Abstract: The present paper explores a Greek case study on optimizing the design of aviation networks under Public Service Obligations (PSO). Based on previous research on airline PSO networks applied to the case studies of the Azores and Norway, optimization models are adapted to minimize not only the cost to the airline, but also the total social costs. Different predictive models to estimate demand are developed and included in the optimization models. It is found that after applying the developed demand and optimization models, the total network costs can be reduced significantly, compared to the actual network´s operation ranging from 4% to 20%.

Keywords: Public Service Obligation; Greece; Flight Scheduling and Fleet Assignment; Integer Linear Programming; Air Passenger Demand Forecast; Aviation Networks

1. Introduction

Airports are key drivers of economic development for their respective catchment area (ACI, 2004; Halpern and Bråthen, 2011; Lieshout, 2012) and are usually accompanied by big investments in airline carriers that can make them international connection points (Lohmann et al., 2009). Airliners' business has high costs and low profit margins involved, making it crucial for an airline's long-term survival to use its resources in the most optimal way possible. There is extensive literature analyzing options to increase the operating margins of airlines (Zou and Chen, 2017; Raynes and Tsui, 2019; Merkert and Swidan, 2019) and optimize their flight scheduling and fleet assignment (FSFA). The objective of that research is to reduce the total operational cost for an airline, as this reduction contributes significantly to a better balance sheet of airline companies. The result is usually the suppression of frequencies in less profitable routes and allocation of the resources to the most profitable ones. However, there are other routes, the main objective of which is not to maximize profits but to provide accessibility to remote areas, and where there is not enough demand for profitable airline operation. Nonetheless, this operation is vital for local communities, and in these networks, the objective is not exclusively to minimize costs, but also to maximize air connectivity provided to passengers. In this research area, there is comparatively less published literature, with an opportunity for important contributions.

The Public Service Obligation (PSO) classification is a tool that can be used by the European states, in order to promote the economic development of regions which may require assistance, besides the normal self-regulation imposed by that market. This is achieved by subsidizing the operation of airline routes in areas where such operation is not profitable but are necessary to allow for businesses to develop, and for residents to have accessibility to the important economic centers adjacent to their region. This grants a subsidy to the operation of an airline, in order to make it profitable to operate, at reasonable ticket prices. All the requirements and conditions to impose these networks are defined by the European Commission's regulation No 1008/2008 (European Commission, 2008).

Currently there are over 170 PSO networks in operation throughout Europe (European Commission, 2019), mostly composed of domestic routes distributed by 8 EU countries plus Iceland and Norway. The most obvious regions where this may be required and which accounts for the majority of PSO networks in force is in islands. Due to their geographical characteristics, they are prone to requiring subsidies for scheduled airline service to be profitable. Nevertheless, there are also several PSO networks, which do not involve islands but require such networks to connect remote areas with adjacent economic centers. As such, the imposition of scheduled airline services is used by the legislators of the European Commission as a tool to promote the development of smaller and usually less populated areas. This scheme has already obtained verifiable positive results since the initial implementation, such as stronger connectivity to important centers for the residents and development of tourism in remote areas where a PSO service was implemented (Wittman et al., 2016).

The basic principles that support the European PSO system are (ERAA, 2016):

- Transparency: all calls for tenders, awards, modification and abolition of PSO routes must be announced in the official journal of the EU. Moreover, airfares and conditions can be quoted to users;
- Market failure: PSO routes are only imposed after market forces have failed to make scheduled air service profitable on the route;
- No obstacle to market functioning: a PSO should not limit the possibility for air carriers to provide a higher level of service (regarding frequency and capacity), than the minimum obligations required under the PSO;
- Necessity: Routes are considered vital for the economic and social development of the region served (routes to an airport serving a peripheral or development region or thin routes to any airport).
- Proportionality and non-discrimination: PSOs must be imposed in a proportionate and non-discriminatory manner (e.g. no restrictions based on passenger's nationality or on the air carrier's state of origin, no selective promotion of specific air carriers/airports);
- No alternative: Inadequacy of alternative transport modes connecting the route(s) under PSO;
- EU law: Full compliance with EU Regulation 1008/2008 (compliance with national law only is insufficient).
- Route-by-route basis: Necessity of PSO award must be assessed for each route separately (no network routes). A PSO cannot link two cities or two regions, routes must be defined from airport to airport.
- Geographic scope: A PSO route between an EU airport and a non-EU (except EEA members) country is not allowed. However, intra-EU routes (not exclusively domestic) are allowed.

There are two types of PSOs: i) Open PSO (22.1% of total European PSO air routes), i.e. any air carrier can operate the PSO if it complies with their requirements, with no exclusivity nor compensation granted; and ii) Restricted PSO (77.9% of total European PSO air routes), i.e. in case no air carrier is interested in operating the route on which the obligations have been imposed, the state concerned may restrict the access to the route to a single air carrier and compensate its operational losses resulting from the PSO. In Restricted PSO, the selection of the operator must be made by public tender at Community level and only one air carrier can operate the PSO, and if exclusivity is not enough to ensure the financial viability of service, then compensation is awarded.

Several regulatory frameworks exist for the support of routes that are not economically viable and are less attractive for airlines to operate. In Europe, the Public Service Obligation (PSO) system allows for national or regional governments to setup PSO networks and awards exclusivity of the operation to the carrier which wins the tender for the period of the contract (European Commission, 2008). The equivalent scheme in the United States of America is applied slightly differently and is called "Essential Air Services" (EAS) (US Department of Transportation, 2017), while in Australia appears as the "Remote Air Service Subsidy" (RASS) (Australian Department of Infrastructure, 2020). Although these three subsidy programs have the same overall purpose, they were implemented in different ways, with different guidelines. Even inside the PSO system within Europe, though under the same subsidy framework, each country has used it in different ways (Williams and Pagliari, 2004; Santana, 2009). Some countries use the PSO scheme in sparse regions of the country, to link remote regions between themselves (as is the example of Norway); while France, on the other hand, uses the PSO scheme to connect smaller regions with Paris, in an effort to promote economic activity in the remote regions, by connecting them to the business centers of the country (Skreikes, 2003). Another example of different adoption of the PSO scheme is given by the United Kingdom, which focused its PSO network on setting up mostly “lifeline” types of services, allowing the population of remote regions to reach a city with more facilities (e.g. hospitals) whenever necessary, not focusing on setting up routes for economic development.

As stated above, the airline business operates in an economically and operationally challenging environment, with high costs and comparatively low profit margins. Although the airlines that operate within PSO networks are financially rewarded for their service, it remains critical for them to operate as efficiently as possible, in order to maximize economic results. On the other hand, the entity responsible for subsidizing the PSO network (usually national or regional government entities) is focused on maximizing the quality of service provided to the users, but is also interested in minimizing the cost of subsidies that it must provide to the airline operating the route. Hence, solving the Integrated Flight Scheduling Fleet Assignment problem (IFSFA), is the suitable tool to optimize such networks.

The IFSFA model builds on the FSFA (which is only focused on airline cost reduction) by adding the minimization of the costs associated with the passenger (financial and connectivity costs), allowing for a more holistic view of the concept of an optimal network which aims not only to reduce costs but also maximize air connectivity. This is very important because these networks are, by definition, sub-optimal as flights are imposed on routes that do not have enough demand to justify their operation. Moreover, if a normal FSFA model was applied to these networks, the result would be a significant reduction in the quality of service provided, which might even violate the minimum frequencies defined by the entity which imposed the PSO, in an attempt to reduce the cost for the airline.

This problem has already been explored in the literature (Pita et al., 2013; Pita et al., 2014) with very positive results, reducing both financial costs for the airline and time costs for the passengers. Therefore, the purpose of the present research is to build on the model developed in Pita et al. (2013) and adapt it in order to apply it to part of the PSO network of the Greek islands by adding the objective of minimizing the connection time of passengers. Therefore, initially the model developed is implemented using a slightly different formulation, and tested through an illustrative example, which will be used to verify the results and demonstrate the capabilities of the model. Then, the model is applied to design two PSO networks in Greece using data provided by the Hellenic Civil Aviation Authority (HCAA) and by Aegean airlines. The model will be further developed to account for the specific characteristics of the PSO network of the Greek islands (e.g. seasonality effects or the specific restrictions of smaller Greek airports).

This paper is structured in seven sections. Section 1 provided an introduction to the PSO topic in airline networks, detailing specific aspects and objectives of a PSO network. Then, section 2 provides a review of the research conducted in the most prominent scientific papers in this area. Section 3 presents the optimization model and its mathematical formulation. An illustrative example is also explored to provide clear understanding on the variables involved. Section 4 presents the two suggested networks detailing the costs associated with each of them. Section 5 explores the predictive models used to estimate demand providing a comprehensive description of the complete process of building such models. Section 6 presents the results obtained by applying the optimization model to the two case studies detailing the costs of the optimized networks, and their key features, while comparing the optimal solutions with the current network designs (previously explored in section 4). Finally, section 7 concludes the present work, highlighting the main conclusions, limitations and further research opportunities.

2. Background research and State of the Art

This section reviews the state-of-the-art and scientific background on two main related topics: i) integrated flight scheduling and fleet assignment (subsection 2.1) and ii) demand prediction in airline networks (subsection 2.2).

2.1. Integrated flight scheduling and fleet assignment

Due to the importance of air transport in general to the economic development of regions, there is significant literature published addressing the optimization of the usage of airline's resources, namely aircraft fleet and crews. Lohatepanont and Barnhart (2004) and Sherali et al. (2010) focused on the problem of flight scheduling and fleet assignment with the sole purpose of maximizing profit for airlines. These papers obtained interesting improvements in their case studies, with several publications building on this objective (Jamili, 2016). Moreover, Liu et al. (2008) minimized the impacts of the inevitable delays associated with airline operation, which imply significant expenses for the airlines. This is achieved through a combination of a traditional genetic algorithm with a multi-objective optimization method, addressing simultaneously multiple objectives such as turn-around times, flight connections and flight swaps. Therefore, it focused on schedule disruption and how to minimize the associated effects.

Focusing on PSO networks, Pita et al. (2013;2014) proposed decision support models that, instead of dealing with the maximization of airline economic results, focused on maximizing the quality of the service provided to passengers. These models were applied to the PSO air networks of Azores and Norway, respectively. For the latter case study, the authors took also into account the expenses and revenues of airport owners associated with these routes. Both case studies obtained interesting results and reduced costs in all the areas considered. These two papers are the main references for the present research, which aims to adapt the models presented in Pita et al. (2013;2014) to a Greek PSO network.

Advancing the previously mentioned research, Antunes et al. (2018) focused on analyzing in depth the network of the Azores operated by SATA considering the demand level of 2012, the fleet size and the implications of possible changes on the level of service offered. By employing real data and reducing the amount of previous assumptions, they suggested new shapes for the imposed PSO network, quantified the potential improvements and concluded that the operating costs could be reduced significantly, saving the government of the Azores a significant amount of funds in subsidies.

From a different perspective of air transport connectivity, Iliopoulou et al. (2015) suggested a seaplane network in Greek islands, which would compete against the locally well-established ferry boat network. The objective was to minimize the travel cost, the size of the fleet and the unsatisfied demand between successive island ports, by proposing a new network, instead of optimizing an existent route, hence it is not straightforward to assess the improvements achieved. Moreover, with the goal of proposing a completely new network, a case study, developed by Dozic & Kalic (2015), performed a comprehensive analysis into all the steps required for designing a new route. This included defining the appropriate fleet mix, fleet size and aircraft selection, with positive results.

Current concerns on the reduction of carbon dioxide emissions have also been considered in the design of airline networks. Ma et al. (2017) developed an optimization model the objective of which was simultaneously maximize profit and minimizing emissions associated with operating the flights. This model is applied to case studies from Asian airlines, with interesting results. The point achievable in reality that was closest to optimality had significant improvements over the current situation, and it was concluded that small reductions in profits may lead to significant reductions in emissions.

The main contributions on aircraft fleet optimization were all compiled into Table 1, for a better comparison of the results. In the last line of Table 1, the features of the present work are also presented, to allow for a better comparison with the remaining literature. The model developed in this work will be analyzed and discussed in next sections.

