Digital Health and Informatics Innovations for Sustainable Health Care Systems
J. Mantas et al. (Eds.)

doi:10.3233/SHTI240784

Sensor-Based Fuzzy Inference of COVID-19 Transmission Risk in Cruise Ships

Georgios TRIANTAFYLLOU[a], Georgia SOVATZIDI[a], George DIMAS[a], Panagiotis G. KALOZOUMIS[a], Dimitris DRIKAKIS[b], Ioannis W. KOKKINAKIS[b], Ioannis A. MARKAKIS[c], Christina GOLNA[c] and Dimitris IAKOVIDIS[a,1]
[a] *Department of Computer Science and Biomedical Informatics, University of Thessaly, Lamia, 35100, Greece*
[b] *Institute for Advanced Modelling and Simulation, University of Nicosia, Nicosia, CY-2417, Cyprus*
[c] *Health Policy Institute, Maroussi, 15123, Greece*

Abstract. Cruise ships are densely populated ecosystems where infectious diseases can spread rapidly. Hence, early detection of infected individuals and risk assessment (RA) of the disease transmissibility are critical. Recent studies have investigated the long-term assessment of transmission risk on cruise ships; however, short-term approaches are limited by data unavailability. To this end, this work proposes a novel short-term knowledge-based method for RA of disease transmission based on fuzzy rules. These rules are constructed using knowledge elicited from domain experts. In contrast to previous approaches, the proposed method considers data captured by several sensors and the ship information system, according to a recently proposed smart ship design. Evaluation with agent-based simulations confirms the effectiveness of the proposed method across various cases.

Keywords. Airborne transmission, fuzzy logic, fuzzy rules, cruise ships, agent-based simulation.

1. Introduction

Cruise ships are closed, densely populated ecosystems that favor rapid infectious disease transmission. Such incidents could be prevented by using a sensor-based system capable of detecting symptoms of a disease in indoor areas of the ship. In this context, knowledge-based and probabilistic approaches have been used for risk assessment (RA) of disease transmission on-board [1]. These methods usually leverage evidence-based risk factors, *e.g.*, occupancy, heating, ventilation, air conditioning, and passenger exposure to the pathogen, retrieved from the literature [1–4]. However, they do not utilize risk factors identifiable by sensors, *e.g.*, microphones for cough detection [1], and only a few aim at assessing the short-term risk of transmission [4]. To this end, this paper proposes a knowledge-based method implemented through fuzzy rules for RA of short-term COVID-19 transmission (Figure 1). A knowledge-based approach was preferred due to the limited data availability of short-term disease transmission in cruise ships. The proposed method considers six risk factors in accord with the sensors, *e.g.*, microphones and thermal

[1] Corresponding Author: Dimitris Iakovidis; E-mail: diakovidis@uth.gr.

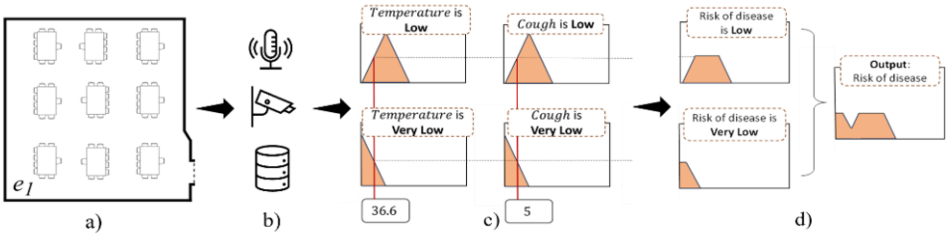

Figure 1. Overview of the RA method. a) Monitored environments; b) Installed sensors; c) Fuzzy rules; d) Risk assessment.

cameras, included in the smart ship design proposed in [1], as part of the HS4U[2] project [5]. The sensors used in this project adhere to the "privacy by design" policy and the passengers consent to be monitored before boarding the ship. By utilizing these sensors, the RA system is activated each time a symptom is detected.

