The Impact of Chinese Airport Infrastructure on Airline Pollutant Emissions: A Hybrid Stochastic-Neural Network Approach Based on Utility Functions

Abstract:

With China being the world's largest emitter of greenhouse gases and its aviation sector burgeoning, the environmental performance of Chinese airlines has global significance. Amidst rising demands for eco-friendly practices from both customers and regulators, the interplay between airport infrastructure and environmental performance becomes pivotal. This research offers an innovative methodology to gauge the environmental performance of Chinese airlines, emphasizing the distance traveled between airports using weighted additive utility functions. Leveraging neural networks, the study investigates the impact of various airport infrastructural characteristics on environmental performance. Noteworthy findings indicate that ground control measures, automatic information services at origin airports, surface concrete on runways at both ends, and a centerline lighting system in destination airports positively influence environmental performance. In contrast, longer and wider runways at origin airports, increased distances to control towers, and asphalt runways at destination airports adversely affect it. These insights not only underscore the importance of strategic infrastructure enhancements for reducing carbon footprints but also hold profound policy implications. As global climate change remains at the forefront, fostering sustainable airport infrastructure in China can significantly contribute to worldwide mitigation efforts.

Keywords: air transport industry; China; environmental performance index; utility functions; distance travelled; neural networks.

Conflict of Interest statement

The authors do not have any conflict of interest to declare.

1. Introduction

The urgency of addressing climate change, driven largely by anthropogenic activities, has never been clearer. The aviation sector, while being indispensable for global connectivity, has drawn scrutiny for its considerable carbon footprint. Mitigating the adverse environmental impacts of this industry is crucial for achieving global sustainability goals. Within this context, understanding and improving the environmental performance of airlines, particularly in rapidly developing regions, becomes imperative.

China, as one of the world's largest economies, plays a pivotal role in global climate change initiatives. As its aviation industry burgeons, there's a pressing need to align its growth with environmental sustainability. This paper seeks to contribute to this endeavor by presenting a novel approach to evaluate the environmental performance of Chinese airlines, shedding light on the significant influence of airport infrastructure on pollutant emissions. Such an analysis not only informs sustainable infrastructure development but also helps policymakers and industry leaders make informed decisions that balance economic growth with environmental responsibility.

According to the statistics provided by the international civil aviation organization, the total number of passengers carried on scheduled services rosed to 4.5 billion in 2019, which is 3.6% higher than 2018. In terms of the number of departures, it reached 38.3 million in 2019, which is 1.7% higher than 2018. With regard to the total scheduled revenue passenger-kilometers (PRKs), an indicator reflecting the total passenger carried by an airline or a group of airlines over a certain period of time, the statistics show that the figure reached 8686 billion, which is 4.9% higher than 2018. Although there has been a growth in relevant indicators reflecting the volumes of activities in the aviation industry, based on the statistics provided by Green Baggage as well as international council on clean transportation, flights produced 915 million tons of CO_2 in 2019, which is slightly lower than the figure in 2018, which is 918 million tons.

In recent years, China's civil aviation industry has experienced rapid development. In 2019, China's domestic routes transported a total of 82.951 billion ton-kilometers, with passenger turnover reaching 852.022 billion person-kilometers, and cargo and mail turnover reaching 7.859 billion ton-kilometers, with an annual growth rate of more than 5% (CAAC, 2020). Although these indicators have declined due to the impact of the pandemic, China remains one of the most active regions in global air transportation. However, high growth is accompanied by high emissions. In 2019, China's domestic airline carbon emissions reached 71.158 million tons, accounting for 8.2% of the global total emissions. The Chinese government has taken many measures to control aviation emissions. In the "14th Five Year Plan" of China's civil aviation, two indicators, namely carbon dioxide emissions per ton kilometer of transportation aviation and energy consumption per passenger at airports, will be reduced to 0.886 kg and 0.853 kg of standard coal by 2025, respectively (CAAC, 2020).

In this research, an innovative stochastic-robust approach is proposed to calculate an overall environmental performance index for Chinese airlines. The index is based on the locally estimated scatterplot smoothing (LOESS) evaluation of the partial utility functions (PUFs) associated with each rotated criterion obtained through SVD. The methodology utilized in this study involves bootstrapping the original decision matrix, which consists of columns representing various pollutants emitted by the airlines, as well as the distance traveled between two airports (criteria), and the lines represent different airline flights within China. In this study, an alternative method is examined for rescaling the rotated criteria. This method involves using quadratic programming to determine the optimal weights for the minimal covariance and joint entropy matrices of the estimated residuals of the Partial Utility Functions (PUFs) obtained through LOESS. By incorporating the singular values and these optimal weights, an overall utility function is derived, which provides a comprehensive assessment of the relative importance of the criteria. Furthermore, the relative importance of airport infrastructure characteristics on the pollutant emissions of airlines is explored through a hybrid approach using neural networks.

This novel approach attempts to fill a research void with respect Chinese airline pollutant emissions. In fact, despite the rapid growth of China's aviation industry and its consequent environmental implications, there lacks a comprehensive and robust method to evaluate the environmental performance of its airlines, taking into account the intricacies of airport infrastructures. Hence, our primary objective is to introduce and validate a novel stochastic-robust approach to develop an environmental performance index for Chinese airlines, offering insights into the role of different airport infrastructure characteristics on pollutant emissions. Differently from previous studies, this paper stands out in blending LOESS and SVD to derive a comprehensive performance index by capturing the nuanced impacts of various airport infrastructures on emissions. Notwithstanding the theoretical and methodological issues, this research also contributes to policy decisions and sustainable growth strategies in the aviation sector.

Our findings suggest that the environmental performance of the Chinese airlines is significantly and positively affected by 1) the ground control in both origin and destination airports; 2) automatic information service in origin airports; 3) the existence of surface concrete in the runways of both origin and destination airports; 4) the centerline lighting system in destination airports; whereas the environmental performance is signficantly and negatively affected by 1) larger runway length and width in origin airports; 2) longer distances to the control tower in origin airports; 3) asphalt runway in destination airports.

The paper has the following structure. In the next section, the Chinese air transport industry, its history, current status, and future perspectives in terms of ESG are discussed. Section 3 of this paper provides a comprehensive literature review. It identifies the research gap by examining previous studies that have investigated the impact of airport infrastructure on the environmental performance of airlines. The review highlights the specific areas of focus, the main methodologies employed, and the key findings and conclusions drawn from these studies. The dataset and the novel approach developed in this paper are described in Section 4. The results are analyzed and discussed in Section 5, Section 6 serves as the conclusion of the paper, where various aspects are addressed. These include presenting the policy and managerial implications derived from the study's findings, discussing the limitations of the research, and providing suggestions for future research directions.

Literature Review

The rapid growth of aviation demand has promoted economic development, but it has also brought significant adverse effects on the environment, especially greenhouse gas emissions (Sreenath et al., 2021). In addition to carbon dioxide (CO2), aircraft activities also generate other emissions, including carbon monoxide (CO), hydrocarbons (HC), nitrogen oxides (NOx), sulfur dioxide (SO2), and particulate matter (PM2.5) (Amanatidis et al., 1998; Koulidis et al., 2020). These aircraft emissions harm the environment and human health (Zhou et al., 2019; Safarianzengir et al., 2020; Yang et al., 2023).

Accounting for aviation emissions provides a basis for promoting aviation carbon emission reduction. The main methods for calculating aviation emissions are the United States EPA (Environmental Protection Agency) method, the European EMEP (European Monitoring and Evaluation Program) method, and the ICAO (International Civil Aviation Organization) method. Based on the EPA method, scholars have calculated the pollutant emissions of aircraft engines at airports (including take-off and landing) (Zhou et al., 2019; Baxter et al., 2020). The EPA method is mainly used to calculate aircraft carbon emissions during the LTO (Landing and Take-Off) phase. The EMEP method assessed the environmental impact of replacing existing aviation fuels with hydrogen or natural gas (Pereira et al., 2014). The EMEP approach focuses on analyzing the emission characteristics of an aircraft engine from a fuel perspective, ignoring the differences between engine types. The ICAO calculation method does not consider the differences between subsequent models, nor can it simultaneously calculate multiple types of pollutants (Wasiuk et al., 2016).

To overcome the shortcomings of existing aircraft emission calculation methods and consider specific aircraft types and flight distances, scholars have proposed an improved fuel percentage method (BFFM2-FOA-FPM) to calculate aircraft emissions during the CCD (Climbing/Cruising/Descending) phase (Cui et al., 2022a, 2022b, 2022c). This method unifies the calculation of carbon dioxide and non-carbon dioxide emissions, making the results more accurate.

There are a number of studies investigating the environmental performance of airlines. Using 48 world's major full-service and low-cost carriers from six different regions between 2007 and 2010, Arjomandi and Seufert (2014) examine the environmental efficiencies of airlines under the boostrapped data envelopment analysis. The findings suggest that the Europe airlines have the best environmental performance, while low-cost carriers are more environmentally oriented comapred to the full-service carriers. Using nine listed Chinese airlines between 2013 and 2018, Chen et al. (2021) examine the environmental performance under a two-stage undesirable network slack-based measure approach. Similar as the findings of Arjomandi and Seufert (2014), they find that low-cost airlines have the best environmental performance. Using 27 global airlines in 2010, Chang et al. (2014) evaluated the envrionmental performance through an extended environmental slacks-based measure data envelopment analysis model with the weak disposability assumption. The results report that the European and American airlines are less efficient than the asia-based airlines. The findings further suggest that the environmental performance is affected by poor fuel consumption. Using 12 US airlines over the period 2013 to 2016, Xu et al. (2021) examine the environmental performance through a directional distance function (DDF) data envelopment analysis (DEA) model, in which flight delay and greenhouse gas (GHG) emissions as joint undesirable outputs.

