Expert Systems With Applications 170 (2021) 114508

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Multi-criteria decision analysis towards robust service quality measurement

Dragan Pamucar [a,b], Morteza Yazdani [c,*], María José Montero-Simo [d], Rafael A. Araque-Padilla [d], Ahmed Mohammed [e]

[a] Informetrics Research Group, Ton Duc Thang University, Ho Chi Minh City, Vietnam
[b] Faculty of Civil Engineering, Ton Duc Thang University, Ho Chi Minh City, Vietnam
[c] ESIC Business & Marketing School, Av. de Valdenigrales, Pozuelo de Alarcón, 28223 Madrid, Spain
[d] Universidad Loyola Andalucía, Department of Management, campus Cordoba, Spain
[e] Faculty of Transport & Logistics, Muscat University, Building 142, Al Ghubra North, Muscat, Oman

ARTICLE INFO

Keywords:
Airport service quality
Grey numbers
MARCOS
Multi criteria decision analysis
SWARA

ABSTRACT

Importance: The role of airports is critical for a region in which it is viewed as an engine for the economic development. Facilities, infrastructure, information and in general the services offered by an airport represent the fuel for this engine. Evidently, customers and travelers expect standard-quality services that need to be framed and measured. Therefore, services in airports should be quantified and maintained, accordingly.
Objectives: This article reports a case study for evaluating quality of services offered by five main airports located in Spain. Quality of service was modelled based on a number of factors such as convenience, comfort, courtesy of staffs, information visibility, prices, security, and transportation facilities. The grey based multi-criteria decision analysis (MCDA) was employed towards a reliable evaluation process by airport experts and to accommodate the several qualitative and conflicting evaluation factors with distinct definitions. To this end, Grey Step-wise Weight Assessment Ratio Analysis (SWARA-G) and grey Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS-G) methods were applied for quantifying relative weights of decision factors and rating airports, respectively. Several sensitivity analysis, simulations, and comparisons were conducted for verifying the preciseness of the revealed results.
Findings: Research findings demonstrate that the proposed SWARA-G-MARCOS-G-based methodology (i) enables decision makers to express their preferences clearly; and (ii) attenuates the embedded subjectivity and uncertainty within the decision-making process. In addition, they revealed that access to the parking and Wi-Fi connection are amongst the critical factors in evaluating service quality of airport.
Contribution: This paper contributes to related literature in presenting a novel decision-making approach for measuring service quality of airports, validated via a real-case study. The employed interval and linguistic grey variables allow experts, in airport operations, to express their opinions with higher flexibility and comfortability. The presented model could be re-applied for other studies or practical cases as a user-friendly decision support system.

Acronym: AAI, Anti-Ideal Solution; *AHP*, Analytic Hierarchy Process; *AI*, Ideal Solution; *ANOVA*, ANalysis Of Variance; *ATM*, Automated Transfer Machine; *CFA*, Confirmatory Factor Analysis; *CoCoSo*, Combined Compromise Solution; *COPRAS*, Complex Proportional Assessment; *DIMs*, Derived Importance Methods; *DRSA*, Dominance Based Rough Set Approach; *EFA*, Exploratory Factor Analysis; *EIFM*, Extended Initial Fuzzy Matrix; *ELECTRE*, ELimination Et Choice Translating Reality; *IGN*, Interval Grey Numbers; *IPA*, Importance Performance Analysis; *IT2HFSs*, Interval Type 2 Hesitant Fuzzy Sets; *MABAC*, Multi-Attributive Border Approximation area Comparison; *MACBETH*, Measuring Attractiveness by a Categorical Based Evaluation Technique; *MARCOS*, Measurement of alternatives and Ranking According to COmpromise Solution; *MCDA*, Multi Criteria Decision Analysis; *MCDM*, Multi Criteria Decision Models; *MUSA*, MUlticriteria Satisfaction Analysis; *PROMETHEE*, Preference Ranking Organization METHod for Enrichment of Evaluations; *QFD*, Quality Function Deployment; *RM*, Rough Modeling; *SAW*, Simple Additive Weighting; *SCC*, Spearmańs Correlation Coefficient; *SERVPERF*, SERVice PERFormance; *SERVQUAL*, SERVice QUALity; *SIMs*, Stated Importance Methods; *SWARA-G*, Step-wise Weight Assessment Ratio Analysis; *TOPSIS*, Technique for Order of Preference by Similarity to Ideal Solution; *VIKOR*, Vlsekriterijumska Optimizacija I KOmpromisno Resenje.

* Corresponding author.
E-mail addresses: dragan.pamucar@tdtu.edu.vn (D. Pamucar), morteza.yazdani@esic.edu (M. Yazdani), jmontero@uloyola.es (M.J. Montero-Simo), raraque@uloyola.es (R.A. Araque-Padilla).

https://doi.org/10.1016/j.eswa.2020.114508
Received 23 August 2020; Received in revised form 11 December 2020; Accepted 14 December 2020
Available online 12 January 2021
0957-4174/

1. Introduction

Quality refers to the ability of a good or service to meet or exceed customer expectations (Heizer, 2016). Ghobadian, Speller, and Jones (1994) presented the quality as a vehicle that drives the popularity, economy, gesture and characteristics of an organization. In industrial dictionary it is divided into several concepts e.g. quality in physical production, quality in design, quality of services, etc. Quality has a paramount role for company reputation, product or service liability and global implications. It is worthy to mention that quality of goods and services has different concepts in terms of considering tangible or intangible factors. Quality of service needs a qualitative and distinct viewpoint compared to quality of a physical goods. Also, quality of service has several elements that must be determined such as reliability, responsiveness, competence, access, courtesy, communication, credibility, security, and customer satisfaction (Gupta, 2018; Lee, Zhao, & Lee, 2019).

The term quality, in many industries, is related to sort of standards, rules and regulations. During the last decade, the airline industry experienced a significant change in terms quality level for its services. This could be reasoned due to global connection of countries and continents, looking at airplanes as a strategic transportation module and the high variation of brand airlines that make the competition bar very high (Singh, 2016). For instance, price variation causes the growth of several low-cost airlines like Ryanair, Easyjet, and Flybe, etc. in the European market. Hence, demand and satisfaction level of passengers and customers were increased. This has enforced executives and policy makers, in airline industry, to rethink and reconcile their airports' performance and operations.

Airports are amongst the essential elements of a transport system in each region in which a huge number of merchants, tourists and passengers will use every year (Arabali, Sakhaeifar, Freeman, Wilson, & Borowiec, 2017). In other words, it is a strategic economic motor for a specific country or region. Mainly that report showed that the global air traffic density has heavily elevated, and this caused the airports in high competition (Fu & Oum, 2014). Depending on the size and geography of main towns, the airports occupy a big portion of its asset. In Europe major airports like Heathrow in London, Schiphol in Amsterdam, Charles de Gaulle of Paris, Frankfurt and Madrid-Barajas have huge contribution to the transportation services all around the world (https://bigseventravel.com[1]). The services offered in airports represents a paramount aspect that affects quality of the airline industry. The vitality of airports as a place for receiving, transiting and handling thousands of passengers per day become more pertinent towards economic growth.

Thereby, measuring quality of services in airports is a very important topic in the airline sector, whereas everyone expects a comfortable and reliable access to its services. Studies brought to indicate essential requirements for evaluating airports services around the world. This led to the fact that this evaluation must consist various factors such as access to information, cleanness, technology, etc. and thus represents a complex activity. Years ago, researchers employed data flow diagrams (DFD) to design service quality management system (Chang & Lin, 1991). However, multi attribute decision analysis techniques were formed to resolve the problem of performance evaluation more promptly and efficiently. For instance, most recently, Martins, Ferreira, Ferreira, and Marques (2020) developed a decision support system to manage service quality in the prosthodontics sector. The researchers utilized measuring attractiveness by a categorical based evaluation technique (MACBETH) algorithm towards an optimal assessment. Zietsman and Vanderschuren (2014) used Analytical Hierarchy Process (AHP) to explore the service quality of several airports in Cape Town, South Africa.

Prakash and Barua (2016) investigated enablers for quality of airport service by using AHP and fuzzy Technique of Order Preference Similarity to the Ideal Solution (TOPSIS). In a case study in Turkey, an integrated version of fuzzy Quality Function Deployment (QFD) and service quality method was used to measure quality of airport service. Essential data is gathered by passengers' needs through QFD and SERVQUAL (Kayapınar & Erginel, 2019). SERVQUAL is a method developed for assessing quality in the service sectors (Pabedinskaitė & Akstinaitė, 2014). In the service context, Lupo and Bellomo (2019) presented a modified Fuzzy TOPSIS method for quantifying improvement of the service level in restaurants at University of Palermo in Italy. In some conditions, gathering such data from experts or databases is a tiring process and often leads to incorrect information. To address this issue, linguistic variables and fuzzy models are being used. Rather than utilization of SERVQUAL, integrated decision-making tools that can analyze the service quality factors and handle vagueness in opinions, due data acieration, are preferred (Pamučar, Petrović, & Ćirović, 2018). In this paper, we project to evaluate the quality factors in the Spanish airports by using analytical decision support models.

Spain is one of the biggest economies in Europe and due to its specific territory surrounding by Mediterranean Sea and Pacific Ocean received enormous attentions. It is a corridor that connects Africa and Latin America to other parts of Europe and Asia. Its cultural diversity, fruitful weather, and social community attract millions of industries, business, students, and residents. Also, this attractive point is due to its geographical closeness to France, Italy, Portugal, and North of Africa (i.e., Morocco) and its connection to strategic ports like south UK. In Spain, the transportation sector is equipped by High speed trains, big international airports and thousands of water-ways (e.g., in Barcelona, Valencia, Cadiz, Malaga, Santander, etc.) (Yazdani, Pamucar, Chatterjee, & Chakraborty, 2020; and Gomez, Papanikolaou, & Vassallo, 2017). This offers a chance for businesses and industries seeking advantages and utilizing this transportation infrastructure as a benefit. Nowadays Barcelona and Madrid are among the most important economic capitals in south and west of Europe. In addition, Spain, every year, hosts more than 80 million of tourists in its territory with target destination of Madrid, Barcelona, Andalucía, Valencia and Asturias. With more than 1000 km of coastal zone, it is one of the best touristic and industrial destinations in the world and Europe. These attractive elements made Spain an appropriate peninsula towards high-quality life. Therefore, it is paramount for its airports to accommodate high quality services and facilities that align with international standard.

According to the above contexts, this research's scope lies in investigating and analyzing the service quality of high-traffic airports in Spain. To this end, this work presents an evaluation methodology that combines SWARA (Keršuliene, Zavadskas, & Turskis, 2010) and MARCOS (Stević, Pamučar, Puška, & Chatterjee, 2020) techniques under grey values (*hybrid SW'MARCOS-G methodology*, henceforth). This model helps decision makers towards better practically and it is capable to be extended and programmed for larger-scale evaluation cases. Experts and managers work in Andalucía airport helped the research team in accessing information and designing/filling the questionnaire developed to gather SWARA-MARCOS-related information. The developed model aims to reduce the difficulty and complexity of evaluating an airport's service levels considering various factors. The model is tested and validated using distinct concepts, comparing to other multi-criteria decision analysis (MCDA) methods. Furthermore, sensitivity analysis was conducted to prove the robustness of the presented methodology.

The remaining of this paper is organized as follows: a wide range of studies dedicating airport service quality are explored to find the research gap (Section 2) and, accordingly, research contributions are presented. In Section 3, methods and materials for the proposed methodology are defined and explained. Case study and model implementation are brought in Section 4. Research implication and discussion are provided in Section 5. Finally, conclusion and future research proposals are drawn out in Section 6.

[1] https://bigseventravel.com/2019/11/the-7-busiest-airports-in-europe/

2. Review of the literature

2.1. Service quality of airports

The global airline industry has continued to grow rapidly in recent years. In 2019, global air traffic passenger demand increased by 4.2 percent on the year before (Statista, 2020). In 2019, the world's airports accommodated 9.1 billion passengers, 120 million metric tons of cargo, and more than 102 million aircraft movements (ACI, 2020a, 2020b). Related to passenger traffic, aviation's center of gravity was continuing to shift eastward in 2019 (ACI, 2020a, 2020b). The largest increases occurred at Asia-Pacific airports, followed by Europe, North America, and Caribbean. Particularly in Spain, the trend is like the rest of the main airports in the world. The data shows an increase in both passenger traffic (4,4%), operations (2,6%) and merchandise traffic (5,6%) (AENA, 2019).

However, the growth forecasts have been cut due to the serious effects generated by the COVID-19 pandemic. This introduces high uncertainty in the sector, where crippling losses in passenger traffic and revenues significant losses are expected. Nevertheless, the sector looks to the future with optimism due to reasons such as the connectivity it provides and the crucial part of the global economic recovery regarding benefits for business and tourism that it represents (ACI, 2020a, 2020b).

Factors such as the growth of global air traffic, as well as strong competition, have generated a growing awareness of the importance of airport quality as a key element of differentiation (Fodness & Murray, 2007; Pabedinskaitė & Akstinaitė, 2014; Pantouvakis & Renzi, 2016). As a transition point, not a destination, the airport represents a service scape where customers find a service package that influences their satisfaction (Bitner, Booms, & Tetreault, 1990; Fodness & Murray, 2007; Bogicevic, Yang, Bilgihan, & Bujisic, 2013). The measurement of the service quality is crucial in several aspects (Lupo, 2015): 1) to evaluate stakeholderś expectations and perceptions regarding a series of criteria; 2) to identify critical aspects for management; and 3) to monitor performance. Likewise, quality has a direct relationship with perceived value and satisfaction, and indirectly with tourism and business activities (Bezerra & Gomes, 2015; Lupo, 2015).

