The competitiveness of global cargo airports employing the Best-Worst Method

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Abstract

Purpose – The global economy and air transport business have been negatively affected owing to the COVID-19 pandemic outbreak. As countries tighten restrictions on international movements, the growing emphasis on air cargo places pressure on airports to maintain and upgrade their cargo policies, facilities and operations. Hence, ensuring the competitiveness of cargo airports is pivotal for their survival under volatile global demand. This study aims to evaluate the importance of competitiveness factors for cargo airports and identify areas for further improvement.

Design/methodology/approach – This study applies the Best-Worst Method (BWM) to assess the cargo airports' competitiveness factors.

Findings – The results identified "Transport Capacity" as the most significant competitiveness factor, implying that airport connectivity is crucial in promoting cargo transportation at hub airports. This result was followed by "Airport Operations' and Facilities' Capacity" and "Economic Growth.". Additionally, the results identified Hong Kong International Airport as the best-performing cargo airport, followed by Aéroport de Paris-Charles de Gaulle and Incheon International Airport, respectively. Furthermore, both selected European airports are the most competitive airports in terms of "Financial Performance" and appear to be aware of the significance of their brand value.

Originality/value – This study forms a reference framework for evaluating cargo airports' competitive positions, which may help identify airports' relative strengths and weaknesses. Moreover, this framework can also serve as a tool to facilitate the strategic design of airports that can accommodate air cargo demand flexibly under demand uncertainty.

Keywords Cargo airports, Competitiveness, Airport competitiveness, Best-Worst Method

Paper type Research paper

1. Introduction

Cargo airports are dynamic hubs that hold a critical position in boosting the global economy and promoting international trade, thereby facilitating the seamless and rapid daily movement of goods worldwide. According to the International Air Transport Association (IATA), airlines manage approximately 35% of global trade by value annually, accounting for USD 5.5 trillion worth of goods per year (IATA, 2017). Additionally, air transport critically contributes in fostering economic growth and competitiveness (Stichhauerova and Pelloneova, 2019); thus, countries with 1% better air cargo policies engage in 6% more

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trade, and governments implementing such policies may boost their trade competitiveness globally (IATA, 2017). Air cargo is a solid measure of trade and GDP growth (Kasarda and Green, 2005). However, in light of the global COVID-19 outbreak and tight restrictions on international movements, the airline industry began executing cargo operations using passenger aircraft. This plays an enormous role in communicating the best practices among stakeholders in the air cargo supply chain (Hughes, 2021), which places a significant burden on airports to maintain and upgrade their cargo policies, facilities and operations. Consequently, ensuring the competitiveness of cargo airports is pivotal for their survival under unforeseeable volatile global demand.

This study measures the competitiveness of airports classified as international primary hubs (Mayer, 2016) that function as both commercial and cargo airports (Maynard *et al.*, 2015). This study selected four major international airports – geographically concentrated in the world's major economic centers – for a case study based on the data availability. Owing to data limitations, the airports under investigation only include Heathrow Airport (LHR), Aéroport de Paris-Charles de Gaulle (CDG), Hong Kong International Airport (HKG) and Incheon International Airport (INC) [1].

Air cargo volumes increased 18.7% year over year in 2021, the second-best annual performance since 1990. Cargo tonne-kilometres (CTKs) rose 3.5% from 2018s peak. The strong demand in 2021 boosted global goods trade by 9.8%, and air cargo growth was twice as strong as the rebound in trade. However, during such times, businesses often face surging demand and turn to air cargo to meet it quickly, resulting in an inventory restocking cycle. Therefore, supply chain issues in 2021 made air cargo more attractive than maritime shipping (IATA, 2021). Hence, with a such sudden rise in demand and insufficient global cargo capacity, ensuring the competitiveness of cargo airports is pivotal for their survival under volatile global demand. Therefore, based on a thorough review of the literature, the applicability and measurability of the factors using Best-Worst Method (BWM), this study identifies 11 evaluation criteria in total to provide an updated framework for comprehensively evaluating cargo airports' competitiveness. The study adopts nine criteria commonly explored in previous research and expands the framework to include two other criteria "Annual Revenue" and "Airport Brand Value". The study then categorizes these criteria into five key evaluation criteria, including sub-criteria, for evaluating cargo airport competitiveness. The main criteria include the following: (1) transport capacity, (2) airport operations and facility capacity, (3) economic growth, (4) financial performance, and finally and (5) airport brand value.

This study differs from previous studies in that it assesses various measurement dimensions derived from previous studies to evaluate the competitiveness of cargo airports, adopting a recent Multi-Criteria Decision-Making Method (MCDM), the BWM, introduced by Rezaei (2015, 2016). The BWM uses substantially fewer pairwise comparisons, reducing the decision-making inconsistency, which is a major concern in other MCDM methods, such as Saaty's Analytical Hierarchy Process (AHP). This study uses this methodology to evaluate cargo airports' competitiveness factors, based on surveys circulated among airport experts in South Korea. This approach integrates numerical data and experts' opinions in the airport industry, thus precipitating a more efficient and informed decision-making process (Chakraborty *et al.*, 2020). Hence, to address the gap in the existing literature, this study aims to achieve the following two objectives concerning cargo airports: (1) to evaluate the importance of the competitiveness factors with respect to cargo airports and (2) to rank the cargo airports' competitive position and identify areas for further improvement.

The analysis may help decision-makers at cargo airports identify areas of strength and weaknesses and evaluate the related performance for current or future business implementation pertaining to air cargo.

