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MODELING AND PREDICTING THE DYNAMICS OF COVID-19 IN MALAYSIA: A STATE-SPACE APPROACH

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ABSTRACT

The emergence of COVID-19 in Malaysia in January 2020 marked the beginning of a significant public health challenge. Despite the transition to the endemic phase on April 1, 2022, the global impact of the virus remains substantial. This research aims to forecast the cumulative number of detected cases and deaths by employing a state-space model derived from the Susceptible-Infectious-Recovered (SIR) model, capturing the multi-wave dynamics of COVID-19. The modeling focuses on estimating the trends within the time interval spanning from week 1 to week 12, commencing in mid-June 2022. Real-time data sourced from the Ministry of Health in Malaysia serve as the basis for model development and validation, utilizing MATLAB and Simulink for simulation purposes. The findings of the simulation reveal a direct correlation between the number of detected cases and deaths, suggesting a positive relationship with the real-life situation. This mathematical representation contributes to a deeper understanding of the ongoing dynamics of COVID-19 and provides a tool for predicting future trends, aiding in public health planning and response efforts.

Keywords: *COVID-19, SIR Model, Simulation, State Space, Mathematical Modelling*

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1. Introduction

In late December 2019, an outbreak of a mysterious pneumonia occurred in Wuhan, Hubei, China (Wu et al., 2020). Chinese scientists reported that the virus had a 96.3% genetic similarity with a Yunnan bat coronavirus RaTG13 and a 70% homology with severe acute respiratory syndrome coronavirus (SARS-CoV). The cause of this epidemic outbreak was a novel coronavirus discovered in 2019 (2019-nCoV) or SARS-CoV-2, and the World Health Organization named the disease coronavirus disease 2019 (COVID-19) (Elengoe, 2020). As of April 19, 2022, there have been 503,131,834 confirmed cases of COVID-19, including 6,200,571 deaths, reported to the World Health Organization.

The first incidence of COVID-19 in Malaysia was discovered on January 25, 2020, and was traced back to three Chinese nationals who had intimate contact with an infected individual in Singapore (Elengoe, 2020). As of April 19, 2022, Malaysia has reported a total of 4,402,234 cases of COVID-19, with 35,449 deaths and 4,274,746 recovered cases, according to the Ministry of Health in Malaysia. Notably, the country has also encountered several COVID-19 variants, including the Delta variant and the Omicron variant.

In December 2020, the Delta variant, discovered in India, exhibited a higher propensity to infiltrate the host's immune system faster than the original strain, leading to its rapid spread to over 60 nations (Shiehzadegan et al., 2021; Ahmad et al., 2020). On November 26, 2021, the World Health Organization recognized the Omicron variant as a variant of concern due to its faster spread than the original SARS-CoV-2 virus and other worrisome variants. Malaysia recorded its first COVID-19 Omicron case on December 2, 2021, involving a 19-year-old South African student returning to Ipoh, Perak (Law et al., 2021).

COVID-19 spreads via direct contact with droplets (such as sweat, saliva, sneezing, or coughing) from an infected person. The contagious nature of this disease is such that even asymptomatic individuals can transmit the infection. Consequently, early case detection is a key strategy implemented by governments worldwide to mitigate the disease's spread (Odetunde at el., (2022).

In addition to tracking the variants, Malaysia has undergone significant public health measures, including Movement Control Orders (MCOs), to curb the spread of the virus. These MCOs, implemented at different levels of severity, aimed to restrict movement and social interactions. The World Health Organization has devised a tight rule to follow throughout the pandemic since there is no safe and effective medication against COVID-19 (Elengoe, 2020). We have all been exposed to a set of quasi-standard procedures implemented by national and local authorities, including wearing masks, social distancing, virus testing and contact tracking (Pejó & Biczók, 2020). Vaccination is also one of the preventive measures taken by the world to reduce the risk of COVID-19 infection. As of April 17, 2022, the total world population was 7,845,261,000. The first dose was given to 5,117,125,986 (65.2%) people, while the second dose was given to 4,616,144,361 (58.8%) people.

