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ORIGINAL ARTICLE

PARAMETER ESTIMATION OF COVID-19 COMPARTMENT MODEL IN INDONESIA USING PARTICLE SWARM OPTIMIZATION

Estimasi Parameter Model Kompartemen COVID-19 di Indonesia Menggunakan Particle Swarm Optimization

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ABSTRACT

Background: The government established a vaccination program to deal with highly reactive COVID-19 cases in Indonesia. In obtaining accurate predictions of the dynamics of the compartment model of COVID-19 spread, a good parameter estimation technique was required. **Purpose:** This research aims to apply Particle Swarm Optimization as a parameter estimation method to obtain parameters value from the Susceptible-Vaccinated-Infected-Recovered compartment model of COVID-19 cases. **Methods:** This research was conducted in April-May 2020 in Indonesia with exploratory design research. The researchers used the data on COVID-19 cases in Indonesia, which was accessed at covid19.go.id. The data set contained the number of reactive cases, vaccinated cases, and recovered cases. The data set was used to estimate the parameters of the COVID-19 compartment model. The results were shown by numerical simulations that apply to the Matlab program. **Results:** Research shows that the parameters estimated using Particle Swarm Optimization have a fairly good value because the mean square error is relatively small compared to the data size used. Reactive cases of COVID-19 have decreased until August 21, 2021. Next, reactive cases of COVID-19 will increase until the end of 2021. It is because the virus infection rate of the vaccinated population is positive $\rho > 0$. If $\rho = 0$ occurs before the stationary point, then the reactive cases of COVID-19 will decrease mathematically. **Conclusion:** Particle Swarm Optimization methods can estimate parameters well based on mean square error and the graphs that can describe the behavior of COVID-19 cases in the future.

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ABSTRAK

Latar Belakang: *Baru-baru ini pemerintah menetapkan program vaksinasi untuk mengatasi tingginya kasus reaktif COVID-19 di Indonesia. Metode estimasi parameter yang baik diperlukan untuk menghasilkan prediksi yang akurat dari dinamika model kompartemen penyebaran COVID-19.* ***Tujuan:*** *Penelitian ini dilakukan untuk mengaplikasikan Particle Swarm Optimization untuk mendapatkan parameter dari model kompartemen Susceptible-Vaccinated-Infected-Recovered untuk kasus COVID-19.* ***Metode:*** *Penelitian ini dilakukan pada bulan April-Mei 2020 di Indonesia dengan desain penelitian eksperimen. Penelitian ini menggunakan data kasus COVID-19 di Indonesia melalui laman covid19.go.id. Perangkat data tersebut memuat banyaknya kasus reaktif, tervaksinasi, dan sembuh. Data tersebut digunakan untuk mengestimasi parameter dari model kompartemen COVID-19. Metode estimasi yang digunakan adalah Particle Swarm Optimization. Hasil penelitian berupa simulasi numerik yang didukung oleh program Matlab.* ***Hasil:*** *Penelitian menunjukkan bahwa parameter yang diestimasi memiliki nilai yang cukup baik karena mean square error cukup kecil jika dibandingkan dengan data yang digunakan. Kasus reaktif COVID-19 mengalami penurunan hingga 21 Agustus 2021. Pada waktu selanjutnya, grafik kasus reaktif COVID-19 akan mengalami kenaikan hingga akhir tahun 2021. Hal ini disebabkan oleh laju infeksi virus populasi tervaksinasi masih bernilai positif,* $\rho > 0$. *Apabila terjadi* $\rho = 0$ *di titik stasioner, maka secara matematis, kasus reaktif COVID-19 akan mengalami penurunan.* ***Kesimpulan:*** *Metode Particle Swarm Optimization dapat mengestimasi parameter dengan baik berdasarkan mean square error dan grafik yang dapat mendeskripsikan perilaku kasus COVID-19 dan solusi dari fenomena yang terjadi di masa depan.*

INTRODUCTION

Coronavirus disease (COVID-19) has become a deadly disease troubling every country in the world. The first COVID-19 case was identified in Hubei Province, Wuhan City, China at the end of 2019 (Riyapan, Shuaib, & Intarasit, 2021). This case spread rapidly to various countries. Until February 2020, the World Health Organization (WHO) declared COVID-19 a pandemic worldwide (Yadav, Kumar, Singh, & Baleanu, 2021). One of the countries that have indicated a COVID-19 case is Indonesia.

