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Air traffic assignment based on daily population mobility to reduce aircraft noise effects and fuel consumption

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Abstract

The paper first investigates the influence of daily mobility of population on evaluation of aircraft noise effects. Then, a new air traffic assignment model that considers this activity is proposed. The main objective is to reduce the number of people affected by noise via lowering as much as possible the noise exposure level L_{den} of individuals or groups of people who commute to the same locations during the day. It is hereby intended to reduce the noise impact upon individuals rather than to reduce the impact in particular– typically densely populated – areas. However, sending aircraft farther away from populated regions to reduce noise impact may increase fuel burn, thus affecting airline costs and sustainability. Therefore, a multi-objective optimization approach is utilized to obtain reasonable solutions that comply with overall air transport sustainability. The method aims at generating a set of solutions that provide proper balance between noise annoyance and fuel consumption. The reliability and applicability of the proposed method are validated through a real case study at Belgrade airport in Serbia. The investigation shows that there is a difference between the number of people annoyed (NPA) evaluated based on the census data and the NPA evaluated based on the mobility data. In addition, these numbers differ significantly across residential locations. The optimal results show that the proposed model can offer a considerable reduction in the

NPA, and in some cases, it can gain up to 77%, while maintaining the same level of fuel consumption compared with the reference case.

Keywords: Air traffic noise; airport noise; aircraft noise; noise annoyance; fuel consumption; multi-objective optimization.

1. Introduction

Proper allocation of aircraft to departure and arrival routes may play an important role in reducing aircraft noise effects on communities located near airports, and this issue has attracted considerable attention of researchers and authorities over the years. Although this topic has been well studied, research is often conducted based on census data, and hence it is assumed that people remain at the same location throughout the day. In reality, however, people spend substantial portion of the day at school, work or other places outside their homes. Consequently, analyses of daily population mobility have been considered in many transportation studies (Hatzopoulou and Miller, 2010; Jiang et al., 2017; Kaddoura et al., 2016; Novák and Sýkora, 2007) as an important factor for a more precise estimation of noise effects. Nevertheless, there is a lack of this kind of research for air traffic assignment problems. This paper, therefore, first investigates the influence of population's daily mobility upon evaluation of aircraft noise effects. Then, a new air traffic assignment model that takes daily movement of population into account is proposed. In the proposed model, the main objective is to minimize the number of people affected by aircraft noise while maintaining fuel consumption as low as possible. In order to achieve this purpose, a multi-objective optimization approach is utilized herein. The method aims at producing a set of solutions that are able to deliver a proper balance between conflicting objectives, i.e., noise annoyance and fuel consumption. An extensive review of the literature that served as the background and that motivated the authors to conduct this research is presented below.

Over the years, significant efforts have been devoted to relieving the noise impact as well as to reducing fuel consumption and pollutant emissions. At the European level, a legislative framework has been introduced, namely the Environmental Noise Directive 2002/49/EC (END) (EC, 2002) for the assessment and management of environmental noise. The Directive regulated the obligation to develop strategic noise maps and noise action plans with the aim of avoiding, preventing and reducing the harmful effects of noise on public health, and these have been successfully implemented at many airports (Glekas et al., 2016; Vogiatzis, 2014, 2012). After more than 15 years of enforcement, both the implementation review and the evaluation of END have been done twice so far, addressing questions related to effectiveness, efficiency, coherence, relevance and EU added value (European Commission, 2016). In addition, common noise assessment methods (CNOSSOS-EU) for the determination of the noise indicators L_{den} and L_{night} have been adopted by the EC through the revision of Annex II of the END in 2015 (Coelho et al., 2011; Kephalopoulos et al., 2014; Vogiatzis and Remy, 2014). CNOSSOS-EU has been developed to improve the consistency and the comparability of noise assessment results across the EU member states, providing a harmonized framework for assessment of each noise source covered by END. Upon the release of the Directive, numerous initiatives to reduce fuel consumption and emissions have been launched in recent years, as well. The examples include the Atlantic Interoperability Initiative to Reduce Emissions (AIRE)[1], Asia and South Pacific Initiative to Reduce Emissions (ASPIRE)[2], ACI Airport Carbon Accreditation[3], and the European Advanced Biofuels Flightpath[4].

In addition to the above initiatives that require enormous budgets and focus more on strategical levels, at a practical level it has been observed that the variation of aircraft/airport operational procedures is one of the feasible options that could bring short-term

[1] https://ec.europa.eu/transport/modes/air/environment/aire_en (assessed 9 September 2018)
[2] https://aviationbenefits.org/case-studies/aspire/ (assessed 9 September 2018)
[3] https://www.airportcarbonaccreditation.org/ (assessed 9 September 2018)
[4] https://www.biofuelsflightpath.eu/about (assessed 9 September 2018)

improvements and could be less costly (Marais et al., 2013). From this perspective, literature shows that research efforts in designing optimal departure and arrival routes with less noise and fuel burn have been well studied over the past decades, and various strategies have been proposed (Prats et al., 2011; Visser, 2005; Visser and Wijnen, 2001). Recently, with the utilization of multi-objective optimization techniques, research has also demonstrated that the obtained optimal routes are beneficial not only from the noise perspective, but also in terms of fuel burn (Ho-Huu et al., 2017; Vinh Ho-Huu et al., 2018; Torres et al., 2011; Zhang et al., 2018). In addition to efforts invested to improve environmentally friendly departure and arrival routes, optimal distribution of aircraft and operational procedures to specific routes could also contribute significantly to environmental impact decrease (Frair, 1984; Heblij et al., 2007; Kuiper et al., 2013; Netjasov, 2008; Nibourg et al., 2012; Zachary et al., 2011, 2010).

In order to assess the impact of flight operations on communities located near airports, it is critical to include distribution data of populations in the vicinity of airports, as done in a number of previous studies. However, census data takes into account only the homes of people, whereas, in reality, people spend substantial portions of the day at work, school, university or other places away from their residential locations. Consequently, the population may experience noise exposures which are very different from the ones predicted when using only the census data. One of the first studies that has called attention to the drawback of relying on census data was carried out by Ott (1982). In this study, the author shows that employees and students usually spend a long time away from their residential locations, and this leads to a different overall impact of, in this case, air pollutants. The same observation is also recognized in a recent study by Kaddoura et al. (2017). In this work, the authors suggest that the evaluation of population's exposure to road traffic noise should take spatial and temporal variations in the population into account, because the use of static data would lead to an overassessment.

One of the first air traffic assignment studies that takes daily mobility of population into account was done by Ganić et al. (2018). In this study, however, the evaluation of noise effects is based only on the change of population at several locations through three different periods of day, and is hence treated as three separate optimization problems. Furthermore, the model of air traffic assignment developed in Ganić et al. (2018) has some limitations, as well. The problem was formulated as a binary nonlinear optimization problem, in which, for each operation, every feasible assignment of routes was considered a decision variable. Therefore, the size of the problem is rather large and hence it is difficult to solve the problem when the number of aircraft operations increases. In addition, only the noise objective is considered, while fuel consumption and local air quality are not considered, and these may very well be adversely affected.

Motivated by the above limitations, the authors of this paper considered the information on daily mobility of population in the air traffic assignment model. To evaluate whether the inclusion of mobility data is necessary or not, the influence of census and mobility data on evaluation of noise effects is investigated first. Then, a new air traffic assignment model that is capable of taking daily mobility of population into account is developed. In order to reduce the number of people affected by aircraft noise, the noise exposure level L_{den} is calculated for each individual or group of people who commute to the same locations during an entire day from 00:00 to 24:00 hours. Afterwards, a noise annoyance criterion recommended by EEA (2010) is employed to obtain the number of people annoyed. Furthermore, to acquire optimal solutions which are able to balance between noise impact and fuel consumption effectively, a bi-objective optimization problem is formulated. In addition, since the considered problem is an integer nonlinear multi-objective optimization problem, it is rather difficult to solve it by nonlinear optimization programming models as applied in Ganić et al. (2018). To allow the problem to be solved with a multi-objective evolutionary algorithm, a new problem formulation is proposed. In the proposed formulation, each operation is considered a decision variable, and its feasible assignments of routes, after taking into account wind conditions, runway configurations and separation minima, are considered its search space. With the application of this formulation, the size of the problem reduces significantly, and hence the problem can be solved effectively by employing an evolutionary algorithm. The proposed approach is then applied to a real case study at Belgrade airport in Serbia.

The structure of the paper is as follows. In Section 2, first the problem definition is presented, and then the mathematical formulation and data preparation are described in detail. Section 3 provides a brief description of the optimization method, namely the non-dominated sorting genetic algorithm (NSGA-II) which is applied to solve the formulated problem. The Belgrade airport case study is presented in Section 4. The results and discussion are presented in Section 5. Finally, some conclusions, remarks and ideas for future work are presented in Section 6.

2. Problem definition

This section presents the model of the air traffic assignment problem in detail. The main idea of the formulated problem is to assign aircraft to suitable routes with the aim of minimizing noise impact on communities close to the airport and fuel consumption. First, the mathematical form is presented. Then, the preparation of the input data is described.

2.1. Mathematical formulation

The mathematical model of the optimization problem is formed based on several assumptions which are explained in detail in subsection 2.2. The model is described through three components: notations, decision variables, and objective functions, as follows.

