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A decision support system for risk reduction in pandemic spread based on the management of passenger air traffic

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Abstract

A significant factor in the early spread of pandemics at an international level is passenger air traffic. Decisions regarding passenger air traffic could assist different countries in managing the risk of pandemic importation. However, flight cancelations would have economic and social impacts, leading to a multiobjective optimization problem. A decision support system (DSS) for reducing the risk of pandemic spread by managing passenger air traffic is introduced. This DSS enables decision makers (DMs) to parameterize the problem to be solved (time period, country of analysis, the percentage of targeted risk reduction, etc.), quantify DM preferences using ordinal information on the objectives, solve the resulting binary single-objective optimization problem using a binary particle swarm optimization metaheuristic, and visualize the optimal solution. The methodology is illustrated using the example of Spain with 38 national airports and 5000 international connections, involving 9678 flights within the time period from September 24 to October 7, 2020.

Keywords: air traffic management; importation of pandemics; risk management; decision support system; binary PSO

1. Introduction

Air travel enables people to quickly cover long distances, connecting regions and countries within a matter of hours. This connectivity can lead to the rapid spread of infectious diseases, as infected individuals can carry the virus to new locations before they even exhibit symptoms (Hufnagel et al., 2004; Tatem et al., 2006; Bajardi et al., 2011). Major international airports serve as important hubs for air travel, with thousands of travelers passing through each day. These airports can become focal points for the introduction and dissemination of infectious diseases. An outbreak at one airport can quickly spread to other locations as travelers connect to various destinations. A straightforward

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and efficient method for modeling the transmission of infectious diseases through transportation networks is introduced in Anypriya et al. (2022), which accounts for widely available aggregate mobility data in the form of a zone-level origin-destination travel flow matrix.

Note that some infectious diseases can be transmitted by individuals who are asymptomatic (showing no symptoms) or presymptomatic (infected but not yet showing symptoms). Air travel allows these individuals to unknowingly spread the disease to others, making it challenging to detect and contain outbreaks. In Bai et al. (2020), a case study is discussed involving the presumed transmission of COVID-19 from an asymptomatic carrier to other individuals. This study highlights the significance of asymptomatic carriers in the spread of the virus and emphasizes the importance of early detection and public health interventions to prevent further transmission.

While airports often implement health screening measures, such as temperature checks and questionnaires, these measures may not be effective in identifying infected individuals, particularly if they are asymptomatic or presymptomatic. Many infectious diseases have relatively long incubation periods, during which individuals may not yet exhibit symptoms or have a temperature.

Furthermore, airplanes often have high passenger densities, with travelers seated in close proximity to each other. This close proximity can increase the risk of transmission of infectious diseases, especially respiratory viruses like influenza and COVID-19. Additionally, shared facilities such as restrooms and cabin air circulation systems can further facilitate disease transmission. The potential for the transmission of severe acute respiratory syndrome (SARS) on commercial aircrafts is investigated in Olsen et al. (2005). This study underscores the importance of implementing measures to identify and isolate potentially infectious individuals during air travel, as well as maintaining good respiratory hygiene practices to reduce the risk of disease transmission on flights.

Note that air travel itself is not the sole driver of pandemic spread. Other factors, such as population density, healthcare infrastructure, public health measures, and individual behaviors, also play significant roles. However, air transport can act as an accelerant, facilitating the rapid spread of infectious diseases worldwide. This underscores the critical need for international cooperation and coordination in managing and mitigating the impact of pandemics.

It is essential to develop analytic and information and communication technology tools to manage the spread of pandemics through passenger air traffic. This involves establishing early warning systems that can detect the emergence of pandemics as quickly as possible and implementing immediate response procedures to prevent or, at the very least, control the spread of pandemics.

Dynamic networks (Chen et al., 2020; Dong et al., 2021) and network analysis (Watts and Strogatz, 1998; So et al., 2020; de Souza et al., 2021) are two of the most widely used methodologies proposed for detecting early warning signals based on confirmed daily cases of COVID-19 and air traffic information. A comparative analysis is conducted in Fragua et al. (2023) within a European context using data from the World Health Organization and Flightradar24 between February 15 and May 1, 2020. The study concludes that various combinations of network analysis based methods, utilizing different adjacency matrices that consider air traffic, yield good results. These methods can predict the evolution of the pandemic around 20 days in advance based on air passenger traffic.

On other hand, governments may implement restrictions on passenger air traffic and border closures to mitigate the spread of the disease. The impact on travel restrictions of the spread of

COVID-19 is investigated in Chinazzi et al. (2020). The study focuses on the early stages of the pandemic and examines how travel restrictions influenced the transmission of the virus. It suggests that travel restrictions implemented during the early stages of the COVID-19 pandemic played a limited but important role in delaying the spread of the virus within and from China. However, the study emphasizes that travel restrictions should be part of a broader strategy that includes public health measures to effectively control the pandemic. The influence of international travel and border control measures on the spread of the novel coronavirus (SARS-CoV-2) responsible for COVID-19 is examined in Wells et al. (2020). The study also focuses on the early stages of the pandemic and investigates how travel restrictions and public health interventions affected the global transmission of the virus.

A complete shutdown of air traffic could slow the spread, but the global impacts of such a measure would be enormous, both economically and socially. Throughout the COVID-19 pandemic, some countries temporarily closed their air traffic with others depending on the status of the pandemic in those countries. However, the level of pandemic incidence is not homogeneous across all countries, and other regions with low epidemiological incidences rate could be adversely affected.

Therefore, it would appear to be necessary to make intelligent decisions at a lower level, specifically concerning air connections between airports. This involves integrating the epidemiological risk of importing the pandemic and considering the economic and social impacts associated with the decisions made regarding air traffic into formal models. This is a multiobjective optimization problem with conflicting objectives (Jiménez-Martín et al., 2023).

In this paper, this optimization problem is addressed, in which international connections with the destination airports of a specific country could be opened or be closed for a certain time period taking into account epidemiological, economic, and political/social impacts. To do this, seven objective functions have been considered. Five of them constitute economic objectives, namely, to minimize: (i) the percentage revenue lost in destination airport catchment areas (business and tourism losses), (ii) the standard deviation of revenue lost in the catchment areas (evenly distributing, insofar as possible the losses between the influence catchment areas), (iii) the standard deviation of the losses of passengers per airline, (iv) the percentage of airport losses due to nonlandings of aircrafts (tax losses), and (v) the standard deviation of airport losses. Two social objectives are also considered: minimize (i) the percentage of passengers who miss their flights and (ii) the loss of connectivity in the passenger air traffic network.

The epidemiological impact is considered not as an objective but as a constraint, since a percentage reduction of the risk of pandemic importation at destination airports is established to be fulfilled by the optimal solution. Moreover, certain sociopolitical decisions could also restrict the solution space. For instance, a minimum level of traffic could be established with certain EU countries or capitals or the rest of the world in the period under analysis.

DM preferences on the relative importance of the objectives under consideration are quantified based on ordinal information, and the sum reciprocal (SR) method (Danielson and Ekenberg, 2014) is used to derive a surrogate weight vector, leading to a single weighted objective function. The binary particle swarm optimization (BPSO) metaheuristic (Nguyen et al., 2021) is then used to solve the binary nonlinear optimization problem to reach a compromise solution.

The methodology proposed in this paper is an improvement on Jiménez-Martín et al. (2023). The improved version incorporates new impacts, such as tourism and business losses in the catchment area of destination airports, as well as the tax losses at destination airport. Besides, a percentage reduction of the risk of pandemic importation, which was considered as an objective in the previous version, is now established as a constraint. Moreover, DM preferences are now quantified and incorporated into the paper, transforming the original multiobjective optimization problem into a single weighted optimization problem. Hence, the BPSO metaheuristic rather than the NSGA-III algorithm is now used to solve the problem and derive a compromise solution.

