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# OPTIMIZATION-BASED METHOD FOR ESTIMATING THE TRANSMISSION RATE OF COVID-19 DURING THE LOCKDOWN IN MALAYSIA

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## Abstract

In this work, the optimization-based method is implemented to investigate the effectiveness of lockdown strategies undertaken to contain the COVID-19 during the first two waves in Malaysia. The well-known Susceptible-Infected-Removed (SIR) epidemiological model was fitted to the actual data of infected cases from the official press to closely reflect the observed COVID-19 outbreak in Malaysia. The Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) were implemented to determine the daily transmission rate $\beta(t)$ that fits the SIR model to the actual data. The best fitness value of PSO is mostly stable at approximately 37.5 with the best value of 37.41 at a population size of 1000, whilst the best value for GA slowly decreased to the best value of 47.45 at a population size of 1000. In addition, PSO requires a lower number of iterations to reach the optimum fitness value for the same population size as compared to GA, while GA is too far to reach the convergence. As the removal rate ($\gamma$) is a constant value fixed at 0.1, the optimized $\beta(t)$ values indicate a high basic reproduction number (average R0 = 1.23) obtained before the Movement Control Order (MCO), followed by a considerable decrease to an average R0 value of 1.23 during the MCO. During the Conditional MCO and Recovery MCO, the basic reproduction number was slightly decreased to an average R0 value less than 1. This is an indication of the success of the government to contain the pandemic during the first two waves as the R0 has been kept below than 1.

Keywords: COVID-19; Susceptible-Infected-Removed; Transmission rate; Genetic Algorithm; Particle Swarm Optimization.

## 1. Introduction

The ongoing pandemic of COVID-19 was initially identified in Wuhan and then has started to spread over the world [1]. The COVID-19 is considered a pandemic due to its fast transmission from people who have been infected to healthy people [2,3]. In Malaysia, the Ministry of Health has confirmed the pandemic on 16th March 2020 since the number of infected cases was dramatically increasing [4]. Up to now, the COVID-19 is not controlled as there is no enough people to get vaccinated, especially in third world countries. Thus, the COVID-19 outbreak has different forms from one country to another based on the behavioural strategies undertaken by the governments to prevent the spread, such as travel entry restrictions and movement control of residents [5]. In Malaysia, the government has undertaken time-variant strategies during the first two waves in response to the COVID-19 outbreak, namely: Movement Control Order (MCO), Conditional Movement Control Order (CMCO), and Recovery Movement Control Order (RMCO) [6]. Table 1 summarizes the regulations undertaken for each strategy. On 16th March, the Malaysian government had announced the MCO in response to the COVID-19 pandemic. After that, Malaysia went through two extended MCOs with all restrictions recommended by the World Health Origination (WHO) to contain the pandemic. On 7th May, the government had clarified that the country has met the criteria identified by WHO to end the MCO. On 10th June, the RMCO has been activated until 31st August 2020 with more lenient restrictions. However, all sectors that are allowed to resume their operations must meet the Standard Operating Procedures (SOPs).

**Table 1. Regulations for each Strategy**

| **Strategy** | **MCO (18 March to 3 May)** | **CMCO (4 May- 9June)** | **RMCO (10 June to 31 August)** |
|---|---|---|---|
| **Allowed** | Public markets and grocery stores selling food and essential items. | Inter-state travel. All business sectors and activities. | Sport and educational activities. Foreign travel. |
| **Not allowed** | Traveling inside and abroad. Mass movements and gatherings, including religious, social, sports, and educational activities. | Mass movements and gatherings. Foreign travel. | Foreign visitors. Any gatherings detrimental to safe social distancing and other measures required by the Health director. |

Fig. 1 depicts the cumulative number of infected and recovered cases during the first two waves from 1st March to 2nd August 2020 in Malaysia [7]. Malaysia is one of the most successful countries to handle and control the transmission rate of COVID-19 such that a total of 8,999 cases are reported at theend of 02 August 2020, breakdown into 210 cases in hospitals, 8,664 recovered cases, and 125 death cases. The transmission rate measures the success of the government's strategies to restrain the COVID-19 spread within the community. The motivation to conduct this study is to measure the daily transmission rate during the MCO, CMCO, and RMCO.

