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A Hybrid Approach for Measuring Productivity in the Global Fitness Industry by Using Grey and DEA Model

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Abstract

Maintaining sustainable development is becoming an important issue for the fitness industry. To solve this problem, the decision-makers need to understand the performance of this industry. This research proposes a hybrid approach based on grey model (GM) and Malmquist productivity index (MPI), to measure operational performance of worldwide fitness manufactures over several periods. From that, decision making units (DMUs) and managers can improve business performance and build a sustainable development strategy. This research conducted on 15 fitness manufactures, by the use of several input and output variables. GM was used to predict the future value of these variables. Following the MPI was used to evaluate performance of all DMUs. The MPI results showed some manufactures become more efficient, while others become less efficient. The results provide past-future insights for decision-maker to sustain fitness requirement manufacturing. The study will be a useful reference for other industries as well.

Keywords: Fitness industry; performance; GM; DEA; MPI.

1. Introduction

Fitness equipment industry produces machines and monitoring devices for various type of healthcare demand. The most commonly observed fitness equipment includes treadmills, stair climbers, stationary bicycles, weightlifting equipment and resistance machinery etc. [1]. Major brands include “Life fitness, Nautilus, Cybex international, Icon health & fitness, Precor, Motus, Nantong Yida sports, Northern lights, Schnell trainingsgeräte, and Tonic fitness technology” [1].

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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 centers at some enterprises, hospitals, schools etc. [3]. The rapid growth is 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, supplier’s negotiation power, 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. This study aim to propose a hybrid assessment approach based on grey model and Malmquist productivity index (MPI). The approach predicts future business, measures operational performance, and analyzes productivity change from past to future in the global fitness industry. We conducted on 15 fitness equipment manufacturers collected from Consumer affairs 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]. The evaluation of productivity is needed to help firms improve performance and 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 was 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.

2. Literature Review

Grey system theory was first introduced by Ju-Long Deng [8]. The system has been applied in a board field to solve uncertainty issues, 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 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].

Data envelopment analysis (DEA) was established by Charnes, Cooper, and Rhodes [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 and his colleagues in 2009 used the GM (1,1) to forecast the growth of Japanese Larch in the Liaoning province [12]. Shi in 2009 proposed an effective and reliable Grey-Fuzzy evaluation to evaluate teaching quality [13].

Lin, Liou, and Huang in 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 and his colleagues in 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 researched to find feasible alliance partner for automobile makers by using an integrated grey theory and DEA [16]. Liang and his colleagues 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 applied DEA to evaluate performance efficiency of 20 stores of the E-Life Mall in Kaohsiung City, Taiwan [18]. Mathur and Paulused the DEA approach, CCR and BCC models to appraise the performance of 20 Indian Non-Life Insurance Companies [19]. Fuentes, Fuster, and Lillo-Bañuls used a three-stage DEA model to measure technical efficiency of learning and teaching [20].

3. Research Development, Data Collection and Methodology

3.1. Research developments

This study proposes a hybrid model to evaluate efficiency and productivity. Figure 1 provides detailed stages.

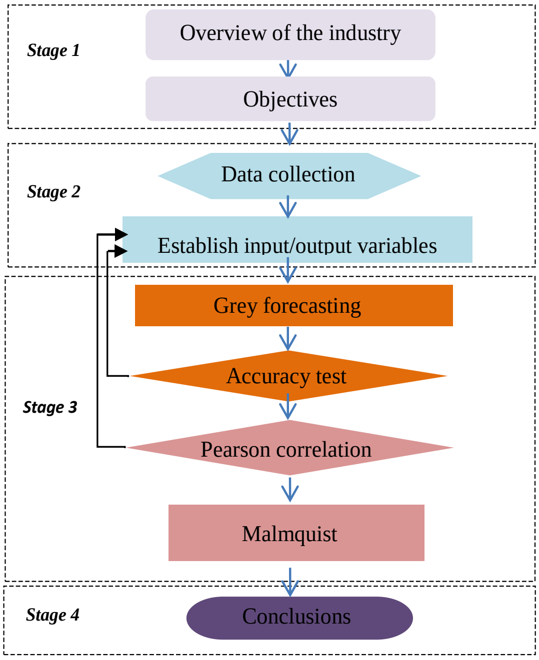

Figure 1: Research development

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.

