,022.55	120,659.08	122,318.12	63524.04	62444.81	61383.92	60341.05	16.02	15.75	15.48	15.22
DMU6	913,629.42	973,669.79	1,037,655.7	1,105,846.71	230656.89	236100.11	241671.79	247374.95	26.97	27.60	28.26	28.93
DMU7	219,108.91	247,255.18	279,017.07	314,859.02	20323.30	23922.28	28158.58	33145.07	2.46	1.77	1.27	0.92
DMU8	290,498.75	303,415.46	316,906.49	330,997.39	13089.95	11400.75	9929.53	8648.16	6.63	5.72	4.94	4.26
DMU9	152,381.10	168,446.89	186,206.52	205,838.57	80780.25	90989.33	102488.64	115441.24	19.12	21.53	24.25	27.31
DMU10	75104.60	65134.50	21879.20	285365.30	1917.26	942.61	463.43	227.84	1.09	0.45	0.18	0.08
DMU11	14,284.14	13,997.80	13,717.21	13,442.23	5480.60	5805.70	6150.09	6514.90	17.23	18.25	19.33	20.48
DMU12	33,547.14	42,602.86	54,103.08	68,707.68	324.70	440.30	395.90	291.70	−0.05	−0.05	6.82	3.21
DMU13	13,138.04	13,776.97	14,446.98	15,149.56	151.86	85.20	47.80	26.81	5.95	3.37	1.90	1.08
DMU14	11,696.07	13,749.55	16,163.56	19,001.40	140.57	93.42	62.08	41.26	9.86	6.58	4.39	2.93
DMU15	7,098.15	7,554.20	8,039.54	8,556.07	57.10	68.00	35.90	39.70	1.22	1.36	0.69	0.59
DMU16	6,603.83	7,228.25	7,911.72	8,659.81	269.88	289.35	310.22	332.60	1.46	1.58	1.70	1.82
DMU17	2,952.48	2,695.00	2,459.98	2,245.45	207114.37	295181.64	420696.07	599580.59	32.84	46.74	66.52	94.67
DMU18	3,121.05	3,327.60	3,547.81	3,782.60	20.85	15.01	10.81	7.78	1.10	0.74	0.50	0.34
DMU19	1,780.98	1,451.45	1,182.90	964.03	140.30	328.50	71.20	8.00	−1.42	0.52	1.69	0.36
DMU20	1,356.48	1,266.35	1,182.21	1,103.66	107.47	106.31	105.15	104.01	8.11	8.02	7.93	7.84
DMU21	1,931.12	1,758.03	1,600.44	1,456.99	102.21	62.37	38.06	23.22	11.63	7.09	4.32	2.63
DMU22	16.10	15.40	110.10	18.30	3.95	2.26	1.29	0.74	0.30	0.17	4.11	3.35
DMU23	6.23	1.14	0.21	0.04	−588.40	−770.00	43.90	−588.40	−7.79	−13.57	7.65	−0.03

Source: calculated by researchers.

Super SBM-O

$$\begin{aligned}\delta^{t}\left(\left(x_{0}, y_{0}\right)^{s}\right) &= \frac{\min_{\lambda, s^{+}} 1}{\left(1-\left((1/q)\sum_{i=1}^{q} s_{i}^{+}\right)/y_{i0}^{t}\right)} \\ \text{subject to } x_{0}^{s} &\geq X^{t}\lambda \\ y_{0}^{s} &\leq Y^{t}\lambda + s^{+} \\ L &\leq e\lambda \leq U \\ \lambda \geq 0, &\quad s^{+} \geq 0.\end{aligned} \tag{7}$$

3.3. Grey Forecasting Model. The researchers use GM(1, 1) model to predict the realistic input/output factors for the next 4 years (2015 to 2018). In this section, the study takes company DMU1 as an example to understand how to compute in GM(1, 1) model in the period 2010–2014. We also take the net sales of DMU1 as an example to explain calculation procedure, and other variables are calculated in the same way. The procedure is carried out step by step as follows.

First, the researchers use the GM(1, 1) model to try to forecast the variance of primitive series.

First, create the primitive series:

$X^{(0)}$ = (13,045.20; 11,465.20; 14,875.50; 13,231.40; 14,888.80).

Second, perform the accumulated generating operation (AGO):

$X^{(1)}$ = (13,045.20; 25,401.40; 40,276.90; 53,508.30; 68,397.10)

$X^{(1)} = x^{(0)}(1) = 13{,}045.20$

$x^{(1)}(2) = x^{(0)}(1) + x^{(0)}(2) = 25{,}401.40$

$x^{(1)}(3) = x^{(0)}(1) + x^{(0)}(2) + x^{(0)}(3) = 40{,}276.90$

$x^{(1)}(4) = x^{(0)}(1) + x^{(0)}(2) + x^{(0)}(3) + x^{(0)}(4) = 53{,}508.30$

$$\begin{aligned}x^{(1)}(5) &= x^{(0)}(1) + x^{(0)}(2) + x^{(0)}(3) + x^{(0)}(4) + x^{(0)}(5) \\ &= 68,397.10.\end{aligned}$$

Third, create the different equations of GM(1, 1).

