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# Hybrid of Data Envelopment Analysis and Malmquist Productivity Index to evaluate efficiency of Solar Companies on Global Supply Chain

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***Abstract :*** *Solar photovoltaic systems are becoming essential in renewable energy sources to help reduce dependence on renewable energy sources, fossil fuels and mitigate climate change. In the world today, many successful businesses bring efficiency to the environment as well as the global economy. However, to evaluate the business performance of the global supply chain, it is necessary to find an appropriate method. This article uses data envelopment analysis (DEA) and Malmquist Productivity Index (MPI) methods to compare performance across businesses in the Solar industry. The author collected from the 20 largest solar companies in the world for five consecutive years (2018-2022). The analysis shows that the top 5 companies with the highest efficiency are: China Three Renewable Group, Enphase Energy, Trina Solar, Emerson Electrics, and Solar Industry India, respectively. This study is a case study on the solar energy industry that helps managers get a broader view of the industry and consider partnering with companies that perform well in the global supply chain.*

***Keywords :*** *Solar Industry, Global Supply Chain, Data Envelopment Analysis, Malmquist Productivity Index.*

## I. INTRODUCTION

Climate change has increased the global temperature by 1.11 ± 0.13 °C above the pre-industrial average from 2021. Along with that, the global mean sea level of 4.5mm increased. This is the highest level ever recorded. The concentration of greenhouse gases, such as CO2, in the earth's atmosphere increases due to increased greenhouse gas emissions. CO2 emissions from fossil fuel combustion and industry will reach an annual peak of 36.3 GT in 2021, up 6% from 2020 [1]. Thus, the economic, environmental, and social costs are increasing worldwide due to the energy production used in the combustion of fossil fuels.

The war between Russia and Ukraine has impacted the global economy, putting pressure on inflation despite high inflation. Disruptions in titanium, palladium, wheat, and corn caused supply chain disruptions. So these items maintain high prices, along with other items, including cars, phones, and aircraft manufacturers. Furthermore, Russia is one of the world's largest oil suppliers, leading to a worldwide energy crisis[2]. Gas prices increased 20% when the war started and are now six times higher than in early 2021. This has led to demand destruction among businesses that use gas, and supply chains are in crisis. Transport enterprises face many difficulties maintaining supply chains; businesses face broken ones. Fertilizer manufacturers that use gas must cut production. Agriculture is also in crisis as farmers must pay more to operate machinery. The lack of gas affects the global economy [3, 4]. Therefore, finding and developing renewable energy sources from solar and wind sources to replace fossil fuels poses significant challenges for businesses globally. The question is how to keep the global supply chain from being disrupted by economic, social, and environmental impacts.

With the emphasis on carbon neutrality achieved by 2050, the International Energy Agency has forecast that global energy demand will fall by 8%. However, the size of the economy will double, and electricity production will account for 90% of renewable energy. Solar and wind energy will account for 70% of total energy. Governments have established a carbon-neutral strategy by 2020 to reduce dependence on fossil fuels and transition to renewable energy [5]. Especially the US, Canada, European countries, and Asian countries such as Vietnam, Hong Kong, Japan, Korea, etc. A great prospect in solar energy development is to reduce carbon emissions. They are worldwide, reducing the economic downturn. C02 emissions were reduced by 696,544 tons through installations for 113,533 US households [6].

When comparing solar energy with mainly mechanized and capital-intensive fossil fuel technologies, solar technologies are more labor-intensive, meaning more jobs and income. The Solar Fund reports that the solar manufacturing industry employed 208,859 workers in the United States for production, installation, and sales, with a growth rate of 20.2%. Also, indirect benefits, such as local shops and restaurants, are due to increased income and working time. Using solar energy will save significant money by not importing fossil fuels from other locations. Solar energy is beneficial in various ways due to favorable taxes, elimination of electricity bills, and high durability[7,8]. Although the solar system requires a significant initial investment, it has low operating costs. In contrast, fossil fuels tend to have significant price fluctuations, so the financial need for solar energy is relatively stable over the long term.

Moreover, solar panels, such as noise pollution and wear, and tear during operation, do not affect the environment. The installation is quite convenient, installed on the roof or attached to the wall of buildings. Modules can be added to improve energy production. Shows the flexibility and certainty of the solar energy system compared to other energy sources[9].

Evaluating the performance of solar power plants is essential during a period of strong growth in renewable energy demand and an uncertain political and economic situation in the world. The most efficient plants will be reviewed and evaluated to complement or enhance the worldwide energy supply chain.

## II. RESEARCH METHOD

### 2.1 Data Collection

In this research, a survey of companies on solar energy industry in the world is conducted. 18 companies are chosen from analysis of downstream and upstream players on the world.

Then, analysis of the data of the 18 companies being stable in market and providing the complete data for 5 consecutive years (2018-2022) in The Wall Street Journal. On the other hand, these are the largest solar companies which can represent the entire solar energy industry in the global market. Therefore, these companies named (Decision Making Unit) DMU1 to DMU20 were arranged randomly as shown in Table 1.

