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Article

Forecasting Public Health Risks in Malaysia: Insights from SEIR Modelling of Infectious Diseases

Nuha Rahim[1], Sakinah Ali Pitchay[1,2], M. A.B. Sahbudin[3], A.H. Azni[1,2] and Ilfita K. Sahbudin[4]

[1]*Faculty of Science and Technology, Universiti Sains Islam Malaysia, 71800, Nilai, Negeri Sembilan, Malaysia.*

[2]*CyberSecurity and Systems (CSS) Research Unit, Universiti Sains Islam Malaysia, 71800, Nilai, Negeri Sembilan, Malaysia.*

[3]*Institute of Applied Data Analytics (IADA), Universiti Brunei Darussalam, Brunei.*

[4]*Rheumatology Research Group, Institute of Inflammation and Ageing, University of Birmingham, United Kingdom.*

Correspondence should be addressed to:
Sakinah Ali Pitchay; sakinah.ali@usim.edu.my

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***Abstract*— During the global pandemic of 2020, the Malaysian government implemented a Movement Control Order (MCO) as a mitigation plan to control the spreading of COVID-19. This effort demonstrates a significant decrease in active cases. However, it is disturbing the nation economically. The lack of a visualization hub to predict the spread of infectious diseases in Malaysia disrupts decision-makers' efficiency in optimizing health sectors. Therefore, this paper aims to forecast infectious diseases in Malaysia using the Susceptible, Exposed, Infectious, Removed (SEIR) model. The SEIR Model predicts the projection of disease-spread cases based on the sample of previous cases. The samples used public health data from the COVID-19 Open Data Repository, which covers 12 states in Malaysia. The finding revealed that the SEIR model demonstrates a sharp decline in susceptible individuals after three months into 2022, a peak in exposed and infectious individuals around the same time, and a steady rise in recovered individuals as most of the population becomes immune. This forecast data can provide earlier insights on the infection trend, allowing actionable recommendations for policymakers and healthcare.**

***Keywords*— Public Health, Infectious Disease, Disease Forecasting, COVID-19, Healthcare**

I. INTRODUCTION

A new coronavirus (2019-nCoV) emerged in Wuhan, China, in December 2019, spreading quickly and leading to a global pandemic [1]. COVID-19 symptoms range from mild issues like fever, dry cough, and fatigue to severe complications such as prolonged symptoms, pneumonia, organ failure, and death [2]. Accordingly, social quarantine, commonly called lockdowns and social distancing measures, has become a universal strategy for controlling the spread of COVID-19 globally [3]. Correspondingly, Malaysian governments took the same approach to control the spread locally.

During the second wave of COVID-19, Malaysia implemented a Movement Control Order (MCO) that consisted of three phases from March 2020 to May 2020. This brings the total strict lockdown period to eight weeks [4]. The order gradually slowed down after vaccination enforcement to achieve herd immunity, and citizens continued their usual routine as before the pandemic.

MCOs evidently reduced the spread of COVID-19, prevented worst-case scenarios, and cooperated with the public and agencies. It also helped flatten the infection curve to stabilize health services during the pandemic [5].

However, MCO disadvantaged Malaysia's economy, potentially leading to a decline and widespread unemployment. According to [6], the country lost approximately RM2.4 billion daily during the MCO period. By the end of April, the estimated loss was around RM63 billion and can reach a total of RM98 billion if MCO is extended. Figure 1 showed Malaysian Gross Domestic Product (GDP) with a steep decline from quarter 4 of 2019 to quarter 2 of 2020 – the duration of strict MCO [7]. This proves the indirect impact of the approach towards the Malaysian economy.

While acknowledging that MCOs reduce infection risks, a more targeted control strategy would be more efficient. By focusing on high-risk areas and activities, human contact can be reduced significantly while allowing economic transactions to continue [8]. Therefore, it is essential to have a forecasting system that can identify critical areas, enabling efficient enforcement of control measures in the next targeted regions [9]. This approach mitigates the economic impacts of complete lockdowns and maintains public health by strategically limiting interactions in critical areas [8] - [9].

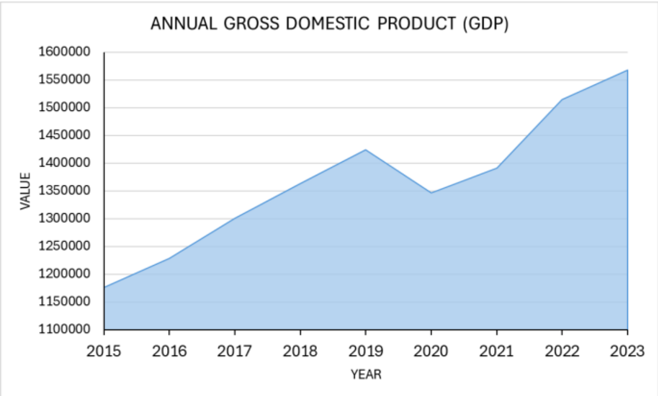

Figure 1. The graph shows that the Malaysian GDP (Gross Domestic Product) value declined from 2019 to 2020, indicating that quarantine does affect the national economy. Source: Department of Statistics Malaysia

Therefore, this paper aims to suggest how the Susceptible, Exposed, Infectious, Removed (SEIR) model can be used to forecast infectious diseases using big data to improve surveillance and prevention. The study focuses on Malaysia, covering 12 states, and includes an in-depth analysis of COVID-19 data. Particularly, the goal is to provide comprehensive knowledge for improved disease management.

