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Forecasting and Measuring Productivity in Vietnamese Plastic Industry by Using Grey and DEA

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***Abstract*—*Improving productivity performance and sustaining development is becoming an important issue for the plastic industry of Vietnam. This research proposes a hybrid approach based on grey model (GM) and Malmquist productivity index (MPI), to predict and measure operational performance of Vietnamese plastic manufacturing companies over several time periods. From that, decision making units (DMUs) and policy-maker can improve business performance and build a sustainable development strategy. The study conducted on 29 plastic companies, which have published their complete information on Vietstock site. The result showed seventeen companies increased in productivity while the other twelve didn't. Technical change was more impact than efficient change in period 2013 – 2016. In general, both of them impact on Vietnam's plastic industry productivity. The results also reflect the fact that the performance change did not depend on company size. The study will be a useful reference for other industries as well.*

***Keywords*—*Plastic industry; productivity; GM; DEA; MPI.*

I. INTRODUCTION

Plastic is an important material for a wide range industries and people life, it has displaced many traditional materials, such as wood, stone, leather, metal, glass, and ceramic, in most of their uses [1]. Plastic material can be differentiated based on the resistance to temperature or based on the uses of material, as in Table I.

TABLE I. Plastic raw materials by reaction to temperature.

Thermoplastic	Thermoset plastic:
PE (Polyethylen),	Epoxy
PP (Polypropylen)	PU (Polyurethane)
PVC (Polyvinyl Chloride)	Phenolic
PS (Polystyren)	Urea/Melamine
PET (Polyethylen Terephthalate)	
ABS (acrylonitrile butadiene styrene)	
Other engineering plastic	

Source: Synthetic by researcher [2]

Vietnamese plastic industry is growing fast with a high growth rate of 16% – 18% (2010 – 2015), ranked after telecommunication and textile industry. The export revenue is $2.4 billion (2015), major exported market includes Japan, US, EU, Asean, and Korea. The total revenue of Vietnamese plastic industry in 2015 are $9 billion. The polymer using volume is 49kgs/person (2015) [3]. There are four manufactured product types includes packaging plastic, building plastic, commodity plastic, and high-tech plastic.

Though Vietnamese plastic industry focused on manufacturing, it lacks of domestic plastic material supplying source. Vietnam imports annually 4.4 million tons polymer material, the domestic market can only supply 900.000tons/year [3]. Vietnam also has to buy and import plastic manufacturing machines mainly from China, Taiwan, and Korea. The characteristic of Vietnam's plastic manufacturing industry is low value-added, while the material cost is about 75% of product cost, so that they will get low benefit. The famous plastic manufacture brands of Vietnam include Binh Minh, Tien Phong, Dong Nai, Dong A, An Phat, Rang Dong, Tan Tien, Ngoc Nghia, and Tan Phu., etc, but the branding rate is low.

Although the Vietnamese plastic industry has great potential. The lack of raw material, technology and knowledge has been questioning Vietnamese government and managers, requires an effective method to maintain competitiveness, improve productivity performance, and stable development.

Therefore, to solve these issues, this research proposes an integrated method based on grey model and Malmquist productivity index (MPI), to provide a long-term analysis of the Vietnamese plastic industry. The aim is to predict future business and evaluate productivity of 29 Vietnamese plastic companies during four consecutive terms (2013-2016). This research chose total asset (TA), cost of goods sold (CoGS), and financial expense (F.Exp) as input, because they are key of financial indicators contributing to the performance of companies in the hydropower industry. The revenues (Rev) and earnings after tax (EAT) were selected as output, because they are important indices for measuring the performance of this industry.

By this study, we can implement performance evaluation of Vietnamese plastic industry not only from 2013 to 2016, but also predict future evaluation in the period 2017-2018. The proposed approach enables Vietnamese policy-maker to guide policy directions toward sustainable development of the plastic industry. For investors or stakeholders, the proposed approach provides a way to assess performance information about a company, as well [4].

II. LITERATURE REVIEW

Researchers typically use a time-series forecast to solve various issues. The approaches have different mathematical backgrounds, include fuzzy, neural networks, trend extrapolation, and grey forecasting. Grey system theory, as an interdisciplinary scientific area, was first introduced by Ju-Long Deng (1982) [5]. From then on, the system has been a popular way to solve uncertainty issues, such as unknown parameters and poor or missing information. Grey system theory is superior to conventional statistical models because it only requires a limited amount of data for predicting [6]. GM (1,1) model is known as a popular model in grey forecasting. Ren demonstrated that GM (1,N) gave a better forecast ability

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result than artificial neural network under scanty data conditions, in forecasting the yield of bio-hydrogen [7].

Data envelopment analysis (DEA) is a non-parametric linear programming. It measures the relative efficiency of a group of decision making units (DMUs) which receive multiple inputs to produce multiple outputs [8]. DEA has been applied to various field, as operations research, management, economics, etc. The most basic models of DEA are CCR, BCC, additive and slack based measure (SBM). Although DEA only required limited data to evaluate performance, the selection of input and output variables is very important, because of affecting on decision-making. The prerequisite condition for using DEA is that the selected factors should maintain an isotonic relationship, which can be tested by correlation analysis [9]. If the correlations are not zero, this means a linear relationship existing and can be used by the DEA model. Otherwise, we need to re-choose these variables.

