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Fuzzy Logic, Pairwise Comparison, and Q-learning Methods to Investigate the Pandemic Infection Risk for Health Monitoring of Airports

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ABSTRACT

A pandemic virus infection risk in air travel by fuzzy Logic, pairwise comparison, and Q-learning methods is investigated in this study. The vastness of airports and the shortage of health monitoring devices for covering all of the airports were one of the problems of general aviation. In this way, this study proposed a risk assessment analysis to find a distribution policy to allocate the health monitoring devices based on the airports' infection risk score. In this paper, Kish Airline's transportation regarding different flight destinations is considered as a case study. Furthermore, fuzzy logic, pairwise comparison, and Q-learning methods were considered for the pandemic infection risk. Furthermore, the infection risk score related to the pandemic infection risk by Pearson correlation coefficient was investigated. Also, flight destinations located in the studied area with a higher infection risk score compared to other areas were analyzed by fuzzy logic, pairwise comparison, and Q-learning methods. Moreover, the three mentioned methods were compared and the results demonstrated that fuzzy logic overcomes the pairwise comparison and Q-learning methods for this study. Finally, results showed this study will be efficient for the next pandemic virus in general aviation.

1. Introduction

In recent years, pandemic diseases have been spread. The spread of infectious diseases caused decreases in passengers in aerial transportation, especially in the initial peak of any pandemic. On the other hand, compliance with health protocols increased airport and airline costs. After that, to reduce costs of respecting health protocols and deal with the decrease in passengers, the airlines were required to research the reduction of the pandemic costs on the general aviation industry besides improving health [1,2].

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Pandemic viruses such as the coronavirus (severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2), COVID-19), which originally emerged in Wuhan, China in December 2019 being officially termed a pandemic by the World Health Organization (WHO) 11 March 2020 [3]. As of 22 November 2020, more than `100 million succumbed to this disease worldwide and more than one million deaths caused by the virus have been recorded [4]. While many countries are still dealing with controlling the COVID-19 outbreak by imposing quarantine orders, governments tried to ease air travel restrictions while considering economic and health concerns at the same time [5,6]. In this way, studying the behavior of pandemic viruses such as COVID-19 in air travel is necessary and will help airports and airlines for the next probable pandemic [7].

Air travel played an important role during the last pandemic outbreak. Populated airport terminals are high-risk places for infection by contagious diseases like COVID-19. In addition, infected passengers could transfer the virus by themselves to other destinations. Due to the necessity of continuing flights during the pandemic outbreak, one of the proposed solutions to reduce the risk of infection in airport terminals and airplanes is to equip the airport gates with health monitoring devices like infrared cameras and rapid test kits to detect the passengers' symptoms [8]. Considering the vastness of airports, full coverage of all flight routes is impossible due to the limited amount of health monitoring devices [9,10]. To address this issue, proposing a risk assessment analysis based on artificial intelligence to find a policy for the distribution of health monitoring equipment based on airports' infection risk score will be necessary for the next world pandemic such as COVID-19.

Several studies have already been reported regarding the air travel roles in spreading viruses in different regions [11-14]. The risk of passengers infected with a pandemic at the different stages of travel such as collecting the boarding pass, airplane boarding, and setting in the airplanes was studied [15-19]. Several prediction methods were studied in risk assessment models in cognitions disses using artificial intelligence. However, their analyzed data sets were limited and their methods cannot apply to complicated flight destinations or their risk assessment models may be optimistic [20,21]. Also, more studies regarding artificial intelligence and aerospace application could be investigated in [22-24].

The last studies have already been reported regarding the air travel roles in spreading viruses by methods that were not mighty in predicting infection risk. So, their analyzed data sets were limited and their methods cannot apply to complicated flight destinations. The novel results of this research demonstrate the flight destinations at the different stages of infection risk by considering allocating more monitoring devices. Hence, considering restriction rules at the destinations with high infection risk score air travel would be much safer and more reliable for passengers. It should be noted, full coverage of all flight routes is impossible due to the limited amount of monitoring. In this paper, Kish Airlines' flight destination airports were considered as a case study. It is necessary to address this issue, proposing a risk assessment analysis based on artificial intelligence such as fuzzy logic, Q learning, and pairwise comparison to find a policy for the distribution of health monitoring equipment based on airports' infection risk. The three mentioned algorithms could be used as a ranking algorithm that scores parameters by classifying them based on the linguistic scores and assigning a number to classified parameters in output. In reinforcement learning, the Q-learning method, where the learner automatically communicates with the environment at each stage by making inferences and actions. The goal of the learner in the reinforcement learning problems is to learn the optimal decision-making policy to maximize the sum of rewards received from the environment during the time of solving the problem. Hence, the mentioned method is suitable for investigating the pandemic risk assessment. Also, fuzzy logic, pairwise comparison, and Q-learning methods were compared to address the verification of the proposed method.