3.2. Data collection and established inputs/outputs variables

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]. These collected manufacturers can represent the entire fitness industry worldwide (Table 1). 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 1: List of 15 fitness equipment manufacturers

DMUs	Companies	Headquarter	Founded Year
DMU1	Nike, Inc.	Oregon, United States	1964
DMU2	Adidas AG	Herzogenaurach, Germany	1949
DMU3	Gap Inc	California, United States	1969
DMU4	Brunswick Corp	Lake Forest, Illinois, United States	1845
DMU5	Amer Sports	Helsinki, Finland	1950
DMU6	Dorel Industries, Inc	Westmount, Canada	1962
DMU7	Life Time Fitness, Inc	Minnesota, United States	2006
DMU8	Skechers USA Inc	California, United States	1992
DMU9	Lululemon Athletica Inc	Vancouver, Canada	1998
DMU10	Invacare Corporation	Ohio, United States	1885
DMU11	Black Diamond Inc	Salt Lake City, United States	1957
DMU12	Planet Fitness, Inc.	New Hampshire, United States	1992
DMU13	Nautilus, Inc.	Washington, United States	1986
DMU14	Escalade, Inc	Indiana, United States	1922
DMU15	Gaiam, Inc	Colorado, United States	1988

Source: Synthetic by researcher [6, 7]

In order to adequately measure efficiency and productivity, the selection of input and output factors should be carefully considered. Literature reviews were done on the DEA, fitness industry's operations, International Accounting Standard (IAS) [21], and the suitable correlation between input and output variables. This research selected three input variables, including assets, equity and goodwill. Revenue and net income are chosen as two output variables. These indicators provide a signal to measure the ability and benefits of firms for all owners and investors. Due to size limitation, researcher can only show the data of 2015 with the millions of US dollar currency units, as in Table 2.

Table 2: 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)

Sources: Synthetic by researcher [7]

3.3. Grey forecasting model

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

Denote AGO sequence by $X^{(1)}$: $X^{(1)} = \left(X^{(1)}(1),\ X^{(1)}(2), \ldots, X^{(1)}(n)\right)$, $n \geq 4$ (3.2)

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

Let adjacent mean value of series $X^{(1)}$ is $Z^{(1)}$: $Z^{(1)} = \left(Z^{(1)}(1),\ Z^{(1)}(2), \dots, Z^{(1)}(n)\right)$ (3.4)

where $Z^{(1)}$(k) is computed as follow:

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

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

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

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

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

$$\begin{bmatrix} a \\ b \end{bmatrix}^T = (B^T B)^{-1} B^T \bar{Y}_N \ \ (3.7), \quad B = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ \dots\dots\dots & \dots \\ -Z^{(1)}(n) & 1 \end{bmatrix} (3.8) \quad \text{and } Y_N = \begin{bmatrix} X^{(0)}(2) \\ \dots\dots\dots \\ X^{(0)}(n) \end{bmatrix} \tag{3.9}$$

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

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

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

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

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

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

$$X^{(0)}(k+1) = \left[X^{(0)}(1) - \frac{b}{a}\right] e^{-ak}(1 - e^{a}) \ \ (k = 1, 2, 3, \dots) \tag{3.12}$$

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

3.4. Evaluation of volatility forecasts

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]:

$$\mathrm{MAPE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{t=1}}^{\mathrm{n}} \frac{|\mathrm{Actual_t} - \mathrm{Forecast_t}|}{\mathrm{Actual_t}} \times 100 \text{ ; where } n \text{ is number of periods.} \quad (3.13)$$

The grade of MAPE declare the forecasting reliability as in Table 3:

Table 3: The grades of MAPE

MAPE evaluation	≤10	10÷20	20÷50	≥50
Accuracy level	Excellent	Good	Qualified	Unqualified