To find Z series, the following steps can be caculated to obtain the results:

$z^{(1)}(2) = (1/2)(13,045.20 + 25,401.40) = 38446.6$

$z^{(1)}(3) = (1/2)(25,401.40 + 40,276.90) = 65{,}678.3$

$z^{(1)}(4) = (1/2)(40,276.90 + 53,508.30) = 93{,}785.2$

$z^{(1)}(5) = (1/2)(53,508.30 + 68,397.10) = 121{,}905.4.$

Fourth, solve equations.

Table 4: Average MAPE of DMUs.

DMUs	Average MAPE
DMU1	10.27%
DMU2	5.42%
DMU3	6.06%
DMU4	1.87%
DMU5	5.42%
DMU6	5.61%
DMU7	10.50%
DMU8	4.42%
DMU9	3.14%
DMU10	15.55%
DMU11	11.40%
DMU12	7.33%
DMU13	12.54%
DMU14	14.65%
DMU15	8.64%
DMU16	5.89%
DMU17	5.56%
DMU18	20.18%
DMU19	10.54%
DMU20	9.15%
DMU21	13.40%
DMU22	8.06%
DMU23	32.48%
Average of all MAPEs: 9.92%	

Table 5: Pearson correlation coefficient.

Correlation coefficient	Degree of correlation
>0.8	Very high
0.6–0.8	High
0.4–0.6	Medium
0.2–0.4	Low
<0.2	Very low

To find a and b, the primitive series values are substituted into the Grey differential equation to obtain

$$\begin{gathered}11,465.20 + a \times 38446.6 = b \\ 14,875.50 + a \times 65,678.3 = b \\ 13,231.40 + a \times 93,785.2 = b \\ 14,888.80 + a \times 121,905.4 = b.\end{gathered} \tag{8}$$

Convert the linear equations into the form of a matrix.

Let

$$B = \begin{bmatrix} -38446.6 \\ -65,678.3 \\ -93,785.2 \\ -121,905.4 \end{bmatrix}, \qquad \hat{\theta} = \begin{bmatrix} a \\ b \end{bmatrix},$$

$$y_N = \begin{bmatrix} 11,465.20 \\ 14,875.50 \\ 13,231.40 \\ 14,888.80 \end{bmatrix}. \tag{9}$$

And then use the least square method to find a and b:

$$\begin{bmatrix} a \\ b \end{bmatrix} = \hat{\theta} = \left(B^T B\right)^{-1} B^T y_N = \begin{bmatrix} -0.0617 \\ 11194.99 \end{bmatrix}. \tag{10}$$

Use the two coefficients a and b to generate the whitening equation of the differential equation:

$$\frac{dx^{(1)}}{dt} - 0.0617 \times x^{(1)} = 11194.99. \tag{11}$$

Find the prediction model from

$$\begin{aligned} X^{(1)}(k+1) &= \left(X^{(0)}(1) - \frac{b}{a}\right) e^{-ak} + \frac{b}{a} \\ x^{(1)}(k+1) &= \left(13045.2 - \frac{11194.99}{-0.0617}\right) e^{0.0617k} + \frac{11194.99}{-0.0617} \\ &= (194487.5)\, e^{0.0696k} - 181442.3. \end{aligned} \tag{12}$$

Substitute different values of k into the equation:

$k = 0$ $X^{(1)}(1) = 13045.20$

$k = 1$ $X^{(1)}(2) = 25423.89$

$k = 2$ $X^{(1)}(3) = 38591.00$

$k = 3$ $X^{(1)}(4) = 52596.73$

$k = 4$ $X^{(1)}(5) = 67494.50$

$k = 5$ $X^{(1)}(6) = 83341.12$

$k = 6$ $X^{(1)}(7) = 100197.02$

$k = 7$ $X^{(1)}(8) = 118126.49$

$k = 8$ $X^{(1)}(9) = 137197.91.$

Derive the predicted value of the original series according to the accumulated generating operation and obtain

$\hat{x}^{(0)}(1) = x^{(1)}(1) = 13045.2$—*for the year 2010*

$\hat{x}^{(0)}(2) = x^{(1)}(2) - x^{(1)}(1) = 12,378.69$—*forecasted for 2011*

$\hat{x}^{(0)}(3) = x^{(1)}(3) - x^{(1)}(2) = 13,167.11$—*forecasted for 2012*

$\hat{x}^{(0)}(4) = x^{(1)}(4) - x^{(1)}(3) = 14,005.73$—*forecasted for 2013*

$\hat{x}^{(0)}(5) = x^{(1)}(5) - x^{(1)}(4) = 17,897.77$—*forecasted for 2014*

$\hat{x}^{(0)}(6) = x^{(1)}(6) - x^{(1)}(5) = 15,846.62$—*forecasted for 2015*

$\hat{x}^{(0)}(7) = x^{(1)}(7) - x^{(1)}(6) = 16,855.90$—*forecasted for 2016*

Table 6: Correlation coefficient (2014).

