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Super-SBM and GM (1,1) Model Approaches for Global Automobile

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ABSTRACT

In the success of many enterprises, the development orientation in the future is an important role. The study measures the performance and ranks the automotive companies around the world by the integration of GM (1,1) model in grey theory and Super-SBM model in data development analysis (DEA). GM (1,1) model is used for predicting the input variables and output variables in the future time. And then, the super-SBM model was used for calculating the efficiency score of each automotive company in every term. Estimated values are standard when their average MAPEs are under 38.332%. The empirical results indicate that four good automotive companies attained efficiency in the previous time; seven good automotive companies are expected to reach the performance in the future time. The research presents an overview observation of the automotive industry around the world.

KEYWORDS: *automobile industry, data development analysis, Grey theory, GM (1,1) model, Super-SBM model*

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1. INTRODUCTION

The automotive industry is an industry that includes designing, developing, manufacturing, marketing, and selling all types of motor vehicles [1].

From the data of the International Organization of Motor Vehicles Manufacturers (OICA) [2], it indicates that the impact of the automotive industry has not softened since then. Based on the survey of OICAs of the biggest automobile enterprises of 2017 [3], the study picked out 20 of the largest automotive company in the world to analyze. These enterprises selected have a major role and could represent the world automobile industry.

In this research, Tata Motors Ltd was selected for business performance analysis and future development prospects. Formerly known as Tata Engineering and Locomotive Company (TELCO), Tata Motors Limited is a major Indian automobile manufacturer headquartered in Mumbai, Maharashtra, India. It belongs to Tata Group, an Indian conglomerate ranked 23th in terms of production volume. Tata's products range from passenger cars, trucks, vans to coaches, buses, sports cars, construction equipment, and military [4]. Tata Motors was listed on the Bombay Stock Exchange (BSE), it is a component of the BSE SENSEX index, the Indian National Stock Exchange, and the New York Stock Exchange. Based on the observations of the revenue of the 20 biggest automobile company in the world from the year 2015-2018 (on Wall Street), it is found that Tata Motors Ltd has stable revenues through 4 years in a row.

In the early 1980s, Grey system theory, an interdisciplinary field of science, was first introduced by Deng [5]. Since its inception, the Grey system theory has become very popular to solve problems of systems that contain partially unknown parameters. Grey models (GM) is a preeminent model compared to conventional statistical models because it only requires a limited amount of data to evaluate the behaviour of unknown systems [6, 7].

GMs have been employed for forecasting. In the research of Kazemi et al. [8], a GM was used based on Markov Chain to forecast the energy demand in Iran until 2020. GM (1,1) was applied in a study of Chang and Kung [9] to improve investment performance. Based on GM (1, 1), Li [10] gave an improved GM to predict revenues of Jingdezhen's tourism from 2003-2010. He concluded that the much better predictive result can be obtained by the improved GM. In a study by Feng and Huang [11], GM (1, 1) was applied to forecast the waste production of Shanghai city.

Data Envelopment Analysis (DEA) is a related new "data-oriented" approach to evaluate the performance of a group of entities called Decision Making Units (DMUs). DEA converts multi-inputs into multi-outputs. The DEA model was quickly recognized as an excellent and easily used methodology for performance evaluations. In the original study of Charnes et al., Data Envelopment Analysis was described as a mathematical programming model that is applied to observational data. It provides a new way of obtaining empirical estimates of relations including the production functions and efficient production possibility surfaces. These are cornerstones of modern economics. DEA has a variety models; however, the super-SBM model can deal with multiple inputs and outputs in order to conduct a separate score and position. For instance, Wang et al., used the super-SBM model for calculating the efficiency of Vietnamese port logistics companies. Zhao et al., measured the efficiency of the green economy via the super-SBM model. Huang et al., evaluated the efficiency of a sustainable hydrogen production scheme. Continuing the previous researches, we also use the super-SBM model to measure the efficiency of automotive companies over the world.

2. METHODOLOGY

2.1. Data Collection

In this research, a survey of the thirteen largest automotive companies around the world is conducted. The list of largest automotive companies gathered from [2] as shown in Table 1. These companies are the largest automobile companies that can represent the entire automotive industry in the global market. The Automotive segment activities include development, design, manufacture, assembly, and sale of vehicles (vehicle financing, sale of related parts, and accessories). The Other Operations segments of the automotive company are activities related to information technology services, machine tools, and automation plant solutions.