In this paper, the web-based decision support system (DSS) for risk reduction in pandemic spread based on the management of passenger air traffic (RRPS-PAT) is also introduced. This DSS allows DMs to parameterize the problem to be solved (time period, country of analysis, the percentage of targeted risk reduction, etc.), quantify their preferences by means of ordinal information, solve the resulting optimization problem using the BPSO metaheuristic and visualize/export solutions.

The paper is structured as follows. Section 2 models the optimization problem mathematically, including decision variables, objective functions, and constraints. In Section 3, the proposed methodology is described, including the quantification of DM preferences and the BPSO metaheuristic. The web-based DSS for RRPS-PAT is described in Section 4. The methodology is illustrated using the example of Spain with 38 national airports, involving 9678 flights during the time period from September 24 to October, 2020, in Section 5. Finally, some conclusions are provided in Section 6.

2. Modeling the problem

In this section, the problem is modeled as a nonlinear multiobjective optimization problem. Let us consider the sets of departure $Dep_i (i = 1, \dots, I)$ and destination airports $Dest_j (j = 1, \dots, J)$ and a time period of D days. For instance, in the illustrative example in Section 5, the destination airports correspond to Spanish airports, the time period is two weeks ($D = 14$ days), and the departure airports are airports around the world with connections to Spanish airports in the two weeks under consideration.

K is the number of airlines operating the flights under consideration and passengers are traveling for different reasons $l = 1, \dots, L$, including business and tourism.

The decision variables and information used in the model are first defined.

Decision variables x_{ij}^d represent the status of the connection between a departure airport $i \in \{1, \dots, I\}$ and destination airport $j \in \{1, \dots, J\}$ on day $d \in \{1, \dots, D\}$. x_{ij}^d are binary variables:

$$x_{ij}^d = \begin{cases} 0, & \text{if the connection between } i \text{ and } j \text{ is closed on day } d \\ 1, & \text{if the connection between } i \text{ and } j \text{ remains open on day } d. \end{cases}$$

F_{ij}^d denotes the set of flights corresponding to the connection between airports i and j on day d . Note that if a connection is closed, all the respective flights are canceled.

The following information is available:

- p_{ijkl}^d : Number of passengers flying from airport i to airport j with airline $k \in \{1, \dots, K\}$ for reason $l \in \{1, \dots, L\}$ on day d .
- b_{ijl} : Average expenditure per passenger traveling for reason $l \in \{1, \dots, L\}$ from the country where the departure airport i is located to the country where destination airport j is located.
- d_{ijf} : Charges paid by aircraft operating flight f from airport i to j .
- c_i : Connectivity of airport i .
- e_k^d : Variable denoting if airline k operates flights on day d :

$$e_k^d = \begin{cases} 0, & \text{if } \sum_{i=1}^I \sum_{j=1}^J \sum_{l=1}^L p_{ijkl}^d = 0 \\ 1, & \text{if } \sum_{i=1}^I \sum_{j=1}^J \sum_{l=1}^L p_{ijkl}^d > 0 \end{cases} \forall k, d.$$

- α_i^d : Variable denoting if there is at least a connection from airport i on day d :

$$\alpha_i^d = \begin{cases} 0, & \text{if } \sum_{j=1}^J \sum_{k=1}^K \sum_{l=1}^L p_{ijkl}^d = 0 \\ 1, & \text{if } \sum_{j=1}^J \sum_{k=1}^K \sum_{l=1}^L p_{ijkl}^d > 0 \end{cases} \forall i, d.$$

The problem simultaneously addresses seven conflicting economic and social objectives. First, the five *economic impacts* under consideration are described, involving airlines, airports and the regions (catchment areas) where airports are located:

- *Minimize the percentage of revenue lost in the catchment area of the destination airports (Z_1)*. The average length of stay and average daily expenditure of visitors by country of origin depending on the reason of the travel (mainly tourism and business) are taken into account to quantify b_{ijl} . Then, the proportion of lost revenue due to flight cancelations during the time period under consideration D is computed as follows:

$$\min Z_1 = \frac{\sum_{d=1}^D \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \sum_{l=1}^L b_{ijl} p_{ijkl}^d (1 - x_{ij}^d)}{\sum_{d=1}^D \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \sum_{l=1}^L b_{ijl} p_{ijkl}^d}.$$

- *Minimize the standard deviation of the percentage of revenue lost in the catchment areas of destination airports (Z_2)*. The aim is that the losses are equally distributed, insofar as possible, among the catchment areas. First, the percentage of revenue losses in each of the catchment areas during the considered period D is computed as the ratio of specific revenue losses in the catchment areas

due to connection closures and the scheduled revenue during the time period D . Then the average percentage and the standard deviation are derived:

$$\min Z_2 = \sqrt{\left(\sum_{j=1}^J \frac{\sum_{d=1}^D \sum_{i=1}^I \sum_{k=1}^K \sum_{l=1}^L b_{ijl} p_{ijkl}^d (1 - x_{ij}^d)}{\sum_{d=1}^D \sum_{i=1}^I \sum_{k=1}^K \sum_{l=1}^L b_{ijl} p_{ijkl}^d} - \frac{\sum_{j=1}^J \frac{\sum_{d=1}^D \sum_{i=1}^I \sum_{k=1}^K \sum_{l=1}^L b_{ijl} p_{ijkl}^d (1 - x_{ij}^d)}{\sum_{d=1}^D \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \sum_{l=1}^L b_{ijl} p_{ijkl}^d}}{\frac{\sum_{d=1}^D \sum_{j=1}^J e_k^d \sum_{i=1}^I \sum_{k=1}^K (1 - x_{ij}^d)}} \right)^2}.$$

- Minimize the standard deviation of the percentage of the losses of passengers per airline (Z_3). The aim is passenger losses, insofar as possible, among the airlines:

$$\min Z_3 = \sqrt{\left(\sum_{k=1}^K \frac{\sum_{d=1}^D \sum_{i=1}^I \sum_{j=1}^J \sum_{l=1}^L p_{ijkl}^d (1 - x_{ij}^d)}{\sum_{d=1}^D \sum_{i=1}^I \sum_{j=1}^J \sum_{l=1}^L p_{ijkl}^d} - \frac{\sum_{k=1}^K \frac{\sum_{d=1}^D \sum_{i=1}^I \sum_{j=1}^J \sum_{l=1}^L p_{ijkl}^d (1 - x_{ij}^d)}{\sum_{d=1}^D \sum_{i=1}^I \sum_{j=1}^J \sum_{l=1}^L p_{ijkl}^d}}{\frac{\sum_{d=1}^D \sum_{k=1}^K e_k^d \sum_{i=1}^I \sum_{j=1}^J (1 - x_{ij}^d)}} \right)^2}.$$

- Minimize the percentage of destination airport losses due to uncharged fees (Z_4). Airports impose fees on aircraft landing at the airport to be paid by the airline operating the flight. These fees depend on the weight of the aircraft, although some airports levy surcharges depending on the noise generated by the aircraft and the time of landing:

$$\min Z_4 = \frac{\sum_{d=1}^D \sum_{i=1}^I \sum_{j=1}^J \sum_{f \in F_{ij}^d} d_{ijf} (1 - x_{ij}^d)}{\sum_{d=1}^D \sum_{i=1}^I \sum_{j=1}^J \sum_{f \in F_{ij}^d} d_{ijf}}.$$

- *Minimize the standard deviation of the percentage of destination airport losses due to uncharged fees (Z_5).* The aim is that the losses are equally distributed, insofar as possible, among the destination airports:

$$\min Z_5 = \sqrt{\sum_{j=1}^J \left(\frac{\sum_{d=1}^D \sum_{i=1}^I \sum_{f \in F_{ij}^d} d_{ijf} (1 - x_{ij}^d)}{\sum_{d=1}^D \sum_{i=1}^I \sum_{f \in F_{ij}^d} d_{ijf}} - \frac{\sum_{d=1}^D \sum_{i=1}^I \sum_{f \in F_{ij}^d} d_{ijf} (1 - x_{ij}^d)}{\sum_{d=1}^D \sum_{j=1}^J \sum_{i=1}^I e_j^d (1 - x_{ij}^d)} \right)^2}.$$