To generate the fuzzy rules, the contribution of each factor to the RA of COVID-19 transmission was defined based on related literature and consulting domain experts. The inference process is easy to understand since it incorporates semantic knowledge encoded by linguistic equivalents enabled by fuzzy logic [6]. Moreover, the uncertainty of the RA process is quantified as a confidence score estimated by the response of the risk membership function. An agent-based modelling (ABM) tool is used to evaluate the proposed method. The ABM tool is validated on real epidemic outbreaks and is capable of simulating airborne disease transmission, as well as pedestrian movement [7].

2. Methodology

2.1. Risk Factors

To perform the RA of airborne disease spread, this work considers the following risk factors: maximum body temperature (BT), room ventilation (RV), exposure time (ET), total number of passengers (TNP) in a room, contact distance (CD), and total number of coughs (TNC).

Fever is commonly associated with infectious diseases; however, it has been reported that elevated BT assists in reducing the pathogen concentration within the infected host [8]. The RV setting is defined as the airflow rate Q (m^3/h) calculated as $Q = ACH \cdot V$, where ACH and V are the number of air changes per hour and the volume of the examined area (m^3), respectively. Based on [9], the optimal ACH is defined as 3.0 ACH, the low ACH as 1.5, whereas high is 6.0 ACH. The resulted fuzzy sets based on these values are: Low $[0, 3V]$, Medium $[1.5V,\ 6V]$, and High $[3V, 6V]$ [9] with 0 indicating no ventilation.

To determine the severity of the risk related to the TNC, the pathogen concentration in a room is estimated based on a modified version of the Wells-Riley probabilistic model [10], defined as $P = 1 - e^{-\frac{b_c \cdot c_l \cdot n_b \cdot t}{Q \cdot ID_{50}}}$, where P is the probability that an individual will be infected, b_c is the number of coughs per hour, c_l is the number of virus copies (VC) per mL emitted in a cough, n_b is the breathing rate (m^3/h), t is the exposure time (h), Q is

[2] https://hs4u.eu/

Table 1. Fuzzy sets for each risk factor.

Fuzzy Set		RV	BT	TNC	TNP	CD	ET	Risk
Low	e_1	[0,3369]	[35,38]	[0,61]	[2,20]	[0,1]	[15,45]	[0,0.3]
	e_2	[0,2400]		[0,44]	[2,10]			
Med.	e_1	[1685,6738]	[36,39]	[25,97]	[10,40]	[0.5,1.5]	[30,60]	[0.1,0.5]
	e_2	[1200,4800]		[17,71]	[5,20]			
High	e_1	[3369,6738]	[38,42]	[61,250]	[20, 81]	[1,2]	[45,120]	[0.3,1]
	e_2	[2400,4800]		[44,200]	[10,44]			

the airflow rate in the room (m^3/h), and ID_{50} the minimum infectious dose that can cause infection in 50% of the population [10]. To find the maximum number of coughs (b_c), the following variables were used : $P \cong 1$, $n_b = 0.5$ m^3/h (3), $t = 1$ h, $ID_{50} = 10^3$ VC/mL [7], $c_l = 10^5$ VC/mL [11], and $Q = 3V$ [9]. According to the Wells-Riley model, the risk increases proportionally to the ET. Furthermore, the occupancy in an indoor space, *i.e.*, TNP, affects the transmission risk of infectious diseases [1]. The area occupied by a person is defined by the surface O (m^2) of a circle with a radius r (m). Assuming that each person occupies $O = 1$ m^2, r can be calculated as: $r = \sqrt{\frac{A}{S \cdot \pi}}$, where A is the surface area of a room and S is the TNP. Subsequently, $2 \cdot r$ denotes the distance between two individuals, *i.e.*, CD. Therefore, considering that droplets emitted through coughing can spread up to 1 m [9], the risk increases when $2 \cdot r < 1$m and decreases when $2 \cdot r \geq 1$m. When $2 \cdot r \geq 2$ m, the distance between individuals is considered as safe [12].

In this study, two indoor environments, *i.e.*, e_1 and e_2 (Figure 1(a)), with a surface area of 351 m^2 and 250 m^2, respectively, and a height of 3.2 m are examined. The capacity of e_1 and e_2 was set to 81 and 44 people, respectively. Based on the above, the resulting fuzzy sets are presented in Table 1. These fuzzy sets are defined in such a way that the overlapping regions cover the range of values of each risk factor.