Source: Synthetic by researcher [23]

3.5. Mamquist productivity index (MPI)

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 component 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 and his colleagues 2005) [24]:

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

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

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).

$$\text{MPI} = \text{Catch-up} \times \text{Frontier-shift} = \left[\frac{\delta_i^{t}(x_0, y_0)^{t+1}}{\delta_i^{t}(x_0, y_0)^{t}} \times \frac{\delta_i^{t+1}(x_0, y_0)^{t+1}}{\delta_i^{t+1}(x_0, y_0)^{t}}\right]^{1/2} \quad (3.15)$$

4. Empirical Results

4.1. Prediction results

GM (1,1) model was used to predict input and output variable of all DMUs, in next years (2016 – 2017), as in Table 4.

Table 4: The derived prediction values of 15 DMUs in 2016 & 2017

Years	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 5.

Table 5: Average MAPE value of DMUs

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 DMUs*	*7.569%*

Source: Calculate by researcher

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 5 showed that the values of MAPE are excellent and good (less than 10%), (based on rules of Table 3). 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.

4.2. Pearson correlation

To apply DEA, a correlation test is necessary to ensure that the relationship between inputs and outputs variables is isotonic [25]. This research employs the Pearson correlation to measure the strength linear relationship of normal distributed variables [26]. 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 [27]. The results of Tables 6 showed strong positive associations and fairly comply with preconditions of the DEA model and can be used for analysis.

Table 6: Correlation of input and output factors

	Assets	Equity	Goodwill	Revenue	Net Income
Assets	1	0.9830373	0.3206639	0.9814931	0.9097991
Equity	0.9830373	1	0.1927062	0.9611065	0.95661
Goodwill	0.3206639	0.1927062	1	0.259832	0.074203
Revenue	0.9814931	0.9611065	0.259832	1	0.9132272
Net Income	0.9097991	0.95661	0.074203	0.9132272	1

4.3. Productivity index analysis

Among DEA models, only the Malmquist model can measure performance over several periods [28]. So that, this research employed Malmquist model to evaluate the performance of all fitness equipment manufacture from past to future. Table 7 shows the results derived of Malmquist O-V model. To facilitate the analysis, the values of efficiency change (catch-up effects), technological change (frontier-shift), and MPI are graphed in Figures 2 to Figure 4.

Table 7: The catch up, frontier, and MPI of DMUs from 2012 to 2017

Catch-up					
DMUs	2012=>2013	2013=>2014	2014=>2015	2015=>2016	2016=>2017
DMU1	1	1	1	1	1
DMU2	0.9300568	0.8707821	1.0903669	0.9483559	0.9847219
DMU3	1	1	1	1	1
DMU4	1	0.6150218	1.0171336	0.9844873	1.0113945
DMU5	1.0563338	0.9035079	0.9403917	0.9457605	0.9739642
DMU6	1.0328005	0.8511921	1.0687495	0.9203471	0.9538298
DMU7	1.0000546	0.9738731	1.1132332	0.9413362	0.8646877
DMU8	1	0.6795322	1.1995935	1.2267494	1
DMU9	1	1	1	0.9698558	0.7833001
DMU10	1.1242762	1.0577705	1.0442324	1.0381142	1.0290925
DMU11	1.3187612	1.1711827	1.1543601	1.0513924	1.0448915
DMU12	0.9179525	4.8233111	1.0000071	1	1
DMU13	1	0.9999986	0.9845124	1.0157209	0.9999953
DMU14	2.3069179	1.000137	1.0000023	1.0000019	0.9999961
DMU15	0.9999697	0.9884652	1.0119654	1.0000015	1.0000016
Frontier					
DMUs	2012=>2013	2013=>2014	2014=>2015	2015=>2016	2016=>2017
DMU1	1.0479718	1.0731697	1.0868189	1.0755419	1.0783252
DMU2	1.0406101	1.0797117	1.0012206	1.0394659	1.0270082
DMU3	0.8711781	1.0209155	0.941335	1.0118771	1.0108706
DMU4	1.3708099	0.7551297	0.9827956	1.011495	1.0161608
DMU5	0.9258683	1.0349944	1.0447824	1.0247542	1.0098081
DMU6	0.9699242	1.0356152	0.9914424	1.0253191	1.0170003
DMU7	0.9592203	0.9590681	0.790463	1.0028485	1.1245868
DMU8	2.3959685	1.0167462	0.9382992	1.0026851	1.3571549
DMU9	1.1290033	0.9073348	0.8789373	0.9742436	1.2085314
DMU10	0.9561707	1.0294687	0.9974897	1.0361254	1.0337106
DMU11	0.8753683	1.0021287	0.941182	1.0838327	1.0986009