	Staff cost	Energy purchase	Other expenses	Equity capital	Net income	Net profit	Basic EPS
Staff cost	1	0.380873213	0.98075502	0.627931207	0.221718204	1	0.380873213
Energy purchase	0.380873213	1	0.418084532	0.844263775	0.39597191	0.380873213	1
Other expenses	0.98075502	0.418084532	1	0.718349623	0.284462435	0.98075502	0.418084532
Equity capital	0.627931207	0.844263775	0.718349623	1	0.501068342	0.627931207	0.844263775
Net income	0.221718204	0.39597191	0.284462435	0.501068342	1	0.221718204	0.39597191
Net profit	1	0.380873213	0.98075502	0.627931207	0.221718204	1	0.380873213
Basic EPS	0.380873213	1	0.418084532	0.844263775	0.39597191	0.380873213	1

$\hat{x}^{(0)}(8) = x^{(1)}(8) - x^{(1)}(7) = 17{,}929.47$—*forecasted for 2017*

$\hat{x}^{(0)}(9) = x^{(1)}(9) - x^{(1)}(8) = 19{,}071.42$—*forecasted for 2018*.

Similarly to the above computation process, the study could get the forecasting results of all DMUs from 2015 and 2018; the detailed numbers are shown in Tables 3 and 4, respectively.

3.4. Forecasting Accuracy. The mean absolute percentage error (MAPE) is a measure of accuracy of a method for constructing fitted time series values in statistics, specifically in trend estimation [19–21]. The MAPE measures the size of the error in percentage terms. Many previous studies focus primarily on the MAPE when assessing forecast accuracy. It is calculated as the average of the unsigned percentage error as follows:

$$\text{MAPE} = \frac{1}{n}\sum \frac{|\text{Actual} - \text{Forecast}|}{\text{Actual}} \times 100; \quad n \text{ is forecasting number of steps.} \tag{13}$$

The parameters of MAPE stating out the forecasting ability are as follows:

MAPE < 10% "Excellent"

10% < MAPE < 20% "Good"

20% < MAPE < 50% "Reasonable"

MAPE > 50% "Poor."

4. Data Analysis and Results

4.1. Forecasting Results. Forecasting results from 2015 to 2018 of 23 Indian mining companies were shown in Table 3.

The authors employed MAPE to test the forecasting accuracy of 23 Indian mining companies and MAPE is a very important tool to solve the mathematical concerns about the forecasting method. As shown in Table 4, average MAPE of each DMU is ranked from 3% to 10%. In particular, the average MAPE of total 23 DMUs is 9.92% which is below 10%; thus, it can conclude that the GM(1, 1) model provides highly accurate prediction for the case of this research.

4.2. Pearson Correlation. To apply DEA model, the authors have to make sure that the relationship between input and output factors is correlated, which means if the input quantity increases, the output quantity could not decrease under the same condition [22]. Firstly, a simple correlation test, *Pearson correlation*, to measures the degree of association between two variables is conducted. Higher correlation coefficient means closer relation between two variables, while lower correlation coefficient means that they are less correlated.

The interpretation of the correlation coefficient is explained in more detail as follows. The correlation coefficient is always between −1 and +1. The closer the correlation is to ±1, the closer it is to a perfect linear relationship. Its general meaning was shown in Table 5.

In the empirical study, the results in Table 6 indicate that the correlation complies well with the prerequisite condition of the DEA model because their correlation coefficient shows strong positive associations. Therefore, these positive correlations also demonstrate very clearly the fact that the researcher's choice of input and output variables at the beginning is appropriate. Obviously, none of variables removal is necessary. From these results, we can justify the reason for why we use these indicators for DEA methodologies. The correlation is also very significant which will affect the performance.

Table 7: Summary of super SBM results for 2014.

Number of DMUs in data: 23
Number of DMUs with inappropriate data: 0
Number of evaluated DMUs: 23
Average of scores: 0.6230249
Number of efficient DMUs: 13
Number of inefficient DMUs: 10
Number of over iteration DMUs: 0

4.3. Performance Rankings of Super SBM. Table 7 shows summary of super SBM results for data of the year 2014. Data are set at value *Returns to Scale = Variable (Sum of Lambda = 1)*. The total number of DMUs is 23 with none of inappropriate data. The number of efficient DMUs is 13, while the result reveals 10 DUMs that work inefficiently. The results demonstrated that SBM has the ability to distinguish all DMUs with significant differences on their scoring. The results also revealed that a large number of inefficient mining companies still exist.

Table 8: Past-present period scores and rankings of Indian mining companies.

Year	2010		2011		2012		2013		2014	
DMUs	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
DMU1	0.08222255	20	0.0656456541	18	0.170071799	17	0.17558929	15	0.138931313	16
DMU2	1	8	1	6	1	7	1	6	1	6
DMU3	0.2055158	15	0.113620718	16	0.162615278	18	0.134712868	16	0.125793692	17
DMU4	0.19229379	16	0.198593163	15	0.291067259	15	0.34429635	14	0.318260742	14
DMU5	1	8	1	6	1	7	1	6	1	6
DMU6	2.16770264	1	2.033090027	1	2.80326237	1	2.31536708	1	1.95872746	1
DMU7	0.77740861	12	0.366271981	13	0.331701432	14	0.451008567	12	0.410027591	13
DMU8	1.15413633	6	1.199295331	5	1.272546625	3	1.289155822	4	1.161877176	4
DMU9	1.42647404	3	0.455163255	10	0.672443382	11	0.917292682	10	0.882773643	10
DMU10	1.46305544	2	1.461774497	3	1.147627203	5	0.084511232	18	0.599494462	11
DMU11	0.45409773	13	0.243722044	14	0.568035889	12	0.673623254	11	0.475303705	12
DMU12	0.12372762	19	0.077112542	17	0.0752215685	19	0.042416986	19	0.000171154	23
DMU13	0.23899823	14	0.418336879	11	0.407331963	13	0.381797764	13	0.270659073	15
DMU14	1.09447397	7	0.369363507	12	1.238128139	4	1.022411301	5	1.018807964	5
DMU15	0.02661588	22	0.0154215465	22	0.009125436	23	0.010363164	21	0.000335555	22
DMU16	0.01421234	23	0.0492145623	20	0.0262563212	21	0.087653698	17	0.091590783	18
DMU17	1.34986652	4	1.323199209	4	1.402620489	2	1.409316421	2	1.457257143	2
DMU18	0.169931707	17	0.0656414141	19	0.176270834	16	0.036263254	20	0.001525555	19
DMU19	0.05345621	21	0.042986456	21	0.039523654	20	0.002632693	22	0.001275366	20
DMU20	1	8	0.99985281	9	1	7	1	6	1	6
DMU21	1.173117286	5	1.503902073	2	1.053500985	6	1.335737125	3	1.417097825	3
DMU22	1	8	1	6	1	7	1	6	0.999033846	9
DMU23	0.159980331	18	0.0090814569	23	0.016914788	22	0.0019455655	23	0.000641568	21