### 2.2 Data Envelopment Analysis

A related new "data-oriented" method for assessing the effectiveness of a collection of entities known as Decision Making Units is called Data Envelopment Analysis (DEA) (DMUs). In the original study by Charnes, Cooper, and Rhodes, DEA was defined as a mathematical programming model that is applied to observational data to offer a new method for obtaining empirical estimates of relations like production functions and efficient production possibility surfaces, two pillars of contemporary economics. Multi-inputs are transformed into multi-outputs via DEA. The DEA model was soon acknowledged as a superior and convenient performance evaluation methodology.

Tone [10] suggested the slacks-based measure (SBM), a non-radial approach. The excess input and inadequate output are referred to as "slacks". By utilizing these slacks, it immediately addresses problems. Tone [10] suggested a different methodology, a non-radial approach, based on SBM, to rank effective DMUs. In order to categorize efficient and inefficient DMUs using Super SBM of Tone, regular SBM must be employed first. Only the efficient DMUs may then be classified using Super SBM.

An extremely effective SBM model is employed in this investigation. The "slacks-based measure of efficiency" (SBM) created by Tone [11] serves as the foundation for this concept.

Assume there are n DMUs, X and Y are input and output matrices, and X and Y are both greater than zero. Where is a non-negative vector in, and the vectors and represent the excess of the input and the deficit of the output, respectively. Following that, Equation (2.1) [11] defines the model's formula, which offers a CRS for the SBM model as follows:

$$\min \rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{io}}{1-\frac{1}{n}\sum_{i=1}^{m} s_i^- / x_{io}} \quad (2.1)$$

$$\text{s.t}\; x_0 = X\lambda + s^-, y_0 = Y\lambda - s^+, \lambda \geq 0, s^- \geq 0, s^+ \geq 0 \quad (2.2)$$

The variables and calculate how far a virtual unit's inputs X and outputs Y are from those of the unit being evaluated. The goal function's numerator and denominator calculate the average distance between inputs and outputs based on the efficiency threshold.

Let's consider the SBM model's ideal solution as. A DMU is SBM-efficient if and only implies that no optimal solution has either input excesses or output deficits. It is not radial, the SBM model. It immediately addresses input and output slacks. The SBM returns and efficiency are measured on a scale of 0 to 1.

The full efficiency status, shown by unity, is possessed by the top achievers. Based on the SBM model, the extremely effective SBM model is created. Using the super-efficiency SBM model, Tone distinguished between and ranked these effective DMUs. Equation defines the super-efficiency SBM model under the assumption that the DMU is SBM-efficient (2.3).

$$\min \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \bar{x}_i / x_{io}}{1 - \frac{1}{n}\sum_{i=1}^{m} \bar{y}_r / y_{io}} \quad (2.3)$$

s.t $\overline{x} \geq \sum_{j=1,\neq 0}^{n} \lambda_j \, x_j, \bar{y} \leq \sum_{j=1,\neq 0}^{n} \lambda_j \, x_j, \bar{x} \geq x_0 \; and \; \bar{y} \leq y_0, \bar{y} \geq y_0, \lambda \geq 0$ (2.4)

If the denominator is 1, the objective function changes to the Super Model SBM's input orientation and returns a value greater than or equal to 1.

A super-efficiency SBM model is thought to handle negative outputs, similar to many DEA models. Negative data, however, cannot be handled by many DEA models, including SBM models. As a result, a new approach was created in the DEA-Solver Pro 13 Manual, as illustrated below:

Let suppose that $y_{r0} \leq 0$ . Then $\bar{y}_r^{+}$ and $\bar{y}_{-r}^{+}$ are defined by.

$$\bar{y}_r^{+} = \max_{j=1,\dots,n} \{y_{rj} | y_{rj} > 0\}, \quad (2.5)$$

$$\bar{y}_{-r}^{+} = \min_{j=1,\dots,n} \{y_{rj} | y_{rj} > 0\}, \quad (2.6)$$

If the output r contains no positive components, it is concluded that. In the objective function, the term is replaced by in the following manner. Constraints on the value do not change.

(1) If $\bar{y}_r^{+} = \bar{y}_{-r}^{+}$ , the term is substituted by

$$s_r^{+} \Big/ \frac{y_{-r}^{+}(\bar{y}_r^{+} - y_{-r}^{+})}{\bar{y}_r^{+} - y_{r0}} \quad (2.7)$$

(2) If $\bar{y}_r^{+} = \bar{y}_{-r}^{+}$ , the term is substituted by

$$s_r^{+} \Big/ \frac{(y_{-r}^{+})^2}{B\,(\bar{y}_r^{+} - y_{r0})} \quad (2.8)$$

Where B is a sizable positive number (B = 100 in DEA-Solver).

Moreover, the distance and the numerator are inversely proportional. Thus, this approach is concerned with the positive amplitude of the non-positive output. The achieved score is independent of the measuring units employed and is units invariant.

#### *2.1.1 Malmquist productivity index*

To explore how productivity will evolve over time, R.S. Fare created the Malmquist Productivity Index in 1994 [12]. This index is based on DEA. Sten Malmquist introduced the Malmquist Productivity Index (MPI), also known as the Malmquist DEA, for the first time in 1953 as a measurement to be employed in the examination of input consumption [13]. The Malmquist is alleged by Coelli [14] , the two parts of the productivity index, "catch up" and "border shift," can theoretically be separated [13]. The index was further split into two parts: one part measures the expansion of the technological frontier, while the other part measures the improvement of technical efficiency [13].

