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Static and Dynamic Relative Efficiency Evaluation of Logistics Companies in ICD - Focused on UIWANG ICD

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Abstract

The purpose of this study is to evaluate and analyze the efficiency of logistics companies located in ICD to enhance the competitiveness of ICD as the role of ICD grows. Efficiency analysis was conducted for 7 years from 2014 to 2020 targeting 10 of the resident logistics companies. DEA and DEA/Window were used for static efficiency analysis and dynamic efficiency analysis, respectively. Financial indicators were used as input and output factors. TE, PTE, and SE were evaluated through static efficiency analysis, and trends in efficiency and stability were evaluated through dynamic efficiency analysis. Through this, logistics companies suggested the need for improvement efforts to improve efficiency by analyzing current efficiency and trends.

Keywords: DEA, DEA/Window, TE, PTE, SE, ICD

1. Introduction

In Korea, there are many ports such as Busan Port and Incheon Port. In the past, it only served as a basic gateway for import and export by simply connecting land and sea, but now it is being reborn as a so-called 'comprehensive logistics base' that creates added value for the whole country and provides various service functions necessary for trade.

Unlike general ports, the Inland Container Depot (ICD) is located inland rather than the sea, but like general ports adjacent to the sea, it is equipped with various cargo handling facilities including containers, perform the function. In addition, ICD provides services such as temporary storage and customs clearance for ‘bonded’ cargo, which means products that have not yet gone through customs procedures. It is also a space that provides various logistics services that create added value, such as collection and mixing of cargo, sorting, packaging, storage, repair, and maintenance.

UIWANG ICD, Korea's representative ICD, is a container logistics complex built in 1984 by joint investment by the government and private companies to reduce logistics costs by improving the distribution structure of import/export container cargo and to strengthen national competitiveness. It is an import/export container base that handles a significant amount of import/export containers in the metropolitan area. By performing rail transportation, inland transportation, inland customs clearance, and inland port functions, it provides fast logistics services to shippers and contributes greatly to improving national competitiveness by reducing logistics costs.

The advantages and features of Uiwang ICD are as follows.

First, one-stop processing of customs duties as all customs-related organizations such as customs, food inspection stations, plant quarantine stations, and customs officers reside

Second, we are supplying empty containers for loading export cargo in the shortest distance, and container transportation companies are resident and jointly use logistics facilities to save time and money.

Third, it is located in the metropolitan area and is conveniently located near the Gyeongbu Line Railway, Yeongdong Expressway, West Coast Expressway, and Gyeongsu Industrial Road, making it easy to access.

Fourth, the Uiwang ICD information computer network is being built to provide shipping companies and shippers with container logistics information in real time.

Specifically, the main facilities of Uiwang ICD include a total area of 752,680 m^2, a container yard (CY) 387,932 m^2, a bonded cargo warehouse (CFS) 10,712 m^2 (3 buildings), an operating building 14,358 m^2 (8 buildings), a railway line 6,262 m (11 routes), etc.

The main equipment status includes 3 transformers for rail transport, 47 reach stackers for yard work, 652 tractors for land transport, and 1,800 trailers.

Based on these facilities, Uiwang ICD has the capacity to process up to 1.37 million TEU of containers per year and is innovating in import/export container transportation. Not only that, it will fully play its role as an important logistics base for the transcontinental railroad linking Asia and Europe in the future.

Meanwhile, there are 21 companies operating container yards (CY) and container freight stations (CFS) in Uiwang ICD. The competitiveness of these companies is the competitiveness of Uiwang ICD, and increasing corporate efficiency is the way to secure the global competitiveness of Uiwang ICD. However, research on efficiency is insufficient, and it is difficult to set improvement goals for enhancing competitiveness.

This study evaluates the efficiency of companies in Uiwang ICD using DEA and DEA/Window methodology, and also analyzes the stability and trend of efficiency to improve corporate competitiveness based on efficiency and ultimately the role of Uiwang ICD This was done for the purpose of maximization.