Table 9: Future scores and rankings of Indian mining companies.

Year	2015		2016		2017		2018	
DMUs	Score	Rank	Score	Rank	Score	Rank	Score	Rank
DMU1	0.229972135	15	0.213906606	17	0.194115582	16	0.16885867	15
DMU2	1	10	1	8	1	7	1	8
DMU3	0.091149209	18	0.065455222	20	0.04547795	20	0.058719106	18
DMU4	0.310139476	14	0.283446393	15	0.24829818	14	0.207261952	14
DMU5	1	10	1	8	1	7	1	8
DMU6	1.706458481	2	1.5043684	2	1.405519183	2	1.376640904	2
DMU7	1.11595166	5	0.366177711	13	0.308945554	12	1.036782468	7
DMU8	1.15220434	3	1.223512939	3	1.205320998	5	1.164404419	5
DMU9	1.04140483	8	1.114485601	5	1.206617814	4	1.288194472	4
DMU10	1.133620135	4	1.076409889	6	0.02375703	21	0.012712324	21
DMU11	1.107899893	6	1.20380724	4	1.263214488	3	1.293168383	3
DMU12	0.047504052	20	0.025649868	22	0.072401558	18	0.058719106	17
DMU13	0.131526256	17	0.085196414	19	0.050240732	19	0.030354919	19
DMU14	1.02542509	9	1.037274478	7	1.062498136	6	1.092104258	6
DMU15	0.02226702	22	0.02306484	23	0.01248637	23	0.011367331	23
DMU16	0.199700493	16	0.239275087	16	0.263227147	13	0.293008055	13
DMU17	1.934646173	1	2.120759681	1	2.286584498	1	2.429443651	1
DMU18	0.040603593	21	0.029652426	21	0.01865052	22	0.012372634	22
DMU19	0.059686158	19	0.12894573	18	0.118590775	17	0.014157442	20
DMU20	1	10	1	8	1	7	1	8
DMU21	1.098633465	7	0.320449656	14	0.206757982	15	0.131634947	16
DMU22	1	10	0.999085759	11	1	7	1	8
DMU23	0.01187598	23	0.997461493	12	1	7	0.997033889	12

Table 8 shows the five-year data with efficiency scores and ranking of DMUs based on DEA-super SBM. This indicates that the ranking of the Indian mining industries is tending to change in a very slight manner on yearly basis. However, the majority of these companies are maintaining their "efficient" levels even after yearly changes on their financial nature.

Table 9 shows forecasting results for companies' future ranking by applying GM(1, 1). In the future, obviously, these mining companies are keeping their performance and they just show slight changes between the efficiency scores. However, we can still see some of the companies are under "1" of efficiency, that is, inefficiency.

4.4. Performance Efficiency Evaluation: Malmquist Radial Model versus Malmquist Nonradial Model. Seiford and Zhu [23] stated that the performance efficiency evaluation is very essential to test the progress of development of an industry. The authors in this case used the two models: *Malmquist Radial* and *Malmquist nonradial*. Then, the results of Malmquist are shown in Table 10. Malmquist radial model has the average score of 0.992449 compared with 3.186667092 of Malmquist nonradial model.

In Table 11, the authors used Wilcoxon to test the differences. The authors, firstly, decide to formulate the null hypothesis as "There is no difference of performance efficiency evaluation between Malmquist radial and Malmquist nonradial models."

The results (shown in Table 11) indicate that the correlations between two pared samples at ($n = 23$, correlation $= -0.264$, $P = 0.223$, $P < 0.05$), which means that there is significant difference between correlations of the two models mentioned.

Next, the results of Wilcoxon test (Table 12) show that $M = -2.39$, SD $= 5.59$, 95% CI $= -4.81$; 2.42, $t = -2.05$, df $= 22$, $P = 0.052$, in which 95% confidence interval of the difference goes through 0 and *P value* > 0.05. Thus, the authors can conclude that there is no significant difference between the two models: Malmquist radial and Malmquist nonradial.

