A Risk Model of Airborne Transmission and Vaccine Efficacy in an Outpatient Room with a Ventilation System

Watchareeporn Boonmeemapasuk, and Nopparat Pochai

Abstract— **Every day, a large number of patients visit the facility, creating a serious infectious transmission problem that might infect patients with respiratory infectious illnesses in outpatient rooms, putting their health at risk. TB, COVID-19, MERS, and SARS are all significant infectious diseases that are transmitted by the air or aerosol via coughing, spitting, sneezing, speaking, or wounds. COVID-19, tuberculosis, MERS, and SARS are all hazards, and the probability of a serious disease increasing the number of people admitted to the hospital. We should also be informed about how patients in the outpatient room are managed. When the number of patients in each room changes over time, it is challenging to measure and manage carbon dioxide in a hospital with a ventilation system. We should also be informed about the management of patients with these conditions. This research investigates the mathematical modeling of carbon dioxide concentration measurement and the risk assessment of airborne infection in an outpatient room with a ventilation system, while the number of patients in each room changes over time. As a result, efficient air quality monitoring, such as carbon dioxide (CO2) concentrations, is required to monitor and decrease the possibility of contaminated air. It is indeed difficult to measure and manage carbon dioxide in a hospital with a ventilation system when the number of patients in each room changes over time. This research provided a risk model of airborne transmission and vaccination effectiveness in an outpatient room with a ventilation system. When the number of people and the rate of ventilation change, the model modifies the carbon dioxide concentration. To approximate the model solution, the fourth-order Runge-Kutta technique is used. In the presented simulations, there are several scenarios for improving air quality. The proposed approach balances the number of people allowed to stay in the room with the capacity of the air ventilation system in the air quality management process. As can be seen, the risk of infection is dependent on the number of people present, the rate of ventilation, and the efficacy of each type of vaccination. If there is a public vaccination database system, this research may be used to help control the risk of airborne infection to the desired level.**

Index Terms— **Risk, Airborne, Transmission, Outpatient Room, Ventilation, Vaccination**

Manuscript received August 21, 2021; revised April 22, 2022.

This paper is supported by the Centre of Excellence in Mathematics, Ministry of Higher Education, Science, Research and Innovation, Bangkok, Thailand.

W. Boonmeemapasuk is a postgraduate student in Applied Mathematics, Department of Mathematics, Faculty of Science, King Mongkut's Institute of Technology Ladkrabang, Bangkok, 10520, Thailand (e-mail: watchareeporn.wb@gmail.com).

N. Pochai is an Assistant Professor of Department of Mathematics, Faculty of Science, King Mongkut's Institute of Technology Ladkrabang, Bangkok, 10520, Thailand (corresponding author to provide phone: 662329-8400; fax: 662-329-8400; e-mail: nop_math@yahoo.com).

I. Introduction

Tuberculosis (TB), Coronavirus Disease Starting in 2019 (COVID-19), Middle East Respiratory Syndrome (MERS), and Severe Acute Respiratory Syndrome (SARS) are a hazardous communicable disease which are transfer from people to people through the air or the aerosol in different ways, such as through coughing, spitting, sneezing, speaking, or through wounds. In [1], In the laboratory, US scientists demonstrated that the virus can survive in an aerosol and remain infectious for at least 3 hours. Tuberculosis (often known as TB) is a communicable illness caused by Mycobacterium Tuberculosis that mostly affects the lungs. At present, we have an effective TB disinfectant. TB can be treated, but recovery takes a long time. If the treatment is not continued, or is incomplete, death may result. Therefore, TB is an important public health issue in Thailand. In [2], a new procedure was developed to study the distribution of epidemics for predicting the possibility of airborne infectious diseases in high-density urban areas. It can analyze the chance of spread in sub-transportation, and it can also help understand dispersion of airborne diseases in public transportation in China. In [3], the researchers studied the behaviors of Korean TB infection. TB transmission dynamic was proposed by using mathematical TB model with exogenous reinfection. Then, the least squares method was used to approximate the considered parameters. From the results, the most significant factor was the case finding effort, which led to a decrease of active TB patients. In [4], the researchers developed an infectious diseases model of SARS by using two methods for estimating both small-scale SARS outbreak parameter at the Amoy Gardens, Hong Kong and large-scale outbreak parameter in the entire Hong Kong Special Administrative Region. In [5], the inpatient nursing records from EMR of the University of Miyazaki Hospital were analyzed by using a text data mining technique. This result indicated that vocabulary related to appropriate treatment methods. The focus of [6] was on airflow and the airborne dissemination of infectious pathogens from an indoor setting. From this, it was confirmed that infected individuals and susceptible individuals should use masks, and also should use personalized ventilation for a short-range airborne route. In [7], the researchers projected that diseased patient in high-rise hospitals would transmit airborne diseases. Using multi-zone airflow simulation and tracer (CFD) simulation, this simulation could examine the ventilation system. In [8], basic epidemiological and multivariate state-space models are proposed to predict