2. Methodology

2.1 DEA

Data envelopment analysis (DEA), a non-parametric efficiency measurement method, differs from other efficiency measurement methods by estimating a specific function form in advance and not estimating parameters, but is based on the linear programming method between the empirical input and output factors of the evaluation target. It is a technique to measure inefficiency by deriving an empirical efficiency frontier using data and comparing how far the evaluation targets are from the efficient frontier (Park, 2017).

On the other hand, it is important to note that when analyzing the measurement results, the efficiently evaluated decision making unit (DMU) is relatively evaluated and not efficient in an absolute sense. Absolute efficiency is expressed as a physical unit or ratio of some sort, such as “dollars/heads”. Therefore, there is no range constraint on the result value. Meanwhile, relative efficiency is a value expressed relative to the maximum value among the efficiencies of an economic agent engaged in production activities.

Until recently, various DEA models have been developed and presented by various scholars. In general, the most used DEA model is the CCR model of Abraham Charnes et al. (1981) and the BCC model of Banker et al. (1984). The CCR model is used under the assumption of constant returns to scale (CRS), and the BCC model is used under the assumption of variable returns to scale (VRS). Also, these two models are divided into input-oriented and output-oriented depending on whether they focus on input or output factors.

In this study, we try to use an input-oriented model that aims to maximize the level of the output factor at the level of the given input factor. First, the formula of the input-oriented CCR model is as follows.

$$\begin{aligned} & Min\ \theta \\ & s.t. \quad x_{ik}\theta \geq \sum_{j=1}^{n} x_{ij}\lambda_j \qquad i = 1, 2, \dots, m \\ & \qquad \sum_{j=1}^{n} y_{rj}\lambda_j \geq y_{rk} \qquad r = 1, 2, \dots, s \\ & \lambda_j \geq 0 \qquad j = 1, 2, \dots, n \\ & x_{ik}: i_{th}\ input\ factor\ of\ k_{th}\ DMU \\ & y_{rj}: r_{th}\ output\ factor\ of\ j_{th}\ DMU \\ & \lambda_j: weight\ of\ j_{th}\ DMU \end{aligned} \tag{1}$$

The formula of the input-oriented BCC model is as follows.

$$\begin{aligned} & Min\ \theta \\ & s.t. \quad x_{ik}\theta \geq \sum_{j=1}^{n} x_{ij}\lambda_j \qquad i = 1, 2, \dots, m \\ & \qquad \sum_{j=1}^{n} y_{rj}\lambda_j \geq y_{rk} \qquad r = 1, 2, \dots, s \\ & \sum_{j=1}^{n} \lambda_j = 1 \\ & \lambda_j \geq 0 \qquad j = 1, 2, \dots, n \\ & x_{ik}: i_{th}\ input\ factor\ of\ k_{th}\ DMU \\ & y_{rj}: r_{th}\ output\ factor\ of\ j_{th}\ DMU \\ & \lambda_j: weight\ of\ j_{th}\ DMU \end{aligned} \tag{2}$$

On the other hand, the scale efficiency model calculates the efficiency by comparing the output of the constant state and the variable state of the scale. The technical efficiency measured in the constant state of scale is the efficiency score of the CCR model, and the scale efficiency is included.

Meanwhile, the pure technical efficiency measured in the state of variable scale is the efficiency score of the BCC model and is the technical efficiency excluding the efficiency of scale. Scale efficiency measures the efficiency of scale by dividing the technical efficiency and scale efficiency scores calculated in the CCR model by the pure technical efficiency scores calculated in the BCC model.

If the efficiency scores of each of the CCR and BCC models are $?^*_{CCR}$ and $?^*_{BCC}$, then Scale Efficiency (SE) is the same as (3).

$$SE = \frac{\theta^*_{CCR}}{\theta^*_{BCC}} \tag{3}$$

Scale efficiency can be analyzed for inefficiency and whether it is caused by inefficient management activities or by circumstances caused by scale.

2.2 DEA/Window

DEA/Window analysis does not use the data from the entire analysis period at once, but creates a window with a certain size and analyzes the data within that period. In each window, even the same DMU is regarded as different DMUs if the period is different.