The remainder of this paper is structured as follows: Section 2 highlights the status of the aviation industry and the existing literature on airport competitiveness and performance. Section 3 introduces the BWM and the ranking methodology of factors and airports. Section 4 summarizes the results of the competitive position of cargo airports. Section 5 discusses the findings. Section 6 presents the concluding remarks.

2. Literature review

The world has changed dramatically since the beginning of the global outbreak of COVID-19. The closing of international borders to prevent the spread of the virus has paralyzed the free flow of trade, consequently bringing the global economy to a near standstill (World Bank, 2020). Sun *et al.* (2021) uncovered the COVID-19 pandemic's impact on both air transport flows and airline businesses worldwide. They suggested recommendations for future studies to examine the expansion of cargo flights as a replacement for passenger transportation, explore using the free cabin space for cargo and consider the potential of combined cargo and passenger operations. Thus, we surveyed the relevant available literature on the competitiveness of the air transportation industry, primarily focusing on air cargo.

The literature on evaluating airport competitiveness, which exhibits heterogeneity in the factors used to measure airport performance, is broad. Several studies have evaluated cargo market competitiveness, performance and efficiency among airports (Chao and Yu, 2013; Gardiner *et al.*, 2005; Ohashi *et al.*, 2005; Zhang, 2003). Chao and Yu (2013) conducted a qualitative evaluation of air cargo competitiveness using the Delphi method and AHP, examining three main factors as follows: airline transport capacity, airport facilities and operations and economic development. Their results indicated that the criterion "airline transport capacity" was relatively more important than the other criteria used in their study. Gardiner *et al.* (2005) explored a different set of factors influencing airport choice from the perspective of freighter-operating airlines and found that factors such as night curfews, freight forwarders and airport charges are important. They further underlined the need for an apron space to load and unload cargo from and off the aircraft. Ohashi *et al.* (2005) highlighted that factors related to time cost rather than monetary cost significantly influenced the choice of air cargo transshipment location. They discussed the correlation between airport congestion and schedule delays, and the limited capacity of airport infrastructure and facilities. They confirmed the significance of airport connectivity in attracting cargo transshipments. Lotti and Caetano (2018) examined the competitive factors influencing airport choice, including cost and time, when exporting perishables from Brazil. Their results suggested that the choice of cargo terminal is sensitive to the time factor of airports' customs operations.

However, Zhang (2003) focused on Hong Kong and explored the competitive factors sensitive to air cargo hubs – including airports' geographical location, costs, delivery times, infrastructure, customs, intermodal transportation and international aviation policy. The study highlighted the significance of competitive factors, such as geographical location, costs and delivery times, in attracting cargo traffic regionally and internationally. Park (2003) analyzed several factors, such as spatial development, infrastructure and facilities and demand factors, at eight major airports in Asia. Their study found that the demand factor – the number of airlines, flight frequency and network connectivity – was the most critical factor defining airports' competitive position. A later study by Chang and Chang (2009) analyzed the causal relationship between economic growth and the effects of air cargo transport in Taiwan. The findings showed that air cargo expansion was significant in promoting Taiwan's economic growth.

Wong *et al.* (2016) examined the factors affecting airport competitiveness in the air cargo market, such as international trade, including the value and commodity types of imports and exports, cargo volume, frequency and connectivity. The results indicated that flight frequency, connectivity and cargo operation types are critical for identifying an airport as a hub in air cargo markets. Similar factors were also included in Burghouwt and de Wit (2005), Burghouwt *et al.* (2009) and De Wit *et al.* (2009). Chung and Han (2013) argued that flight connectivity and frequency are common factors in the literature on cargo operations and airport choice. Furthermore, Boonekamp and Burghouwt (2017) stated that the intercontinental connectivity of an airport had a significant impact when selecting an airport for cargo operations.

Chakraborty *et al.* (2020) evaluated the performance of international airports in India by considering competitiveness factors, such as annual revenue, passenger numbers, cargo volumes and other factors. They suggested that the criterion "annual revenue" was the most significant evaluation criterion. Additionally, several other studies incorporated factors including global cargo networks, the number of aircraft movements, air cargo gates and lanes and cargo terminals to examine airports' competitiveness (Assaf, 2009; Barros, 2008; Chung and Han, 2013; Chung *et al.*, 2015; Fernandes and Pacheco, 2002; Gillen and Lall, 2001; Martín-Cejas, 2002; Oum and Yu, 2004; Sarkis, 2000; Pels *et al.*, 2001, 2003; Yoshida, 2004). Finally, the brand value and reputation of airports were also investigated as factors influencing the competitiveness of airports. Chung *et al.* (2017) showed that airport brand is the most important factor for measuring airport competitiveness. Moreover, Kupfer *et al.* (2016) suggested that a desirable reputation diminishes collaboration uncertainty among airports and airlines.

Based on the existing literature on competitiveness factors in the air transportation industry and Sun *et al.* (2021), it was clear that an urgent need existed to re-evaluate not only airports but also the measurement factors contributing to their competitiveness. Therefore, aiming to maintain an updated framework for comprehensively evaluating cargo airports' competitiveness, this study uses similar measurement criteria explored in previous research and expands them to include other measurement criteria such as "Airports Financial Performance" and "Airport Brand Value" (Table 1).