Table 1. Summary of relevant research in fleet optimization

	Objective	Case study	Time to find optimum solution	Order of magnitude of improvement	Solution method
Lohatepanont & Barnhart (2004)	Maximize profit to the airline	Undisclosed major US airline	12 hours	5%	Branch and Bound
Liu et al. (2008)	Minimize delays, flight swaps and connections	Reopening of Sungshan and Taichung airports	Not more detailed than “minutes”	Not disclosed	Multi-objective Genetic Algorithm
Sherali et al. (2010)	Maximize net revenue	United Airlines	24 hours	10%	Benders Decomposition
Pita et al. (2013)	Minimize operating costs for the airline and travel time	PSO network in the Azores	88 minutes	10%	Branch and Bound
Pita et al. (2014)	Minimize operating costs for both the airline and airport, travel time	PSO network in Norway	20 hours	30%	Branch and Bound
Iliopoulou et al. (2015)	Minimize travel cost, number of route, passengers not served	Prospective Seaplane network in Greece	45 minutes	N/A	Genetic algorithm coupled with a hybrid process
Dozic & Kalic (2015)	Minimize fleet required, operating costs	Hypothetical airline based in Belgrade	Not disclosed	N/A	Fuzzy logic, heuristic, analytic approaches and multi-criteria decision making
Jamili (2016)	Maximize profit to the airline	Not disclosed	1 hour	N/A	Hybrid with simulated Annealing and particle swarm optimization
Ma et al. (2017)	Alternatively maximize profit or minimize emissions	Jetstar Asia and undisclosed Chinese airline	Not disclosed	8%	Compromise method to the Pareto Solution
Present work	Minimize operating costs for the airline and travel time	Two segments of Greek PSO network	24 hours	10%	Branch and Bound

2.2. Demand Prediction in airline operations

Predicting demand is a challenging task due to the difficulty in obtaining reliable estimates (de Neufville and Odoni, 2003). Early research in the field (Jorge-Calderón, 1997) indicated the applicability of multiple variable regression analysis in predicting demand for scheduled airline services based on data from the entire European network in 1989. This research was innovative at the time and r came up with several significant conclusions that nowadays are widely accepted in specialized literature, such as the importance of population, GDP and frequency of flights as explanatory variables. Grosche et al. (2017) suggested two possible gravity models indicating that airlines may not relying solely on a single model but could gather the information from different models to predict the demand for their possible future routes. It is applicable to new markets, with the advantage of not relying on traditionally used inputs that are not yet available to airlines before starting to operate the route (e.g. service-related factors or passenger income). Instead, the model uses mainly geo-economic variables as independent factors. Focused on more commonly analyzed markets, Barnhart et al. (2012) analyzed how to improve reliability in the air transportation segment in the US and the EU through managing capacity and demand in already established networks. The results suggested changes in several areas, such as tactical adjustments and real-time interventions, from medium to short term. This stressed the importance of technological progress in these improvements, in order to have a more “flexible” network which would be able to withstand the challenges that will be imposed in the future. This will be crucial with the continuous expansion of already saturated areas, such as airports (on the ground and in the surrounding airspace). Moreover, Demirsoy (2012) studied the significant expansion of the Turkish airline transport market, proposing and testing six hypotheses to explain such growth. The research concluded that, unlike what most published literature finds for other markets, in the Turkish market the population did not have an effect on demand in the long term but only in the short term. Another interesting feature is the analysis of the effect of deregulation (in 2003) in the demand for the Turkish market, which was significant. It was also concluded that the high-speed railway network would not affect demand for the Turkish air transport market in the short term, although it could affect it in the long term, when its network would be more mature. This is interesting for the present research, because it is also expected that the competition of ferry boat services would affect demand in the case studies. The differences in the results of Demirsoy’s case study from most published literature demonstrate that in such a complex subject, it is not possible to use solutions which were applicable to other markets straightforward, but a thorough analysis and adaptation must be performed to that specific market.

Adeniran and Adeniran (2017) focused on determining the correlation between international air travel demand in Nigeria and several econometric indicators. It is interesting to verify that the results were not what was expected by the authors, due to problems related with correlation and multicollinearity of the independent variables. This stresses the fact that, although an attempt to add as much independent variables as possible might seem a good method to increase the quality of the forecast, this is usually not the case in these regressions. Hence, attention must be paid when performing the regression, in order to maximize the predictive capacity of the model. Another interesting feature of this research was the significant impact of that variation in the value of local currencies compared to the US dollar. This is especially important in currencies with a smaller base of users, relative to, for example, the Euro which although still affected, is more stable. Carmona-Benítez et al. (2017) proposed an econometric dynamic model to estimate passenger demand, applying it to the Mexican market and proposing an approach to solve the airline airport hub location problem. This paper highlights the economic importance of the airline business to cities, by using economic indicators as explanatory variables for the model. It concluded that the increase of economic activity promotes air travel demand, and that economic indicators can be used correctly as explanatory variables to predict demand, at the state, city or airport level. This model is validated by two different tests, proving its suitability to predict demand for air travel. Moreover, Cook et al. (2017) perform an analysis applied specifically to the European market, hence its interest to this research. Their results can be analyzed in order to predict particular features of the European market, and later to compare the particularities of the Greek market, from the results of this research. Their paper focuses on determining the relation between passenger air travel demand and factors such as the GDP, the urbanization level, the geographical location and the degree of education, proving that the first, third and fourth indicators were statistically significant. The GDP of a country is commonly seen as a statistically significant variable in this area of research, but the other two indicators also deliver interesting results, and may influence the Greek case study. An interesting niche of the present research topic is the demand prediction for markets with very strong touristic activity, as they carry important specificities (such as seasonality, less importance of GDP when compared to more traditional business markets, very high ratios of tourist to inhabitant, etc). This type of markets has already been analyzed, when Devoto et al. (2002) published their research focused on determining how demand could be predicted in them, specifically using tourism variables (e.g. resident population, number of tourist beds, per capita beds and tourist arrivals), applying them to a case study in Sardinia (Italy) and analyzing three different airports, with the resident population always being statistically significant as a predictor of demand. Besides the city population adjacent to the three airports, there was a different variable related to tourism which was considered significant for each airport, demonstrating that the effect of tourism cannot be ignored and indicating that there is no consensus on which variable is more suitable. This happens even within three airports contained within a relatively small area, in a similar market. More recently, Erjongmanee & Kongsamutr (2018) published a research focusing on demand forecasting in Thailand, considering the effect of tourism, with significant results as predicted. This paper also studies and compares the suitability of machine learning algorithms for demand forecasting, which is a promising method worth more research in the future, due to the current capabilities and significant evolution that these algorithms have been characterized recently.

Table 2: Summary of relevant research in air transport demand prediction

	Population variable	**Economic variable**	**Price of transport**	**Frequency of transport**	**Duration of trip**	**Geographic variable**	**Importance of tourism**
Jorge-Calderón (1997)	Sum of inhabitants of O&D	Weighted average income per capita of O&D	Cheapest fare on the route	Number of return weekly flights	N/A	Distance between airports	Ratio of hotel guests to inhabitants
Erjongmanee & Kongsamutr (2018)	Population of O&D	GDP/capita of O&D	Average cost of ticket	N/A	Travel time between O&D	Distance between airports	Number of tourists of O&D
Carmona-Benítez et al. (2017)	Economically active population	Consumer price index	N/A	Total number of flights in each airport	N/A	N/A	Hotel occupancy index
Devoto et al. (2002)	Resident population in the market	N/A	N/A	N/A	N/A	N/A	Number of tourist beds, tourist arrivals
Demirsoy (2012)	Population in the market	Average Income, oil prices	N/A	N/A	N/A	N/A	N/A
Adeniran & Adeniran (2017)	N/A	Change in: currency value and GDP	N/A	N/A	N/A	N/A	N/A
Cook et al. (2017)	Population in the market and degree of urbanization	GDP/capita	N/A	Number of air trips per capita	N/A	Variable defining whether the country is in an island	N/A

Present Work	Logarithm of Product of O/D Population	N/A	N/A	Frequency of Flights	Travel time between O&D	Distance between O&D	N/A

Table 2 compiles a summary of the most used explanatory variables in demand forecasting, namely: population, economic variables, price, frequency, trip duration, geographic variables and tourism related variables. Again, in the last line of Table 2, the key data from the present work is also presented to allow comparison. A comprehensive analysis and description of the development of the predictive models for the Greek case studies will be presented in section 5.

3. Integer Linear Programming model to design PSO network

This section presents the formulation of the optimization model. The present mathematical formulation finds a design of flights for the PSO network that minimizes the operating costs and the social costs associated with the time spent by passengers. The cost of time is disaggregated depending whether a passenger is on board (CB) or waiting on ground (CWT). Moreover, there is a limited number of aircrafts of each type (z_r) and a maximum number of seats in each aircraft type (s_r). The PSO imposes a minimum number of flights in a specific route $\left(x_{min_f}\right)$ and also a minimum number of seats in each flight route (s_{min_f}).

3.1. Inputs

First, the following constants are defined:

- NA is the number of airports in the network;
- NR is the number of aircraft types available;
- NW is the number of possible time periods waiting on the ground, by a passenger, for a connecting flight;
- NT is the number of time periods;
- NF is the number of possible flight routes (one between each O/D pair in each way).

Then, the associated sets were defined:

- A (ranging from 1 to NA) has all the airports;
- R (ranging from 1 to NR) has all the aircraft types;
- W (ranging from 1 to NW) has all the possible waiting times;
- T (ranging from 1 to NT) has all the time periods;
- F (ranging from 1 to NF) has all the possible flight routes.

With the sets defined, the inputs to the model are also defined as constants or as arrays:

- CB: cost of time for being on board an aircraft for the passengers (euros/h);
- CWT: cost of time for waiting on the ground for the passengers (euros/h);
- z_r: number of aircraft of each type;
- s_r: seat capacity of each aircraft type;
- x_{min_f}: minimum number of flights in flight route f, as imposed by the PSO;
- s_{min_f}: minimum number of seats available in route f, as imposed by the PSO;
- TF_f: travel time to complete flight route f;

- TA_{a_1,a_2}: travel time between airports a_1 and a_2;
- CF_r: direct operating cost to perform a flight with aircraft type r per time period;
- $CS_{a,r}$: cost of having an aircraft of type r on the ground, in airport a, per time period;
- q_f: passenger demand for flight route f;
- l_f: maximum load factor that the airline will sell, for flight route f;
- AD_f: airport of departure for flight route f;
- AA_f: airport of arrival for flight route f;

One important remark is that TF_f and TA_{a_1,a_2} represent the same travel time, but TF_f is in the form of a vector, and TA_{a_1,a_2} in the form of a matrix. This is necessary as the decision variables, which will be presented in subsection 3.3, u_0 and u_2 only have as inputs the route f, whereas u_1 is referenced to one route f and one airport a.

3.2. Pre-processed parameters

Some pre-processed parameters were defined to make the specification of the model easier, while reducing the number of itineraries considered to a maximum of three flights (direct, one-stop itineraries and two-stop itineraries). To these pre-processed parameters will be assigned the value of 1 for possible entries, and the value of 0 to impossible entries. The chosen pre-processed parameters were:

1. $D0_{f,t}$: equal to 1 if the flight route f, leaving at time period t arrives at destination until the last time period;
2. $D1_{f,a,t,w}$: equal to 1 if itinerary includes flight route f, and then continues to final airport destination a, represents a possible itinerary, first departing at time t and waiting for time w for a connection;
3. $D2_{f_1,f_2,t,w_1,w_2}$: equal to 1 if itinerary includes three flights, with the first and last flights, f_1 and f_2 respectively, and the middle flight the route that connects the arrival of f_1 with the departure of f_2 is plausible. This helps to reduce the amount of memory required, allowing for a larger size problem to be solved. Only the itineraries that are possible will have the value of 1 (e.g. an itinerary that in the end returns to the initial airport would never make sense for a passenger, hence will have the value of 0).

3.3. Decision Variables

The following decision variables are defined:

1. $y_{a,t,r}$: number of aircrafts of type r that are on the ground in airport a, from time t to $t+1$;
2. $x_{f,t,r}$: number of aircrafts of type r that fly route f, departing at time t and thus, arriving at time $t + TF_f$. This variable is binary, in order to prevent solutions with several aircrafts flying the same route departing at the same time;
3. ${u_0}_{f,t}$: number of passengers assigned to route f, taking off at t and landing at $t + TF_f$;
4. ${u_1}_{f,a,t,w}$: number of passengers assigned to the one-stop itinerary which contains route f, and then continues to final airport destination a. Initial departure time is t, waiting time on the ground for connection is w. Hence, the time of final arrival is given by $t + TF_f + w + TA_{AA_f,a}$.
5. ${u_2}_{f_1,f_2,t,w_1,w_2}$: number of passengers assigned to the two-stop itinerary which contains f_1 as the first flight and f_2 as the third flight, and has a middle flight joining two airports as the second flight. Initial departure time is t and the waiting times on the ground are respectively w_1 and w_2.