The findings show that fleet age, ownership type, freight traffic, market share, and carrier type affect airlines' environmental efficiency. Using 149 airlines in the world over the period 2012 to 2016, Payán-Sánchez et al. (2022) investgiated the relationship between Network ambidexterity and environmental performance. The environmental performance is measured by the environmental performance indicator of the Atmosfair Airline Index (AAI). The results from the hirarchical regression analysis shows that code-sharing is a critical source for improving environmental efficiency and the moderating role of network ambidexterity in the impact of alliances on environmental performance is identified. Finally, using 252 airlines in the world over the period 2010 to 2016, Payán-Sánchez et al. (2019) analyze whether the alliance membership of airlines has an effect upon their environmental performance. The measurement of environmental performance follows the one of Payán-Sánchez et al. (2022), while the impact of alliance membership on environmental performance is evaluated through the Regression and Analysis of Variance. The findings suggested that there is a strong and inverse relationship between environmental performance and belonging to an alliance.

Few studies have attempted to propose and use neural networks in analyzing relevant relationships in the aviation/airline industry. Using 73 observations for cost-focused airlines and 62 observations for full-service arilines in the US between 1998 and 2009, Parast and Golmohammadi (2021) examined the effect of operational slack on the relationship between service disruption and quality. The investigation was facilitated by the use of multiple regression analysis and the authors also used nerual networks approach as the robustness test. The findings support the role of slack resources in mitigating the impact of service failure—in the form of flight cancellations—on passengers' perceived service quality. Using a sample of 29 African airlines over the period 2010-2013, Barros and Wanke (2015) provided an analysis of efficiency with a two-stage Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) and neural network approach. In the first stage, TOPSIS was used to evaluate the airline efficiency, followed by the second stage, in which the neural networks approach was employed to evaluate the determinants of efficiency. The findings suggest that fleet mix, public ownership and network size are the efficiency drivers. Using the data collected from a cross-sectional questionnaire to 300 passengers at the Kuala Lumpur International Airport (KLIA) for duration of two weeks, Leong et al. (2015) examined the effects of SERVPERF on customer satisfaction and loyalty under the Structural Equation Modeling (SEM)–artificial neural network approach. The findings show that 63.1% and 55.6% of variance in customer satisfaction and loyalty are explained are explained by SERVPERF. Using the US airline data between March 1st, 2020 to December 12th 2020, Truong (2021) examined the impact of COVID-19 on air travel using neural network and Monte Carlo simulation. The findings show that air travel is significantly affected by weekly economic index, daily trips by distance and travel restrictions. Rather than focusing on the airline industry, Wanke et al. (2023) investigate the sustainability of the Chinese transporation section and its drivers using the monthly data between January 1999 and December 2017, faciliated by the principal component analysis and neural networks. The findings show that trade and fixed asset investments, as well as monetary and fiscal policies have a signifcant and positive impact on sustainability in the Chinese transporation industry. The neural neworks approach was also proposed and applied in other economic sectors, such as the banking industry (Antunes et al., 2022).

3. Methodology

Aircraft emissions include CO2, CO, HC, NOx, SO2, and PM2.5 (Cui et al., 2022a, 2022b, 2022c). This paper uses emission data from China's domestic routes between 2014 and 2019, obtained from the Aviation Emissions Accounting Databases (http://www.aeads.com.cn/). The data covers emissions from both the Landing and Take-Off (LTO) cycle and the Climbing/Cruising/Descending (CCD) stage. The number of routes during this period was 311, 327, 367, 384, 415, and 492, respectively, while the number of flights was 1,947,211, 2,224,617, 2,277,024, 2,495,904, 2,610,068, and 3,116,880, respectively.

Table 1. Descriptive statistics summary for pollutants emitted and distance travelled between airports.

Variables	Unit	Criteria	Min	Max	Mean	Median	SD	CV	Skewness	Kurtosis
Distance	km	pc	245,02	3317,52	1223,54	1164,77	515,79	0,42	0,83	1,30
CO2 CCD		nc	3,53	1196316,00	20515,93	11663,47	32900,61	1,60	10,36	211,09
CO CCD		nc	3,12	3217,77	165,57	98,83	213,22	1,29	5,79	49,98
HC CCD		nc	0,01	373,07	15,64	9,11	23,31	1,49	6,75	66,17
NOx CCD		nc	0,31	6742,92	150,54	77,23	298,05	1,98	9,51	125,46
PM2.5 CCD		nc	0,04	49,57	2,16	1,28	2,84	1,32	5,96	54,14
SO2 CCD		nc	0,00	1466,50	25,15	14,30	40,33	1,60	10,36	211,09
CO2 LTO		nc	1,16	119981,81	4134,88	2315,42	5420,68	1,31	7,08	84,03
CO LTO		nc	0,33	385,36	17,24	9,72	21,70	1,26	6,43	65,66
HC LTO		nc	0,00	51,47	1,59	0,92	2,24	1,41	8,15	111,64
NOx LTO		nc	0,28	656,50	16,13	8,17	29,89	1,85	10,59	156,26
PM2.5 LTO		nc	0,01	7,37	0,26	0,14	0,36	1,39	7,87	96,44
SO2 LTO		nc	0,00	147,08	5,07	2,84	6,64	1,31	7,08	84,03

pc = positive criteria; nc = negative criteria
LTO = landing and take-off
CCD = climbing, cruising, and descending

Table 2. Descriptive statistics summary (for the airports of origin).

Variable	Unit	Type	Min	Max	Mean	Median	SD	CV	Skewness	Kurtosis
Elevation	meters	Runway	3,05	3566,16	313,98	66,14	494,37	1,57	2,27	5,18
Qnt Runways	unit	Runway	1,00	3,00	1,22	1,00	0,55	0,45	2,42	4,58
Runway Length (Mean)	meters	Runway	2200,00	3804,65	3371,85	3400,00	307,12	0,09	-1,24	1,16
Runway Width (Mean)	meters	Runway	44,80	60,00	49,33	45,10	6,08	0,12	0,93	-0,91
Surface Asphalt	unit	Runway	0,00	2,00	0,14	0,00	0,43	3,04	3,16	9,39
Surface Concrete	unit	Runway	0,00	3,00	1,03	1,00	0,60	0,58	0,95	2,82
Surface Part Concrete or Asphalt	unit	Runway	0,00	1,00	0,05	0,00	0,23	4,20	3,96	13,66
Approach Control	unit	Airport Infrastructuct	0,00	8,00	1,95	1,00	2,06	1,06	1,50	1,84
Automatic Terminal Information Service	unit	Airport Infrastructuct	0,00	2,00	1,09	1,00	0,38	0,35	0,85	3,13
Clearance Delivery	unit	Airport Infrastructuct	0,00	1,00	0,25	0,00	0,43	1,74	1,16	-0,64
Ground Control	unit	Airport Infrastructuct	0,00	5,00	1,16	1,00	0,82	0,70	3,06	12,36
Tower	unit	Airport Infrastructuct	1,00	3,00	1,18	1,00	0,46	0,39	2,52	5,68

Centerline Lighting System	unit	Lighting System	0,00	3,00	1,21	1,00	0,56	0,47	2,19	4,28
High Intensity Runway Lights	unit	Lighting System	0,00	3,00	1,16	1,00	0,50	0,43	1,76	4,51
ALSF 1	unit	Lighting System	0,00	1,00	0,82	1,00	0,38	0,46	-1,71	0,92
Precision Approach Path Indicator (PAPI)	unit	Lighting System	0,00	3,00	1,22	1,00	0,55	0,45	2,37	4,54
Center row	unit	Lighting System	0,00	1,00	0,00	0,00	0,04	24,28	24,24	585,47
Sequenced Flashing Lights	unit	Lighting System	0,00	3,00	0,91	1,00	0,80	0,88	0,91	0,75
Touchdown Zone Lighting	unit	Lighting System	0,00	3,00	0,58	0,00	0,70	1,21	1,32	2,12
ALSF 2	unit	Lighting System	0,00	3,00	0,46	0,00	0,71	1,54	1,73	3,08
Runway End Identifier Lights	unit	Lighting System	0,00	1,00	0,21	0,00	0,41	1,95	1,44	0,06
Lights	unit	Lighting System	0,00	2,00	0,32	0,00	0,63	1,97	1,78	1,78
SALS or SALSF	unit	Lighting System	0,00	1,00	0,12	0,00	0,33	2,65	2,27	3,17
Medium Intensity Runway Lighting System	unit	Lighting System	0,00	1,00	0,01	0,00	0,08	12,32	12,24	147,71

Table 3. Contextual Variables Descriptive statistics (for the airports of destination).