Despite the importance of industry service quality, marketing did not seem to have played an important role until the 1990s (Fodness & Murray, 2007), perhaps because airports were understood more as a public service, oblivious to competitive dynamics. Therefore, the passenger's perspective had traditionally been ignored (Fodness & Murray, 2007). Benchmarking methods were more focused on workload unit costs and revenues measurement (Bogicevic et al., 2013). Currently, a growing demand for airport services has generated the need of more efficient processes. The increase in the level of competitiveness in the European, North-American and Asian markets has expanded the possibilities of choice of airlines in relation to airports (Pabedinskaitė & Akstinaitė, 2014). As a result, methods of analyzing and comparing the quality of service at airports have evolved towards a perspective more customer-oriented (Bogicevic et al., 2013).

2.2. Methods for service quality of airports

Research on quality of airport services remains an inconclusive question, and currently is being carried out from highly diverse perspectives, approaches or methods. There is not a consensus in the literature about which criteria must be selected to evaluate and measure service quality. The complicated nature of airport services has led to the development of conceptual models that reflect different dimensions of quality, or that focus on highlighting the drivers that lead to user satisfaction (Pantouvakis & Renzi, 2016). In order to model unstructured data in measuring airline service quality, Korfiatis, Stamolampros, Kourouthanassis, and Sagiadinos (2019) used Structural Topic Models (STM) and probabilistic extension to Latent Dirichlet Allocation (LDA) methodologies on airline passengers' online reviews. It is generally assumed that the quality of service at an airport can be discomposed into a discrete number of dimensions. All research tends to coincide with three basic dimensions that function as descriptors of airport quality (Pantouvakis & Renzi, 2016): service scape of the airport, signage, or the level and quality of information, and the service. But the number and composition of dimensions and sub-dimensions varies across the literature. Nevertheless, a correct selection of quality attributes is essential for an effective strategy. Methods used to this can be classified in three categories (Lupo, 2015): 1) Stated importance methods (SIMs); 2) Derived importance methods (DIMs); and 3) Multi-criteria decision-making (MCDM) approaches. Table 1 presents related literature on employed methods.

Stated importance ratings can sometimes be useful, easy to apply,

Table 1
The information of the relevant methods.

Authors	Publication Year	Methods	Objectives
Sohail and Al-Gahatani	2005	ANOVA tests	Assessment traveler's perceptions of airport service quality (using SERVQUAL)
Fodness y Murray	2007	Qualitative study EFA CFA	Development of a conceptual model of service quality in airports
Lubbe, Douglas and Zambellis	2010	ANOVA tests	Evaluate passengerś perceptions of airport service quality and implications of its use in a different cultural context
Bogicevic, Yang, Bilgihan and Bujisic	2013	Qualitative analysis (content analysis)	To explore most frequently mentioned attributes of airport service quality and distinguish key drivers for passengers satisfaction in the airport context
Pabedinskaitėa and Akstinaitė	2014	Descriptive analysis	Assessment of the quality of airport services provided to airlines (using SERVQUAL)
Bezerra and Gomes	2015	EFA Ordinal Logistic Regression Model	1) Identify service quality dimensions related to airports. 2) To examined the effects of those dimensions with passengers overall satisfaction
Pantouvakis and Renzi	2016	Rash Modeling CFA ANOVA tests Multinomial logistic regression analysis	To determine the specific service quality components that can lead to increased traveler satisfaction in an international airport, and to evaluate the degree to which passenger perceptions of airport facilities, as well as levels of satisfaction, vary according to different nationalities.
Kurniawan, Sebathu and Davoudi	2017	T-test analysis	To provide strategic support as complaint handling on people mover system to enhancing airport service quality (using Kano model and SERVQUAL)

but often prevent discrimination between attributes preferences. For example, if the subjects tend to rate high all the proposed attributes, it is impossible to know which of them are more relevant for a global evaluation of the quality of the service. On the other hand, Derived or statistically inferred methods make it possible to detect the underlying dimensions of quality and their relationship to overall perceived quality or customer satisfaction, but they are based on a series of restrictions -normal data, linear relationships, multi-co-linearity- which reduces the guarantee of generalization (Tsai, Hsu, & Chou, 2011). More recently, to overcome those weaknesses, multi-criteria decision-making models such as AHP, TOPSIS, VIKOR or PROMETHEE are increasingly used in the literature.

Allen, Bellizzi, Eboli, Forciniti, and Mazzulla (2020) modelled airport service quality as dynamic equation problem to investigate the relationship among considered variables, and between the observed variables and the latent factors. The research outcome demonstrated that airport service quality is mainly based on factors such as service availability, operations control and environment in the terminal. However, this research was based on passengers 'perspective neglecting experts in the field. Kurniawan (2017) studied the case of Soekarno-Hatta International Airport (SHIA), one of the major international airports that serve the greater Jakarta area as one of the gates into Indonesia. They build a questionnaire based on questions of Kano Model and SERVQUAL (Perceived and Expected) and used T-test analysis. The authors based on secondary data collected via websites and media that lack direct opinions of related experts from the case company. Bezerra and Gomes (2015) used a probabilistic approach to identify service quality dimensions related to airports and examine the effects of those dimensions on passenger's overall satisfaction in the Guarulhos International Airport, in Brazil. Exploratory Factor analysis was combined with an ordinal logistic regression model. However, the research lacked behind passenger behaviors and expectations, and motivations. The latter represents significant considerations towards airport service quality. Pabedinskaitė and Akstinaitė (2014) investigated the quality of airport services for airlines using the classical SERVQUAL method. Based on the analysis of literature to specify dimensions and criteria, they carried out an experts̋ survey to establish the relative importance of airport service quality assessment criteria in respect of airlines, taking the case of the Vilnius International airport. SERVQUAL approach was also employed for Sohail and Al-Gahtani (2005) in a case study at King Fahd International Airport (Saudi Arabia) to measure the travelers' evaluation of airport services. Chi-Square and ANOVA were used to explore relations among control variables. Fodness and Murray (2007) created a conceptual model of the quality of airport service which was empirically tested by interviewing nearly one thousand passengers frequently using the services of airports. They used both qualitative and quantitative methods. It was noticed that the research focused solely on passengers' expectations that wouldn't reflect the entire picture of an airport's service quality. The same limitation was found in Lubbe, Douglas, and Zambellis (2011) where conducted a study, based on the model proposed by Fodness and Murray (2007), at the O.R. Tambo International Airport (South Africa) to evaluate passengers' perceptions of the importance of airport service quality dimensions, using ANOVA technique to analyze differences among categories of travelers. In the same context, Pantouvakis and Renzi (2016) developed a cross-cultural perspective in their study. Drawing evidence from 911 multinational passengers departing from Fiumicino Airport in Rome, Italy (Aeroporti di Roma), they employed Rasch Modeling (RM) techniques in order to examine users' perceptions, independently of the instrument used to measure them, or their nationality. Quality service dimensionality has also been explored using qualitative methods. Bogicevic et al. (2013) and Marketing et al. (2013) employed various data mining techniques to conduct a content analysis of 1095 traveler comments posted between 2010 and 2013 on an airport review web site in order to identify satisfiers/dis-satisfiers. Buonanno, D'Urso, Prisco, Felaco, Meliado, Mattei, Palmieri, and Ciuonzo (2012) used the swarm logic to develop an integrated intelligent system towards enhanced monitoring performance of large facilities such as airport terminals. However, such systems might suffer from information issues that Siergiejczyk and Krzykowska (2014) tried to analyse. In this context of monitoring and detection, Ciuonzo, Buonanno, D'Urso, and Palmieri (2011) presented two sub-optimal decision-making fusion methods are presented to classify multiple-moving targets towards a cost-effective quality decision.

Multi-criteria Decision making methods aims to handle such decision-making problems incorporating practitioners' expertise for a set of options considering various, possibility conflicting, factors (Mohammed et al., 2020; Mohammed, 2020; Siksnelyte-Butkiene, Zavadskas, & Streimikiene, 2020). Multi Criteria Decision Analysis approach is increasingly used in airport service quality studies as an alternative methodology to the usual methods in this field. Most recently, Tsai et al. (2011) proposed a integrated AHP-VIKOR method to explore both perceived and expected service quality from airport passengers' perspective. The importance–performance analysis (IPA) technique was employed to significance quality factors according to the 'voice of the customer'. It can be noticed that the employed deterministic methods lacking behind uncertainty in the given evaluation by customers. Deveci, Özcan, John, and Öner (2018) proposed an evaluation approach by using Interval type-2 hesitant fuzzy set theory towards potential improvement in Istanbul airport. The evaluation considered customers expectations and operations performance. The study was limited in terms of considering services offered by two airlines companies rather the airport services. Pandey (2020) performed a study at an airport in Thailand considering low cost airlines using quality function deployment (QFD) under fuzzy values. Although the authors tried to capture uncertainty by employing the fuzzy set theory, the QFD method ignores crucial factors such costs and available resources. Kratudnak and Tippayawong (2018) Exploratory Factor Analysis (EFA) was deployed to analyze the data from the survey to categorize into subfactors. Analytic Hierarchy Process (AHP) was also used to evaluate the weight factors via pairwise comparison in three regional airports in Thailand. The research ignored the validity of the revealed evaluation via EFA; in addition the collected data might not be closer to reality considering its deterministic nature. Lupo (2015), in an empirical study of the three international airports in Sicily (Italy), combined a fuzzy extension of the SERVPERF service conceptual model with the Multi-criteria decision-making ELECTRE III method, both to estimate quality scores of fundamental service criteria and to highlight the quality ranking of service alternatives. Similarly, a concern for the limited use of linguistic expression and fuzzy approach in the literature led to Kayapınar and Erginel (2019) to use an integrated approach involving fuzzy Quality Function Deployment (QFD) based on SERVQUAL, along to a fuzzy multi-objective decision model. The model was implemented at the Anadolu University Airport in Turkey. Tsai et al. (2011) provided an empirical case study of passenger services at Taoyuan International Airport (Taiwan) to demonstrate the usefulness of multi-criteria evaluation models. In order to evaluate the theoretical gap between perceptions and expectations, they combined a multi-criteria evaluation model with the analytic hierarchy process method, the VIKOR (Multi-criteria Optimization and Compromise Solution), and the importance-performance analysis (IPA) technique. It can be noticed that this research did not consider experts' opinions in this field. Pandey (2016) analysed the service quality of two gateway airports of Thailand, Suvarnabhumi (BKK) and Don Mueang (DMK). The service quality of the airport was investigated using the Fuzzy Multi Criteria Decision Making Method and it employed Improvement Performance Analysis using a fuzzy expert system that renders the managerial implications pertaining to identification of improvement areas. However, the authors limited the research by one season which limits the applicability and generality of its methodology. Borda and Analytic Hierarchy Process were applied in an integrated manner, in Medeiros in study of Rocha, Barros, Silva, and Costa (2016), using database of the performance report from the

Brazilian Department of Civil Aviation. The evaluations issued by 18,062 respondents regarding 15 airport terminals considering 8 evaluation criteria. Kazemi et al. (2016) generated a fuzzy MCDM method by integrating concepts of VIKOR and TOPSIS technique to deal with the evaluation of service quality problems in Iranian airports. Liou, Tang, Yeh, and Tsai (2011) used the dominance-based rough set approach, to evaluate an International Airport (Taiwan) service quality. Thus, this research ignores the aggregation of experts' opinions, in addition to uncertainty, considering various airports. Tsafarakis, Kokotas, and Pantouvakis (2018) showed how MUSA, a multi-criteria satisfaction analysis method - that combines MCDM and IPA, can be utilized in order to measure passengers' satisfaction from a large set of services dimensions, as well as to indicate those dimensions that need to be improved, through the application to Aegean airlines. Liou, Hsu, Yeh, and Lin (2011) applied a modified grey relation method to improve service quality among domestic airlines in Taiwan. Haghighat (2017) redesigned SERQUAL questionnaire items to adopt with Iranian airlines requirements and environmental circumstances. After collecting customer opinions and using criteria weights determined by experts, ranking of these airlines was calculated using trapezoidal fuzzy TOPSIS, and finally parametric or non-parametric tests were applied for analysing passengers' responses. Table 2 presents further related works on airport service quality evaluation.

2.3. Research contributions

After reviewing the literature and the relevant studies, the following gaps rise:

- Our review declares that studies over service quality assessment of airports in Spain were rare. A major gap is that in Spain as a one of the most touristic destination of the world, how major airports measure the services, and is there any mechanism?
- Another point is to know how decision making operations and algorithm can direct us to measure quality service of airports suitably considering requirements of passengers, travelers, and business owners etc.?
- As airport service quality evaluation is a qualitative study, then how can the research deal with uncertainty of those qualitative variables and facilitate the experts judgment and comparisons.

Focusing on the above gaps, we address our proposed decision analysis model that seeks the following contributions:

- We are optimizing the evaluation process by using new hybrid group MCDM framework named SW'MARCOS-G; that is consisted of grey SWARA and grey MARCOS analytical tools.
- One of the contributions developed in this paper is the introduction of the SW'MARCOS-G model that provides more objective expert evaluation of criteria in a subjective environment.
- The improved MCDM methodology suggested provides purchasing managers with another tool for evaluation of airport service quality and helps successfully reduce the gaps in the field.
- The present methodology enables the evaluation of alternative solutions despite dilemmas in the decision making process and lack of quantitative information.
- This review has applications rather than theoretical orientation, and enables the rational processing of the uncertainties that occur while using quantitative information for evaluation of airport service quality.