Parameter estimation of the epidemic model can describe the characteristics of epidemic spread and provide estimates of future events (Ceylan, 2020). Suppose the COVID-19 transmission model parameters are well estimated with credible data. In that case, the estimation results can be used in predicting the evolution of COVID-19 in the region of data used (Cotta, Naveira-cotta, & Magal, 2020). Therefore, it is important to use a good parameter estimation of the COVID-19 transmission model to provide an overview in the future. Furthermore, the estimation results can be used as consideration for decision making, such as vaccine selection and so on.

On March 2, 2020, the two first cases were indicated in Indonesia (Tosepu et al., 2020). The spread of this virus is so fast that until June 2020, the total number of cases in Indonesia has reached 32,000 cases (Rayungsari, Aufin, & Imamah, 2020). It has motivated several researchers to carry out mathematical models of the COVID-19 pandemic. Rayungsari et al. (2020) estimated the parameters of the phenomenological model of

growth in cumulative cases of COVID-19 using the generalized Richards model with the Genetic Algorithm (GA) method. The Generalized Richards model is a general form of the Richards model, logistics, and exponential (Wu, Darcet, Wang, & Sornette, 2020). The phenomenological model used by Rayungsari et al. (2020) cannot explain the transmission that occurred (Darti, Suryanto, Panigoro, & Susanto, 2020). Therefore, most researchers use a mechanistic compartment model to analyze the dynamics of COVID-19 cases such as SIR, SEIR, and various other modifications (Chen, Li, Xiao, & Yang, 2020; Cooper, Mondal, & Antonopoulos, 2020; Postnikov, 2020; Zhang, Gul, & Zeb, 2020).

Some researchers are motivated to estimate parameters using various models, methods, and data for COVID-19 cases. Zreiq et al. (2020) estimate the parameters of the SIR model for COVID-19 cases in Saudi Arabia using Particle Swarm Optimization (PSO). PSO requires a shorter time and fewer iterations than GA, so PSO is better than GA (Shabir & Singla, 2016). Therefore, the parameters of the mechanistic compartment model of the COVID-19 case will be estimated using the PSO.

The mechanistic compartment model to be estimated certainly considers the field's existing data. The latest condition states that the COVID-19 pandemic has been prevented through vaccination trials (Sonawane, Troisi, & Deshmukh, 2021). In Indonesia, vaccination trials began to be carried out in the community at the end of February 2021. Therefore, the vaccinated population size data is still categorized as new data. April 2021 COVID-19 case data in Indonesia consists of reactive, cured, and vaccinated cases. Estimating the COVID-19 case epidemic model parameters with vaccination has not been done, especially using the PSO method. Therefore, this research will estimate parameters using the Susceptible – Vaccinated – Infected - Recovered (SVIR) model and existing data in Indonesia.

METHODS

The SIR model for the COVID-19 case from Zreiq et al. (Zreiq et al., 2020) and Cooper et al. (2020) was given by the system of differential equations (1).

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

In model (1), there were compartments S, I, R that represented the size of the susceptible population, the infected population, and the cured population, respectively. The parameter β represented the rate at which a susceptible population may become infected due to contact. The parameter γ deputized the cure rate for the infected population. Model (1) was a simple model that did not consider the mortality rate due to COVID-19 and the natural mortality rate. Therefore, the model will be modified considering both of them, changing the recovered compartment to the vaccinated population compartment. The method used to estimate the model parameters was Particle Swarm Optimization (PSO). Figure 1 showed the flowchart of the PSO method (See Figure 1).

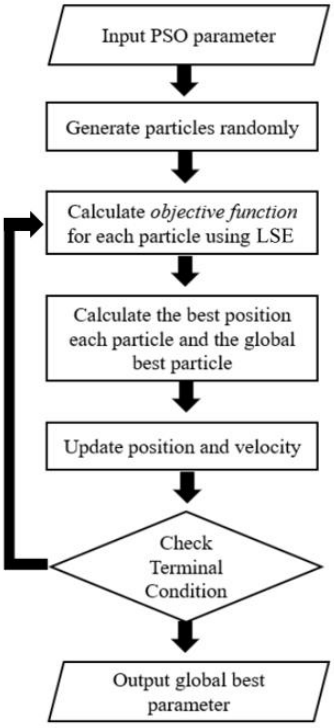

Figure 1. The Flowchart of Particle Swarm Optimization

Initially, each parameter of the model was input, which would be used to determine the best fitness value. Then, generated the number of particles in a domain. The position of each particle will determine the fitness value calculated based on the least square error (LSE), that was,