While the additions to the basic MPI have shown to be beneficial in capturing the relative performance change of the DMUs, these models frequently lack realism in multi-output setups. We can identify two primary restrictions in those circumstances. First, traditional MPI models assume that all inputs produce all outputs simultaneously (i.e., a black box modeling), however in multi-output scenarios, each input may be allocated differentially to the production of each output. Second, outcomes from traditional MPI models are limited to the aggregate production process. Regulators and managers need more specific results (i.e., results for each output production process) in multi-output situations in order to make wise judgments [15].

## III. Results

### 3.1 Data Collection

The efficiency change index consists of only the relative technical performance change. DEA is the most common method to evaluate a company or an organization's performance. Based on input and output, they are combined with mathematical programming to produce results. After researching the solar energy industry, the author selected the top 20 companies and then collected and analyzed data over five years (2018-2022). The list of companies is given in the table below:

**Table 1: List of Solar Companies**

| Number Order | Code DMUs | Companies name | Headquarter |
|---|---|---|---|
| 1 | DMU1 | First Solar | America |
| 2 | DMU2 | Siemen AG | Germany |

| | | | |
|---|---|---|---|
| 3 | DMU3 | Canadian Solar | Canada |
| 4 | DMU4 | Jinko solar | Japan |
| 5 | DMU5 | Sun Corp Group | Australia |
| 6 | DMU6 | China three renew group | China |
| 7 | DMU7 | Sharp | Japan |
| 8 | DMU8 | Solar Industries India | India |
| 9 | DMU9 | Trina Solar | China |
| 10 | DMU10 | Solartron PLC | Thailand |
| 11 | DMU11 | Kyocera | Japan |
| 12 | DMU12 | Eaton Corp | America |
| 13 | DMU13 | Powell Industry companies | America |
| 14 | DMU14 | Generacholdings | America |
| 15 | DMU15 | Emerson Electrics | America |
| 16 | DMU16 | Sunrun | America |
| 17 | DMU17 | Enphase Energy | America |
| 18 | DMU18 | Sun Power Corp | America |
| 19 | DMU19 | Array technology | America |
| 20 | DMU20 | Maxeon technology | Japan |

*Source: Caculated by the Author*

After selecting the appropriate companies, the author selects the inputs and outputs based on previous studies evaluating the company's performance using the DEA method.

Input variables:

- Total Asset: the total number of assets owned by a solar company.
- Total Equity: the remaining amount of assets available to share holders after all liabilities have been paid, equal assets subtract liabilities.
- Sale Expense: the accumulated total of all the costs used to create a product or service, which has been sold.

Output Variables:

- Revenue (REV): the total amount of money that will be earned by consuming products, providing services, financial activities, and other activities of the enterprises.
- Profit (PRO): profits earned by the company after deducting costs related to selling products.

### 3.2 Pearson correlation

The correlation coefficients of input and output variables well comply with the prerequisite coefficient of the DEA model, it indicates strong positive associations, this mean that those data are proper for the prerequisite of DEA model.

If input and output factors have a positive linear correlation, these factors will be linked and set into the DEA model. If input and output factors have a negative linear correlation, these factors need to review again until the prerequisite is satisfied.

**Table 2: Pearson correlation coefficient**

| Correlation coefficient | Degree of correlation |
|---|---|
| > 0.8 | Very high |
| 0.6-0.8 | High |

| | |
|---|---|
| 0.4-0.6 | Medium |
| 0.2-0.4 | Low |
| < 0.2 | Very low |

Table 2 show the correlation between input and output variables, it well complies with the prerequisite coefficient of the DEA model. Accordingly, these positive correlations also indicate clearly the fact that original choose of input and output variables is suitable. This means that these variables can be applied for the analysis for DEA calculations.