DEA and grey theory have been applied by various research communities across a wide range of industries. Hui et al. (2009) used the GM (1,1) to forecast the growth of Japanese Larch in the Liaoning province [10]. Shi (2009) proposed an effective and reliable Grey-Fuzzy evaluation to evaluate teaching quality [11]. Lin, Liou, and Huang (2011) applied the grey forecasting model to estimate future CO2 emissions in Taiwan from 2010 until 2012. The results showed that the average residual error of the GM (1,1) was below 10% [12]. Wu et al. (2006) applied DEA Malmquist productivity index to evaluate the influence of intellectual capital on competitive advantages. The study dealt with 39 Taiwanese IC design companies as sample, and used ROA method to measure the intellectual capital stocks of them [13]. Chen and Chen [14] used DEA and MPI to explore Taiwanese chip manufacturing company operating performance. Nguyen and De Borger (2008)[15] applied DEA Malmquist model to evaluate 15 Vietnamese commercial banks and found that the productivity of these banks was on a downtrend. Liang et al. (2008) applied DEA to investigate production efficiency the biotech industry before and after integration. The study had analyzed the possible integrative targets of a particular Taiwanese biotech company [16].

Although grey theory and DEA have been applying in a board filed, this is the first time the models are used to predict future business, measure operational performance and productivity change in the plastic industry of Vietnam. The combine model will help the hydropower companies and government adjust business performance and build a sustainable development strategy.

III. Research Development, Data Collection and Methodology

This research proposes an integrated model to evaluate long-term performance efficiency. Fig. 1 provides detailed applied stages. The stage of introduction states current status of Vietnamese plastic industry and define motivations and objectives. Data collection and input – output variable selection are next works in this paper. Stage three implements empirical works, by the use of hybrid GM (1, 1) and MPI models to predict future business and evaluate performance efficiency. In order to ensure that the forecast errors are reliable, mean absolute percent error (MAPE) is applied to measure the prediction accuracy in this step. Once the error rate is too high, the study has to reselect the input and output variables. The Pearson Correlation Coefficient Test is used to check correlation values between inputs and outputs, whether or not they are positive. If there is a negative coefficient, it will be removed, and stage of data collection will be repeated to establish a new factor. This is done until it can meet our requirements. GM (1, 1) and MPI models are employed to calculate with realistic data in this stage. The purpose is to predict and assess the productivity efficiencies of DMUs for our analysis works. The conclusions and suggestions will be stated in stage of conclusion.

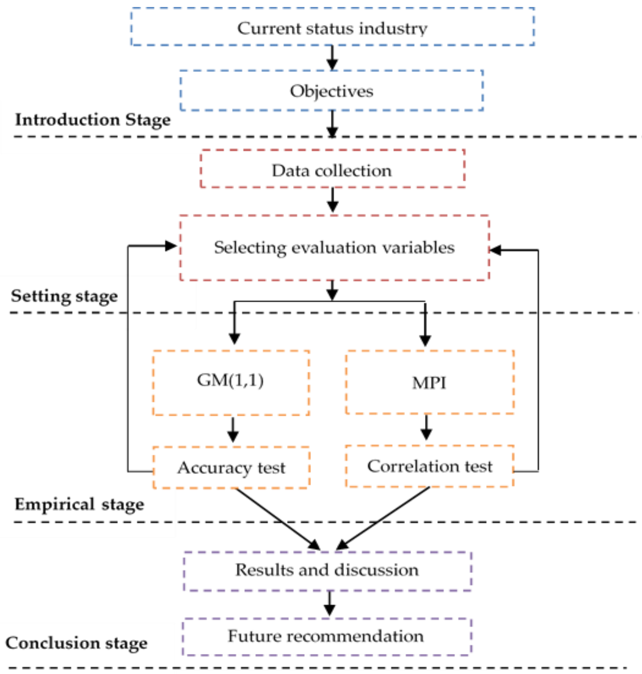

Fig. 1. Research development.

Based on the research procedure proposed, 29 Vietnamese plastic companies were selected for the study. These companies are the top companies in the plastic industry of Vietnam. They are qualified with transparent financial data, which was collected from the stock market observation posting system of Vietstock.vn [17]. Vietstock is a premier site providing business and financial market infomation in Vietnam. Due to printed space limitations, only the data of the year 2016 are listed in Table II.

TABLE II. The historical data of 29 DMUs in 2016.

DMUs	Inputs (Billions of VND)			Outputs (Billions of VND)	
	(I)TA	(I)CoGS	(I)F.Exp	(O)Rev	(O)EAT
DMU1	3,078.00	1,837.00	54.00	2,144.00	143.00
DMU2	225.00	109.00	0.53	129.00	5.70
DMU3	2,891.00	2,248.00	42.00	3,309.00	627.00
DMU4	272.00	146.00	3.10	203.00	22.00
DMU5	24.00	52.00	0.97	57.00	0.30
DMU6	3,375.00	2,606.00	87.00	3,287.00	261.00