2.2. Fuzzy Rules

To perform RA of COVID-19 transmission, a Mamdani fuzzy inference system is defined [13]. A total number of 154 fuzzy rules were elicited by combining the considered risk factors and then empirically selected by domain experts. An indicative example rule is as follows: "IF Room Ventilation is *Low* AND Body Temperature is *Low* AND Total Number of Coughs is *Low* AND Total Number of Passengers is *Low* AND Contact Distance is *Low* AND Exposure Time is *Low* THEN Risk is *Low*". The activation of the fuzzy rules depends on the input entries and the utilized logic operators. Finally, the output membership functions are aggregated and defuzzified, resulting in a final crisp output, *i.e.*, risk and confidence (Figure 1(d)).

2.3. Experimental Setup

The examined environments e_1 and e_2 were used to define different cases with varying RV, BT, TNC, TNP, and CD configurations over a period of up to 120 min. The method was evaluated in 20 cases, 6 of which are indicatively presented in Table 2, where the fuzzy sets are indicated as (L)ow, (M)edium and (H)igh and the risk inferred by the fuzzy rules as R_F. The confidence score is defined as the degree of membership to the fuzzy set responsible for RA. In addition, the ABM tool was employed for the evaluation by

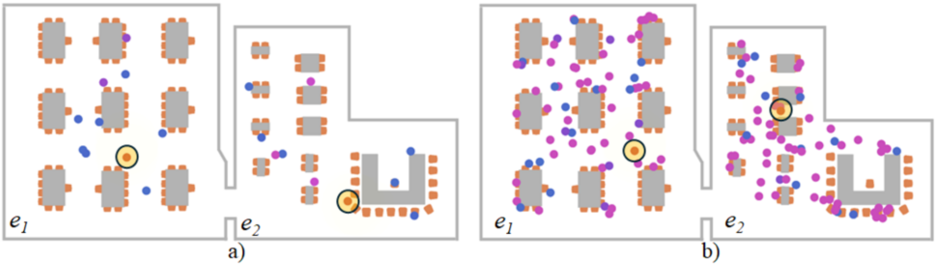

Figure 2. Snapshots of two different cases for a) Case 2 and b) Case 6 (Table 2). Blue circles indicate healthy passengers, red circles indicate infectious individuals, purple circles are infected individuals, and yellow circles represent the spread of droplets emitted from a cough.

approximating the transmission risk (R_T) *i.e.*, the total number of infected people at the end of the simulation.

3. Results

The results presented in Table 2 show that the proposed method aligns with the ABM tool for RA, with high confidence in estimating the transmission risk across most cases. Nevertheless, increased TNC, TNP, and ET lead to higher transmission risk even with optimal RV. Snapshots of the ABM simulations for Cases 2 and 6 (Table 2) are depicted in Figure 2. It can be observed that closer interaction between infected and healthy individuals is more probable in certain cases. In most cases, the RA performed by the proposed method is comparable to the results obtained from the ABM simulations, with an accuracy of 83.3% for 20 cases. The inaccurately predicted risk, *i.e.*, for e_2 in Case 1 (Table 2), estimated by the proposed method can be attributed to factors related to passenger movement and interactions that are not accounted for in the rules, since they cannot be detected by the utilized sensors.

Table 2. Input risk factors and RA for e_1 and e_2.

N_o	RV	BT	TNC	TNP	CD	ET	R_F	Confidence	R_T
	e_1 / e_2	$e_{1,2}$	e_1 / e_2	e_1 / e_2	$e_{1,2}$	$e_{1,2}$	e_1 / e_2	e_1 / e_2	e_1 / e_2
1	L/L	L	M/M	L/M	M	M	L/H	0.88 / 0.26	L/L
2	L/L	M	M/M	L/M	M	M	M/M	0.36 / 0.79	M/M
3	M/M	M	H/H	H/H	L	H	H/H	0.39 / 0.38	H/H
4	M/M	H	H/H	M/H	M	H	H/H	0.71 / 0.75	H/H
5	M/M	H	H/H	H/H	H	H	H/H	0.43 / 0.74	H/H
6	M/M	M	H/H	H/H	H	H	H/H	0.58 / 0.74	H/H