Variable	Unit	Type	Min	Max	Mean	Median	SD	CV	Skewness	Kurtosis
Elevation	meters	Runway	3,05	3566,16	284,55	32,61	548,35	1,93	3,00	10,97
Qnt Runways	unit	Runway	1,00	3,00	1,26	1,00	0,66	0,53	2,22	2,98
Runway Length (Mean)	meters	Runway	2566,10	3804,65	3374,77	3400,00	286,76	0,08	-1,14	0,79
Runway Width (Mean)	meters	Runway	44,80	60,00	47,53	45,10	4,93	0,10	1,74	1,32
Surface Asphalt	unit	Runway	0,00	2,00	0,28	0,00	0,56	2,00	1,88	2,47
Surface Concrete	unit	Runway	0,00	3,00	0,93	1,00	0,69	0,75	1,29	3,02
Surface Part Concrete or Asphalt	unit	Runway	0,00	1,00	0,05	0,00	0,21	4,46	4,24	15,94
Approach Control	unit	Airport Infrastructuct	0,00	8,00	2,11	1,00	2,39	1,13	1,45	0,99
Automatic Terminal Information Service	unit	Airport Infrastructuct	0,00	2,00	1,01	1,00	0,33	0,32	0,21	6,43
Clearance Delivery	unit	Airport Infrastructuct	0,00	1,00	0,27	0,00	0,44	1,66	1,05	-0,90
Ground Control	unit	Airport Infrastructuct	0,00	5,00	1,23	1,00	1,01	0,82	2,95	8,65
Tower	unit	Airport Infrastructuct	1,00	3,00	1,18	1,00	0,52	0,44	2,78	6,44
Centerline Lighting System	unit	Lighting System	0,00	3,00	1,24	1,00	0,67	0,54	2,17	3,06
High Intensity Runway Lights	unit	Lighting System	0,00	3,00	1,14	1,00	0,57	0,50	1,91	4,74
ALSF 1	unit	Lighting System	0,00	1,00	0,70	1,00	0,46	0,66	-0,85	-1,27
Precision Approach Path Indicator (PAPI)	unit	Lighting System	0,00	3,00	1,24	1,00	0,67	0,55	2,12	2,99
Center row	unit	Lighting System	0,00	1,00	0,02	0,00	0,13	7,84	7,71	57,39
Sequenced Flashing Lights	unit	Lighting System	0,00	3,00	1,14	1,00	0,77	0,67	1,41	1,85
Touchdown Zone Lighting	unit	Lighting System	0,00	3,00	0,78	1,00	0,81	1,04	1,09	1,01
ALSF 2	unit	Lighting System	0,00	3,00	0,65	0,00	0,84	1,29	1,31	1,16
Runway End Identifier Lights	unit	Lighting System	0,00	1,00	0,18	0,00	0,38	2,15	1,68	0,83
Lights	unit	Lighting System	0,00	1,00	0,13	0,00	0,34	2,55	2,16	2,67
SALS or SALSF	unit	Lighting System	0,00	1,00	0,15	0,00	0,35	2,43	2,02	2,06

Medium Intensity Runway Lighting System	unit	Lighting System	0,00	1,00	0,03	0,00	0,18	5,42	5,23	25,37

3.1. Weighted-Additive PUFs

In many cases, a decision-maker's preferences regarding the benefits derived from a specific product or service are captured through a utility function (Chakrabarti and Roy, 2010). Although this study does not specifically examine the preferences of decision-makers regarding consumption, in the context of overall environmental performance, we can conceptualize the utility function as the intrinsic benefit underlying different airlines' emission of fewer pollutants in relation to the distance traveled for a given airport pair.

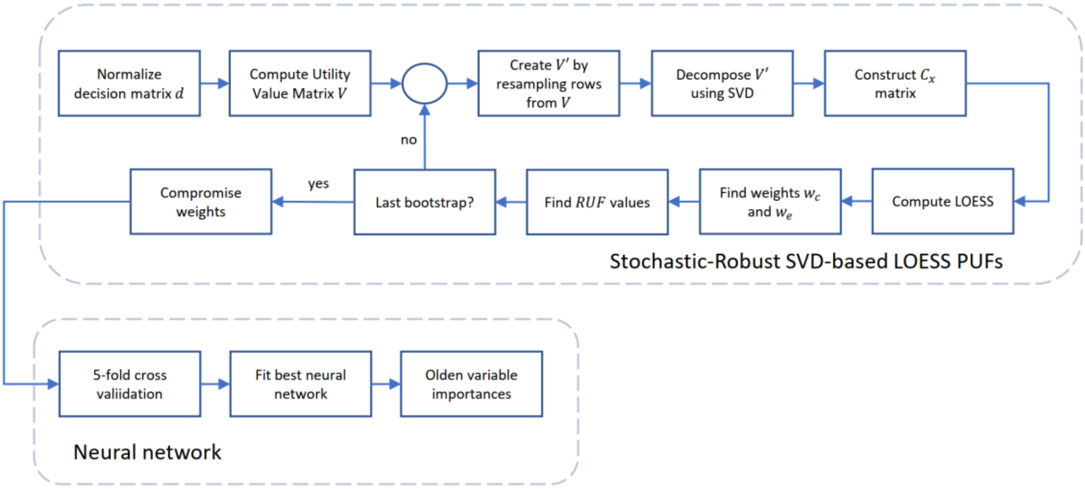

Figure 1 – Proposed methodology flowchart

Jacquet-Lagreze and Siskos (1982) introduced utility functions as popular techniques in multicriteria decision-making. This approach is easily comprehensible to decision-makers as it does not impose stricter constraints beyond the aggregation formula (Pavan and Todeschini, 2009). Typically, the process begins by normalizing the data locally for each criterion, ranging between 0 and 1, by considering the best and worst alternatives available.

Consider a set of d pairs of airline travels from a specific origin airport to a designated destination airport. o positive criteria $(pos_{d,o})$ and i negative criteria $(neg_{d,i})$ for performance are included in each pair, where d ranges from 1 to n, o ranges from 1 to m, and i ranges from 1 to s. The positive and negative criteria are represented by the matrices pos and neg, respectively, with dimensions of $n \times m$ and $n \times s$. The highest attainable utility value for each negative criterion i, across all d airline-travel pairs, is determined using the $max(neg_i)$ function. Similarly, the maximum utility value for each positive criterion o is obtained by applying the $max(pos_o)$ function to all d airline-travel pairs. The calculation of normalized values for each negative criterion i and positive criterion o for each airline is based on the reference values obtained from the maximum utility, as outlined below:

$$x_{d,o} = \frac{\left(pos_{d,o} - min(pos_o)\right)}{\left(max(pos_o) - min(pos_o)\right)} \quad \forall o, \forall d \tag{1}$$

$$x_{d,i} = \frac{\left(max(neg_i) - neg_{d,i}\right)}{\left(max(neg_i) - min(neg_i)\right)} \quad \forall i, \forall d \tag{2}$$

Let's consider $x_{d,o}$ as the normalized value of positive criterion o for airline-travel pair d, and $x_{d,i}$ as the normalized value of negative criterion i for airline d. Please note that the maximum values of positive criteria result in a normalized value of 1. On the contrary, the maximum values of negative criteria lead to a normalized value of 0. This facilitates the simultaneous incorporation of both positive and negative criteria in a normalized decision-making matrix x, which has a size of $nx(m+s)$. In Table 1, it is shown that distance represents the only positive criterion, while all other pollutants emitted during the travel between airports form the negative criteria.

Additionally, let us define w as a column vector of weights allocated to the criteria c represented in x, where c ranges from 1 to k, and k represents the total number of criteria, which is equal to $m+s$. For each alternative d, the overall utility value V is calculated in the following manner:

$$V_d = \sum_{c=1}^{k} x_{d,c} * w_c, \text{where } \sum_{c=1}^{k} w_c = 1 \tag{3}$$

Furthermore, the decision matrix V with weighted normalization ca be expressed as follows:

$$\mathbf{V} = \begin{bmatrix} x_{1,1} * w_1 & \cdots & x_{1,k} * w_k \\ \vdots & \ddots & \vdots \\ x_{d,1} * w_1 & \cdots & x_{d,k} * w_k \end{bmatrix} \tag{4}$$

In this depiction, V encapsulates the criteria with weighted normalization, with each sub-column vector representing the partial weighted utility vector for all airline-travel pairs (d) concerning a particular criterion (c). This matrix serves as a crucial element for interpreting the results of the singular value decomposition (SVD), as discussed in the subsequent section. The significance of this decision-making matrix representation is emphasized in the next section, as outlined by Wanke et al. (2022).

3.2. SVD

In this research, the singular value decomposition (SVD) method is utilized to examine a rectangular decision-making matrix V. This matrix comprises environmental performance criteria for every airline-travel combination. The SVD process decomposes the matrix into three separate components, as described by Alter et al. (2000) and Greenberg (2000):

$$V_{n\times k} = C_{n\times n} * S_{n\times k} * L_{k\times k}^{T} \tag{5}$$

Although the interpretations of these components may sometimes be complex (Klema and Laub, 1980), in the context of this study, it can be inferred that:

• The loading-factor matrix, denoted as L, captures the weights assigned to the k rotated criteria, which are derived through the use of "internal regressions", a method outlined by Jolliffe et al. (2003), which involves analyzing the original criteria to obtain the new set of criteria.

• The rotated criteria in L define the k-dimensional space, which is scaled by the matrix S. The singular values found in it represent the inherent significance or weight attributed to each rotated criterion. Acal et al. (2020) emphasize the significance of these singular values in determining the criteria's relative importance. To facilitate practical calculations, the singular values can be assigned as weights in the form of a column vector s, which is applied to the matrix C, following the suggestion by Drineas et al. (2004).