Hence, the time of final arrival is given by $t + TF_{f_1} + w_1 + TA_{AA_{f_1},AD_{f_2}} + w_2 + TF_{f_2}$.

6. $g_{a,t,r}$: equal to 1 if aircraft r has been on the ground in airport a for more than 2 hours, starting at time t;

Note that decision variables u_0, u_1 and u_2 are only created (i.e. only exist) if the associated pre-processed parameter D_0, D_1 and D_2 are equal to 1, respectively. Associated subscripts are here omitted to improve understanding. A graphical presentation of is included in Figure 1 to show three flight connections and two ground connections represented.

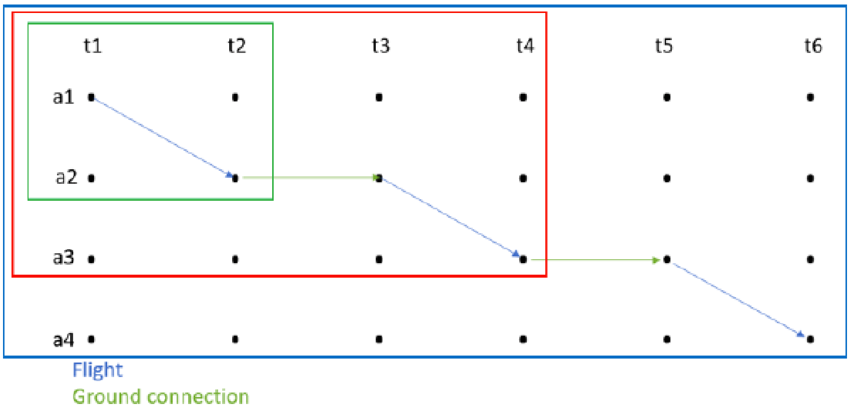

Figure 1: A possible itinerary for a passenger from airport a_1 to airport a_4.

3.4. Objective function

In the present formulation, the objective function will be minimized. It was defined as the sum of the following seven components (O_1 to O_7). This first component O_1 (1) reflects the direct costs for the airline, resulting from the operation of the flights, summing for all the flights, time periods and aircraft types, the product of the cost of each time period of flight in that aircraft with the number of time periods the flight took and with the number of flights. The second component O_2 (2) accounts for the costs to the airline, of having an aircraft of type r, parked on the ground in airport a, at time t (when it exceeds 2 hours). This is achieved by summing, for all airports, time periods and aircraft types, the product of the respective parking cost with the number of aircrafts of that type parked in that airport, for more than 2 hours. The third, fourth and fifth components O_3, O_4 and O_5 (3-5) account for the social cost to the passengers, quantified by the cost of time for them, for direct, one-stop and two-stop itineraries, respectively. Hence, it is obtained by summing the product of all the time on board an aircraft with the number of passengers and the cost of time on board for passengers. The sixth and seventh components O_6 and O_7 (6-7) account for the social cost to the passengers, of having to wait between two flights, on the ground, in an airport, respectively for one- and two-stop itineraries. Hence, it is obtained by summing the product of all the time on the ground in an airport, with the number of passengers and the cost of time on the ground for passengers. Therefore, the objective function O is given by the sum of the above seven components and the optimization problem will be defined by the minimization of O: Minimize $O = O_1 + O_2 + O_3 + O_4 + O_5 + O_6 + O_7$.

$$O_1 = \sum_{f \in F} \sum_{t \in T} \sum_{r \in R} CF_r \,.\, TF_f \,.\, x_{f,t,r} \tag{1}$$

$$O_2 = \sum_{a \in A} \sum_{t \in T} \sum_{r \in R} CS_{a,r} \cdot g_{a,t,r} \tag{2}$$

$$O_3 = \sum_{f\in F}\sum_{t\in T} CB\,.\,TF_f\,.\,u_{0_{f,t}} \tag{2}$$

$$O_4 = \sum_{f\in F}\sum_{a\in A}\sum_{t\in T}\sum_{w\in W} CB\,.\left[TF_f + TA_{AF_f,a}\right]\,.\,u_{1_{f,a,t,w}} \tag{3}$$

$$O_5 = \sum_{f_1\in F}\sum_{f_2\in F}\sum_{t\in T}\sum_{w_1\in W}\sum_{w_2\in W} CB\,.\left[TF_{f_1} + TA_{AA_{f_1},AD_{f_2}} + TF_{f_2}\right].\,u_{2_{f_1,f_2,t,w_1,w_2}} \tag{4}$$

$$O_6 = \sum_{f\in F}\sum_{a\in A}\sum_{t\in T}\sum_{w\in W} CWT\,.\,w\,.\,u_{1_{f,a,t,w}} \tag{5}$$

$$O_7 = \sum_{f_1\in F}\sum_{f_2\in F}\sum_{t\in T}\sum_{w_1\in W}\sum_{w_2\in W} CWT\,.\,[w_1 + w_2].\,u_{2_{f_1,f_2,t,w_1,w_2}} \tag{6}$$

3.5. Constraints

Several constraints are specified to support the definition of the problem and get logical relations between the variables and parameters involved. Additional constraints were defined to reduce the required computation time. The first constraint (8) ensures that the sum of aircrafts on the ground and in the air, at any time period, is equal to the available number of aircrafts of that type. With set $T(t,f)$ defined as the set of time periods such that $T(t,f) = \{t_1 \in T :\ t_1 \le t < t_1 + TF_f\}$. The second constraint (9) imposes continuity in each node. It imposes that the sum of the number of aircrafts arriving into an airport and aircrafts already parked there, is equal to the sum of aircrafts departing from that airport and aircrafts that will stay parked there. Set $F_1(a,t)$ is defined as the set of flights such that $F_1(a,t) = \{f \in F : AA_f = a \wedge t > TF_f\}$ and set $F_2(a)$ defined as the set of flights $F_2(a) = \{f \in F : AD_f = a\}$.

Constraint (10) imposes that there are never more passengers assigned to a flight than the maximum allowed number of passengers to that flight. This is achieved by specifying that for all time periods and flights, the sum of all passengers in direct or connecting flights is lower or equal to the number of available seats. The number of available seats is calculated by summing for all aircraft types, the product of the number of aircrafts operating that route, with their capacity and with the maximum load factor. It requires the definition of the following sets to support the summations in constraint (10):

$S_1 = S_1(f,a,t,w) = \{f_1 \in F, a \in A, t_1 \in T, w \in W : AA_{f_1} = AD_f \wedge AA_f = a \wedge t_1 + TF_{f_1} + w = t\}$

$S_{2A} = S_{2A}(f,t) = \{f_1, f_2 \in F, t_1 \in T, w_1, w_2 \in W : AA_{f_1} = AD_f \wedge AD_{f_2} = AA_f \wedge t_1 + TF_{f_1} + w_1 = t\}$

$$S_{2B} = S_{2B}(f,t) = \left\{f_1 \in F, t_1 \in T, w_1, w_2 \in W :\ t_1 + TF_{f_1} + w_1 + TA_{AA_{f_1},AD_f} + w_2 = t\right\}$$

Constraint (11) ensures that the demand is satisfied, i.e. that all the passengers that must travel from one airport to another will either be assigned to a direct, a one-stop or a two-stop itinerary. It requires the definition of the following sets to support the summations in constraint (11):

$S_3 = S_3(f) = \{f_1 \in F, a \in A : AD_f = AD_{f_1} \wedge AA_f = a\}$

$S_4 = S_4(f) = \{f_1, f_2 \in F : AD_f = AD_{f_1} \wedge AA_f = AA_{f_2}\}$

Constraints (12) and (13) impose that, respectively, the minimum number of flights and seats between any two airports is fulfilled. Constraints (14), (15), (16), (17) and (18) impose that, respectively the number of aircrafts on the ground, in the air, and passengers carried in direct, one-stop and two-stops itineraries are all positive integers. Constraints (19) and (20) impose that the fleet starts ($t = 1$) and ends ($t = NT$) the day at the hub ($a = a_{hub}$). This constraint was imposed due to information received from airlines operating these routes, and it is aligned with crew constraints. Constraints (21) and (22) allow the model to only consider aircraft ground fees if an aircraft stays on the ground for more than 2 hours, by imposing that $g_{a,t,r}$ is a binary variable (constraint 21). Constraint (23) imposes that there are not two different flights operating on the same route, with an interval smaller than 3 hours. This had to be imposed because one solution fulfilled all the frequencies imposed by the PSO with very small intervals, which is not practicable.

Minimize $O = \sum_{i=1}^{7} O_i = O_1 + O_2 + O_3 + O_4 + O_5 + O_6 + O_7$

s.t.

$$\sum_{a\in A} y_{a,t,r} + \sum_{f\in F} \sum_{t_1 \in T(t,f)} x_{f,t_1,r} = z_r, \;\; \forall\, t \in T, r \in R \tag{8}$$

$$y_{a,t-1,r} + \sum_{f\in F_1(a,t)} x_{f,t-TF_f,r} = y_{a,t,r} + \sum_{f\in F_2(a)} x_{f,t,r} \;\; \forall a \in A, t \in T\backslash\{1\}, r \in R \tag{7}$$

$$\sum_{r\in R} l_f . s_r . x_{f,t,r} \geq u_{0_{f,t}} + \sum_{a\in A}\sum_{w\in W} u_{1_{f,a,t,w}} + \sum_{(f_1,a,t_1,w)\in S_1} u_{1_{f_1,a,t_1,w}} + \sum_{f_1\in F}\sum_{\{w_1,w_2\}\in W} u_{2_{f,f_1,t,w_1,w_2}} + \sum_{(f_1,f_2,t_1,w_1,w_2)\in S_{2A}} u_{2_{f_1,f_2,t_1,w_1,w_2}} + \sum_{(f_1,t_1,w_1,w_2)\in S_{2B}} u_{2_{f_1,f,t_1,w_1,w_2}}, \;\; \forall f \in F, t \in T \tag{8}$$

$$\sum_{t\in T} u_{0_{f,t}} + \sum_{(f_1,a)\in S_3(f)} \sum_{t\in T}\sum_{w\in W} u_{1_{f_1,a,t,w}} + \sum_{(f_1,f_2)\in S_4(f)} \sum_{t\in T} \sum_{\{w_1,w_2\}\in W} u_{2_{f_1,f_2,t,w_1,w_2}} = q_f, \;\; \forall f \in F \tag{11}$$

$$\sum_{t\in T}\sum_{r\in R} x_{f,t,r} \geq x_{min_f} \;\; ,\forall f \in F \tag{12}$$

$$\sum_{t\in T}\sum_{r\in R} s_r \,. x_{f,t,r} \geq s_{min_f} \;\; ,\forall f \in F \tag{13}$$

$$y_{a,t,r} \in \mathbb{Z} \;\; ,\forall\, a \in A, t \in T, r \in R \tag{14}$$

$$x_{f,t,r} \in \{0,1\} \;\; ,\forall\, f \in F, t \in T, r \in R \tag{15}$$

$$u_{0_{f,t}} \in \mathbb{Z} \;\; ,\forall\, f \in F, t \in T \tag{16}$$

$$u_{1_{f,a,t,w}} \in \mathbb{Z} \;\; ,\forall\, f \in F, a \in A, t \in T, w \in W \tag{17}$$

$$u_{2_{f_1,f_2,t,w_1,w_2}} \in \mathbb{Z} \;\; ,\forall\, \{f_1; f_2\} \in F, t \in T, \{w_1; w_2\} \in W \tag{18}$$

$$\sum_{f\in F | AD_f = a_{hub}} x_{f,1,r} + y_{a_{hub},1,r} = z_r \;\; ,\forall\, r \in R \tag{19}$$

$$y_{a_{hub},NT,r} = z_r \;\; ,\forall\, r \in R \tag{20}$$

$$g_{a,t,r} \in \{0,1\} \;\; ,\forall\, a \in A, t \in T, r \in R \tag{21}$$

$$g_{a,t,r} \geq \sum_{t_0=t}^{t+3} y_{a,t_0,r} - 3.5 \;, \qquad \forall\, a \in A, t \in T \setminus \{NT-2, NT-1, NT\}, r \in R \tag{22}$$

$$\sum_{r\in R}\sum_{t_0=t}^{t+5} x_{f,t_0,r} \leq 1, \;\; \forall\, f \in F, t \in T \setminus \{NT-4, NT-3, NT-2, NT-1, NT\} \tag{23}$$

1

Besides the above-mentioned constraints, which are necessary for the correct specification of the problem, other “speed-up” constraints were added in order to reduce the computation time by narrowing down the range of possible solutions only to reasonable ones in practice. This removed from the scope of analysis unreasonable solutions, such as placing passengers in itineraries which end the day in the same airport as the departure. Some examples of these constraints which were attempted, some with and some without success were:

1. Whenever an aircraft departs from the “hub” airport, all the fleet departs from the “hub” airport at that time. This potentializes the hub effect and increases the possibility of connections in the hub requiring less flights overall;
2. At any time period there is a maximum of one aircraft operating in each route;
3. A maximum of one flight for the whole time of the analysis is considered, for all the routes that have no minimum amount of flights assigned by the PSO network, or have low demand;
4. Connecting itineraries, which imply a total flown distance longer than 150% of the direct distance between origin and final destination, do not have passengers placed there.