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DMUs	Inputs (Billions of VND)			Outputs (Billions of VND)	
	(I)TA	(I)CoGS	(I)F.Exp	(O)Rev	(O)EAT
DMU7	1,075.00	1,271.00	30.00	1,393.00	53.00
DMU8	2,518.00	1,121.00	70.00	1,455.00	96.00
DMU9	44.00	53.00	6.20	67.00	3.00
DMU10	2,815.00	2,660.00	83.00	3,361.00	395.00
DMU11	158.00	105.00	1.00	126.00	8.00
DMU12	50.00	50.00	1.30	66.00	2.40
DMU13	168.00	304.00	1.80	365.00	21.00
DMU14	2,345.00	1,100.00	74.00	1,630.00	70.00
DMU15	173.00	60.00	1.30	81.00	9.60
DMU16	3,420.00	2,784.00	56.00	4,354.00	398.00
DMU17	116.00	126.00	2.70	153.00	9.20
DMU18	143.00	245.00	3.00	286.00	10.30
DMU19	220.00	433.00	1.40	456.00	2.80
DMU20	1,077.00	1,033.00	28.00	1,184.00	53.00
DMU21	55.00	121.00	0.07	145.00	10.90
DMU22	125.00	147.00	5.90	180.00	6.00
DMU23	1,035.00	793.00	49.00	913.00	21.00
DMU24	724.00	728.00	13.00	909.00	66.00
DMU25	600.00	650.00	10.00	702.00	21.00
DMU26	377.00	398.00	14.50	500.00	19.00
DMU27	926.00	1,176.00	11.00	1,405.00	106.00
DMU28	444.00	229.00	16.00	236.00	29.00
DMU29	182.00	325.00	8.00	367.00	5.00

GM (1, 1) model in this work was established based on two basic operations (accumulated generation operation (AGO) and inverse accumulated generation (IAGO)) [5]. The model constructing process is summarized as follows:

Establish sequence of original series $X^{(0)}$:

$$X^{(0)} = \left(X^{(0)}(1), X^{(0)}(2), \dots, X^{(0)}(n)\right), n \geq 4 \quad (3.1)$$

Denote AGO sequence by $X^{(1)}$:

$$X^{(1)} = \left(X^{(1)}(1),\ X^{(1)}(2), \dots, X^{(1)}(n)\right),\ \ n \geq 4 \quad (3.2)$$

Where $X^{(1)}(1) = X^{(0)}(1)$ and

$$X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}_{(i)},\quad k = 1, 2, 3, \dots, n. \quad (3.3)$$

Let adjacent mean value of series $X^{(1)}$ is $Z^{(1)}$:

$$Z^{(1)} = \left(Z^{(1)}(1),\ Z^{(1)}(2), \dots, Z^{(1)}(n)\right) \quad (3.4)$$

Where $Z^{(1)}$(k) is computed by:

$$Z^{(1)}(k) = 0.5 \times \left(X^{(1)}(k) + X^{(1)}(k-1)\right),\quad k = 2, 3, \dots, n. \ (3.5)$$

GM (1, 1) model can be built by establishing first order differential equation for $X^{(1)}(k)$.

$$\frac{dX^{(1)}(k)}{dk} + aX^{(1)}k = b \quad (3.6)$$

Where parameter a is developing coefficient and b is grey input.

A solution of solving (3.6) can be found by using the least square method to find parameters a and b:

$$\begin{bmatrix} a \\ b \end{bmatrix}^T = (B^T B)^{-1} B^T \bar{Y}_N \quad (3.7),\quad B = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ \dots\dots\dots & \dots \\ -Z^{(1)}(n) & 1 \end{bmatrix} \quad (3.8)$$

$$\text{and } Y_N = \begin{bmatrix} X^{(0)}(2) \\ \dots\dots\dots \\ X^{(0)}(n) \end{bmatrix} \quad (3.9)$$

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

According to (3.6), the solution of $X^{(1)}$ (k) at time k:

$$\hat{X}^{(1)}(k+1) = \left[X^{(0)}(1) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a} \quad (k = 1, 2, 3, \dots) \ (3.10)$$

We acquired $\hat{X}^{(1)}$ from (3.10). Let $\hat{X}^{(0)}$ be the GM (1,1) fitted and predicted series.

$$\hat{X}^{(0)} = \left(\hat{X}^{(0)}(1), \hat{X}^{(0)}(2), \dots, \hat{X}^{(0)}(n), \dots\right), \quad (3.11),$$

$$where\ \hat{X}^{(0)}(1) = X^{(0)}(1)$$

Finally, to obtain predicted value of the primitive data at time (k+1), IAGO is used to establish the following grey model:

$$X^{(0)}(k+1) = \left[X^{(0)}(1) - \frac{b}{a}\right] e^{-ak}(1 - e^{a}), (k = 1, ..n) \ (3.12)$$

In general, GM (1, 1) is constructed on a single sequence, it use behavioral sequence of the system without considering any external action sequences.

The forecasting method is implemented to predict future results via present incomplete information; thus, it always carries errors and risks. Hence, a mean absolute percent error (MAPE) is employed to measure the accuracy values in statistics. The smaller value of MAPE demonstrates that the forecasting value is more reasonable. Stevenson and Sum (2010) stated MAPE in their book as the following equation [18-19]:

$$\text{MAPE} = \frac{1}{n} \sum_{t=1}^{n} \frac{|\text{Actual}_t - \text{Forecast}_t|}{\text{Actual}_t} \times 100 \quad (3.13),$$

where *n* is number of periods.

The grade of MAPE declare the forecasting reliability as in Table III.

TABLE III. The grades of MAPE.