The transmission rate (or infection rate) indicates the probability of disease transmission from one infectious case to susceptible cases [8]. In calculating the transmission rate, the asymptotic statistical theory is a common method, in which the least-squares algorithm has been used to determine the optimum transmission rate that minimized the difference between the actual and estimated number of infected cases [9]. Many mathematical methods have been used to estimate the number of infected cases such as the classical Susceptible–Infectious–Removed (SIR) model, Logistic Growth model, and Susceptible–Exposed–Infectious–Removed (SEIR) model [10]. Among them, the SIR and SEIR models are widely used for their easy implementation. Besides, they provide a better understanding of how the disease spreads within the country by estimating the transmission, recovery, and death rates [11]. Early studies focusing on the COVID-19 outbreak in Malaysia did not provide an accurate prediction for the number of infected cases using SIR and SIER models as: 1) there was no enough actual data to fit the models, the government interventions to decline the transmission rate was not considered, and 3) the transmission rate was considered to be constant while predicting the cases for the next upcoming months [12-14]. In our previous work, the Genetic Algorithm (GA) was used to predict the transmission rate that would minimize the disparity between the factual and estimated number of infected people, while the SEIR model was implemented to estimate the number of infected people [15]. Due to the absence of actual data, the estimated number of infected cases with Poisson noise was assumed to represent the actual data. Besides, the government intervention to restrain the outbreak was assumed to be minimal in the early days so that the transmission rate was assumed to be constant for the next upcoming months.

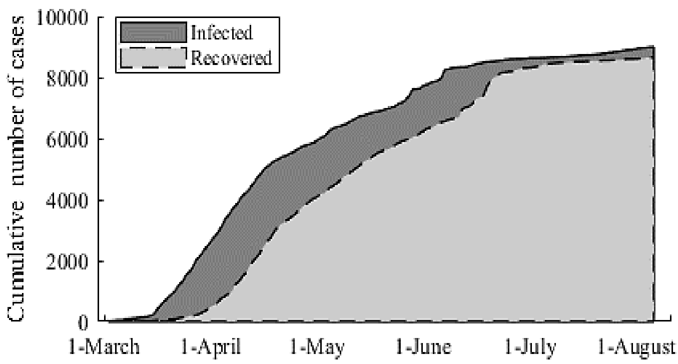



**Fig. 1. Cumulative number of infected and recovered cases in Malaysia**

In this work, the government interventions to flatten the curve over time is measured by estimating the transmission rate values during the MCO, CMCO, and RMCO. Two optimization methods of GA and PSO are implemented to estimate the daily transmission rate that would minimize the difference between the estimated data based on the SIR model and the actual data of infected cases in Malaysia.

## 2. Methods

### 2.1. Characterizing the COVID-19

The SIR model that characterizes the COVID-19 epidemic with involving the mortality rate is described as follows [14]:

$dS(t)/d(t) = -\beta(t)S(t)I(t)$

$$dI(t)/d(t) = \beta(t)S(t)I(t) - (\gamma+D)\, I(t) \tag{1}$$

$$dR(t)/d(t) = \gamma I(t)$$

where *S*, *I*, and *R* are the number of susceptible, infective, and removed cases reported at day t. The coefficients $\beta$, $\gamma$, and *D* are the transmission, removal, and death rates given at day t. Recent research related to COVID-19 reported that the transmission rate ($\gamma^{-1}$) is 10 days; that is, $\gamma$ value is 0.1 [16,17]. The death rate *D* is about 0.016 in Malaysia. The transmission rate $\beta$ is often assumed to be constant but is dependent on governmental interventions of lockdown. This implies that $\beta$ is time-variant as interventions of MCO, CMCO, and RMCO were applied with different strategies on certain periods. We fixed $S + I + R = 1$, thus each population implies the proportion to the total population. Let consider that a single infected case was detected at day $t = 1$ within Malaysia population of $N = 32.6 \times 10^6$. Then, the number of infected cases (*X*) estimated at day *t* is formulated as:

$$X(t) = NI(t) \tag{2}$$

The basic reproduction number $R_0$ is the number of infected cases produced from a single infectious case. It is calculated as a function of transmission and recovery rates as follows [15]:

$$\mathscr{R}_0\,(t) = \frac{\beta(t)}{\gamma}\left(1 - \frac{1}{N}\right) \approx \frac{\beta(t)}{\gamma} \tag{1}$$

The basic reproduction number solely relies on the removal ($\gamma$) and transmission rates ($\beta$) in the case that the number of population is high. Note that the $\beta$ values at day *t* are estimated using GA and PSO optimization algorithms as presented in the next subsection. Then, the basic reproduction number at day *t* is calculated using Eq. (3).