II. RELATED WORKS

Related works examine the current state of COVID-19 forecasting systems in Malaysia and worldwide, highlighting the need to adapt the SEIR model to the Malaysian context.

Several sophisticated forecasting systems have been developed in the United States to predict COVID-19 trends. One prominent example is the COVID-19 Forecast Hub [10], which integrates multiple models to produce comprehensive predictions. These models include mechanistic approaches like the SEIR model, which simulates the transmission dynamics of the disease. Additionally, statistical models such as AutoRegressive Integrated Moving Average (ARIMA) are employed to identify patterns in historical data and project future trends. Machine learning models, such as random forests and neural networks, improve forecasting accuracy by identifying complex, non-linear patterns within the data [11].

Following the COVID-19 outbreak in Wuhan, the Chinese government and nongovernmental organizations proactively leveraged big data technology to prevent, contain, and manage the disease's spread [12]. Meanwhile, in India, ARIMA models are employed to forecast future outbreaks [13], proving big data is useful for epidemiological surveillance.

The model developed by [14] for predicting COVID-19 outbreaks in Japan is a simple mathematical framework that utilizes machine learning techniques like regression analysis to analyze epidemic waves. The model demonstrated a significant periodicity of approximately 140 days in COVID-19 cases, achieving high accuracy in predicting [14]. A study by [15] presented two advanced machine learning models, Encoder-Decoder long short-term memory (LSTM) and Attention LSTM, for forecasting COVID-19 infection rates in Russia.

In contrast, Malaysia's approach to COVID-19 forecasting has been more basic. Key data sources include the Ministry of Health Malaysia and local hospitals. However, these models often face limitations such as data quality issues and a lack of comprehensive integration of various forecasting techniques. For example, in [16], the model may not account for external factors such as changes in government policies, public behaviour, and healthcare capacity. This can influence the effectiveness of government intervention and the spread of the virus. The same goes for work in [17], which can only forecast daily cases in the short term.

Considering these differences, there is a clear need to adapt the forecasting system [18] to be applied in Malaysia. Tailoring these advanced models to the local context can enhance its relevance and accuracy. Thus, incorporating Malaysian epidemiological, demographic, and socioeconomic data will allow for more precise predictions and better-informed public health interventions. Adaptation involves customizing model parameters to reflect local conditions and integrating local data sources into the forecasting system.

A. Current Implementation of Ensembled Forecasting Model

Ensemble forecasting models are widely employed in various fields to improve prediction accuracy, including infectious disease forecasting. This ensemble approach has been effectively used in the COVID-19 Forecast Hub [10] and FluSight Network [19]. Both are officially used as the main reference for disease forecasting in the United States.

The COVID-19 Forecast Hub aggregates predictions from multiple models to comprehensively forecast COVID-19 trends, such as daily hospitalizations. Similarly, the FluSight Network employs ensemble forecasting models to predict influenza activity in the United States. The network combines forecasts from various models to improve the accuracy of predictions related to Influenza-Like Illness (ILI).

III. METHODOLOGY

This section outlines the implementation of a forecasting algorithm using the obtained data source and applying it to the SEIR model.

A. Proposed Method

The proposed method involves the integration of SEIR into the Malaysian context. This includes adjusting model parameters to reflect Malaysian demographics and epidemiological patterns and incorporating local data sources. Thus, we anticipate significant improvements in prediction accuracy and public health response. Adaptation also involves continuous model refinement and validation using historical Malaysian COVID-19 data.

B. Data Source

Relevant variables or attributes are crucial for the predictive model to function. Data collected is existing open-source data from Google COVID-19 Open Data Repository [20]. This site has a collective updated source of COVID-19 data, covering over 20,000 global locations and offers diverse data types and variables. Examples of collected data are presented in Table I, and Table II explains the function of each parameter.

TABLE I. EXAMPLE OF COLLECTED DATA

Date	Confirmed	Deceased	Recovered	Tested	Hospitalized_Patients	Population
06/6/2021	6241	87	5133	86239	1460	32655400
07/6/2021	5271	82	7548	80166	1380	32655400
08/6/2021	5566	76	6962	94606	1350	32655400
09/6/2021	6239	75	7386	105870	1269	32655400
10/6/2021	5671	73	7325	101818	1306	32655400
11/6/2021	6849	84	7749	96787	1303	32655400

TABLE II. KEY PARAMETERS FOR THE FORECASTING MODELS

Parameter	Description
confirmed	Historical data on daily confirmed COVID-19 cases.
deceased	Historical data on daily confirmed deaths caused by COVID-19.
recovered	Historical data on daily recovered COVID-19 cases.
tested	Number of COVID-19 tests conducted daily.
hospitalized_patients	Number of people hospitalized due to COVID-19
population	Number of population

C. Implementation of SEIR Model

The implementation of the SEIR model involves simulating the spread of infectious diseases by dividing the population into four compartments—Susceptible, Exposed, Infectious, and Recovered [21]. This section outlines the key steps involved in adapting and applying the SEIR model to real-world epidemiological data.

