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Applying Grey Model and DEA for the Productivity Evaluation of Global Fitness Industry

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Abstract— *Maintaining sustainable development is becoming an important issue for the fitness industry. This research proposes a hybrid approach based on grey model (GM) and Malmquist productivity index (MPI), to predict future business and measure operational performance of worldwide fitness manufactures over several time periods. From that, decision making units (DMUs) and managers can improve business performance and build a sustainable development strategy. The study conducted on 15 fitness manufactures, which have published their complete information on Google finance site. The result showed that eight manufactures increased in productivity while the other seven didn't. Technical change was more impact than efficient change in period 2012 – 2015. In general, both of them impact on fitness 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—*Fitness industry; productivity; GM; DEA; MPI.*

I. INTRODUCTION

Fitness equipment industry provides machines and monitoring devices required for various type of healthcare demand. The most commonly observed fitness equipment includes treadmills, stair climbers, stationary bicycles, weightlifting equipment and resistance machinery etc. Major brands include "Nautilus, Cybex international, Icon health & fitness, Life fitness, Precor (all based in the US), Motus (South Korea), Nantong Yida sports (China), Northern lights (Canada), Schnell trainingsgeräte (Germany), and Tonic fitness technology (Taiwan)" [1]. The global fitness equipment market is expected to reach a total of $12.5 billion by 2021 with registered compound annual growth rate (CAGR) at 3.89% [2-3]. Fitness equipment market types are segmented into different groups, such as wearable/non-wearable machines for training, monitoring, tracking, or treatment. The user segment comprises of home/individual and health club. A major commercial segment includes equipment procured by resort/hotels, wellness centres at some enterprises, hospitals, schools etc. Fig. 1 shows the forecasted revenue of global fitness equipment market in period 2015 – 2021 [3].

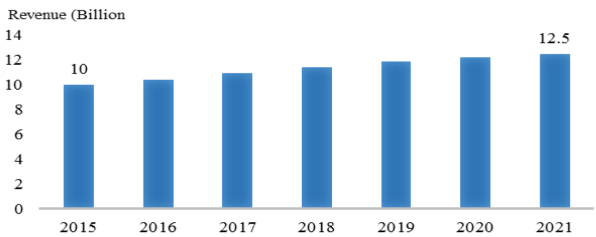

Fig. 1. Global fitness equipment market, 2015 – 2021 [3].

This industry is growing fast recently, but rapid growth is also leading to stronger competition between manufacturers in this industry. "Large companies have some advantages in brand recognition, but small companies can compete effectively by building unique products" [4]. According to Michael Porter's five force model, this industry is also faced with high rivalry of itself, threat of new potential entrants, negotiation power of supplier, threat of substitution products, and customer's requirements [5]. The resale of used fitness equipment will also have an effect to limit growth in the future. The lack of integrity research and development, education, or professionalism in this field also leads to a poor innovative and less performance products.

The purpose of this study is to propose an assessment approach based on grey model and Malmquist productivity index. The approach predicts future business, measures operational performance, and analyzes productivity change in the global fitness industry. We conducted on 15 fitness equipment manufacturers collected from Consumeraffairs 2016's report and Google finance [6-7]. They are famous brands and can offer complete data for four consecutive financial years (2012 – 2015) [7]. Recently, they met massive challenges regarding maintaining competitiveness, improving operational performance, and expand new business. Therefore, an evaluation productivity is needed to help firms adjust business strategies. This research chooses asset, equity and goodwill as input, because they are key of financial indicators and value of brand contributing to the performance of companies. The revenues and net income is selected as output, because they are important indices for measuring the performance of this industry. The approach can then analyze input resource utilization and compare efficiency to help them improve performance. The results of this study will provide useful information for worldwide fitness manufacturers, investors and consumers.

II. LITERATURE REVIEW

Grey system theory has been applied in a board field to solve uncertainty issues, unknown parameters and poor or missing information, it was first introduced by Ju-Long Deng [8]. Grey system theory is superior to conventional statistical models because it only requires a limited amount of data to predict the action of unknown systems [9]. GM (1,1) is known as a popular model in grey forecasting. Ren demonstrated that GM (1,N) gave a better forecast ability result than artificial neural network under scanty data conditions, in forecasting the yield of bio-hydrogen [10].