Simultaneously, Malaysia has been actively engaged in a vaccination program to mitigate the impact of COVID-19. Vaccination efforts have been crucial in achieving widespread immunity and preventing severe cases and deaths. This research adopts a basic compartmental approach, specifically the susceptible-infectious-recovered (SIR) model, to understand and predict the dynamics of COVID-19 in Malaysia. The SIR model divides the population into susceptible, infectious, and recovered individuals, considering factors such as vaccination, quarantine, and disease (Zhou & Ji, 2020). This research contributes to a comprehensive understanding of the epidemiological situation and informs future public health strategies in the context of evolving variants and vaccination progress in Malaysia.

In the field of control engineering, a state-space model serves as a fundamental mathematical representation of a physical system. This model captures the dynamics of the system through a set of first-order differential equations, linking inputs, outputs, and state variables. State variables are dynamic entities whose values evolve over time and depend on the inputs provided. The values of output variables, in turn, are determined by the current state and input variable values. The utilization of state-space models is prevalent in control analysis and dynamic process studies, forming the basis for various methods in these domains (Ashaari et al., 2014).

This section focuses on exploring state-space models specifically for continuous-time linear systems. Results for discrete-time systems can be derived through duality with their continuous-time counterparts. The state-space representation of a continuous-time dynamic system can be derived from either a system model presented in the time domain through differential equations or its transfer function representation (Munirah et al., 2014).

Continuous-time linear systems are particularly relevant in control engineering, and their state-space models provide valuable insights into system behavior. The transition from a system's differential equation or transfer function to its state-space representation allows for a more versatile and comprehensive analysis of the system's dynamics. This approach facilitates the application of various control techniques and methodologies, making it a crucial aspect of control engineering studies. In subsequent sections, we will delve into the principles of constructing and analyzing state-space models for continuous-time systems, exploring their practical implications in control system design and analysis (Friedland, B.,2012).

2. Methodology

Controlling complex systems has been integral to the advancement of modern civilization and technology. As systems evolve to have multiple inputs and outputs, addressing their intricacies requires concerted efforts and specific approaches. A multivariable system, encompassing input, state variables, and output, is characterized by a set of first-order differential equations (Ismail, 2005). To effectively manage and analyse such systems, a state-space representation is employed, organizing the system model in a vector-matrix format.

The mathematical description of the system, influenced by the principles outlined by Ogata (1997), is structured within the state space framework. This representation enables a comprehensive understanding of the system's behaviour and facilitates the application of control strategies. The state space model encapsulates the dynamics of the system, providing a versatile and powerful tool for control engineers.

$$x(t) = Ax(t) + Bu(t) \tag{1}$$

$$y(t) = Cx(t) + Du(t) \tag{2}$$

Where A is a state matrix, B is the input matrix, while the equations x(t) = d(x)/dt is the time derivatives of the state equations and u(t) is the constants input. Moreover, the output equations are conveyed in a linear form as in equations (2) since C is assigned as the output and D is the directed transmission matrix. Furthermore, the vectors y(t) stands for the output variable, while u(t) and x(t) symbolize the input and the state equations (Friedland, B., 2012).

Despite the implementation of stringent restrictions and effective prevention measures by the local government to contain virus transmission within communities, COVID-19 continues to proliferate rapidly in Malaysia, posing a significant public health concern. Therefore, it is imperative to comprehend the magnitude of this outbreak. Various methodologies and approaches have been emphasized to assess the severity of the situation and devise solutions to address this pandemic (Mohd Idris at el., 2022). Modelling the SIR model for the COVID-19 outbreak is crucial for establishing a simple framework to analyse the disease's transmission within Malaysian communities (Mahat at el., 2023). This study aims to explore the SIR model of COVID-19 using weekly case data in Malaysia to depict the outbreak's progression over time.

