

Applying Grey Model and DEA for the Productivity Evaluation of Vietnamese Hydropower Industry

Chia Nan Wang*, XuanTho Nguyen*

*Department of Industrial Engineering and Management, National Kaohsiung University of Applied Sciences, Taiwan

Abstract- Maintaining sustainable development is an important issue for the hydropower industry of Vietnam. 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 Vietnamese hydropower companies over several time periods. From that, government and decision making units (DMUs) can improve business performance and build a sustainable development strategy. The study conducted on 19 hydropower companies, which have published their complete information on Vietstock site. The result showed twelve companies increased in productivity while the other seven didn't. Technical change was more impact than efficient change in period 2013 – 2016. In general, both of them impact on Vietnam's hydropower 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.

Index Terms- DEA, GM, Hydropower industry, MPI, Performance

I. INTRODUCTION

Vietnamese electricity industry is made up of a diverse combination of power generation, including hydropower, fossil fuels thermal power (coal, gas, and oil), and other power. The total installed capacity is 38,553MW, in which the hydropower occupies 38% with a capacity of 14,636MW [1]. Along with the demand of energy for development, the government had approved to build hydropower dams on ten major largest river basins, with a total of 473 projects (2017). The largest installed hydropower dams are Son La, HoaBinh and Ialy with capacity of 2400MW, 1920MW and 720MW respectively [1]. The statistic of Vietnam's potential hydropower capacity by major river basin is shown as in Table 1 [2].

Table 1: The statistic of Vietnam's potential hydropower capacity by major river basin

No.	Name of river	Total potential capacity (MW)	Number of current hydropower factories
1	Ma river	890	14
2	Da river	6960	13
3	Other small rivers	1000-3000	12
4	Gia Vu – Thu Bon river	1360	11
5	Lo – Gam – Chay river	1120	10
6	La Nga – Dong Nai	2870	10
7	Ca river	520	9
8	Sesan – Srepok river	2680	8
9	Huong river	480	5
10	Ba river	670	5

Source: Synthetic by research [2]

There is 60% of them is located in the northern, 27% located in the central highland, and 13% located in the southern of country, by geography [3]. The long shape geography and the difference regional weather causes challenge in hydropower operation and electricity transmission. As a report of Vietcombank Securities (VCBS, 2016 [4], the demand of electricity in Vietnam increases 10.7% per year, but the domestic recent supply volume dose not enough in the period 2016 – 2018. In 2016, the total power production of Vietnam was 184 billion KWh, but imported 3.1% from China and Lao. The average standard hour electricity sale price ranges from 1,388 to 2320VND (6.1-10.2 U.S. cent) per kilowatt hour (KWh). The giant state owned EVN reported \$32 million loss in 2016 [1].

An advantage of hydropower in Vietnam is that it plays the role of providing both energy and water supply services (e.g., irrigation and flood control), thus bringing economic and social benefits. Otherwise, hydropower contributes to reduce dependence on fossil fuels, cut of greenhouse gas (GHG). Hydropower plant typically operates at an electrical efficiency of 85% to 95%. This compares to about 55% for combined-cycle gas turbines and 30% for wind power [5]

Although, hydropower was “the most available, mature, reliable and flexible, renewable, and cost-effective electricity generation technology”. It causes huge loss of land and displace large populations, loss of environmental and social costs that far outweigh any benefit provide to society [5]. So that, the sustainable of hydropower and renewable development issues have been questioned Vietnamese government and managers, requires an effective method to improve productivity performance. By the views of decision-makers and stakeholders in hydropower industry, a good productivity is an important key for them to setup their operational strategy and adjust their business. The performance indexes are not just counted for a single period; they should be combined with several periods for catching development trends [6]. Therefore, this research proposes an integrated method, which use of grey model with Malmquist productivity index (MPI), to provide a long-term analysis of the Vietnamese hydropower industry. All data was carefully collected from annual financial reports and classified into inputs and outputs. The aim is to predict future business and evaluate productivity of 19 Vietnamese hydropower companies during four consecutive terms (2013-2016). This research chose total asset (TA), cost of goods sold (CoGS), financial expense (F.Exp), administration expenses (Ad.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 hydropower industry not only from 2013 to 2016, but also predict future evaluation in the period 2017-2018. The proposed approach enables Vietnamese government to guide policy directions toward sustainable development of the hydropower industry. For investors or stakeholders, the proposed approach provides a method to assess performance information about a company, as well [7].

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) [8]. 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 [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) is a non-parametric linear programming approach. It measures the relative efficiency of a group of decision making units (DMUs) which receive multiple inputs to produce multiple outputs [11]. 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 for decision-making. The prerequisite condition for using DEA is that the selected variables should have an isotonic relationship, which can be tested by correlation analysis [12]. If the correlations are not zero, meaning existing linear relationship 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 [13]. Shi (2009) proposed an effective and reliable Grey-Fuzzy evaluation to evaluate teaching quality [14]. 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% [15]. 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 [16]. Chen and Chen [17] used DEA and MPI to explore Taiwanese chip manufacturing company operating performance. Nguyen and De Borger (2008)[18] 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 [19]. Chen, Hsieh, and Chen (2010) applied DEA to evaluate performance efficiency of 20 stores of the E-Life Mall in Kaohsiung City, Taiwan [20]. Mathur and Paul (2014) used the DEA approach, CCR and BCC models to appraise the performance of 20 Indian Non-Life Insurance Companies [21]. Fuentes, Fuster, and Lillo-Bañuls (2016) used a three-stage DEA model to measure technical efficiency of learning and teaching [22]. Piran et al. (2016) used DEA to evaluate effects of product modularization on the efficiency of the product engineering and the production process of a bus manufacturer. The results showed that product modularization provides significant improvements in efficiency [23].