Notations:

O is the set of aircraft movements departing from and arriving at an airport during a considered day;

S_i is the set of feasible routes to which aircraft movement i can be assigned, and which takes into account runway configuration, wind conditions and separation minima, $i \in O$;

L is the number of considered locations;

J is the set of individual persons or groups of people commuting to the same location during an entire day (from 00:00 to 24:00 hour);

T is the number of time periods;

SEL_{itl} is the sound exposure noise level (SEL) generated by the movement i at the time t and the location l, $i \in O$, $t \in T$, $l \in L$;

p_j is the number of people in the group of people j who commute to the same location at the same time during the day, $j \in J$;

Decision variables:

x_i is an integer design variable of route assignment of the movement i, which is selected from the set of feasible operational options S_i ($x_i \in S_i$). It should be noted that the noise level SEL at all locations in L and the fuel consumption for an entire flight are predefined for each option within S_i.

x is the vector of the design variable x_i, containing the optimal assignments of all movements to routes.

Objective functions:

With the aim of finding optimal solutions that are capable of balancing effectively between the number of people affected by aircraft noise and fuel consumption, an optimization problem with two objectives is considered. The first one is the total number of people annoyed (hereinafter referred to as NPA), which is defined as follows:

$$NPA(\mathbf{x}) = \sum_{j \in J} \%PA_j \cdot p_j \tag{1}$$

where $\%PA_j$ is the percentage of the group of people j who are annoyed due to being exposed to a certain level of aircraft noise. According to EEA (2010), it is based on the L_{den} cumulative noise metric, and estimated as follows:

$$\%PA_j = 8.588 \times 10^{-6} (L_{\text{den}_j} - 37)^3 + 1.777 \times 10^{-2} (L_{\text{den}_j} - 37)^2 + 1.221\ (L_{\text{den}_j} - 37) \tag{2}$$

where $L_{\text{den}\,j}$ is the day-evening-night noise level to which the group of people j is exposed during the day, and it is determined as follows:

$$L_{\text{den}_j} = 10 \log_{10} \left(\frac{1}{T_d} \left(\sum_{i \in O} \sum_{t \in T} 10^{\frac{SEL_{itl} + w_{\text{den}}}{10}} \right) \right), \forall j \tag{3}$$

where $w_{\text{den}} = \{0, 5, 10\}$ is the weighting factor to account for day, evening and night time operations, and it is defined based on the time at which the movement i takes place. T_d is the considered time period of an entire day in seconds (T_d = 24×3600 seconds). It should be noted that, for further analyses in the later sections, the number of people who are highly annoyed (hereinafter referred to as NPHA) is used as well. This criterion is also developed by EEA (2010) and defined as follows:

$$NPHA(\mathbf{x}) = \sum_{j \in J} \%PHA_j \cdot p_j \tag{4}$$

where $\%PHA_j$ is the percentage of the group of people j who are highly annoyed due to their exposure to a certain level of aircraft noise, and it is calculated by

$$\%PHA_j = 9.199 \times 10^{-5} (L_{\text{den}_j} - 42)^3 + 3.932 \times 10^{-2} (L_{\text{den}_j} - 42)^2 + 0.2939\ (L_{\text{den}_j} - 42) \tag{5}$$

The second objective is the total fuel burn. The EMEP/EEA air pollutant emission inventory guidebook – 2016 (Part B: sectoral guidance chapters, 1.A.3.a Aviation 2016) (Winther et al., 2017) is used to calculate the fuel consumption for each operation. Particularly, the LTO and Master Emission calculators in Annex 5 of this document, which use the data from the ICAO Aircraft Engine Emissions Databank (ICAO, 2017), are applied. These calculations have been done in the previous study (Ganić et al., 2018), and they are again to be used in this research. Then, the fuel objective is defined as follows:

$$T_{fuel}(\mathbf{x}) = \sum_{i \in O} fuel(x_i) \tag{6}$$

where $fuel(x_i)$ is the fuel consumption for the movement i.

2.2. Data requirements

As described in the notations, the model needs the following input data:

- air traffic data,
- departure and arrival routes for each runway with a predefined set of feasible routes,
- population locations,
- noise data for each location caused by all aircraft operating on all feasible routes,
- fuel consumption of all aircraft operating on all feasible routes,
- population data,
- daily mobility patterns.

The air traffic data includes information about origin and destination, aircraft type, actual take-off time, arrival time, and runway in use. This information can be obtained from Air Traffic Control. Real radar data can be used to represent departure and arrival routes, or the routes can be obtained from Aeronautical Information Publication (AIP). In this research radar data were used. Runway configuration, wind condition forecasts from METAR reports and separation minimum are taken into account to determine the set of feasible routes for each aircraft operation.

The noise levels caused by each aircraft movement on all feasible routes need to be determined a priori and stored in a database. The locations at which the noise is determined coincide with the census data and the data on population's daily mobility. Considering the low level of detail required for this research, each settlement can be represented as a single point, i.e., location since it is not required to observe each housing unit in particular.

The fuel consumption is calculated by using the EMEP/EEA air pollutant emission inventory guidebook – 2016 (Winther et al., 2017). Fuel burn for Landing and Take-Off (LTO) flight phases is assessed by using the origin and destination information of airports, as well as aircraft type (engine type, number of engines), duration for each LTO phase (taxi, take off, climb out, approach) and rate of fuel burn (kg/s/engine). For Climb/Cruise/Descent (CCD) flight phases fuel consumption is calculated based on CCD stage length and aircraft type.

Static population data are collected for each location based on the census data. Census data essentially represent home addresses of the population. To account for daily mobility patterns the population is divided into groups of people commuting to the same locations during the day at the same time period. Daily mobility presented in this paper includes a special form of spatial mobility of economically active populations (who perform an occupation), pupils and students. This data for each municipality around the airport is available at National Statistical Office (Statistical Office of the Republic of Serbia, 2013).

3. Optimization algorithm

As described in Section 2, the formulated problem is an integer nonlinear optimization problem with two objective functions. Thus, it is rather challenging to solve it using gradient-based optimization methods or nonlinear programming models. The difficulties lie in two aspects. Firstly, the decision variables are options that do not link directly to the objective functions, and hence they are difficult to solve with gradient-based optimization methods and nonlinear programming models. Secondly, even under the assumption that these models can be applied, they need to be combined with other techniques, such as weight methods, to solve the multi-objective optimization problem. Nevertheless, it is still hard to decide which weight vectors should be used. In addition, it is challenging to obtain a well-distributed Pareto front by applying these approaches when the considered problem is nonlinear.

Fortunately, many evolutionary algorithms capable of effectively dealing with similar problem have been proposed in recent years. Among them, the non-dominated sorting genetic algorithm II (NSGA-II) proposed by Deb et al. (2002) has emerged as one of the most powerful methods. The algorithm has been successfully applied in various engineering applications, for instance, structural optimization problems (Thang et al., 2018; Vo-Duy et al., 2017), scheduling problems (Martínez-Puras and Pacheco, 2016; Wang et al., 2017), allocation problems (Abouei and Taghi, 2018; Alikar et al., 2017), noise abatement departure trajectories (Hartjes and Visser, 2016), etc.

The NSGA-II algorithm is the improved version of NSGA developed earlier by Srinivas and Deb (1994) with a fast non-dominated sorting procedure and a crowded-comparison technique. Due to the outstanding features of these techniques, the performance of NSGA-II has been significantly enhanced in comparison to the previous version. In NSGA-II, the optimization process is started with a random number of solutions called the initial population P_t, in which t is the generation. Then, for each candidate solution in the population, the objective functions are evaluated. In order to gradually evolve the population towards the optimal solutions, from the previous (parent) population, an offspring population Q_t is generated by using genetic operators, such as tournament selection, crossover and mutation. Similarly, the objective function information of these solutions is also assessed. Next, both the parent population and the offspring population are combined and denoted as R_t. From the combined population R_t, the fast non-dominated sorting procedure and the crowded-comparison technique are applied to obtain a new population P_{t+1} for the next generation. The algorithm repeats the same procedures until the maximum generation or a stopping condition is reached. Once the search process of the algorithm is terminated, the set of optimal solutions called the Pareto front is obtained. They are non-dominated solutions that can provide a sound basis for users to make decisions. A brief description of NSGA-II for one generation is shown in Fig. 1 (Deb et al., 2002).

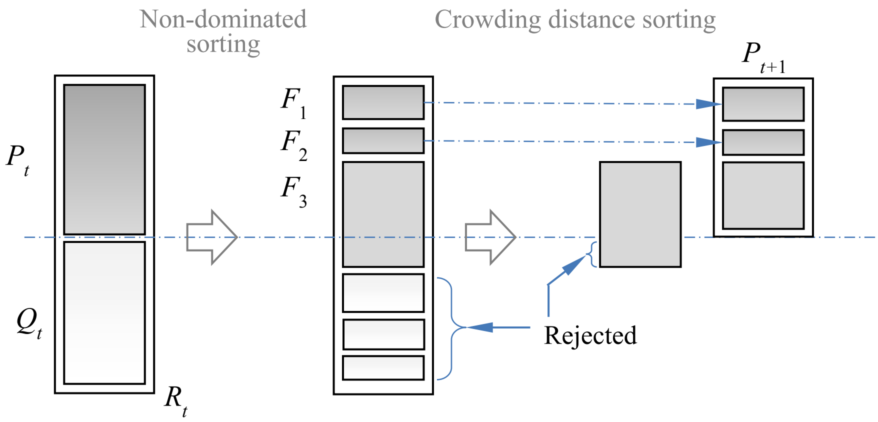

Fig. 1. Illustration of NSGA-II procedure.

Due to its outstanding performance, NSGA-II has been implemented in various programming languages including MATLAB, which is used in this paper. However, this version handles only the optimization problem with continuous design variables. Therefore, to enable the algorithm to solve the presented problem with integer design variables, a rounding technique is applied. By using this technique, whenever the algorithm introduces new candidate solutions, these solutions are all rounded to their nearest integer values before their objective functions are evaluated. Although the technique is rather simple, it has been demonstrated to be effective when dealing with discrete and integer design variables in evolutionary algorithms (V. Ho-Huu et al., 2018).