Finally, in order to verify the implementation of the model, an illustrative example was developed, which demonstrates that the model is correctly solving the given problem. This example will be presented in the next subsection.

3.6. Illustrative example

This section provides an example to illustrate the application of the mathematical model. This illustrative example optimizes the routes for a network comprised of NA=4 airports (1, 2, 3 and 4), during NT=10 time periods (each time period represents one hour, going from 10 am to 7pm). A specified demand of passengers (to be detailed below) must be fulfilled, and there are two types of aircraft available (NR=2).

1. type A which can carry 60 passengers on board, has an operating (in flight) cost of 2000 €/h, a ground cost of 100 €/h and there is 1 aircraft of this type available;
2. type B, which carries 120 passengers on board, has an operating cost of 3000 €/h, a ground cost of 100 €/h and there is 1 aircraft of this type available.

It was imposed that no passenger will have to wait for more than 3 hours on the ground for a connection, and the demand to be fulfilled is presented in Table 3.

Table 3: Demand (in number of passengers) to be fulfilled in the illustrative example.

Demand					
		Arrival (Destination)			
		Airport 1	Airport 2	Airport 3	Airport 4
Departure (Origin)	Airport 1		5	10	20
	Airport 2	30		20	25
	Airport 3	120	51		70
	Airport 4	15	10	20	

A minimum amount of flights and/or seats between certain airports are imposed to the PSO routes:

- 1 flight per day (round trip) between airports: 1-2, 1-4, 2-3;
- 60 seats from 1 to 2;
- 50 seats from 2 to 1;

- 120 seats from 1 to 4 and from 4 to 1;
- 100 seats from 2 to 3 and from 3 to 2;

The following travel times between airports are also defined:

- 1 hour between: 1-2, 1-4, 2-4, 3-4 (for each direction);
- 2 hours between: 1-3, 2-3 (for each direction);

Maximum allowed load factors, i.e. the number of occupied seats divided by the number of installed seats, for each route are also defined in Table 4:

Table 4: Maximum load factor for the illustrative example.

Maximum load factor (%)					
		Arrival (Destination)			
		Airport 1	Airport 2	Airport 3	Airport 4
Departure (Origin)	Airport 1		90	95	98
	Airport 2	100		98	99
	Airport 3	100	98		95
	Airport 4	100	99	100	

The optimal solution is found in less than 3 seconds. The solution is presented graphically below, in Figure 2, where each row represents an airport (1 to 4), and each column one hour of the day, from 10 to 19.

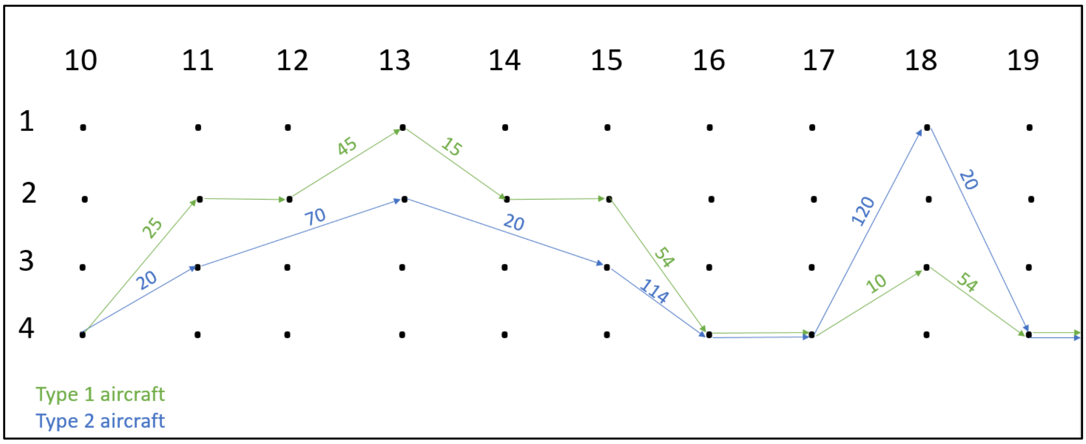

Figure 2: Graphical results from the illustrative example.

Note that the constraints related with the demand were all respected, including the maximum time on the ground waiting for a connection flight (only once equal to 3 hours, and never greater). Now, regarding the constraints related to the flights:

- It was required to have round trips between 1-2, 1-4, 2-3 which is verified;
- It was required to have 60 seats from 1 to 2, and 50 seats from 2 to 1. This round-trip flight is performed by a type 1 aircraft, so this constraint is verified;
- 120 seats from 1 to 4 and from 4 to 1. This round-trip flight is performed by a type 2 aircraft, so this constraint is verified;
- 100 seats from 2 to 3 and from 3 to 2. This round-trip flight is performed by a type 2 aircraft, so this constraint is verified.

The last verification is that the maximum load factors were never exceeded. In Figure 3, for each flight the number of passengers on board is shown, followed in brackets by the maximum number of passengers allowed. As an example, a flight departing from airport 4 at 10:00 and arriving to airport 2 at

11:00 carries 25 passengers with a maximum of 60. This number was obtained by multiplying the maximum load factor for that route, with the capacity of the type of aircraft which operated the flight.

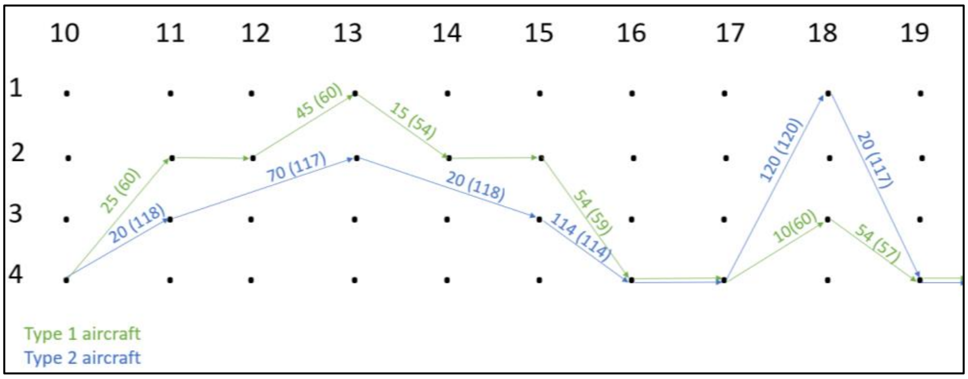

Figure 3: Demonstration of the capability to not exceed the maximum load factor.

4. Two PSO networks in the Greek region: Rhodes network and Thessaloniki network

In this section, the optimization model is applied to two case studies designed for the existing Greek PSO network: one "based" in Rhodes airport and another "based" in Thessaloniki airport. Excluding Athens airport, all the other Greek airports connected through PSO routes were joined into two networks. The decision on the two hubs is aiming to (i) improve connectivity within the network without relying on the largest hub in the country (Athens airport) for connecting flights, (ii) result into routes and schedules that could be attractive and viable for airlines and finally, contribute to the planning of more efficient operations for these airports, as previous research has highlighted (Fragkoudaki and Gkiokas, 2016), and maintain their efficiency (Fragkoudaki and Gkiokas, 2020). The European PSO scheme has transparency as one of its core values, and the information regarding each PSO network is made publicly available in the European Commission's website (European Commission, 2019). Table 5 was compiled extracting key information for the PSO networks under analysis.

In Table 5, the first two columns detail the airports involved, and they are given as a sequence, e.g. in the first row it is imposed that a flight must depart from Rhodes, with final destination Kasos, but with an intermediate stop in Karpathos. The return flight (i.e. Kasos to Rhodes, with an intermediate stop in Kasos) is also imposed. The third column specifies the minimum weekly frequencies imposed by the PSO. In the lines where there are 3 values (e.g. 3/4/6), each value represents the imposed frequency for one season of the year, as the Greek aviation sector divides the year in three seasons, according to the expected demand. The highest values correspond to the summer months, the lowest values to the winter months, with the remaining values corresponding to the mid-season. The fourth, fifth, sixth and seventh columns are self-explanatory. In the fifth column there are percentages of load factor greater than 100% because the value is calculated as the number of actual passengers, divided by the minimum number of seats imposed by the PSO, while typically load factor represents occupied seats divided by total available seats. The next column specifies the minimum number of seats that must be made available annually to the public by the airline (as imposed by the PSO). The following column specifies if the route is part of an open or restricted PSO determining whether other airlines can offer competitive air services to the subsidized route or not. Then, a column details how many bids were submitted in the tender process, when imposing that specific route. Afterwards, the name of the airlines which were granted the operation in that route are shown Routes specified as restricted (R) have one only airline operating. The last column specifies the date when that PSO network was imposed.

Table 5: Key data regarding the PSO scheme [10]

Airport	Airport	No. of weekly return frequencies	PSO passengers in 2017	Load Factor (pax/minimum seats)	Annual economic compensation (€)	Type of aircraft	Annual seats required by the PSO	Open or Restricted PSO (O/R)	Number of bids in the tender process	Airlines Operating (names)	PSO in force from
Rhodes	Karpathos-Kasos	3/4/6	18 741	141.98%	795 000	ATR-42	13200	R	2	Sky Express	1-Oct-2016
Rhodes	Kastelorizo	2/2/3	7 023	79.81%	919 199	Dash 8-100	8800	R	1	Olympic Air	1-Oct-2016
Rhodes	Kos-Kalymnos-Leros-Astypalaia	3/4/6	3 415	56.45%	1 089 000	ATR-42	6050	R	2	Sky Express	1-Jun-2018
Thessaloniki	Kerkyra	2	15 547	166.10%	99 000	ATR-42	9360	R	3	Sky Express	12-Apr-2018
Thessaloniki	Limnos-Ikaria	3/4/6	14 646	110.95%	528 000	ATR-72	13200	R	1	Astra Airlines	1-Oct-2016
Thessaloniki	Samos	3/4/6	23 581	89.32%	N/A	Dash8-100/400	26400	O	N/A	Astra Airlines, Olympic Air, Sky Express	1-Oct-2016
Thessaloniki	Skyros	2	2 496	40.00%	250 000	ATR-42	6240	R	1	Sky Express	1-Apr-2017
Thessaloniki	Chios	3/4/6	31 331	118.68%	N/A	Dash8-100/400	26400	O	N/A	Astra Airlines, Olympic Air, Sky Express	1-Oct-2016
Thessaloniki	Kalamata	3/4/6	12 810	58.23%	N/A	Dash8-100/400	22000	R	1	Olympic Air	1-Oct-2016

After describing the PSO impositions, the two networks are presented. Each network is comprised of 8 airports, including the "hub" airport, with 56 possible routes. These networks were chosen because, though they have the same number of airports and are located relatively close to each other, they are different in terms of the number of aircrafts employed, passengers transported, and frequencies imposed by the PSO, which will allow for a more comprehensive analysis of the Greek market. The goal is again to reduce the total costs of the networks to the lowest possible values in terms of the objective function. The total cost to be considered is the sum of the following four components:

1. **Aircraft direct operating costs** which represent the direct cost for an airline to operate a flight, and include the fuel, the crew, the airport and airspace fees, maintenance costs etc. Based on the Eurocontrol Standard inputs for cost benefit analysis (Eurocontrol, 2018), the cost per block hour (the time the engines are operating in a flight) was estimated to be:
    a. 1502 €/h for the Bombardier Dash 8-Q100 aircraft type;
    b. 1502 €/h for the ATR 42 aircraft type;
    c. 2376 €/h for the Bombardier Dash 8-Q400 aircraft type.
2. **Aircraft ground costs** which represent the cost for the airline to have the aircraft on the ground after reaching the limit of 2 hours (de Neufville and Odoni, 2003). These were estimated to be 10% of the aircraft direct operating costs (Pita et al., 2013). It is common in the airline industry for airlines not to pay parking fees if the aircraft is on the ground for less than 2 hours;
3. **Passenger on board time cost** which represent the cost of the time spent on board for a passenger. It was estimated to be 10€/h for the passengers in these networks, of which business travelers account for a small percentage of the overall demand (Eurocontrol, 2018);
4. **Passenger ground connection time cost** which represents the cost of the time spent in an airport waiting for a connection from the passenger perspective. It was estimated to be 10€/h for this network assuming it mostly comprises of tourist passengers. This is justified by the fact that for tourists, there is no significant difference between time spent on board or on the ground.

