A Predictive Vaccination Strategy Based on a Swarm Intelligence Technique for the Case of Saudi Arabia: A Control Engineering Approach

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ABSTRACT

The COVID-19 pandemic caused high damage to health, social, and economic systems globally. Saudi Arabia has conducted a relatively successful experience in mitigating the virus. Saudi authorities have started a vaccination campaign by the end of 2020 with more than 60 million doses being administered to citizens and residents by February 2, 2022. The objective of this study is to propose an optimal vaccination strategy in short and medium terms in order to help the local health authorities to first assess the vaccination campaign and to propose a predictive vaccination plan for eradicating the disease. For this purpose, a control engineering approach was used where the disease dynamics was identified and an optimal control law using the daily number of vaccines as input and the daily number of new infections as output was proposed and evaluated. The vaccination process was modeled as a discrete-time transfer function. The parameters of the transfer function were identified based on the Particle Swarm Optimization (PSO) algorithm while considering the Routh-Hurwitz stability criterion for analyzing the system stability. The final step of this study was dedicated to synthesize three controller variants (P, PI, and PID) for the case study of Saudi Arabia. The obtained results for the modeling and the controllers' design were found to be promising. The results were found to be generic and can therefore be used to control other diseases or any other occurrence of COVID-19 or similar viruses.

Keywords-COVID-19; optimal control; model identification; vaccination strategy; disease mitigation

I. INTRODUCTION

Despite the control measures including social distancing, compulsory mask wearing, and schools' closure (switching to online education), COVID-19 disease continues to spread worldwide with several severe economic and public health consequences. Around the end of 2020, many vaccines have been approved and adopted. Saudi Arabia has faced the first wave of the disease successfully and continues implementing several measures to eradicate it. However, the disease is showing a fluctuating behavior and multiple waves have appeared. Vaccination is considered among the most important actions to be taken to control the disease spread and progressively return to the normal lifestyle. However, a trade-off (compromise) between pharmaceutical intervention such as vaccine and "Non-Pharmaceutical Interventions" (NPIs) like partial or complete lock-downs as well as social distancing practices, were highly required to ensure some kind of balance. Despite the relative resistance to the vaccine at the beginning of the vaccination campaign (December 17, 2020), the number of administered doses in Saudi Arabia has increased reaching more than 60 million as of February 28, 2022.

Several researchers and healthcare specialists have worked on COVID-19 mitigation from analysis, prediction, forecasting, and control perspectives. However, few works have handled the disease dynamics and control from a pure engineering control perspective. Authors in [1] evaluated the impact of mass vaccination in Ontario, Canada using an agent-based transmission model. They reported that Pfizer-BioNTech and Moderna vaccines have contributed to reduce hospitalization by 27% and deaths by 31%. They concluded also that vaccination can substantially eradicate the virus. Authors in [2] studied the modeling of COVID-19 dynamics in a heterogenous population based on a compartmental model. The estimated structure of the disease has been then used to assess the effect of mass vaccination on the future progression of the epidemic. Vaccination has been found to contribute to stopping the disease in a heterogenous population composed of two sub-populations with high and low disease transmission (HT and LT). Authors in [3] proposed optimal vaccination schedules (how and when). Several scenarios exploring the efficacy of vaccines in reducing the number of deaths were proposed. The main contribution of the paper was the design of optimal vaccine policies and its application to the case study of Mexico. The proposed schedules may help the decision-makers to mitigate the disease. The authors in [4] have proposed a

Decision-Making Supporting System (DMSS) for predicting the COVID-19 effects under several control measures including vaccination. Different data from several countries and regions were used. The results showed reduced number of deaths if 25% of the population is vaccinated. Authors in [5] considered the quantification of the uncertainty of a mathematical model for COVID-19 epidemic. A compartmental model including the vaccination as control variable was considered. Social distancing measures are found to introduce uncertainty in the model which should be quantified correctly. This approach has been found to help in mitigating the disease under different strategies including two doses. The authors proposed a schedule for mass vaccination. Since COVID-19 dynamics are known to be complex, authors in [6] developed dynamic models for the disease based on data from the UK. They reported that vaccination alone is insufficient in eradicating the disease and that Non-Pharmaceutical Interventions (NPIs) are needed. Based on the modified SIR model, authors in [7] tackled the problem of optimally reaching the end of COVID-19 pandemic under an effective vaccination plan in India, Brazil, and USA. The case of gamma variant of COVID-19 in Brazil was studied in [8] where an optimal vaccination strategy was designed and different scenarios were considered. Moreover, authors in [9] analyzed the effect of different vaccination profiles in Italy. Additional insights about the effect of vaccination strategies for different variants, under various scenarios and in different countries/locations can be found in [10-14]. Other aspects of COVID-19 pandemic related research include early detection of the virus based on image processing [15], machine and deep learning (ML/DL) techniques for detection, forecasting, analysis and control of the disease [16], and contactless thermometer for temperature measurement [17], to cite a few.