4. Case study: Belgrade Airport

In order to validate and demonstrate the reliability and applicability of the proposed approach, Belgrade Airport is selected as the case study in this paper. The airport is the largest and the busiest international airport in Serbia, located 18 km west of the Belgrade capital. With a single runway 3,400 m long (direction 12/30), the airport handled more than 5 million passengers and approximately 60 thousand aircraft operations in 2018.

As presented in Section 2, detailed air traffic data is required to prepare the input data for the model. The operations on September 16th, 2016 were chosen as it was a summer day with relatively heavy traffic. In addition, some of the data have been already available from the previous study (Ganić et al., 2016), which included measured noise levels at locations near the airport as well. Daily traffic comprised of 220 operations, consisting of 109 departures and 111 arrivals. The distribution of operations between runways was slightly in favor of runway 12, which handled 128 operations (58.2%), while runway 30 was used for 92 operations (41.8%). Departure and arrival routes for each runway were obtained from the radar data (flightradar24.com) because the Standard Instrument Departure (SID) and Standard Arrival Routes (STAR) could be less accurate, as most aircraft are vectored at Belgrade Airport.

From the radar tracks presented in Fig. 2a, 27 representative routes were selected, each representing a SID or STAR route. There are seven departure routes and seven arrival routes from runway 12 (Fig. 2b), and six departure routes and seven arrival routes from runway 30 (Fig. 2c). Departure routes are marked blue, and arrival routes are marked red. Note that since operations in solutions obtained by the proposed model could be assigned to arrival/departure routes that are different from the ones assigned in the reference case (the base-case scenario), the routes shown in Fig. 2b and Fig. 2c are complemented by parts of the route which connect them with border corridors applied in the reference case. For more details, interested readers may refer to Ganić et al. (2018). Noise and fuel data have to be defined for each aircraft type.

For the observed day, the fleet mix consisted of 25 different aircraft types. However, in an effort to simplify the calculations, the aircraft were classified into 11 groups based on the similarity of aircraft types using principles of acoustic equivalency and noise significance (ECAC, 2016). Thereby, 85% of the operations are presented by the aircraft types that were actually operated that day, while the remaining 15% are presented by aircraft types that have approximately the same level of noise exposure and fuel consumption as their representative type. Table 1 shows the number of departure and arrival operations for different periods with different aircraft types that are categorized based on the INM (Federal Aviation Administration, 2007). The classification of these aircraft types in AzB databases is also provided and it can be used as an alternative when the AzB noise model is applied (AzB-08, 2008; Isermann and Vogelsang, 2010).

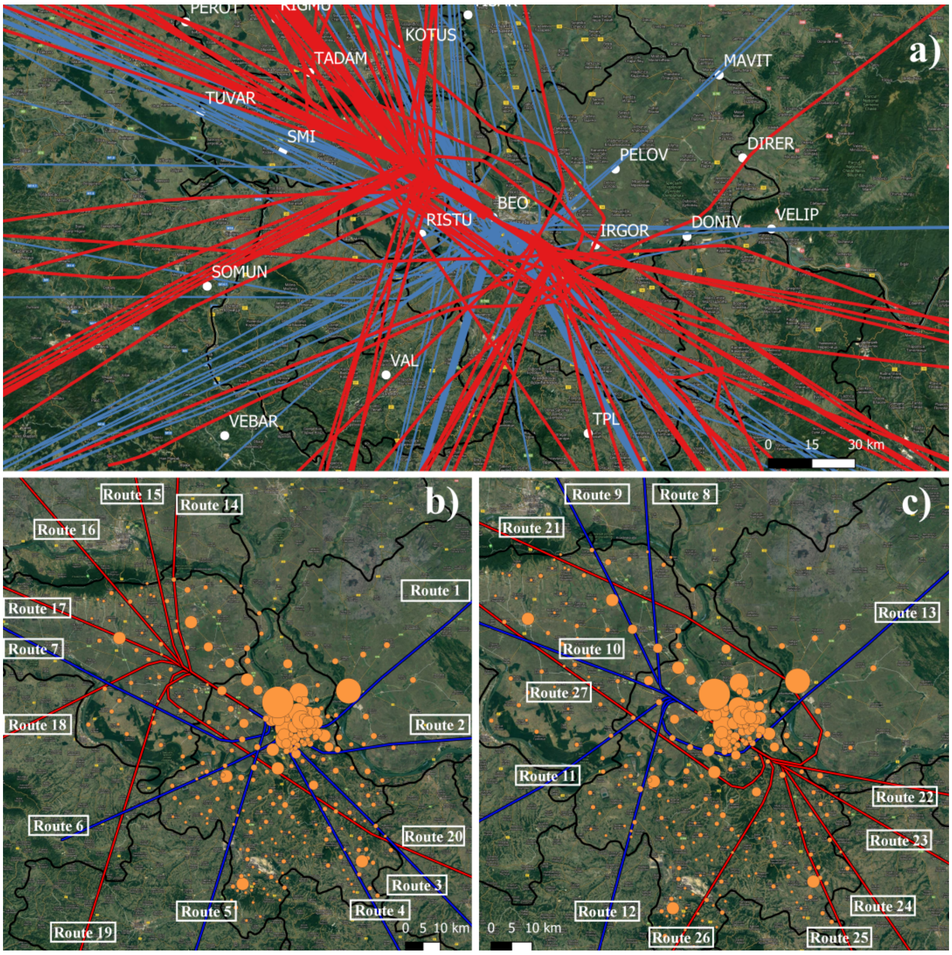

Fig. 2. Radar data and representative departure and arrival routes (source: Flightradar24.com using QGIS).

Table 1. Flight statistics and aircraft classifications

Aircraft type	Assigned AzB class	INM airplane code	Departure			Arrival		
			Day	Evening	Night	Day	Evening	Night
Boeing 737-300	S 5.2	737300	6	1	1	5	2	2
Boeing 737-800	S 5.2	737800	2	2	1	3	0	1
Airbus A319	S 5.2	A319-131	18	5	5	19	2	8
Airbus A320	S 5.2	A320-211	15	3	3	14	3	5
Airbus A330-200	S 6.1	A330-301	1	1	0	0	1	1
Beechcraft King Air	P 1.4	CNA441	1	0	1	1	0	0
Cessna 560 XL	S 5.1	CNA560XL	3	0	1	2	1	1
Swearingen Metroliner	P 2.1	DHC6	3	1	0	3	0	1
ATR 42	P 2.1	DHC8	1	3	0	3	1	0
ATR 72	P 2.1	DO328	14	6	5	12	6	8
Embraer 190	S 5.2	EMB190	5	1	0	6	0	0
		Total	69	23	17	68	16	27

The sound exposure levels (SEL) at each location caused by each aircraft type on the different routes are calculated by the INM software, which is used as input for the noise objective in the optimization model. For each operation, the standard INM profile settings are used and the fact that different aircraft types overfly locations at different altitudes and thrust settings is taken into account. In addition, different profile parameters for each aircraft type are also assigned, including take-off and landing weights, thrust and flaps settings, climb rate, and descent angle.

Before calculating the noise data, it is crucial to choose reasonable numbers and positions of locations for which the noise data and the population data will be obtained. Since the airport is surrounded by populated areas, 23 different municipalities are considered to be affected by aircraft noise, *viz*. 17 municipalities of Belgrade and 5 municipalities of Stara Pazova, Indjija, Irig, Ruma, Pecinći and Pančevo. In this case study, the SEL was calculated for 306 locations with each location representing one settlement in these 23 municipalities around the airport. Table 2 shows the population data and the number of settlements/locations for each municipality and for each period of time in accordance with human mobility patterns and 2011 census data (Statistical Office of the Republic of Serbia, 2013).

Table 2. Population data and the number of settlements for municipalities around the airport.

Municipality	Number of settlements	Census population (2011)	Period				
			1	2	3	4	5
Barajevo	14	27,110	25,050	24,422	26,020	25,559	26,497
Čukarica	9	181,231	166,349	159,679	172,064	168,848	176,209
Grocka	15	83,907	76,011	73,679	78,942	78,573	81,748
Lazarevac	34	58,622	60,304	62,146	59,584	60,969	59,545
Mladenovac	22	53,096	51,297	51,024	52,022	52,108	52,752
Novi Beograd	16	214,506	222,238	226,900	218,799	222,321	217,613
Obrenovac	29	72,524	69,586	68,859	70,803	70,635	71,802
Palilula	13	173,521	176,540	174,006	175,343	172,061	172,950
Rakovica	13	108,641	96,108	90,980	100,827	98,808	104,699
Savski venac	1	39,122	75,290	88,058	61,474	65,749	49,778
Sopot	17	20,367	19,270	19,054	19,930	19,711	20,122
Stari grad	1	48,450	88,436	96,797	73,554	71,702	57,748
Surčin	7	43,819	41,546	41,638	42,342	43,130	43,544
Voždovac	24	158,213	160,242	155,406	159,370	153,766	156,380
Vračar	1	56,333	64,953	66,643	61,698	61,250	58,312
Zemun	5	168,170	170,663	169,291	169,851	167,703	167,986
Zvezdara	11	151,808	147,073	140,364	148,991	143,108	148,303
Pančevo	10	123,414	119,466	119,439	121,154	121,946	122,873
Indjija	11	47,433	45,032	44,657	46,029	46,160	46,930
Irig	12	10,866	10,336	10,328	10,533	10,669	10,786
Pećinci	15	19,720	18,965	19,155	19,447	19,579	19,670
Ruma	17	54,339	51,925	52,171	52,991	53,643	54,060
Stara Pazova	9	65,792	61,430	61,113	63,249	63,797	65,018
Total	306	1,981,004	2,018,110	2015809	2,005,017	1,991,795	1,985,325
People living in other municipalities, but commuting to these 23 municipalities or vice versa		88,942	51,836	54,137	64,929	78,151	84,621

In order to take into account human mobility patterns and to simulate working shifts of employees, pupils and students, the day has been divided into five periods, as shown in Fig. 3. The periods are defined in such a way that the number of people at each location remains constant for the duration of the period. This data was made available by the Statistical Office of the Republic of Serbia.