In DEA/Window analysis, trend and stability can be confirmed by performing DEA analysis through a moving average using Equation (4). The DEA/Window analysis should determine the width of the period to observe dynamic changes.

When the window width is p and the analysis period is k, it is determined using Equation (4) (A Charnes et al., 1984).

$$p = \begin{cases} \dfrac{k+1}{2} & k \text{ is odd} \\ \dfrac{k+1}{2} \pm \dfrac{1}{2} & k \text{ is even} \end{cases} \tag{4}$$

The number of windows (w) becomes w=k-p+1 as in <Table 1>.

Table 1. The number of DEA/Window

	1	**2**	**3**	**·**	**·**	**·**	**·**	**·**	**·**	**k**
1	1	·	·	p						
2		2	·	·	p+1					
3			3	·	·	p+2				
·					·	·				
·						·	·			
w=k-p+1								k-p+1	·	k

When the window width (p) is determined, the window efficiency evaluation is sequentially analyzed through a moving average. That is, when the number of DMUs is n, pn DMUs are targeted from period 1 to p in the first window, and pn DMUs are targeted from period 2 to p+1 in the second window. In this way, it moves backward by one period and evaluates to the last window. And, window characteristics can be obtained as shown in <Table 2> when the number of DMUs is n.

Table 2. The character of DEA/Window

The number of window (w)	**w=k-p+1**
The number of DMUs for each window	np
The total number of DMUs	npw
window width (p)	$p = \begin{cases} \frac{k+1}{2} & k \text{ is odd} \\ \frac{k+1}{2} \pm \frac{1}{2} & k \text{ is even} \end{cases}$

3. Empirical Efficiency Analysis

3.1 Analysis target and factor selection

This study targets 10 companies listed on the stock market among 21 companies in UIWANG ICD. Assets, liabilities, and capital were selected as input factors, and sales, operating profit, and net profit were selected as output factors. This is to secure transparent and objective data for reliable analysis. Data are collected and used for analysis by collecting input and output factors from 10 companies for 7 years (<Table 3.>). The company to be analyzed is called a DMU and is indicated by a corresponding symbol.

Table 3. Descriptive Statistics of Input/Output Factors(unit: hundred million won)

Factors	Statistics	2014	2015	2016	2017	2018	2019	2020
Asset	Max	55,417	10,884	79,675	81,857	86,878	101,297	108,987
	Min	927	2,015	1,468	1,882	1,996	2,758	3,017
	Ave	20,376	7,809	29,092	30,731	34,637	41,007	43,731
	SD	21,810	5,021	31,827	33,752	38,380	44,452	47,546
Liabilities	Max	29,790	42,767	44,900	41,961	47,378	54,595	58,323
	Min	482	2,016	895	1,252	1,326	2,039	2,322
	Ave	9,847	24,748	15,803	16,326	18,753	23,549	24,605
	SD	11,379	20,780	17,950	18,243	21,714	25,568	26,759
Capital	Max	29,790	2,017	34,774	39,895	42,602	46,703	50,664
	Min	482	1,022	573	630	670	719	686
	Ave	15,614	1,552	13,289	14,404	15,884	17,458	19,126
	SD	10,413	501	14,277	15,799	17,121	19,351	21,143
Sales	Max	111,668	2,264	153,406	163,583	168,656	182,700	165,199
	Min	2,108	1,150	3,498	3,646	4,004	4,462	4,887
	Ave	29,461	1,811	41,090	44,733	49,424	54,157	52,438
	SD	42,767	585	59,143	63,597	67,469	73,702	67,881
Operational Profit	Max	4,232	25,135	7,288	7,271	7,101	8,765	6,622
	Min	74	2,019	-153	101	95	111	107
	Ave	1,022	16,367	1,640	1,696	1,718	2,201	1,903
	SD	1,617	12,527	2,908	2,872	2,787	3,409	2,605
Net Profit	Max	42,767	14,196	5,057	6,805	4,374	5,023	6,061
	Min	74	2,020	54	-470	53	-29	-19
	Ave	9,942	9,098	1,112	1,225	1,010	951	1,337
	SD	18,414	6,325	1,947	2,754	1,665	2,004	2,374

3.2 Static Efficiency Analysis

In this study, the efficiency of the DMU was evaluated as the Technical Efficiency (TE) of the CCR-I model, the Pure Technical Efficiency (PTE) from the BCC-I model, and the Scale Efficiency (SE) by dividing TE by PTE. were analyzed separately. <Table 4> shows the static efficiency analysis results of 10 companies for 7 years from 2014 to 2020.