$$\varepsilon_i = \sum_{k=1}^{m} \sum_{j=1}^{n} (x(i)_{j,k} - y(i)_{j,k})^2$$

with ε_i denoted the fitness value of the ith particle, $x(i)_{j,k}$ represented the approximate value of the k-th data of j-th compartment of the i-th particle, $y(i)_{j,k}$ represented the k-th data of the j-th compartment of the i-th particle (See Table 1), m represented the number of data, and n represented the number of compartments of the model that would be optimized. Next, we determine the best position for each particle and the best position globally. After determining the best position, the current particle position and velocity were updated (Zreiq et al., 2020). The iteration ended when the variance of the particle position was small enough.

The research steps were epidemic modeling of COVID-19, parameter estimation, and numerical simulations. In the simulation, further phenomena would be observed to interpret the vaccination policy mathematically. Assume that on March 14th, the initial population at risk was 250 million. For further discussion, define the times of March 14th and April 12th as $t_0 = 0$ and $t_n = 29$, respectively. This research has ethical permission from the Department of Mathematics, Brawijaya University (No. 2307/UN10.F09.14/PT.02/2021).

RESULTS

This research constructs a compartment model of COVID-19 to estimate its parameters. The results of parameter estimation are given by numerical simulations. Therefore, the results of this research are divided into three parts.

Table 1
Data on COVID-19 Cases from March to April 2021 in Indonesia (per Thousand Cases)

Date	Reactive (a)	Vaccinated (b)	Recover (c)
14-Mar	137.91	1460.22	1243.11
15-Mar	136.52	1572.78	1249.94
16-Mar	134.21	1716.74	1257.66
17-Mar	131.69	1876.14	1266.67
18-Mar	131.75	1948.53	1272.95
19-Mar	131.82	2221.20	1278.96
20-Mar	131.61	2301.98	1284.72
21-Mar	129.84	2312.60	1290.79
22-Mar	128.26	2494.42	1297.96
23-Mar	126.44	2941.01	1304.92
24-Mar	123.92	2977.52	1312.54
25-Mar	125.31	3015.19	1317.19
26-Mar	124.49	3233.81	1322.88
27-Mar	124.51	3235.03	1327.12
28-Mar	124.23	3330.64	1331.40
29-Mar	123.69	3411.61	1336.81
30-Mar	122.32	3496.33	1342.69
31-Mar	122.52	3664.71	1348.33
1-Apr	121.22	3854.45	1355.57
2-Apr	121.01	3867.76	1361.01
3-Apr	120.06	3939.51	1366.21
4-Apr	116.71	4014.80	1375.87
5-Apr	114.47	4221.74	1381.73
6-Apr	114.57	4431.50	1386.04
7-Apr	113.60	4555.13	1391.74
8-Apr	111.27	4697.39	1399.38
9-Apr	110.13	4884.82	1405.66
10-Apr	111.13	5079.04	1409.29
11-Apr	109.95	5200.01	1414.50
12-Apr	109.37	5322.50	1419.79

Source: covid19.go.id, 2021

Compartment Model of COVID-19 Cases

The SVIR model for the COVID-19 case was constructed by modifying the model (1) by considering vaccinations, natural deaths, and deaths due to COVID-19. The SVIR model is given by the system of differential equations (2) and compartment diagram in Figure 2.

$$\begin{aligned}
\frac{dS}{dt} &= -\beta SI - (\sigma + \delta)S, \\
\frac{dV}{dt} &= \sigma S - \rho VI - \delta V, \\
\frac{dI}{dt} &= \beta SI + \rho VI - (\delta + \kappa + \gamma)I, \\
\frac{dR}{dt} &= \gamma I - \delta R
\end{aligned} \tag{2}$$

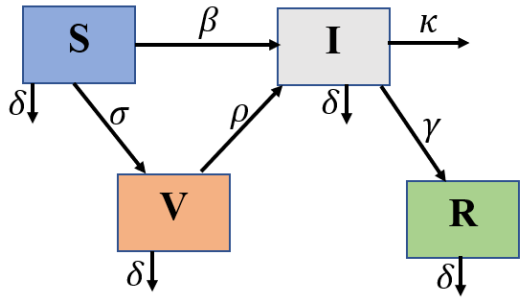

Figure 2. Compartment Diagram of Model (2)