optimal control measure strategies. This approach can be used for various diffusion diseases include Ebola, MERS. In [9],[10], a vaccination strategy for the SEIR model was designed. It was oriented towards the measurement and used for the infectious population to epidemic models for designs the general time-varying, the vaccination control rule. In [11], a new discrete-time SEIR epidemic model was presented by using the Forward-Euler difference method. Besides, the numerical simulations were presented to compare the continuous-time epidemic and discrete-time system. In [12],[13],[14],[15], and [16], they proposed that infectious disease of airborne such as tuberculosis (TB) spread in several gathering locate areas with infectors and poor ventilation per person rates, [12],[13],[14],[15], and [16]. In [17],[18],[19], and [15], they proposed infectors could be dangerous if there no is a high concentration of indoor rebreathed air because it could contain infector-borne infectious particles, which could lead to the spread of airborne infectious diseases like tuberculosis. In [17], and [20], they proposed carbon dioxide be used as an indicator of air quality indoor, built on the notion that people release carbon dioxide at a rate dictated by their body weight and bodily movement, and that levels of carbon dioxide indoor are measured by fresh air clearance. In [17],[21], and [20], they propose carbon dioxide concentration in the air of approximately 400 ppm in a room, but when but people enter it, exhaled air concentration begins to rise, depending on the rate of ventilation per person, the length of the room, and the number of persons who are present in the room, because of their oxygen intake, respiratory quotient, and bodily movement, person in the room add to the rise in rebreathed air. In [15] and [13], they argued that when the concentration of exhaled air in a room grows in the presence of infectors, the risk of vulnerable persons developing infectious illnesses communicated by the air rises. This is due to the fact that contaminated people's exhaled air contains infectious airborne particles inside the nucleus with droplets that may remain airborne for lengthy periods of time and infect a vulnerable individual when inhaled. In [13],[22], and [23], they proposed the immune system's condition of the host, host physiology, and the virulence of the Mycobacterium tuberculosis (Mtb) infectious strain are all important factors in the advancement of infection to TB disease. The major method of transmission in [24] is droplet or airborne transfer, and the risk of infection is known to be substantially lower outside where ventilation is greater. As winter approaches in the northern hemisphere, opportunities for socializing and outdoor activity become more difficult, and fears of COVID-19 transmission increase. In [25], They proposed that about the efficacy of ventilation systems for human thermal comfort in terms of ceiling height, which contributes to green building architectures. Other advantages of ventilation, which we gain in high-ceilinged dwellings, cannot be overlooked. This would also assist to minimize moisture, smoke, odor, heat, dust, and germs. In this research, several numerical models of carbon dioxide concentration measurement in an outpatient room with an opened ventilation system is introduced. [29] describes a mathematical model that predicts the risk of airborne infectious diseases, such as TB, under steady-state and non-steady-state situations by monitoring infectors' breath in a confined area. This research used a risk model of airborne transmission and vaccination efficacy in an outpatient room with a ventilation system. [30] presents a logistic regression model for predicting high-risk patients' failure to complete their TB treatment regimen. In [31] and [32], air quality assessment models are considered.

This research used a risk model of airborne transmission and vaccination efficacy in an outpatient room with a ventilation system.

II. GOVERNING EQUATION

In general, the rate of exhaled air generation and ventilation per person [17], [19], and [20] determines the elevated concentration of indoor carbon dioxide. Carbon dioxide levels can be utilized as a substitute for exhaled air since ill people's exhaled air contains airborne infectious particles [17], [18], [15], and [26]. Exhaled air has around 40,000 parts per million of carbon dioxide, compared to 400 parts per million in ambient air [17], [15], and [14]. We suppose that an interior area, such as a room with a volume, has a carbon dioxide concentration of roughly 400 ppm at the start of the day and is occupied by n people. Based on the rate of ventilation and the number of people in the room, the concentration of exhaled air that may include airborne infectious particles may tend to grow in the room if infectors are present. We simply assume that everyone in the room contributes a significant amount of carbon dioxide to the atmosphere, which acts as a generator for exhaled air. Considering the volume proportion of exhaled air as a generator. The exhaled air rate generated by inhabitants plus the rate of carbon dioxide environmental, minus the ventilation rate that removes exhaled air, is equal to the exhaled air rate generated by inhabitants plus the rate of carbon dioxide environmental, minus the ventilation rate that removes exhaled air:

$$V\frac{dC}{dt} = npC_a + QC_E - QC \tag{1}$$

where C is the concentration of indoor air exhaled (ppm), p is the rate of breathing(L/s) for each person in the room and C_a is the carbon dioxide fraction included in inbreathed air. t is the duration time and T is the stationery simulation time. Initial condition $C(0) = C_0$ where C_0 is the latent carbon dioxide concentration.