To the best of our knowledge, only a handful of studies have studied the vaccination process of COVID-19 from a control engineering perspective. For that purpose, the main objective of the present study is to provide an optimal mass vaccination strategy to be applied in Saudi Arabia under different scenarios. This study will first model the disease dynamics and identify its parameters and then design a control strategy in terms of vaccination schedules optimal controllers.

II. METHODOLOGY

In this section, the steps of implementing an optimal vaccination strategy for the case study of Saudi Arabia will be presented in detail. First, the overall architecture of the work will be outlined. Second, a transfer function model using the daily number of administered vaccines as input and the number of daily new infections as output will be established and calibrated. Third, different optimal controllers (three variants of the Proportional-Integral-Differential (PID) controller) will be synthesized under different scenarios using real records. Figure 1 depicts the architecture of the followed steps.

In this study, the vaccine administration and its effect on the daily new infections are viewed as a dynamic system modeled using the transfer function:

$$F(z) = \frac{Y(z)}{V(z)} \quad (1)$$

$$F(z) = \frac{a_0 + a_1 z^{-1} + \cdots + a_{n-1} z^{n-1} + a_n z^{-n}}{1 + b_1 z^{-1} + \cdots + b_{m-1} z^{m-1} + b_m z^{-m}} \quad (2)$$

Based on the previous equations, the effect of the daily number of administered vaccines and the number of daily new infections is expressed as:

$$y(t) = \sum_{j=0}^{j=n} a_j V(t-j) - \sum_{l=1}^{l=m} b_l y(t-l) \quad (3)$$

where $y(t)$ is the number of daily new infections and $V(t)$ is the number of vaccines administered daily to control the evolution of $y(t)$, both considered at the t^{th} day. z is an operator such that z^{-1} indicates the one-day delay.

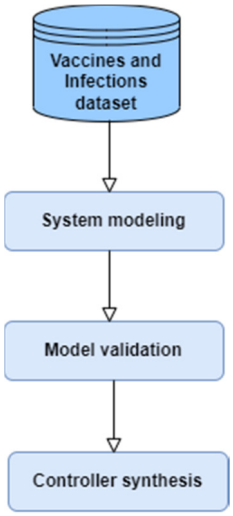

Fig. 1. Architecture of the optimal vaccination strategy.

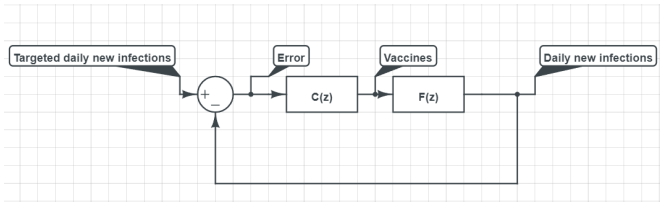

Fig. 2. Optimal vaccination strategy closed loop representation.

In the first step, the system will be considered as an open loop to identify its parameters (coefficients in (3)). For this purpose, the PSO technique is used (see the flowchart in Figure 3). The transfer function parameters are assigned to the position vector components (j) of the i^{th} particle, $Pos(i,j)$. As per the PSO paradigm, velocity, $Vel(i,j)$, personal best position, $Pers(i,j)$, and the global best position, $Glob(i,j)$ are also associated. After a random initialization inside the search-space of each component and for each dimension, the swarm (group) of particles is flown progressively toward the sub-optimal solution of the optimization problem. In the current study, the objective of the optimization problem is to minimize the quadratic between the actual daily number of infections and the same number provided by (3).

$$\text{Minimize } \sum_1^N (y_{act} - y_{est}{}^2) \quad (4)$$

where N is the number of observations (daily administered vaccines and daily new infections).