1) SIR Model (Susceptible-Infectious-Removed): The SIR model is a mathematical model used to describe the spread of infectious diseases [22]. [23] categorized people into three groups: susceptible, infected, and removed. In particular, susceptible individuals are healthy yet vulnerable to infection upon exposure to the virus. Meanwhile, infected individuals are those currently carrying and capable of transmitting the disease. Moreover, the removed group is those who have either recovered from the disease or died from it, with the assumption that they can no longer participate in the disease's spread. The following set of differential equations are used to describe the model, according to [21]:

$$\begin{aligned} \frac{dS}{dt} &= -\beta SI \\ \frac{dI}{dt} &= \beta SI - \gamma I \, . \\ \frac{dR}{dt} &= \gamma I \end{aligned} \tag{1}$$

In Equation (1), (S) denotes the number of susceptible individuals, (I) the number of infected individuals, and (R) is the number of recovered individuals. The parameters beta (β) and gamma (γ) are constants representing the transmission rate and recovery rate, respectively. The population is expected to be constant, with (S + I + R = N), where (N) is the total population size.

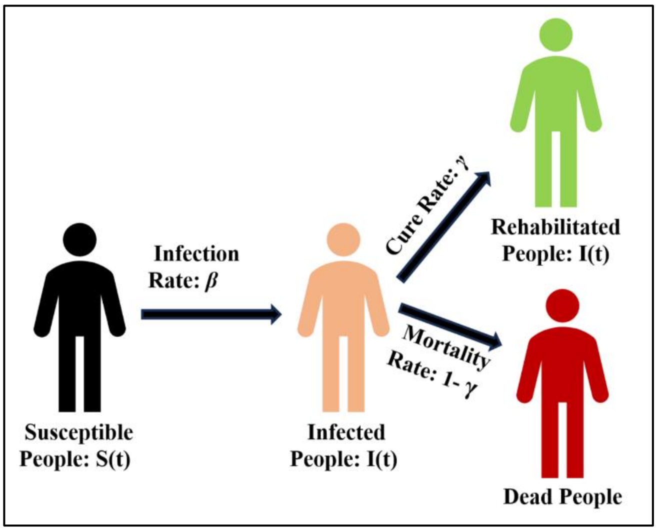

Figure 2. SIR (Susceptible-Infectious-Removed) Model

2) SEIR Model (Susceptible-Exposed-Infectious-Removed): Considering various infectious illnesses' incubation periods, susceptible individuals might not exhibit symptoms right after infection [21]. This model expands upon the SIR model by including an 'Exposed' category. This group consists of individuals exposed to the infection but are not yet symptomatic. It represents a phase where they could either recover without developing further symptoms or progress to become infectious.

The SEIR model is described by the following differential equations:

- Susceptible (S):

$$\frac{dS}{dt} = -\beta \frac{SI}{\text{population}}. \tag{2}$$

In Equation (2), the transmission rate (β) has an impact on the negative rate of change of susceptible individuals, the number of susceptible individuals (S) and the number of infectious individuals (I). The term SI/population indicates the rate at which susceptible individuals are exposed to the virus [21].

- Exposed (E):

$$\frac{dE}{dt} = \beta \frac{SI}{\text{population}} - \sigma \cdot E. \tag{3}$$

Equation (3) indicates that the rate of change of exposed individuals is governed by the rate at which susceptible individuals become exposed and how exposed individuals transition to the infectious state. Here, the rate of progression from infectious exposure is denoted by (σ) [21].

- Infectious (I):

$$\frac{dI}{dt} = \sigma \cdot E - \gamma \cdot I. \tag{4}$$

The rate of change of infectious individuals is determined by the progression from exposed to infected (σ·E) and the recovery of infected individuals (γ·I), as given in Equation (4) [21].

- Recovered (R):

$$\frac{dR}{dt} = \gamma \cdot I. \tag{5}$$

Equation (5) indicates that the rate of change of recovered individuals is directly proportional to the recovery rate (γ) and the number of infected individuals (I) [21].

