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The Transmission Dynamic of the COVID 19 Outbreak: A Predictive Dashboard

(Dinamik Penyebaran Wabak COVID 19: Suatu Ramalan Papan Pemuka)

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ABSTRACT

COVID 19 outbreak gives a great impact worldwide. The disaster of this pandemic has resulted in a large number of human lives being lost. As all countries implemented quarantine and social distancing, the great lockdown all over the world lead to multiple crises including health, economy, financial, and collapse in industrial and educational activities. Movement Control Order (MCO) and social distancing which have been implemented as control measures in Malaysia also affected many sectors. The landscape now has successfully reduced the number of infected people. However, from the economic point of view, the Retail Group Malaysia (RGM) has projected the country's retail industry suffers a negative growth rate for the first time in 22 years. If the epidemic continues, society will reach an impasse, a time when the lockdown will become more than some of them can tolerate. As recognized by the World Health Organization (WHO), modelling the outbreak based on the prior input data is more appropriate than the 'risk of bias' for decision-makers. Thus, this research is conducted to model the outbreak of the disease using the susceptible-infected-recovery-death (SIRD) compartmental model accompanying with the varying infection rate due to changes in MCO measures. The model assumes under the unavailability of the vaccine, recovered people can be reinfected. The epidemic parameters and reproduction numbers are estimated and fitted from the transmission model to the actual data using the Monte Carlo Markov Chain (MCMC) of Metropolis-Hasting. The model is solved using a numerical algorithm of the Runge-Kutta method. The predictive dashboard of a graphical user interface (GUI) is developed, hence monitoring and predicting the outbreak under the control measures of the two different types of MCO scenarios (which are called constant and alternate scenarios) can be performed. GUI for the dynamic transmission of the COVID 19 provides insight for the future outbreak, hence may help the respective stakeholders to propose the best policy of a new norm for all sectors. From the GUI, we can see that, when no or loose MCO is implemented or compliance of the public to the COVID 19 standard operating procedure (SOP), the infected case will increase rapidly up to 7.5 million. With strict MCO regulation or public obedient to the SOP, the infected case will decrease rapidly, but even after a long period of strict regulation, once the quarantine is stopped, the infected case will rise again. An alternative MCO scenario is suggested where a cyclic pattern of strict and loose MCO regulation is upheld, and it shows to flatten the curve while allow periods of less restricted lifestyle. This can be one of the alternatives to balance the life and livelihood.

Keywords: COVID 19; modelling; Monte Carlo Markov Chain; reproduction number; Runge-Kutta

ABSTRAK

Wabak COVID 19 memberi kesan yang besar kepada seluruh dunia. Kemusnahan daripada wabak ini telah mengakibatkan banyak kematian. Semua negara melaksanakan kuarantin, penjarakan sosial dan penutupan negara di seluruh dunia yang akhirnya menyebabkan pelbagai krisis termasuk kesihatan, ekonomi, kewangan dan kelumpuhan sektor industri serta pendidikan. Perintah Kawalan Pergerakan (MCO) dan penjarakan sosial yang telah dilaksanakan sebagai langkah kawalan di Malaysia juga mempengaruhi banyak sektor. Landskap kini berjaya mengurangkan bilangan yang dijangkiti. Namun, dari sudut ekonomi, Kumpulan Peruncitan Malaysia (RGM) telah mengunjurkan industri runcit negara kini mengalami kadar pertumbuhan negatif untuk pertama kalinya dalam tempoh 22 tahun. Sekiranya wabak ini berlanjutan, masyarakat akan menemui jalan buntu dengan penutupan pelbagai sektor tidak lagi dapat ditoleransi oleh mereka. Seperti yang diakui oleh Organisasi Kesihatan Sedunia (WHO), pemodelan berdasarkan input data yang ada adalah lebih baik daripada 'risiko pincangan' oleh pembuat keputusan tanpa menggunakan model ramalan. Oleh itu, penyelidikan ini dilakukan untuk memodelkan epidemik penyakit ini menggunakan model SIRD dengan kadar jangkitan yang berbeza-beza susulan daripada perubahan MCO. Model ini mengandaikan dengan ketiadaan vaksin, orang yang pulih dapat dijangkiti semula. Parameter epidemik dan nombor reproduksi dianggar dan disuaikan dengan data sebenar menggunakan kaedah Monte Carlo Markov Chain (MCMC) Metropolis-Hasting. Penyelesaian model dihitung *menggunakan algoritma kaedah berangka Runge-Kutta. Antara muka pengguna grafikal (GUI) dibangunkan bagi peramalan epidemik mengikut dua situasi MCO yang berbeza (situasi tetap dan gantian). GUI bagi transmisi dinamik COVID 19 memberikan gambaran berkaitan keadaan wabak pada masa hadapan, seterusnya dapat membantu pihak berkepentingan untuk mengusulkan kaedah norma baharu yang terbaik bagi semua sektor. Daripada GUI, apabila tiada atau hampir tiada penguatkuasaan MCO atau ketidakpatuhan rakyat kepada prosedur operasi piawai (SOP), kes keberjangkitan meningkat sehingga mencecah 7.5 juta kes. Apabila MCO dikuatkuasakan secara ketat atau kepatuhan rakyat kepada SOP, kes akan menurun secara mendadak, tetapi walaupun setelah menjalankan kuarantin selama tempoh yang panjang, sejurus selepas kuarantin diberhentikan, kes akan meningkat sekali lagi. Suatu cadangan diketengahkan iaitu kekerasan MCO dilakukan secara berfasa berulang alik. Menggunakan kaedah ini, kes positif dapat diratakan manakala wujud tempoh dengan cara hidup yang kurang terikat dibenarkan. Ini boleh menjadi suatu alternatif bagi mengimbangi kehidupan dan punca pendapatan.*

Kata kunci: COVID 19; Monte Carlo Markov Chain; nombor reproduksi; pemodelan; Runge-Kutta