## 2.2. *β*(t) Estimation using GA and PSO

In this work, the estimation of daily transmission rate during the MCOs has been accomplished using two optimization methods of GA and PSO. It is assumed that $X(t)$ (shown in Eq. 2) and $Y(t)$, $t = 1, 2, \ldots, 155$, is the expected number and the actual number of daily infected cases in Malaysia from 1st March to 2nd August 2020, respectively. The GA and PSO optimization methods can be applied to estimate the transmission rate ($\beta$) for each day from 1st March to 2th August. The $\beta$ values that minimize the difference between $X(t)$ and $Y(t)$ represent the transmission rate at day *t*. This difference is defined as the fitness function and represented by the mean square errors between the estimated infected cases (*X*) and the actual infected cases (*Y*) as in the following equation:

$$C(\beta) = \sqrt{\frac{\sum_{t=1}^{155}[\mathrm{X}(t)-\mathrm{Y}(t)]^2}{T}} \tag{2}$$

where *T* is the total number of days. To determine the $\beta$ values which minimize the fitness function, the GA algorithm is firstly applied using the following five steps [18-20]:

1. Population initialization is the first step in which the GA initially produces a number of populations to find the possible solution to the problem of the fitness function. In each population, individuals (chromosomes) are randomly encoded. The fitness values of the produced populations are then computed.

2. Selection is the second step in which the GA ranks every individual based on its associated fitness and the corresponding individual fitness is selected. Based on that, the best individuals from every population are selected and fitness function with smaller value has a larger opportunity to be selected. Upon that, the solutions selected from every population are used to create a new population. This procedure aims to find a better population than the old one. The generation gap is adjusted to be fixed using a certain function for the selection process. The selected individuals are then recombined.
3. Crossover is the third step in which new children (offspring) are generated for next iteration. The individuals selected in the previous step are crossovered with a crossover probability.
4. The mutation is the fourth step in which information of individuals (chromosomes) are revised. The old genes are then mutated to generate novel genes. Based on that, the multifariousness of the population can be controlled and the search capacity in the solution space is also enhanced.
5. Evaluation is the last step in which the fitness function is evaluated for each individual. The number of iterations is selected as the stopping criteria for the GA process. The $\beta$ values for the minimum fitness function are recorded that represent the estimated infection rates at day $t$ in Malaysia.

The GA flowchart to estimate the $\beta$ values is shown in Fig. 2. Table 2 summarizes the GA parameters and its values which are chosen according to the trial and error method. The five GA steps are conducted using the optimization Toolbox of MATLAB® software.