Table 2
The methods and models of MCDM for airline sector.

Authors	Publication Year	MCDM Methods	Objectives
Tsai, Hsu and Chou	2011	AHP VIKOR IPA	To evaluate the customer gap between perceptions and expectations and analyse appropriate strategies to reduce it
Liou, Tang, Yeh and Tsai	2011	DRSA	To evaluate the passengers perception of the airporťs level of service
Liou, Hsu, Yeh and Lin	2011	Modified grey relation method	To explore the grey gap and ranking of four domestic airlines in terms of service criteria (using SERVQUAL)
Lupo	2014	ELECTRE III	To develop a new approach to measuring airport service quality that allows for comparisons with other airports (using a fuzzy extension of SERVPERF)
Pandey	2016	QFD under fuzzy variables IPA	To evaluate the service quality of two airports and identify the scope of improvements keeping in view the changes of consumers' needs
Da Rocha, De Barros, Da Silva and Gomes	2016	De Borda AHP	To perform a comparative analysis of the operational performance of the main Brazilian airport terminals
Kazemi, Attari and Khorasani	2016	VIKOR TOPSIS	To provide an effective method to evaluate service quality of Iranian airports
Kayapinar and Erginel	2017	Fuzzy QFD	New integrated approach to develop airport service quality
Tsafarakis, Kokotas and Pantouvakis	2017	MUSA	To demonstrate the applicability of the method to measure passenger's satisfaction and indicates the critical service dimension that need to be improve
Haghighat	2017	TOPSIS Parametric and non-parametric tests	To evaluate airlines service quality from the perspective of passengers' view (using a redesigned SERVQUAL)
Deveci, Özcanb, John and Önerc	2018	IT2HFSs	To evaluate the service quality of domestic airlines
Katrudnak and Tippayawong	2018	EFA AHP	To categorize service quality factors

3. Materials and methods

This section presents the methods, mathematical equations, relations and definitions we need to model our decision-making system.

3.1. The MCDA-based research model

In this section of the paper, the mathematical concept of a multi-criteria methodology based on grey numbers is presented. Grey numbers allow processing of uncertainties that arise during expert

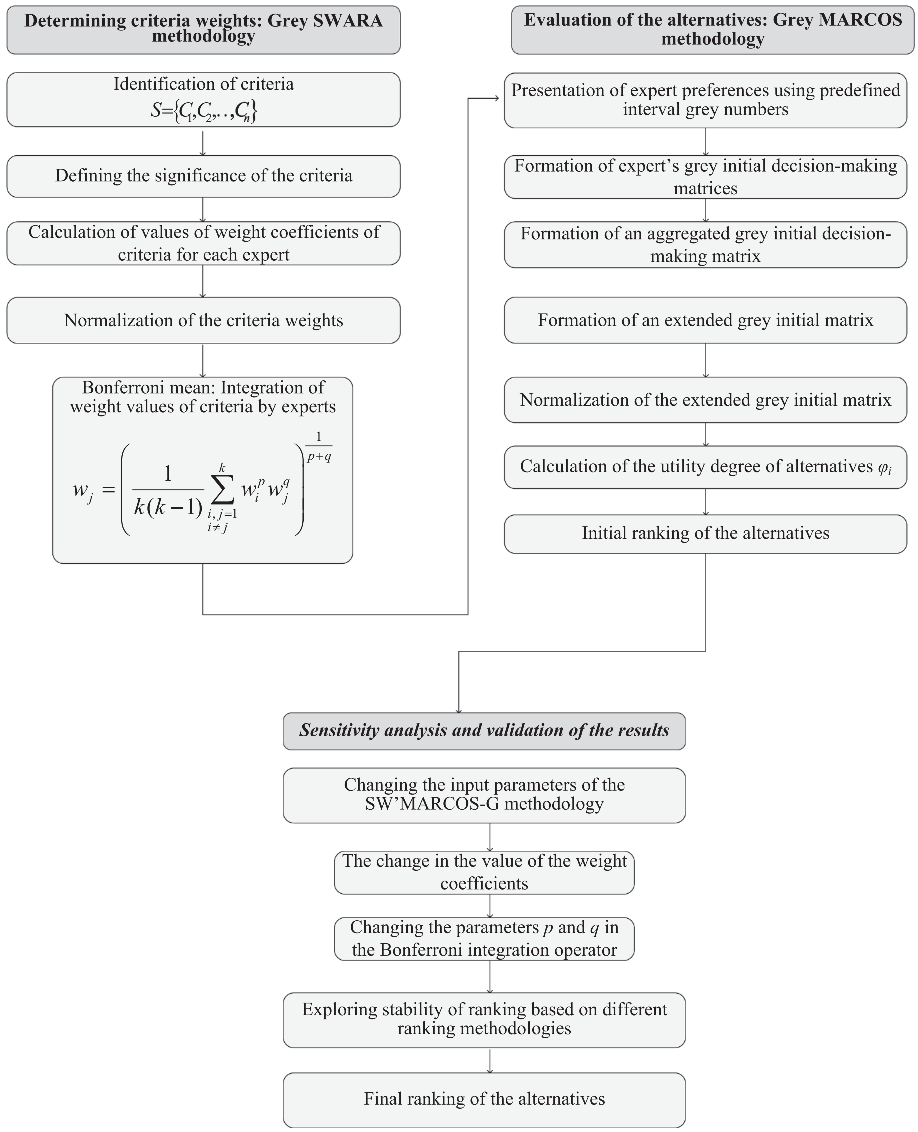

Fig. 1. Proposed MCDM model.

estimation of input variables in a multi-criteria model. The proposed MCDA methodology is based on the integration of the Step-wise Weight Assessment Ratio Analysis (SWARA) into the grey Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS-G). Fig. 1 shows the step by step proposed decision making model. At first we configure the criteria achievement by Grey SWARA. Afterwards we indicate the evaluation of alternatives (airports) by grey MARCOS and ultimately in third phase several tests and validation process are designed. The SWARA method has been extended by integrating Bonferroni operator to integrate expert preferences when defining the significance of criteria. The MARCOS-G methodology was used to evaluate alternatives.

3.1.1. Step-wise weight Assessment Ratio analysis (SWARA)

The SWARA methodology (Keršulienė et al., 2010) was chosen to determine the weighting coefficients of the criteria due to several advantages that set it apart from existing subjective models: 1) The SWARA method can be used successfully to coordinate and collect data from experts; 2) It has a simple mathematical apparatus that allows experts to easily understand the impact of their preferences on the final values of the criteria weights; 3) Provides the possibility of determining the weighting coefficients in the case of a large number of criteria. In other methods (such as AHP) it is difficult to obtain consistent preferences for problems with more than eight criteria, which is not the case with the SWARA method; 4) Any suitable scale can be used to express expert preferences in the SWARA method. This feature gives significant flexibility to this method, which allows easy adaptation of the SWARA model to the specific situation (Djalic, Stevic, Karamasa, & Puska, 2020).

The SWARA methodology involves the application of an algorithm that is implemented through four steps that are presented in the next section:

Step 1: *Identification of a set of criteria and their ranking.* The set of criteria for the evaluation of alternatives is identified based on the analysis of the available literature and the experience of experts participating in the research. Suppose that there is a group of k experts $E = \{E_1, E_2, \ldots, E_k\}$ and that a set of criteria $C = \{C_1, C_2, \ldots, C_n\}$ is defined, where n represents the total number of criteria. After defining a set of criteria, it is necessary for experts to rank the criteria according to their significance.

Step 2: *Defining the significance of the criteria*. After ranking the criteria according to their significance, the experts evaluate the significance of the criteria. In this step, the experts determine the comparative significance of the criteria s_j^e $(1\leqslant e\leqslant k, j=1,2,\ldots,n)$.

Step 3: *Calculation of values of weight coefficients of criteria*. The values of the weight coefficients of the criteria for each expert are obtained individually by applying the expression (1).

$$\varphi_j^e=\begin{cases}1 & j=1\\ \dfrac{\varphi_{j-1}^e}{s_{j+1}^e} & j>1\end{cases};\ 1\leqslant e\leqslant k;\quad j=1,2,\ldots,n \tag{1}$$

where φ_j^e represents experts preferences in relation to the observed criteria.

By applying expression (2), the values φ_j^e are transformed into the interval [0,1] so that the condition is fulfilled $\sum_{j=1}^n\varphi_j^e=1$. By normalizing the values φ_j^e, we get the optimal values of the criteria for each expert from the group

$$w_j^e=\frac{\varphi_j^e}{\sum_{j=1}^n\varphi_j^e} \tag{2}$$

where w_j^e represents the criteria weight for the expert e $(1\leqslant e\leqslant k)$.

Step 4: *Integration of weight values of criteria by experts*. Since k experts participate in the research, the values w_j^e obtained for each expert are integrated into the optimal value of the criteria weight w_j using the Bonferroni integration operator, the expression (3). The Bonferroni mean operator (Bonferroni, 1950) was used to integrate the values of the criteria weights as it allows the representation of the interrelationships between the elements.

$$w_j=\left(\frac{1}{k(k-1)}\sum_{\substack{i,j=1\\ i\neq j}}^{k} w_i^p w_j^q\right)^{\frac{1}{p+q}} \tag{3}$$

where k represents the number of experts participating in the research, while $p,q\geq 0$ are set of non-negative numbers. It is recommended to define the values of the parameters $p=q=1$ to obtain the optimal values of criteria weights. Also, the authors recommend that during the validation of the final results, an analysis of the impact of the change of the parameters p and q on the final decision be performed.

3.1.2. A grey measurement of alternatives and ranking according to compromise solution (MARCOS-G) method

This subsection shows the extension of the MARCOS model in an grey environment. The MARCOS methodology (Stević et al., 2020) is based on defining the relationship between the considered alternative and the reference points. The relationships between alternatives and ideal/anti-ideal points are defined through the utility degree of the alternatives. In relation to the existing multi-criteria models, the proposed MARCOS-based methodology excels in: 1) showning an enviable stability compared to other multi-criteria methodologies based on the comparison of alternatives and reference points (Badi & Pamucar, 2020); 2) providing reliable and robust solutions in a dynamic environment; 3) presenting robust and stabile outcome when processing larger data sets. The MARCOS-G methodology is implemented through seven steps which are presented in the next section.

Step 1: *Formation of aggregated interval grey numbers (IGN) initial decision matrix*. Evaluation of the alternatives per each criteria by e $(1\leqslant e\leqslant k)$ expert is denoted as $\otimes\xi_{ij}^{(e)}=\left[\underline{\xi}_{ij}^{(e)},\overline{\xi}_{ij}^{(e)}\right]$, where: $i=1,\ldots,b; j=1,\ldots,n$. The judgment of k expert is presented as matrix $\Phi^{(e)}=[\otimes\xi_{ij}^{(e)}]_{m\times n}$, where $1\leqslant e\leqslant k$.

$$\Phi^{(e)}=\begin{bmatrix}\otimes\xi_{ij}^{(e)} & \otimes\xi_{12}^{(e)} & \cdots & \otimes\xi_{1n}^{(e)}\\ \otimes\xi_{21}^{(e)} & \otimes\xi_{22}^{(e)} & \cdots & \otimes\xi_{2n}^{(e)}\\ \vdots & \vdots & \ddots & \vdots\\ \otimes\xi_{b1}^{(e)} & \otimes\xi_{b2}^{(e)} & \cdots & \otimes\xi_{bn}^{(e)}\end{bmatrix}_{b\times n};1\leqslant i\leqslant m;\ 1\leqslant j\leqslant n;\ 1\leqslant e\leqslant k \tag{4}$$

where $\otimes\xi_{ij}^{(e)}=[\underline{\xi}_{ij}^{(e)},\overline{\xi}_{ij}^{(e)}]$ represents experts preferences.

In accordance with this, $\Phi^{(1)},\Phi^{(2)},\ldots,\Phi^{(e)},\ldots,\Phi^{(k)}$ matrices are judgment matrices of each of k experts. For each matrix $\Phi^{(e)}=[\otimes\xi_{ij}^{(e)}]_{m\times n}$ we get grey sequence $\otimes\xi_{ij}^{(e)}=\left[\underline{\xi}_{ij}^{(e)},\overline{\xi}_{ij}^{(e)}\right]$ on the position (*i,j*) and finally by applying Eq. (5), we get the averaged grey number $\otimes\xi_{ij}=\left[\underline{\xi}_{ij},\overline{\xi}_{ij}\right]$.

$$\otimes\xi_{ij}=\left[\underline{\xi}_{ij},\overline{\xi}_{ij}\right]=\begin{cases}\underline{\xi}_{ij}=\left(\dfrac{1}{k(k-1)}\sum_{\substack{i,j=1\\ i\neq j}}^{k}\underline{\xi}_i^p\underline{\xi}_j^q\right)^{\frac{1}{p+q}}\\[2ex] \overline{\xi}_{ij}=\left(\dfrac{1}{k(k-1)}\sum_{\substack{i,j=1\\ i\neq j}}^{k}\overline{\xi}_i^p\overline{\xi}_j^q\right)^{\frac{1}{p+q}}\end{cases} \tag{5}$$

where $\underline{\xi}_{ij}$ and $\overline{\xi}_{ij}$ represents lower and upper limit of grey interval, respectively.