In the table, a DMU with an efficiency score of '1' is evaluated as efficient, and if it is less than '1', it is evaluated as an inefficient DMU. TE, PTE, and SE by year and their respective averages are shown.

Table 4. Summary of Static Efficiency Analysis Results

DMU	14			15			16			17			18			19			20		
	TE	PTE	SE	TE	PTE	SE	TE	PTE	SE	TE	PTE	SE	TE	PTE	SE	TE	PTE	SE	TE	PTE	SE
D01	0.55	0.99	0.56	0.54	0.99	0.55	1	1	1	1	1	1	1	1	1	0.76	0.99	0.76	0.96	0.99	0.96
D02	0.89	0.97	0.91	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
D03	0.94	0.94	0.99	0.78	0.87	0.90	0.31	0.32	0.96	0.40	0.46	0.88	0.38	0.42	0.91	0.52	0.52	0.99	0.65	0.65	0.99
D04	0.85	0.85	1.00	0.91	0.99	0.91	0.83	0.87	0.95	0.66	0.69	0.95	1	1	1	0.90	0.93	0.96	0.88	1	0.88
D05	0.35	0.35	1.00	0.39	0.42	0.94	0.55	0.65	0.84	0.42	0.53	0.79	0.53	0.74	0.72	0.57	0.76	0.75	0.80	0.91	0.88
D06	0.95	1	0.95	1	1	1	1	1	1	1	1	1	1	1	1	0.65	0.68	0.96	1	1	1
D07	0.48	0.73	0.67	0.60	0.93	0.64	0.54	0.63	0.87	0.49	0.61	0.80	0.50	0.73	0.68	0.52	0.72	0.72	0.58	0.81	0.72
D08	0.32	0.34	0.94	0.30	0.75	0.40	0.39	0.46	0.84	0.25	0.44	0.58	0.41	0.42	0.99	0.43	0.46	0.95	0.43	0.60	0.71
D09	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.82	1	0.82	0.96	1	0.96
D10	0.99	1	0.99	0.94	1	0.94	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
AVE.	0.73	0.82	0.90	0.75	0.89	0.83	0.76	0.79	0.95	0.72	0.77	0.90	0.78	0.83	0.93	0.72	0.81	0.89	0.82	0.90	0.91

3.3 Dynamic Efficiency Analysis

3.3.1 Efficiency Ranking

For dynamic efficiency analysis, DEA/Window method is used.

<Table 5> shows the results of obtaining CCR efficiency by collecting data from 10 companies for 7 years from 2014 to 2020. Here, the total number of DMUs (n) is 10, the total comparison period (k) is 7 years, and the window width (p) is 4 when calculated by Equation (4). So, the number of windows (w=k-p+1) is 4, the number of DMUs (np) for each window is 40, and the total number of DMUs (npw) is 160.

If the width of the window is increased, the number of DMUs used for analysis for each window is maximized, so the degree of freedom increases. In particular, it is advantageous even when the number of DMUs is small. On the other hand, if the length of the window is shortened, the number of windows is increased, and there is little difference from the static efficiency analysis result. And the width of the window is different depending on whether a window is included at a specific point in time.

The results of DEA/Window analysis are shown in <Table 5>. Win-Ave. represents the average of each window. DMU-Ave. is the average of Win-Ave. and represents the average of efficiency over 7 years. The efficiency ranking was analyzed in the order of DMU D02-D09-D10-D01-D06-D07-D05-D03-D08.