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Data envelopment analysis (DEA) was proposed by Charnes, Cooper, and Rhodes (1978) [11]. This method can deal with multiple inputs and outputs of multiple peer decision-making units (DMUs,) by the use of deterministic non-parametric frontier with rarely need of assuming. The DMU entities can be manufacturer units, bank branches, schools, universities, hospitals etc. DEA has been recognized as a robust tool of operation research for measuring technical efficiency and has been widely applied in both private and public sectors.

Grey theory and DEA 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 [12]. Shi (2009) proposed an effective and reliable Grey-Fuzzy evaluation to evaluate teaching quality [13]. 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% [14]. 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 [15]. Wang, Nguyen, and Wang (2016) researched to find feasible alliance partner for automobile makers by using an integrated grey theory and DEA [16]. 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 [17]. Chen, Hsieh, and Chen (2010) applied DEA to evaluate performance efficiency of 20 stores of the E-Life Mall in Kaohsiung City, Taiwan [18]. Mathur and Paul (2014) used the DEA approach, CCR and BCC models to appraise the performance of 20 Indian Non-Life Insurance Companies [19]. Fuentes, Fuster, and Lillo-Bañuls (2016) used a three-stage DEA model to measure technical efficiency of learning and teaching [20].

Although grey theory and DEA have been applying in a board filed, this is the first time the hybrid econometric model is used to predict future business, measure operational performance and productivity change in the global fitness equipment industry. From that, the fitness manufactures can adjust business performance and build a sustainable development strategy.

III. Research Development, Data Collection and Methodology

This study proposes a hybrid model to evaluate efficiency and productivity. Fig. 2 provides detailed applied steps. The steps of data collection and input – output variable selection are initial works in this paper. Step 3 implements prediction work, by the use of GM (1, 1) model to predict the business value of fitness industry in future years. In order to ensure that the forecast errors are reliable, a mean absolute percent error (MAPE) is applied to measure the prediction accuracy in Step 4. Once the error rate is too high, the study has to reselect the input and output variables. Step 5 uses the Pearson Correlation Coefficient Test 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 Step 2 will be repeated to establish a new factor. This is done until it can meet our requirements. Mamlquist of DEA is applied to calculate with realistic data in Step 6. The purpose of this step is to find out efficient ranking of all DMUs. This step also evaluates productivity change for all fitness manufacturers, analyzes reasons of changing, and discusses the way to help inefficient DMUs improve its operational performance. The conclusions and suggestions will be stated in Step 7.

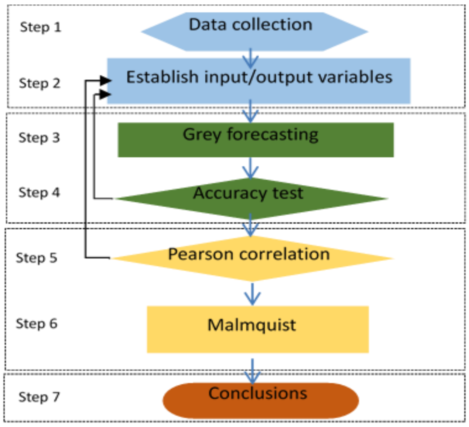

Fig. 2. Research development.

This research only conducted on 15 fitness equipment manufacturers in Consumeraffairs's 2016 report and Google finance [6, 7]. They are stable in the market and can offer complete data for four consecutive financial years (2012 – 2015), according to Google finance site [7]. The collected DMUs information is shown in Table I. These historical data of them is shown in Table II. Recently, fitness industry makers met massive challenges regarding to maintain competitiveness, improve operational performance, and open new business. Hence, an evaluation of efficiency and productivity is needed to help firms review and reorganize business strategies.

TABLE I. List of 15 fitness equipment manufacturers.

DMUs	Companies	Headquarter
DMU1	Nike, Inc.	Oregon, United States
DMU2	Adidas AG	Herzogenaurach, Germany
DMU3	Gap Inc	California, United States
DMU4	Brunswick Corp	Lake Forest, Illinois, United States
DMU5	Amer Sports	Helsinki, Finland
DMU6	Dorel Industries, Inc	Westmount, Canada
DMU7	Life Time Fitness, Inc	Minnesota, United States
DMU8	Skechers USA Inc	California, United States
DMU9	Lululemon Athletica Inc	Vancouver, Canada
DMU10	Invacare Corporation	Ohio, United States
DMU11	Black Diamond Inc	Salt Lake City, United States
DMU12	Planet Fitness, Inc.	New Hampshire, United States
DMU13	Nautilus, Inc.	Washington, United States
DMU14	Escalade, Inc	Indiana, United States
DMU15	Gaiam, Inc	Colorado, United States

In order to adequately measure productivity, the selection of input and output factors should be carefully considered. Literature reviews were done on the DEA, fitness industry's operations, the International Accounting Standard (IAS) [21], and the suitable correlation between input and output variables.

