DOI 10.2478/sbe-2020-0037

SBE no. 15(2) 2020

ESTIMATING THE DEMAND FOR NEW DESTINATIONS FOR A REGIONAL AIRPORT BASED ON ITS CATCHMENT AREA

ȚICHINDELEAN MIHAI

Lucian Blaga University of Sibiu, Romania

MIHAIU DIANA MARIETA

Lucian Blaga University of Sibiu, Romania

OPREANA ALIN

Lucian Blaga University of Sibiu, Romania

TILEAGA COSMIN

Lucian Blaga University of Sibiu, Romania

Abstract:

Estimating accurately demand both at market and company level for specific goods and services can be considered a necessity for every organization. Traditional demand estimation methods may not be relevant for estimating the demand for new destinations to be introduced by a regional airport. The present paper proposes to fill this gap and to develop the demand estimation literature by presenting a novel demand estimation method. Two research objectives are developed in this regard: (1) determining the catchment area of Sibiu International Airport (a regional airport in Romania) for destinations operated by competitor airports and not by Sibiu International Airport and (2) estimating the demand for new destinations based on the identified catchment area.

Key words: *demand estimation, catchment area, regional airport*

1. Introduction

Estimating accurately demand both at market and company level for specific goods and services can be considered a necessity for every organization. By having accurate demand estimation, an organization can increase the efficiency and effectiveness of specific activities like production planning, pricing, negotiation with suppliers, human resource management, supply chain management. There are several traditional methods that can be used to estimate the company's demand, surveying the customer's buying intention being the most known one. Qualitative demand estimation

methods include composite of sales force opinions and industries' expert opinion; past-sales analysis and market-test (and the mentioned survey) being quantitative ones.

For a regional airport, demand analysis and estimation of actual, operating routes are not easy to perform, but methods like past-sales analysis could provide accurate results if the proper data analysis techniques are used. Arguable are the methods which should be applied and the data which should be collected for estimating the demand for new routes to be introduced by one regional airport. In this regard, past traffic data does not exist and the preferences for new routes of the prospective passenger can differ from their actual buying behavior and from the route operating strategy of the airline companies, thus surveying these preferences may be obsolete.

The present paper proposes a novel demand estimation method for new routes for a regional airport (Sibiu International Airport, Romania) by considering the airport's catchment area. Within the first part of the paper, a thorough literature review is performed regarding (1) the existing methods used by airports for estimating the traffic demand and (2) the catchment area of airports. The research section contains the proposed method of estimating the demand for new destinations for Sibiu International Airport, a regional airport in Romania. Two research objectives are developed for that respect: (1) determining the catchment area of Sibiu International Airport for destinations operated by competitor airports and not by Sibiu International Airport and (2) estimating the demand for new destinations based on the identified catchment area.

2. Literature Review

In terms of demand analysis, studies show a predisposition for quantitative analyses of demand through econometric models, and the trend is to use models based on the interaction between consumers, characterized by a set of socio-economic variables, and airport facilities. From this interaction, the models used in similar studies identify the behavioral reactions of consumers and potential consumers to the services and facilities provided by the airport, as well as airline companies. The results of applied studies and research lead to the segmentation of airports according to the potential demand and the served air traffic. Further, we explore certain studies that have examined air traffic demand considering different models and methodologies.

Starting from the issue of demand forecasting, Blinova proposes a neural network model for estimating short-term demand by including 28 time-lagged feed-forward artificial neural networks (Tatiana Blinova, 2007).

Moreover, the quantitative approach to determining short- and medium-term demand through econometric models is also used by Fildes, Wei and Ismail using autoregressive distributed lag (ADL) models, time-varying parameter (TVP) models and an automatic method for econometric model specification (Robert Fildes, Yingqi Wei, Suzilah Ismail, 2011).

Also, Bao, Xiong and Hu proposed an ensemble empirical mode decomposition (EEMD) based support vector machines modeling framework including a slope-based method to restrict the end effect issue which takes place during the shifting process of EEMD (Yukun Bao, Tao Xiong, Zhongyi Hu, 2012).