Group Number	Period → / Time of the day →	Period 1 08:00 - 14:00	Period 2 14:00 - 16:00	Period 3 16:00 - 20:00	Period 4 20:00 - 22:00	Period 5 22:00 - 08:00
1	Employees 1st shift	Working location		Residential location		
2	Employees 2nd shift	Residential location	Working location			Residential location
3	Employees 3rd shift	Residential location			Working location	
4	Students 1st shift	Studying location	Residential location			
5	Students 2nd shift	Residential location	Studying location		Residential location	
6	Staying at home	Residential location				
Number of aircraft movements		76	14	51	13	66

Fig. 3. Groups of people and periods based on working shifts of employees, pupils and students.

The definition provided in the 2011 Census methodology describes daily migrants as persons who work or go to school/university outside the place of their usual residence, but they return on a daily basis or several times a week (Statistical Office of the Republic of Serbia, 2013). The daily mobility data is the key to calculate the total daily inflow and outflow of inhabitants for each settlement. This was used as the basis to calculate groups of people commuting to the same location at the same period of time during the day.

Having in mind that human mobility patterns are obtained for the whole day only, and not for separate periods of the day, some assumptions are needed in order to assess how many people would actually be present at each location during a defined period of time. Therefore, it has been assumed that 50% of employees work first shift, 30% work second shift, and 20% work night shift. Out of the total pupils and students going to schools or universities, 60% follows the first shift, and 40% the second. Hereby, 76,423 groups of people were observed, and the population data calculated based on the census data and the daily mobility data show a difference in the number of people at each location in the pre-defined periods. The total number of residents living within these 306 locations based on the census data was 1,981,004. This research also includes the mobility of people living outside the 23 municipalities mentioned above, but working or studying in some of these municipalities, and vice versa.

By comparing the total number of people for different periods with the census population data, it can be seen that the highest absolute difference is 2% for Period 1. The reason behind is the fact that this study takes into account only the daily mobility of employees going to work and pupils and students going to schools and universities.

5. Results and discussions

As mentioned in Section 1, although the influence of the mobility data on evaluation of noise effects has been well recognized in previous transportation studies (Kaddoura et al., 2017, 2016), the investigation of mobility data influence in air traffic models is still limited.

Therefore, before executing the optimization problem, the influence of the mobility patterns on evaluation of aircraft noise effects is assessed first. Afterwards, the optimal solutions based on the mobility data and derived from the proposed model are obtained and analyzed.

5.1. Influence of daily population mobility on evaluation of aircraft noise effects

In order to assess the influence of census data and mobility data on evaluation of aircraft noise effects, the real air traffic operations on 16 September 2016 are used, which is hereinafter referred to as the reference case. The L_{den} noise contours caused by all the operations are shown in Fig. 4, where the NPA at each (residential) location is also indicated. At first glance, it can be observed that there is a significant difference between the census data and the mobility data among noise-affected locations. In fact, with the census data (depicted by triangles), only people at locations enclosed in the noise contours are affected. Meanwhile, when using the mobility data (depicted by circles), the noise effects occur not only at these locations, but also at locations outside of the noise contours. This can be explained by considering that people who live outside the area affected by aircraft noise may work or study within these areas at some time during the day, and are therefore affected by aircraft noise.

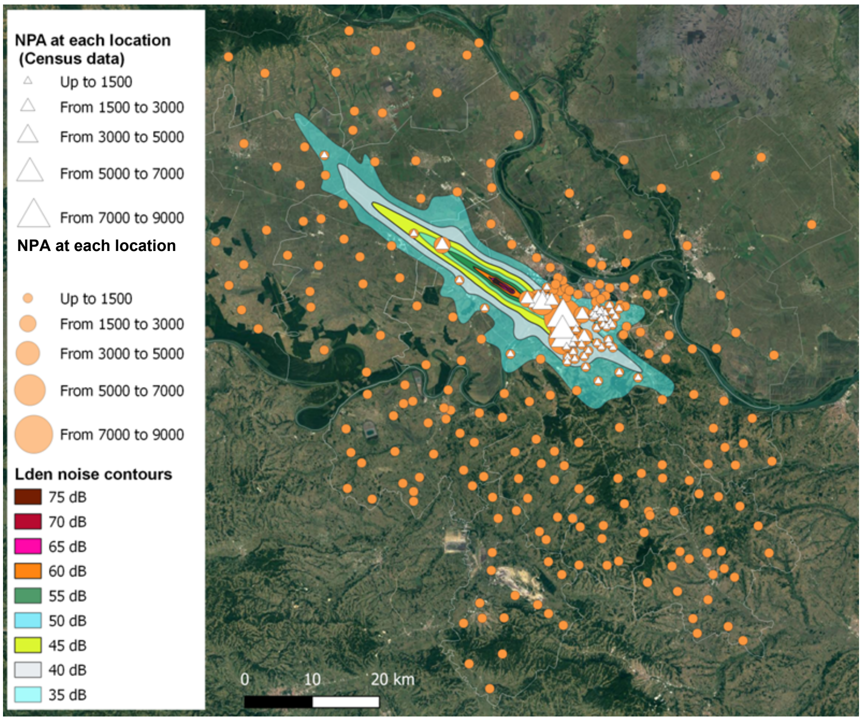

Fig. 4. Illustration of people at locations affected by noise with $L_{\text{den}} \geq 37$ dB.[5]

For a specific evaluation, the NPA at the locations covered by L_{den} noise contours ≥ 37 dB ($L_{\text{den}} \geq 37$ dB), as shown in Fig. 4, is estimated for both datasets and presented in Table 3. As seen from the table, the total NPA at these locations for the census data is 57,519, which is by 2.18% relatively higher (by 1,228 in absolute numbers) than the NPA based on the mobility data. The same situation is observed for the NPHA, where the difference is even higher, 5.24%. These observations show that even though people live inside the noise contours, some of them are still not annoyed by aircraft noise due to their mobility for working or studying purposes to locations far away from the airport.

Table 3. Number of people affected by noise at locations enclosed in $L_{\text{den}} \geq 37$dB.

Criterion	Census data	Mobility data	Absolute difference	Relative difference
NPA	57,519	56,291	1,228	2.18%
NPHA	10,583	10,056	527	5.24%

Furthermore, in order to see how many people live outside the noise contours, but still experience noise impact, the NPA based on the mobility data at all locations is evaluated and presented in Table 4. The table shows that the total NPA is 60,265, more than 7.05% of whom

[5] All the figures with the Google earth background are created using the open source software, QGIS (https://qgis.org/en/site/)

live outside the $L_{den} \geq 37$ dB. The same trend is observed for the total NPHA as well. This is easily explained when considering that people who live farther away from the airport may still work or study in the areas affected by aircraft noise.

Table 4. Number of people affected by noise based on mobility data.

Criterion	All locations	Only locations enclosed in $L_{den} \geq 37$dB	Absolute difference	Relative difference
NPA	60,265	56,291	3,974	7.05%
NPHA	10,499	10,056	443	4.40%

Apart from the observations in the above tables, it is also noted that although the absolute difference of the total NPA between the census data and the mobility data is relatively small, the difference in the NPA at each location is rather significant, as shown in Fig. 5. Summarizing the relative difference at all locations compared to the NPA obtained by the census data can add up to 52.9%. This number indicates that there is a significant change in the number of people at each location during the day. For example, for location 220, the NPA based on the census data is 0, while the NPA based on the mobility data is 307; and for location 15, the NPA based on the census data is 8,286, whereas the NPA based on the mobility data is 7,936.

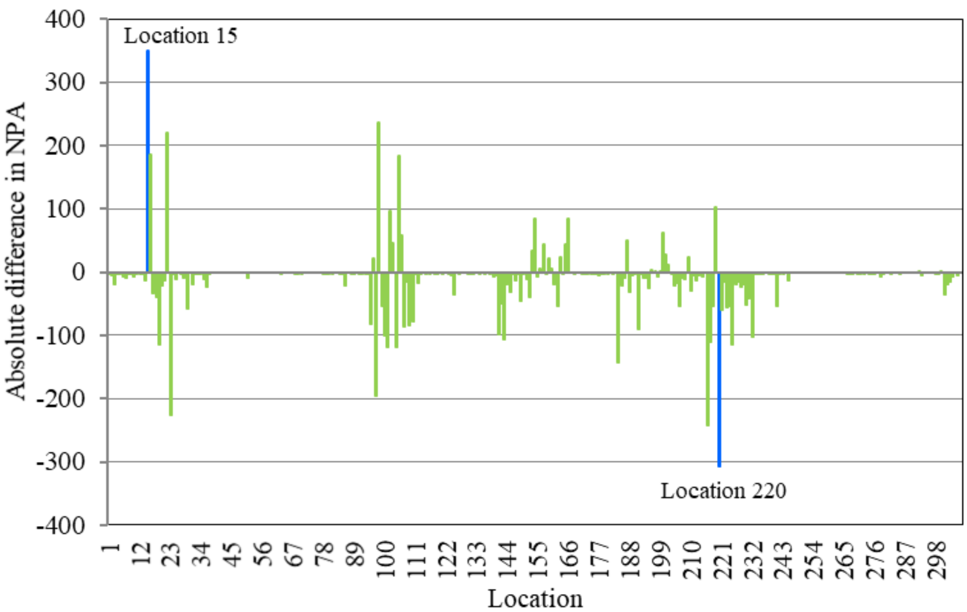

Fig. 5. Difference in the NPA between census data and daily mobility data at all locations.