• The matrix C is assigned as the utility coefficient matrix for the decision matrix x. It consists of various sub-column vectors that represent the coefficients of rotation for the original alternatives d with respect to a specific criterion c, as explained by Zhao and Ye (2011). Consequently, the decision matrix obtained by multiplying C and x element-wise contains column vectors that represent the Partial Utility Functions (PUFs). These PUFs capture the utility values for all alternatives (or airline-travel pairs) d in relation to each criterion c.

$$\mathrm{C_x} = \begin{bmatrix} c_{1,1} * x_{1,1} & \cdots & c_{1,n} * x_{1,n} \\ \vdots & \ddots & \vdots \\ c_{d,1} * x_{d,1} & \cdots & c_{d,n} * x_{d,n} \end{bmatrix} \tag{6}$$

As elaborated in the subsequent section, the modeling of the relationships between $\mathrm{PUF}_c = f(\mathrm{x}_c)$ for all c involves the application of LOESS estimation. Here, PUF_c represents the sub-column vector specific to each criterion c within the decision matrix C_x, while x_c corresponds to the respective sub-column vector within the matrix x.

3.3. LOESS

Local polynomial regression, also known as moving regression, is an advanced technique that combines the concepts of polynomial regression and combined moving averages methods (Garimella, 2017). It encompasses various approaches, such as LOESS, which is a flexible non-parametric regression method. LOESS integrates polynomial regression models, specifically of degree 1 or 2, with a local search framework based on k-nearest neighbors (kNN) (Fox and Weisberg, 2018; Harrel, 2015). The key parameter of interest in LOESS is the coverage span of the neighboring data. In this research, the sum of squared residuals vector for each criterion c, known as the sum-square vector of the LOESS residual, is represented as $\mathrm{R_c}$ and is defined as follows:

$$R_c = \sum_{d=1}^{n} (\mathrm{PUF}_c - \mathrm{Ax}_c)^{\mathrm{T}} * \mathrm{w}_d\,(\mathrm{x}_c) * (\mathrm{PUF}_c - \mathrm{Ax}_c) \tag{7}$$

In the given scenario, a square matrix is denoted by A containing coefficients that correspond to the degree of the polynomial fit. In contrast, the vector w_d signifies a Gaussian vector comprising weights allocated to individual alternatives, d. These weights are calculated by considering the data range's mean and variance in the local vicinity, which is determined through a k-nearest-neighbor (kNN) search.

3.4. Compromise weighting

To explore different weighting schemes for the criteria, quadratic programming is employed as an additional technique. This approach presents a contrast to utilizing the singular value vector, ws, derived from equation (5)'s main diagonal of S. In this case, the matrices of joint entropy and square covariance are created for the residuals calculated in equation (7), and these matrices are then minimized by optimizing the weight vectors w_c and w_e, respectively. The aim of minimizing the residual covariance is to ensure an impartial overall financial performance when integrating various partial utility functions for each criterion (Keeney and Raiffa, 1993). On the other hand, minimizing joint entropy is closely associated with maximizing mutual information (Smith, 2015), which results in the optimal combination of criteria that facilitates continuous improvement initiatives and the ability to learn from one another (Greco et al., 2001). Consequently, the following relationship holds:

For the square matrix of residuals with minimal covariance $\left(\mathrm{Cov}(\mathrm{R}_c)\right)$

$$\begin{aligned}
&Minimize\ 0.5 * \mathrm{w}_c^{\mathrm{T}} * \mathrm{Cov}(\mathrm{R}_c) * w_c \\
&Subject\ to \\
&\sum\nolimits_{c=1}^{k} w_{c_c} = 1 \\
&0 \le w_{c_c} \le 1 \quad \forall c
\end{aligned} \tag{8}$$

For the square matrix of residuals with minimal Joint Entropy $\left(E(R_c)\right)$

$$\begin{aligned}
&Minimize\ w_e^T * E(R_c) * w_e \\
&Subject\ to \\
&\sum\nolimits_{c=1}^{k} we_c = 1 \\
&0 \le w_{e_c} \le 1 \ \forall c
\end{aligned} \tag{9}$$

In conclusion, the calculation of the overall rotated utility value (RUV) for each alternative (d) utilizing compromise weights involves the estimation of the LOESS value.

$$RUV_d = \sum\nolimits_{c=1}^{k} \overbrace{x_{d,c} * a_{d,c}}^{LOESS\ estimate} * \frac{wc_c + we_c + ws_c}{3} \tag{10}$$

Where:

$\sum_{c=1}^{k} wc_c = 1$

$\sum_{c=1}^{k} we_c = 1$

$\sum_{c=1}^{k} ws_c = 1$

3.5. Stochastic-Robust SVD-based LOESS PUFs

The complete proposed methodology is summarized in Figure 1, and the pseudo-code for Stochastic-Robust SVD-based LOESS PUFs is in Table 4. The procedures outlined in subsections 3.1 to 3.4 underwent 100 bootstrap replications. Each replication involved 100 line-resamples drawn randomly, without repetition, from the original decision matrix x.

Table 4. Pseudo-code.

1) Normalize decision matrix d matrix using equations (1) and (2)	
2) Compute Utility Value Matrix V following equation (4)	
3) for B from 1 to 100 do	
	3.1) Create Matrix V' by sampling rows from V
	3.2) Decompose V' using SVD
	3.3) Construct matrix C_x following equation (6)
	3.4) Compute LOESS following eq (7)
	3.5) Evaluate model (8) to find weights that minimize covariance matrix
	3.6) Evaluate model (9) to find weights that minimize joint entropy matrix
	3.7) Find RUV values for criteria d following equation (10)
end loop	

Given:

- $\boldsymbol{d}$**:** Set of pairs of airline travels (decision matrix)
- $\boldsymbol{n_{boot}}$**:** Number of bootstraps replications

Step 1: Normalize decision matrix d using equations (1) and (2):

$$x_{d,o} = \frac{\left(pos_{d,o} - min(pos_o)\right)}{\left(max(pos_o) - min(pos_o)\right)} \quad \forall o, \forall d$$

$$x_{d,i} = \frac{\left(max(neg_i) - neg_{d,i}\right)}{\left(max(neg_i) - min(neg_i)\right)} \quad \forall i, \forall d$$

Step 2: Compute Utility Value Matrix V following equation (4):

$$\mathbf{V} = \begin{bmatrix} x_{1,1} * w_1 & \cdots & x_{1,k} * w_k \\ \vdots & \ddots & \vdots \\ x_{d,1} * w_1 & \cdots & x_{d,k} * w_k \end{bmatrix}$$

Step 3: for B from 1 to n_{boot} do:

- **Step 3.1:** Create Matrix V' by sampling rows from V
- **Step 3.2:** Decompose V' using SVD such that $V'_{n\times k} = C_{n\times n} * S_{n\times k} * L^T_{k\times k}$
- **Step 3.3:** Construct matrix C_x following equation (6)

$$C_x = \begin{bmatrix} c_{1,1} * x_{1,1} & \cdots & c_{1,n} * x_{1,n} \\ \vdots & \ddots & \vdots \\ c_{d,1} * x_{d,1} & \cdots & c_{d,n} * x_{d,n} \end{bmatrix}$$

- **Step 3.4:** Compute LOESS following eq (7)

$$R_c = \sum_{d=1}^{n} (\mathrm{PUF}_c - \mathrm{Ax}_c)^{\mathrm{T}} * \mathrm{w}_d\,(\mathrm{x}_c) * (\mathrm{PUF}_c - \mathrm{Ax}_c)$$

- **Step 3.5:** Evaluate model (8) to find weights that minimize covariance matrix

$$\begin{aligned} &Minimize\ 0.5 * \mathrm{w}_c^{\mathrm{T}} * \mathrm{Cov}(\mathrm{R}_c) * w_c \\ &Subject\ to \\ &\sum_{c=1}^{k} w_{c_c} = 1 \\ &0 \le w_{c_c} \le 1 \quad \forall c \end{aligned}$$

- **Step 3.6:** Evaluate model (9) to find weights that minimize joint entropy matrix

$$\begin{aligned} &Minimize\ w_e^T * E(R_c) * w_e \\ &Subject\ to \\ &\sum_{c=1}^{k} we_c = 1 \\ &0 \le w_{e_c} \le 1 \ \forall c \end{aligned}$$

- **Step 3.7:** Find RUV values for criteria d following equation (10)

$$RUV_d = \sum_{c=1}^{k} \overbrace{x_{d,c} * a_{d,c}}^{LOESS\ estimate} * \frac{wc_c + we_c + ws_c}{3}$$

Investigating the relationship between airport infrastructure characteristics and the environmental performance of airlines holds significant societal benefits. Firstly, such research can lead to more sustainable and eco-friendly air travel practices, reducing the aviation industry's environmental impact. This includes lowering greenhouse gas emissions, noise pollution, and air quality degradation in and around airports, which directly benefits nearby communities and the environment.

Moreover, understanding how infrastructure features like runway length and width, surface materials (asphalt or concrete), and lighting systems impact environmental performance can inform airport planning and development. It can guide decisions on runway design, construction materials, and lighting technologies, aiming for greater efficiency and reduced environmental disruption during airport expansions or renovations.

Investigations into infrastructure characteristics also promote safety and operational efficiency. For instance, automatic terminal information services, clearance delivery, ground control, and tower systems not only contribute to environmental performance but also enhance the overall safety and reliability of air travel. This directly benefits passengers, airline staff, and aviation professionals by reducing the risk of accidents and delays.