Introduction

Since the coronavirus disease 2019 (COVID 19) outbreak in Wuhan, China in December 2019, exported cases to other parts of China and many countries were recorded globally in which the infected persons have a history of travel to Wuhan. By January 31, global confirmed cases had reached 9,776 with a total number of deaths of 213, and the WHO declared the outbreak as a public health emergency of international concern (Weston & Frieman 2020; WHO 2020). The global death toll had climbed to 811 by February 9, greater than the total death toll of the 2003 severe acute respiratory syndrome (SARS) epidemic. On March 11, WHO declared the COVID 19 outbreak a worldwide pandemic, when 114 countries and all continents except Antarctica have reported cases. Globally, the confirmed cases emerge periodically and by August 2021 have affected 221 countries and territories, with the numbers of confirmed cases are 213,752,662 people and the total of deaths is 4,459,381. By 27 August 2021, Malaysia had recorded a cumulative of 1,616,244 cases with the total deaths are 14,818 (0.917%). As the government and the Ministry of Health (MoH) in Malaysia and other impacted countries respond to the outbreaks by implementing possible countermeasures to control the transmission of the disease, it is crucial for modelers to predict the severity of the epidemic. It was recognized by WHO 2020, mathematical models that are timely, play an important role in informing evidence-based decisions. Information based on the predictive models can help the public health agencies in making the decisions. It is crucial to predict the total number of infected, total deaths, and the basic reproduction number and to predict the time course of the epidemic, the arrival of its peak time, and total duration (Weston & Frieman 2020). In 2021, more comprehensive information is required to understand the status and epidemiology of the outbreak. How we respond this year will be critical in influencing the trajectory of the national epidemics. Estimation of changes over time provides insight into the epidemiological situation and identifies whether outbreak control measures are having a measurable effect (Adam et al. 2020). Several modelers and researchers around the world have reported estimations and predictions for the COVID-19 epidemic in journal publications or on websites, for an incomplete list see Anastassopoulou et al. (2020), Azar et al. (2020), Bai et al. (2020), Hao and Yan (2020), Imai et al. (2020), Rajesh and Adikari (2020), Read et al. (2020), Tang et al. (2020a), Weston and Frieman (2020), Leung et al. (2020), You et al. (2020), Zhang et al. (2020) and Zhuang et al. (2020). Modelling the spread of COVID 19 can be in the form of deterministic and stochastic (probabilistic) models. It is known that when dealing with a large population, deterministic or compartmental mathematical model have often been used to explain the disease outbreaks. The deterministic or compartmental models of Susceptible-Exposed-Infected-Recovery (SEIR), Susceptible Infected-Recovery (SIR), and Susceptible-Infected-Recovery-Death (SIRD) are amongst the prominent models of the disease outbreak. Weston and Frieman (2020) perform model calibration and model selection using Bayesian inference (BIC) and Akaike Information Criterion (AIC), respectively, for the COVID 19 epidemic in Wuhan city after the lockdown on January 23, 2020. Using AIC model selection, they conclude that for the information containing the confirmed case data of COVID 19 in Wuhan city, the SIR model shows better performance than an SEIR model. Nevertheless, the models do not consider the death state and the effect of randomness. It is crucial to consider the death state in the model since death is part of the real scenario of the COVID 19 outbreak globally. Discrete-time modelling using the SIRD model was conducted by Anastassopoulou et al. (2020). The analysis is based on the publicly available data of the new confirmed daily cases reported for the Hubei province from January 11 until February 10, 2020. The basic reproduction number is estimated from the SIRD model. However, the SIRD model studied by Anastassopoulou et al. (2020) neglects many factors that are crucial in the dynamic of the disease such as the effect of the incubation period in the transmission dynamics, the heterogeneous contacts transmission networks, the countermeasure has been taken to combat the epidemic and the population demographics (age and people who had health problems). SIR model of the spread of novel coronavirus that considers both age and social contact structure for COVID 19 outbreak in India was proposed by Rajesh and Adhikari (2020). This model although neglecting the death state, it has significant information for the assessment of the differential impact of social distancing measures. Tang et al. (2020a, 2020b) proposed a deterministic compartmental model of SEIR modification based on the clinical progression of the disease, epidemiological status of the individuals, and intervention measures. Estimation of the basic reproduction number for the prevention policy was performed based on 2019-novelcoronavirus (2019-nCoV) cases data in Wuhan China, until 22 January 2020 (prior to the lockdown of Wuhan city) by Tang et al. (2020a). The mean control of reproduction number was estimated to be as high as 6.47 (95% CI 5.71-7.23) which is consistent with the expert opinion that the virus has gone through at least three to four generations of transmission during this period of study (Tang et al. 2020a). Under countermeasure of locked down Wuhan city on 23rd January 2020, Tang et al. (2020b) use the same model and refit the model to the data available until 29th January 2020. The daily reproduction number has been re-estimated and has already fallen below one, which shows the effectiveness of the control strategy. As recognized by WHO no single 'one-size-fits-all' approach is appropriate to assess the quality of modelling studies. However, the concept of the 'credibility' of the model, which takes the conceptualization of the problem, model structure, input data, different dimensions of uncertainty, as well as transparency and validation into account, is more appropriate than 'risk of bias'. Thus, during this outbreak, modelling is one of the appropriate approaches to strengthen public health decision-making. However, for the policymaker, the predictive model needs to be embedded behind the user-friendly dashboard so that they are able to predict and monitor the outbreak along with the implemented control measures. Although potentially useful, no predictive dashboard has been proposed to the extent of author's knowledge. This research develops a predictive dashboard of the Malaysia COVID 19 outbreak using the SIRD model by assuming that the recovered people can be reinfected under the unavailability of the vaccine. The algorithm for model simulation is formulated based on two different scenarios of MCO (constant and alternate) control measures so that the policymaker is able to predict the future outbreak under the intervention measure implemented. The predictive dashboard is able to predict the basic reproduction number based on the MCO starting and lifting date choose by the policymaker.

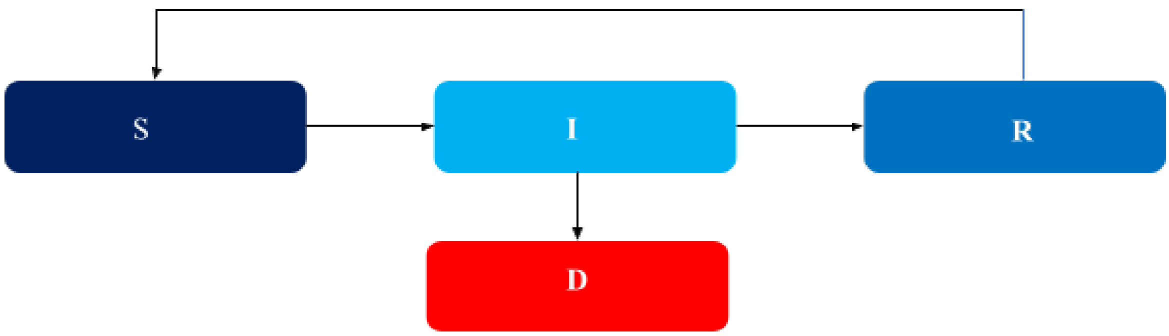

FIGURE 1. Diagram of SIRD Model

Mathematical Model

Epidemiological Model

The model is developed based on the compartmental diagram as depicted in Figure 1.

S is referred to as the stage of the susceptible person at a time, t. At all times when the spreading starts, all Malaysian populations become susceptible. COVID 19 spreading amongst susceptible persons is highly influenced by the percentage rate of the public to obey the MCO. The rate of spreading will be severed if there is inconsistent respect and abide by the MCO rules. The number of susceptible persons at the initial time is the difference between the Malaysian population and the infected person (assuming that there is no birth and death in the system, the total population, N is constant and initially only one person is infected). Therefore, the susceptible person at the initial time t_0, S_0 is $N-1$ and the initial infected person is $I(t_0)=1$. Initially, no recovery, R and death, D cases in this stage and at the initial time, $R(t_0)=D(t_0)=0$. Once the infected person is recognized, contact tracing to the infected person will be investigated. This person is categorized as the individual under investigation (PUI) and will be quarantined. PUI also refers to the person who has an acute respiratory infection with/without fever, being traveled to, or resided in a foreign country within 14 days before the onset of the illness, close contact in 14 days before illness onset with the confirmed case of COVID 19 and attended an event associated with known COVID 19 outbreaks. Once PUI has been tested positive (symptomatic/asymptomatic) of COVID 19, they will be isolated and treated as an infected person, $I(t)$. Then, once recovered, they will be transformed into a stage of recovery person, $R(t)$. Death is also a part of the real scenario of the COVID 19 outbreak; hence the stage of death is included in the model. The death person at a time t, $D(t)$ is those who are infected and die due to this outbreak. SIRD model describing the outbreak is in (1) and the description of the notation presented in Table 1.

$$\begin{aligned}
\frac{dS}{dt} &= -\frac{\alpha IS}{N} + \delta R \\
\frac{dI}{dt} &= \frac{\alpha IS}{N} - \beta I - \gamma I \\
\frac{dR}{dt} &= \beta I - \delta R \\
\frac{dD}{dt} &= \gamma I
\end{aligned} \tag{1}$$

TABLE 1. Parameters and description used in the SIRD model

Parameters	Description
	Variables
S	Number of susceptible persons at time t
I	Number of the infected person and hospitalized to get treatment at time t
R	Number of the recovery person at time t
D	Number of the death at time t
t	time in days (t = 1, 2, 3, …)
	Transition rate parameters
α / N	Rate of the susceptible person become infected (isolate and treat)
β	The recovery rate of the infected person
γ	The fatality rate of the infected person
δ	The rate of immune lost
	Constant
N	Number of the population (Malaysian population is approximately 32.37 million)

The assumptions in modelling the SIRD model. First, the net population growth due to natural birth and death rate is constant, and Second, individuals are assigned to one of the following disease states at one time - Susceptible (S) or infected (I) or Recovery (R) or Death (D) .