Because of no significant difference between the Malmquist radial and Malmquist nonradial models, the authors decided to use one type of Malmquist models which is nonradial O-V model, as it was mentioned above that the radial approaches suffer from one general problem, that is, the neglect of slacks. Avkiran [24] and Chen and Sherman [25] have developed the nonradial measures of efficiency and super-efficiency. Table 13 and Figure 1 show the efficiency change or what is named "catch-up" of the India mining industry over the year periods of time interval.

Figure 1 shows the efficiency change or what is named "catch-up" of the India mining industry. The efficiency changes are inconsistent because the activities of DMU financial management show its inconsistent nature over the years. Figure 1 also pointed out that wildly fluctuations of the changes exit among DMU19 (Facor Alloy), DMU15 (Impex Ferro), DMU12 (Rohit Ferro Tech), and DMU16 (Ferro Alloys Corporation), whereas the rest of Indian mining companies in this study have no big or very slight efficiency changes.

The technical or the frontier-shift changes of the companies over the period from 2010 to 2014 in the Indian mining industry are shown in Table 14 and Figure 2. Figure 2 shows that the tendency to change technical or innovative effect of most of the Indian mining companies is inconsistent. For example, DMU19 (Facor Alloy) and DMU16 (Ferro Alloys Corporation) have their up and down changes in efficiency, which again notably made some abrupt in technical changes over the beginning years and then go smoothly with the overall trend of the companies in the industry.

Figure 2 shows frontier change over the period 2010 to 2014.

Finally, the most important element in the performance evaluation of the industry is Malmquist Productivity Index (MPI), which is clearly indicated in Table 15 and Figure 3. Overall, most of the companies have done well in their performance when the indices are larger than 1 (>1).

Table 10: The average indices of Malmquist radial and Malmquist nonradial models.

DMUs	Average of Malmquist radial model	Average Malmquist nonradial model
DMU1	1.133494181	1.787272636
DMU2	1.151012585	1.078393423
DMU3	0.952467408	0.392025795
DMU4	1.076600714	1.090141392
DMU5	1.151012585	1.078393423
DMU6	0.803070747	0.802696168
DMU7	0.922470548	0.446041138
DMU8	1.173203288	1.048869372
DMU9	0.713581338	0.714687685
DMU10	0.868461435	0.58990751
DMU11	1.074534927	1.245075457
DMU12	0.907476297	6.041737971
DMU13	1.165347005	0.918020595
DMU14	1.014276704	0.969117286
DMU15	0.842045652	25.50093872
DMU16	1.197349339	8.304036297
DMU17	2.506109416	2.060379686
DMU18	0.948798068	0.011004036
DMU19	0.832072153	16.49060082
DMU20	0.904174513	0.969111616
DMU21	1.269170129	1.359494943
DMU22	0.209590622	0.382229953
DMU23	0.01	0.013167199
Mean	**0.992449**	**3.186667092**
Max	2.506109	25.50093872
Min	0.01	0.011004036
SD	0.443929	6.083926361

Table 11: Paired samples correlations.

	N	Correlation	Sig.
Nonradial and radial	23	−0.264	0.223

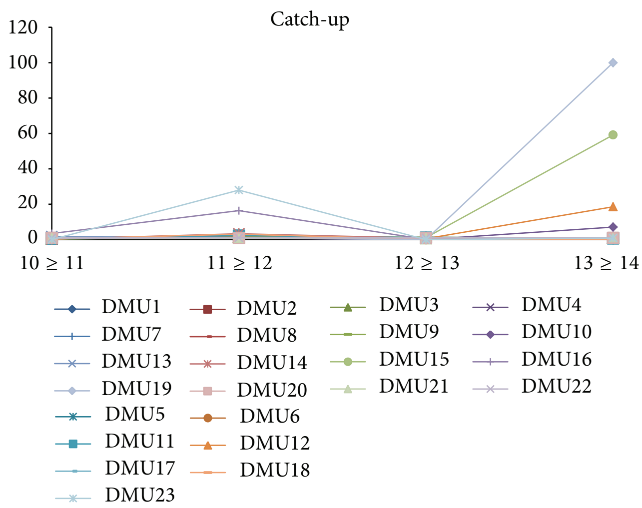

FIGURE 1: Efficiency change of the India mining industry.

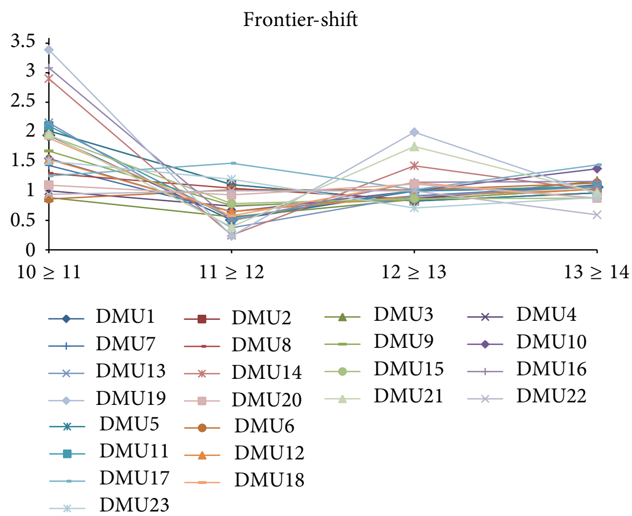

FIGURE 2: Frontier change over the period 2010 to 2014.