Now, the two *social impacts* under consideration are described, accounting for canceled passenger flights and the loss of airport connectivity:

- *Minimize the percentage of passengers who miss their flights (Z_6).* The number of passengers lost in the time period D is computed as the sum of all passengers unable to travel in that period on connections that have been closed, divided by the number of passengers who were scheduled to travel:

$$\min Z_6 = \frac{\sum_{d=1}^D \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \sum_{l=1}^L p_{ijkl}^d (1 - x_{ij}^d)}{\sum_{d=1}^D \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \sum_{l=1}^L p_{ijkl}^d}.$$

- *Minimize the loss of air transport network connectivity (Z_7).* The connectivity data from the Airports Council International (ACI) Europe report using the NetScan method (ACI Europe, 2023) are considered. The disadvantage of these data is that they do not account for all international airports but are confined to airports in Europe, together with a few others dotted around the world. Therefore, when calculating connectivity loss, it was necessary to assign a default value of 0 to airports with no connectivity:

$$\min Z_7 = \sqrt{\sum_{i=1}^I \left(\frac{\sum_{d=1}^D \sum_{j=1}^J c_i (1 - x_{ij}^d)}{\sum_{i=1}^I c_i} - \frac{\sum_{i=1}^I \frac{\sum_{d=1}^D \sum_{j=1}^J c_i (1 - x_{ij}^d)}{\sum_{i=1}^I c_i}}{\sum_{d=1}^D \sum_{i=1}^I e_i^d} \right)^2}. \quad (1)$$

Regarding the *constraints* of the optimization problem under consideration, the percentage risk of pandemic importation at destination airports during the time period under consideration must not exceed a certain threshold. To do this, the risk of pandemic importation at a destination airport j on day d is computed as $r_j^d = \sum_{i \in A_j^d} r_{ij}^d$, where r_{ij}^d is the risk of pandemic importation at destination airport j from the departure airport i on day d , and A_j^d is the set of departure airports connected with the destination airport j on that day. This accounts for all flights from departure airport i to destination j on day d , $r_{ij}^d = \sum_{f \in F_{ij}^d} r_{ijf}^d$. For each flight, the optimization problem accounts for the epidemiological status of the catchment area of the departure airports i , the risk of contagion at departure airport i , and the risk of infection occurring during flight, which will depend on the duration on the flight and the separation between passengers (depending on the flight occupancy rate).

The first approach for quantification of the risk of virus transmission at airports based on deep learning and computer vision techniques was proposed in Rodríguez-Escabias (2023), such as the *YOLO V3* network used in the people detection (Redmon and Farhadi, 2018) or *Inception* used for mask recognition (Szegedy et al., 2016). There are also novel techniques for calculating interpersonal distances and close contacts. Moreover, the computation of the probability of passengers arriving at an airport being infected based on population mobility information sourced from the geolocation of mobile terminals was analyzed in a Spanish context with information from the Spanish Ministry of Transport, Mobility, and Urban Agenda in Carbonell (2022).

Besides, the epidemiological status at the end of the flight depends on the initial epidemiological status of the flight, its duration, and the safety measures taken on board the aircraft, which are calculated using the susceptible-infectious-recovered (SIR) method (Kermack and McKendrick, 1927). The SIR method proposes a system of difference equations that describes the transmission dynamics of viruses. It can be used to analyze the evolution of in-flight infection on the aircraft, and it depends on a number of parameters that have to be fixed for the virus under consideration (infection or disease transmission rate and recovery rate) and the context in which it is applied, that is, an aircraft in this case (García et al., 2021). A team of public health researchers studied how random movements on an aircraft can change the likelihood of passenger infection (Hertzberg et al., 2020). For instance, the Flight Health Research Team observed the behavior of passengers

and staff on 10 3.5 to 5 hours U.S. flights in order to estimate how many close encounters could lead to transmission on transcontinental flights.

Then, the risk of pandemic importation at the destination airports in the time period under consideration if all flights are operated is $\sum_{d=1}^D \sum_{j=1}^J r_j^d$, and the constraint is as follows:

$$\frac{\sum_{d=1}^D \sum_{i \in A_j^d} \sum_{j=1}^J \sum_{f \in F_{ij}^d} r_{ijf}^d x_{ij}^d}{\sum_{d=1}^D \sum_{j=1}^J \sum_{f \in F_{ij}^d} r_{ijf}^d} \leq R,$$

where R establishes a percentage reduction of the risk of pandemic importation at the destination airports for the solutions under consideration.

Finally, certain sociopolitical decisions could restrict the problem-solving space under consideration. For instance, a minimum level of traffic with certain EU countries or capitals or the rest of the world could be established in the period under analysis. This type of decisions can be easily modeled and incorporated into the problem-solving procedure. For instance, if it is established that at least one connection between Spain and all EU capitals should be kept open in the time period under consideration, the constraint would be modeled as follows:

$$\sum_{d=1}^D \sum_{i \in C, j \in S} x_{ij}^d \geq 1,$$

where C and S are the sets of airports located at EU capitals and Spanish airports, respectively.

3. Methodology

In this section, the proposed methodology based on the use of a metaheuristic to solve the multiobjective optimization problem under consideration is described. First, we focus on weighting methods based on ordinal information. The problem should account for DM preferences in terms of the relative importance of the objectives by means of a simple ranking of importance, arranged in descending order from the most to the least important objective.

Thus, the original multiobjective optimization problem is transformed into a single-objective weighted optimization, whose optimal solution is a compromise/satisfying solution since it incorporates DM preferences. The BPSO metaheuristic is proposed to solve this optimization problem.

Finally, a DSS that allows the DMs to parameterize the optimization problem under consideration (time period, country of analysis, the percentage of targeted risk reduction, etc.) and to visualize results (optimal solution with values for the economic and social impacts and maps showing canceled flights) is briefly described.

3.1. Quantifying decision maker preferences based on ordinal information

As pointed out above, multiobjective optimization problem solving leads to an approximation of the Pareto (efficient) set. Then, DM preferences in terms of weights representing the relative importance of the objectives could be incorporated to the problem to derive a compromise or satisfying solution within the Pareto set. Alternatively, DM preferences could be quantified before solving the problem and then a single-objective optimization problem would have to be solved leading to the corresponding optimal/compromise solution, which implies a shorter problem-solving execution time.

However, weight elicitation is considered to the most complex task in multiobjective decision-making processes (Rezaei et al., 2022). Experience suggests that DMs are often unable to provide accurate information about the relative importance of the objectives under consideration, leading to what is known as decision making with partial information (Rios Insua and French, 1991; Puerto et al., 2006; Sarabando et al., 2016). Different weighting methods can be found in the literature, highlighting the use of ordinal information on weights, where the DM has to provide a ranking of importance of objectives, arranged in descending order from the most to the least important ones. This is less stressful on the DM and makes it suitable for group decision making, where individual preferences might be captured through the corresponding ranking. Moreover, DMs could provide additional information in terms of the strength of the differences between the weights of consecutive objectives in such a ranking by means of a ranking of differences, a semantic scale, precise/imprecise cardinal information, ratio-based methods, or preference statements.

See Chergui and Jiménez-Martín (2024) for a review of weighting methods in the literature dealing with ordinal information on objectives only, including surrogate weighting methods (SWMs) (Barron and Barrett, 1996; Roberts and Goodwin, 2002; Danielson and Ekenberg, 2014; Hatefi, 2023), methods based on the notions of pairwise and absolute dominance (Eum et al., 2001; Salo and Hamalainen, 2001; Mateos et al., 2007; Ahn and Park, 2008; Sarabando and Dias, 2009; Aguayo et al., 2014), and the SMAA2 method (Lahdelma and Salminen, 2001). Weighing methods used when additional information is available (Danielson et al., 2014; de Almeida et al., 2016; Ahn, 2017; Danielson and Ekenberg, 2017; Pamučar et al., 2018) are also reviewed in Chergui and Jiménez-Martín (2024), also examining the analyses carried out by different authors to compare their performance with the aim of recommending a weighting method for each scenario of available ordinal information.