MAPE evaluation	< 10	10÷20	20÷50	> 50
Accuracy level	Excellent	Good	Qualified	Unqualified

Malmquist productivity index (MPI) was used to calculate productivity changes of many decision making unit entities. MPI provides performance analysis over a period time based on DEA model. The MPI denotes two major of productivity change including efficient change (catch-up) and technical change (frontier-shift or innovation). MPI >1 means that productivity increases; while MPI= 1 means productivity do not change; and MPI < 1 demonstrates that productivity decreases (from period t to another t+1). The efficient change and technical change can be formulated as follow equation (Coelli et al, 2005) [20]:

$$\text{Catch-up} = \frac{\delta_i^{t+1}(x_0, y_0)^{t+1}}{\delta_i^{t}(x_0, y_0)^{t}} \text{ and}$$

$$\text{Frontier-shift} = \left[\frac{\delta_i^{t}(x_0, y_0)^{t}}{\delta_i^{t+1}(x_0, y_0)^{t}} \times \frac{\delta_i^{t}(x_0, y_0)^{t+1}}{\delta_i^{t+1}(x_0, y_0)^{t+1}}\right]^{1/2} \quad (3.14)$$

Where:

$(x_0, y_0)^t$ and $(x_0, y_0)^{t+1}$ denote the DMU data in periods t and (t+1);

$\delta_i^t(x_0, y_0)^t$ and $\delta_i^t(x_0, y_0)^{t+1}$ represent the efficiencies in period t frontier;

$\delta_i^{t+1}(x_0, y_0)^t$ and $\delta_i^{t+1}(x_0, y_0)^{t+1}$ represent the efficiencies in period (t+1).

The MPI can be further interpreted as a geometric average of efficient change and technical change in period (t) and period (t + 1).

MPI = Catch-up×Frontier-shift

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$$= \left[\frac{\delta_i^t(x_0,y_0)^{t+1}}{\delta_i^t(x_0,y_0)^t} \times \frac{\delta_i^{t+1}(x_0,y_0)^{t+1}}{\delta_i^{t+1}(x_0,y_0)^t}\right]^{1/2} \quad (3.15)$$

IV. EMPIRICAL RESULTS

Prediction results: This research predicts the inputs and outputs for the future by the use of GM (1,1) model. By the use historical data (2013 – 2016), the derived forecasted value (2017 – 2018) is shown in Table IV

TABLE IV. The derived prediction values of 29 DMUs in 2017 & 2018.

DMUs	Inputs (Billions of VND)			Outputs (Billions of VND)	
	(I)TA	(I)CoGS	(I)F.Exp	(O)Rev	(O)EAT
2017					
DMU1	4,404.91	2,081.77	76.29	2,464.63	194.74
DMU2	230.30	102.81	0.44	128.42	10.24
DMU3	3,530.35	2,528.00	59.27	3,853.23	803.69
DMU4	261.94	137.19	4.37	194.63	23.88
DMU5	23.06	47.90	0.92	51.05	0.08
DMU6	3,259.91	2,848.18	104.40	3,473.09	230.06
DMU7	1,252.55	1,422.83	29.00	1,562.33	69.51
DMU8	3,292.95	1,615.26	124.71	2,183.00	170.69
DMU9	45.85	51.27	6.30	66.25	5.16
DMU10	2,728.53	2,762.09	69.47	3,421.31	429.94
DMU11	162.33	109.86	0.54	138.51	12.28
DMU12	53.15	44.73	1.49	59.34	2.71
DMU13	181.16	291.99	0.83	0.00	21.05
DMU14	2,569.18	993.38	80.26	1,538.93	110.29
DMU15	207.68	62.37	1.79	83.57	11.73
DMU16	3,989.90	3,195.43	68.62	5,212.60	441.53
DMU17	123.17	119.67	1.92	147.28	8.45
DMU18	163.45	285.76	3.48	329.71	10.70
DMU19	191.49	289.27	0.86	303.89	0.26
DMU20	1,267.90	1,061.44	30.37	1,239.50	77.89
DMU21	50.54	106.21	0.09	130.39	12.22
DMU22	106.15	104.65	6.58	126.55	1.69
DMU23	1,213.97	876.18	50.11	1,005.78	32.34
DMU24	836.49	697.07	10.59	873.16	66.81
DMU25	544.18	624.81	11.99	677.61	27.30
DMU26	399.94	436.70	14.38	545.39	24.90
DMU27	727.33	1,074.46	6.51	1,329.34	174.50
DMU28	362.42	148.09	11.18	156.12	24.46
DMU29	209.68	388.56	10.91	432.14	0.76
2018					
DMU1	6,557.47	2,428.62	102.93	2,925.92	416.76
DMU2	231.80	96.46	0.35	126.51	16.15
DMU3	4,300.79	2,877.86	84.84	4,513.93	1,024.04
DMU4	252.37	135.16	6.08	194.11	27.94
DMU5	22.16	43.60	0.83	45.48	0.03
DMU6	3,231.79	2,984.58	110.47	3,527.55	204.10
DMU7	1,452.97	1,589.80	28.51	1,750.32	92.17
DMU8	8,908.33	2,398.90	268.13	3,415.87	323.37
DMU9	48.13	46.45	6.35	62.17	9.25
DMU10	2,589.93	2,880.25	54.21	3,478.57	453.03
DMU11	167.79	114.24	0.35	149.83	18.72
DMU12	55.96	39.62	1.69	53.27	3.04
DMU13	196.55	285.72	0.46	2,048.00	21.59
DMU14	2,896.81	876.99	75.97	1,424.78	170.80
DMU15	241.76	65.87	2.00	88.28	14.92
DMU16	4,554.52	3,720.35	82.02	6,290.66	488.00
DMU17	138.06	116.33	1.49	145.30	8.00
DMU18	187.16	319.53	3.94	365.32	10.80
DMU19	174.30	215.88	0.60	226.83	0.07
DMU20	1,552.29	1,096.93	32.03	1,297.79	103.17
DMU21	47.48	93.27	0.03	117.36	13.66
DMU22	93.74	77.33	7.65	94.46	0.93
DMU23	1,442.57	972.19	51.75	1,113.70	56.06
DMU24	1,000.59	664.42	9.70	835.67	65.43
DMU25	520.64	604.86	10.51	658.84	38.59
DMU26	439.42	380.28	14.22	489.12	31.77
DMU27	631.61	1,000.56	3.61	1,278.68	304.57
DMU28	312.19	90.15	7.82	94.98	23.44
DMU29	221.76	442.14	10.56	484.63	0.25

