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A WINDOW DEA BASED EFFICIENCY EVALUATION OF THE PUBLIC AIRPORTS IN TURKEY: 2014–2019 CASE

Abstract. *Aviation is strategically important because of its enormous contribution to the economy, as well as being the field of application and production of new technologies. The efficiency of airports comes to the fore in efficiency researches in aviation. However, efficiency analyzes with Data Envelopment Analysis (DEA) using single-year data may not be sufficient to determine the trend. Therefore, output-oriented Window-DEA (W-DEA) using multi periods was performed in this study. Moreover, W-DEA provides information about the increases and decreases in the efficiency trends of airports. The research was carried out with the data of 42 Turkish airports for the period 2014-2019. The findings show that two airports in Istanbul as well as Adana, Van and Antalya airports have high efficiency. With this study, measuring the performance of Turkish airports with W-DEA has been brought to the literature. This study will shed light on the feasibility studies of new investments as well as the sustainability and competitiveness studies.*

Keywords*: Window-DEA, airport efficiency, aviation, Turkish airports*

JEL Classification: C02, C14, M11, L93

1. Introduction

The economic development of countries largely depends on the development of transportation and access networks. Among the transportation systems, the aviation has two major importance as the primary application area of technological developments and its leading role in the production of new technologies. The level of development in aviation is one of the main indicators of economic development and social welfare. For this reason, the projects, investments and steps to be taken in aviation play a strategic role not only for the

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transportation, but also for shaping the future vision of their countries (SHGM in Turkish acronym, 2019).

The importance of air transport and its contribution to the development of countries result in the steady growth. The efficiency of airports gains even more importance in the ever-evolving air transport.

The rapid development of air transportation all over the world since the 1980s (Jiang et al., 2019, p. 49), and in parallel with this, the implementation of liberal economic policies in Turkey in the same years enabled the development of air transportation in Turkey (Pata, 2019, p. 20271).

In today's competitive environment, one of the most effective ways to maintain sustainability is efficiency measurement tools. Data Envelopment Analysis (DEA), which is one of them and mostly uses multi or single year data to measure efficiencies. Although it is a widely used and well-known technique for measuring efficiency in any decision-making-unit (DMU) dataset.

DEA provides information to managers, researchers, policy makers and other stakeholders. Although annual data, which is used for DEA may not be sufficient to make long-term decisions for strategic management. Therefore, examining the data in multiple-year windows allows for more consistent inferences by eliminating single-period anomalies.

Despite the importance of Turkish aviation in Europe and its ranking in the world, it has not been adequately studied. In the limited number of studies examining the efficiency of Turkish airports, annual efficiency is discussed based on annual data. However, the analysis using multiple years may provide more consistent results to measure efficiency and trend in this strategically important sector. Therefore, the aim of this study is to examine Turkish airports in three-year window periods with Window-DEA (W-DEA). To the best of our knowledge, the efficiency of airports has never been investigated by current studies with W-DEA analysis. Therefore, this gap is also tried to be filled with this study.

The rest of this paper is organized as follows: Section 2 reviews the literature on airport efficiency, W-DEA and studies on the efficiency of Turkish airports. Section 3 describes the methodology. Section 4 includes the dataset, factors, descriptive statistics and window selection. Section 5 shares the empirical results. Section 6 reports the conclusion, discussion, limitations, and suggestions for future studies.

2. Literature review

There are several DEA methods to benchmark and measure the efficiency and performance of airports. Based on Farell's (1957) study of productive efficiency, Charnes et al. (1978) developed the constant to return scale (CRS) model known as CCR. Then, Banker et al. (1984) proposed the variable return scale (VRS) model known as BCC. Although these two models are called conventional DEA models, considering that these two models are outdated, they are still used in efficiency measurement in many fields.

W-DEA analysis, which was first introduced to terminology by Charnes et al. (1984), is used in DEA, evaluation of perennial data, and trend determination. W-DEA analysis treats each DMU as a different unit, so data on DMUs in different time zones are included in the model, treating them as different DMUs. Working on the principle of moving averages and measuring the relative level of efficiency over a given period of time, called a window, W-DEA helps to overcome the problem of potentially unstable efficiency indices produced by conventional single-year DEA models (Ha et al., 2010).