Although grey theory and DEA have been applying in a board filed, this is the first time the models is used to predict future business, measure operational performance and productivity change in the hydropower 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

3.1 Research development

This research proposes an integrated model to evaluate long-term performance efficiency. Figure 1 provides detailed stages. The stage of introduction states current status of Vietnamese hydropower 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 factors. 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.

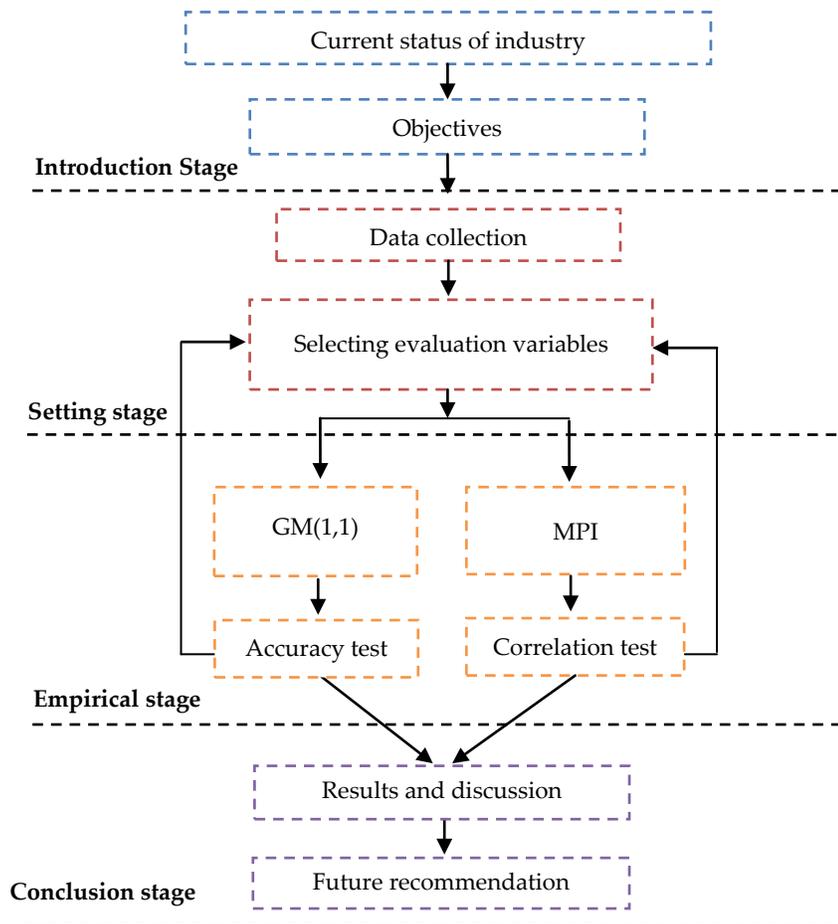


Figure.1. Research development

3.2 Data collection

Based on the research procedure proposed in Section 3, Table 2 shows 19 Vietnamese hydropower companies selected for the study. These companies are the top companies in the hydropower industry of Vietnam. They are qualified with transparent financial data, which was collected from the stock market observation posting system of Vietstock.vn [24]. Vietstock is a premier site providing business and financial market information in Vietnam. Due to printed space limitations, only the data of the year 2016 are listed in Table 3.

Table 2: List of Vietnamese hydropower companies.

No.	DMUs	Companies name
1	DMU1	Vietnam Electricity Corporation (EVN)
2	DMU2	Vinh Son - Song Hinh Hydropower Joint Stock Company
3	DMU3	Central Hydropower Joint Stock Company
4	DMU4	Thac Mo Hydro Power Joint Stock Company
5	DMU5	Can Don Hydro Power Joint Stock Company
6	DMU6	Hydro Power Joint Stock Company – Power No.3

No.	DMUs	Companies name
7	DMU7	Se San 4A Hydro Power JSC
8	DMU8	Southern Hydropower JSC
9	DMU9	Thac Ba Hydropower Joint Stock Company
10	DMU10	Nam Mu Hydropower Joint Stock Company
11	DMU11	Daklak Power Hydroelectric JSC
12	DMU12	Gia Lai Hydropower JSC
13	DMU13	Huong Son Hydro Power Joint Stocks Company
14	DMU14	DakDoa Hydropower Joint Stock Company
15	DMU15	IdicoScrokPhuMieng Hydro Power Joint Stock Company
16	DMU16	DinhBinh Hydro Power Joint Stock Company
17	DMU17	A Vuong Hydropower JSC
18	DMU18	Naloi Hydropower Joint Stock Company
19	DMU19	Tay Nguyen Electricity Investment JSC

Source: Synthetic by researcher [24]

Table 3: The historical data of the input and output variables of 19 DMUs in 2016