DMU12	1.1885078	0.6428102	1.1124888	0.9935902	0.8988932
DMU13	1	1.0000007	0.9881445	0.9961379	0.8692069
DMU14	0.4429555	0.9999315	0.9271957	1.0345168	0.9163792
DMU15	0.728143	1.0745355	1.055867	0.9999993	0.9999992
MPI					
DMUs	2012=>2013	2013=>2014	2014=>2015	2015=>2016	2016=>2017
DMU1	1.0479718	1.0731697	1.0868189	1.0755419	1.0783252
DMU2	0.9678266	0.9401936	1.0916978	0.9857836	1.0113175
DMU3	0.8711781	1.0209155	0.941335	1.0118771	1.0108706
DMU4	1.3708099	0.4644213	0.9996344	0.9958039	1.0277394
DMU5	0.978026	0.9351257	0.9825047	0.9691721	0.983517
DMU6	1.0017382	0.8815075	1.0596036	0.9436495	0.9700452
DMU7	0.9592727	0.9340106	0.8799697	0.9440175	0.9724164
DMU8	2.3959685	0.6909118	1.1255776	1.2300434	1.3571549
DMU9	1.1290033	0.9073348	0.8789373	0.9448758	0.9466427
DMU10	1.075	1.0889417	1.0416111	1.0756165	1.0637838
DMU11	1.1544018	1.1736758	1.0864629	1.1395335	1.1479187
DMU12	1.0909938	3.1004734	1.1124966	0.9935902	0.8988932
DMU13	1	0.9999993	0.9728405	1.0117981	0.8692028
DMU14	1.021862	1.0000685	0.9271978	1.0345187	0.9163756
DMU15	0.728121	1.0621409	1.0685008	1.0000007	1.0000008