Charnes et al. (1984) used W-DEA analysis to measure the efficiency of maintenance activities of US Air Force Aircrafts and brought the window analysis approach to the field of DEA. Although the first application of the method was in the field of aviation, it is widely used in banking (Nguyen et al., 2014), agriculture (Sardar Shahraki et al., 2018), and health institutions (Flokou et al., 2017) but the use of the method in aviation is quite rare.

As far as we know, the first application of W-DEA for airport performance was carried out by Yu (2004) with the model proposed by Son Nghiem and Coelli (2002). In the study, output-oriented DEA was carried out with the data of Taiwan's 14 domestic airports, the period between 1994-2000. The runway area, apron area, terminal area and route were taken as inputs, the numbers of movements and passengers were taken as the desired output, and the aircraft noise was taken as the undesired output. As a result of the research, it was concluded that Taiwan airports can provide more aircraft movements, therefore new physical infrastructure or infrastructure expansion investments may not be necessary.

Yu et al. (2008) examined the productivity growth at 4 Taiwan domestic airports and performed W-DEA using two-year windows with data from 1995-1999. In the study, employee expenses, operating expenses, capital were taken as inputs, sum of aeronautical revenue and non-aeronautical revenue was taken as desired output, aircraft noise was taken as undesired output.

Ha et al. (2010) empirically evaluated the efficiency level and efficiency change of major Northeast airports (Tokyo (Narita), Osaka (Kansai), Seoul (Incheon and Gimpo), Beijing Capital, Shanghai Hongqiao, Guangzhou and Hong Kong) with W-DEA, with data for the period 1994-2007. In the study, runway length, terminal size and employees are taken as inputs, while passenger volume, cargo volume and aircraft movements are taken as outputs. As a result of the research, they note that the airports recorded an increase in efficiency over the period, indicating that this finding may have resulted from the fact that a series of deregulation measures adopted by the Chinese government may have worked in increasing airport efficiency.

Bezić et al. (2010), in their study aiming to evaluate the efficiency of Croatian airports during the 2004-2008 five-year period, took the operating cost and the number of employees as inputs, and total revenues were taken as output.

Croatian 7 airports were examined in the three-variable study, input-oriented W-DEA with CRS assumption model was performed with cover three-year windows.

Rabar et al. (2017), in their study aiming to evaluate the efficiency of seven Croatian airports for the period 2009-2014, took personnel expenses, total expenditures and total assets as inputs, and total income was taken as output. The airports were examined in the study, which included four variables, and input-oriented both VRS and CRS assumptions for W-DEA was performed for in a single window.

Hong and Domergue (2018) examined the relative efficiencies of low cost carrier firms in Korea with W-DEA. Since airport efficiency is not the subject of the research, the study is seen as a study conducted with W-DEA in the field of aviation. Three-year windows were used in the study covering the period 2009-2013.

Lu et al. (2019) examined the efficiency of 27 Chinese airports between 2014 and 2018 with W-DEA for three-year windows. Six inputs used in the study are the number of gates, capital, routes, the number of runways, terminal area and three outputs are aircraft movement, cargo throughput and the number of passengers.

Ngo and Tsui (2020), who examined the efficiencies of 11 New Zealand airports in the period 2006-2017, used W-DEA in the first stage of the study. They examined a total of ten windows by creating three-year windows in the twelve-year data period. In the study, aeronautical incomes, non-aeronautical incomes and aircraft movements were taken as outputs, runway length, employee expenses and operating expenses were taken as inputs.

Despite Turkey's importance and rising trend in the field of aviation, it is noteworthy that there are not enough studies on Turkish airports. As far as we know, the efficiency of Turkish airports has never been studied with Window-DEA before.

3. Methodology

DEA models can be the input-oriented and output-oriented model. In the input-oriented model, the inputs are attempted to be reduced while the outputs are kept at their own level. In the output-oriented model, the outputs are attempted to be increased while the inputs are kept at their own level. In the DEA model used to measure the relative efficiency of airports, let x_{ij} $(i = 1, \ldots, m)$ and y_{rj} $(r = 1, \ldots, s)$ represent the input and output amounts of j^{th} airport. The output-oriented model is as follows under evaluation of 0^{th} airport:

