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An Approach to Measure the Performance and the Efficiency of Future Airport Infrastructure

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Abstract: The aim of this paper is to design an approach to evaluate the expected efficiency and performance of future airport infrastructure. First, an airport sampling method to select similar airports is developed based on socioeconomic and operational airport variables that are summarized in a proxy variable; second, the ARIMA-GARCH-Bootstrap method is applied to forecast the selected outputs (PAX and ATMS) whilst the selected inputs (Cities, Gates, Runaways, Airport Size, Pax carriers, and Num. of employees) remain constant; and third, the VRS-OO and the CRS-OO DEA models are implemented to evaluate the efficiency and performance of the airports in the current and future years. The proposed approach is used to evaluate the future airport infrastructure of the new Mexico City Airport against 19 representative worldwide airport hubs. The proposed approach is applied to analyze the Mexico City Airport multi-airport system infrastructure as a case study. The results show that this multi-airport system requires more airside infrastructure that must be added by the new Mexico City Airport, airlines should operate aircrafts with more capacity to serve more PAX per ATM, and airlines must open new connections at the new Mexico City Airport to increase the expected efficiency and performance of this multi-airport system.

Keywords: airport planning; air transport infrastructure; productivity; efficiency; data envelopment analysis

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1. Introduction

The air transport industry highly contributes to the development of the economy and society of any country in the world, mainly because it generates jobs and stimulates social and economic activities [1]. This industry is a catalyst of economic growth and social development [2,3] by supporting tourism and facilitating trade between countries, states, and cities. Therefore, it is important to plan new airport infrastructure based on future performance, analyzing actual and forecasting data and proposing management strategies to assure that future airport infrastructure will be as efficient and sustainable as possible [4–6]. Thus, the aim of this paper is to propose an approach that evaluates the expected efficiency and performance of future airport infrastructure and, with the results, establish airport management strategies to reach efficiency.

Commonly, the viability of future airport infrastructure is evaluated with a cost-benefit analysis [7]. The precision of a cost-benefit analysis depends mainly on the accuracy of traffic forecasts (enplaned passenger demand (PAX) and air transport movements (ATMS)) and construction costs forecasts [8]. PAX and ATMS are forecasted because they are output variables that give an idea about the traffic volume that an airport would probably have to operate in the future, and hence, these are the most important indicators of airport operational performance [9]. However, PAX and ATMS forecasts are likely to be wrong [10] and the uncertainty over 50% because forecasting methods cannot guarantee 100% accuracy [11]. So, future airport infrastructure is expected to be either under-dimensioned if traffic forecast is low at the end or over-dimensioned if traffic forecast is too high. Consequently, new airports might be inefficient, and airport managers must design methodologies to develop and implement airport management strategies in advance to assure efficiency of future airport infrastructure.

Airport performance studies have been developed for some time [9] applying different methodologies, but mainly, Data Envelopment Analysis (DEA), Stochastic Frontier Analysis, econometric theory, and through the development of benchmark indexes. However, lately, the amount of research that applies DEA to study Airport performance has grown [12]. This is because airports are homogeneous decision-making unites (DMUs) that use the same inputs to produce the same outputs, and DEA is a non-parametric optimization model for evaluating the relative efficiencies of a set of homogeneous DMUs that uses the same inputs and outputs variables [13]. Therefore, different DEA models have been proposed to study airport efficiency or airport performance by evaluating different inputs and outputs variables [2,3,9,12,14–37].

Most DEA applications use the constant returns-to-scale DEA model (CRS) proposed by [38], also known as the CCR model, and/or the variable return-to-scale DEA model (VRS) proposed by [39]. The difference between the CRS model and the VRS model is that the CRS model supposes complete proportionality between inputs and outputs, and the VRS model is based on the axioms of convexity and free disposability and does not assume this form of proportionality. The efficiency of a DMU calculated by the VSR model is higher than its efficiency calculated by the CRS model. This is because the discriminant of the CRS model is better than that of the VSR models when the proportionality assumption is satisfied. Therefore, the VRS efficiency can be described as overoptimistic, and the CRS model cannot be used if this assumption is not valid [40]. DEA models can measure efficiency in two different orientations: input-oriented DEA models determine the minimum input needed, if used efficiently, to achieve the same output and output-oriented DEA models determine the maximum potential output that can be reached if the given inputs are used efficiently [41]. With these arguments in mind, in this paper, we use the CRS model proposed by [38] from an output orientation (CRS-OO) to plan future airport infrastructure performance. We choose this DEA model because [3,42] found that airports operate under a constant return on scale and also because it is possible to assume that, in this study, the selected inputs (Cities, Gates, Runaways, Airport Size, Pax carriers, and Num. of employees) and the selected outputs (PAX and ATMS) can be classified as physical levels because these measures are actual amounts of products that are often assumed to be proportional to resources, and therefore, they satisfy the assumption of proportionality [40]. However, since [18] propose to apply the VRS DEA model from an output orientation (VRS-OO) to maximize the use of airport infrastructure to satisfy the increasing demand of PAX and ATMS, we also use the VSR-OO model proposed by [39] to compare the results between the CRS-OO and the VSR-OO.

In the literature, many variables have been proposed to study airports performance [2,3,9,12,14–21,24–29,31–37]. Most of the proposed input variables are related, similar, and try to measure the same that some of the variables chosen to study future airport infrastructure performance in this paper, which are: the number of runways (Runways), airport size (Airport Size), the number of employees (Num. of Employees), the number of city connections (Cities), the number of gates (Gates), and the number of pax carriers (Pax Carriers). The output variables are PAX and ATMS because they are the most important indicators of airport operational performance [9].

In the literature, many forecasting methods have been developed to predict PAX and ATMS. Normally, quantitative forecasting methods are used to forecast PAX and ATMS. Quantitative forecasting methods can be divided in causal models or explanatory models (multiple-regressions, data panel and gravity models) and time-series forecasting methods [7]. Both causal models and time-series forecasting methods need historic data to be used. The main disadvantage of causal methods is their necessity of finding and gathering enough data of different independent variables (socioeconomic and/or operational variables) to forecast PAX and ATMS. However, the problem is that independent variables must be predicted to forecast PAX and ATMS adding more uncertainty than time-series methods. Knowing this problem, in this study, we decide to use a time-series method. Trend, seasonality, volatility, and distribution are the characteristics of time-series data, and they must be considered to forecast PAX and ATMS [43]. In the literature, most time-series methods only consider trend and seasonality but not volatility and distribution [43]. For these reasons, new forecasting methods have been developed as the combination of multiple individual forecasting methods to substantially improve forecast accuracy [43]. In this paper, we use the ARIMA-GARCH-Bootstrap forecasting method to forecast PAX and ATMS because [44] probed that this method is more suitable for long-term PAX and ATMS forecasts than four of the most used models in the air transport industry: ARIMA, Holt-Winters Additive, Holt-Winters Multiplicative, and the Damp Trend Grey Model (DTGM), which has been proven to be better than the Grey Model [45].

Many studies have been proposed to measure performance using DEA models [46]. However, few of them address the problem of airport performance [29]; only one of them evaluates future airport performance for airport sustainability planning in short-term, and neither of them estimates the efficiency or performance of future airports infrastructures projects in mid and long term. So, we attempt to add to the literature by evaluating the efficiency and performance of future airport infrastructure in the mid-term.

This study evaluates the future airport infrastructure performance of the new Mexico City Airport against 19 representative worldwide airport hubs: Atlanta (ATL), Houston (IAH), Miami (MIA), Los Angeles (LAX), Dallas Fort Worth (DFW), San Francisco (SFO), La Guardia (LGA), John F. Kennedy (JFK), Newark (EWR), Bogota (BOG), Chicago O'Hare (ORD), Dubai (DXB), London Heathrow (LHR), Hong Kong (HKG), Paris Charles de Gaulle (CDG), Amsterdam (AMS), Frankfurt (FRA), Singapore (SIN), and Denver (DEN). In the first step of the proposed approach, we select an airport's sample based on four characteristics: market size through time, the level of socioeconomic activities in the metropolitan area where the airports are located, local airport competition or the existence of a multi-airport system, and the airport competitiveness index. These characteristics aims to select similar airports that can be compared. In the second step, the ARIMA-GARCH-Bootstrap forecasting method is applied to forecast the selected outputs (PAX and ATMS), and the selected inputs (Cities, Gates, Runaways, Airport Size, Pax carriers, and Num. of employees) remain constant. Finally, in the third step, the VRS-OO and the CRS-OO DEA models are used to evaluate the performance of the airports in the sample in current and future years. In the literature, many papers evaluate the performance and efficiency of an airport's infrastructure, and few of them forecast and evaluate airports' systems to analyze their sustainable development. However, there is no paper to our knowledge that evaluates the expected efficiency and performance of future airport infrastructure. This paper also contributes to the air transport management and to the Mexican air transport industry by studying the efficiency of MEX and concluding the required infrastructure for the new Mexico City Airport, which just began construction. We select to study the performance of MEX and the new Mexico City Airport infrastructure as a multi-airport system because the Mexican government is currently building a new airport for Mexico City for two main reasons: MEX has been congested since 2014, and the demand of PAX and ATMS are expected to grow in the coming years, mostly in its domestic and international connectivity markets [47]. This airport is going to be part of Mexico City multi-airport system form by three main airports (MEX, Toluca International Airport (TLC), and the new Mexico City airport). MEX has a location advantage over TLC and the new Mexico City airport because it is located inside Mexico City, and therefore, it is very close to demand. So, TLC and the new Mexico City airport will not represent competition, airlines will use these airports only because MEX is congested, and they do not have access to slots at MEX. Therefore, it is highly probable that the new Mexico City airport will become a secondary airport only to alleviate the congestion at MEX. It is important to remember that this has happened in the past, TLC was used as a secondary airport operated by low-cost carriers (LCCs), but once Mexicana Airlines bankrupted and its slots were available at MEX, LCCs moved operations from TLC to MEX, even when aircrafts turn-around times and aeronautical fees were considerable lower in TLC than in MEX. The advantage of the new Mexico City airport over TLC is that TLC has operational restrictions because of its altitude, where heavy and big aircrafts might not be allowed to land and take off. Knowing this, it is possible to conclude that the new Mexico City airport infrastructure should be set to satisfy the demand of PAX and ATMS that MEX cannot operate. Therefore, in this paper, the proposed approach is used to establish airport management strategies and to determine the required infrastructure of the new Mexico City airport to efficiently satisfy the expected demand of PAX and ATMS as an airport system where the new airport will have to operate efficiently to satisfy the excess of PAX and ATMS that MEX cannot satisfy.

The results suggest that the new Mexico City airport system would require mostly airside infrastructure that must be covered by the new Mexico City airport, and the management strategies suggest that airlines should operate aircrafts with more capacity (big aircrafts) to serve more PAX per ATM, and airlines must open new connections or new destinations in this airport to increase the Mexico City airport system network.