DMUs	Inputs (Billions of VND)				Outputs (Billions of VND)	
	(I)TA	(I)CoGS	(I)F.Exp	(I)Ad.Exp	(O)Rev	(O)EAT
DMU1	692,216	233,671	22,360	10,535	272,703	4,431
DMU2	6,110	181	19.6	21.7	448	258
DMU3	3,084	253	111	38	650	258
DMU4	1,299	256	77	31	449	110
DMU5	1,411	154	17.2	52.4	374	143
DMU6	136	25	2.3	4.5	64	34.3
DMU7	1,280	85	67	5.8	225	69
DMU8	2,646	274	116	22	513	98
DMU9	880	99	23	29	241	110
DMU10	486	91	22	21	160	23
DMU11	108	11	6.7	1	24	4.6
DMU12	363	41	2.3	3.7	116	69
DMU13	660	61	36	13	135	24.6
DMU14	219	20	9.3	2.9	39	7.3
DMU15	901	97	34	10.8	163	20
DMU16	112	23	0.6	3.8	60	31
DMU17	2,056	333	108	29	597	123
DMU18	127	29	0.036	5.3	50	16.2
DMU19	260	12.8	1	3.4	28.3	30

Source: Synthetic by researcher [24]

3.3 Grey forecasting model

The GM(1,1), which is pronounced as “Grey Model First Order One Variable,” can only be used in positive data sequences [25]. This model is a time series forecasting model. The differential equations of the GM(1,1) model have time-varying coefficients.

Let $X(0) = (x(0)(1), x(0)(2), \dots, x(0)(n))$ be sequences of raw data. Denote its accumulation generated sequences by $X(1) = (x(1)(1), x(1)(2), \dots, x(1)(n))$. Then $X^{(0)}(k) + ax^{(1)}(k) = b$ (1) is referred to as the original form of the GM(1,1) model, where the symbol GM(1,1) stands for first order grey model in variables. Consider $X^{(0)}(k) + az^{(1)}(k) = b$ (2) as the basic form of this model. Denote $Z^{(1)} = (z^{(1)}(2), z^{(1)}(3), \dots, z^{(1)}(n))$, we have $z^{(1)}(k) = (1/2)(x^{(1)}(k) + x^{(1)}(k-1))$, with $k=2, 3, \dots, n$.

Theorem 1: Let $X^{(0)}$, $X^{(1)}$, and $Z^{(1)}$ be the same as the above except that $X^{(0)}$ is nonnegative. If $a = (a,b)^T$ is a sequence of parameters.

$$Y = \begin{bmatrix} X^{(0)}(2) \\ X^{(0)}(3) \\ X^{(0)}(4) \\ \vdots \\ X^{(0)}(n) \end{bmatrix} B = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ -Z^{(1)}(3) & 1 \\ -Z^{(1)}(4) & 1 \\ \vdots & \vdots \\ -Z^{(1)}(n) & 1 \end{bmatrix} \quad (3)$$

Then satisfies $\hat{a} = (B^T B)^{-1} B^T Y$, so from theorem 1 notations, if $[a,b]^T = (B^T B)^{-1} B^T Y$, then $dx^{(1)}/dt + ax^{(1)} = b$.

Theorem 2: Let B , Y , \hat{a} be the same as in Theorem 1. If $\hat{a} = [a,b]^T = (B^T B)^{-1} B^T Y$, then

(1) The solution of $dx^{(1)}/dt + ax^{(1)} = b$ is given by

$$X^{(1)}(t) = \left(X^{(1)}(1) - \frac{b}{a} \right) e^{-at} + \frac{b}{a}, \quad (4)$$

(2) The time response sequence of $dx^{(1)}/dt + ax^{(1)} = b$ is given as follow:

$$\hat{X}(1)(k+1) = \left(X^{(0)}(1) - \frac{b}{a} \right) e^{-ak} + \frac{b}{a}, \quad k=1,2,3,\dots,n. \quad (5)$$

(3) The restored values of $x^{(0)}(k)$ are given with marked as equation:

$$\begin{aligned} \hat{x}(0)(k+1) &= \alpha(1)\hat{x}(1)(k+1) = \hat{x}(1)(k+1) - \hat{x}(1)(k) \\ &= (1-ea)\left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak} \end{aligned} \quad (6)$$

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 [26]:

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

The grade of MAPE declare the forecasting reliability as in Table 4:

Table 4: The grades of MAPE.

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

Source: [27]

3.5 Malmquist 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 components 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) [28]:

$$\begin{aligned} \text{Catch-up} &= \frac{\delta_i^{t+1}(x_0, y_0)^{t+1}}{\delta_i^t(x_0, y_0)^t} \text{ and} \\ \text{Frontier-shift} &= \left[\frac{\delta_i^t(x_0, y_0)^t}{\delta_i^{t+1}(x_0, y_0)^t} \times \frac{\delta_i^t(x_0, y_0)^{t+1}}{\delta_i^{t+1}(x_0, y_0)^{t+1}} \right]^{1/2} \end{aligned} \quad (7)$$

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 $(t + 1)$.

$$MPI = \text{Catch-up} \times \text{Frontier-shift} = \left[\frac{\delta_i^t(x_0, y_0)^{t+1}}{\delta_i^t(x_0, y_0)^t} \times \frac{\delta_i^{t+1}(x_0, y_0)^{t+1}}{\delta_i^{t+1}(x_0, y_0)^t} \right]^{1/2} \quad (8)$$

IV. EMPIRICAL RESULTS

4.1 Results of prediction for all DMUs

This research predicts the future business of hydropower companies by the use of GM (1,1) model. The results will be shown in following Table 5 and Table 6