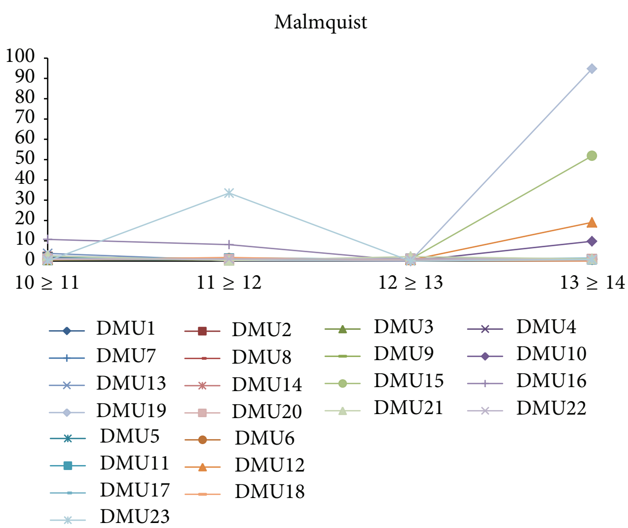

FIGURE 3: Productivity index (MPI) change over the period 2010 to 2014.

Table 12: Paired samples test.

	Paired differences					t	df	Sig. (2-tailed)
	Mean	Std. deviation	Std. error mean	95% confidence interval of the difference Lower	Upper			
Nonradial-radial	−2.39159063	5.58656757	1.16487986	−4.80740361	2.42223412	−2.053	22	0.052

Table 13: Efficiency (catch-up) change over the period 2010 to 2014.

Catch-up	2010 => 2011	2011 => 2012	2012 => 2013	2013 => 2014	Average
DMU1	0.797164	2.59442	1.032442	0.791229	1.303814
DMU2	1	1	1	1	1
DMU3	0.552856	1.431211	0.828415	0.933791	0.936568
DMU4	1.032759	1.465646	1.182876	0.92438	1.151415
DMU5	1	1	1	1	1
DMU6	0.937901	1.378819	0.825954	0.845968	0.997161
DMU7	0.471145	0.905615	1.359682	0.909135	0.911394
DMU8	1.039128	1.061079	1.013052	0.90127	1.003632
DMU9	0.319083	1.477367	1.364119	0.962369	1.030734
DMU10	0.999124	0.785092	0.073613	7.096281	2.238527
DMU11	0.536717	2.330671	1.185882	0.705593	1.189716
DMU12	0.62322	0.975688	0.562964	18.58698	5.187213
DMU13	1.750376	0.973694	0.937314	0.708907	1.092573
DMU14	0.33748	3.352059	0.825772	0.996476	1.377947
DMU15	0.578274	0.584548	1.151855	59.18462	15.37482
DMU16	3.469142	16.39564	0.107797	1.053356	5.256485
DMU17	0.980244	1.060022	1.004774	1.033946	1.019747
DMU18	0.33236	3.121029	0.205235	0.042027	0.925162
DMU19	0.792118	0.940237	0.065941	100	25.44957
DMU20	1	1	1	1	1
DMU21	1.281971	0.699462	1.269806	1.060911	1.078037
DMU22	1	1	1	1	1
DMU23	0.05752	28.01865	0.010044	0.880411	7.241656
Average	**0.908199**	**3.197868**	**0.826415**	**8.765985**	**3.424616**
Max	3.469142	28.01865	1.364119	100	25.44957
Min	0.05752	0.584548	0.010044	0.042027	0.911394
SD	0.670389	6.293493	0.434709	23.49756	5.821886

Figure 3 shows that DMU19, DMU15, DMU12, and DMU10 have slight changes over the beginning years; however, their MPI scores are going up sharply in the period of 2013–2014. DMU23 was shaking over the period 2010–2013, and finally in 2014 it goes to 0. The rest of the companies have also increased and decreased in their MPI scores but very slightly.

GM(1, 1) was used to forecast the future performance of the industry for the next four years (2015–2018) based on the results of Malmquist Productivity Index collected from 2010–2014. MPI change over the forecasted future period is done by Malmquist nonradial O-V model, which is illustrated in Table 16 and Figure 4. In the forecasting period (2014–2018), most of the MPIs of companies can reach the "efficiency" level or positive change year over year. Although some of companies still work inefficiently, we obviously see the stable changes of mining industry in the future period.

In the future, DMU23 and DMU18 will show a rocket-fuelled increase in their MPI up to the level of over 90 in the period of 2015-2016; however, in the next two periods, 2016-2017 and 2017-2018, they keep going down at around 1 of efficiency level.

Besides, we noticed that DMU7 will show its better performance in the future. Even though MPI scores of DMU7 will go down at around 1 of efficiency level in the period of 2015-2016, the scores will gradually keep going up in the next two periods, 2016-2017 and 2017-2018. The rest of the companies have also increased and decreased in their MPI scores but very slightly for the whole period.

5. Conclusion

In this study, the authors attempt to measure productive efficiency of 23 mining companies in India. The data covered

Table 14: Technical (Frontier) change over the period 2010 to 2014.