The SR (Danielson and Ekenberg, 2014) is a recommended method when the DM can provide only ordinal information, since it outperforms the other SWMs, as well as the modification of classical decision rules and dominance measuring methods, in all the comparison analyses carried out.

Like all SWMs, the SR method selects a weight vector from a set of admissible weights to represent the set. It is an additive combination of the rank sum and rank reciprocal weight functions (Stillwell et al., 1981). If the ordinal information provided by the DMs is represented as

$$\mathbf{w} \in W = \left\{ \mathbf{w} = (w_1, \dots, w_n) \mid w_1 \geq w_2 \geq \dots \geq w_n \geq 0, \sum_{i=1}^n w_i = 1 \right\},$$

where n is the number of objectives, then the weight vector derived from the SR method is computed as follows:

$$w_i = \frac{1/i + \frac{n+1-i}{n}}{\sum_{j=1}^n (1/j + \frac{n+1-j}{n})}, i = 1, \dots, n.$$

If the DM is capable of providing additional information, the method to be applied will depend on the nature of such information. Specifically, the minimizing squared deviations from extreme points method (Ahn, 2017) will be used if a ranking of the differences between the weights of consecutive objectives is provided, whereas the corresponding preference strength SR method (Danielson and Ekenberg, 2017) will be applied when the strengths of the differences between the weights of consecutive objectives are represented by a semantic scale (equally important, slightly more important, more important, and much more important).

In all the above cases, ordinal information with or without additional information, a weight vector will be derived and incorporated into a weighted additive function, which incorporates normalized objectives, leading to a single-objective optimization problem.

3.2. Binary particle swarm optimization

The BPSO (Nguyen et al., 2021) is an extension of the traditional particle swarm optimization (PSO) algorithm to binary problems. PSO is a population-based metaheuristic inspired by the social behavior of flocks of birds and schools of fish.

BPSO has been applied in multiple practical scenarios. For instance, it has been used to generate association rules from transactional datasets (Sarath and Ravi, 2013), to detect available frequencies in cognitive radio to enhance the utilization of system resources (Taha and al Nadi, 2013), to explore highly profitable item sets instead of frequent item sets in transactional database (Lin et al., 2017), to select features with the goal of enhancing performance in spam detection problems (Zhang et al., 2012), or to allocate workload to sensors in a network to achieve energy efficiency and reduce communication volume (Yang et al., 2014).

The basic idea of the BPSO is as follows. The first population of particles is randomly generated. Each particle has a velocity and a position in the solution space. The velocity determines the direction and magnitude of the particle's movement. The position represents the current candidate solution.

The velocity and position of each particle are updated based on its previous best-known position (personal best) and the best-known position of any particle in the entire population (global best). The update formulas incorporate inertia, personal cognitive factors, and social factors to guide particles toward better solutions.

Since BPSO deals with binary solutions, additional mechanisms are in place to handle binary representation. For instance, a threshold may be used to convert real-valued positions to binary values.

The algorithm iteratively updates particle positions until a termination criterion is met. The best solution found during the optimization process, typically the global best position, is considered the final optimized solution to the problem.

Now, let us introduce the BSPO algorithm in more detail. It is assumed that the search space is d -dimensional, $d = I \times J$, and the i th particle of the swarm can be represented by a d -dimensional position vector $X_i = (x_{i1}, x_{i2}, \dots, x_{id})$. The velocity of the particle is the rate at which the particle changes its bit values. Two vectors, $\vec{V}_i^0$ and $\vec{V}_i^1$, are considered for each particle, representing the probabilities of the bits of the particle changing to zero or to one, respectively. Then, the probability of change in the j th bit of the i th particle is as follows:

$$V_{ij}^c = \begin{cases} V_{ij}^1, & \text{if } x_{ij} = 0 \\ V_{ij}^0, & \text{if } x_{ij} = 1 \end{cases}. \quad (2)$$

$\vec{V}_i^1$ and $\vec{V}_i^0$ are updated as follows. The best position visited so far for a particle is denoted as P_{ibest} and the global best position for the particle as P_{gbest} . Then,

$$\begin{aligned} \text{if } P_{ibest}^j = 1, & \text{ then } d_{ij,1}^1 = c_1 r_1 \text{ and } d_{ij,1}^0 = -c_1 r_1, \text{ else } d_{ij,1}^0 = c_1 r_1 \text{ and } d_{ij,1}^1 = -c_1 r_1, \\ \text{if } P_{gbest}^j = 1, & \text{ then } d_{ij,2}^1 = c_2 r_2 \text{ and } d_{ij,2}^0 = -c_2 r_2, \text{ else } d_{ij,2}^0 = c_2 r_2 \text{ and } d_{ij,2}^1 = -c_2 r_2, \end{aligned}$$

where d_{ij}^1 and d_{ij}^0 are two auxiliary variables, r_1 and r_2 are uniform random values in $(0,1)$, which are generated in each iteration, and c_1 and c_2 represent the importance of the best solution obtained by each particle individually and of the best global solution achieved by all the particles collectively, respectively. Then,

$$V_{ij}^1 = wV_{ij}^1 + d_{ij,1}^1 + d_{ij,2}^1, \text{ and } V_{ij}^0 = wV_{ij}^0 + d_{ij,1}^0 + d_{ij,2}^0, \quad (3)$$

where w is the inertia term, which represents the intensity of particle movement in the search space.

After updating particle velocity, $\vec{V}_i^0$ and $\vec{V}_i^1$, the velocity of change is calculated according to Equation (2).

A normalization process is performed using a sigmoid function:

$$V'_{ij} = \text{sig}(V_{ij}) = \frac{1}{1 + e^{-V_{ij}}}, \quad (4)$$

and the next particle state is established as

$$x_{ij}(t+1) = \begin{cases} \hat{x}_{ij}(t), & \text{if } r_{ij} < V'_{ij} \\ x_{ij}(t), & \text{if } r_{ij} > V'_{ij} \end{cases}, \quad (5)$$

where $\hat{x}_{ij}$ is the complementary of x_{ij} , that is, if $x_{ij} = 0$, then $\hat{x}_{ij} = 1$, and if $x_{ij} = 1$, then $\hat{x}_{ij} = 0$. r_{ij} is randomly generated from $U[0, 1]$.

The algorithm for the binary PSO can be summarized as follows (Ahmadi, 2007):

1. Initialize the swarm X_i , the particle positions are randomly initialized within the hypercube. Elements of X_i are randomly selected from binary values 0 and 1.
2. Evaluate the performance F of each particle, using its current position $X_i(t)$.

3. Update the best performance so far of each particle if necessary: if $F(X_i(t)) < F(P_{ibest})$, then $F(P_{ibest}) = F(X_i(t))$ and $P_{ibest} = X_i(t)$.
4. Update the global best particle if necessary: if $F(X_i(t)) < F(P_{gbest})$, then $F(P_{gbest}) = F(X_i(t))$ and $P_{gbest} = X_i(t)$.
5. Change the particle velocity, $\vec{V}_i^0$ and $\vec{V}_i^1$, according to Equation (3).
6. Calculate the change of bit velocity, $\hat{V}_i^c$, according to Equation (2).
7. Randomly generate r_{ij} and move each particle to a new position using Equation (5).
8. Go to step 2, and repeat until convergence.

The adaptation of the BPSO metaheuristic to the problem under consideration and the parameter setting is as follows. First, the number of particles corresponds to the number of connections in the analyzed period, since a high number of particles implies a larger coverage of the search space.

The inertia parameter (w) is updated after each iteration using the following expression, $w = w_{init}u^{-t}$, where $w_{init} = 0.9$ is the initial value of w , $u = 1.005$, and t is the iteration number (Rathore and Sharma, 2017). This method was chosen because a high value promotes exploration, while a value close to 0 promotes exploitation, thus balancing both.