Based on expression (1) and (5) we obtain averaged grey initial decision-matrix

$$\Phi=\begin{bmatrix}\otimes\xi_{11} & \otimes\xi_{12} & \cdots & \otimes\xi_{1n}\\ \otimes\xi_{21} & \otimes\xi_{22} & \cdots & \otimes\xi_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ \otimes\xi_{b1} & \otimes\xi_{b2} & \cdots & \otimes\xi_{bn}\end{bmatrix}_{b\times n}=\begin{bmatrix}\left[\underline{\xi}_{11},\overline{\xi}_{11}\right] & \left[\underline{\xi}_{12},\overline{\xi}_{12}\right] & \cdots & \left[\underline{\xi}_{1n},\overline{\xi}_{1n}\right]\\ \left[\underline{\xi}_{21},\overline{\xi}_{21}\right] & \left[\underline{\xi}_{22},\overline{\xi}_{22}\right] & \cdots & \left[\underline{\xi}_{2n},\overline{\xi}_{2n}\right]\\ \vdots & \vdots & \ddots & \vdots\\ \left[\underline{\xi}_{b1},\overline{\xi}_{b1}\right] & \left[\underline{\xi}_{b2},\overline{\xi}_{b2}\right] & \cdots & \left[\underline{\xi}_{bn},\overline{\xi}_{bn}\right]\end{bmatrix}_{b\times n} \tag{6}$$

where $\otimes\xi_{ij}=\left[\underline{\xi}_{ij},\overline{\xi}_{ij}\right]$ denotes the value of the *i*-th alternative for the*j*-th criterion $(i=1,2,\ldots,b;j=1,2,\ldots,n)$. The matrix elements $\otimes\xi_{ij}=\left[\underline{\xi}_{ij},\overline{\xi}_{ij}\right]$ in Eq. (6) are grey numbers determined by the experts or by using the aggregation of the experts' decisions.

Step 2: *Formation of an extended initial matrix (X)*. In this step, the extension of the initial matrix is performed by defining the ideal (AI) and anti-ideal (AAI) solution.

$$X = \begin{array}{c} \\ AAI \\ A_1 \\ A_2 \\ \ldots \\ A_b \\ AI \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\ \begin{bmatrix} \otimes\xi_{aa1} & \otimes\xi_{aa2} & \ldots & \otimes\xi_{aan} \\ \otimes\xi_{11} & \otimes\xi_{12} & \ldots & \otimes\xi_{1n} \\ \otimes\xi x_{21} & \otimes\xi_{22} & \ldots & \otimes\xi_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ \otimes\xi_{b1} & \otimes\xi_{b2} & \ldots & \otimes\xi_{bn} \\ \otimes\xi_{ai1} & \otimes\xi_{ai2} & \ldots & \otimes\xi_{ain} \end{bmatrix} \end{array} \tag{7}$$

where $\otimes\xi_{ij} = \left[\underline{\xi}_{ij}, \overline{\xi}_{ij}\right]$ denotes the value of the i-th alternative for the$j$-th criterion ($i = 1, 2, \ldots, b; j = 1, 2, \ldots, n$).

The anti-ideal solution (AAI) is the worst alternative while the ideal solution (AI) is an alternative with the best characteristic. Depending on the nature of the criteria, AAI and AI are defined by applying expressions (8) and (9):

$$AAI = \begin{cases} \min_i \left\{\underline{\xi}_{ij}\right\} & if \quad j \in B \\ \max_i \left\{\overline{\xi}_{ij}\right\} & if \quad j \in C \end{cases} \tag{8}$$

$$AI = \begin{cases} \max_i \left\{\overline{\xi}_{ij}\right\} & if \quad j \in B \\ \min_i \left\{\underline{\xi}_{ij}\right\} & if \quad j \in C \end{cases} \tag{9}$$

where B represents a benefit group of criteria, while C represents a group of cost criteria and $\underline{\xi}_{ij}$ and $\overline{\xi}_{ij}$ represents lower and upper limit of grey number $\otimes\xi_{ij} = \left[\underline{\xi}_{ij}, \overline{\xi}_{ij}\right]$.

Step 3: Normalization of the extended initial matrix X. Elements of the normalised matrix $\widehat{Y} = \left[\otimes\widehat{y}_{ij}\right]_{b\times n}$ are defined by setting the expression:

a) For criteria of "*benefit*" type (greater value of criteria is desirable)

$$\otimes\widehat{y}_{ij} = \frac{\otimes\xi_{ij}}{\max\limits_{1\leqslant i\leqslant m}\left\{\overline{\xi}_{ij}\right\}} = \left(\frac{\underline{\xi}_{ij}}{\max\limits_{1\leqslant i\leqslant m}\left\{\overline{\xi}_{ij}\right\}}, \frac{\overline{\xi}_{ij}}{\max\limits_{1\leqslant i\leqslant m}\left\{\overline{\xi}_{ij}\right\}}\right) \tag{10}$$

where $\otimes\xi_{ij} = \left[\underline{\xi}_{ij}, \overline{\xi}_{ij}\right]$ represents the elements of the extended initial matrix X.

b) For criteria of "*cost*" type (lower value of criteria is desirable)

$$\otimes\widehat{y}_{ij} = \frac{\min\limits_{1\leqslant i\leqslant m}\left\{\underline{\xi}_{ij}\right\}}{\otimes x_{ij}} = \left(\frac{\min\limits_{1\leqslant i\leqslant m}\left\{\underline{\xi}_{ij}\right\}}{\overline{\xi}_{ij}}, \frac{\min\limits_{1\leqslant i\leqslant m}\left\{\underline{\xi}_{ij}\right\}}{\underline{\xi}_{ij}}\right) \tag{11}$$

where $\otimes\xi_{ij} = \left[\underline{\xi}_{ij}, \overline{\xi}_{ij}\right]$ represents the elements of the extended initial matrix X.

Step 4: Determination of the IGN weighted matrix $V = \left[\otimes v_{ij}\right]_{b\times n}$. The weighted matrix V is obtained by multiplying the normalized matrix $\widehat{Y}$ with the IGN weight coefficients of the criterion w_j ($j = 1, 2, \ldots, n$).

Step 5: Calculation of the utility degree of alternatives $\otimes K_i$. By applying expressions (12) and (13), the utility degrees of an alternative in relation to the anti-ideal and ideal solution are calculated.

$$\otimes K_i^- = \frac{\otimes S_i}{\otimes S_{aai}} = \left(\frac{\underline{S}_i}{\overline{S}_{aai}}, \frac{\overline{S}_i}{\underline{S}_{aai}}\right) \tag{12}$$

$$\otimes K_i^+ = \frac{\otimes S_i}{\otimes S_{ai}} = \left(\frac{\underline{S}_i}{\overline{S}_{ai}}, \frac{\overline{S}_i}{\underline{S}_{ai}}\right) \tag{13}$$

where $\otimes S_i$ ($i = 1,2,\ldots,m$) represents the sum of the elements of the weighted matrix V.

$$\otimes S_i = \sum_{i=1}^{n} \otimes v_{ij} = \left(\sum_{i=1}^{n} \underline{v}_{ij}, \sum_{i=1}^{n} \overline{v}_{ij}\right) \tag{14}$$

where $\otimes v_{ij} = \left[\underline{v}_{ij}, \overline{v}_{ij}\right]$ represents the elements of the weighted matrix $V = \left[\otimes v_{ij}\right]_{b\times n}$.

Step 6: Determination of the IGN utility function of alternatives $\otimes f(K_i)$. The utility function is the compromise of the observed alternative in relation to the ideal and anti-ideal solution. The utility function of alternatives is defined by expression (15).

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1-f\left(K_i^+\right)}{f\left(K_i^+\right)} + \frac{1-f\left(K_i^-\right)}{f\left(K_i^-\right)}}; \tag{15}$$

where $f\left(K_i^-\right)$ represents the utility function in relation to the anti-ideal solution, while $f\left(K_i^+\right)$ represents the utility function in relation to the ideal solution.

Grey utility functions in relation to the ideal and anti-ideal solution are determined by applying expressions (16) and (17).

$$\otimes f\left(K_i^-\right) = \frac{\otimes K_i^+}{\max\limits_{1\leqslant i\leqslant m}\left\{\otimes K_i^+ + \otimes K_i^-\right\}} \tag{16}$$

$$\otimes f\left(K_i^+\right) = \frac{\otimes K_i^-}{\max\limits_{1\leqslant i\leqslant m}\left\{\otimes K_i^+ + \otimes K_i^-\right\}} \tag{17}$$

where $\otimes K_i^-$ and $\otimes K_i^+$ represents the utility degrees of an alternative in relation to the anti-ideal and ideal solution, respectively.

Since crisp values are used in expression (15), it is necessary to transform the grey values $\otimes f\left(K_i^+\right)$, $\otimes f\left(K_i^-\right)$, $\otimes K_i^-$ and $\otimes K_i^+$ into crisp values. The transformation of grey numbers into crisp was performed using the expression $f_\lambda = (1-\lambda)\cdot\underline{f} + \lambda\overline{f}$, where λ refers to the whitening coefficient and is in the interval $\lambda \in [0,1]$. A value is adopted for the crisp value calculation $\lambda = 0.5$.

Step 7: *Ranking the alternatives*. Ranking of the alternatives is based on the final values of utility functions. It is desirable that an alternative has the highest possible value of the utility function.

4. Model formulation and implementation

4.1. Case study

This study concentrates on evaluating the service quality factors and also ranking of main airports in Spain. According to the national aviation and data of last year, the five traffic passengers of Spain are Madrid-Barajas, Barcelona-el Prat, Palma de Mallorca, Malaga airport and Alicante (www.statista.com). We have discussed with the experts' team a list of the fundamental factors we presented to them. Experts at airport

Table 3
The grey linguistic values and the equivalent numbers.

Linguistic values	Related grey numbers
Very bad	(1–10)
Bad	(11–20)
Moderately bad	(21–30)
Fair	(31–40)
Moderately good	(41–50)
Good	(51–60)
Very good	(61–70)

of Andalucía have realized 14 factors as important as with respect to the availability of information, accessibility and adaptation to the related airports need and making sense.

Experts formed a meeting and enclosed us a list of fourteen Indicators (for the current decision model, we call them criteria). In addition, they proposed seven fundamental factors like convenience, comfort, courtesy of staffs, Information visibility, prices, security, and transportation facilities. According to these factors, such indicators are supposed; Courtesy and helpfulness of staffs, information desk and security (c_1), Cleanness of airport facilities and services (c_2), Variety of shops & restaurants (c_3), Access to ATM (c_4), Exchange offices availability (c_5), Lighting system (c_6), Air-conditioning systems (c_7), Flight display information (c_8), Access to underground, bus or main transportation systems (c_9), Parking (c_{10}), Car rental offices (c_{11}), check-in process efficiency (c_{12}), Wi-Fi open access (c_{13}), and Baggage claim (c_{14}). The *anonymous* airports under investigation are named as A_1-A_5 and are called alternatives. For this study, two experts participated and collaborated from the beginning of the research and data acieration. Our experts are composed by a senior director (age of 48 years old and approximate experience of 22 years in airline industry; $\mathbf{E_1}$), and an assistant of airport operations (40 years old and 8 years of experience; $\mathbf{E_2}$).

To rate alternatives, we utilize the grey linguistic parameters as shown in Table 3. Experts firstly, select the linguistic category they have in mind (they judge), then within the interval of grey numbers they have flexibility of stating the quantitative values. Suppose that we show the function of evaluating Alternative i on indicator j as Ai (Cj). If someone rates the Alternative 1 has a *Moderately Bad* condition on check in efficiency indicator; $A_1(C_{12})$, he/she will be asked to deliver the worst (minimum) and best (maximum) score among that specific category. In this case that can be any pair values in interval of 21 to 30. For instance, if they choose (25,28) means that in the most pessimistic way Alternative 1 can have an score of 25, while in the most optimistic way 28. Grey theory allows decision makers to have a chance of rating a problem with two values due to any probable doubt or uncertainty. This gives the expert or decision maker a power of judgment even it is within a particular category. This enhances the chance of getting accurate decision and quality of decision process in general.

