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MODELING FRAMEWORK FOR CONNECTIVITY OPTIMIZATION OF AIRPORT OPERATION ENTERPRISES

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Abstract

Air connectivity plays a crucial role in enhancing economic growth by facilitating tourism and inward foreign direct investment and supporting trade in goods and services. Air connectivity improvement enhanced socio-economic benefits as air travel tend to be less expensive and more accessible – due to air transport liberalization, increase of low-cost carriers, and technological developments made air transport network more efficient. The aim of this paper is to improve connectivity between two hub airports, by developing a modeling framework for indicating the best scheduling times for aircraft arrivals and departures. The results would be essential for comparison to other similar cases.

Keywords: Airport management, Optimization, Multi-objective modeling, Airport enterprises

Introduction

During the last decades, among other variables employed to evaluate airport performance, connectivity is on top of the agenda. According to OECD/ITF 2018, the potential of air connectivity to deliver socio-economic benefits increases as air travel becomes less expensive and more accessible – due to air transport liberalization, increase of low-cost carriers, and technological developments that have improve network efficiency. Aviation stakeholders, airports and airlines managers, focus on air connectivity improvement to enhance optimum performance and efficiency. Governments and stakeholders focus on the effects of connectivity on the local and national economy, especially as regards the socioeconomic effects of connectivity (Dimitriou and Sartzetaki, 2018).

Air connectivity measures can inform decisions and policy making on performance of the aviation sector at a national, regional, and airport level. Stakeholders and governments should develop different approaches to measure air connectivity to allow for tracking air connectivity trends over time and help improve appraisal of any potential investments in air transport (OECD/ITF, 2018).

The contribution of tourism and air transport to regional development stimulate the research interest, providing evidence that the selection of the final tourist destination is related to air transport performance, transport infrastructures and supply chain management. For high demanded tourism destinations, the air transport and tourism business sectors are interlinked (Dimitriou et al, 2018).

Conventional wisdom of the paper is the development of a modeling framework highlight the optimum scheduling times for arrivals and departures at hub airports to enhance air transport demand and improve airport connectivity. The results would be useful for the planners and managers in air transport, promoting outputs to support decisions towards network efficiency, pricing policy and flight schedule optimization.

Air connectivity and tourism

Air connectivity is the essence of international mobility, the engine of the globalized world and the essential element of both national and regional accessibility and development. The different types of air connectivity indexes - direct, indirect and hub connectivity – are useful metrics for airports, as well as for policy makers that consider connectivity parameters and data for decision-making process. Connectivity data provides a measure that is related to its societal benefits – in economic terms. Indeed, a 10% increase in direct air connectivity generates a 0.5% additional increase in GDP per capita according to ACI, 2019. Therefore air connectivity is a fundamental factor economic and social development – highlighting that airports are vital infrastructure facilitating tourism, foreign direct investment and business development (ACI, 2019).

According to IATA (2016), air passenger demand worldwide experienced a 3.7% annual compound average growth rate over the last decade. The spectacular growth in the international air transport market and the development of new markets has greatly contributed to improved global connectivity. Air connectivity can drive county's economic growth, because it enables the country to attract business investment and human capital. Many authorities and professional bodies place on the top of their agenda the contribution of air connectivity to economic development and they promote that investment prioritization and feasibility in air transport industry should be based on evaluation of changes in connectivity and network capacity (ACI et al, 2017).

The direct connectivity is affecting the biggest markets: intra-Europe (+0.7%) and Europe-North America (-0.8%) based on ACI, 2019. Direct connectivity from Europe to the rest of the World keeps is increasing with Europe-Africa (+11.1%) leading, followed by Europe-Middle East (+9.9%), Europe-Asia Pacific (+6.9%) and Europe-Latin America (+4.5%) (ACI, 2019).

