

MODELLING TRANSMISSION DYNAMICS OF COVID-19 DURING PRE-VACCINATION PERIOD IN MALAYSIA: A GUI-BASED SEIRD PREDICTIVE MODEL USING STREAMLIT

(Pemodelan Dinamik Penyebaran COVID-19 Sebelum Tempoh Pervaksinasi di Malaysia: Model Peramalan SEIRD Berasaskan GUI Menggunakan Streamlit)

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ABSTRACT

Coronavirus disease (COVID-19) is a major health threat worldwide pandemic, first identified in Malaysia on 25 January 2020. This outbreak can be represented in the mathematical expressions of a non-linear system of ordinary differential equations (ODEs). With the lack of a predictive SEIRD model in terms of Graphical Users Interface (GUI) in Malaysia, this paper aims to model the COVID-19 outbreak in Malaysia during the pre-vaccination period using the Susceptible-Exposed-Infected-Recovered-Death (SEIRD) model with time-varying parameters, then develop a GUI-based SEIRD predictive model using Streamlit Python library. The GUI-based SEIRD predictive model called GUI-mSEIRDsr predictor considers various values for the proportion of the quarantine-abiding population (r) and three different decisions regarding the MCO lifting date to forecast the number of active cases (I) on 15 October 2020. This information provides insightful information not only to government agencies but public as well, in understanding the effects of population behaviour to COVID-19 spread. The mathematical model is solved using the Scipy odeint function, which uses the Livermore Solver for Ordinary Differential Equations with an Automatic method switching (LSODA) algorithm. The time-varying coefficients of the SEIRD model that best fit the real data of COVID-19 cases are obtained using the Nelder-Mead optimisation algorithm. This extended SIRD model with exposed (E) compartment becoming SEIRD, leads to a robust model. It adequately fitted two datasets of Malaysian COVID-19 indicated by the slightest average values of Root Mean Square Error (RMSE) as compared to other existing models. The results highlight that the larger the values of the proportion of the quarantine-abiding population (r) and the later the date of the lifted MCO, the lower the spread of COVID-19 which eventually helps Malaysia to reach disease-free equilibrium in a shorter duration.

Keywords: COVID-19; GUI-SEIRD predictive model; pre-vaccination; Malaysia

ABSTRAK

Penyakit Coronavirus (COVID-19) merupakan ancaman kesihatan utama yang telah menjadi pandemik di seluruh dunia, pertama kali dikenal pasti di Malaysia pada 25 Januari 2020. Wabak ini boleh diwakili dalam ungkapan matematik sistem persamaan pembezaan biasa (ODE) bukan linear. Dengan kekurangan model SEIRD yang boleh meramalkan dalam penggunaan antara muka pengguna grafik (GUI) di Malaysia, makalah ini bertujuan untuk memodelkan wabak COVID-19 di Malaysia semasa tempoh pra-vaksinasi menggunakan model Susceptible-Exposed-Infected-Recovered-Death (SEIRD) dengan parameter yang berubah-ubah mengikut masa, kemudian membangunkan model ramalan SEIRD berasaskan GUI menggunakan perpustakaan Streamlit Python. Model ini juga dikembangkan menjadi model ramalan SEIRD berbasis GUI menggunakan perpustakaan Streamlit Python. Model ramalan SEIRD berasaskan GUI yang dipanggil sebagai peramal GUI-mSEIRDsr ini mempertimbangkan pelbagai nilai untuk bahagian penduduk yang mematuhi kuarantin (r) dan tiga keputusan berbeza mengenai tarikh pengangkatan Perintah Kawalan Pergerakan (MCO) untuk meramalkan bilangan kes aktif (I) pada 15 Oktober 2020. Maklumat ini memberikan

pandangan yang kepada agensi Kerajaan. Model matematik ini diselesaikan menggunakan fungsi Scipy odeint, yang menggunakan Penyelesaian Livermore untuk Persamaan Pembezaan Biasa dengan algoritma Automatic method switching (LSODA). Parameter-parameter dalam model SEIRD yang paling sesuai dengan data sebenar kes COVID-19 diperoleh dengan menggunakan algoritma pengoptimuman Nelder-Mead. Model SIRD yang diperluaskan dengan kompartmen terdedah (E) menjadi SEIRD, menghasilkan model yang kukuh. Berdasarkan analisis terhadap dua set data COVID-19 di Malaysia, ditemukan bahwa model ini memiliki nilai Purata Akar Ralat Min Kuasa (RMSE) yang paling rendah berbanding dengan model-model yang sedia ada. Hasil ini menunjukkan bahwa semakin tinggi bahagian penduduk yang mematuhi kuarantin (r) dan semakin lewat tarikh MCO diangkat, maka semakin sedikit penyebaran kes COVID-19 yang akan membantu Malaysia mencapai keseimbangan bebas wabak dengan lebih cepat.

Kata kunci: COVID-19; GUI-SEIRD model ramalan; pra-vaksinasi; Malaysia

1. Introduction

COVID-19, known as coronavirus disease that was first reported on 31 December 2019 in Wuhan, China, was declared a global pandemic on 11 March 2020, by the World Health Organisation (WHO), according to Cucinotta and Vanelli (2020). Malaysia has been significantly impacted by three COVID-19 waves, cumulatively 23,881 active cases (I) as of 15 October 2022. The first wave occurred between 25 January 2020 and 16 February 2020. The second wave occurred between 27 February 2020 and 8 July 2020, where the unexpected increase of infected (I) cases and widespread outbreak made the situation in Malaysia perilous rather than under control which started the first movement control order (MCO) utilising strong suppression measures by the Malaysian government on 18 March 2020 (Aziz *et al.* 2020). The movement control order (MCO) was eased on 4 May 2020 and labelled a conditional movement control order (CMCO). On 10 June 2020, measures were further eased into a recovery movement control order (RMCO) – a transitional phase before suppression measures were lifted entirely. The third wave started on 8 September 2020, and continues to the present, 2023.