3. Methodology

3.1 Best-Worst Method (BWM)

The BWM has been recently added to MCDMs and was first introduced by Rezaei (2015). This method allows the decision-maker to first determine the best (or the most important) and the worst (or the least important) criterion among a list of criteria with respect to a specific goal, which, in this case, is the competitiveness of cargo airports. Subsequently, the decision-maker compares the selected best criterion to the other criteria expressing the best criterion's preference level on a scale of 1–9. Similarly, it compares the other criteria to the worst criterion expressing the preference level of the other criteria on the same scale. The comparison results produce two vectors. In the final step, a simple linear programming model algorithm is used to estimate the optimal weights from the two vectors (Rezaei, 2016).

The BWM outperforms other MCDM by providing a structured way to make the pairwise comparisons. Prior to conducting pairwise comparisons, identifying the best and worst criteria allows the decision-maker to have a clear understanding of the range of evaluation, resulting in more reliable and consistent pairwise comparisons. Furthermore, considering only two pairwise comparison vectors with two opposite references (best and worst) in a single decision-making framework reduces decision-making bias. Other MCDMs, such as Saaty's AHP, which relies on a full pairwise comparison matrix, may be inefficient in terms of data and time. In such cases, asking the decision-maker too many questions may lead

Main criteria	Sub-criteria	Operational definition	Literature
Transport Capacity (C_1)	• No. of airlines operating at an airport	An airport with a large number of airlines operating indicates that it has enough passengers and cargo to become a hub.	Park (2003), Chao and Yu (2013), Mayer (2016)
	• No. of flights	The more frequent flights for both passengers and cargo indicates superior cargo transport capacity.	Sarkis (2000), Park (2003), Chao and Yu (2013), Wong *et al.* (2016), Shojaei *et al.* (2018), Chakraborty *et al.* (2020), Ersoy (2021)
	• Global air network (destinations)	A large number of destination cities indicates a wide flight network and better cargo transport accessibility	Park (2003), Zhang (2003), Chao and Yu (2013), Wong *et al.* (2016)
Airport operations and facilities' capacity (C_2)	• No. of terminals (including cargo terminals) • Airport cargo capacity • No. of aprons and aircraft stands	Competitive airports with adequate facilities and infrastructure are able to handle large amounts of cargo traffic.	Basso and Zhang (2010), Suryani *et al.* (2012), Adenigbo (2016)
Economic growth (C_3)	• Cargo volumes	International trade, high-volume trade and GDP affect cargo volumes.	Sarkis (2000), Chao and Yu (2013), Wong *et al.* (2016), Chakraborty *et al.* (2020), Ersoy (2021)
	• Cargo growth rate	Cargo volumes indicate an airport's current cargo-wise performance, while growth rate indicates its growth potential.	Chao and Yu (2013)
	• GDP	Moreover, a higher national income can increase demand for air-transported high-value products.	Park (2003), Suryani *et al.* (2012), Chao and Yu (2013)
Financial performance (C_4)	• Annual revenue	Airports that are financially efficient are airports that use their assets to achieve self-sufficiency, that is, to increase revenues to levels sufficient to finance their current and future operations and activities.	Sarkis (2000), Wilbert *et al.* (2017), Shojaei *et al.* (2018), Chakraborty *et al.* (2020)
Airport brand value (C_5)		Brand value is an important marketing tool that is defined as a brand's sale value. The greater an airport's brand value, the greater its shareholder value, and thus its competitiveness.	Kupfer *et al.* (2016), Chung *et al.* (2017)

Source(s): Authors' own work based on the literature review

Table 1. Cargo airport competitiveness factors: Criteria and literature summary

to confusion and inconsistency on his or her part. The BWM method is the most data and time-efficient method, allowing for consistency validation and pairwise comparisons (Rezaei, 2020). This section describes the steps (Munim *et al.*, 2020) to derive the optimal weights of the competitiveness criteria and obtain the final scores of cargo airports' competitiveness.

Step No. 1: Designing the problem

In this step, based on a thorough analysis of the existing literature, competitiveness criteria {C_1, C_2, …, C_n} are determined to evaluate cargo airports' competitiveness. The study considers five main criteria {Transport capacity (C_1), Airport operations' and facilities' capacity (C_2), economic growth (C_3), financial performance (C_4), airport brand value (C_5)} and sub-criteria under {C_1, C_2, C_3}, as presented in Table 1.

Step No. 2: Choosing the best and the worst criterion

In this stage, from the list of criteria determined in Step 1, the decision-maker identifies the best (or the most important) and the worst (or the least important) criterion in connection to the goal (cargo airport competitiveness). The same procedure applies to the sub-criteria, whereby the decision maker selects the best (or the most important) and the worst (or the least important) sub-criterion in connection with the study's main criteria and goals.

Step No. 3: Determining the best criterion's preference over all the other criteria

The decision-maker ranks the importance level of the criterion that is most important over all the other criteria set on a 1–9 scale (see Table 2), where 1 denotes that both criteria are equally important and 9 denotes that one criterion is exceptionally more important than the other. This step results in the formulation of the Best-to-Others comparison vector, as follows:

$$A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn}) \tag{1}$$

where a_{Bj} denotes the best criterion B's preference level over another criterion j, and j(1,2, …, n) denotes the number of criteria measured in the research. Tables 3 and 4 show the resulting Best-to-Others comparison vectors based on expert opinions received from the respondents.