$$\frac{1}{E_0} = min \ \sum_{\mathrm{i}=1}^{m} \mathrm{v_i} X_{i0}$$
$$\sum_{\mathrm{r}=1}^{s} u_r Y_{r0} = 1 \qquad (1)$$
$$-\sum_{r=1}^{s} u_r y_{rj} + \sum_{i=1}^{m} v_i x_{ij} \leq 0, \quad j = 1, \dots, n$$
$$u_r, v_i \geq \varepsilon, r = 1, \dots, s; \ i = 1, \dots, m$$

where m is the number of inputs, s is the number of outputs of evaluated n airports. Furthermore, E_0 is efficiency score, ε is a small positive number, u_r is weight of output r and v_i is weight of input i. If $E_0 = 1$, 0^{th} airport is considered an efficient airport; otherwise, it is considered an inefficient airport (Charnes et al., 1978).

W-DEA analysis was proposed by Charnes et al. (1984) based on the approach of moving averages for panel or dynamic data. The performance of each DMU is compared both with the performance of other DMUs in the same and following periods and with its own performance in the following periods. Therefore, each DMU is considered a different DMU in the W-DEA analysis. To perform a W-DEA analysis in the case of N DMUs (n= $1,2,\dots,$ N) using γ inputs and δ outputs in T time periods ($t = 1,2, \dots, T$) this will produce a sample of $N \times T$ observations where an observation n in period t (DMU_t^n) has an γ dimensional input vector $x_n^t = \begin{bmatrix} x_n^{1t} \\ \vdots \\ x_n^{\gamma t} \end{bmatrix}$, and an s dimensional output vector $y_n^t = \begin{bmatrix} y_n^{1t} \\ \vdots \\ y_n^{st} \end{bmatrix}$ of the form.

If the window begins at time n ($1 \leq n \leq T$) with a width equal to w (1 ≤ w ≤ T-n) then the inputs and outputs matrices can be presented as

$$x_{vw} = \begin{bmatrix} x_1^v & x_2^v & \cdots & x_N^v \\ x_1^{v+1} & x_2^{v+1} & \cdots & x_N^{v+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{v+w} & x_2^{v+w} & \dots & x_N^{v+w} \end{bmatrix}$$
$$y_{vw} = \begin{bmatrix} y_1^v & y_2^v & \cdots & y_N^v \\ y_1^{v+1} & y_2^{v+1} & \cdots & y_N^{v+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_1^{v+w} & y_2^{v+w} & \dots & y_N^{v+w} \end{bmatrix}$$

The substitution of inputs and outputs in the appropriate model specifications as in the CCR and BCC models provide us with the W-DEA analysis results (Halkos and Polemis, 2018). In this study, the output-oriented W-DEA model was preferred for airports management efficiency.

4. Dataset, factors and window selection

The data cover the years between 2014-2019 for forty-two Turkish airports. Because of the Covid-19 pandemics effects, 2020 data were not included in the analysis. The data of 41 airports collected from annual reports of DHMI (General Directorate of State Airports Authority), single data for Sabiha Gökçen Airport (SAW) taken from the annual reports of the airport. Due to the transfer of Istanbul Atatürk (ISL) airport to the new Istanbul Grand Airport (IST) at the April 2019, the outputs of these two airports were sum and inputs of the new airport were used. As DEA is extremely sensitive to missing data, 42 airports with complete data were included in the analysis. Moreover, military airports were excluded from the analysis. Names of the airports and IATA codes are given at Table 1.

Table 1: Airports and IATA Codes

#	Name of the airport	IATA Code	#	Name of the airport	IATA Code	#	Name of the airport	IATA Code
1	Istanbul	IST or ISL	15	Batman	BAL	29	Kocaeli	KCO
2	Sabiha Gokcen	SAW	16	Bingol	BGG	30	Konya	KYA
3	Esenboga	ESB	17	Bursa	YEI	31	Malatya	MLX
4	Izmir	ADB	18	Denizli	DNZ	32	Mardin	MQM
5	Antalya	AYT	19	Diyarbakir	DIY	33	Mus	MSR
6	Dalaman	DLM	20	Elazig	EZS	34	Kapadokya	NAV
7	Bodrum	BJV	21	Erzincan	ERC	35	Ordu Giresun	OGU
8	Adana	ADA	22	Hakkari Yuksekova	YKO	36	Samsun	SZF
9	Trabzon	TZX	23	Hatay	HTY	37	Siirt	SXZ
10	Erzurum	ERZ	24	Igdir	IGD	38	Sinop	NOP
11	Gaziantep	GZT	25	Kahramanmaras	KCM	39	Sivas	VAS
12	Adiyaman	ADF	26	Kars	KSY	40	Sanliurfa	GNY
13	Agri	AJI	27	Kastamonu	KFS	41	Sirnak	NKT
14	Amasya	MZH	28	Kayseri	ASR	42	Van	VAN