This outbreak can be represented using mathematical expressions in a non-linear system of ordinary differential equations (ODEs), which is a powerful tool for modeling dynamic processes, including the transmission dynamics of COVID-19 (Miao *et al.* 2011). It aids in the analysis and prediction of future trends in COVID-19 cases, helping governments make informed decisions for control measures. In Malaysia, breakouts have been modelled using the SEIR model in preliminary research as studied by Mahmud and Lim (2020), Mwalili *et al.* (2020) and Gill *et al.* (2020). To anticipate the COVID-19 transmission dynamics with greater accuracy, a more comprehensive model known as the SEIRD model that takes the group of deceased (D) into account can be used as adopted by Mukaddes *et al.* (2020), Piccolomini and Zama (2020) and Maugeri *et al.* (2020).

Therefore, our study will implement a compartmental SEIRD model with some modifications, taking into account sporadic cases, reinfection cases, and the non-stationarity of epidemiological parameters as proposed by Zulkarnain *et al.* (2023a). This will be done to develop a Graphical User Interface (GUI)-based SEIRD model predictor for COVID-19 cases. Such a tool may facilitate government agencies and other stakeholders without programming expertise in analysing the effects of population behaviour and the government's decision making on MCO lifting date as well as for informed decision-making. Additionally, this study is an extension works of Zulkarnain *et al.* (2023a).

The primary purpose of this study is to develop a GUI-based SEIRD predictive model using the Streamlit Python library based on proposed Susceptible-Exposed-Infected-Recovered-Death (SEIRD) model by Zulkarnain *et al.* (2023a) with time-varying parameters. In this paper, we first present the mathematical model formulation under the Method section. It is subsequently followed by the Results and Discussion section, which are divided into two subsections i) Model performance validation and ii) Prediction of COVID-19 cases with optimised parameters via Graphical Users Interface (GUI). The prediction considers different values of the proportion of the quarantine-abiding population (r) at three different decisions of MCO lifting date. Then, we summarised our findings in the concluding part of the paper.

2. Methodology

This section will be divided into four subsections i) epidemiological compartmental model, ii) formulation of time-varying parameters, iii) research designs and iv) epidemic data and initial values. The subsections are presented accordingly.

2.1. Epidemiological compartmental model

In this subsection, we mainly highlight different SEIRD models formulation for determining the robust model that may fit different datasets of COVID-19 cases during the pre-vaccination period which are the modified SEIRD model considering sporadic possibility (mSEIRDs), the modified SIRD model considering reinfection possibility (mSIRDr), the conventional SEIRD model (cSEIRD) and the modified SEIRD model considering sporadic and reinfection possibilities (mSEIRDsr).

2.1.1. Modified SEIRD model considering sporadic possibility for prediction of COVID-19 cases (mSEIRDs) and modified SIRD model considering reinfection possibility for prediction of COVID-19 cases (mSIRDr)

A modified SEIRD model that characterises transmission dynamics of COVID-19 by considering the possibility of sporadic cases (Mukaddes *et al.* 2020) and a modified SIRD model (Jamil *et al.* 2022) without exposed (E) compartment considering reinfection possibility are described in Eq. (1) and Eq. (2), respectively, where S is susceptible, E is exposed, I is infected, R is recovered and D is death as variables. Meanwhile, for parameters, β_I and β are the infection rate between S and I , β_E is the infection rate between S and E , σ is the incubation rate, γ is the recovery rate, μ is the death rate and δ is the reinfection rate. mSEIRDs involves constant parameters while mSIRDr involves time-varying parameters:

$$\begin{aligned} \frac{dS(t)}{dt(t)} &= -\frac{\beta_I(t)S(t)I(t)}{N} - \frac{\beta_E(t)S(t)E(t)}{N} \\ \frac{dE(t)}{dt(t)} &= \frac{\beta_I(t)S(t)I(t)}{N} + \frac{\beta_E(t)S(t)E(t)}{N} - \sigma E(t) \\ \frac{dI(t)}{dt(t)} &= \sigma E(t) - \gamma(t)I(t) - \mu(t)I(t) \\ \frac{dR(t)}{dt(t)} &= \gamma(t)I(t) \\ \frac{dD(t)}{dt(t)} &= \mu(t)I(t) \end{aligned} \tag{1}$$

The factor of sporadic cases is represented by the existence of two types of infection rates, β_I and β_E while reinfection is represented by $\delta(t)R(t)$ leaving R compartment and entering into S compartment again.

$$\begin{aligned}\frac{dS(t)}{dt(t)} &= -\frac{\beta(t)S(t)I(t)}{N} + \delta(t)R(t) \\ \frac{dI(t)}{dt(t)} &= \frac{\beta(t)S(t)I(t)}{N} - \gamma(t)I(t) - \mu(t)I(t) \\ \frac{dR(t)}{dt(t)} &= \gamma(t)I(t) - \delta(t)R(t) \\ \frac{dD(t)}{dt(t)} &= \mu(t)I(t)\end{aligned}\tag{2}$$

2.1.2. Conventional SEIRD Model (cSEIRD) and modified SEIRD model considering sporadic and reinfection possibilities (mSEIRDSr) for prediction of COVID-19 cases

A Conventional SEIRD model which is the extended SEIR model with death (D) compartment is inspired by the formulation of SEIR (Mahmud & Lim 2020) in forecasting the COVID-19 trend in Malaysia for preliminary study. The model characterises the COVID-19 outbreak without considering the possibility of sporadic and reinfection cases is described in Eq. (3). This conventional model adopted constant parameters.

$$\begin{aligned}\frac{dS(t)}{dt(t)} &= -\frac{\beta(t)S(t)I(t)}{N} \\ \frac{dE(t)}{dt(t)} &= \frac{\beta(t)S(t)I(t)}{N} - \sigma E(t) \\ \frac{dI(t)}{dt(t)} &= \sigma E(t) - \gamma(t)I(t) - \mu(t)I(t) \\ \frac{dR(t)}{dt(t)} &= \gamma(t)I(t) \\ \frac{dD(t)}{dt(t)} &= \mu(t)I(t)\end{aligned}\tag{3}$$

In this subsection, we also highlight the modified SEIRD model which considers both possibilities of sporadic and reinfection cases with time-varying parameters in terms of ordinary differential equations (ODEs) as in Eq. (4). These two factors that were taken into account are the uniqueness of this model. The assumption that the total population is a constant is represented by Eq. (5), denoted by N. Further details of this modified SEIRD model can be referred to Zulkarnain *et al.* (2023b).