Source: Calculate by researcher

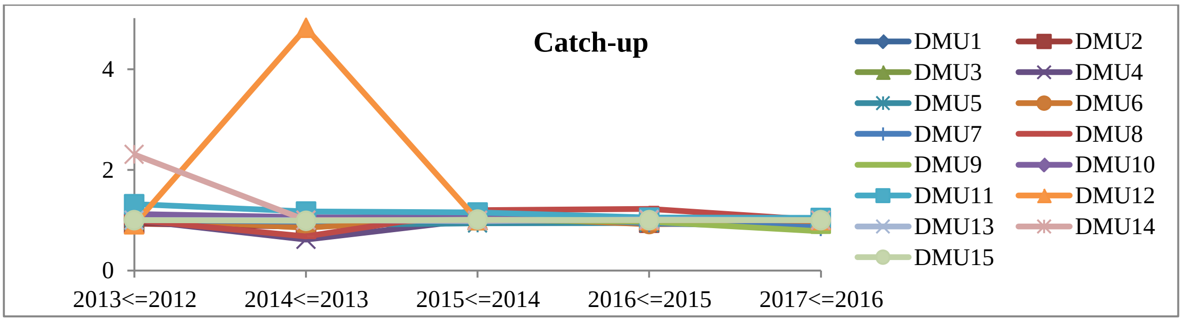

Figure 2: Annual efficiency changes from 2012 to 2017

Figure 2 expresses the efficient change of 15 DMUs over period 2012 – 2017. The results showed that the efficiency of them is unstable over period 2012 – 2015, and is going down in 2015 – 2017. The only six DMUs showed efficient improvement in period 2012 – 2013, including (DMU5, DMU6, DMU7, DM10, DMU11, and DMU14). Seven DMUs had no change in their efficiency and the other two DMUs lost to improve their efficiency in this period. DMU10, DMU11 and DMU obtained the highest improvement. DMU12 had experienced a dramatic efficiency rise in period 2013 – 2014, while other DMUs lose efficiency. The period 2014 – 2015 came with the improvement of efficiency for all DMUs, exclude DMU5 and DMU15. However, the trend of efficiency is decreasing for all DMUs from 2015 – 2017. Except for DMU8, which had slight efficiency changes in 2015 – 2016. In general, DMU1, DMU3, DMU10, DMU11, DMU12, and DMU14 are found with a stable efficiency, but they had not improved their in the current and forecasted future years. From the trend of Figure 2, we can determine and predict the efficient changes of all DMUs. Technical change is called ‘‘innovation’’ or “frontier-shift” effects. Figure 3 indicated that, the efficient trend of DMUs is undulate. It is found that, except DMU1, DMU2, and DMU8, other DMUs had experienced and downward technical change. Eight of them had efficiency drop during 2013 – 2014. In which the DMU14 and DMU15 had dramatic drop in technical change, while the DMU8 had a highest improvement of technology. In the period 2013 – 2014, it is found that, DMU12 and DMU4 are deteriorated in technical change, it means that it has decreased in output production or unimproved technology. After a downward trend was found in 2014 – 2015, the technical change of all DMUs is going up in periods 2015 – 2017. The trend showed that, most DMUs will be improved technology in future.

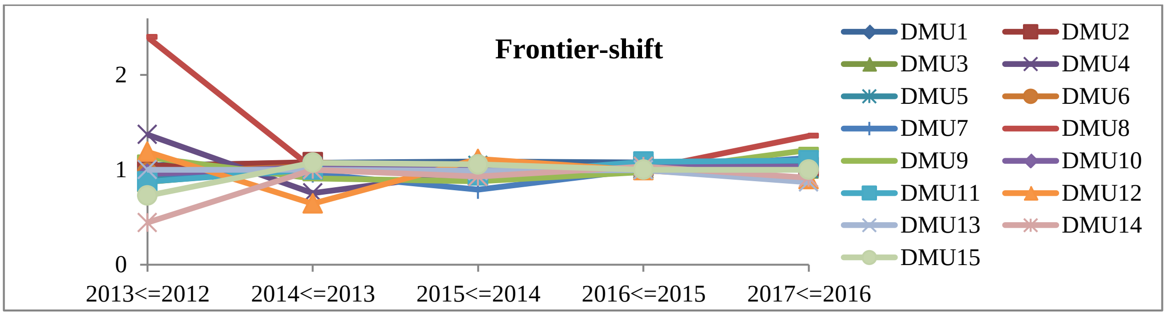

Figure 3: Annual technical changes from 2012 to 2017

Figure 4 shows the productivity index (MPI) of 15 DMUs from 2012 – 2017. The results indicated that, DMU1, DMU8, DMU10, DMU11, and DMU15 had a long-term upward trend during 2011 – 2017. However DMU8 had a drop in period 2013 – 2014, DMU15 had a drop in period 2012 – 2013. In term productivity, they are top five best companies, while the other DMUs are unstable in productivity. In summary, to improve performance of fitness equipment industry, the decision-maker in this field need to improve in both efficiency and production, especially for DMU2, DMU3, DMU4, DMU5, DMU6, DMU7, DMU12, and DMU13.