If the value of Q assumed by Q_{in} and Q_{out}, then these values are named the inlet ventilation rate and the outlet ventilation respectively and in a simple scenario, a number of people are unstable then a number of people depend on the time assumed by $n(t)$. In this study preferred to use Eq.(1) as follow:

$$V\frac{dC}{dt} = n(t)pC_a + Q_{in}C_E - Q_{out}C\ , \tag{2}$$

for all $0 \le t \le T.$

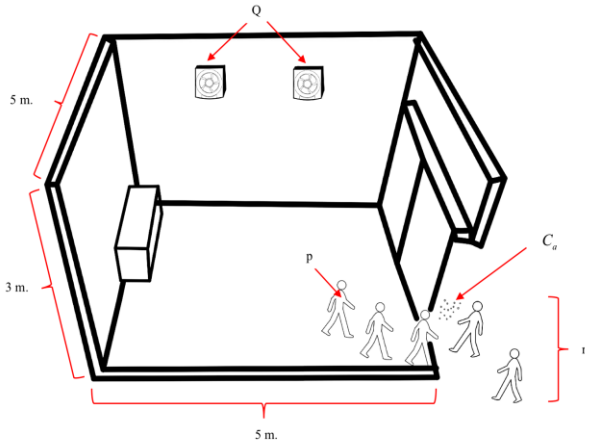

Fig.1 An outpatient room model

The concentration of sampled exhaled air in the given space is calculated by dividing the difference between indoor and outdoor exhaled air concentrations by the ventilation rate:

$$\frac{dC}{dt} = \frac{n(t)pC_a + QC_E - QC}{V} \tag{3}$$

Taking the volume fraction of exhaled air into consideration, f, is given by the sampled exhaled air concentration Eq.(3) in the space divided by carbon dioxide fraction in breathed air (C_a), we get

$$f(t) = \frac{C(t)}{C_a}, \tag{4}$$

for all $0 \le t \le T$.

Some infectious particles, on the other hand, can become lodged in the upper respiratory tract or be reflected into other parts of the body where the danger of infection is minimal. Let β represent the overall rate of airborne infectious particle generation emitted by an infector (particles/s) and μ represent the mortality rate of airborne infectious particle production by the infector that does not reach the alveoli (particles/s). As a result, the survival rate of infectious particles released by the infector and reaching the susceptible individual's target infection area to cause infection is $\beta - \mu$ particles/s.

The concentration of airborne infectious particles, N, that cause infection, is equal to the average volume fraction of rebreathed air by infectors $(If(t)/n(t))$, multiplied by the concentration of airborne infectious particles released by infectors in the space that reach the target infection site of the respiratory tract $(\beta-\mu)/p$:

$$N(t) = \frac{If(t)(\beta-\mu)}{n(t)p}, I \ge 1 \text{ and } (\beta-\mu) \ge 1 \tag{5}$$

for all $0 \le t \le T$.

Let θ be a respiratory deposition percentage of airborne infectious particles that successfully reach and deposit at the target infection site of the host, because not all infected particles can reach and deposit at the alveoli. As a result, the product of the volume of breathed air by susceptible (pt), respiratory deposition fraction of airborne infectious particles, $\theta(0<\theta<1)$, and the concentration of airborne infectious particles $N(t)$ released by infectors equals the average number of airborne infectious particles, λ, breathed by a susceptible individual that causes infection,

$$\lambda(t) = pt\theta N(t), t > 0 \tag{6}$$

where t is the time spent in the space up to the point of infection.

Considering Wells (1955) assumed that TB transmission follows a Poisson distribution [29], we express TB transmission probability as

$$P(T \le t | I, Q, V, p, \theta, \mu, \beta) = 1 - e^{-\lambda(t)} \tag{7}$$

III. NUMERICAL TECHNIQUES

A continuous approximation to the solution $C(t)$ will not be obtained; instead, approximations to C will be generated at various values, called mush points, in the interval $[0,T]$.

Interpolation can be used to find the approximate solution at additional points in the interval once the approximate solution at the points has been determined. We start by assuming that the grid points are spread evenly over the interval $[0,T]$. This requirement is met by picking a positive integer N and the grid points $t_i = a + ih$ for each $i = 0,1,2,...,N$. The common distance between the points $h = (T-0)/N = t_{i+1} + t_i$ is called the step size.