The importance of the best solution found by each particle individually and of the best global solution found by all the particles collectively, c_1 and c_2 , is rated as 1.5 (Engelbrecht, 2007). Note that if $c_1 \gg c_2$, then each particle is overly individualistic, making convergence difficult, whereas if $c_2 \gg c_1$ premature convergence to a possible local optimum can occur because the particles will follow a single particle. Furthermore, it is known that convergence is assured if the parameters satisfy the condition $1 > w > (1/2) * (c_1 + c_2) - 1 \geq 0$.

The stopping condition is based on the amount of diversity in the population (Zielinski and Laur, 2007). After each iteration, the particles are ordered from best to worst fitness, and the run is stopped if a percentage P of the best particles are within M of the global best particle. Due to the computational burden of having to sort the individuals after each iteration, a relatively low percentage P of 25% is chosen, which was, nevertheless high enough to achieve reliable convergence. On the other hand, the parameter M is 0.001. This value was chosen empirically by observing how fitness evolves in this particular problem by altering the bits of a solution.

Finally, the choice of some solutions over others is based on three rules to calculate the best solution for each particle and the best global solution. When comparing two solutions: (i) if both solutions are feasible, the one with the better fitness is chosen; (ii) if one of the solutions is infeasible, the feasible solution is chosen; and (iii) if both solutions are infeasible, the one with the smaller constraint violation is chosen. In this problem, the constraint violation is computed as the distance between the imported epidemiological risk of the solution to the limit specified before the execution.

The implementation of the BPSO algorithm in Java has been validated using the test problems in Ahmadi (2007) including the following functions: sphere (continuous, convex, and unimodal functions), Rosenbrock (the global optimum lies inside a long, narrow, parabolic shaped flat valley), Griewangk (the function interpretation changes with the scale: the general overview suggests a convex function, the medium-scale view suggests the existence of local extrema, and, finally, a zoom on the details indicates a complex structure of numerous local extrema) and Rastrigin (highly multimodal function).



Fig. 1. Login.

4. A decision support system for risk reduction in pandemic spread based on the management of passenger air traffic

A web-based DSS for the RRPS-PAT system has been designed and developed to parameterize and solve the corresponding binary single-objective optimization problem and visualize the results.

A Neo4J graph-oriented database is used, including flight information from Flightradar (purchased by the Spanish ATM Research, Development and Innovation Reference Center, CRIDA), aircraft occupancy data from the International Transport Association, information on global pandemic incidence from the John Hopkins University, and connectivity data from the ACI.

The front-end of the application was developed with Angular Framework 16 using Typescript and HTML languages, whereas the back-end (BPSO metaheuristic, Neo4j database queries, etc.) was programmed with Spring Boot 3 using Java.

Figure 1 shows an application welcome message prompting the user to log in. Once the user has logged in, the application home page displays the main menu, including the *New project*, *Load project*, *About*, and *Logout* options.

If the *New project* option is selected, the dialog box shown in Fig. 2 is displayed, where the user can parameterize the problem to be solved, including the dates, the required percentage reduction of the risk of pandemic importation at the destination airports (using a horizontal slider bar), sociopolitical constraints on air traffic, the user preferences on the objectives under evaluation, and the parameters associated with the BPSO metaheuristic.

Regarding the user preferences on the objectives under evaluation, he/she must drag and drop economic and social objectives listed on the left into the right-hand side boxes to compile a ranking in descending order of importance. This ranking serves as input for the SR method, which determines the weights of the objectives.

The screenshot displays the 'Project description' interface, which is divided into several sections:

- Project description:** Includes a 'Project name' field (marked as mandatory) and a 'Run optimization' button.
- Dates:** Features 'Start date' and 'End date' fields, both set to 01/01/2020.
- Problem constraints:** Contains a slider for 'Maximum percentage risk of pandemic importation at Spanish airports during optimization' set at 50%, and radio buttons for 'Connections to be maintained to capitals in each region' (Europe, North America, South America, Asia, Africa).
- Quantification of decision maker's preferences:** This section is further divided into:
 - Economic objectives:** A list of objectives including 'Losses in the catchment area of destination airports', 'Uniform distribution of losses in catchment areas', 'Uniform distribution of passenger losses per airline', 'Airport losses', and 'Uniform distribution of airport losses'.
 - Social objectives:** A list of objectives including 'Cancelled passenger Rights' and 'Loss of connectivity'.
 - Objectives ranking:** A column with empty boxes for ranking the objectives, with up and down arrows for reordering.

Arrows indicate the flow from the 'Project description' section to the 'Dates' and 'Quantification of decision maker's preferences' sections.

Fig. 2. Project description.

Note that the objective value ranges for the scenario under consideration are clearly indicated in order to avoid the well-known range bias in weight elicitation processes (von Nitzsch and Weber, 1993). As shown in Fig. 2, when the DM hovers the mouse over the target names, a text box containing information about the value range for that target in the scenario under consideration appears. In Fig. 2, the mouse is positioned over the “Losses in the catchment area of destination airports” objective and the text shown is “If all connections were cancelled in the time period under consideration, the losses in the catchment areas would be over 610,621,844 euros.”

Regarding the sociopolitical constraints on air traffic, the user must use check buttons to identify the capitals all over the world (Europe, North America, South America, and Asia) whose connections should be kept open.

Note that default values for the parameters of the BPSO metaheuristic are proposed. However, they could be modified by an advanced and experienced user with in-depth knowledge of the metaheuristic, as shown in Fig. 3, which explains the role that each parameter plays in the BPSO metaheuristic.

Once the problem to be solved has been parameterized, the user clicks on the *Run optimization* button to solve the problem and visualize the results.

As shown in Fig. 4, the optimal solution will be displayed on a map, where the blue nodes represent destination airports and the green nodes represent departure airports. If the corresponding connection between airports is in red, then the connection is closed, whereas connections in black remain open. If the user clicks on a connection, then information about the airports that it connects

Fig. 3. Parameters of the BPSO metaheuristic.

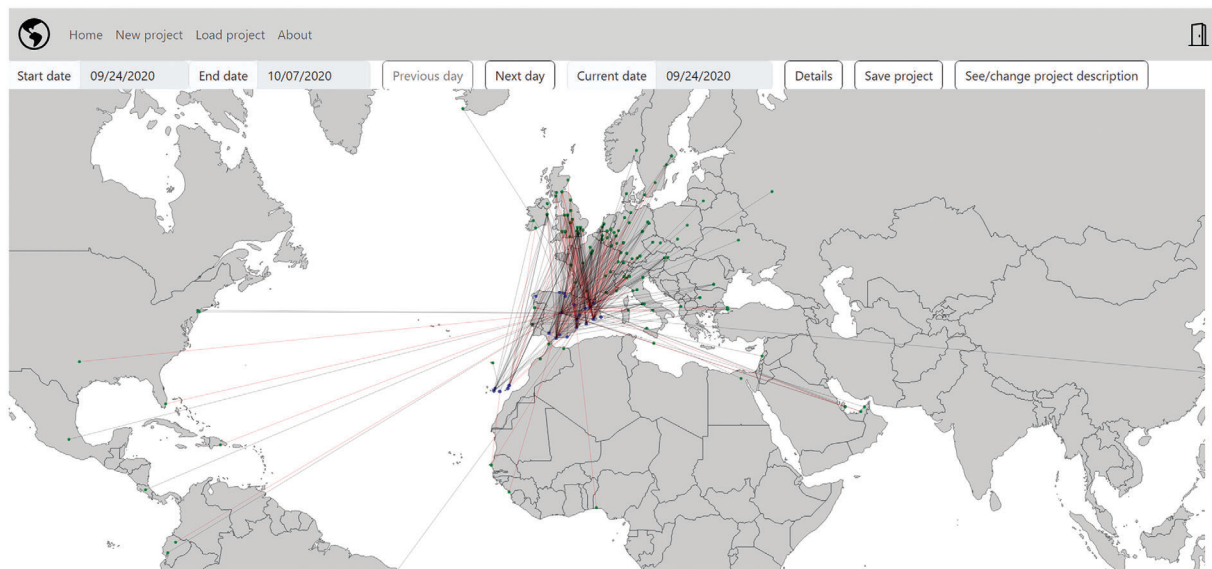


Fig. 4. Graphical solution to the problem.

and the number of passengers traveling on the specified date are displayed. Finally, the problem parameterization and corresponding optimal solution can be saved into a project file that can be loaded in the application in the future.