DEA models have been developed to benchmark the Technical Efficiency (TE), Pure Technical Efficiency (PTE), and the productivity of multiple industries, being transportation systems where DEA models are commonly used to assess public and private infrastructure [48]. These models can assess the performance of transport systems, such as road (highways), air (airlines and airports), maritime (ports), railway (trains), the sustainability of transport infrastructure, and other transportation issues [49].

The authors of [32] use a DEA model called Robust Data Envelopment Analysis (RDEA) to study the performance of 21 Iranian airports. RDEA allows handling the uncertainty in the data. The results show that most of the Iranian airports are inefficient. Even with the government subside, the number of employees in each terminal is not enough to cover the PAX. In a similar study, Ref. [50] applies a CRS DEA model to analyze the relations between airport infrastructure and passenger processing. The aim of [50]'s paper is to benchmark the level of service of 19 Brazilian airports to maintain an appropriate level. Considering the total number of passengers that the airport receives with the internal services availability as number of checks in counters or number of parking spaces, these studies helped to identify airports whose level of service would be prejudiced in short term. In the same way, Ref. [3] use a VRS DEA model to study the Italian airport system (31 out of 49 airports are tested). The airport sample includes fully privatized airports and mixed regimes (public and private). The authors of [3] analyze the rotation on capital with the total of passengers and the private or partially private status. Their results proved that most of the Italian Airports are highly efficient, with differences between those that are privately owned and those that are under a mixed regime. The authors of [25] use different DEA models (CRS DEA, VRS DEA, and Hull DEA models) to evaluate the operational performances of 20 major airports around the world. The results indicate that some airports are optimal, while others have the worst self and peer appraisal. In this study, the number of runways and number of parking slots are the most important input variables to improve airport TE, the number of PAX contribute more to airport performance than to ATMS, and airport TE is related to the existence of an airport hub and to the economic growth. The authors of [18] analyze the productivity of 18 Italian airports operatively and financially. They use the CRS-OO DEA model. Their results show that airports operational efficiency declined in 2001, but financially, they mostly improved in the aeronautical revenue considering the labor cost of each 10,000 m^2 as the input variable. The probable cause is the introduction of an aeronautical service price that provoked a bad investment in service capacity, affecting the TE in operational services. The author of [26] studies the efficiency and productivity of 10 airports in East Asia from 2009 to 2013 by applying a network DEA model. The results indicate that the number of carriers, the number of routes, non-aeronautical revenues, and service levels are variables that increase the productivity of an airport. The reason is because as the number of carriers that operate the airport and the number of routes that the airport operates increase, its productivity grows. The increment in non-aeronautical services or commercial services increases efficiency because airports earn more streams of revenue. Airport service quality is an indication of the good performance of an airport. The author of [15] proposes to evaluate the performance of international airports across the world. This study indicates that the productivity of an airport is influenced by exogenous variables such as shifts in government policies and technological advances rather than endogenous variables driven by improvements in managerial practices. The authors of [20] also evaluate the operating efficiency and productivity changes of the Greek airports during the economic crisis (2010–2014) using DEA and the Malmquist Productivity index (MPI). In [20], the author's main goal is to determine whether the total productivity improved during the Greek economic crisis. Their results indicate that despite the economic crisis, airport efficiency and productivity improved due to exogenous variables such as international tourism growth. In [14], the authors apply a Graphical Gaussian Model to CRS and VRS DEA models to estimate the financial performance of the most important regional airports in Italy. The results indicate that their return on investment and their return on equity improve due to ATMS in each airport. The author of [35] use DEA models to study the operational efficiency of three Brazilian airports. The aim of this paper is to find the efficient variables of each airport. The results indicate that these Brazilian airports are mostly basing their operations to concession fees and mandatory investments. In the same year, Ref. [51] also uses DEA models to study the potential costs of airports inefficiency. They study 12 airports in Pakistan. They conclude that the technical inefficiencies of Pakistan airports are caused by overstaffing and over-investing in capacity. The author of [52] evaluates the TE of 14 Iranian airlines. They add undesirable outputs and uncertainty to a DEA model. They found that any of the airlines analyzed are TE. The authors of [53] study the TE of 11 airports in New Zealand. They propose a two-stage methodology: In the first stage, they use the Slack-Based Measure DEA-Window model. In the second stage, they use a Tobit model with an instrumental variable to solve the endogeneity problem. Their results confirm the economic variables that have a positive impact and negative impact on the efficiency of the New Zealand Airports. The author of [37] presents a slacks-based measure network data envelopment analysis (SBM-NDEA) model with quasi-fixed inputs of runway, terminal, apron areas, and free linking capacity provisions. Airport operations efficiency is decomposed in production and service efficiency. Their results indicate that the efficiency of airport production does not imply efficiency in the service of domestic airports in Taiwan, and vice versa. The author of [12] applies the network DEA approach that considers the system as composed by distinct stages with its own inputs and outputs and with intermediate flows among the stages. They applied it to analyze 39 Spanish airports and conclude that network DEA models have a greater discriminant power than conventional. The main drawbacks are the need for more detailed data and the greater complexity of the models. The authors of [24] develop a multi-period two-stage DEA model, which can measure the overall and period efficiencies at the same time. The non-life insurance industry in Taiwan is used to verify the proposed model. In [28], the application of the weak disposability to modeling network DEA with undesirable products is studied, which, in this paper, is studied as final outputs or as intermediate measures. The proposed approaches has been illustrated in a real case on 39 Spanish Airports in 2008. The author of [27] uses the multi-period network data envelopment analysis to analyze how internal operating sub-processes and annual operations of airports influence the overall efficiency for East Asia airport companies. The results indicate that the overall efficiencies are affected by the system and the sub-processes' efficiencies in individual periods during a specific period. The author of [29] considered sustainability of airports through a multi-perspective, multi-system, and multi-process operation. They explore an extension of fuzzy dynamic network performance measurement approach to determine the efficiency of an Iranian airport system. Ref. [33] uses DEA models to measure the efficiency of Italian airports and it is evaluated at cost, operations, and revenue stages, while network-slack based measure DEA (NSBM-DEA) is adopted to generate efficiency measurements for the airports at each stage. Their results indicates that this model performs better than the traditional DEA model. The author of [9] evaluates airport performance for eight Chinese airports and four representative Asian airports from 2014 to 2021 with actual and forecasted data to plan airport sustainability. The performance of airports is evaluated from the process level to the airport level using the Network DEA with forecasted data obtained from the gray model. The results indicate that HKG has been and will be efficient for the entire study period. Finally, Scheme 1 resumes the input and output variables most analyzed in the literature review.

This paper is organized as follows: in Section 1, a literature review about DEA models applied to analyze the air transportation industry is presented; Section 2 details the proposed approach that evaluates the expected efficiency and performance of future airport infrastructure. In Section 3, the empirical application is presented, and the results are analyzed. Finally, Section 4 concludes this paper and provides future works.

2. Materials and Methods

In this paper, a three-step approach is proposed to evaluate the expected efficiency and the performance of future airport infrastructure. In the first step, an airport sampling method is proposed to select airports that can be compared. In the second step, the ARIMA-GARCH-Bootstrap forecasting method is applied to forecast the selected outputs (PAX and ATMS), and the selected inputs (Cities, Gates, Runaways, Airport Size, Pax carriers, and Num. of employees) remain constant. Finally, in the third step, the VRS-OO and the CRS-OO DEA models are used to evaluate the performance of the airports in the sample in the current and future years.

2.1. Step 1: Airport Sampling Method

The objective of the airport sampling method is to select airports that are similar and, therefore, can be comparable. In this paper, we propose to select the airports in the sample based on four characteristics: market size through time, the size of the economy of the metropolitan area where the airports are located, airport competition, and the airports competitiveness index.

Literature	Inputs	Outputs	Reference
Performance evaluation of Italian airports: A data envelopment analysis	Labor costs, capital invested and operational costs (excluding labor costs), private status.	Number of planes, PAX, cargo, aeronautical receipts, handling receipts and commercial receipts	(Barros and Dieke, 2007)
Operational performance evaluation of international major airports: An application of data envelopment analysis	Ownership of airport, airport size, hub airport, location of the airport and economic growth rate of country.	Operational performance from efficiency frontier (efficient/inefficient)	(Lin and Hong, 2006)
An empirical study of Iranian regional airports using robust data envelopment analysis	Number employees, Terminal Area, Length of runway.	ATMS, PAX, amount of cargo, revenue	(Roghanian and Foroughi, 2010)
Measuring airport quality from the airlines' viewpoint: An application of data envelopment analysis	Quality: Airport amenities (restaurants, transport of passengers, processing time) Efficiency: Delay data, runway capacity, local labor force cost and reliability of airport traffic control	Efficiency and quality of airports	(Adler and Berechman, 2001)
Airport Economic Efficient Frontier	Runway length, passenger terminal area, number of employees and apron area	Number of airplanes, PAX, revenues and cargo	(Yoshimoto, Pinto Alves and Caetano, 2018
Environmental efficiency assessment of U.S. transport sector: A slack-based data envelopment analysis approach	Btu of energy consumption, number of employees, production in transportation GDP and emission of CO2	carbon efficiency (CE), potential carbon reduction (PCR)	(Park et al.,2018)
Applying the data envelopment analysis to discuss performance evaluation of customer relationship management in shipping industry	All costs for introducing customer relationship management, manpower cost	Response time to customer needs or complaints. Operation performance of a company	(Chen et al., 2018)
Developing measures of airport productivity and performance: An application of data envelopment analysis	Airline prices, fees and retail prices, income, PAX	Profit, revenue	(Gillen, 1997)
A distance friction minimization approach in data envelopment analysis: A comparative study on airport efficiency	Runways, terminal space (m2), gates, number of employees	PAX and ATMS	(Suzuki, Nijkamp, Rietveld and Pels, 2010)
Human resource rightsizing using centralized data envelopment analysis: Evidence from Taiwan's airports	Number of workers, time of production, total number of operations per worker, number of regular and periodic time workers	Manpower cost, production cost	(Yu et al., 2013)
Evaluating the multi-period operating efficiency of international airports using data envelopment analysis and the Malmquist productivity index	Land Area, Length of runway, passenger terminal, Cargo terminal	Number of flights, PAX, annual cargo throughput	(Ahn and Min, 2014)
Operational and financial performance of Italian airport companies: A dynamic graphical model	PAX, ATMS overall number of cargo movements, %low cost carrier passenger	Return on investment, return on equity, return on sales, Equity-Debt ratio, Asset turnover ratio	(Abruzzo et al., 2016)
Productivity efficiency analysis of the airlines in China after deregulation	Labor, fuel, number of aircrafts	Total flights, revenues of passenger and freight	(Cao et al., 2015)
Disentangling the European Airlines efficiency puzzle: A network data envelopment analysis approach	Number of aircrafts, labor, supplies and outside services	Revenue	(Duygyn et al., 2016)
Efficiency and productivity changes in Greek airports during the crisis years 2010-2014	Runway length, apron size, passenger terminal size	PAX, ATMS tons of cargo handled	(Fragoudaki et al., 2016)
New evidence on the efficiency of Italian airports: A bootstrapped DEA analysis	Number of employees, runways, apron size, airport size, labour costs, other costs	ATMS, PAX, amount of cargo, aeronautical revenue, non-aeronautical revenue	(Curi et al., 2011)
Assessment of airport performance using the SBM-NDEA model	ATMS, domestic cargo, PAX	Labor, runway area, apron area, terminal area	(Yu, 2010)
Network DEA models in transportation. Application to airports	Runway area, number of stands, number of boarding gates number of check-in counters, number of baggage belts	ATMS and Cargo	(Lozano et al., 2009)
Multi-period efficiency and Malmquist productivity index in two-stage production systems	Operating expenses, insurance expenses	Underwriting profit, investment profit	(Kao and Hwang, 2014)
Two-stage network structures with undesirable outputs: a DEA based approach	Runway area, apron capacity, number of boarding gates, number of baggage belts number of check-in counters	ATMS, cargo landed	(Maghbouli, Amirteimoori and Kordrostami, 2014)
Measuring aeronautical service efficiency and commercial service efficiency of East Asia airport companies: An application of Network Data Envelopment Analysis	Runway area, staff costs, other operating costs	ATMS, PAX, cargo, operating revenues	(Liu, 2016)
Evaluating the multi-period efficiency of East Asia airport companies.	Runway area, staff costs, other operating costs	ATMS, PAX, cargo, non-aeronautical revenues	(Liu, 2017)
A dynamic network efficiency measurement of airports performance considering sustainable development concept: a fuzzy dynamic network-DEA approach	Policy making based on sustainable development concept, budget	Non-aviation income, sollutions levels, satisfaction	(Olfat et al., 2016)
The analysis of the cost-revenue production cycle efficiency of the Italian airports: a NSBM DEA approach	Soft operating expenditures, labor cost, terminal size, apron size, area of runways number of employees	ATMS, PAX, cargo, aviation revenues non-aviation revenues	(Storto, 2018)
Sustainable airport development with performance evaluation forecasts: A case study of 12 Asian airports	Runway area, passenger terminal area	Airport total revenues, airport net income, ATMS, PAX, cargo	(Wang and Song, 2020)