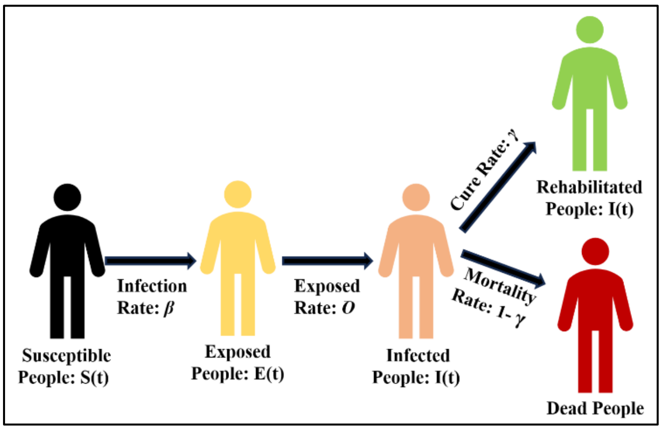

Figure 1. SEIR (Susceptible-Exposed-Infectious-Removed) Model

D. Model Algorithm

This current section encompasses the development of the SEIR model in the R programming language.

TABLE III. ALGORITHM 1: SEIR MODEL FUNCTION

Algorithm 1: SEIR model function
1. ***Input***: *dataset, library (deSolve)*
2. ***Output***: *dS, dE, dI, dR*
3. *Function SEIR_model(time, state, parameters):*
4. *Extract S, E, I, R FROM state*
5. *Extract β, γ, σ FROM parameters*
6. *Compute dS = -β* (S * I) / population*
7. *Compute dE = (β* (S * I) / population) - (σ* E)*
8. *Compute dI = (σ* E) - (γ* I)*
9. *Compute dR = γ* I*
10. ***Return*** *(dS, dE, dI, dR)*

IV. RESULTS

The results section presents the key findings derived from the data analysis, highlighting the outcomes of the implemented methods. Accordingly, it systematically addresses the objectives outlined earlier in the study by focusing on interpreting the data trends and patterns relevant to the research questions.

A. Findings

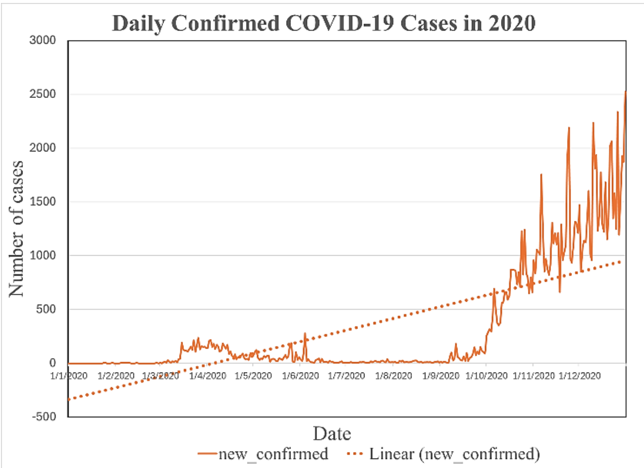

Figure 4. Graph of daily confirmed COVID-19 cases in Malaysia from January 2020 to December 2020

Figure 4 depicts the daily confirmed COVID-19 cases in Malaysia from January to December 2020, illustrating fluctuating peaks and notable surges in cases. These sharp increases indicate key periods of accelerated virus transmission, likely associated with specific events or clusters that contributed to the spikes in infection rates.

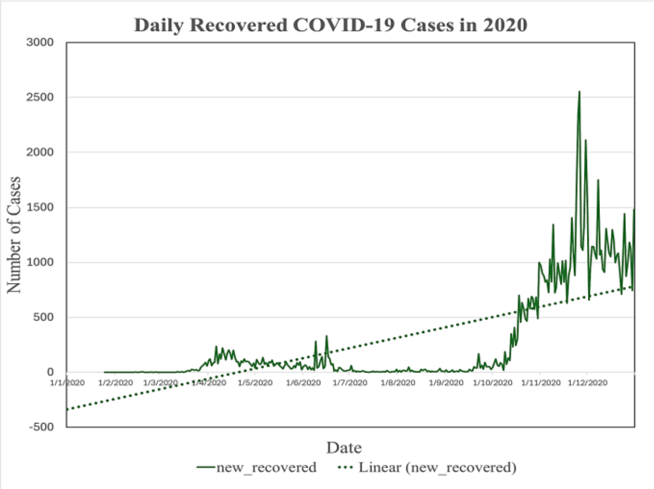

Figure 5. Graph of daily recovered COVID-19 cases in Malaysia from January 2020 to December 2020

Figure 5 illustrates the daily recoveries from COVID-19 during the same period, revealing a gradual upward trend. This trend reflects the healthcare system's increasing capacity to manage and treat patients effectively. Over time, recoveries begin to align more closely with the number of confirmed cases.