The map has a zoom option, and the user can use the buttons in the top left corner to visualize the solution for the different days within the specified time period.

The results can also be displayed in different tables (*Details* button in Fig. 4), which provide information on the impacts of the optimal solution on the economic and social objectives, on the flights under consideration (origin, destination, airline, number of passengers, whether it is canceled, etc.),

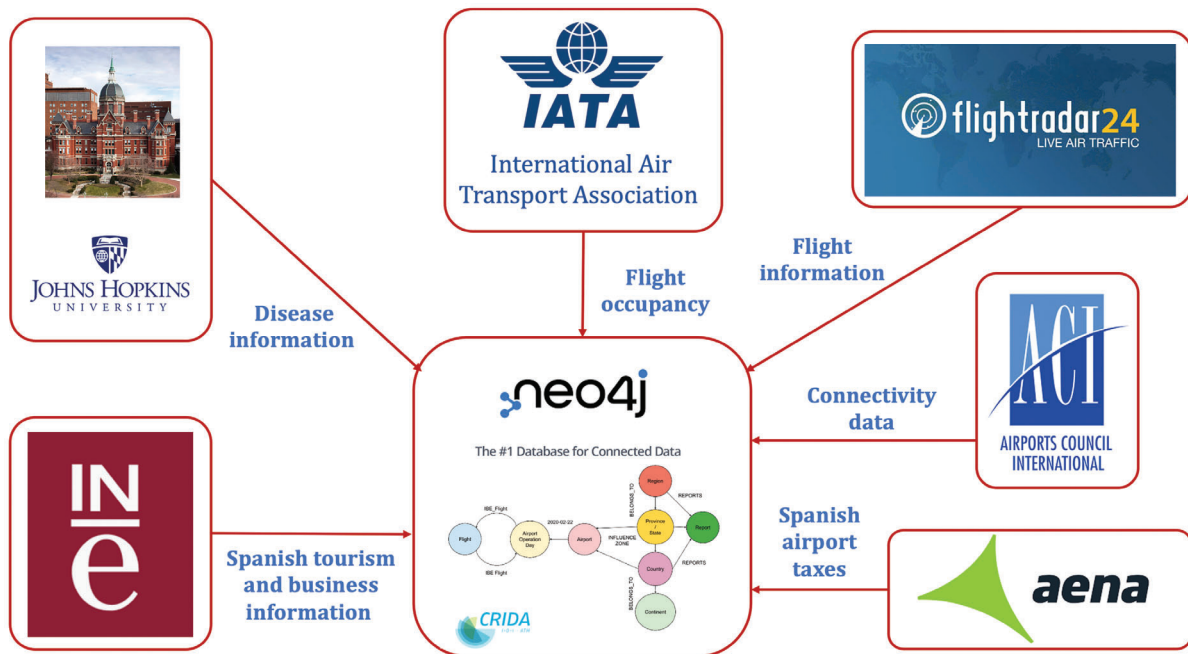


Fig. 5. Data sources.

on the destination airport catchment areas, airlines, and airports; see Fig. 6). These maps and tables can be exported into HTML and Excel files, respectively.

The Typescript and HTML languages were used to develop the interface of the RRPS-PAT system, whereas Java was used to codify the BPSO metaheuristic and its communication with the interface and the Neo4J database. A demo version of the RRPS-PAT system is available at <https://138.4.92.155:8081/>.

5. Illustrative example

In this section, the proposed methodology with the COVID-19 pandemic is illustrated in a Spanish context, involving the 38 Spanish airports with international air traffic for a two-week period, from September 24, 2020 to October 7, 2020. This amounts to 5000 connections with 9678 flights from 237 international airports to Spanish airports. The airports with the highest number of connections were the Adolfo Suárez Madrid-Barajas (820), Josep Tarradellas-El Prat Barcelona (767), Palma de Mallorca (641), and Málaga-Costa del Sol airports (610).

For the analysis, the Neo4J graph-oriented database was extended containing flight information, aircraft occupancy data, information on global pandemic incidence, and connectivity data; see Fig. 5.

Specifically, Spanish airport taxes available at www.aena.es/es/aerolineas/tarifas.html were also incorporated to the Neo4J graph-oriented database. These taxes mainly depend on aircraft weight. However, some airports (Alicante-Elche, Barcelona-El Prat, Bilbao, Gran Canaria, Ibiza, Adolfo Suarez Madrid Barajas, Málaga-Costa del Sol, Palma de Mallorca, Seville, Tenerife North, Tenerife

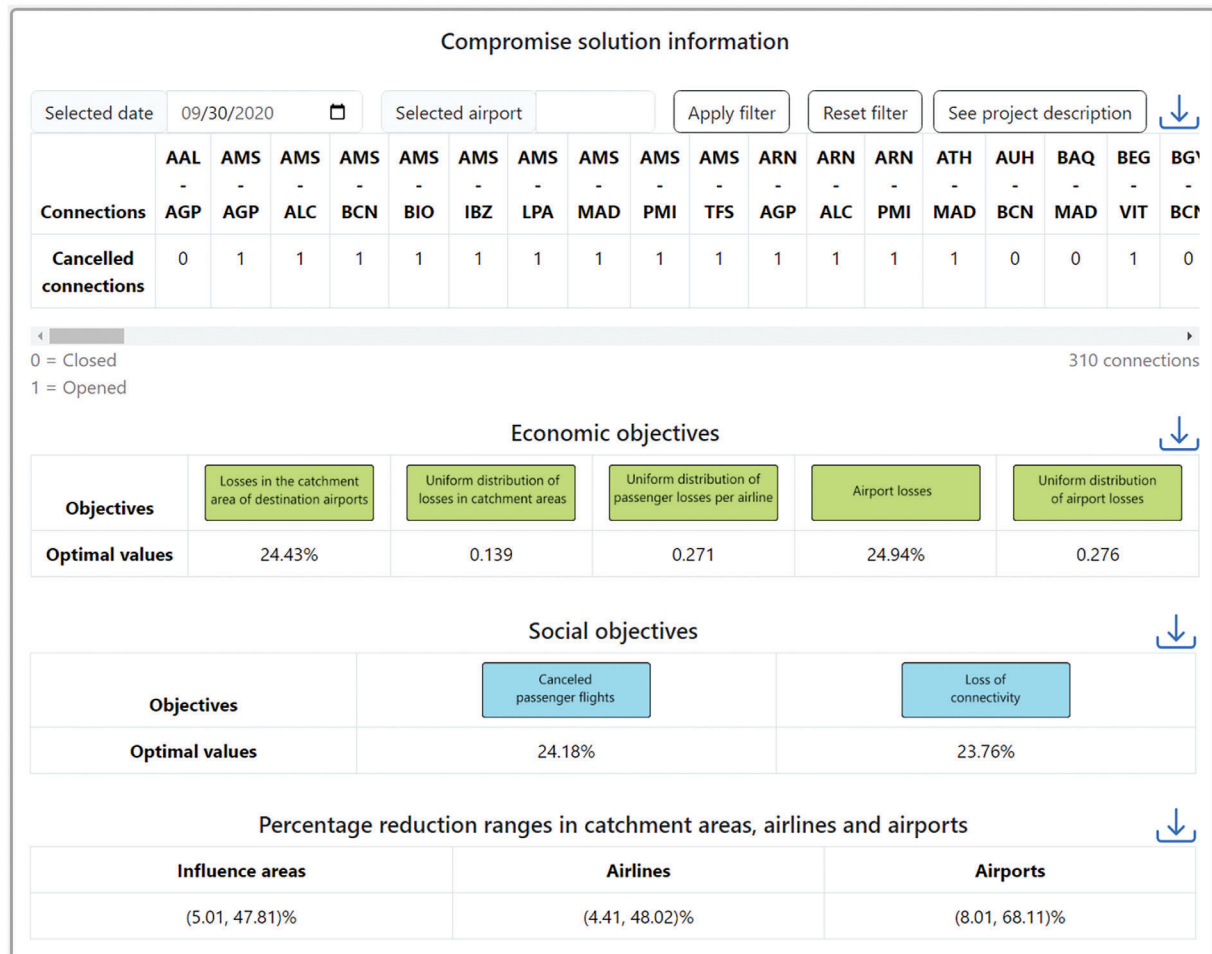


Fig. 6. Compromise solution information.