TABLE III. The historical data of 15 fitness equipment manufacturers (2015).

DMUs	Inputs (Millions of US Dollars)			Outputs (Millions of US Dollars)	
	(I) Assets	(I) Equity	(I) Goodwill	(O) Revenue	(O)Net Income
DMU1	21,600.00	12,707.00	131.00	30,601.00	3,273.00
DMU2	14,495.00	6,155.00	1,512.00	18,375.00	695.00
DMU3	7,473.00	2,545.00	180.00	15,797.00	920.00
DMU4	3,152.50	1,281.30	298.70	4,105.70	241.40
DMU5	2,862.72	1,064.00	387.52	2,838.08	136.64
DMU6	2,529.96	1,206.98	544.78	2,677.55	(21.27)
DMU7	2,681.62	1,105.12	61.10	1,290.62	114.37
DMU8	2,047.41	1,327.56	158.00	3,147.32	231.91
DMU9	1,296.21	1,089.57	24.41	1,797.21	239.03
DMU10	838.14	462.82	361.68	1,142.34	(26.19)
DMU11	228.59	176.00	29.63	155.27	(7.597)
DMU12	699.18	(15.38)	176.98	330.54	18.52
DMU13	315.91	126.99	60.47	335.76	26.60
DMU14	143.74	96.48	20.05	155.54	11.61
DMU15	128.54	83.94	15.45	188.02	(11.71)

GM (1, 1) model in this work was established based on two basic operations (accumulated generation operation (AGO) and inverse accumulated generation (IAGO)) [9]. 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 $X^{(1)}$:

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

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

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

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:

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

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:

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

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:

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

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 [22]:

$$\mathrm{MAPE} = \frac{1}{\mathrm{n}} \sum_{\mathrm{t=1}}^{\mathrm{n}} \frac{|\mathrm{Actual_t} - \mathrm{Forecast_t}|}{\mathrm{Actual_t}} \times 100 \quad (3.13),$$

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) [23]:

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

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

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 (2012 – 2015), the derived forecasted value (2016 – 2017) is shown in Table IV

TABLE IV. The derived prediction values of 15 DMUs in 2016 & 2017.

DMUs	Inputs (Millions of US Dollars)			Outputs (Millions of US Dollars)	
	(I) Assets	(I) Equity	(I) Goodwill	(O) Revenue	(O)Net Income
2016					
DMU1	23,720.87	13,310.49	130.98	33,603.83	3,725.00
DMU2	13,730.45	5,542.01	1,381.95	17,316.29	439.07
DMU3	7,302.40	2,392.15	177.35	15,781.97	850.23
DMU4	3,307.66	1,426.00	302.81	4,381.22	75.21
DMU5	3,179.76	1,185.14	427.58	3,058.93	149.99
DMU6	2,731.53	1,191.46	555.27	2,730.76	4.21
DMU7	3,048.16	1,139.29	77.74	1,380.48	118.94
DMU8	2,452.72	1,572.87	1.58	4,059.93	413.01
DMU9	1,459.16	1,235.03	23.64	2,058.34	233.89
DMU10	734.25	387.38	324.49	1,069.85	-124.77
DMU11	210.50	167.81	28.02	160.42	0.18
DMU12	772.67	14.39	190.67	412.68	21.63
DMU13	456.32	149.66	8.73	413.63	12.52
DMU14	139.71	100.33	24.46	166.51	12.94
DMU15	123.74	77.29	16.45	205.47	-5.70
2017					
DMU1	26,401.15	14,313.73	130.97	36,947.59	4,307.19
DMU2	13,070.30	4,998.79	1,314.67	16,752.11	331.95
DMU3	7,125.83	2,189.84	175.40	15,612.77	732.79
DMU4	3,436.43	1,582.17	306.40	4,679.22	35.43
DMU5	3,580.37	1,324.84	475.15	3,338.97	186.72
DMU6	2,922.18	1,146.60	540.25	2,835.35	1.44
DMU7	3,464.90	1,155.70	99.02	1,477.29	120.77
DMU8	2,960.49	1,885.31	1.58	5,305.01	760.91
DMU9	1,612.40	1,358.46	22.88	2,353.81	220.69
DMU10	642.40	322.51	287.76	991.31	-235.31
DMU11	180.58	144.90	21.59	154.89	0.18
DMU12	864.20	5.20	201.83	511.71	19.42
DMU13	706.72	175.63	14.56	511.08	8.24
DMU14	140.64	105.17	30.59	180.46	14.00
DMU15	117.96	70.43	17.25	226.31	-3.68

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 15 DMUs in 2016 & 2017.