Having detailed the input values, each network will be discussed separately: section 4.1 explores the Rhodes network and section 4.2 the Thessaloniki network.

4.1. Rhodes Network

This first case study uses Rhodes airport as a PSO hub. It is a relatively simple network compared to the second one as it has a smaller number of frequencies imposed, a smaller number of aircraft operating in the network and smaller costs involved. Seven connections are imposed by the PSO as represented in Figure 4. All these connections are operated in both directions and thus 14 routes in total, considering outbound and inbound legs separately. The fleet considered is composed of one Bombardier Dash 8 Q100 aircraft and two ATR42 aircrafts. Regarding the aircraft operating costs, based on data provided by the HCAA for summer 2019, the number of movements and aircraft types associated with each O/D pair was noted (Table 6).

The total aircraft operating cost for this network is estimated to be 53,771€ (for a total of 50 flights), resulting in an average cost of 1,075€ per flight. Since parking fees are only charged when an aircraft stays on the ground for more than 2 hours, the aircraft ground costs were considered equal to zero. Regarding the Passenger time costs, the total travel time for each O/D pair was compiled and is presented in Table 7. For each O/D pair, the travel times of at least one full week were verified through travel planner websites and the shortest value was considered. This was done in order to allow for a fair comparison since there are days of the week which allowed for better connections than others. Some routes have direct flights, whereas others have long connections, explaining the broad range of values for the travel time. Therefore, for each O/D pair the passenger time costs were estimated using the following expression:

$$TPC = CT \times TT \times NP \tag{9}$$

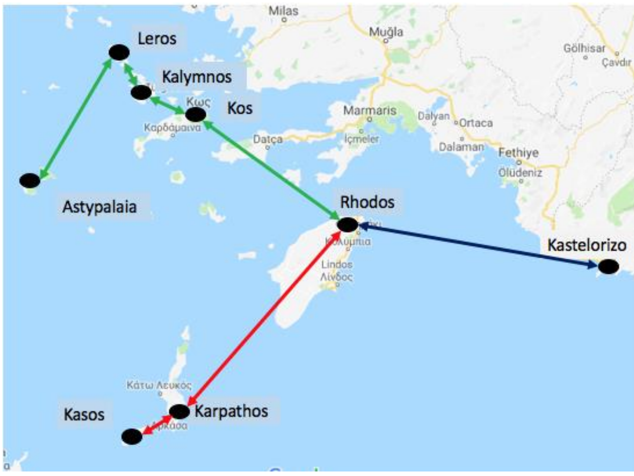

Figure 4: Graphical representation of the current Rhodes network.

Table 6: Number of flights per O/D pair in the current design of the Rhodes network.

Flights in Rhodes network									
		Arrival (Destination)							
		Astypalaia	Kalymnos	Karpathos	Kasos	Kastelorizo	Kos	Leros	Rhodes
Departure (Origin)	Astypalaia		2	0	0	0	1	1	1
	Kalymnos	1		0	0	0	1	1	2
	Karpathos	0	0		4	0	0	0	4
	Kasos	0	0	4		0	0	0	3
	Kastelorizo	0	0	0	0		0	0	3
	Kos	1	1	0	0	0		0	1
	Leros	2	1	0	0	0	0		2
	Rhodes	0	2	3	3	3	1	2	

Table 7: Travel time per O/D pair in the current design for the Rhodes network

Travel time (hours) in Rhodes network									
		Arrival (Destination)							
		Astypalaia	Kalymnos	Karpathos	Kasos	Kastelorizo	Kos	Leros	Rhodes
Departure (Origin)	Astypalaia		1.2	4.0	4.8	20.0	2.0	0.5	3.0
	Kalymnos	1.2		2.5	3.3	12.3	0.5	0.5	1.5
	Karpathos	5.5	7.0		0.3	9.8	7.8	5.3	0.6
	Kasos	14.0	13.5	0.3		14.3	8.3	17.5	1.3
	Kastelorizo	9.0	4.8	7.5	9.0		4.0	5.8	0.6
	Kos	1.9	0.5	1.6	2.3	8.5		1.2	0.5
	Leros	0.5	0.5	3.3	4.0	14.6	1.2		2.2

	Rhodes	2.8	1.3	0.6	1.3	0.6	0.5	2.0	

where CT is the cost of time for the passengers, TT the travel time and NP the number of passengers in that route. The total passenger time costs were then calculated by summing all the passenger time costs for each O/D pair associated with that network. The total passenger time costs were estimated to be 6,470€ for a total of 375 passengers, resulting in an average travel time of 1 hour and 44 minutes per passenger. Summing all these components, the total cost for the Rhodes network was estimated to be 60,241€, for the period under analysis.

4.2. Thessaloniki Network

This second network is also composed of 7 connections in both directions and, thus, 14 routes considering outbound and inbound routes separately, as presented in Figure 5. All of them are imposed by the PSO and fulfilled by 2 Dash 8 Q100, 2 Dash 8 Q400 and 1 ATR 42 aircrafts. The larger fleet size and geographical distances require a larger dimension of this network which leads to larger costs. In Table 8 the number of movements per O/D pair are presented.

The total aircraft operating costs were estimated to be 134,424€ (for a total of 62 flights), resulting in an average cost of 2,168€ per flight (which is more than twice the average operating cost for the Rhodes network). The aircraft ground costs for the Thessaloniki network were assumed to be null. Regarding the passenger time costs, using the same expression for the previous network, the total travel time for each O/D pair was compiled and is presented in Table 9.

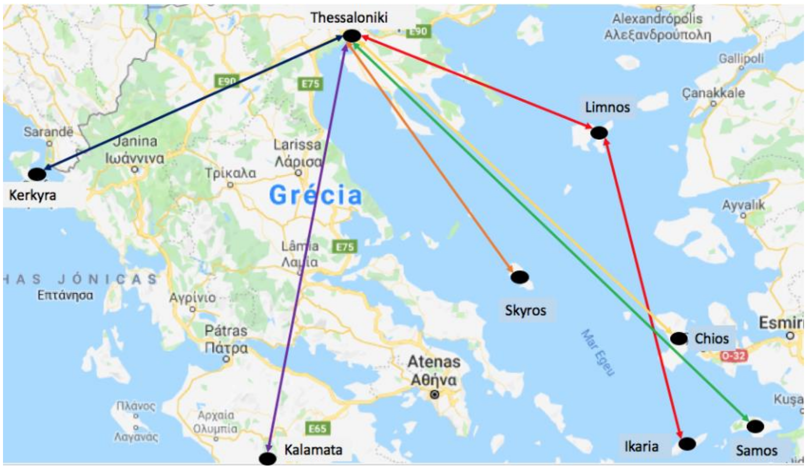

Figure 5: Existing/current design of the Thessaloniki network

Table 8: Number of flights/week per O/D pair in the Thessaloniki network

Flights in Thessaloniki network									
		Arrival							
		Chios	Ikaria	Kalamata	Kerkyra	Limnos	Samos	Skyros	Thessaloniki
Departure	Chios		0	0	0	2	0	0	5
	Ikaria	0		0	0	3	0	0	3
	Kalamata	0	0		1	0	0	0	4
	Kerkyra	0	0	1		0	0	0	3
	Limnos	2	3	0	0		0	0	3
	Samos	1	0	0	0	1		0	5

	Skyros	0	0	0	0	0	0		1
	Thessaloniki	5	3	3	3	3	5	2	

Table 9: Travel time per O/D pair for the existing/current design of the Thessaloniki network

Travel time (hours) in Thessaloniki network									
		Arrival							
		Chios	Ikaria	Kalamata	Kerkyra	Limnos	Samos	Skyros	Thessaloniki
Departure	Chios		4.0	3.2	4.0	3.8	0..5	4	1.5
	Ikaria	4.5		16.5	3.3	0.8	3.0	13.3	1.5
	Kalamata	4.5	15.2		8.0	10.8	14.0	12.0	1.5
	Kerkyra	3.0	3.8	2.8		4.5	2.5	4.8	1.0
	Limnos	1.8	0.8	6.0	2.5		2.8	5.3	1.0
	Samos	0.6	3.2	60	3.6	2.8		4.2	1.3
	Skyros	3.5	4.3	4.8	2.8	3.0	5.0		0.8
	Thessaloniki	1.6	1.2	1.5	1.3	1.5	1.0	3.0	

Using equation (24), the total passenger time costs for the Thessaloniki network were estimated to be 27,637€ for a total of 1357 passengers (three times more passengers than in the Rhodes network), resulting in an average travel time of 2 hours and 1 minute per passenger. Finally, by summing all the cost components, the total cost for the Thessaloniki network was estimated to be 162,061€.

5. Demand Prediction Model

The optimization model described in Section 3 employees passenger demand for the network as an input. This fifth section explores predictive models to estimate air passenger demand in all possible O/D pairs in the network. Predicting demand is usually identified as the most important input to the optimization of an airline network. This forecasting activity needs to be performed for the current network and for O/D pairs which are candidates to future routes. The calculating process may be complex and involves significant uncertainty in the estimated demand (de Neufville and Odoni, 2003). The network under analysis is comprised of 16 airports, and thus there are 240 (16x15) O/D pairs, the passenger demand of which will be predicted. Currently, the operating flights in the existing network serve 66 of the O/D pairs of the network. In order to estimate the remaining potential demand of air transport among the nodes of the studied network, multivariate linear regression is employed and Generalized Linear Models (GLM) are developed. GLMs allow that: i) the dependent variable may not be continuous and ii) the effect of the explanatory variables may not be linear and have 3 components:

1. A systematic component, usually a linear predictor such as $\eta_i = \beta . X$, where X is a vector of explanatory variables, β are the calibration parameters and η_i is the link function;
2. A link Function, which describes how the mean, $E[Y_i] = \mu_i$, depends on the linear predictor $g(\mu_i) = g(E[Y_i]) = \eta_i$ and, inversely, $\mu_i = g^{-1}(\eta_i)$;
3. A random component, usually a probability distribution from the exponential family.

In applications to predict passenger demand, typical GLM models use the Poisson distribution or the Negative Binomial. In PSO networks the demand is relatively low (compared to normal, profitable airline routes), and there are significant discrepancies in the values of demand for different origin-destination (O/D) pairs. In fact, in this case study's data there were demand values of around 10 and others around 5500, i.e. 550 times higher.

In the Poisson regression, a common link function is the logarithmic function, leading to:

$$E[Y_i] = \lambda_i = \exp\left(\beta_0 + \sum_{j=1}^{p} x_{ij}\beta_j\right) \qquad \text{(Washington et al., 2010)}$$

where $E[Y_i] = \lambda_i$ represents the expected value for the variable being estimated, β_0 and β_j represent the coefficients of the regression and x_{ij} represent the values of the p explanatory variables. An important assumption with the Poisson distribution is that there is no overdispersion, i.e. the variance and the mean are equal. In cases where there is overdispersion (e.g. when there are too many zeros in the dataset), the alternative is the Negative Binomial distribution. In the Negative Binomial regression, the only difference is the addition of the error term ε_i, which adds additional variance, and allows for overdispersion. Checking for overdispersion is done through a Lagrange multiplier test. For further information on the theoretical concepts behind these statistical regressions, the reader is directed to McCullagh and Nelder (1989) or Silva and Turkman (2000).