The inputs and outputs used in DEA are selected as follows according to the literature (Gillen & Lall, 1997); Six inputs are the number of runways, terminal area, the number of boarding gates, apron aircraft capacity, the number of check-in counters and the number of employees. Three outputs are annual number of aircraft, the number of passenger and cargo amount. The conceptual model of the inputs and outputs of the airports as a DMU is shown in Figure 1.

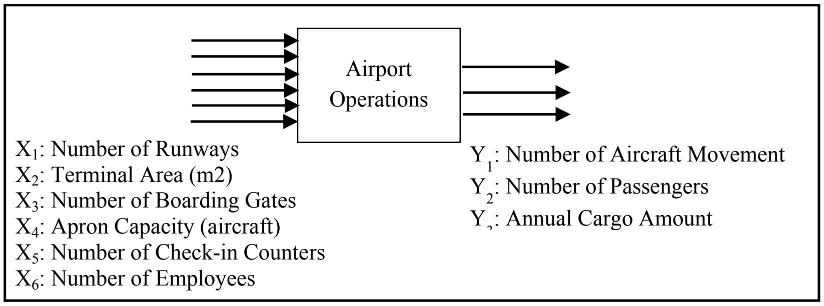

Figure 1: DEA model for airport efficiency

A window with $n \times w$ observations is denoted starting at time t $(1 \leq t \leq T)$ with window width $(1 \leq w \leq T - t)$. In the current study, there are 42 airports from Turkey and a time period of 6 years (2014–2019) of efficiencies needs to be examined, so $n = 42$ and $T = 6$. In this study, following Halkos and Polemis (2018), Bezić et al., (2010), Hong & Domergue, (2018) Ngo & Tsui, (2020), we chose a narrow window with the width of three ($w = 3$) to get credible airport efficiency results. Therefore, the first three years of 2014, 2015 and 2016 construct the first window. Then the window moves on a one-year period by dropping the original year and adding a new year. Thus, the next three years of 2015, 2016 and 2017 form the second window. This process continues until the last window, which contains the last three years of 2017, 2018 and 2019, is constructed. At last, we obtain four windows which are performed for each airport and the number of DMUs in each window becomes 126 ($n \times w = 42 \times 3$). Windows and their distribution by years are shown in Table 2.

Table 2: Windows Breakdown

	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6
Window 1	2014	2015	2016			
Window 2		2015	2016	2017		
Window 3			2016	2017	2018	
Window 4				2017	2018	2019

5. Empirical results

According to the findings obtained from W-DEA, the efficiency of each window of the airports that are efficient on average and are in the top five rankings are shown in Table 3. The efficiency of all airports included in the study and their average efficiency in the determined windows with their rankings are presented in Appendix-A.

Table 3: Average Efficiencies of Selected Airports

IATA Code	2014	2015	2016	2017	2018	2019	Window Mean	Airport Mean	Rank
ADA	0.9743	0.9202	0.9506				0.9484	0.9398	1
		0.9113	0.9566	0.9956			0.9545		
			0.9148	0.9956	0.9964		0.9689		
				0.7364	0.9964	0.9294	0.8874		
IST or ISL	0.9492	0.9298	0.8613				0.9134	0.8905	2
		0.8686	0.9872	0.7908			0.8822		
			0.9823	0.9821	0.7197		0.8947		
				0.9915	0.7197	0.9045	0.8719		
SAW	0.8620	0.8324	0.7841				0.8262	0.8701	3
		0.8183	0.8209	0.9399			0.8597		
			0.7830	0.9423	0.9195		0.8816		
				0.8111	0.9950	0.9330	0.9130		
VAN	0.8950	0.8337	0.8441				0.8576	0.8267	4
		0.7812	0.8970	0.8487			0.8423		
			0.8970	0.8487	0.8198		0.8552		
				0.5331	0.8450	0.8777	0.7519		
AYT	0.8920	0.8759	0.5918				0.7866	0.8001	5
		0.8757	0.5917	0.8125			0.7600		
			0.5876	0.8091	0.9850		0.7939		
				0.7610	0.9156	0.9034	0.8600		

Table 3 shows the three-year windows for the six-year period. The first window covers the efficiencies for 2014, 2015 and 2016, the second window covers 2015 through 2017 and so on. Moreover, Table 4 shows the arithmetic average airport efficiencies in each window, which is presented for understanding efficiency trends over three-year periods (windows).