$$\begin{aligned}\frac{dS(t)}{dt(t)} &= -\frac{\beta_I(t)S(t)I(t)}{N} - \frac{\beta_E(t)S(t)E(t)}{N} + \delta(t)R(t) \\ \frac{dE(t)}{dt(t)} &= \frac{\beta_I(t)S(t)I(t)}{N} + \frac{\beta_E(t)S(t)E(t)}{N} - \sigma E(t) \\ \frac{dI(t)}{dt(t)} &= \sigma E(t) - \gamma(t)I(t) - \mu(t)I(t)\end{aligned}\tag{4}$$

$$\begin{aligned}\frac{dR(t)}{dt(t)} &= \gamma(t)I(t) - \delta(t)R(t) \\ \frac{dD(t)}{dt(t)} &= \mu(t)I(t) \\ N &= S(t) + E(t) + I(t) + R(t) + D(t)\end{aligned}\quad (5)$$

2.2. Formulation of time-varying parameters

Epidemiological parameters, especially infection rate β , recovery rate γ and death rate μ are functions of time, so it is important to determine what type of functions should be employed. Inspired by SIRD model (Jamil *et al.* 2022), time-varying infection rate $\beta_i(t)$, recovery rate $\gamma(t)$ and death rate $\mu(t)$ are formulated as piecewise functions, as in Eq. (6) – Eq. (9). While for the infection rate $\beta_E(t)$, it is based on the SEIRD model (Mukaddes *et al.* 2020), where they considered $\beta_E = 5\beta_i$, based on COVID-19 cases in China. In general, one can assume $\beta_E(t) = p\beta_i(t)$, where $p \geq 1$ and therefore $\beta_E(t)$ is defined as Eq. (7). Time interval of these piecewise functions was divided into three phases:

- Phase I: Before Movement Control Order (MCO), $t < t_{\text{lock}}$ (27/2/20-17/3/20)
- Phase II: During Movement Control Order (MCO) and Conditional Movement Control Order (CMCO), $t_{\text{lock}} \leq t < t_{\text{lift}}$ (18/3/20-9/6/20)
- Phase III: During Recovery Movement Control Order (RMCO), $t \geq t_{\text{lift}}$ (10/6/20-23/2/21)

$$\beta_i(t) = \begin{cases} \beta_1 t + \beta_2, & t < t_{\text{lockdown}} \\ \beta_0 e^{-((t - t_{\text{lockdown}})/(\tau_\beta))}, & t_{\text{lockdown}} \leq t < t_{\text{lift}} \\ (1 - r)(\beta_1(t - t_{\text{lift}}) + \beta_2), & t \geq t_{\text{lift}} \end{cases}, \quad (6)$$

$$\beta_E(t) = p\beta_i(t) \quad (7)$$

$$\gamma(t) = \begin{cases} \gamma_2(t) + \gamma_3, & t < t_{\text{lockdown}} \\ \gamma_0 + \frac{\gamma_1}{1 + e^{(-t + t_{\text{lockdown}} + \tau_\gamma)}}, & t \geq t_{\text{lockdown}} \end{cases} \quad (8)$$

$$\mu(t) = \begin{cases} \mu_2(t) + \mu_3, & t < t_{\text{lockdown}} \\ \mu_0 e^{-((t - t_{\text{lockdown}})/(\tau_\mu))} + \mu_1, & t_{\text{lockdown}} \leq t < t_{\text{lift}} \\ \mu_2(t - t_{\text{lift}}) + \mu_3, & t \geq t_{\text{lift}} \end{cases} \quad (9)$$

$$\delta(t) = 0 \quad (10)$$

The explanation of these formulated time-varying parameters can be referred from Zulkarnain *et al.* (2023b).

2.3. Research designs

The flowchart for the computational work of this study is depicted in Figure 1 where Python via Jupyter Notebook is the programming platform. The SciPy odeint function is used to solve the ODEs. The ODEs require initial values to obtain the unique solutions, in this case, the

initial values for each of the population states are as given in Table 1. In order to fit the model to the actual cases in Malaysia during the optimisation process, there are a total of 16 parameters that need to be optimised by virtue of Nelder-Mead (NM). Since Nelder-Mead is an iterative method, they require initial guesses to begin with to speed up the convergence to the actual optimised solutions. The initial guesses for all 16 parameters are summarised in Table 2.

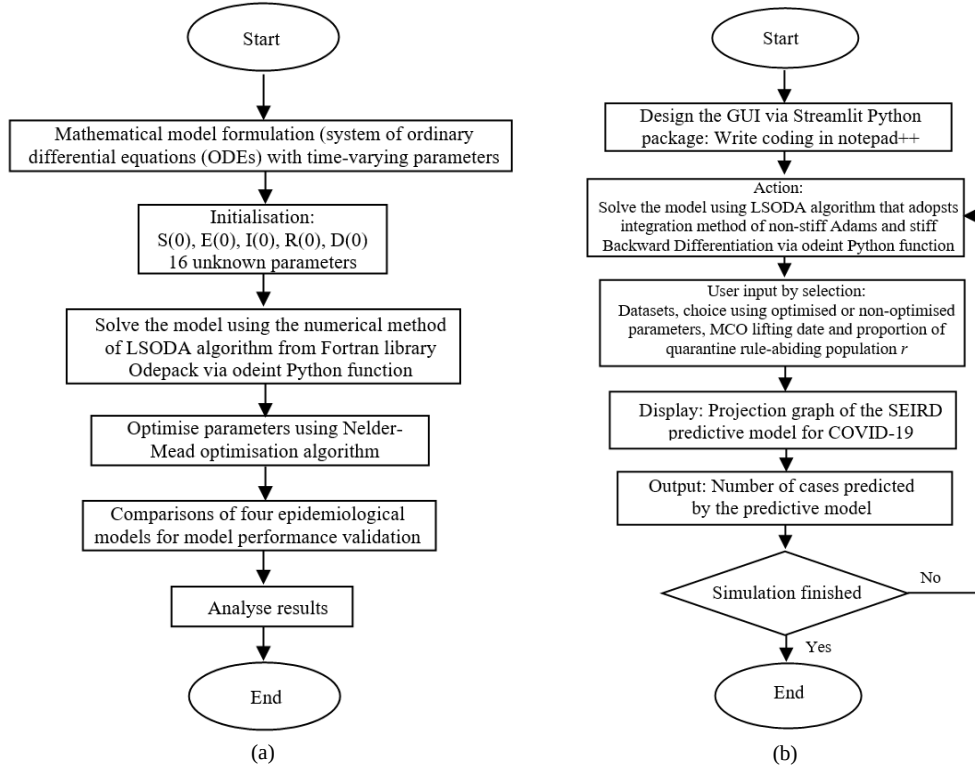


Figure 1: Process flowcharts: (a) Flowchart of developing an improved SEIRD model for COVID-19 (b) Flowchart of developing GUI-SEIRD predictive model for COVID-19 using Streamlit Python package