To build the multivariate linear regression for the case study, important explanatory variables from published literature (Section 2) were considered:

1. **GDP** (either summing or multiplying both origin and destination, either total or per capita);
2. **Population** (either summing or multiplying both origin and destination);
3. **Importance of tourism** (either by number of tourist arrivals, hotel beds or per capita beds);
4. **Cost of ticket** (either absolute, or compared to its competition (e.g. rail, car, boat…));
5. **Travel time**;
6. **Distance between airports**.

Since the present case study has some particularities, additional variables were considered, and their statistical significance was assessed in the multivariate linear regression analysis, such as:

1. **Existence of significant cruise ship terminals in the islands** as it is assumed that if an island has a cruise ship terminal with significant activity, demand for airline tickets will increase;
2. **Competition of ferry boats** as it is assumed that the higher the quality of the service provided by the ferry boat (fast travel times or low-ticket prices), the lower the demand for airplane seats will be.
3. **Effect of population ageing** as it is assumed that the higher the share of older population, the less the business activity developed and hence, the less trips the population will be making.

5.1. Case study data

The data was collected for all the previously mentioned explanatory variables (for each of the 240 O/D pairs). Note that both Rhodes and Thessaloniki networks were joined into one network for predictive purposes. This data was collected through several sources and refers to the month of August 2018:

1. For the sociodemographic variables: Population, GDP per capita, and population ageing, values were taken from official statistics sources (Hellenic Statistical Authority, 2011);
2. For the variables describing the transport market: existence of a ferry between origin and destination, cost of airplane ticket, cost of ferry ticket, existence of direct flight, airplane travel time (including connections if applicable), direct distance between airports and minimum number of weekly flights, as established by the PSO, values were taken from the official website of the European commission (2019), and from online travel websites (for the ticket prices, travel times and the existence of direct flights or ferries);
3. For the economic variables, related to tourism: sum of number of hotel beds in origin and destination and existence of cruise ship terminals, information was retrieved from the Hellenic Chamber of Hotels (2018), and from official tourism websites, developed by the national and local governments;

As many demand observations as possible were obtained from the HCAA (passengers carried in scheduled direct inbound and outbound flights between origin and destination) and from the connecting tickets emitted by Aegean/Olympic airlines. In total, values for 54 direct routes, and 12 connecting routes were obtained. The collected information was then the basis for predicting the demand values among the rest of the O/D pairs. Initially the creation of two demand models was considered, one with the data from direct routes only and another with the data from connecting itineraries but as the available data was not enough for two separate models, it was then decided to opt for a single model for all the market under study. Hence, the decision was to create a single model including the 66 routes with available demand values obtained from HCAA and Aegean airlines on emitted tickets since there was no information on real demand data. The statistical models were estimated using IBM's SPSS software.

5.2. Statistical modelling

Several specification tests were conducted to reach the most reasonable statistical model possible. First, overdispersion was analyzed through the Lagrange test. Then, the statistical significance of the parameters was verified through the Wald test and associated p-values. Afterwards, the predictive capacity of the model was assessed using the Omnibus test. Finally, different model specifications were compared in order to choose the most suitable one.

The initial modelling step was to test using all the explanatory variables. As a first step, a Negative Binomial regression was run but as the Lagrange multiplier test failed, it was decided that a Poisson regression model would be a better modelling option. Hence, the impact of the following variables on passenger demand was then assessed in a Poisson model:

- **Cost of an airplane ticket**, from the origin to the destination, even if this implies having connections. If there is no ticket offered (even with connections), will have the value of zero, expected to have a negative impact on the demand, as its value increases;
- **Total travel time (in hours)**, expected to have a negative impact on the demand, as its value increases. Corresponds to the time required to reach the destination from the departing time of the first flight and includes the time waiting for ground connections, for non-direct flights;
- **Straight line distance (in nautical miles)**, between origin and destination airports, expected to have a positive impact on the demand, as its value increases;
- **Frequency of direct flights**, for the period of analysis (one month). If there is no direct flight, the value will be zero, expected to have a positive impact on the demand, as its value increases;
- A Dummy variable used as an offset variable obtaining the value of 1 for the **biggest markets** (one of the connecting airports serves high demand levels), and the value of 0 for the smaller markets.

Then, the statistical significance was assessed for all effects associated with explanatory variables, to include them in the model. Five different model specifications were concluded and are presented in Table 10 with the associated statistical indicators for model comparison. The rest of the considered variables were also tested for their capacity to explain demand levels but were not found to be statistically significant and were omitted from the presented models. Extensive testing and stepwise procedures were carried out to estimate different model specifications. For certain variables, certain transformations to the explanatory variables were also tested (e.g. logarithm, exponential or dividing one by another), in various logic combinations, but without successfully explaining demand.

The five models were assessed based on the validity of the coefficients´ signs, the AIC value, the value of the deviance and pseudo-R^2. Models M2 and M5 could be characterized as the moderate and the optimistic one, respectively. They were considered the best models as they exhibited the lowest deviance values and the highest AIC values, indicating these models fit better the data than the others; and the highest pseudo-R^2 values, indicating that the variables included can explain a higher percentage of the independent variable (demand). Out of the two best performing models, the moderate one (M2) will be employed to predict the demand of the O/D pairs for which no data was provided from the two data sources. To choose which model will be applied, their prediction performance was assessed based on which of the two best fits the existing data. The plot with the fit of the predicted and actual values is presented in Figures 6 and 7. Speculation of the values obtained from model M2 and model M5 led to the conclusion that model M5 was strongly overestimating the demand in smaller markets and slightly overestimating it in larger markets. Since the predictive model is applied to PSO routes characterized by low demand, model M2 was considered appropriate for the demand estimation of the O/D pairs, for which the passenger volumes were missing.

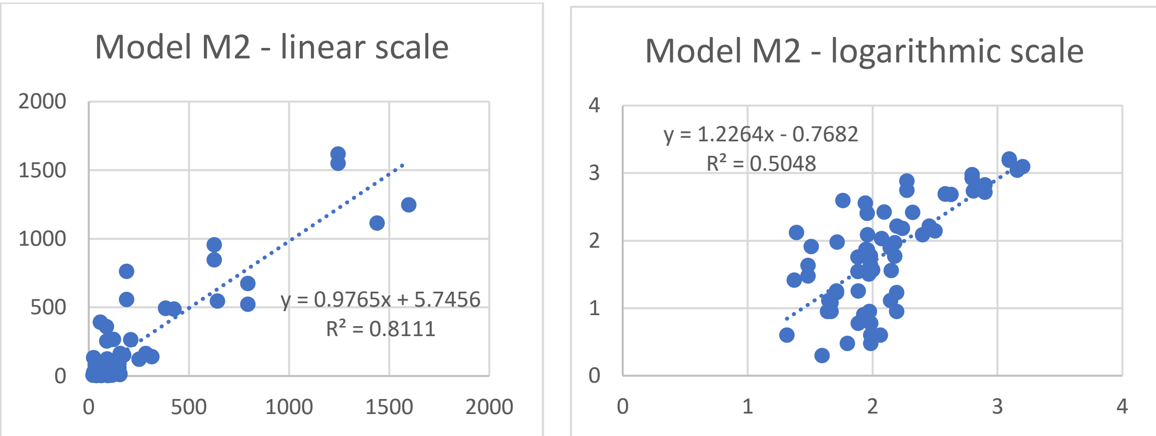

Figure 6. Fit results of moderate model - linear and logarithmic scale

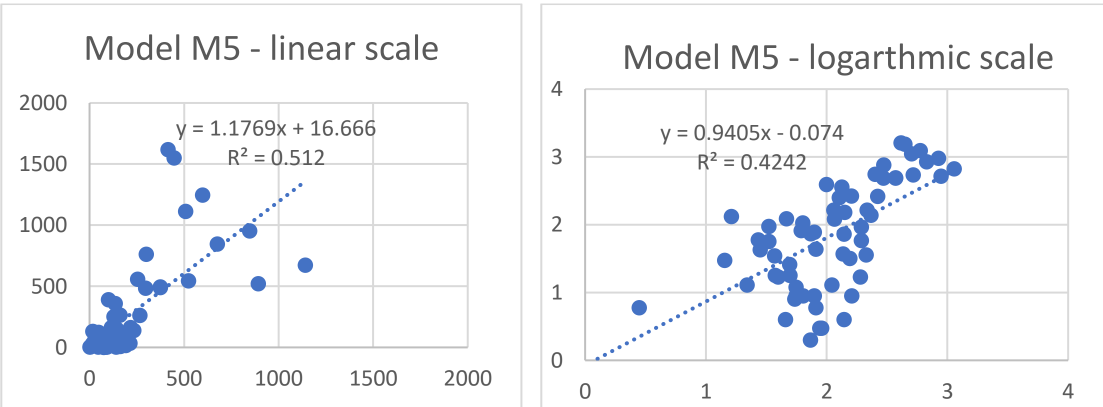

Figure 7. Fit results of optimistic model (M5)- linear and logarithmic scale

By assuming the moderate model (M2), the passenger daily demand for the two networks was estimated so that it is used as input in the optimization model. Tables 11 and 12 provide the passenger demand estimated using model M2 for the Rhodes and Thessaloniki networks, respectively, per flight. It is observed that some small demand values are obtained from the demand estimation model. These results correspond to flights that operate consecutively connecting airports in small islands with small population. Similar results have been obtained in previous work for PSO routes in Azores (Pita et al., 2013).

Table 10: Model comparison (five final model specifications M1 to M5), associated estimates and statistical indicators.

Model	M1	M2	M3	M4	M5
offset included?	No	No	Yes	No	Yes
Variables	**Estimated values of variables´ coefficients**				
Intercept	2.56***	2.21***	2.21***	3.57***	3.38***
Log (O/D Population Product)	0.56***	0.30**	0.30**	0.47***	0.19*
Distance	0.01*	0.01***	0.01***	0.01**	0.01***
Frequency of flights	0.09***	0.10***	0.11***	0.07***	0.07***
Cost ticket air	-0.01*	----------	----------	-0.01*	----------
Big market	----------	0.10***	----------	----------	----------
Travel time	----------	----------	----------	-0.46*	-0.55**
Goodness of fit indicators					
# of parameters					
AIC	8710.9	7414.4	7412.4	7749.1	6339.7
log-likelihood	-4350.5	-3702.2	-3702.2	-3868.6	-3164.8
Deviance	8314.1	7017.5	7017.5	7350.3	5942.8
Pseudo R^2	0.687	0.734	0.734	0.722	0.772

**p-value <= 0.15; **p-value <=0.10 and *** p-value < 0.01*

Table 11: Passenger demand values for each O/D pair for the Rhodes network.

		Arrival (Destination)							
		Astypalaia	Kalymnos	Karpathos	Kasos	Kastelorizo	Kos	Leros	Rhodes
Departure (Origin)	Astypalaia		1	2	1	2	2	1	7
	Kalymnos	1		2	2	2	1	4	1
	Karpathos	2	2		11	2	1	2	57
	Kasos	1	2	7		1	2	2	16
	Kastelorizo	2	2	2	1		2	2	45
	Kos	2	4	2	2	2		2	4
	Leros	1	2	2	2	2	2		1
	Rhodes	4	1	57	19	41	29	1	

Table 12: Estimated passenger demand values for each O/D pair for the Thessaloniki network.

		Arrival (Destination)							
		Chios	Ikaria	Kalamata	Kerkyra	Limnos	Samos	Skyros	Thessaloniki
Departure (Origin)	Chios		2	8	1	7	3	2	179
	Ikaria	2		7	10	4	2	2	64
	Kalamata	8	7		1	8	9	5	128
	Kerkyra	11	10	2		7	1	5	2
	Limnos	5	4	8	7		4	2	63
	Samos	3	2	9	13	12		3	98
	Skyros	2	2	5	5	2	3		8
	Thessaloniki	187	88	144	1	56	110	14	

6. Analysis and Discussion

At this point, the optimization model (explored in section 3) is applied to the case studies, the current design of which was detailed in section 4 using the passenger demand estimated with the predictive models developed in section 5. After running the optimization implemented in IBM's FICO Xpress software, feasible results were obtained for both networks. They are presented and discussed in this section separately for each network. Moreover, a scenario analysis is also conducted to assess the impact of some modelling assumptions. The commercial solver was run in a Windows 10 Pro operating system in a computer with an Intel(R) Core(TM) i7-3770K CPU @ 3.50 GHz, and 8 GB of RAM memory.