South or Valencia) charge more depending on the aircraft noise level and the time of landing. For this purpose, AENA (the company responsible for airport management in Spain) has established a classification of the aircraft according to their noise level, which is used to calculate the surcharge.

Besides, the Spanish Institute of Statistics (INE) publishes the average expenditure of a passenger arriving in Spain depending their country of origin and the reason (business and leisure/holiday/other) for their visit to Spain. Specifically, the following information is incorporated into the Neo4J database:

- Number of visitors by Spanish region of destination, reason for traveling, and country of origin/residence (Visitors) in order to calculate the number of people per flight traveling for business or for holiday/leisure.
- Average daily expenditure per person classed by reason for traveling and country of origin (Expenditure).

Table 1

Defined scenarios based on the reduction of the risk of pandemic importation and the relative importance of objectives

	% Reduction of the risk of pandemic importation	Economic objectives	Social objectives	Overall
Scenario 1	25	$\{Z_1 > Z_2 > Z_3 > Z_4 > Z_5\}$	$\{Z_6 > Z_7\}$	Economic > Social
Scenario 2	25	$\{Z_1 > Z_4 > Z_2 > Z_5 > Z_3\}$	$\{Z_6 > Z_7\}$	Economic > Social
Scenario 3	25	$\{Z_1 > Z_2 > Z_3 > Z_4 > Z_5\}$	$\{Z_6 > Z_7\}$	Social > Economic
Scenario 4	25	$\{Z_1 > Z_4 > Z_2 > Z_5 > Z_3\}$	$\{Z_6 > Z_7\}$	Social > Economic
Scenario 5	50	$\{Z_1 > Z_2 > Z_3 > Z_4 > Z_5\}$	$\{Z_6 > Z_7\}$	Economic > Social
Scenario 6	50	$\{Z_1 > Z_4 > Z_2 > Z_5 > Z_3\}$	$\{Z_6 > Z_7\}$	Economic > Social
Scenario 7	50	$\{Z_1 > Z_2 > Z_3 > Z_4 > Z_5\}$	$\{Z_6 > Z_7\}$	Social > Economic
Scenario 8	50	$\{Z_1 > Z_4 > Z_2 > Z_5 > Z_3\}$	$\{Z_6 > Z_7\}$	Social > Economic
Scenario 9	75	$\{Z_1 > Z_2 > Z_3 > Z_4 > Z_5\}$	$\{Z_6 > Z_7\}$	Economic > Social
Scenario 10	75	$\{Z_1 > Z_4 > Z_2 > Z_5 > Z_3\}$	$\{Z_6 > Z_7\}$	Economic > Social
Scenario 11	75	$\{Z_1 > Z_2 > Z_3 > Z_4 > Z_5\}$	$\{Z_6 > Z_7\}$	Social > Economic
Scenario 12	75	$\{Z_1 > Z_4 > Z_2 > Z_5 > Z_3\}$	$\{Z_6 > Z_7\}$	Social > Economic

- Average duration (in days) of stays by country of origin (Duration).

It is assumed that the country of residence of all passengers on a flight is the country of origin of that flight, since it is not possible to ascertain exactly where all passengers on a flight reside. It is also assumed that no passenger is transferring, that is, the country of destination for all passengers is always Spain.

In this illustrative example, 15 scenarios are considered. First, three different levels for the percentage reduction of the risk of importing COVID-19 at Spanish airports are considered: 25, 50, and 75. Note that the number of closed connections (and canceled flights) is obviously expected to be higher for scenarios requiring a greater reduction of the risk of pandemic importation.

Furthermore, the relative importance of objectives may lead to different scenarios. As ordinal information (a ranking from the most to least important objective) is used to represent DM preferences, two situations in which economic impacts are more important than the social effects, and vice versa, are accounted for. With regard to social impacts, it is considered that the percentage of passengers who miss their flights (Z_6) is more important than the loss of connectivity (Z_7) in all scenarios. The economic impact on catchment areas of destination airports is more important than the impact on airports, which is, in turn, more important than the impact on airlines.

Thus, the 12 scenarios shown in Table 1 will be considered. Note that the difference between Scenarios 1-2, 3-4, 5-6, 7-8, 9-10, and 11-12 is that the objectives representing the equal distribution of economic damage caused across catchment areas (Z_2), airports (Z_5), and airlines (Z_3) are considered less important than the total impact on the catchment areas where airports are located (Z_1), and the percentage of losses at airports due to uncharged landing fees (Z_4).

In addition to the scenarios described in Table 1, Scenarios 1a, 5a, and 9a are considered, which are same as Scenarios 1, 5, and 9, respectively, but account for a political decision on air traffic as a constraint. This decision refers to opening each of the connections with the capital of EU countries on at least one day of the period under analysis.

The values in the objective functions of the optimal solutions for the different scenarios are shown in Table 2.

Table 2

Optimal values in the objective functions for the compromise solution

	Z_1 (%)	Z_2	Z_3	Z_4 (%)	Z_5	Z_6 (%)	Z_7 (%)
Scenario 1	24.43	0.139	0.271	24.94	0.276	24.18	23.76
Scenario 1a	24.51	0.140	0.275	25.10	0.280	24.56	23.34
Scenario 2	24.50	0.139	0.272	24.91	0.265	24.31	23.70
Scenario 3	24.91	0.191	0.281	24.53	0.288	24.77	23.88
Scenario 4	24.93	0.180	0.298	24.19	0.265	24.22	23.68
Scenario 5	49.33	0.207	0.318	44.26	0.326	44.31	41.00
Scenario 5a	49.98	0.229	0.337	45.29	0.342	45.61	42.95
Scenario 6	49.29	0.206	0.317	43.16	0.306	43.42	37.20
Scenario 7	49.74	0.220	0.316	43.66	0.326	44.08	36.42
Scenario 8	49.90	0.221	0.324	43.85	0.287	44.09	37.49
Scenario 9	74.61	0.277	0.348	71.80	0.373	70.78	67.78
Scenario 9a	74.97	0.347	0.397	74.63	0.429	74.49	69.02
Scenario 10	74.30	0.278	0.348	71.30	0.334	70.43	66.77
Scenario 11	74.94	0.269	0.354	71.26	0.373	70.52	64.86
Scenario 12	74.79	0.268	0.345	72.19	0.280	71.02	67.09

First, we find that the values of the optimal solution for the seven objectives corresponding to the first four scenarios are lower than for the next four scenarios, and they are, in turn, lower than for the last four scenarios. This is logical since a higher reduction of the risk of pandemic importation implies a higher number of closed connections and, consequently, greater economic and social impacts.

It is striking that the percentage loss with respect to objective Z_1 (percentage of revenue lost in the catchment area of destination airports) is very close to 25%, 50%, and 75%, if the risk of pandemic importation is reduced by 25%, 50%, and 75%, respectively.

A similar phenomenon is observed for objectives Z_4 (percentage of airport losses), with percentage reductions of (24.19, 25.19)%, (43.16, 44.27)%, and (71.80, 72.19)% when the risk of pandemic importation is reduced by 25%, 50%, and 75%, respectively.