A. *Fourth-order Runge-Kutta method*

$$C \cong C_i \tag{8}$$

$$C_{i+1} = C_i + \frac{1}{6}[F_1 + 2F_2 + 2F_3 + F_4] \tag{9}$$

$$F_1 = hf(t_i, C_i) \tag{10}$$

$$F_2 = hf(t_i + \frac{h}{2}, C_i + \frac{F_1}{2}) \tag{11}$$

$$F_3 = hf(t_i + \frac{h}{2}, C_i + \frac{F_2}{2}) \tag{12}$$

$$F_4 = hf(t_i + h, C_i + F_3) \tag{13}$$

from Eq.(2), we get the classical fourth-order RK method

$$\frac{dC}{dt} = f(t_i, C_i) \tag{14}$$

$$f(t_i, C_i) = \frac{1}{V}(n(t)pC_a + Q_{in}C_E - Q_{out}C_i) \tag{15}$$

IV. Numerical Experiments and Results

*A. **Simulation1**: When the number of patients in an outpatient room remains consistent, there is a possibility of airborne infection and vaccination effectiveness. We will create 4 scenarios in which there are 60, 50, 40, and 30 people who are staying in the room.*

We assume that $C_0 = 10$ is the initial carbon dioxide concentrations.

TABLE I
PHYSICAL PARAMETERS.

V	C_E	C_a	p	Q	I	θ
75	0	0.04	0.12	1	2	0.25

TABLE II
COMPARE THE EFFECTIVENESS OF VACCINES.

vaccine types	A	B	C	D	E	F
vaccine efficacy (%)	95	94.5	89.3	70.4	66	50.4

TABLE III
THE PROBABILITY OF INFECTION WHEN THE NUMBER OF PEOPLE IN AN OUTPATIENT ROOM IS CONSTANT, BY CONSIDERING THE CASE OF 30 PEOPLE.

vaccine types	probability of infection			
	P(10)	P(30)	P(60)	P(90)
A	0.0501	0.1120	0.1486	0.1514
B	0.0550	0.1224	0.1622	0.1652
C	0.1042	0.2244	0.2912	0.2963
D	0.2624	0.5049	0.6141	0.6217
E	0.2951	0.5540	0.6650	0.6726
F	0.3996	0.6921	0.7972	0.8038

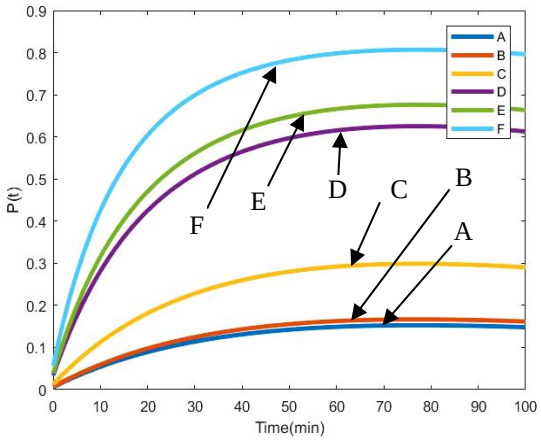

Fig.2 The probability of infection for case 30 people

TABLE IV
THE PROBABILITY OF INFECTION WHEN THE NUMBER OF PEOPLE IN AN OUTPATIENT ROOM IS CONSTANT, BY CONSIDERING THE CASE OF 40 PEOPLE.

vaccine types	probability of infection			
	P(10)	P(30)	P(60)	P(90)
A	0.0379	0.0854	0.1142	0.1170
B	0.0416	0.0935	0.1249	0.1279
C	0.0793	0.1739	0.2286	0.2338
D	0.2042	0.4104	0.5123	0.5213
E	0.2308	0.4550	0.5617	0.5710
F	0.3181	0.5875	0.6998	0.7090

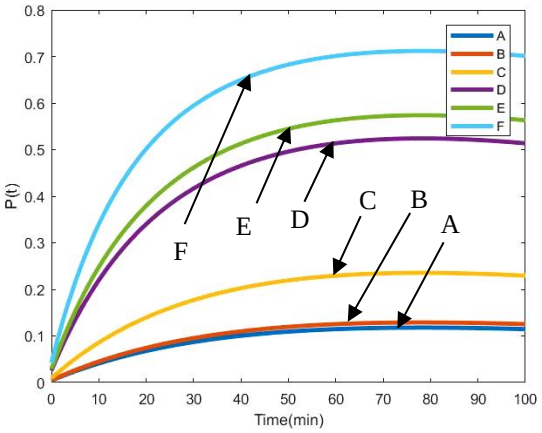

Fig.3 The probability of infection for case 40 people

TABLE V
THE PROBABILITY OF INFECTION WHEN THE NUMBER OF PEOPLE IN AN OUTPATIENT ROOM IS CONSTANT, BY CONSIDERING THE CASE OF 50 PEOPLE.