4.2. Results, sensitivity analysis, comparison with other decision tools

4.2.1. Application of SW'MARCOS-G methodology

The **hybrid SW'MARCOS-G methodology** consists of two segments. The first segment represents the SWARA algorithm used to determine the weights of the criteria (i.e., service quality factors; c1-c14). The second segment represents the MARCOS-G algorithm used to evaluate and rank alternatives (i.e., airports; A_1-A_5).

a) weighting coefficients of criteria: The SWARA method
   This section presents the application of SWARA method employed for determining criteria weights as follows:

Step 1: *Identification of a set of criteria and their ranking*. Based on the analysis of the literature and the experience of the experts who participated in the research, a total of 14 evaluation criteria $C = \{C_1, C_2, \ldots, C_{14}\}$ were identified. The research involved two experts $E = \{E_1, E_2\}$ who ranked the criteria according to their importance:

E_1 rank order: C13 > C10 > C11 > C12 > C2 > C14 > C1 > C9 > C5 > C6 > C3 > C7 > C8 > C4;

E_2 rank order: C2 > C10 > C13 > C7 > C11 > C1 > C12 > C6 > C3 > C8 > C14 > C9 > C5 > C4;

Step 2: *Defining the significance of the criteria*. The experts evaluated the criteria and presented their preferences through the comparative significance of the criteria

$$s_j^1 = \begin{array}{c} C13\\ C10\\ C11\\ C12\\ C2\\ C14\\ C1\\ C9\\ C5\\ C6\\ C3\\ C7\\ C8\\ C4 \end{array}\begin{bmatrix} 1.000\\ 0.150\\ 0.200\\ 0.350\\ 0.250\\ 0.150\\ 0.310\\ 0.150\\ 0.300\\ 0.350\\ 0.150\\ 0.300\\ 0.350\\ 0.250 \end{bmatrix}; \quad s_j^2 = \begin{array}{c} C2\\ C10\\ C13\\ C7\\ C11\\ C1\\ C12\\ C6\\ C3\\ C8\\ C14\\ C9\\ C5\\ C4 \end{array}\begin{bmatrix} 1.000\\ 0.080\\ 0.120\\ 0.150\\ 0.200\\ 0.250\\ 0.200\\ 0.280\\ 0.300\\ 0.200\\ 0.250\\ 0.250\\ 0.300\\ 0.320 \end{bmatrix}$$

Step 3: Calculation of values of weight coefficients of criteria. By applying expression (1), the significance of the criteria is calculated φ_j^e

$$\varphi_j^1 = \begin{array}{c} C13\\ C10\\ C11\\ C12\\ C2\\ C14\\ C1\\ C9\\ C5\\ C6\\ C3\\ C7\\ C8\\ C4 \end{array}\begin{bmatrix} 1.0000\\ 0.8696\\ 0.7246\\ 0.5368\\ 0.4294\\ 0.3734\\ 0.2850\\ 0.2479\\ 0.1907\\ 0.1412\\ 0.1228\\ 0.0945\\ 0.0700\\ 0.0560 \end{bmatrix}; \quad \varphi_j^2 = \begin{array}{c} C2\\ C10\\ C13\\ C7\\ C11\\ C1\\ C12\\ C6\\ C3\\ C8\\ C14\\ C9\\ C5\\ C4 \end{array}\begin{bmatrix} 1.0000\\ 0.9259\\ 0.8267\\ 0.7189\\ 0.5991\\ 0.4793\\ 0.3994\\ 0.3120\\ 0.2400\\ 0.2000\\ 0.1600\\ 0.1280\\ 0.0985\\ 0.0746 \end{bmatrix}$$

Thus, by applying expression (1), for criterion C_1 we obtain $\varphi_{C1}^1 = 0.3734/(0.310+1) = 0.2850$ and $\varphi_{C1}^2 = 0.5991/(0.200+1) = 0.4793$. In a similar way we get the remaining values φ_j^e. By normalizing the values φ_j^e, expression (2), the final values of the weight of the criteria according to the SWARA methodology are generated:

$$w_j^1 = \begin{array}{c} C1\\ C2\\ C3\\ C4\\ C5\\ C6\\ C7\\ C8\\ C9\\ C10\\ C11\\ C12\\ C13\\ C14 \end{array}\begin{bmatrix} 0.067\\ 0.123\\ 0.031\\ 0.011\\ 0.027\\ 0.039\\ 0.068\\ 0.023\\ 0.034\\ 0.160\\ 0.119\\ 0.085\\ 0.164\\ 0.049 \end{bmatrix}; \quad w_j^2 = \begin{array}{c} C1\\ C2\\ C3\\ C4\\ C5\\ C6\\ C7\\ C8\\ C9\\ C10\\ C11\\ C12\\ C13\\ C14 \end{array}\begin{bmatrix} 0.078\\ 0.162\\ 0.039\\ 0.012\\ 0.016\\ 0.051\\ 0.117\\ 0.032\\ 0.021\\ 0.150\\ 0.097\\ 0.065\\ 0.134\\ 0.026 \end{bmatrix}$$

Step 4: *Integration of weight values of criteria by experts*. By applying the Bonferroni integration operator, expression (3), the final values of the weighting coefficients are achieved. For the calculation of the final values of the weighting coefficients, the values $p = q = 1$ were adopted.

Table 4
Initial decision-making matrices for each expert.

Crit.	A_1	A_2	A_3	A_4	A_5
Expert 1					
C_1	[55 , 56]	[57, 59]	[58, 59]	[58, 60]	[59, 60]
C_2	[56, 56]	[56, 56]	[56, 56]	[54, 55]	[57, 58]
C_3	[53, 54]	[52, 53]	[52, 53]	[52, 53]	[54, 55]
C_4	[49, 50]	[48, 49]	[48, 49]	[49, 50]	[52, 53]
C_5	[53, 54]	[52, 53]	[53, 54]	[52, 53]	[54, 55]
C_6	[56, 57]	[58, 59]	[58, 59]	[56, 57]	[59, 60]
C_7	[56, 57]	[56, 57]	[55, 56]	[56, 57]	[55, 56]
C_8	[45, 46]	[44, 45]	[44, 45]	[46, 47]	[49, 50]
C_9	[56, 57]	[57, 58]	[58, 59]	[58, 59]	[59, 60]
C_{10}	[55, 56]	[57, 58]	[59, 60]	[57, 58]	[59, 60]
C_{11}	[56, 57]	[57, 59]	[59, 61]	[57, 59]	[59, 61]
C_{12}	[46, 47]	[49, 50]	[49, 50]	[49, 50]	[51, 52]
C_{13}	[55, 56]	[57, 58]	[56, 57]	[56, 57]	[59, 60]
C_{14}	[53, 54]	[55, 56]	[53, 54]	[52, 53]	[55, 56]
Expert 2					
Crit.	A_1	A_2	A_3	A_4	A_5
C_1	[51, 54]	[35, 38]	[55, 58]	[58, 60]	[56, 59]
C_2	[32, 38]	[56, 56]	[55, 58]	[54, 55]	[55, 56]
C_3	[53, 54]	[52, 53]	[52, 53]	[52, 53]	[54, 55]
C_4	[49, 50]	[48, 49]	[48, 49]	[49, 50]	[34, 38]
C_5	[53, 54]	[52, 53]	[53, 54]	[32, 37]	[54, 55]
C_6	[33, 36]	[34, 39]	[58, 59]	[35, 39]	[59, 60]
C_7	[56, 57]	[56, 57]	[55, 56]	[53, 55]	[55, 56]
C_8	[42, 47]	[42, 44]	[44, 45]	[43, 45]	[45, 48]
C_9	[56, 57]	[57, 58]	[58, 59]	[55, 57]	[56, 58]
C_{10}	[54, 58]	[57, 58]	[59, 60]	[55, 58]	[58, 59]
C_{11}	[56, 57]	[54, 55]	[44, 46]	[52, 53]	[52, 54]
C_{12}	[46, 47]	[47, 49]	[54, 58]	[45, 47]	[55, 56]
C_{13}	[53, 56]	[57, 58]	[34, 37]	[53, 55]	[34, 37]
C_{14}	[53, 54]	[52, 56]	[53, 54]	[52, 53]	[55, 56]

$$
w_j = \begin{array}{c} C1 \\ C2 \\ C3 \\ C4 \\ C5 \\ C6 \\ C7 \\ C8 \\ C9 \\ C10 \\ C11 \\ C12 \\ C13 \\ C14 \end{array}
\begin{bmatrix} 0.072 \\ 0.141 \\ 0.035 \\ 0.012 \\ 0.021 \\ 0.044 \\ 0.089 \\ 0.027 \\ 0.027 \\ 0.155 \\ 0.108 \\ 0.074 \\ 0.148 \\ 0.036 \end{bmatrix}
$$

Using expression (3), for the criterion C_1 we attain the final value of the criteria weight:

$$
w_1 = \left(\frac{1}{2(2-1)} \left(0.067^1 \cdot 0.078^1 + 0.067^1 \cdot 0.078^1\right) \right)^{\frac{1}{1+1}} = 0.072
$$

In a similar way we compute the remaining values w_j. It is observed that access to parking, wi-fi accessibility, and cleanness of the airport facilities are the most important indicators.

b) evaluating alternatives: The MARCOS-G method

Step 1: Construction of the initial decision matrix (Y). Grey linguistic variables from the set $G = \{g_i | i = 1, 2, ..., 7\}$ were defined for the expert evaluation of alternatives, Table 3. During the evaluation of alternatives, the experts performed evaluations in accordance with the recommendations defined by the grey scale shown in Table 3. During the evaluation of alternatives, the experts adjusted the width of the interval of grey linguistic variables in fitted to the preferences.

Table 5
Aggregated initial decision-making matrix.

Crit.	A_1	A_2	A_3	A_4	A_5
C_1	[52.96, 54.99]	[44.67, 47.35]	[56.48, 58.5]	[58, 60]	[57.48, 59.5]
C_2	[42.33, 46.13]	[56, 56]	[55.5, 56.99]	[54, 55]	[55.99, 56.99]
C_3	[53, 54]	[52, 53]	[52, 53]	[52, 53]	[54, 55]
C_4	[49, 50]	[48, 49]	[48, 49]	[49, 50]	[42.05, 44.88]
C_5	[53, 54]	[52, 53]	[53, 54]	[40.79, 44.28]	[54, 55]
C_6	[42.99, 45.3]	[44.41, 47.97]	[58, 59]	[44.27, 47.15]	[59, 60]
C_7	[56, 57]	[56, 57]	[55, 56]	[54.48, 55.99]	[55, 56]
C_8	[43.47, 46.5]	[42.99, 44.5]	[44, 45]	[44.47, 45.99]	[46.96, 48.99]
C_9	[56, 57]	[57, 58]	[58, 59]	[56.48, 57.99]	[57.48, 58.99]
C_{10}	[54.5, 56.99]	[57, 58]	[59, 60]	[55.99, 58]	[58.5, 59.5]
C_{11}	[56, 57]	[55.48, 56.96]	[50.95, 52.97]	[54.44, 55.92]	[55.39, 57.39]
C_{12}	[46, 47]	[47.99, 49.5]	[51.44, 53.85]	[46.96, 48.48]	[52.96, 53.96]
C_{13}	[53.99, 56]	[57, 58]	[43.63, 45.92]	[54.48, 55.99]	[44.79, 47.12]
C_{14}	[53, 54]	[53.48, 56]	[53, 54]	[52, 53]	[55, 56]

Table 6
Normalized grey initial decision matrix.

Crit.	AAI	A_1	A_2	A_3	A_4	A_5	AID
C_1	[0.74, 0.79]	[0.88, 0.92]	[0.74, 0.79]	[0.94, 0.97]	[0.97, 1]	[0.96, 0.99]	[0.97, 1]
C_2	[0.74, 0.81]	[0.74, 0.81]	[0.98, 0.98]	[0.97, 1]	[0.95, 0.97]	[0.98, 1]	[0.98, 1]
C_3	[0.95, 0.96]	[0.96, 0.98]	[0.95, 0.96]	[0.95, 0.96]	[0.95, 0.96]	[0.98, 1]	[0.98, 1]
C_4	[0.84, 0.9]	[0.98, 1]	[0.96, 0.98]	[0.96, 0.98]	[0.98, 1]	[0.84, 0.9]	[0.98, 1]
C_5	[0.74, 0.81]	[0.96, 0.98]	[0.95, 0.96]	[0.96, 0.98]	[0.74, 0.81]	[0.98, 1]	[0.98, 1]
C_6	[0.72, 0.75]	[0.72, 0.75]	[0.74, 0.8]	[0.97, 0.98]	[0.74, 0.79]	[0.98, 1]	[0.98, 1]
C_7	[0.96, 0.98]	[0.98, 1]	[0.98, 1]	[0.96, 0.98]	[0.96, 0.98]	[0.96, 0.98]	[0.98, 1]
C_8	[0.88, 0.91]	[0.89, 0.95]	[0.88, 0.91]	[0.9, 0.92]	[0.91, 0.94]	[0.96, 1]	[0.96, 1]
C_9	[0.95, 0.97]	[0.95, 0.97]	[0.97, 0.98]	[0.98, 1]	[0.96, 0.98]	[0.97, 1]	[0.98, 1]
C_{10}	[0.91, 0.91]	[0.96, 1]	[0.94, 0.96]	[0.91, 0.92]	[0.94, 0.97]	[0.92, 0.93]	[0.96, 1]
C_{11}	[0.89, 0.92]	[0.98, 0.99]	[0.97, 0.99]	[0.89, 0.92]	[0.95, 0.97]	[0.97, 1]	[0.98, 1]
C_{12}	[0.85, 0.87]	[0.85, 0.87]	[0.89, 0.92]	[0.95, 1]	[0.87, 0.9]	[0.98, 1]	[0.98, 1]
C_{13}	[0.75, 0.79]	[0.93, 0.97]	[0.98, 1]	[0.75, 0.79]	[0.94, 0.97]	[0.77, 0.81]	[0.98, 1]
C_{14}	[0.93, 0.95]	[0.95, 0.96]	[0.95, 1]	[0.95, 0.96]	[0.93, 0.95]	[0.98, 1]	[0.98, 1]

By evaluating the alternatives, an initial decision-making matrix for each expert can be produced, Table 4:

Using expression (5), the expert evaluations of alternatives presented in Table 4 were aggregated into a main initial decision matrix, Table 5.

Value aggregation using expression (5) is shown for the value located at position C_1-A_1 in Table 5:

$$\otimes\xi_{11} = \left[\underline{\xi}_{11}, \overline{\xi}_{11}\right] = \begin{cases} \underline{\xi}_{11} = \left(\dfrac{1}{2(2-1)}(55{\cdot}51 + 51{\cdot}55)\right)^{\frac{1}{1+1}} = 52.96 \\ \overline{\xi}_{ij} = \left(\dfrac{1}{2(2-1)}(56{\cdot}54 + 54{\cdot}56)\right)^{\frac{1}{p+q}} = 54.99 \end{cases}$$

The remaining values from Table 5 were obtained in a similar way.

Step 2 and 3: Formation of an extended initial fuzzy matrix (EIFM) and normalization of the elements of the EIFM. By applying expressions (7)–(11), the grey matrix was expanded and the elements of the extended decision matrix were normalized, Table 6.