The linkage between transport and tourism sectors is widely recognized. Tourism plays an important role in the regional economic development, and in some cases, it significantly contributes to regional economic development, representing the main source of income. Despite the high competition in aviation industry, the volatility and cyclicality in economic environment and the not very fast innovation improvement in aviation sustainable development, air transport achieve the highest shares of market in tourism demand (Dimitriou, 2016). Mediterranean tourism activities in MENA have undergone enormous growth during the last decade, which in turn has significantly increased the demand for air travel and placed under discussion the adequacy of the available infrastructures (Dimitriou, 2018).

Moreover, international tourist arrivals (overnight visitors) worldwide increased 6% in 2018 to 1.4 billion according to UNWTO, 2019. Given the remarkable growth of international arrivals in recent years, 1.4 billion targets has been reached two years ahead of UNWTO's long-term forecast issued in 2010. In 2017, consolidated a growth of +7%, the second higher growth since 2010. Middle East (+10%) and Africa (+7%) led growth, while arrivals to Asia and the Pacific and Europe (both +6%) increased in line with the world average. Overall results were driven by a favorable economic environment and strong outbound demand from major source markets (UNWTO, 2019).

Optimization Modelling Methodology

Resources optimization framework have been applied to different fields such as transportation systems resource constrained projects and sensor networks. Such problems are appraised by one or more objective maximizing or minimizing functions and various restrictions that must be met for a valid solution (Zheng X.L et al, 2015). The formulation of an optimization framework taking into consideration each connection as a key objective of the modelling formulation presented in this paper. The benefits of this approach are to provide essential results to planners, managers and decision makers about important changes to flight schedule between two airports that improve the connectivity of a destination. The aim of this research is the construction of a modeling framework to highlight the best scheduling times for aircraft arrivals and departures at two hub airports A and B to attract more passenger and to select the air carrier over their competitors, with an appropriate pricing policy tailored to both market conditions and the strategic positioning of the airline enterprise.

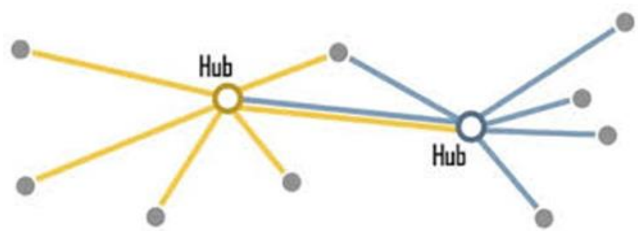

Figure 1. Depiction of network between two hub airports A and B.
Where: d_A = *Departures from hub airport A;*
a_A = *Arrivals at hub airport A;*
d_B = *Departures from hub airport B;*
d_{A-B} = *Departure from hub airport A to hub airport B;*

In the modeling framework, the time of arrivals and departures to and from a hub airport address the question of optimization, by applying the appropriate criteria.

In this way, passengers give a different level of "importance" depending on each city of origin/destination. Equation 1 calculates the level of importance of each flight for both arrivals and departures in Airport A, excluding flights between Airport A and Airport B:

$$FIF^{A}_{a|d} = \sum_{t}^{t+1} \quad (k * c)_{a|d} \qquad (1)$$

where:

FIF = sum of the Factors of Importance for the Flights over time interval;

a = index which refers to each arrival flight to airport A;

d = index which refers to each departure flight to airport A;

c = available seats for of each type of aircraft serving a direct arrival\departure flight;

k = adjusted variable representing the significance for each flight

Subject to:

$$FIF_{a|d} \geq 0 \text{ and}$$

$$0 \leq t \leq 23$$

The adjusted variable k is calculated based on the following equation:

$$k = \frac{p*h*g}{3} \qquad (2)$$

where:

p, h, g = adjusted multipliers calculated using the equation (3) and

p = population of the city of origin / destination;

h = mileage replacement based on the distance, assuming that more passengers are likely to come from a larger, more populous city than a smaller one.

g = the country's weighted GDP relative to Europe's total GDP;

In some cities, there is already a direct link to major hub airports, and this is a complete substitution. Therefore, these cities demonstrated zero coefficients in this criterion. Fully substituted cities demonstrated zero values and maximum multipliers responded to cities with the greatest mileage from the nearest airport arriving by direct flight from Airport A.