The movement equations are described as follows:

$$Vel^{t+1}(i,j) = w^t Vel^t(i,j) + C_1 r_1 \left(Pos^t(i,j) - Pers^t(i,j)\right) + C_1 r_1 \left(Pos^t(i,j) - Glob^t(i,j)\right) \quad (5)$$

$$Pos^{t+1}(i,j) = Pos^t(i,j) + Vel^{t+1}(i,j)$$

where t is the iteration number, w is an inertia weight decreasing from 0.9 to 0.4, C_1 and C_2 are two constant parameters and r_1 and r_2 are two random numbers inside the interval [0 1]. For more details about the PSO technique, the interested reader can refer to [18] and the references therein.

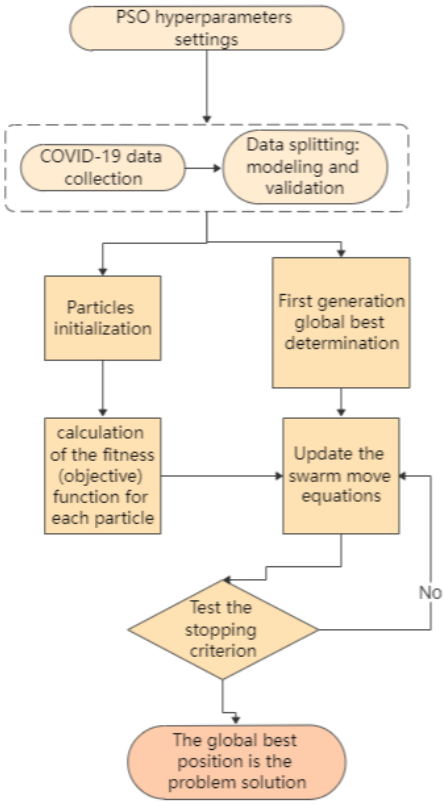

Fig. 3. PSO flowchart for modeling COVID-19 dynamics.

As per Routh–Hurwitz stability criterion for discrete-time linear systems, the search-space limits for all coefficients are chosen to be the interval [-1 1]. Routh–Hurwitz stability criterion has been extensively used in stability analysis. The main feature of this criterion is that it allows deciding about the stability of linear and nonlinear systems only through analyzing the model coefficients without any need to calculate the eigenvalues [19]. Due to its practicability, the Routh-Hurwitz criterion has been used in many applications such as grid-connected filters and connectors [20] and tuberculosis disease transmission stability [21].

III. RESULTS AND DISCUSSION

The dataset used to conduct this study was collected from [22]. It included records of COVID-19 around the world (infections, recoveries, deaths, vaccines, hospitalizations, etc.). 358 observations of new daily infections and administered vaccines in Saudi Arabia covering the period between 2021-3-8 and 2022-2-28 were used. N=300 observations were used for the identification of the model open-loop parameters of (3) using the algorithm described above. The remaining 58 observations were used to validate the calibrated model.

Three metrics were used to measure the quality of the model and to justify the extent it can reproduce real observations. These metrics are described as follows [18]:

Mean Absolute Percentage Error ($MAPE$):

$$MAPE = \frac{100}{N} \sum_{t=1}^{N} \frac{|y_{act}(t) - y_{est}(t)|}{\overline{y_{act}}} \quad (7)$$

Coefficient of determination (R^2):

$$R^2 = 1 - \frac{\frac{1}{N}\sum_{t=1}^{N}(y_{act}(t) - y_{est}(t))^2}{\frac{1}{N}\sum_{t=1}^{N}(y_{act}(t) - \overline{y_{act}})^2} \quad (8)$$

Root Mean Square Error ($RMSE$):

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_{act}(t) - y_{est}(t))^2} \quad (9)$$

where y_{act} and y_{est} are the estimated and the actual number of new infections recorded at the t^{th} day and $\bar{y}$ is the average value.