For a better illustration of the daily mobility of population outside and inside the noise contours, movements at locations 15 and 220 are highlighted in Fig. 6 and Fig. 7, respectively. Fig. 6 shows that location 15 is located nearby the airport and enclosed in the noise contours of L_{den}> 45 dB. However, some of the people living at this location may experience less noise than others, as they work or study outside the area. Therefore, the total NPA calculated using the mobility data at this location is less than the NPA obtained by the census data. In contrast, an opposite situation can be observed for location 220 in Fig. 7. At this location, people who live outside the noise contours work or study at locations close to the airport, and hence they can experience significant noise impact. This explains the significant difference in the NPA at each location. In addition, the combined mobility at locations 15 and 220 explains why the difference in the total NPA between the census data and mobility data is relatively small.

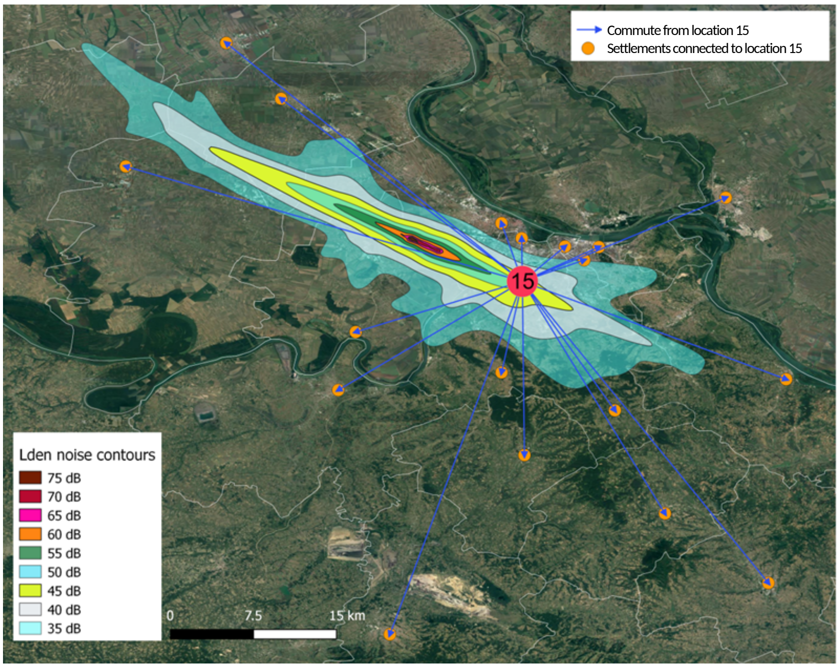

Fig. 6. Illustration of population at location 15 commuting outside L_{den}≥ 37 dB.

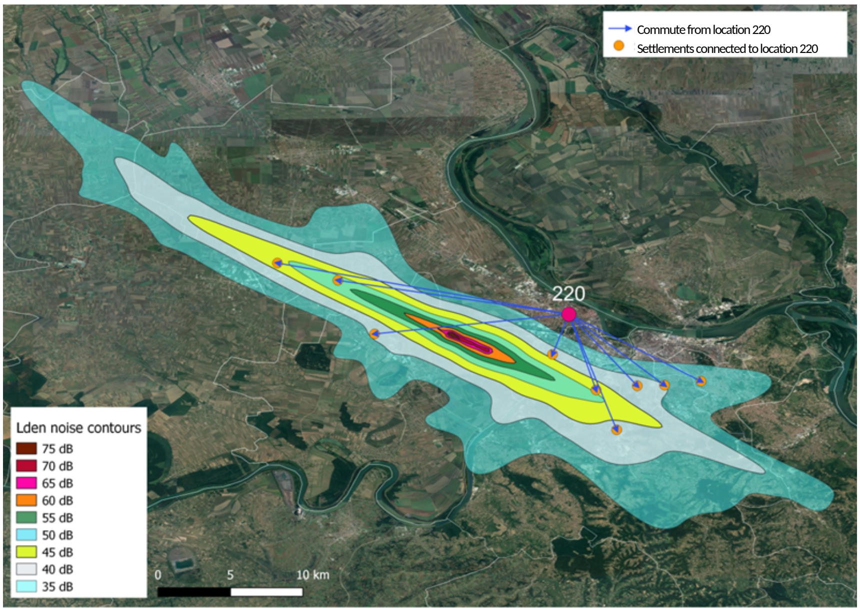

Fig. 7. Illustration of population at location 220 commuting inside $L_{den} \geq 37$.

To enable further examination of the influence that mobility data has on the number of people affected by aircraft noise during the night, the sleep disturbance criteria[6] based on L_{night} recommended by WHO (2009) are also evaluated. These evaluations are provided in Table 5 and Table 6. As can be seen in the tables, the results obtained by using L_{night} also have the same trend as those obtained by using L_{den} even though during the night only the mobility of employees is considered. The explanation for this is that, according to the mobility data, groups of employees account for a significant portion in the mobility of the entire population, which is approximately twice as high as the groups of students. In addition, the noise impact during the night is more sensitive compared to the noise impact during the day and evening, and hence the percentage of disturbed people in each group is higher. Consequently, the mobility data also has a noticeable impact on the estimation of aircraft noise effects during the night.

Table 5. Number of people affected by noise at locations enclosed in L_{night} noise contour ≥ 30 dB.

Criterion	Census data	Mobility data	Absolute difference	Relative difference
NSD	33,750	32,601	1,149	3.52%
NHSD	21,103	20,381	722	3.54%

[6] $\%SD = 13.714 - 0.807\ L_{night} + 0.01555\ (L_{night})^2$, and $\%HSD = 18.147 - 0.956\ L_{night} + 0.01482\ (L_{night})^2$, where $\%SD$ and $\%HSD$ are the percentages of the group of people whose sleep is disturbed and highly disturbed, respectively (WHO, 2009).

Table 6. Number of people affected by noise based on mobility data.

Criterion	All locations	Only locations enclosed in L_{night} > 30 dB	Absolute difference	Relative difference
NSD	33,809	32,601	1,208	3.71%
NHSD	21,138	20,381	757	3.71%

Based on the above considerations, it can be concluded that evaluation of aircraft noise effects is significantly dependent on population data (i.e., the census data and the mobility data). Although the difference in the total NPA between these data is small, the difference in the NPA at each individual location is considerable as a result of the daily mobility. From the perspective of air traffic assignment, variations of population at each location may lead to different optimal assignments compared to the case when solely census data are used. This is because, in order to reduce the noise impact, optimal allocation of aircraft should avoid locations at which most people are present during the day, rather than just their home addresses. Consequently, developing a methodology that is capable of creating optimal air traffic assignments based on mobility data is important and necessary. In the following section, therefore, the methodology presented in the previous sections is applied to solve the optimization problem of the air traffic assignment. The obtained results are analyzed and compared to those obtained by the reference case. Since the main aim of the research is to find optimal air traffic assignments for an entire day, only the noise criteria based on L_{den} are employed for the optimization problems and further analyses as well.

5.2. Air traffic assignment based on daily population mobility

The NSGA-II algorithm with a population size of 70 and a maximum generation (Gen.) of 1500 is applied to solve the multi-objective optimization problem stated in Section 2. The method is set with an intermediate crossover rate of 1.5 and the Gaussian mutation technique with a scale of 0.8 and a shrink of 0.1. All the simulations are run on an Intel Core i5, 8GB RAM desktop and MATLAB 2016b.

Fig. 8 presents the optimal solutions obtained in comparison with that of the reference case. Fig. 8 shows that the proposed approach generates solutions which are much better than that of the reference case. When a population size of 70 is used, the Pareto font contains 70 distinct non-dominated solutions, and all of them dominate the reference case. Generally, all solutions will have the same weight of advantages, which spread from noise to fuel preference. Basically, decision makers can, therefore, choose any of the solutions based on their specific needs. However, to arrive at acceptable trade-off solutions from all of them, systematic analyses which are not considered in this study are needed. Therefore, only some representative solutions are chosen for further analyses later on.

In terms of computational cost, Fig. 9 shows the convergence history of results after specific generations with a particular amount of computational time. As seen from Fig. 9, the results seem to converge faster after 800 generations, and there are no significant improvements after 1200 generations. The computational cost (CPU time) is also recorded after each generation. To reach the last generation, the method spends almost 24 hours, mostly on calculating Eq. (3) for all 76,423 groups of people. Although the computation time is high, the algorithm is still applicable as the flight schedule can be obtained some days in advance. Moreover, with the development of powerful computers such as cluster and cloud computing, this issue can be addressed relatively easily.

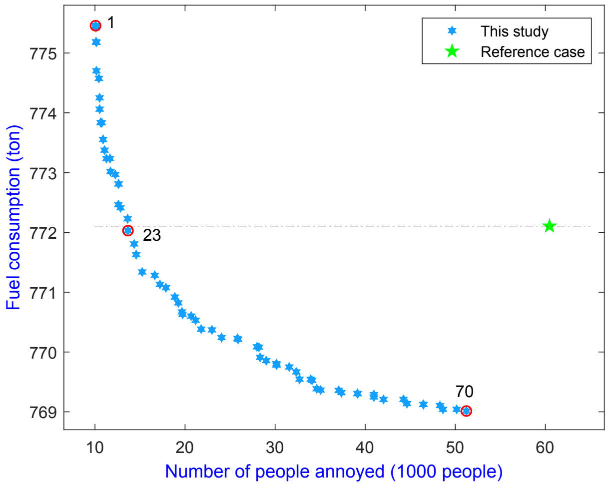

Fig. 8. Illustration of optimal solutions obtained by proposed method and reference case.