Step No. 4: Finding Others-to-Worst preference

In this step, the decision-maker ranks the importance level of the other criteria over the worst criterion on a scale of 1–9 (Table 2), where 1 denotes that both criteria are of equal importance and 9 denotes that one criterion is extremely more important than the other. This step results in the formulation of the Others-to-Worst comparison vector.

$$A_W = (a_{1W}, a_{2W}, \ldots, a_{nW})^T \tag{2}$$

where a_{jW} indicates criterion j's preference over W, the worst criterion, and j(1,2, …, n) denotes the number of measured criteria. Tables 3 and 5 show the resulting Others-to-Worst comparison vectors based on the expert opinions received from the respondents.

Scale	Definition
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate value between adjacent scales

Source(s): Saaty (1994)

Table 2.
1–9 scale

$$\begin{aligned} & min\, \xi^L \\ & s.t. \\ & |w_B - a_{Bj} w_j| \leq \xi^L, for\ all\ j \\ & |w_j - a_{jW} w_W| \leq \xi^L, for\ all\ j \\ & \sum_j w_j = 1 \\ & w_j \geq o,\ \ for\ all\ j \end{aligned} \tag{3}$$

Best-to-others vector

Respondent	Best criterion	Transport capacity (C1)	Airport operations capacity (C2)	Economic growth (C3)	Financial perform. (C4)	Airport brand value (C5)
Respondent 1	Airport operations capacity	2	1	4	8	6
Respondent 2	Transport capacity	1	3	4	5	6
Respondent 3	Transport capacity	1	2	5	6	8

Others-to-worst vector

Respondent	Worst criterion	Transport capacity (C1)	Airport operations capacity (C2)	Economic growth (C3)	Financial perform. (C4)	Airport brand value (C5)
Respondent 1	Financial perform	7	8	5	1	3
Respondent 2	Airport brand value	7	6	4	2	1
Respondent 3	Financial perform	8	7	5	1	3

Source(s): Authors' own work based on the survey responses

Table 3. Best-to-others and others-to-worst vectors for the main criteria

Sub-criteria under C1

Respondent	Best criterion	No. of airlines	No. of flights	Global network
Respondent 1	Global network	7	4	1
Respondent 2	Global network	5	3	1
Respondent 3	No. of flights	5	1	7

Sub-criteria under C2

Respondent	Best criterion	No. of terminals	Airport cargo capacity	No. of aprons
Respondent 1	Airport cargo capacity	4	1	7
Respondent 2	Airport cargo capacity	3	1	5
Respondent 3	Airport cargo capacity	4	1	7

Sub-criteria under C3

Respondent	Best criterion	Cargo volumes	Cargo growth rate	GDP
Respondent 1	Cargo volumes	1	4	7
Respondent 2	GDP	5	3	1
Respondent 3	Cargo volumes	1	5	7

Source(s): Authors' own work based on the survey responses

Table 4. Best-to-others vector

Table 5.
Others-to-worst vector

Sub-criteria under C1				
Respondent	Worst criterion	No. of airlines	No. of flights	Global network
Respondent 1	No. of airlines	1	4	7
Respondent 2	No. of airlines	1	3	5
Respondent 3	Global network	3	7	1
Sub-criteria under C2				
Respondent	Worst criterion	No. of terminals	Airport cargo capacity	No. of aprons
Respondent 1	No. of aprons	4	7	1
Respondent 2	No. of aprons	3	5	1
Respondent 3	No. of aprons	3	7	1
Sub-criteria under C3				
Respondent	Worst criterion	Cargo volumes	Cargo growth rate	GDP
Respondent 1	GDP	1	3	5
Respondent 2	Cargo volumes	1	6	4
Respondent 3	GDP	7	4	1

Source(s): Authors' own work based on the survey responses

Step No. 5: Finding the criteria optimal weights

In this stage, based on Rezaei's (2016) linear BWM model (which has a unique solution rather than multiple optimal ones); the absolute differences $\{|w_B\text{-}a_{Bj}w_j|, |w_j\text{-}a_{jW}w_W|\}$ for all j are minimized to determine the optimal criteria weights. This process is performed by solving the following equations using linear programming:where a_{Bj} denotes B, the best criterion's preference level over criterion $j(1, 2, \ldots, n)$, and a_{jW} denotes criterion $j(1, 2, \ldots, n)$'s preference level over W, the worst criterion. w_B, w_W and w_j represent the optimal weights of the best, worst and other criteria, respectively.

The optimal weights of the criteria w_j $(w_1^*, w_2^*, \ldots, w_n^*)$ and the comparison consistency ratio ξ^{L*} can be obtained by solving equation (3).

STEP No. 6: Obtaining the final scores of cargo airport competitiveness

To obtain the final scores of the cargo airport's competitiveness, we first collect secondary airport data reflecting the five measurement criteria and sub-criteria (in Table 1) and then normalize the data values by dividing each measurement value by the column-wise maximum value (Table 6). Next, to obtain the global weights, we multiplied each criterion weight with the sub-criteria weights for each respondent separately. Subsequently, the normalized secondary data values are multiplied by their respective global weights for each response to obtain the final cargo airport competitiveness scores (Table 7). Finally, the final

Table 6.
Normalized data and criteria weights (Respondent 1 example)

Airport	C1.1	C.1.2	C.1.3	C2.1	C2.2	C2.3	C3.1	C3.2	C3.3	C4	C5
Global weight	0.0227	0.0568	0.1932	0.0947	0.322	0.0379	0.045	0.058	0.033	0.0455	0.0909
(LHR)	0.700	0.989	0.617	0.400	0.254	0.669	−0.914	0.887	0.346	0.796	1.000
(CDG)	0.958	1.000	1.000	0.900	0.537	1.000	−1.264	0.858	0.421	1.000	0.592
(HKG)	1.000	0.889	0.669	0.700	1.000	0.700	1.000	1.000	1.000	0.476	0.359
(INC)	0.733	0.806	0.526	1.000	0.746	0.662	0.743	0.689	0.576	0.471	0.802

Source(s): Authors' own work based on data collected from the websites of LHR, CDG, HKG and INC airports, the Port Authority of New York and New Jersey website, Haigh (2019), Mazareanu (2019), World Bank, and survey data received from airport experts in South Korea priority scores for each competing cargo airport were obtained by taking the row-wise averages for each respondent (Table 8).

$$F_i = \sum_{j=1}^{n} w_j x_{ij}^{norm} \quad (4)$$

F_i indicates the final score of alternative i, and x_{ij}^{norm} are the normalized scores of criterion j under alternative i (Munim *et al.*, 2020).