Step 4 and 5: *Determination of the weighted grey matrix and calculation of $\otimes S_i$ grey matrix*. By multiplying the weight coefficients of the criteria with the elements of the normalized matrix (Table 6), we can estimate an aggravated grey matrix. Using expression (14), the elements of the aggregated matrix are summed and the values are obtained $\otimes S_i$

$$\otimes S_i = \begin{array}{c} AAI \\ A1 \\ A2 \\ A3 \\ A4 \\ A5 \\ AID \end{array} \begin{bmatrix} [0.828, 0.860] \\ [0.891, 0.925] \\ [0.922, 0.944] \\ [0.902, 0.929] \\ [0.917, 0.944] \\ [0.923, 0.947] \\ [0.965, 0.989] \end{bmatrix}$$

Step 6: Calculation of the utility degree of alternatives. By applying expressions (12) and (13), the grey utility degrees are calculated:

$$\begin{array}{c} \\ AAI \\ A1 \\ A2 \\ A3 \\ A4 \\ A5 \\ AID \end{array} \begin{array}{c} \begin{array}{cc} \otimes K_i^- & \otimes K_i^+ \end{array} \\ \begin{bmatrix} [0.962, 1.039] & [0.837, 0.891] \\ [1.036, 1.118] & [0.901, 0.959] \\ [1.072, 1.14] & [0.932, 0.978] \\ [1.049, 1.122] & [0.912, 0.962] \\ [1.066, 1.141] & [0.927, 0.978] \\ [1.073, 1.145] & [0.933, 0.981] \\ [1.123, 1.195] & [0.976, 1.025] \end{bmatrix} \end{array}$$

The values $\otimes K_i^-$ and $\otimes K_i^+$ for alternative A_1 were computed as follows:

$$\otimes K_i^- = \frac{[0.891, 0.925]}{[0.828, 0.860]} = \left[\begin{array}{l} min\left\{\dfrac{0.891}{0.828}, \dfrac{0.891}{0.860}, \dfrac{0.925}{0.828}, \dfrac{0.925}{0.860}\right\}, \\ max\left\{\dfrac{0.891}{0.828}, \dfrac{0.891}{0.860}, \dfrac{0.925}{0.828}, \dfrac{0.925}{0.860}\right\} \end{array}\right] = [1.036, 1.118]$$

$$\otimes K_i^+ = \frac{[0.891, 0.925]}{[0.965, 0.989]} = \left[\begin{array}{l} min\left\{\dfrac{0.891}{0.965}, \dfrac{0.891}{0.989}, \dfrac{0.925}{0.965}, \dfrac{0.925}{0.989}\right\}, \\ max\left\{\dfrac{0.891}{0.965}, \dfrac{0.891}{0.989}, \dfrac{0.925}{0.965}, \dfrac{0.925}{0.989}\right\} \end{array}\right] = [0.901, 0.959]$$

Other values $\otimes K_i^-$ and $\otimes K_i^+ (i = 1, 2, ..., 5)$ are obtained in a similar way.

Step 7. Determination of utility functions in relation to the ideal $\otimes f(K_i^+)$ and anti-ideal $\otimes f(K_i^-)$ solution. Using expressions (16) and (17), values $\otimes f(K_i^+)$ and $\otimes f(K_i^-)$ can be produced:

$$\begin{array}{c} \\ A1 \\ A2 \\ A3 \\ A4 \\ A5 \end{array} \begin{array}{c} \begin{array}{cc} \otimes f(K_i^-) & \otimes f(K_i^+) \end{array} \\ \begin{bmatrix} [0.487, 0.526] & [0.424, 0.451] \\ [0.504, 0.536] & [0.438, 0.460] \\ [0.493, 0.528] & [0.429, 0.452] \\ [0.501, 0.537] & [0.436, 0.460] \\ [0.505, 0.538] & [0.439, 0.462] \end{bmatrix} \end{array}$$

Step 8: *Determination of the utility function of alternatives $f(K_i)$ and ranking the alternatives*. By applying expression (15) we receive the utility function of alternatives:

$$f(K_i) = \begin{array}{c} A1 \\ A2 \\ A3 \\ A4 \\ A5 \end{array} \begin{bmatrix} 0.2784 \\ 0.2948 \\ 0.2830 \\ 0.2932 \\ 0.2962 \end{bmatrix}$$

By applying the expression (15) the utility function for A_1 is observable:

$$f(K_1) = \frac{0.930 + 1.077}{1 + \frac{1-0.437}{0.437} + \frac{1-0.507}{0.507}} = 0.6155$$

In the similar way we get values $f(K_i)$ for the remaining alternatives, i.e. we get the following rank of alternatives: $A_5 > A_2 > A_4 > A_3 > A_1$.

In order to compare these results and indicate some guidelines to the worst airport, we look at the Table 3, where the aggregated opinion of experts appears. Our best-ranked candidate (A_5) in many indicators has priority than others. We have discussed this with experts and it has been realized that Airport 5, offered effective information sharing strategies and friendly staff, clean and tidy environment, accessible exchange offices. Our evidence shows that high quality restaurants with reasonable prices, shops and rest rooms, parking availability, check-in procedure and baggage claim are competitive advantages in that airport. These items lead Airport 1 to fail. Our results can be a report of excellent services for lower rank airports as A_3 and A_1. Management and operation system in these airports must rethink of the expected services and enhance the quality indicators in the above aspects.

4.2.2. Sensitivity analysis and validation of the results

Numerous authors in their research emphasized that sensitivity analysis in multi-criteria problems is an indispensable step to confirm the robustness of the obtained solutions (Saaty & Ergu, 2015; Simanaviciene & Ustinovicius, 2012; Stewart, French, & Rios, 2013; Zolfani, Yazdani, Pamucar, & Zarate, 2020). Some authors (Mukhametzyanov & Pamučar, 2018; Stewart et al., 2013) suggest checking the robustness of solutions in MCDA problems by changing the input parameters of the model. More of that, various researches (Bozanic, Tešić, & Kočić, 2019; Diyaley & Chakraborty, 2019; Nenadić, 2019) conducted solution validation through comparison with other multi-criteria techniques from the literature. In accordance with the above recommendations, in the following section, the robustness of our proposed decision model is tested by checking the input parameters of the model (section **a**) plus comparing it with other multi-criteria techniques (section **b**).

a) changing the input parameters of the SW'MARCOS-G methodology

In this section, the influence of the change of input parameters of the proposed MCDA model on the results is analyzed. The input parameters of the multicriteria model here meant the weight coefficients of the criteria and the free parameters (p and q) Bonferroni of the integration operator.

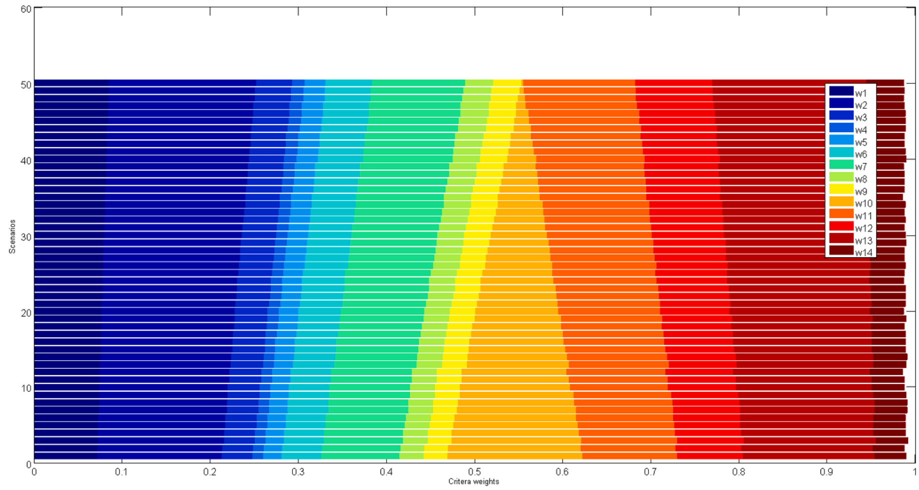

Fig. 2. Criteria weights revealed through 50 scenarios.

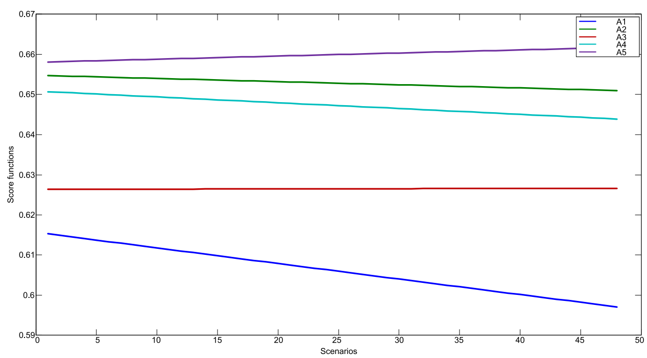

Fig. 3. Influence of changing weight of criterion C_{10} on the utility functions of alternatives.

The change in the value of the weight coefficients was performed through 50 scenarios through which the change in the value of the weight coefficient of the best criterion C_{10} in the interval $w_{10} \in [0.002, 0.155]$ was simulated. In the first scenario, the value of criterion C_{10} was reduced by 1%, while the values of the remaining criteria were proportionally adjusted to meet the condition $\sum_{j=1}^{14} w_j = 1$. In each subsequent scenario, the value of criterion C_{10} was corrected by 2%. The correction of the values of the remaining criteria in each scenario was performed using the proportion $w_n : (1 - w_{10}) = w_n^* : (1 - w_{10}^*)$, where w_{10}^* represents the corrected value of the weight coefficient of criterion C_{10}, w_n^* represents the reduced value of the considered criterion, $w_n$represents the original value of the considered criterion and w_{10} represents the original value of criterion C_{10}. The vectors of weight coefficients thus formed are shown in Fig. 2.

After the formation of the new 50 vectors of weight coefficients, the influence of the new values of the weight of the criteria on the change in the value of the utility function of alternatives was analyzed. Changes in the utility functions of alternatives are shown in Fig. 3.

The results of the change in utility functions of alternatives (Fig. 3) show that the first-ranked alternative (A_5) has a sufficient advantage over the remaining alternatives. Through all 50 scenarios in which the

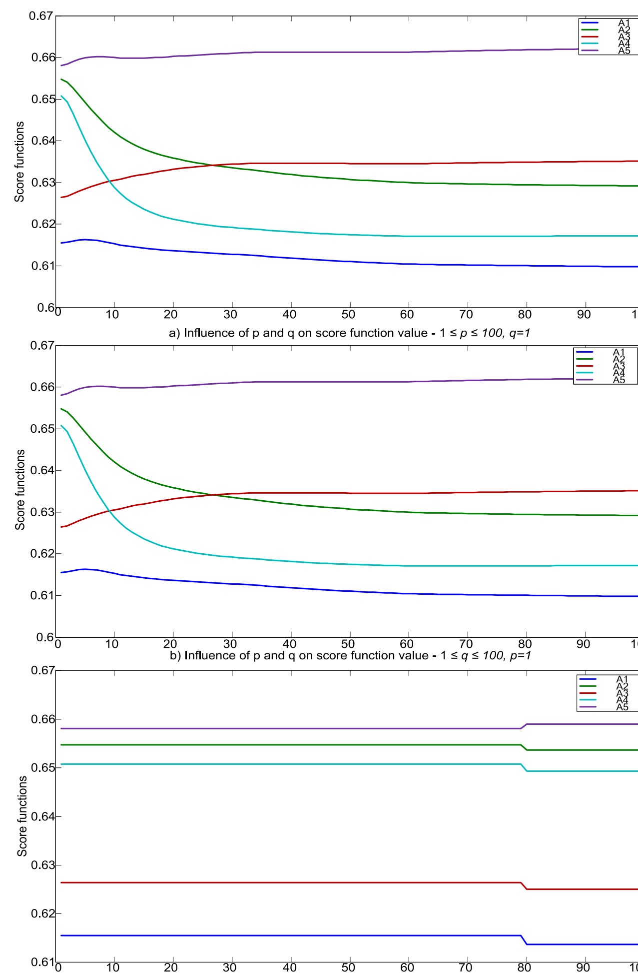

Fig. 4. Influence of changing parameters *p* and *q* on the utility function of alternatives.

change of the value of criterion C_{10} was simulated, the initial rank $A_5 > A_2 > A_4 > A_3 > A_1$ was confirmed.

In the following section, the influence of changing the parameters p and q in the Bonferroni integration operator is analyzed. The Bonferroni integration operator is used to integrate the values of the criterion weight coefficients in the SWARA model and to integrate expert preferences in the MARCOS-G model. The initial rank $A_5 > A_2 > A_4 > A_3 > A_1$ is defined for the values of the parameters $p = q = 1$. However, changing the values of the parameters p and q leads to the transformation of the mathematical expression of the Bonferroni integration operator. Therefore, in the following section, the influence of changing the parameters p and q on the value of utility functions of alternatives is studied. The change of p and q parameters was analyzed in the interval $[1, 100]$. A total of 300 scenarios were formed. In the first 100 scenarios, the impact of parameter p change was measured in interval $p \in [1, 100]$, while the parameter q value was $q = 1$, Fig. 4a. In the next 100 scenarios, the impact of parameter q change for interval $q \in [1, 100]$ was analyzed, while the value of the parameter p was $p = 1$, shown by Fig. 4b. At the end, in the last 100 scenarios, the change of both parameters was simulated in interval $p, q \in [1, 100]$, as it draws in Fig. 4c.