Table 5: The derived prediction values of 19 DMUs in 2017

DMUs	Inputs (Billions of VND)				Outputs (Billions of VND)	
	(I)TA	(I)CoGS	(I)F.Exp	(I)Ad.Exp	(O)Rev	(O)EAT
DMU1	883,923.66	283,307.26	25,092.65	20,888.89	352,542.38	8,661.15
DMU2	7,864.13	192.48	31.90	23.11	390.44	196.88
DMU3	2,990.47	268.44	88.68	39.67	691.60	309.12
DMU4	1,251.91	233.70	92.75	17.71	366.62	94.32
DMU5	1,483.15	148.47	18.11	68.88	365.62	133.07
DMU6	134.00	28.00	2.35	4.41	63.60	34.60
DMU7	1,256.98	85.35	68.52	6.44	192.93	35.65
DMU8	2,402.76	307.66	114.67	22.26	491.50	73.13
DMU9	812.97	80.49	22.73	28.52	202.37	94.92
DMU10	446.39	103.83	16.19	37.09	174.35	27.77
DMU11	107.01	10.09	5.47	0.91	19.16	2.11
DMU12	342.79	41.88	1.00	3.29	111.59	76.71
DMU13	631.41	66.01	32.79	17.99	150.94	39.02
DMU14	204.92	22.95	7.80	2.43	35.27	4.16
DMU15	834.84	98.02	27.05	10.69	135.26	11.58
DMU16	110.45	24.53	0.36	4.22	69.98	41.55
DMU17	1,465.83	390.81	29.29	26.71	536.99	168.75
DMU18	133.68	35.54	0.01	5.56	57.13	17.85
DMU19	260.34	25.88	0.01	5.38	58.46	29.21

Source: Calculated by researcher.

Table 6: The derived prediction values of 19 DMUs in 2018

DMUs	Inputs (Billions of VND)				Outputs (Billions of VND)	
	(I)TA	(I)CoGS	(I)F.Exp	(I)Ad.Exp	(O)Rev	(O)EAT
DMU1	1,094,072.92	340,258.94	28,307.38	36,584.30	445,906.86	15,340.26
DMU2	10,059.11	206.24	46.62	24.42	349.54	163.50
DMU3	2,882.57	283.89	72.05	40.72	703.57	333.35
DMU4	1,140.78	215.59	126.11	13.11	297.33	68.04
DMU5	1,546.37	144.25	19.54	92.80	357.58	118.61
DMU6	133.01	28.00	2.46	4.53	63.55	34.75
DMU7	1,238.61	84.86	59.03	6.90	171.81	27.71
DMU8	2,183.03	341.38	109.86	20.12	457.67	50.52
DMU9	768.64	69.39	23.28	27.95	176.54	84.31
DMU10	406.45	115.00	11.80	74.53	185.04	28.71
DMU11	106.04	9.98	4.67	0.83	17.40	1.53
DMU12	316.67	40.56	0.43	2.92	107.49	85.06
DMU13	602.96	70.69	29.99	22.43	166.64	63.54
DMU14	191.80	24.60	6.81	2.16	31.54	2.71
DMU15	773.42	99.04	21.98	10.26	113.81	6.53
DMU16	108.10	26.33	0.18	4.67	80.21	53.18
DMU17	1,133.71	447.47	12.79	25.35	495.65	208.85
DMU18	142.62	39.66	0.00	5.66	63.35	21.26

DMUs	Inputs (Billions of VND)				Outputs (Billions of VND)	
	(I)TA	(I)CoGS	(I)F.Exp	(I)Ad.Exp	(O)Rev	(O)EAT
DMU19	260.84	50.28	0.00	8.97	112.54	28.06

Source: Calculated by researcher.

In this study, the MAPE was used to test the accuracy of prediction to ensure appropriate predictive methods. The results are shown in Table 7.

Table 7: Average MAPE of 19 DMUs

DMUs	Average MAPE	DMUs	Average MAPE
DMU1	26.054%	DMU11	13.154%
DMU2	7.340%	DMU12	1.629%
DMU3	3.289%	DMU13	4.068%
DMU4	9.551%	DMU14	4.007%
DMU5	1.699%	DMU15	1.135%
DMU6	10.629%	DMU16	3.317%
DMU7	11.998%	DMU17	8.709%
DMU8	3.240%	DMU18	8.825%
DMU9	2.719%	DMU19	27.079%
DMU10	5.054%	<i>Average all MAPE</i>	8.079%

Source: Calculated 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 10 indicated that the values of MAPE are excellent and good (less than 10%), (based on rules of Table 4). The average of all MAPE is 8.079%, this means the predicted results have a high level of accuracy. It forcefully affirms that GM(1,1) model is suitably to approach in this research.

4.2 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 [29]. The results are shown in Tables 8.

Table 8: Correlation of inputs and outputs

	(I)TA	(I)CoGS	(I)F.Exp	(I)Ad.Exp	(O)Rev	(O)EAT
(I)TA	1	0.999967	0.999960	0.999966	0.999974	0.997697
(I)CoGS	0.999967	1	0.999981	0.999989	0.999999	0.997225
(I)F.Exp	0.999960	0.999981	1	0.999976	0.999986	0.997391
(I)Ad.Exp	0.999966	0.999989	0.999976	1	0.999992	0.997425
(O)Rev	0.999974	0.999999	0.999986	0.999992	1	0.997329
(O)EAT	0.997697	0.997225	0.997391	0.997425	0.997329	1

Source: Calculated by researcher.

The results of the Pearson correlation coefficient showed that the variables used in this study have a strong linear relationship. This means that is consistent with the conditions of DEA and can be used for analysis.

4.3 Analysis of efficiency change

The changes of efficiency are called “catch-up” effects. The annual efficient change index for each experiment is shown in Table 9 and Figure 2.