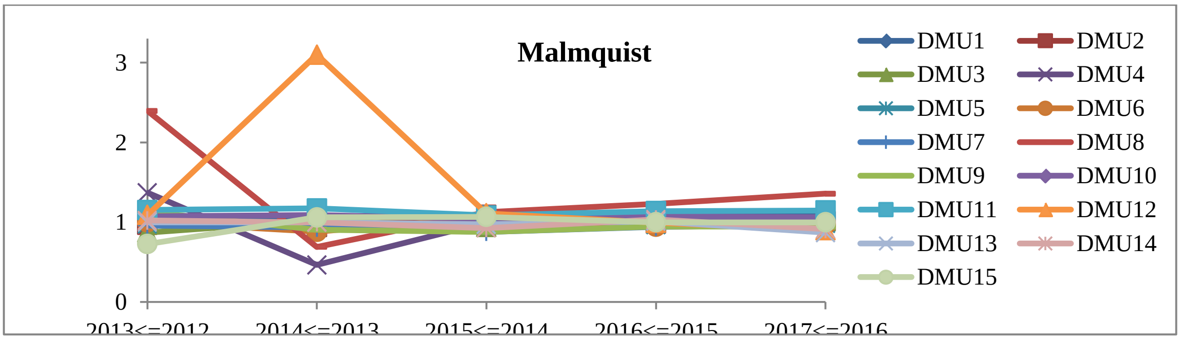

Figure 4: Annual productivity change (MPI) from 2012 to 2017

5. Conclusions

For improvement of the fitness equipment industry, 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. Based on the completed public historical data (2012 - 2015), the study employed GM (1,1) model to predict future business in (2016 – 2017) for selected manufactures. The accurate forecasting value had been tested by average MAPE and received a reliable percentage of 7.5685%.

Based on the historical and forecasted data, the Malmquist model is applied to calculate DMU's performance. The results provide insight views into the global fitness equipment industry in terms of "efficiency changes", "technological changes", and productivity (MPI) from "past-current-future". In a conclusion, to sustain the development of global fitness equipment industry, the manufactures and stake-holder should take management in both efficiency and technology for these inefficient companies (DMU2, DMU3, DMU4, DMU5, DMU6, DMU7, DMU12, and DMU13). The results also reflect the fact that the MPI's changes did not depend on company size.

This hybrid approach reduces the errors and risks in decision-making. 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 application provides useful information for practitioners and academics.

This proposed approach has been applied to the fitness equipment industry; however, it only includes 15 companies. Including more companies can provide further focus. In addition, other input and output variables (such as the number of staff, number of branches, retain earning, research and development, etc.) can be taken to measure the performance. Furthermore, this approach can be applied to other industries.

References

[1] Research and Market. "Fitness Equipment Manufacturing". Internet: http://www.researchandmarkets.com/reports/1052502/fitness_equipment_manufacturing [May. 15, 2017].

[2] Allied market research. "Global Fitness Equipment Market—Size, Industry Analysis, Trends, Opportunities, Growth and Forecast, 2014–2020". Internet: https://www.alliedmarketresearch.com/fitness-equipment-market [May. 15, 2017].

[3] Zion market research. "Global fitness equipment market, 2015 – 2021". https://www.zionmarketresearch.com/news/fitness-equipment-market [Aug. 20, 2017].

[4] Hoovers. "Fitness Equipment Manufacturing Industry Overview". Internet: http://www.hoovers.com/industry-facts.fitness-equipment-manufacturing.1201.html [May. 18, 2017].

[5] Porter, M. E. Competitive strategy: Techniques for analyzing industries and competitors; New York: Simon and Schuster, 2008.

[6] Consumeraffairs. "Compare Reviews for Fitness Equipment Companies". Internet: https://www.consumeraffairs.com/health/fitness-equipment [June. 15, 2016].

[7] Google Finance. "Financial statement". Available online: http://www.google.com/finance [June. 15, 2016].

[8] Ju-Long, D. "Control problems of grey systems", Systems & Control Letters, vol. 1(5), pp. 288-294, 1982.

[9] Ju-Long, D. "Introduction to grey system theory", The Journal of grey system, vol. 1(1), pp. 1-24, 1989.

[10] Ren, J.; Gao, S.; Tan, S.; Dong, L. Prediction of the yield of biohydrogen under scanty data conditions based on GM (1,N). Int. J. Hydrog. Energy, vol. 38, pp. 13198–13203, 2013

[11] Charnes, A.; Cooper, W. W.; Rhodes, E. "Measuring the efficiency of decision making units", European journal of operational research, vol. 2(6), pp. 429-444, 1978.