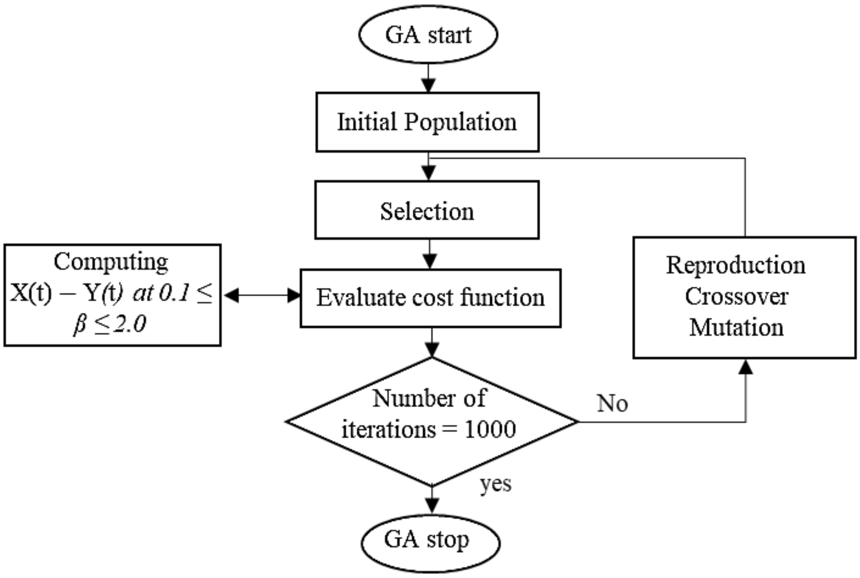



**Fig. 2. GA flowchart for β estimation.**

**Table 2. GA parameters**

| GA parameter | Value | GA parameter | Value |
|---|---|---|---|

| | | | |
|---|---|---|---|
| Population size | 25-500 | Mutation rate | 0.02 |
| Number of iterations | 2000 | Mutation percentage | 0.9 |
| Crossover percentage | 0.95 | | |

Second, the $\beta$ values that minimize the fitness function are estimated using PSO, which is one of the common stochastic optimization methods. The PSO criteria involves a random selection of particles (populations) in the search space and the generations iteratively are subsequently updated to obtain the optima [21]. Two outstanding particles are then used to update each particle. The first particles is called 'pbest' which is the own best solution achieved by the particles. Second particle is called 'gbest' which is the whole best solution obtained within particles in the population [22]. The flowchart of PSO process is depicted in Fig. 3. The first process is to initialize velocities and locations to start the initial particles (population). Subsequently, every particle is statistically evaluated using regression analysis. The PSO process stops when the best fitness rate meets the stopping criterion. Otherwise, velocities and locations of the particles have to be updated under two cases. The first case is when the particle fitness is superior and higher than the gbest fitness, the factors of the gbest fitness are updated. Another one, when the particle fitness is superior and higher than the pbest, the pbest fitness parameters are then updated. Lastly, the process directed to the second step again in which further particles should be evaluated [23]. Table 3 summarizes the PSO parameters which are obtained using the trial and error method. The optimized parameter of daily transmission rate using PSO and GA is then used to form the SIR model for comparison with actual data. For that, Pearson's product-moment correlation coefficients are determined using correlation package of SPSS® v21

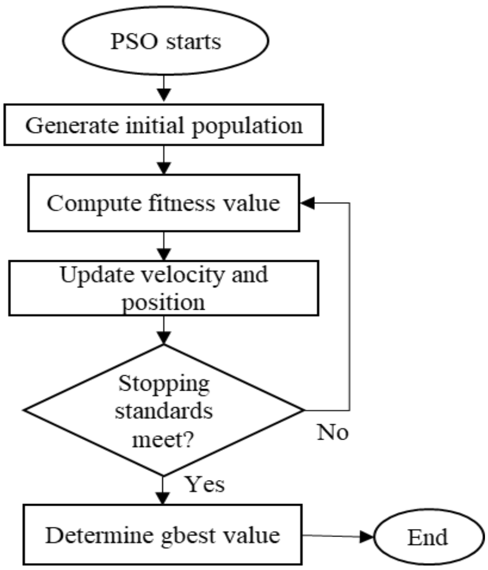



**Fig. 3. GA flowchart for β estimation.**

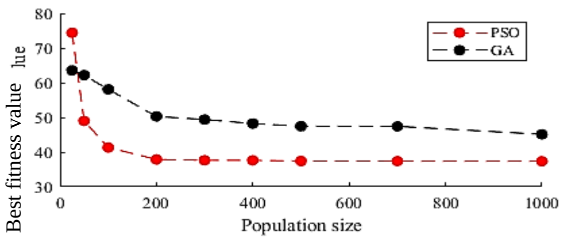
software.