In this study, the MAPE was used to test the accuracy of forecasting to ensure appropriate predictive methods. The results are shown in Table V

TABLE V. The derived prediction values of 29 DMUs in 2017 & 2018.

DMUs	Average MAPE	DMUs	Average MAPE
DMU1	14.51%	DMU16	1.68%
DMU2	17.80%	DMU17	3.14%
DMU3	1.42%	DMU18	2.59%
DMU4	6.07%	DMU19	15.81%
DMU5	6.40%	DMU20	7.94%
DMU6	4.83%	DMU21	10.47%
DMU7	0.81%	DMU22	18.85%
DMU8	10.26%	DMU23	18.09%
DMU9	3.17%	DMU24	17.09%
DMU10	3.48%	DMU25	8.20%
DMU11	5.72%	DMU26	6.95%
DMU12	3.51%	DMU27	4.39%
DMU13	17.70%	DMU28	5.70%
DMU14	18.66%	DMU29	18.45%
DMU15	8.78%		
Average MAPE of 29 DMU			9.05%

This research applied a quantitative model forecasting approach, through re-simulating the past actual data. So that, if the error is within the allowable limits, then the model is reliable and usable. Table VI showed that the values of MAPE are excellent and good (less than 10%), (based on rules of Table III). The average of all MAPE is 9.05%, this means the predicted results have a high level of accuracy. It forcefully affirms that GM(1,1) model offers an accurate prediction in this research.

Pearson correlation: In this research, we use the Malmquist productivity index model to analyze productivity of DMUs, where the condition for using DEA is the correlation coefficient, which could not be negative or equal to 0. Thus, the authors used the Pearson correlation coefficient to determine the data used in this study, which is in accordance with the DEA standards. Correlation coefficients are always in the range of (-1) to (1); if a value is as close to (1), it is a perfect linear relation [21]. The results of Tables VI showed strong positive associations and fairly comply with preconditions of the DEA model and can be used for analysis.

TABLE VI. Correlation of input and output factors.

	(I)TA	(I)CoGS	(I)F.Exp	(O)Rev	(O)EAT
(I)TA	1	0.9454	0.9154	0.9428	0.7783
(I)CoGS	0.9454	1	0.836	0.9891	0.851
(I)F.Exp	0.9154	0.836	1	0.8135	0.5902
(O)Rev	0.9428	0.9891	0.8135	1	0.8817
(O)EAT	0.7783	0.851	0.5902	0.8817	1

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Analysis of efficiency change: The efficiency change also called "catch-up" effects. The annual efficient change index for each experiment is shown in Table VII and Figure 2.

TABLE VII. Annual efficiency change from 2012 to 2015.

DMUs	2013~2014	2014~2015	2015~2016
DMU1	1.119725243	0.909151181	0.970976034
DMU2	1.000000472	0.999998612	0.958387346
DMU3	1	1	1
DMU4	1.0236536	0.999999828	0.999999843
DMU5	1	0.999998931	0.999999628
DMU6	1	1	0.877649786
DMU7	1	1	1
DMU8	1.162172218	0.892714777	0.946574858
DMU9	0.999999812	1.000000659	0.999999990
DMU10	1	1	1
DMU11	0.955147129	1.042544698	0.953699065
DMU12	1.000000058	0.999999416	1.000000584
DMU13	1	1	1
DMU14	0.988526537	1.002426084	1.023102238
DMU15	1.000000569	0.999999714	1.000000286
DMU16	1	1	1
DMU17	0.986482048	0.982610668	0.923051983
DMU18	1	0.980721767	0.967685039
DMU19	1	1	1
DMU20	0.98090584	1.019465844	0.902657317
DMU21	1	1	1
DMU22	1.04949437	0.930329492	0.996893025
DMU23	1.026133721	1.044087625	1.001978781
DMU24	1	1	0.866786746
DMU25	0.966548104	1.019914919	1.015743421
DMU26	0.972541988	1.028233241	0.88042379
DMU27	0.874490403	1.143523126	1
DMU28	0.956170103	0.998713271	1.250217471
DMU29	1	1	1
Average	1.002137663	0.999808064	0.983994042