2. Problem Statement

This study encompassed weekly infection risk assessment in Kish Airlines as a case study for flight destinations between different cities. All of the cities confirmed the pandemic disease in the selected destinations. The risk of pandemic disease infection risk in the destination airports is considered based on three key parameters namely: a) pandemic disease infection rate, b) destination city population, and c) the number of departures flight in the airports. It should be noted, the source of data belonged to World Health Organization (WHO) as reported in [3,4].

3. Methods

In this study, Fuzzy Logic, pairwise comparisons method, and Q-learning methods approaches were employed for risk assessment associated with pandemic disease infection risk in air travel. The three mentioned algorithms could be used as a ranking algorithm that scores parameters by classifying them based on the linguistic scores and assigning a number to classified parameters in output.

3.1. Fuzzy Logic

To deal effectively with the ever-increasing complexity of investigating problems, studying, modeling, and solving new problems and many other various matters, it is necessary to create and innovate new computing methods that are closer to the ways of thinking and learning of humans. The main goal is that, as far as possible, computers can investigate and solve very complex scientific issues and problems with the same ease that the human mind is capable of understanding and making quick and appropriate decisions.

Fuzzy logic is a multi-valued logic in which the logical value of variables can be any real number between 0 and 1 and themselves. This logic is used to implement the concept of partial correctness so that the degree of correctness can be any value between completely true and completely false. Fuzzy logic is one of the multi-valued logics and relies on the theory of fuzzy sets. Fuzzy sets themselves result from the generalization and expansion of definite sets.

Numerical variables are used in mathematical calculations and linguistic variables are used in fuzzy theory. Linguistic variables in fuzzy theory are expressed based on the linguistic values that are in the set of expressions. Linguistic expressions are attributes of linguistic variables. Fuzzy logic has the following subsections:

Rules - includes all the rules and conditions provided by experts for the decision-making system.

Fuzzification - This stage converts crisp inputs or numbers into fuzzy sets.

Inference Engine - Determines the degree of matching between the fuzzy input and the rules. According to the input section, a decision is made about the rules to be activated.

Defuzzification - The defuzzification process converts fuzzy sets into definite values. In Fuzzification and Defuzzification, there are membership functions that play the main role.

A membership function is a graph that defines how each point of the input space is mapped to a membership value between 0 and 1. If the degree of membership of an element of a set is equal to zero, it means that the member does not exist in the set, and if the degree of membership of a member is equal to one, it means that the member is completely included in the set. But if the degree of membership of a member is between zero and one, this number represents the degree of gradual membership [25,26].

3.2. Pairwise comparisons method

Pairwise comparison analysis is useful for weighing the relative importance of different alternatives. This method is especially useful in cases where priorities are not clear precisely, cases where the options are completely different, cases where the evaluation criteria are subjective, or cases where the options are competing in terms of importance. The purpose of the pairwise comparison analysis is to reduce the maximum number of external sources of dispersion by forming similar pairs concerning the desired variable. In such cases, instead of analyzing with the help of observations, the difference between the observations is checked as a variable.

This tool provides a framework for comparing each option against the other options and shows the difference in importance between the options. Moreover, the mentioned method is useful when the choice between many different options is uncertain. This becomes more challenging when the choices are quite different from each other or the selection criteria are quite relative.

Pairwise comparison analysis helps to obtain the relative importance of some different options. In other words, the analysis of paired comparison or double comparison helps to measure the importance of some options relative to each other. This makes it easier to choose the most important problem to solve or to choose a solution more effectively. It also helps to set priorities when there are conflicting demands on resources [27]. Scoring of statistical variables based on the method of pairwise comparisons is one of the advantages of this method.