DMUs	Average MAPE	DMUs	Average MAPE
DMU1	1.321%	DMU9	1.926%
DMU2	3.925%	DMU10	17.813%
DMU3	1.746%	DMU11	21.224%
DMU4	4.275%	DMU12	24.092%
DMU5	5.418%	DMU13	9.750%
DMU6	11.808%	DMU14	2.486%
DMU7	1.049%	DMU15	4.327%
DMU8	2.368%		
Average MAPE of 15 DMU			7.569%

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 V 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 7.569%, 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: To apply DEA, a correlation test is necessary to ensure that the relationship between inputs and outputs variables is isotonic [24]. This research employs the Pearson correlation to measure the strength linear relationship of normal distributed variables [25]. The correlation coefficient is always between -1 and +1. If the correlation coefficients are positive, the factors have strong linear relation and will be put into the DEA model, while the factor that has a weak isotonic relation will be re-inspected [26]. 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.

	Assets	Equity	Goodwill	Revenue	Net Income
Assets	1	0.979724	0.444566	0.981635	0.914744
Equity	0.979724	1	0.314345	0.955304	0.957901
Goodwill	0.444566	0.314345	1	0.371692	0.061424
Revenue	0.981635	0.955304	0.371692	1	0.928698
Net Income	0.914744	0.957901	0.061424	0.928698	1

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 3.

TABLE VII. Annual efficiency change from 2012 to 2015.

Catch-up	2012~2013	2013~2014	2014~2015
DMU1	1.397093	1.093409	1.31899
DMU2	1.218582	0.637365	1.229542
DMU3	0.826354	1.164762	0.934729
DMU4	0.451088	0.440126	1.103229
DMU5	0.955357	0.875372	1.744287
DMU6	0.814181	0.675224	3.223616
DMU7	1.079404	0.910098	1.024691
DMU8	1	0.569281	1.405389
DMU9	0.939913	1.017564	0.957674
DMU10	12.34102	3.915582	1.026431
DMU11	9.419161	0.739875	1.694424
DMU12	1.11529	4.886311	0.987719
DMU13	1	1	0.875214
DMU14	1.653629	1	1.583139
DMU15	1	0.994051	1.005985
Average	2.347405	1.327935	1.341004

Source: Calculate by researcher

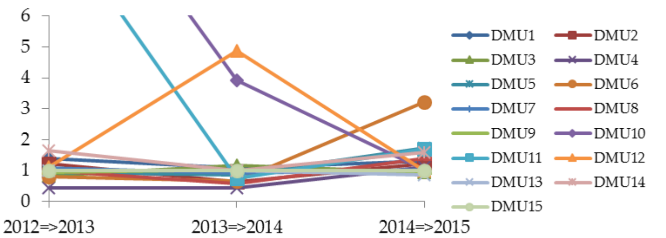

Fig. 3. Annual efficiency changes from 2012 to 2015.

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Seven DMUs showed efficient improvement in period 2012 – 2013. They are DMU1, DMU2, DMU7, DM10, DMU11, DMU12, and DMU14 with efficient change scores larger than one. This means that these DMUs improved performance efficiency between 2012 and 2013. Three DMUs has no change in their efficiency and the other five DMUs lost to improve their efficiency in this period. DMU10 and DMU11 obtained the largest improvement; they scored of 12.34102 and 9.419161, respectively. While on the other hand, DMU4 had a largest declines of 0.451088.

In the period 2013 – 2014, only five DMUs improved efficiency, including DMU1, DMU3, DMU9, DMU10 and DMU12. Eight DMUs were decreased and two DMUs do not change in efficiency. DMU12 obtained the highest improvement of efficiency (increasing 389%), while DMU4 still had a worst declines of 56%, followed by DMU8 (43%) and DMU2 (37%).

In the period 2014 – 2015, all DMUs improved efficiency, except DMU3, DMU9, DMU12, and DMU13. DMU6 has a largest efficient improvement of 223%, while DMU13 had a highest decline of 13% in efficiency.