2.4. Epidemic data and initial values

The Ministry of Health Malaysia (MOH) is the main source of the data used in this study. The COVID-19 data were available to the public on the Ministry's GitHub page. Daily data of COVID-19 infected (I), recovered (R), and death (D) cases from the first to the beginning of the third wave (from 25 January to 21 October 2020) are collected, gathered, sorted in a spreadsheet file before importing them to the Pandas DataFrame for Python simulation of SEIRD and SIRD model. The data then is separated into two datasets for model performance validation which are dataset 1 (DS_1) and dataset 2 (DS_2). According to DOSM (2020), Malaysian total population is considered unchanged over the time interval of the simulation. Thus, we set the constant $N = 32657300$. Other values of variables at initial states are summarised in Table 1. Table 2 shows the initial guesses of parameter input for the optimisation procedures.

Table 1: Initial conditions for solving the ODEs of SEIRD model

Datasets	Initial States	Values	Sources
DS ₁ :	Susceptible, $S(0)$	32657297	Eq. (5)
25/1/20	Exposed, $E(0)$	0	Assumption
18/9/20	Infected, $I(0)$	3	MOH's Github
	Recovered, $R(0)$	0	MOH's Github
	Death, $D(0)$	0	MOH's Github
DS ₂ :	Susceptible, $S(0)$	32657177	Eq. (5)
27/2/20	Exposed, $E(0)$	100	Assumption
15/10/20	Infected, $I(0)$	1	MOH's Github
	Recovered, $R(0)$	22	MOH's Github
	Death, $D(0)$	0	MOH's Github

Table 2: Initial parameter input for the optimisation procedures

Parameters	Values	Sources
Infection rate, $\beta(t)$	$\beta_0 = 0.16100732$ $\beta_1 = 0.00142347$ $\beta_2 = 0.07373335$	Jamil <i>et al.</i> (2022)
Incubation rate, σ	0.15	Li <i>et al.</i> (2020)
Recovery rate, $\gamma(t)$	$\gamma_0 = 0.02590983$ $\gamma_1 = 0.0267004$ $\gamma_2 = 8.3000e-05$ $\gamma_3 = 0.00606688$	Jamil <i>et al.</i> (2022)
Mortality rate, $\mu(t)$	$\mu_0 = 0.00151062$ $\mu_1 = 1.5316e-04$ $\mu_2 = 8.0126e-05$ $\mu_3 = 2.5064e-04$	Jamil <i>et al.</i> (2022)
Characteristic time of transmission, τ_β	21.7321554	Jamil <i>et al.</i> (2022)
Characteristic time of recovery, τ_γ	12.3593006	Jamil <i>et al.</i> (2022)
Characteristic time of death, τ_μ	26.3593227	Jamil <i>et al.</i> (2022)
Proportion β_E over β_I, p	1	Assumption

β_2 , γ_3 and μ_3 are the initial values on the first day of MCO for each respective epidemiological rate which will be used as a constant value of parameters adopted by cSEIRD and mSEIRDS.

3. Results and Discussions

In this section, we discuss the results obtained from model performance validation to highlight the comparisons between different epidemiological models and analyse the effects of two human actions: firstly the behavior of the Malaysian population, defined by the proportion of the quarantine-abiding population (represented by 'r') and secondly, to examine the government's decision regarding the lifting date of the Movement Control Order (MCO) using a GUI-based SEIRD predictive model.

3.1. Model performance validation

Model performance validation is needed to assess how well the model generalises to new and unseen future data. In this study, we have validated mSEIRDSr model as presented by Eq. (4) in Methodology section by comparing the accuracy metrics of the performance of various epidemiological models. These metrics were obtained through simulation using optimised parameters achieved via the Nelder-Mead optimisation algorithm, and the predicted data were

compared with actual data. There are two datasets involved in the validation to select the robust model before developing the GUI-based mSEIRDsr predictive model. Figure 2 shows how close mSEIRDsr model fitted to the actual data of COVID-19 cases in Malaysia using non-optimised and optimised parameters for two datasets. Accuracy metrics in terms of Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) obtained based on simulation in Figure 2 are summarised in Table 3. Based on Table 3, the use of Nelder-Mead optimisation algorithm has reduced the measurement error of RMSE up to 66%, 52% and 75% for DS₁ and DS₂, respectively, highlighting the importance of parameter optimisation in mathematical modelling.

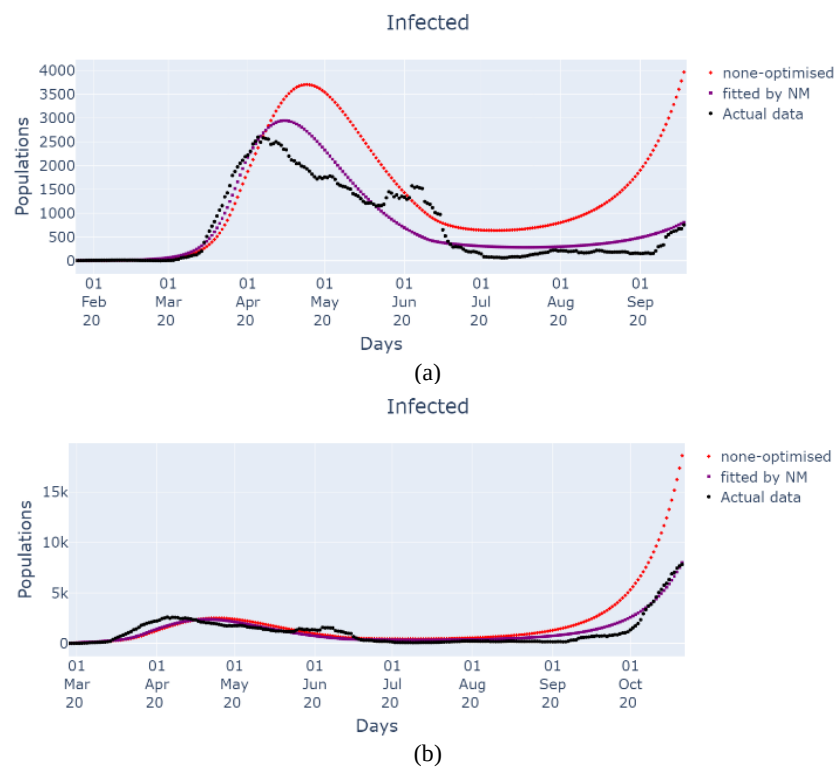


Figure 2: Infected cases of COVID-19: (a) infected curve for DS₁ and (b) infected curve for DS₂