CONSERVATION OF POPULATION AND EQUILIBRIUM

For proving the conservation of population as stated in the first assumption, using the total number of populations $N = S + I + R + D$, we have

$$\frac{dN}{dt} = \frac{dS}{dt} + \frac{dI}{dt} + \frac{dR}{dt} + \frac{dD}{dt} \tag{2}$$

By substituting (1) into (2),

$$\begin{aligned} \frac{dN}{dt} &= \left(-\frac{\alpha IS}{N} + \delta R\right) + \left(\frac{\alpha IS}{N} - \beta I - \gamma I\right) + (\beta I - \delta R) + (\gamma I) \\ \frac{dN}{dt} &= -\frac{\alpha IS}{N} + \frac{\alpha IS}{N} + \delta R - \delta R - \beta I + \beta I - \gamma I + \gamma I \\ \frac{dN}{dt} &= 0 \end{aligned} \tag{3}$$

Therefore, there is no change in the total population N, showing the conservation of total population.

To find the equilibrium points of the state variables, the rate of change in system in (1) is equated to 0. Based on the death rate equation in (1)

$$\begin{aligned} \gamma I^* &= 0 \\ I^* &= 0 \end{aligned} \tag{4}$$

I^* is substituted into the recovered equation,

$$\begin{aligned} \beta I^* - \delta R^* &= 0 \\ \beta(0) - \delta R^* &= 0 \\ R^* &= 0 \end{aligned} \tag{5}$$

I^* is substituted into the infected equation,

$$\begin{aligned} \frac{\alpha I^* S^*}{N} - \beta I^* - \gamma I^* &= 0 \\ I^*\left(\frac{\alpha S^*}{N} - \beta - \gamma\right) &= 0 \\ S^* &= N\frac{(\beta+\gamma)}{\alpha} \end{aligned} \tag{6}$$

Using (4) - (6) and total number of populations,

$$\begin{aligned} S^* + I^* + R^* + D^* &= N \\ D^* &= N - S^* \\ D^* &= N - N\frac{(\beta+\gamma)}{\alpha} \end{aligned} \tag{7}$$

Thus, the equilibrium points are $\left(N\frac{(\beta+\gamma)}{\alpha}, 0, 0, N - N\frac{(\beta+\gamma)}{\alpha}\right)$. This shows during equilibrium, the disease will die out as the infected cases will reach the equilibrium point, $I^* = 0$.

From Equation (4), if the term $\frac{\beta+\gamma}{\alpha} > 1$, the value for $S^* > N$, which is not possible since S is bounded from 0 to N. Therefore, the equilibrium $\left(N\frac{(\beta+\gamma)}{\alpha}, 0, 0, N - N\frac{(\beta+\gamma)}{\alpha}\right)$ only true for value $\frac{\beta+\gamma}{\alpha} < 1$.

For $\frac{\beta+\gamma}{\alpha} > 1$, the initial condition of I_0 and S_0 are substituted into the infected equation of the system in (1) such that

$$\frac{dI}{dt} = I_0\left(\frac{\alpha S_0}{N} - \beta - \gamma\right) \tag{8}$$

Let, $I_0 = 1$ and $S_0 \approx N, S_0 / N \approx 1$, Equation (8) is written as

$$\frac{dI}{dt} = \alpha - (\beta + \gamma) \tag{9}$$

and from $\frac{\beta+\gamma}{\alpha} > 1$, $\alpha - (\beta+\gamma) < 0$ which then imply

$$\frac{dI}{dt} < 0 \tag{10}$$

Hence, removed the first infected case, leaving $I^* = 0$, and the equilibrium point for $\frac{\beta+\gamma}{\alpha} > 1$ is $(N, 0, 0, 0)$.

It is observed that From Figure 2, the infected case initially increases rapidly at t below 35. Due to this, susceptible population decreases rapidly, and both recovered, and death cases rises. This is caused by the high infectivity of the epidemic. As the susceptible cases drop to 40% of the original population, we can observe that the infected cases drop even with the same infectivity rate. This shows even in high infectivity epidemic, low numbers of the susceptible class will lead to the extinction of virus. Similar result by artificially reducing the susceptible class by quarantine, and social distancing will give a similar result. This shows in high infectivity epidemic, social distancing and quarantine is a major factor in decreasing the disease spread.

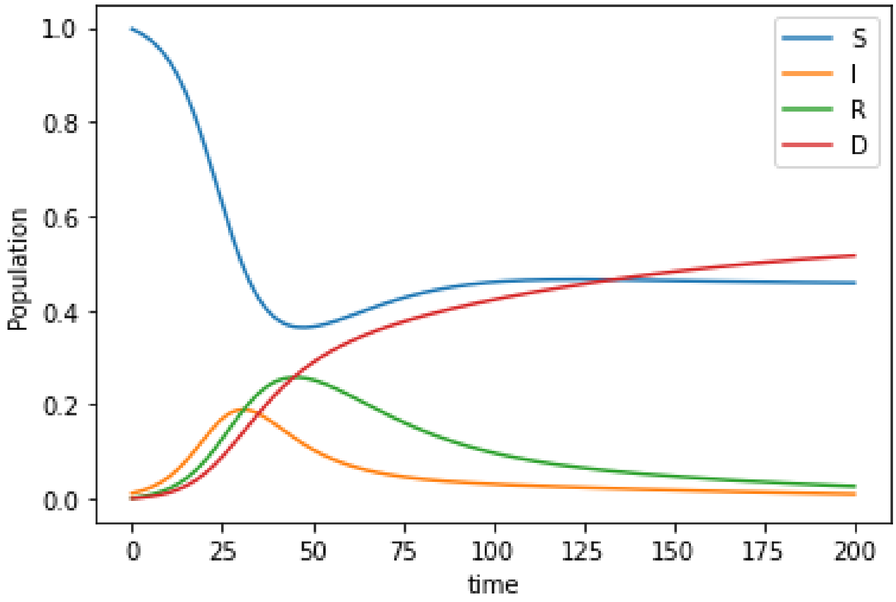

FIGURE 2. Numerical simulation of first equilibrium, $\alpha, \beta, \gamma, \delta = 0.3, 0.1, 0.05, 0.05$

PARAMETER ESTIMATION

The epidemiological parameters are estimated using MCMC of the Metropolis-Hasting algorithm. The algorithm associated with a target density, π requires the choice of a conditional density q also called proposal. The transition from the value of the Markov Chain ($X^{(t)}$) at the time t and its value at time $t+1$ is computed using the following algorithm.