For whole period 2012 – 2015, the average efficient change ranged from 2.347 to 1.341. An average efficiency improved of 134% from 2012 to 2013, but slightly decline in next two periods (2013 – 2014 and 2014 – 2015) with a number of 33% and 34%, respectively. DMU10 and DMU11 have largest decline in efficiency across 2013 to 2015.

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 Figure 4 reports annual index of technical progress or regress.

TABLE VIII. Annual technical changes from 2012 to 2015.

Frontier	2012~2013	2013~2014	2014~2015
DMU1	0.882853	1.028518	0.929267
DMU2	1.06699	1.074274	0.974405
DMU3	0.97575	0.938779	0.991815
DMU4	1.701107	0.904599	0.889279
DMU5	1.383597	0.716307	0.8803
DMU6	1.220244	0.801478	0.916788
DMU7	0.909326	0.995714	0.858154
DMU8	1.400655	0.94101	0.884189
DMU9	1.103041	0.928782	0.939225
DMU10	1.360616	0.874545	0.998483
DMU11	1.044534	0.829473	0.947103
DMU12	1.05677	0.668387	1.426982
DMU13	1	1	1.047147
DMU14	0.496716	1	0.728656
DMU15	0.832443	1.037816	1.028478
Average	1.095643	0.915979	0.962685

Source: Calculate by researcher

In the period 2012 – 2013, there are total five DMUs with scores of technical change smaller than one, which expressed that technical regressing in this period. It is also meaning that there were too much investment in technology but were reduced in revenues and income. DMU14 has a worst technical regressing of 51.4%, while on the other case DMU4 and DMU8 had a largest progressing of 70% and 40%, respectively.

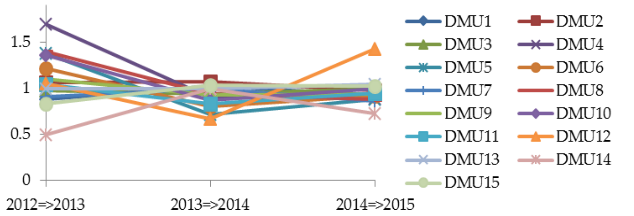

Fig. 4. Annual technical changes from 2012 to 2015.

From 2013 to 2014, ten DMUs were regressed in technology, only three DMUs showed technical progress, which are DMU1, DMU2 and DMU15. The other two DMUs had no change in technology. In this period, we found that the highest technical progress (DMU2) is 7%, while the worst deteriorated is 44% (DMU12). The same bad trend was shown in period 2014 – 2015, when having twelve DMUs showed technical regressing except DMU12, DMU13 and DMU15. In which DMU14 had a worst technical regressing of 28%.

For whole period 2012 – 2015, the average technical change ranged from 9.5% to -8.5%. The results indicated that technology progresses in period 2012 – 2013, while it is deteriorated in period 2013 – 2014, and period 2014 – 2015.

Analysis of productivity change: The greater than one Malmquist productivity value will denote an improvement in the performance of business management. Table IX and Figure 5 displays the calculation of annual productivity changes of fitness equipment industry over the period 2012 – 2015.

TABLE IX. Annual technical changes from 2012 to 2015.

MPI	2012~2013	2013~2014	2014~2015
DMU1	1.233428	1.12459	1.225694
DMU2	1.300215	0.684704	1.198072
DMU3	0.806315	1.093455	0.927079
DMU4	0.767349	0.398137	0.981078
DMU5	1.321829	0.627035	1.535496
DMU6	0.9935	0.541177	2.955373
DMU7	0.98153	0.906198	0.879342
DMU8	1.400655	0.535699	1.242629
DMU9	1.036763	0.945095	0.899471
DMU10	16.79139	3.424355	1.024874
DMU11	9.838634	0.613707	1.604795
DMU12	1.178605	3.265949	1.409457
DMU13	1	1	0.916478
DMU14	0.821383	1	1.153563
DMU15	0.832443	1.031642	1.034633
Average	2.686936	1.146116	1.265869

Source: Calculate by researcher

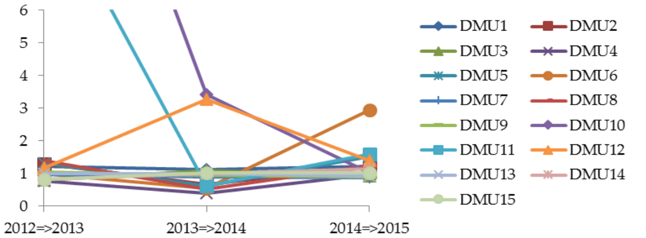

Fig. 5. Annual productivity change (MPI) from 2012 to 2015.