Source: Calculate by researcher

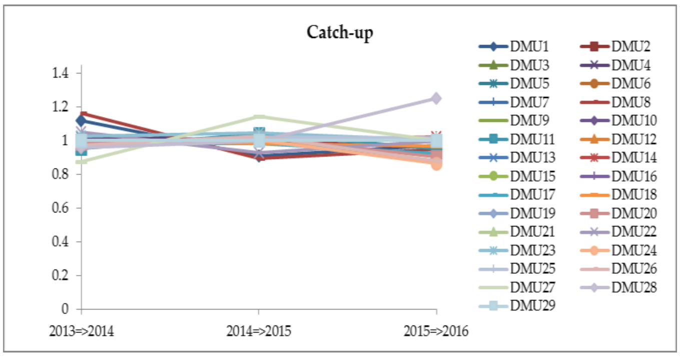

Fig. 2. Annual efficiency changes from 2013 to 2016.

Eight DMUs had showed efficient improvement in period 2013 – 2014. They were DMU1, DMU2, DMU4, DMU8, DM12, DMU15, DMU22, and DMU23 with efficient change scores larger than one. This means that these DMUs improved performance efficiency in this period. Twelve DMUs had no change in their efficiency and the other nine DMUs lost to improve their efficiency in this period. DMU8 and DMU1 achieved the largest improvement; they scored of 1.162172 and 1.119725, respectively. While on the other hand, DMU27 had a largest declines of 0.874490.

From 2014 to 2015, only eight DMUs improved efficiency, including DMU9, DMU11, DMU14, DMU20, DMU23, DMU25, DMU26 and DMU27. Eleven DMUs were decreased and ten DMUs do not change in efficiency. DMU27 achieved the highest improvement of efficiency (increasing 14%), while DMU8 had a worst declines of 11%, followed by DMU1 (10%).

In the period 2015 – 2016, a half of DMUs were decreased efficiency, except DMU12, DMU14, DMU15, DMU23, DMU25, and DMU28. The other nine DMUs have no efficient change. The only DMU28 got a largest efficient improvement of 23%, while DMU24 had a highest decline of 14%, follow by DMU6 (13%) and DMU26 (12%).

For whole period 2013 – 2016, the average efficient change has downtrend. An average efficiency improved of 0.2% from 2013 to 2014, but slightly decline in next two periods (2014 – 2015 and 2015 – 2016) with a number of -1% and -2%, respectively. DMU24, DMU6 and DMU26 have largest decline in efficiency across 2013 to 2016.

Analysis of technical change: Technical change, also called ''innovation'' or "frontier-shift" effects, is the second component of the MPI. This component show the effects of the shift in frontier of the individual experiment productivity change for an exposition of technical change's effect on productivity change using production functions. Table VIII and Fig. 3 reports annual index of technical progress or regress.

TABLE VIII. Annual technical changes from 2013 to 2016.

DMUs	2013~2014	2014~2015	2015~2016
DMU1	0.960996	1.0222615	1.0469021
DMU2	1.163865	1.2560075	1.0096219
DMU3	0.8875436	0.9463069	0.9248136
DMU4	0.9885986	0.9846103	1.0641052
DMU5	0.8305868	1.0635146	0.8249809
DMU6	1.0713306	1.0699711	1
DMU7	1.059561	1.0045385	1.0395224
DMU8	0.6453093	1.0195506	1.1991836
DMU9	0.9868987	1.1683238	0.9985149
DMU10	0.9110724	1.150856	1
DMU11	1.0091029	1.0909139	0.9447814
DMU12	0.9686363	1.192308	0.9668815
DMU13	0.9350028	1.2231033	0.9344805
DMU14	1.0448948	1.0019338	0.9364713
DMU15	0.833523	1.1964043	1.1225819
DMU16	1.4273436	0.9873373	0.9984477
DMU17	0.9972751	0.9125988	1.0429839
DMU18	0.8743597	1.0298776	0.963503
DMU19	1.1211712	0.7881448	1.0137912
DMU20	0.9443089	0.9915185	1.0016154
DMU21	1.1524363	1.8379931	4.4543818
DMU22	0.9876441	1.0114388	1.0276259
DMU23	0.9964587	0.9652063	1.0194563
DMU24	1.0448037	1.0174508	0.9587656
DMU25	1.0342325	0.9805457	1.0402521
DMU26	0.9669309	1.1729222	0.772739
DMU27	0.9504993	1.0407159	3.8577089
DMU28	0.974242	0.9893194	3.0804915
DMU29	1.0613152	0.3685113	0.9999509
Average	1.0188228	0.9789828	1.3318041

Source: Calculate by researcher

In the period 2013 – 2014, there are total eighteen DMUs with scores of technical change smaller than one, which expressed that technical regress or innovation deteriorated in this period. It is also meaning that there were a shortfall in outputs (revenues and earnings). DMU8 has a worst technical regress of 36%, while on the other case DMU16 and DMU2 and DMU21 had highest progress of 42%, 16% and 15%, respectively.