6.1. Application to Rhodes Network

This first network is considerably smaller than the second network; its current total costs are 42% of the value of the current total costs of the Thessaloniki network. The feasible solution found for the Rhodes network was obtained after 14 hours and 41 minutes of computation with an optimality gap of 8.58%. The costs associated with this solution, and the comparison with the current/existing network design are:

- **Flight operating costs**: 48,815€ for a total of 46 flights, compared to 53,771€ for the current network, which requires 50 flights, a reduction of 9.2% in cost;
- **Aircraft ground costs**: 75€ compared with 0€ for the current network. This increase is considered negligible when compared to the other reductions obtained by the model, especially having in mind that these 75€ apply for only one aircraft which exceeded the 2 hour limit for staying on the ground, for only 30 minutes, and this happened at the hub;
- **Passenger time costs**: 3,995€ for the time passengers spent on board, and 860€ for the time passengers spent waiting on the ground for a connecting flight, in a total of 4,855€ resulting in an average travel time of 1 hour and 17 minutes per passenger, compared with 6,470€ for the current network and an average travel time of 1 hour and 44 minutes per passenger. This means a reduction of 24.9% in cost;
- **Total cost of the network**: 53,745€ compared with 60,241€ for the current network. This means a reduction of 10.7% in the total cost of the network, with reductions in all the parameters, except a negligible increase from 0 to 75€ in the aircraft ground costs, fulfilling the objective of not only reducing the financial costs associated with the network, but also improving the quality of service provided to the passengers, through reduction of the door to door travel time.

The movement of aircrafts and passengers in the network were compiled in a graph, presented in Figure 8, where each line represents one of the 8 airports and each column represents one hour of the day. Each color represents one aircraft, and the numbers associated with each flight represent the passengers transported on board. There are 3 aircrafts operating. Horizontal lines represent an aircraft which is stopped on the ground in the airport associated with that line, while diagonal lines represent the flights. The airport is identified on the left of the line through its IATA (International Air Transport Association) code.

One of the immediate conclusions is the fact that there are several flights operated with zero passengers transported. This is a result of the nature of this network, inserted in a PSO scheme, as its main goal is not profit, but assuring accessibility to these low demand regions, and thus there is a need for government subsidies. The fleet used in this network was based on the actual fleet operating these routes and is comprised of 2 ATR 42 aircraft (with 48 seats each) and 1 Dash 8 Q100 (with 37 seats).

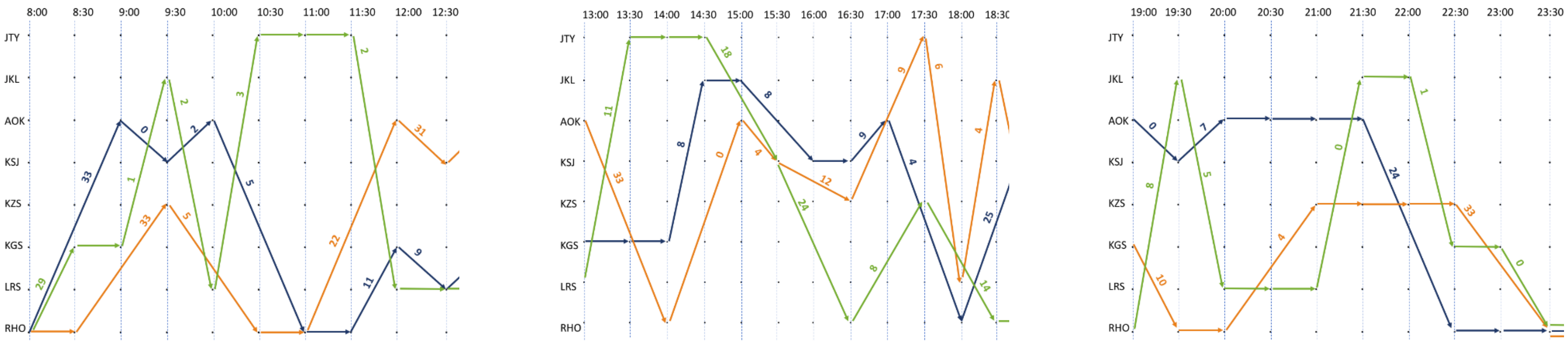

Figure 8: Representation of the flights in the Rhodes network.

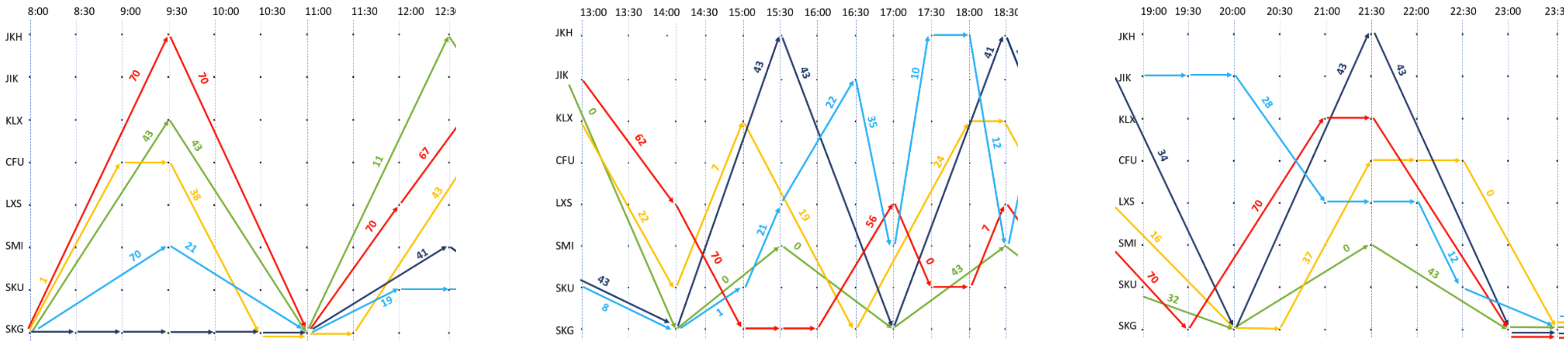

Figure 9: Representation of the flights in the Thessaloniki network.

6.2. Application to Thessaloniki Network

This second network is significantly larger than the first one. The optimized solution was found after 5 hours and 30 minutes of computation, with an optimality gap of 11.26%. The model was then left running for another 15 hours, without successfully finding any other feasible solution.

The costs associated with this solution and the comparison with the current network's costs are:

- **Flight operating costs**: a reduction of is achieved as 12.2% 117,978€ are required for a total of 54 flights compared to 134,424€ for the current network which requires 62 flights;
- **Aircraft ground costs**: 225€ compared with 0€ for the current network. This increase is considered negligible when compared to the other reductions obtained by the model, because as happened with the Rhodes network, this value is due to only one aircraft exceeding for 30 minutes the 2 hours on the ground, and this happened at Thessaloniki airport (considered the "hub");
- **Passenger time costs**: 21,900€ for the time passengers spent on board the aircraft, and 3,565€ for the time passengers spent waiting on the ground for a connecting flight, in a total of 25,465€ resulting in an average travel time of 1 hour and 52 minutes per passenger, compared with 27,637€ for the current network and an average travel time of 2 hours and 02 minutes per passenger. This means a decrease of 7.86% in cost;
- **Total cost of the network**: 143,668€ compared with 162,061€ for the current network. This means a reduction of 11.3% in the total cost of the network, having reduced once again both the direct financial costs to the airlines, as well as the time costs for the passengers. The explanation for the smaller improvements in this network's optimization, when compared to those obtained in Rhodes network's is thought to be related to the fact that, being a network with larger geographical distances and restrictions, there is a smaller margin for improvement. Moreover, the network's characteristics have a greater similarity to those of a normal (non-subsidized) network, when compared with Rhodes network's characteristics.

The results are plotted in a graph demonstrating the flights in the network and is presented in Figure 9. The flights of this network and the airports are represented by their IATA codes. This network is more complex than the previous one. There is a fleet of 5 aircrafts in operation, comprised of 2 Dash 8 Q100 (37 seats), 2 Dash 8 Q400 (78 seats) and 1 ATR 42 (48 seats), based on actual information collected from the fleet operating these routes.

6.3. Scenario analysis

In order to address variations in the results of the optimization model according to variations of the inputs, various scenarios were assumed to count for changes in the demand levels among the O/D pairs, the employed demand prediction model, the passenger value of time, the imposed frequencies, the seat and flight impositions. As discussed in section 5, two demand models (M2 and M5) are considered statistically viable to estimate passenger demand. The moderate model M2 was considered as suitable for this case compared to the optimistic model M5 that was overestimating demand in some cases. However, in order to count for the impact of the demand model on the optimization results, the demand values were now estimated by the optimistic model M5, as well in the sensitivity analysis to verify whether the optimization results would change significantly, if model M5 was used. Hence, the set of demand scenarios comprises of scenarios that employ different prediction models (M2 and M5) and changes in the demand levels (-40%, -30%, -20%, -10, +10%, +20%, +30%, +40%). Given that (a) the imposed frequencies is a parameter decided by the regulating authorities and may vary every time the PSO requirements are announced and that (b) the current pandemic has caused tremendous losses in airlines and airports posing at risk the connectivity of many regions through economically viable routes, it was decided to assess the operation of the network after considering changes in the imposed frequencies. Finally, the passenger perspective on the value of time was addressed through the exploration of the influence of variations of this parameter and its impact on the optimization results. The optimization model was run for the Rhodes airport and the sensitivity analysis results are presented in Table 13.

6.3.1 Impact of variations in the demand levels when employing the moderate demand prediction model (M2) on the optimized Rhodes PSO network

As presented in Table 13, cost reductions remain in all the sensitivity scenarios that consider demand variations either increasing positive or decreasing. The results in flights costs are more sensitive to small demand changes mainly due to the smaller number of flights that are required to satisfy the demand (44 - 47 flights) compared to current state (50 flights). Passenger time costs face a considerable reduction as demand increases or decreases significantly and the respective number of required flights increases. The combination of the variations in aircraft and passenger costs lead to a tendency of lower cost reductions as demand increases in the network.

6.3.2 Impact of variations in the value of time on the optimized Rhodes PSO network

Maintaining the use of the moderate demand prediction model (M2), more scenarios were also created to capture the impact of variations in the passengers´ value of time. This was considered an important aspect of the model, since it is susceptive to passenger perceptions that are poorly studied in the literature. In this case, a minimum of 2.5€/h and a maximum value of 20€/h were considered. The optimization results indicate that total costs can be reduced by a maximum 20.5% under the assumption of significantly low value attributed to the required time (2.5€/h); while under a possible increase by 100% (20€/h), the total costs would remain at the same level as in the current state. Trade-offs among the passenger and airline-related costs may be seen when an increase in the value of time is considered, while possible reductions in the perceived value of time result into reductions of all cost categories. When considering the extreme case of doubling the value of time (20€/h), a significant decrease in the travel time was also seen (-37%), while in the other scenarios a minimum 25% reduction is seen. A decrease in this variable can result into lower requirements in the total number of flights (-12%), in contrast to possible increases that would not have a considerable impact on the flights´ number (-6%).

6.3.3 Impact of variations in policy implications on the optimized Rhodes PSO network

Finally, a set of scenarios related to imposed policies were created to analyze the dependency of the optimization results to the requirements of regulating and policy agents. Hence, the sensitivity of the network design costs, travel time and flights were assessed towards changes in the number of imposed frequencies, minimum seat and flight constraints. The changes in the imposed frequencies are followed by the respective adjustments in the available seats and always respect the minimum of one frequency in each connecting pair. The relaxation of all those constraints resulted into the reduction of all types of costs in the operations while satisfying the demand in the network, highlighting that, as long as a weekly connection is ensured among the PSO O/D pairs, the airlines could have more flexibility in the definition of the operational requirements, so that they can operate closer to efficient margins. This could have implications in the formulation of the tenders for PSO operations.