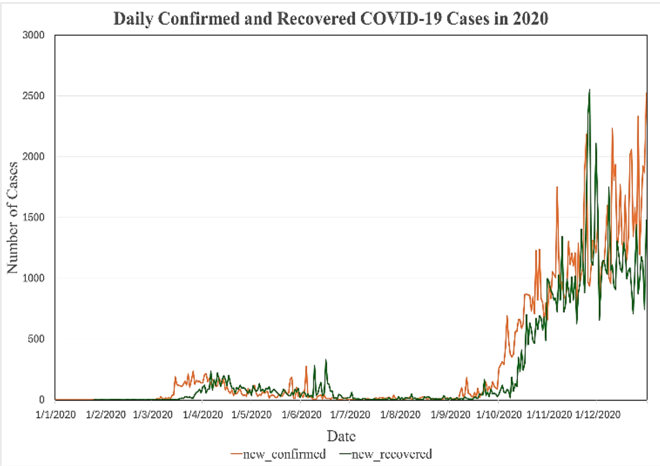

Figure 6. Graph of daily confirmed infected and recovered COVID-19 cases in Malaysia from January 2020 to December 2020

Figure 6 compares daily confirmed infections with daily recoveries throughout 2020. This comparison highlights the delay between infection surges and subsequent recovery spikes, demonstrating how the healthcare system gradually adjusted to manage the rising cases.

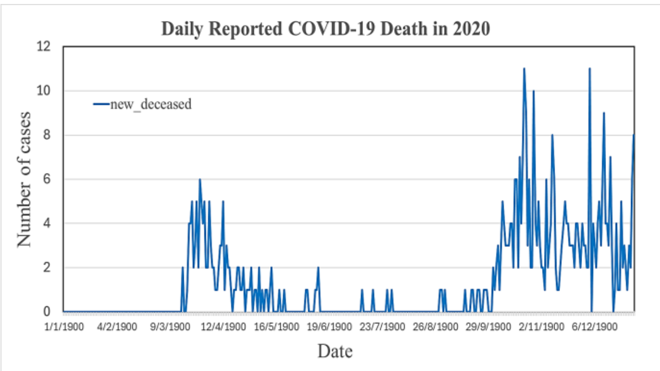

Figure 7. Graph of daily reported deaths due to COVID-19 in Malaysia from January 2020 to December 2020

Figure 7 displays the daily reported COVID-19 deaths in Malaysia for 2020, highlighting the mortality trend. It suggests that severe outbreaks were followed by corresponding increases in the death toll, particularly during peak infection periods. Together, these numbers demonstrate Malaysia's experience with the COVID-19 epidemic, illustrating trends in infections, recoveries, and fatalities. The data suggests that while infection spikes were significant, recovery rates improved, and death rates, though rising, were mitigated by public health interventions.

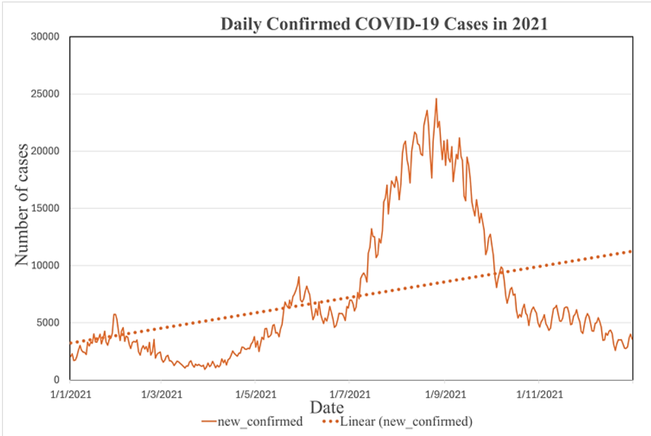

Figure 8. Graph of daily confirmed COVID-19 cases in Malaysia from January 2021 to December 2021

Figure 8 depicts the daily confirmed COVID-19 cases in Malaysia from January to December 2021. In comparison to the previous year, there are significant surges in cases, particularly in mid-2021, suggesting new waves of the pandemic. These increases may be attributed to the emergence of new variants or reduced adherence to public health restrictions, resulting in larger outbreaks than in 2020.

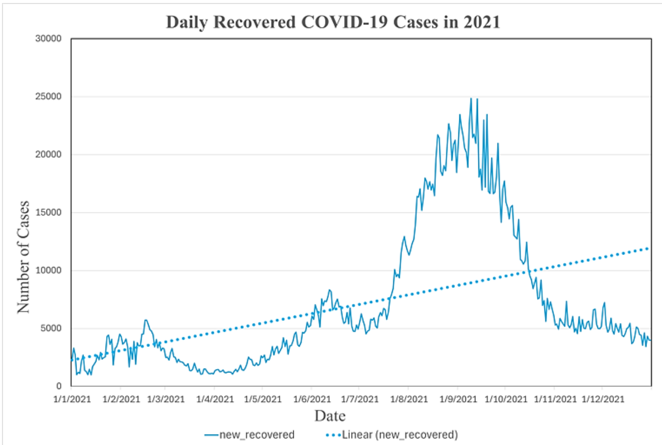

Figure 9. Graph of daily recovered COVID-19 cases in Malaysia from January 2021 to December 2021

Figure 9 displays the daily recovered COVID-19 cases over the same period (January to December 2021). The data reflects an upward trend in recoveries, mirroring the rise in confirmed cases, indicating that the healthcare system further adapted to the increasing number of infections. Recovery peaks follow major infection surges, demonstrating a delayed yet consistent response in patient recovery.