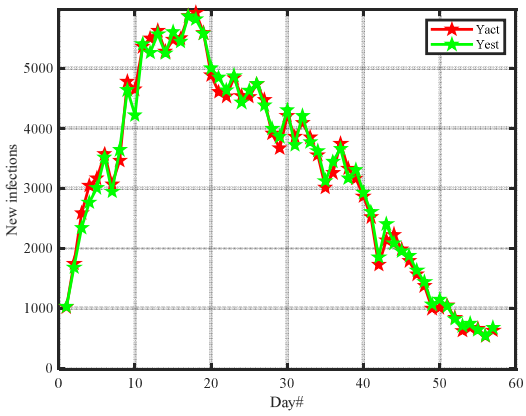

Fig. 4. Actual and estimated new daily infections during the testing phase.

The model coefficients and performance metrics (obtained for the testing phase) are shown in Table I. As depicted in Figures 4-5, the actual and estimated curves are almost the same. In addition, the performance metrics are high since the coefficient of determination is almost close to 1 (1 corresponds to the ideal fit) and the $MAPE$ is low (3.1675%). An $RMSE$ of 132 can be considered as interesting when compared to the total number of infections. The open-loop transfer function identification convergence process is depicted in Figure 6. It can be observed that the optimal criterion started from high values at the beginning of the PSO-based optimization process

and converges to small values (around zero) starting from iteration 30 (the number of iterations was chosen as 100 and that was considered as the stopping criterion of the optimization process). The model coefficients are all inside the unit circle (between -1 and 1) as per the Routh-Hurwitz criterion of stability.

TABLE I. MODEL OPTIMAL PARAMETERS AND PERFORMANCE METRICS FOR THE TESTING PHASE

Parameter	***MAPE***	R^2	***RMSE***	a_0	a_1	a_2	b_1	b_2	b_3
Value	3.1675%	0.9933	132	5.3523e-05	1.0446e-04	-1.7041e-04	-0.995	0.327	-0.334

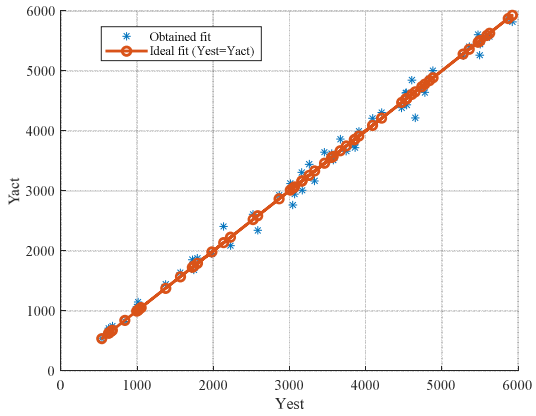

Fig. 5. Scattered plot of actual and estimated (by the model) new daily infections during the testing phase.

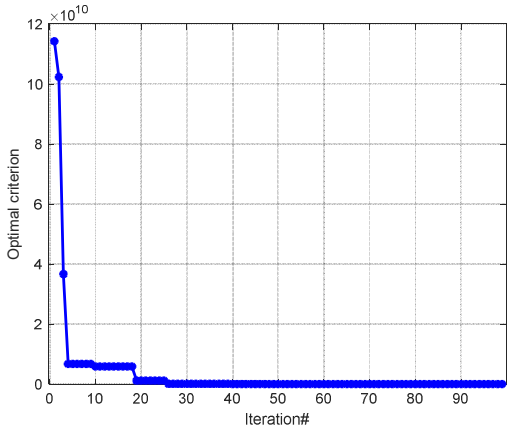

Fig. 6. Convergence of the model identification process.

TABLE II. OPTIMAL CONTROLLERS FOR THE VACCINATION PROCESS IN SAUDI ARABIA

Controller type	**Controller parameters**
P	$Pc(z) = Kp$ = -235
PI	$PIc(z) = Kp + Ki\frac{Ts}{z-1}$ with Kp = -1.57e+03, Ki = -4.54, Ts = 1
PID	$PIDc(z) = Ts = Kp + Ki\frac{Ts}{z-1} + Kd\frac{z-1}{Ts}$ with Kp = 8.76, Ki = 0.00016, Kd = 1.2e+05, Ts = 1

Using Matlab's proportional-integral-derivative (PID) tune command, proportional (P), proportional-integral (PI), and PID controllers were synthesized. The transfer functions of the regulators as well as the corresponding closed-loop transfer functions are provided in Table II. The main objective of the designed PID controller is to force the output (daily new infections) to follow a predefined profile imposed by the decision makers. This imposed profile may have as a purpose to flatten the disease spread curve within a fixed period. In addition, disturbance factors such as unpredictable events or pilgrims coming from different countries for performing Hajj and Umrah (as Saudi Arabia is hosting the two Holey Mosques in Makkah and Madinah) are considered as disturbances which are rejected by the PID (or derivative) controller.