The multipliers calculated based on max/ min framework as follows and are adjusted in a scale from 0.1 to 1:

$$\frac{V - V_{min}}{V_{max} - V_{min}} * (f - j) + j \qquad (3)$$

where:

f = the maximum value of the scale and a = 1;

j = the minimum value of the scale and b = 0.1;

V = actual value of each variable for which the multiplier will be calculated;

V_{min} = The lowest value of the variable V for the chosen sample and

V_{max} = The highest value of the variable V for the chosen sample

The purpose of the model is to maximize the sum of variable FIF_a of the arrivals and variable FIF_d of the departures in Airport A, based on the above restrictions. Then, the objective function of optimization is defined as:

$$\max \sum \quad (FIF_a + FIF_d) \quad (4)$$

Hypothesis and assumptions

In this research, 85 destinations/cities with direct European and domestic flights to/from Athens International airport are taken into consideration. The assumptions considered are:

- Minimum connection time is defined as the half hour. Calculating the time of landing, luggage waiting, check-in and boarding, as well as any possible delay, the above assumption specifies that the arrival of the aircraft to Airport A at a time t cause departures from this airport to take place after t + 1.5 hours.
- At the same time, for departure time from Airport A to Airport B, a minimum of 1.5 hours is the reverse, as departing the aircraft at time t will cause arrivals at Airport A up to t-1.5 hours at the latest so that passengers arriving from other cities have enough time for boarding.
- Maximum connection time is 5 hours. There is a maximum amount of time between connections as: when arriving at Airport A at time t, passengers whose flights depart at time t + 5 at the latest, unless a wait of more than 5 hours is preferred at airport area.
- The waiting time of the aircraft and crew is 3 hours.
- The calculations of equation 1 are made for flights over one-hour period.

Case study

Network features

In order to apply the modeling framework, the numerical application is the optimization of the connection of Dubai International Airport with Athens International Airport, as, on one hand, Athens International Airport, is a hub in a significant geographical location, connecting Western Europe and the Middle East. On the other hand, Emirates is the only company that offers a direct connection on the route Dubai-Athens and Athens-Dubai, being in monopoly conditions.

Dubai International Airport (DXD) is the primary international airport serving Dubai, United Arab Emirates and is the world's busiest airport in terms of international passenger traffic. It is also the third-busiest airport in the world in terms of passenger traffic, the sixth busiest in terms of cargo traffic airport in world, the busiest airport for Airbus A380 and Boeing 777 movements, and the airport with the highest average number of passengers per flight. In 2017, DXB handled 88 million passengers, 2.65 million tons of cargo and 409,493 aircraft movements. In July 2019, Dubai International airport installed the largest solar energy system in the region's airports as part of Dubai's goal to reduce 30 percent of the city energy consumption by 2030 (Dubai Airports, 2019).

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Athens International Airport (ATH) in 2018 recorded an all-time high performance, with 24.14 million passengers, surpassing previous year traffic by 2.4 million (+11%). This outcome was driven by the strong growth of the international market (+2 million or +13.8%), combined with the healthy increase of the domestic market (+400 thousands or +5.6%). The following pictures show European and domestic destinations that Athens International Airport is directly connected (Athens International Airport, 2019).

According to ACI Connectivity Report 2019, Dubai International Airport is in 11th place in the ranking of top 20 airports worldwide and emerging hubs, with 250,8% growth in hub connectivity in 2019 compared to 2009. Also, according to the same source, Athens International Airport has increased its hub connectivity by 88, 3% over the same period (ACI, 2019).

Figure 2. Map of direct European flights to / from AIA (www.aia.gr)

Figure 3. Map of direct domestic flights to / from AIA (www.aia.gr)

Traffic features

As shown in following figures, both airports, show their highest passenger traffic during summer months. However, in contrast to Athens International Airport, Dubai International Airport demonstrates smaller changes in the traffic in terms of passengers throughout the year. In addition, both airports demonstrated a significant increase in passenger traffic over lase year.

