Estimation of Case Numbers at Pandemics and Testing of Hospital Resource's Sufficiency with Simulation Modeling

Pınar Miç and Melik Koyuncu

Abstract Influenza pandemics have occured throughout the past two centuries, killed millions of people worldwide. Although it is impossible to predict when/where the next pandemic will occur, proper planning is still needed to maximize efficient use of hospital resources and to minimize loss of life and productivity. Thus, it is highly important to estimate case numbers and to test hospital resources' sufficiency to take actions about this area. One of the most common tools used to estimate case numbers in an influenza pandemic is Basic Reproduction Number (R_0). In this study, we estimated case numbers using different R_0 values for a possible influenza pandemic. The developed simulation model used the estimated case numbers as input parameters, for testing important healthcare resources' sufficiency, which are non-ICU (non-intensive care unit) hospital beds, ICU (intensive care unit) hospital beds and ventilators.

Keywords Pandemic influenza · Basic reproduction number (R_0)
Simulation modelling · Health services

1 Introduction

Commonly known as flu, influenza is one of the long-lasting major health issues throughout the world. This single disease alone causes hundreds of thousands of deaths annually. The most severe known pandemic influenza is "The Spanish Flu"

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P. Cappanera et al. (eds.), *Health Care Systems Engineering*, Springer Proceedings
in Mathematics & Statistics 210, https://doi.org/10.1007/978-3-319-66146-9_13

(A/H1N1) pandemic of 1918–1919, estimated to be resulted in 20–50 million deaths worldwide, with unusually high mortality among young adults [1]. "The Asian Flu" (A/H2N2) at 1957 and "The Hong Kong Flu" (A/H3N2) at 1968 pandemics were less severe, with the highest mortality in the elderly [2]. Lots of influenza pandemics emerged many times around the world until late history such as at Hong Kong in 1997, at Thailand, Vietnam, Indonesia, Cambodia and China in 2003 and in 2006 at Turkey, Russia, Europe and some African nations resulting 225 cases [3].

This global threat requires advanced planning, early preparedness and rapid action. Not only may it increase demand upon health services, but it may also result in substantial socioeconomic problems and loss of life [5]. Because of these important reasons, policymakers have begun to realize the severity of this threat and they have started to develop preparedness plans across many layers of government [4]. These plans are based on World Health Organization (WHO) guidelines (published at 1999). But, with the emergence of H5N1 avian influenza virus in Asia and the outbreaks in the Europe and elsewhere, concerns about human influenza have grown up more [6]. Thus, in April 2005, WHO represented its concern about the general lack of global preparedness for influenza pandemics and updated its 1999 global influenza preparedness plan to outline the components that each country's plan should involve [7].

In the Risk Assessment section of WHO checklist (updated at 2005); possible case numbers (numbers of an instance of disease with its attendant circumstances [9]), hospital admissions and deaths are asked for with conduct modelling [8]. In addition, in the "Health Service Facilities" section of WHO checklist, it is requested to determine potential alternative sites for medical care. Therefore, some of the most important health care resources in an influenza pandemic are non-ICU hospital beds, ICU hospital beds and ventilators [10]. It is required to estimate the need of these resources at the recommended alternative sites as WHO checklist offered and it should be suitable making these estimates with models.

By examining related literature, we realized that there is not any study of case numbers in Turkey using Basic Reproduction Number (R_0). Furthermore, there is not common study testing hospital resource's sufficiency based on this estimation in a pandemic case. This paper aims to fill this gap at this area. In this way, hospitals can rationalize their inadequate resources and can be prepared to the possible future pandemic.

Thereby, we can divide our methodology into two sections; (1) Estimation of case numbers by using different R_0 and average duration of infectiousness (D) (which is the duration of infection's stay within individual's body) values, (2) Testing the most critical healthcare resources by a simulation model, which uses estimated case numbers as input parameters.