IV. CONCLUSION

In this paper, an optimal vaccination strategy for COVID-19 was designed based on the discrete-time linear system theory and the swarm intelligence approach, namely the Particle Swarm Optimization (PSO). The vaccination process modeled as a transfer function having the daily number of administered vaccines as input and the daily number of new infections as output, was optimally tuned taking into consideration stability issues based on Routh-Hurwitz necessary and sufficient stability condition (the poles of the transfer function should be inside the unit circle). Three different controllers (P, PI, and PID) were designed. The designed controllers should generate optimal vaccination profiles (control signals) that should drive the number of new daily infections to track any profile of new infections that may be targeted by the decision-makers. The obtained results are generic in their broad sense and they can be easily extended to other diseases. As perspectives, we can expect to collect datasets from other diseases and test the feasibility of the approach presented in this paper. In terms of decision-making, the proposed approach constitutes a strong tool that can help the decision makers to mitigate the virus and limit its spread using pharmaceutical interventions such as vaccines in addition to non-pharmaceutical interventions.

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REFERENCES

[1] T. N. Vilches, K. Zhang, R. Van Exan, J. M. Langley, and S. M. Moghadas, "Projecting the impact of a two-dose COVID-19 vaccination campaign in Ontario, Canada," *Vaccine*, vol. 39, no. 17, pp. 2360–2365, Apr. 2021, https://doi.org/10.1016/j.vaccine.2021.03.058.

[2] V. Volpert, M. Banerjee, and S. Sharma, "Epidemic progression and vaccination in a heterogeneous population. Application to the Covid-19 epidemic," *Ecological Complexity*, vol. 47, Sep. 2021, Art. no. 100940, https://doi.org/10.1016/j.ecocom.2021.100940.

[3] M. A. Acuña-Zegarra, S. Díaz-Infante, D. Baca-Carrasco, and D. Olmos-Liceaga, "COVID-19 optimal vaccination policies: A modeling

study on efficacy, natural and vaccine-induced immunity responses," *Mathematical Biosciences*, vol. 337, Jul. 2021, Art. no. 108614, https://doi.org/10.1016/j.mbs.2021.108614.

[4] C. A. Varotsos, V. F. Krapivin, Y. Xue, V. Soldatov, and T. Voronova, "COVID-19 pandemic decision support system for a population defense strategy and vaccination effectiveness," *Safety Science*, vol. 142, Oct. Art. no. 105370, 2021, https://doi.org/10.1016/j.ssci.2021.105370.

[5] A. Olivares and E. Staffetti, "Uncertainty quantification of a mathematical model of COVID-19 transmission dynamics with mass vaccination strategy," *Chaos, Solitons & Fractals*, vol. 146, May 2021, Art. no. 110895, https://doi.org/10.1016/j.chaos.2021.110895.

[6] S. Moore, E. M. Hill, M. J. Tildesley, L. Dyson, and M. J. Keeling, "Vaccination and non-pharmaceutical interventions for COVID-19: a mathematical modelling study," *The Lancet Infectious Diseases*, vol. 21, no. 6, pp. 793–802, Jun. 2021, https://doi.org/10.1016/S1473-3099(21)00143-2.

[7] D. Chaturvedi and U. Chakravarty, "Predictive analysis of COVID-19 eradication with vaccination in India, Brazil, and U.S.A," *Infection, Genetics and Evolution*, vol. 92, Aug. 2021, Art. no. 104834, https://doi.org/10.1016/j.meegid.2021.104834.

[8] L. S. Ferreira *et al.*, "Modelling optimal vaccination strategies against COVID-19 in a context of Gamma variant predominance in Brazil," *Vaccine*, vol. 40, no. 46, pp. 6616–6624, Nov. 2022, https://doi.org/10.1016/j.vaccine.2022.09.082.

[9] M. Coccia, "Optimal levels of vaccination to reduce COVID-19 infected individuals and deaths: A global analysis," *Environmental Research*, vol. 204, Mar. 2022, Art. no. 112314, https://doi.org/10.1016/j.envres.2021.112314.