In summary, research into the interplay between airport infrastructure characteristics and the environmental performance of airlines leads to a more sustainable, efficient, and safer aviation sector. These improvements benefit society by reducing environmental harm, enhancing safety, and improving the overall quality of air travel experiences for passengers and communities surrounding airports.

4. Analysis and Discussion of Results

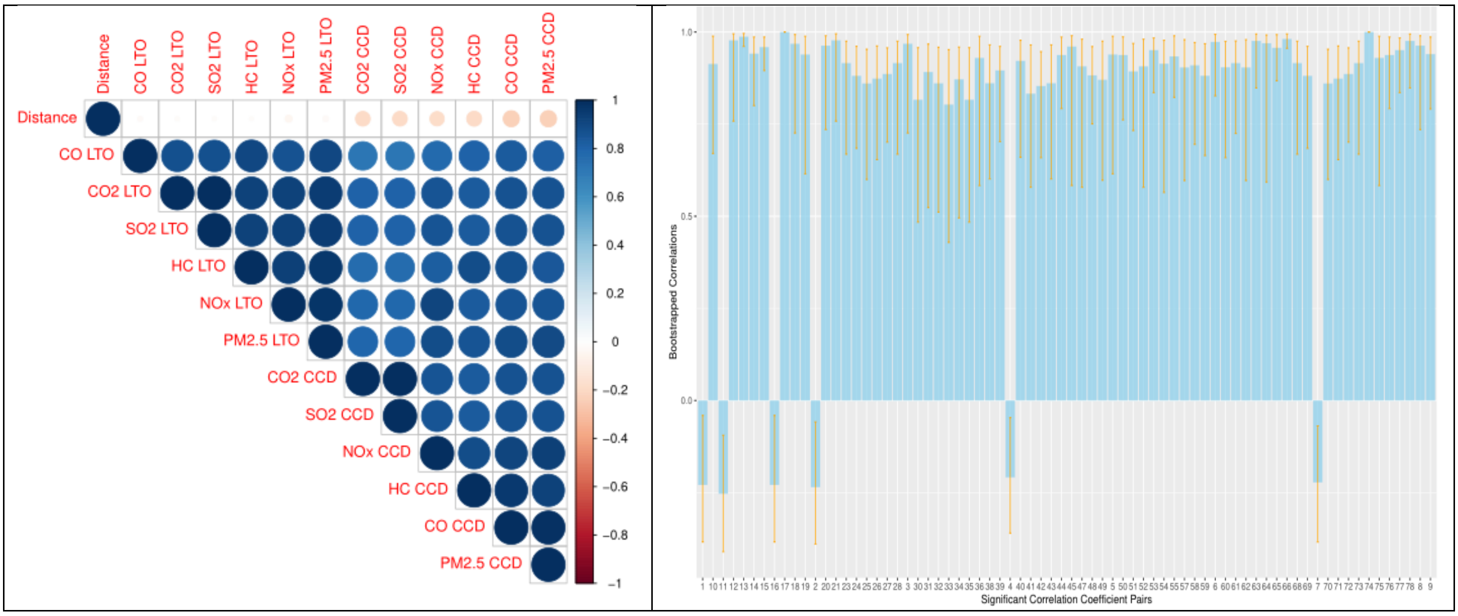

Fig. 2. Correlogram (left) and significant correlation pairs (right).

Fig. 2 illustrates the correlation findings for both the original and bootstrapped decision matrices. While it is expected for distance and pollutant emissions to be strongly and positively correlated in both LTO and CCD operations, one can note some significantly negative correlated pairs. These appear to be the key criterion for achieving higher overall environmental performance in Chinese airlines. According to the significant correlation pair list reported in Appendix 1, distance is negatively correlated with CO2, CO, and NOx emissions in CCD, and with PM2.5 and CO2 in LTO. This suggests the existence of groups of airports where infrastructure can play a significant role in reducing pollutant emissions. It is also noteworthy that there is a negative correlation pair between CO2 and PM2.5 emissions in CCD. This suggests that airport infrastructure could have an impact on pollutant emissions during climbing, descent operations, and cruise control.

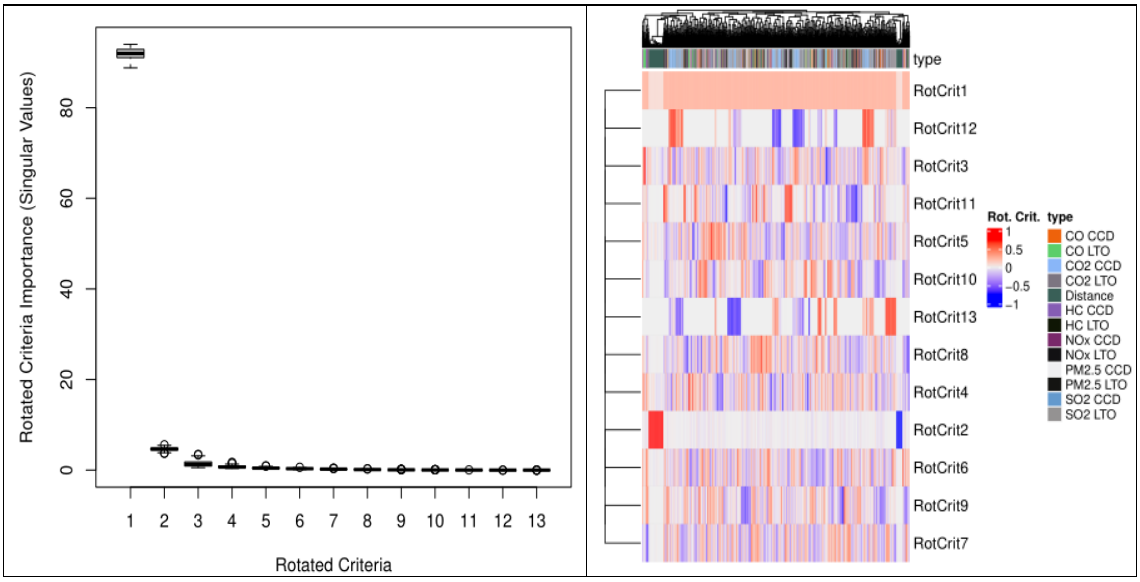

Fig 3. Bootstrapped results for the singular values (**S**, on the left) and respective factor loadings (**L**, on the right).

An intricate relationship network between positive and negative criteria is suggested by the results of the bootstrapped rotated criteria, as shown in Fig. 3. It can be easily observed that the most important rotated criteria predominantly determine the overall importance of the SVD, accounting for over 90% of the importance. Additionally, this set of criteria is almost equally composed of the original criteria. In contrast, the weights for the remaining rotated criteria vary significantly among the original criteria (refer to Fig. 3 on the right). Despite their declining importance, the remaining rotated criteria still contribute to the prediction of the overall utility function, which serves as a proxy for environmental performance concerning the distance between airports. This contribution is possible because these criteria reflect different trade-off balances among the original criteria, resulting in noticeable contrasts represented by the colors red and blue.

The results obtained from the quadratic programming solutions for different weighting schemes of the rotated criteria, considering both the minimal covariance and joint entropy matrices, are presented in Figure 4 and Table 5. It is important to note that while rotated criterion 1 continues to hold the highest average importance, the relative significance of the other rotated criteria differs significantly from what is derived from the singular value decomposition (SVD). This finding suggests that the computation paths, whether through unbiased utility function calculation using the minimal covariance matrix or through learning approaches that facilitate continuous improvement where one criterion can be learned based on another due to maximal mutual entropy, deviate from the orthonormal base of the rotated criteria established by singular values.

Table 5 presents the optimal average span values for the LOESS estimation of each rotated criterion. The average span values range from 0.74 to 0.85, with an overall compromise average span value of 0.80 being used. Furthermore, a polynomial degree of order 1 is applied when calculating the overall financial performance, approximated by the utility functions. These calculations are performed using the original decision matrix and the compromise weighting outlined in Table 5.

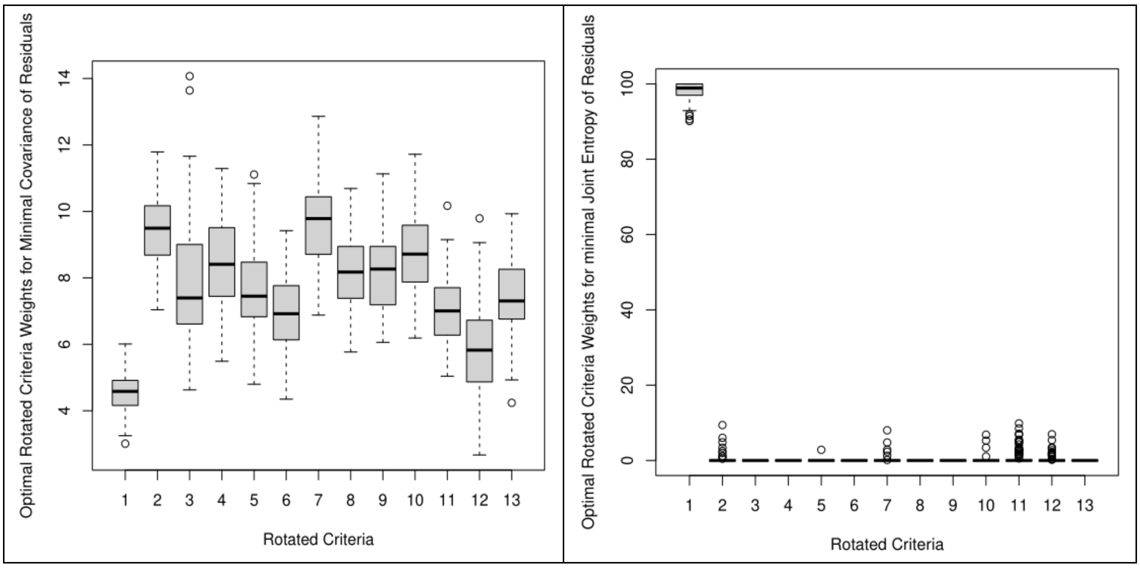

Fig. 4. Bootstrapped results for w_c (left) and w_e (right) weight vectors.