Classification of statistical variables based on importance is one of the important topics in statistical modeling. Deciding to determine the importance of each parameter when the relationship between the function variables of each parameter is not transparent to each other is a difficult and time-consuming process. To rank the importance of statistical variables to each other, decision-making methods are based on the type of data. The number of dependent variables and the amount of information provided for each variable have been compiled and presented. Decision-making methods for classifying variables based on variable structure include deterministic classification, random classification, and multi-mode decision-making [28].

In this article, to score the variables related to the risk of the COVID-19 virus, the method of paired comparisons has been used. The method of paired comparisons is one of the multi-mode decision-making methods that is used to score and rank the members related to a category in various [29]. In the method of paired comparisons, the studied parameters such as (population, percentage of population over 50 years old, rate of infection with the covid-19 virus, etc.) are measured two by two concerning each other, in the case where the member α with probability $\mathbf{M_{ij}} = (0,1)$ is superior to β member.

The importance of each parameter is determined and scored based on ***Table 1***. The output of the pairwise comparison method is considered a random and non-independent variable from a statistical point of view. The method of classifying the members based on the unpredictable score $\boldsymbol{\tau_i}$, which is the probability of the member α winning over the selected comparative member β, is defined as ***Eq. (1)***.

$$\tau_i \coloneqq \frac{1}{n-1}\sum_{j\neq 1} M_{ij} \tag{1}$$

Table 1. Definition of descriptive and numerical scores

Score descriptive score	Numerical
Not preferred	0
Somewhat preferred	0.25
Reasonably preferred	0.5
Highly preferred	0.75
Absolutely preferred	1

In order to determine the importance of each of the selected variables, first, by using the method of pairwise comparisons, the influence coefficient of each of the selected parameters was obtained based on ***Table 1*** and ***Eq. (1)***.

3.3. Q-learning Method

In reinforcement learning, the learner automatically communicates with the environment at each stage by making inferences and actions. At each stage, the learner chooses action A by understanding the state S located in the environment. Action *A* causes a change in the state S and sends the scalar signal R which represents the amount of reward in each stage to the learner so that the quality of the decision taken at that stage can be analyzed by the learner (see ***Figure 1***).

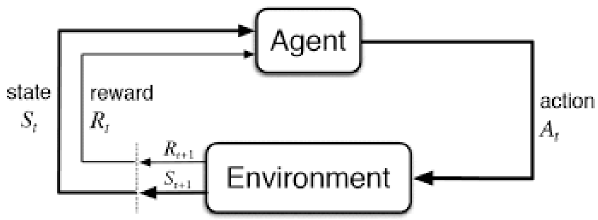

Figure 1. Q-learning Method

The goal of the learner in the reinforcement learning problems is to learn the optimal decision-making policy to maximize the sum of rewards received from the environment during the time of solving the problem. The policy Π:S→A represents a function that informs the learner of the decided quality level at each stage. The reinforcement learning problem can be expressed as a problem with a limited number of actions and states in discrete time based on the Markov decision process learning process.

Markov’s learning process consists of four main variables S, A, T and R. Variables S and A respectively express the finite number of states and actions that can be performed in the problem. Also, the variable T is equal to the expression S×A→Π(S), which is the state transfer function. In this expression, Π(S) represents the distribution probability of the variable of finite states or S.

Also, T (A, S, S') indicates the probability of moving from state S to S' by performing action A. Finally, the variable R is expressed by the expression S×A→R, which represents the scalar reward function.

The aim of the learner in the reinforcement learning algorithm is to learn the optimal policy Π*:S→A, which expresses how state S is performed by accepting action A. Also, the variable Π represents the optimal policy that is learned by the learner by repeating the trial-and-error process during the learning process. To solve problems related to the distribution of resources, the Q-learning method, which is one of the most widely used algorithms based on reinforcement learning, can be used [30,31]. Q learning method was introduced to learn the optimal Π* strategy in problems where R and S variables are known. Considering Q* (S, A) as the amount of prize earned by the learner for state S and action A, and also considering the variable γ as the learning coefficient, which has a numerical value between 0 and 1. Setting the algorithm's heuristic policy is defined by ***Eq. (2)***. The optimal policy Π* can be defined as Π*≡max Q* (S, A) (***Eq. (3)***). The simplified form of ***Eq. (3)*** can be rewritten as ***Eq. (4)***, in which R is the square matrix of the law that defines the framework of permissible behaviors for each state-action pair Q* (S, A).

$$Q^*(S,A) = R(S,A) + \gamma \sum_{s' \in S} T(A,S,S') \tag{2}$$

$$Q^*(S,A) = R(A,A) + \gamma \sum_{s' \in S} T(A,S,S')\, max_{a'}.\, Q^*(S',A') \tag{3}$$

$$Q^*\big(S(i),A(i)\big) = R\big(S(i),A(i)\big) + \gamma\, ma\, x\big[Q\big(S(i+1),A(i \in [1,N])\big)\big] \tag{4}$$

In ***Eq. (4)***, ***i*** is the order of learning and N is the final number of repetitions of the learning method.