vaccine types	probability of infection			
	P(10)	P(30)	P(60)	P(90)
A	0.0304	0.0691	0.0930	0.0957
B	0.0334	0.0757	0.1018	0.1048
C	0.0640	0.1420	0.1885	0.1937
D	0.1671	0.3454	0.4388	0.4487
E	0.1895	0.3853	0.4850	0.4954
F	0.2639	0.5083	0.6202	0.6314

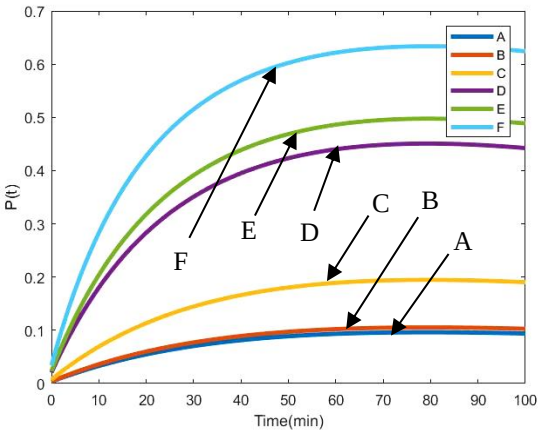

Fig.4 The probability of infection for case 50 people

TABLE VI
THE PROBABILITY OF INFECTION WHEN THE NUMBER OF PEOPLE IN AN OUTPATIENT ROOM IS CONSTANT, BY CONSIDERING THE CASE OF 60 PEOPLE.

vaccine types	probability of infection			
	P(10)	P(30)	P(60)	P(90)
A	0.0254	0.0580	0.0785	0.0812
B	0.0279	0.0636	0.0860	0.0890
C	0.0536	0.1201	0.1605	0.1658
D	0.1414	0.2980	0.3838	0.3943
E	0.1607	0.3340	0.4266	0.4378
F	0.2255	0.4473	0.5557	0.5684

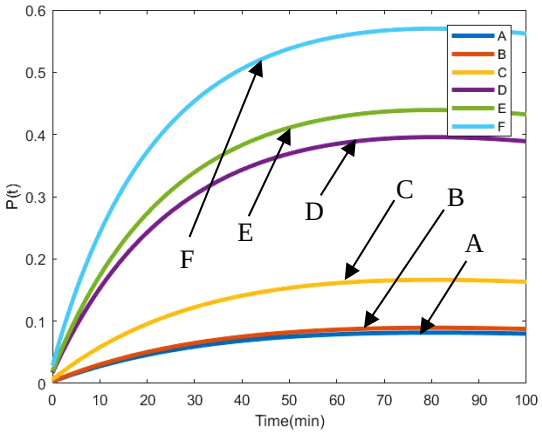

Fig.5 The probability of infection for case 60 people

B. ***Simulation2:*** *When the air ventilation rate in an outpatient room is considered, there is a possibility of airborne infection and vaccination effectiveness. We will create 4 scenarios in which the ventilation rate inside the room is 0.5, 1.5, 2.5, and 3.0 and there are 30 people who are staying in the room.*

We assume that $C_0 = 10$ is the initial carbon dioxide concentrations.

TABLE VII
PHYSICAL PARAMETERS.

V	C_E	C_a	p	n	I	θ
75	0	0.04	0.12	30	2	0.25

TABLE VIII
THE PROBABILITY OF INFECTION WHEN THE AIR VENTILATION RATE INSIDE AN OUTPATIENT ROOM IS 0.5

vaccine types	probability of infection			
	P(10)	P(30)	P(60)	P(90)
A	0.0531	0.1341	0.2114	0.2551
B	0.0583	0.1465	0.2300	0.2767
C	0.1103	0.2652	0.3985	0.4675
D	0.2762	0.5736	0.7550	0.8250
E	0.3101	0.6243	0.8012	0.8650
F	0.4182	0.7603	0.9053	0.9461

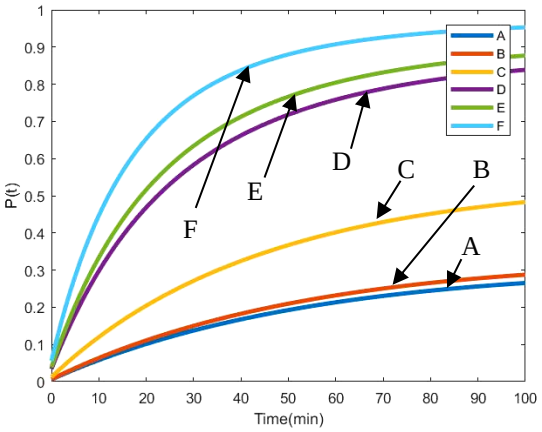

Fig.6 The probability of infection for the ventilation rate inside an outpatient room is 0.5