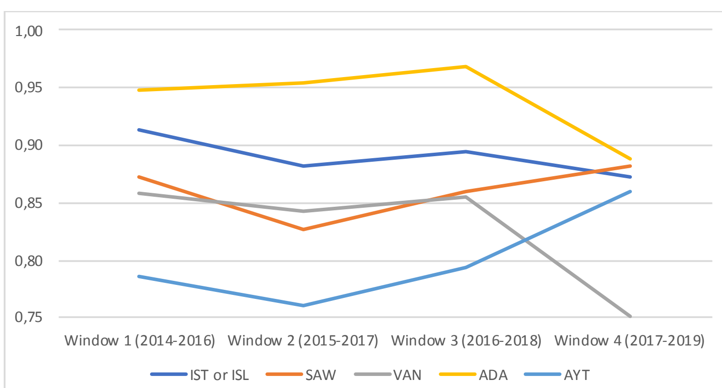

Figure 2: Efficiency Trends for the First Five Airports

The efficiency trends of the airports, which are in the top five in the average efficiency ranking, are shown in Figure 2. It is seen that the efficiency trends are above 0,80 for the first three airports, while the efficiency decreases to

0,75 for window-3 only in the VAN airport. Although there is a slight decrease in IST/ISL airport efficiency in the last window, it is thought that the reason for this decrease is the relocation of IST airport to ISL airport and the enormous increase in inputs such as the number of runways and terminal area. However, while the efficiency for AYT airport was between 0,75-0,80 in the first three windows, it moved above 0,85 in the last window. This increase in the efficiency of the AYT airport, which is located in one of Turkey's tourism centers, is thought to be due to the rapid rise in the tourism sector in recent years and the partial reduction of geopolitical tensions.

In addition, as seen in Appendix-A, there was a serious decline in the efficiency of AJI, SXZ and NOP airports. It is noteworthy that these airports, which are located in the eastern and northern regions of the country, have a low population density in the settlements where they are located and the total provincial population is below the country average. OGU, BAL, MZH and NAV are the airports with significant increases in airport efficiency.

As can be seen in Table 2 and Figure 4, the input and output factors affecting airport efficiencies increase over the years. This increase indicates that the aviation sector is growing in Turkey and that there is an increase in investments. In this study, where the efficiency analysis for each DMU is analyzed with three-year windows, it is seen that the efficiency of the airports has increased for 28 (67 %) airports between first and last window (Appendix-A). The development of airport efficiencies shows that the growth in the aviation sector in Turkey is accompanied by airport efficiencies. However, airport efficiency remained the same or decreased at 14 (33%) airports.

6. Summary and conclusion

This study was conducted to examine the efficiency of 42 airports in Turkey in the period of 2014-2019. The efficiency of Turkish airports has been analyzed by output-oriented W-DEA analysis. Aviation, which is one of the important sectors in terms of economy, also has strategic importance for countries. In the field of aviation, where large investments are made, annual data can be affected by temporary events and even by climate. For this reason, the efficiency of airports has been examined by considering three-year periods, which cover longer periods, instead of annual data.

The variables used to measure airport efficiency are as follows; the number of runways, terminal area, number of boarding gates, apron aircraft capacity, check counter number and number of employees are inputs, annual number of aircraft, number of passengers and annual cargo amount are outputs. Since DEA is extremely sensitive to missing data, airports with complete data were included in the study.

The efficiency of ADA is over 0,90 and four of (IST/ISL, SAW, AYT and VAN) is over 0,80. In terms of window efficiency, it can be concluded that these airports efficient on the average of every four windows. In Turkey, where the research was conducted, large and strategic investments continue in the aviation sector, so airport efficiencies are crucial from a managerial perspective.