Finally, one study objective is evaluating the importance of the competitiveness factors of cargo airports, and noticeably, different airports and airlines operate under different settings and requirements; moreover, the BWM method estimates the optimal weights of a set of parameters based solely on one expert preference. Therefore, we obtain the geometric mean of the set of individual priorities (Aggregating Individual Priorities [2] and not judgements, AIP) to capture the aggregate perspective of the participating experts, as suggested by Forman and Peniwati (1998), Ossadnik *et al.* (2016) and Munim *et al.* (2020). We used the excel solver for the Linear BWM model to estimate individual and aggregate priorities.

3.2 Data collection

The BWM data required for evaluating the competitiveness factors of cargo airports were based on the opinions of field experts. Hence, in the early stages of the study, we attempted to contact global field experts selected through purposive sampling to measure the competitiveness of international airports. However, due to the challenges of contacting and finding experts willing to participate in the survey globally, in April 2021, we contacted a professor at Incheon National University in South Korea, for guidance. The professor volunteered to assist and circulated the questionnaires to qualified experts in the airport industry in South Korea, selected through snowball sampling. Snowball sampling is one of

Airport	C1.1	C.1.2	C.1.3	C2.1	C2.2	C2.3	C3.1	C3.2	C3.3	C4	C5
Global weight	0.0227	0.0568	0.1932	0.0947	0.322	0.0379	0.045	0.058	0.033	0.0455	0.0909
(LHR)	0.016	0.056	0.119	0.038	0.082	0.025	−0.041	0.052	0.012	0.036	0.091
(CDG)	0.022	0.057	0.193	0.085	0.173	0.038	−0.056	0.050	0.014	0.045	0.054
(HKG)	0.023	0.051	0.129	0.066	0.322	0.027	0.045	0.058	0.033	0.022	0.033
(INC)	0.017	0.046	0.102	0.095	0.240	0.025	0.033	0.040	0.019	0.021	0.073

Source(s): Author' own works based on data collected from the websites of LHR, CDG, HKG and INC airports, the Port Authority of New York and New Jersey website, Haigh (2019), Mazareanu (2019), World Bank, and survey data received from airport experts in South Korea

Table 7. Results of multiplying the normalized data by their respective global weights (Respondent 1 example)

Airport	Row-wise averages
(LHR)	0.044
(CDG)	0.061
(HKG)	*0.073*
(INC)	0.065

Source(s): Authors' own work based on data collected from the websites of LHR, CDG, HKG and INC airports, the Port Authority of New York and New Jersey website, Haigh (2019), Mazareanu (2019), World Bank, and survey data received from airport experts in South Korea

Table 8. Final priority scores for the competing cargo airports (Respondent 1 example)

the non-probabilistic sampling techniques in which researchers enlist the assistance of a research subject in identifying and possibly encouraging additional subjects to participate in the study (Berg, 2006). It is a highly effective sampling technique that is often necessary, irreplaceable and advantageous when the researcher may not have access to a population of potential participants for their studies (Berg, 2006; Waters, 2015; Taherdoost, 2016; Kirchherr and Charles, 2018). Accordingly, we successfully received completed questionnaires from three respondents in the field (Table 9). The BWM allows for a minimum of three expert opinions (applying the AIP method, as practiced by Munim *et al.* (2020)).

The expert details part of the questionnaire shows that all respondents have a minimum of 15 years of relevant experience and possess a high level of knowledge of cargo airports from working in the field. Additionally, two of the respondents represent airline companies and specialize in air cargo planning and development, and one represents an airport and specializes in strategic airport management planning, network analysis and passenger/logistics marketing.

The study initially intended to analyze airports listed in the top 20 cargo volume-wise performing international airport lists. However, there were data limitations caused by inconsistencies and the unavailability of public data. Moreover, because many airports provide data in specific details and units that are inconsistent with the units of measurement and period used in this study, we selected four international airports to conduct the second part of the study. Therefore, based on the cargo volume ranking of international airports (Table 10) and the status of the airports (Table 11), we decided to analyze Heathrow Airport

	Expert 1	Expert 2	Expert 3
Years of relevant experience	>15	>15	>15
Affiliation type	Airline company (in charge of cargo)	Airline company (in charge of cargo)	Incheon International Airport Corporation
Area of expertise	Air cargo IT development support	Cargo business planning	Airport management strategic planning, network analysis, passenger/logistics marketing
Company Position	≥ Department head	≥ Department head	≥ Department head
Knowledge in the field on a scale of 1–9 (1 = strongly disagree and 9 = strongly agree)			
Cargo airport knowledge	9	8	8
Airport knowledge	8	7	9
General aviation industry Knowledge	9	7	8