Table 9: Annual efficiency change from 2013 to 2016

DMUs	2013~2014	2014~2015	2015~2016	DMUs	2013~2014	2014~2015	2015~2016
DMU1	1	1	1	DMU11	1.0000032	0.9999987	1
DMU2	1	1	1	DMU12	1	1	1
DMU3	0.9483737	1.0544366	1	DMU13	1.0371984	1.1084924	1.0555641
DMU4	1	1	1	DMU14	1.3507149	0.8030357	0.9894512
DMU5	1	1	1	DMU15	1.1989457	0.8639746	0.8810726
DMU6	1	1	0.9838042	DMU16	1.0000014	1.0000033	1

DMUs	2013~2014	2014~2015	2015~2016	DMUs	2013~2014	2014~2015	2015~2016
DMU7	1	1	1	DMU17	1	0.8844233	1.1306803
DMU8	0.9367886	0.9378068	1.1265099	DMU18	1.0000066	1	1
DMU9	0.9857248	1.0144819	1	DMU19	1	1	1
DMU10	1.2226007	0.9563523	1.0919917	Average	1.0358083	0.9801582	1.0136355

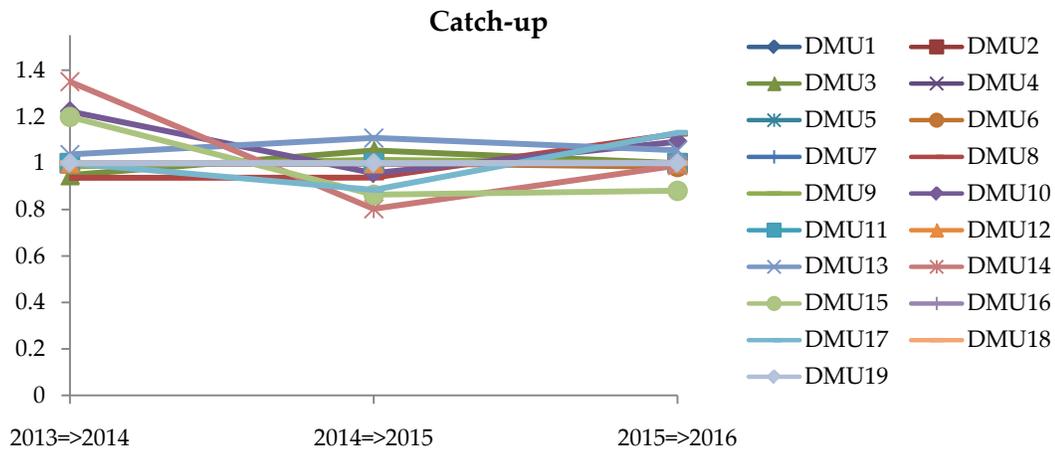


Figure 2: Annual efficiency changes from 2013 to 2016

Seven DMUs showed efficient improvement in period 2013 – 2014. They are DMU10, DMU11, DMU13, DMU14, DMU15, DMU16, and DMU18 with efficient change scores larger than one. This means that these DMUs improved performance efficiency between 2013 and 2014. Nine DMUs has no change in their efficiency and the other three DMUs lost to improve their efficiency in this period. DMU14 and DMU10 obtained the largest improvement; they scored of 1.35071 and 1.22260, respectively. While on the other hand, DMU8 had a largest declines of 0.93678, following by DMU3 and DMU9.

From 2014 to 2015, only four DMUs improved efficiency, including DMU3, DMU9, DMU13 and DMU16. Six DMUs were decreased and nine DMUs do not change in efficiency. DMU13 obtained the highest improvement of efficiency (increasing 10.8%), while DMU14 had a worst declines of 20%, followed by DMU15 (14%) and DMU17 (12%).

In the period 2015 – 2016, only four DMUs improved efficiency, including DMU8, DMU10, DMU13, and DMU17. DMU17 has a largest efficient improvement of 13%, while DMU15 had a highest decline of 12% in efficiency.

For whole period 2013 – 2016, the average efficient change ranged from 0.980 to 1.035. An average efficiency improved of 3% from 2013 to 2014, slightly decline in period (2014 – 2015) with a number of 2%, and re-increase 1% in periods (2015 – 2016). DMU14, DMU15 and DMU17 have largest decline in efficiency across 2014 to 2015.

4.4 Analysis of technical change

Technical change, also called “innovation” or “frontier-shift” effect is the second component of the Malmquist productivity change index. This component shows the effect 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 10 and Figure 3 reports annual index of technical progress or regress.

Table 10: Annual technical changes from 2012 to 2015

DMUs	2013~2014	2014~2015	2015~2016	DMUs	2013~2014	2014~2015	2015~2016
DMU1	1	0.3892133	0.9955872	DMU11	0.9744398	0.9769933	1.0043696
DMU2	6.225231	0.1195965	1.1383126	DMU12	0.8975201	1.0584761	1.4561878
DMU3	1.5620620	1.1742677	0.2320586	DMU13	0.9073718	0.9314945	0.9689560
DMU4	1.8315457	0.9266133	0.7152448	DMU14	0.9703644	0.9434307	1.0095128
DMU5	1.4259536	0.9265972	0.7258004	DMU15	0.9703412	0.9582678	1.0047975
DMU6	0.8788788	1.0503358	1.0086759	DMU16	0.9747521	1.1048392	1.3939657
DMU7	1.2401531	0.6445131	1.1353878	DMU17	1.2756553	0.9873285	0.8633467
DMU8	1.7690334	0.9640251	0.8900178	DMU18	1.7936488	2.6242811	2.6451094
DMU9	0.9624337	0.9618837	0.9304664	DMU19	2.4329067	0.4479694	0.9415516
DMU10	0.8888026	0.9571915	0.9589611	Average	1.5253207	0.955122	1.0535953