Further, Wenbin Wei and Mark Hansen applied a logarithmic function for demand estimation of air traffic considering a set of independent variables, such as frequency of flights, seat numbers available in an airplane, price of the ticket, distance of the flight, a network's spoke number, capacity of the airport, income level of the population in the area of the airport, number of local travelers who fly from spoke S to a hub H via airline A, total number of initiated passenger trips originating from spoke S (Wenbin Wei, Mark Hansen, 2006).

A comparable model, called the Econometric Dynamic Model (EDM) was utilized to forecast the quantity of passengers as indicated by economic variables, consumer price index, economically active population, flights number, average hotel occupancy rate, rate of foreign currency exchange considering international arrivals (Rafael Bernardo Carmona-Benítez, Maria Rosa Nieto, Danya Miranda, 2016).

In a different study, Fernandes and Pacheco examine the causal relationship between economic growth and domestic air passenger traffic in Brazil, using Granger's causality test (Elton Fernandes, Ricardo Rodrigues Pacheco, 2010). Also, a recent study highlights the link between socio-economic factors and air traffic in Romanian airports (Bogdan Avram, 2018).

Additionally, Marcucci and Gatta propose for the determination of demand a methodology of consumer segmentation starting from the statistical relevance of the correlation between socio-economic variables with a set of attributes that characterize the airport facilities (Edoardo Marcucci, Valerio Gatta, 2011). Nonetheless, Carballo-Cruz and Costa analyze the demand from the perspective of the correlation' intensity between airport facilities and the rapid increase in traffic and the number of routes (Francisco Carballo-Cruz, Vania Costa, 2014).

Considering the theoretical models already available, a major contribution of the present study is the fact that we adjust the model for estimating the air traffic demand by considering the key role of the catchment area analysis.

Although there is no unanimously accepted method of determining one airport's catchment area, identifying it as accurately as possible is, however, essential for the airport because of the following: to estimate the potential demand for a particular airport (Heng Zhoua, Jianhong Cecilia Xiaa, Qingzhou Luob, Gabi Nikolovac, Jie Sund, Brett Hughesc, Keone Kelobonyea, Hui Wangf, Torbjorn Falkmere, 2018), to analyze the opportunity of launching new routes operated from the airport, to fundament the development plans of the airport's infrastructure, to develop marketing strategies tailored to the potential customers' needs. In this regard, this topic is of major importance for both the airport's management and for the present and potential airline companies. Nevertheless, the catchment area is influenced by factors that drive passengers' airport choice, which may differ depending on the characteristics of the area and of the airport's features. Therefore, studying the methods for determining one airport's catchment area is of major interest.

Some authors argue for studying the people's behavior in choosing their departure airport, and not for determining the catchment area as a geographical delimitation within which the prospective passenger live. In this regard, for business travelers the access time to the airport and flight frequencies are main influence factors in their airport's choice

(according to some studies, business travelers do not allocate more than 1 hour access time to and from the airport), while leisure travelers emphasize the choice of an airport based on: air fare, access time, and frequency of available flights (Norman Ashford, Messaoud Benchemam, 1988) and can allocate 2 hours to access time to and from the airport (Wojciech Augustyniak, Lukasz Olipra, 2014). We consider that before determining the catchment area for an airport, an analysis of the flight behavior of the passengers must be performed, based on which the potential demand of the analyzed airport is determined (see figure 1). There is a close interdependence between the size of the catchment area and the potential demand.

Figure 1: Passenger choice analysis (National Academies of Sciences, Engineering, and Medicine, 2013)

The size of the catchment area also differs depending on the type of airport, whether it is a national, regional or a small airport, located in a tourist destination, such as an airport in a ski resort (Pere Suau-Sanchez, Augusto Voltes- Dorta, 2019). Catchment areas of competitor airports may overlap geographically, thus, it is useful for one airport's management to know the factors that influence the passengers' airports choice in order to *hook* the maximum number of passengers from the respective catchment area (Ioulia Poulaki, Andreas Papatheodorou, Dimitrios P. Stergiou, 2013). Also, the catchment area is a factor that determines the market power of an airport, being adjusted with GDP in this regard (Sven Maertens, 2012).