4. Results

Firstly, by using the method of pairwise comparison in ***Table 2***, the linguistic parameter of the infection risk is scored regarding ***Eq. (1)***.

Table 2. Scoring of parameters related to the risk of the COVID -19 virus

	population	Percent of the population over 50years old	The rate of infection with COVID -19	The total number of infected people	Active bed regarding population	The total number of flights
population	_	0.25	0.5	0.25	0.25	0.5
Percent of the population over 50years old	0.75	_	0.75	1	0.5	0
The rate of infection with COVID -19	0.5	0.25	_	0.5	0.25	0.5
The total number of infected people	0.75	0	0.5	_	0.5	0.5
Active bed regarding population	0.75	0.5	0.75	0.5	_	0.5
The total number of flights	0.5	1	0.5	0.5	0.5	_

In the next step, to measure the correlation between the related parameters to the pandemic infection risk the scores were calculated regarding the Pearson correlation coefficient based on the ***Eq. (5)*** for each parameter. Finally, an optimal policy for the distribution of health monitoring devices based on the infection risk is assessed [32-34].

$$r = \frac{(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \tag{5}$$

Where $r =$ correlation coefficient, $x_i =$ values of the x-variable in a sample, $\bar{x} =$ mean of the values of the x-variable, $y_i =$ values of the y-variable in a sample, $\bar{y} =$ mean of the values of the y-variable.

Furthermore, ***Table 3*** investigates the number of departures flight, COVID-19 infection rate, and population of Kish airline.

Table 3. Airports departures flight, COVID-19 infection rate, and population for Kish airline

City	Airport	Number of departures flight	COVID-19 infection rate	Population
Tehran	Mehrabad International Airport	130533	39.650	8693706
Mashhad	Shahid Hasheminejad International Airport	67726	4.550	3001184
Isfahan	Isfahan International Airport	41248	15.390	1961260
Shiraz	Shiraz Shahid Dastgheib International Airport	21942	3.927	1565572
Yazd	Yazd-Shahid Ayatollah Sadooghi Airport	6143	5.637	529673
Bnader Abbas	Bandar Abbas International Airport	36644	1.150	526648
Abadan	Abadan International Airport	6798	3.453	231476
Asaluyeh	Asalouyeh Airport	9466	0.427	73958
Kish	Kish International Airport	26992	1.150	39853

Moreover, data associated with the pandemic infection risk in Kish airline destination airports was collected. The study process was shown in ***Figure 2***.