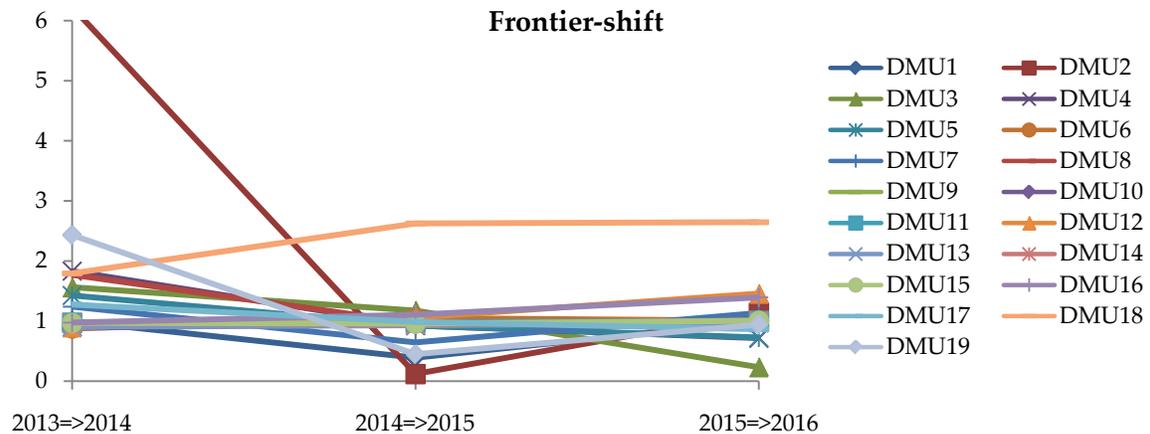


Figure 3: Annual technical changes from 2013 to 2016

In the period 2013 – 2014, there are total nine DMUs with scores of technical change smaller than one, which expressed that technical regressed or innovation deteriorated in this period. It is also meaning that there were too much expenses but were reduced in output (revenues and earnings). DMU16 has the worst technical regress of 13%, while on the other case DMU2 and DMU19 had the highest progress of 522% and 143%, respectively.

From 2014 to 2015, fourteen DMUs were regressed in technical change, other five DMUs showed technical progress (DMU3, DMU6, DMU12, DMU16 and DMU18). In this period, we found that the highest technical progress is 162% (DMU18), while the worst deteriorated is 89% (DMU2). The same bad trend was shown in period 2015 – 2016, when having eleven DMUs showed technical regressing. In which DMU3 had the worst technical regressing of 77%.

For whole period 2013 – 2016, the average technical change ranged from 0.955% to 1.525%. The results showed that technical change progresses in period 2013 – 2014, while it is deteriorated in period 2014 – 2015 and slightly increase in period 2015 – 2016.

4.5 Analysis of productivity change

As presented in Eq. (8), a greater than one Malmquist productivity value will denote an improvement in the performance of business management. Table 11 and Figure 4 displays the calculation of annual productivity changes of Vietnam’s hydropower companies over the period 2013 – 2016.

Table 11: Annual productivity change (MPI) from 2013 to 2016

DMUs	2013~2014	2014~2015	2015~2016	DMUs	2013~2014	2014~2015	2015~2016
DMU1	1	0.3892133	0.9955872	DMU11	0.9744429	0.9769921	1.0043696
DMU2	6.225231	0.1195965	1.1383126	DMU12	0.8975201	1.0584761	1.4561878
DMU3	1.4814186	1.2381909	0.2320586	DMU13	0.9411245	1.0325546	1.0227951
DMU4	1.8315457	0.9266133	0.7152448	DMU14	1.3106857	0.7576085	0.9988636
DMU5	1.4259536	0.9265972	0.7258004	DMU15	1.1633864	0.8279191	0.8852995
DMU6	0.8788788	1.0503358	0.9923396	DMU16	0.9747535	1.1048429	1.3939657
DMU7	1.2401531	0.6445131	1.1353878	DMU17	1.2756553	0.8732164	0.9761691
DMU8	1.6572103	0.9040692	1.0026139	DMU18	1.7936606	2.6242811	2.6451094
DMU9	0.9486948	0.9758136	0.9304664	DMU19	2.4329067	0.4479694	0.9415516
DMU10	1.0866507	0.9154123	1.0471775	Average	1.5547301	0.9365377	1.0652263