Algorithm	Metropolis-Hastings

Given $X^{(t)} = x^{(t)}$ Generate $Y_t \sim q\left(y \middle| x^{(t)}\right)$

Take

$$X^{(t+1)} = \begin{cases} Y_t & \text{with probability} \quad \rho\left(x^{(t)}, Y_t\right) \\ x^{(t)} & \text{with probability} \quad 1-\rho\left(x^{(t)}, Y_t\right) \end{cases}$$

where

$$\rho(x, y) = \min\left\{\frac{\tilde{\pi}(y)}{\tilde{\pi}(x)} \frac{q(x|y)}{q(y|x)}, 1\right\}$$

The parameters are estimated from the COVID 19 Malaysia data obtained from http://covid-19.moh.gov.my, 25 January 2020 to 24 January 2021. The epidemiological parameters are presented in Table 2. The model is designed to handle varying infection rate for both past simulation and predicted simulation, where the values for past simulation are obtained from the parameter estimation and for predicted are obtained from values assigned by the user.

TABLE 2. Estimation of the epidemiological parameter based on MCO control measures in Malaysia

Starting Date	End Date	Infection rate, α	Recovery rate, β	Immune Lost rate, γ	Fatality rate, δ
24/1/2020	13/2/2020	0.1191200	0.0199990	0.00139640	0.00017965
14/2/2020	25/2/2020	0.0592960	0.1463800	0.01232200	0.00556370
26/2/2020	14/3/2020	0.2386200	0.0162440	1.0547×10^{-7}	0.00073866
15/3/2020	25/3/2020	0.2277500	0.0247450	0.01892400	0.00231060
26/3/2020	07/4/2020	0.0864070	0.0390170	0.00625460	0.00296470
08/4/2020	28/5/2020	0.0504110	0.0660400	0.00519710	0.00063741
29/5/2020	09/6/2020	0.0647300	0.0546540	0.00350820	0.00207740
10/6/2020	09/7/2020	0.0334590	0.1283000	0.00025825	0.00166760
10/7/2020	18/9/2020	0.0874380	0.0551310	1.0021×10^{-7}	0.00052585
19/9/2020	30/10/2020	0.1691900	0.0878360	0.00517200	0.00089812
31/10/2020	23/11/2020	0.1287900	0.1166700	0.01551100	0.00033274
24/11/2020	09/12/2020	0.1567200	0.1807500	0.01412000	0.00027618
10/12/2020	04/1/2021	0.1016000	0.0707640	1.5601×10^{-5}	0.00032804
05/1/2021	10/1/2021	0.2261300	0.1911100	0.03531600	0.00032800
11/1/2021	23/1/2021	0.2750000	0.2485000	0.06195000	2.2972×10^{-7}

PROGRAM FEATURES OF THE PREDICTIVE DASHBOARD

The program code for the predictive dashboard is written in Python. The model was simulated using the fourth-order Runge-Kutta method and the parameter is fitted via MCMC of the Metropolis-Hastings method. The data and simulated results are displayed in the form of number of active cases, cumulative death, and cumulative recovery cases. For future approximations, infection rate approximations are estimated from the historical data and can guide the user in choosing the values based on the MCO control measures. The recovery, fatality, and immune lost rate for future approximation are considered equal to the average rate and calculated from the data and assumed to be constant throughout the approximations. This first option simulates constant scenario MCO measures throughout time. The weakness of this approximation is it does not reflect the varying strictness of MCO measures and initiating and closing of quarantine that was previously done by the Malaysian Government. The second option, the alternating scenario MCO measures simulates if the MCO is repeatedly opened and closed for a certain duration. The infection rate in the period of MCO and out of MCO period as well as the duration are set as input in GUI. The third option, the structured MCO, uses the same value of infection rate as the second option but the date of initiating and ending the MCO is set by the user. This option reflects the MCO planning the best among the three options. The program features of the predictive dashboard algorithm are depicted in Figure 3 and the dashboard is illustrated in Figure 4.