Table 3: Comparison of measurement errors between simulated cases obtained by mSEIRDsr model and the actual COVID-19 infection (*I*) cases using both non-optimised and optimised parameters

Datasets	Optimisation Algorithms	MAE	MAPE	RMSE
DS ₁ : (25/1/2020-18/9/2020)	None	740.53	295.92	1027.60
	Nelder-Mead (NM)	245.028	142.06	346.102
DS ₂ : (27/2/2020-21/10/2020)	None	1130.25	192.13	2054.83
	Nelder-Mead (NM)	403.421	113.34	506.464

Table 4 displays the comparison of measurement errors between simulated cases and the actual COVID-19 infected (*I*) cases in Malaysia obtained using different epidemiological models for two datasets. These errors are obtained based on predicted values optimised by the

selected Nelder-Mead optimisation algorithm. mSEIRDsr model is proven to be robust indicated by the least average of MAE, average of MAPE and average of RMSE compared to other models considered in this study. The mSEIRDsr model, which takes into account the possibility of sporadic and reinfected cases in formulating the system of the ODEs, can fit COVID-19 actual data using different datasets distinguished by the first and last dates of the simulation time window.

Table 4: Comparison of measurement error between simulated cases obtained by the epidemiological models to the actual COVID-19 infected (I) cases in Malaysia using different datasets

Datasets	Measurement error	cSEIRD	mSEIRDs (Mukaddes <i>et al.</i> 2020)	mSIRD (Jamil <i>et al.</i> 2022)	mSEIRDsr (Zulkarnain <i>et al.</i> 2023a)
DS ₁ : (25/1/2020- 18/9/2020)	MAE	6.7752×10^2	6.7813×10^2	1.78387×10^2	2.45028×10^2
	RMSE	10.6921×10^2	10.6965×10^2	3.10317×10^2	3.46102×10^2
DS ₂ : (27/2/2020- 21/10/2020)	MAE	11.0151×10^2	10.8823×10^2	11.7703×10^2	4.03421×10^2
	RMSE	17.6461×10^2	17.4793×10^2	18.6067×10^2	5.06464×10^2
Average values of error for 2 datasets	Average of MAE	8.8952×10^2	8.8318×10^2	6.777085×10^2	3.242245×10^2
	Average of RMSE	14.0857×10^2	14.0879×10^2	10.854935×10^2	4.262835×10^2

3.2. Prediction of COVID-19 cases via graphical users interface (GUI)-based mSEIRDsr model

In developing the GUI-based SEIRD predictive model for understanding the effects of human behaviours represented by values of r and decision-making represented by MCO lifting date, mSEIRDsr is chosen and DS₁ is used as the actual data for COVID-19 cases prediction. Further exploration of the prediction of COVID-19 cases can be made through this deployed web application (Zulkarnain 2023). The effects of four different values of the quarantine rule-abiding population proportion (r) at three different decisions of MCO lifting date which have been chosen are observed throughout the GUI-based mSEIRDsr predictive model simulation as in Figure 3–5. Figure 3 displays the predicted I cases on 15th October 2021 based on different values of r when advanced MCO lifting date is selected. Meanwhile, Figure 4 and Figure 5 display the predicted I cases when actual and delayed MCO lifting is selected, respectively.

Table 5 provides the key insights extracted from Figure 3 – Figure 5. It portrays the forecasted number of active cases (I) on day 264 (15 October 2020) when considering different proportions of the quarantine rule-abiding population (r) and different decisions of MCO lifting dates which are advanced, actual and delayed lifting dates of MCO. The predicted I case on 15 October 2020 is ideal to be selected in analysing the effects of human actions because it is the possible date for the simulated I cases to be zero. Based on this table, we observe the larger the values of the proportion of the quarantine-abiding population (r) and the later the date of the lifted MCO, the lower the spread of COVID-19. The duration to achieve disease-free equilibrium based on different scenarios is presented in Table 6. Based on Table 6, the larger the values of r and the later the MCO lifted date, the shorter the duration Malaysia will reach disease-free equilibrium. If the value of r is 80% and below, there is a chance for a new second peak of infection to be reported yet still maintain the lower spread of COVID-19 according to the number of I cases. However, for values of r which are lower than 80%, the larger values of r do not promise a shorter duration to achieve disease-free equilibrium because the predicted second peak of I is lower compared to the lesser values

of r . The lower predicted second peak of I will result in a higher number of populations who can possibly get infected. Hence, it needs more time to achieve disease-free equilibrium.