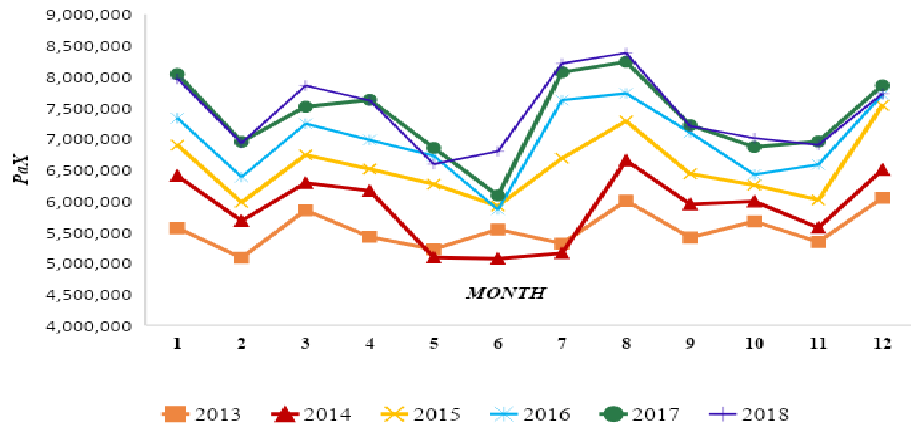

Figure 4. Passenger traffic per month at Dubai International Airport, (2012-2018)

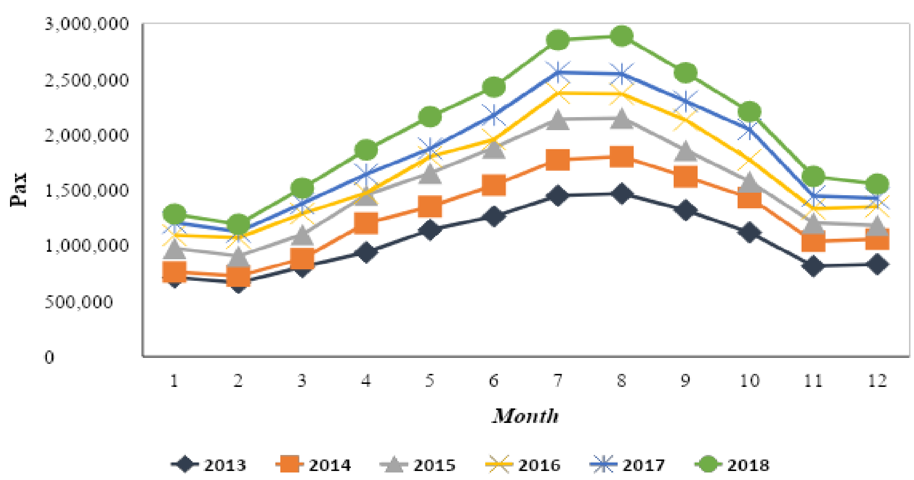

Figure 5. Passenger traffic per month at Athens International Airport, (2013-2018)

In order to apply the modeling framework, a typical daily day of May (Thursday 9th May 2019) and a weekend day (Saturday 11th May 2019) were selected. For the purpose of this research, a typical aircraft type (A320) with 200 available seats for European flights and 150 available seats for domestic flights to/from Athens International Airport is considered.

Case study results

According to equation (2), as depicted in figure 6 the cities with the highest values of the variable k, thus the highest level of importance in the sample, are Berlin and then Palermo.