4. Discussion and Conclusions

In this paper, a knowledge-based method using fuzzy rules has been proposed with the aim of performing airborne transmission estimation on cruise ships. To define the fuzzy rules, the proposed method considers data provided by the sensors and the information system of the ship in accordance with a recently proposed smart ship design. These sensors enable early detection of infectious diseases, while the fuzzy knowledge-based system provides an automated and interpretable RA process that can be used to prevent disease transmission. In contrast, other studies have focused on long-term transmission [2,3] or used probabilistic models without using sensors [4] that could prove ineffective in containing an epidemic outbreak. Evaluation through ABM simulations confirmed the effectiveness of the proposed method in various cases for two enclosed areas. Future work will integrate additional risk factors, such as the use of masks, investigation of the effect of behavioral dynamics of pedestrians in the RA process, and a detailed implementation of an enhanced RA process to account for the entire population of the cruise ship.

Acknowledgment

This paper is supported by the European Union's Horizon Europe Research and Innovation Actions programme under grant agreement No 101069937, project name: HS4U (HEALTHY SHIP 4U). Views and opinions expressed are those of the author(s) only and do not necessarily reflect those of the European Union or the European Climate, Infrastructure, and Environment Executive Agency. Neither the European Union nor the granting authority can be held responsible for them.

References

[1] Triantafyllou G, Kalozoumis PG, Cholopoulou E, Iakovidis DK. Disease Spread Control in Cruise Ships: Monitoring, Simulation, and Decision Making. The Blue Book: Smart sustainable coastal cities and blue growth strategies for marine and maritime environments. Springer; 2024. p. 93–141.

[2] Azimi P, Keshavarz Z, Cedeno Laurent JG, Stephens B, Allen JG. Mechanistic transmission modeling of COVID-19 on the Diamond Princess cruise ship demonstrates the importance of aerosol transmission. Proceedings of the National Academy of Sciences. National Acad Sciences; 2021;118(8):e2015482118.

[3] Zheng L, Chen Q, Xu J, Wu F. Evaluation of intervention measures for respiratory disease transmission on cruise ships. Indoor and built environment. SAGE Publications Sage UK: London, England; 2016;25(8):1267–1278.

[4] Xia Z, Guan H, Qi Z, Xu P. Multi-Zone Infection Risk Assessment Model of Airborne Virus Transmission on a Cruise Ship Using CONTAM. Buildings. MDPI; 2023;13(9):2350.

[5] Rassia ST. The Blue Book: Smart Sustainable Coastal Cities and Blue Growth Strategies for Marine and Maritime Environments. Springer; 2024.

[6] Sovatzidi G, Vasilakakis M, Iakovidis DK. Constructive Fuzzy Cognitive Map for Depression Severity Estimation. MIE. 2022. p. 485–489.

[7] Rahn S, Gödel M, Köster G, Hofinger G. Modelling airborne transmission of SARS-CoV-2 at a local scale. Plos one. Public Library of Science San Francisco, CA USA; 2022;17(8):e0273820.

[8] Wrotek S, LeGrand EK, Dzialuk A, Alcock J. Let fever do its job: the meaning of fever in the pandemic era. Evolution, medicine, and public health. Oxford University Press; 2021;9(1):26–35.

[9] Ritos K, Drikakis D, Kokkinakis IW. The effects of ventilation conditions on mitigating airborne virus transmission. Physics of Fluids. AIP Publishing; 2024;36(1):013322.

[10] Sze To GN, Chao CYH. Review and comparison between the Wells–Riley and dose-response approaches to risk assessment of infectious respiratory diseases. Indoor air. Wiley Online Library; 2010;20(1):2–16.

[11] Wang Y, Xu G, Huang Y-W. Modeling the load of SARS-CoV-2 virus in human expelled particles during coughing and speaking. PLoS One. Public Library of Science San Francisco, CA USA; 2020;15(10):e0241539.

[12] Organization WH, others. Coronavirus disease (COVID-19) advice for the public. 2020 [Internet]. 2020. Available from: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public

[13] Gopal M. Applied machine learning. McGraw-Hill Education; 2019.