**Table 3: Correlation of input and output data from 2018 to 2022**

| | **Corellation** | **Inputs variables** | | | **Outputs variables** | |
|---|---|---|---|---|---|---|
| | | **Total asset** | **Total Eq.** | **Sale Exp** | **Rev.** | **Net profit** |
| 2018 | Total asset | 1 | 0.9283047 | 0.93270796 | 0.92185 | 0.90193219 |
| | Total Eq. | 0.9283047 | 1 | 0.95058304 | 0.950242 | 0.94886892 |
| | Sale Exp | 0.932708 | 0.950583 | 1 | 0.996448 | 0.99471364 |
| | Rev. | 0.9218496 | 0.9502419 | 0.99644788 | 1 | 0.99302957 |
| | Net profit | 0.9019322 | 0.9488689 | 0.99471364 | 0.99303 | 1 |
| 2019 | Total asset | 1 | 0.9363416 | 0.92696405 | 0.912652 | 0.90432549 |
| | Total Eq. | 0.9363416 | 1 | 0.95517026 | 0.945018 | 0.95133078 |
| | Sale Exp | 0.926964 | 0.9551703 | 1 | 0.99215 | 0.99521043 |
| | Rev. | 0.9126516 | 0.9450177 | 0.99215013 | 1 | 0.99003867 |
| | Net profit | 0.9043255 | 0.9513308 | 0.99521043 | 0.990039 | 1 |
| 2020 | Total asset | 1 | 0.8941565 | 0.91911263 | 0.906104 | 0.88195839 |
| | Total Eq. | 0.8941565 | 1 | 0.90946777 | 0.90899 | 0.90918396 |
| | Sale Exp | 0.9191126 | 0.9094678 | 1 | 0.99101 | 0.99150543 |
| | Rev. | 0.9061042 | 0.9089904 | 0.99101017 | 1 | 0.98889504 |
| | Net profit | 0.8819584 | 0.909184 | 0.99150543 | 0.988895 | 1 |
| 2021 | Total asset | 1 | 0.9133778 | 0.9349234 | 0.913284 | 0.89645411 |
| | Total Eq. | 0.9133778 | 1 | 0.9354056 | 0.924821 | 0.92878769 |
| | Sale Exp | 0.9349234 | 0.9354056 | 1 | 0.990516 | 0.99044293 |
| | Rev. | 0.9132843 | 0.9248211 | 0.99051577 | 1 | 0.98960651 |
| | Net profit | 0.8964541 | 0.9287877 | 0.99044293 | 0.989607 | 1 |
| 2022 | Total asset | 1 | 0.8848128 | 0.91910329 | 0.914104 | 0.88664315 |
| | Total Eq. | 0.8848128 | 1 | 0.93130875 | 0.929574 | 0.93768012 |
| | Sale Exp | 0.9191033 | 0.9313088 | 1 | 0.991965 | 0.9921933 |
| | Rev. | 0.9141044 | 0.9295736 | 0.99196495 | 1 | 0.98913369 |
| | Net profit | 0.8866432 | 0.9376801 | 0.9921933 | 0.989134 | 1 |

*Source: Caculated by the Author*

Through the table above, the correlation of the data at "Very high" is consistent with the prerequisites of the DEA model, so the selection of Input and Output is reasonable and consistent with the research objectives.

### 3.3 Empirical result

#### 3.3.1 Performance of companies from 2018-2022

Through the Super SBM IC model, we can evaluate the operational efficiency of solar energy-producing companies. The table shows that DMU6 (China Three Renew Group) is rated the highest based on functional performance and followed by DMU17 (Enphase Energy), DMU8 (Solar Industry India), DMU9 (Trina Solar), DMU18 (Sun Power Corp). The list of the top 5 most effective companies shows that these companies use resources effectively and overcome difficulties caused by the Covid 19 pandemic and the impact of the global supply chain due to instability.

**Table 4: Results from DEA model**

| DMU | 2018 | | 2019 | | 2020 | | 2021 | | 2022 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Score | Rank | Score | Rank | Score | Rank | Score | Rank | Score | Rank |
| DMU1 | 0.436 | 16 | 0.201 | 7 | 0.217 | 6 | 0.612 | 9 | 0.315 | 18 |
| DMU2 | 0.551 | 14 | 0.146 | 14 | 0.133 | 16 | 0.563 | 12 | 0.537 | 11 |
| DMU3 | 0.800 | 11 | 0.176 | 12 | 0.155 | 12 | 0.497 | 14 | 0.467 | 14 |
| DMU4 | 1.055 | 7 | 0.176 | 13 | 0.169 | 11 | 0.580 | 11 | 0.514 | 13 |
| DMU5 | 0.274 | 20 | 0.108 | 19 | 0.084 | 19 | 0.197 | 19 | 0.205 | 19 |
| DMU6 | 3.294 | 1 | 3.705 | 1 | 1.000 | 1 | 2.451 | 1 | 3.142 | 1 |
| DMU7 | 1.032 | 8 | 0.124 | 17 | 0.115 | 18 | 0.737 | 8 | 0.667 | 9 |
| DMU8 | 1.140 | 4 | 0.283 | 4 | 0.221 | 5 | 1.025 | 6 | 1.127 | 5 |
| DMU9 | 1.067 | 6 | 0.254 | 5 | 0.176 | 9 | 1.134 | 3 | 1.176 | 3 |
| DMU10 | 1.010 | 9 | 1.002 | 3 | 0.477 | 3 | 0.541 | 13 | 1 | 6 |
| DMU11 | 0.398 | 17 | 0.134 | 16 | 0.135 | 15 | 0.340 | 17 | 0.385 | 16 |
| DMU12 | 0.586 | 13 | 0.182 | 10 | 0.177 | 8 | 0.583 | 10 | 0.617 | 10 |
| DMU13 | 0.449 | 15 | 0.135 | 15 | 0.145 | 14 | 0.402 | 16 | 0.444 | 15 |
| DMU14 | 1.082 | 5 | 0.202 | 6 | 0.211 | 7 | 1.055 | 4 | 0.933 | 8 |
| DMU15 | 1.197 | 3 | 0.180 | 11 | 0.174 | 10 | 1.027 | 5 | 1.130 | 4 |
| DMU16 | 0.347 | 18 | 0.050 | 20 | 0.035 | 20 | 0.122 | 20 | 0.135 | 20 |
| DMU17 | 2.742 | 2 | 0.198 | 8 | 0.223 | 4 | 1.142 | 2 | 1.248 | 2 |
| DMU18 | 0.279 | 19 | 0.119 | 18 | 0.127 | 17 | 0.452 | 15 | 0.525 | 12 |
| DMU19 | 1 | 10 | 1.014 | 2 | 1.000 | 1 | 1 | 7 | 1 | 6 |
| DMU20 | 0.601 | 12 | 0.190 | 9 | 0.146 | 13 | 0.336 | 18 | 0.328 | 17 |