There are 6 parameters of the model (2). Parameters $\beta, \sigma, \gamma, \delta, \kappa$ represent disease transmission rate, vaccination rate, recovery rate, natural mortality rate, and death due to COVID-19, respectively. In model (2), there is an assumption that vaccinated people can be infected with the virus at the rate ρ because of intensive contact with the infected person or failure in the vaccine efficacy (Ghostine, Gharamti, Hassrouny, & Hoteit, 2021). Parameter ρ can be expressed as $\beta(1-\alpha)$ with α represent the vaccine efficacy (Musafir, Suryanto, & Darti, 2021).

Parameter Estimation

In PSO, we first set some required weights value, initial conditions for all time-dependent variables, and domains for all parameters. The number of particles, first and second social constants, inertia weight, and a number of iterations is 30, 1.49, 0.70, and 200, respectively (Eberhart & Shi, 2000). Since the total population size in Indonesia is around 250 million and using the initial data value in Table 1, we set $S(0) = 250000$, $V(0) = 1460.2$, $I(0) = 137.9$, and $R(0) = 1243.1$. Several studies show that $\beta = 0.43 \times 10^{-1}$, $\delta = 0.12$ (Nurlaila, Hidayat, & Pardamean, 2021), $\gamma = 0.14$, $\kappa = 0.16$ (Ndii, Hadisoemarto, Agustian, & Supriatna, 2020), $\rho = (1-0.94)\beta = 0.25 \times 10^{-2}$, and $\sigma = 3.50 \times 10^{-4}$ (Musafir et al., 2021). We set parameter domains such that these parameter values are the center of parameter domains. Hence, we have domain parameters as follows:

$$\begin{aligned}
&\beta < 0.86 \times 10^{-1}, \\
&\sigma < 7 \times 10^{-4}, \\
&\delta < 0.24, \\
&\rho < 0.50 \times 10^{-2}, \\
&\kappa < 0.32, \\
&\gamma < 0.28,
\end{aligned}$$

After particles (parameter values in their domain) are randomly generated, we calculate objective functions or fitness value e_i for all particles as follow:

$$e_i = \sum_{j=1}^{29} [A^2 + B^2 + C^2]$$

with $A = (I(t_{j/0.01}) - a(j))$ $B = (V(t_{j/0.01}) - b(j))$, $C = (R(t_{j/0.01}) - c(j))$. We use the fourth order Runge-Kutta method with a step size of 0.01 to determine $I(t_{j/0.01}), V(t_{j/0.01}), R(t_{j/0.01})$.

We next determine the best position of all particles. Let $Z_i(r)$ is a position of i-th particle in r-th iteration. The position of i-th particle can be determined by following formula.

$$Z_i(r) = \begin{matrix} Z_i(r-1), \text{ if } e_i(Z_i(r)) \geq e_i(Z_i(r-1)) \\ Z_i(r), \text{ if } e_i(Z_i(r)) < e_i(Z_i(r-1)) \end{matrix}$$

The particles that have best position becomes new particles in next iteration. Based on 100 iterations, the best values of parameters estimation are obtained as follows:

$$\begin{aligned}
\beta &= 3.642131 \times 10^{-7}, \\
\sigma &= 5.412314 \times 10^{-4}, \\
\delta &= 6.123122 \times 10^{-4}, \\
\rho &= 13.61231 \times 10^{-7}, \\
\kappa &= 4.612032 \times 10^{-2}, \\
\gamma &= 5.562312 \times 10^{-2},
\end{aligned} \tag{3}$$

with fitness value $e = 10.69 \times 10^{3}$. This MSE is quite small compared to data size and amount of data.

Numerical Simulation

The numerical simulation uses the results of parameter estimation (3) to compare the numerical approximation with real data on COVID-19 cases in Indonesia. The interesting compartments to simulate are the dynamics of the reactive population of COVID-19 and the vaccinated population. The numerical simulation uses the Matlab program and the fourth order Runge-Kutta method with a step size 0.01. The initial values used based on real data are $S(0) = 250000$, $V(0) = 1460.2$, $I(0) = 137.9, R(0) = 1243.1$.