Table 5. Summary of Dynamic Efficiency Analysis Results

DMU	Win.	14	15	16	17	18	19	20	Win-Ave.	DMU-Ave.	Rank
D01	W1	0.416	0.471	1	0.721				0.652	0.758	4
	W2		0.471	1	0.721	0.873			0.766		
	W3			1	0.730	0.911	0.557		0.799		
	W4				0.951	1	0.760	0.548	0.815		
D02	W1	0.802	1	1	1				0.950	0.970	1
	W2		1	1	1	0.866			0.966		
	W3			1	1	0.880	1		0.970		
	W4				1	0.969	1	1	0.992		
D03	W1	0.744	0.736	0.262	0.345				0.522	0.412	9
	W2		0.736	0.280	0.380	0.323			0.430		
	W3			0.302	0.380	0.323	0.301		0.326		
	W4				0.401	0.355	0.347	0.385	0.372		
D04	W1	0.682	0.860	0.824	0.568				0.733	0.725	6
	W2		0.860	0.824	0.568	0.573			0.706		
	W3			0.823	0.558	0.756	0.874		0.753		
	W4				0.480	0.725	0.754	0.878	0.709		
D05	W1	0.318	0.314	0.491	0.376				0.375	0.446	8
	W2		0.331	0.506	0.409	0.495			0.435		
	W3			0.506	0.409	0.495	0.509		0.480		
	W4				0.416	0.499	0.518	0.544	0.494		
D06	W1	0.842	0.839	0.663	0.511				0.714	0.741	5
	W2		0.871	0.734	0.617	0.641			0.716		

DMU	Win.	14	15	16	17	18	19	20	Win-Ave.	DMU-Ave.	Rank
	W3			1	0.843	1	0.434		0.819		
	W4				0.843	1	0.450	0.573	0.717		
D07	W1	0.464	0.503	0.484	0.434				0.471	0.469	7
	W2		0.573	0.505	0.440	0.388			0.477		
	W3			0.505	0.462	0.433	0.450		0.462		
	W4				0.486	0.453	0.465	0.459	0.466		
D08	W1	0.269	0.280	0.234	0.229				0.253	0.283	10
	W2		0.290	0.234	0.229	0.220			0.243		
	W3			0.330	0.226	0.291	0.412		0.315		
	W4				0.238	0.290	0.371	0.388	0.322		
D09	W1	1	1	0.957	0.961				0.980	0.942	2
	W2		1	0.957	0.961	0.952			0.968		
	W3			1	0.932	0.905	0.807		0.911		
	W4				0.961	0.944	0.821	0.917	0.911		
D10	W1	0.883	0.820	1	1				0.926	0.940	3
	W2		0.820	1	1	0.944			0.941		
	W3			1	1	0.944	0.959		0.976		
	W4				1	0.946	1	0.717	0.916		
Ave.		0.642	0.689	0.714	0.645	0.680	0.639	0.641			

3.3.2 Trend analysis

<Table 6> and <Fig. 1> show the average of the efficiency per window to understand the efficiency change for all 10 DMUs over the past 7 years.

In <Table 6>, the average value of each window average was highest in DMU D02 and lowest in D08. In the case of DMU, which has a large increase and decrease in efficiency by year, it is not easy to understand the trend of efficiency. However, it is easier to understand the trend of efficiency based on Window.

The average efficiency per window started from 0.658 in the first window (14-15-16-17) and increased to 0.681 in the third window (16-17-18-19), but in the last window (17-18-19-20) dropped to 0.675.

Table 6. Average through Window

DMU	14-15-16-17	15-16-17-18	16-17-18-19	17-18-19-20	Rank
D01	0.652	0.766	0.799	0.815	4
D02	0.950	0.966	0.970	0.992	1
D03	0.522	0.430	0.326	0.372	9
D04	0.733	0.706	0.753	0.709	6
D05	0.375	0.435	0.480	0.494	8
D06	0.714	0.716	0.819	0.717	5
D07	0.471	0.477	0.462	0.466	7
D08	0.253	0.243	0.315	0.322	10
D09	0.980	0.968	0.911	0.911	2
D10	0.926	0.941	0.976	0.916	3
Ave.	0.658	0.665	0.681	0.671	