TABLE 1 LIST OF AUTOMOBILE MANUFACTURING COMPANIES

No	Automobile manufacturing companies	Countries	DMUs
1	Toyota Motor Corporation	Japan	DMU1
2	Fiat Chrysler Automobiles N.V.	Italy	DMU2
3	Volkswagen AG	Germany	DMU3
4	Hyundai Motor Company	Korea	DMU4
5	Nissan Motor Co., Ltd.	Japan	DMU5
6	Honda Motor Co., Ltd.	Japan	DMU6
7	Suzuki Motor Corporation	Japan	DMU7
8	Subaru Corp	Japan	DMU8
9	Daimler AG	Germany	DMU9
10	BAIC Motor Corp. Ltd.	HongKong	DMU10
11	Geely Automobile Holdings Ltd.	China	DMU11
12	Isuzu Motors Ltd.	Japan	DMU12
13	Kia Motors Corp	Japan	DMU13

2.2. Establishing Input / Output Variables

Based on the knowledge of DEA and the operation process of an automobile company, the researcher decided to select four inputs factors including total assets (Tal.as), total equity (Tal.eq) and operating expenses (O.exp); and two output factors including revenues (Rev) and net incomes (Net.in). These data were collected from the International Accounting Standards (IASs) [12].

2.3. Grey forecasting model

The research [6] was introduced the grey theory that can deal with the poor and shortage of data. The GM(1,1) model in the grey theory system is a forecasting tool that predicts the future value based on the minimum historical time series as four consecutive points at an equal interval. Based on two basic operations that include Accumulated Generation Operations (AGO) and Inverse Accumulated Generation Operations (IAGO), the process of establishment of the GM (1, 1) model is presented as follows:

Step 1: Create the initial series $X^{(0)}$:

$$X^{(0)} = (X^{(0)}(1), X^{(0)}(2), \dots, X^{(0)}(n)) / n \geq 4 \ (2.1)$$

It is a sequence of raw data. Whereas, $X^{(0)}$ is a non-negative sequence; n is the number of data observed.

Step 2: Generate time-series data $X^{(1)}(k)$ from $X^{(0)}$, then transform $X^{(0)}$ into a series of accumulated data $X^{(1)}$. In this step, AGO is used to generate a series of accumulated data $X^{(1)}$, which is:

$$X^{(1)} = (X^{(1)}(1), X^{(1)}(2), \dots, X^{(1)}(n)) / n \geq 4 \ (2.2)$$

Where

$$X^{(0)}(k) = \begin{cases} X^{(0)}(1) \\ \sum_{i=1}^{k} X^{(0)}(i) \end{cases}, k = 1, 2, 3 \dots, n$$

Step 3: Generate a series of mean values $Z^{(1)}$, the generated mean sequence $Z^{(1)}$ of $X^{(1)}$ is defined as:

$$Z^{(1)} = (Z^{(1)}(1), Z^{(1)}(2), \dots, Z^{(1)}(n)) / n \geq 4 \ (2.3)$$

$Z^{(1)}(k)$ is the mean value of adjacent data and it is calculated as follows:

$$Z^{(1)}(k) = 0.5 \times (X^{(1)}(k) + X^{(1)}(k-1)) / k = 2, 3, \dots, n \ (2.4)$$

Step 4 Calculate developing coefficient a and grey input b. Formation of the GM(1.1) model by setting up a first-order grey differential equation:

$$x^{(0)}(k) + aZ^{(1)}(k) = b / k = 1, 2, 3, \dots, n \ (2.5)$$

The values (a, b) are the coefficients. a is considered as a developing coefficient and b is considered as grey input.

Set the data matrix by using the least square estimate sequence and solve the parameter values a and b. $[a, b]^T$ can be estimated by the Ordinary Least Squares (OLS) method:

$$[a, b]^T = (B^T B)^{-1} B^T Y \ (2.6)$$

Transform the matrix as bellows:

$$Y = \begin{bmatrix} X^{(0)}(2) \\ X^{(0)}(3) \\ \vdots \\ X^{(0)}(k) \end{bmatrix}, B = \begin{bmatrix} -Z^{(0)}(2) & 1 \\ -Z^{(0)}(3) & 1 \\ \vdots & \\ -Z^{(0)}(h) & 1 \end{bmatrix} / (k = 1, 2, \dots n) \ (2.7)$$

B is called a data matrix, Y is called the data series, and $[a, b]^T$ is call parameter series.