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In period 2012 – 2013, the result showed that, total eight manufactures have MPI's values larger than one; it means that productivity growing in this period. The other six manufactures have MPI less than 1, which means loss of productivity; one manufacture does not change. DMU10 and DMU11 had the highest productivity growth over this period while on the other hand DMU4 had the largest loss, followed by DMU3.

From 2013 to 2014, a half of DMUs had productivity loss, except DMU1, DMU3, DMU10, DMU12, DMU13, DMU14 and DMU15. The results showed that DMU4 had the largest productivity loss, followed by DMU8, DMU6 and MDU2. In the period of 2014 to 2015, ten manufactures had productivity growth and the other five manufactures had productivity loss. DMU7 had the largest productivity growth, followed by DMU9.

In general, the whole period 2012 – 2015 showed productivity gains. In which the period 2012 – 2013 recorded a highest growth (168%); the other two periods were 14.6% and 26.5%, respectively.

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 declining, or technique regressing, or both. Table X presents the MPI's results of the fifteen fitness manufacturers from 2012 to 2015. The average percentage productivity change ranged from -29% (DMU4) to 608% (DMU10). DMU10 and DMU11 had the highest productivity growth from 2012 – 2015.

TABLE X. Annual average productivity change from 2012 to 2015.

DMUs	2012~2015 Annual average efficient change	2012~2015 Annual average technical change	2012~2015 Annual average productivity change (MPI)
DMU1	1.269831	0.946879	1.194571
DMU2	1.028496	1.038556	1.060997
DMU3	0.975282	0.968782	0.942283
DMU4	0.664814	1.164995	0.715522
DMU5	1.191672	0.993401	1.161453
DMU6	1.571007	0.979503	1.496683
DMU7	1.004731	0.921065	0.922357
DMU8	0.991557	1.075285	1.059661
DMU9	0.971717	0.990349	0.960443
DMU10	5.761011	1.077881	7.080205
DMU11	3.951153	0.94037	4.019045
DMU12	2.329774	1.050713	1.951337
DMU13	0.958405	1.015716	0.972159
DMU14	1.412256	0.741791	0.991649
DMU15	1.000012	0.966246	0.966239
Average	1.672114	0.991435	1.69964

Source: Calculate by researcher

From 2012 to 2015, there are eight manufactures with average MPI values lager than one, which means its productivity growing in this period. The other seven manufactures have average MPI's small than one, which indicates decreasing in productivity. In other words, eight manufactures improved their performance efficiency, whereas the other seven manufactures failed to improve their efficiency during the four-year period. Productivity loss for DMU4 and DMU13 was mainly caused by a decline of "catch-up" effect. The results also indicated that these manufactures need to minimize inputs and maximize outputs to enhance efficient operation. Conversely, productivity loss for DMU7, DMU14, and DMU15 was mainly driven by technological regress, so that these firms needs to maximize production to enhance efficient performance. Especially, productivity loss for DMU3 and DMU9 was driven by both catch-up and frontier-shift effect. It means that these manufactures have still great space for improvement business efficiency, by either minimizing input resources or maximizing output productivity. In general observations, the productivity of fitness 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") impacted on the productivity change of fitness industry.

V. CONCLUSIONS

This research applies grey prediction and MPI models to forecast future business and evaluate productivity change in the global fitness equipment industry. The study conducts an empirical experiment on 15 fitness equipment manufactures in the period 2012－2015. Based on the completed public data, the study employed GM (1,1) model to predict future business results. The accurate forecasting value had been tested by average MAPE and received a reliable percentage of 7.5685%.

The MPI's results indicated that eight manufactures increased productivities and the other seven manufactures were decreased in productivities. In a conclusion, to sustain the development of global fitness equipment industry, the manufactures and stake-holder should help inefficient companies managing their performance. Which could be divided into three groups including (group 1: DMU4 and DMU13 - need to improve in efficiency) group 2: DMU7, DMU14, and DMU15 - need to improve in output production) and (group 3: DMU3 and DMU9 - need to improve in both efficient and production). The results also reflect the fact that the MPI's changes did not depend on company size.

The results provide a meaningful reference to help fitness equipment manufactures to improve their operating efficiency, speed up business management change, set challenging goals, and strengthen core competitiveness. The research argues that control of performance efficiency and productivity are necessary jobs for keeping competitive ability and determining the failures or successes of manufacturers in this industry. The application provides useful information for practitioners and academics.

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