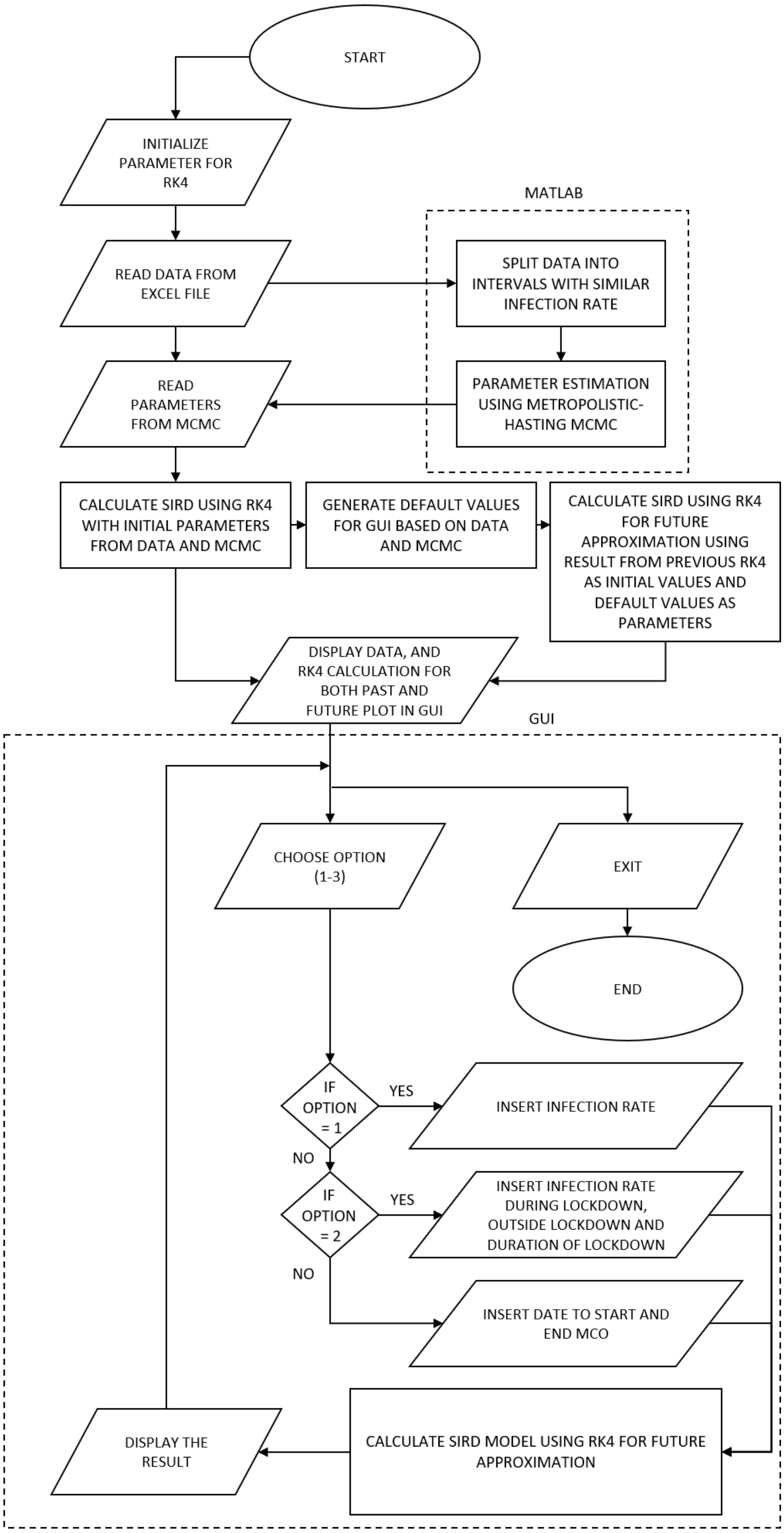

FIGURE 3. Flowchart of the algorithm

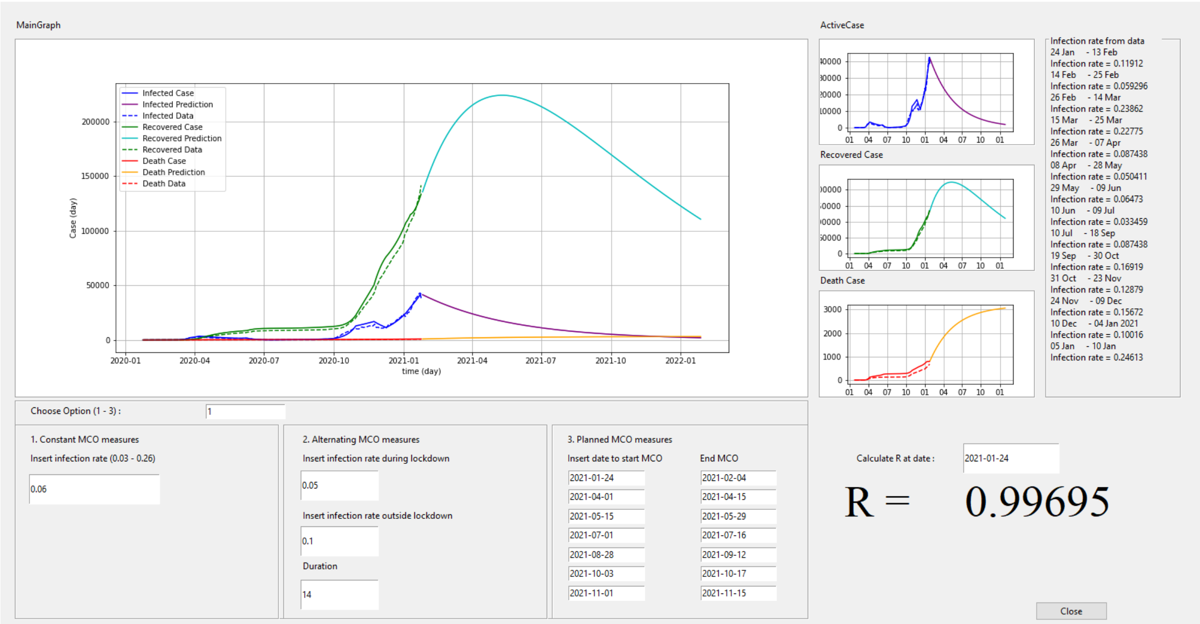

FIGURE 4. Graphical User Interface

The value for the real time reproduction number of R is calculated for a specific day chosen by the user. The approach used in calculating R for a specific day is by taking a ratio of the active case population for the date to the active population for the previous 14 days, written as

$$R(t) = 1 + \left(\ln\left(\frac{I(t)}{I(t-14)} \right) / 14 \right) \tag{11}$$

Results and Discussion

This section presents the predictive measures of the outbreak under different types of MCO control measures. Malaysia has implemented various types of partial lockdown including movement control order (MCO), conditional movement control order (CMCO), and recovery movement control order (RMCO). The prediction is performed based on three different types of MCO which are loose MCO (RMCO), strict MCO (CMCO) with different time of lifting date, and alternate MCO (14 days MCO and 14 days no MCO, then repeatedly continue till the curve is flattened). Alternate MCO is a choice of the adopted control measure to balance the lives and livelihoods. The result is discussed in terms of the trend of active cases, recovered cases, and death cases and the effects of the MCO.

Simulation Result Under Loose MCO

The first situation is simulated by assuming loose MCO measures are taken and after the MCO lifting date, all sectors can resume under standard operating procedure (SOP) of the social distancing, checking the temperatures, and wearing masks. Some gatherings are allowed such as meetings, seminars, weddings, religious gatherings, and social activities with a limited number of guests. The sectors under tourism, wellness, and foot massage centers and spas are allowed to operate. Historically, similar regulations have been conducted and the observed infection rate ranges from 0.12879 (31 October 2020 - 23 November 2020) to 0.22613 (5 January 2021 - 10 January 2021), assuming the difference is due to public compliance toward the SOP. The infection rate of 0.16 is chosen for this simulation. For the input of the GUI, this simulation in Figure 5 is achieved by using ‘Choose option = 1, Infection rate = 0.16’.

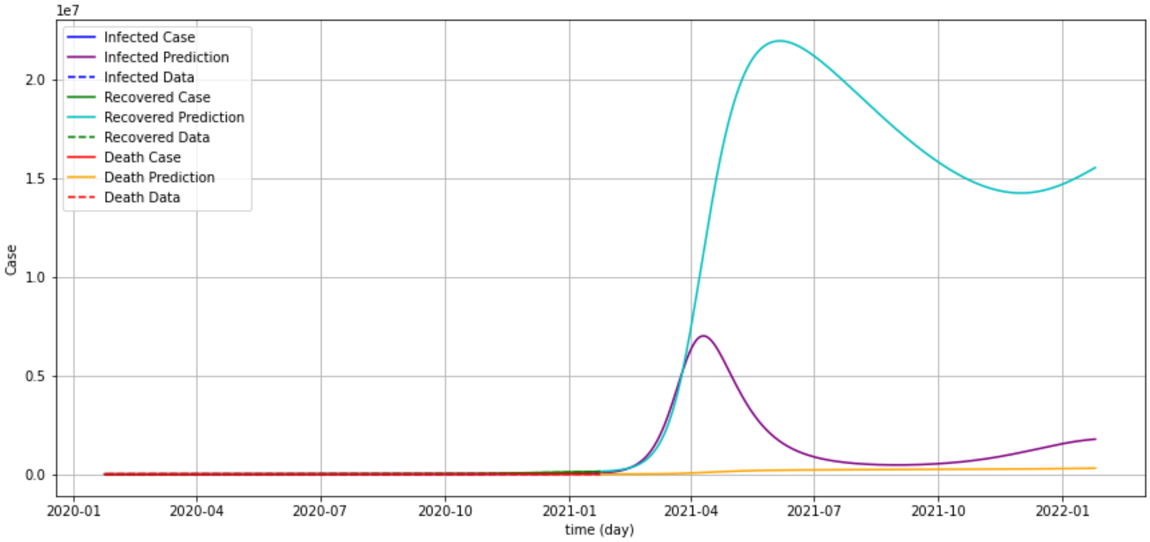

FIGURE 5. Result using constant MCO option and infection rate of 0.16

Figure 5 shows the active cases increase rapidly and peaked when reached about 7.5 million active cases from January 2021 until late April 2021 and then declined until September 2021. This is caused by high recovered cases at the time. Even with the low immune loss, the recovered started declining and the reinfection could be seen will occur in October 2021 as the active case increase. This method is not viable as the active case peaked at 7.5 million infected at once which is far more than any countries' medical infrastructure could handle and the total fatality cases will be significantly higher than approximated which is already approximated at 0.3 million in early 2022.

SIMULATION RESULT UNDER STRICT MCO

This simulated results in this section are performed assuming the constant strict MCO measures are taken for a certain period. In this strict MCO, schools and universities are closed. Some essential economic activities are allowed but they are limited to shorter operating hours with a limited number of workers. Interstate travel is not permitted. Historically, a similar restriction is conducted and the result for the infection rate are 0.033459 (10 June 2020 – 9 July 2020) and 0.059296 (14 February 2020 – 25 February 2020). We can replicate the result by inserting 'Choose option = 1, infection rate = 0.033459'.