Step 5: Generate the predicted accumulating series $\hat{X}^{(1)}$. Let $\hat{X}^{(1)}$ represent the predicted AGO series and generate the predicted accumulating series $\hat{X}^{(1)}$ defined in Equation (2.8).

$$\hat{X}^{(1)} = (\hat{X}^{(1)}(1), \hat{X}^{(1)}(2), \dots, \hat{X}^{(1)}(n)) \ (2.8)$$

In which:

$$\hat{X}^{(1)}(k) = \begin{cases} \hat{X}^{(0)}(1) \\ \hat{X}^{(0)}(1) - \frac{b}{a})e^{-ak} + \frac{b}{a} \ (2.9) \end{cases}$$

$k = 1, 2, \dots n$

Step 6: Apply inverse accumulated generation operation (IAGO) to get forecasting data. IAGO is applied to transform the predicted AGO data series back into the original data series with the equation (2.11), which $\hat{X}^{(0)}$

$\hat{X}^{(0)} = (\hat{X}^{(0)}(1), \hat{X}^{(0)}(2), \dots . \hat{X}^{(0)}(n))$ $\hat{X}^{(0)}$ is the predicted original data series.

$$\hat{X}^{(0)} = (\hat{X}^{(0)}(1), \hat{X}^{(0)}(2), \ldots. \hat{X}^{(0)}(n)) \quad (2.10)$$

Where:

$$\hat{X}^{(0)}(k+1) = \begin{cases} \hat{X}^{(0)}(1) \\ \hat{X}^{(0)}(k+1) - \hat{X}^{(1)}(1) \end{cases} \quad (2.11)$$

$$(k = 0, 1, 2, \ldots, n)$$

We can simplify (2.11) as follows:

$$\hat{X}^{(0)}(k+1) = (1 - e^{a})(\hat{X}^{(1)}(1) - \frac{b}{a})e^{-ak} \; / \; k = 1, 2, \ldots, n$$

$$(k = 0, 1, 2, \ldots, n) \quad (2.12)$$

2.4. Super efficiency model (super-efficiency SBM model)

The super-efficiency model (SBM) in DEA is based on a "slacks-based measure of efficiency" (SBM) developed by Tone, it gives the super efficiency and non-radial measurement with the technical efficiency and relative efficiency. This model deals with multiple inputs (x) and outputs(y), all participate values for calculation are positive.

The production possibility (P) of specific DMU is given by:

$$P = (X, Y) \quad (2.13)$$

Subject to

$$x \geq X\lambda; \, y \leq Y\lambda; \, \lambda \geq 0$$

Values such as x_0 and y_0 are calculated by:

$$\begin{aligned} x_0 &= X\lambda + s^- \\ y_0 &= Y\lambda - s^+ \end{aligned} \quad (2.14)$$

Two valuations including s^- and s^+ represent for input excess and output shortfall, respectively. The efficiency is counted by:

$$p = \frac{1 - \frac{1}{m}\sum_{k=1}^{m} s_k^- / x_{k0}}{1 - \frac{1}{s}\sum_{k=1}^{m} s_k^+ / y_{k0}} \quad (2.15)$$

The supper efficiency of a specific DMU is determined as follows:

$$\min p = \frac{\frac{1}{m}\sum_{k=1}^{m} \bar{x}_k / x_{k0}}{\frac{1}{s}\sum_{k=1}^{m} \bar{y}_k / y_{k0}} \quad (2.16)$$

Whereas,

$$\bar{x} \geq \sum_{k=1\neq 0}^{m} \lambda_k x_k \, ; \bar{y} \geq \sum_{k=1\neq 0}^{m} \lambda_k y_k / \left\{ \bar{x} = x_0; 0 \leq \bar{y} \leq y_0; \lambda \geq 0 \right\}$$

The DMU has efficiency when $\min p \geq 1$.

The DMU does not have efficiency when $\min p < 1$

3. EMPIRICAL RESULTS AND ANALYSIS

3.1. Forecast inputs/ Outputs

The GM (1,1) model was used for forecasting the future time from 2020 to 2023 of the thirteen largest automotive companies based on their realistic values over the period of 2016 - 2019. The company as DMU1 was selected to clarify the calculation of the GM (1, 1) model in the period 2016–2019, the forecasting process is carried on as follows:

The primitive series is established as follows:

$X^{(0)} = 446294; 458739; 473401; 488727)$ (3.1)

The new sequence $X^{(1)}$ is generated by the accumulated operation.