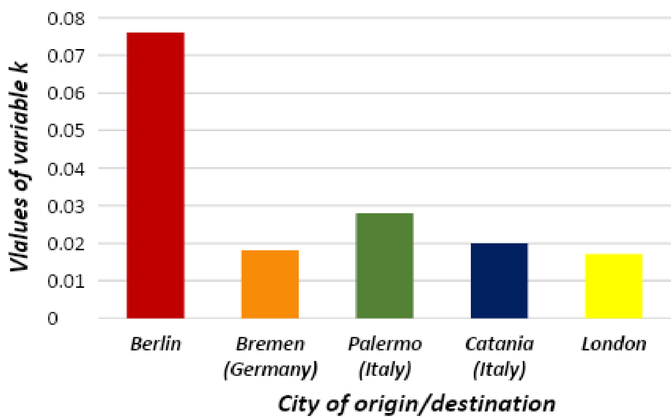

Figure 6. Cities with higher values of variable k

Applying the modeling framework to a typical day (Thursday 9th May) and a weekend day (Saturday 11th May), Table 1 below depicts the results based on equation (1) for the values of the variable INF for both arrivals (FIF_a) and departures (FIF_d) in Athens International Airport. Each variable FIF value corresponds to the sum of the individual values of the variable over one hour period. The zero values in the table indicate that there was no connection between Athens Airport and the cities of the sample over those hours.

Table 1. Values of variables FIF_a and FIF_d for both Thursday 9th May and Saturday 11th May typical days

	Thursday 9th May		**Saturday 11th May**	
Time	FIF_a	FIF_d	FIF_a	FIF_d
0:00				
1:00	1,196		1,196	
5:00		0,636	1,98	0,924
6:00		9,976		10,31
7:00	3,228	2,332	7,434	2,032
8:00	3,212	17,961	1,662	20,7
9:00	5,308	10,978	3,966	10,07
10:00	1,89	1,365	4,966	2,16
11:00	8,764	1,803	7,5	6,721
12:00	10,183	9,849	17,458	6,695
13:00	10,469	25,941	13,097	31,61

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14:00	13	14,716	10,179	12,53
15:00	7,568	14,45	8,533	11,37
16:00	18,616	5,363	9,699	8,255
17:00	12,819	21,077	6,804	8,87
18:00	14,018	10,528	12,821	4,623
19:00	4,52	12,334	6,309	18,23
20:00	33,95	5,666	49,203	16,38
21:00	13,9	19,504	7,335	19,46
22:00	8,839	2,262	7,356	2,358
23:00	6,164	5,304	5,108	1,65
24:00:00	5,479		5,157	

Analyzing the empirical findings, it is concluded that there are indeed differences, indicating that changes in flight planning may affect optimization. The values that are pointed with the green arrow (higher values of bothFIF_a and FIF_d) are comparatively more important than the others, highlighting that optimum planning would be better to move closer to these hours.

Specifically, as shown in following figures, Athens airport scheduled arrival on Dubai-Athens route on May 9th was at 15:00 (green arrow), according to assumptions, and departures between 16:30 and 20:00 (FIF_d = 45.475), while the scheduled departure was at 18:00 (blue arrow) serving arrivals from 13:00 to 16:30 (FIF_a= 33.939). In total, the sum stands at 79.414, and the analysis indicates the programming planning optimization to maximize this sum.

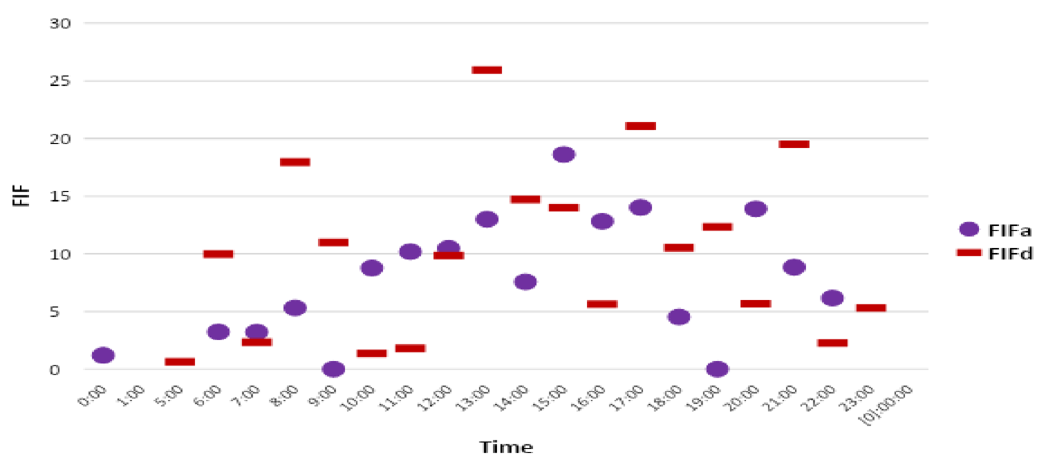

Figure 7. Variance of FIF for the case study (typical day: Thursday 9th May 2019)