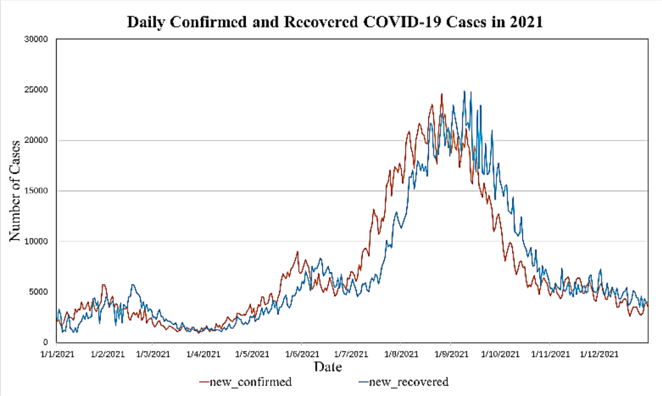

Figure 10. Graph of daily confirmed infected and recovered COVID-19 cases in Malaysia from January 2021 to December 2021

Figure 10 compares daily confirmed infections with daily recoveries for 2021. The gap between confirmed cases and recoveries is most pronounced during the mid-year spike. Notably, new infections outpaced recoveries, suggesting a period of heightened strain on the healthcare system, potentially leading to delays in patient recovery or increased hospital burden.

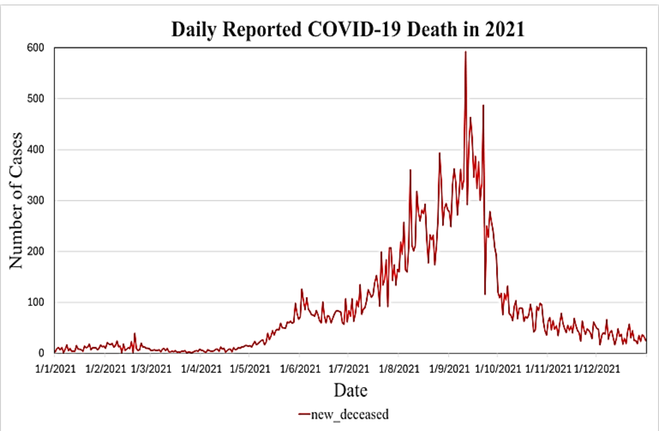

Figure 11. Graph of daily reported deaths due to COVID-19 in Malaysia from January 2021 to December 2021

Figure 11 illustrates the daily reported COVID-19 deaths from January to December 2021. The death toll rises in tandem with confirmed cases, particularly during the significant infection surges, emphasizing the heightened severity of the pandemic in 2021. The increased mortality, compared to the previous year, likely reflects the higher number of infections and the growing strain on the healthcare system.

In summary, these figures for 2021 depict a more severe phase of the pandemic compared to 2020, with higher peaks in confirmed cases, recoveries, and deaths. The data indicates that while the healthcare system managed to facilitate patient recovery, the larger infection spikes, especially in mid-2021, were associated with a significant rise in mortality. This underscores the ongoing challenges posed by the pandemic and the strain placed on Malaysia's public health infrastructure.

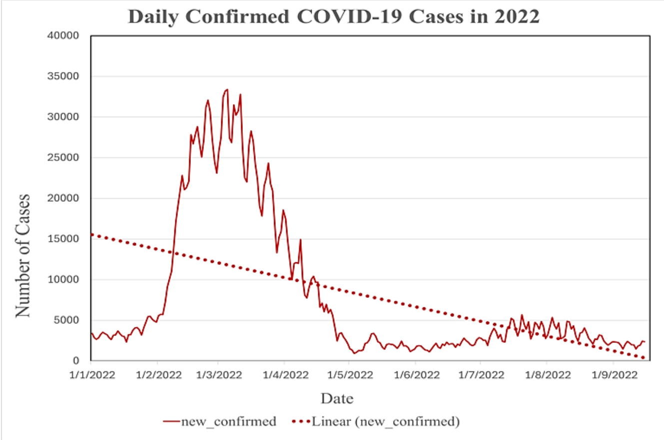

Figure 12. Graph of daily confirmed COVID-19 cases in Malaysia from January 2022 to September 2022

Figure 12 depicts Malaysia's daily confirmed COVID-19 cases from January to September 2022. This data reveals a substantial reduction in daily cases compared to previous years, suggesting enhanced control over the pandemic during this period. The observed decrease may be attributed to extensive vaccination coverage, improved public health interventions, or a reduction in viral transmission due to the accumulation of natural immunity within the population.