The differential equations are taken from (Beira & Sebastiao, 2021) to develop the state space equation of COVID 19 endemic.

$$\frac{dS}{dt} = k_{PS}P - k\frac{I}{N}S \tag{3}$$

$$\frac{dI}{dt} = \frac{1}{\tau_I}E - \left[\frac{(1-d)}{\tau_R} + \frac{d}{\tau_{Id}}\right]I \tag{4}$$

$$\frac{dR}{dt} = \frac{1}{\tau_R}[(1-l)I_d + (1-d)I] + v - k_{RP}R \tag{5}$$

Equations (3), (4), and (5) can be written as matrix equations and can be defined as:

$$\begin{pmatrix} S' \\ I' \\ R' \end{pmatrix} = \begin{pmatrix} -k\frac{I}{N} & 0 & \frac{k_{PS}P}{R} \\ \frac{E}{\tau_I S} & \left[\frac{(1-d)}{\tau_R} + \frac{d}{\tau_{Id}}\right] & 0 \\ 0 & \frac{(1-d)}{\tau_R} & -k_{RP} \end{pmatrix} \begin{pmatrix} S \\ I \\ R \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ \frac{(1-l)}{\tau_R} \end{pmatrix} \begin{pmatrix} P \\ E \\ I_d \end{pmatrix} \tag{6}$$

Such that the state matrix A = $\begin{pmatrix} -k\frac{I}{N} & 0 & \frac{k_{PS}P}{R} \\ \frac{E}{\tau_I S} & \left[\frac{(1-d)}{\tau_R} + \frac{d}{\tau_{Id}}\right] & 0 \\ 0 & \frac{(1-d)}{\tau_R} & -k_{RP} \end{pmatrix}$

Input matrix B = $\begin{pmatrix} 0 \\ 0 \\ \frac{(1-l)}{\tau_R} \end{pmatrix} \begin{pmatrix} P \\ E \\ I_d \end{pmatrix}$

The output equation is written as y(t)= Cx(t) + Du(t), where C and D are the output direct transmission matrices. The state is represented by the vector x(t), whereas the input and output variables are represented by the vectors u(t) and y(t). However, the D variable is assumed as 0 in this study, implying that there is no direct communication between the input u(t) and the output y. (t). The following is the state space's output equation.

$$\begin{pmatrix} N_{T_d} \\ N_D \end{pmatrix} = \begin{pmatrix} 0 & \frac{d}{\tau_{Id}}t & 0 \\ 0 & \frac{\left(\frac{ld}{\tau_{Id}\tau_D}I\right)}{\left(\frac{1-l}{\tau_R} + \frac{l}{\tau_D}\right)} & 0 \end{pmatrix} \begin{pmatrix} S \\ I \\ R \end{pmatrix} \tag{7}$$

Such that matrix C = $\begin{pmatrix} 0 & \frac{d}{\tau_{Id}}t & 0 \\ 0 & \frac{\left(\frac{ld}{\tau_{Id}\tau_D}I\right)}{\left(\frac{1-l}{\tau_R} + \frac{l}{\tau_D}\right)} & 0 \end{pmatrix}$

3. Result and Discussion

In this research, MATLAB computer software has been employed as a crucial tool. MATLAB programming is utilized to execute and analyse the data based on the linear matrix state space representation given by x' = Ax + Bu and y = Cx + Du. The modelling process involves estimating trends during the specific time interval from week 1 to week 12, starting in the middle of June 2022.

Table 1 provides a comprehensive definition of terms and concepts utilized in this research, drawing upon the work of Beira and Sebastiao (2021). This table serves as a reference guide, ensuring clarity and consistency in the use of terminology throughout the study. The utilization of MATLAB as a computational tool enhances the efficiency and accuracy of data analysis, facilitating the extraction of meaningful insights from the state-space model. The research methodology underscores the importance of robust computational tools in advancing our understanding of the dynamic patterns of COVID-19 and contributes to the ongoing efforts in public health planning and response.

Table 1: The Definition of Terms and Concepts (Beira at el., 2021).