*Source: Caculated by the Author*

To better understand the performance of companies in the global supply chain, we analyze the performance year by year using the DEA-Malmquist model.

**3.3.2 Catch-Up Index (CA)**

**Table 5: Catch-up Index (Eficiency change)**

| Catch-up | 18=>19 | 19=>20 | 20=>21 | 21=>22 | Average |
|---|---|---|---|---|---|
| DMU1 | 0.4608 | 1.0791 | 2.8218 | 0.5143 | 1.2190 |
| DMU2 | 0.2631 | 0.9158 | 4.3272 | 0.9344 | 1.6101 |
| DMU3 | 0.2191 | 0.8812 | 3.2188 | 0.9385 | 1.3144 |
| DMU4 | 0.1667 | 0.9618 | 3.4494 | 0.8858 | 1.3659 |
| DMU5 | 0.3948 | 0.7701 | 2.3601 | 1.0398 | 1.1412 |
| DMU6 | 0.7847 | 1.1281 | 1.1164 | 0.8916 | 0.9802 |
| DMU7 | 0.1195 | 0.9234 | 6.4827 | 0.9052 | 2.1077 |
| DMU8 | 0.2465 | 0.7851 | 4.6581 | 1.0996 | 1.6973 |
| DMU9 | 0.2393 | 0.6922 | 6.1205 | 1.0541 | 2.0265 |
| DMU10 | 1.0219 | 0.3033 | 3.5578 | 1.2584 | 1.5353 |
| DMU11 | 0.3342 | 1.0130 | 2.5237 | 1.1316 | 1.2506 |
| DMU12 | 0.3099 | 0.9694 | 3.3087 | 1.0588 | 1.4117 |
| DMU13 | 0.2986 | 1.0750 | 2.7821 | 1.1053 | 1.3153 |
| DMU14 | 0.1849 | 1.0469 | 5.0386 | 0.8835 | 1.7885 |
| DMU15 | 0.1478 | 0.9745 | 5.9541 | 1.0693 | 2.0364 |
| DMU16 | 0.1411 | 0.6999 | 3.5420 | 1.1128 | 1.3739 |

| | | | | | |
|---|---|---|---|---|---|
| DMU17 | 0.1191 | 1.1274 | 5.1517 | 1.0931 | 1.8728 |
| DMU18 | 0.4067 | 1.1085 | 3.5883 | 1.1623 | 1.5665 |
| DMU19 | 3.8590 | 1.6337 | 0.5067 | 1.7721 | 1.9429 |
| DMU20 | 0.3147 | 0.7708 | 2.3048 | 0.9761 | 1.0916 |
| Average | 0.5016 | 0.9430 | 3.6407 | 1.0443 | 1.5324 |
| Max | 3.8590 | 1.6337 | 6.4827 | 1.7721 | 2.1077 |
| Min | 0.1191 | 0.3033 | 0.5067 | 0.5143 | 0.9802 |

*Source: Caculated by the Author*

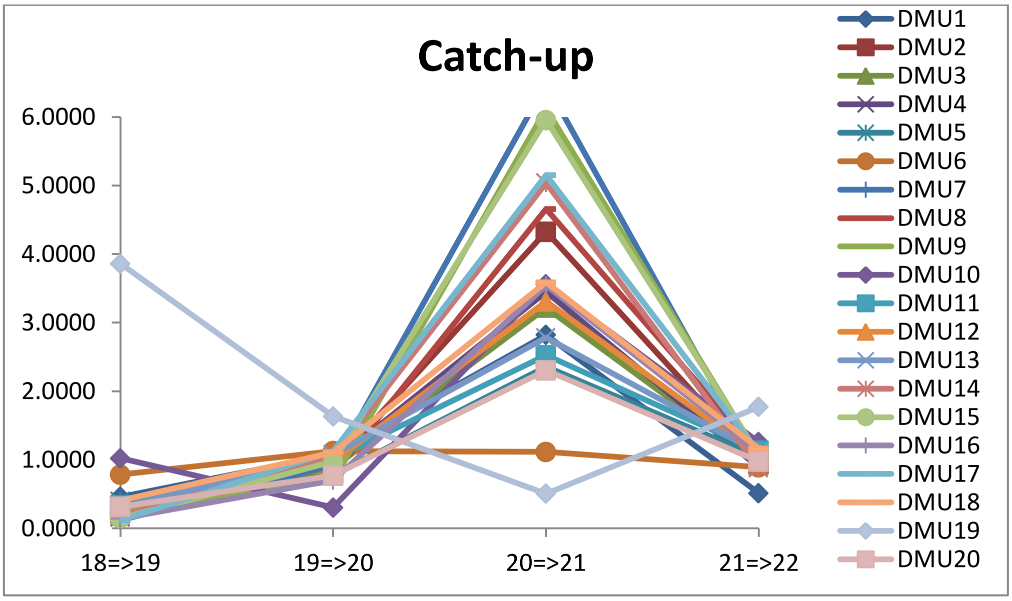


Figure 1: Technical efficiency change (Source: Caculated by researcher)