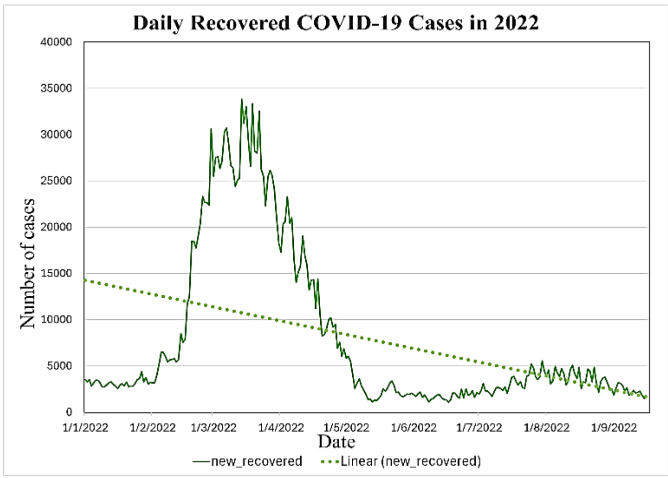

Figure 13. Graph of daily recovered COVID-19 cases in Malaysia from January 2022 to September 2022

Figure 13 presents the daily number of COVID-19 recoveries for the same timeframe (January to September 2022). The data indicate a general decline in recoveries, corresponding to the reduction in confirmed cases. This trend suggests that as the incidence of infections decreases, the demand for recoveries correspondingly diminishes, reflecting a positive impact on the healthcare system.

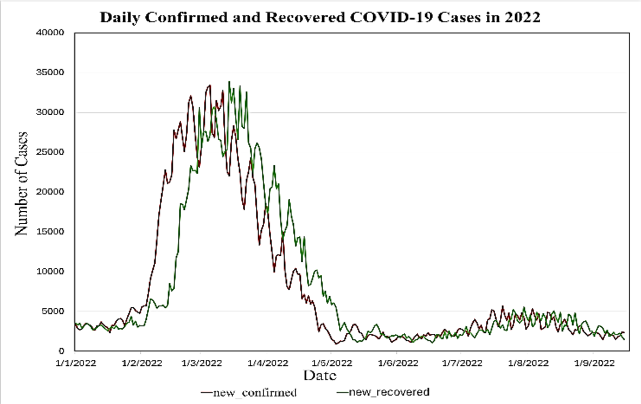

Figure 14. Graph of daily confirmed infected and recovered COVID-19 cases in Malaysia from January 2022 to September 2022

Figure 14 compares the daily confirmed cases with daily recoveries in 2022. The alignment between these two metrics is noticeably closer than in previous years, suggesting that the healthcare system was better equipped and not overwhelmed. The synchronization of recovery rates with infection rates demonstrates improved management of patient care and recovery processes during this phase of the pandemic.

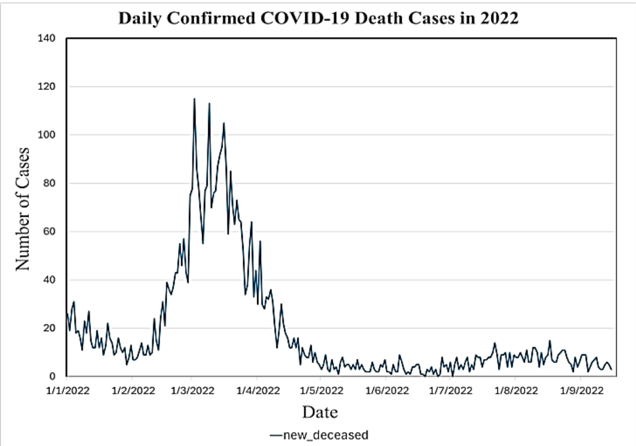

Figure 15. Graph of daily reported deaths due to COVID-19 in Malaysia from January 2022 to September 2022

Figure 15 illustrates the daily reported COVID-19 deaths in Malaysia from January to September 2022. There is a marked decrease in mortality compared to earlier periods, indicating the effectiveness of vaccination campaigns, advancements in treatment protocols, and enhanced public health measures. The reduction in death rates in 2022 signifies a notable improvement in the country's capacity to mitigate the pandemic's health impacts.

The 2022 data indicate a significant advancement in controlling COVID-19 in Malaysia. The declines in confirmed cases, recoveries, and deaths highlight the success of public health strategies, vaccination initiatives, and natural immunity. Compared to 2020 and 2021, the situation in 2022 is characterized by greater stability, fewer severe outbreaks, and a healthcare system that is more adept at managing the disease's effects.

B. Prediction Graph Analysis

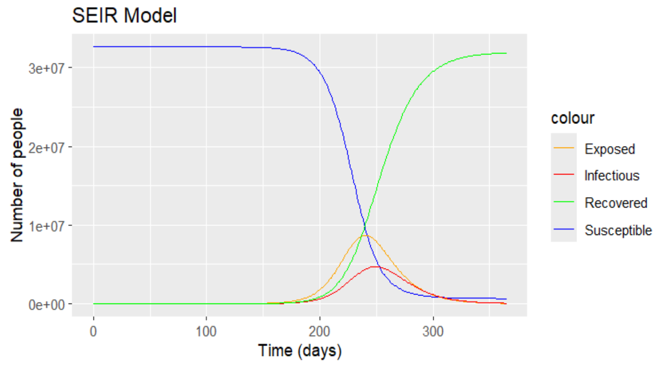

Figure 16. Forecast result of Malaysian COVID-19 data from January 2020 to September 2022 for a maximum of 32655400 population for 991 days

Figure 16 consists of the X-axis and Y-axis, where the X-axis (Time in Days) represents the temporal progression of the simulation, measured in days. It reflects the duration over which the SEIR model is simulated, providing a chronological framework for observing the dynamics of the disease. Meanwhile, the Y-axis (Number of Individuals) presents the number of people in each SEIR model element. The values for the X-axis are scaled by (1 ×10^5) to facilitate a more precise representation of the data and to accommodate the typically large numbers involved in such epidemiological models.