Table 5. Compromise weights summary (Bootstrap averages)

Rotated Criteria	Importance Weights (Singular Values)	Minimal Covar of Residuals (Minimal Bias)	Minimal JE of Residuals (Maximum MI)	Mean Compromise Weights	Optimal Span Values	Polynomial Fit of Order
1	91.88	4.56	98.04	64.83	0.814	1
2	4.66	9.4	0.31	4.79	0.742	1
3	1.4	7.82	-	3.07	0.78	1
4	0.76	8.5	-	3.09	0.827	1
5	0.47	7.64	0.03	2.71	0.779	1
6	0.33	6.93	-	2.42	0.805	1
7	0.22	9.69	0.19	3.37	0.816	1
8	0.13	8.27	-	2.8	0.802	1
9	0.07	8.18	-	2.75	0.811	1
10	0.05	8.78	0.17	3	0.819	1
11	0.02	7.01	0.85	2.63	0.832	1
12	-	5.86	0.41	2.09	0.846	1
13	-	7.36	-	2.45	0.814	1

Figure 5 illustrates the collective environmental performance of Chinese airline travel between airport pairs, represented by the weighted sum of partial utility functions, using different weighting schemes. The figure demonstrates that the environmental performance of Chinese airline travel remains relatively consistent across various weighting schemes when considering 10 or more rotated criteria in the computation of the utility function. However, the utility function, calculated using mean compromise weights from Table 5, was used as the dependent variable in a neural network regression. In this regression, the characteristics of both the origin and destination airport infrastructure (refer to Tables 2 and 3) were used as explanatory variables.

In terms of the neural network design, Figure 6 presents the results of 5-fold cross-validation for various alternative structures, including the number of layers (ranging from 1 to 4) and the number of neurons per layer (ranging from 100 to 400). The figure shows that the lowest Mean Absolute Error (MAE) values were obtained with a four-layer architecture consisting of over 300 neurons. To analyze the sensitivity of the neural network architecture, Olden et al. (2004) proposed analytical steps. Figure 7 displays the results of this analysis, showing the relative importance of infrastructure characteristics for both the origin and destination airports in terms of their impact on environmental performance.

Readers should note that infrastructure characteristics were clustered by similarity, for the sake of readability and interpretation of results, into three smaller plots, namely: (overall) infrastructure, runway (infrastructure), and lighting (infrastructure). As regards the infrastructure features with the highest positive impact on environmental performance, it is noteworthy: the ground control in both origin and destination airports, as well as automatic information service in origin airports; the existence of surface concrete in the runways of both origin and destination airports; the centerline lighting system in destination airports. On the other hand, as regards the negative impacts on infrastructure performance, larger runway length and width in origin airports, longer distances to the control tower in origin airports, and asphalt runways in destination airports appear to be keys for improvement and design of public policies to better align Chinese airports with ESG initiatives.

The research bridged a significant knowledge gap by highlighting the role of airport infrastructure in determining airlines' environmental performance. It showcased the importance of factors often overlooked, like runway materials and lighting systems, thus providing a nuanced understanding of their influence. By employing a novel combination of SVD, LOESS, and neural networks, the study introduced a new paradigm in the analysis of airlines' environmental performance. This approach yields more nuanced insights and offers a template for future studies in the field. The study’s findings bear significant policy implications, providing policymakers with concrete data and insights to inform future sustainable infrastructure development, ultimately contributing to global efforts to mitigate climate change.

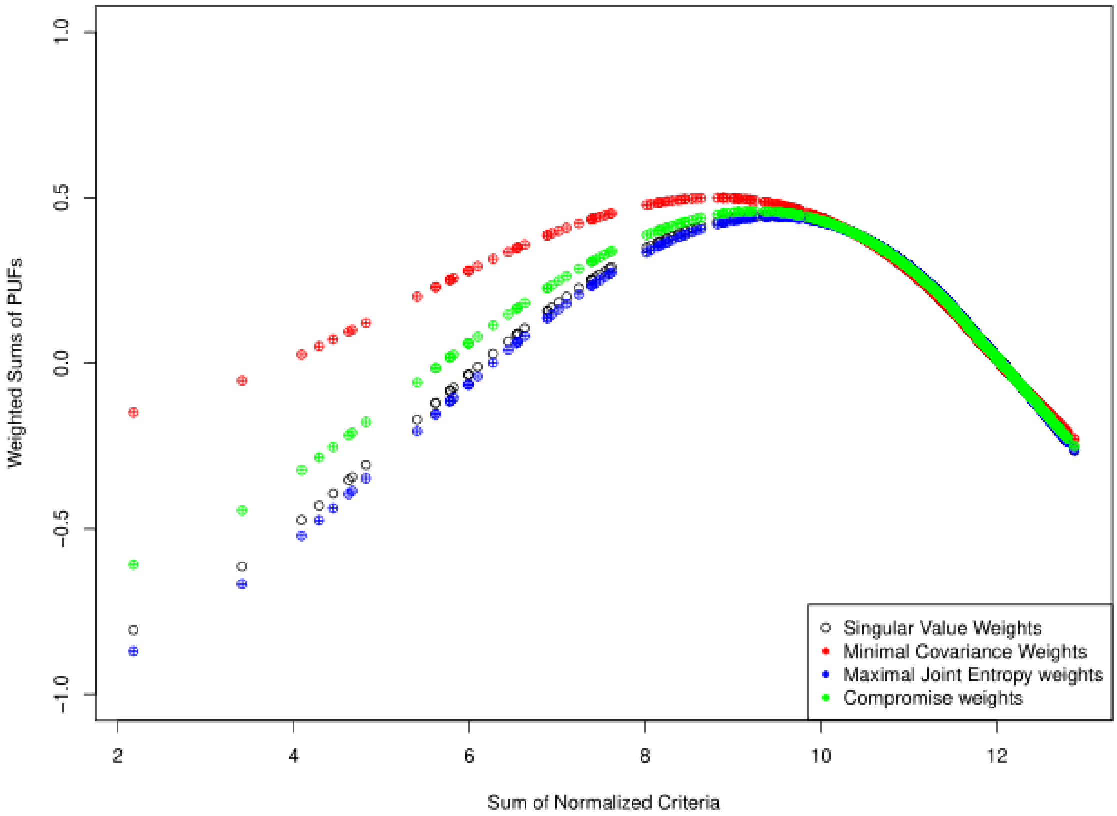

Fig. 5. Overall environmental performance (as proxied by utility functions) for Chinese airline travels between airport pairs under different weighting assumptions.