Since airports have large-scale, long-term, and strategic importance, feasibility studies that should be done before investment are very important. It has been determined that there is a serious decrease in the efficiency of AJI, SXZ and NOP airports. In order to increase the efficiency of these airports, downsizing policies can be considered in some inputs. At OGU, BAL, MZH and NAV airports, where airport efficiency increases rapidly, studies should be carried out for the sustainability of the increased efficiency.

The high efficiency scores of Istanbul, Antalya and Adana airports are in line with many studies (Keskin & Köksal, 2019; Koçak, 2011; Ulutas & Ulutas, 2009) in the literature. With this study, the efficiency of Turkish airports has been examined with output-oriented W-DEA method and brought to the literature.

In future studies, it is recommended to compare Turkish airports with equivalent rival country airports. The limitation of the study is that some civil airports, which were generally built with the build-operate-transfer model, could not be included in the study due to insufficient data.

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Appendix-A :

Airport	2014	2015	2016	2017	2018	2019	Mean	Mean	Rank
IST	0.9492	0.9298	0.8613				0.9134	0.8905	2
IST		0.8686	0.9872	0.7908			0.8822		
IST			0.9823	0.9821	0.7197		0.8947		
IST				0.9915	0.7197	0.9045	0.8719		
SAW	0.8620	0.8324	0.7841				0.8262	0.8701	3
SAW		0.8183	0.8209	0.9399			0.8597		
SAW			0.7830	0.9423	0.9195		0.8816		
SAW				0.8111	0.9950	0.9330	0.9130		
ESB	0.4929	0.4135	0.4100				0.4388	0.4619	17
ESB		0.4146	0.4100	0.4846			0.4364		
ESB			0.4106	0.4862	0.5303		0.4757		
ESB				0.5165	0.5385	0.4351	0.4967		
ADB	0.6017	0.6674	0.6604				0.6432	0.6662	11
ADB		0.6767	0.6697	0.7127			0.6864		
ADB			0.6248	0.6543	0.7080		0.6624		
ADB				0.6589	0.7085	0.6513	0.6729		
AYT	0.8920	0.8759	0.5918				0.7866	0.8001	5
AYT		0.8757	0.5917	0.8125			0.7600		

Airport	2014	2015	2016	2017	2018	2019	Mean	Mean	Rank
AYT			0.5876	0.8091	0.9850		0.7939		
AYT				0.7610	0.9156	0.9034	0.8600		
DLM	0.2856	0.3025	0.2368				0.2749	0.2774	31
DLM		0.2989	0.2343	0.2571			0.2634		
DLM			0.2343	0.2571	0.3189		0.2701		
DLM				0.2657	0.3335	0.3045	0.3012		
BJV	0.2878	0.2913	0.2499				0.2763	0.2616	33
BJV		0.2887	0.2475	0.2226			0.2529		
BJV			0.2475	0.2226	0.2581		0.2427		
BJV				0.2435	0.2826	0.2974	0.2745		
ADA	0.9743	0.9202	0.9506				0.9484	0.9398	1
ADA		0.9113	0.9566	0.9956			0.9545		
ADA			0.9148	0.9956	0.9964		0.9689		
ADA				0.7364	0.9964	0.9294	0.8874		
TZX	0.6067	0.6889	0.7567				0.6841	0.7667	6
TZX		0.6966	0.7693	0.8594			0.7751		
TZX			0.7466	0.8338	0.8220		0.8008		
TZX				0.8331	0.8198	0.7678	0.8069		
ERZ	0.3146	0.3483	0.3866				0.3498	0.3934	21
ERZ		0.3481	0.3863	0.4345			0.3897		