2 Materials and Methods

2.1 Estimation of Case Numbers

Estimation of case numbers' methods can be divided into two main categories in literature:

(i) Clinical attack rate: Clinical attack rate is defined as a biostatistical measure of frequency of morbidity, or speed of spread, in an 'at risk population' [11]. An 'at risk population' is defined as one that has no immunity to the attacking pathogen which can be either a novel or established pathogen [12].
(ii) Estimating case numbers by using Basic Reproduction Number [9]: The second and more common method is Basic Reproduction Number and usually denoted by "R_0". It is the most frequently used approach in the estimation of case numbers to be occured in a pandemic and time-dependent case numbers can be estimated using R_0 [13].

2.1.1 Estimation of Case Numbers with Basic Reproduction Number

The basic reproduction number, R_0, defined as the average number of secondary cases generated by a primary case introduced into a completely susceptible population, is a crucial quantity for identifying the intensity of interventions required to control a pandemic [10].

At this point, the model structure should reflect the natural history of the infection and therefore important disease categories and transitions need to be described as well as important categories in the population itself. The Susceptible-Pre-infectious-Infectious-Recovered (SEIR) model which shows fitting spreading of the infection to the influenza is used in this study. Many researchers used the SEIR model such as Chowell et al. [9], Flahault et al. [13], Dukic et al. [14], Verikios et al. [15], Pollicott et al. [16] and Farah et al. [5] in their studies for pandemic influenza.

Tables 1 and 2 are the summary of commonly used symbols and basic formulas used in the study to estimate case numbers via R_0 [11].

At Table 2, there are some notations need-to-know:

S_{t+1} Number of susceptible individuals at time $t + 1$,
E_{t+1} Number of pre-infectious individuals at time $t + 1$,
I_{t+1} Number of infectious individuals at time $t + 1$,
R_{t+1} Number of immune individuals at time $t + 1$,
$R_{t=0}$ Number of immune individuals at time $t = 0$ (at the start),
$I_{m(0)}$ Rate of infectious individuals at the start,

Table 1 Summary of the commonly used symbols [14]

Symbol	Definition
β	Rate at which two specific individuals come into effective contact per unit time (equivalent to the per capita rate at which two specific individuals come into contact). This notation is used when we assume that individuals mix randomly
D	Duration of infectiousness
E_t	Number of individuals who are infected but not yet infectious at time *t*
f	Rate of onset of infectiousness
l_t	Number of individuals who are infectious at time t
λ_t	Force of infection at time *t* (rate at which individuals are infected per unit time)
N	Total population size
r	Rate at which individuals recover from being infectious
R_t	Number of individuals who are immune ('recovered') at time *t*
R_o	Basic reproduction number (average number of secondary infectious persons resulting from the introduction of an infectious person into a totally susceptible population)
s_t	Number of susceptible individuals at time *t*
t_e	Average time to the infectiousness

Table 2 Summary of basic formulas used in the study [14]

$\beta = \frac{R_0}{N \cdot D}$	$\lambda_t = \beta \cdot I_t$	$f = 1/t_e$	$r = 1/\mathrm{D}$
$S_{t+1} = S_t - \lambda_t \cdot St$	$E_{t+1} = Et + \lambda t \cdot St - f \cdot Et$	$I_{t+1} = I_t + f \cdot E_t - r \cdot I_t$	$R_{t+1} = Rt + r \cdot It$
$R_{t=0} = N \cdot I_{m(0)}$	$\mathrm{NC}_{t+1} = E_t \cdot f \cdot \mathrm{CI}$	$I_{new(t+1)} = E_t \cdot f$	

$I_{new(t+1)}$ Total number of new infectious individuals per unit time,
NC_{t+1} Total number of new reported case numbers per unit time,
CI Proportion of those infectious who are reported as cases.

In this study, case numbers are estimated with formulas explained above, according to the method given in "An Introduction to Infectious Disease Modelling" by Vynnycky and White [14].