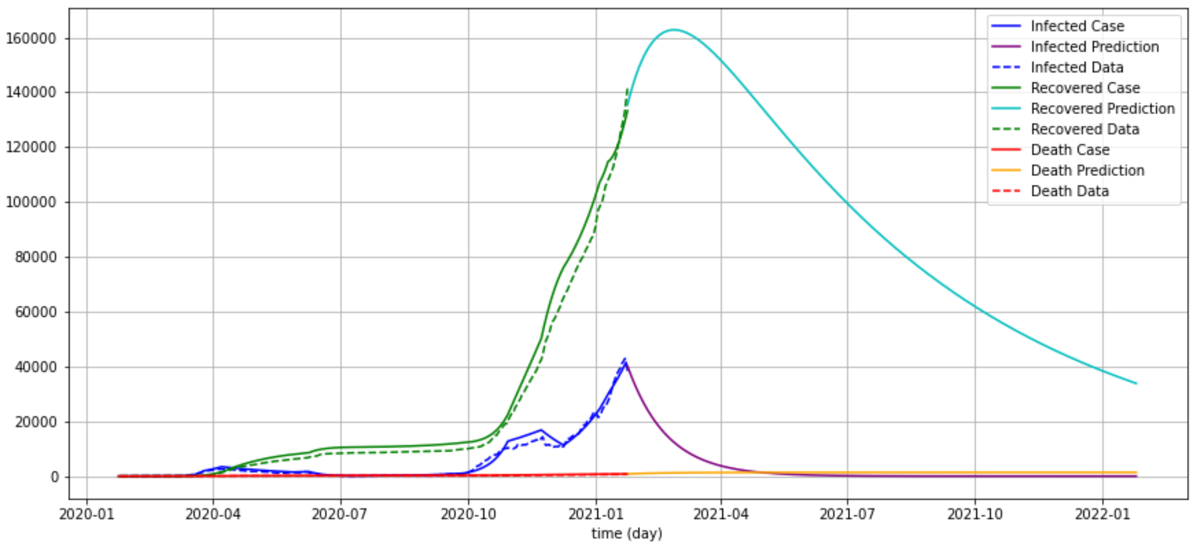

FIGURE 6. Result using constant MCO option, infection rate 0.033459

Figure 6 as expected shows the active case decreases rapidly. Though, this option needs an exit strategy as the strict MCO measures for a long period will lead to the collapse in economy, starvation among the poverty, and depression among the public. In real life situation, prolonged strict MCO will cause the public's compliance to drop, thus, making the infection rate higher than simulated. Thus, the lifting date needs to be planned. Next subsection the strict MCO is simulated for a certain lifting date.

Simulation Result under Strict MCO with Opening Lockdown Date of 1/7/2021

This simulation is replicated by the user using 'Choose option = 3, infection rate during lockdown = 0.033459, infection rate outside lockdown = 0.16, Date to start MCO = 2021-01-24, Date to end MCO = 2021-07-01'. The prediction result is simulated in Figure 7.

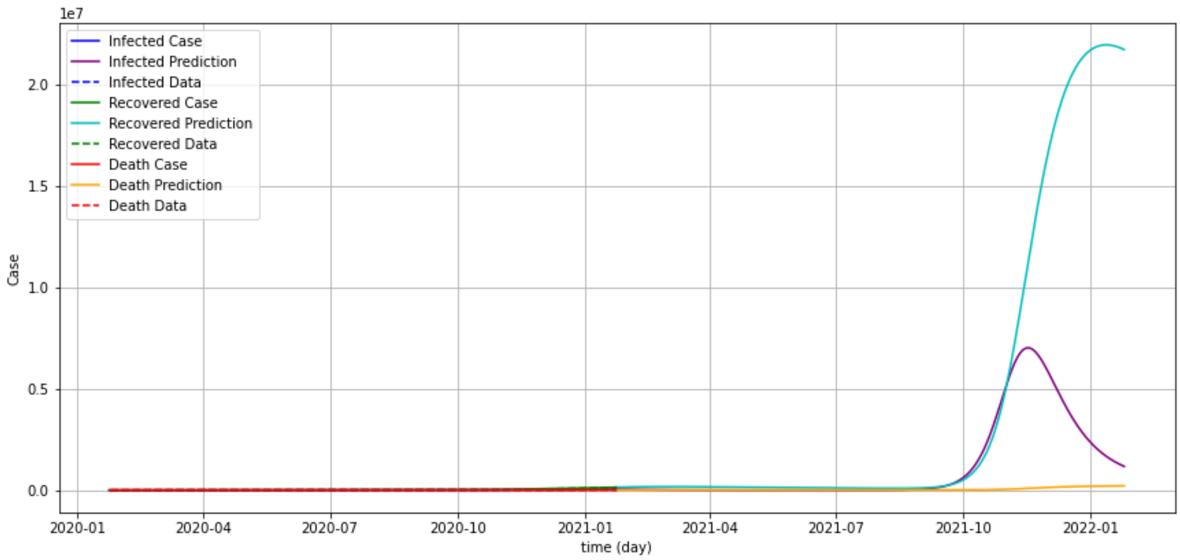

FIGURE 7. Result using strict MCO, infection rate 0.033459 with exit date 1/7/2021

Figure 7 illustrates the number of active cases, recovered cases, and death cases that are low during the MCO. Once the date is lifted the active cases increase rapidly which is resemble with the simulated result in Figure 4. This shows that even after six months of strict lockdown, the cases will show a soaring trend. Obeying SOP may decline the infection rate, however, with the limited number of workers and social distancing may give an impact on the economic sectors in a long run.

Simulation Result under Strict MCO with Opening Lockdown Date of 1/10/2021

This simulation is replicated by the user using 'Choose option = 3, infection rate during lockdown = 0.033459, infection rate outside lockdown = 0.16, Date to start MCO = 2021-01-24, Date to end MCO = 2021-10-01'. The result is depicted in Figure 8. The simulated results show that the curve is flattened during MCO. Once the date is lifted, the active cases increase rapidly which is resemble with the simulated result for loose and strict MCO of lifting date 1/7/2021.

SIMULATION RESULT UNDER ALTERNATING MCO MEASURES

A more sustainable method is to control the infection at a rate that is optimal in order to reduce the infection as well as maintaining the negative effects of strict MCO. Since most regulations in MCO exist in a binary form such as opening or closing a certain sector or allowing cross border or not, a method of achieving the optimal rate is by periodically opening and closing MCO. This method will allow most sectors to be relatively active while allow to periodically reduce the infection rate. The period of