Source(s): Authors' own work based on the survey responses

Table 9.
Expert details

Airport	2017	2018	2019	2020
	Ranking per year			
LHR	18	19	18	23
CDG	10	14	11	16
HKG	1	1	1	2
INC	4	4	5	6

Source(s): Port Authority of New York and New Jersey (2018, 2019, 2020, 2021)

Table 10.
International airport rankings based on cargo volumes

Airport	Opened	Status/advantages as an air cargo hub	2018 cargo volume (short tons)
LHR	1946	• UK's only hub airport • 2019 trade value of approximately £188 billion – of which 56% came from imports • 95% of air freight is carried in the belly hold of passenger aircraft • 90% of the UK's trade by volume is transported by sea, and high value goods are transported by air • UK's largest port by value, accounting for over a fifth (21%) of UK trade in goods by value	1,952,570
CDG	1974	• No. one French airport • Second main European airport • A powerful hub situated for connecting traffic that feeds long-haul traffic • Europe's number one hub in terms of intercontinental connectivity • Fourth largest European hub for global connectivity • Accommodates all the major international cargo industry players	2,376,944
HKG	1998	• World's busiest international cargo airport since 1996 • In 2021, handled 5 million tonnes of total cargo throughput, 42% of the total value of Hong Kong's external trade • Advantages as an air cargo hub: world's freest economy • Geographical advantage • Excellent connectivity • State-of-the-art facilities • Sufficient cargo handling capacity • Efficient cargo handling and security	5,644,728
INC	2001	• World's second largest global cargo hub in 2021 • Achieved a cumulative 50 million tons of air cargo • 39% of total air cargo is transshipment cargo • Preparing to become the air cargo mega hub (after phase 4 construction project) • Started operation of perishable cargo terminal • Expanding the free-trade zone to accelerate advance as a global cargo hub	3,254,159

Source(s): Authors own work based on data collected from the websites of LHR, CDG, HKG and INC airports, see "Notes" for more details, and the Port Authority of New York and New Jersey website

Table 11. An overview of the status of selected airports

(LHR), Aéroport de Paris-Charles de Gaulle (CDG), Hong Kong International Airport (HKG) and Incheon International Airport (INC). These airports are already well established and are listed in the top 20 international airports by airport traffic. Thus, comparing their relative strengths and weaknesses may help other less-established airports. Therefore, the secondary dataset, which reflects the criteria for measuring the competitiveness of cargo airports (Table 12), was collected from airport websites, annual reports and other databases (Port Authority of New York and New Jersey, 2018, 2019; Haigh, 2019; Mazareanu, 2019; World Bank, 2021).

4. Results

In this study, we used the BWM Solver Linear Excel file for the BWM model. Table 13 summarizes the results of the competitiveness study. Table 14 and Figure 1 (aggregate expert

Secondary data	Criterion	Year
(1) No. of airlines operating at an airport	Sub-criteria	2018
(2) No. of flights		
(3) Global air network (destinations)		
(4) No. of terminals (including cargo)	Sub-criteria	2018
(5) Airport cargo capacity		
(6) No. of aprons and aircraft stands (including cargo)		
(7) Cargo volumes	Sub-criteria	2018
(8) Cargo growth rate change		2017–2018
(9) GDP (per capita)		2018
(10) Financial performance	Main criteria	2018
(11) Airport brand value	Main criteria	Published June 2019

Source(s): Authors' own work based on data collected from the websites of LHR, CDG, HKG and INC airports, the Port Authority of New York and New Jersey website, Haigh (2019), Mazareanu (2019) and World Bank

Table 12. Secondary data

Criteria	Respondent 1	Respondent 2	Respondent 3	Geometric mean	Rankings
Transport capacity (C1)	0.273	*0.470*	*0.455*	*0.388*	*1*
Airport operations' and facilities' capacity (C2)	*0.455*	0.202	0.299	0.301	2
Economic growth (C3)	0.136	0.151	0.119	0.135	3
Financial performance (C4)	0.045	0.121	0.052	0.066	5
Airport brand value (C5)	0.091	0.056	0.075	0.072	4
Airport (Alternatives)					
Heathrow Airport (LHR)	0.044	0.059	0.051	0.051	4
Aéroport de Paris-Charles de Gaulle (CDG)	0.061	*0.077*	0.059	0.065	2
Hong Kong International Airport (HKG)	*0.073*	0.068	*0.077*	*0.073*	*1*
Incheon International Airport (INC)	0.065	0.057	0.069	0.063	3

Source(s): Authors own work based on data collected from the websites of LHR, CDG, HKG and INC airports, the Port Authority of New York and New Jersey website, Haigh (2019), Mazareanu (2019), World Bank, and survey data received from airport experts in South Korea

Table 13. Priorities using BWM

opinion) show that respondent No. 1's answer suggests that the criterion "Airport Operations' and Facilities' Capacity" is the most important criterion, while respondents No. 2 and 3 suggest the criterion "Transport Capacity" as the most important measurement factor for achieving cargo airport competitiveness.