In practice, the catchment area for an airport is determined either from a geographical perspective, either in terms of demand or a combination of these two perspectives. From a geographical point of view, the catchment area of a regional airport is in the form of circles (Karsten Fröhlich, Hans-Martin Niemeier, 2011) with a radius that represents either a predetermined distance (about 100 km or 200 km) or a distance which involves a duration of about 1 or 2 hours of driving from the place of origin to the airport. From the demand perspective " *the airport catchment area can be defined as the number of travelers using a given airport, where origins of travelers can be identified in a surrounding study area whose size depends on the characteristics of the airport itself, but that does not necessarily represent the geographical extension of the airport catchment area* " (M. Nadia Postorino, 2010, pp. 80). The geographical method of determining the catchment area is indicated to be used for a new airport to determine its optimal location from a geographical point of view considering the distances from other airports. The

method of determining the catchment area from the demand perspective is used when there are competing airports in the area and in this case, the catchment areas determined strictly from a geographically perspective overlap.

Some practical methods to determine the catchment area of a regional airport use an accessible tool, that of surveying airport customers, collecting information about the zip codes of origin (Guido Perboli, Marco Ghirardi, Luca Gobbato, Francesca Perfetti, 2015). Then, to build the catchment area, it takes into account the distance from the airport, the driving time to the airport, the inhabitants of the respective localities, the propensity to fly of the inhabitants, the competing airports and the routes operated from the competing airports (Kurt Fuellhart, 2007). The most used models are gravity models, and lately IT solutions have appeared, which facilitate the automatic calculation of the catchment area size in the form of the number of inhabitants included in it, with the help of the CORINE dataset tool and the GIS analysis (Pere Suau-Sanchez, Guillaume Burghouwt, Montserrat Pallares-Barbera, 2014).

The existence of international airports in the proximity of a regional and/or national airport significantly influences the catchment area of the latter. Especially customers in the leisure segment prefer to travel more, in exchange for more advantageous rates, thus, in this case, the geographical factor is not decisive in influencing the choice of an airport, but flight rates and airport services do (Jon Inge Lian, Joachim Rønnevik, 2011). The regional airports face the problem of small sized catchment area which overlaps with those of competing airports. According to the study performed by Fabio Carlucci, Andrea Cirà and Paolo Coccorese (Fabio Carlucci, Andrea Cirà and Paolo Coccorese, 2018) the following factors are important for ensuring their efficiency and sustainability: the airport size, the presence of low-cost carriers and the presence of cargo traffic.

Moreover, if the analyzed airport is in the proximity of another airport located in a foreign country, studies have shown that crossing the border to fly is a psychological barrier for residents, and this aspect favorably influences the catchment area of the first airport, regardless of other factors. (Dejan Paliska, Samo Drobne, Giuseppe Borruso, Massimo Gardina, Dasa Fabjan, 2016).

Some studies have proposed the introduction of new routes, relatively short in flight time of about 5 hours, as a measure for increasing one airport's traffic; the new routes positively impact the airport demand and its catchment area (Chuntao Wu, Ji Han, Yoshitsugu Hayashi, 2011). Considering all the above, it can be stated that the catchment area of a regional airport is not static, but changes over time and it is mainly influenced by the routes operated from that airport (Rogier Lieshout, 2012), by the development of the airport accessibility through improving highways, railways or maritime infrastructure, as well as by other features of the airport (Ioulia Poulaki, Andreas Papatheodorou, 2013).

3. Research Methodology

The purpose of the present paper is to propose a novel research methodology for estimating the demand for new destinations which could be introduced by Sibiu International Airport, a regional airport in Romania. For achieving the mentioned purpose, the following two research objectives are established:

- (1) Determining the catchment area of Sibiu International Airport for destinations operated by competitor airports and not by Sibiu International Airport
- (2) Estimating the demand for new destinations based on the identified catchment area

Secondary data analysis was used as research method (Malhotra, 2019). External data sources/databases managed by the National Institute for Statistics (<https://insse.ro/cms/en>) and ASM – Global Route Development (<https://www.asm-global.com/>) provided the input data for the model development.