Frontier	2010 => 2011	2011 => 2012	2012 =>2013	2013 => 2014	Average
DMU1	1.939121602	0.504629603	0.996300267	1.06244232	1.125623448
DMU2	2.015905198	1.10571636	0.82675343	0.964586441	1.228240357
DMU3	0.886326283	0.558239264	0.854416817	1.163988937	0.865742825
DMU4	1.000476644	0.741267265	0.870616146	1.100278455	0.928159628
DMU5	2.015905198	1.10571636	0.82675343	0.964586441	1.228240357
DMU6	0.861710382	1.018301532	1.014340243	1.130278256	1.006157603
DMU7	1.430118052	0.647589191	0.913795938	1.088321211	1.019956098
DMU8	1.295194694	1.04381169	0.851005728	1.030519595	1.055132927
DMU9	1.674444152	0.750046037	0.847017068	1.035738188	1.076811361
DMU10	1.546932314	0.645062431	1.000197233	1.374187295	1.141594818
DMU11	2.100229237	0.534814478	1.001097942	1.07648664	1.178157074
DMU12	1.531741397	0.645525171	0.906630074	1.025145953	1.027260649
DMU13	2.152459816	0.373558899	0.909365366	1.066824671	1.125552188
DMU14	2.899201454	0.247983445	1.423331621	1.003169142	1.393421416
DMU15	1.937809329	0.783532361	0.866668618	0.875736904	1.115936803
DMU16	3.081717159	0.493051054	1.145757947	1.157888408	1.469603642
DMU17	1.252853816	1.467478027	1.019956535	1.439608261	1.29497416
DMU18	1.891744104	0.577088174	1.14044083	0.876535166	1.121452069
DMU19	3.388616607	0.23432004	1.99304714	0.947786186	1.640942493
DMU20	1.095824176	0.931013697	1.11412316	0.874974664	1.003983924
DMU21	1.959059779	0.389859532	1.749978617	0.969696801	1.267148682
DMU22	0.940015391	1	1	0.593251026	0.883316604
DMU23	1.503821085	1.195321455	0.709459198	0.888087167	1.074172226
Average	**1.756575125**	**0.738866351**	**1.042654493**	**1.030874701**	**1.142242668**
Max	3.388616607	1.467478027	1.99304714	1.439608261	1.640942493
Min	0.861710382	0.23432004	0.709459198	0.593251026	0.865742825
SD	0.681955633	0.321859374	0.302317354	0.171291998	0.184302772

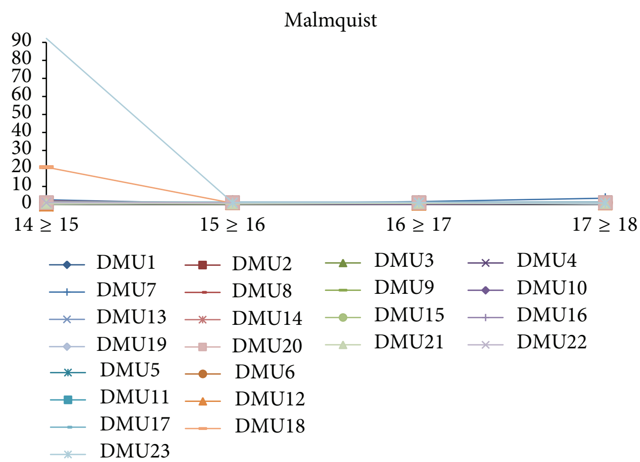

Figure 4: Productivity index (MPI) change over the period 2014–2018.

the period from 2010 to 2014 and were collected from the websites of Bombay Stock Exchange and Money Control that contain the financial data of these companies. The results of rankings from super SBM model indicated that the ranking of the Indian mining industries is tending to change in a very slight manner on yearly basis. However, the majority of these companies are maintaining their "efficient" levels even after yearly changes on their financial nature.

The results also clearly stated out that during the period 2010–2014 the Coal India Ltd (DMU17), National Mineral Development Corporation (DMU6), Hindalco Industry (DMU8), Maithan Alloys (DMU14), and Sandur Manganese

Table 15: Productivity index (Malmquist-MPI) change over the period 2010 to 2014.

Malmquist	2010 => 2011	2011 => 2012	2012 => 2013	2013 => 2014	Average
DMU1	1.545797114	1.309221254	1.028622365	0.840635021	1.181068938
DMU2	2.015905198	1.10571636	0.82675343	0.964586441	1.228240357
DMU3	0.490011136	0.798958453	0.70781135	1.08692264	0.770925894
DMU4	1.033251374	1.086435341	1.029830568	1.01707566	1.041648236
DMU5	2.015905198	1.10571636	0.82675343	0.964586441	1.228240357
DMU6	0.808198851	1.404053105	0.837798856	0.956179723	1.001557634
DMU7	0.673792601	0.586466544	1.242472165	0.989430703	0.873040503
DMU8	1.345873019	1.10756626	0.862113	0.928776162	1.06108211
DMU9	0.53428624	1.108093608	1.155431935	0.996761875	0.948643415
DMU10	1.545577938	0.506433239	0.073627354	9.751618997	2.969314382
DMU11	1.127229082	1.246476571	1.187183531	0.759561202	1.080112596
DMU12	0.954612304	0.629831235	0.510399744	19.05436823	5.287302877
DMU13	3.767615006	0.363731928	0.85236047	0.75627938	1.434996696
DMU14	0.978423652	0.831255052	1.175347113	0.999633621	0.99616486
DMU15	1.120585111	0.458012204	0.998276177	51.83015232	13.60175645
DMU16	10.69091327	8.083889578	0.123509827	1.219668695	5.029495342
DMU17	1.228103042	1.555559234	1.024825525	1.488477741	1.324241385
DMU18	0.628739377	1.801108782	0.234058131	0.036837705	0.675185999
DMU19	2.684183223	0.220316389	0.131423949	94.77861863	24.45363555
DMU20	1.095824176	0.931013697	1.11412316	0.874974664	1.003983924
DMU21	2.511457379	0.272691989	2.222132539	1.028761724	1.508760908
DMU22	0.940015391	1	1	0.593251026	0.883316604
DMU23	0.086500142	33.49129408	0.01	0.781881615	8.59241896
Average	**1.731426079**	**2.652340925**	**0.833689331**	**8.37821914**	**3.398918869**
Max	10.69091327	33.49129408	2.222132539	94.77861863	24.45363555
Min	0.086500142	0.220316389	0.01	0.036837705	0.675185999
SD	2.119828504	6.898136352	0.49641247	21.87797994	5.533163948