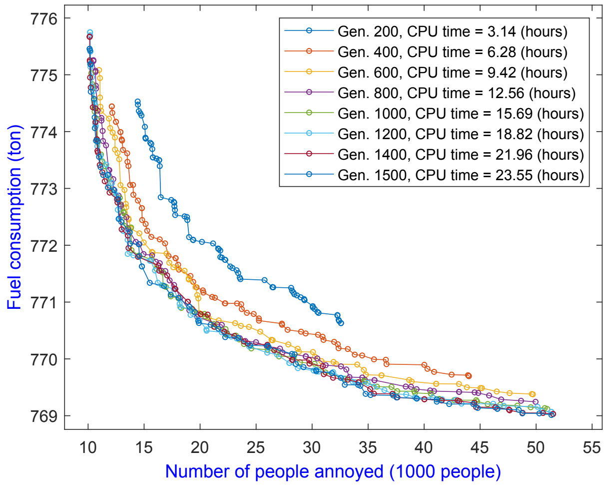

Fig. 9. Convergence history of optimal solutions.

For a better overview on the optimal solutions, three distinct solutions are selected, *viz*. 1, 23 and 70 as marked in Fig. 8, for further examinations. For these solutions, solutions 1 and 70 represent the minimum noise and fuel solutions, respectively, while solution 23 shows the same fuel consumption as the reference case, but has significantly better noise performance. Table 7 presents the objective values of the optimization problem (i.e., the total NPA and fuel consumption) and other concerned metrics obtained by the representative solutions and the reference case. At first glance, the table indicates that all the solutions have better NPA and NPHA in comparison with the reference case. Particularly, the total NPA of solutions 1, 23 and 70 are, respectively, 10,061, 13,663 and 51,234, and hence there is a reduction of 83.31%, 77.33% and 14.99%, respectively, compared to that of the reference case (with 60,265 people annoyed). Similar relative amounts of the reduction are observed for the NPHA as well.

Regarding the total fuel consumption and route length, due to focusing on the noise preference and hence assigning aircraft to routes which are farther away from the populated regions, solution 1 generates more fuel consumtion than the reference case with an increase of 0.43%. However, even though it results in a significant reduction of the noise impact, solution 23 still keeps the total fuel consumption slightly lower than that of the reference case, whilst with a still smaller amount of noise impact reduction, solution 70 provides the best option for fuel preference. The same trend is also recognized for the total route length, except for solution 23. For this solution, although the total fuel burn is slightly less than that of the reference case, the total route length is still higher. This can be explained by considering the distribution of aircraft types. Even though the total route length has increased, the route length of aircraft with higher fuel burn has reduced, leading to an overall reduction in fuel consumption.

It is also worth noting that the reason for the relatively small difference in fuel burn between the solutions and the reference case is due to the fact that departure and arrival operations account only for a small part of the flight. Nevertheless, there is an identifiable effect when considering the absolute values. Specifically, for solution 70, 3,093 kg can save airline companies around $ 2,327 per day (with an average cost of jet-A1 fuel of $ 86.1 per barrel[7] in 2018), and generate roughly 9.7 ton of CO_2[8] emission less.

Table 7.Comparison of different metrics of representative solutions and reference case.

Method	Case number	NPA	NPHA	Fuel consumption (kg)	Route length (NM)
This study	Solution 1	10,061	2,059	775,457	124,771
	Absolute reduction	-50,204*	-8,440	+3,351	+935
	% reduction	-83.31	-80.39	+0.43	+0.76
	Solution 23	13,663	2,308	772,030	124,139
	Absolute reduction	-46,602	-8,191	-76	+303
	% reduction	-77.33	-78.02	-0.01	+0.24
	Solution 70	51,234	8,892	769,013	123,391
	Absolute reduction	-9,031	-1607	-3,093	-445
	% reduction	-14.99	-15.31	-0.40	-0.36
Reference case		60,265	10,499	772,106	123,836

*The signs "+" and "–" indicate increase and reduction compared to reference case, respectively.

Besides the evaluation of the criteria as given in Table 7, the number of people enclosed in specific L_{den} noise contours is also evaluated and provided in Table 8. A comparison of the representative solutions and the reference case shows that the number of people enclosed in the higher noise contours reduces for solutions with more emphasis on noise. This behavior is

[7]https://www.iata.org/publications/economics/fuel-monitor/Pages/index.aspx (assessed 19 January 2019)
[8]https://www.icao.int/environmental-protection/Carbonoffset/Pages/default.aspx(assessed 19 January 2019)

expected, and it is comparable with the trends of the NPA and the NPHA in Table 7. According to the formula in Eq. (2), it is obvious that the higher the value L_{den} each group of people is subjected to, the greater the number of people annoyed that group has.

Table 8. Comparison of the number of people enclosed in specific L_{den} noise contours.

Method		Noise band						
		< 40	[40-45)	[45-50)	[50-55)	[55-60)	[60-65)	> 65
This study	Solution 1	1,987,474	59,075	5,326	10,860	7,211	0	0
	Solution 23	1,970,373	72,420	7,897	8,891	10,365	0	0
	Solution 70	1,654,134	241,767	125,281	41,829	3,684	3,251	0
Reference case		1,595,717	253,308	156,340	57,587	1,803	5,191	0

In order to perceive the difference between the optimal solutions in terms of air traffic assignments as well as the noise contours and the NPA at each location, the features of solutions 1, 23 and 70 are further analyzed. The optimal assignment of these solutions is shown in Table 9, which provides the number of aircraft assigned to each route, while their L_{den} noise contours and the NPA at each location are depicted in Fig. 10, Fig. 11 and Fig. 12, respectively.

Table 9 shows that the distribution of aircraft over the routes between the solutions is rather different. For example, for route 5, solution 1 has 31 operations, and solution 23 has 24 operations, while solution 70 has only 11 operations. On the other hand, for route 27, there is no operation from solution 1, but 5 operations from solution 23, and 15 operations from solution 70. More specifically, solution 1 tends to send more aircraft to route 5 as it is positioned farther away from the populated regions. However, this selection will result in longer routes for aircraft that have their final destination in a different direction, and it will consequently cost more fuel. Meanwhile, solution 70 tends to directly send aircraft along routes in the direction of their final destinations disregarding populated areas, and hence leading to an increase in the NPA. Solution 23 tends to balance between noise and fuel concerns, and hence its distribution falls in the middle of those of solutions 1 and 70.

The above examinations are even more apparent when looking at Fig. 10, Fig. 11 and Fig. 12. In these figures, the variation in the NPA between the solutions can be observed in the region that is highlighted by the white dotted line. In fact, for solution 1, there are only 3 locations which have people affected by noise due to their daily mobility, while 8 locations are recognized in solution 23, and up to 18 locations in solution 70. Moreover, upon a closer look at the legends on the figures, it is also noted that the scale of the NPA at each location of these solutions is rather different. A further distinction of this comparison can be clearly recognized in Fig. 13. It can be seen from the figure that the difference of the NPA occurs not only at the highlighted region, but also at other locations.

Table 9. Comparison of optimal route assignments of three representative solutions.

Route number	Number of operation			Route number (continued)	Number of operation		
	Solution 1	Solution 23	Solution 70		Solution 1	Solution 23	Solution 70
1	0	3	7	15	4	10	3
2	0	1	3	16	10	7	1
3	0	0	2	17	8	2	5
4	0	2	19	18	9	7	7
5	31	24	11	19	12	12	10
6	0	1	0	20	24	26	22
7	3	11	9	21	2	7	9
8	20	13	12	22	16	8	6
9	19	15	15	23	0	1	9
10	23	19	18	24	0	2	1
11	0	6	7	25	0	0	0
12	10	6	4	26	0	1	4
13	3	8	2	27	0	5	15
14	26	23	19				

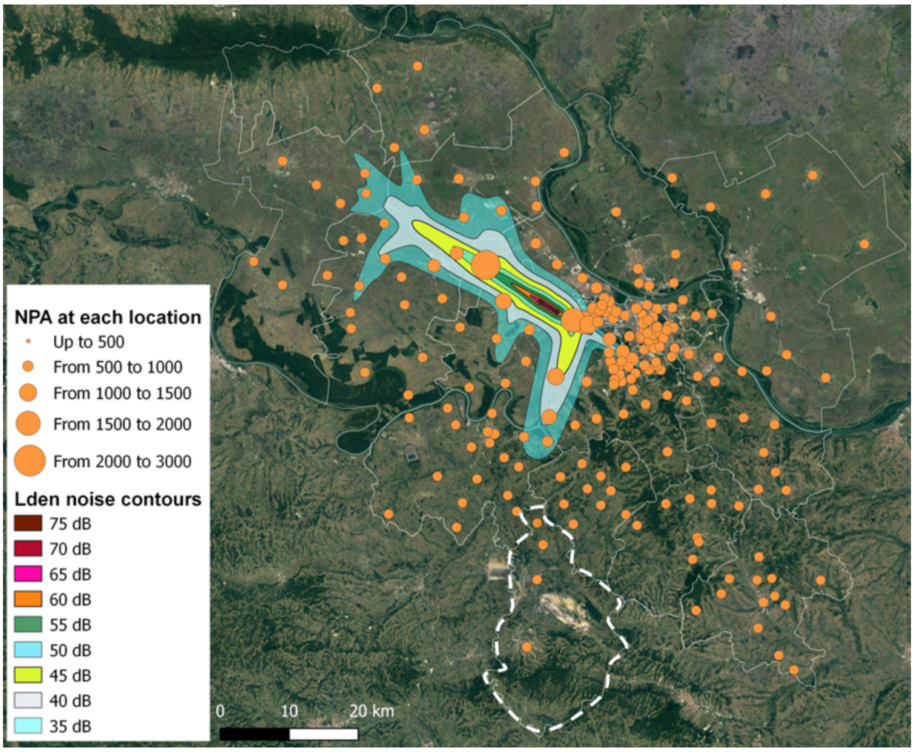

Fig. 10. Illustration of NPA at each location (solution 1).