Scheme 1. Literature review input and output variables.

- First characteristic: select similar airports by market sizes. Airports can be classified according with the total number of enplanement passengers per year. For example, The United States Federal Aviation Administration (FAA) categories airports by the percentage of their U.S. annual commercial enplanements per year. In this paper, we propose to select the airports in the sample according to their PAX demand through time. To do so, we propose to select airports using the Airports Council International world database.
- Second characteristic: select similar airports by the size of the economy of the metropolitan area where they are located. In this paper, we propose to select the airports in the sample according with the gross domestic product (GDP) of the metropolitan area where they are located. To do so, we propose to cluster the airports in the sample by the size of the GDP of the metropolitan areas where they are located using the OECD and the World Bank databases (data.oecd.org and data.worldbank.org) (accessed on 4 August 2021).
- Third characteristic: select similar airports by the existence of airport competition. A metropolitan area has a multi-airport system when they have two or more airports serving commercial traffic, and consequently, they compete for passengers and airlines. In multi-airport systems, the behavior of the airports is influenced by passengers and airlines because they have the possibility of taking airport traffic elsewhere if fees and quality of services are not satisfactory. So, PAX demand depends on region, population, economic activity, airline management, and airport management [54]. On the contrary, in a single airport system, PAX demand depends on region, population, and economic activity [54]. For these reasons, we propose to classify the airports in the sample as part of a multi-airport system or not to consider if the airports in the sample have a certain level of local competition or not. It is important to say that multi-airport systems do not have the same level of competition; some have a higher level of competition than others.
- Fourth characteristic: select similar airports by their airport competitiveness index (ACI). The airport competitiveness index proposed by [55] evaluates whether the airports in the sample are similar in terms of their level of competition. ACI is composed of 13 indicators and a safety factor (SAF). The indicators are used to calculate four subindexes that measure: market potential, accessibility, airport fees, and previous traffic results. The market potential index (Im) is the average of five indicators related to the metropolitan area where the airport is located: population size (POP), GDP per capita (GDPppp), tourism (TRS), airport hub (HUB), and liberalization of air transport (LIB). The accessibility index (Ii) is the average of three indicators related to the airport ground and air access infrastructure: road infrastructure (RDS), public transport systems (PTS), and airport delays (DEL). The airport fees index (Ich) is the average of two indicators related to airports aeronautical charges: airport fees for services and facilities (CHA) and curfews (CUR). The previous traffic results index (It) is the average of three indicators related to airports latest performances: PAX demand, the number of airlines operating flights at the airport (ARL), and the number of destinations or city connections (DES). Scheme 2 explains how the 13 indicators and the safety factors are determined and the database they were obtained. Equation (1) calculates the airport competitiveness index [55].

$$ACI = 0.25SAF[I_m + I_i + I_{ch} + I_t] \quad (1)$$

ACI Indicator	Source	Note
POP	Airport Council International Database	Grancay (2009) sets an upper limit to 3 million people. All the metropolitan areas above this limit get the highest score 1; and all the metropolitan areas under this limit get the direct proportion from the upper limit.
GDP	data.oecd.org and data.worldbank.org	Grancay (2009) sets an upper limit to 35000 usd in 2009, today is worth approx. 42675 usd. All the metropolitan areas above this limit get the highes score 1; and all the metropolitan areas under this limit get the direct proportion from the upper limit.
TRS	Global Destination Cities Index by Master Card	In this paper, we decided that any city ranked in top 20 in its world region gets scored 1, if not gets score 0.
HUB	Airports websites	Grancay (2009) indicates that all airports serving as a hub of a full-service carrier get scored 1; airports with strong presence of low-cost airlines get 0.7; airports that serve more than 10 million pax per year, but they are not hub of any full-service carrier get 0.4; airports serving as a hub of a small-service carrier get 0.4; and all others get score 0.
LIB	European Commission, Mobility and Transport, Status of aviation relations by country; and US Department of State, Civil Air Transport Agreements, Open Skies Partners, Division of Transport Affairs	Grancay (2009) determines the degree of liberalization of air transport based in the open sky agreements signed between the country where the airport is located and the two largest air transport markets (US and EU). Hence, the US and EU airports get score 1. Airports located in other countries get 0.5 for having signed an open sky agreement with the US and 0.5 for having signed an open sky agreement with the EU.
RDS	All the busiest airports in the world have multi-lane highways, which is probably not the case for small and regional airports located in Asia and Africa (Grancay, 2009).	Grancay (2009) determines that airports that have multi-lane highways connecting them with the metropolitan area where they are located score 1, if not score 0. Grancay (2009) distinguishes between four transport modes: high-speed
PTS	Airports websites	train score 1, regular train score 0.75, subway score 0.5, and shuttle or bus service score 0.25.
DEL	www.flightradar24.com/data/airports	In this paper, we decided to use the airport rating reported by my flightradar24 because the Bureau of transport statistics only publishes US airports delay data
CHA	Airports annual reports and financial statements	In this paper, we decided to calculate the average annual airport revenue per enplaned pax. The airport with the max average annual airport revenue per enplaned pax (upper limit) gets the highest score 1, and the other airports get the direct proportion from the upper limit.
CUR	www.boeing.com/commercial/noise/list.page	Grancay (2009) decides that airport with imposed curfews get score 0, others get score 1.
PAX	Airport Council International Database	For each airport, Grancay (2009) analysis PAX growth rates for the last five consecutive years. Airports get score 0 if PAX growth decline or stagnation between years. Airports get score 1 if PAX growth rates are over 100%. Finally, the score of airports is equal to the last annual growth rate if PAX growth between 0 and 100%.
ARL	www.flightsfrom.com/	Grancay (2009) decides that an airport serving 20 or more airlines gets score 1, otherwise gets score 0.
DES	www.flightsfrom.com/	In this paper, airports get score 1 if the number of destinations (city connections) they serve is equal or greater than 200, otherwise their score is equal to the direct proportion from the upper limit of 200.
SAF	Fragile States Index Annual Report published by the Fund for Peace (FFP)	Grancay (2009) establishes that Airports located in countries with a fragile state index ranked as ”very sustainable”, ”sustainable”, ”very stable”, and ”more stable” get score 1. Airports located in countries with a fragile state index ranked as ”warning”, ”elevated warning”, and ”high warning” get score 0.8. Finally, Airports located in countries with a fragile state index ranked as ”alert”, ”high alert”, and ”very high alert” get scored 0.5.

Scheme 2. Airport competitiveness index indicators and safety factor.

2.2. Step 2: ARIMA-GARCH-Bootstrap Forecasting Method

We assume that PAX and ATMS structure can be represented by the next models

$$PAX_t = \mu_t^1 + \sigma_t^1 \varepsilon_t^1 \tag{2}$$

$$ATMS_t = \mu_t^2 + \sigma_t^2 \varepsilon_t^2 \tag{3}$$

where μ_t^i is the conditional mean, σ_t^i the conditional standard deviation, and ε_t^i is the error term with zero mean and unit variance. We estimate each element of the model using the ARIMA-GARCH-Bootstrap forecasting method proposed by [44].

μ_t^1 is estimated using a SARIMA method as follows

$$\mu_t^1 = (\phi_1 B + \ldots + \phi_p B^p)\left(\phi_S B^S + \ldots + \phi_{PS} B^{PS}\right) PAX_t + (-\theta_1 B - \ldots - \theta_q B^q)\left(-\theta_S B^S - \ldots - \theta_{QS} B^{QS}\right)\sigma_t^1 \varepsilon_t^1 \tag{4}$$

where B is a lag operator $(BPAX_t = PAX_{t-1})$, and p, q, P, and Q are SARIMA model orders. A similar equation is set for μ_t^2.

σ_t^1 is estimated using a GARCH(1,1) model as follows

$$\sigma_t^{12} = \alpha_0 + \alpha_1 \sigma_{t-1}^{12} \varepsilon_{t-1}^{12} + \beta_1 \sigma_{t-1}^{12} \tag{5}$$

where $\alpha_0 > 0$, $\alpha_1 \geqslant 0$ and $(\alpha_1 + \beta_1) < 1$.

Finally, the Bootstrap method is applied to estimate the behavior of ε_t^1 at the same time using the procedure proposed by [56]. Similar equations are set for μ_t^2, σ_t^2 and ε_t^2.

2.3. Step 3: Data Envelopment Analysis Models

Data envelopment analysis models are vast. We apply the CRS DEA and the VRS DEA models. DEA models measure the efficiency and productivity with different orientations. Output-oriented DEA models maximize outputs for given inputs, indicating how much a firm can increase its outputs for given inputs. In this paper, we analyze how much outputs (PAX and ATMS) can change given the infrastructure of the analyzed airports.