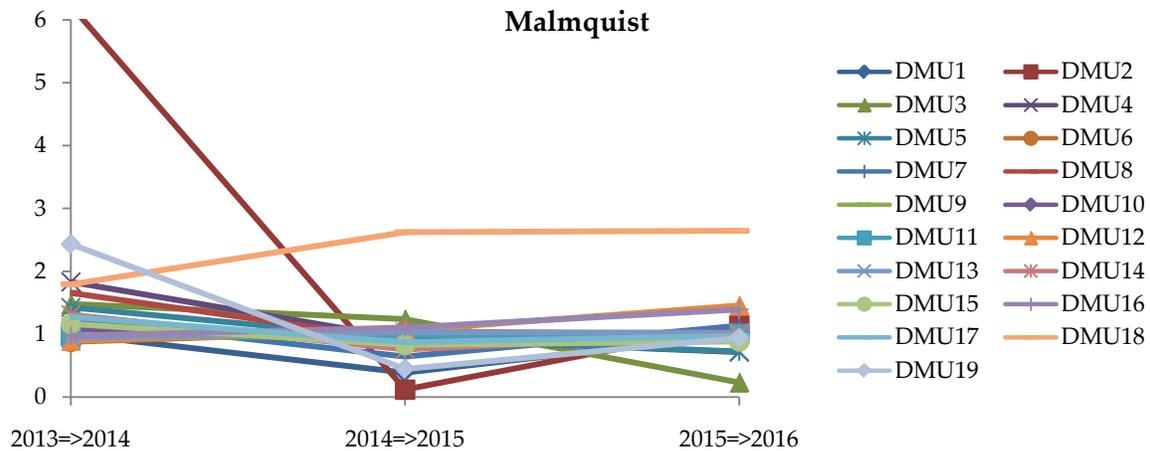


Figure 4: Annual productivity change (MPI) from 2013 to 2016

In period 2013 – 2014, the result showed that, total twelve companies has MPI values larger than one; it means that productivity growing in this period. The other six companies have MPI less than 1, which means loss of productivity; one company does not change. DMU2 and DMU19 had the highest productivity growth over this period while on the other hand DMU6 had the largest loss, followed by DMU12.

From 2014 to 2015, thirteen DMUs had productivity increase except DMU3, DMU6, DMU12, DMU13, DMU16 and DMU18. The results showed that DMU2 had the largest productivity loss, followed by DMU1, DMU19 and DMU7. In the period of 2015 to 2016, nine companies had productivity growth and the other ten companies had productivity loss. DMU3 had the largest productivity growth, followed by DMU4 and DMU5.

In general, the whole period 2013 – 2016 showed average productivity gains. The period 2013 – 2014 recorded a highest growth (55%); but slightly decrease 7% in period 2014 – 2015.

As mentioned in Section 3.2, 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 12 presents the MPI's results of the 19 hydropower companies from 2013 to 2016. The average percentage productivity change ranged from 79% (DMU1) to 249% (DMU2). DMU2 had the highest productivity growth from 2013 – 2016, followed by DMU18, DMU19 and DMU8.

Table 12: 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	1	0.7949335	0.7949335
DMU2	1	2.4943800	2.4943800
DMU3	1.0009368	0.9894628	0.9838893
DMU4	1	1.1578013	1.1578013
DMU5	1	1.0261171	1.0261171
DMU6	0.9946014	0.9792968	0.9738514
DMU7	1	1.0066847	1.0066847
DMU8	1.0003684	1.2076921	1.1879645
DMU9	1.0000689	0.9515946	0.9516583
DMU10	1.0903149	0.9349851	1.0164135
DMU11	1.0000006	0.9852676	0.9852682
DMU12	1	1.1373947	1.1373947
DMU13	1.067085	0.9359407	0.9988248
DMU14	1.0477339	0.9744360	1.0223860
DMU15	0.9813310	0.9778022	0.9588683
DMU16	1.0000016	1.1578524	1.1578541
DMU17	1.0050345	1.0421102	1.0416803
DMU18	1.0000022	2.3543464	2.3543504
DMU19	1	1.2741425	1.2741425

	2013~2016	2013~2016	2013~2016
DMUs	Annual average efficient change	Annual average technical change	Annual average productivity change (MPI)
Average	1.0098673	1.1780127	1.185498

From 2013 to 2016, there are twelve companies with average MPI values larger than one, it means productivity growing in this period. The other seven companies have average MPI's value less than one, which indicates decreasing in productivity. In other words, twelve companies improved their performance efficiency, whereas the other seven companies failed to improve their efficiency during the four-year period. Productivity loss for DMU6 and DMU15 was driven by both catch-up and frontier-shift effect. The results also indicate that these two companies have still great space for improvement business and need to cut of input resources waste and maximize output production to enhance efficient operation. Conversely, productivity loss for DMU1, DMU3, DMU9, DMU11, and DMU13 was mainly driven by technological regress, so that these firms need upgrade technology and maximize production to enhance efficient performance.

In general observations, the average efficient change and technical change of all companies were 100% and 117%, respectively. Therefore, the productivity change was due to improvement innovation in technology rather than in efficiency. The productivity of Vietnam's hydropower companies 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 predominately attributed to Vietnam's hydropower industry productivity growth.

V. CONCLUSION

Since DEA has been applying in a board filed, this is the first time GM(1,1) and MPI models were used to forecast future business and evaluate productivity change in Vietnam's hydropower industry. This research conducts an empirical experiment on 19 Vietnam's hydropower companies in the period 2013–2016. Based on the completed public data, the study employed GM (1,1) model to predict future business performance. The accurate forecasting value had been tested by average MAPE and received a reliable percentage of 8.079%.

The MPI's results showed that twelve companies increased productivities and the other seven companies were decreased in productivities. Productivity loss for DMU6 and DMU15 was driven by both catch-up and frontier-shift effect. Conversely, productivity loss for DMU1, DMU3, DMU9, DMU11, and DMU13 was mainly driven by technological regress. The average efficient change and technical change of all companies were 100% and 117%, respectively. Therefore, 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 hydropower industry productivity growth. The results also reflect the fact that the MPI's changes did not depend on company size. DMU2 is the most efficient company with a highest MPI of 249%, and will be a good reference model for other companies. In contrasted, these inefficient companies should more invest technology and improve performance to reach efficient level.

In a conclusion, to sustain the development of Vietnamese hydropower industry, the government should help these companies. Which could be divided into two groups including (group 1: DMU1, DMU3, DMU9, DMU11, and DMU13 - need to improve output production) and (group 2: DMU6 and DMU15 - need to improve both efficient and production).