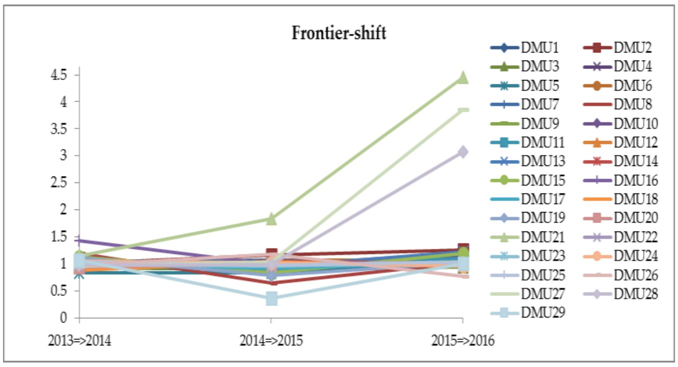

Fig. 3. Annual technical changes from 2013 to 2016.

From 2014 to 2015, ten DMUs were regressed in technical change, nineteen DMUs showed technical progress. In this period, we found that the highest technical progress (DMU2) equal to 25%, while the worst deteriorated (DMU29) equal to 64%. The same trend was shown in period 2015 – 2016, when having fifteen DMUs showed technical regress, except DMU6 and DMU10 had no change. Three DMU had an outstanding improvement in technical change (DMU14, DMU27 and DMU28). In which, DMU14 had a highest technical progress of 345%, follow by DMU27 (285%) and DMU28 (208%).

For whole period 2013 – 2016, the average technical change ranged from -3.2% to 33%. The results indicated that production performance deteriorated in period 2014 – 2015, but re-progresses in period 2015 – 2016.

Analysis of productivity change: The greater than one Malmquist productivity value will denote an improvement in the performance of business management. Table IX and Fig. 4 displays the calculation of annual productivity changes of fitness equipment industry over the period 2013 – 2016.

TABLE IX. Annual productivity changes from 2013 to 2016.

DMUs	2013~2014	2014~2015	2015~2016
DMU1	1.1722427	0.8736907	0.9925914
DMU2	1.0096224	1.1638634	1.2037417
DMU3	0.9248136	0.8875436	0.9463069
DMU4	1.0892751	0.9885985	0.9846102
DMU5	0.8249809	0.8305859	1.0635142
DMU6	1	1.0713306	0.9390599
DMU7	1.0395224	1.059561	1.0045385
DMU8	1.3936578	0.5760771	0.965081
DMU9	0.9985148	0.9868993	1.1683238
DMU10	1	0.9110724	1.150856
DMU11	0.9024053	1.0520349	1.0404036
DMU12	0.9668816	0.9686357	1.1923087
DMU13	0.9344805	0.9350028	1.2231033
DMU14	0.9257267	1.0474298	1.0250807
DMU15	1.1225825	0.8335228	1.1964047
DMU16	1.4273436	0.9873373	0.9984477
DMU17	0.9837940	0.8967293	0.9627284
DMU18	0.8743597	1.0100234	0.9323674
DMU19	1.1211712	0.7881448	1.0137912
DMU20	0.9262782	1.0108192	0.9041155
DMU21	1.1524363	1.8379931	4.4543818
DMU22	1.0365270	0.9409714	1.024433
DMU23	1.0224999	1.0077599	1.0214736
DMU24	1.0448037	1.0174508	0.8310453
DMU25	0.9996355	1.0000732	1.0566292
DMU26	0.9403809	1.2060376	0.6803378
DMU27	0.8312025	1.1900827	3.8577089
DMU28	0.9315410	0.9880464	3.8512843
DMU29	1.0613152	0.3685113	0.9999509
Average	1.0226895	0.9805458	1.3339524

Source: Calculate by researcher

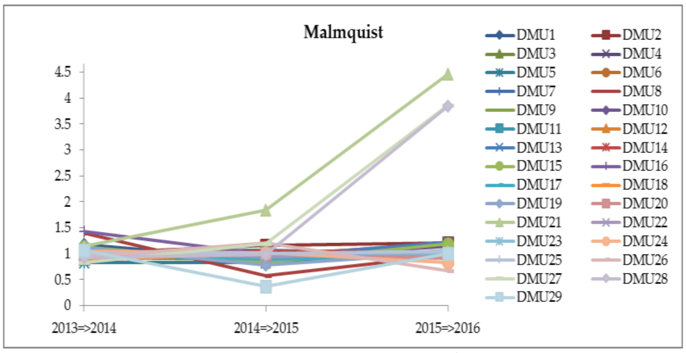

Fig. 4. Annual productivity change (MPI) from 2012 to 2015.

In period 2013 – 2014, the result showed that, total thirteen manufactures have MPI values larger than one; it means that productivity growth in this period. The other fourteen manufactures have MPI less than 1, which means loss of productivity; two manufacture does not change. DMU16 and DMU8 had the highest productivity growth over this period while on the other hand DMU5 had the largest loss, followed by DMU27 and DMU18.

From 2014 to 2015, Total sixteen DMUs had productivity loss and other DMUs improve their MPI; the results showed that DMU29 had the largest productivity loss (-64%), followed by DMU8 (-43%) and MDU19 (-22%). In the period of 2015 to 2016, seventeen companies had productivity growth and the other twelve companies had productivity loss. There are only three DMUs (DMU21, 22 and 23) got an outstanding improvement in MPI. DMU21 had the largest productivity growth, followed by DMU27 and DMU28.