TABLE IX
THE PROBABILITY OF INFECTION WHEN THE AIR VENTILATION RATE INSIDE AN OUTPATIENT ROOM IS 1.5

vaccine types	probability of infection			
	P(10)	P(30)	P(60)	P(90)
A	0.0473	0.0933	0.1033	0.0879
B	0.0519	0.1021	0.1130	0.0962
C	0.0984	0.1891	0.2081	0.1787
D	0.2493	0.4400	0.4755	0.4199
E	0.2806	0.4862	0.5235	0.4650
F	0.3566	0.6215	0.6608	0.5985

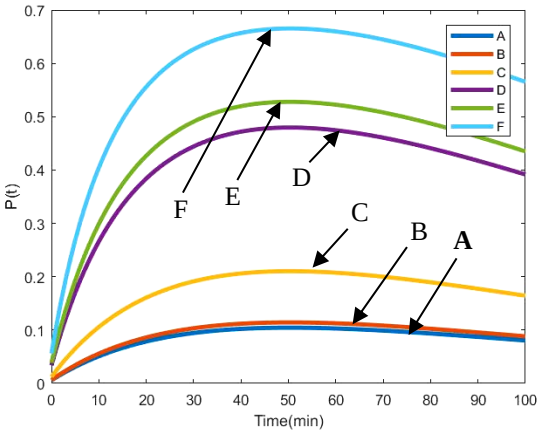

Fig.7 The probability of infection for the ventilation rate inside an outpatient room is 1.5

TABLE X
THE PROBABILITY OF INFECTION WHEN THE AIR VENTILATION RATE INSIDE AN OUTPATIENT ROOM IS 2.5

vaccine types	probability of infection			
	P(10)	P(30)	P(60)	P(90)
A	0.0420	0.0645	0.0491	0.0292
B	0.0462	0.0707	0.0538	0.0321
C	0.0878	0.1329	0.1021	0.0615
D	0.2245	0.3260	0.2576	0.1610
E	0.2533	0.3644	0.2897	0.1826
F	0.3470	0.4838	0.3929	0.2549

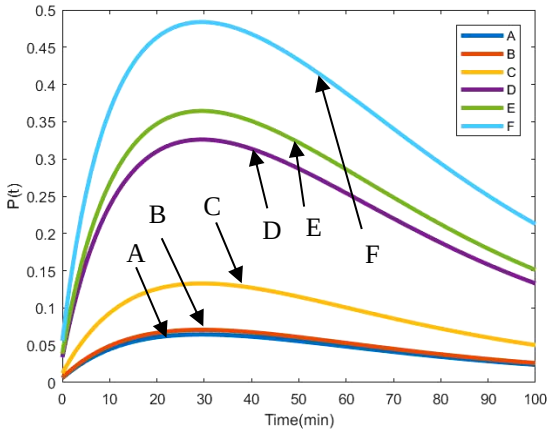

Fig.8 The probability of infection for the ventilation rate inside an outpatient room is 2.5

TABLE XI
THE PROBABILITY OF INFECTION WHEN THE AIR VENTILATION RATE INSIDE AN OUTPATIENT ROOM IS 3.0

vaccine types	probability of infection			
	P(10)	P(30)	P(60)	P(90)
A	0.0446	0.0776	0.0713	0.0506
B	0.0489	0.0850	0.0782	0.0555
C	0.0930	0.1588	0.1464	0.1052
D	0.2366	0.3801	0.3546	0.2646
E	0.2667	0.4227	0.3953	0.2975
F	0.3639	0.5513	0.5200	0.4026

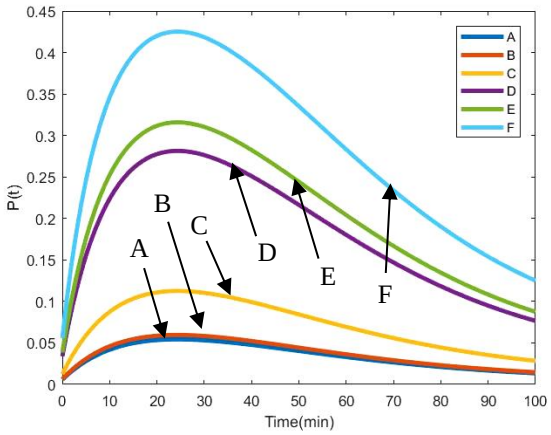

Fig.9 The probability of infection for the ventilation rate inside an outpatient room is 3.0

C. ***Simulation3:*** *When the air ventilation rate and number of stayed people in an outpatient room are considered, there is a possibility of airborne infection and vaccination effectiveness. We will create 4 scenarios in which the ventilation rate inside the room is 0.5, 1.5, 2.5, and 3.0 and the number of people staying in the room is listed in Table XIII.*

We assume that $C_0 = 10$ is the initial carbon dioxide concentrations.

TABLE XII
PHYSICAL PARAMETERS.