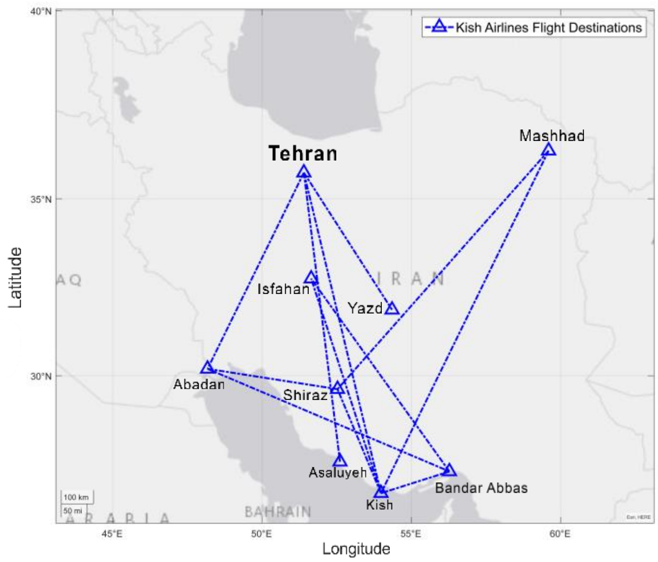

Figure 2. Kish airline flights distribution

In the first step, the infection risk score for the selected airports was investigated by pairwise comparison method (see ***Table 2***). In the second step, fuzzy logic, pairwise comparison, and Q-learning were used to calculate infection risk in selected airports. In fuzzy logic, it is important to assign membership functions. In this way, the infection risk score by selected methods was normalized by the gauss-shape membership functions. Also, pairwise comparison and Q-learning calculation are considered concerning the ***Eqs. (1-5)***. The estimation of the relationship between infection risk scores was studied by fuzzy logic and Q-learning. Moreover, the associated parameters to the pandemic infection risk score are done by calculating the Pearson correlation coefficient (see ***Figures 3-5***). A positive Pearson correlation coefficient close to +1 means a positive linear correlation between the calculated scores and the selected parameters. Furthermore, the relationship between infection risk scores calculated by fuzzy logic, pairwise comparison, and Q-learning methods and associated parameters to pandemic infection risk score is achieved (In this way, see ***Table 4***).

Table 4. Pearson correlation coefficient for fuzzy logic, pairwise Comparison, and Q-Learning

Input Parameter	Fuzzy Logic	Pairwise Comparison	Q-Learning
Number of departures in	0.976	0.957	0.876
Population	0.964	0.934	0.913
COVID-19 infection rate	0.954	0.940	0.895

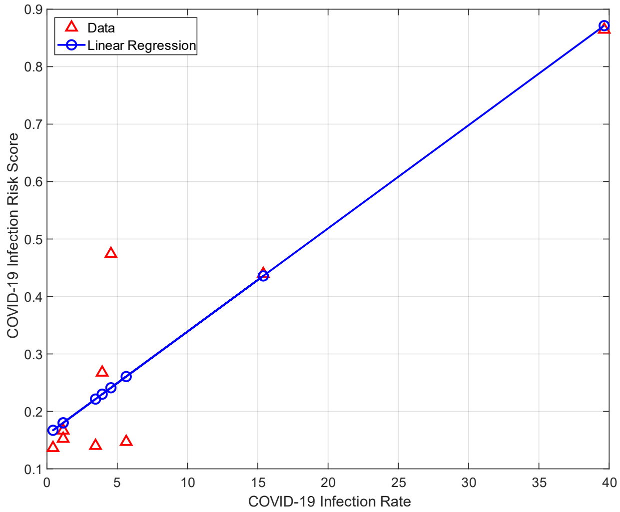

Figure 3. COVID-19 Infection Risk Score versus COVID-19 Infection Rate

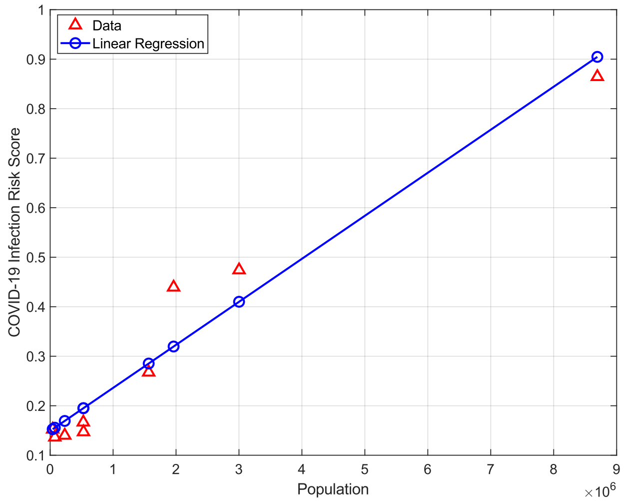

Figure 4. COVID-19 Infection Risk Score versus Population

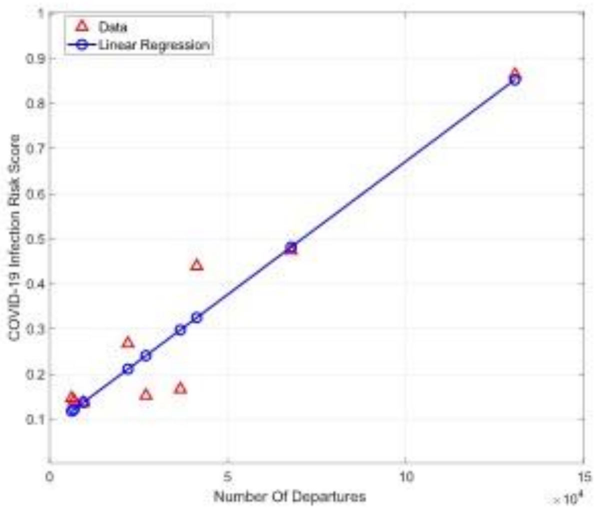

Figure 5. COVID-19 Infection Risk Score versus Number of Departures

Table 5 compares fuzzy logic, pairwise comparison and Q-learning methods.