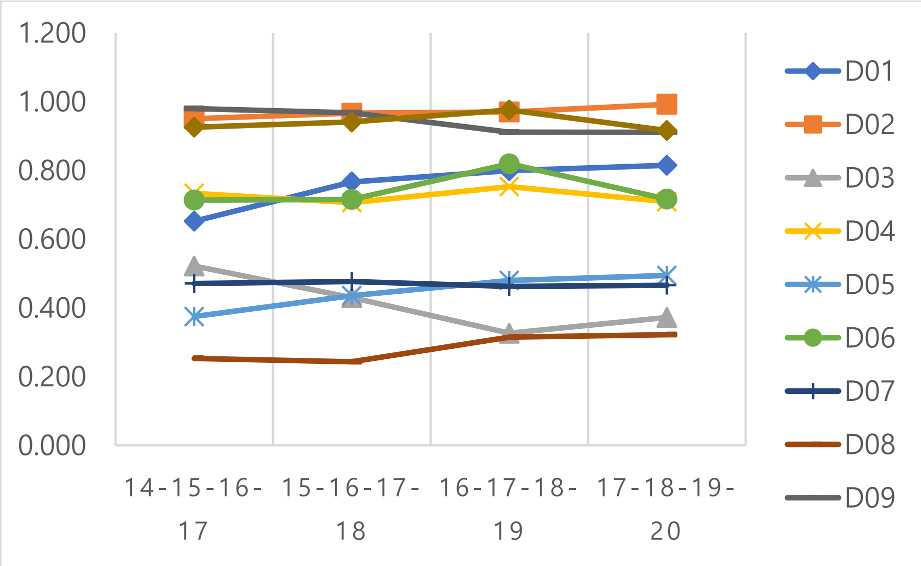

Fig. 1. Variation through window

As can be seen from <Fig. 1>, the efficiency window trend for each DMU is continuously uptrend for DMU D01, D02, and D05, and for DMU D10, the uptrend was up until the 3rd window, but changed to a downtrend in the last window. DMU D09 has a continuous downward trend, and the rest of the DMUs are showing a repeating trend of rising, falling or falling.

3.3.3 Stability analysis

In evaluating efficiency, stability is also important along with trends in efficiency. High stability means small fluctuations in efficiency. In this study, stability is evaluated by three measures of volatility: SD, LDY, and LDP. By analyzing these values, it is possible to grasp the efficiency trend of companies over the past 7 years and their stability against changes.

SD is the standard deviation of the average of four windows, and the lower the value, the more stable the window efficiency is. The largest difference between scores in the same year (LDY) means the maximum value among the differences in the efficiency scores of each DMU within the same year, and a lower value indicates that the efficiency is stably maintained by year. The largest difference between scores across the entire period (LDP) refers to the difference between the maximum and minimum values of the efficiency score during the entire analysis period, and a lower value means less change in efficiency during the entire analysis period. The results of these scales are shown in <Table 7>.

Table 7. Efficiency stability

DMU	SD	LDY	LPD
D01	0.213	0.230	0.584
D02	0.062	0.103	0.198
D03	0.166	0.055	0.481
D04	0.135	0.183	0.398
D05	0.078	0.041	0.230
D06	0.192	0.359	0.566
D07	0.041	0.071	0.185
D08	0.062	0.096	0.192
D09	0.058	0.048	0.193
D10	0.086	0.041	0.283

The DMU with the smallest SD has the most stable efficiency variability with a D07 of 0.041, and the DMU with the largest SD has a D01 of 0.213, which can be analyzed as the most unstable of the efficiency variability in each window.

And, the DMU with the smallest LDY has the most stable annual efficiency fluctuations with D05 and D10 of 0.041, whereas DMU D06 has the largest LDY with 0.359, which can be interpreted as the most unstable year-to-year efficiency fluctuations.

On the other hand, as for LPD, DMU D07 was the smallest at 0.185, indicating a small change in efficiency during the entire analysis period.

4. Conclusion

This study analyzed the static and dynamic efficiency of 10 logistics companies located in Uiwang ICD for 7 years from 2014 to 2020.

For static efficiency, TE, PTE, and SE were analyzed by year using the CCR-I model and BCC-I model, and for dynamic efficiency, the change in efficiency over 7 years was analyzed using the DEA/Window model.