Parameter	Definition	Parameter	Definition
P	Protected population	N	$S + I + R$
S	Susceptible population	k_{PS}	Transition rate $P \rightarrow S$
E	Exposed	k	Rate describing $S \rightarrow E$
I	Infected responsible for spreading	τ_I	Time of progression $E \rightarrow I$
I_d	Infected detected	τ_{Id}	Transition time $I \rightarrow I_d$
R	Total recovered	d	Fraction of I that is detected
l	Fraction of I that dies	k_{RP}	Characteristic reinfection rate
τ_R	Characteristic recovery time	v	Daily vaccinated
τ_D	Characteristic death time		

The output result from MATLAB programming is presented in Figure 1. Figure 1 a) Cumulative Number of Detected Cases. Figure 1 b) Cumulative Number of Deaths Versus Time (weeks).

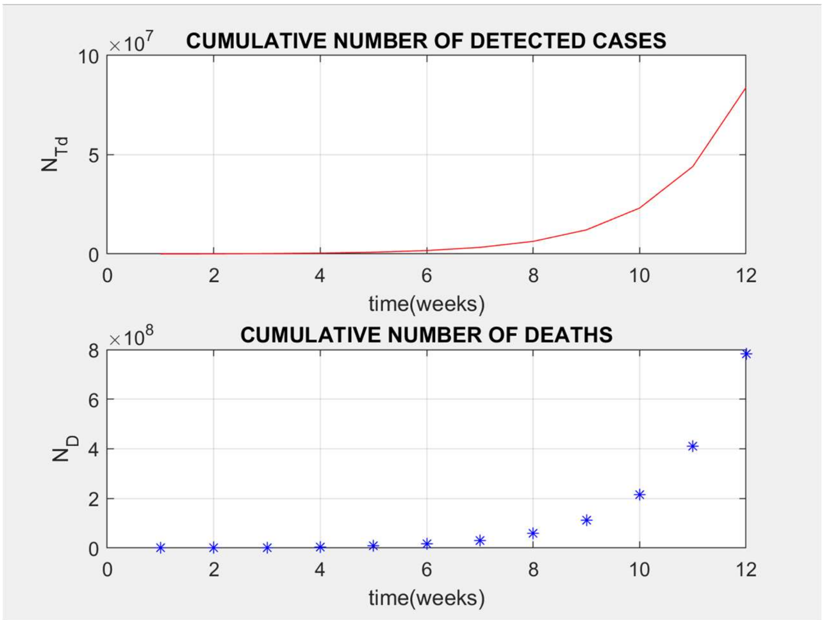


Figure 1: a) Cumulative Number of Detected Cases. b) Cumulative Number of Deaths Versus Time (weeks).

The simulation results, as depicted in Figure 2, likely provide a visual representation of the dynamic behaviour of the state-space model. These simulations are crucial for understanding how the system evolves over time in response to various inputs and initial conditions. If Figure 2 is available, it would offer valuable visual insight into the outcomes of the state-space model and aid in the interpretation of the system's response to different scenarios.