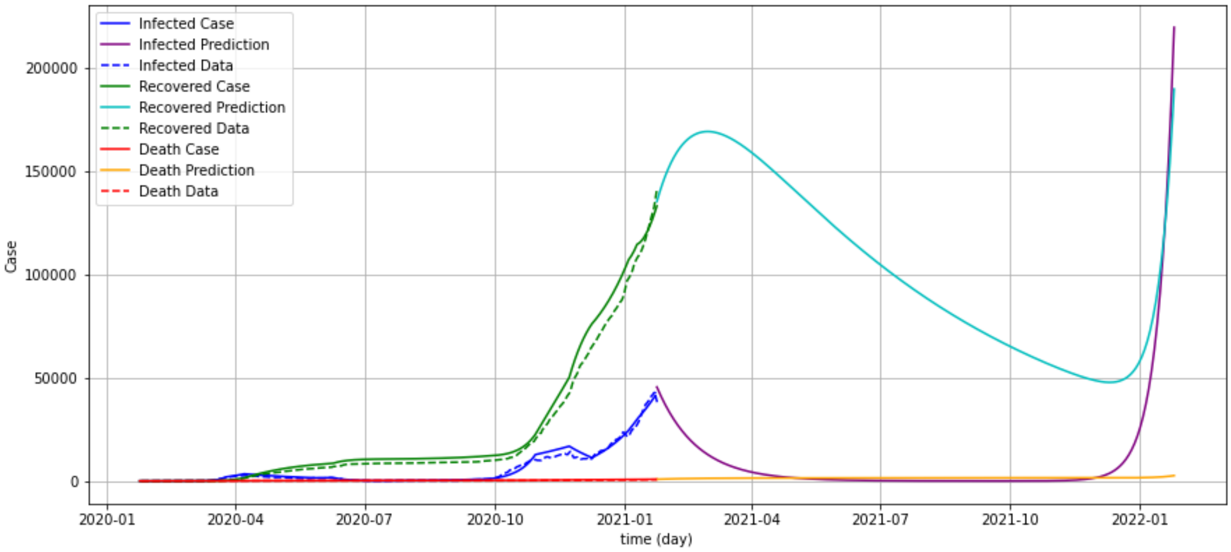

FIGURE 8. Result using strict MCO, infection rate 0.033459 with the exit date 1/10/2021

active MCO could also be chosen in such a way, during the period asymptomatic infected would be quarantined.

The assumption for the simulations is the lockdown periodically initiated every 28 days and the lockdown has a duration of 14 days. During the lockdown, all governments and private sectors are closed, no interstate travel is allowed, and SOP compliance is high. Only essential services those involved in water, electricity, energy, telecommunications, postal, transportation, irrigation, oil, gas, fuel, lubricants, broadcasting, finance, banking, health, pharmacy, fire, prison, port, airport, safety, defense, cleaning, retail, and food supply can operate. The infection rate during lockdown is assuming to be 0.033459. Outside of lockdown, most business sectors are allowed but still maintaining SOP. The first simulation is performed by using 'Choose option = 2, Infection rate during lockdown 0.033459, Infection rate outside lockdown = 0.16, duration = 14'. The predictive result is illustrated in Figure 9.

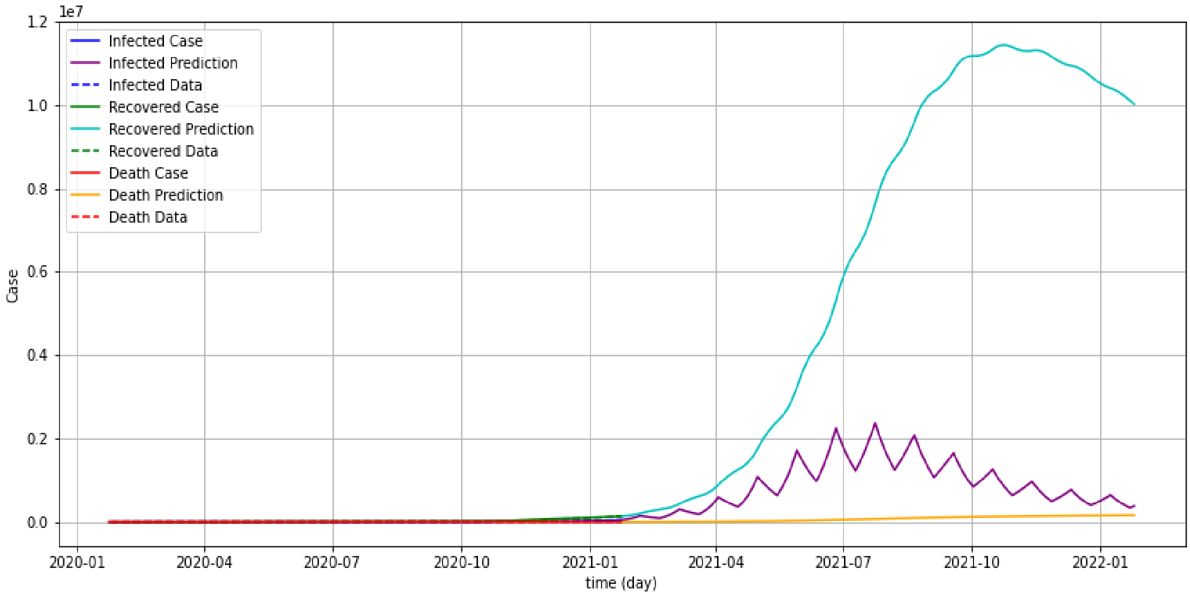

FIGURE 9. Alternating MCO measures, infection rate 0.033459 and 0.16, duration 14 days

The second simulation is performed using 'Choose option = 2, Infection rate during lockdown 0.033459, Infection rate outside lockdown = 0.1 (assuming the infection rate is low), duration = 14', as the result is illustrated in Figure 10.

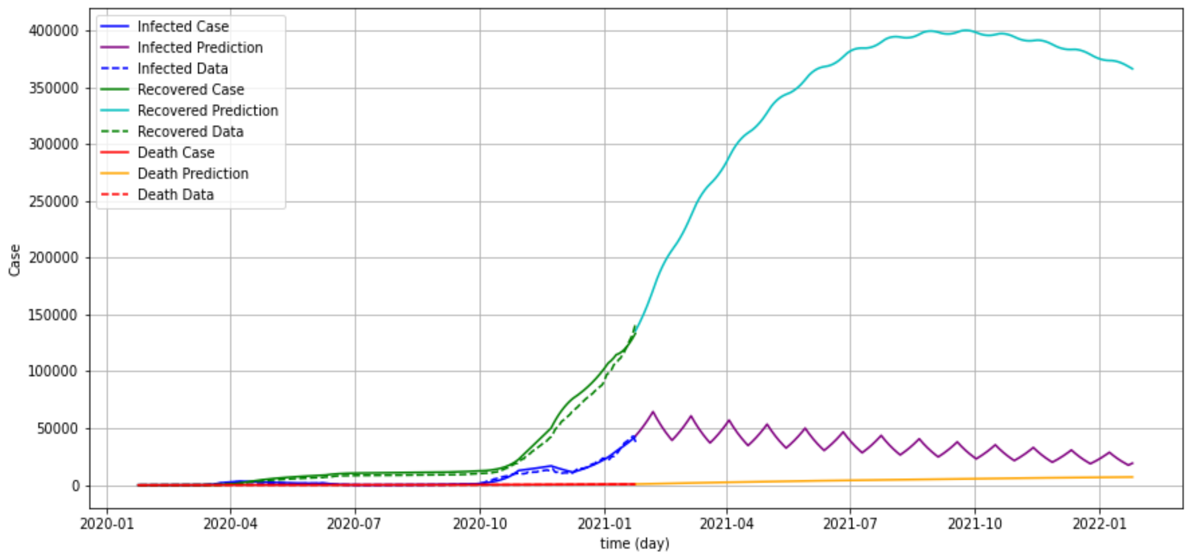

FIGURE 10. Alternating MCO measures, infection rate 0.033459 and 0.1, duration 14 days

For both cases, the infection rate during MCO is 0.033459. The infection rate outside of lockdown is 0.16 and 0.1 for simulations 1 and 2, respectively. This shows even with regular strict regulation during the lockdown, the active case could only be controlled by reducing the infection rate outside lockdown. Maintaining the active case from increasing rapidly, will prevent the exhaustion of the medical infrastructures and the economic sectors can still be operated. During the 14 days' lockdown, the workers can still work from home. Online teaching and learning still can be implemented for education sectors. The third simulation is performed using 'Choose option = 2, Infection rate during lockdown 0.033459, Infection rate outside lockdown = 0.1 (assuming the infection rate is low), duration = 5'. The prediction result of 5 days alternating MCO is shown in Figure 11.