**Table 3. GA parameters**

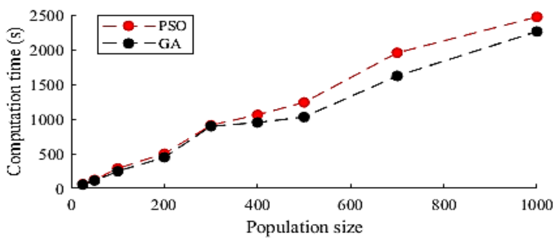
| PSO parameter | Value | PSO parameter | Value |
|---|---|---|---|
| Particles number | 25-500 | Inertia weight damping ratio | 0.99 |
| Number of iterations | 2000 | Cognitive acceleration | 1 |
| Inertia weight | 0.5 | Social acceleration | 2 |

## 3. Results and Discussion

The accuracy and efficiency of the GA and PSO are investigated based on how close the best solution at convergence to the global optimum and how fast it converges to the best solution, respectively. In the optimization process to estimate the $\beta$ values, the population size was selected in the range of 25 to 500. Subsequently, the best fitness value and computation time for GA and PSO are shown in Fig. 4. The best fitness values of GA and PSO sharply decrease at population sizes 25, 50, and 100. However, the best fitness of PSO is mostly stable at an approximate value of 37.5, and the best value is 37.41 at the population size of 1000. The GA fitness values slowly decrease to the best value of 47.45 at a population size of 1000. The PSO fitness values are mostly better than the values of GA regardless of the population size, except for the population size of 25. The best fitness values of PSO are better than those of GA by an average of 24%. Thus, PSO shows better accuracy than GA. This is consistent with previous studies reported that PSO requires a lower number of iterations to reach the optimum fitness value for the same population size as compared to GA, while GA is too far to reach the convergence [24,25]. Furthermore, GA is susceptible to fall into local minima leading to premature convergence, and this possibility can be minimized by increasing the number of iterations and population size [26]. However, the




(a) **Best cost values**




(b) **Computation time of GA and PSO with population size**

**Fig. 3. Results of cost values and computation time**

computation time of GA is less than that of PSO to perform 2000 iterations, especially at population sizes of 400, 500, 700, and 1000.

The GA has the best fitness value at the population size of 1000, which is the closest value to the best fitness value of PSO as well, labelled in Fig. 4(a). Subsequently, the 1000 population size is selected as the most suitable one to compare between GA and PSO. The change of fitness value for each optimization method with 2000 iterations is shown in Fig. 5. During the optimization process, the fitness value of GA decreases with a constant pattern before the 2000th iteration, while that of the PSO almost attains the best fitness value before the 800th iteration. This means that PSO achieves better efficiency than GA such that the PSO quickly converges to the solution. The optimized parameter of daily transmission rate $\beta$(t) estimated using GA and PSO is shown in Fig. 6. It is observed that the transmission rate is relatively high before the MCO with an average of 0.56, followed by a sharp decrease during the MCO with an average of 0.123. The transmission rate continues to decrease slowly during the CMC and RMCO to averages of 0.093 and 0.069, respectively. The decrease in the transmission rate indicates that the lockdown undertaken by the government is effective to flatten the COVID-19 curve as well as to contain the pandemic. As the removal rate is constant over the entire period, Table 4 summarizes the basic reproduction number s R0 at removal rate ($\gamma$) of 0.1 during the MCO, CMCO, and RMCO. Before the MCO, the $R_0$ is relatively high, and continuing with this number would have made the epidemic is out of control. However, the MCO strategy was able to stabilize the infection within the population as the $R_0$ value is close to 1. The next two strategies later have decreased the $R_0$ value down under 1, resulting in a tangible decline in the number of infected cases. It is observed that the $R_0$ has some spikes above 1 during CMCO and RMCO, indicating that the duration of pandemic has been taking a longer time after the curve flattened in April. As of the end of July, 2020, the number of infected cases has been increased which is probably due to home-quarantine policy for those coming from overseas. As the COVID-19 is not going way easily in the case of new clusters during the RMCO, the government should take a step to strengthen the lockdown policy for those coming from overseas.