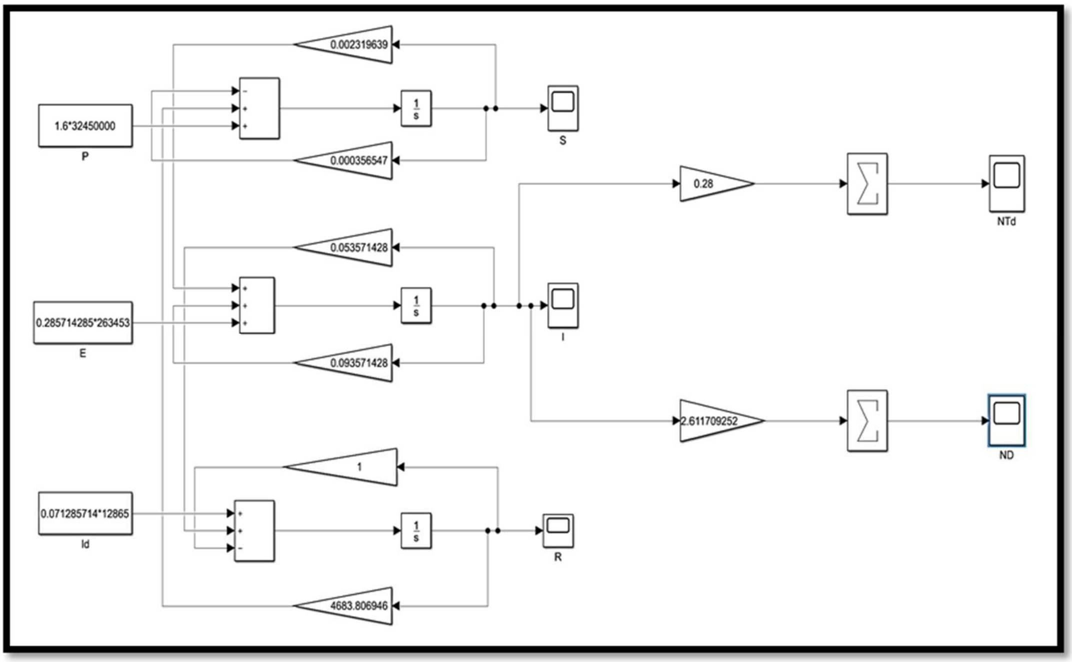


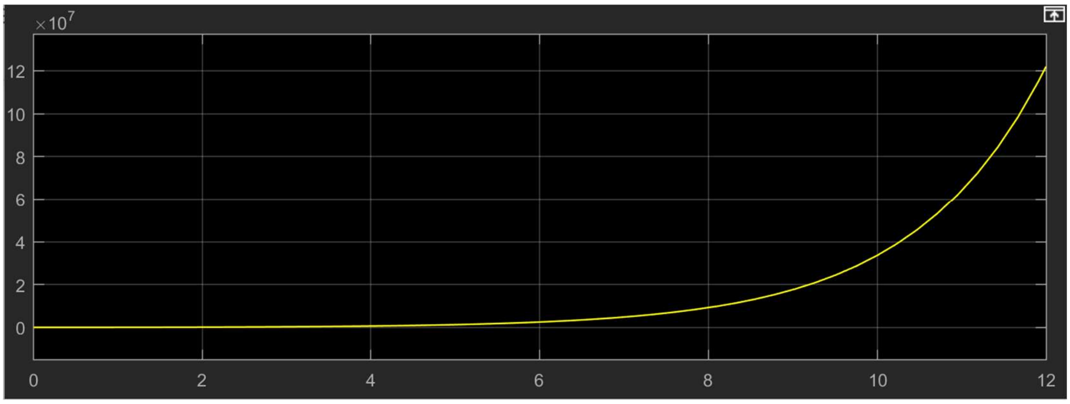
Figure 2: MATLAB Simulink Programming of COVID-19 Endemic

In this study, the investigation into the functioning of state-space systems is conducted using Simulink through a block diagram to simulate the state-space model equations. This method represents a direct implementation of the transfer function. The graphical representation of the cumulative number of detected cases and the cumulative number of deaths over time (weeks) using MATLAB SIMULINK is illustrated in Figure 3. It is noteworthy that the results obtained from MATLAB Simulink closely align with the outcomes derived from the programming analysis.