By analyzing the results presented in Fig. 4, we notice that for changes in the values of the parameters $1 \leqslant p \leqslant 100$ and $1 \leqslant q \leqslant 100$ (Fig. 4c) there is no change in the rank of alternatives and that the initial rank $A_5 > A_2 > A_4 > A_3 > A_1$ is confirmed through all 100 scenarios. When changing parameter values $1 \leqslant p \leqslant 100$;$q = 1$ and $1 \leqslant q \leqslant 100$;$p = 1$ (Fig. 4a and 4b) there are changes in the values of the utility function of alternatives. Throughout all 200 simulations, the A5 alternative remained ranked first, confirming its dominance over the remaining alternatives. Also, the worst alternative A1, through all 200 scenarios, remained the last ranked. The second-ranked alternative A2 kept the initial rank for the values of parameters $1 \leq p, q \leq 26$, while for the values of parameters $27 \leq p, q \leq 100$ it took the third position. Similar changes occurred for the third-ranked alternative (A4). For the values of $1 \leq p, q \leq 9$ it kept the initial rank, while for the values of $10 \leq p, q \leq 100$ it took the fourth rank. The biggest changes in the value of utility functions occurred with alternative A3. For the values of the parameters $1 \leq p, q \leq 9$, the alternative A3 kept the initial rank (fourth position). However, for the values of the parameters $10 \leq p, q \leq 26$ it became the third ranked, while for the values of $27 \leq p, q \leq 100$ it took the second rank.

The simulation output demonstrates that changes in the values of the parameters p and q affect the change in the utility function of alternatives, so the analysis of the influence of the values of the parameters p and q is an indispensable step in the direction of initial rank validation. In the first 200 simulations, there are changes in the range of alternatives A_2, A_4 and A_3. While in the last 100 simulations, the initial rank $A_5 > A_2 > A_4 > A_3 > A_1$ was confirmed. Through all 300 simulations, the dominance of the best alternative A_5 was confirmed. Also, it was confirmed that alternative A_1 is the worst alternative. The changes that occur in the ranks of the remaining alternatives are not extreme; this is confirmed by Spearman's correlation coefficient (SCC) of ranks that was used to determine the statistical significance of the difference between the initial rank and the values obtained through 300 scenarios. SCC is suitable for application when there are ordinal variables and ranked variables, which is the case in this study. The initial revealed rank (i.e., $A_5 > A_2 > A_4 > A_3 > A_1$) was considered as a reference value for the SCC application. The mean value of SCC (SCC = 0.76) shows that there is a significant correlation across 300 scenarios. Based on the analysis shown, we can conclude that there is a satisfactory reliability and robustness of the initial solution presented in the case study.

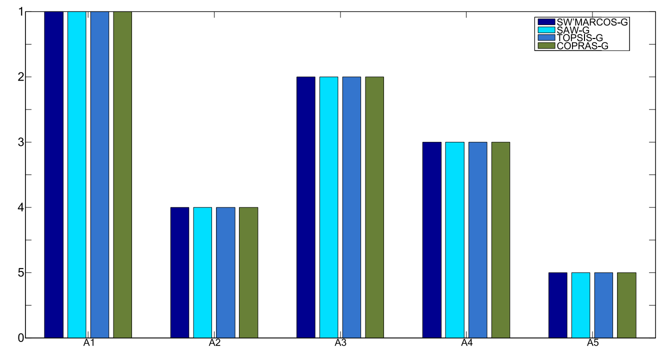

Fig. 5. The comparison of different MCDA methodologies.

b) exploring stability of ranking based on different ranking methodologies

The robustness check of the initial rank of the SW'MARCOS-G model was performed by comparison with three multi-criteria techniques developed in the grey environment: SAW-G method (Zavadskas, Vilutiene, Turskis, & Tamosaitiene, 2011), TOPSIS-G method (Zavadskas et al., 2011) and the COPRAS-G method (Zolfani, Chen, Rezaeiniya, & Tamošaitienė, 2012). A comparative overview of the ranks generated using the above multi-criteria techniques is shown in Fig. 5.

Based on a comparison of the results shown in Fig. 5, the ranking order of the SW'MARCOS-G model is similar to the order proposed by the multi-criteria techniques developed in Zavadskas et al. (2011) and Zolfani et al. (2012). The results in Fig. 5 confirm the applicability of the proposed improvement of the SWARA-MARCOS model. From the proposed analysis we can infer that by applying different MCDA techniques based on different aggregation operators the same results are obtained, and this can prove the validity of the proposed model in this paper.

5. Research implication and discussion

The proposed SW'MARCOS-G methodology enables decision makers to express their preferences as clearly as possible, and to reduce the subjectivity and uncertainty that exists in the decision-making process. Interval grey numbers (IGNs) can better express the diversified and utilized information that affect the rationality of decision results. IGNs can flexibly express uncertain, imprecise and inconsistent information that widely exist in real-life situations. The operation and ranking method for IGNs plays a vital role in development of grey system theory. Using the kernel and the degree of greyness of interval grey number, authors propose IGN Bonferroni aggregation operator. Based on the above operator and transforming linguistic scale of rating alternative attributes into interval grey numbers, a novel interval grey based SWARA and MARCOS is proposed considering the interaction between attributes which has influenced on decision results. The basic idea of applying algorithms in the decision making process that are based on the interval approach includes the application of IGNs for presenting attribute values. On the basis of proposed improvement, the proposed hybrid method can be used more efficiently for solving a larger number of complex real-world decision-making problems, especially those associated with an uncertainty. The usability and effectiveness of the proposed approach are checked by the numerical illustration and final results of the methodology are observable in result discussion section.

However, one of the limiting factors of the presented methodology is a complex mathematical apparatus, which is based on complex mathematical formulations for fusion of group decisions and manipulation with grey numbers. Therefore, the acceptance of this methodology by a wide range of users may be limited. Most users of multi-criteria models accept mathematically simple and easy-to-understand decision-making tools. This situation applies to most mathematically complex approaches. However, tools that require the processing of group information, while respecting the uncertainties that exist in group preferences, are by their nature complex decision-making tools. The very nature of the problems that such tools solve requires a complex mathematical formulation. Therefore, the model used in this paper does not fall into the mathematically easy-to-understand category of decision-making tools. However, the integration of the SW'MARCOS-G model into the decision-making system will make it more acceptable for solving a large number of real world problems. Such integration will make it acceptable for decision makers who face uncertain and imprecision information during decision making. The proposal of a user-oriented decision support system was prepared during the preparation of this study and is based on the application of Visual Basic and Matlab software packages.

This article has several implications for researchers and airline industry owners. First of all, establishing a service quality system reflects a positive point to the passengers' expectations. Our comparison for airports was done by independent, unbiased, experts from other airports. This reduces the bias in data collection and enhances the reliability of results. Another implication is the unique combined decision model we used to decrease difficulty of a qualitative evaluation. As discussed, we used grey values and linguistic variables to facilitate preference judgment for experts and at the same time giving them enough flexibility. This study determines the service quality level of the most crowded and traffic airports in Spain. We surely state that this decision-making structure is unique and has not presented in other studies.

Customers and passengers' perception should be a fundamental source of information that could close us to the feeling and direct opinion of the elements that received those services. Thus, one of the limitations of this research may fall in the passenger-driven framework for the airport service quality measurement. This could be accommodated by conducting a survey for passengers and customers asking for their preferred service quality factors. Another restriction for research team was that we are not eligible to declare the name of the airports, so we used A_1-A_5 codes. It must be stated that the proposed model can be generalized to wider studies with more variables and dimensions, participation of 4 or 5 experts and more airports in Spain or Europe. Other limitations of our study include the relatively large number of criteria used to evaluate alternatives, the small sample size, and the possible impact of survey formatting on study results. Further research is recommended on a larger sample of respondents familiar with the context of the decision and considering the possibility of grouping certain criteria into clusters in order to reduce the number of criteria.

6. Conclusion and future research lines

The service quality has turned to a fundamental discipline in airport management. Its contribution was investigated over decades since it has substantial advantages on the economy, marketing, and tourism sectors. A system that enables to measure and control the airport service quality is an instant need for responsible directors and executives. As discussed in Section 3, we proposed a measurement model for perceived service quality at several airports in Spain using a decision-making analysis model and grey operators. We believe our model can be a reference for improvement of airport performance and in other side can esteem further guidelines in area of air industry management. Our research points out directions for managers who look for solutions in service quality as a practical support to the global strategy of the airports.

For evaluation process, two experts participated, and several meetings were handled in order to comprehend the research objectives and dimension. Five airports and fourteen criteria were involved. The experts delivered their opinion using grey and verbal values. Using the SWARA and MARCOS methods we have identified the most important criterion in service quality of airports. In addition, we ranked the airports with respect to those criteria and their importance. Our observation released that parking and access to internet Wi-Fi are recognized as the most influencing service parameters while ATM availability has the least significance among rest of them. Once again, the MARCOS algorithm identified that A_5 is selected as the top airport in terms of service quality and might be seen as an ideal reference for other entities. The benefit of using MCDA methods is that the low ranked alternatives can learn and benchmark from top ones. The strength and weaknesses appear in this stage and decision makers can work and take corrective actions. All these steps were tested with our definitive simulations and analysis and additional possible comparisons with SAW, TOPSIS and COPRAS. The sensitivity analysis and simulations interpreted the accuracy of the achievements and moreover, the comparisons with other MCDA tools showed a high level of confidence to the results. We can report that A_5 is the most qualified airport due to its standards and attitudes in managing airport operation based on out expert team opinion. It is concluded that a key managerial implication is to address the desirable aspects of A_5 in order to be a pattern for other airport, like they are able to invest and take required actions.

Last but not least, this research could be extended by performing evaluation considering commercial passengers and cargo service, individually, where normal passengers might have different quality evaluation criteria compared to managers that use airports 'cargo services. Also, further research should be directed towards the development of a universal decision-making tool based on the SW'MARCOS-G methodology and which enables the implementation of a different number of criteria/sub-criteria for decision-making. In addition, it is necessary to think in the direction of extending the proposed methodology by applying rough set theory. This extension will allow the formation of limit values for interval grey-rough numbers based on the uncertainties that exist in expert preferences, rather than on the assumptions that apply to grey numbers. Finally, it would be interesting to perform a thorough investigation with managers at the considered airports that showed weak performance, mainly, to explore challenges towards improvement avenues and strategies embedding current evaluation factors. Integrating other tools like quality function deployment (QFD) for customer satisfaction and utilization of fuzzy MCDA methods like combined compromise solution (CoCoSo) and Multi-Attributive Border Approximation area Comparison (MABAC) must be interesting are sort of actions for future investigators.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Dr. Ahmed Mohammed would like to express his gratitude for the Research Project Funding from the Ministry of Higher Education, Research and Innovation/The Research Council (TRC) of the Sultanate of Oman, under Commissioned Research Program, Contract NO. TRC/CRP/MU/COVID-19/20/15.

Appendix. Questionnaire form for experts

Universidad LOYOLA	**Universidad Loyola Andalucia** Airport evaluation	**Date** / **/ 2020**

A) Expert General Information Please indicate your Personal Information by (X)					**1. Gender**	Male		Female	
2. Position	Senior Level		Middle Level		Junior Level			
3. Education	Diploma		Bachelor		Master		Phd	
4. Year of experience	Less than 5		5 to 10		11 to 15		More than 15	
5. Age group	Below 30		30 to 39		40-49		over 50	

B) Expert evaluation & Judgment
In each evaluation system, we have Alternatives and Indicators. For this study, our alternatives are Airports (4 airports in Spain) and indicators are list of 14 criterion (C1-C14).
In this step, experts are asked to rate the criteria first. For example each expert determines the priority of each criterion and then the importance of each criterion on the next one is identified. Like example of below:

B.1.) Suppose that we have 14 indicators: Courtesy and helpfulness of staffs, information desk and security (c1), Cleanness of airport facilities and services (c2), Variety of shops & restaurants (c3), Access to ATM (c4), Exchange offices availability (c5), Lighting system (c6), Air-conditioning systems (c7), Flight display information (c8), Access to underground, bus or main transportation systems (c9), Parking (c10), Car rental offices (c11), check-in process efficiency (c12), Wi-Fi open access (c13), and Baggage claim (c14).

Indicators	**Priority Indicators**	**Importance over the next criterion**
C1		
C2		
C3		
C4		
C5		
C6		
C7		
C8		
C9		
C10		
C11		
C12		
C13		
C14		

B.2.) Alternative (airports) evaluation
In this section, we have to compare airports with respect of the each criterion using the linguistic variables appeared below. To rate alternatives we utilize the grey linguistic parameters as shown in this Table below. Experts firstly, select the linguistic category they have in mind (they judge), then within the interval numbers they have flexibility of selecting the quantitative values. Suppose that we show the function of evaluating Airport 1 on indicator (c_{12}), If someone rates is a Moderately Bad condition on check in efficiency indicator; $A_1(C_{12})$, he/she is asked to deliver the worst (minimum, pessimistic) and best (maximum, optimistic) score among that specific category. In this case that can be any pair values in interval of 21 to 30. For instance if they may choose (25,28) means that in the most pessimistic way Airport 1 can have an score of 25, while in the most optimistic way 28.

Airports										
	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10
A1										
A2										
A3										
A4										

Airports	c11	c12	c13	c14
A1				
A2				
A3				
A4				

References

ACI (2020). ACI's World releases most comprehensive Airport Traffic Dataset. Retrieved from https://aci.aero/news/2020/07/20/acis-world-releases-most-comprehensive-airport-traffic-dataset/.

ACI (2020). The global challenge of securing the sustainable growth of aviation. Retrieved from https://www.internationalairportreview.com/article/84971/sustainable-aviation-growth-globally/.

AENA, 2019. http://www.aena.es/en/corporate/cr-report.html.