As shown in Table 5, the average catch-up index = 1.5324 (average CA > 1), reflecting that most of the 19 DMUs achieved technical efficiency. DMU6(China Three Renewable Group) has fared admirably over the years, ranking among the top corporations, and is the only one close to attaining the catch-up Index. As a result, they are unwilling to enhance their processes to make the supply chain more efficient. To stay at the forefront of the global solar business in the future, this company will require more creative solutions.

Figure 1 also shows the technical efficiency of 20 DMUs in the 2018–2020 period. Almost all DMUs had enhanced technical benefits, except for DMU6. DMU7 (Sharp) demonstrated the best performance with CA = 2.1077, while DMU6 (China Three Renewable Group) had the worst performance with CA = 0.9802.

In 2018-2019, most companies only achieved the Catch-up Index for DMU10(Solartron PLC) and DMU19(Array Technology). However, in the following periods, companies have made significant progress in achieving this indicator. From 2019 to 2020, companies have made significant improvements, which are DMU6, DMU11, DMU13, DMU14, DMU17, DMU18, and DMU19.

Between 2020 and 2021, although companies were affected by the pandemic, the boom and robust development of solar power made companies develop and achieve remarkable achievements. The company with the highest Catch-up index is DMU7 (Sharp), and the lowest is DMU19 (Array Technology).

More specifically, in 2021-2022, we can see solar energy production companies slowing down compared to 2020-2021. They have invested in developing the company in the previous period. Therefore, companies reduce investment in technology to focus on other goals to bring more efficiency to business operations. However, companies in this period also need to pay attention to investing in technology to keep up with the development pace of other solar power plants in the world.

### 3.3.3 Frontier Shift Index

**Table 6: Frontier-shift index (technological change)**

| Frontier | 18=>19 | 19=>20 | 20=>21 | 21=>22 | Average |
|---|---|---|---|---|---|
| DMU1 | 2.6243 | 0.9905 | 0.4507 | 0.9590 | 1.2561 |
| DMU2 | 3.6395 | 1.0180 | 0.2458 | 1.0836 | 1.4967 |
| DMU3 | 5.3358 | 1.0176 | 0.2768 | 1.0290 | 1.9148 |
| DMU4 | 5.0837 | 0.9686 | 0.2896 | 1.0067 | 1.8371 |
| DMU5 | 3.4011 | 0.9915 | 0.3690 | 0.9972 | 1.4397 |
| DMU6 | 0.9360 | 1.1101 | 0.9361 | 0.8668 | 0.9623 |
| DMU7 | 8.0078 | 1.0257 | 0.1576 | 1.0263 | 2.5543 |
| DMU8 | 4.2217 | 1.0185 | 0.2369 | 0.9648 | 1.6105 |
| DMU9 | 4.5433 | 0.9677 | 0.2914 | 1.0241 | 1.7066 |
| DMU10 | 1.5706 | 3.5706 | 0.1889 | 0.9898 | 1.5800 |
| DMU11 | 2.9284 | 1.0165 | 0.3581 | 1.0051 | 1.3270 |
| DMU12 | 3.2658 | 1.0171 | 0.3177 | 0.9807 | 1.3953 |
| DMU13 | 3.8459 | 0.9684 | 0.3113 | 0.9694 | 1.5238 |
| DMU14 | 4.8838 | 1.0195 | 0.2215 | 0.9507 | 1.7689 |
| DMU15 | 6.3587 | 1.0228 | 0.1702 | 0.9545 | 2.1265 |
| DMU16 | 5.2495 | 0.9955 | 0.2944 | 0.9792 | 1.8796 |
| DMU17 | 7.7758 | 1.0188 | 0.1781 | 0.9787 | 2.4878 |
| DMU18 | 4.8495 | 0.9982 | 0.2697 | 0.9990 | 1.7791 |
| DMU19 | 1.1876 | 1.3233 | 0.4168 | 0.7133 | 0.9102 |
| DMU20 | 4.1190 | 0.9685 | 0.4325 | 1.0151 | 1.6338 |
| Average | 4.1914 | 1.1514 | 0.3207 | 0.9747 | 1.6595 |
| Max | 8.0078 | 3.5706 | 0.9361 | 1.0836 | 2.5543 |
| Min | 0.9360 | 0.9677 | 0.1576 | 0.7133 | 0.9102 |