The aim is to measure the efficiency and productivity of n units $DMU_1, DMU_2, \ldots, DMU_n$. Each unit produces a vector y of s outputs, $y \in \mathbb{R}_+^s$, while consuming a vector x of m inputs, $x \in \mathbb{R}_+^m$. Let us write an input matrix $X = [x_{ij}, i = 1, \ldots, m,\ j = 1, \ldots, n]$ and an output matrix $Y = [y_{rj}, r = 1, \ldots, s,\ j = 1, \ldots, n]$.

The shape of the efficient frontier is different depending on the scale. Two scale assumptions are the most widely implemented in the literature: CRS and VRS. Productive units employ CRS if a change in inputs results in a change on outputs in the same proportion. Under the VRS assumption, the efficient frontier is convex, which means that the average productivity varies along the frontier. Hence, marginal productivity always diminishes.

2.4. Output Oriented CRS DEA Model

The technology production possibility set for an Output Oriented CRS (CRS-OO) DEA model is $T = \{(x, y) | x \geqslant X\lambda, y \leqslant Y\lambda, \lambda \geqslant 0\}$. We can estimate the efficiency score solving the following linear program for each DMU:

$$\max_{\theta,\lambda} \theta \tag{6}$$

$$\begin{aligned} & s.t \\ & X\lambda \leq x \\ & \theta y \leq Y\lambda \\ & \lambda \geq 0 \end{aligned}$$

where λ is the optimization variable, which is a variable that measures the relationship importance between the DMU's and the DMU under analysis. The optimum θ^* is such that, $(x, \theta^* y) \in T$. The next step is to use the optimum to calculate the slack variables s^+ and s^- , where $s^- = x - X\lambda$ and $s^+ = Y\lambda - \theta^* y$. If $\theta^* = 1$ and all slacks are zero, a DMU is TE. If the results indicate that $\theta^* > 1$ and nonzero slacks, then a DMU is inefficient [38].

2.5. Output Oriented VRS DEA Model

The technology production possibility set for an Output Oriented VRS (VRS-OO) DEA model is $T = \left\{(x, y)|x \geqslant X\lambda, y \leqslant Y\lambda, \lambda \geqslant 0, \sum_{j=1}^{n} \lambda_j = 1\right\}$. We can estimate the efficiency score solving the following linear program for each DMU:

$$\max_{\phi,\lambda} \phi \tag{7}$$

$$\begin{aligned} &s.t \\ &X\lambda \leq x \\ &\phi y \leq Y\lambda \\ &\lambda \geq 0 \end{aligned}$$

The optimum ϕ^* is such that $(x, \phi^* y) \in T$. The next step is to use the optimum to calculate the slack variables s^+ and s^-, where $s^- = x - X\lambda$ and $s^+ = Y\lambda - \phi^* y$. If $\phi^* = 1$ and all slacks are zero, a DMU is PTE. If the results indicate that $\phi^* > 1$ and nonzero slacks, then a DMU is inefficient [39].

2.6. Bootstrapping DEA

Bootstrap techniques are applied to correct the uncertainty in point estimations of DEA efficiency scores calculated previously [57]. Bootstrap distributions of the efficiency scores can be approximated to derive statistical inference for each DMU, for example, the correction of the efficiency by the estimation bias and confidence intervals.

The estimation bias of the CRS-OO DEA model can be calculated as follows:

$$Bias(\theta^*) = \frac{\sum\limits_{b=1}^{B} \theta^*_{i,b}}{B} - \theta^*_i, \qquad i = 1, \ldots, n \tag{8}$$

where $\theta^*_{i,b}$ is the efficiency score for bootstrap replicate b. Thus, the efficiency correction is obtained by subtracting the *Bias* from θ^*_i.

An approximation of the confidence intervals for the efficiency score is calculated using the bootstrap distribution of θ^*_i

$$P\left[q^*_\alpha \leq \theta_i \leq q^*_{1-\alpha}\right] = 1 - \alpha \tag{9}$$

where q^*_α and $q^*_{1-\alpha}$ are the quartiles of the bootstrap distribution.

Similarly, the estimation bias and confidence intervals can be calculated for the VRS-OO efficiency scores.

3. Results

The proposed approach is applied to evaluate the future airport infrastructure performance of the new Mexico City Airport against 19 representative worldwide airport hubs: ATL, IAH, MIA, LAX, DFW, SFO, LGA, JFK, EWR, BOG, ORD, DXB, LHR, HKG, CDG, AMS, FRA, SIN, and DEN. Airport management strategies to reach efficiency are proposed based on the results. We select these airports using the proposed airports sampling method presented in Section 3.1.

First characteristic: select similar airports by market sizes. MEX and 18 of the selected airports in the sample belong to the list of the top 35 busiest airports measure by PAX since 2000 according with the Airports Council International database. We choose the busiest airports in the world because MEX belongs to this list since 2000, and this paper aims to evaluate the future airport infrastructure performance of the new Mexico City Airport against similar airports hubs. However, as all these airports are located mainly in USA, Europe, and Asia, we decide to also include BOG. We find important to include another airport hub from Latin-America apart from MEX even if it is not a top 35 busiest airport measure by PAX. However, BOG is the third biggest airport in Latin America following MEX and Sao Paulo (GRU), which is not included in the sample because of a lack of data.

Second characteristic: select similar airports by the size of the economy of the metropolitan area where they are located. The selected airports in the sample belong to the list of the top 50 richest cities and urban areas by GDP in the world, except of BOG, according with data.oecd.org and data.worldbank.org.

Third characteristic: select similar airports by the existence of airport competition. All the airports in the sample are in metropolitan areas where multiple airports serve commercial traffic forming a multi-airport system.

Fourth characteristic: select similar airports by their ACI index. Scheme 3 shows the four characteristics for each airport in the sample. The airports in the sample have a similar ACI index. The sources or databases used to calculate the ACI index of the airports in the sample are shown in Scheme 2. The sample ACI index mean is 0.80, the median is 0.82, and the standard deviation is 0.09. The most competitive airports are ATL and IAH with an ACI index of 0.94 and 0.91, respectively. The less competitive airports are BOG and MEX with an ACI index of 0.65 and 0.67, respectively. The country safety factor (SAF) hardly affects the airport competitiveness index of MEX and BOG because, after calculating the same index without considering SAF, the airports in the sample competitive index mean is 0.82, the median is 0.84, and the standard deviation is 0.06; and MEX airport competitiveness index is 0.84, which is slightly over the mean of the sample and equal to the median of the sample, whilst BOG airport competitiveness index is 0.81, which is slightly under the mean of the sample. This characteristic confirms that the airports in the sample are quite similar in terms of competitiveness. Scheme 4 shows the market potential index, the accessibility index, the airport fees index, the previous traffic result index, and the SAF for each airport in the sample. The airport with the worst market potential index is FRU. Most of the airports in the sample have a market potential index equal to 1. The market potential index of MEX is 0.93, which is slightly under the mean of the sample (0.94) and under the sample median (1.00). The airports with the worsts accessibility index are LGA and LAX with 0.64 and 0.67, respectively. The airports with the best accessibility index are AMS and DXB with 0.96, followed by FRA and LHR with 0.94. The accessibility index of MEX is 0.73, which is less than one standard deviation (0.10) under the mean of the sample (0.81) and under the sample median (0.79). The airports with the worsts airport fees index are LHR and CDG with 0.00 and 0.02, respectively. In general, the European airports have low airport fees index because their airport charges are the most expensive of the sample and all of them have curfews. LAX is the only American airport with a curfew according to www.boing.com. The airports with the best airport fees index are ATL, BOG, DEN, and LGA with 0.92. The airport fees index of MEX is 0.86, which is over the mean of the sample (0.64) and over the sample median (0.76). Finally, the airports with the worst previous traffic results index are LGA and BOG with 0.81 and 0.82, respectively. Most of the airports in the sample have a previous traffic results index equal to 1. The market potential index of MEX is 0.85, which is more than one standard deviation (0.06) under the mean of the sample (0.96) and under the sample median (0.99).

Airport	Global top 35 busiest airports	Global top 50 richest cities and urban areas by GDP	Cities with a multi-airport system	ACI index	ACI index without SAF
AMS	Yes	Yes	Yes	0.81	0.81
ATL	Yes	Yes	No	0.91	0.91
BOG	No	No	No	0.62	0.78
CDG	Yes	Yes	Yes	0.76	0.76
DEN	Yes	Yes	No	0.82	0.82
DFW	Yes	Yes	Yes	0.83	0.83
DXB	Yes	Yes	Yes	0.88	0.88
EWR	Yes	Yes	Yes	0.81	0.81
FRA	Yes	Yes	Yes	0.74	0.74
HKG	Yes	Yes	Yes	0.64	0.80
IAH	Yes	Yes	Yes	0.88	0.88
JFK	Yes	Yes	Yes	0.77	0.77
LAX	Yes	Yes	Yes	0.75	0.75
LGA	Yes	Yes	Yes	0.75	0.75
LHR	Yes	Yes	Yes	0.74	0.74
MEX	Yes	Yes	Yes	0.65	0.81
MIA	Yes	Yes	Yes	0.81	0.81
ORD	Yes	Yes	Yes	0.77	0.77
SFO	Yes	Yes	Yes	0.80	0.80
SIN	Yes	Yes	No	0.83	0.83

Scheme 3. Characteristics of the airports in the sample.

Airport	*Im*	*Ii*	*Ich*	*It*	SAF	Airport	*Im*	*Ii*	*Ich*	*It*	SAF
AMS	0.98	0.96	0.28	1.00	1.00	IAH	1.00	0.77	0.89	0.98	1.00
ATL	1.00	0.86	0.92	1.00	1.00	JFK	1.00	0.76	0.73	0.98	1.00
BOG	0.81	0.68	0.92	0.82	0.80	LAX	1.00	0.67	0.19	1.00	1.00
CDG	1.00	0.91	0.02	1.00	1.00	LGA	1.00	0.64	0.92	0.81	1.00
DEN	0.80	0.80	0.92	1.00	1.00	LHR	1.00	0.94	-	1.00	1.00
DFW	0.80	0.86	0.90	1.00	1.00	MEX	0.93	0.73	0.86	0.85	0.80
DXB	0.99	0.96	0.58	1.00	1.00	MIA	1.00	0.77	0.80	0.94	1.00
EWR	1.00	0.74	0.79	0.98	1.00	ORD	0.80	0.85	0.68	1.00	1.00
FRA	0.78	0.94	0.25	1.00	1.00	SFO	1.00	0.77	0.78	0.90	1.00
HKG	0.90	0.76	0.72	0.93	0.80	SIN	1.00	0.82	0.70	0.92	1.00

Scheme 4. ACI subindexes and the SAF.