The results provide a meaningful reference to help hydropower companies to improve their operating efficiency, make an effective production plan, speed up business management change, strengthen core competitiveness, and achieve balance development. The research argues that control of performance efficiency and productivity are necessary jobs for keeping competitive ability and determining the failures or successes of companies in this industry. The application provides useful information for practitioners and academics in this field.

REFERENCES

- [1] Vietnam Electricity Annual Report 2016 (EVN). Available online: <http://www.evn.com.vn/> (accessed on 19 October 2017).
- [2] Vietnam Power Report 2015. Available online: [http://www.fpts.com.vn/FileStore2/File/2015/07/20/VietnamPowerReport2015\(2\).pdf/](http://www.fpts.com.vn/FileStore2/File/2015/07/20/VietnamPowerReport2015(2).pdf/) (accessed on 8 August 2017).
- [3] Vietnam Energy. Available online: <http://nangluongvietnam.vn/news/en/home/> (accessed on 8 August 2017).
- [4] Vietcombank Securities (VCBS). Electricity report 2016. Available online: <http://www.vCBS.com.vn/vn/> (accessed on 10 August 2017).
- [5] Ty, P. H. (2015). Dilemmas of hydropower development in Vietnam: between dam-induced displacement and sustainable development. *Eburon*.
- [6] Wang, C. N.; Lin, H. S.; Hsu, H. P.; Le, V. T.; & Lin, T. F. (2016). Applying Data Envelopment Analysis and Grey Model for the Productivity Evaluation of Vietnamese Agroforestry Industry. *Sustainability*, 8(11), 1139.
- [7] Wang, C.N.; Nguyen, X.T.; Wag, Y.H. Automobile industry strategic alliance partner selection: The application of a hybrid DEA and Grey theory model. *Sustainability* 2016, 8, 273.
- [8] Ju-Long, D. "Control problems of grey systems", *Systems & Control Letters*. **1982**, 1(5), 288-294.
- [9] Ju-Long, D. "Introduction to grey system theory", *The Journal of grey system*. **1989**, 1(1), 1-24.

- [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* 2013, 38, 13198–13203.
- [11] Banker, R. D.; Charnes, A.; & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management science*, 30(9), 1078-1092.
- [12] Golany, B.; Roll, Y. An application procedure for DEA. *Omega* 1989, 17, 237–250.
- [13] 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*. **2009**, 5(3-4), 522-527.
- [14] Shi, H. “A grey fuzzy comprehensive model for evaluation of teaching quality”. In *Test and Measurement, 2009. ICTM 2009. IEEE international conference*. **2009**, 2, 244-247.
- [15] Lin, C. S.; Liou, F. M.; Huang, C. P. “Grey forecasting model for CO2 emissions: a Taiwan study” *Applied Energy*. **2011**, 88(11), 3816-3820.
- [16] 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*. 2006, 36(5), 531-545.
- [17] Chen, Y.S.; Chen, B.Y. Applying DEA, MPI, and grey model to explore the operation performance of the Taiwanese wafer fabrication industry. *Technol. Forecast. Soc. Chang*. 2011, 78, 536–546.
- [18] Nguyen, X. Q., & De Borger, B. (2008). Bootstrapping efficiency and Malmquist productivity indices: An application to Vietnamese commercial banks. *Asia-Pacific Productivity Conference* 2008.
- [19] 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*. **2008**, 25(1), 140-148.
- [20] 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*. **2010**, 278-283.
- [21] Mathur, T.; Paul, U. K. “Performance appraisal of Indian non-life insurance companies: A DEA approach”, *Universal Journal of Management*. **2014**, 2(5), 173-185.
- [22] 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*. 2016, 48, 89-99.
- [23] Piran, F. A. S.; Lacerda, D. P.; Camargo, L. F. R.; Viero, C. F., Dresch, A.; Cauchick-Miguel, P. A. “Product modularization and effects on efficiency: An analysis of a bus manufacturer using data envelopment analysis (DEA)”, *International Journal of Production Economics*. 2016,182, 1-13.
- [24] Viet stock. Available online: <https://vietstock.vn/> (accessed on 20 August 2017)
- [25] Liu, S., & Forrest, J. Y. L. (2010). *Grey systems: theory and applications*. Springer.
- [26] Stevenson, W. J., & Sum, C. C. *Operations management: an Asian perspective*. (9th ed.). New York: McGraw-Hill Education. 2010.
- [27] G. D. Li, S. Masuda, M. Nagai, “An Optimal Prediction Model using Taylor Approximation Method”, *Journal of Grey System* 2011, vol. 11, pp. 91-100.
- [28] Coelli, T.J.; Rao, D.S.P.; O'Donnell, C.J.; & Battese, G.E. *An Introduction to Efficiency and Productivity Analysis*. (2nd ed.). Springer: Philadelphia, PA, USA. 2005.
- [29] F. Y. Lo, C. F. Chien, and J. T. Lin, “A DEA study to evaluate the relative efficiency and investigate the district organization of the Taiwan Power Company”, *IEEE Transactions on Power Systems*, vol.16, no.1, pp.170–178, 2001.

AUTHORS

First Author – Chia Nan Wang, Professor, Department of Industrial Engineering and Management, National Kaohsiung University of Applied Sciences, Taiwan, cn.wang@cc.kuas.edu.tw

Second Author –XuanTho Nguyen, Ph.D candidate, Department of Industrial Engineering and Management, National Kaohsiung University of Applied Sciences, Taiwan, nguyenhanam188@gmail.com

Correspondence Author –XuanTho Nguyen, nguyenhanam188@gmail.com,