For developing the catchment area for Sibiu International Airport, we have considered that the catchment area for Sibiu International Airport varies according to the destination (Rogier Lieshout, 2012), airport competitors operating the destination (Kurt Fuellhart, 2007) and travel time of the prospective passengers from the home-destination to the airport (Pere Suau-Sanchez, Guillaume Burghouwt, Montserrat Pallares-Barbera, 2014; Dejan Paliska, Samo Drobne, Giuseppe Borruso, Massimo Gardina, Dasa Fabjan, 2016). Ticket price was not included as an influence factor of the catchment area size because it is a direct result of the airline company pricing strategy. On October 2017, the following new destinations were analyzed for developing the associated catchment areas for Sibiu International Airport:

Table 1: New destinations considered for developing the associated catchment areas for Sibiu International Airport

New Destinations	(CLJ)	(TSR)	(OTP)	(CRA)	(TGM)	(SBZ)
Alicante	1	0	1	0	0	0
Barcelona	1	1	1	1	0	0
Bari	1	1	1	0	0	0
Basel	1	0	1	0	0	0
Berlin	1	1	1	0	0	0
Billund	1	0	1	0	0	0
Birmingham	1	0	1	0	0	0
Bologna	1	1	1	1	0	0
Bratislava	1	0	1	0	0	0
Budapest	1	1	1	1	1	0
Charleroi	1	1	1	0	0	0
Doncaster	1	0	1	0	0	0
Dubai	1	0	1	0	0	0
Dublin	1	0	1	0	0	0
Dusseldorf	1	1	1	1	1	0
Eindhoven	1	1	1	0	0	0
Frankfurt	1	1	1	1	1	0
Hamburg	1	0	1	0	0	0
Istanbul	1	0	1	0	0	0
Cologne	1	0	1	0	0	0
Larnaca	1	0	1	0	0	0
Liverpool	1	0	1	0	0	0
Malaga	1	0	1	0	0	0
Malmo	1	0	1	0	0	0

Malta	1	0	1	0	0	0
Nice	1	0	1	0	0	0
Palma de Mallorca	1	0	1	0	0	0
Paris	1	1	1	1	1	0
Rome	1	1	1	1	1	0
Stockholm	1	0	1	0	0	0
Tel Aviv	1	0	1	0	0	0
Treviso/Venice	1	1	1	1	0	0
Valencia	1	1	1	1	0	0
Warsaw	1	0	1	0	0	0
Zaragoza	1	0	1	0	0	0

The upper destinations were new for Sibiu International Airport at the time of the analysis (October, 2017) because none of them was operated by the airport at that time, but managed by at least two competitor airports. In this regard, the symbol of “0” stands for a destination (row) which is not operated by an airport (column), while “1” represents a destination (row) operated by an airport (column). Moreover, the studied competitor airports are: Cluj Avram Iancu International Airport (CLJ), Timișoara Traian Vuia Airport (TSR), Bucharest Henri Coandă International Airport (OTP), Craiova International Airport (CRA), and Transylvania Airport Târgu Mureș (TGM).

Four scenarios were created given the competitor airports operating the table 1 destinations:

Table 2: Scenarios developed based on destinations operated by competitor airports

Scenarios	(CLJ)	(TSR)	(OTP)	(CRA)	(TGM)	(SBZ)
Scenario 1	1	1	1	1	1	0
Scenario 2	1	1	1	1	0	0
Scenario 3	1	1	1	0	0	0
Scenario 4	1	0	1	0	0	0

For the present article, only destinations included in Scenario 1 will be considered for determining the associated catchment area for Sibiu International Airport, these destinations being: Budapest, Dusseldorf, Frankfurt, Paris, and Rome. In identifying the catchment area for these destinations, we have considered that travel time is more important than travel distance for the prospective passenger when choosing an airport for a given destinations, all other factors (including ticket price) being equal. Based on the upper mentioned idea and by using the free tools Google Earth and Google Maps, borders were drawn to separate the catchment areas of the competitor airports for the Scenario 1 destinations (Figure 2).

Figure 2: Catchment Area for Scenario 1 airports and destinations

The different colors from Figure 2 represent the catchment areas of the five airports (Scenario 1) based on the travel-time of a possible passenger from his/her home to an airport, all other factors being equal. Hereof if a person *lives* on the line that separates two catchment areas, he/she will have a 0.5 probability to choose either the first or the second airport, all other factors which could influence his/her decision being considered equal. If Sibiu International Airport would introduce and operate one, some or all Scenario 1 destinations, the catchment areas from figure 1 would change due to the appearance of SIA catchment area. As before, travel-time was the main factor considered in creating the catchment area for SIA for Scenario 1.