3.1. Experimental Data

The infrastructure of an airport can be divided into airside and terminal side. Airside infrastructure limits the capacity of airport operations measured as ATMS [1]. ATMS is a productivity output variable of an airport airside infrastructure. ATMS accounts to the numbers of landings and take offs in a certain period [58]. The number of landings and take offs are restricted to the number of runways (Runways) that can be operated simultaneously, the size of the airport (Airport Size), and the number of gates (Gates). Moreover, the Airport Size and Gates are also restricted by the capacity of the airport to handle a certain number of airline passenger carriers (Pax Carriers). Therefore, in this paper, the airports airside infrastructure productivity or ATMS is measured analyzing the relation among these input variables. Scheme 5 shows the airside infrastructure productivity variables studied in this paper.

The level of service is the most important measure for an airport terminal infrastructure. The level of service is calculated with PAX during a certain period. Then, PAX is a productivity output variable of an airport terminal side infrastructure. PAX is restricted to the airport size (Airport Size) because this input variable is related to the capacity of an airport to handle PAX [1]. Cities variable is the total number of cities connecting with the airport in direct flights and defines its level of connection and shows how big is the airport network. Cities is a connectivity indicator that allows measuring the connection quality of an airport, which is related to the level of service that the airport terminal infrastructure can provide. This variable is related to airport terminal infrastructure because the infrastructure of an airport is highly influenced by the kind of destinations it operates, i.e., international or national connections. Finally, labor productivity is measured dividing the total output over the number of employees (Employees). Scheme 5 also shows the terminal side infrastructure productivity variables studied in this paper.

Scheme 5 also shows the input and output variables for the four scenarios studied in this paper. Scenario 1 studies the TE and PTE of the airside and terminal side infrastructure together. Scenario 2 studies the TE and PTE of airside and terminal side infrastructure productivity measures. Scenario 3 only studies the TE and the PTE of the terminal side infrastructure productivity measures. Scenario 4 only studies the TE and the PTE of the airside infrastructure productivity measures. These scenarios are proposed in this paper based on the variables studied in the literature review.

Scenario	Data						
1	Inputs:	Cities	Gates	Runways	Airport size (m2)	Pax Carriers	Num. of employees
	Outputs:	Pax (millions)	ATMS				
2	Inputs:	Cities	Gates / Runways	Airport size (m2)	Pax carriers	Employees / Gates	Gates
	Outputs:	Pax (millions)	ATMS				
3	Inputs:	Cities	Airport size (m2)	Pax Carriers	Employees / Gates		
	Outputs:	Pax (millions)					
4	Inputs:	Gates	Gates / Runways	Airport size (m2)	Pax Carriers		
	Outputs:	ATMS					

Scheme 5. Productivity measures and scenarios under study.

3.2. DEA Models Results

The authors of [59] demonstrate that DEA models should be applied to study one input and one output variables rather than multiple inputs and multiple outputs variables because reducing the dimensionality of the sample provides better efficiencies estimates. Therefore, they suggest developing one input or one output factor called proxy, which are linear combinations of input and output variables. An input proxy must satisfy a positive correlation with input variables, and in a similar way, an output proxy must satisfy a positive correlation with output variables. The authors of [60] explain in detail how to calculate the proxy. In this study, Appendix A shows linear correlations among variables and the proxy variables calculated for DEA implementation.

In 2019, the input proxy calculated for scenario 1 indicates that 94.42% of variability is explained by the linear combination of four input variables (Cities, Gates, Runways, and Airport Size) from the six under study (Scheme 1). Two are found to be irrelevant (Employees and Pax Carriers) because they do not add additional information. The output proxy calculated for scenario 1 indicates that 98.44% of variability is explained by the linear combination of two output variables (PAX and ATMS).

The number of connections (Cities) operated by the airports is the most relevant input variable because it adds most of the information to proxy (Appendix A, Table A1) since it is the most correlated variable with the proxy. This means, when airports increase the number of connections by opening operations with more cities, the proxy explains more variability, and vice versa. PAX and ATMS are equally relevant to the output proxy because both are equally correlated to the proxy (Appendix A, Table A2).

This result is important to analyze because, in this study, DEA methodologies are applied using the proxy as the unique input parameter. The results of the application of DEA methodologies to scenario 1 indicate the TE airports and the technical inefficient airports, with these results it is possible to calculate by how much the proxy must be increased to the inefficient airports to become efficient (Scheme 6a).

DEA MODEL	CRS-OO		VRS-OO	
	TE	1/TE	PTE	1/PTE
ATL	1.63	0.61	1.10	0.91
IAH	2.97	0.34	2.04	0.49
MIA	2.73	0.37	1.96	0.51
LAX	1.67	0.60	1.18	0.85
DFW	2.70	0.37	1.56	0.64
SFO	2.26	0.44	1.63	0.61
LGA	1.74	0.57	1.83	0.55
JFK	2.31	0.43	1.64	0.61
EWR	2.44	0.41	1.79	0.56
MEX	**1.32**	**0.75**	**1.38**	**0.72**
BOG	1.09	0.92	1.28	0.78
ORD	1.93	0.52	1.21	0.82
DXB	1.85	0.54	1.33	0.75
LHR	2.46	0.41	1.67	0.60
HKG	1.10	0.91	1.15	0.87
CDG	2.39	0.42	1.62	0.62
AMS	2.82	0.35	1.80	0.56
FRA	2.43	0.41	1.65	0.61
SIN	2.08	0.48	1.58	0.63
DEN	2.74	0.37	1.71	0.59

(**a**)

DEA MODEL	CRS-OO		VRS-OO	
	TE	1/TE	PTE	1/PTE
ATL	2.05	0.49	1.12	0.90
IAH	4.93	0.20	3.20	0.31
MIA	4.54	0.22	3.52	0.28
LAX	2.71	0.37	1.97	0.51
DFW	4.58	0.22	2.16	0.46
SFO	3.28	0.30	2.56	0.39
LGA	2.97	0.34	2.89	0.35
JFK	2.41	0.41	1.79	0.56
EWR	3.85	0.26	3.02	0.33
MEX	**1.45**	**0.69**	**1.38**	**0.72**
BOG	1.11	0.90	1.38	0.73
ORD	3.23	0.31	1.65	0.61
DXB	1.43	0.70	1.12	0.89
LHR	2.73	0.37	1.65	0.61
HKG	1.22	0.82	1.16	0.86
CDG	3.00	0.33	1.80	0.56
AMS	2.47	0.40	1.28	0.78
FRA	3.33	0.30	2.01	0.50
SIN	1.99	0.50	1.58	0.63
DEN	2.56	0.39	1.30	0.77

(**b**)

Scheme 6. (**a**) Scenario 1 DEA methodologies results for 2019. (**b**) Scenario 1 DEA methodologies results for 2030.

Scheme 6a shows the TE and the PTE for all the airports in the sample in scenario 1. The TE and the PTE of MEX are 1.32 and 1.38 for the CRS-OO and VRS-OO DEA models, respectively. These results indicate that MEX output variables (PAX and ATMS) must be increased by 1.32 for the CRS-OO DEA model or by 1.38 for the VRS-OO DEA model to reach TE = 1.00 and PTE = 1.00 because 1/TE is 0.75 for the CRS-OO and 1/PTE is 0.72 for the VRS-OO. We propose different strategies to achieve so: one, increase the number of connections (Cities); two, increase the total number of gates (Gates); three, increase the number of runways (Runways); and four, to expand the airport size (Airport Size). However, in the case of MEX, only the first strategy can be applied, but during non-peak hours, because the airport infrastructure cannot be expanded by any means (Gates, Runways, and Airport Size). In this scenario, MEX unique opportunity to become efficient is by increasing the number of connections (Cities) or to build a new airport (Airport Size) in another site (the new Mexico City Airport). According to these results, in 2019, MEX needed to handle 1.32 times the output proxy variable (PAX and ATMS) for the CRS-OO and 1.38 times the output proxy variable (PAX and ATMS) for the VRS-OO. This extra capacity (0.32 for the CRS-OO and 0.38 for the VRS-OO) could had been covered only if the new Mexico City airport would have been built and operating.

In 2030, the input proxy calculated for scenario 1 is the same as in 2019 (Appendix A, Table A1). Contrary, the output proxy changes because, in this paper, PAX and ATMS are forecasted in the mid-term for 2030 applying the ARIMA + GARCH + Bootstrap method [44]. It is important to understand that any forecasting method could not consider the pandemic effect. Moreover, the 2020 data are not considered in the sample. PAX and ATMS forecasts grow for the 20 airports in the sample. The output proxy calculated for scenario 1 indicates that 93.66% of variability is explained by the linear combination of two output variables (PAX and ATMS). In this case, PAX is more relevant than ATMS to the output proxy because PAX is more correlated to proxy than ATMS (Appendix A, Table A3).

Scheme 6b shows the DEA methodologies results for 2030 scenario 1. In the case of MEX, the TE and the PTE are 1.45 and 1.38 for the CRS-OO and VRS-OO models, respectively. These results indicate that MEX output variables (PAX and ATMS) have to be increased by 1.45 for the CRS-OO DEA model or by 1.38 for the VRS-OO DEA model to reach TE = 1.00 and PTE = 1.00 because, if inputs do not change, the expected 1/TE is 0.69 for the CRS-OO and the 1/PTE is 0.72 for the VRS-OO. The strategies proposed for 2019 can also be applied in 2030 for this scenario, but in this case, the effect of the proposed strategies in the output would show a bigger impact in PAX than in ATMS. This allows proposing another strategy where airlines should operate aircrafts with more capacity to increase PAX in a bigger proportion than ATMS. According to these results, in 2030, MEX airport and the new Mexico City airport would need to handle the 1.45 times the output proxy variable (PAX and ATMS) for the CRS-OO and 1.38 times the output proxy variable (PAX and ATMS) for the VRS-OO. This suggests that the new Mexico City airport infrastructure would need to handle at least 0.45 times the output proxy variable (PAX and ATMS) for the CRS-OO and 0.38 times the output proxy variable (PAX and ATMS) for the VRS-OO. It is possible to conclude that the new Mexico City airport needs to operate aircrafts with high PAX capacity, which requires big facilities in terminal side infrastructure and also in air side infrastructure.

In 2019, the input proxy calculated for scenario 2 indicates that 94.02% of variability is explained by the linear combination of four input variables (Cities, Gates, Pax Carriers, and Gates/Runways) from the six under study (Scheme 5). Two are found to be irrelevant (Employees/Gates and Airport Size) because they do not add additional information. The output proxy calculated for scenario 2 indicates that 98.44% of variability is explained by the linear combination of two output variables (PAX and ATMS).

The number of gates (Gates) at airports is the most relevant input variable because it adds most of the information to proxy since it is the most correlated variable with the proxy (Appendix A, Table A4). This means airports need to invest in airport infrastructure adding more gates to their terminals. PAX and ATMS are equally relevant to output proxy because both are equally correlated to proxy (Appendix A, Table A5).