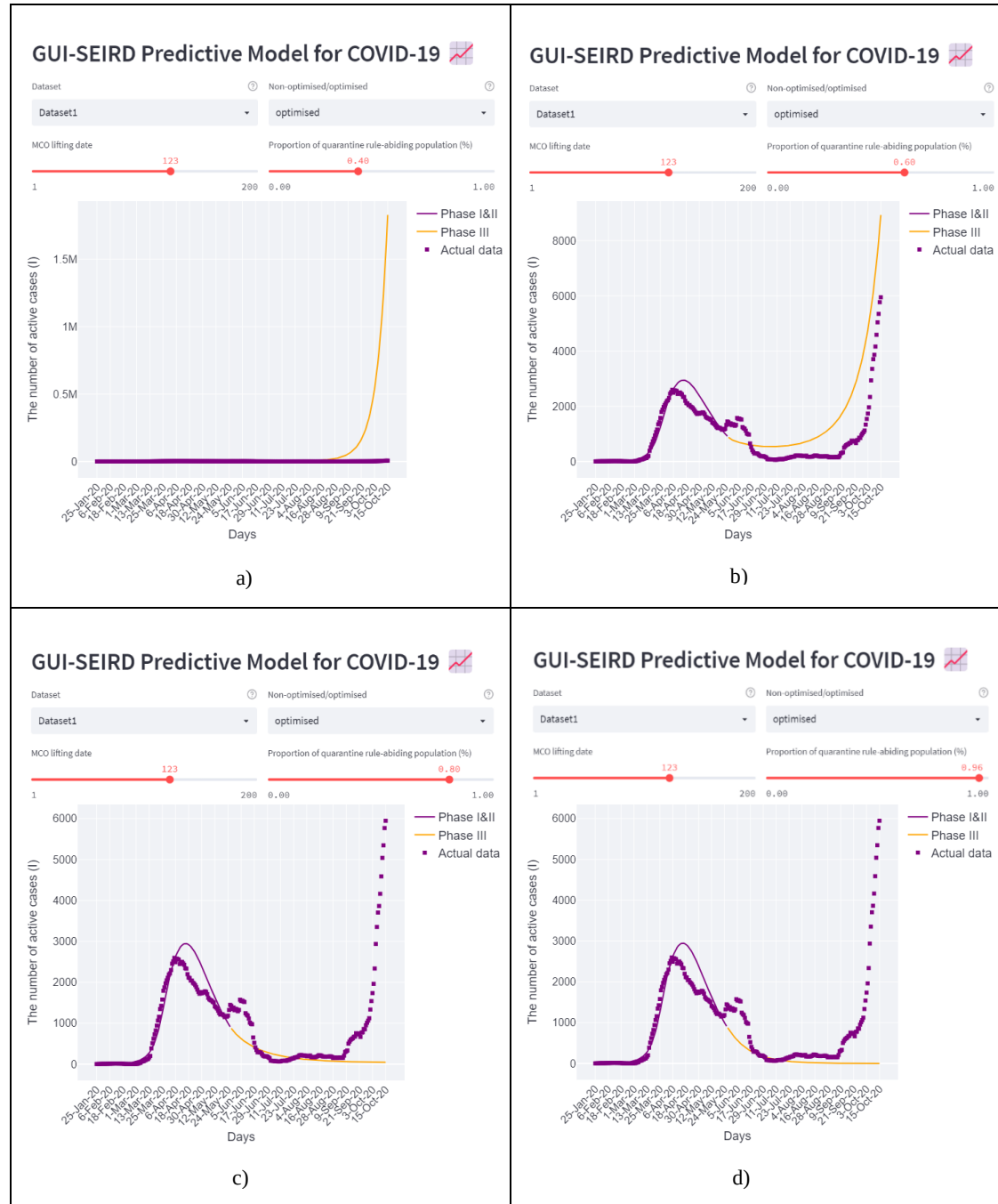


Figure 3: GUI-based mSEIRDSr model predictor using advanced MCO lifting date on day 123 (27/5/2020) with different values of quarantine rule-abiding population proportion r : a) 40%, b) 60%, c) 80% and d) 96%