The bolded black line sets apart the SIA catchment area from the catchment areas of the other 5 competitor airports of Scenario 1. Prospective passengers from cities like Hunedoara, Deva, and Făgăraș are more prone to choose Sibiu International Airport as departure airport for a specific destination than Timișoara Traian Vuia International Airport, Cluj Avram Iancu International Airport, and Transylvania Airport Târgu Mureș, respectively, if Scenario 1 destinations will be introduced and operated by SIA while all other factors are being equal. It can be seen from figure 3 and deduced that SIA catchment area for Scenario 1 catches or *brakes* parts from the initial figure 2 catchment areas of the competitor airports.

Figure 3: Catchment Area for Sibiu International Airport for Scenario 1

By adapting Reilly's law of retail gravitation (Reilly, 1931 and Converse, 1950) to the article's specifics, we propose the following formulas to be used for estimating the demand for Scenario 1 destinations if introduced by Sibiu International Airport:

$$c_{kij} = \frac{\sum_{i=1}^n P_i}{\sum_{j=1}^m P_j} \times \frac{\sum_{i=1}^n \frac{GDP_i}{P_i}}{\sum_{j=1}^m \frac{GDP_j}{P_j}}$$

Formula 1 – SIA attraction coefficient of the traffic generated by competitor airport k where:

c_{kij} = SIA attraction coefficient of the traffic generated by competitor airport k for the previous year, $k = \overline{1, o}$, o being the number of competitor airports;

i = locality within the catchment area of SIA taken from the catchment area of competitor airport k, $i = \overline{1, n}$, n being the number of localities;

j = locality within the catchment area of competitor airport k, $j = \overline{1, m}$, m being the number of localities;

P_i = population of the i_{th} locality;

P_j = population of the j_{th} locality;

GDP_i = Gross Domestic Product of the i_{th} locality;

GDP_j = Gross Domestic Product of the j_{th} locality.

The attraction coefficient (c_{kij}) takes in consideration (1) the ratio between the populations of every pair of overlapping catchment areas, ratio which can be considered a weight for the future demand estimation and (2) the ratio between the GDP/capita of every pair of overlapping catchment areas which can approximate the purchasing power of the respective areas. Thus, the demand estimation presented in the following (formula 2) takes in consideration the adjacent population and its purchasing power.

$$D_{lk} = \sum_{k=1}^o c_{kij} \times T_{lk}$$

Formula 2 – Demand estimation based on SIA attraction coefficient and previous year's competitor airport's traffic for a given destination

D_{lk} = Demand estimation for destination l considering the previous year's generated traffic by airport k for destination l ;

l = Scenario 1 destinations, $l = \overline{1,5}$;

c_{kij} = SIA attraction coefficient of the traffic generated by competitor airport k ;

T_{lk} = traffic generated by airport k for the previous year for destination l .

Data for T_{lk} (May 2016 – April 2017) was retrieved from ASM – Global Route Development (<https://www.asm-global.com/>) for Point-to-Points flights (direct flights A-B type and indirect flights tip A-X-B type, A being the competitor airport k and B being the l_{th} destination). A summary of the applied formulas is presented in the table below:

Table 3: Demand estimation for Scenario 1 destinations if introduced by SIA

Scen.	Destination (l_h)	Coef. CLJ (c_i)	Coef. TSR (c_i)	Coef. OTP (c_i)	Coef. CRA (c_i)	Coef. TGM (c_i)	Traffic CLJ (T_{lk})	Traffic TSR (T_{lk})	Traffic OTP (T_{lk})	Traffic CRA (T_{lk})	Traffic TGM (T_{lk})	Estimated demand for SIA	Weekly freq.
1	Budapest	0.09	0.17	0.05	0.03	0.38	20,754		43,586		9,986	7,841	1
1	Dusseldorf	0.09	0.17	0.05	0.03	0.38		2,191				372	1
1	Frankfurt	0.09	0.17	0.05	0.03	0.38	8,254	25,531	65,906		7,696	11,302	2
1	Paris	0.09	0.17	0.05	0.03	0.38	33,884	13,125	177,472	1,214	7,920	17,200	3
1	Rome	0.09	0.17	0.05	0.03	0.38	22,334	12,484	291,185	17,410	11,475	23,574	3
Total							85,226	53,331	578,149	18,624	37,077	60,289	-

It is worth mentioning, that some of the five Scenario 1 destinations were new destinations for a part of the 5 competitor airports in summer 2017 when the analysis was done, thus the empty cells for their previous year's traffic.