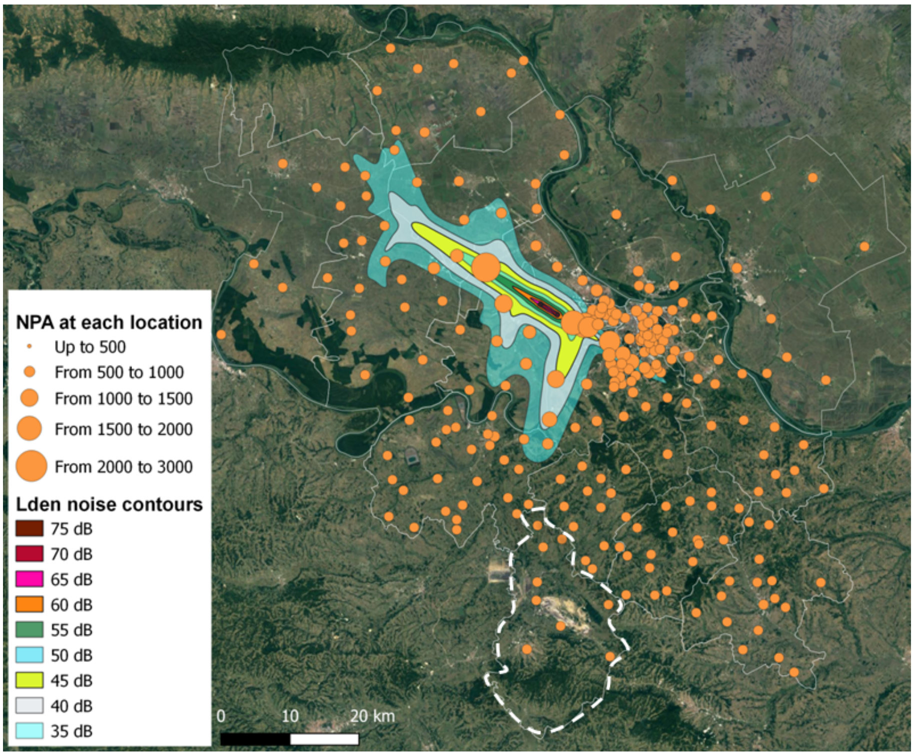

Fig. 11. Illustration of NPA at each location (solution 23).

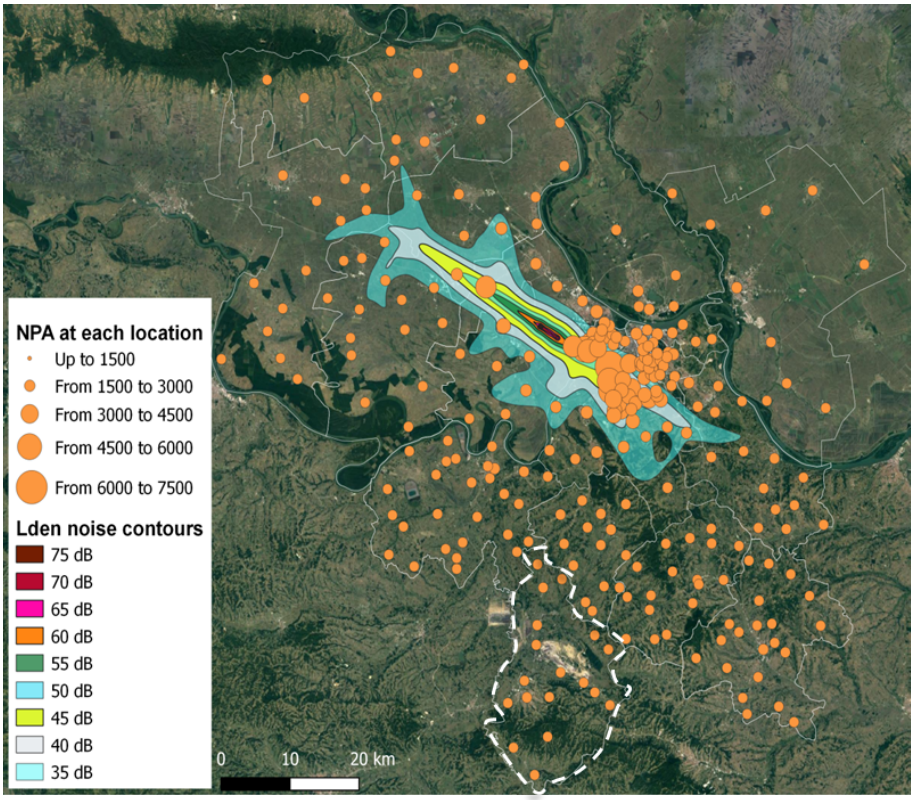

Fig. 12. Illustration of NPA at each location (solution 70).

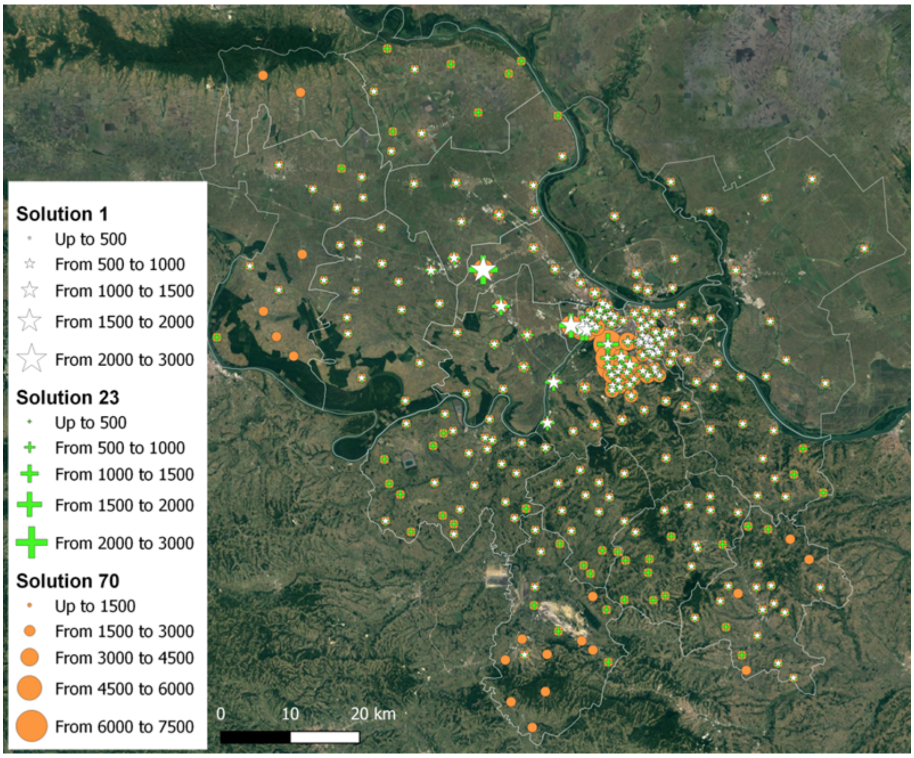

Fig. 13. Comparison of NPA between solutions 1, 23 and 70 at each location.

5.3. Evaluation of optimal assignments based on census data and mobility data

As noted earlier at the end of Section 5.1, the variation of population at each location between the census data and the mobility data during the day may lead to a change in the optimal assignments obtained by these data as well. Therefore, to estimate this concern for the applied case study, the air traffic assignment problem based on the census data is also performed. The obtained results are then compared with those based on the mobility data.

Fig. 14 and Fig. 15 compare the objective functions (i.e., the total NPA and fuel consumption) for both datasets. In Fig. 14, the comparison is made based on the optimal assignments using the census data, whereas the comparison in Fig. 15 is made based on the optimal assignments using the mobility data. Both figures indicate that there is a small difference in the NPA between solutions evaluated based on the difference of datasets. Note that since the assignments for each comparison in each figure are the same, consequently the fuel consumption will be the same regardless of the data used. The variation increases from solution 1 to solution 70. Therefore, there is a difference in their optimal assignments. The variation of the optimal assignments between both sets of solutions can be readily explained. As mentioned earlier in Section 5.1, due to the daily mobility, the population at each location changes at different times of the day. Therefore, to reduce the noise impact, the optimal assignments should be changed as well. It should also be noted that although the change in the total NPA between the census data and the mobility data is relatively small, the change of the NPA at each location can be rather large, which has been discussed earlier in Section 5 as well.

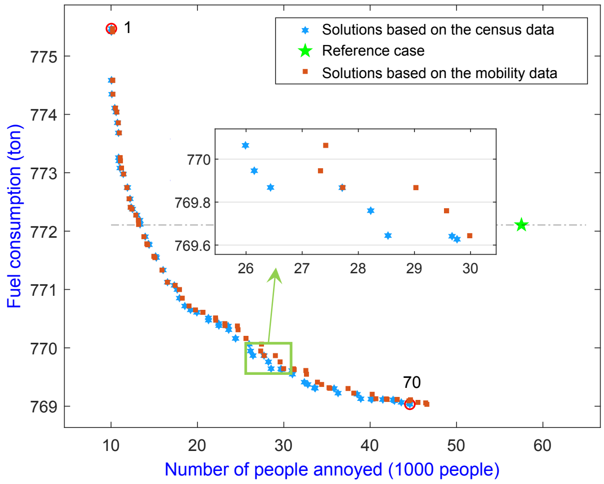

Fig. 14. Comparison based on the optimal assignments using the census data.