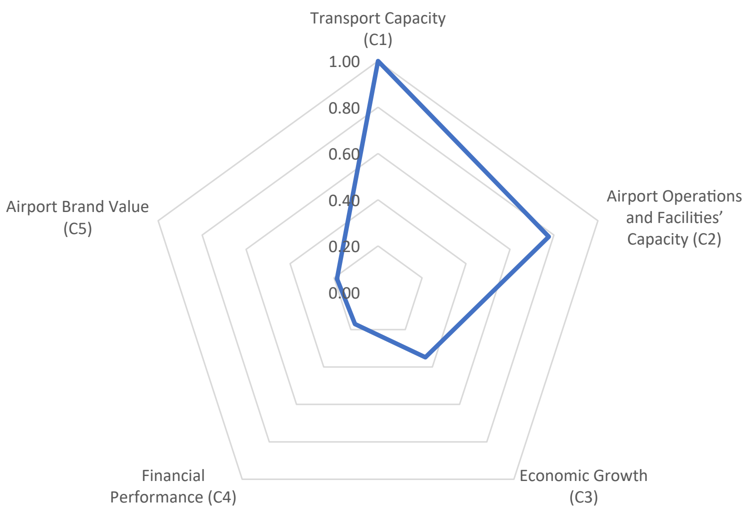
The geometric mean indicates that "Transport Capacity," with a score of 0.388, is the most important factor for cargo airport competitiveness, followed by "Airport Operations' and Facilities' Capacity," and "Economic Growth." The "Financial Performance" and "Airport Brand Value" are the least important factors with regard to cargo airport competitiveness.

At the sub-criteria level, the results are shown in Table 14. It shows that respondents Nos. 1 and 2 answers suggest that "Global Network" is the most significant sub-criterion to focus on, while respondent No. 3's answer indicates that the "Number of Flights" is the most valued criterion for cargo airport competitiveness.

Criteria	Respondent 1	Respondent 2	Respondent 3	Geometric mean
Main criteria priorities				
Transport capacity	0.273	*0.470*	*0.455*	*0.388*
Airport Operations and Facilities' Capacity	*0.455*	0.202	0.299	0.301
Economic growth	0.136	0.151	0.119	0.135
Financial performance	0.045	0.121	0.052	0.066
Airport brand value	0.091	0.056	0.075	0.072
ξ^{L*}	0.091	0.134	0.142	
Sub-criteria (1) priorities				
No. of airlines	0.083	0.111	0.169	0.116
No. of flights	0.208	0.244	*0.740*	0.335
Global network	*0.708*	*0.644*	0.091	*0.346*
ξL*	0.125	0.089	0.104	
Sub-criteria (2) priorities				
No. of terminals	0.208	0.244	0.197	0.216
Airport cargo capacity	*0.708*	*0.644*	*0.712*	*0.688*
No. of aprons	0.083	0.111	0.091	0.094
ξL*	0.125	0.089	0.076	
Sub-criteria (3) priorities				
Cargo volumes	0.327	0.091	*0.738*	0.280
Cargo growth rate	*0.429*	0.291	0.179	*0.281*
GDP	0.245	0.618	0.083	0.233
ξL*	1.388	0.255	0.155	

Note(s): ξ^{L*}: Consistency ratio: acceptable (Liang *et al.*, 2020)
Source(s): Authors' own work based on the survey responses

Table 14. BWM application result



Source(s): Authors' own work based on the surveys

Figure 1. Competitiveness criteria priorities normalized geometric mean

All of the respondents' answers suggest that "Airport Cargo Capacity" is significantly more important than the other listed sub-criteria under the primary criterion "Airport Operations' and Facilities' Capacity." However, under "Economic Growth," respondent No. 3's answer indicates that "Cargo Volumes" is the most valued criterion under "Economic Growth" to ensure the cargo competitiveness of airports.

The geometric mean suggests that the "Global Network" (0.346), and the "Airport Cargo Capacity" (0.688) are the most important sub-criteria in connection to cargo airport competitiveness and the relevant main criteria, followed by the "Number of Flights" and the "Number of Terminals."

According to Table 13, it can be inferred that Hong Kong International Airport (HKG) is the best-performing cargo airport with a score of 0.073, followed by Aéroport de Paris-Charles de Gaulle (CDG) and Incheon International Airport (INC), respectively.

Tables 15 and 16 show the results of the criterion-wise competitiveness performance for competing airports. Noteworthily, Hong Kong International Airport (HKG) scored the highest (0.045) in "Number of Airlines," "Cargo Capacity," and the whole sub-criteria under "Economic Growth." Incheon International Airport (INC) scored best in the "Number of

Transport capacity (C1)			
Airport	No. of airlines	No. of flights	Global air network (Destinations)
(LHR)	0.032	0.129	0.083
(CDG)	0.043	*0.130*	*0.134*
(HKG)	*0.045*	0.116	0.090
(INC)	0.033	0.105	0.071
Airport operations' and facilities' capacity (C2)			
Airport	No. of terminals	Cargo capacity	No. of aprons
(LHR)	0.019	0.040	0.034
(CDG)	0.042	0.085	*0.050*
(HKG)	0.033	*0.159*	0.035
(INC)	*0.047*	0.119	0.033
Economic Growth (C3)			
Airport	Cargo growth	GDP	Cargo volumes
(LHR)	−0.037	0.032	0.011
(CDG)	−0.051	0.031	0.013
(HKG)	*0.040*	*0.036*	*0.032*
(INC)	0.030	0.025	0.018

Source(s): Authors own work based on data collected from the websites of LHR, CDG, HKG and INC airports, the Port Authority of New York and New Jersey website, Haigh (2019), Mazareanu (2019), World Bank, and survey data received from airport experts in South Korea

Table 15. Criterion-wise geometric mean for competing airports

Airport	Revenue	Brand value
(LHR)	0.053	*0.072*
(CDG)	*0.066*	0.043
(HKG)	0.031	0.026
(INC)	0.031	0.058

Source(s): Authors' own work based on data collected from the websites of LHR, CDG, HKG and INC airports, the Port Authority of New York and New Jersey website, Haigh (2019), Mazareanu (2019), World Bank, and survey data received from airport experts in South Korea

Table 16. Criterion-wise geometric mean for competing airports

Terminals" sub-criterion. Additionally, Heathrow Airport (LHR) scored the highest in "Brand Value," whereas Aéroport de Paris-Charles de Gaulle (CDG) obtained the highest score in "Financial Performance" and "Number of Flights."