Table 5. Comparing fuzzy logic, pairwise comparison and Q-learning methods

	Fuzzy Logic		Pairwise Comparison		Q-Learning		
City	Infection risk score	score	Infection risk score	score	Infection risk score	score	Risk color
Tehran	0.964	1.00	0.932	1.00	0.910	0.981	RED
Mashahd	0.574	0.463	0.569	0.276	0.552	0.255	YELLOW
Isfehan	0.739	0.716	0.651	0.698	0.681	0.311	ORANGE
Shiraz	0.267	0.180	0.226	0.103	0.211	0.098	YELLOW
Yazd	0.846	0.914	0.844	0. 816	0.765	0.807	ORANGE
Bnader-e-Abbas	0.366	0. 416	0.325	0.402	0.306	0.395	YELLOW
Abadan	0.245	0.150	0.228	0.132	0.202	0.124	YELLOW
Asaluyeh	0.136	0.06	0.092	0.05	0.087	0.03	YELLOW
Kish	0.252	0.121	0.132	0.118	0.104	0.103	YELLOW

Finally, ***Figure 5*** shows the bubble maps for the infection risk in flight destinations regarding the average score of the three mentioned methods in ***Table 5***.

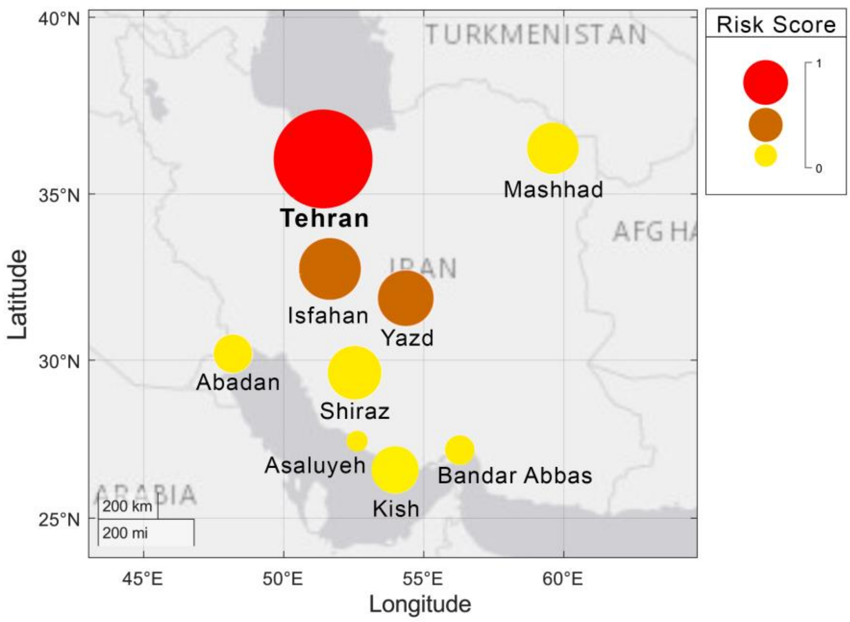

Figure 6. Bubble maps for the infection risk in flight destinations

Based on ***Table 5***, ***Figure 6*** demonstrates categorizing flights and destinations into three different groups namely, red, orange, and yellow. In the red group flight destinations with an infection risk score of 0.666 to 1 are selected. Tehran is the only flight destination that has a full score of 1 which is located in the red group. Furthermore. In the yellow group, the flight destinations with an infection risk score of 0.333 to 0.666 were allocated. Isfahan and Yazd are the cities with the middle risk of infecting risk at their airports. Finally, in the yellow group, 66% of all selected flight destinations with small chances of infection are located. Most of the selected destinations include Mashhad, Shiraz, Bnader-e-Abbas, Abadan, Asaluyeh, and Kish are located in this group.

Since fuzzy logic and pairwise comparison methods have better results based on ***Tables 4,5***, in ***Figure 7*** the amounts of COVID-19 infection risk regarding the two mentioned methods for different cities are given.