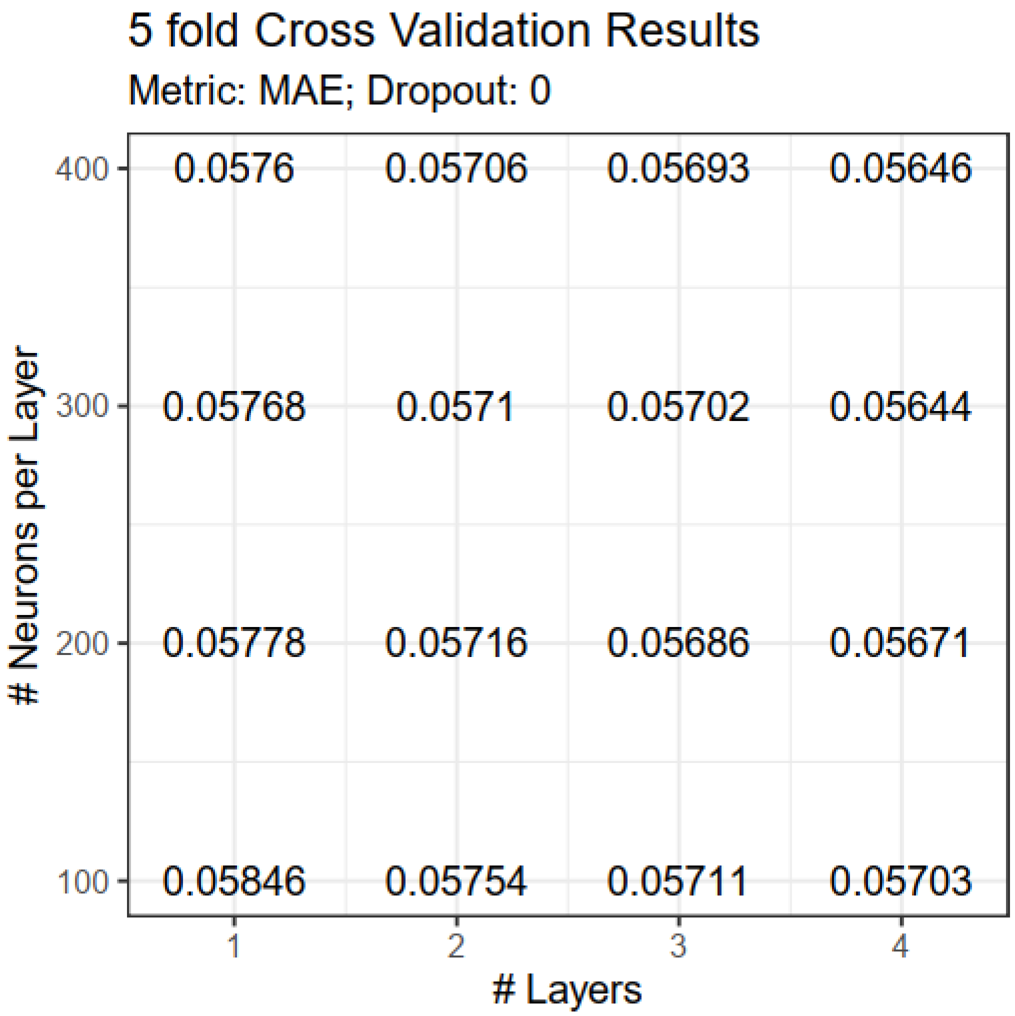

Fig. 6. 5-fold cross-validation results

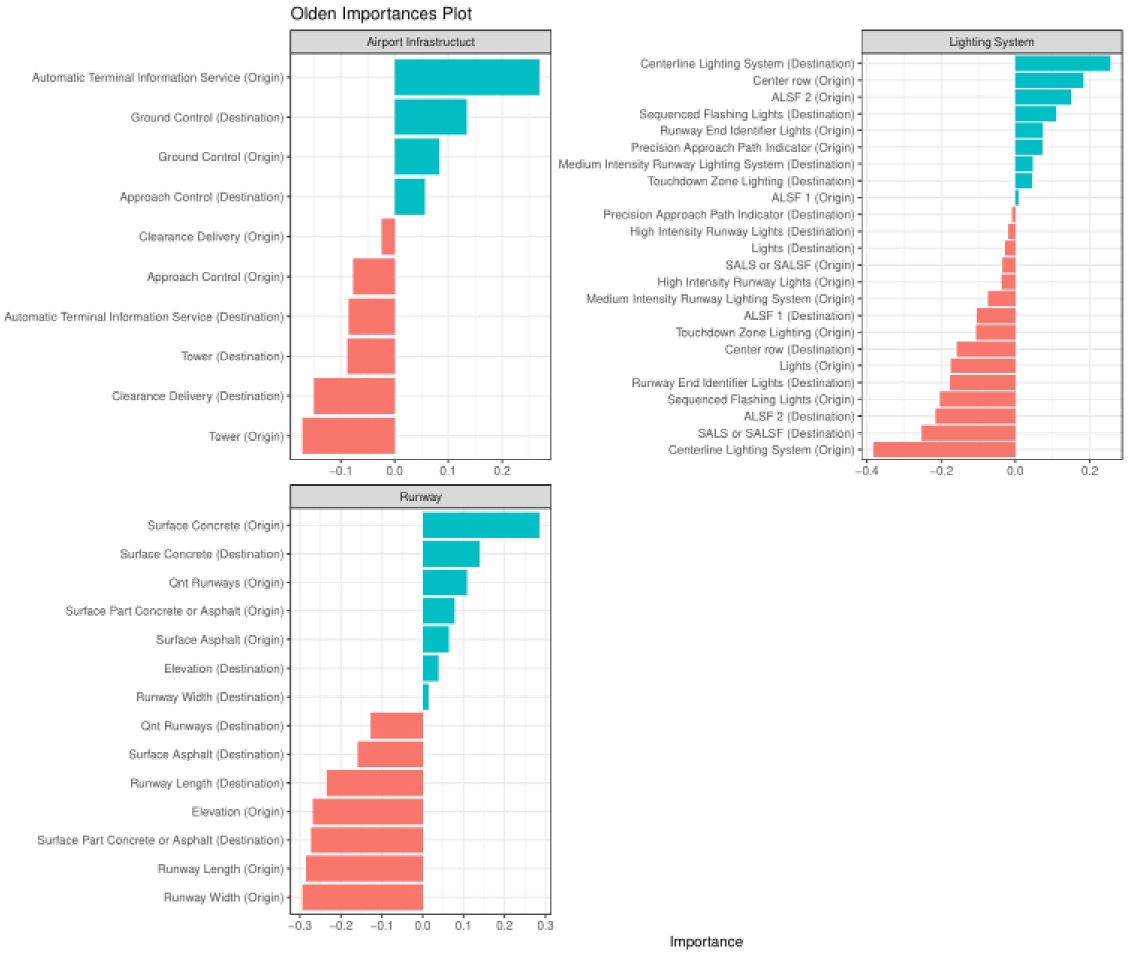

Fig. 7. Olden et al. (2004) sensitivity analysis on relative importance of business environment variables.

5. Conclusions

The environmental performance of Chinese airlines is becoming increasingly important due to growing concerns over climate change and air pollution. China is the world's largest emitter of greenhouse gases, and its aviation industry is one of the fastest growing in the world. Therefore, the environmental impact of Chinese airlines has significant global implications. There is a growing demand from both customers and regulators for airlines to adopt more environmentally friendly practices, such as investing in more fuel-efficient aircraft and reducing their carbon emissions. Improving the environmental performance of Chinese airlines is not only important for meeting global climate targets, but it can also help to reduce air pollution in China's cities, where poor air quality is a major public health concern. Therefore, it is essential that Chinese airlines prioritize their environmental performance to reduce their carbon footprint, improve their operational efficiency, and demonstrate their commitment to sustainable development. Figure 8 resumes the main findings of this work.

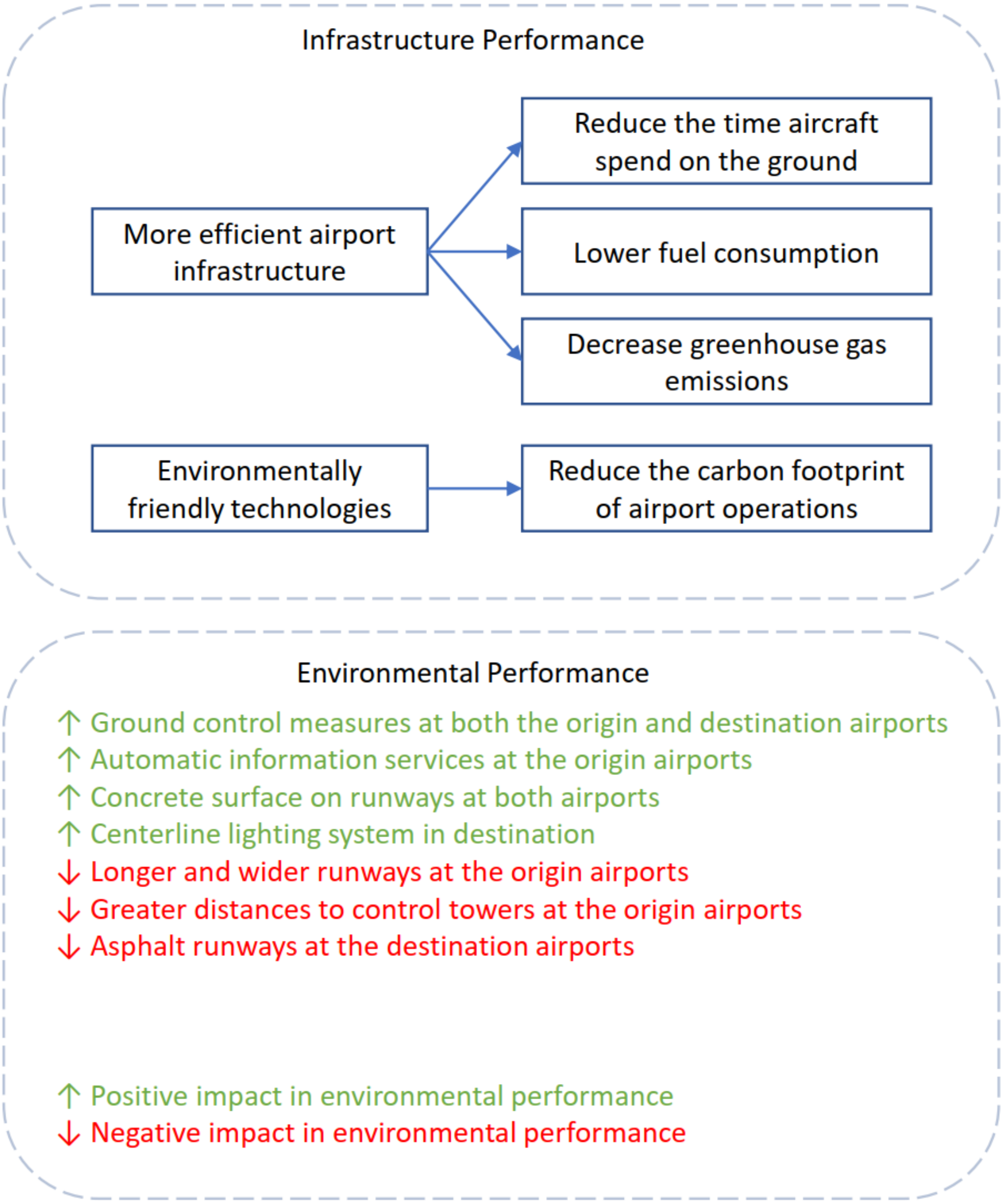

Figure 8 – Main findings of Chinese Environmental Performance of Airlines

There is a strong link between airport infrastructure and the environmental performance of Chinese airlines. The infrastructure of airports, including runways, terminals, and support facilities, has a significant impact on the energy consumption and carbon emissions of airlines. More efficient airport infrastructure can help to reduce the time aircraft spend on the ground, lower fuel consumption, and decrease greenhouse gas emissions. Additionally, the use of more environmentally friendly technologies, such as electric ground support equipment and renewable energy sources, can further reduce the carbon footprint of airport operations. The Chinese government has recognized the importance of sustainable airport infrastructure and has made significant investments in the development of green airports, including the implementation of renewable energy technologies and the use of eco-friendly building materials. As such, improving the environmental performance of Chinese airlines requires a comprehensive approach that involves not only airlines but also airports and the broader transportation system. Collaborative efforts between airlines and airports to adopt more sustainable practices can lead to significant reductions in carbon emissions and contribute to global efforts to address climate change.