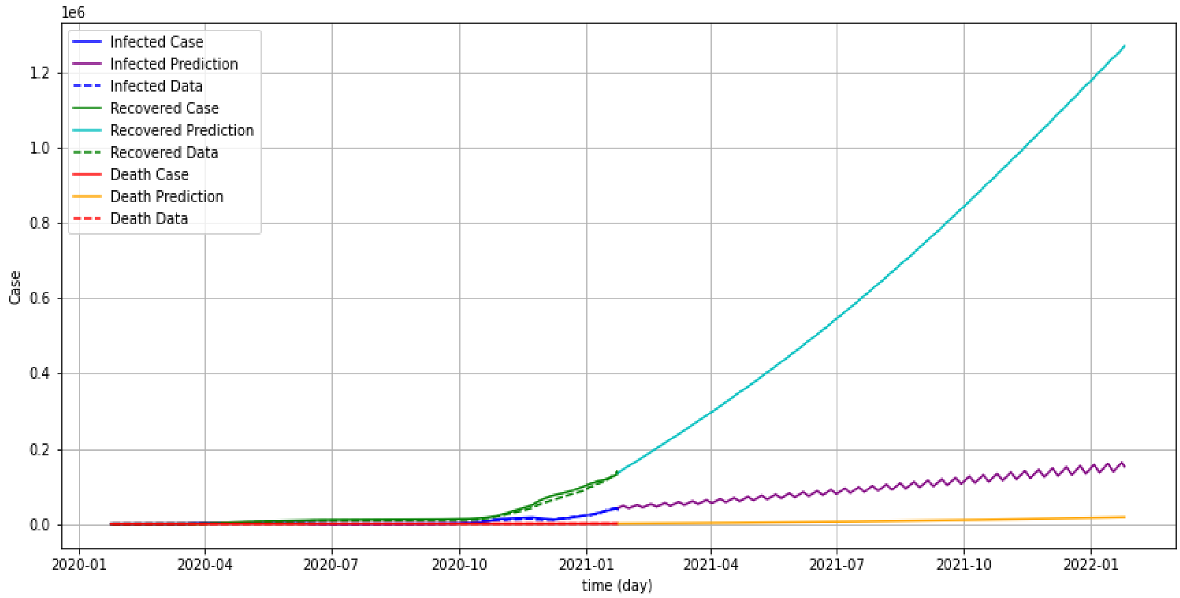

FIGURE 11. Alternating MCO measures, infection rate 0.033459 and 0.1, duration 5 days

Surprisingly, even the only difference is the duration, the active case is steadily increasing unlike the simulation of alternating MCO for the period of 14 days. This may be occurred due to the incubation period which can take up three to fourteen days (compared to one to four days' flu). The transmission from person to person can still happen after 5 days of quarantine and isolation period. Study shows that after SARSCoV2 has invaded a person via his mouth, nose, or eyes, the first symptoms in most of the cases will only appear around four to five days after exposure. 97.5 percent of the infected people who develop symptoms will do so within 11.5 days.

SIMULATION RESULT UNDER PLANNED MCO MEASURES

The third option provided to the user is to plan the initial and terminal date of MCO with different period. This provides user the choice to plan and design MCO contain measure. The user can insert up to 7 different lockdown period. The values for infection rate during and outside lockdown are taken from option 2 in the GUI.

The functionality of this option is shown in Simulation Result under Strict MCO with Opening Lockdown Date of 1/7/2021 and Simulation Result under Strict MCO with Opening Lockdown Date of 1/10/2021 sections in planning exit strategy. Another example, if the guideline planned by the policymakers is MCO regulations will become strict if the active case at any time reaches 50,000 cases and the strict policy is kept until the active cases decrease below 25,000. In this example, the infection rate values used during lockdown are 0.0504110 and outside of lockdown is 0.1287900. Figure 12 shows the approximation by implementing the aforementioned policy.

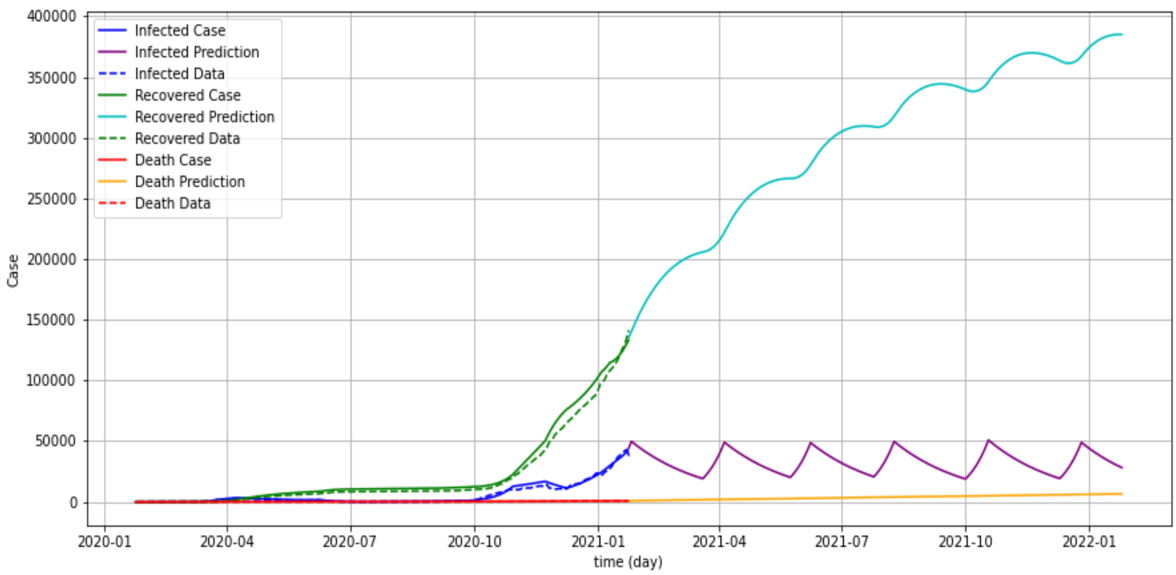

FIGURE 12. Planned MCO measures, infection rate 0.0504110 and 0.1287900

By following this policy, six strict MCO duration is needed in one year with a duration of over a month each. By using the GUI, user can see the frequency and duration of strict MCO needed to achieve a certain policy, and whether the planned policy is viable to be implemented.

CONCLUSION

COVID-19 is an epidemic that greatly affected citizens of Malaysia not only in health, but economically, socially, financially, and even emotionally. The MCO implementation is a great short-term solution in flattening the graph of infected cases, and greatly helps to preserve our medical facilities to ensure every infected person receives proper care. Thus, the fatality and severity rate in our country is among the least around the world. However, many other factors should be considered if the MCO is continued, the poor getting poorer, industrial activities plummeted and educational activities are in halt. Therefore, GUI is created as a tool in strategy making by using historical data and parameters as an example of possible action that could be taken to curb the spreading of COVID 19 and developing a sustainable plan. The model proposed is embedded in the proposed predictive dashboard which considering simple SIRD model. Currently, the proposed model is in progress to be improved by considering incubation period of the virus as well as the stochastic effect which influences the spread of the disease. The proposed predictive dashboard is also currently being improved by including the simulation of the economic impact in the presence of the various types of MCO control measures.

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