The results of the application of DEA methodologies to scenario 2 indicate the TE and the PTE airports and the inefficient airports, and using these results, it is possible to calculate how much the proxy must be increased for the inefficient airports to become efficient (Scheme 7a).

DEA MODEL	CRS-OO		VRS-OO	
	TE	1/TE	PTE	1/PTE
ATL	1.50	0.67	1.11	0.90
IAH	2.53	0.39	1.90	0.53
MIA	2.98	0.34	2.19	0.46
LAX	1.87	0.53	1.38	0.72
DFW	2.07	0.48	1.53	0.65
SFO	2.43	0.41	1.79	0.56
LGA	2.15	0.46	1.89	0.53
JFK	2.58	0.39	1.90	0.53
EWR	2.76	0.36	2.04	0.49
MEX	**1.59**	**0.63**	**1.39**	**0.72**
BOG	1.11	0.90	1.31	0.76
ORD	1.76	0.57	1.22	0.82
DXB	2.64	0.38	1.67	0.60
LHR	3.75	0.27	1.78	0.56
HKG	1.57	0.64	1.28	0.78
CDG	2.79	0.36	1.72	0.58
AMS	2.77	0.36	1.79	0.56
FRA	2.83	0.35	1.77	0.57
SIN	2.62	0.38	1.93	0.52
DEN	1.98	0.51	1.47	0.68

(**a**)

DEA MODEL	CRS-OO		VRS-OO	
	TE	1/TE	PTE	1/PTE
ATL	1.87	0.53	1.09	0.92
IAH	4.20	0.24	2.59	0.39
MIA	4.94	0.20	2.93	0.34
LAX	3.04	0.33	1.78	0.56
DFW	3.51	0.28	2.05	0.49
SFO	3.52	0.28	2.11	0.47
LGA	3.67	0.27	2.89	0.35
JFK	2.69	0.37	1.58	0.63
EWR	4.35	0.23	2.59	0.39
MEX	**1.75**	**0.57**	**1.37**	**0.73**
BOG	1.13	0.89	1.34	0.75
ORD	2.95	0.34	1.66	0.60
DXB	2.04	0.49	1.10	0.91
LHR	4.17	0.24	1.68	0.59
HKG	1.75	0.57	1.23	0.81
CDG	3.51	0.28	1.85	0.54
AMS	2.43	0.41	1.32	0.76
FRA	3.88	0.26	2.07	0.48
SIN	2.50	0.40	1.47	0.68
DEN	1.85	0.54	1.12	0.90

(**b**)

Scheme 7. (**a**) Scenario 2 DEA methodologies results for 2019. (**b**) Scenario 2 DEA methodologies results for 2030.

Scheme 7a shows the TE and the PTE for all the airports in the sample in scenario 2. The TE and the PTE of MEX are 1.59 and 1.39 for the CRS-OO and VRS-OO DEA models, respectively. These results indicate that MEX output variables (PAX and ATMS) must be increased by 1.59 for the CRS-OO DEA model or by 1.39 for the VRS-OO DEA model to reach TE = 1.00 and PTE = 1.00 because MEX 1/TE is 0.63 for the CRS-OO and 1/PTE is 0.72 for the VRS-OO. We propose different strategies to achieve so: one, increase the number of connections (Cities); two, increase the total number of gates (Gates); three, increase the Pax Carriers operating at MEX; and four, increase the Gates/Runaways proportion. The results of this scenario are consistent with the results of scenario 1 (2019), indicating the actual necessity of building the new airport to serve more PAX and ATMS. According to these results, in 2019, MEX needed to handled 1.59 times the output proxy variable (PAX and ATMS) for the CRS-OO and 1.39 times the output proxy variable (PAX and ATMS) for the VRS-OO. This extra capacity (0.59 for the CRS-OO and 0.39 for the VRS-OO) could have been covered if the new Mexico City airport would have been built by adding more gates to the airport system (MEX and the new Mexico City Airport).

In 2030, the input proxy calculated for scenario 2 is the same as in 2019 (Appendix A, Table A4), and the output proxy calculated for scenario 2 is the same as in the 2030 for scenario 1 (Appendix A, Table A6). Scheme 7b shows the DEA methodologies results for 2030. In the case of MEX, the TE and the PTE of MEX are 1.75 and 1.37 for the CRS-OO and VRS-OO models, respectively. These results indicate that MEX output variables (PAX and ATMS) have to be increased by 1.75 for the CRS-OO DEA model or by 1.37 for the VRS-OO DEA model to reach TE = 1.00 and PTE = 1.00 because, if inputs do not change, the expected 1/TE is 0.57 for the CRS-OO and the 1/PTE is 0.73 for the VRS-OO. The strategies proposed for 2019 can also be applied in 2030 for this scenario, but in this case, the effect of the proposed strategies in the output would show a bigger impact in PAX than in ATMS. In this scenario, the proposed strategy where the new Mexico City airport adds more gates to the airport system allows airlines to increase the city connections expanding the airport system network. According to these results, in 2030, MEX airport and the new Mexico City airport need to handle 1.75 times the output proxy variable (PAX and ATMS) for the CRS-OO and 1.37 times the output proxy variable (PAX and ATMS) for the VRS-OO. This suggests that the new Mexico City airport infrastructure would need to add enough gates to handle at least 0.75 times the output proxy variable (PAX and ATMS) for the CRS-OO and 0.37 times the output proxy variable (PAX and ATMS) for the VRS-OO. It can be concluded that the new Mexico City airport must increase the airside infrastructure to the airport system by adding enough gates to the airport system.

Scenario 3 is planned to only study the variables related to the terminal side. The input proxy calculated indicates that 95.65% of variability is explained by the linear combination of two input variables (Pax Carriers and Cities) from the four under study (Scheme 5). However, two variables are found to be irrelevant (Employees/Gates and Airport Size) because they do not add additional information to proxy, and the relevant input variables are more related to airport accessibility and attractiveness. In this scenario, an output proxy is not calculated because the scenario only considers one output variable (PAX).

The number of connections (Cities) operated by the airports is the most relevant input variable (Appendix A, Table A7). Like in scenarios 1 and 2, this input variable must be considered by the airports to develop new strategies that enable them to become efficient.

Scheme 8a shows the TE and the PTE for all the airports in the sample in scenario 3. The TE and the PTE of MEX are 1.92 and 1.99 for the CRS-OO and VRS-OO DEA models, respectively. These results indicate that MEX output variable (PAX) must be increased by 1.92 for the CRS-OO DEA model or by 1.99 for the VRS-OO DEA model to reach TE = 1.00 and PTE = 1.00 because the 1/TE is 0.52 for the CRS-OO and the 1/PTE is 0.50 for the VRS-OO. This could be achieved by developing strategies to increase the number of connections (Cities) operated by MEX and to attract more Pax Carriers to increase its accessibility and attractiveness. According to these results, in 2019, MEX needs to handle 1.92 times the output variable (PAX) for the CRS-OO and 1.99 times the output variable (PAX) for the

VRS-OO. This extra capacity (0.92 for the CRS-OO and 0.99 for the VRS-OO) could had been covered if the new Mexico City airport would had been built by 2019 to attract airlines and fly to new cities, thus increasing the airport system (MEX and the New Mexico City Airport) network.

DEA MODEL	CRS-OO		VRS-OO	
	TE	1/TE	PTE	1/PTE
ATL	1.28	0.78	1.14	0.87
IAH	3.03	0.33	2.71	0.37
MIA	3.39	0.29	2.62	0.38
LAX	2.31	0.43	1.46	0.69
DFW	2.36	0.42	1.67	0.60
SFO	2.95	0.34	1.99	0.50
LGA	2.12	0.47	1.53	0.65
JFK	2.81	0.36	1.85	0.54
EWR	3.45	0.29	2.53	0.39
MEX	**1.92**	**0.52**	**1.99**	**0.50**
BOG	1.88	0.53	1.32	0.76
ORD	2.01	0.50	1.39	0.72
DXB	1.98	0.50	1.23	0.81
LHR	2.72	0.37	1.55	0.65
HKG	1.13	0.89	1.25	0.80
CDG	3.34	0.30	1.49	0.67
AMS	2.97	0.34	1.58	0.63
FRA	3.27	0.31	1.61	0.62
SIN	2.38	0.42	1.79	0.56
DEN	2.08	0.48	1.86	0.54

(**a**)

DEA MODEL	CRS-OO		VRS-OO	
	TE	1/TE	PTE	1/PTE
ATL	1.08	0.93	1.16	0.86
IAH	3.65	0.27	3.90	0.26
MIA	3.83	0.26	3.57	0.28
LAX	2.42	0.41	1.83	0.55
DFW	2.71	0.37	2.30	0.43
SFO	2.96	0.34	2.40	0.42
LGA	2.53	0.40	2.52	0.40
JFK	2.02	0.50	1.59	0.63
EWR	3.71	0.27	3.29	0.30
MEX	**1.36**	**0.73**	**1.42**	**0.70**
BOG	1.28	0.78	1.38	0.73
ORD	2.47	0.41	2.04	0.49
DXB	2.43	0.41	1.81	0.55
LHR	2.12	0.47	1.45	0.69
HKG	1.13	0.88	1.18	0.85
CDG	3.17	0.32	1.70	0.59
AMS	1.71	0.59	1.09	0.92
FRA	3.31	0.30	1.95	0.51
SIN	1.68	0.60	1.52	0.66
DEN	1.21	0.83	1.30	0.77

(**b**)

Scheme 8. (**a**) Scenario 1 DEA methodologies results for 2019. (**b**) Scenario 1 DEA methodologies results for 2030.

In 2030, the input proxy calculated for scenario 3 is the same as in 2019 (Appendix A, Table A7). In contrast, the PAX forecast for 2030 is used as an output variable. PAX forecasts grow for all airports in the sample. Scheme 8b shows the DEA methodologies results for 2030. In the case of MEX, the TE and the PTE are 1.36 and 1.42 for the CRS-OO and VRS-OO models, respectively. These results indicate that MEX output variable (PAX) have to be increased by 1.36 for the CRS-OO DEA model or by 1.42 for the VRS-OO DEA model to reach TE = 1.00 and PTE = 1.00 because, if inputs do not change, the expected 1/TE is 0.73 for the CRS-OO and the 1/PTE is 0.70 for the VRS-OO. Contrary to the results of scenarios 1 and 2, in this scenario, MEX TE and PTE are expected to increase in the future. The results indicate that if the number of carriers (Pax Carriers) operating at the airport and the number of connections (Cities) remain the same, the TE and the PTE of MEX would improve meaning that PAX could be attended by the carriers that were operating at MEX in 2019. Therefore, these results oppose the strategies proposed to increase MEX TE and PTE in scenarios 1 and 2 because, in this scenario, the results indicate that it would not be necessary to increase the number of connections (Cities) and the number of carriers (Pax Carriers) in 2030 to reach efficiency. In scenario 1 and 2, the inputs variables include airport size, and the results indicate that in 2030 MEX would become more inefficient. In this scenario, the effect of the airport size input variable is not considered, and therefore, the conclusion is that, if the terminal side infrastructure do not change, MEX would become more efficient. Finally, this suggests that MEX future efficiency depends mainly on airport size.