If operated by SIA, the highest demand appears to be for Rome (23,574 pax), followed by Paris (17,200 pax), and Frankfurt (11,302 pax). By dividing the estimated demand successive to 151 (80% load factor of a 189 seats plane) and to 52 (weeks in a year), the needed weekly frequencies were computed for operating the Scenario 1 destinations. Weekly frequencies are an important factor in terms of profitability of the route for both the airport and the airline company.

4. Conclusion and managerial recommendation

Our paper proposes a novel approach for estimating the demand for new destinations to be introduced by Sibiu International Airport, a Romanian regional airport. The airport's catchment area(s) were considered as starting point(s) for the demand estimations.

A first novelty resides in the passengers' travel-time and not the travel-distance considered when drawing up the catchment areas of SIA for new destinations. Travel-time and probability of choosing one airport for a wanted destination are in an indirect relationship, *ceteris paribus*. A destination is new if it is operated by competitor airports and not (yet) by SIA. Thus, travel-time (consumer related motive) and competition (industry related factor) were used for creating catchment areas for every new destination which could be operated by SIA.

Secondly, an original method was developed for estimating the demand for all new destinations (included in Scenario 1). This method is influenced by Reilly's law of retail gravitation and considers one area's population and its purchasing power as influence factors of the demand, *ceteris paribus*.

The obtained results provide valuable information for the airport's decision makers. In this regard, knowing one (new) destination's catchment area may be used by the airport for promoting this future destination(s) in a bounded space for stimulating future demand. Moreover, transportation means and infrastructure could be optimized for reducing travel time to and from the airport. Demand forecast represents a focal point of marketing and of an airport's business. Our proposed model estimates the demand for possible destinations which could be operated by an airport. These estimations help the airport in computing the weekly frequencies and timelines for operating these possible destinations. Furthermore, they serve as decisional backbone for the airport in negotiating the tariffs paid by the airline companies for introducing these destinations.

5. References:

- ASM – Global Route Development (<https://www.asm-global.com/>)
- Avram, B. (2018). *The Route Development Strategies of Romanian Airports: A Key Challenge in Modern Aviation*. Expert Journal of Business and Management 6, 110-126.
- Ashford, N., Benchemam, M., (1988), *Passengers' Choice of Airport: An Application of the Multinomial Logit Model*, Transportation Research Record, 1147.
- Augustyniak, W., Olipra, L., (2014), *The potential catchment area of Polish regional airports*, Journal of International Studies, Vol. 7, No 3, 144-154.
- Bao, Y., Xiong, T., Hu, Z. (2012), *Forecasting Air Passenger Traffic by Support Vector Machines with Ensemble Empirical Mode Decomposition and Slope-Based Method*, Hindawi Publishing Corporation, Discrete Dynamics in Nature and Society, Volume 2012, Article ID 431512, 12 pages.
- Blinova, T. O. (2007). *Analysis of possibility of using neural network to forecast passenger traffic flows in Russia*, Aviation, 11:1, 28-34.