V	C_E	C_a	p	I	θ
75	0	0.04	0.12	2	0.25

TABLE XIII
THE NUMBER OF PEOPLE WHO STAYED IN AN OUTPATIENT ROOM AT EACH PERIOD OF TIME.

t	0	10	20	30	40	50	60	70	80	90	100
n(t)	50	33	40	35	54	25	33	40	34	42	40

TABLE XIV
THE PROBABILITY OF INFECTION WHEN THE AIR VENTILATION RATE INSIDE AN OUTPATIENT ROOM IS 0.5 WHEN THE NUMBER OF PEOPLE IN AN OUTPATIENT ROOM VARIES OVER TIME.

vaccine types	probability of infection			
	P(10)	P(30)	P(60)	P(90)
A	0.0471	0.1195	0.2326	0.2036
B	0.0516	0.1306	0.2526	0.2215
C	0.0980	0.2383	0.4325	0.3856
D	0.2483	0.5291	0.7914	0.7401
E	0.2795	0.5790	0.8347	0.7873
F	0.3801	0.7169	0.9276	0.8954

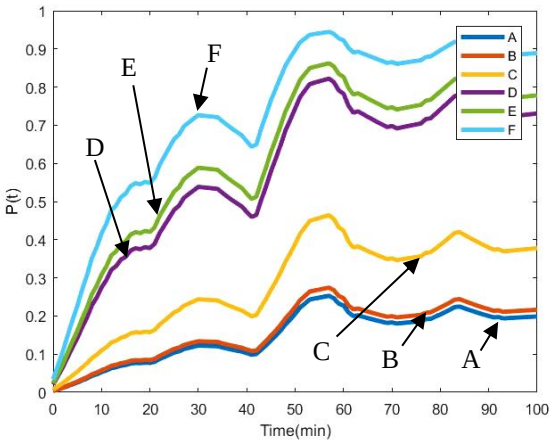

Fig.10 The probability of infection for the number of people in an outpatient room is not constant and the ventilation rate inside an outpatient room is 0.5

TABLE XV
THE PROBABILITY OF INFECTION WHEN THE AIR VENTILATION RATE INSIDE AN OUTPATIENT ROOM IS 1.5 WHEN THE NUMBER OF PEOPLE IN AN OUTPATIENT ROOM VARIES OVER TIME.

vaccine types	probability of infection			
	P(10)	P(30)	P(60)	P(90)
A	0.0419	0.0829	0.1145	0.0689
B	0.0459	0.0908	0.1252	0.0756
C	0.0874	0.1691	0.2291	0.1417
D	0.2236	0.4010	0.5132	0.3448
E	0.2523	0.4449	0.5626	0.3847
F	0.3457	0.5763	0.7007	0.5076

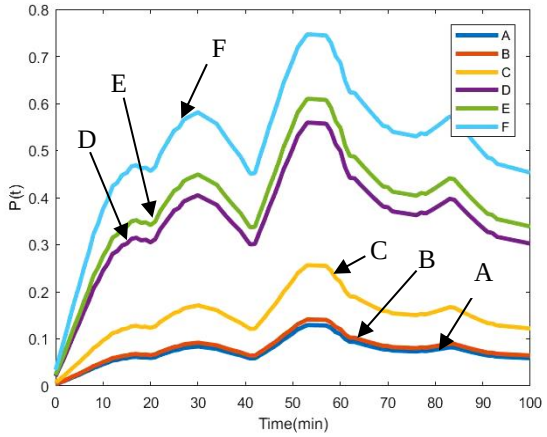

Fig.11 The probability of infection for the number of people in an outpatient room is not constant and the ventilation rate inside an outpatient room is 1.5

TABLE XVI
THE PROBABILITY OF INFECTION WHEN THE AIR VENTILATION RATE INSIDE AN OUTPATIENT ROOM IS 2.5 WHEN THE NUMBER OF PEOPLE IN AN OUTPATIENT ROOM VARIES OVER TIME.

vaccine types	probability of infection			
	P(10)	P(30)	P(60)	P(90)
A	0.0372	0.0572	0.0547	0.0230
B	0.0409	0.0628	0.0600	0.0253
C	0.0780	0.1185	0.1133	0.0485
D	0.2011	0.2945	0.2831	0.1286
E	0.2274	0.3302	0.3177	0.1463
F	0.3136	0.4427	0.4274	0.2060