In 2019, the input proxy calculated for scenario 4 indicates that 93.20% of variability is explained by the linear combination of three input variables (Gates, Pax Carriers, and Gates/Runways) from the four under study (Scheme 5). However, one variable is found to be irrelevant (Airport Size) because it did not add additional information to the proxy. In this scenario, an output proxy is not calculated because the scenario only considers one output variable (ATMS).

The number of gates (Gates) is the most relevant input variable (Appendix A, Table A8). The airport hubs in the sample should focus and develop strategies mainly in this input variable to become efficient.

Scheme 9a shows the TE and the PTE for all the airports in the sample in scenario 4. The TE and the PTE of MEX are 1.97 and 1.53 for the CRS-OO and VRS-OO DEA models, respectively. These results indicate that the MEX output variable (ATMS) must be increased by 1.97 for the CRS-OO DEA model or by 1.53 for the VRS-OO DEA model to reach TE = 1.00 and PTE = 1.00 because the 1/TE is 0.51 for the CRS-OO and the 1/PTE is 0.65 for the VRS-OO. This could be achieved by developing strategies to increase: the number of gates (Gates); the ratio between the number of gates and the number of runaways (Gates/Runways); and the number of pax carriers (Pax Carriers) operating at MEX. According to these results, in 2019, MEX needed to handle 1.97 times the output variable (ATMS) for the CRS-OO and 1.53 times the output variable (ATMS) for the VRS-OO. This extra capacity (0.97 for the CRS-OO and 0.53 for the VRS-OO) could had been covered if the new Mexico City airport would had been built by 2019 adding more gates to the airport system (MEX and the new Mexico City Airport).

DEA MODEL	CRS-OO		VRS-OO	
	TE	1/TE	PTE	1/PTE
ATL	1.92	0.52	1.10	0.91
IAH	2.74	0.36	1.73	0.58
MIA	3.92	0.26	2.27	0.44
LAX	2.39	0.42	1.37	0.73
DFW	2.21	0.45	1.32	0.76
SFO	3.55	0.28	2.05	0.49
LGA	2.83	0.35	2.00	0.50
JFK	3.72	0.27	2.14	0.47
EWR	3.11	0.32	1.87	0.53
MEX	**1.97**	**0.51**	**1.53**	**0.65**
BOG	1.15	0.87	1.35	0.74
ORD	2.06	0.49	1.09	0.92
DXB	5.32	0.19	2.40	0.42
LHR	6.64	0.15	2.04	0.49
HKG	3.25	0.31	1.98	0.51
CDG	3.83	0.26	1.97	0.51
AMS	3.87	0.26	1.98	0.51
FRA	3.84	0.26	1.91	0.52
SIN	4.66	0.21	2.56	0.39
DEN	2.28	0.44	1.39	0.72

(**a**)

DEA MODEL	CRS-OO		VRS-OO	
	TE	1/TE	PTE	1/PTE
ATL	3.52	0.28	2.25	0.44
IAH	4.87	0.21	3.40	0.29
MIA	8.45	0.12	5.45	0.18
LAX	5.78	0.17	3.70	0.27
DFW	4.83	0.21	3.20	0.31
SFO	7.15	0.14	4.58	0.22
LGA	5.16	0.19	4.03	0.25
JFK	5.93	0.17	3.79	0.26
EWR	6.02	0.17	4.02	0.25
MEX	**3.03**	**0.33**	**2.61**	**0.38**
BOG	1.24	0.81	1.58	0.63
ORD	3.65	0.27	2.33	0.43
DXB	1.98	0.50	1.29	0.77
LHR	11.87	0.08	5.27	0.19
HKG	3.36	0.30	2.27	0.44
CDG	6.25	0.16	3.99	0.25
AMS	6.53	0.15	4.18	0.24
FRA	6.71	0.15	4.31	0.23
SIN	6.63	0.15	4.23	0.24
DEN	3.37	0.30	2.29	0.44

(**b**)

Scheme 9. (**a**) Scenario 1 DEA methodologies results for 2019. (**b**) Scenario 1 DEA methodologies results for 2030.

In 2030, the input proxy calculated for scenario 4 is the same as 2019 (Appendix A, Table A8). On the contrary, the ATMS forecast for 2030 is used as an output variable. ATMS forecasts growth for all airports in the sample. Scheme 9b shows the DEA methodologies results for 2030. In the case of MEX, the TE and the PTE are 3.03 and 2.61 for the CRS-OO and VRS-OO models, respectively. These results indicate that MEX output variable (ATMS) has to be increased by 3.03 for the CRS-OO DEA model or by 2.61 for the VRS-OO DEA model to reach TE = 1.00 and PTE = 1.00 because, if inputs do not change, the expected 1/TE is 0.33 for the CRS-OO and the 1/PTE is 0.38 for the VRS-OO. These results are consistent with the results of scenarios 1 and 2. In this scenario, TE and PTE are expected to decrease in the future. The results indicate that MEX airside infrastructure would need to expand to attend the ATMS in 2030. The natural strategy would be to increase the number of gates (Gates) and the number of runways (Runways). However, MEX does not have the possibility to expand its terminal side infrastructure or its airside infrastructure. Therefore, the unique possible strategy is to increase airport size by building the new airport in the Santa Lucia Base as it is currently being built. According to these results, in 2030, MEX airport and the new Mexico City airport would need to handle 3.03 times the output variable (ATMS) for the CRS-OO and 2.61 times the output variable (ATMS) for the VRS-OO. This suggests that the new Mexico City airport infrastructure needs to add enough airside infrastructure (Gates/Runways and Gates) to handle at least 2.03 times the output variable (ATMS) for the CRS-OO and 1.61 times the output variable (ATMS) for the VRS-OO. Therefore, it can be concluded that the new Mexico City airport must increase the airside infrastructure to the airport system. The results suggest to increase Gates because it is the variable that impact the input proxy the most. It is important to assure that the variable Gates/Runways is in equilibrium because if the number of gates increases too much and the number of runways does not change, operatively, the efficiency could not increase, but it may actually decrease. The reason is because the capacity of the runways become the bottleneck, and the number of ATMS could not increase even if the airport has more gates. Therefore, increasing the number of gates, at some point, requires increasing runways.

The TE is a point estimation of the real TE. It is important to analyze the uncertainty of this estimation using confidence intervals because this limits the range of values of TE. Figure 1 shows the TE and the Bootstrap confidence intervals for the CRS-OO of each airport in the sample for 2019 (left panel) and for 2030 (right panel). In general, Figure 1 shows that airports are more efficient in 2019 than they are expected to be in 2030. However, at the same time, the uncertainty due to the lengths of the confidence intervals is greater in 2019 than they are expected to be in 2030. It means that the estimated TE vary among a wide range. Hence, the probability that airports could be more efficient exists, but the probability that airports could be more inefficient also exists. Figure 1 also shows that the distances between the lower bound (dotted line) and the estimated TEs' (continuous line) are closer than the distances between the upper bound (dashed line) and the estimated TEs. Therefore, it is more likely to be inefficient than efficient.

The results of Figure 1 indicate that the 20 airports of the sample are expected to become inefficient. Therefore, airport companies and governments must invest in infrastructure and develop strategies to assure the efficiency. In particular, the calculated TEs' of scenario 4 have more uncertainty than in the other scenarios. In this scenario, the output and inputs estimate TEs' with a greater margin of errors. This result is more evident for 2030 than for 2019.

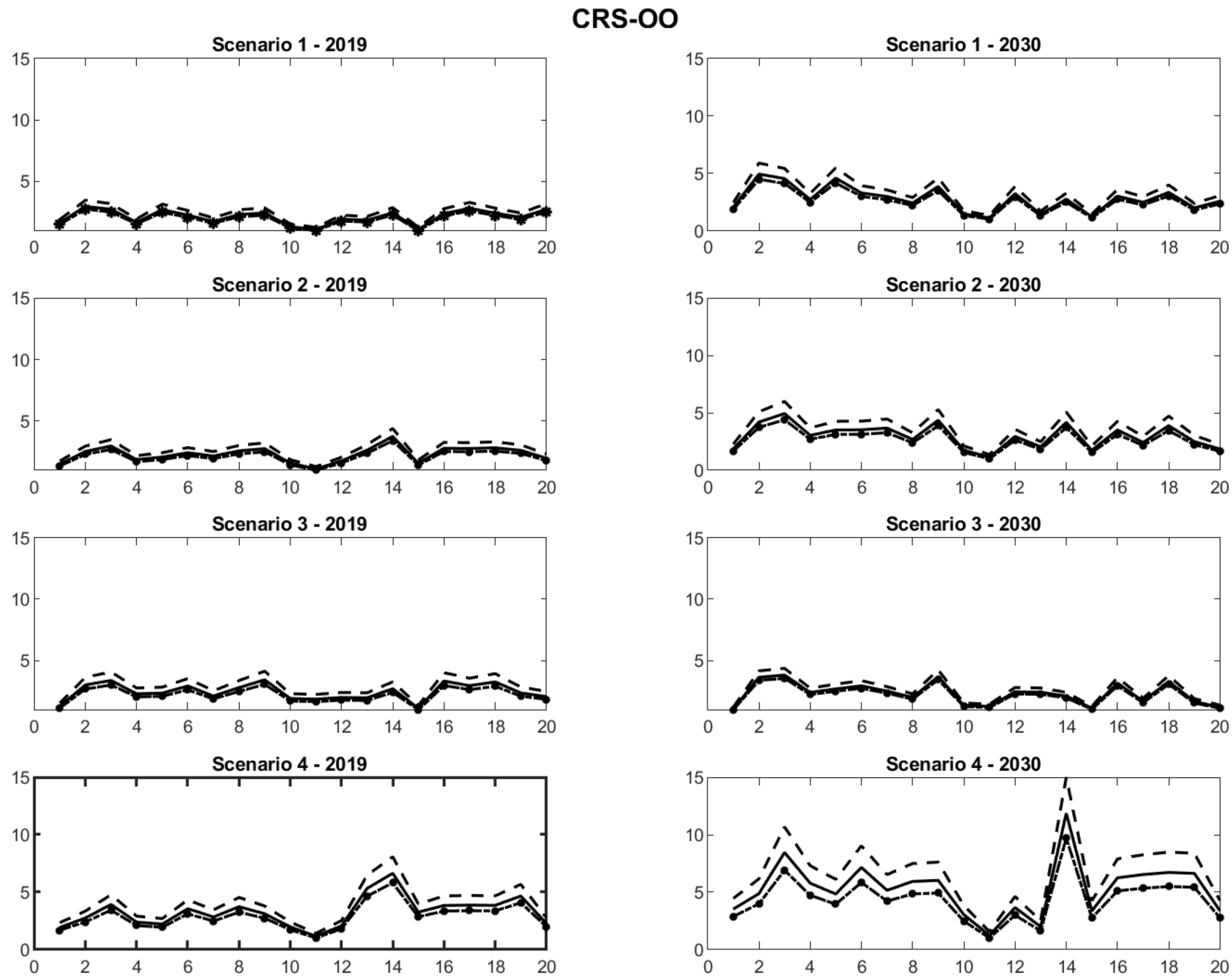

Figure 1. TE and Bootstrap confidence intervals for 2019 and 2030.