$X^{(1)} = (446294; 905033; 1378434; 1867160)$ (3.2)

We generate a mean sequence $Z^{(1)}$ of $X^{(1)}$ by:

$Z^{(1)}(k) = (675663; 1141733; 1622797)$ (3.3)

The coefficient a and grey input b are defined and the original series values are substituted into the Grey differential equation:

$$\begin{cases} X^{(0)}(2) + a \times Z^{(1)}(2) = b \\ X^{(0)}(3) + a \times Z^{(1)}(3) = b \\ X^{(0)}(4) + a \times Z^{(1)}(4) = b \end{cases} ; \begin{cases} 458739 + a \times 675663 = b \\ 473401 + a \times 1141733 = b \\ 488727 + a \times 1622797 = b \end{cases} \quad (3.4)$$

The linear equations are converted into the form of a matrix.

$$Y = \begin{bmatrix} 458739 \\ 473401 \\ 488727 \end{bmatrix}, B = \begin{bmatrix} -675663 & 1 \\ -1141733 & 1 \\ -1622797 & 1 \end{bmatrix}, ET = \begin{bmatrix} -675663 & -1141733 & -1622797 \\ 1 & 1 & 1 \end{bmatrix} (3.5)$$

Each value such as a and b is determined when using the least square method.

$$\theta = \begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y_N = \frac{-0.03166}{437314.02} \quad (3.6)$$

The coefficient a and coefficient b is used for generating the whitening equation of the differential equation.

$$\frac{dX^{(1)}}{dk} + 0.03166 \times X^{(1)} = 437314.02 \quad (3.7)$$

$$x^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a} \right] e^{-ak} + \frac{b}{a} = \left[446294 - \frac{437314.02}{-0.03166} \right] e^{-0.03166k} + \frac{437314.02}{-0.03166} \quad (3.8)$$

The different value of k into the equation is utilized to find $x^{(1)}$ series.

$x^{(1)} = (446294; 904961; 1378384; 1867036; 2371407; 2892004; 3429347; 3983976)$ (3.9)

The predicted value of the original series from the accumulated generating operation is conducted as follows:

$\hat{x}^{(0)} = (446294; 458668; 473422; 488652; 504371; 520596; 537343; 554629)$ (3.10)

From the above computation process, the result of all DMUs from 2020 to 2023 is computed.

3.2. Forecasting Accuracy

Forecasting plays an important and necessary role in modern management in planning for effective operations. It is indisputable that forecasting always remains some errors, thus, all estimated values must check the accuracy level by the Mean Absolute Percentage Error (MAPE) for each DMU over the primary period of 2016–2019 as shown in Table 2.

TABLE 2 MAPE OF AUTOMOBILE COMPANIES

DMUs	MAPE	DMUs	MAPE
DMU1	23.904	DMU8	11.123
DMU2	9.737	DMU9	11.766
DMU3	11.991	DMU10	25.612
DMU4	38.332	DMU11	24.111
DMU5	15.316	DMU12	18.805
DMU6	14.601	DMU13	12.359
DMU7	8.426		

Table 2 indicates that all MAPEs are lower than 38.332 so that the MAPEs of all forecasting values are standard. These predicted values over the period of 2020 – 2023 have high reliability that can use for computing efficiency.

3.3. Pearson Correlation

According to the rule of DEA, all input and output variables must test the correlation coefficients to ensure “isotonic” among two variables. The correlation coefficient is ranged from -1 to +1 and it has a perfect linear program when this value is closer -1 and +1. In this study, the correlation coefficients are from 0.4638 to 1 so that it has a good relationship. Therefore, all actual and forecasted input and output variables are proper for the prerequisite of DEA model, they can apply to the super-SBM model for the next calculation.

3.4. Efficiency Measurement

TABLE 3 EFFICIENCY OF AUTOMOBILE FROM PAST TO FUTURE

DMU	2016	2017	2018	2019	2020	2021	2022	2023
DMU1	1.0000	1.1013	1.0483	1.1935	1.0777	1.0946	1.1122	1.1306
DMU2	1.7312	0.4032	1.7820	1.7784	2.4112	3.3913	4.4379	4.4656
DMU3	1.1692	1.1087	1.2114	1.0970	1.1206	1.1103	1.1002	1.0901
DMU4	0.5438	2.7535	0.3678	0.5290	0.4705	0.5059	0.5450	0.5911
DMU5	0.7691	0.3063	0.8955	0.5979	0.5673	0.5846	0.6023	0.6219
DMU6	0.5994	0.2346	1.0455	0.7114	0.7756	0.8623	1.1640	1.1687
DMU7	1.3279	0.3566	0.7951	1.5205	1.2126	1.2483	1.2868	1.3230

DEA has many models such as EBM, SBM, and so on, but they cannot give separate efficiency, moreover, their highest efficiency scores only reach to 1. In contrast, the super-SBM model can conduct separate value and unlimited values in efficient cases. In this research, the effectiveness of the DMUs is calculated by the Super-SBM model for actual and estimated data over the period of 2016–2023 as shown in Table 3.