Allen, J., Bellizzi, M. G., Eboli, L., Forciniti, C., & Mazzulla, G. (2020). Latent factors on the assessment of service quality in an Italian peripheral airport. *Transportation Research Procedia, 47*, 91–98.

Arabali, P., Sakhaeifar, M. S., Freeman, T. J., Wilson, B. T., & Borowiec, J. D. (2017). Decision-Making guideline for preservation of flexible pavements in general aviation airport management. *Journal of Transportation EngineeringPart B: Pavements, 143*(2), 04017006.

Badi, I., & Pamucar, D. (2020). Supplier selection for steelmaking company by using combined Grey-Marcos methods. *Decision Making: Applications in Management and Engineering, 3*(2), 37–48.

Bezerra, G. C. L., & Gomes, C. F. (2015). The effects of service quality dimensions and passenger characteristics on passenger's overall satisfaction with an airport. *Journal of Air Transport Management, 44-45*, 77–81.

Bitner, M. J., Booms, B. H., & Tetreault, M. S. (1990). The service encounter: diagnosing favorable and unfavorable incidents. *Journal of marketing, 54*(1), 71–84.

Bogicevic, V., Yang, W., Bilgihan, A., & Bujisic, M. (2013). Airport service quality drivers of passenger satisfaction. *Tourism Review, 68*(4), 3–18. https://doi.org/10.1108/TR-09-2013-0047

Bonferroni, C. (1950). Sulle medie multiple di potenze. *Bollettino dell'Unione Matematica Italiana, 5*(3–4), 267–270.

Bozanic, D., Tešić, D., & Kočić, J. (2019). Multi-criteria FUCOM – Fuzzy MABAC model for the selection of location for construction of single-span bailey bridge. *Decision Making: Applications in Management and Engineering, 2*(1), 132–146.

Buonanno, A., D'Urso, M., Prisco, G., Felaco, M., Meliado, E.F., Mattei, M., Palmieri, F. and Ciuonzo, D., 2012, September. Mobile sensor networks based on autonomous platforms for homeland security. In 2012 Tyrrhenian Workshop on Advances in Radar and Remote Sensing (TyWRRS) (pp. 80-84). IEEE.

Chang, C.-H., & Lin, J. T. (1991). Data flow model of a total service quality management system. *Computers & Industrial Engineering, 21*(1-4), 117–121.

Ciuonzo, D., Buonanno, A., D'Urso, M., & Palmieri, F. A. (2011). Distributed classification of multiple moving targets with binary wireless sensor networks. In *14th International Conference on Information Fusion* (pp. 1–8). IEEE.

Deveci, M., Özcan, E., John, R., & Öner, S. C. (2018). Interval type-2 hesitant fuzzy set method for improving the service quality of domestic airlines in Turkey. *Journal of Air Transport Management, 69*, 83–98. https://doi.org/10.1016/j.jairtraman.2018.01.008

Diyaley, S., Chakraborty, S. (2019). Optimization of multi-pass face milling parameters using metaheuristic algorithms, Facta universitatis series: Mechanical Engineering, 17(3), 365 – 383.

Djalic, I., Stevic, Z., Karamasa, C., & Puska, A. (2020). A novel integrated fuzzy PIPRECIA – interval rough SAW model: Green supplier selection. *Decision Making: Applications in Management and Engineering, 3*(1), 126–145.

Fodness, D., & Murray, B. (2007). Passengers' expectations of airport service quality. *Journal of Services Marketing, 21*(7), 492–506.

Fu, X., & Oum, T. H. (2014). Air transport liberalization and its effects on airline competition and traffic growth – An overview. *The Economics of International Airline Transport, 4*, 11–44.

Ghobadian, A., Speller, S., & Jones, M. (1994). Service quality: Concepts and models. *International Journal of Quality & Reliability Management, 11*(9), 43–66. https://doi.org/10.1108/02656719410074297

Gomez, J., Papanikolaou, A., & Vassallo, J. M. (2017). Users' perceptions and willingness to pay in interurban toll roads: Identifying differences across regions from a nationwide survey in Spain. *Transportation, 44*(3), 449–474.

Gupta, H. (2018). Evaluating service quality of airline industry using hybrid best worst method and VIKOR. *Journal of Air Transport Management, 68*, 35–47.

Haghighat, N. (2017). Proposing a framework for airline service quality evaluation using Type-2 Fuzzy TOPSIS and non-parametric analysis. Journal of Sustainable Development of Transport and Logistics, 2(2), 6–25. DOI:10.14254/jsdtl.2017.2-2.1.

Heizer, J. (2016). Operations management, 11/e. Pearson Education India.

Kayapınar, S., & Erginel, N. (2019). Designing the airport service with fuzzy QFD based on SERVQUAL integrated with a fuzzy multi-objective decision model. *Total Quality Management & Business Excellence, 30*(13-14), 1429–1448. https://doi.org/10.1080/14783363.2017.1371586

Kazemi, A., Attari, M. Y. N., & Khorasani, M. (2016). Evaluating service quality of airports with integrating TOPSIS and VIKOR under fuzzy environment. *International Journal of Services, Economics and Management, 7*(2–4), 154–166.

Keršuliene, V., Zavadskas, E. K., & Turskis, Z. (2010). Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA). Journal of business economics and management, 11(2), 243-258.

Korfiatis, N., Stamolampros, P., Kourouthanassis, P., & Sagiadinos, V. (2019). Measuring service quality from unstructured data: A topic modeling application on airline passengers' online reviews. *Expert Systems with Applications, 116*, 472–486.

Kratudnak, S., & Tippayawong, K. Y. (2018). Analysis of key factors for airport service quality: A case study of three regional airports in Thailand. *Proceedings of the International Conference on Industrial Engineering and Operations Management*.

Kurniawan, R. (2017). Passenger'S Perspective Toward Airport Service Quality (Asq) (Case Study At Soekarno-Hatta International Airport). *Journal of the Civil Engineering Forum, 3*(1), 291. https://doi.org/10.22146/jcef.26547

Lee, C.-H., Zhao, X., & Lee, Y.-C. (2019). Service quality driven approach for innovative retail service system design and evaluation: A case study. *Computers & Industrial Engineering, 135*, 275–285.

Liou, J. J. H., Hsu, C.-C., Yeh, W.-C., & Lin, R.-H. (2011). Using a modified grey relation method for improving airline service quality. *Tourism Management, 32*(6), 1381–1388. https://doi.org/10.1016/j.tourman.2011.01.013

Liou, J. J. H., Tang, C. H., Yeh, W. C., & Tsai, C. Y. (2011). A decision rules approach for improvement of airport service quality. *Expert Systems with Applications, 38*(11), 13723–13730. https://doi.org/10.1016/j.eswa.2011.04.168

Lubbe, B., Douglas, A., & Zambellis, J. (2011). An application of the airport service quality model in South Africa. *Journal of Air Transport Management, 17*(4), 224–227. https://doi.org/10.1016/j.jairtraman.2010.08.001

Lupo, T. (2015). Fuzzy ServPerf model combined with ELECTRE III to comparatively evaluate service quality of international airports in Sicily. *Journal of Air Transport Management, 42*, 249–259. https://doi.org/10.1016/j.jairtraman.2014.11.006

Lupo, T., & Bellomo, E. (2019). DINESERV along with fuzzy hierarchical TOPSIS to support the best practices observation and service quality improvement in the restaurant context. *Computers & Industrial Engineering, 137*, 106046.

Martins, S.M., Ferreira, F.A.F., Ferreira, J.J.M. and Marques, C.S.E. (2020), "An artificial-intelligence-based method for assessing service quality: insights from the prosthodontics sector", Journal of Service Management, DOI:10.1108/JOSM-03-2019-0084.

Mohammed, A. (2020). Towards 'gresilient' supply chain management: A quantitative study. *Resources, Conservation and Recycling, 155*, 104641.

Mohammed, A., Harris, I., Soroka, A., Naim, M., Ramjaun, T., & Yazdani, M. (2020). Gresilient supplier assessment and order allocation planning. *Annals of Operations Research*, 1–28.

Mukhametzyanov, I., & Pamučar, D. (2018). A Sensitivity analysis in MCDM problems: A statistical approach. *Decision Making: Applications in Management and Engineering, 1*(2), 51–80.

Nenadić, D. (2019). Ranking dangerous sections of the road using MCDM model. *Decision Making: Applications in Management and Engineering, 2*(1), 115–131.

Pabedinskaitė, A., & Akstinaitė, V. (2014). Evaluation of the airport service quality. *Procedia - Social and Behavioral Sciences, 110*, 398–409.

Pamučar, D., Petrović, I., & Ćirović, G. (2018). Modification of the Best–Worst and MABAC methods: A novel approach based on interval-valued fuzzy-rough numbers. *Expert Systems with Applications, 91*, 89–106.

Pandey, M. M. (2016). Evaluating the service quality of airports in Thailand using fuzzy multi-criteria decision making method. *Journal of Air Transport Management, 57*, 241–249. https://doi.org/10.1016/j.jairtraman.2016.08.014

Pandey, M. M. (2020). Evaluating the strategic design parameters of airports in Thailand to meet service expectations of Low-Cost Airlines using the Fuzzy-based QFD method. *Journal of Air Transport Management, 82*, 101738.

Pantouvakis, A., & Renzi, M. F. (2016). Exploring different nationality perceptions of airport service quality. *Journal of Air Transport Management, 52*, 90–98. https://doi.org/10.1016/j.jairtraman.2015.12.005

Prakash, C., & Barua, M. K. (2016). A robust multi-criteria decision-making framework for evaluation of the airport service quality enablers for ranking the airports. *Journal of Quality Assurance in Hospitality & Tourism, 17*(3), 351–370.

Rocha, P. M.d., Barros, A. P.d., Silva, G. B.d., & Costa, H. G. (2016). Analysis of the operational performance of Brazilian airport terminals: A multicriteria approach with De Borda-AHP integration. *Journal of Air Transport Management, 51*, 19–26.

Saaty, T. L., & Ergu, D. (2015). When is a decision-making method trustworthy? Criteria for evaluating multi-criteria decision-making methods. *International Journal of Information Technology & Decision Making, 14*(06), 1171–1187.

Siergiejczyk, M., & Krzykowska, K. (2014). Some issues of data quality analysis of automatic surveillance at the airport. *Diagnostyka, 15*(1), 25–29.

Siksnelyte-Butkiene, I., Zavadskas, E.K. and Streimikiene, D., 2020. Multi-criteria decision-making (MCDM) for the assessment of renewable energy technologies in a household: a review. Energies, 13(5), p.1164.

Simanaviciene, R., & Ustinovicius, L. (2012). A new approach to assessing the biases of decisions based on multiple attribute decision making methods. *Elektronika ir Elektrotechnika, 117*(1), 29–32.

Singh, A.K. (2016), "Competitive service quality benchmarking in airline industry using AHP", Benchmarking: An International Journal, 23(4), 768-791. DOI:10.1108/BIJ-05-2013-0061.

Sohail, M. S., & Al-Gahtani, A. S. (2005). Measuring service quality at King Fahd International Airport. *International Journal of Services and Standards, 1*(4), 482–493. https://doi.org/10.1504/IJSS.2005.007473

STATISTA (2020). Global air traffic - annual growth of passenger demand 2006-2021. Retrieved from https://www.statista.com/statistics/193533/growth-of-global-air-traffic-passenger-demand/.

Stević, Ž., Pamučar, D., Puška, A., & Chatterjee, P. (2020). Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to COmpromise solution (MARCOS). *Computers & Industrial Engineering, 140*, 106231. https://doi.org/10.1016/j.cie.2019.106231

Stewart, T. J., French, S., & Rios, J. (2013). Integrating multicriteria decision analysis and scenario planning—Review and extension. *Omega, 41*(4), 679–688. https://doi.org/10.1016/j.omega.2012.09.003

Tsafarakis, S., Kokotas, T., & Pantouvakis, A. (2018). A multiple criteria approach for airline passenger satisfaction measurement and service quality improvement. *Journal of Air Transport Management, 68*, 61–75. https://doi.org/10.1016/j.jairtraman.2017.09.010

Tsai, W.-H., Hsu, W., & Chou, W.-C. (2011). A gap analysis model for improving airport service quality. *Total Quality Management & Business Excellence, 22*(10), 1025–1040. https://doi.org/10.1080/14783363.2011.611326

Yazdani, M., Pamucar, D., Chatterjee, P., & Chakraborty, S. (2020). Development of a decision support framework for sustainable freight transport system evaluation using rough numbers. *International Journal of Production Research*, 1–27. https://doi.org/10.1080/00207543.2019.1651945

Zavadskas, E. K., Vilutiene, T., Turskis, Z., & Tamosaitiene, J. (2011). Contractor selection for construction works by applying SAW-G and TOPSIS grey techniques. *Journal of Business Economics and Management, 11*(1), 34–55.

Zietsman, D., & Vanderschuren, M. (2014). Analytic Hierarchy Process assessment for potential multi-airport systems – The case of Cape Town. *Journal of Air Transport Management, 36*, 41–49. https://doi.org/10.1016/j.jairtraman.2013.12.004

Zolfani, S. H., Chen, I.-S., Rezaeiniya, N., & Tamošaitienė, J. (2012). A hybrid MCDM model encompassing AHP and COPRAS-G methods for selecting company supplier in Iran. *Technological and Economic Development of Economy, 18*(3), 529–543.

Zolfani, S. H., Yazdani, M., Pamucar, D., & Zarate, P. (2020). *A VIKOR and TOPSIS focused reanalysis of the MADM methods based on logarithmic normalization*. Facta universitatis series: Mechanical Engineering.