Figure 3 compares the approximate graph with real data for the vaccinated population (See Figure 3). The approximation results looked quite good and could represent 30 data from March to April 2021. It also resulted in the approximation graph being used to reference the behavior of the vaccinated population data $t > 30$.

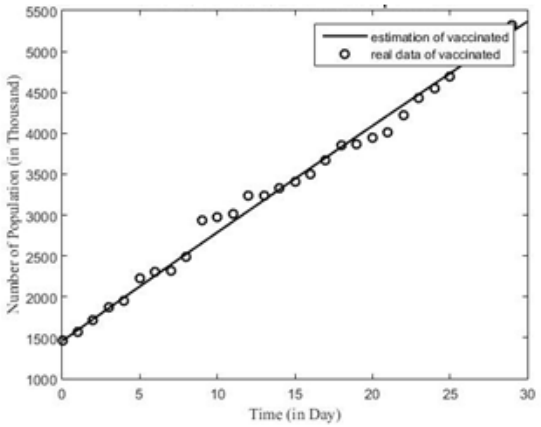

Figure 3. The Approximation Versus Real Data on Vaccinated Cases of COVID-19 in Indonesia.

Figure 4 shows the comparison of the results for the infected population (See Figure 4). As with the vaccinated population, the reactive case approximation looks quite good on the behavior of the data, although it is not accurate for many data. Since the results of the approximation can represent the real data behavior, the approximation can also be a reference for $t > 30$.

The next simulation is done by selecting a larger time domain, namely $0 < t < 300$. The simulation for compartment I shows a stationary point at $t_1 \approx 160$ with $I(t_1) \approx 70$. As a result, a local minimum occurs at t_1 (See Figure 5).

Figure 3 to Figure 5, using a parameter (3). The reactive population graph will increase in $[160, 300]$ due to the parameter value is $\rho > 0$. When the parameter value is $\rho = 0$, the reactive population graph will decrease at the same interval (See Figure 6). As a result, in the value of the parameter ρ changes, changing how the graph for compartment I works.In this case, the parameter ρ is called the shape parameter. Changes in the shape of the graph make the parameter ρ very important to consider the local minimum value, the global minimum value, and the convergence of $I(t)$.

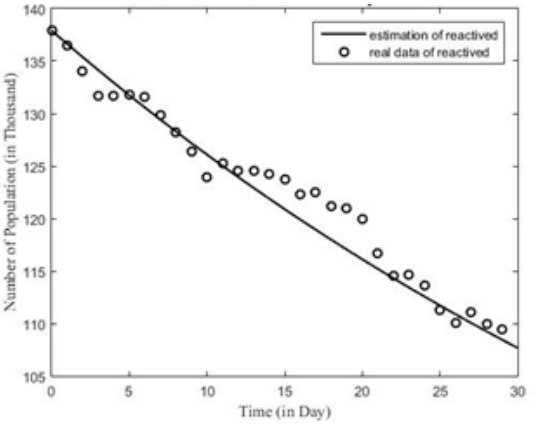

Figure 4. The Approximation Versus Real Data on Reactive Cases of COVID-19 in Indonesia.