- Carballo-Cruz, F., Costa, V. (2014). *Success factors of regional airports: The case of Oporto airport*. Tourism & Management Studies 10 (2014) 37-45.
- Carlucci, F., Cirà, A., Coccoresse, P., (2018), *Measuring and Explaining Airport Efficiency and Sustainability: Evidence from Italy*, Sustainability, 10.
- Carmona-Benítez, R. B., Nieto, M. R., Miranda, D. (2016). *An Econometric Dynamic Model to estimate passenger demand for air transport industry*, Transportation Research Procedia 25, 17–29.
- Converse, Paul, D. (1949), *New Laws of Retail Gravitation*, Journal of Marketing, 14 (Jan), 379 – 384
- Fernandes E., Pacheco, R.R. (2010). *The causal relationship between GDP and domestic air passenger traffic in Brazil*, Transportation Planning and Technology, 33:7, 569-581.
- Fildes, R., Wei, Y., Ismail, S. (2011), *Evaluating the forecasting performance of econometric models of air passenger traffic flows using multiple error measures*, International Journal of Forecasting 27, 902-922.
- Fröhlich, K., Niemeier, H.- M., (2011), *The importance of spatial economics for assessing airport competition*, Journal of Air Transport Management, 17, 44-48.
- Kotler, P., Keller, K.-L. (2016): *Marketing Management, 15th Global Edition*, Pearson Education Limited.
- Kurt Fuellhart (2007), *Airport catchment and leakage in a multi-airport region: The case of Harrisburg International*, Journal of Transport Geography, 15, 231–244.
- Lian, J., I., Rønnevik, J., (2011), *Airport competition – Regional airports losing ground to main airports*, Journal of Transport Geography, 19, 85–92.
- Lieshout, R., (2012), *Measuring the size of an airport's catchment area*, Journal of Transport Geography, 25, 27–34.
- Maertens, S., (2012), *Estimating the market power of airports in their catchment areas – a Europe-wide approach*, Journal of Transport Geography, 22,10–18.
- Malhotra, N. (2019): *Marketing Research: An Applied Orientation, 7th Edition*, Pearson, New York.
- Marcucci, E., Gatta, V. (2011). *Regional airport choice: Consumer behaviour and policy implications*, Journal of Transport Geography, 19,70-84.
- National Academies of Sciences, Engineering, and Medicine, (2013). *Understanding Airline and Passenger Choice in Multi-Airport Regions*. Washington, DC: The National Academies Press.
- National Institute for Statistics (<https://insse.ro/cms/en>)
- Paliska, D., Drobne, S., Borruso, G., Gardina, M., Fabjan, D., (2016), *Passengers' airport choice and airports' catchment area analysis in cross-border Upper Adriatic multi-airport region*, Journal of Air Transport Management, 57, 143 – 154.
- Perboli, G., Ghirardi, M., Gobbato, L., Perfetti, F., (2015), *Flights and Their Economic Impact on the Airport Catchment Area: An Application to the Italian Tourist Market*, Journal of Optimization Theory and Applications, 164, 1109 – 1133.
- Postorino, M., N., (2010), *Air demand modelling: overview and application to a developing regional airport*, WIT Transactions on State of the Art in Science and Engineering, Vol 38, WIT Press, pp. 80.
- Poulaki, I., Papatheodorou, A., Stergiou, D., P., (2013), *Expanding cross border airport catchment areas using intermodality: the case of Izmir Adnan Menderes Airport*, Tourism Today, no.13.
- Poulaki, I., Papatheodorou, A., (2013), *Rethinking "Airport Catchment Area": Intermodality for an Air Travel Alternative*, 17th Annual World Conference of the Air Transport Research Society.
- Reilly, William, J. (1931): *The Law of Retail Gravitation*, University of Texas.

- Suau - Sanchez, P., Burghouwt, G., Pallares-Barbera, M., (2014), *An appraisal of the CORINE land cover database in airport catchment area analysis using a GIS approach*, Journal of Air Transport Management, 34, 12-16.
- Suau - Sanchez, P., Voltes - Dorta, A., (2019), *Drivers of airport scheduled traffic in European winter tourism areas: Infrastructure, accessibility, competition and catchment area*, Journal of Air Transport Management, 81.
- Wei, W., Hansen, M. (2006). *An aggregate demand model for air passenger traffic, in the huband-spoke network*, Transportation Research Part A 40, 841–851.
- Wu, C., Han, J., Hayashi, Y., (2011), *Airport Attractiveness Analysis through a Gravity Model: A Case Study of Chubu International Airport in Japan*, Proceedings of the Eastern Asia Society for Transportation Studies, Vol.8.
- Zhoua, H., Xiaa, J., Luob, Q., Nikolovac, G., Sund, J., Hughesc, B., Kelobonyea, K., Wangf, H., Falkmer, T., (2018), *Investigating the impact of catchment areas of airports on estimating air travel demand: A case study of regional Western Australia*, Journal of Air Transport Management 70, 91–103.