2.2 *Analyzing the Healthcare Resource's Sufficiency with Simulation Model*

For different values of R_0, case numbers can be estimated as explained at Sect. 2.1.1. A major part of these cases will get over the disease with mild symptoms, but some patients will need critical medical interventions. The patients will generally need non-ICU hospital beds, ICU hospital beds and ventilators for these interventions [10].

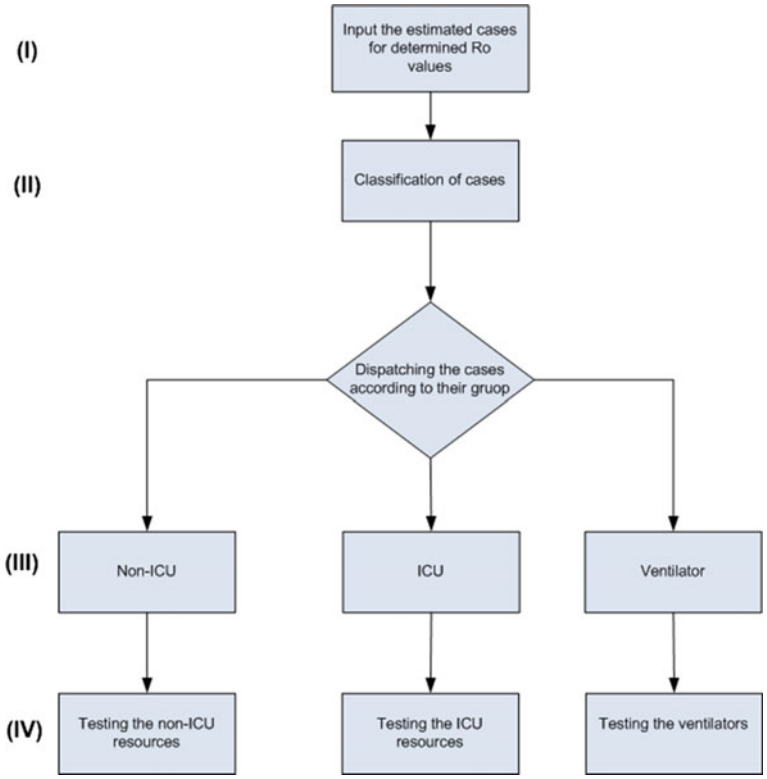

Fig. 1 The flow chart of developed simulation model

Developed simulation model enables to test the sufficiency of critical and important resources under different scenarios. Figure 1 shows the flow chart of the developed simulation model.

I. stage of model consists of input parameters which are the estimates of case numbers calculated by the method detailed in Sect. 2.1.1 [14]

When a pandemic influenza emerged in a population, because of the illnesses in the past and chronic diseases, all cases will not affected by the influenza at the same severity. Within the population, a definite percentage of community may have more medical risk. For this reason, it should be better to break down the population into risk groups. For this reason, at II. stage of simulation model, the population is divided into six risk groups according to age and medical risk. Table 3 shows the notation of the risk groups and their assumed proportions in the total population. Table 4 shows the hospitalization rates of these groups. Both Tables 3 and 4 are the notations and values of some input parameters based on the references given. Considering the past influenza pandemic data, its reasonable to consider that the

Table 3 The rates of high and non-high risk groups [10]

Risk groups	Age groups		
	0–19	20–64	65+
High risk	%2.24	%8.32	%2.83
Non-high risk	%32.88	%49.45	%4.25

Table 4 Population-based rates (per 1000 persons) of pandemic influenza hospitalizations [10]

Influenza outcome	Rate per 1000 persons		
	Minimum	Most likely	Maximum
Hospitalizations			
High risk			
0–19 years old	2,1	2,9	9
20–64 years old	0,83		5,14
65+ years old	4		13
Non-high risk			
0–19 years old	0,2	0,5	2,9
20–64 years old	0,18		2,75
65+ years old	1,5		3

severity of influenza pandemics are different. Therefore, the severity of the pandemic influenza is divided into three categories as of minimum, most likely and maximum as at Table 4.