*Source: Calculated by Author*

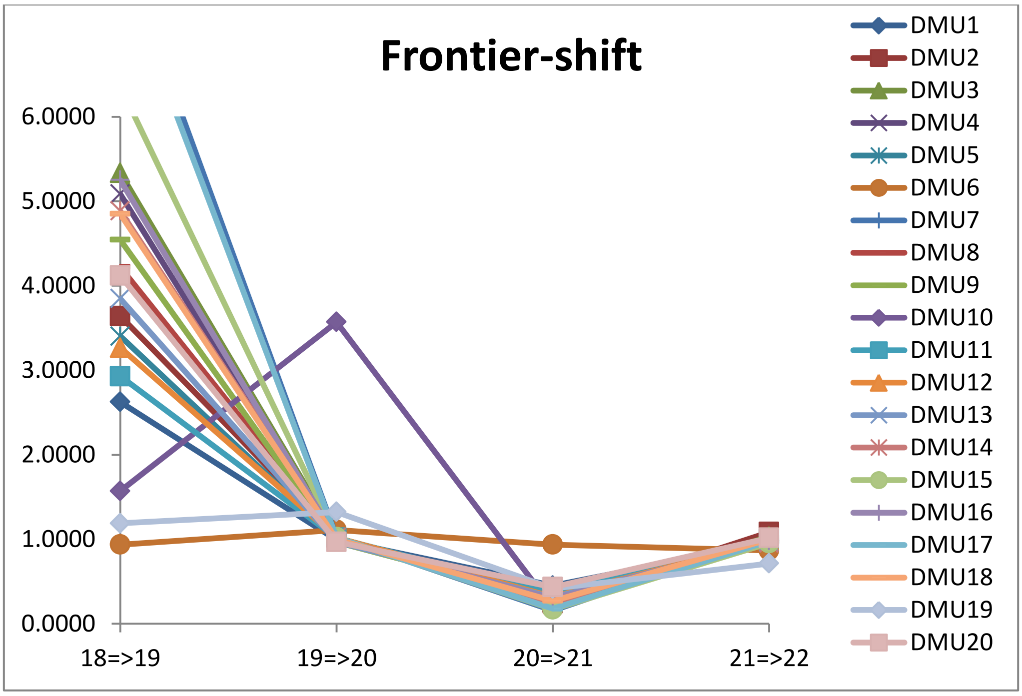


Figure 2: Technological Efficiency Frontier

Table 6 shows that the technological efficiency of solar energy companies tended to decrease in the 2019-2022 period. Because in the period 2018-2019 and previous periods, DMUs have increased their technology enhancement while increasing overall technical efficiency.

In 2018–2019, most DMUs achieved technological efficiency (average FR > 1) except for DMU 6. DMU7 exhibited the best efficiency performance, while DMU6 exhibited the worst. This demonstrates that this DMU was not applied well to the high tech in this period.

This illustrates the above statement, which mentions that the technological efficiency of manufacturers was seriously reduced during this period. DMU7 showed the best performance, with an FR=2.5543. However, after poor technology performance, the enterprises focused on investing technology in production to improve their effectiveness in 2019–2022.

As a result, the average frontier index is greater than 1 (FR = 1.15014), revealing that the Solar Energy companies successfully applied advanced technology to their production processes. There is only DMU6 (China Three Renewable Group) that could not achieve technological efficiency (average FR < 1) during this time, and this company needs to improve its technology in the future.

#### 4.4.3 *Malmquist Index (MI)*

**Table 7: Malmquist Index (Total Productivity Change)**

| Malmquist | 18=>19 | 19=>20 | 20=>21 | 21=>22 | Average |
|---|---|---|---|---|---|
| DMU1 | 1.209 | 1.069 | 1.272 | 0.493 | 1.011 |
| DMU2 | 0.957 | 0.932 | 1.064 | 1.013 | 0.991 |
| DMU3 | 1.169 | 0.897 | 0.891 | 0.966 | 0.981 |
| DMU4 | 0.848 | 0.932 | 0.999 | 0.892 | 0.917 |
| DMU5 | 1.343 | 0.764 | 0.871 | 1.037 | 1.004 |
| DMU6 | 0.734 | 1.252 | 1.045 | 0.773 | 0.951 |
| DMU7 | 0.957 | 0.947 | 1.022 | 0.929 | 0.964 |
| DMU8 | 1.041 | 0.800 | 1.103 | 1.061 | 1.001 |
| DMU9 | 1.087 | 0.670 | 1.783 | 1.080 | 1.155 |
| DMU10 | 1.605 | 1.083 | 0.672 | 1.246 | 1.151 |
| DMU11 | 0.979 | 1.030 | 0.904 | 1.137 | 1.012 |
| DMU12 | 1.012 | 0.986 | 1.051 | 1.038 | 1.022 |
| DMU13 | 1.148 | 1.041 | 0.866 | 1.071 | 1.032 |
| DMU14 | 0.903 | 1.067 | 1.116 | 0.840 | 0.982 |
| DMU15 | 0.940 | 0.997 | 1.014 | 1.021 | 0.993 |
| DMU16 | 0.741 | 0.697 | 1.043 | 1.090 | 0.892 |
| DMU17 | 0.926 | 1.149 | 0.917 | 1.070 | 1.015 |
| DMU18 | 1.973 | 1.107 | 0.968 | 1.161 | 1.302 |
| DMU19 | 4.583 | 2.162 | 0.211 | 1.264 | 2.055 |
| DMU20 | 1.296 | 0.747 | 0.997 | 0.991 | 1.008 |
| Average | 1.273 | 1.016 | 0.990 | 1.009 | 1.072 |
| Max | 4.583 | 2.162 | 1.783 | 1.264 | 2.055 |
| Min | 0.734 | 0.670 | 0.211 | 0.493 | 0.892 |