The implications of the analysis results of this study are as follows.

First, the scale efficiency during the analysis period showed an excellent level with an overall average of 0.9 or higher, except for 2014 and 2019. Only three years (2016, 2017, 2018) for technological efficiency, four years for pure technical efficiency (2016, 2017, 2018, 2020), and three years for scale efficiency (2016, 2017, 2018), the number of efficient companies exceeds half It shows that logistics companies need to increase their overall efficiency. In particular, in the case of technological efficiency, there is only one year in 2020 where the average exceeded 0.80 during the analysis period, so it can be seen that measures to increase technological efficiency through activities such as benchmarking high-efficiency companies are necessary.

Second, as a result of the dynamic analysis, the average efficiency trend for each window showed an upward trend from the first window to the third window, but turned into a downward trend in the last window (17-18-19-20). It can be seen that the efficiency trend for each company is divided into three groups: Group I (D02, D09, D10), Group II (D01, D04, D06), and Group III (D03, D05, D07, D08). Strategies and measures to improve efficiency are urgently needed.

In terms of stability, DMU D07, which has the smallest SD, is the most stable in the efficiency variability of each window, but it is in a low state of efficiency, so measures are required to improve efficiency. On the other hand, the DMU D01, which has the largest SD, is the most unstable in the efficiency volatility of the window, but it can be analyzed as positive because the efficiency improvement trend is reflected.

And DMUs D05 and D10, which have the smallest LDY, have the most stable efficiency fluctuations by year, but since the efficiency of D05 is low, efforts to improve the efficiency are absolutely necessary. Meanwhile, DMU D06, which has the largest LDY, has the most unstable efficiency fluctuations by year, but it can be interpreted as having a positive aspect that the efficiency greatly improved during the third window period.

On the other hand, LPD is the smallest in DMU D07, so there is little change in efficiency during the entire analysis period, and it is very negative because there is no change in the state with low efficiency, and improvement measures are urgently needed. And it can be seen that DMU D01 has the largest change due to the trend of improving efficiency during the entire analysis period.

The results of this study are the results of analyzing the efficiency of logistics companies located in Uiwang ICD. Although there is a limit to spreading the results to other ICDs, it will be sufficiently applicable as an approach methodology for evaluating and analyzing efficiency.

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References

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. https://doi.org/10.1287/mnsc.30.9.1078

Charnes, A., Clark, C., Cooper, W., & Golany, B. (1984). A developmental study of data envelopment analysis in measuring the efficiency of maintenance units in the US air forces. Annals of Operations Research, 2(1), 95-112. https://doi.org/10.1007/BF01874734

Charnes, A., Cooper, W. W., & Rhodes, E. (1981). Evaluating program and managerial efficiency: an application of data envelopment analysis to program follow through. Management science, 27(6), 668-697. https://doi.org/10.1287/mnsc.27.6.668

Färe, R., & Grosskopf, S. (1992). Malmquist productivity indexes and Fisher ideal indexes. The Economic Journal, 102(410), 158-160. https://doi.org/10.2307/2234861

Goh, H. (2016). A Study on Evaluating Management Productivity for Logistics-IT Corporations. Advanced Science and Technology Letters, 133, 201-206. http://dx.doi.org/10.14257/astl.2016.133.38

Goh, H. (2021). Enhancing Management Efficiency through Analysis of Efficiency Trends and Stability of IT-Service Companies. Review of International Geographical Education Online, 11(8), 1998-2005. https://rigeo.org/submit-a-menuscript/index.php/submission/article/download/2393/1858

Mwangi, J. G. ., & Nasieku, T. . (2022). Effect of Ownership Structure on Earnings Management in Listed Manufacturing Firms at Nairobi Securities Exchange, Kenya. *Asian Themes in Social Sciences Research*, 6(1), 12–24. https://doi.org/10.33094/atssr.v6i1.66

Park, M. H. (2017). A Study on Discrimination Evaluation of DEA Models. The Journal of the Korea Contents Association, 17(1), 201-212. https://doi.org/10.5392/JKCA.2017.17.01.201