The patients grouped in the II. stage are sent to related hospital resources (non-ICU hospital beds, ICU hospital beds and ventilators) according to the rates determined by the user at the III. stage of the model. For the patients who will need related hospital resources at a case of pandemic influenza, the sufficiency (whether they are enough for all patients or not) of these resources are tested by developed simulation model with the parameters identified by the user in the last and fourth stage of the model.

3 Case Study and Results

3.1 Case Study

Table 5 shows the population and hospital resources in a county, Adana, Turkey, which are used to test the developed simulation model.

For the I. stage of developed simulation model; case numbers are estimated starting with $R_0 = 2$ and it is increased by 0.5 range until $R_0 = 4$ and these case numbers are entered to the model as input parameters.

Table 5 Inputs and assumptions (assumptions are based on [10])

	Default
Inputs	
Population of locale by age groups	
0–19	753,159
20–64	1.241,61
65+	130,863
Total non-ICU beds	6236
Assumed occupancy rate (%)	75
Total ICU beds	556
Assumed occupancy rate (%)	75
Total number of ventilators	452
Assumed occupancy rate (%)	75
Influenza pandemic duration (weeks)	28
Basic reproduction number (interval)	2,0–4
Assumptions	
1. Average length of non-ICU hospital stay for influenza-related illness (days)	5
2. Average length of ICU hospital stay for influenza-related illness (days)	10
3. Average length of ventilator usage for influenza-related illness (days)	10
4. Average proportion of admitted influenza patients will need ICU care (%)	15
5. Average proportion of admitted influenza patients will need ventilators (%)	7,5

Table 6 The constant input parameters' notation, definition and supposed values determined by user

Notation	Definition	Supposed value
N	Total population size	2.125.635 person
$I_{t=0}$	Number of infectious individuals at the start	0,8 person
CI	Proportion of those infectious who are reported as cases	0.77
$PI_{t=0}$	Proportion immune at the start	0.3
API	Average pre-infectious period (days)	2 days
R_0	Basic reproduction number	[2–4]
D	Average duration of infectiousness	[1.5–2.5]

The constant input parameters, which are used to estimate the case numbers in this study, notations, definitions and assumed values are shown at Table 6.

Figure 2 shows the comparison of daily case number estimations for $R_0 = 2, 5$ and D = 1, 5; 2 and 2, 5 values. For example, for D = 2 value, case numbers have reached to the maximum level at about 45th day (6th week) and case numbers on the peak of pandemic for D = 2 is approximately 65,000 cases.

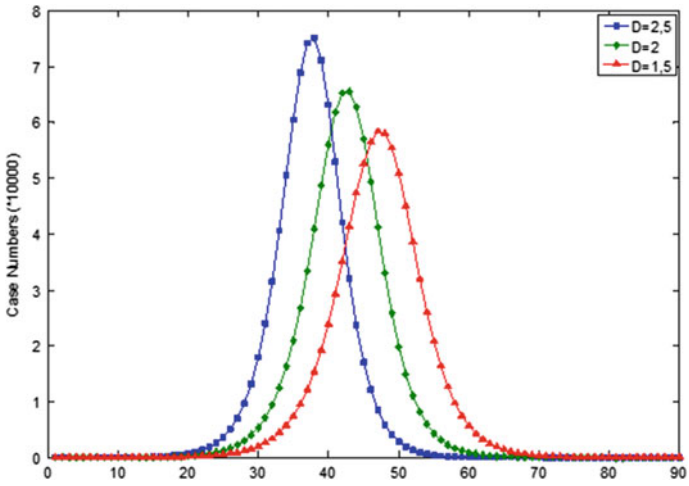

Fig. 2 The comparison of daily estimated case numbers for D = 1,5; 2 and 2,5 and R_0 = 2,5

3.2 Results

As a result of the analyses for all scenarios (maximum, most likely and minimum), its concluded that all resources are insufficient for maximum scenario and its necessary to increase them due to the possible needs. Due to the page limit, here we present only some of maximum scenario analyses.