According to the figure below, one suggestion is to schedule arrival at 17:30 and departure at 20:30 (purple arrows), and serve FIF_a = 38,635 (arrival) and FIF_d = 50.172 (departure) with the overall result: 88.807 increasing by 11.83% in the total sum compared to the scheduled flights (green and blue arrows) of the company.

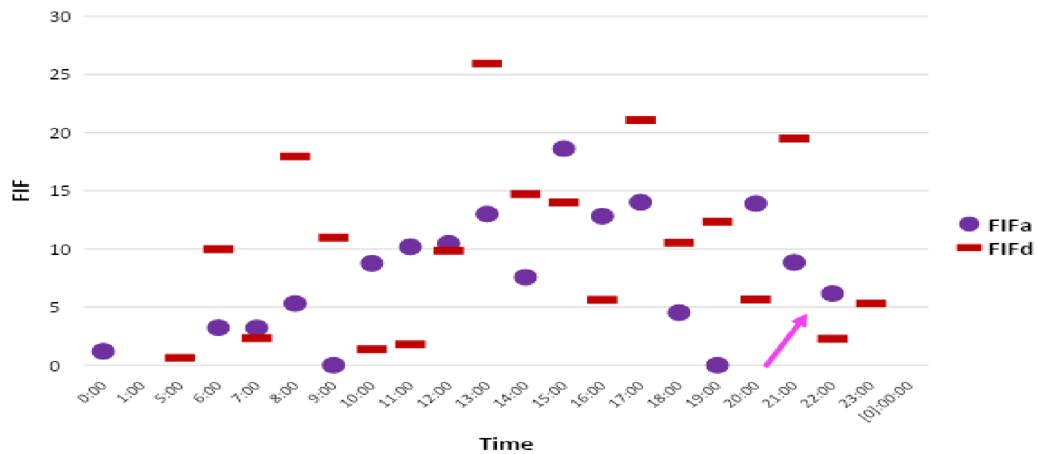

Figure 8. Variance of FIF for the proposed suggestions of scheduling (scenario 1) for the case study (typical day: Thursday 9th May 2019)

In addition to suggestion to increase the sum, various combinations such as the one mentioned above can produce results that can be used in a variety of ways. In the case shown below (blue arrows), an arrival at 11:30 (FIF_a = 20.837) and a departure at 14:30 (FIF_d =58.934) suggests a result almost equivalent to that of scheduled flights, giving the company an alternative to rescheduling flights without.

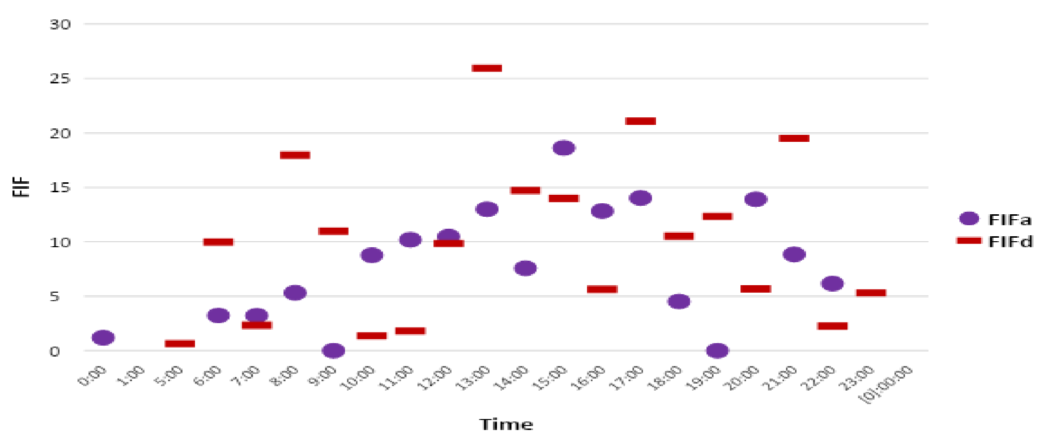

Figure 9. Variance of FIF for the proposed suggestions of scheduling (scenario 2) for the case study (Typical day: Thursday 9th May 2019)