Iron Ores (DMU21) always keep the ranking of the top five companies among 23 DMUs regarding the performance scores.

However, for the future period 2015–2018 (forecasting with GM(1, 1)), although the Coal India Ltd. (DMU17), National Mineral Development Corporation (DMU6), and Hindalco Industry (DMU8) are still on top, Maithan Alloys (DMU14) and Sandur Manganese Iron Ores (DMU21) will be replaced by Hindustan Zinc Limited (DMU9) and Gujarat Mineral Development Corporation (DMU11) on the top performance scores.

Furthermore, Facor Alloys (DMU19), 20 Microns (DMU18), and Impex Ferro Tech (DMU15) were noticed as the inefficient companies which have the lowest score of performance over the past-present-future period. These DMUs need urgent action for improving the performance over partners in the research industry.

The results of Wilcoxon test (Table 12) show that there are no differences between the Malmquist radial and Malmquist nonradial models, so the authors used Malmquist nonradial model as a tool for measuring the productivity change of coal mining sectors during different time periods (2010–2014). The results have revealed that all companies in the mining industry have not shown sudden changes on their scores over the past-present-future period. This indicates that, although suffering from the financial crisis, the industry just only shows slight changes on the score performance, except some little changes between companies which are explained in the previous section.

After applying a hybrid DEA and Grey system theory on analyzing performance of 23 Indian mining companies, the authors have found many meaningful and noticeable results for this industry. Firstly, it minimizes the methodology limitation problems by deeply employing the best sides of an integration method. Secondly, it provides detailed insights of Indian mining industry as it is the core of the economy. Furthermore, according to forecasted MPI, companies with inefficient level (<1) need to be positive in changing or improving their management activities, business trends, size, or any other methods to make progress in the future time. By completing this research, the authors are aiming to suggest this case as a better model of performance analysis among the decision makers of variety of industries.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Table 16: MPI change over the forecasted period 2014 to 2018.

Malmquist	2014 => 2015	2015 => 2016	2016 => 2017	2017 => 2018	Average
DMU1	1.155377644	1.036943532	1.047454651	1.05440683	1.073545665
DMU2	0.941154142	0.941808396	0.946455953	0.962595312	0.948003451
DMU3	0.709387778	0.807083952	0.803241667	0.805875709	0.781397276
DMU4	1.050990953	1.032766941	1.026102588	1.029176837	1.03475933
DMU5	0.941154142	0.941808396	0.946455953	0.962595312	0.948003451
DMU6	0.953788767	0.950848108	0.979051059	1.00181251	0.971375111
DMU7	2.608808968	0.328959024	1.575407484	3.50365797	2.004208362
DMU8	1.014221762	1.030899367	0.995572443	0.970905349	1.00289973
DMU9	1.150544925	1.078417389	1.090671738	1.085395159	1.101257303
DMU10	1.940672028	0.340427772	0.02251981	0.560101027	0.715930159
DMU11	1.276180243	1.08751783	1.050084819	1.036211195	1.112498522
DMU12	0.169997844	0.875829328	0.611861239	0.784462215	0.610537657
DMU13	0.226873084	0.591108199	0.578352236	0.577229556	0.493390769
DMU14	1.869237094	0.973919273	1.024055164	1.039153116	1.226591162
DMU15	0.031602939	0.948432575	0.500567996	0.929526595	0.602532526
DMU16	0.873867965	1.0795813	1.083671912	1.086164776	1.030821488
DMU17	1.403725525	1.326313141	1.351549367	1.385723238	1.366827818
DMU18	20.67554712	0.718647781	0.618935022	0.652760872	5.666472699
DMU19	0.250804329	0.681482367	0.957742973	0.138790391	0.507205015
DMU20	1.028020624	0.985195792	0.985199371	0.985197534	0.99590333
DMU21	0.453076135	0.288464627	0.634050426	0.626207563	0.500449688
DMU22	1	0.915095672	1	0.818778182	0.933468464
DMU23	92.21332042	1	1	0.823358538	23.75916974
Average	**5.823406714**	**0.867893511**	**0.905608864**	**0.992177643**	**2.147271683**
Max	92.21332042	1.326313141	1.575407484	3.50365797	23.75916974
Min	0.031602939	0.288464627	0.02251981	0.138790391	0.493390769
SD	19.28212645	0.264628932	0.311183931	0.601826474	4.823734506

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