The current study significantly contributes to the literature in airport transportation and sustainability by proposing an innovative method to investigate the environmental performance of Chinese airports based on weighted additive utility functions given the distance travelled between airports. In addition, the impact of several infrastructure characteristics of origin and destination airports on environmental performance is examined through neural networks. Our findings suggest that ground control measures at both the origin and destination airports, along with automatic information services at the origin airports, and the presence of surface concrete on runways at both airports and a centerline lighting system in destination airports, have a noteworthy and favorable effect on environmental performance. Conversely, longer and wider runways at the origin airports, greater distances to control towers at the origin airports, and asphalt runways at the destination airports have a significant and detrimental impact.

Managerial implications

The research findings presented in this study offer valuable insights with direct managerial policy implications for the Chinese aviation industry. To encourage more sustainable practices, policymakers could incentivize the adoption of environmentally friendly technologies and processes in airport construction and operations. This could include mandating the use of surface concrete on runways, investing in more efficient lighting systems, and providing support for the adoption of renewable energy technologies. Additionally, policymakers could focus on reducing the negative impact of infrastructure factors that have a significant impact on the environment, such as longer and wider runways and greater distances to control towers. By prioritizing sustainable airport infrastructure, policymakers can support the transition to a more environmentally friendly aviation industry in China and contribute to global efforts to mitigate the impact of climate change.

Theoretical Policy Implications:

From a theoretical standpoint, this research contributes to the development of environmental performance assessment methodologies within the aviation sector. The introduction of the environmental performance index based on weighted additive utility functions offers a theoretical framework for evaluating airlines' sustainability efforts. Researchers and policymakers can further refine this approach and adapt it to other regions and industries, contributing to the broader field of environmental performance measurement. The research also highlights the importance of airport infrastructure characteristics in influencing environmental performance. The theoretical implication is that infrastructure investments should be considered as a strategic aspect of sustainability policy. Policymakers can explore incentives or regulations that encourage airports to adopt eco-friendly infrastructure practices. Additionally, the study underscores the importance of runway design and materials in reducing emissions. This insight can inform theoretical discussions on the environmental impact of infrastructure development, guiding policymakers in making informed decisions regarding runway construction and maintenance. In summary, this research not only offers practical guidance for airlines and airports to improve environmental performance but also contributes to the theoretical development of sustainability assessment methodologies and infrastructure-related policy discussions within the aviation industry and beyond.

Although the current study proposed an innovative method to evaluate the environmental performance for Chinese airlines and used neural networks to predict the impact of several infrastructure characteristics of origin and destination airports on environmental performance, it still suffers a number of limitations as below: 1) the current study lacks the robustness check regarding the measurement of environmental performance; 2) lack of robustness check is also related to the investigation into the determinants of environmental performance. Besides the issue of lack of robustness, the data used in the current study covers the period between 2014 and 2019, considering that we are now nearly reaching the end of 2023, the data is a bit out of date. Finally, the current study focuses on the overall environmental performance evaluation, little insights can be provided in terms of the specific performance of different dimensions of environmental performance, which limits itself from its inability to provide more accurate and concrete policy implications.

In order to deal with the above-mentioned limitations, we suggest that future research can focus on the following aspects: 1) the level of environmental performance can be double checked through using an alternative estimation technique. One of the methods that can be considered to use for this robustness check is the non-parametric data envelopment analysis (Wang et al., 2017); 2) the robustness of the results regarding the determinants of environmental performance can be further checked by using an altermative method. Some of the advanced methods that could be considered as an alterantive approach including the Geodetector model (Guo et al., 2022) and the integrated Multi-Layer Perceptron/Hidden Markov model (Tan et al., 2021); 3) future research can also consider to expand the data period to the most recent year, i.e. up to 2022, to see whether the results hold; 4) in order to provide more detailed information regarding the level of enviornmental performance and consequently make more concrete policy implications, future research could consider to decompose the overall environmental performance into different dimensions, including emission reduction, resource reduction and production innovation (Tan et al., 2017).

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Appendix. Significant criteria correlation pairs (legends to Fig. 1 – right).

Code	Significant Correlation Pair	Sign
[1]	**"Distance CO2 CCD"**	**(-)**
[2]	**"Distance CO CCD"**	**(-)**
[4]	**"Distance NOx CCD"**	**(-)**
[11]	**"Distance PM2.5 LTO"**	**(-)**
[7]	**"Distance CO2 LTO"**	**(-)**
[3]	"Distance HC CCD"	(+)
[5]	"Distance PM2.5 CCD"	(+)
[6]	"Distance SO2 CCD"	(+)
[8]	"Distance CO LTO"	(+)
[9]	"Distance HC LTO"	(+)
[10]	"Distance NOx LTO"	(+)
[12]	"Distance SO2 LTO"	(+)
[16]	**"CO2 CCD PM2.5 CCD"**	**(-)**
[13]	"CO2 CCD CO CCD"	(+)
[14]	"CO2 CCD HC CCD"	(+)
[15]	"CO2 CCD NOx CCD"	(+)
[17]	"CO2 CCD SO2 CCD"	(+)
[18]	"CO2 CCD CO2 LTO"	(+)
[19]	"CO2 CCD CO LTO"	(+)
[20]	"CO2 CCD HC LTO"	(+)
[21]	"CO2 CCD NOx LTO"	(+)
[23]	"CO2 CCD SO2 LTO"	(+)
[24]	"CO CCD HC CCD"	(+)
[25]	"CO CCD NOx CCD"	(+)
[26]	"CO CCD PM2.5 CCD"	(+)
[27]	"CO CCD SO2 CCD"	(+)
[28]	"CO CCD CO2 LTO"	(+)
[30]	"CO CCD HC LTO"	(+)
[31]	"CO CCD NOx LTO"	(+)
[32]	"CO CCD PM2.5 LTO"	(+)
[33]	"CO CCD SO2 LTO"	(+)
[34]	"HC CCD NOx CCD"	(+)

[35]	"HC CCD PM2.5 CCD"	(+)
[36]	"HC CCD SO2 CCD"	(+)
[38]	"HC CCD CO LTO"	(+)
[39]	"HC CCD HC LTO"	(+)
[40]	"HC CCD NOx LTO"	(+)
[41]	"HC CCD PM2.5 LTO"	(+)
[42]	"HC CCD SO2 LTO"	(+)
[43]	"NOx CCD PM2.5 CCD"	(+)
[44]	"NOx CCD SO2 CCD"	(+)
[45]	"NOx CCD CO2 LTO"	(+)
[47]	"NOx CCD HC LTO"	(+)
[48]	"NOx CCD NOx LTO"	(+)
[49]	"NOx CCD PM2.5 LTO"	(+)
[50]	"NOx CCD SO2 LTO"	(+)
[51]	"PM2.5 CCD SO2 CCD"	(+)
[52]	"PM2.5 CCD CO2 LTO"	(+)
[53]	"PM2.5 CCD CO LTO"	(+)
[54]	"PM2.5 CCD HC LTO"	(+)
[55]	"PM2.5 CCD NOx LTO"	(+)
[57]	"PM2.5 CCD SO2 LTO"	(+)
[58]	"SO2 CCD CO2 LTO"	(+)
[59]	"SO2 CCD CO LTO"	(+)
[60]	"SO2 CCD HC LTO"	(+)
[61]	"SO2 CCD NOx LTO"	(+)
[62]	"SO2 CCD PM2.5 LTO"	(+)
[63]	"SO2 CCD SO2 LTO"	(+)
[64]	"CO2 LTO CO LTO"	(+)
[65]	"CO2 LTO HC LTO"	(+)
[66]	"CO2 LTO NOx LTO"	(+)
[68]	"CO2 LTO SO2 LTO"	(+)
[69]	"CO LTO HC LTO"	(+)
[70]	"CO LTO NOx LTO"	(+)
[71]	"CO LTO PM2.5 LTO"	(+)
[72]	"CO LTO SO2 LTO"	(+)
[73]	"HC LTO NOx LTO"	(+)
[74]	"HC LTO PM2.5 LTO"	(+)
[75]	"HC LTO SO2 LTO"	(+)
[76]	"NOx LTO PM2.5 LTO"	(+)
[77]	"NOx LTO SO2 LTO"	(+)
[78]	"PM2.5 LTO SO2 LTO"	(+)