Susceptible (Orange Line). This line begins at a high value and exhibits a downward trajectory over time. The decreasing trend signifies a reduction in the number of individuals who remain prone to the disease as the outbreak progresses and as more individuals transition to the exposed or infectious compartments.

Exposed (Blue Line): Initially, this line displays an upward trend, reflecting the increasing number of individuals exposed to the disease. The line reaches a peak, indicating the maximum number of exposed individuals, and subsequently declines as these individuals advance to the infectious state.

Infectious (Red Line): This line demonstrates a pronounced increase, reaching a peak at the point of maximum disease prevalence. The subsequent decline in the line represents the decrease in the number of infectious individuals as they recover and move to the recovered group.

Recovered (Green Line): The green line represents a continuous upward trend, representing the accumulation of individuals who have recovered from the disease. This increasing trend reflects the ongoing transition of individuals from the infectious state to the recovered state, indicating a growing number of individuals who are no longer inclined to the disease.

In the early phases of the outbreak, according to Figure 16, the proportion of susceptible individuals is notably high, while the counts of exposed and infectious individuals are relatively low, as displayed in Figure 6. This phase reflects the pre-epidemic state (year 2020, Figures 4 –7), where the disease has not yet been significantly disseminated.

As the epidemic progresses, there is an apparent increase in the number of exposed individuals, leading to a rise in infectious cases, as illustrated in Figure 8. The curve representing infectious individuals exhibits a sharp peak, indicative of a rapid escalation in disease transmission and prevalence during this period (2021, Figures 8 – 11).

Over time, the number of recovered individuals steadily increases, reflecting the accumulation of individuals who have successfully overcome the disease. This is proven by the decreasing number of new confirmed cases, as portrayed in Figure 12. Concurrently, there is a corresponding decline in the susceptible population as these individuals transition to the recovered state.

The system eventually approaches a state of equilibrium characterized by a stabilization in the number of susceptible people. Most people are either fully recovered or still exposed and contagious at this juncture.

According to Figure 16, at the start of the epidemic (Day 0), nearly the entire population is susceptible (blue line). This is consistent with real-world scenarios where, at the onset of a new outbreak, most individuals are unexposed to the pathogen. As time progresses, the exposed population (orange line) increases, reflecting a rising number of infected people who are not yet infectious. This could correspond to the initial phase of the pandemic when awareness is low and containment measures have not yet been fully implemented.

The infectious population (red line) sharply rises following the exposed population, reaching a peak around Day 100. This peak signifies the point at which the disease is most prevalent, with the highest number of active infectious individuals in the population. This represents a critical period during which hospitals are likely overwhelmed by the surge in cases, particularly if interventions such as MCOs or vaccination campaigns have not yet been fully effective.

The peak of infection is followed by a rapid decline as more individuals recover and move into the recovered compartment (green line). This reduction indicates that immunity is building up in the population through natural recovery or medical interventions such as vaccinations.

By around Day 200 to Day 300, the model reveals a stabilization in the susceptible population, with the majority of individuals either recovered or immune. This likely reflects the achievement of herd immunity, where sufficient proportions of the population have gained immunity, either through recovery or vaccination, such that the virus can no longer spread easily. This equilibrium state, marked by a low number of susceptible individuals and minimal new infections, highlights the long-term impact of sustained public health interventions in Malaysia. However, it also underscores the need for continued surveillance and possible booster vaccinations to prevent future outbreaks and maintain control over the disease.

V. CONCLUSION

The study emphasizes how vital SEIR analytics is in improving the management and forecasting of infectious diseases. Utilizing information from Google's COVID-19 Open Data Repository, the research offers a strong foundation for forecasting the spread of illness and guiding public health initiatives. The SEIR model highlights critical trends that help public health forecast decision-making in selecting a specific duration of control order and targeting the most vulnerable area.

A sharp decline in the susceptible population in the second quarter of 2022 indicates when a large portion has been exposed or vaccinated, guiding the timing of mass vaccination campaigns or stricter health measures. The alignment of the infectious peak with the exposed population peak marks a crucial period for healthcare capacity planning, allowing policymakers to allocate resources like hospital beds and medical staff efficiently. Additionally, the recovery curve demonstrates how swiftly individuals recover compared to new infections, helping leaders determine when to relax restrictions or reduce emergency measures as recovery rates surpass

To ensure thorough readiness for future outbreaks, further work should improve predicting accuracy by broadening the data coverage to include additional factors such as vaccination rate and control order.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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