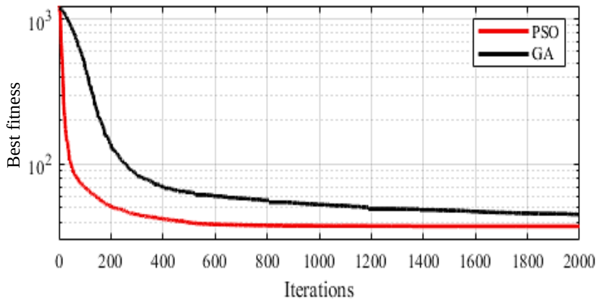



**Fig. 4. Best cost values of GA and PSO at population size of 1000.**

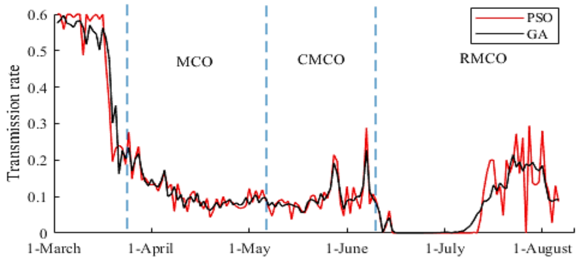



**Fig. 5. Daily transmission rate using GA and PSO**

**Table 3. $\mathscr{R}_0$ values during the lockdown**

| Lockdown category | GA | PSO |
|---|---|---|
| **Before MCO** | 5.55 | 5.56 |
| **MCO** | 1.24 | 1.22 |
| **CMCO** | 0.93 | 0. 93 |
| **RMCO** | 0.69 | 0.7 |

To validate the optimized parameter, the daily transmission rates were used to fit the SIR model described in Equation 2. Then, the fitted SIR model was evaluated against the actual data based on the Pearson's product moment correlation coefficients. Fig. 7 depicts the actual and estimated number of infected cases using the SIR model. It is observed that the PSO and GA curves are almost close to the actual curve of the number of infected cases, indicates high fitting accuracy. As demonstrated in Table 5, both fitted SIR models achieves a very high correlation with the actual data. However, the SIR model optimized using PSO is slightly better than that of GA. Previous studies reported that GA and PSO achieve the same effectiveness on average, but PSO is more computationally better in terms of efficiency [21,27].

**Table 4. Pearson's correlation coefficients for fitted sir model**

| Lockdown category | GA | PSO |
|---|---|---|
| **Before MCO** | 0.998 | 0.998 |
| **MCO** | 0.988 | 1 |
| **CMCO** | 0.98 | 0.998 |
| **RMCO** | 0.971 | 0.985 |
| **Average** | **0.984** | **0.995** |

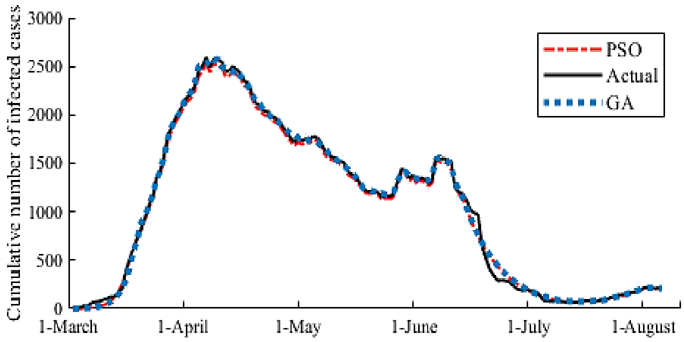



**Fig. 6. Actual and estimated data based on SIR model optimized using GA and PSO**

## 4. Conclusions

SIR model is an effective tool in dealing with the pattern of COVID-19 outbreaks. It provides a useful estimation in the impact of interventions in decreasing the number of infected cases. In this work, the daily transmission rate was calculated by fitting estimated data based on the SIR model to the actual data of COVID-19 in Malaysia using GA and PSO optimization methods. The PSO was far faster than GA to reach the best fitness value. In Malaysia, the reproduction number was decreased to a value of 1 within the first month of lockdown which is an indication of the success of the government to contain the pandemic. Although the peak number of infected cases was in mid-April, the pandemic has not finished yet as the daily transmission rate has been increased recently. The GA and PSO were then validated by re-forming the SIR model using the optimized parameter of transmission rates. The results show that the predictions from SIR model have high correlation with actual data in the case of GA and PSO. The proposed model can be applied to other countries, which represents an important contribution to suggest strategies to face the COVID-19.

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