In general, the whole period 2013 – 2016 showed productivity gains. The results indicated that performance deteriorated in period 2014 – 2015 (-2%), but re-progresses in period 2015 – 2016 (33%).

The MPI is a multiplicative composite of efficiency and technical change. The major cause of productivity improvements can be ascertained by comparing values of efficiency change and technical change indexes. Put differently, the productivity losses described can be the result of either efficiency declines, or technique regresses, or both. Table X presents the MPI's results of the twenty nine plastic companies of Vietnam from 2013 to 2016. The average percentage productivity change ranged from -20% (DMU29) to 148% (DMU21). For whole period (2015 – 2016), there are only three DMUs including (DMU21, 22 and 28) got an outstanding MPI score, which indicated that they had highest productivity growth from 2013 – 2016.

TABLE X. Annual average productivity change from 2013 to 2016.

DMUs	2013~2016 Annual average efficient change	2013~2016 Annual average technical change	2013~2016 Annual average productivity change (MPI)
DMU1	0.9999508	1.0100532	1.0128416
DMU2	0.9861288	1.1431648	1.1257425
DMU3	1	0.9195547	0.9195547
DMU4	1.0078844	1.012438	1.0208279
DMU5	0.9999995	0.9063608	0.9063603
DMU6	0.9592166	1.0471006	1.0034635
DMU7	1	1.0345406	1.0345406
DMU8	1.0004873	0.9546811	0.978272
DMU9	1.0000002	1.0512458	1.051246
DMU10	1	1.0206428	1.0206428
DMU11	0.983797	1.0149327	0.9982812
DMU12	1	1.0426086	1.0426087
DMU13	1	1.0308622	1.0308622
DMU14	1.004685	0.9944333	0.9994124
DMU15	1.0000002	1.0508364	1.0508367
DMU16	1	1.1377095	1.1377095
DMU17	0.9640482	0.9842859	0.9477506
DMU18	0.9828023	0.9559134	0.9389168
DMU19	1	0.9743691	0.9743691
DMU20	0.9676763	0.9791476	0.947071
DMU21	1	2.4816038	2.4816038
DMU22	0.992239	1.0089029	1.0006438
DMU23	1.0240667	0.9937071	1.0172445
DMU24	0.9555956	1.0070067	0.9644333
DMU25	1.0007355	1.0183434	1.0187793
DMU26	0.9603997	0.9708641	0.9422521
DMU27	1.0060045	1.9496414	1.9596647
DMU28	1.0683669	1.681351	1.9236239
DMU29	1	0.8099258	0.8099258
Average	0.9953133	1.1098699	1.1123959

Source: Calculate by researcher

From 2013 to 2016, there are seventeen companies with average MPI values lager than one, which means its productivity growths in this period. The other twelve companies have average MPI's less than one, which indicates a decreasing in productivity. In other words, seventeen companies improved their performance efficiency, whereas the other twelve companies failed to improve their performance during the four-year period. Productivity loss for DMU11 and DMU24 was mainly caused by a decline of "catch-up" effect. The results indicate that this two companies need to cut of input resources waste or maximize output production to enhance efficient operation. Conversely, productivity loss for DMU3, DMU8, DMU14, DMU19, and DMU29 was mainly driven by technical change regress, so that these four companies have to improve performance of output production. Especially, productivity loss for DMU5, DMU17, DMU18, DMU20 and DMU26 was driven by both catch-up and frontier-shift. This means that these five companies can improve performance by both minimize input and maximize output.

In general observations, the average efficient change and technical change of all Vietnam's plastic companies were 99% and 110%, respectively. Therefore, the productivity change was due to improvement in technical change rather than in efficient change. The productivity of plastic industry over the past four years is quite good. Technical change was more impact than efficient change, in terms of contribution to MPI improvement. However, both "catch-up" and "innovations" ("frontier-shift") effects were predominately attributed to Vietnam's plastic manufacturing industry productivity growth.

V. CONCLUSIONS

GM(1,1) and MPI models were used to forecast future business and evaluate productivity change in Vietnam's plastic industry. This research conducts on 29 Vietnam's plastic manufactures in the period 2013 — 2016. Based on the completed public data, the study employed the GM (1,1) to predict future business performance. The accurate forecasting value had been tested by average MAPE and received a reliable accuracy of 9.05%.

The MPI's results indicated that seventeen companies increased productivities and the other twelve companies were decreased in productivities. The technical change was more impact than efficient change, in terms of contribution to MPI improvement. However, both "catch-up" and "innovations" ("frontier-shift") effects impact on Vietnam's plastic manufacturing industry productivity growth. The results also reflect the fact that the MPI's changes did not depend on company size.

In a conclusion, to sustain the development of Vietnamese plastic industry, the government should help these companies. Which could be divided into three groups including (group 1: DMU11 and DMU24 - need to improve in efficiency), (group 2: DMU3, DMU8, DMU14, DMU9, and DMU29 - need to improve in output production) and (group 3: DMU5, DMU17, DMU18, DMU20 and DMU26 - need to improve in both efficient and production).

The results provide a meaningful reference to help plastic manufactures to improve their operating efficiency and productivity. The proposed approach can help decision-makers and policy-maker in making decision and strategies for sustain the development of Vietnamese plastic industry. The application can be applied to other industries, by the use of other DEA model and more input and output variables.

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