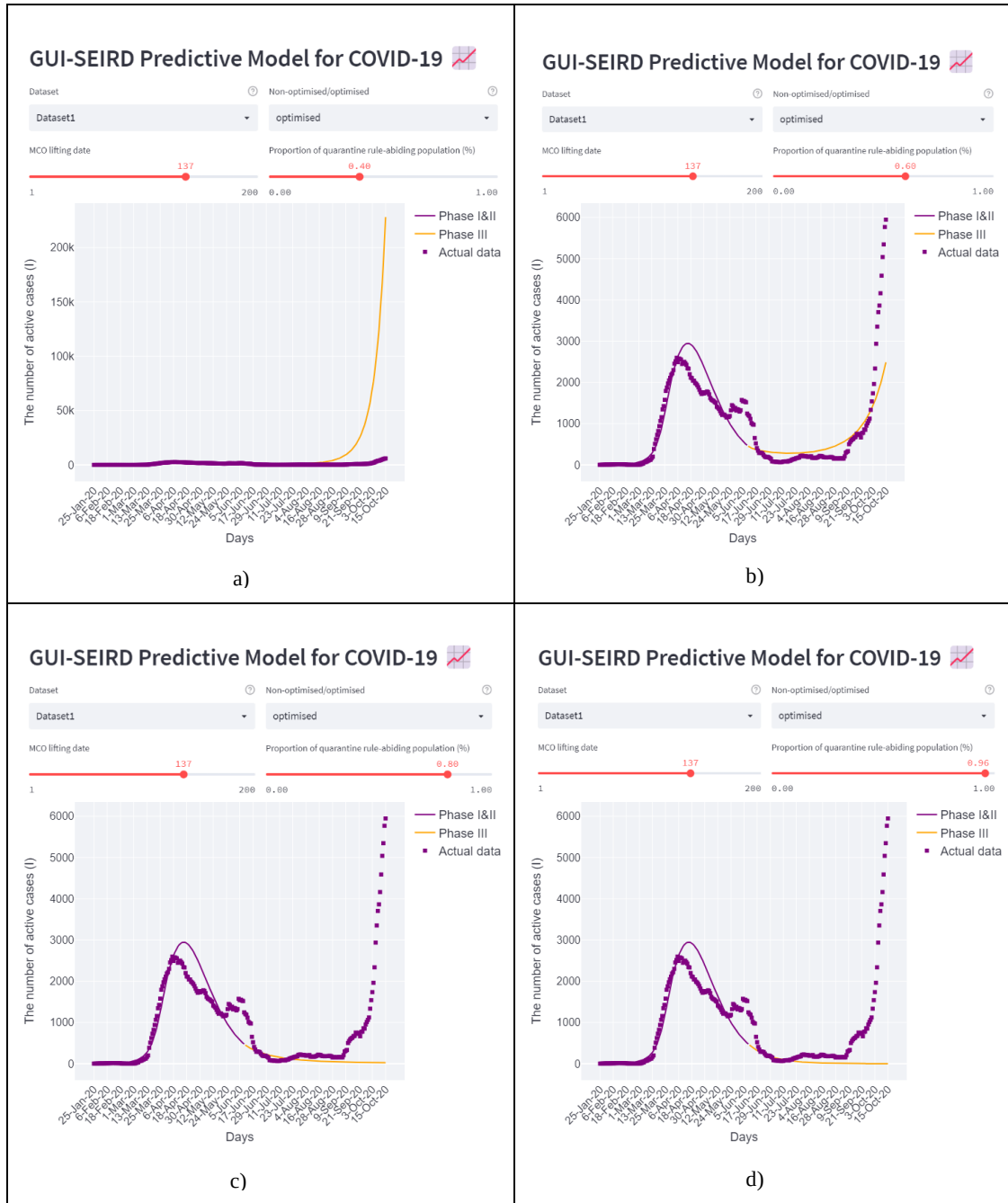


Figure 4: GUI-based mSEIRDsr model predictor using actual MCO lifting date on day 137 (10/6/2020) with different values of quarantine rule-abiding population proportion r : a) 40%, b) 60%, c) 80% and d) 96%

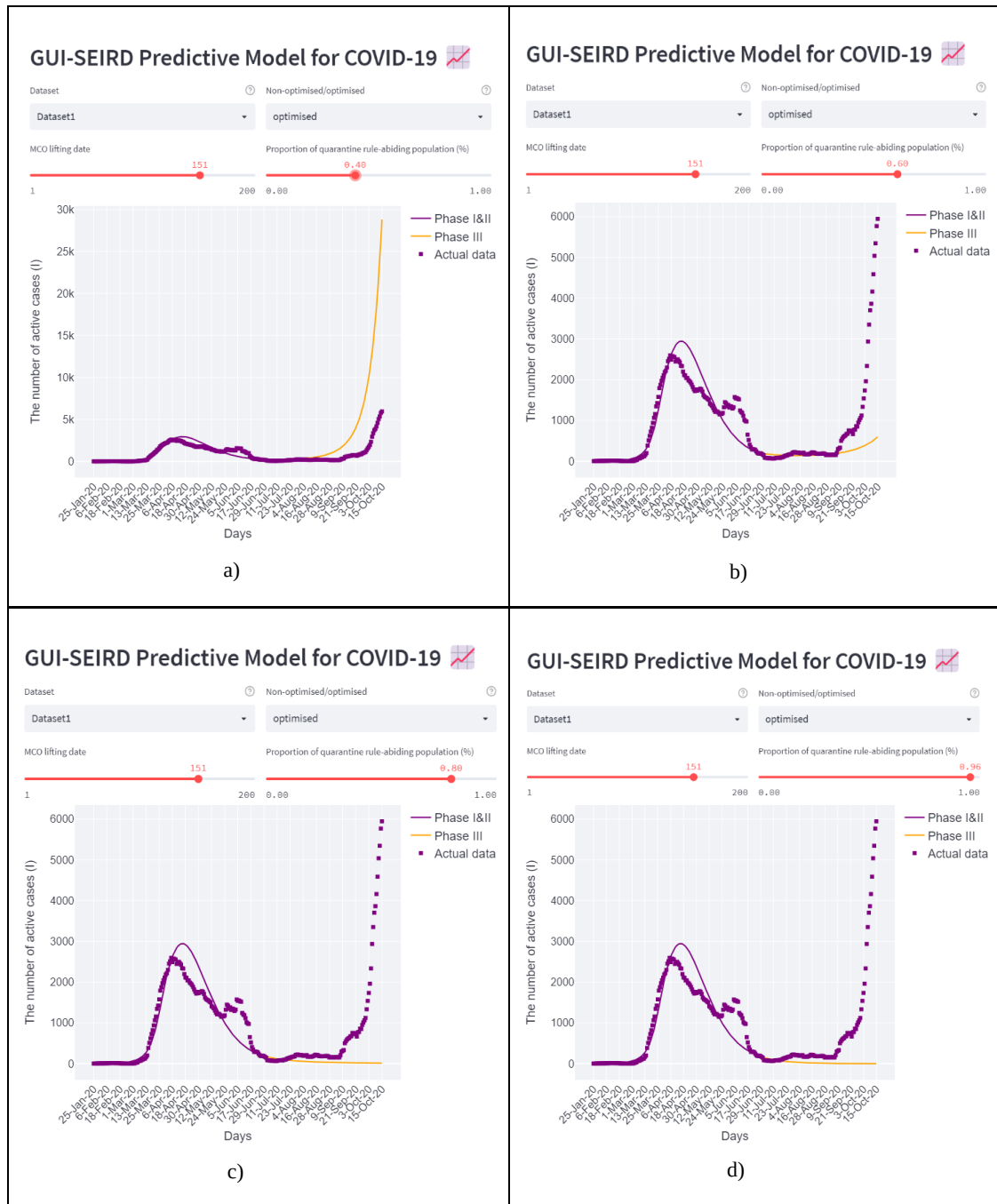


Figure 5: GUI-based mSEIRDsr model predictor using delayed MCO lifting date on day 151 (24/6/2020) with different values of quarantine rule-abiding population proportion r: a) 40%, b) 60%, c) 80% and d) 96%

Table 5: Forecasted number of active cases (I) on day 264 (15 October 2020) based on different proportions of the quarantine rule-abiding population (r) and different decisions of MCO lifting date

Proportion of the quarantine rule-abiding population, r (%)	MCO lifting date		
	27/5/2020 (advanced)	10/6/2020 (actual)	24/6/2020 (delayed)
96	0	0	0
80	50	27	15
60	10,1894	2489	655
40	1,669,833	209,027	26,749

Table 6: Duration to achieve disease-free equilibrium

Proportion of the quarantine rule-abiding population, r (%)	Duration to achieve disease-free equilibrium		
	27/5/2020 (advanced)	10/6/2020 (actual)	24/6/2020 (delayed)
96	142 days	128 days	114 days
80	802 days, second peak I : 4.2 million**	804 days, second peak I : 4.3 million**	806 days, second peak I : 4.4 million**
60	536 days, second peak I : 7.3 million**	536 days, second peak I : 7.8 million**	537, second peak I : 7.9 million**
40	444 days, second peak I : 9.9 million**	444 days, second peak I : 10 million**	445 days, second peak I : 10.1 million**

Footnotes:** = cannot be produced by an existing proposed GUI-SEIRD predictor as this study mainly focuses on the pre-vaccination period. Predicted cases beyond 23rd February 2021 are considered far-fetched.