Airport	2014	2015	2016	2017	2018	2019	Mean	Mean	Rank
ERZ			0.3897	0.4382	0.4583		0.4287		
ERZ				0.4338	0.4546	0.3280	0.4055		
GZT	0.5603	0.6121	0.6059				0.5928	0.6444	12
GZT		0.6136	0.6098	0.6921			0.6385		
GZT			0.6062	0.6842	0.6825		0.6576		
GZT				0.6885	0.6968	0.6806	0.6887		
ADF	0.0707	0.0849	0.0942				0.0833	0.0985	41
ADF		0.0900	0.1007	0.1068			0.0992		
ADF			0.0974	0.1062	0.1092		0.1043		
ADF				0.1093	0.1109	0.1020	0.1074		
AJI	0.5847	0.6177	0.0990				0.4338	0.2385	36
AJI		0.6177	0.1049	0.1166			0.2797		
AJI			0.1049	0.1142	0.1283		0.1158		
AJI				0.1172	0.1306	0.1258	0.1245		
MZH	0.4002	0.4083	0.2561				0.3549	0.4692	16
MZH		0.4429	0.2758	0.6596			0.4594		
MZH			0.2741	0.6619	0.5396		0.4919		
MZH				0.6612	0.5482	0.5029	0.5708		
BAL	0.2827	0.1280	0.2695				0.2267	0.2979	30
BAL		0.1412	0.3013	0.3559			0.2662		
BAL			0.2833	0.3240	0.4191		0.3421		
BAL				0.3255	0.4222	0.3220	0.3566		

Airport	2014	2015	2016	2017	2018	2019	Mean	Mean	Rank
BGG	0.1894	0.1681	0.1766				0.1780	0.2090	37
BGG		0.1839	0.1980	0.2066			0.1962		
BGG			0.2010	0.2093	0.2647		0.2250		
BGG				0.2068	0.2649	0.2391	0.2369		
YEI	0.3980	0.3607	0.3756				0.3781	0.3801	23
YEI		0.3928	0.4091	0.4643			0.4221		
YEI			0.4122	0.4678	0.3006		0.3936		
YEI				0.4314	0.2772	0.2712	0.3266		
DNZ	0.2750	0.2780	0.2812				0.2781	0.3827	22
DNZ		0.2964	0.2997	0.6960			0.4307		
DNZ			0.3017	0.7041	0.2652		0.4237		
DNZ				0.6827	0.2528	0.2602	0.3986		
DIY	0.7676	0.9977	0.6237				0.7963	0.6900	8
DIY		0.9639	0.6068	0.6298			0.7335		
DIY			0.6310	0.6416	0.6467		0.6397		
DIY				0.6159	0.6207	0.5346	0.5904		
EZS	0.3941	0.4218	0.3389				0.3849	0.3587	26
EZS		0.4160	0.3546	0.3568			0.3758		
EZS			0.3518	0.3416	0.3443		0.3459		
EZS				0.3424	0.3436	0.2987	0.3282		
ERC	0.1187	0.1216	0.1319				0.1241	0.1580	40
ERC		0.1216	0.1319	0.1580			0.1371		

Airport	2014	2015	2016	2017	2018	2019	Mean	Mean	Rank
ERC			0.1538	0.1825	0.1984		0.1782		
ERC				0.1955	0.2101	0.1716	0.1924		
YKO	0.0203	0.0181	0.0325				0.0237	0.0825	42
YKO		0.0188	0.0340	0.1243			0.0590		
YKO			0.0339	0.1256	0.1577		0.1057		
YKO				0.1195	0.1483	0.1569	0.1416		
HTY	0.4064	0.4033	0.3950				0.4016	0.3946	20
HTY		0.4211	0.4124	0.4402			0.4246		
HTY			0.4124	0.4219	0.3180		0.3841		
HTY				0.4301	0.3579	0.3162	0.3680		
IGD	0.2337	0.2474	0.2523				0.2445	0.2759	32
IGD		0.2469	0.2517	0.2887			0.2624		
IGD			0.2631	0.3017	0.3187		0.2945		
IGD				0.2939	0.3185	0.2949	0.3024		
KCM	0.5534	0.6925	0.7245				0.6568	0.6869	9
KCM		0.7646	0.7999	0.8468			0.8038		
KCM			0.7979	0.8543	0.4819		0.7114		
KCM				0.8302	0.4914	0.4051	0.5756		
KSY	0.1900	0.2067	0.2552				0.2173	0.2544	34
KSY		0.2055	0.2538	0.2770			0.2454		
KSY			0.2538	0.2770	0.2773		0.2694		
KSY				0.2975	0.2940	0.2651	0.2855		