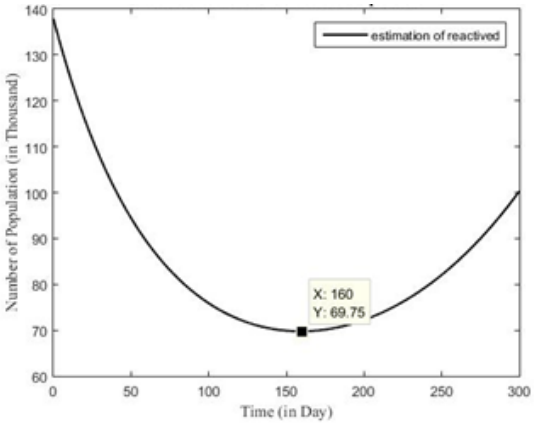

Figure 5. The Simulation of Reactive Cases

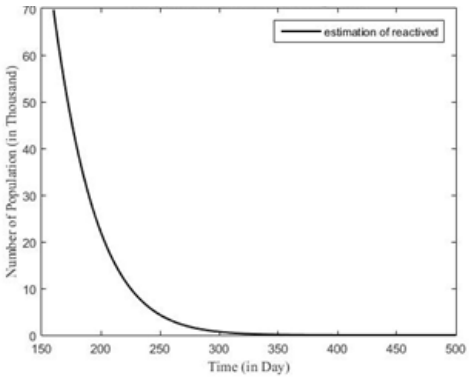

Figure 6. The Simulation of Reactive with $\rho = 0$ on $160 < t < 500$

The change in the value of the $\rho = 0$ parameter is proportional to the change in model (2), namely in model (2), the rate of infection of the COVID-19 virus in the vaccinated population is removed. In other words, Figure 5, represents the compartment I graph for the SIR model with vaccinations in general. Changing the value of this parameter also causes the compartment I graph to have a global local minimum value at zero and $I(t)$ converges to 0.

DISCUSSION

Estimating parameters is more complex to apply to mechanistic compartment models than phenomenological models (Darti et al., 2020). Rayungsari et al. (Rayungsari et al., 2020) stated that the phenomenological model uses cumulative data. It differs from the mechanistic compartment model, which uses time-per-time data (Darti et al., 2020). As a result, the parameters of the mechanistic compartment model to be estimated have a relatively small size domain. The parameter domain is obtained through *trial and error*.

The parameter estimation results using Particle Swarm Optimization are quite good. It is indicated by the small mean square error when compared to the population size in the data, which is $\bar{e} = 10.69 \times 10^3$ for 30 data in hundreds and thousands. Particle Swarm Optimization in this compartment model provides estimated parameter values based on real data (Shabir & Singla, 2016). The thing to note in this estimate is the real data used, namely data from March to April 2021 in Indonesia. Therefore, the reactive population size graph estimates that there is no new variant of COVID-19, so the injected vaccine has no effect on infection with the new variant of the COVID-19 virus.

The COVID-19 vaccination has been implemented in most countries. Some people are enthusiastic about vaccinating, and others are not sure about the COVID-19 vaccine (Shen et al., 2021). The existence of people who are unsure of the COVID-19 vaccine has caused the government to take actions such as education through social media, disseminating data on vaccine success, and administrative requirements (Musafir et al., 2021). It has increased the number of people being vaccinated (See Figure 3). Based on data and approximation using Particle Swarm Optimization, the vaccination rate is 5.41×10^{-4}. This is quite large for a susceptible population of around 250 million. Therefore, government intervention measures and policies are quite effective in increasing the rate of vaccination.

The research findings state that the estimated parameters have provided good approximations to be interpreted realistically. The values $\rho \approx 13.6 \times 10^{-7}$ can be interpreted as 13.6 infected interactions out of 10 million interactions between vaccinated people and infected people. In other words, if 100 thousand vaccinated people interact with 1 thousand infected people, then 130 vaccinated people are infected by the virus. This matter shows that the COVID-19 vaccine used is imperfect. Based on parameter estimation in this study, the transmission rate of vaccinated people is greater than that of susceptible people. It could be due to the declining quality of health protocols for vaccinated people. Government needs to educate vaccinated people to emphasize health protocols.

In the model used, there is an assumption that vaccinated individuals can be infected with the COVID-19 virus. Gómez et al. (2021) stated that the difference in efficacy of the vaccine was caused by environmental factors, individual habits, and types of vaccine. Knoll and Wonodi (2021) state that the AstraZeneca-type vaccine for COVID-19 has more than 90% efficiacy. In addition, Mahase (2020) also stated that the Moderna-type vaccine for COVID-19 has more than 90% efficiacy. On the other hand, the BNT162b2 mRNA-type vaccine for COVID-19 has an efficacy of around 95% (Polack et al., 2020). The findings of this study indicate that the efficacy failure rate is around 13×10^{-7}. Therefore, the efficacy of vaccines in Indonesia is also above 90%, but it is below 100%. Therefore, the parameter estimation results are quite good and do not contradict the existing facts.

The simulation's phenomenon shows that Indonesia's vaccination program is quite effective because the reactive cases of COVID-19 are decreasing. It was also found in Fuady et al. (2021) research that vaccinations with high vaccine efficacy can reduce the number of reactive populations. The simulation shows that reactive COVID-19 cases will decrease until August 21th, 2021. In other words, reactive COVID-19 cases in Indonesia will decline for approximately 160 days after the vaccination program is implemented. It can be seen in Figure 5, which shows a minimum decrease in reactive cases on the 160th day with 69.75 thousand reactive cases.