[12] Hui, S.; Yang, F.; Li, Z. H. E. N. Z. H. E. N.; Liu, Q.; Dong, J. "Application of grey system theory to forecast the growth of larch", International Journal of Information and Systems Sciences, vol. 5(3-4), pp. 522-527, 2009.

[13] Shi, H. "A grey fuzzy comprehensive model for evaluation of teaching quality". In Test and Measurement, 2009. ICTM 2009. IEEE international conference, vol. 2, pp. 244-247), 2009.

[14] Lin, C. S.; Liou, F. M.; Huang, C. P. "Grey forecasting model for CO2 emissions: a Taiwan study" Applied Energy, vol. 88(11), pp. 3816-3820, 2011.

[15] Wu, W. Y.; Tsai, H. J.; Cheng, K. Y.; Lai, M. "Assessment of intellectual capital management in Taiwanese IC design companies: using DEA and the Malmquist productivity index", Journal of R&D Management, vol. 36(5), pp. 531-545, 2006.

[16] Wang, C. N.; Nguyen, X. T.; Wang, Y. H. Automobile industry strategic alliance partner selection: The application of a hybrid DEA and grey theory model. Sustainability, vol. 8(2), pp. 173, 2016.

[17] Liang, S. K.; Jiang, J. L.; Lai, C. T. "Effects of integrative strategies on the production efficiency of biotech firms: A data envelopment analysis", International Journal of Management, vol. 25(1), pp. 140-148, 2008.

[18] Chen, J. F.; Hsieh, P. Y.; Chen, H. W. "Evaluation of efficiency of capital sources utilization and company performance of E-Life mall in Kaohsiung city based on data envelopment analysis", In Computational Aspects of Social Networks (CASoN), 2010 IEEE International Conference, pp. 278-283, 2010.

[19] Mathur, T.; Paul, U. K. "Performance appraisal of Indian non-life insurance companies: A DEA approach", Universal Journal of Management, vol. 2(5), pp. 173-185, 2014.

[20] Fuentes, R.; Fuster, B.; Lillo-Bañuls, A. "A three-stage DEA model to evaluate learning-teaching technical efficiency: Key performance indicators and contextual variables", Expert Systems with Applications, vol. 48, pp. 89-99, 2016.

[21] Deloitte. International accounting standards (IAS). Internet: http://www.iasplus.com/en/standards/ias / [May. 30, 2017].

[22] Stevenson, W. J., & Sum, C. C. Operation management: an Asian perspective. (9^{th} ed), New York: McGraw-Hill Education, 2010.

[23] G. D. Li, S. Masuda, M. Nagai, “An Optimal Prediction Model using Taylor Approximation Method”, Journal of Grey System, vol. 11, pp. 91-100, 2011.

[24] Coelli, T.J.; Rao, D.S.P.; O’Donnell, C.J.; & Battese, G.E. An Introduction to Efficiency and Productivity Analysis. (2nd ed). Philadelphia, PA: Springer, 2005.

[25] Golany, B.; Roll, Y. “An application procedure for DEA”, Omega, vol. 17(3), pp. 237-250, 1989.

[26] Pruessner, J. C.; Kirschbaum, C.; Meinlschmid, G.; Hellhammer, D. H. “Two formulas for computation of the area under the curve represent measures of total hormone concentration versus time-dependent change”, Psychoneuroendocrinology, vol. 28(7), pp. 916-931, 2003.

[27] Lo, F. Y.; Chien, C. F; Lin, J. T. “A DEA study to evaluate the relative efficiency and investigate the district reorganization of the Taiwan power company”, IEEE Transactions on Power Systems, vol. 16(1), pp. 170-178, 2001.

[28] Banker, R.D.; Charnes, A.; Cooper, W.W. Some models for estimating technological and scale inefficiencies in data envelopment analysis. Manag. Sci, vol. 30, pp. 1078–1092, 1984.