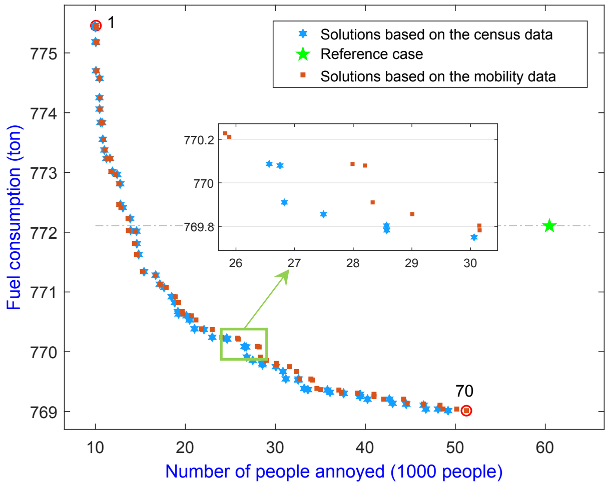

Fig. 15. Comparison based on the optimal assignments using the mobility data.

In order to further analyze the difference above, the optimal assignments of two representative solutions, *viz.* 1 and 70 obtained by using both datasets are extracted and presented in Table 10. This table shows that the optimal assignments are slightly different. For example, for route 9 of solution 1, the difference in the number of operations is 6, whilst for route 15 of solution 70 it is 3. It should be also noted that although the number of operations on each route for both datasets used is more or less the same, the distribution of aircraft types also contributes to the variation in the NPA.

To get a better insight into the effect of the change in the optimal assignments, the resulting L_{den} noise contours for these assignments are illustrated in Fig. 16 and Fig. 17, for solutions 1 and 70, respectively. As seen in the figures, the noise contours are rather different, especially for solution 70.

Table 10. Comparison of the optimal route assignments of solutions 1 and 70 based on both data.

Route number	Number of operation				Route number (continued)	Number of operation			
	Solution 1		Solution 70			Solution 1		Solution 70	
	Census data	Mobility data	Census data	Mobility data		Census data	Mobility data	Census data	Mobility data
1	0	0	6	7	15	5	4	0	3
2	0	0	5	3	16	14	10	2	1
3	0	0	1	2	17	5	8	2	5
4	0	0	16	19	18	10	9	10	7
5	28	31	12	11	19	10	12	10	10
6	0	0	0	0	20	21	24	21	22
7	6	3	8	9	21	3	2	7	9
8	17	20	12	12	22	15	16	9	6
9	25	19	14	15	23	0	0	6	9
10	22	23	17	18	24	0	0	3	1
11	0	0	9	7	25	0	0	0	0
12	8	10	7	4	26	0	0	3	4
13	3	3	2	2	27	0	0	16	15
14	28	26	22	19					

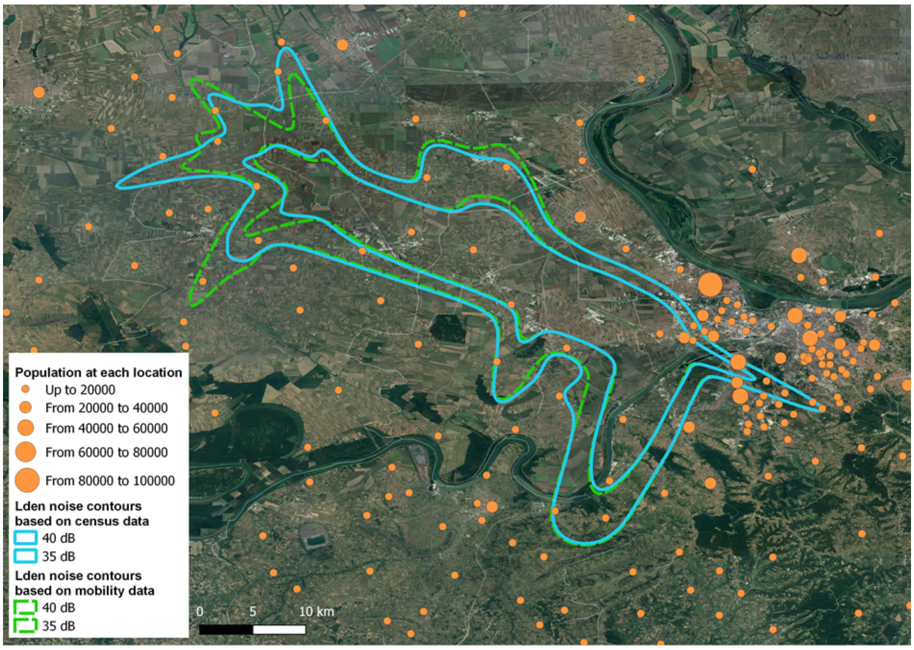

Fig. 16. Comparison of L_{den} noise contours based on census data and on daily mobility data (solution 1).

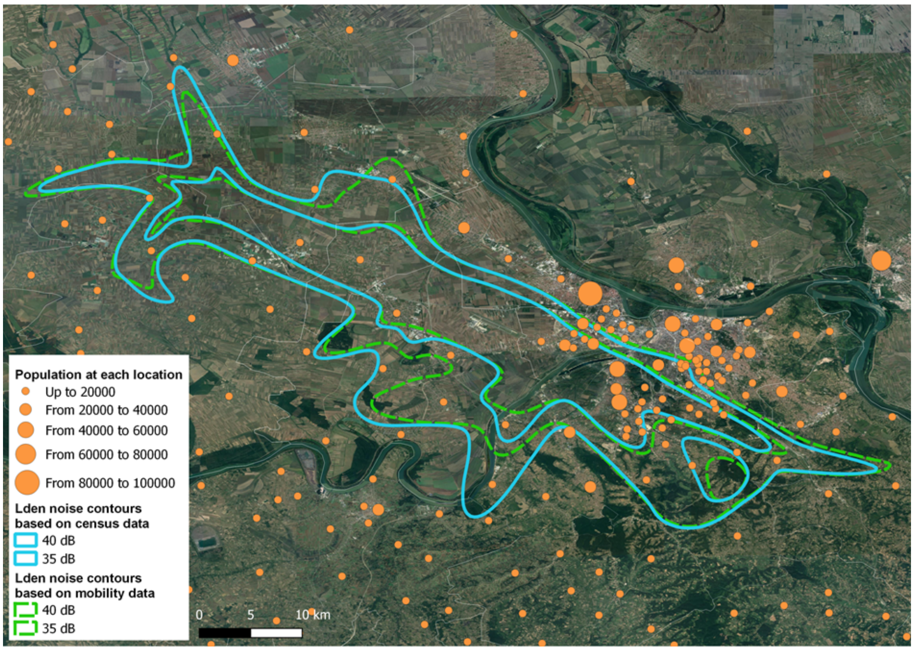

Fig. 17. Comparison of L_{den} noise contours based on census data and on daily mobility data (solution 70).

6. Conclusions and future work

This paper introduces a new air traffic assignment model which is capable of taking the daily mobility of a city's population into account, in addition to having a acceptable trade-off between conflicting objectives (i.e., the NPA and fuel consumption). Furthermore, substantial efforts have been invested to investigate the influence of the data used on the evaluation of aircraft noise effects. Then, the optimal solutions of the air traffic assignment based on the mobility data are obtained and compared with that of the reference case and those based on the census data. The following conclusions can be drawn from this work:

1) The evaluation of aircraft noise impact is influenced by the daily population mobility data used. Specifically, when the census data are used, only people who live inside the noise contours get annoyed, whereas it has been found that people living outside the noise contours could be annoyed when the mobility data are used. Moreover, not all of the annoyed people suggested from the census data will actually be annoyed if their daily mobility is taken into account. Although the total NPA obtained by using either

census data or mobility data is very similar, the NPA at each location is significantly different.

2) Compared to the reference case herein, the proposed methodology can generate solutions that are much improved in terms of both the total NPA and fuel consumption. Even with a small change in the total fuel consumption, the method can still offer a solution which can reduce the total NPA up to 77%. Furthermore, the proposed approach also provides a wide range of solutions with different benefits to either noise or fuel burn, and these solutions can serve as a valuable input for authorities and policymakers in their decision making.
3) The optimal assignments obtained by both datasets are different since there is a significant difference in the number of people at each location during the day. The evaluation thereof also indicates that the difference in the optimal assignments is rather dependent on the case study under consideration, and on whether the variation of population at each location is significant or not, relative also to the population distribution and airport layout.

Some inherent limitations of the work which have not yet been considered in this study are also worth mentioning. First, the mobility data are considered only for three distinct groups of people, including students, employees and people staying at home. This assumption may lead to variations in optimal assignments as a result of the change of population at each location during the day if other types of mobility are also considered. Further research should also investigate to a larger extent the assumption regarding the allocation of employees and students to shifts. Second, for the air traffic assignment model, only the feasible options for each operation are considered, while the runway and airspace capacity (e.g., aircraft sequencing), which can lead to delay of flights, are not yet considered. This model could be regarded as pre-tactical and intended to be used for planning purposes since it takes into account forecasted data for the whole day and it is not resistant to any disruption in the pre-defined timetable. In order to render it suitable for tactical use in real-time operations, changes in runway in use, aircraft changes as well as delays should be included in the model. Therefore, these issues will be dealt with in further work. Furthermore, by using the mobility data, changes in population at sensitive regions such as schools and hospitals, can be recognized. These more detailed mobility data can help develop more realistic, applied solutions in terms of applying more complex fair weightings for each different category.

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