For objective Z_6 (percentage of passengers whose flight is canceled), the percentage reduction is about 24%, 44%, and 70%, whereas they amount to about 23% (36.42, 41.00)% and (64.86, 67.78)%, respectively, for Z_7 (percentage of connectivity loss).

The difference for a given percentage risk reduction in the specified scenarios for objectives Z_1 , Z_4 , and Z_6 is less than 1%. This implies that decision making is more or less irrelevant with respect to these objectives. The same applies to objective Z_7 for a risk reduction rate of 25%. However, if risk reduction is set at 50% and 75% for Z_7 for Scenarios 5 and 7, differences peak at 4.58% and 2.94%, respectively. This could be explained by the fact that economic impacts are more important than social impacts in Scenario 5, whereas social impacts are considered more important in Scenario 7, where the reduction for the social objective Z_7 is smaller (i.e., it has a better value).

What about the other three objectives? Note that they establish that losses should be equally distributed across catchment areas (Z_2), airlines (Z_3), and airports (Z_5).

First, the dispersion increases when the percentage of imported risk reduction is greater in all three cases. However, homogeneity is higher (dispersion is less) for catchment areas (Z_2) than for airlines (Z_3), which, in turn, is slightly more homogeneous than for airports (Z_5).

Table 3
Percentage reduction ranges in catchment areas, airlines and airports

	Influence areas (%)	Airlines (%)	Airports (%)
Scenario 1	(5.01, 47.81)	(4.41, 48.02)	(8.01, 68.11)
Scenario 1a	(4.85, 48.02)	(4.30, 48.11)	(7.95, 68.14)
Scenario 2	(5.07, 47.90)	(5.41, 66.04)	(5.01, 50.17)
Scenario 3	(5.16, 48.20)	(4.37, 48.90)	(7.90, 68.14)
Scenario 4	(4.96, 47.74)	(6.68, 67.90)	(4.62, 49.42)
Scenario 5	(10.83, 64.26)	(10.67, 67.08)	(9.33, 79.29)
Scenario 5a	(7.96, 66.11)	(6.20, 70.81)	(5.92, 81.48)
Scenario 6	(10.92, 64.41)	(9.26, 79.02)	(10.51, 66.95)
Scenario 7	(10.41, 65.21)	(10.71, 67.01)	(9.44, 80.30)
Scenario 8	(10.60, 64.01)	(9.29, 79.17)	(10.83, 68.41)
Scenario 9	(13.37, 70.77)	(12.41, 72.75)	(13.89, 85.01)
Scenario 9a	(8.31, 76.69)	(7.53, 79.93)	(7.60, 90.12)
Scenario 10	(13.22, 70.54)	(12.76, 85.61)	(11.79, 72.10)
Scenario 11	(12.98, 70.36)	(12.83, 73.14)	(12.42, 84.95)
Scenario 12	(13.43, 71.02)	(13.03, 84.71)	(12.31, 73.44)

Finally, regarding Scenario 1a, where an additional constraint is incorporated regarding connections with EU capitals, the results are very similar to Scenario 1. This could be explained by the fact that the optimal solution in Scenario 1 is very similar to Scenario 1a, fulfilling the constraint on EU capital connections since the percentage reduction of the risk of pandemic importation is 25%. The difference between Scenarios 5 and 5a and Scenarios 9 and 9a since the percentage reduction of the risk of pandemic importation is now 50% and 75%, respectively. As a result, a higher number of flights are canceled, leading to solutions that differ more than when only a 25% is considered.

Table 3 shows the minimum and maximum percentage reduction of revenue in catchment areas, losses of airline passengers and of revenue at destination airports, respectively. The higher the percentage reduction of the risk of pandemic importation, the wider the range of percentage reductions in all three cases. Besides, ranges are narrower for catchment areas than for airlines and airports, as expected on the basis of the dispersion (Z_2 , Z_3 , and Z_5).

The intervals for Scenarios 1a, 5a and 9a are always wider than for scenarios where there is no constraint on the connection between Spain and EU capitals. Moreover, variability increases as the risk of pandemic importation is reduced, that is, the difference between the intervals of Scenarios 9 and 9a is greater than between Scenarios 5 and 5a, which is larger than between Scenarios 1 and 1a.

Figure 6 shows the RRPS-PAT system outputs for Scenario 1, including both the optimal objective function values for the compromise solution and the corresponding percentage reduction ranges in catchment areas, airlines, and airports, together with a list of flights specifying their status, that is, pointing out whether they have been canceled.

6. Conclusions

This paper deals with a complex optimization problem aimed at determining the connections between airports that should be closed to ensure that a country's risk of pandemic importation during

a time period is reduced by a specified percentage. A web-based DSS has been implemented, which allows the DM to parameterize the problem, quantify his/her preferences, solve the resulting binary single-objective optimization problem, and visualize/export the optimal solution.

The potential of the DSS has been illustrated in several scenarios (with different percentage reductions of the risk of pandemic importation and DM preferences) focused on Spanish airports for a two-week time period. The DSS helps DMs to take intelligent decisions at the air connection level taking into account different economic and social impacts, whose relative importance is quantified. It helps the DM to study different scenarios and analyze the consequences of possible decisions.

Regarding the current limitations of the RRPS-PAT system, note that the Neo4J database includes historical information (flights, aircraft occupancy data, and information on global pandemic incidence) for the time period from January 22, 2020 to October 20, 2020, and tourist and business information and airport taxes in Spain. Therefore, the system can only be used for scenarios referred to that time period and in Spanish.

It would be necessary to dynamically update the Neo4J database with information for the time period under consideration (as of the date on which the analysis is performed) to use the RRPS-PAT system in a real context. Besides, the Neo4J graph-oriented database should be extended to incorporate all the applicable information at a European level (airport fees, tourism, and business information, etc.) in order to apply the RRPS-PAT system to countries other than Spain.

Another limitation of the RRPS-PAT system is that it requires global pandemic incidence information at analysis time. Therefore, no information on the evolution of incidence rates would be available about the time period under analysis. For the time being, the incidence rate is considered to be constant during the time period under evaluation. However, a model for predicting the evolution of incidence could be built into the system. This is proposed as a future research line.

There are several potential improvements for the web-based DSS RRPS-PAT, which are also proposed as future research lines. Currently, the DSS does not include information on passenger ticket prices, which would allow an accurate analysis of the loss of airline revenue due to flight cancelations (economic impact). At the moment, only the number of passengers whose flights have been canceled (social impact) is considered.

The execution time for a scenario is about 5 hours with a laptop (Intel Core i7-116G7 4.7 GHz, 32 GB RAM). One proposed future research line is to improve the metaheuristic to reduce the response time by analyzing a more advanced version of the BPSO and incorporating parallelization techniques.

The WELLBY concept was proposed in Frijters and Krekel (2021). WELLBY is a subjective measure of the well-being for individuals. WELLBYs are cardinal measures, whereby countries can aggregate and compare their scores, even at different moments in time. This measure could be incorporated into the analysis as a social impact. The formula and methodological details on how this measure is calculated are reported in Frijters and Sanchis (2024), and the WELLBY World Database was recently created and updated using Economics @Intelligence (Economics @Intelligence, 2022).

Besides, a tweet sentiment analysis tool, such as the one described in Aguarón et al. (2024) based on the analysis of X messages and the use of lexicons in a Spanish context, could be integrated with the RRPS-PAT system in order to incorporate a new social impact to the analysis: the impact of the decisions made on passenger air traffic on population sentiment. Note that decisions on air traffic would be revised periodically. Then, the impact of previous decisions on population sentiment

could be taken into account to predict the impact of a new decision. To do this, the percentage of canceled flights in previous decisions could be saved together with the accumulated valence of related X messages during a specific time period from the date the decision was taken. Then, a function on the basis of this historical data could be dynamically built to predict the impact of new decisions on population sentiment.

Finally, another proposed future research line is to incorporate other weighting methods to the RRPS-PAT system, prompting the DM to provide other types of information than ordinal information. Thus, the DM would be able to use the weighting method that requires the information he/she is willing/able to provide.

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