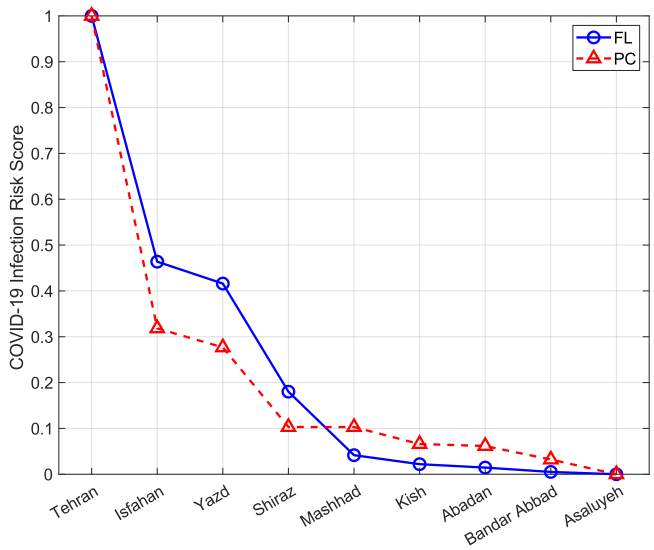

Figure 7. COVID-19 infection risk regarding fuzzy logic and pairwise comparison methods

5. Discussion

This study analyzed a pandemic infection risk (such as COVID-19) in the domestic flight destinations of Kish Airlines in nine different cities in Iran. This study reported herein that due to the risk of infecting the virus in closed and populated places such as airports. The pandemic virus outbreak is a serious public health problem for people who need to choose air travel during pandemics. Several studies have investigated pandemic infection risk in air travel, but few of them calculate infection risk in flight destinations including the virus transition risk in the airport terminals and airplanes for specific flight routes.

The results of this research demonstrate the flight destinations at the different stages of infection risk by considering allocating more monitoring devices. Hence, considering restriction rules at the destinations with high infection risk score air travel would be much safer and more reliable for passengers.

From ***Figure 5*** a more infection risk in airports that took place in populated cities was observed. Importantly, the highest infection risk is belonging to Mehrabad Airport in Tehran which acts as a flight hub for distributing airplanes to different flight destinations in Iran. By considering the high infection rates in Tehran, Mehrabad international airport can act as a central station for sending the pandemic virus into other cities. These findings warn of the important role of the populated airport in the central cities in increasing infection rates by sending infected passengers to a wide range of cities on domestic flights.

Furthermore, destinations located in the central area of Iran including Isfahan and Yazd has higher infection risk score in comparison to flight destinations located at the south and east side regions of Iran. This means cities that are located in the central regions are eligible to have a higher infection rate. Thus, in the mentioned regions health authorities should be considered imposing restriction rules in the airport to control the infection risk. Tourism and economic factors are important to a better understanding of pandemic infection risk in air travel in different cities and provinces. In Tehran, Isfahan, and Yazd cities that are important due to their tourism, many people choose them for travel, consequently the number of pandemic cases growth rapidly. Consequently, the strengthening of health monitoring stations at the airport terminals in the cities with the high infection risk such as Tehran, Isfahan, and Yazd we recommend. These cities are among the most popular travel destination on domestic flights in Iran. Additionally, Shiraz, Mashhad, and Kish have high air traffic, which probably they will encounter an increase in their infection risk if they do not consider establishing health stations at their flight terminals.

The pandemic infection risk analysis enabled us to visualize the airports and air travels roles in the spread of the pandemic in the destinations. Besides, the detection of airports with a high infection risk, geostatistical models can guide national public health authorities to impose more strict rules and controls to make air travel more reliable and safer for passengers through the pandemic outbreak.

6. Conclusion

Altogether, the results of this study showed that the pandemic outbreak affected the reliability and safety of air travel. The results demonstrate the risk of infection in the flight destinations of Kish Airlines in Iran. The flight destinations located in the populated cities in central regions of Iran had a higher infection risk score compared to the other analyzed cities. Fuzzy logic, pairwise comparison, and Q-learning methods are considered to assess the infection risk. Also, the results demonstrate the three mentioned methods are compared, and fuzzy logic has the best results. Pandemic outbreaks represent a serious public health problem in air travel, and its impact may be greater, considering the capability of air travels in transferring infected cases to other safe regions. Thus, by the allocation of health monitoring devices in airports with higher infection risk scores the risk of infection could be decreased considerably.

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