Figure 6 portrays the effects of human actions in terms of population behaviour and government decision on MCO lifting date when MCO is lifted during peak infection which is on day 74 (5 April 2020) from a start date of the simulation. Based on this figure, the lifting of the MCO during peak I cases should only be permissible if the government can assure that at least 80% of the total population need to adhere to quarantine measures, to reduce the spread of COVID-19 within the community and, consequently, lower the number of reported daily I cases. Otherwise, lower adherence can create another new peak of I cases.

Figure 7 shows the close up figure on disease-free equilibrium achieved based on Figure 3 – Figure 5 d) when the value of r is set to 96% at three different government's decision making on MCO lifting date which is advanced (27 May 2020), actual (10 June 2020) and delayed (24 June 2020).

4. Conclusion

The development of a Graphical User Interface (GUI)-based mSEIRDsr predictive model in terms of web application presented in this study can facilitate in decision-making in future outbreaks, especially in deciding how to facilitate human actions in curbing COVID-19 cases in Malaysia. This GUI-based mSEIRDsr predictive model is not only beneficial for government agencies and researchers but also very impactful for laypersons in understanding the dynamics of COVID-19's continued transmission and predicted cases in Malaysia upon the MCO lifted date. In this study, different MCO lifting dates and various values of quarantine rule-abiding population proportion (r) has been considered in observing the spread

of COVID-19 particularly in 15th October 2020. Based on the presented results, by maintaining the proportion of the quarantine rule-abiding population r to 96% despite three different decisions of the MCO lifting dates, Malaysia will be able to reduce the transmission of COVID-19 throughout the community and bring down the number of infected (I) cases to 0 (zero cases) which gives meaning to free-disease equilibrium in Malaysia. It is feasible to achieve a 96% compliance rate among the Malaysian population with quarantine rules if full awareness of their importance is fostered.



Figure 6: GUI-based mSEIRDSr model predictor using advanced MCO lifting date on day 74 (5/4/2020) during peak I cases with different values of quarantine rule-abiding population proportion r : a) 40%, b) 60%, c) 80% and d) 96%

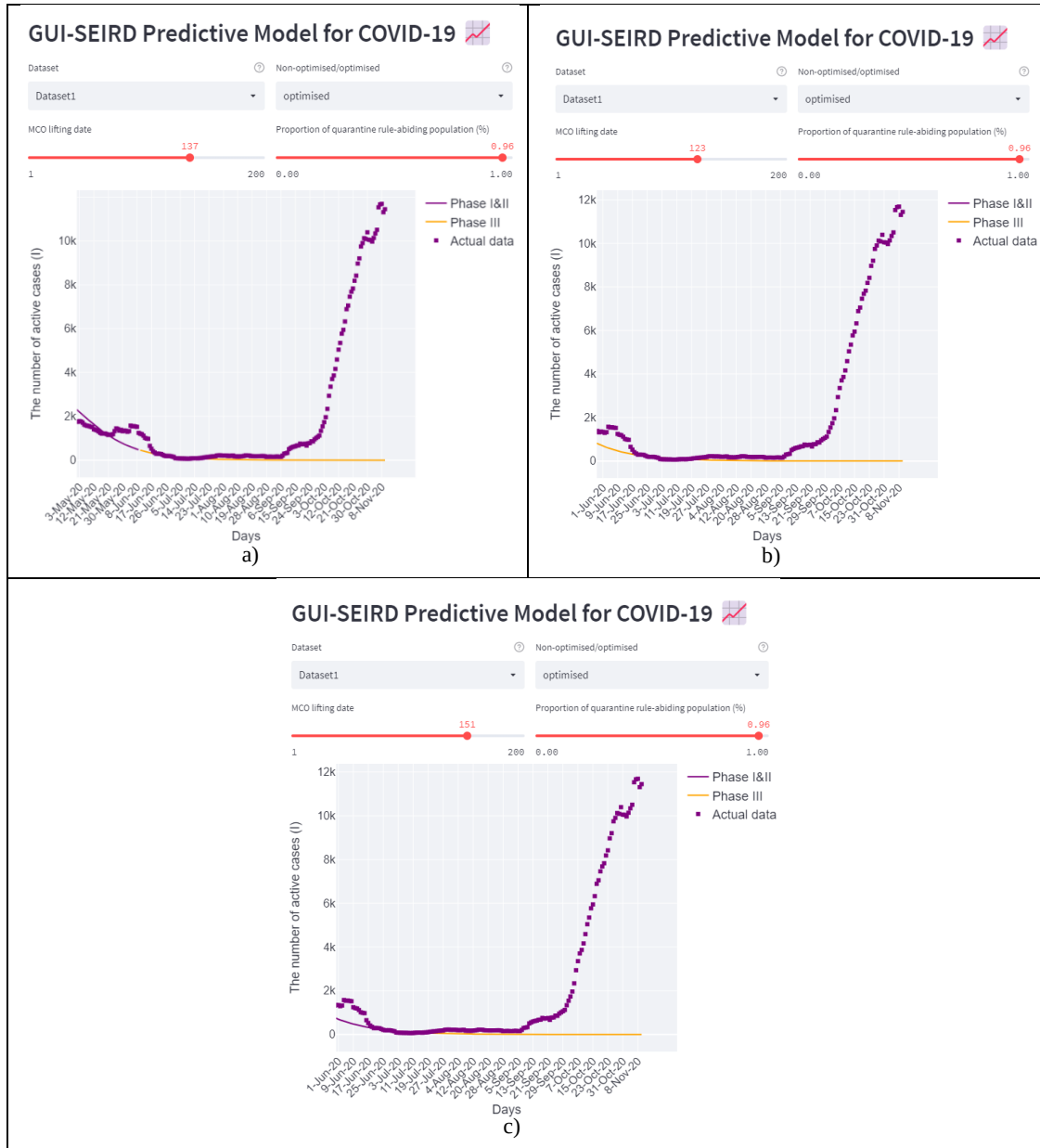


Figure 7: Zoom in for showing disease-free equilibrium achieved when the values of r is 96% despite of three different government's decision on MCO lifting date (advanced, actual and delayed)

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