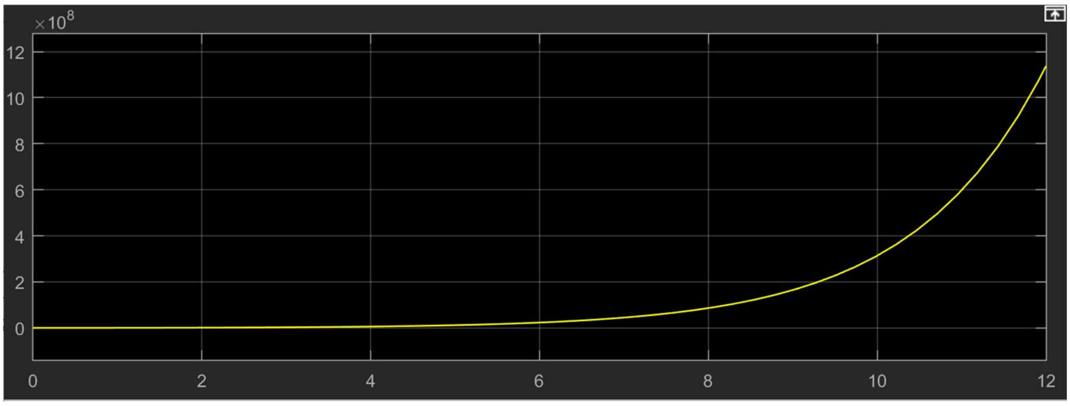
Figure 3 visually presents the dynamic trends of COVID-19, reflecting the cumulative impact on detected cases and deaths throughout the specified time interval. The use of Simulink in conjunction with MATLAB enhances the simulation capabilities, providing a clear and illustrative representation of the state-space model's behaviour. The congruence between the MATLAB Simulink results and the programming analysis underscores the reliability and consistency of the modelling approach employed in this research. These visualizations contribute to a more intuitive comprehension of the predicted trends, facilitating informed decision-making in the context of public health planning and response strategies.

The information provided in Figure 3 and the associated analysis highlights a proportional increase in the cumulative number of deaths and detected cases over time. Both outputs exhibit a similar pattern, with a noticeable growth starting around week 5. This observation aligns with the indication that COVID-19 cases are transitioning towards an endemic phase, where the rate of increase becomes more gradual.

The term "cumulative" emphasizes that the numbers are continuously building up or remaining constant; they cannot decrease. The results underscore the importance of ongoing public awareness efforts. While the numbers are not rapidly surging, they still show an upward trend, emphasizing the need for sustained vigilance and precautionary measures. Continuous public awareness campaigns are crucial to either prevent the graph from further increasing or, at the very least, slowing down the rate of increase. This proactive approach is essential for managing and mitigating the impact of COVID-19 even as the situation transitions into an endemic phase.



a) Cumulative Number of Detected Cases



b) Cumulative Number of Deaths

Figure 3: a) Cumulative Number of Detected Cases. b) Cumulative Number of Deaths using MATLAB Simulink

4. Conclusion

This research has revealed that the number of COVID-19 infections in Malaysia continues to increase, indicating that the country is still in the transition phase toward endemicity. The modelling outputs closely mirror the real-life situation, demonstrating a substantial and ongoing incidence of infections among Malaysians. The predicted numbers of detected cases and deaths align closely with the observed data, validating the effectiveness of the state-space model, derived from the Susceptible-Infectious-Recovered (SIR) model, in capturing the multi-wave dynamics of COVID-19.

As Malaysia navigates through this transition phase, the research underscores the significance of continuous monitoring, public health interventions, and public awareness campaigns. The proactive use of mathematical modelling, particularly state-space models, serves as a valuable tool for forecasting and understanding the evolving dynamics of the pandemic. The congruence between the model predictions and real-life data enhances the reliability of the insights gained, contributing to informed decision-making for public health planning and response efforts. Moving forward, the findings from this research can guide strategies to manage and mitigate the impact of COVID-19 in Malaysia, promoting a resilient and effective approach to public health challenges.

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Author Contribution

Wan Munirah Wan Mohamad - Oversaw the article writing.
Syazwani Mohd Salleh - Prepared the literature review.
Tengku Farah Busyra Tengku Nadzion - Wrote the research methodology.
Abdul Latif Bin Mohd Riza - Conducted the MATLAB analysis.
Azmirul Ashaari – Interpreted the results.

Conflict of Interest

The authors have no conflicts of interest to declare.

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