*Source: Caculate by the Author*

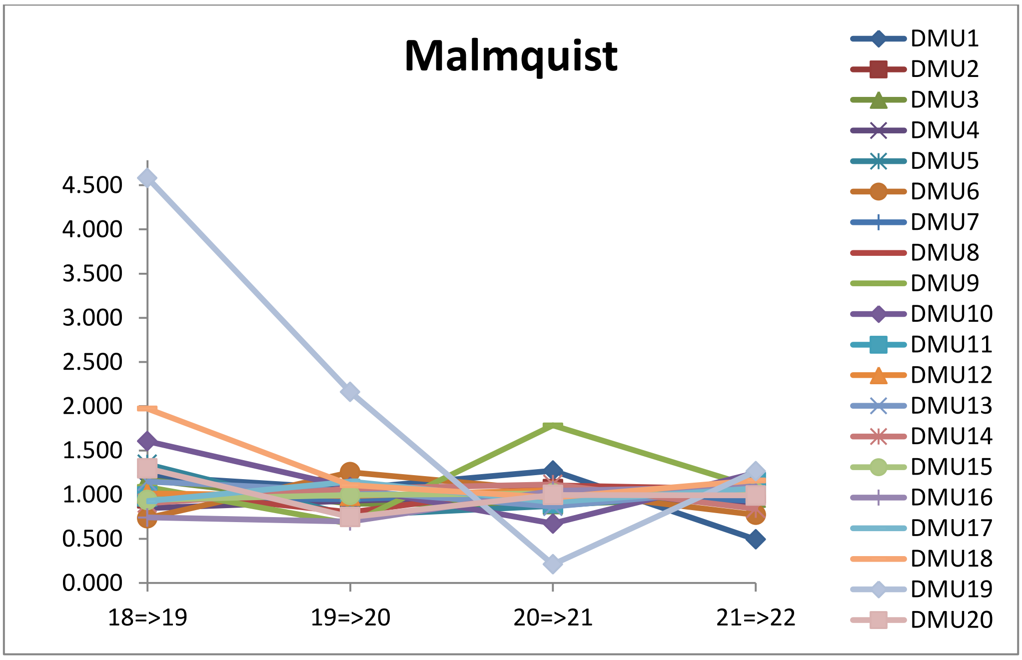


Figure 3: Total Factor Productivity Change

As shown in Table 7, the average Malmquist index of DMUs is greater than 1 (MI = 1.072), indicating an increase in total factor productivity growth for 2019–2022.

During the 2018–2019 period, the overall total factor productivity gap between DMUs can be seen. Remarkably, several DMUs exhibited highly efficient performances, such as DMU19 (Array Technology with MI =4.583) and DMU 18( Sun Power Corp with MI = 1.973). On the other hand, others are in the opposite position, with DMU6 (China Three Renewable Group) exhibiting the worst performance with MI=0.734. The results show that technical and technological investments between fishing firms are unstable during this time.

Table 7 and Figure 3 show two distinct trends in the Malmquist index in 2018–2022. There are companies with a high MI index in 2018 but a decline in 2022, such as DMU1, DMU3, DMU5, DMU10, DMU18, DMU19, and DMU20. Meanwhile, some companies tend to increase during this period, such as DMU2, DMU11, DMU15, and DMU17. The remaining companies tend to keep the MI index unchanged. This shows the strategy of the companies during this period.

The Malmquist index is the product of the change in technological progress and the change in technical efficiency, so companies with an MI > 1 mean that companies are making technological advances and technical efficiency. Those companies are DMU1, DMU5, DMU8, DMU9, DMU10, DMU11, DMU12, DMU13, DMU17, DMU18, DMU19, DMU20. Of which the highest is DMU19 (Array Technology). In contrast, companies with an MI < 1 need to rethink their technology and technical efficiency investments. To achieve new strides in the next phase, the clean and renewable energy boom.

## IV. Sumary and Prospect

In recent years, global warming and the greenhouse effect caused by emissions in the production process have greatly affected the whole world. Replacing fossil fuel sources with renewable fuels, such as solar power, wind energy, etc., is urgently needed. Companies worldwide are also making efforts to add to the worldwide supply chain. Evaluating the performance of solar plants is essential and adds value to the global supply chain. The author used the DEA method and Malmquist Index to evaluate the performance of the world's 20 largest Solar power plants. This combination brings a better overview for executives and investors. Help them navigate and make future decisions, defining their place in the global supply chain. The solar power generation industry is one of the promising and thriving industries due to the increasing demand for renewable energy worldwide in recent years, so the author can use the following methods: to evaluate the performance of factories more accurately.

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