In addition, if the constraint imposed on the construction of the model, that aircraft's strict three-hour waiting time at Athens airport results in a significant increase. Specifically, with the arrival time constant at 11:30 (FIF_a = 58.934) but the departure time at 15:30 (FIF_d = 30.361) the overall result increases by 12.44%. Finally, there is significant improvement with arrivals at 18:30 (FIF_a =31.866) and departure at 22:30 (FIF_d =62.099) for the 18.32% of scheduled flights.

The methodology framework was also applied for the typical day Saturday 11th May, with a total score of 72.51, as shown in following figure.

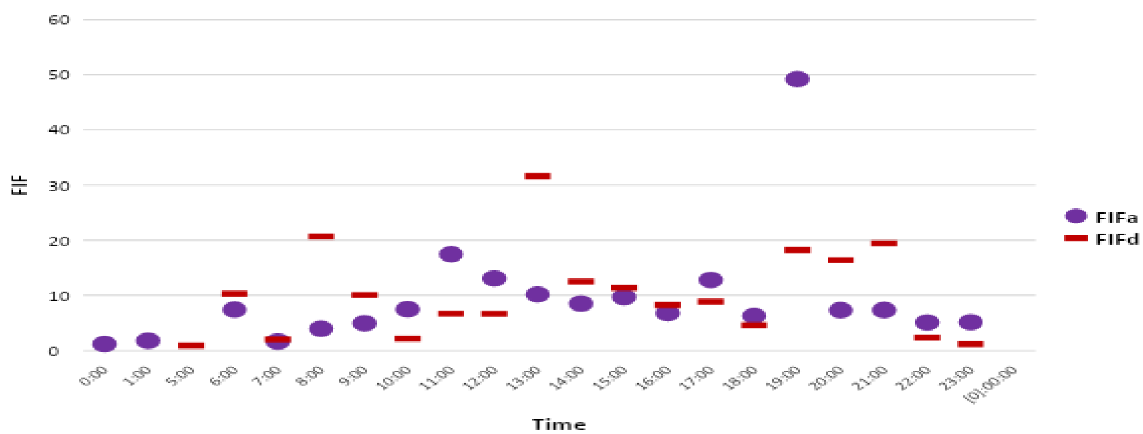

Figure 10. Variance of FIF for the proposed suggestions of scheduling (scenarios 1 and 2) for the case study (Typical day: Saturday 11th May 2019)

An indicative suggestion is for the arrival at 19:30 ($FIF_a = 23.468$) and departure at 22:30 ($FIF_d = 71.735$) –purple arrows- increasing the sum to 95.203, an increase of 31.30%. In case of reconsidering the 3-hour restriction, with arrival time 11:30 ($FIF_a = 59.638$) and departure time 15:30 ($FIF_d = 40.538$) - blue arrows- the sum is raised to 100.176 increasing by 38.15%.

Concluding Remarks

In conclusion, the empirical findings of the modeling framework highlight that in two typical days, based on framework's criteria and assumptions, the Athens airport air connectivity can be improved, as well as of the company's (Emirates Airlines) scheduled flight operational efficiency. It is proposed that the air carrier should consider the option of staying an additional 1-hour at Athens International Airport on days and hours that are considered quite efficient.

The model developed in this research presents a methodology that highlights the value of optimum programming, in order to improve the connectivity between two hub airports, improving air carrier's operational efficiency and airports performance optimization. Therefore, it could be an essential tool for the management of airports and airlines, as well as for planners, analysts and researchers.

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