Table 3 indicates the performance of all automotive companies from past to future time, most of them have a fluctuation smoothly. There are three automotive companies including DMU1, DMU3, and DMU11 that reach to the efficiency with an efficiency score above 1 in both previous time and future time. DMU2 holds high scores in many terms, but its score was deducted sharply and did not attain the performance as 0.4032 in 2017. The remaining terms in the previous time owned an efficiency score from 1.7312 to 1.7820. With the full effort, it is expected that it will increase and reach a high score as 2.4112; 3.3913; 4.4379, and 4.4656, respectively from 2020 to 2023. DMU9 has a similar change as DMU2; however, future efficiency is from 1.1657 to 1.2668. DMU7 and DMU12 have the same dramatic that reduced the score under 1 during the time period of 2017–2018, and are expected to extend in the future time. The performance of DMU6 and DMU10 in whole term increases and reduces consecutively, they attain the efficiency in three years from past to future time. DMU8 is a unique automotive company which obtained a high score of 2.2354 in 2016, then, their scores are been down sharply and do not get the efficiency in the remaining time. The remaining automotive companies including DMU4, DMU5, and DMU13 are the worst companies that do not approach the performance in the whole term because their scores are always lower than 1.

3.5. Ranking

Based on the efficiency score, the position of DMUs in every year is exhibited as seen in Table 4 particularly.

TABLE 4 POSITION OF THE THIRTEEN LARGEST AUTOMOBILE COMPANIES AROUND THE WORLD

DMU	2016	2017	2018	2019	2020	2021	2022	2023
DMU1	8	5	5	4	6	6	7	7
DMU2	3	9	2	1	1	1	1	1
DMU3	5	4	3	6	5	5	8	9
DMU4	13	2	13	13	13	13	13	13
DMU5	9	11	7	12	12	12	12	12
DMU6	12	13	6	11	10	9	5	6
DMU7	4	10	8	2	3	2	3	3
DMU8	2	8	11	9	9	10	11	11
DMU9	7	6	4	5	4	4	4	4
DMU10	11	1	9	7	11	11	10	8
DMU11	1	3	1	3	2	3	2	2
DMU12	6	7	10	8	7	7	6	5
DMU13	10	12	12	10	8	8	9	10

All DMUs have variation scores so that none of them maintains the first position in the whole term. DMU2 holds the first rank from 2019 to 2013; it was in the second, third, and ninth positions for the years 2018, 2016, and 2017, respectively. DMU11 reached to the first rank in 2016 and 2018, remaining years are second and third classification. DMU10 attained the first rank in 2017, but other terms are the low position from seventh to eleventh. DMU4 made a good effort in operational progress in order to catch up on the second position in 2017; however, it is been down to the final rank in the remaining years. DMU5 ranked ninth, eleventh, and seventh positions in 2016, 2017, and 2018, respectively, and twelfth position in remaining years.

The above analysis implies that DMU11 does not have a highest efficiency score, it's score is seen to be stable and its position keeps first, second, and third rank. DMU4 and DMU5 are the two worst automotive companies that always have the low efficiency scores and rank the bottom position.

Besides, the empirical result indicates that remaining automotive companies do not come to the first rank; they range from the second position to the final position. Their positions in every year always change consecutively.

4. CONCLUSION

Nowadays, the automobile industry is developing sharply in many countries over the world because economic development is the potential to make a foundation for the growth of automobile companies. In this study, we give a performance measurement of thirteen automotive companies around the world from past to future by using GM(1,1) model and super-SBM model.

The standard accuracy estimated values are conducted by GM(1,1) with the average MAPE of each company under 38.332%. And then, all actual and forecasted data are utilized to measure the performance from past to future time. The final analysis result found out four good automotive companies including DMU1, DMU2, DMU3, and DMU11 in which always reach the efficiency in the whole time. In contrast, three automotive companies including DMU4, DMU5, and DMU13 are determined to be the worst companies that they do not obtain the performance at any time.

The study conducts the performance and position of each automotive company each year over the time period of 2016–2023 but it still has some limitations. Firstly, the amount of large automotive companies does not gather fully because their financial statements have not been published, further study should found out more companies to have a full observation. Secondly, the next study should present more multiple inputs and outputs.

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