Figure 3.a shows the rejected patients for non-ICU hospital beds, ICU hospital beds and ventilators. We estimated that increasing the number of non-ICU hospital beds to 2270 instead of 1559, the number of ICU hospital beds to 570 instead of 139 and the number of ventilators to 280 instead of 113 will be sufficient even the worst scenario.

4 Suggestions for Further Studies

Case numbers can be estimated with different parameter values. In addition, grouping the population to non-high risk and high risk groups and the rates of hospitalizations can be altered and revised in the simulation model; thereby this process might bring a different approach to the analyses. Furthermore, the simulation model can be developed and analyses can be carried out for larger districts and countries.

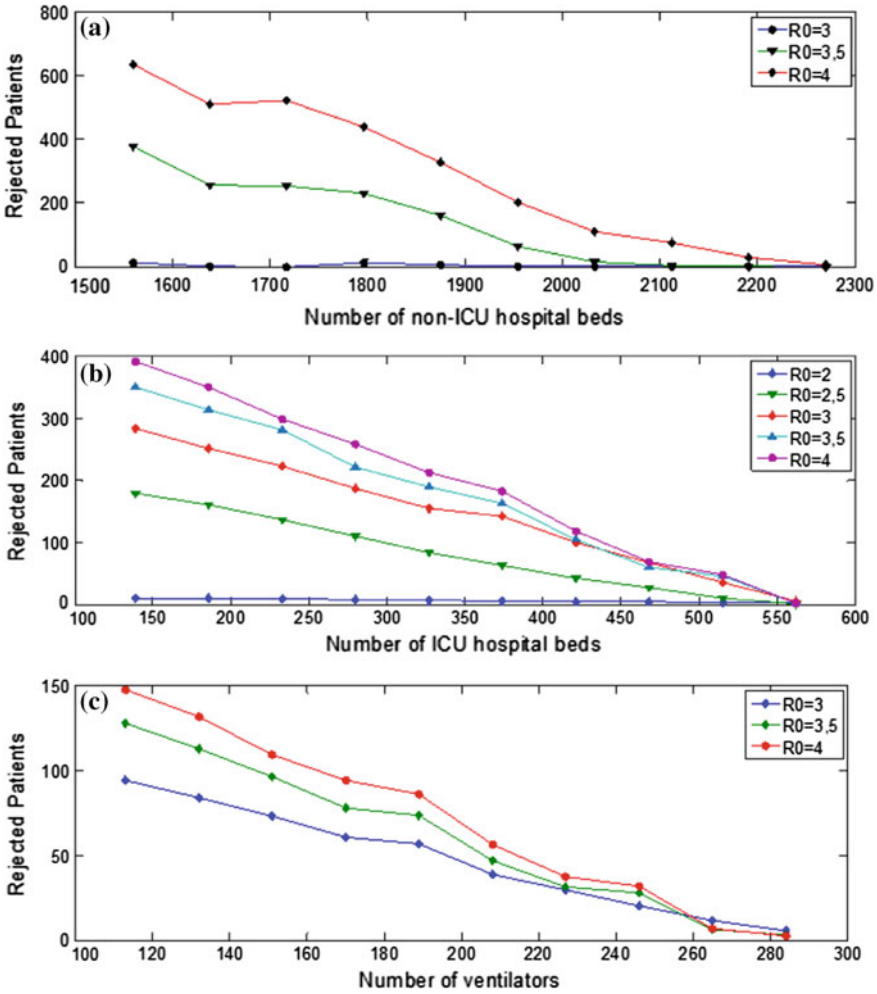

Fig. 3 Rejected patients due to insufficient capacity **a** for non-ICU hospital beds, **b** for ICU hospital beds, **c** for ventilators

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