Airport	2014	2015	2016	2017	2018	2019	Mean	Mean	Rank
KFS	0.1314	0.1298	0.1591				0.1401	0.1746	39
KFS		0.1545	0.1893	0.1680			0.1706		
KFS			0.1918	0.1701	0.2575		0.2065		
KFS				0.1519	0.2303	0.1613	0.1812		
ASR	0.5013	0.5184	0.5096				0.5097	0.5364	14
ASR		0.5189	0.5307	0.5623			0.5373		
ASR			0.5434	0.5489	0.5434		0.5452		
ASR				0.5426	0.5422	0.5760	0.5536		
KCO	0.1511	0.1848	0.2351				0.1903	0.2403	35
KCO		0.1998	0.2543	0.2277			0.2273		
KCO			0.2390	0.2355	0.3277		0.2674		
KCO				0.2522	0.3509	0.2259	0.2763		
KYA	0.3949	0.3525	0.3620				0.3698	0.3785	24
KYA		0.3490	0.3584	0.3854			0.3643		
KYA			0.3993	0.4226	0.3894		0.4038		
KYA				0.4261	0.3915	0.3107	0.3761		
MLX	0.3970	0.4217	0.3897				0.4028	0.4403	18
MLX		0.4714	0.4356	0.4792			0.4621		
MLX			0.4418	0.4879	0.4561		0.4620		
MLX				0.4723	0.4526	0.3783	0.4344		
MQM	0.4094	0.2690	0.3262				0.3349	0.3246	29
MQM		0.2923	0.3511	0.3500			0.3311		

Airport	2014	2015	2016	2017	2018	2019	Mean	Mean	Rank
MQM			0.3511	0.3138	0.3285		0.3311		
MQM				0.3138	0.3285	0.2619	0.3014		
MSR	0.6531	0.7090	0.7760				0.7127	0.6755	10
MSR		0.7429	0.8131	0.9519			0.8359		
MSR			0.8152	0.9544	0.2826		0.6840		
MSR				0.9497	0.2826	0.1761	0.4694		
NAV	0.3711	0.4630	0.7905				0.5415	0.5933	13
NAV		0.5070	0.8655	0.3677			0.5800		
NAV			0.8003	0.3348	0.8895		0.6748		
NAV				0.2605	0.7638	0.7061	0.5768		
OGU	0.4523	0.0923	0.3251				0.2899	0.3633	25
OGU		0.0954	0.3446	0.4884			0.3095		
OGU			0.3446	0.4675	0.4179		0.4100		
OGU				0.4764	0.4222	0.4327	0.4438		
SZF	0.7160	0.7902	0.9320				0.8127	0.7353	7
SZF		0.8268	0.9751	0.5519			0.7846		
SZF			0.9607	0.5457	0.6870		0.7311		
SZF				0.4998	0.6789	0.6599	0.6129		
SXZ	0.2769	0.7326	0.9585				0.6560	0.5025	15
SXZ		0.7521	0.8795	0.2520			0.6278		
SXZ			0.9575	0.2520	0.2745		0.4946		
SXZ				0.2039	0.2316	0.2592	0.2316		

Airport	2014	2015	2016	2017	2018	2019	Mean	Mean	Rank
NOP	0.7236	0.6839	0.3431				0.5835	0.3480	27
NOP		0.7223	0.3431	0.1903			0.4186		
NOP			0.3431	0.1989	0.1332		0.2251		
NOP				0.2059	0.1503	0.1377	0.1647		
VAS	0.2081	0.2479	0.1606				0.2056	0.1804	38
VAS		0.2440	0.1607	0.1622			0.1889		
VAS			0.1598	0.1612	0.1651		0.1621		
VAS				0.1663	0.1689	0.1606	0.1652		
GNY	0.2861	0.3029	0.3339				0.3076	0.3308	28
GNY		0.3031	0.3339	0.3608			0.3326		
GNY			0.3513	0.3821	0.3218		0.3517		
GNY				0.3868	0.3215	0.2856	0.3313		
NKT	0.3580	0.3982	0.4033				0.3865	0.4307	19
NKT		0.4141	0.4225	0.4192			0.4186		
NKT			0.4243	0.4152	0.5197		0.4530		
NKT				0.4203	0.5193	0.4546	0.4647		
VAN	0.8950	0.8337	0.8441				0.8576	0.8267	4
VAN		0.7812	0.8970	0.8487			0.8423		
VAN			0.8970	0.8487	0.8198		0.8552		
VAN				0.5331	0.8450	0.8777	0.7519		