Another interesting phenomenon is not only the decline in reactive COVID-19 cases. It is because vaccine efficacy is below 100% still raises the assumption that vaccinated individuals can be infected with the virus. Suppose there is no vaccine that no vaccine has such an efficacy level that there is an assumption that vaccinated individuals cannot contract the COVID-19 virus. In that case, reactive cases of COVID-19 will not experience a plateau. The simulation shows that reactive cases will increase from August 22nd, 2021 to the end of 2021. The failure of the vaccine efficacy supports this is below 10% (Wirawan, Mahardani, Cahyani, Laksmi, & Januraga, 2021), with vaccine efficacy failure being below 1% in this study.

One solution is to find a vaccine that has such a high efficacy that the assumption that the vaccinated population cannot be infected with the COVID-19 virus. If the vaccine is found before August 21th, 2021, then based on research simulations, reactive cases of COVID-19 in Indonesia can be suppressed so that there is no increase in the cases (See Figure 6). It is also supported by the research of Domingo & Perales (2021) that a vaccine with high efficacy should be done when the case reaches a stationary state (the time when the position of the valley is graphical). When this happens, the reactive cases of COVID-19 will decrease until they become extinct.

On the other hand, numerical simulations show that reactive cases will decrease when the vaccine has 100% efficacy. In reality, a vaccine cannot have 100% efficacy for every population. Frenck Jr et al. (2021) conducted a vaccine efficacy study that could produce 100% efficacy for patients aged 12-15. The vaccine used in this study was BNT162b2 mRNA. It can happen because the immunity of patients aged 12-15 can increase rapidly. It does not always apply to patients with other diseases such as coronary heart disease, autoimmune, and other acute diseases. It also includes consideration of vaccine efficacy (Gómez et al., 2021). Therefore, 100% vaccine efficacy for all population groups is impossible.

Another solution to overcome the impossibility of 100% vaccine efficacy is to maintain good habits and comply with government intervention policies. It serves as an effort to mitigate COVID-19, such as obeying health protocols, locking, a quarantine or self-isolation, limiting mobility, and limiting the capacity of an event (López & Rodó, 2021; Musafir et al., 2021; Riyapan et al., 2021). The individual's habits can improve the vaccine quality even though the vaccine efficacy is not 100% (Gómez et al., 2021). Individual habits and adherence to government intervention policies can cause reactive cases to decline because the quality of individual immunity and physical contact restrictions can prevent the transmission of the COVID-19 virus. Therefore, it is important for the government to always educate the public in mitigating the spread of COVID-19 so that economic, social, and educational problems can be resolved.

Research Limitations

This research uses a data set of COVID-19 cases from March to April 2021. The data set contains a number of reactive, vaccinated, and recovered cases. The data on undetected cases, such as asymptomatic reactive cases, was not considered reactive case data in this research.

CONCLUSION

Estimating of parameters of the SVIR model using the Particle Swarm Optimization method has been carried out. The application of Particle Swarm Optimization to the Susceptible-Vaccinated-Infected-Recovered model is more complex than the phenomenological model. The estimated parameter has small mean square error. These parameters are good enough to describe the dynamics of COVID-19 cases in the future.

Reactive cases of COVID-19 in Indonesia have decreased after the government's vaccination program was implemented in the middle of the first quarter of 2021. Based on simulation and the data used, these cases continued to decline until the end of the third quarter. In the fourth quarter, there was an increase in reactive COVID-19 cases again. The cause of this increase is the failure of vaccine efficacy which is still high so that the COVID-19 virus can still infect the vaccinated population. In other words, the viral infection rate of the vaccinated population is still positive. If the virus infection rate of the vaccinated population is almost zero, the vaccination program will experience a monotonous decrease until the reactive COVID-19 cases become extinct. Therefore, it is necessary to develop a vaccine that eliminates the assumption that vaccinated individuals can become infected with the virus before the third quarter ends in 2021.

CONFLICT OF INTEREST

All authors declare that there is no conflict of interest.

AUTHOR CONTRIBUTION

RRM compiled this research which was supervised by SA. RRM led the conceptualization, manuscript writing, data curation, numerical simulation, analysis, and interpretation of research findings. SA led the conceptualization, methodology, the Matlab program used in this research, review, and editing. All authors have approved the content of this manuscript.

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