5. Discussion

Based on the results of the criterion-wise competitiveness performance for the competing airports in Tables 15 and 16, it can be noted that although Hong Kong International Airport (HKG) and Incheon International Airport (INC) are overall ranked as the most competitive airports, they still fall behind with respect to the sub-criterion "Number of Flights" and "Global Air Network" under the criterion "Transport Capacity," "Financial Performance" and "Brand Value." this may indicate that both airports need to work on internal and external levels with their governments to strengthen their transport capacity and establish new global networks, allowing for better connectivity. Additionally, the management of both airports may also be required to develop competitive strategic plans to uplift their annual revenues and better promote their brand value.

Noteworthily, both selected European airports are the most competitive airports under the "Financial Performance" and seem to have sufficient awareness of the significance of their brand value. Therefore, the results may imply that both airports may be required to concentrate less on annual revenue-making policies and instead invest more in elevating the cargo policies and facilities and boosting their global connectivity and economic growth.

Tables 15 and 16 identify cargo airports' relative strengths and weaknesses and suggest further improvement areas for less competing cargo airports. The results of this study may also act as a competitiveness guideline for other airports with respect to cargo airports. This would support airport decision-making authorities to adopt policies and strategies to diminish the weaknesses in cargo airports while bringing them to a competing international level by adopting better strategies and planning better service facilities.

6. Concluding remarks

This study contributes to the current literature on cargo airport competitiveness by applying the BWM to assess the cargo airport competitiveness factors encompassed in the criteria (Table 1) and the cargo-related competitiveness performance of four major international cargo airports: two in Asia and two in Europe. The study identifies the weights of the five main evaluation criteria using BWM through questionnaires received from three experts in the airport industry. Unlike other widely used MCDMs, such as the AHP method, the BWM technique proves itself a robust methodology, as it requires a minimum number of criteria pairwise comparisons, reducing the inconsistency that may occur in the decision-making process.

Applying the insights of the existing literature and analyzing the results of the current study on airport competitiveness in the air cargo context, this study illustrates the complexity of the related competitiveness framework. This study's findings (Table 13) clearly identify that the main criterion "Transport Capacity" is the most significant in the air cargo competitiveness evaluation problem. This finding supports the findings of Chao and Yu (2013). However, the results of this study negate the findings of the research conducted by Chakraborty *et al.* (2020), which focused on the broad-spectrum performance of airports in India. Their study indicated that annual revenue is the most important evaluation criterion ensuring airport competitiveness, while in this study, the annual revenue of airports is the least important. This inconsistent result may be attributed to the use of different data and different methods. Moreover, Chung *et al.* (2017) identified airport brand as the most valuable factor for measuring airport competitiveness, which contradicts the findings of this study.

This study's results further suggest that Hong Kong International Airport (HKG) is the best-performing cargo airport, which secures the competitive position of Hong Kong as a hub for air cargo. The aggregate geometric mean results also indicate that Aéroport de Paris-Charles de Gaulle (CDG) is the second-most competitive airport, followed by Incheon International Airport (INC) and Heathrow Airport (LHR).

This study forms a new reference framework for evaluating cargo airports, as it may help to identify the relative strengths and weaknesses of each cargo airport while enabling a proper benchmarking tool that allows these airports to exchange the best practices. Moreover, this framework can also serve as a tool to facilitate the futuristic strategic design of airports that offer policies and facilities to accommodate both air cargo and passenger demand flexibly under demand uncertainty.

In addition to this study, to boost cargo airports' competitiveness and improve the quality of their operational performance, services and airport facilities, airports are recommended to refer to the IATA's Regulations Manuals, which helps airlines and cargo handlers operate more effectively and improve efficiency and safety in air cargo operations. Moreover, with the guidance of proper research and educational programs, airport decision-makers may better understand the requirements of innovative air cargo operations and uplift airports' competitive position.

We admit that a more extensive set of data should be analyzed to improve generalizability. Therefore, future studies on cargo airports' competitiveness may consider encompassing other criteria, such as customs clearance services, quality, performance and cargo security aspects. Further, future studies may include more cargo airports (the top 20 cargo airports in the world) for comparison, if the data becomes available. Additionally, other methodologies and populations may also be combined to achieve a more robust and holistic quantitative and qualitative analysis.

7. Notes

Airport Suppliers, Paris-Charles De Gaulle Airport Information. https://www.airport-suppliers.com/airport/paris-charles-de-gaulle/

Heathrow Airport. https://www.heathrow.com/

Hong Kong International Airport. https://www.hongkongairport.com/

Incheon International Airport. https://www.airport.kr/ap/en/index.do

Paris - Charles De Gaulle Airport. https://www.parisaeroport.fr/en

Statistics for Paris Charles de Gaulle Airport. https://pariscdgairport.com/statistics/

Notes

1. The detailed explanation regarding the data limitations herein is provided in the methodology section.
2. Aggregation of Individual Priorities method (AIP) is employed when the participant group is assumed to act as separate individuals (Forman and Peniwati, 1998).

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