[10] D. Kim and Y. J. Lee, "Vaccination strategies and transmission of COVID-19: Evidence across advanced countries," *Journal of Health Economics*, vol. 82, Mar. 2022, Art. no. 102589, https://doi.org/10.1016/j.jhealeco.2022.102589.

[11] G. B. Libotte, F. S. Lobato, G. M. Platt, and A. J. Silva Neto, "Determination of an optimal control strategy for vaccine administration in COVID-19 pandemic treatment," *Computer Methods and Programs in Biomedicine*, vol. 196, Nov. 2020, Art. no. 105664, https://doi.org/10.1016/j.cmpb.2020.105664.

[12] M. Angeli, G. Neofotistos, M. Mattheakis, and E. Kaxiras, "Modeling the effect of the vaccination campaign on the COVID-19 pandemic," *Chaos, Solitons & Fractals*, vol. 154, Jan. 2022, Art. no. 111621, https://doi.org/10.1016/j.chaos.2021.111621.

[13] A. Thongtha and C. Modnak, "Optimal COVID-19 epidemic strategy with vaccination control and infection prevention measures in Thailand," *Infectious Disease Modelling*, vol. 7, no. 4, pp. 835–855, Dec. 2022, https://doi.org/10.1016/j.idm.2022.11.002.

[14] H. Tiirinki, M. Viita-aho, L.-K. Tynkkynen, M. Sovala, V. Jormanainen, and I. Keskimäki, "COVID-19 in Finland: Vaccination strategy as part of the wider governing of the pandemic," *Health Policy and Technology*, vol. 11, no. 2, Jun. 2022, Art. no. 100631, https://doi.org/10.1016/j.hlpt.2022.100631.

[15] N. Kumar, A. Hashmi, M. Gupta, and A. Kundu, "Automatic Diagnosis of Covid-19 Related Pneumonia from CXR and CT-Scan Images," *Engineering, Technology & Applied Science Research*, vol. 12, no. 1, pp. 7993–7997, Feb. 2022, https://doi.org/10.48084/etasr.4613.

[16] S. A. A. Biabani and N. A. Tayyib, "A Review on the Use of Machine Learning Against the Covid-19 Pandemic," *Engineering, Technology & Applied Science Research*, vol. 12, no. 1, pp. 8039–8044, Feb. 2022, https://doi.org/10.48084/etasr.4628.

[17] N. K. Al-Shammari, H. B. Almansour, and M. B. Syed, "Development of an Automatic Contactless Thermometer Alert System Based on GPS and Population Density," *Engineering, Technology & Applied Science Research*, vol. 11, no. 2, pp. 7006–7010, Apr. 2021, https://doi.org/10.48084/etasr.4103.

[18] R. Zrieq, S. Boubaker, S. Kamel, M. Alzain, and F. D. Algahtani, "Analysis and modeling of COVID-19 epidemic dynamics in Saudi Arabia using SIR-PSO and machine learning approaches," *The Journal of Infection in Developing Countries*, vol. 16, no. 01, pp. 90–100, Jan. 2022, https://doi.org/10.3855/jidc.15004.

[19] S. Bourafa, M.-S. Abdelouahab, and A. Moussaoui, "On some extended Routh–Hurwitz conditions for fractional-order autonomous systems of order $\alpha \in (0, 2)$ and their applications to some population dynamic models," *Chaos, Solitons & Fractals*, vol. 133, Apr. 2020, Art. no. 109623, https://doi.org/10.1016/j.chaos.2020.109623.

[20] F. A. Hasan, L. J. Rashad, and A. T. Humod, "Integrating Particle Swarm Optimization and Routh-Hurwitz's Theory for Controlling Grid-Connected LCL-Filter Converter," *International Journal of Intelligent Engineering and Systems*, vol. 13, no. 4, pp. 102–113, Aug. 2020, https://doi.org/10.22266/ijies2020.0831.10.

[21] R. Mahardika, Widowati, and Y. D. Sumanto, "Routh-hurwitz criterion and bifurcation method for stability analysis of tuberculosis transmission model," *Journal of Physics: Conference Series*, vol. 1217, no. 1, Feb. 2019, Art. no. 012056, https://doi.org/10.1088/1742-6596/1217/1/012056.

[22] "owid/covid-19-data," *GitHub*. https://github.com/owid/covid-19-data.