Table 13. Results of sensitivity analysis

		Flight operating costs		Aircraft ground costs		Passenger time costs		Total network cost		# of flights		Average travel time	
		Total	**% change**	**Total**	**% change**	**Total**	**% change**	**Total**	**% change**	**Total**	**% change**	**Total**	**% change**
Current state		53,771 €		0		6,470 €		60,241 €		**50**		1h 44 min	
Optimized state under demand variations	-40%	48,815 €	-9.2%	375 €	400.0%	2,570 €	-60.3%	51,760 €	-14.1%	47	-6%	1h 09 min	-34%
	-30%	48,815 €	-9.2%	0 €	-100.0%	3,100 €	-52.1%	51,915 €	-13.8%	47	-6%	1h 12 min	-31%
	-20%	46,562 €	-13.4%	0 €	-100.0%	3,900 €	-39.7%	50,462 €	-16.2%	46	-8%	1h 14 min	-29%
	-10%	48,815 €	-9.2%	0 €	-100.0%	4,480 €	-30.8%	53,295 €	-11.5%	47	-6%	1h 18 min	-25%
	0%	48,815 €	-9.2%	75 €	-	4,855 €	-25.0%	53,745 €	-10.8%	47	-6%	1h 17 min	-26%
	10%	45,811 €	-14.8%	0 €	-100.0%	4,850 €	-25.0%	50,661 €	-15.9%	44	-12%	1h 12 min	-31%
	20%	45,060 €	-16.2%	150 €	100.0%	5,060 €	-21.8%	50,270 €	-16.6%	44	-12%	1h 10 min	-33%
	30%	48,815 €	-9.2%	150 €	100.0%	6,235 €	-3.6%	55,200 €	-8.4%	45	-10%	1h 16 min	-27%
	40%	48,815 €	-9.2%	0 €	-100.0%	6,355 €	-1.8%	55,170 €	-8.4%	47	-6%	1h 12 min	-31%
Optimized state under value of time variations (€/h)	20.0	51,068 €	-5.0%	300 €	300.0%	8,240 €	69.7%	59,608 €	-1.1%	47	-6%	1h 06 min	-37%
	15.0	48,064 €	-10.6%	75 €	0.0%	6,638 €	36.7%	54,777 €	-9.1%	47	-6%	1h 11 min	-32%
	10.0	48,815 €	-9.2%	75 €	-	4,855 €	-	53,745 €	-10.8%	47	-6%	1h 17 min	-26%
	7.5	45,811 €	-14.8%	0 €	-100.0%	3,289 €	-32.3%	49,100 €	-18.5%	45	-10%	1h 10 min	-33%
	5.0	46,562 €	-13.4%	0 €	-100.0%	2,388 €	-50.8%	48,950 €	-18.7%	46	-8%	1h 16 min	-27%
	2.5	43,558 €	-19.0%	0 €	-100.0%	1,213 €	-75.0%	44,771 €	-25.7%	44	-12%	1h 18 min	-25%
Optimized state under changes in the imposed frequencies	minus 1	43,558 €	-19.0%	0 €	0.0%	4,305 €	-11.3%	47,863 €	-20.5%	44	-12%	1h 18 min	-25%
	plus 1	48,815 €	-9.2%	150 €	0.0%	4,900 €	0.9%	53,865 €	-10.6%	47	-6%	1h 18 min	-25%
Optimized state under changes in model´s constraints	exclude (13)	43,558 €	-19.0%	75 €	-75%	4,520 €	-30.1%	48,153 €	-20.1%	44	-12%	1h 18 min	-25%
	exclude (12)	43,558 €	-19.0%	0 €	0%	4,305 €	-33.5%	47,863 €	-20.5%	44	-12%	1h 18 min	-25%
	exclude (12) and (13)	43,558 €	-19.0%	0 €	0%	4,305 €	-33.5%	47,863 €	-20.5%	44	-12%	1h 18 min	-25%

Current state of the PSO network M5		53,771 €		0 €		19,042 €		72,813 €		50		3h 30 min	
Optimized state under demand variations	-40%	43,558 €	-19.0%	375 €	375%	5,205 €	-72.7%	49,138 €	-32.5%	44	-12%	1h 35 min	-55%
	-30%	48,064 €	-10.6%	675 €	675%	5,915 €	-68.9%	54,654 €	-24.9%	44	-12%	1h 31 min	-57%
	-20%	48,815 €	-9.2%	150 €	150%	6,130 €	-67.8%	55,095 €	-24.3%	46	-8%	1h 24 min	-60%
	-10%	46,562 €	-13.4%	0 €	0%	7,330 €	-61.5%	53,892 €	-26.0%	44	-12%	1h 30 min	-57%
	0%	48,815 €	-9.2%	0 €	0%	9,285 €	-51.2%	58,100 €	-20.2%	47	-6%	1h 42 min	-51%
	10%	47,313 €	-12.0%	225 €	225%	9,385 €	-50.7%	56,923 €	-21.8%	44	-12%	1h 32 min	-56%
	20%	49,566 €	-7.8%	75 €	75%	9,520 €	-50.0%	59,161 €	-18.7%	46	-8%	1h 27 min	-59%
	30%	49,566 €	-7.8%	0 €	0%	10,535 €	-44.7%	60,101 €	-17.5%	46	-8%	1h 29 min	-58%
	40%	48,064 €	-10.6%	150 €	150%	11,610 €	-39.0%	59,824 €	-17.8%	44	-12%	1h 31 min	-57%

6.3.4 Impact of variations in the demand levels when employing the optimistic demand prediction model (M5) on the optimized Rhodes PSO network

These results show that by using model M5 as the predictive model to estimate passenger demand, the optimization model found significant improvements (20.2%) in the total cost of the network, reducing both the direct cost to the airlines and the indirect time costs for the passengers. For a total of 47 flights, the total **flight operating costs** are 48,815€, compared to 53,771€ for the current network, which requires 50 flights, and represents a reduction of 9.2% in cost. Interestingly, this is the same value of flight operating costs for the optimization that was performed with the previous demand model. It is believed that this is explained by the fact that since this network has such a low demand, and a comparatively high amount of imposed flights (by the PSO), the model does not need to exceed the imposed flights unless demand increases significantly. No **aircraft ground costs** are imposed in this scenario meaning that in this optimization, the model is able to avoid leaving an aircraft on the ground for more than 2 hours, compared to the previous calculation (with the main demand model), where the solution implied an aircraft staying for 2 hours and 30 minutes on the ground. The component of the passenger time costs increases in this case. The total p**assenger time costs** is 6,820€ for the time passengers spent on board the aircraft, and 2,465€ for the time passengers spent waiting on the ground for a connecting flight, in a total of 9,285€ resulting in an average travel time of 1 hour and 42 minutes per passenger, compared with 19,042€ for the current network and an average travel time of 3 hours and 30 minutes per passenger. These costs were calculated for the new values of demand, as a higher demand for passengers will imply higher overall social costs. This optimization obtained a reduction of 51.2% in cost. This value is obviously very significant, and the proposed explanation for such a high value is the demand model imposing a demand too high for the current network, which is not prepared for it, leading to long waiting times in routes that are being considered as having high demand. Overall, the **total cost of the network** amounts to 58,100€ compared to 72,813€ for the current network. This means a reduction of 20.2% in the total cost of the network, with reductions in all the parameters. This higher improvement of the optimized network when compared to the previous demand model, is obviously driven by the significant reduction of the passenger time costs, but validates the quality of the results obtained by the previous optimization, whose demand input is expected to be more exact.

Regarding the results obtained when demand variations are analyzed, they indicate the passenger time costs reduce significantly as demand increases resulting into significant variations in the total costs as well. The aircraft-related costs present a mixed variation with a maximum reduction (-20%) in the scenario of maximum demand drop (-40%) and further reductions ranging from 7.8% to 13.4% when demand varies from -30% to +40%. A similar pattern is observed for aircraft ground costs, while significant gains are observed by the use of the optimized network in the passenger waiting time which, however, are slightly affected by changes in the demand. In all the cases, a lower number of flights can satisfy demand compared to the actual scenario.

6.4. Alternative optimization scenarios

Different scenarios were also considered in an attempt to achieve better results on the network but they did not result into more efficient PSO networks. First, it was attempted to re-design the network, in terms of the impositions by the PSO. Hence, different configurations were attempted in the optimization model, in order to compare the obtained result with the best result already achieved for that particular network. To do this, by looking at the demand values obtained, and to the geographical position of the different islands, new possible configurations were tested, as well as one network where the PSO imposition was that every island had to have a direct flight to its network's hub. Unfortunately, none of these attempted networks resulted in a better overall cost, which led them to be discarded. Then, it was attempted to divide the optimization model into two different days. The first day, would have flights imposed for all of the routes which have a PSO in force, but would have less frequencies in the busier routes. The remaining flights would be fulfilled in the second day, which would only have these remaining frequencies imposed. The reasoning behind this attempt was to "relieve" the network from so many flights for certain routes, which are flown with no passengers assigned, in the result of the optimization. This attempt also resulted into a higher total cost and ended up being discarded as well.

In the difficult moments that airlines are facing nowadays with the unexpected advent of the coronavirus pandemic and the devastating impact on aviation, and especially on airlines, insights of proper flight frequencies can be beneficial for the recovery of the airline sector. Several airlines have announced operational reductions.

7. Conclusions and Future Research

The present work deals with the issue of PSO aviation network planning and management. Methodologically, it combines the development of demand predictive models and optimization models for flight scheduling and fleet planning in this context and contributes to previous research with the introduction of passenger connecting time minimization in a linear integer programming optimization model. To demonstrate the applicability of the suggested methodology, the geographical area of Greece and the operations of PSO routes are set as the scope of the analysis. Two Greek PSO networks based in Rhodes and Thessaloniki airports were analyzed to allow for a broader characterization of the Greek market. The two case studies represent, within the same country, networks with different characteristics, in terms of the number of passengers carried, the number of connecting flights and the covered geographical distances. Previously suggested optimization models on PSO networks (Pita et al., 2013; Pita et al., 2014) were adapted and applied to the two case studies. Five predictive models were developed and two of them were employed for the estimation of the demand of the routes under analysis. Both demand models were tested as demand inputs in the optimization models. Regardless of the employed demand prediction model, the application of the optimization model leads to reduced total network costs indicating the usefulness of this approach. The results demonstrated that the current network can be improved, not only from an airline point of view but also regarding the passenger experience. In terms of costs, the results showed significant improvements, in the order of 10% in both networks, while complying with all the constraints required. Considering the passenger connecting time, gains of 50% were estimated with the employment of the optimization model. To count for variations in the inputs of the optimization model, a sensitivity analysis was conducted and demonstrated gains in the total network cost in all cases.

Considering the impact of the current pandemic on aviation and airline operations, the need to consider more carefully for "deprived" routes entailing in PSO state arises prominently. The same need appears for the redesign of aviation networks since the recovery of air traffic is expected to be slow (IATA, 2020) and the reassessment of routes will be required within the next three years (Serrano and Kasda, 2020). At the same time, the number of airlines requesting state aid in Europe is increasing (Abate et al., 2020), leaving unanswered the question which of those will cease operations, which of those will survive, and if this happens what nodes will be part of their networks. In countries as Greece, with geomorphological peculiarities and a high number of islands, the risk of, previously, economically viable routes turning into unviable is high and so does the assurance or transport connectivity through non-subsidized services. Hence, the current work can serve, as well, as a support for the restructuring of aviation networks under both demand and supply uncertainties.

In a technologically, continuously, developing environment where new modes arise, the work presented in this paper can be employed lead to the development of competitive, viable and sustainable transport systems. The presented work allows the launching of PSO routes in groups which might be an attractive option for airlines. In addition, the synergies of air and sea connectivity with the rise of seaplanes can be further analyzed to design transport networks that will employ aircrafts and seaplanes to cover the demand needs in remote or low-demand regions, especially in the upcoming years when commercial routes are likely to decrease due to the impact of COVID-19 on tourism and international connectivity.

Further work can expand the presented research. Extending the analyzed dataset might provide better predictive models including variables related to tourism and the competition of the ferry boat service. Optimizing aviation networks that are very influenced by tourism is also a research opportunity. In fact, markets with such strong seasonality effects may require network designs and PSO requirements adapted to specific effects. Moreover, another research gap is to conduct similar research, but involving a larger network, testing if such formulation would find better feasible solutions (than the existing ones) in useful computational time. Finally, a more integrated formulation, which could include the effect of ticket pricing, flight frequency, and other network design characteristics on passenger demand, would provide more realistic models to support PSO network design.

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