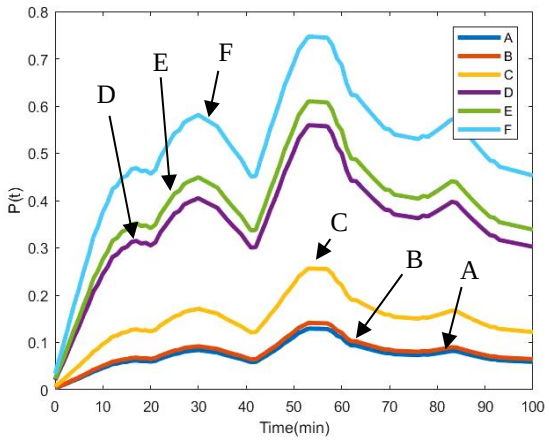

Fig.12 The probability of infection for the number of people in an outpatient room is not constant and the ventilation rate inside an outpatient room is 2.5

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TABLE XVII
THE PROBABILITY OF INFECTION WHEN THE AIR VENTILATION RATE INSIDE AN OUTPATIENT ROOM IS 3.0 WHEN THE NUMBER OF PEOPLE IN AN OUTPATIENT ROOM VARIES OVER TIME.

vaccine types	probability of infection			
	P(10)	P(30)	P(60)	P(90)
A	0.0351	0.0475	0.0376	0.0135
B	0.0385	0.0521	0.0413	0.0149
C	0.0736	0.0988	0.0788	0.0288
D	0.1906	0.2502	0.2032	0.0776
E	0.2157	0.2816	0.2296	0.0886
F	0.2984	0.3827	0.3165	0.1266

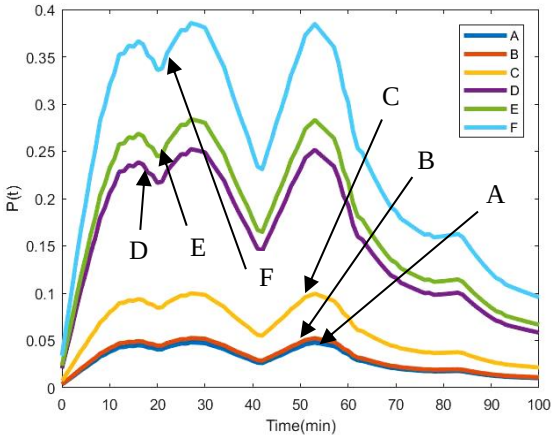

Fig.13 The probability of infection for the number of people in an outpatient room is not constant and the ventilation rate inside an outpatient room is 3.0

V. DISCUSSION

In simulation 1, with n=30 cases, we observe from Table II that the probability of infection is lowest when receiving types, A and B vaccinations compared to the remainder. At the same time, as shown in Figure 2, the longer people stay in an outpatient room, the more probable it will be that normal people will get infected. And when the number of people in an outpatient room is increased statically to 40, 50, and 60, we found that the probability of infection was shown in Tables IV, V and VI, respectively. When the number of people in an outpatient room is fixed at 60, the probability of infection becomes the lowest.

Consider the rate of ventilation in an outpatient room in Simulation 2. We determined that when outpatient room ventilation rates were 0.5, 1.5, 2.5, and 3.0, the probability of infection was 0.5, as shown in Table VIII, with types A and B vaccines having a very low probability of infection. At the same time, as shown in Figure 6, the longer people stay in an outpatient room, the more probable people are to become infected. Tables IX, X, and XI show the probability of infection when the ventilation rate in an outpatient room is increased to 1.5, 2.5, and 3.0, respectively.

Consider a situation where the number of people in the room changes from Table XIII and the ventilation rates are 0.5, 1.5, 2.5, and 3.0. At a ventilation rate of 0.5, the probability of infection varies with the number of people in an outpatient room at that time, as shown in Table XIV. A and B are also less likely to be infected than the remaining four types, as shown in Figure 10. And when the ventilation rate was increased in an outpatient room to 1.5, 2.5, and 3.0,

respectively, it was found that the probability of infection was as shown in Tables XV, XVI and XVII. They will be less infected as shown in Figures 11, 12 and 13.

VI. Conclusion

A risk model of airborne transmission in an outpatient room with a ventilation system is provided for variable patient quantities and vaccine efficacy. As can be seen, the likelihood of infection is affected by the number of people present, the rate of ventilation, and the effectiveness of each form of immunization. Using the RK4 method in the most optimum conditions, we show that the proposed strategy works for actual issues. Numerical models have been shown to provide beneficial results. In the air quality management process, the suggested model balances the number of people permitted in an outpatient room with the ventilation system's ability to control the risk of infection within an outpatient room. We can see that the sufficiently ventilated system and the efficacy of each type of vaccination can reduce the risk of airborne infection in an outpatient room in a hospital. This research could be utilized to help control the risk of airborne infection to the desired level if there is a public vaccination database system.

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W. Boonmeemapasuk is an assistant researcher of Centre of Excellence in Mathematics, MHESI, Bangkok 10400, Thailand.

N. Pochai is a researcher of Centre of Excellence in Mathematics, MHESI, Bangkok 10400, Thailand.