Figure 2 shows the PTE and the Bootstrap confidence intervals for the VRS-OO of each airport for 2019 (left panel) and for 2030 (right panel). In general, Figure 1 shows that the airport hubs in the sample are more efficient in 2019 than they are expected to be in 2030. However, at the same time, the uncertainty due to the lengths of the confidence intervals is greater in 2019 than they are expected to be in 2030. It means that the estimated PTE vary among a wide range. Hence, the probability that airports could be more efficient exists, but the probability that airports could be more inefficient also exists. Figure 2 also shows that the distances between the lower bound (dotted line) and the estimated PTEs' (continuous line) are closer than the distances between the upper bound (dashed line) and the estimated PTEs. Therefore, it is more likely to be inefficient than efficient.

Technical inefficiencies are greater when using the CRS-OO DEA than the VRS-OO DEA. This is because TEs are greater than PTEs for some DMUs except for those DMUs with optimum TE and PTE.

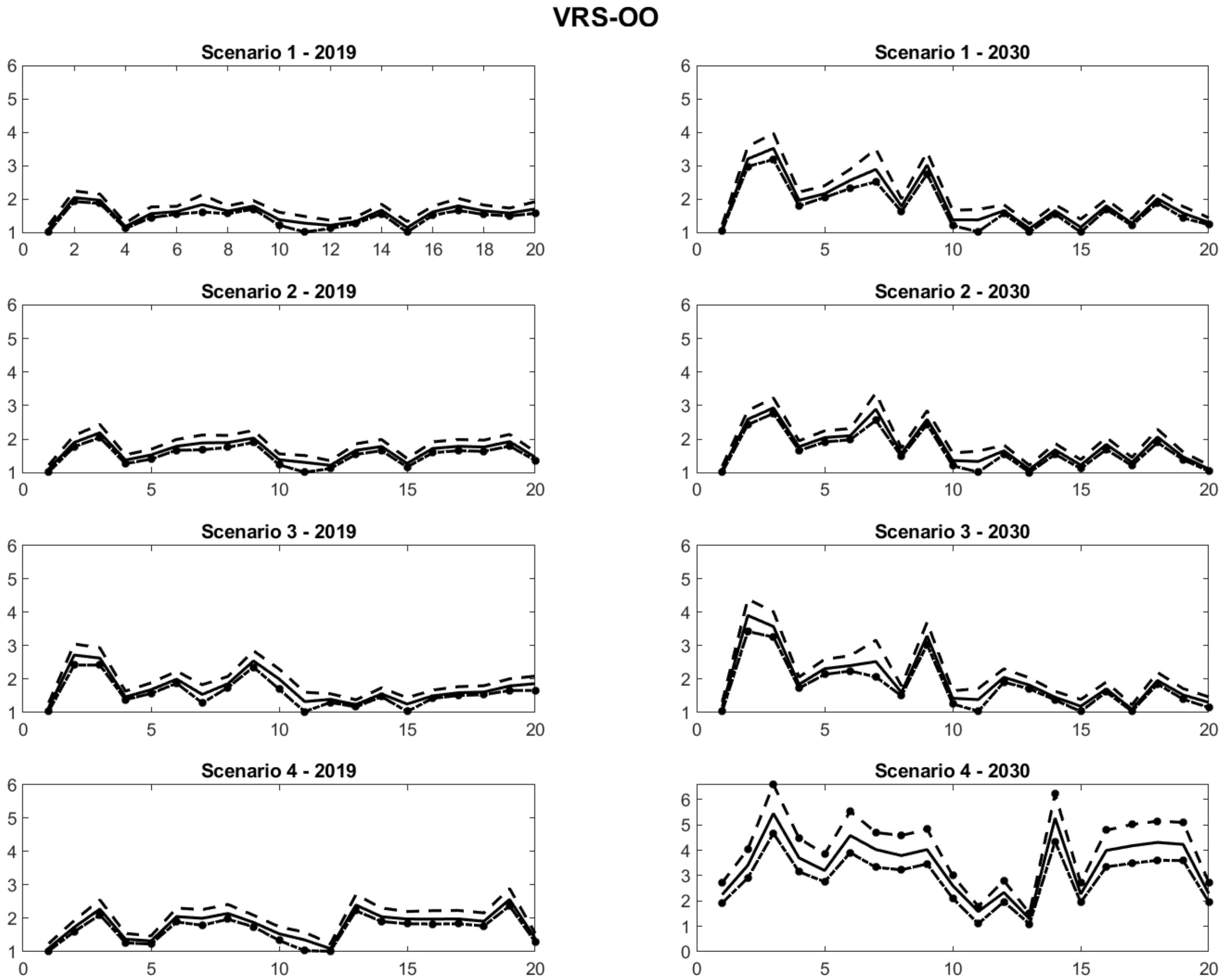

Figure 2. PTE and Bootstrap confidence intervals for 2019 and 2030.

4. Conclusions

The main contribution of this paper is an approach that evaluates the expected efficiency and performance of future airport infrastructure and establishes airport management strategies to reach efficiency with the results. The proposed approach can be applied to evaluate the expected efficiency and performance of any airport in the world. The proposed approach consists of three steps. In the first step, an airport sampling method to select similar airports is developed based on socioeconomic and operational airport variables that are summarized in a proxy variable. In the second step, the ARIMA-GARCH-Bootstrap forecasting method is applied to forecast the selected outputs, whilst the infrastructure input variables remain constant. Finally, in the third step, the VRS-OO and the CRS-OO DEA models are used to evaluate the performance of the airports in the sample in current and future years. The CRS model is used from an output orientation because the selected inputs (Cities, Gates, Runaways, Airport Size, Pax carriers, and Num. of employees) and the selected outputs (PAX and ATMS) can be classified as physical levels because these measures are actual amounts of products that are often assumed to be proportional to resources, and therefore, they satisfy the assumption of proportionality; and the VRS model is used for comparison purposes.

The proposed approach is applied to Mexico because it is currently building a new airport with the purpose of satisfying the increasing demand of ATMS and PAX and enhancing economic growth. This new airport is part of the metropolitan area of Mexico City multi-airport system, which is going to provide air transport services. The results of our analysis indicate the required infrastructure that should be built to assure efficiency in comparison with 19 of the most important airport hubs worldwide, and based on these results, we propose different strategies to become efficient by analyzing four scenarios developed based on the literature review. Therefore, the second contribution of this paper is to the air transport management industry, in particular, to the Mexican air transport industry. The general conclusion is that the Mexico City airport system would require mostly airside infrastructure.

In this paper, Bootstrap DEA models are applied to study the current and future TE and PTE of MEX against 19 international airports hubs worldwide. To study the future TE and PTE of MEX, the ARIMA + GARCH + Bootstrap is applied to forecast PAX and ATMS for 2030. The forecasts indicate that ATMS and PAX are going to grow. The results indicate that MEX was operating at medium levels of efficiency in 2019, and if the new airport would not be built, MEX is expected to perform worse in 2030.

The third contribution of this paper is the productivity measures proposed for the study of airport terminal side TE and PTE (Employees/Gates) and for the study of airport airside TE and PTE (Gates/Runways). These productivity measures are based on a literature review of research that studies the efficiency and productivity of air transport systems, such as airlines and airports. The fourth contribution of this paper is the development of input and output proxy variables to ensure the DEA models robustness because one input and one output variables reduce the dimensionality of the mathematical problem providing better estimates. The fifth contribution are the four scenarios proposed to study the required infrastructure of the airport hubs. These scenarios are proposed in this paper based on the literature review. Finally, the sixth contribution is the proposition of different management strategies to assure that the level of efficiency of Mexico City multi-airport system will be greater than or at least equal to the most important airport hubs worldwide.

Analyzing the results of Scenarios 1, 2, 3, and 4, it is possible to conclude that MEX's future efficiency depends mainly on increasing airport size infrastructure, and the management strategies could be that airlines should operate aircrafts with more capacity (big aircrafts) to serve more PAX per ATM and airlines must open new connections to increase the airport system network. These results indicate that MEX requires airside infrastructure in 2019, which validates the model estimations because the current congestion of MEX is in the airside.

The advantage of applying the proposed approach is the capacity of analyzing the infrastructure of future airports by looking outward and inwards, which allows planning strategies that can significantly affect the performance of the airports and increase their level of efficiency. The disadvantage of applying DEA models through a proxy variable is the fact that these methods can only indicate the expected impact but not quantify the exact changes in the input variables to achieve efficiency. If this is the case, instead of using proxy, the input variables are directly used. However, the risk of having multiple input and multiple output variables is the possibility of calculating wrong efficient estimates. In this paper, we prefer to calculate better efficiency estimates and propose strategies to improve efficiencies rather than propose strategies to calculate the change of the input variables based on wrong efficiency estimates.

The first limitation of the proposed methodology is the availability and reliability of the data needed to build the airport sample as proposed in this paper. The second limitation is that the efficiency and productivity measures provided by a DEA model depend on the airports in the sample. For this reason, building a representative airport sample is critical because if airports are not comparable according to their socioeconomic and operational variables, the results can be biased, and the forthcoming strategies can lead airports managers and governments to bad decisions.

Future research will focus on mathematically validating the proposed approach.

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Appendix A

Linear correlations among variables and proxy for DEA implementation.

Table A1. Input variables Scenario 1 (2019 and 2030).

Cities	Gates	Runaways	Airport Size (m^2)
0.8958	0.8460	0.8227	0.5685

Table A2. Output variables Scenario 1 (2019).

PAX	ATMS
0.8884	0.8981

Table A3. Output variables Scenario 1 (2030).

PAX	ATMS
0.8580	0.6889

Table A4. Input variables Scenario 2 (2019 and 2030).

PAX Carriers	Cities	Gates	Gates / Num of Runaways
0.6159	0.8147	0.8851	0.5836

Table A5. Output variables Scenario 2 (2019).

PAX	ATMS
0.8884	0.8981

Table A6. Output variables Scenario 2 (2030).

PAX	ATMS
0.8580	0.6889

Table A7. Input variables Scenario 3 (2019 and 2030).

PAX Carriers	Cities
0.7714	0.8741

Table A8. Input variables Scenario 4 (2019 and 2030).

Gates	Gates / Num of Runaways	PAX Carriers
0.8334	0.7656	0.6589

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